Retraction

Retracted: Big Data's Analysis and Prediction Method of Art Education Based on the BP Neural Network

Security and Communication Networks

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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.

References

[1] X. Zhu, "Big Data's Analysis and Prediction Method of Art Education Based on the BP Neural Network," *Security and Communication Networks*, vol. 2022, Article ID 9588460, 9 pages, 2022.

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Research Article

Big Data's Analysis and Prediction Method of Art Education Based on the BP Neural Network

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The traditional art education analysis and prediction are mainly based on the evaluation of human supervisors, and the evaluation results given by different evaluators vary greatly. The traditional analysis and prediction is difficult to reflect the objectivity and fairness of art education evaluation. This paper proposes a new idea of using the BP neural network model to analyze and forecast art education to improve the objectivity and impartiality of art education evaluation by big data. The work first constructed the art education evaluation index system covering the content of art education comprehensively and extensively. Then the BP neural network of art education analysis and prediction model was established. According to the content of art education evaluation system, the BP neural network's input vector contains 30 evaluation indexes that affect art education, and its output vector is the art education evaluation results. The BP neural network with the structure of $30 \times 10 \times 1$ was trained using the collected data. Finally, the work verified the scientificity of the evaluation model. The results of empirical analysis show that the established art education evaluation index system is reasonable and can reflect the artistic level of students, and the model of BP neural network has reliability in the analysis and prediction of art education big data and can objectively evaluate the level of art education.

1. Introduction

Artificial neural network is a system consisting of a large number of neurons (processing units) [1]. This system has strong independent learning ability and nonlinear and nonlocal characteristics. It is proposed based on modern neuroscience research achievements and attempts to design a new machine to make it have the information processing ability similar to the human brain by simulating the way of processing and remembering information of the brain neural network [2].

As an excellent tool for the study of complex problems, neural network technology gives full play to its super performance in the fields of identification filtering, pattern recognition, automatic control, such as student performance prediction, equipment failure diagnosis, and weather prediction. Through continuous trial and learning, the neural network can find regularity in complex data, which is the biggest advantage compared with other evaluation modes. In the evaluation system of art education, the artificial neural network can not only solve the relationship between quantitative and qualitative problems but also overcome the difficult problem of establishing complex mathematical model in the traditional evaluation process. In addition, it can overcome the artificial subjectivity and improve the efficiency of evaluation. Any noncontinuous function problem with precision approximation can be dealt with accurately in the modeling process by using the neural network method. At the same time, information storage and processing occur simultaneously in this process, which makes the neural network to be with high error correction and high processing speed. The input and output of neural network can be freely selected, and the multivariable system or single-variable system can be calculated with a general model. In the calculation process, there is no need to consider the influence of each system, and the qualitative information and quantitative information can be comprehensively processed.

The back propagation neural network (BP neural network) uses the error back propagation algorithm to learn

autonomously [3]. According to the characteristics and rules of functions, the BP neural network can automatically learn the experience from the complex data samples provided. It carries out scientific and reasonable analysis on complex problems and finds the most effective strategy and method to solve the problem. It has three layers, the input layer belongs to the front part, the hidden layer belongs to the middle part, and the output layer belongs to the end part, which forms the BP neural network.

The traditional evaluation of art education is subjective and tendentious, and the evaluation results are easily affected by the subjective judgment of the evaluators. At present, art education evaluation is also developing with the development of education big data, and gradually diversifying to the quality dimension. Therefore, in the evaluation of art education, it is necessary to collect multiple index data from multiple perspectives. The evaluation of art education also needs long-term and continuous monitoring, and the traditional evaluation method of art education is difficult to achieve timely and continuous unified standard evaluation. In order to achieve the goal of big data analysis and prediction of art education, researchers need to explore more objective and quantitative evaluation methods to achieve multidimensional and long-term evaluation.

The emergence of neural network provides hope for solving the problems of big data analysis and prediction in art education. The characteristic information of evaluation object should be collected in advance, and it becomes the input vector of neural network, and the corresponding comprehensive evaluation can only be used as the output of neural network. The trained neural network can be regarded as a tool with qualitative and quantitative functions, and the objects for comprehensive evaluation can cover the objects beyond the sample. The BP neural network is used to analyze and forecast the big data of art education, which provides theoretical support and more diversified evaluation methods for the reform and development of art education. The big data analysis and prediction method of art education based on the BP neural network enriches the evaluation theory of art education, provides new ideas for the evaluation of art education, and is conducive to the construction and development of the discipline. On the other hand, this paper provides a new thinking direction and research ideas for the follow-up related evaluation research. The analysis and prediction of art education evaluation can also help teachers improve their teaching strategies and promote the quality of art education cultivation.

2. Literature Review

2.1. BP Neural Network. The neural network consists of a large number of individual neuron nodes and the weighted values of the interactional connections between them [4]. Each node in the network represents an operation, which is called activation function. It makes neural network have a judgment and reasoning ability similar to human's through mathematical statistical method.

After more than half a century of development, the BP algorithm becomes the most widely used and successful so far [5]. The BP neural network is a network model with the topology structure of the input layer, hidden layer, and output layer. The number of layers of the neural network is correlated with the prediction accuracy. Increasing the number of layers of the neural network is beneficial to improving the output accuracy of the model, but it also increases the training time of the network. Nodes between adjacent layers of the BP network are interconnected, but nodes at the same layer are not [6]. Here, the three-layer neural network structure with a topology of $1 \times 1 \times 1$ is taken as an example, as shown in Figure 1.

