Research Article

Design of Online Learning Early Warning Model Based on Artificial Intelligence

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Received 22 February 2022; Revised 22 March 2022; Accepted 1 April 2022; Published 6 May 2022

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Students have produced a large number of learning logs and a large number of educational data through online learning. In order to extract useful information from these massive information, support teachers’ teaching activities, improve teaching quality, provide learners with personalized learning support, and teach students according to their aptitude, educational big data analysis has attracted extensive attention of educators [3, 4]. At the same time, online education policies at different levels have been introduced one after another. People gradually understand, accept, and get used to online learning methods, which has promoted the development of online education [5].

Under the impact of informationization, education and information technology are deeply integrated, and online education is on the rise. At the same time, the theory and methods of artificial intelligence are gradually applied to the field of education, and analysis methods such as learning analysis and data mining provide effective analysis methods for online learning process and learning effect [6, 7]. Artificial intelligence is one of the “three cutting-edge technologies in the 21st century.” With the continuous emergence and application of artificial intelligence such as machine learning and neural network, the extraction, mining, analysis, early warning, and decision-making guidance of database data have been realized, and it has been successfully

1. Introduction

Under the background of globalization, with the development of information technology, the concept of Internet plus has made rapid progress in the field of education, especially in the construction of digital campus network and higher education. The concept of online learning has been recognized by more and more universities, including Peking University, Tsinghua University, Shanghai Jiao Tong University, and other online learning platforms. These platforms have rich curriculum resources and strong teachers [1, 2]. Through online learning, students have produced a large number of learning logs and a large amount of educational data. In order to extract useful information from these massive information to support teachers’ teaching activities, improve teaching quality, provide personalized learning support for learners, and teach students according to their aptitude, educational big data analysis has attracted extensive attention of educators [3, 4]. At the same time, online education policies at different levels have been introduced one after another. People gradually understand, accept, and get used to online learning methods, which has promoted the development of online education [5].

Under the impact of informationization, education and information technology are deeply integrated, and online education is on the rise. At the same time, the theory and methods of artificial intelligence are gradually applied to the field of education, and analysis methods such as learning analysis and data mining provide effective analysis methods for online learning process and learning effect [6, 7]. Artificial intelligence is one of the “three cutting-edge technologies in the 21st century.” With the continuous emergence and application of artificial intelligence such as machine learning and neural network, the extraction, mining, analysis, early warning, and decision-making guidance of database data have been realized, and it has been successfully
applied in the fields of finance, medicine, food, electric power, coal mine, etc., which has triggered the innovative thinking and exploration of natural gas purification enterprises [8]. The characteristics of online learning environment, such as classroom virtualization, conscious learning behavior, flexible learning methods, and fragmented learning time, are becoming more and more obvious. Only when computers have enough learning data can they become more and more “intelligent” through training, such as Alpha dogs and driverless drivers [9, 10]. An important branch of artificial intelligence is machine learning, and deep learning is an important branch of machine learning. Constructing a quantitative research model of online learning under the background of artificial intelligence and effectively monitoring and improving the learning effect have become the key problems to be solved urgently. Learner performance refers to the learning achievements, effects, and benefits achieved by learners when they complete a certain task in a certain time and under certain conditions [11, 12].

Since the existing research mainly focuses on the online learning and early warning model of artificial intelligence and uses single or two important characteristic parameters to build the online learning and early warning model, there are some problems such as the model characteristic parameters are not fully covered and the early warning false alarm rate is high [13, 14]. On the basis of understanding the artificial intelligence algorithm, we should also select the corresponding detection indicators according to the objectives of the online learning early warning model and the needs of the actual work of network operation and maintenance. Then, follow the corresponding data flow of AI technology to analyze data preprocessing, feature selection, and model training [15].

