

Retraction

Retracted: Learning Behavior Based on Data Mining Technology

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This article has been retracted by Hindawi, as publisher, following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of systematic manipulation of the publication and peer-review process. We cannot, therefore, vouch for the reliability or integrity of this article.

Please note that this notice is intended solely to alert readers that the peer-review process of this article has been compromised.

Wiley and Hindawi regret 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 Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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- [1] J. Wang, Q. Zhang, and M. Guan, "Learning Behavior Based on Data Mining Technology," *Security and Communication Networks*, vol. 2022, Article ID 6155704, 10 pages, 2022.

Research Article

Learning Behavior Based on Data Mining Technology

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With the release of the Education Informatization 2.0 Action Plan and the rapid development of learning analysis technology, educational data mining becomes a new research direction. Data mining can improve teachers' teaching methods and students' learning skills by acquiring information hidden in the educational data. Based on the learning behavior data of college students, this paper uses BP neural network, a data mining method, to predict their comprehensive evaluation results. The results show that there is a close relationship between students' learning behavior and their comprehensive scores. In addition, models of naive Bayes, logistic regression, and decision tree are established for verification and comparison. Compared with other models, BP neural network model has higher prediction accuracy and better performance. It can serve as an important basis to improve students' learning methods and teachers' teaching methods.

1. Introduction

In the "Age of Big Data," data are impacting all walks of life. Big data not only have a great potential in the business field but also change the education field. How to find, understand, and effectively use the information hidden in the massive educational data and analyze students' learning behavior have become a focus of research. Educational data mining (EDM), a technology to extract useful information from large-scale educational data, can not only promote personalized learning but also help teachers in decision-making, intervention, and improvement. The classification and prediction of student performance, graduation rates, and instructor achievement may all be done using educational data mining. Learners may choose programs more effectively and efficiently with its assistance, while instructors can evaluate the progress of students to enhance their instructional techniques.

In recent years, data mining of educational data has gained much attention in the research field. Jia-Jiunn et al. studied the path, browsing order, and study habits of e-learners and found out their learning styles to recommend related learning resources for students [1]. To improve the effectiveness of adaptive learning, Chellatamilan

et al. collected data from a web-based learning management system and predicted students' learning style via data mining [2]. Banu et al. used the social network to discuss various learning tools available online [3]. Their study aimed to increase students' educational awareness and improve their learning habit, knowledge-sharing habit, and academic performance.

With the technology of big data and data mining, teachers can assess students' learning behavior from a new perspective. They can observe students' learning levels, which were difficult to quantify before, and customize courses for students based on their needs. Big data help teachers select the most effective teaching method and thus improve their work efficiency. Although teachers' working method changes, their work will not be replaced by machines. Conversely, big data enable teachers to focus on comprehensive evaluation and improve the overall effectiveness. This paper analyzed 210 groups of data on college students' daily learning behavior. The data were handled with statistical analysis software and analyzed with modeling and data mining technology. Analytical results about students' learning behavior and factors that affected their learning effect were derived [4].

2. Concepts and Technologies

2.1. Definition of Learning Analysis. Learning analysis was first presented by EDUCAUSE in 2010 in the “Next Generation Learning Challenge.” The Next Generation Learning Challenges (NGLC) program promotes a technologically assisted instructional approach to significantly raise college preparedness and graduation levels in the United States. By investigating new methods, technology, and avenues for academic achievement, NGLC is aiming to reimagine teaching. It was able to “predict and process students’ learning behavioral trajectories with data and models” [5]. Siemens, an expert in learning analysis, argued that learning analysis adopts intelligent data, student-generated data, and analysis models to tap the connection between information and the society [6]. It is a good way to predict learning behavior and give suggestions for adaptive learning. Learning analytics is the process of using these connections to improve e-learning settings, whereas educational information mining alludes to finding the correlations buried in massive data. Adding to the body of knowledge about potential tendencies for these ideas is among the objectives of the research [7].

Malcolm Brown held that learning analysis, with learning behavior as the focus, included five elements [8, 9]. They are data collection, data analysis, student learning, feedback, and intervention. Analysis results can be used by an individual student or a learning group and reported back to students, teachers, managers, and researchers. They are good materials for teaching intervention and for individual or institutional decision-making [10].

2.2. Data Mining. Data mining is an analysis step for Knowledge Discovery in Databases (KDD) [11]. Knowledge discovery in databases is to finding true, original, possibly helpful, and eventually intelligible trends or correlations inside a collection in systems is a difficult procedure that helps decision-makers. It describes the general process of finding information in information and places emphasis on the advanced uses of certain data mining methods. To accomplish the necessary information retrieval, several widely employed methods include visual elements, inductive, neural networks, and rule-based algorithms. Data mining, commonly referred to as knowledge discovery in databases, is the labor-intensive process of extracting latent, unknown-before details from datasets that may be beneficial. Data mining aims to uncover patterns and other valuable information by sorting through large data sets [12]. As a discipline of computer science, its techniques include statistics, online analysis processing, intelligence retrieval, machine learning, expert system, and pattern recognition [13, 14]. Typical data mining methods include decision tree, artificial neural network (ANN), support vector machine (SVM), and naive Bayes classifier.