In the process of forward transmission of the BP neural network, neurons at the latter layer receive input signals transmitted by neurons at the previous layer, assign weight to these signals, and compare the sum result with the threshold value of current neurons, and then process the result through the activation function to obtain the output of neurons [7]. Common activation functions include Sigmoid activation function, tanh activation function, ReLU activation function, and leaky ReLU activation function. In the BP neural network, the continuously differentiable sigmoid function is often selected as the activation function [8]. The sigmoid function is shown in formula (1), and its image is shown in Figure 2.

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

When sigmoid function is used, the relationship between the input layer and the output layer is

$$\text{Input } X = x_1 w_2 + x_2 w_1 + x_3 w_3 + \cdots + x_n w_n,$$

$$\text{Output } Y = f(X) = \frac{1}{1 + e^x}. \tag{2}$$

Input X is the input matrix, which contains the input vector $x = (x_1, x_2, x_3, \ldots, x_n)$, and Output Y is the output matrix.

The core of the BP neural network algorithm is to realize the forward propagation of signals and then reverse propagation of errors. It reverses transmission of errors from the hidden layer to the input layer through the dynamic adjustment of weights between neurons [9, 10].

A BP neural network should include Input X and expected Output Y. The BP neural network has a topological structure of $m \times l \times n$, where the input vector $x = (x_1, x_2, x_3, \ldots, x_m)$, the hidden layer input vector $hi = (hi_1, hi_2, hi_3, \ldots, h_o)$, hidden layer output vector $ho = (ho_1, ho_2, ho_3, \ldots, ho_l)$, the output layer input vector $yi = (yi_1, yi_2, yi_3, \ldots, yi_n)$, the output layer output vector $yo = (yo_1, yo_2, yo_3, \ldots, yo_n)$, and $x = (d_1, d_2, d_3, \ldots, d_n)$ is the expected output vector. The BP neural network mainly includes the weight matrix between the three layers, which are w_{hi} and w_{ho}, respectively [11]. The threshold values of the hidden layer and the output layer are t_h and t_o, respectively.

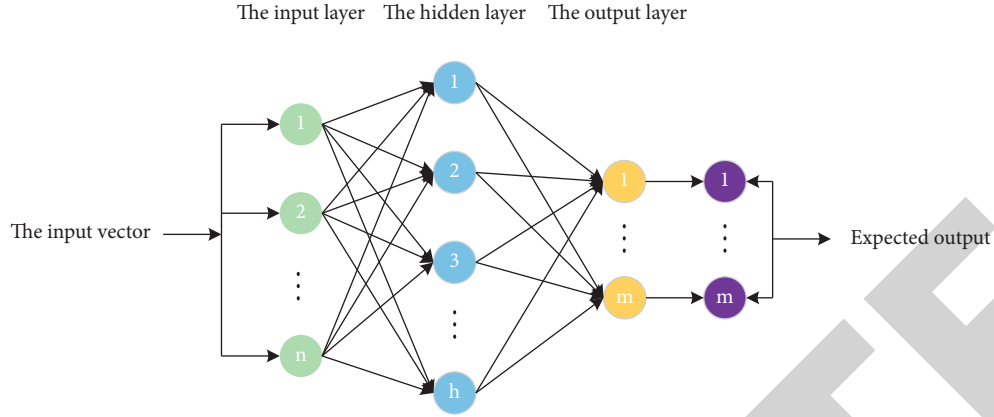Input and output neurons could be calculated in the hidden layer and output layer:

The input layer   The hidden layer   The output layer

The input vector →

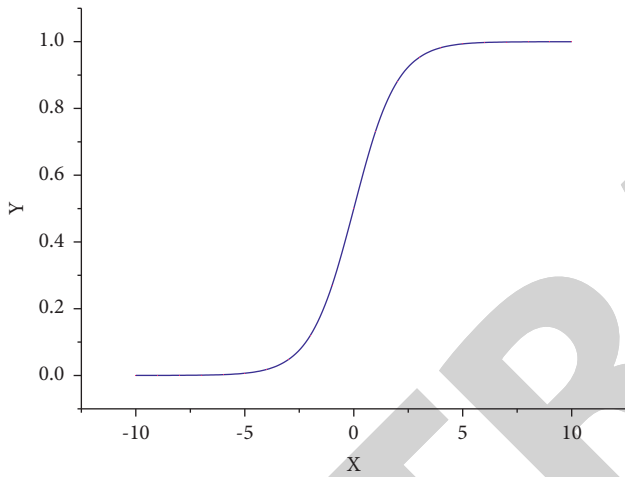Expected output

FIGURE 1: The BP neural network model.

FIGURE 2: Sigmoid function.

$$hi_h = \sum_{i=1}^{m} w_{ih} x_i - b_h, \quad h = 1, 2, \ldots, l, \tag{3}$$

$$yi_o = \sum_{h=1}^{l} w_{ho} ho_h - b_o, \quad o = 1, 2, \ldots, n, \tag{4}$$

$$yi_o = \sum_{h=1}^{l} w_{ho} ho_h - b_o, \quad o = 1, 2, \ldots, n, \tag{5}$$

$$yo_o = f(yi_o), \quad o = 1, 2, \ldots, n. \tag{6}$$

When the expected value is not equal to the actual value, the error will occur. The feedback loop is used to reduce the error and then the global error is calculated with Formula (7):

$$e = \frac{1}{2} \sum_{0=1}^{m} (d_0 - yo_o)^2. \tag{7}$$

Substitute (4)–(5) into (7), then we will get

$$e = \frac{1}{2} \sum_{o=1}^{m} \left[d_o - f\left(\sum_{h=1}^{l} w_{ho} hho_h - b_o \right) \right]^2$$

$$= \frac{1}{2} \sum_{o=1}^{m} \left\{ d_o - f\left[\sum_{h=1}^{l} w_{ho} f(hi_h) - b_o \right] \right\}^2. \tag{8}$$

It can be seen from (8) that the error term is a functional expression of weights between layers.