2. Related Work

Literature [16] suggests that online learning monitoring and early warning model can include online learning risk information, describe the dynamic process of monitoring key factors, evaluate the degree of deviation of monitoring object state from early warning line, and send early warning signals to decision makers. In literature [17], through the method of big data analysis, in the visual early warning system, the learning dashboard system of Khan College is more representative. The system combines the learning management system with visualization tools; records and tracks learners’ learning behaviors, habits, and interests by using information tracking technology and mirror technology; analyzes data such as test scores, learning time, and learning paths; and gives feedback and early warning according to the mastery of knowledge points to help learners improve their knowledge points and learning skills. Literature [18] research shows that data analysis technology is used to analyze the data stored in the learning management system, and decision tree algorithm is used to diagnose the crisis. Once learners are found to have a crisis, early warning information is sent by e-mail, resource recommendation, pop-up window, etc. in time to assist learners’ learning activities to proceed smoothly. Literature [19] pointed out that the application of online learning early warning model can improve the probability of system identifying potential crisis, avoid the adverse impact brought by crisis outbreak, and strengthen the foresight and effectiveness of management decision-making. In literature [20], through the big data analysis method, in the mining of educational data, most of them focus on the analysis of the data itself, lacking in-depth analysis of educational value. In the modeling and analysis of educational data, it mainly focuses on the establishment of theoretical models and property analysis, while the research on mining and analysis based on the establishment of machine learning models on real teaching data is rare. The algorithm of the early warning model is single, and the mainstream machine learning algorithm is not adopted, and the technologies such as cross-validation and confusion matrix are rarely used to evaluate and select the appropriate model. Literature [21] shows that the online learning environment is characterized by virtual classroom, conscious learning behavior, flexible learning style, and fragmented learning time. From the theoretical point of view, the key problem to improve the quality of online learning is to solve the problem of information asymmetry under the constraints of complex network environment. Literature [22] proposes to cluster learners according to the similarity of learning behavior and provide targeted suggestions for each type of learners after analyzing the clustering results. Through the big data analysis method, literature [23] gives an all-round early warning to learners with learning crisis, which can avoid the failure of academic examination, in order to better solve the problems of low learning quality and poor learning effect. Therefore, through the learning early warning system based on teaching data analysis, learning resources such as learning video materials and online chapter testing can be shared among different students. Teachers can master students’ basic information and learning behavior, and teachers and students can also communicate through the discussion area of the system. Literature [24] research shows that in order to play the role of big data in improving the quality of online education, online learning monitoring and early warning are two of the important research directions. In literature [25], the realization of online learning early warning platform mainly realizes the system function through the design in the demand analysis stage and coding and gives a brief introduction by giving some codes and screenshots.

The above contents are the research and analysis of online learning early warning model, but there are still deficiencies. Therefore, this paper proposes an artificial intelligence method to study the online learning early warning model. The system platform is used to collect and save learners’ learning behavior information online, realize learners’ learning intervention without time and space constraints, realize the file records in the process of continuous uploading of learners’ learning behavior, and help learners master learning progress. At the same time, online education policies at all levels have been issued one after another. People gradually understand, accept, and get used to the way of online learning, which promotes the development of online education. The results show that through the effective
analysis and data mining of teaching data, this paper can give early warning to learners’ academic performance, so as to improve students’ learning quality and efficiency.

3. Algorithm and Model of Artificial Intelligence

It is noteworthy that social presence is divided into three aspects: emotional expression, open communication, and team cohesion. It is the basis of teaching presence and cognitive presence. “It supports cognitive presence, indirectly promotes the formation of critical thinking process in students’ community, and is a direct contributor to learners’ learning experience.” After artificial intelligence, the model has been improved. The core content of the model has not changed, but the original framework has been refined, and three factors of teaching situation, discipline standard, and application have been added on the basis of communication media, as shown in Figure 1.

Preprocessing of input model data. Several related data are selected as training samples and detection samples. The preprocessing of model input data is an important problem to be solved at the beginning of model establishment, and it is the interface between research object and network model. For the pretreatment of qualitative input samples, “expert scoring method” is generally used to quantify. The advantage of the expert scoring method is that it is simple, is easy to understand, and saves time. In this paper, according to the usual practices and methods used in practical work, the scores of each input factor are given, which are divided into five grades: 1.0, 0.5, 0, -0.5, and -1. The order of scores corresponds to risks: {low, low, average, high, high}.

