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Retraction

Retracted: Research on Education Teaching Quality Analysis Based on the Neural Network Model

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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

References

[1] Y. Zhu, "Research on Education Teaching Quality Analysis Based on the Neural Network Model," *Security and Communication Networks*, vol. 2022, Article ID 2644032, 8 pages, 2022.

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Research Article

Research on Education Teaching Quality Analysis Based on the Neural Network Model

Ying Zhu

Zhejiang Institute of Economics and Trade, Hangzhou 310018, Zhejiang, China

Correspondence should be addressed to Ying Zhu; zhuyingguomao@zjiet.edu.cn

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Universities emphasize quality review and monitoring. To effectively evaluate classroom teaching effectiveness, a trustworthy model of teaching quality evaluation is required. Due to the fact that teaching is a dynamic process, numerous elements influence teaching quality, and the link between assessment index and teaching effect is complex and nonlinear. There are numerous methods for measuring the quality of classroom instruction, but the vast majority of it relies on a single machine learning algorithm, making it difficult to construct an accurate and reliable mathematical model. In this paper, we employ the AdaBoost's multicore neural network learning algorithm to learn several weak classifiers and combine them into a single strong classifier. We also transfer the classification probabilities into teaching quality outcomes to obtain the final teaching quality results. Our model offers a new, effective way for evaluating the quality of classroom instruction, and it can serve as a solid theoretical resource for reforming classroom instruction.

1. Introduction

The classroom is the primary location for cultivating talent, where lectures are presented. The primary focus of university teaching quality monitoring and management is a reasonable assessment of classroom teaching quality [1]. By establishing a set of scientific, reasonable, and dependable teaching quality evaluation methods, it is possible to detect problems in the teaching process in real time and provide a solid foundation for the teaching quality management departments of colleges and universities to formulate corresponding measures, which is a significant guarantee for improving teaching quality. It is essential to establish an evaluation index system and model for teaching quality. The degree of influence of the influencing elements on teaching quality varies, and the link between evaluation indexes and teaching effect is complex and nonlinear. As a result, the development of mathematical models for evaluating teaching quality is a current hot topic.

The evaluation of teaching quality establishes a functional connection between the teaching effect and teaching quality evaluation indicators. Universities often use a combination of absolute assessment, rating, relative assessment, rubric, and comprehensive evaluation to determine the performance of their classmates in class. These methods are simple to implement, but they are overly subjective, and their outcomes significantly depart from the actual teaching quality. Teaching quality evaluation utilizes fuzzy cluster analysis, gray correlation, neural network, and the support vector machine [2]. The inability of these methods to characterize nonlinear issues, as well as difficulty in setting weights, strong human subjectivity, and high arbitrariness, limits their promotion and application. An innovative model of evaluating teaching quality with minimal human subjectivity, high reliability of outcomes, and customizable model parameters is a current trend and challenge in the field of study.

With the development and promotion of artificial intelligence algorithms-neural networks, a large number of academics have investigated on how neural networks might improve the evaluation of teaching quality, achieving better results than old techniques [3]. However, it is difficult to construct the structure of a neural network algorithm, and it is possible to fall into a local optimum; algorithm results are unstable when tiny samples are employed, and its theoretical base is not flawless. In response to the limitations of BP neural networks, the support vector machine algorithm was applied to the evaluation of classroom teaching quality, and the evaluation accuracy was improved to some extent; however, the kernel function and parameters of this algorithm are more difficult to determine [4].

This study analyzes a paradigm for evaluating the quality of instruction based on multicore augmented learning. Multiple single-kernel single-feature neural network classifiers are used as weak classifiers, and an Adaboost augmented learning algorithm is used to create a strong classifier iteratively. Its primary benefits are as follows:

(1) The training sample set is designed to simulate the human propensity to compare two courses side-by-side while doing subjective evaluations, establishing preference labels for the samples produced by the machine learning algorithm.

(2) Each weak classifier incorporates several image features and kernel functions, and the Adaboost algorithm then learns a strong classifier. The single machine learning algorithm data features are directly connected into a high-dimensional feature vector, and then a single regression function is used to simulate the mathematical relationship between these characteristics and the results.