Therefore, the error level of the BP neural network is reduced by adjusting the weight to achieve the desired goal [12]. The partial derivative δ of the error function is calculated to obtain a more specific weight adjustment formula using (10):

$$\frac{\partial e}{\partial w_{ho}} = \frac{\partial e}{\partial yi_o} \frac{\partial yi_o}{\partial w_{ho}}. \tag{9}$$

According to (5),

$$\frac{\partial yi_o}{\partial w_{ho}} = \frac{\partial \sum_{h=1}^{l} w_{ho} ho_h - b_o}{\partial w_{ho}} = ho_h, \quad h = 1, 2, \ldots, l. \tag{10}$$

According to (7),

$$\frac{\partial e}{\partial yi_o} = -(d_o - yo_o) f'(yi_o), \quad o = 1, 2, \ldots, n. \tag{11}$$

Making $\delta o = (d_0 - yo_o) f'(yi_o)$, then we get $\partial e / \partial yi_o = -\delta o$, namely, $\partial e / \partial yi_o = -\delta o$,

Then modifying the weight w_{ho} and w_{ih} by using the δ_o δ_h and of each neuron in layers, and the results are as follows:

$$\Delta w_{ho} = -\eta \frac{\partial e}{\partial w_{ho}} = \eta \delta o ho_h, \tag{12}$$

$$\Delta w_{ih} = -\eta \frac{\partial e}{\partial w_{ih}} = \eta \delta_h x_i. \tag{13}$$

According to (12) and (13), the impression factors of weight adjustment include training rate η, error signal δ of this layer, and input value x (or y).

The operation principle of the BP neural network derived above not only includes the three-layer neural network but
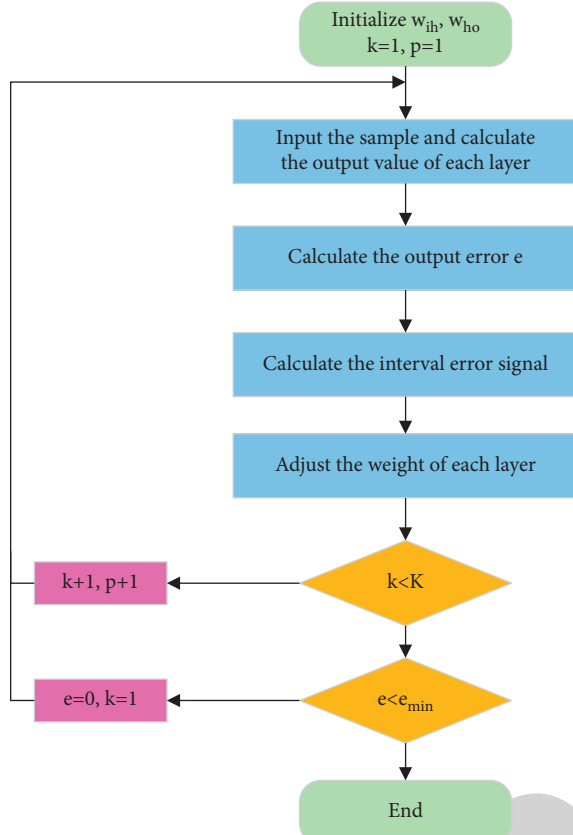
FIGURE 3: Flow chart of the BP neural network algorithm.

also applies to the multilayer neural network. According to the weight adjustment formula between adjacent layers, the operation rules and adjustment speed of the whole neural network can be obtained [13].

2.2. The BP Neural Network Algorithm.

This paper mainly uses the following steps to complete sample data processing and analyze the final results [14].

First, the sample mode and training times counter (k, p) are reset to 1, the systematic error e is reset to 0, the training rate η is set to 0–1 decimal, and the network training precision $e_{\min}$ is preset [15]. At the same time, the weight matrix w_{ih} and who are initialized with random numbers. Second, the sample x and expected vector d were input, and the output vector ho and the actual output value yo of the hidden layer were calculated with (2)–(5) [16]. Then the error e corresponding to different samples was calculated with (6), and all the errors were summarized to obtain the total error of the network. The error signal δ of the hidden and output layers is calculated and the weight adjustment values Δw_{ho} and Δw_{ih} are obtained according to (10) and (11), and then the new weight matrix of w_{ih} and who is obtained. Finally, comparing the number of input samples with the size of counter k to determine whether all samples participated in the training [17] and if all samples did not participate in the training, then we return to formula (2) for sample training again and compare the overall error e with the preset error

$e_{\min}$. If $e < e_{\min}$, the loop was jumped out, and the whole neural network training ended; otherwise, the step of (2) continued [18]. The algorithm flow chart is shown in Figure 3.