The nonparametric unsupervised teaching method used for prediction and regression applications is the tree structure. It is organized hierarchically as well as has a cluster center, branching, intermediate nodes, and

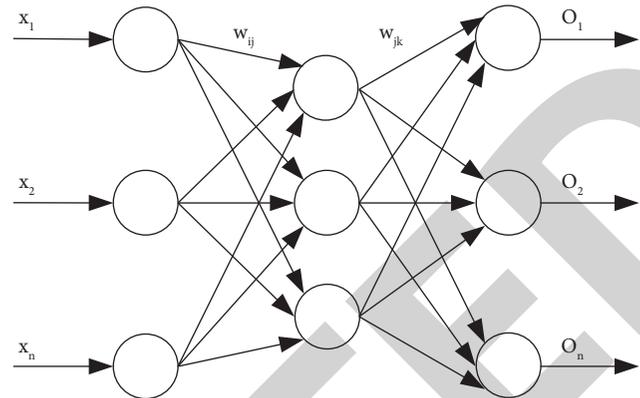


FIGURE 1: BP neural network structure.

connected by edges. A neural system is a combination of techniques that, by mimicking the functioning of the human brain, identify fundamental correlations in a piece of information. The artificial neural network (ANN) handles data similarly to how the human mind does. A controlled approach to machine learning called support vector machine (SVM) is utilized for both categorization as well as prediction. Although we often refer to recurrence concerns, categorization is the most appropriate term. Finding a higher dimensional space in an N -dimensional environment that clearly distinguishes the sets of data is the goal of the SVM method. It is a linear classifier built on the Bayes theorem and predicated on the idea of predicting independent. A naive Bayes classification, to put it simply, believes that the existence of one information in a category has nothing to do with the existence of any additional characteristic [15, 16].

2.3. BP Neural Network. Backpropagation is a gradient descent-based supervision training method for artificial neural networks. The approach determines the slope of the absolute error with regard to the components of the synthetic neural network provided an iterative method as well as a multilayer perceptron. BP neural network is a multilayer feedforward neural network. It is highly capable of data recognition and time series forecasting. BP neural network learning algorithm is trained according to the error backpropagation algorithm. It mainly includes forward propagation of signals and backward propagation of errors. A neuron’s activity status is determined by an input signal. By employing easier numerical methods, it will determine the extent to which the neuron’s contribution towards the system is significant throughout the probability model. Forward propagation of signals refers to the transmission of input signals to the output layer under various neuronal activation functions, while backward propagation of errors means that errors are propagated backward and are minimized by constant adjustment for connective weights and thresholds.

BP neural networks usually have three or more layers. There is no feedback or connections within a layer. The

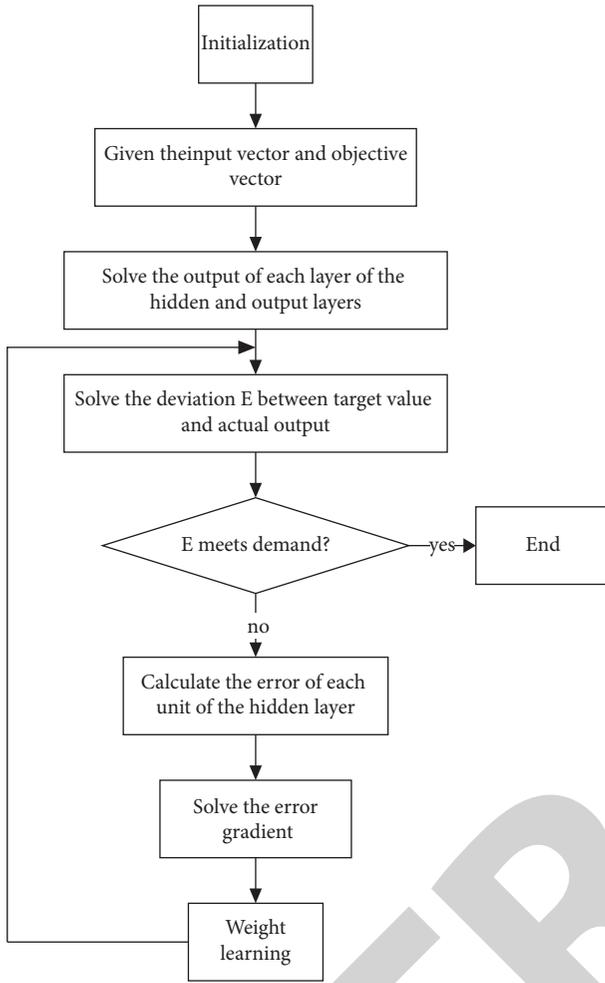


FIGURE 2: Flow chart of BP neural network algorithm.

structure of a typical BP neural network is shown in Figure 1, where the leftmost layer is the input layer, the rightmost layer is called the output layer, and layers in the middle are named hidden layers. Neurons in adjacent layers of the BP neural network are fully connected, but neurons within the same layer are not connected [17–19]. The three types of layers that make up the neural network are information for the neural system is in the input nodes. Between the input source and outlet levels are hidden layers, which serve as the hub for all computing. Create the desired outcome for the input variables in the output neuron.