This study looks at a model for assessing the teaching quality of multicore augmented learning. As weak classifiers, the method employs numerous single-kernel single-feature SVM classifiers and an Adaboost augmented learning algorithm to develop a strong classifier through iterative training. Experiments show that our powerful classifier has a high level of robustness, assessment outcomes, and quality.

2. Related Work

2.1. Classroom Teaching Evaluation. In foreign countries, the more famous course evaluation questionnaires include the National Student Learning Engagement Questionnaire, the Australian Student Course Experience Questionnaire, and the National Student Survey in the United Kingdom, among which the NSSE is the most influential teaching evaluation questionnaire in higher education in the United States, which mainly takes students as the evaluation subject. In comparison, the NSSE in the United States is more comprehensive, and its questionnaire includes not only course learning experiences but also other experiences outside the classroom, which play a crucial role in student learning and development [5].

Europe and the United States have more mature teaching evaluation systems, such as Cisco, which has developed an advanced student evaluation system, and the company makes continuous improvements to the program and curriculum based on the evaluation data [6]. A learning performance assessment system based on k-means clustering, gray correlation theory, fuzzy inference, and fuzzy association rules. Student sentiment mining, teacher evaluation index extraction, and analysis are the focus of research [7].

At present, scholars have focused on correlation research in the teaching evaluation index system [8]. At the early stage of the index system, the pursuit of the comprehensiveness of the indexes often leads to too many indicators and overlapping causes index structure distortion and questions the evaluation's objectivity. Principal component analysis, factor analysis, the entropy value method, and correlation coefficient calculation eliminate indicator correlation [9]. Literature [10] used correlation coefficient analysis to determine teaching evaluation indicator correlation. In the literature [11], partial correlation analysis and factor analysis were mostly used to look at how each index affects the quality of teaching, and multiple linear regression was used to find useful index patterns based on the results of the analysis. In the actual system of teaching evaluation indexes, there are some connections among the evaluation indicators to some extent, which may be linear correlation or some other connections, and sometimes errors may occur with one quantitative analysis method, so it is still necessary to analyze and consider from several perspectives.

2.2. Teaching Evaluation Using Machine Learning. New technologies are combining qualitative and quantitative teaching assessment techniques although quantitative data analysis typically requires great data models [12].

Weighted average, expert evaluation, AHP hierarchical analysis [13], fuzzy comprehensive evaluation, the neural network model, and the Markov chain [14] are currently the mostly used instructional assessment approaches. Using fuzzy comprehensive evaluation and hierarchical analysis, [15] academics establish teaching evaluation index weights. Li et al. [16] combine hierarchical analysis with fuzzy evaluation to increase the scientific rigor and dependability of evaluation outcomes by including fuzzy evaluation.

Relevant research on incorporating machine learning technology into university teaching evaluation systems includes the application of rough set theory to solve the problem of unreasonable index weights, the introduction of decision trees to analyze teaching evaluation data [17], and the use of an association rule algorithm to analyze teaching quality factors. Numerous researchers have approximated education evaluation using artificial neural networks. Peng et al. [18] introduced artificial neural networks into the evaluation of teaching quality in ethnic colleges and universities, built relevant mathematical models, synthetically quantified the indices, and constructed BP neural network models. On the basis of wavelet neural networks, a mathematical model for evaluating teaching quality has been suggested [19]. Neural networks have disadvantages, including local extreme value points and significant sample reliance. In recent years, scholars have made progress in teaching evaluation. More research studies have been conducted on teaching evaluation theory than teaching evaluation methodologies and procedures. Utilizing data mining and machine learning to enhance traditional teaching assessment calls for additional research studies [20].

2.3. Development and Research Status of Neural Networks. Artificial neural networks (ANNs) are made up of many interconnected artificial neurons. Its concept was initially further proposed based on the study of modern biology and information processing of human nerves, and this algorithm has strong adaptivity, good deep learning capability, nonlinear mapping capability in addition to strong robustness and high fault tolerance [21]. With the increasing complexity of the controlled objects, the requirements for control systems have become more stringent, especially in some control objects with nonlinearity, uncertainty, time-varying, etc. The complexity of control systems is more demanding [22]. The functions and characteristics of artificial neural networks are fully applied in the field of modern control technology and system intelligence, which can make the traditional control technology and system engineering construction to a new era.