2.3. Evaluation of Art Education.

In the course of human development, evaluation and prediction are common and important decision-making processes. The evaluation of advantages and disadvantages or value is called evaluation, which covers the activity of judging and describing behavior. The estimation of future development direction is prediction. Art education evaluation is the collecting, recording, analyzing of students' learning process, and learning outcome data, which is an important link of art education. Some scholars define art education evaluation as "the process of evaluating students' behaviors according to certain standards" [19]. In art education, the main purpose of evaluating students' learning process or results through certain standards is to diagnose students' realization of the expected goals, examine whether each student's potential has been maximized in teaching, and test its teaching effect. The evaluation of art education is of great significance in the whole teaching [20]. The measurement evaluation in the development of teaching plan helps teachers to understand the needs and interests of students and, on this basis, to improve the teaching plan. The formative and diagnostic evaluation in the teaching process can give feedback on students' learning status in time so that teachers can improve the teaching focus and teaching mode constantly according to students' specific learning situation. Summative evaluation at the end of teaching not only reflects students' learning results but also verifies the realization of teaching objectives and inspires teachers to make new teaching plans.

Due to the particularity of art education, teachers' subjective evaluation is still often used in the current evaluation methods, lacking unity and objectivity. Big data are characterized by large quantification and diversification. This paper collects a large number of diversified evaluation index data of art education. The big data analysis and prediction method of art education provides quantitative and objective technical support for the evaluation of art education and helps to promote the evaluation and prediction of art education objectively and fairly.

3. Method

3.1. Index Construction and Grade Determination of the Art Education Evaluation Index System

3.1.1. Extraction of Art Education Evaluation Index Elements.

Based on the perspective of literature, case analysis, and in-depth interview, this paper extensively collects the evaluation index elements of art education, then removes the elements with low frequency and integrates the elements with the same phrase semantics, and conducts in-depth discussion with experts and scholars on the preliminary evaluation index elements of art education. Finally, an art education index system with 10 first-level indexes and 30 second-level indexes is constructed.
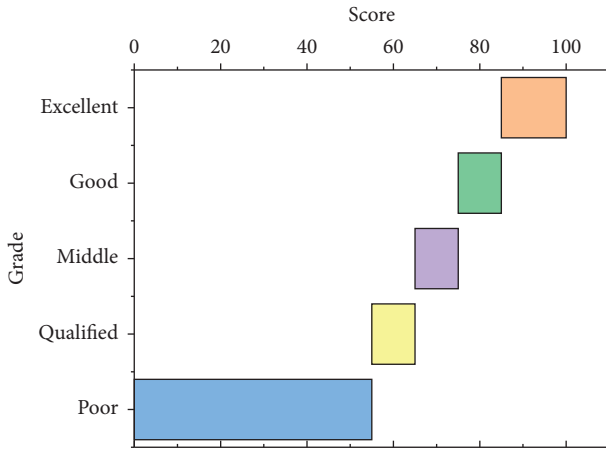
FIGURE 4: Evaluation grading.

3.1.2. Using the Delphi Method to Create Art Education Evaluation Grade.

To measure the grade of art education, this work uses the Delphi method to judge the grade of art education of prototype objects. The first is the selection of experts. The selection of experts is the key to the success of Delphi method [21]. In the selection of expert members, attention should be paid to the inclusion of experts in different fields, highlighting the heterogeneity, and only a single field of education "peer experts" is not scientific and comprehensive. The second is the implementation of the Delphi law. Step 1: state the objective of the evaluation and the target to be achieved by the indicator system. The research content is presented, and the experts answer the questions in an open-ended manner. Step 2: synthesize the answers of the experts in the previous step and evaluate the order according to the importance. Step 3: according to the first two steps, each indicator is listed in turn according to the importance of the majority of experts and then compared with each expert on whether it meets the expectations of each expert standard; if not, please say or fill in their own reasons. Step 4: based on the above three steps, the final art education grade can be made and a relatively consistent conclusion can be drawn.

The sample objects are divided into the following five grade with the score of art education level, and the results are as shown in Figure 4. The scale can be given as the poor grade: 0–55, the qualified grade: 55–65, the middle grade: 65–75, the good grade 75–85, and the excellent grade: 85–100.

3.2. Designing of the Art Education Evaluation Model Based on the BP Neural Network

3.2.1. Determining the Number of Neural Network Layers.
In 1998, Robert Hecht-Nielson verified that the BP neural network is a complete network that can realize complete mapping. The premise of the verification is that any closed interval is a continuous function, and then the mapping from n dimension to m dimension is realized through the process of infinite squeezing of the BP network with the
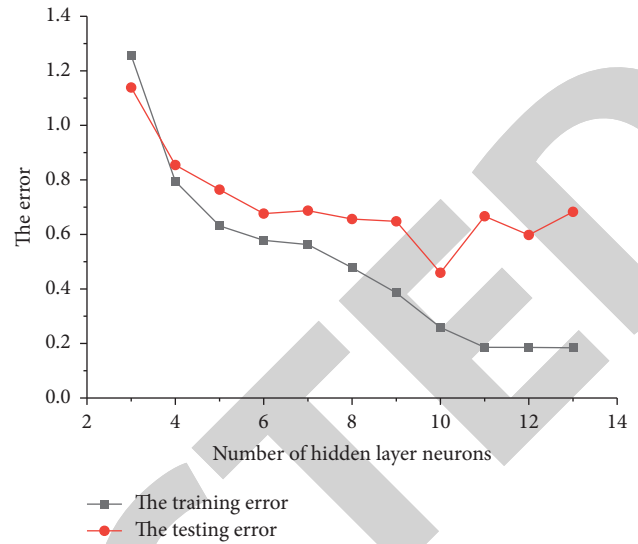