2.4. Algorithmic Flow. The flow chart of BP neural network algorithm is shown in Figure 2.

(1) Initialize the weights and thresholds of the network. Assume that the number of nodes in the input layer, the hidden layer, and the output layer were n , l , and m , respectively. Weights from the input layer to the hidden layer and from the hidden layer to the output layer were w_{ij} and w_{jk} , respectively. The bias from the input layer to the hidden layer and from the hidden layer to the output layer was a_j and b_k , respectively. The learning rate was η . An activation function is applied to a linear combination of sources, and the outcome is

used as a resource for the subsequent stage. The outcome of this component will constantly vary from 0 to 1 whenever the input layer of a synapse is a sigmoid function. The sigmoid function was adopted as the activation function $g(x)$.

(2) Enter the value of training sample x_i into the nodes of the input layer and calculate the output of each neuron layer until the output layer was reached. The formulas for deriving the output H_j of the hidden layer and the output O_k of the output layer were

$$H_j = g\left(\sum_{i=1}^n w_{ij}x_i + a_j\right), \quad (1)$$

$$O_k = \sum_{j=1}^l H_j w_{jk} + b_k.$$

(3) For each unit of the network, errors of each layer were calculated, and the weights were update. The formula for error calculation was

$$E = \frac{1}{2} \sum_{k=1}^m (Y_k - O_k)^2. \quad (2)$$

The formula for updating the weight was

$$w_{ij} = w_{ij} + \eta H_j (1 - H_j) x_i \sum_{k=1}^m w_{jk} e_k, \quad (3)$$

$$w_{jk} = w_{jk} + \eta H_j e_k.$$

The formula for updating the bias was

$$a_j = a_j + \eta H_j (1 - H_j) \sum_{k=1}^m w_{jk} e_k, \quad (4)$$

$$b_k = b_k + \eta e_k,$$

where Y_k was the desired output, $i = 1 \dots n$, $j = 1 \dots l$, $k = 1 \dots m$.

(4) Determine whether the requirements were met. If the requirements were not met, the algorithm would return to the second step to recalculate the results until they met the requirements.

3. Model Construction

3.1. Dataset. When they are learning, college students will produce a huge amount of data, which can be used as a database for the learning analysis model. This paper has collected 210 groups of data in total. They are about the daily learning records and web logs of college students, including their courses, the times of hand-raising in classroom, participation in discussions after class, and looking up online course resources, and their comprehensive evaluation. Precisely identifying a person's abilities and requirements is the goal of a thorough examination as well as a review. In academic contexts, the concept of assessing is employed in a wide range of situations for a number of objectives, comprising individualized and collective, structured and unstructured, and types of assessment. Through the examination of individuals' achievement in both kinds of activities, CCE seeks to lighten the burden of the curriculum

TABLE 1: Some of the datasets.

Courses	Times of raising hands in class	Times of after-class discussions	Times of accessing online course resources	Comprehensive evaluation
C language (C)	22	6	20	C
Data structure (DS)	75	17	62	A
Computer network (CN)	80	68	89	A
Network engineering design (NED)	10	41	0	C
Computer organization principle (COP)	55	40	90	B
Principles and applications of database (PAD)	88	10	81	B
Digital logic and digital circuit (DLDC)	69	75	77	B

TABLE 2: Data preprocessing results.

	Time of hand-raising in class	Times of after-class discussions	Number of accessing online course resources	Comprehensive evaluation
Mean	52.50	62.25	56.50	0.25
Std	29.89	24.40	34.35	0.50
Min	12.00	44.00	20.00	0.00
25%	39.75	45.50	32.00	0.00
50%	59.00	61.50	56.00	0.00
75%	71.75	81.25	80.50	0.25
Max	80.00	94.00	94.00	1.00