Positive quantitative indicators are indicators whose values are as large as possible. For such indicators, the minimum value of the line is selected as the benchmark value of the indicator, and dimensionless processing is carried out as follows:

\[
H = \begin{cases} 
1 & H \geq H_{\text{max}}, \\
\frac{H - H_{\text{min}}}{H_{\text{max}} - H_{\text{min}}} & H_{\text{min}} < H < H_{\text{max}}, \\
0 & H \leq H_{\text{min}}.
\end{cases}
\] (1)

A negative indicator is an indicator whose value is as small as possible. For this kind of index, we select the maximum value of this line as the ideal value of this index and make dimensionless processing as follows:

\[
H = \begin{cases} 
1 & H_{\text{i}} \leq H_{\text{min}}, \\
\frac{H_{\text{max}} - H_{\text{i}}}{H_{\text{max}} - H_{\text{min}}} & H_{\text{min}} < H_{\text{i}} < H_{\text{max}}, \\
0 & H_{\text{i}} \geq H_{\text{max}}.
\end{cases}
\] (2)

Moderate index refers to the index membership function that the closer the index value is to a certain fixed value, the better. The dimensionless treatment is as follows:

\[
H = \begin{cases} 
\frac{H_{\text{i}} - H_{\text{min}}}{H_{\text{m}} - H_{\text{min}}} & H_{\text{min}} \leq H_{\text{i}} \leq H_{\text{m}}, \\
\frac{H_{\text{max}} - H_{\text{i}}}{H_{\text{max}} - H_{\text{m}}} & H_{\text{m}} < H_{\text{i}} \leq H_{\text{max}}, \\
0 & H_{\text{i}} \geq H_{\text{max}}, H_{\text{i}} \leq H_{\text{min}},
\end{cases}
\] (3)

Figure 1: Online learning early warning model of artificial intelligence.
where $h$ represents the quantified evaluation index value; $H_i$ represents the actual evaluation value; $H_{\text{min}}$ represents the evaluation reference value; $H_{\text{max}}$ represents the maximum value of the indicator in this line; and $H_m$ represents a fixed value.

Among the forward three-layer BP network algorithms, the weight correction method has a greater impact on the network performance. This paper adopts the following methods:

$$W_{jk}(t+1) = W_{jk}(t) - \eta \frac{\partial E}{\partial W_{jk}} + \alpha (W_{jk}(t-1)), \quad (4)$$

$$W_{hi}(t+1) = W_{hi}(t) - \eta \frac{\partial E}{\partial W_{hi}} + \alpha (W_{hi}(t) - W_{hi}(t-1)). \quad (5)$$

$T$ is the number of iterations, $\eta$ is for learning rate, $\alpha$ is the momentum factor, $W_{jk}$ is the connection weight between the input layer nodes, and $w_{hi}$ is the connection weight between the middle layer nodes and the output layer nodes. The weight correction is carried out layer by layer in the process of error backward propagation. When the ownership values of the network are updated once, the network goes through a learning cycle.

The basic principle of independent sample $t$-test is as follows:

Calculation formula $t$ statistic

$$t = \frac{|\bar{X} - \mu_0|}{S/\sqrt{n}} = \frac{\bar{X} - \mu_0}{S/\sqrt{n}}. \quad (6)$$

Degree of freedom: $v = n - 1$.

Judging the difference degree between the average of two groups of samples, the formula for calculating the statistic $T$ value is as follows:

$$T = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\sum x_1^2/2 + \sum x_2^2/2} \times ((n_1 + n_2)/((n_1 + n_2)))}.$$

The significance level is specified. The significance level of the difference between theoretical values is usually $q = 0.01$ or $q = 0.05$, which indicates that when the decision to accept the original hypothesis is made, the correct probability (probability) is 99% or 95%. The theoretical values of significance levels of different degrees of freedom are recorded as $t$ (DF) 0.01 and $t$ (DF) 0.05.

Different degrees of importance correspond to different scores. After $n(n - 1)/2$ comparisons, the decision matrix can be obtained:

$$B = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{bmatrix} = (\sigma_{ij})_{n \times n}. \quad (8)$$

Then, the eigenvalues and eigenvectors of the decision matrix are calculated $\lambda$, i.e.,

$$BW = \lambda_{\text{max}} W. \quad (9)$$

Normalize $B$:

$$\bar{\sigma}_{ij} = \frac{\sigma_{ij}}{\sigma_{ij} + \sigma_{2j} + \cdots + \sigma_{nj}}, \quad (10)$$

where $I, j = 1, 2, \cdots, n$. Then, sum the normalized $B$ according to the row direction:

$$\bar{\sigma}_i = \bar{\sigma}_{i1} + \bar{\sigma}_{i2} + \cdots + \bar{\sigma}_{in}. \quad (11)$$

The trigger mechanism of rule early warning comes from the detection rules set by teachers after publishing the teaching progress. The trigger time and trigger events of detection can also be adjusted according to the situation. Its implementation route is shown in Figure 2.

