Political teaching application in high vocational care courses based on machine learning systems

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Research Article

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Abstract

Higher vocational colleges need to use video system technology to transform teaching methods to transform ideological and political teaching into more vivid, more attractive and infectious forms, thereby effectively assisting students to actively learn. This article studies a video system based on machine learning, and has developed a type of high -vocational nursing course political teaching system. The system uses the principle of machine learning to build a learning early warning monitoring algorithm, then the performance and accuracy of the model are evaluated by using the algorithm.This article finds that the module can extract the hidden characteristics of traffic, and is not affected by the knowledge. The design of the high -vocational nursing course political teaching system is equipped with multiple modules such as video on -demand, management, interaction, and recording. Compared with the group comparison, it is very efficient to find that the high -vocational nursing course political teaching system in this article is very efficient. This article studies machine learning technology and applies it to the construction process of high -vocational nursing curriculum political teaching video systems.

1. Introduction

Ideological theory is the key course in the training of talents in colleges and universities. The practical educational effect of such courses is closely related to China's strategy of strengthening the country, and it is also the key way to provide high-quality talents[1]. Its teaching process and method affect the actual teaching effect and the training process of talents. Therefore, in the new era environment, how to do a good job of ideological and political teaching in higher vocational colleges is a major challenge in the field of education reform[2]. In the Internet age, the use of multimedia technology and information technology can effectively change the teaching methods and make them more suitable for the current preferences of students [3]. Optimizing the teaching process by combining relevant technologies can improve the attraction of the classroom to students, thus cultivating information technology professionals, which is also one of the important objectives of education reform. The main channel for students to receive ideological and political education is higher vocational education, which needs to be based on mobile Internet technology to meet the actual needs of students from the background of the new era[4]. Keep pace with the times, change according to the situation, and adopt new media and new technologies to make the classroom environment more vivid. In recent years, the video teaching method represented by hybrid learning method has appeared and gradually developed [5]. Compared with single online teaching or traditional teaching methods, video system teaching has unique advantages. It can combine traditional teaching with video courses, so as to carry out collaborative learning, structured learning and unstructured learning [6].

2. Relevant Work

The literature emphasizes the management optimization of educational administration system, which requires such systems to actively communicate with foreign schools to promote information interaction while following the operation and design standards[7]. The system needs to be regularly updated and maintained, including innovative talent training mode and active information service mode. Then, the construction technology and performance requirements of the educational administration management system are analyzed [8]. The literature specially studied the software engineering course, and through the construction of good characteristics, combined with the mixed learning environment data of the University online learning platform and offline classroom, the early warning learning task was scored [9]. As for knowledge points and problem types, the "knowledge point feature network + other feature network" and "problem type feature network + other feature network" based on the neural network model are designed to deal with the two types of features respectively, which can solve the early warning problems

of high granularity problems and score the early warning problems [10–11]. Aiming at the learning withdrawal warning task based on students' course selection and learning data in the teaching network of a certain university, the literature summarizes the course selection scenario as the regression classification problem class, and uses the good integration effect to learn the classification problem of numerical type. The lightgbm method model clustering strategy solves the problem of low accuracy in the classification warning problem to a certain extent [12]. A semi supervised feature selection algorithm (srr-lsa) based on improved ReliefF and ACO algorithms is proposed in the literature. The improved ReliefF algorithm improves the limitation that the original ReliefF algorithm only evaluates the importance of features, can quickly reduce the size of features, and can provide good prior knowledge for the improved ACO algorithm. During feature extraction, candidate features are randomly combined by ReliefF algorithm for weight calculation [13]. The algorithm uses Spearman correlation coefficient to perform correlation analysis and preliminarily eliminate redundant features. In this paper, a combination of feature engineering input model and fixed length time series packet is proposed for deep learning to identify encrypted traffic. In addition to some characteristics indicating the flow and information in the packet header, the feature vector of the packet is also added to the first 60 bytes of the data layer of the application program [14]. The packet vector group is a sequence of 5 packets, which are respectively used as a token. Then, CNN is used to learn spatial features and LSTM is used to learn time series features. The model weights the output probabilities of unencrypted and encrypted modules to obtain the final probability estimation. Experimental results show that the feature selection algorithm can effectively reduce the complexity of feature subset, achieve better classification effect, and make the system itself have better generalization and classification ability [15]. A target classification model is derived in the literature. This process is realized by using bagging-c4.5 training samples. This sample will generate similar C4.5 base classifiers in the actual model training process, so it will increase the training time and reduce the accuracy. It needs to use classification algorithms such as genetic algorithms to integrate the base classifiers to reduce the training time [16]. When predicting the graduation status, the system needs to use C4.5 decision algorithm and naive Bayesian classification to train the model, improve the classification accuracy of the model, and finally design a reasonable strategy to obtain the final prediction model [17].

3. Research On Key Technology Of Machine Learning

3.1 Traditional machine learning theory

The return of Logic Slim is a simple linear model, which is easy to achieve. It is a classification model represented by conditional probability distribution. It is often used in the field of classification and recommendation. As shown in the formula (1).

$$\mathrm{P}(\mathrm{Y}=\mathrm{K} \mid \mathrm{x})=\frac{1}{1+\sum_{\mathrm{k}=1}^{\mathrm{K}-1} \exp \left(\mathrm{w}_{\mathrm{k}} \cdot \mathrm{x}\right)}$$

1

Among them, x is the input feature, and w is the feature weight. In other words, the output of the number of like - minded models is represented by the input linear model.