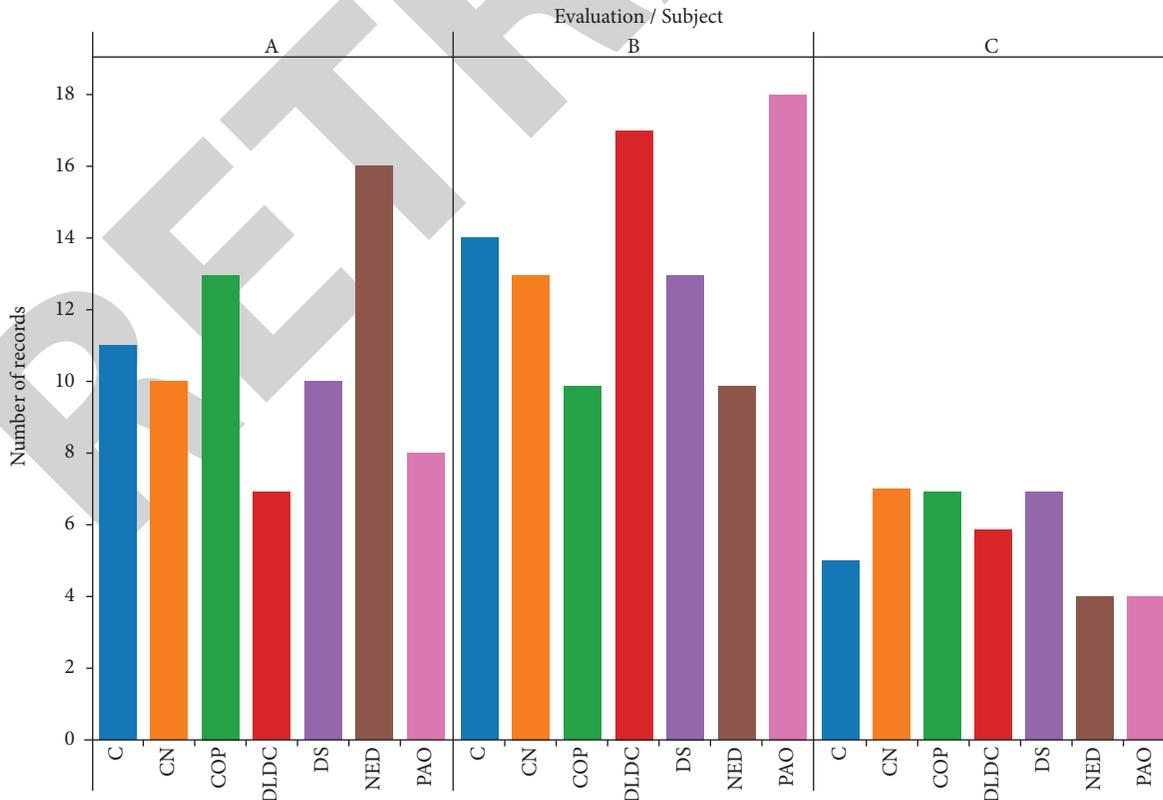


FIGURE 3: Graphical representation of statistics of the comprehensive evaluations of students in all courses and number of records.

TABLE 3: Statistics of the comprehensive evaluations of students in all courses.

Comprehensive evaluations	A	B	C
C	10.45	13.19	4.97
CN	9.622	12.39	6.76
COP	12.39	9.58	6.76
DLDC	6.8	16.12	5.85
DS	9.58	12.35	6.76
NED	15.17	9.622	3.98
PAD	7.71	17.00	3.98

on classmates and to enhance their general talents and skills. It can also be used by teachers to evaluate how well their children participate in extracurricular activities. Some of the datasets are shown in Table 1.

3.2. Data Preprocessing. To ensure the learning analysis model is scientific and useable, it is necessary to collect, integrate, and clean the multisource heterogeneous educational data. Big data fusion has both potential and problems as a result of multisource large datasets. Every information having a significant level of variation in data varieties and formats is considered heterogeneity. As a result of incomplete data, significant data repetition, and deceitfulness, they may be unclear and poor quality. Such educational data contain structural, semistructural, and nonstructural components. The process is to transform them into valid data for effective analysis. Data cleansing, the most important step in data preprocessing, aims to ensure the data are correct, consistent, and useable. The actual process of data cleansing may involve removing possible outliers, uncertain and invalid values, or heterogeneous data. After cleansing, the data quality is improved. The cleaned data were classified into valid datasets for the call of the data analysis module. The results of data preprocessing are shown in Table 2.

Figure 3 and Table 3 show the statistics of the comprehensive evaluations of students in all courses. The evaluations were at middle and upper levels, indicating that the students' academic performances of this class were at middle and upper levels.

3.3. Model Training and Evaluation Indicators. The datasets were divided into the training set and the test set, which included 140 and 70 groups of data, respectively. Before training the network, the weight was initialized to a small value, and the size of the hidden layer was set as 3 to reflect the training characteristics. The learning rate was put to 0.3. The training would reach the end when the model precision could not be significantly improved anymore.

This paper used accuracy, precision, recall, F1, root mean squared error (RMSE), relative absolute error (RAE), and root relative squared error (RRSE) to evaluate the precision of the model. Among the methods, most frequently utilized to assess the accuracy of forecasts is root mean square deviation, also referred to as root mean square variance. It illustrates the Euclidean distance between observed actual values and forecasts. A decent indicator of