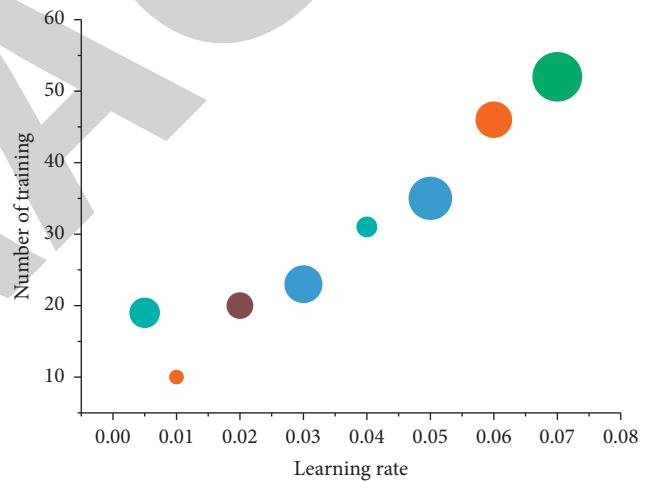FIGURE 5: The relation between the number of neuron and error.

FIGURE 6: Error comparison under different learning rates and training times.

hidden layer [22]. Kolmogorov theorem reveals that even three-layer neural network has a wide range of applications and strong performance, so a three-layer neural network can approach the set function with any error, provided that the number of hidden layer nodes is not limited [23]. Increasing the number of hidden layers has both advantages and disadvantages. Therefore, in order to obtain a lower training error, the optimal choice is to create a three-layer neural network model.

3.2.2. Defining the Number of Neurons at Each Layer.
Determining the number of neurons in the input layer. The number of neurons in the input layer is an important internal characteristic of the neural network. On this basis, the evaluation indexes and the number of neurons are equivalent and unified, and the evaluation indexes are 30, so the number of neurons in the input layer is $n = 30$.

TABLE 1: Performance of different training functions.

Algorithm	Function	The training steps	Performance
Levenberg–Marquardt algorithm	TRAINLM	1000	4.93
Rprop algorithm	TRAINRP	68	2.86
Scaled conjugate gradient algorithm	TRAINSCG	1000	1.71
One-step secant algorithm	TRAINSOSS	1000	1.35
Gradient descent method	TRAINGD	1000	2.69
Gradient descent method with adaptive learning rate and the momentum factor	TRAINDX	235	2.89

Determining the number of neurons in the hidden layer and output layer. The actual output value of the network is equal to the number of neurons in the output layer, that is, $m = 1$. If the number of neurons is few, there is few information; if the number is large, it will lead to poor fault tolerance, too long training time, and "excessive match." Therefore, the optimal value exists, which can be obtained by the formula

$$l = \sqrt{n + m} + a. \tag{14}$$

Through analysis, it is found the hidden layer contains 3–13 neurons and the training error decreases continuously, indicating that there is association. The test error fluctuates when the value of hidden layer neurons is 10–13. In general analysis, the number of hidden layer neurons is 10, which is the best choice, as shown in Figure 5.

3.2.3. Determining the Learning Rate. The efficiency of neural network training and testing were affected by learning rate. The learning rate is equivalent to η. When the learning rate is large, the weight is large and the convergence is fast, leading to the network fluctuation. Low learning rate leads to variable network efficiency and slow convergence. Such problems can be solved by introducing the momentum term α.

$$\Delta \mathscr{W}_{ij}(n) = \alpha \Delta \mathscr{W}_{ij}(n - 1) + \eta \delta_j(n) \mathscr{V}_i(n). \tag{15}$$

According to the evaluation results, the errors and training times in Figure 6 are analyzed; with the change of learning rate, the number of training also changes. When the learning rate is 0.01, the number of training is the smallest. Therefore, the learning rate of text selection is not 0.01.

3.2.4. Determining the Training Function. Six kinds of training functions with representation which are widespread used are listed in Table 1. The training results of different training functions are compared from the training steps and performance, respectively, and the performance advantages of different training functions are highlighted. The Levenberg–Marquardt algorithm is the most widely used nonlinear least squares algorithm. It is the use of gradient to find the maximum (small) value of the algorithm, figuratively speaking, and it is a "mountain climbing" method. It has the advantages of both the gradient method and Newton method. Previous studies have shown that the Levenberg–Marquardt algorithm has the best performance and the minimum mean square error. Therefore, it is the optimal

choice to select the Levenberg–Marquardt algorithm as training function in this paper.

3.2.5. Determining the Momentum Factor α. The momentum factor plays an important role to the neural network, especially in the process of training which can effectively avoid network which produces the phenomenon such as local minimum and local maximum, trial and error method summarized according to the experiment, and the momentum factor value of 0.85 or so commonly; therefore, in this paper, based on the experimental trial and error method, the momentum factor value is 0.9, and the neural network model achieves the best effect of the experiment.

3.2.6. Data Initialization. The BP neural network has been trained by the collected data, the verified and tested data becomes an effective prediction model, and the corresponding art education grade categories are summarized according to the Delphi method.

4. Results

In this work, 2546 research samples were selected. The research objects were all sophomores in art colleges, who had certain artistic ability, which is helpful to objectively measure their artistic level. The art education evaluation indexes were taken as the input vector of BP neural network model, and the corresponding score of the art education level was taken as the output vector, respectively, into the neural network model for model training, and then the accuracy of the model was verified, and finally the evaluation model was tested.