Neural network, as the name suggests, is an intelligent algorithm that allows mechanical devices to simulate the nervous system of the human brain to achieve visual and auditory perception, as well as higher level learning and logical judgment. The neural network is designed to be highly reliable, robust, adaptive, and easy to use to handle complex control systems with high dimensionality, nonlinearity, strong disturbances, large time lags, and difficult modeling.

The BP neural network has strong adaptability to external disturbances and environmental changes, in addition to the self-learning, self-adaptive approximation to nonlinear function features of the BPNN itself, and is extensively used in industrial control.

The benefits of the BPNN algorithm: due to the fact that the BPNN algorithm employs the gradient descent approach, its advantages and limitations are pretty evident; the principal advantages are depicted in Ref. [23].

(1) Nonlinear mapping capabilities: the activation function enhances the nonlinear capabilities of the neural network, allowing it to approximate any complex function.

(2) Capacity for self-learning and self-adaptation: during the process of sample training, the neural network can automatically compare the reasonable relationship between input samples and output outcomes (weight change) and then adaptively add this connection to the network's weights.

(3) Generalization aptitude: the neural network extracts the corresponding laws (stored in the weights) based on the known input sample features and categories, and if unknown samples are input to the network again, the network is able to classify the new unknown samples based on the previously obtained laws, that is, the capacity to apply the learning results to the new samples.

(4) Fault tolerance: when a certain degree of local issue exists in a neural network, the network can nevertheless function normally.

3. Method

3.1. NN Classifier. The classifier of the evaluation model mainly needs to rely on the BPNN framework to classify the data information. Based on this, this paper will use the BP neural network as the basis of classifier design and construct the classification model initially. The specific process is divided into BP neural network training and generalization classification as shown in Figure 1.

3.1.1. Overall Structure. The neural network used to create the classifier is presented below. As illustrated in Figure 2, it consists of four conceptual network layers: the data input layer, the fuzzy output layer, the computational hidden layer, and the output data defuzzification layer. The input layer obtains accurate data and the fuzzy layer discretizes correct data to obtain a fuzzy signal, which is then used as the input signal by BPNN and supplied to the hidden layer of the neural network for training and weight adjustment. The result of the fuzzy signal operation is still a fuzzy signal that requires processing by the defuzzification layer in order to arrive at an accurate conclusion.

3.2. Adaboost Algorithm. Adaboost algorithm is a classical integration algorithm, which is a special case of boosting algorithm. After a long time of research and improvement, the Adaboost algorithm mainly includes Adaboost M1 algorithm and Adaboost M2 algorithm [24]. With each iteration of the Adaboost algorithm, the weights of training samples will be redefined once, and it organically combines multiple weak classifiers to classify through a voting mechanism, and as the number of iterations increases, the Adaboost algorithm will focus the classification on some indistinguishable samples to achieve an increase in the overall recognition accuracy.

In AdaBoost, all training samples are weighted by a weighted average, and each sample's weight represents its likelihood of being used in the next iteration. If the weak classifier correctly classifies a sample, the sample is less likely to be used as the training set for the next weak classifier. If the current classifier cannot quasi-classify a sample, its weight is increased in the next training [25]. The AdaBoost algorithm ensures that the learning algorithm gradually focuses on the more difficult training samples. For difficult samples, combining the results of each weak classifier after focused learning can improve classification accuracy. As shown in Figure 3, it is the principle of the Adaboost algorithm.

3.2.1. Realization Process. The Adaboost algorithm implementation procedure is as follows: segregate data into training and testing, input the training set, and initialize the