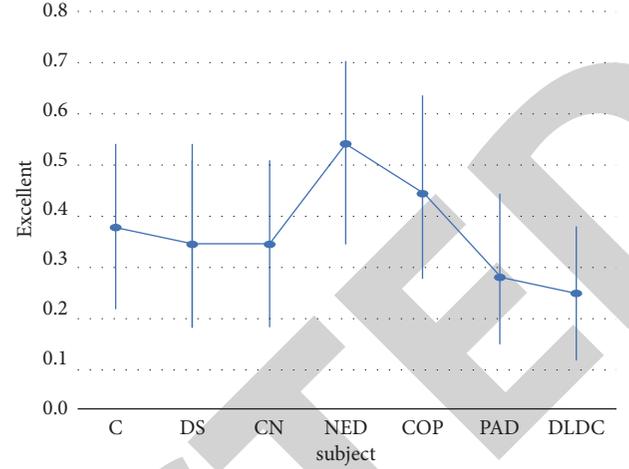


FIGURE 4: Relationship between course and comprehensive evaluation.

how effectively the system forecasts the reaction is the RMSE. If the primary goal of the modeling is forecasting, then this fit criterion is crucial. The aims of the study will determine the most appropriate model fit measurement, while others might be helpful. A predictive model's effectiveness can be evaluated using the relative absolute error (RAE) metric. It is mostly utilized in operational administration, data gathering, and computer vision. When a simple prediction had been employed, the root relative squared error (RRSE) would have been decreased. This straightforward prediction only represents the median of the measured results.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F_1 = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{t=1}^n (p_t - y_t)^2}, \quad (5)$$

$$\text{MAE} = \frac{1}{n} \sum_{t=1}^n |p_t - y_t|$$

$$\text{RAE} = \frac{\sum_{t=1}^n |p_t - y_t|}{\sum_{t=1}^n |y_t - \bar{y}|}$$

$$\text{RRSE} = \sqrt{\frac{\sum_{t=1}^n (p_t - y_t)^2}{\sum_{t=1}^n (y_t - \bar{y})^2}}$$

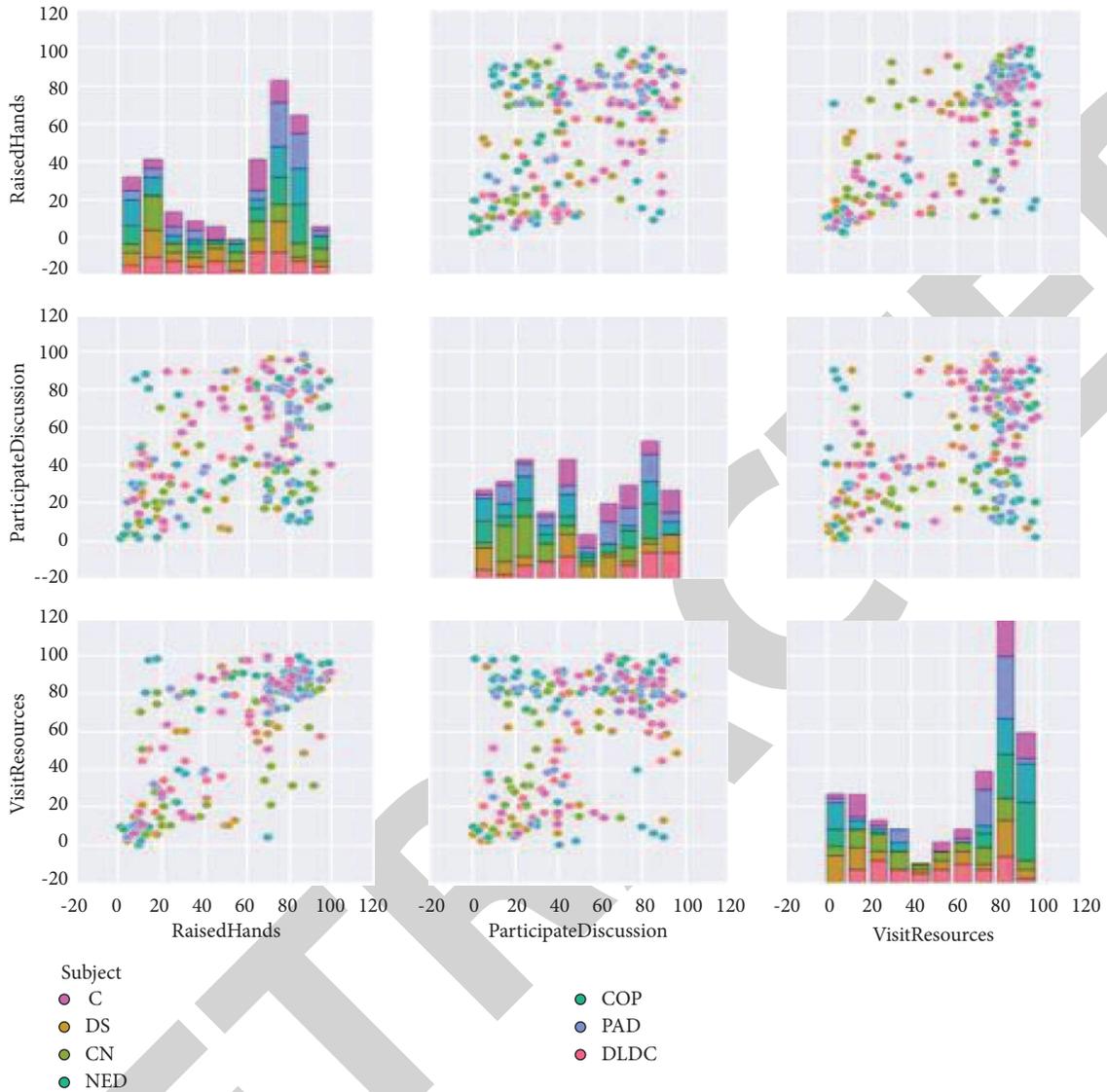


FIGURE 5: Scatter diagram.

