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Retraction

Retracted: Quality Evaluation and Satisfaction Analysis of Online Learning of College Students Based on Artificial Intelligence

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1].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) Manipulated or compromised peer review

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] S. Yun, Y. Bai, and B. Jongnam, "Quality Evaluation and Satisfaction Analysis of Online Learning of College Students Based on Artificial Intelligence," *Security and Communication Networks*, vol. 2022, Article ID 6322570, 10 pages, 2022.

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Research Article

Quality Evaluation and Satisfaction Analysis of Online Learning of College Students Based on Artificial Intelligence

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In order to better study the quality and satisfaction of online learning of college students, this paper analyzes and researches online learning of college students based on relevant theories of artificial intelligence. Through the traditional machine learning method to evaluate the quality of online learning, the deep learning theory is applied to the satisfaction analysis of college students'' online learning. The results show that different statistical indexes have different influences on traditional machine learning, but they all show a gradually decreasing trend. The main reason for the different degrees of influence is that the emphasis of different statistical indexes is different, and the order from large to small is MAE > RMSE > MAPE > TIC. Statistical indicators can better describe the first stage of test data, while the corresponding quality indicators can better characterize the second stage of test data. It indicates that statistical and quality indexes should be considered comprehensively to analyze the test data accurately. The increase of evaluation indexes based on traditional machine learning can improve the evaluation indexes of online learning quality of college students. And the improvement of statistical indicators and evaluation factors can promote the accuracy of online learning quality evaluation of college students. Based on the theory of artificial intelligence, the quality and satisfaction of online learning of college students are analyzed and evaluated by using the traditional machine learning method and deep learning method, respectively. Relevant research can provide a research basis for artificial intelligence in online learning methods of college students.

1. Introduction

Artificial Intelligence (AI) has been widely applied in various fields: water turbine engine [1], optimization of high-rise buildings [2], renewable energy [3], immune analysis of smartphones [4], and automatic detection [5]. Artificial intelligence includes traditional machine learning and deep learning, and different contents have different application fields. In order to better analyze the data of images, the deep learning and the traditional machine learning algorithms used in image processing can be seen through the contrast analysis of the two algorithms. While deep learning under the theory of image processing precision is higher and has more obvious advantages, traditional machine learning has a good application in sample data [6].

Traditional machine learning has significant applications in biology, programming, etc. In order to promote the application of traditional machine learning algorithms in cell feature recognition, a comprehensive segmentation method based on traditional machine learning theory was proposed in [7]. This method avoids the relevant problems existing in the application process of traditional technology and can better carry out further slice analysis of cells. Moreover, the experimental verification shows that the time of the slice is greatly shortened, and the precision of the corresponding cell cutting technology is greatly improved. In view of a series of problems existing in deep learning methods in the process of gene coding, a kind of coding tool and model based on traditional machine learning algorithm was proposed in [8]. This model overcomes the shortcoming that the original model cannot reflect the internal structure of cells well, and the model can be used to organize and replicate a large number of cells, and the replication results are highly consistent with the shape of the original sample. Finally, the accuracy of the model is verified by relevant experiments. In the process of online communication, we often encounter related problems such as slow language coding conversion speed, which will have a great impact on communication and work times. In order to further improve the speed of language conversion in communication engineering, a programming step based on a traditional machine learning algorithm is added on the basis of the original language conversion. By using the traditional machine learning algorithm, a large amount of data in the process of language communication can be classified and processed specifically. In this way, the speed of data extraction of each part is increased, and the grouping analysis algorithm is adopted to provide the targeted output of relevant languages. This step can be carried out before language communication, so as to greatly improve the speed of language conversion [9].

Deep learning has different application prospects in different fields. Artificial intelligence and theories related to deep learning are adopted to conduct targeted research on the learning framework and training methods of music. Through analysis, it is found that deep learning has a good application prospect in simulating music, and the use of deep learning algorithms can further improve the control and communication functions of music, and verify the accuracy of the model through practical tests [10]. In view of the problems existing in the process of facial expression recognition, a deep learning algorithm is proposed to improve the accuracy of facial recognition [11]. This model adopts the method of multi-angle analysis. The problems existing in traditional facial recognition are improved so that the optimized deep learning algorithm can adapt to face recognition in a complex environment. Firstly, the optimized algorithm is used to accurately identify the face. At this stage, accurate recognition of the face can improve the efficiency of the next step of the analysis. The optimized extraction algorithm can make the recognition and extraction of facial parameters more targeted. By inputting relevant keyword parameters, the targeted recognition data can be obtained. In this way, the identification accuracy can be improved and the interference of useless data can be reduced. The facial recognition data obtained by the optimization algorithm are imported into machine learning. Through the further calculation of machine learning, the derived data can more accurately reflect the facial features of each sample. So as to better apply the data analysis method, experimental verification is an important step to test samples. By using 300 samples to test the optimization scheme, the results show that the accuracy of the optimization scheme is about 20% higher than the original method. Demonstrate the reliability of machine learning methods. In order to further improve the application of deep learning in medical diagnosis, a new research method based on deep learning theory was proposed in [12]. The method realizes the diagnosis and analysis of the lesion site through the diagnosis, analysis, and treatment of the lesion site, and then realizes the application of deep learning in the medical field. In order to further verify the diagnostic accuracy of the model, laboratory experiments are used to illustrate the superiority of deep learning. Deep learning can also be used to describe the folding and separation of proteins [13]. The quantitative characterization and description of proteins can be achieved by using an accurate deep learning model, providing a new research direction for the model. In view of the existing problems in the field of the lithium battery, the deep learning method was adopted to construct relevant models [14], so as to obtain different types of targeted analysis methods. The optimization model imports the relevant data of the lithium battery into the corresponding learning algorithm. Through the analysis and extraction of the algorithm, the feature vector and feature parameter relationships of the lithium battery under the algorithm are found. Then, feature vectors and curves corresponding to feature relations are put into the analysis plate. The corresponding relationship between the characteristic vector and characteristic parameter curve of a lithium battery can be studied in this plate, and the quantitative relationship between them can be found. The characteristic parameter curves are used to characterize feature vectors so that the two factors are transformed into one factor. The analysis plate can greatly compress the calculation data of the lithium battery, so as to greatly reduce the calculation time and improve the calculation speed in the process of data export. Finally, this method is used to verify the model.