4.1. Creating the BP Neural Network. According to the test requirements and characteristics, this work used MATLAB to complete the construction of neural network model, choose neural network fitting tools, data fitting, and modeling.

First, questionnaires were issued according to the evaluation indicators of art education, data were collected, and evaluation grades were determined according to the Delphi method. Second, the BP neural network model is established to determine the number of nodes in each layer of the neural network and determine the learning rate, and then the data is imported into the neural network model to train the neural network. When the error range is met or the training number is the maximum, the training is finished. Finally, the test data and expected data are input for
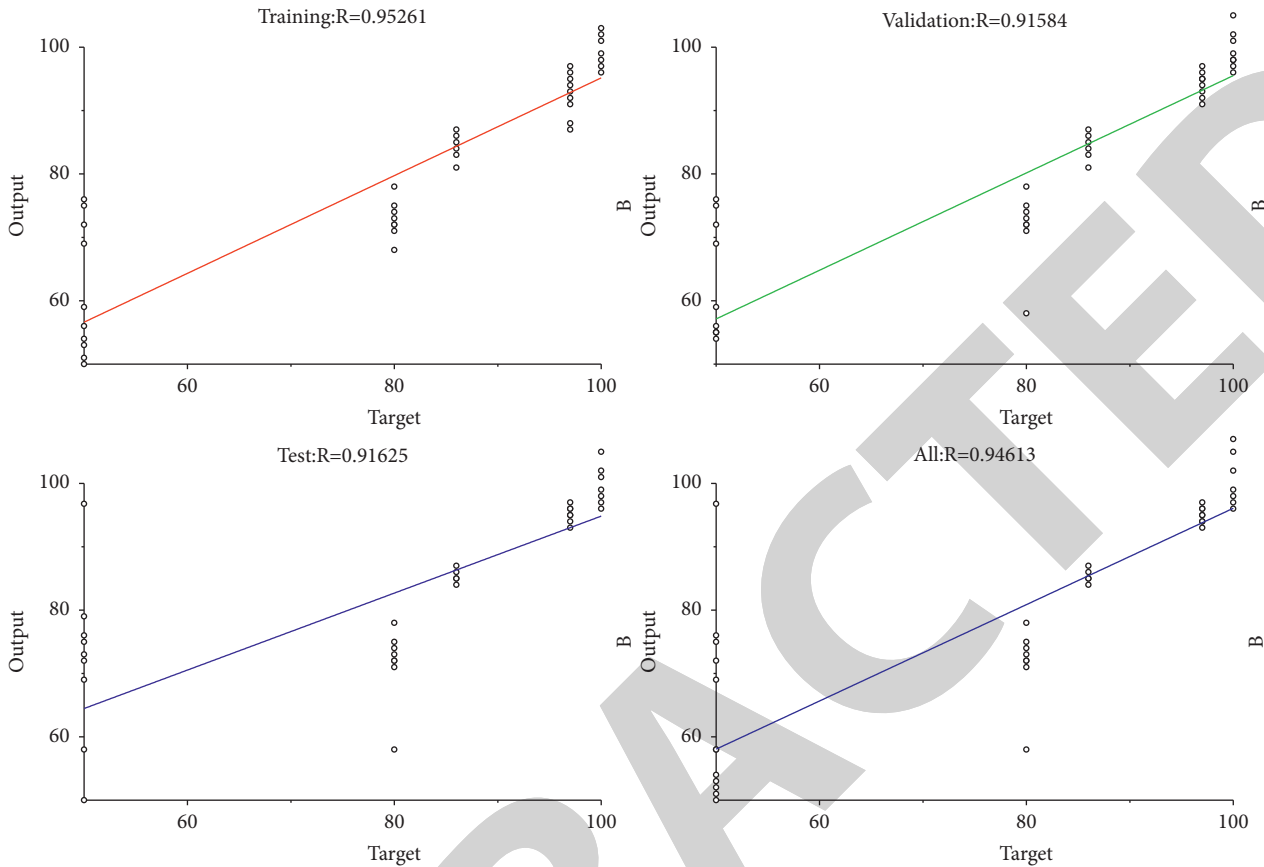
FIGURE 7: Fitting the regression analysis graph with the neural network.

simulation experiments. Among them, the art education evaluation index data are imported into the neural network model platform as input vector, and the expected value is imported into the network model as target vector to provide data support for the next network model training. As long as the data are imported correctly, the model can be more scientific and reasonable.

In the data group of training, verification, and testing, the data collected are divided into 70% training data, 15% verification data, and 15% testing data according to the principle of random allocation of data. Data partitioning plays a key role in the accuracy and rationality of the network model.

When the number of hidden layer nodes is 3–13, after comparison, adjustment, and re-experiment, the results show that when the number of nodes in the hidden layer is 3–9, the fit degree is low, while when the number of nodes in the hidden layer is 11 and 12, the over-fit degree is serious. Therefore, the best fit degree is when the number of nodes in the hidden layer is 10, which is more in line with the requirements of the simulation experiment. At this time, the BP neural network model has higher accuracy and effectiveness. Therefore, the number of hidden layer nodes in the final experiment is determined to be 10.

4.2. Training the BP Neural Network.

The BP neural network model was applied and created on the MATLAB software platform. According to the above analysis, the three-layer

neural network structure of the BP neural network model was set as $30 \times 10 \times 1$. Input vector P and target vector T are imported into the BP neural network model with all parameters set. Data are randomly divided during the neural network training algorithm. The training algorithm is the L-M algorithm, and the performance is mean square error. There are also attributes of training time, performance, gradients, and verification checks in the training process.