Rule detection automatically intervenes the nonconformities by setting the rule whitelist, such as failing to perform the specified learning behavior or finishing the homework on time. Screening detection automatically intervenes those who meet the rules by setting the blacklist of rules, such as forum participation below the threshold and video watching time below the threshold. The overall hierarchy diagram of the artificial intelligence teaching signal system is shown in Figure 3.
Process the original online learning data in the same direction and standardization; and determine the number of main factors based on the variance proportion that can be explained by the retained factors. The synthetic risk monitoring index is used to describe the learning performance. The index system is divided into four levels, including the overall index that can show the comprehensive status of online learning performance; second-level indicators that can further show online learning performance, that is, dimensions such as learning behavior, learning results, and learning satisfaction that can be monitored; and further design three-level indicators that can reflect the connotation of monitoring dimension elements. The theoretical research on this problem needs to organically integrate the relevant theories of pedagogy, economics, and management and give consideration to the logic, systematicness, and innovation of the research. The factor comprehensive score is defined as the monitoring and early warning index of learning performance in the digital environment, and the impact of each index on the comprehensive index is analyzed.

4. Research on Design of Online Learning Early Warning Model

4.1. Design of Online Learning Early Warning Model Based on Artificial Intelligence. The online learning early warning model design based on artificial intelligence can take the online learning environment as a comprehensive and complex system and build a hierarchical online learning performance monitoring and early warning index system based on the theoretical model. The index system is divided into four levels, including the overall index that can show the comprehensive status of online learning performance; second-level indicators that can further show online learning performance, that is, dimensions such as learning behavior, learning results, and learning satisfaction that can be monitored; and further design three-level indicators that can reflect the connotation of monitoring dimension elements; and the fourth level, that is, each specific...
measurable quantitative index. The main steps include combining literature research, content analysis, and other methods; learning, screening and absorbing the existing indicators; completing the scientific screening of the index system; and constructing the "general" index system. By means of data mining, learning analysis, and other means, the connotation and main contents of monitoring and early warning elements are analyzed, measurable quantitative indicators are identified, and evaluation indicators are designed, screened, and adjusted according to the construction principle of online learning monitoring and early warning indicator system to ensure the integrity and rationality of the indicator system, combined with expert interviews, questionnaires, and other methods to determine the final indicators.

Table 3: Evaluation indexes of academic achievement classification prediction model.

| TP rate | FP rate | Precision | Recall | F-measure | MCC   | ROC area | PRC area | Class  |
|---------|---------|-----------|--------|-----------|-------|----------|----------|--------|
| 0.772   | 0.192   | 0.757     | 0.772  | 0.764     | 0.577 | 0.838    | 0.771    | Middle |
| 0.849   | 0.050   | 0.856     | 0.849  | 0.853     | 0.792 | 0.967    | 0.886    | Low    |
| 0.767   | 0.088   | 0.783     | 0.767  | 0.775     | 0.682 | 0.908    | 0.811    | High   |
| Weighted Avg | 0.791  | 0.124     | 0.791  | 0.791     | 0.667 | 0.893    | 0.813    |        |

Figure 4: Influence degree of different algorithms on online academic performance.

Figure 5: Influence degree of different algorithms on online academic performance.
Process the original online learning data in the same direction and standardization; and determine the number of main factors based on the variance proportion that can be explained by the retained factors. The synthetic risk monitoring index is used to describe the learning performance. The factor comprehensive score is defined as the monitoring and early warning index of learning performance in the digital environment, and the impact of each index on the comprehensive index is analyzed.

4.2. Experimental Results and Analysis. In the experiment, three single classifiers are trained by BN, DT, and Ann algorithms. Three single classifiers are used as base classifiers, and six integrated classifiers are trained by bagging and lifting methods, respectively. Taking DT classifier as the base classifier, a total of 12 classifiers are trained by random forest algorithm. The performance indicators of each classifier are shown in Table 1.

The results show that, for Bayesian network (BN), decision tree (DT), and artificial neural network (ANN), the classification performance can be improved to varying degrees by constructing the integrated classifier, and the true rate, precision, and recall rate are all improved, while the false-positive rate is reduced. Taking the ANN algorithm as an example, the accuracy of a single classifier is 0.722, while the accuracy of the ensemble classifier trained by the bagging
method is 0.769, and the accuracy of the ensemble classifier trained by the lifting method is 0.767. Although the improvement of accuracy is not obvious, if the number of test samples is large, the number of examples that can be correctly classified will still be quite different.

