Improving the Efficiency of College Art Teaching Based on Neural Networks

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ABSTRACT

How to develop a teaching management system to improve the teaching efficiency of art courses has become an important challenge at present. This article takes university art teaching courses as the research object, uses dynamic L-M algorithm to optimize a large number of parameters, proposes an improved neural networks evaluation model, comprehensively analyzes the main influencing factors of art course teaching effectiveness, and establishes a teaching efficiency index evaluation system. The research results indicate that equating the number of hidden layer nodes to the number of samples can improve the performance of neural networks. The improved L-M algorithm was used to train the neural networks, and the maximum error of all test samples was only 0.04, verifying the feasibility and rationality of the improved neural networks model for evaluating course teaching effectiveness. The research results provide theoretical data support for neural networks to improve the efficiency of university art education.

KEYWORDS

Art Course, Indicator System, L-M Algorithm, Neural Networks

INTRODUCTION

As China enters a new stage of economic development, the quality of higher education has become a new challenge that affects the country's economic and social development (Gang & Weishang, 2021). In the context of comprehensive implementation of teaching reform, the teaching focuses on quality education. It is necessary to continuously promote the reform and innovation of quality education and improve the comprehensive literacy of college students (Xing et al., 2021). Although the art teaching system in universities is undergoing tremendous changes, teachers do not attach enough importance to art courses, and it is not easy to truly integrate them into the concept of quality education (Rivas et al., 2021). Art education can improve students' observation, imagination, and creativity, and the evaluation of art teaching level has great theoretical value and practical significance for art classroom education (Xu & Xia, 2022).

Some research results have been achieved in improving the quality of university teaching. Some researchers have explored the core competencies, teaching systems, and methods of university

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education in different disciplines by analyzing the core concepts of quality education (Liu, 2022). It is concluded that art education can strengthen students' visual literacy and enhance their other qualities. By focusing on the main manifestations of art literacy and combining individual differences and characteristics, the overall effectiveness of art education can be effectively improved. In the context of national first-class curriculum construction, some researchers focus on a scientific curriculum quality evaluation system and conduct in-depth analysis of the standards for first-class curriculum construction by analyzing the problems in existing evaluation systems (Alemdar et al., 2017). Some researchers have studied and developed methods for evaluating the quality of university teaching.

Some researchers have studied the impact of intelligent teaching apps on university course teaching, and analyzed the impact of university teaching quality through satisfaction evaluation. Based on the current situation of using intelligent teaching apps in ordinary universities in Shanxi, 780 satisfaction survey questionnaires on using apps were collected. A regression model for teaching quality evaluation was established using factor analysis, and the factors that affect the satisfaction of teachers and students with using apps were identified, including subjective attitude, learning effectiveness, course design, and communication interaction. Therefore, corresponding measures to improve the quality of school teaching were proposed. Some researchers have proposed innovative teaching methods in art classroom teaching activities by analyzing core literacy concepts. By deeply integrating the curriculum's core competencies and designing the optimal teaching context, teachers can optimize and improve the core competencies, summarize the shortcomings of situational teaching methods, and propose targeted optimization and improvement measures. Some researchers believe that reforming university teaching methods has helped improve teaching quality and efficiency (Bhatkalkar et al., 2020). Some researchers have focused on art teaching and proposed the concept of cultivating core competencies. It is believed that the integration of core competencies in the teaching process of fine arts in China should be based on the cultivation of aesthetic literacy so that students can genuinely acquire the ability to perceive, evaluate, and create beauty. Taking art graduate teaching courses as the research object, this paper analyzes the problems in art graduate education and establishes an art teaching quality evaluation system from four dimensions: final testing, achievement evaluation, work evaluation, and intermediary evaluation. By analyzing the laws of the self-construction of the art discipline, we continuously optimize the teaching quality evaluation system to improve the teaching quality of art graduate students.

Art education courses are the primary way of students' aesthetic education, which is a means to promote and guide students to evaluate beauty, create beauty, and improve students' comprehensive quality. The evaluation method of art teaching is relatively single, and the manual evaluation method is influenced by experience, which has significant limitations and affects the development of art teaching work and the improvement of students' abilities. Taking university art teaching courses as the research object, this paper uses dynamic L-M algorithm to optimize a large number of parameters, proposes an evaluation model to improve neural networks, comprehensively analyzes the main influencing factors of art course teaching effects, establishes a teaching efficiency index evaluation system, evaluates the teaching effect of university art courses, and provides theoretical data support for neural networks to improve the efficiency of university art education.