According to the parameters of the BP neural network model and the training results, it is proved that the training process and verification process of the BP neural network as well as the overall test results are quite ideal. According to the analysis in Figure 7, the R value in the fitting regression of training process is equal to 0.91584, the R value in the fitting regression of verification process is equal to 0.91759, and the R value in the fitting regression of overall process is equal to 0.91625. According to literature [24], the closer the R is to 1, the fitting effect of the BP neural network model is more ideal, which also shows that the experimental data and model have a certain degree of discipline and rationality. The accuracy of the experiment was further verified by fitting the regression analysis graph with the neural network.

4.3. Testing the BP Neural Network.

After training the BP neural network, the test data are randomly selected to test the BP neural network model to obtain the corresponding evaluation value of art education. The comparison between
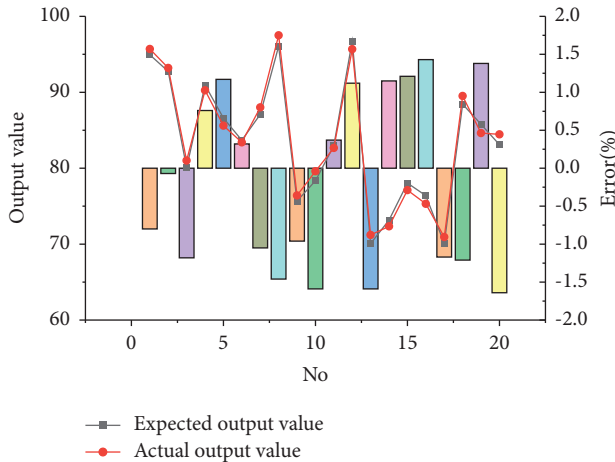
FIGURE 8: BP neural network test results.

the actual value of the network output and the expected value and errors is shown in Figure 8. The overall analysis of results shows that the actual value is basically consistent with the expected value without significant change. It also reflects the reliability of the neural network model and the rationality of the collected data. Through the BP neural network test and output of the actual value, the actual value is valid, the expected value is reasonable, and the maximum relative error of the two is 1.72%, which basically tends to the ideal state. The actual value of the neural network after training is basically consistent with the expected value, except that local fluctuation occurs at the numbers 9, 10, 15, 16, 19, and 20, which is also within the acceptable range.

4.4. Analysis of Evaluation Results. According to the analysis, the comparison result of the actual value and the expected value is relatively ideal. Each scoring result corresponds to the data of 30 evaluation indexes of a student, which is mapped to the art education ability level through different scoring values. Therefore, the evaluation results are analyzed as follows. The higher the evaluation score, the stronger the artistic foundation. Some of the students who scored above 85 had participated in art competitions. Most of the students who scored above 75 had many years of art training experience.

5. Discussion

Although this research has made some progress and breakthrough, there are still some deficiencies to be further studied. The training results of the BP neural network will be directly affected by sample data, so how to select representative data is of great importance and is one of the directions for further research in the future. Although the simulation experiment shows that BP neural network can be used in this research and the effect is good, there is still a lack of effective test for the results of artificial neural network, which makes the results less convincing.

At the same time, when the error of standard BP algorithm decreases, it will inevitably produce the oscillation phenomenon, which will seriously affect the convergence

speed of the network. For some complex problems, the BP algorithm may need several hours or even longer learning and training, and the biggest weakness of learning is that convergence is difficult to master. The learning error of the BP neural network often stays at a standstill during the descent process. After thousands of iterations, it can recover to a fast descent speed. In the process of training, a decrease in the stagnant state of error often occurs because the network falls into the local minimum point. When the BP neural network is trapped in the local minimum, it is difficult for the error to continue to decrease, and it is likely to stop learning the structure of the BP neural network because it mistakenly thinks that the optimal weight is found. The determination of the structure of the BP neural network lacks sufficient theoretical basis. When using the BP neural network, the first difficulty encountered is to determine the optimal structure of the network. In practical application, different structure determination principles are followed, and a large number of simulation experiments are needed to verify the rationality of the selected structure. How to determine the number of network layers and nodes to be selected for each layer is mostly determined by experience, and the theoretical basis is not sufficient.

The big data analysis and prediction of art education based on the BP neural network also needs to solve which method to initialize sample data and how to select indicators for different objects in different periods. It is suggested that researchers in this field should combine the neural network algorithm with the traditional detection method in the next stage to improve the evaluation process of art education. Because of the complexity of different problems, the number of training sample sets, the number of thresholds, target errors, and many other factors affect the selection of neural network types, and the modeling methods needed in different environments are completely different, so it is still necessary to find a reasonable model to solve the modeling problems in the future work.

6. Conclusion

This study proposes and uses the BP neural network to analyze and forecast the big data of art education. It has the characteristics of high convergence speed and strong learning ability, which can effectively analyze and forecast art education. The big data analysis and prediction of art education based on the BP neural network overcome the complexity of traditional art education evaluation, make the evaluation simulation results more accurate and conform to the actual situation, and weaken the influence of human factors in the traditional model. In the simulation experiment, the model can give full play to the superiority of artificial neural network and is a brand-new evaluation method of art education, which can objectively reflect the quality of education, put forward suggestions for improvement, and cultivate artistic talents. This paper innovatively uses the BP neural network technology and big data

technology to predict art education and improve the accuracy of art education prediction.

Data Availability

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Y. C. Wu and J. W. Feng, "Development and application of artificial neural network," *Wireless Personal Communications*, vol. 102, no. 2, pp. 1645–1656, 2018.