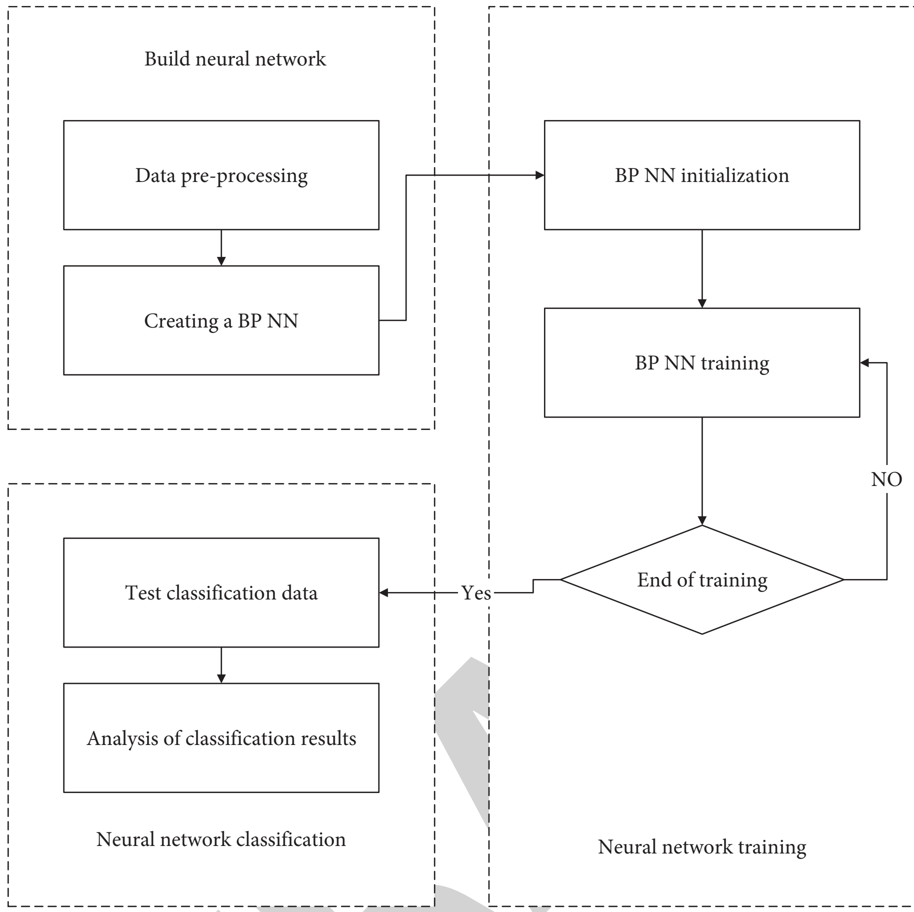

Figure 1: BP neural network classifier overall process design.

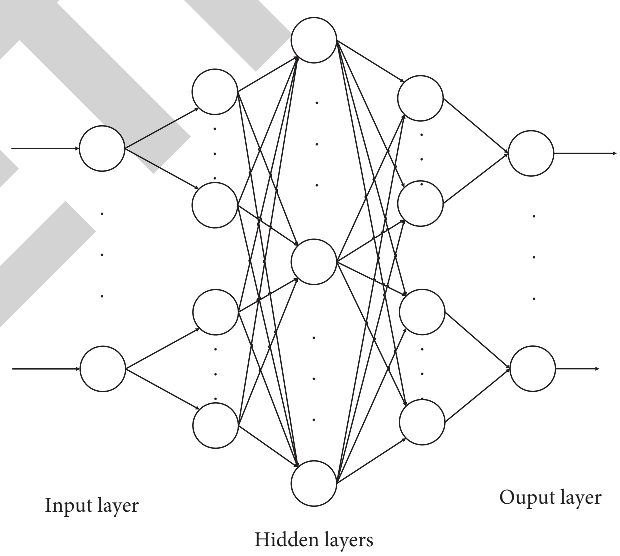

Figure 2: BP network structure diagram.

training sample weights. D_1 represents the collection of weights, N represents the number of samples, and ω represents the weight of each sample as in the following equation (generally, the initial weights are set to $1/N$):

$$D_1 = \left(\omega_{11}, \omega_{12}, \ldots, \omega_{1i}, \ldots, \omega_{1N}\right),$$
$$\omega_{1i} = \frac{1}{N}, \quad i = 1, 2, \ldots, N. \tag{1}$$