where TP, TN, FP, and FN indicate the number of true positives, true negatives, false positives, and false negatives, respectively. Moreover, \hat{y}_t , y_t , and \bar{y} denote the predictive value, the target value, and the mean, respectively, and n represents the number of samples.

4. Result Analysis

4.1. Correlation Analysis. Figure 4 is the relationship between the courses and comprehensive evaluations.

According to Figure 4, the comprehensive evaluation values were high for NED and low for DLDC. The scatter diagram (Figure 5) and correlation diagram of learning behavior (Figure 6) also showed that there were many times of hand-raising in classroom and accessing online course resources, which indicated that students who were active in class kept active after class.

4.2. Visualization Analysis. As an important analysis and processing technology, data visualization uses graphics to represent data. In this way, complex data can be simplified for better understanding. This paper adopted data visualization to present the relationship between students' learning behavior and comprehensive evaluation results. The box plots of the times of hand-raising in classroom, accessing online course resources, and after-class discussions are shown in Figure 7.

According to Figure 7, there was a close relationship between students' learning behavior and the results of comprehensive evaluations. Students who were active in class often participated in discussions and frequently visited online resources after class had higher comprehensive scores. Figures 8–10 revealed the relationships of the times of hand-raising in class, accessing online resources, and after-class discussions to students' comprehensive scores.

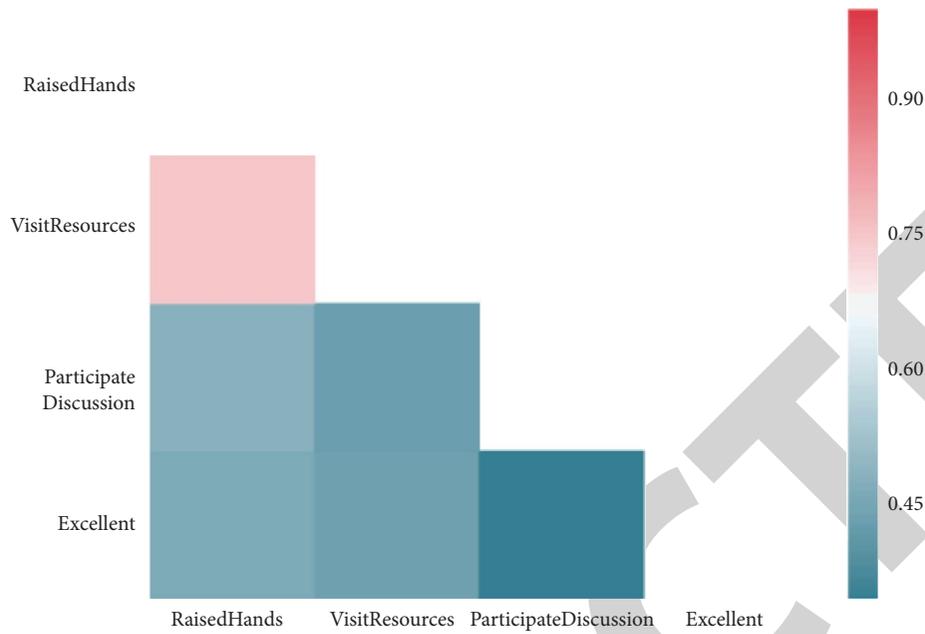


FIGURE 6: Correlation diagram.