The abovementioned research is mainly based on the relevant theories of artificial intelligence and adopts the traditional machine learning and deep learning algorithms to apply biology, information recognition, and other aspects. In order to further promote the application of artificial intelligence in online learning of college students. This paper evaluates the online learning quality of college students based on the evaluation model of traditional machine learning theory and combined with the theory of artificial intelligence. Based on deep learning algorithm, the satisfaction degree of online learning of college students is analyzed. Finally, the accuracy of relevant indicators is verified by two experiments. This study can provide theoretical support for AI in the online learning of college students and other aspects.

2. The Basic Theory of Traditional Machine Learning

2.1. Prediction Module Design. Machine learning is an interdisciplinary subject and the core of artificial intelligence. It covers multidisciplinary theoretical knowledge such as statistics and methodology. By using computer-aided tools in the context of big data to target and simulate behaviors and methods related to human activities. The performance of relevant models is optimized by theoretical analysis and experimental verification. With the advent of the era of big data, more and more data analysis methods and means are applied to model construction and data analysis. Machine learning can effectively extract knowledge from data and provide technical support for the industry. This has created unprecedented opportunities for the development of machine learning. Machine learning has superior performance in regression tasks and is considered as a favorable tool for studying online learning and the education of college students because of its better accuracy and pertinence.

Whale Optimization Algorithm (WOA) is a typical traditional machine learning algorithm [15]. The whale optimization algorithm simulates the hunting behavior of humpback whales, which consists of searching for prey, surrounding prey, and "bubble net" foraging. Tests on mathematical optimization and structural engineering problems show that the whale optimization algorithm has an excellent performance in exploration, utilization, avoiding local optimization, and convergence [16]. The analysis mechanism of WOA is shown in Figure 1, and the corresponding mathematical model can be divided into the following aspects:

2.1.1. Data Collection. WOA first defines the optimal algorithm for relevant data, and then approaches the search operation process of other data toward the optimal one, so as to update the data. The relevant formula is as follows:

$$\begin{cases} \vec{D} = \left[\vec{C} \times \vec{X}^{*}(t) - \vec{X}(t)\right], \\ \vec{X}(t+1) = \vec{X}^{*}(t) - \vec{A} \times \vec{D}, \end{cases} \tag{1}$$

where t is the current iteration; $\vec{X}^{*}$ is the position vector; $\vec{X}$ is the position vector; $\vec{A}$ and $\vec{C}$ are coefficient vectors.

$$\begin{cases} \vec{A} = 2\vec{a} \times \vec{r} - \vec{a}, \\ \vec{C} = 2\vec{r}, \end{cases} \tag{2}$$

where $\vec{r}$ is the random vecto and $\vec{a}$ decreases linearly from 2 to 0 during iteration.

2.1.2. Data Calculation. The $\vec{a}$ value in formula (2) is used to realize data calculation, and the fluctuation range $\vec{A}$ is reduced accordingly.

The corresponding positions of the data can be analyzed by establishing the helix equation:

$$\begin{cases} \vec{X}(t+1) = \vec{D}^{*} \times e^{bl} \times \cos(2\pi l) + \vec{X}^{*}(t), \\ \vec{D}^{*} = \left|\vec{X}^{*}(t) - \vec{X}(t)\right|, \end{cases} \tag{3}$$

where $\vec{D}^{*}$ is the distance from the i-th data to the optimal solution; b is the constant of the logarithmic spiral shape; l is a random number in $[-1, 1]$.

$$\vec{X}(t+1) = \begin{cases} \vec{X}^{*}(t) - \vec{D} \times \vec{A}, & \text{if } p < 0.5, \\ \vec{D}^{*} \times e^{bl} \times \cos(2\pi l) + \vec{X}^{*}(t), & \text{if } p \geq 0.5, \end{cases} \tag{4}$$

where p is a random number in $[0, 1]$.