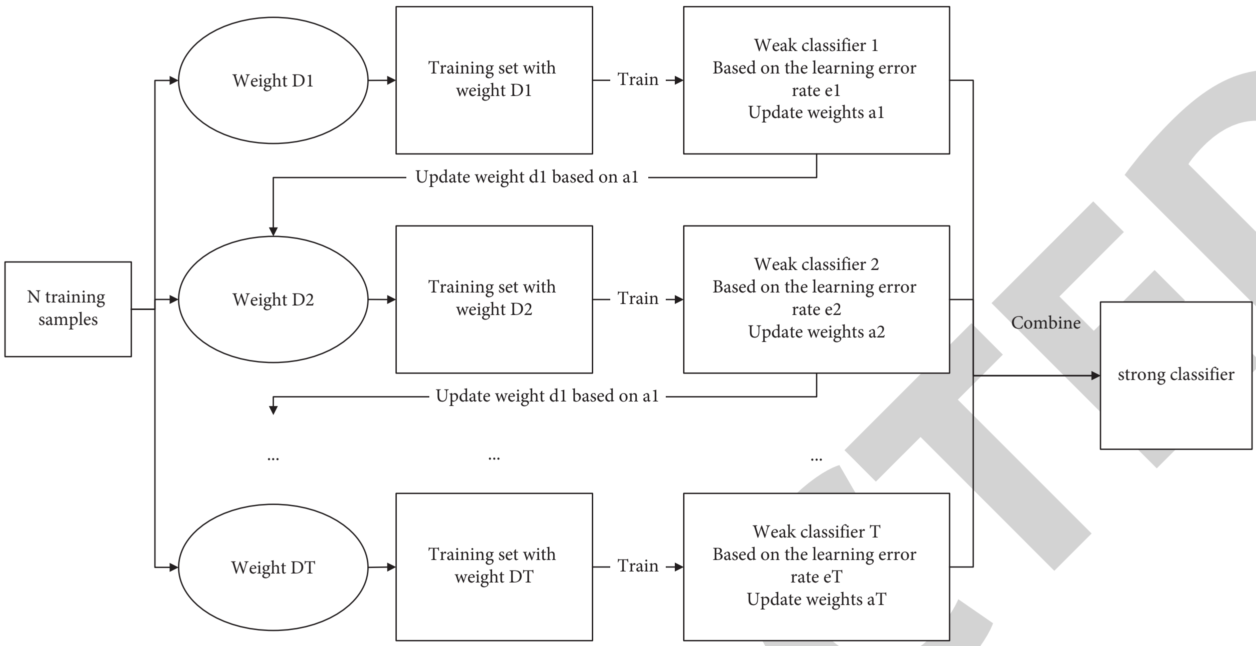

FIGURE 3: Diagram of the Adaboost algorithm.

The algorithm uses the processed dataset to create one-to-many (OAA) and one-to-one (OAO) classifiers for training and testing, respectively.

Calculate the weak classifier's error rate e_m after each iteration process.

$$\begin{aligned} e_m &= P\left(G_m\left(x_i\right) \neq y_i\right) \\ &= \sum_{i=1}^{N} \omega_{mi} I\left(G_m\left(x_i\right) \neq y_i\right). \end{aligned} \tag{2}$$

After m iterations, determine the scale factor a_m based on the weak classifier error for each weak classifier in the final classification set.

$$a_m = \frac{1}{2}\log\frac{1-e_m}{e_m}. \tag{3}$$

After each algorithm drop, update OAA classifier weights, m1D denotes the set of iterations to the $m+1$st sample weight, and m1 denotes the $m+1$st sample weight.

$$\begin{aligned} D_{m+1} &= \left(\omega_{m+1,1}, \omega_{m+1,2}, \ldots, \omega_{m+1,i}, \ldots, \omega_{m+1,N}\right), \\ \omega_{m+1,i} &= \frac{\omega_{mi}}{Z_m}\exp\left(-a_m y_i G_m\left(x_i\right)\right),\ i = 1, 2, \ldots, N. \end{aligned} \tag{4}$$

After that, the coefficients (weights) of the weak classifiers are normalized and saved for classification.

Input the test set, invoke the OAO classifier, and use the voting mechanism for quality evaluation.

$$Z_m = \sum_{i=1}^{M} \omega_{mi}\exp\left(-a_m y_i G_m\left(x_i\right)\right). \tag{5}$$

The final classifier is obtained as follows:

$$f(x) = \sum_{m=1}^{M} a_m G_m\left(x_i\right). \tag{6}$$

3.2.2. Analyzing Adaboost's Performance. As a hybrid method and an upgraded version of the bagging algorithm, the Adaboost algorithm offers its own benefits. The three most significant properties of the Adaboost algorithm [26] are as follows:

(1) There is a maximum error rate for an algorithm, a lower upper error rate indicating a more efficient algorithm, and the maximum error rate of the Adaboost algorithm grows as the number of iterations increases.

(2) It is possible to train the Adaboost algorithm multiple times without overfitting.