[2] Y. Wu, "Application of artificial neural network in communication signal processing [J]," *Agro Food Industry Hi-Tech*, vol. 28, no. 3, pp. 1920–1924, 2017.

[3] L. Zhang, F. Wang, T. Sun, and B. Xu, "A constrained optimization method based on BP neural network," *Neural Computing & Applications*, vol. 29, no. 2, pp. 413–421, 2018.

[4] L. Zheng, H. Shi, and M. Gu, "Infrared traffic image enhancement algorithm based on dark channel prior and gamma correction," *Modern Physics Letters B*, vol. 31, no. 19-21, p. 1740044, 2017.

[5] L. Wang, J. Shen, Q. Zhou, Z. Shang, H. Chen, and H. Zhao, "An evaluation of the dynamics of diluted neural network," *International Journal of Computational Intelligence Systems*, vol. 9, no. 6, pp. 1191–1199, 2016.

[6] R. Wang and B. Zha, "A research on the optimal design of BP neural network based on improved GEP," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 33, no. 03, p. 1959007, 2019.

[7] H. Koyuncu, "Determination of positioning accuracies by using fingerprint localisation and artificial neural networks," *Thermal Science*, vol. 23, no. Suppl. 1, pp. 99–111, 2019.

[8] S. R. Chiluveru, M. Tripathy, and B. Mohapatra, "Accuracy controlled iterative method for efficient sigmoid function approximation," *Electronics Letters*, vol. 56, no. 18, pp. 914–916, 2020.

[9] F. Cao, K. Yao, and J. Liang, "Deconvolutional neural network for image super-resolution," *Neural Networks*, vol. 132, pp. 394–404, 2020.

[10] P. Cheng, D. Chen, and J. Wang, "Research on prediction model of thermal and moisture comfort of underwear based on principal component analysis and Genetic Algorithm–Back Propagation neural network," *International Journal of Nonlinear Sciences and Numerical Stimulation*, vol. 22, no. 6, pp. 607–619, 2021.

[11] P. Cheng, D. Chen, and J. Wang, "Research on underwear pressure prediction based on improved Ga-bp algorithm [J]," *International Journal of Clothing Science & Technology*, vol. 33, no. 4, pp. 619–642, 2021.

[12] M. Lupo Pasini, J. Yin, and Y. W. Li, "A scalable constructive algorithm for the optimization of neural network architectures [J]," *Arxiv E-Prints*, vol. 11, no. 1909, pp. 1–5, 2019.

[13] Y. Dong, X. Li, and J. Zhang, "Application of fractional theory in quantum back propagation neural network[J]," *Mathematical Methods in the Applied Sciences*, vol. 19, no. 003, p. 63, 2021.

[14] S. Wang, J. Zhang, M. Liu, B. Liu, J. Wang, and S. Yang, "Large-signal behavior modeling of GaN P-hemt based on GA-ELM neural network," *Circuits, Systems, and Signal Processing*, vol. 41, no. 4, pp. 1834–1847, 2021.

[15] D. Wei, "Network traffic prediction based on RBF neural network optimized by improved gravitation search algorithm," *Neural Computing & Applications*, vol. 28, no. 8, pp. 2303–2312, 2017.

[16] X. Pang, Z. Li, M. L. Tseng, K. Liu, K. Tan, and H. Li, "Electric vehicle relay lifetime prediction model using the improving fireworks algorithm–grey neural network model," *Applied Sciences*, vol. 10, no. 6, p. 1940, 2020.

[17] A. A. Movassagh, J. A. Alzubi, and M. Gheisari, "Artificial neural networks training algorithm integrating invasive weed optimization with differential evolutionary model," *Journal of Ambient Intelligence and Humanized Computing*, vol. 5, no. 1, pp. 1–9, 2021.

[18] M. Banno, Y. Tsujimoto, and Y. Kataoka, "The majority of reporting guidelines are not developed with the Delphi method: a systematic review of reporting guidelines," *Journal of Clinical Epidemiology*, vol. 124, no. 1, pp. 50–57, 2020.

[19] G. Ma, "Enlightenments of uncertainty in aesthetic evaluation standards on arts education[J]," *Agro Food Industry Hi-Tech*, vol. 28, no. 3, pp. 2408–2411, 2017.

[20] J. Mirkovic, M. Dark, W. Du, G. Vigna, and T. Denning, "Evaluating cybersecurity education interventions: three case studies," *IEEE Security & Privacy*, vol. 13, no. 3, pp. 63–69, 2015.

[21] D. Taze, C. Hartley, and A. W. Morgan, "Developing consensus in Histopathology: the role of the Delphi method," *Histopathology*, vol. 3, no. 1, pp. 1–9, 2022.

[22] Y. Zhang, S. Wang, and W. Xu, "Novel feedback-Bayesian BP neural network combined with extended Kalman filtering for the battery state-of-charge estimation," *International Journal of Electrochemical Science*, vol. 16, no. 6, pp. 1–13, 2021.

[23] J. Schmidt-Hieber, "The Kolmogorov–Arnold representation theorem revisited," *Neural Networks*, vol. 137, no. 1, pp. 119–126, 2021.

[24] Y. Liu, C. Hu, and Y. Hong, "Electric energy substitution potential prediction based on logistic curve fitting and improved BP neural network algorithm," *Elektronika ir Elektrotechnika*, vol. 25, no. 3, pp. 18–24, 2019.