2.1.3. Data Analysis. When $\vec{A}$ greater than 1 or less than -1, the data search process will be far away from the optimal value. The analysis method of artificial intelligence can highlight the process of exploration and enable the WOA algorithm to conduct a global search. The corresponding mathematical model is as follows:

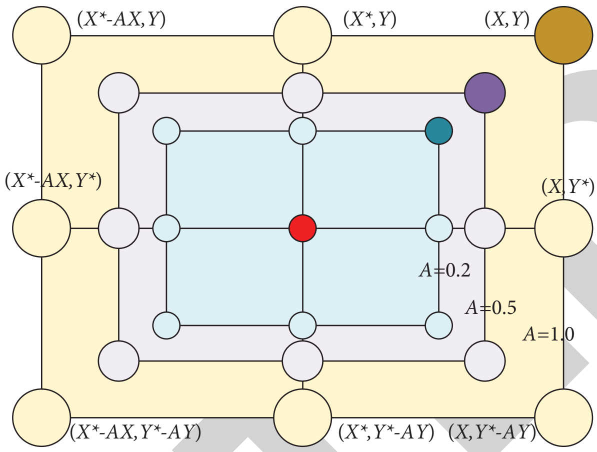

Figure 1: WOA computer graphics.

$$\begin{cases} \vec{D} = \left|\vec{C} \times \vec{X}_{\text{rand}} - \vec{X}\right| \\ \vec{X}(t+1) = \vec{X}_{\text{rand}} - \vec{A} \times \vec{D}, \end{cases} \tag{5}$$

where $\vec{X}_{\text{rand}}$ is the vector.

The whale optimization algorithm starts its calculation with a set of random solutions. During each iteration, the search agent updates its position based on the randomly selected search agent or the currently obtained optimal solution. When parameter a decreases from 2 to 0, exploration and utilization can be guaranteed. When $\vec{A}$ is greater than, a random search agent can be selected. The optimal solution is chosen when $\vec{A}$ is less than 1. According to the change of p value, the whale optimization algorithm can switch between spiral and circular movement. When the termination condition is met, the iteration stops. The WOA algorithm has a relatively low computational speed during calculation. In order to further improve the computational speed of this algorithm, relevant theories of extreme learning machine are introduced into the WOA algorithm [17], so as to obtain extreme learning machine (ELM). ELM has good generalization ability, and its learning speed is thousands of times faster than mainstream models [18] (Figure 2). The network structure diagram of an extreme learning machine can be divided into the input hiding layer and output layer according to the different analysis functions. The data are first imported into the input layer, through which the data are analyzed and processed, and then the analyzed data are imported into the hidden layer. Then through the relevant algorithms of the hidden layer to modify the data, and then the modified data are imported into the output layer for further optimization, and finally, the corresponding data are exported.

ELM can randomly generate independent samples w and b before training, and the hidden neuron threshold β can be calculated by determining L and H [19]. To further analyze the influence of parameters on ELM, the weight proportion

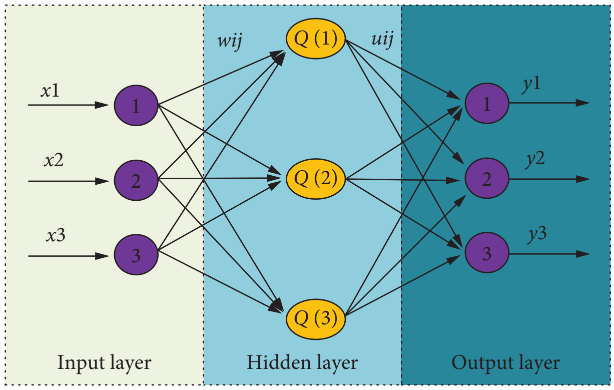

Figure 2: The network structure diagram of the extreme learning machine.

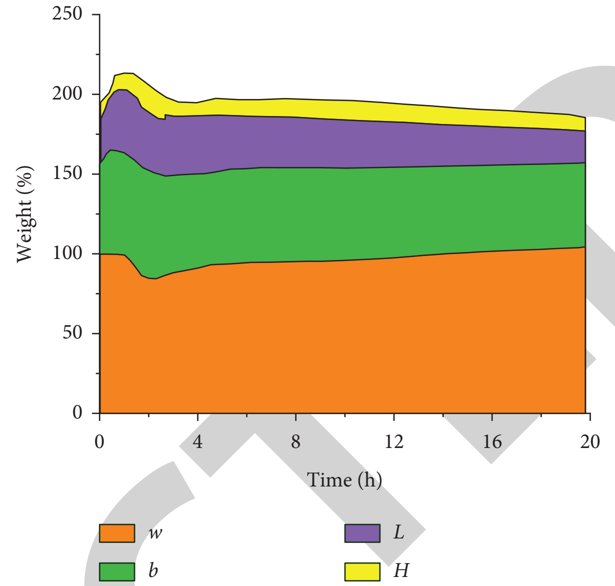

Figure 3: The weight diagram of different parameters on ELM.

curves under different parameters were drawn, as shown in Figure 3.

According to the weight proportion of different parameters in the ELM algorithm, different parameters have different impacts on ELM. Among them, parameter w has the greatest influence, which accounts for about 1/3 of the weight of ELM on the whole. The performance is first gentle and then gradually declines, and finally gradually rises and tends to a steady increase in the changing trend. Secondly, parameter b is next to parameter w in weight proportion. The overall variation trend of parameter b is basically consistent with parameter w, accounting for about 1/5 of the weight of ELM. The weight of parameter H was the lowest, and the weight of parameter L was slightly higher than that of parameter H. Therefore, the weight of different parameters on ELM was in the following order: $w > b > L > H$.