(3) The Adaboost method exhibits exceptional generalization and adaptability to fresh data samples. The paper examines the first distinguishing feature in depth.

The top limit of the Adaboost algorithm's error rate for training data drops exponentially; hence, the Adaboost algorithm's error rate lowers as the number of training rounds increases.

Overfitting is not a problem for the Adaboost algorithm because, in the subsequent process, the algorithm pays less attention to sample data that has been explicitly classified and instead focuses on difficult samples that are difficult to distinguish; therefore, the Adaboost algorithm does not exhibit overfitting [27].

Generalization ability refers to an algorithm's ability to adapt to new training samples, and the algorithm can classify new samples quickly and accurately, indicating a strong generalization ability; however, when new data samples are input into the algorithm, the algorithm does not recognize the new samples accurately, resulting in a significant decrease in the algorithm's overall classification accuracy, indicating a weak generalization ability. After the samples are received by the Adaboost algorithm, the classifier assigns a higher weight to the more difficult samples and focuses on them. This has less of an impact on the overall classification accuracy when new samples are input into the algorithm, indicating that the Adaboost algorithm has a good generalization ability.

4. Experimental and Analysis

4.1. Datasets. Using the literature [28], 11 classroom theory teaching quality evaluation indexes were identified, including clear teaching purpose (x1), outstanding focus and difficulty (x2), scientific teaching knowledge (x3), inspiring teaching (x4), learning method guidance (x5), rich teaching methods (x6), rigorous teaching attitude (x7), proficient teaching content (x8), no lateness and no delay in class (x9), teaching goal achievement (x10), and attention to student learning (x11) (Y). Late and no delay in class (x9), teaching objectives achieved (x10), emphasis on student feedback (x11), and teaching quality (x12) are all indicators of an effective teacher (Y). The teaching quality rating scale of higher education institutions was used to ask teaching specialists, related instructors, listening teachers, and class students to rate the professors of the classes. Evaluation samples with more consistent ratings were then chosen as cases. The sample data are displayed in Table 1 for the eighteen samples collected.

4.2. Data Preprocessing. In order to standardize the range of values of the data, we avoid the phenomenon of slowing down or even failing to converge the network due to the large difference in values. We normalize the data by transforming the data to the range [0, 1] to obtain better learning efficiency and prediction accuracy. As shown in the figure below, we compare the model's learning performance to and without data normalization.

As shown in Figure 4, the prediction results of the neural network are more accurate and within the error value after unifying the field values of the sample data by an order of magnitude, indicating that the robustness and accuracy of the network learning are significantly enhanced after unifying the field values of the sample data.

If all data that depart from the genuine assessment value are considered as abnormal, the data may lose their potential usefulness. We run outlier-based identification on the dataset again to reduce data mistakes.

Figure 5 depicts our sample 25 group data for LOF local outlier identification; the threshold value is used in the experiment is 10; we can see that two of the points do not fall within our range; thus, we must exclude them.

Table 1: Classroom theory teaching quality data.

Index	x_1	x_2	x_3	...	x_5	Y
1	0.84	0.94	0.90	...	0.84	0.82
2	0.92	0.78	0.86	...	0.87	0.86
3	0.94	0.93	0.98	...	0.9	0.96
4	0.85	0.90	0.91	...	0.84	0.90
5	0.73	0.82	0.79	...	0.8	0.81
...	...	...	...	...	...	...
17	0.94	0.83	0.9	...	0.94	0.88
18	0.97	0.94	0.94	...	0.99	0.95

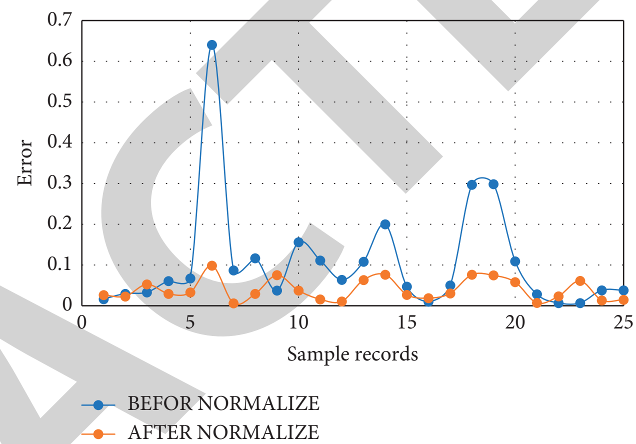

Figure 4: Learning performance comparison using preprocessed sample data.