EXPERIMENTAL METHODS

Neural Networks

With the development of information network technology, neural networks have been applied to various industries, and their good prediction function is widely used in practical work. Neural networks can quickly and efficiently propose solutions for actionable behaviors with clear rules, typical universal laws, and programmable implementations with general characteristics (Lan & Fan, 2022). Their efficiency is almost a million times that of neurons in the human brain. They have the advantages of fast and accurate computing speed, providing technological means for achieving automation and intelligence (Gedeon & Turner, 1993).

As a high-order spatial interpolation technique, a neural network is an approximate non-linear function. With outstanding generalization ability and fast convergence speed it can effectively handle laws that cannot be analyzed. It has been applied to fields such as time series analysis, image pattern recognition, image processing, and intelligent control of fault analysis. The basic principle of neural networks is to map low-dimensional spatial data to high-dimensional space through hidden units, and fit the synthesized curve in the high-dimensional space, achieving training data fitting (Wei et al., 2022).

The neural network used in this article is a forward neural network that is divided into three layers. The first layer is the input layer of the signal source data, the second layer is the hidden layer, which describes the problem of determining the number of hidden units, and the third layer is the linear output layer (Chen, 2021). Neural networks can approach any continuous function and solve various evaluation problems. When all kinds of samples are one, all samples can be classified separately into one class, and the classification problem becomes an approximation problem. Therefore, the number of hidden layer nodes in the network is the number of samples. The approximation effect is not ideal when the number of samples is large. However, for classification problems, equating the number of hidden layer nodes to the number of sample classes can significantly improve the neural network's performance (Luo & Ning, 2022).

Evaluation Indicators of Art Teaching

Teaching evaluation is currently the most commonly used method of education quality evaluation in universities, which conducts a systematic and multidimensional dynamic evaluation of course teaching quality based on the evaluation process. Due to differences in the participation and evaluators of teaching, conducting teaching evaluation directly is not easy to draw scientific conclusions (Yujie et al., 2022). A teaching quality indicator factor evaluation system or model is established to conduct teaching quality evaluation by analyzing the indicators that affect teaching effectiveness. The main methods for evaluating the quality of course teaching include quantitative evaluation and qualitative evaluation (Abiodun et al., 2018). In Chinese universities's teaching quality evaluation systems, qualitative evaluation is mainly used, with evaluation results set as excellent, good, moderate, qualified, and unqualified.

Establishing a scientific and reasonable evaluation system for teaching quality indicators is a process of gradual optimization. A preliminary indicator system is established through analysis, and characteristic structures and hierarchical indicators are established. However, it cannot meet every requirement, so it is necessary to optimize the indicators. The optimization methods mainly include: comprehensive testing, where each indicator system takes into account all aspects of the target, and there should be no direct or indirect relationships that are repetitive or disguised; independence test, and there should be no relevant or partial duplication of the same layer and indicators; validity testing mainly involves selecting indicators that have no impact on the evaluation results, mainly through the screening methods of mean variance and dispersion (Yadav & Jadhav, 2019).

This article establishes an indicator system for the comprehensive evaluation of the teaching effectiveness of art courses through literature research. Building an art course teaching evaluation model based on neural networks mainly includes determining the network structure, constructing training samples, and training neural networks. The network structure refers to the number of nodes in the input, hidden, and output layers of the neural network. The training samples are mainly divided into input and output samples. In selecting indicators, the training of neural networks is to approximate the mapping relationship between input and output. Samples evaluated by experts are used to ensure the accuracy of the training samples. The improved L-M algorithm is used to train the neural network, which has a fast second-order convergence speed and greatly improves the convergence speed of the network (Baboo & Shereef, 2010).

EXPERIMENTAL RESULTS

Art Teaching Evaluation Model Using Neural Networks

Teaching reform is the main way to improve the quality of teaching, and the reform of art courses is mainly reflected in the learning style, time, place, content, homework, examination, and assessment (Er et al., 2016). In terms of course learning methods, it primarily adopts blended learning that combines internet learning with traditional teaching, using internet teaching resources and classroom teachers to complete classes, questions, interactions, assignments, exams, and other content (Shi, 2022). In terms of the learning time and location of the course, the internet learning time and location can achieve relative freedom (Kongsakun & Fung, 2012). Classroom teaching is conducted according to the teaching schedule and plan at the designated time and location (Furlanello et al., 2018). On the course learning content, click on the selected course and watch the course teaching video online according to the course plan.