2.2. Evaluation Module Design for Traditional Machine Learning. To evaluate the prediction performance of the ELM model, different statistical indicators were used to analyze the model [20]: aiming at the application of traditional machine learning in online learning of college students, in order to better analyze the quality of online learning of college students, different indicators are used to evaluate traditional machine learning. The specific meanings of different indicators are shown as follows: MAE can accurately reflect the size of prediction error. RMSE is similar to MAE but more sensitive to outliers. MAPE can reflect the deviation of forecast values. TIC is a common indicator to measure the prediction ability of the model, while r can reflect whether the model can accurately predict the changing trend of pollution.

Mean Absolute Error (MAE) is as follows:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|F_i - Q_i\right|. \tag{6}$$

Root Mean Square Error (RMSE) is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(F_i - Q_i\right)^2}. \tag{7}$$

Mean Absolute Percentage Error (MAPE) is as follows:

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{F_i - Q_i}{Q_i}\right|. \tag{8}$$

Theil Inequality Coefficient (TIC):

$$\mathrm{TIC} = \frac{\sqrt{(1/N)\sum_{i=1}^{N}\left(F_i - Q_i\right)^2}}{\sqrt{(1/N)\sum_{i=1}^{N}F_i^2} + \sqrt{(1/N)\sum_{i=1}^{N}Q_i^2}}. \tag{9}$$

Correlation coefficient r is as follows:

$$r = \frac{\sum_{i=1}^{N}\left(F_i - \overline{F}\right)\left(Q_i - \overline{Q}\right)}{\sqrt{(1/N)\sum_{i=1}^{N}\left(F_i - \overline{F}\right)^2} + \sqrt{(1/N)\sum_{i=1}^{N}\left(Q_i - \overline{Q}\right)^2}}. \tag{10}$$

where N is the number of samples. F_i and Q_i are the forecast value and actual value of the i-th sample, respectively. $\overline{F}$ and $\overline{Q}$ are the average of the forecast value and the actual value, respectively.

To further analyze the influence of the abovementioned parameters on the model, change curves of the model under different parameters were drawn, as shown in Figures 4 and 5, respectively. It can be seen from Figure 4 that different parameters have different specific values of change, but the overall trend of change is gradually decreasing, indicating that with the increase of iteration times, the influence degree of corresponding parameters is gradually decreasing. The reason is that the parameters of the model are further modified and optimized by the traditional machine learning algorithm, which leads to the gradual decline of corresponding parameters. Specifically, it can be concluded that the value of parameter MAE is the largest, and that of parameter RMSE is second only to that of parameter MAE. The influence degree of parameter MAPE is higher than that of parameter TIC, and the influence degree of parameter TIC is the least.

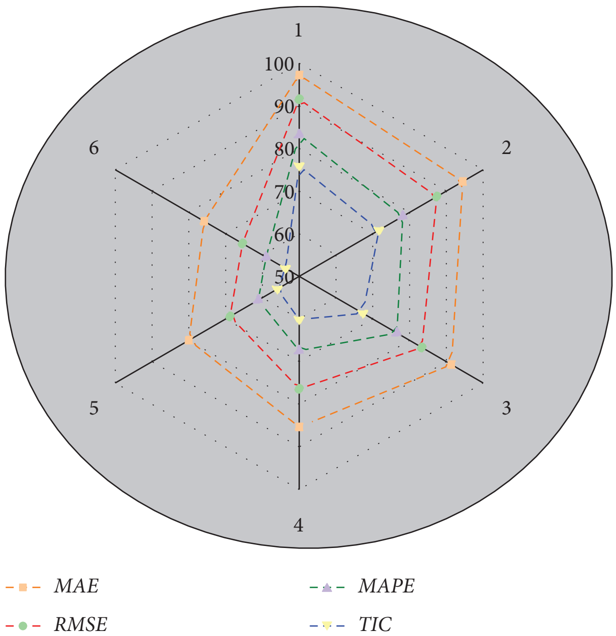

Figure 4: The variation trends of different parameters.

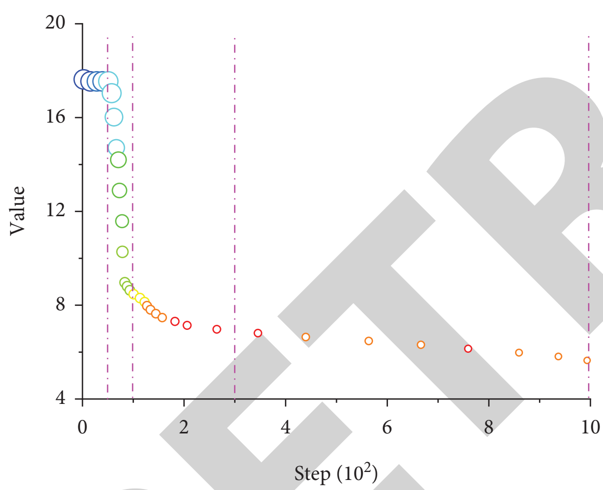

Figure 5: The variation trend of correlation coefficient r.