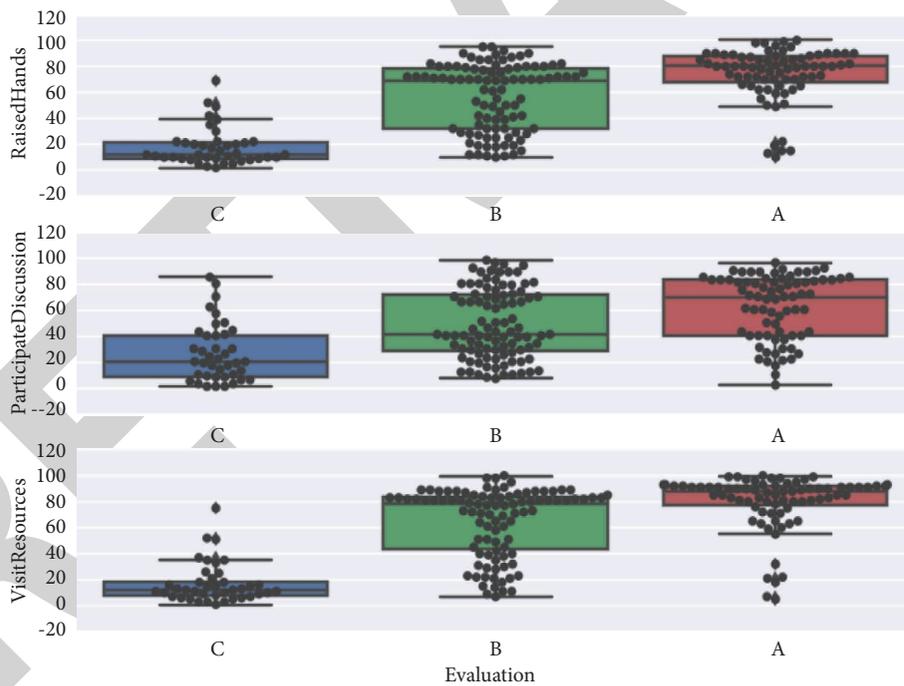


FIGURE 7: Box plots.

According to the comprehensive scores in Figures 8 and 9, students receiving A were the most active in class, and those receiving C were the least active in class. Students with low comprehensive scores rarely looked up online resources after class. Figure 10 revealed the relationship between the number of students who participated in discussions and their comprehensive scores.

4.3. *Predictive Analysis.* After setting the parameters of the model, the BP neural network model was launched to obtain evaluation indicators, as shown in Table 4.

According to Table 4 and Figure 11, the precision and F1 were the highest for students who received A in the comprehensive evaluation. The recall was the highest for students who obtained C and was the lowest for students receiving

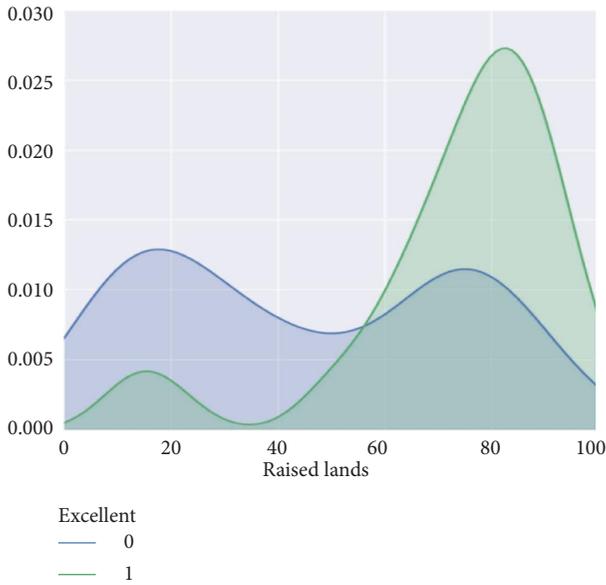


FIGURE 8: Relationship between the times of students raising hands in the classroom and their comprehensive evaluation.

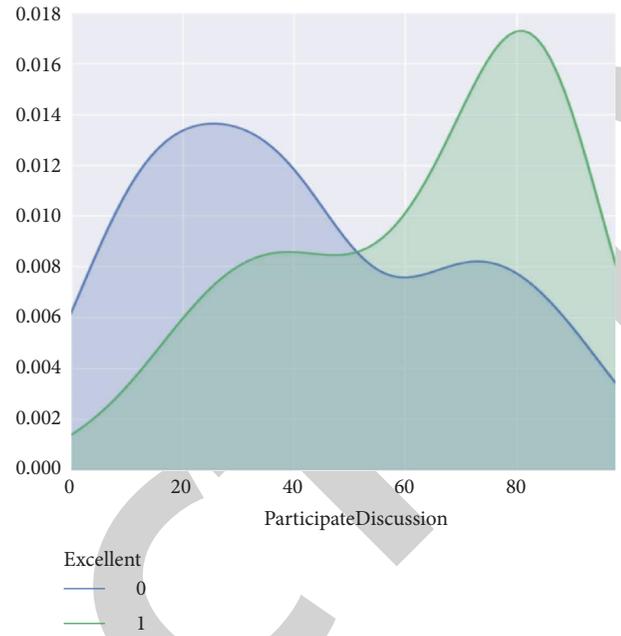


FIGURE 10: Relationship between the times of students participating in discussions and their comprehensive scores.

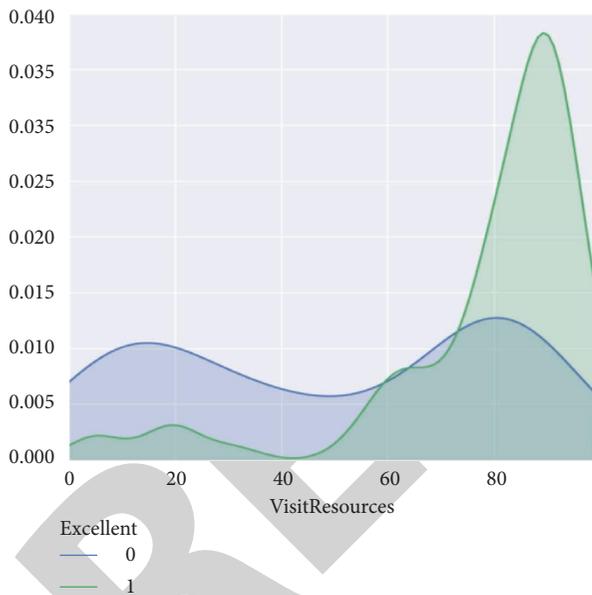


FIGURE 9: Relationship between the times of students accessing online resources and their comprehensive scores.