According to the previous experimental results, the random forest ensemble classifier with the best classification performance is selected as the base classifier, and the bagging method is used to train the ensemble classifier, that is, the nesting of ensemble learning, and the parameters in the training process are adjusted to construct the classification and prediction model of academic achievement. The performance summary of the academic achievement classification prediction model is shown in Table 2.

The classifier can correctly classify 400 out of 500 examples, and the classification accuracy rate is 79.1867%, which has been further improved. The kappa coefficient is 0.6985, and it is generally considered that the kappa coefficient is [0.6, 0.8] and it can be judged that the classification performance is better. The real rate (TP rate), recall rate (recall),
precision (precision), ROC area of the operator, and other indicators of the classifier are shown in Table 3.

The classification prediction model is more accurate for the classification prediction of academic achievement class = low, which is also in line with the practical application, because one of the main purposes of classification prediction is to find the learners with poor academic achievement as soon as possible and intervene in time. In order to determine the influence of artificial intelligence on online academic performance, this experiment uses deep learning algorithm, data mining algorithm, decision tree algorithm, and this algorithm for three experimental comparisons. The experimental results are shown in Figures 4–6.

From Figure 4 to Figure 6, it can be seen that in the comparison of deep learning algorithm, data mining algorithm, decision tree algorithm, and this algorithm, the artificial intelligence of this algorithm has the greatest impact on online learning performance, and the decision tree algorithm has the least impact. Therefore, the rationality of curriculum arrangement; the interest of curriculum content; the interaction and recognition with teachers; the communication and recognition with online learning peers; the significance of peer performance, learners’ time planning, learners’ autonomous learning ability, and learners’ learning motivation; and the limitations of online learning platform were significantly correlated with students’ academic performance ($P < 0.05$). In order to solve the above problems effectively, early warning came into being. The construction of learning early warning system based on teaching data analysis is an important key to be solved in network teaching. This paper is aimed at warning learners’ academic performance and improving students’ learning quality and efficiency through effective analysis and data mining of teaching data.

This experiment selects these five features as the learning behavior characteristics of the prediction model. Improve students’ thinking activity in the learning process. The completion of task points can enable students to complete in time under the condition of task driving, which is conducive to students’ review and consolidation of knowledge. The experiments were compared four times, and the results are shown in Figures 7–10.

It can be seen from Figures 7–10 that after summarizing and screening out the key learning characteristics of learning behavior, five groups of historical data corresponding to five quality training indicators and special scores are taken as training samples of neural network. The artificial intelligence algorithm is used to learn the training samples, and the neural network after learning can reflect the functional relationship between quality training indicators and special scores, that is, to obtain the prediction model of learners’ scores. The online learning early warning model design based on artificial intelligence can take the online learning environment as a comprehensive and complex system and build a hierarchical online learning performance monitoring and early warning index system based on the theoretical model. In this study, five predictors closely related to learners’ academic performance are selected, and six input neurons need to be set. According to the Kolmogorov theorem, a hidden layer is selected, and the number of neurons is set to 12.

5. Conclusions

Under the impact of informatization, education and information technology are deeply integrated, and online education is in the ascendant. In theory, the key to solve the problem of information asymmetry in complex network environment is to improve the quality of network. The
theoretical research on this issue needs to organically combine the relevant theories of pedagogy, economics, and management and give consideration to the logic, systemativeness, and innovation of the research. The realization of online learning early warning platform mainly realizes the system function through the design and coding in the demand analysis stage and gives a brief introduction by giving some codes and screenshots. Finally, in the test and evaluation of artificial intelligence online learning and early warning platform, the black box test method is used to test the system, and test cases are designed to test the system to judge whether the system meets the design requirements. Based on the integration of performance management, crisis early warning theory, and big data technology, an effective online learning performance monitoring and early warning quantitative model based on artificial intelligence collection and processing is designed, which can predict the crisis signal in time. It has also become a key problem to be solved in the research of online education. The factor comprehensive score is defined as the monitoring and early warning index of learning performance in the digital environment, and the influence of each index on the comprehensive index is analyzed.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no competing interest.

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