The change curve of correlation coefficient r is shown in Figure 5, from which we can see that this parameter shows a fluctuating trend. On the whole, it can be divided into four stages according to the trend of change. (1) In the stable stage, the influence value of correlation coefficient R shows a gentle change trend in this stage, indicating that the influence degree of correlation coefficient in this stage remains unchanged. (2) In the drop stage, the curve suddenly drops as the number of iterations increases. The main reason for the sudden drop in the curve is the difference in model data. After the rapid decline of the second stage, the curve suddenly drops. (3) In the flat stage, the change curve of correlation coefficient R enters the third stage, during which the data of correlation coefficient gradually decreases, and the slope of corresponding data shows a trend of zero. (4) In the stable stage, at last, with the increase of the number of iterations, the change of the data tends to be gentle and finally stable, indicating that the data has reached a stable degree, and also indicating that the calculation results of the corresponding traditional machine learning model tend to be stable.

The abovementioned analysis enables us to have a deep understanding of the basic theory of traditional machine learning. In order to further improve the evaluation accuracy of online learning quality of college students, a machine learning algorithm is introduced to build the corresponding model architecture, as shown in Figure 6. The component diagram of the online learning quality evaluation model of college students under machine learning can be divided into three modules, namely, preprocessing module, analysis module, and evaluation module. The preprocessing module mainly includes data insertion and supplements. In this stage, the data can be further analyzed and processed to make the obtained data have better extraction characteristics. Then the data are imported into the analysis module, which mainly includes signal analysis and network optimization. The data are imported into the neural network. After the analysis through the neural network, the data are imported into the estimation module, and further statistical analysis and evaluation of the data in the module are carried out through the five different parameters mentioned above. Finally, the obtained data are exported from the model architecture diagram.

3. Related Theories of Deep Learning

3.1. Design of Prediction Model Based on Deep Learning Theory. Convolutional Neural Networks (CNN) are feedforward Neural Networks containing Convolutional operations and deep structures and are classic deep learning algorithms [21] (Figure 7). A convolutional neural network mimics the construction of a biological visual perception mechanism, which can carry out supervised and unsupervised learning. The parameter sharing of a convolutional kernel in the hidden layer and the sparsity of interlayer connections enable the convolutional neural network to dot lattice features with a small amount of computation. The evaluation and analysis of the online learning quality of college students have a stable effect and no additional feature engineering requirements for data. The corresponding calculation formula is as follows:

$$\begin{cases} Z^{l+1}(i,j) = \left[Z^l \otimes w^{l+1}(i,j)\right] + b \\ L_{l+1} = \dfrac{L_l + 2p - f}{s_0} + 1, \end{cases} \tag{11}$$

where Z^l and Z^{l+1} are the input and output of convolution at layer $l+1$; L_{l+1} is the size of Z_{l+1}; b is the number of convolution layers; p is the number of filling layers; f is the activation function in the convolutional layer.

$$A^l_{i,j,k} = f\left(Z^l_{i,j,k}\right), \tag{12}$$

where f is the convolution layer. The parameters of the convolutional layer include the size, step size and fill of the

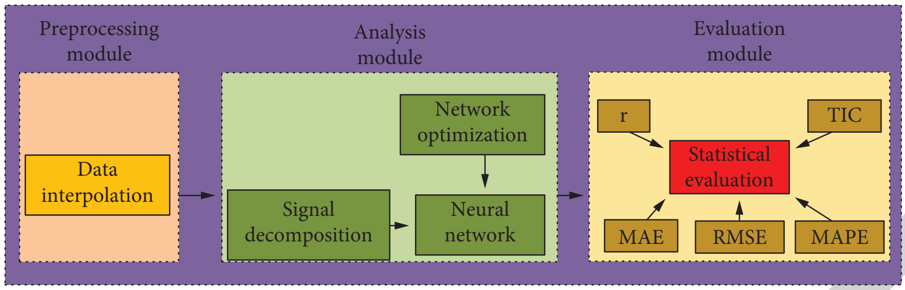

Figure 6: The structure diagram of the online quality evaluation model for college students under machine learning.

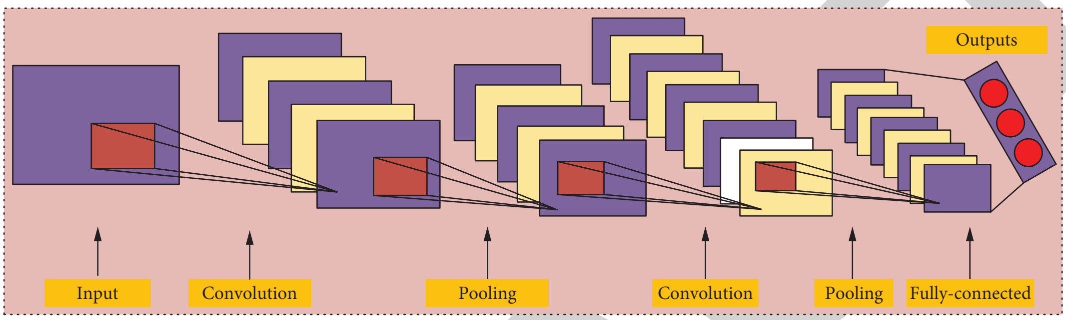

Figure 7: The model architecture diagram of Convolutional Neural Network (CNN).