Through self-learning and reference materials, ask questions and engage in interactive discussions based on the learned knowledge (Liu, 2019). During the learning process, students complete video learning, homework, and interactive discussions according to their learning arrangements to master the knowledge points of the course. To get a good final result, students must complete homework and various exams on time. In the assessment criteria, students' learning performance is measured by setting weights for videos, assignments, and exams, with 40% for videos, 20% for assignments, and 40% for exams (Deng et al., 2017).

Based on existing literature and the effectiveness of art course teaching, this article divides the evaluation results of course teaching quality into five levels: excellent, good, moderate, qualified, and unqualified (Yu & Dai, 2022). Table 1 provides the standards for teaching evaluation levels, the corresponding output values for teaching evaluation levels. Table 1 and Figure 1 show that when the output value of teaching evaluation is 0.9~1.0, the evaluation result is excellent; When the output value of teaching evaluation is below 0.6, the evaluation result is unqualified.

The scientific and reasonable selection of the structural model of neural networks can effectively reduce the number of network training and improve the accuracy of network learning. Neural networks are very suitable for solving evaluation problems, using an improved L-M algorithm to train the network. The network structure includes connection methods, network layers, and the number of nodes at each level. The problem of evaluating the quality of art teaching courses is a non-linear mapping from input teaching quality evaluation indicators to output teaching quality evaluation results.

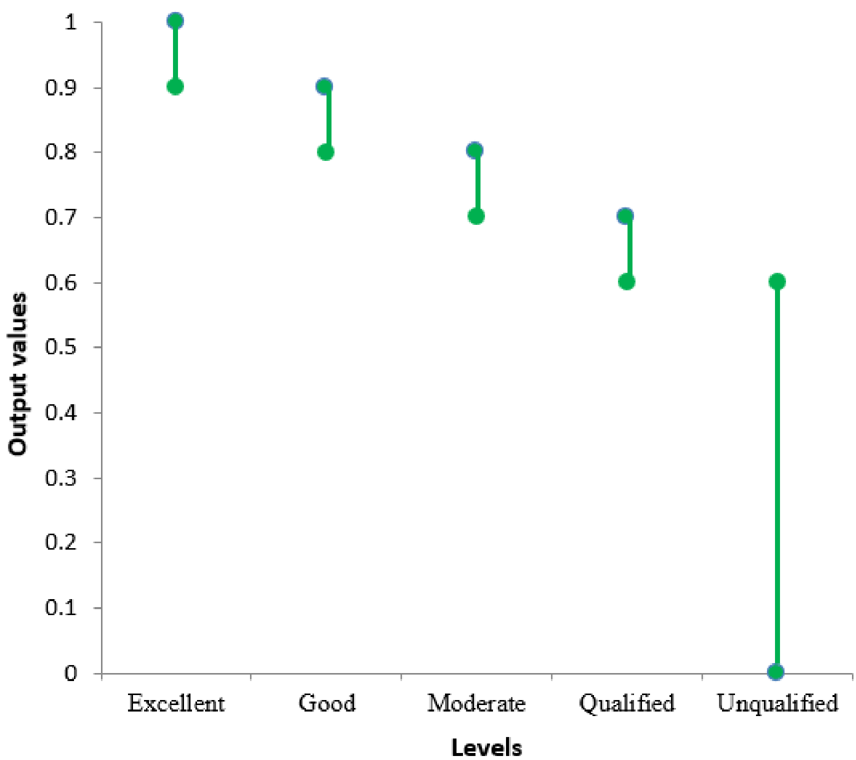
Analysis of Neural Networks Evaluation Model

The training result of the neural network directly proves the performance of the neural network. As a good training sample, it is necessary to ensure the number and the quality of samples. This article uses student evaluation information as input data for neural networks to ensure the completeness of various indicators when setting up the evaluation table. Input the number of items into the classroom teaching quality evaluation system, evaluate the student scoring situation, and analyze the quality of art teaching courses (Cheng et al., 2018). For the expected results, this article evaluated curriculum

Table 1. Standards for teaching evaluation levels

Levels	Excellent	Good	Moderate	Qualified	Unqualified
Output values	0.9~1.0	0.8~0.9	0.7~0. 8	0.60~0. 7	0.6 or less

Figure 1. Output values corresponding to teaching evaluation levels



by school curriculum supervision teachers. The training data used students' evaluation scores to obtain the evaluation results of art curriculum teaching through online training and simulated the core evaluation indicators of supervision teachers (Xiao & Luo, 2022).