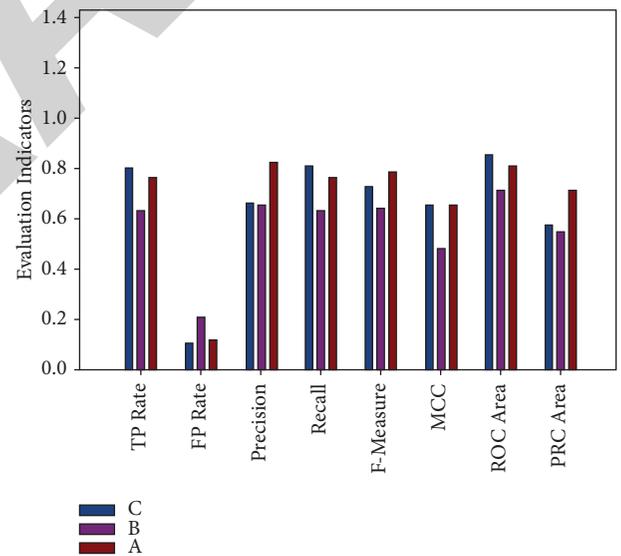


FIGURE 11: Graphical representation of evaluation indicators.

B. The accuracy was high for students at both ends of the comprehensive evaluation.

To evaluate the performance of the model, the models of naive Bayesian, logistic regression, and decision tree were established using the same data samples. The results predicted by the four models were compared and shown in Table 5.

Table 5 and Figure 12 show the performance of the four models. According to the results, the model of the BP neural network yielded the smallest error and had better

TABLE 4: Evaluation indicators.

	C	B	A
TP rate	0.800	0.630	0.759
FP rate	0.107	0.205	0.119
Precision	0.667	0.654	0.815
Recall	0.800	0.630	0.759
F-measure	0.727	0.642	0.786
MCC	0.650	0.428	0.648
ROC area	0.846	0.709	0.817
PRC area	0.576	0.544	0.717

TABLE 5: Comparison of the results of the four models.

	MAE	RMSE	RAE	RRSE
BP neural network	0.1925	0.3870	0.4502	0.8203
Naive Bayesian	0.2779	0.4208	0.6500	0.8959
Logistic regression	0.3123	0.4052	0.7305	0.8626
Decision tree	0.2631	0.4123	0.6153	0.8239

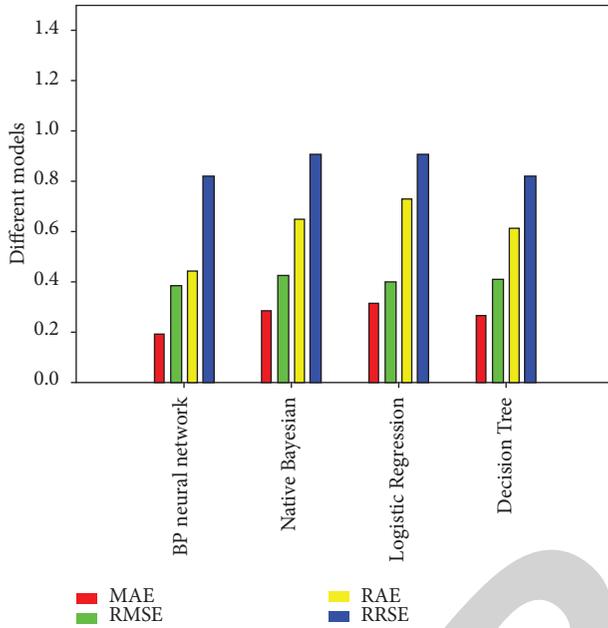


FIGURE 12: Graphical representation of results of four models.

performance. Therefore, it was the most suitable classification model for the learning-behavior-based evaluation.

5. Conclusion

Learning behavior analysis is a “bridge” to connect students with teachers and improve the learning efficiency. It is also a baton to coordinate students, teachers, and managers. This paper used technologies of data mining and data visualization to model students’ learning behavior and predicts their comprehensive evaluation results. It aims to provide teachers with targeted teaching guidance for better intervention and serve as a scientific basis for the enhancement of teaching quality.

When there are a large number of students, it is beyond a teacher’s individual capability to know all students’ learning levels within a short period of time. Learning analysis technology can help them find out students’ learning style and timely adjust teaching strategies according to students’ types. Such technology also provides students with suitable resources and helps them learn about their strengths and shortcomings, so that students can adjust their learning plans and strategies accordingly.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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