convolution kernel, which jointly determines the size of the output feature graph of the convolutional layer and are the hyperparameters of the convolutional neural network. The size of the convolution kernel can be specified as any value smaller than the size of the input image. The larger the convolution kernel is, the more complex the input features can be extracted. By analyzing and extracting characteristic parameters of college students' online learning, the relevant parameters of the convolutional neural network are used to optimize online learning, so as to obtain accurate calculation results.

$$A_k^l(i,j) = \left[\sum_{x=1}^{f}\sum_{y=1}^{f} A_k^l(s_0 i + x, s_0 j + y)^p\right]^{1/p}, \tag{13}$$

where p is the preset parameter, and s_0 is the convolution step.

Hidden layers of convolutional neural networks include three common constructs: convolutional layer, pooling layer, and full connection layer. Some more modern algorithms may have complex constructs such as the Inception module and residual block. Among the common architectures, the convolutional layer and pooling layer are special to the convolutional neural network. The convolution kernel in the convolution layer contains weight coefficients, while the pooling layer does not. An implicit layer of a convolutional neural network can be used to evaluate and analyze college students' online learning.

It can be seen from the abovementioned analysis that the preset parameters have a certain influence on the activation function in the model. To analyze the impact of the preset parameters on the model results in detail, the model data output curves under different preset parameters are drawn, as shown in Figure 8. Through the influence curve of the

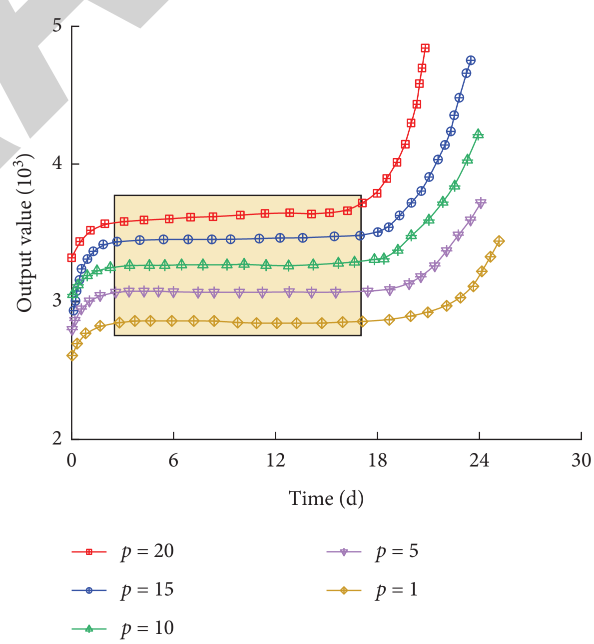

Figure 8: The influence of preset parameter p on the prediction model.

preset parameter P on the prediction model, we can see that different preset parameters will have a great impact on the operation results of the model. Corresponding curve changes can be divided into three stages. The first stage is the stage of slow increase, in which the output value of the corresponding model parameters shows a trend of gradual increase, but the slope of the corresponding curve gradually decreases and eventually approaches zero. Thus, model parameters enter the second stage. In the stable increase stage, the output value of model parameters tends to be stable, and the corresponding curve slope tends to zero. After a long period of stability, the model enters the third stage. In the acceleration stage, the data of the curve shows a rapidly increasing trend. It indicates that the longer the model runs, the greater the influence on the output value of model parameters. It can be seen from the size of different preset parameters P that, with the gradual increase of preset parameters. The output value of the corresponding model shows a trend of rapid increase, indicating that the larger the preset parameter value is, the greater the influence on model parameters is.

3.2. Evaluation Model Based on Deep Learning. Model evaluation indexes based on deep learning mainly include statistical indexes and quality indexes [22]:

(1) *Statistical Indicators*. Normalized Mean Bias (NMB) is as follows:

$$\mathrm{NMB} = \frac{\sum_{i=1}^{N} (F_i - Q_i)}{\sum_{i=1}^{N} Q_i}. \tag{14}$$

(2) *Quality Index (QI)*. The calculation formula for analysis accuracy of the QI Index is as follows:

$$\mathrm{QI} = \frac{n_{\mathrm{QI}}}{N_{\mathrm{QI}}}, \tag{15}$$

where QI is the analysis accuracy rate; n_{QI} is the number of samples for analyzing accurate indicators; and N_{QI} is the total number of samples.