This article selects ten courses based on the ratings of various supervising experts and distributes a questionnaire survey to students. Each teaching evaluation indicator includes five options: very satisfied, satisfied, average, dissatisfied, and very dissatisfied, with corresponding values of 4, 3, 2, 1, and 0, respectively. At the same time, students are required to select only one item for each indicator. Table 2 presents the student evaluation questionnaire. Each questionnaire can be identified as one training sample, and the network is trained using this data to form a non-linear mapping relationship between the evaluation indicators of each course and their corresponding evaluation levels.

According to the sample construction method, this article selects six courses for training: animation design, outline of modern history, mental health education, gem appreciation, ethnic music appreciation, and art appreciation. Using a questionnaire survey method, obtain sample data and conduct neural network training on the course sample data. Figure 2 shows the number of course survey questionnaires distributed and evaluation results for six courses.

Figure 2 shows that a comprehensive questionnaire survey was conducted on the course, resulting in a total of 670 statistical samples. The number of questionnaires for the six courses of animation design, outline of modern history, mental health education, gem appreciation, ethnic music appreciation, and art appreciation is 153, 87, 130, 64, 120, and 116, respectively. This indicates that sufficient measures have been taken in study's sample construction to ensure the effectiveness and reliability of the samples. The first 554 are used as neural network training, and the last 116 are used as neural network generalization achievement tests. The results of expert qualitative evaluation are

Table 2. Student evaluation questionnaire

Number	First-Level Indicators	Second-LEVEL indicators	Scores				
			Very Satisfied	Satisfied	Average	Dissatisfied	Very Dissatisfied
1	Student listening effects	Learning gains	4	3	2	1	0
2		Learning interests	4	3	2	1	0
3		Discover problems	4	3	2	1	0
4		Solve the problem	4	3	2	1	0
5		Learning methods	4	3	2	1	0
6	Teaching effectiveness	Subjective initiative	4	3	2	1	0
7		The effect of lesson preparation	4	3	2	1	0
8		Dedication	4	3	2	1	0
9		Passion for lecturing	4	3	2	1	0
10		Interestingness	4	3	2	1	0
11		Clarity	4	3	2	1	0
12	Teaching methods	Lecture style	4	3	2	1	0
13		Teacher-student relationship	4	3	2	1	0
14		Teacher-student interaction	4	3	2	1	0
15		Course exams	4	3	2	1	0
16		Student evaluation	4	3	2	1	0
17		Depth of content	4	3	2	1	0
18		Lecture content	4	3	2	1	0
19		Lecture progress	4	3	2	1	0

taken as quantitative results, which are the expected outputs of the sample, to enhance the convenience of neural network training. Figure 3 provides the course evaluation results.

Figure 3 shows the average quantitative evaluation results of six courses, with animation design receiving the highest score of 0.93, modern history outline receiving 0.87, mental health education receiving 0.75, gem appreciation receiving 0.66, ethnic music appreciation receiving the lowest score of 0.47, and art appreciation receiving 0.82. These results indicate that evaluating the six courses in this study has a certain degree of credibility and effectiveness and provides data support for subsequent research.

Analysis of Evaluation Results

This article selects suitable data samples and uses the maximum minimum method to normalize the data, normalizing the input values of various indicators to between [0,1]. This method can effectively preserve the authenticity of data, avoid data distortion, reduce the complexity of neural network models, enhance robustness, and improve the accuracy and accuracy of training neural networks. Using commonly used accuracy and misjudgment rates as evaluation criteria for the algorithm. Accuracy refers to the accuracy of teaching quality evaluation, represented by the percentage of samples evaluated accurately to the total number of samples. The misjudgment rate refers to defining the evaluation classification A as B and comparing it to the total number of samples to obtain the misjudgment rate. Based on all evaluation indicators, the input layer is set to 35 nodes, and the teaching