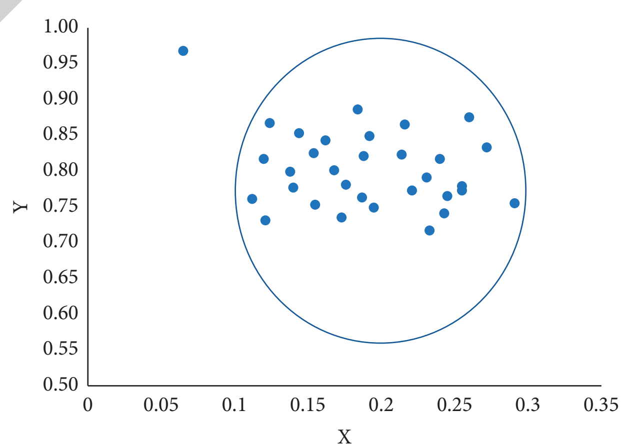

Figure 5: Outlier detection.

4.3. Accuracy Comparison. We chose 240 records for training and 80 for testing in cross-validation experiments. The classification accuracy of the simple SVM algorithm and the algorithm in this paper was measured using cross-validation, as shown in Figure 6.

The average classification accuracy of each SVM algorithm on this dataset is 0.813, while the average is 0.85. In general, the Adaboost enhanced learning algorithm has a better classification accuracy than the traditional SVM algorithm on the teaching evaluation dataset.

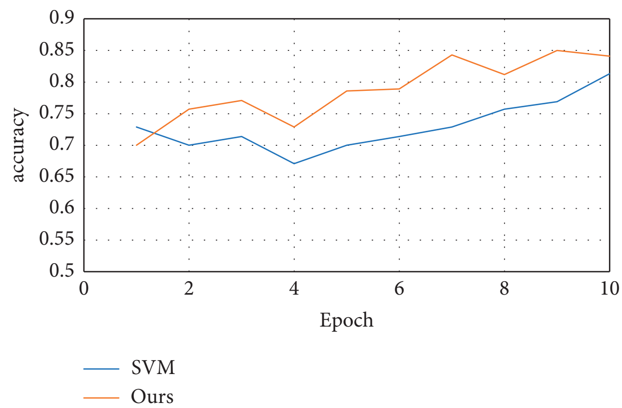

Figure 6: Comparison of classification accuracy.

Table 2: NN algorithm partial results.

True	Rating	Predicted	Error	Forecast grade
0.999	Excellent	0.927	0.072	Excellent
0.948	Excellent	0.908	0.04	Excellent
0.976	Excellent	0.928	0.048	Excellent
0.987	Excellent	0.946	0.041	Excellent
0.969	Excellent	0.953	0.016	Excellent
0.97	Excellent	0.924	0.046	Excellent
0.933	Excellent	0.918	0.015	Excellent
0.916	Excellent	0.927	−0.011	Excellent
0.545	Good	0.619	−0.074	Good
0	Unqualified	0.091	−0.091	Unqualified

4.4. The Experimental Results. To gather the experimental data for the BPNN algorithm experiments, 240 records are randomly selected as the training set and 80 records are selected as the test set. After performing experimental debugging, the optimal experimental parameters are as follows: the activation function is tanh(), the learning rate is 0.01, and the number of cycles is 10000. Following are the test results received after training the NN algorithm, see Table 2.

As shown in Table 2, our predicted results are within 0.1 of the real results, and the predicted and real grades correspond to each other.

5. Conclusion

In recent years, machine learning algorithms have been utilized in teaching quality evaluation and have yielded specific outcomes. However, these methods continue to be hampered by challenges in weighting, strong human subjectivity, high arbitrariness, and inability to represent nonlinear situations, which hinders their promotion and application. Therefore, this work investigates a model for evaluating the teaching quality of multicore augmented learning. The method employs several single-kernel single-feature SVM classifiers as weak classifiers and an Adaboost augmented learning algorithm to learn a strong classifier via iterative training. Experiments demonstrate that the robustness, assessment results, and quality of our powerful classifier are high.

Data Availability

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

Conflicts of Interest

The author declares that he has no conflicts of interest.

Acknowledgments

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