Figure 9 shows the evaluation and analysis curves of the model under two different indicators. It can be seen from the evaluation and analysis diagrams of the model under different indicators that the statistical indicators and quality indicators are typically segmented. In the first stage, the statistical indicators show typical linear characteristics, and the corresponding curve slope is approximately constant. When falling to the second stage, the curve shows a nonlinear downward trend. The corresponding slope shows a rapid decline at first and then tends to gentle change, which also indicates that the corresponding statistical index value will gradually tend to be stable. The changing trend of the corresponding quality index was opposite to that of the statistical index. The quality index increased slowly in the first stage and then rapidly tended to the maximum value. The slope of the corresponding curve increased slowly at first and then rapidly. When the curve enters the second stage, it shows a relatively gentle decline and the corresponding slope is basically stable, indicating that the corresponding data curve shows an approximately linear trend of change. It can be seen from the test data that the test data showed obvious linear characteristics in both stages, showing a linear increase in the first stage and a linear decline in the second stage. In addition, the slope of the curve in the first stage is larger than that in the second stage, indicating that neither a single statistical index nor a

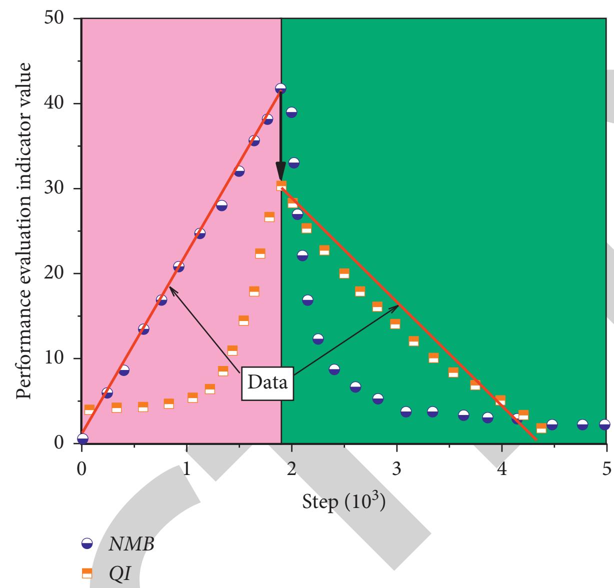

FIGURE 9: The analysis diagram of model evaluation with different indicators.

quality index can better reflect the changing trend of data. Therefore, the experimental data can be described and analyzed by combining the statistical index and quality index.

Through the abovementioned analysis of relevant theories under deep learning, the design and analysis of model architecture under deep learning can be obtained, as shown in Figure 10. Through the model architecture diagram of deep learning, we can see that the model architecture can be divided into three parts: data preprocessing module, feature module selection, and feature module construction. Among them, the data processing module is mainly to import the data into the corresponding module and normalize the data. Secondly, the data are imported into the feature module, and the effective feature parameters are obtained through feature analysis and extraction of the data. Finally, the extracted parameters are imported into the feature building module, and the corresponding learning module is finally obtained through the decomposition of the feature combination. Through the learning module, the parameters of the model can be further processed, and finally, the corresponding satisfaction evaluation model under deep learning can be obtained.

4. Application of Artificial Intelligence in Online Learning of College Students

Contemporary college students spend more and more time on online learning, so different models are needed to evaluate and analyze learning quality and satisfaction [23]. AI has a wide range of applications in various aspects, among which traditional machine learning theory and deep learning as the two most typical artificial intelligence that can be used in learning evaluation. The relevant theories of traditional machine learning can be used to evaluate the quality of online learning of college students, and the relevant theories

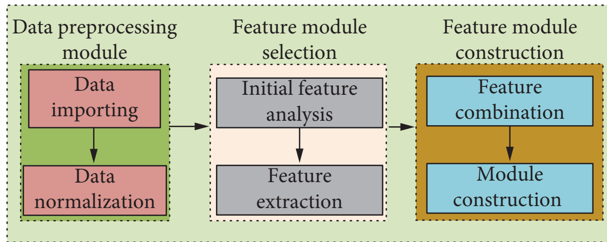

Figure 10: The model architecture diagram based on deep learning.

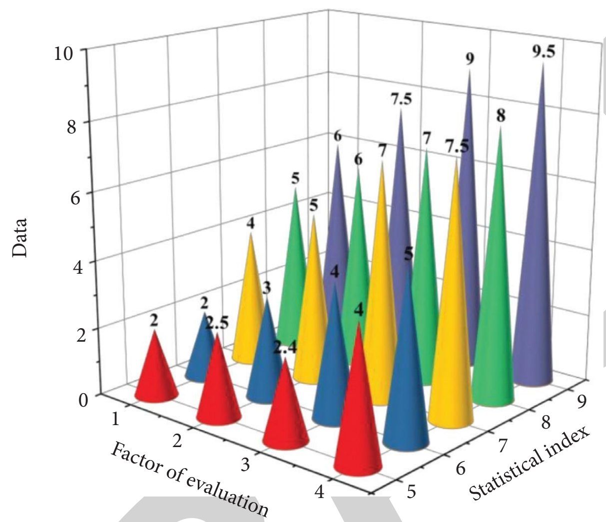

Figure 11: The quality evaluation diagram of statistical indexes under different evaluation factors.

of deep learning can be used to analyze the satisfaction of online learning of college students.

4.1. Evaluation of Online Learning Quality of College Students Based on Traditional Machine Learning. The evaluation of the online learning quality of college students can be mainly divided into four aspects: pre-class preview, classroom performance, homework, and examination [24]. Based on the relevant theories of traditional machine learning, the evaluation of online learning quality of college students can be realized through the design of corresponding evaluation modules, and statistical data curves under different evaluation factors can be obtained, as shown in Figure 11. The corresponding data are shown in Table 1. Among them, 1–4, respectively, represent pre-class preview, class performance, homework, and exam, and 5–9, respectively, represent MAE, RMSE, MAPE, and TIC. According to the quality evaluation change data of statistical indicators under different evaluation factors, it can be seen that with the gradual improvement of evaluation factors, the corresponding statistical quality indicators show a gradually increasing trend. It shows that the improvement of the evaluation index can improve the evaluation quality index. It can be seen from statistical indicators that different statistical indicators have different quality evaluation results. With the increase of statistical indexes, the corresponding quality indexes also show an increasing trend, indicating that the higher the evaluation index factors and statistical indexes are, the higher the corresponding data output value will be. It shows that the quality of online learning and quality evaluation of college students are higher.