Figure 2. Number of course questionnaires distributed

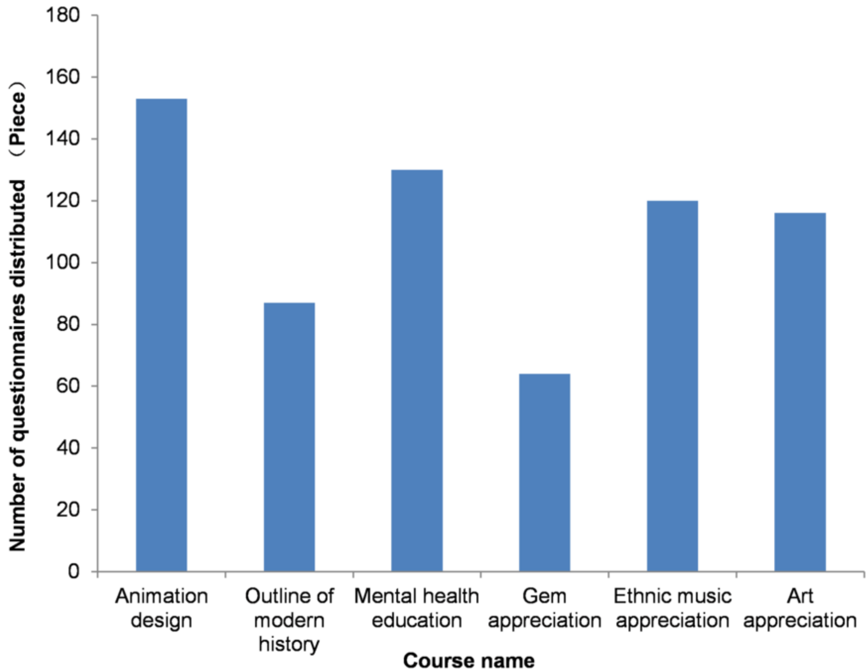
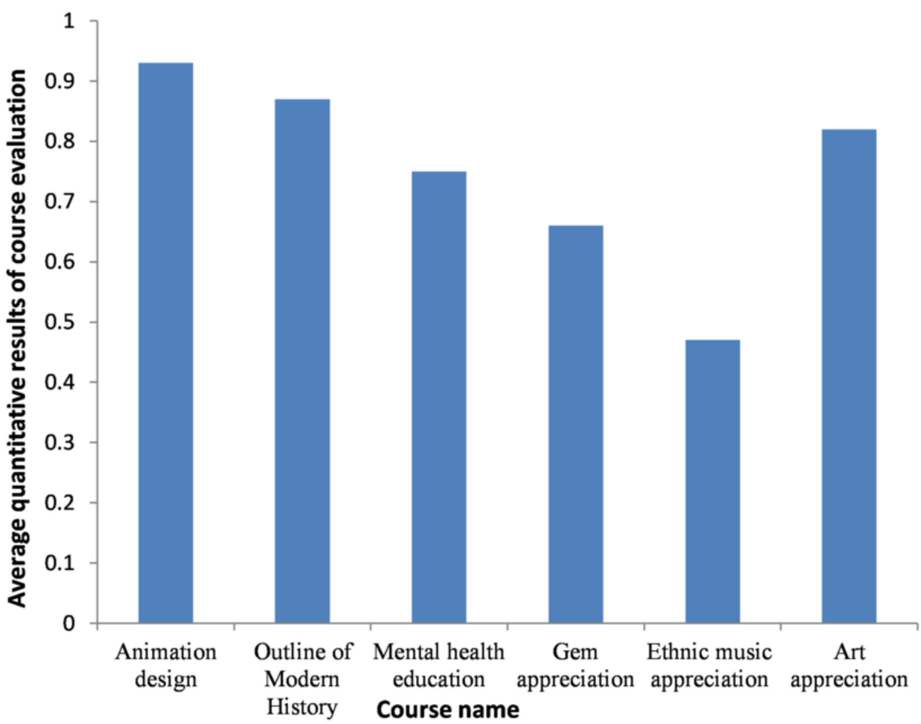


Figure 3. Chart of course evaluation results

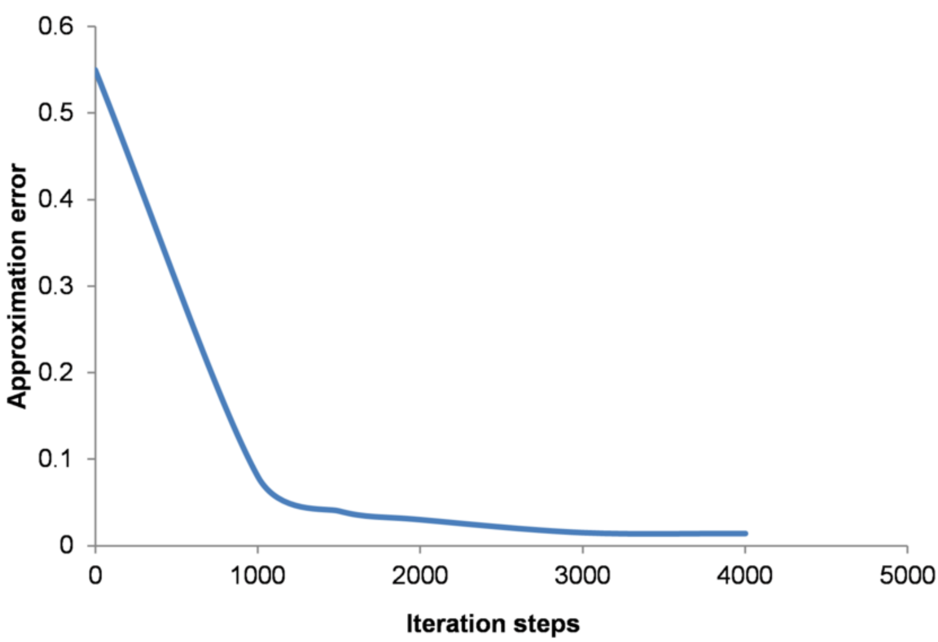


evaluation level is divided into five levels. Each level corresponds to a class of samples, and the output layer is set as a node to obtain evaluation results. Using the K-means clustering algorithm with L-M iteration, initialize the number of clusters k and continuously iterate N. Randomly select k centers and assign them to the nearest center class to obtain the performance indicators of the new centers after reassignment. This article sets the clustering number K to 5, takes the minimum deviation of 5^{-10}, and sets the number of iterations to 100. Add 554 sample data from the first five courses to the neural network for training and converge after 4453 iterations. Figure 4 shows the decline curve of approximation error in the training process.

The network output of this article is real numbers, and quantitative values must be converted into qualitative evaluation levels. When the output result of the sample exceeds 0.9, the teaching quality of the art course is evaluated as excellent. When the sample output result is below 0.6, evaluating the teaching quality of art courses is considered a failing. By obtaining the trained network, if it is necessary to evaluate the teaching effectiveness of a new course in the future, simply by distributing a questionnaire survey to specific students and inputting the statistical sample data into the neural network, the teaching evaluation results of the course can be obtained humorously.

The quality of neural network training is directly related to its feasibility, a crucial criterion for the objective evaluation of neural networks. More successful models rely on well-trained networks, improving the real-world application. This article conducts training tests on 116 samples of art appreciation courses using trained neural networks and ultimately obtains all test samples. The maximum error of the test is only 0.04, with 100 samples showing correct results, 15 samples showing excellent results, and five samples showing moderate results. The accuracy rate of teaching quality evaluation using neural networks is 86%. The improved neural network-based model for evaluating course teaching effectiveness has a strong promotion ability. It can be considered a feasible and reasonable evaluation model, providing a new method for comprehensively evaluating the teaching effectiveness of art courses in universities.

Figure 4. Decline curve of approximation error in the training process



CONCLUSION

This article takes university art teaching courses as the research object, improves the evaluation model of neural networks using dynamic L-M algorithm, and establishes an evaluation system for teaching efficiency indicators. Research has found that equating the number of hidden layer nodes to the number of sample classes can significantly improve the performance of neural networks. The improved L-M algorithm trains neural networks with fast second-order convergence speed, significantly improving the convergence speed of the network. Training and testing were conducted on 116 samples of art appreciation courses, and the maximum error of all test samples was only 0.04, proving that the improved neural network model for evaluating course teaching effectiveness has strong promotion ability. Research provides new methods for comprehensively evaluating the teaching effectiveness of art courses in universities. This study has established an evaluation index system, which can further explore the correlation and weight allocation between various indicators in the future and build a more comprehensive and accurate evaluation index system.

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