4.2. Analysis of College Students' Learning Satisfaction Based on Deep Learning. In order to better analyze the satisfaction of online learning of college students under deep learning, the evaluation model of deep learning is used to analyze the corresponding satisfaction indicators, which mainly include knowledge application, memorized knowledge, proficiency, energy investment, and classroom perception [25]. Statistical data of college students' satisfaction with online learning under different factors are obtained through analysis, as shown in Table 2, and corresponding change curves are drawn, as shown in Figure 12.

Through the satisfaction analysis chart of statistical indicators under different evaluation factors, we can see that different factors have different influences on the satisfaction of specific indicators. Among them, according to NMB factor analysis, memorizing knowledge is the most important factor affecting satisfaction, followed by proficiency, classroom perception, energy investment, and knowledge application. However, QI analysis factors are different from NMB, in which knowledge application is the most influential factor in satisfaction, followed by proficiency, classroom perception, energy involvement, and memory knowledge. It

Table 1: The quality evaluation table under different factors.

Number	Factor	Statistical index	Data	Number	Factor	Statistical index	Data
1	Preclass preview	MAE	2	11	Homework	MAE	2.4
2		RMSE	2	12		RMSE	4
3		MAPE	4	13		MAPE	7
4		TIC	5	14		TIC	7
5		r	6	15		r	9
6	Classroom performance	MAE	2.5	16	Examination	MAE	4
7		RMSE	3	17		RMSE	5
8		MAPE	5	18		MAPE	7.5
9		TIC	6	19		TIC	8
10		r	7.5	20		r	9.5

Table 2: statistical table of satisfaction under different factors.

Number	Factor	Analysis index	Data
1	NMB	Knowledge application	0.787
2		Memory of knowledge	0.952
3		Proficiency	0.869
4		Energy input	0.8
5		Class awareness	0.846
6	QI	Knowledge application	0.825
7		Memory of knowledge	0.628
8		Proficiency	0.769
9		Energy input	0.682
10		Class awareness	0.751

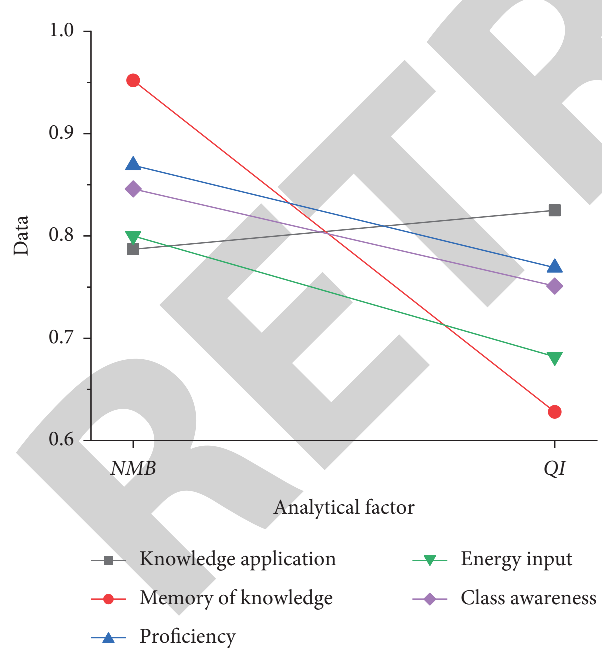

Figure 12: The satisfaction analysis of statistical indexes under different evaluation factors.

indicates that the satisfaction of NMB and QI is different from that of statistical indicators. Therefore, it is necessary to comprehensively consider the two factors to obtain the correct results for the online learning satisfaction analysis of college students.

5. Conclusion

(1) The correlation coefficient r can be divided into the stable stage, falling stage, gentle stage, and stable stage according to the changing trend. The large variation range of this parameter indicates that it has a great influence on the evaluation module in traditional machine learning.

(2) According to the weight proportion diagram of different parameters in the ELM algorithm, it can be seen that different parameters have different impacts on ELM. The main reason is that the difference in independent samples will lead to the difference in the training random generation process, and the weight function of the input layer and the hidden layer will change. As a result, the output matrix is different, and finally, the weight ratio of parameters to ELM is different. The proportion of parameter w is the largest, and that of parameter H is the smallest.

(3) The influence curve of the preset parameter p on the forecast model can be divided into three stages according to the variation trend and model rule: slow increase stage, steady increase stage, and acceleration stage. And the gradual increase of preset parameter p will lead to the rapid increase of the corresponding model.

(4) According to the satisfaction survey results of college students based on deep learning, the influence degree of knowledge memorization is the highest under the NMB parameter, while the influence degree of

knowledge application is the highest under the QI index.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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