The target function of XGBOOST is shown in formulas (2) (3).

$$\mathrm{obj} = \sum_{i=1}^{N} L\left(y_i, \widehat{y}_l\right) + \sum_{m=1}^{M} \Omega\left(f_m\right)$$

2

$$\Omega\left(f_m\right) = \gamma J + \frac{1}{2}\lambda|\omega|^2$$

3

The goal is to make the weight of the network similar to the weight of the real model. First, initialize the connection weight and the value of each unit and multiply by the random number, and then enter the training data for network parameter optimization, and finally get the actual results of each layer.

$$x^{(l)} = f\left(s^{(l)}\right) = f\left(w^{(l)} x^{(l-1)}\right)$$

4

Calculate the training error based on the difference between the actual output value and the expectation value, as shown in formula (5) and formula (6).

$$\delta_j^{(l)} = \left[d_{qj} - x_j^{(l)}\right] f'\left(s_j^{(l)}\right)$$

5

$$\delta_j^{(l)} = f'\left(s_j^{(l)}\right) \sum \delta_k^{(l+1)} w_{kj}^{(l+1)}$$

6

Reverse propagation learning right values and training target functions are shown in formulas (7) and formulas (8).

$$w_{ji}^{(l)}[k+1] = w_{ji}^{(l)}[k] + \eta \delta_j^{(l)} x_i^{(l-1)}$$

7

$$E = \sum E_q, E_q = \frac{1}{2} \sum \left(d_{qj} - y_{qj}\right)^2$$

8

Among them, η is the learning rate. Eq is the expected error at the end of the q round of training. E is the sum of the expected errors of all rounds.

3.2 Learning behavior monitoring and early warning algorithm

The biggest difficulty of using Bayesian to seek the probability after seeking the probability is that the conditional probability of a class is the combination probability of all attributes, but it is difficult to directly obtain its value in a limited data sample. The simple Bayesian algorithm needs to be used for classification. This process is

independent. For the training data set, the characteristics are independent of the characteristics, and the input and output data probability research is performed based on this point. Then the calculation of the postponent probability of the Bayesian theorem through the sample classification of the model, and the highest value category results as such samples as such samples.

Among them, C is a category of category set c about C. There are only two types of graduates and non -graduates in the study of graduation state. n is a characteristic number of parts of the data set, and xi is the characteristic attribute value of the I of the sample x. C's probability. For each category, P (x) is the same, so according to the Bayesian criteria above, we get the formula classification of simple Bayesian:

$$\mathrm{h}\left(\mathrm{x}\right)=\mathrm{argmaxP}\left(\mathrm{c}\right)\prod_{\mathrm{i}=1}^{\mathrm{n}}\mathrm{P}\left(\mathrm{x_i}\mid\mathrm{c}\right)$$

9

It can be seen from the above formula that training a simple Bayesian classifier is to use the data concentrated data to calculate the initial probability of each class and the condition of each attribute. The formula for calculating the prior probability of a class is as follows:

$$\mathrm{P}\left(\mathrm{c}\right)=\frac{\left|\mathrm{D_c}\right|}{\left|\mathrm{D}\right|}$$

10

Calculation of conditional probability is related to data types. If the characteristic attribute data is a discrete value, the conditional probability is the i -i value of the characteristic attribute of the characteristic attribute of the class tag of the training data set. The total number of samples | Dc, xi | Class tags as the ratio of samples in C | Dc |, the formula is as follows:

$$\mathrm{P}\left(\mathrm{x_i}\mid\mathrm{c}\right)=\frac{\left|\mathrm{D_{c,x_i}}\right|}{\left|\mathrm{D_c}\right|}$$

11

If the characteristic attribute is continuous data, according to the probability density function, assuming the condition probability obey the normal distribution, the calculation formula is as follows:

$$\mathrm{P}\left(\mathrm{x_i}\mid\mathrm{c}\right)=\frac{1}{\sqrt{2\pi\sigma_{\mathrm{c,i}}}}\exp\left(-\frac{\left(\mathrm{x_i}-\mu_{\mathrm{c,i}}\right)^2}{2\sigma_{\mathrm{c,i}}^2}\right)$$

12

When using the simple Bayesian attribute weighted algorithm to obtain the student's prediction model, first of all, according to the effects of the characteristics on the classification results, to obtain the appropriate weight, and then use the weighted coefficient to fix the simple Bayesian formula. Use the simple Bayesian formula to obtain the weight, defined as the formula (13):

$$h = \operatorname{argmax} P(c) \prod_{i=1}^{n} P(x_i \mid c)^{w_i}$$

13

Information gain is usually used to select the attributes of the segmentation characteristics in the decision tree algorithm. In information acquisition, the more information brought by the characteristic properties to the classification system, the greater the importance of the characteristic attribute to the entire classification system. The so -called amount of information is the information entropy, so this chapter uses the information amount brought by the feature attribute to the system as the basis for judging the importance of characteristic attributes, and determines the weight according to this.

$$\operatorname{Gain}(D, A) = H(D) - H(D \mid A)$$

14

The calculation formula of the experience entropy and condition entropy in the formula is as follows:

$$H(D) = -\sum_{k=1}^{K} \frac{|C_k|}{|D|} \log_2 \frac{|C_k|}{|D|}$$

15

$$H(D \mid A) = -\sum_{j=1}^{m} \frac{|D_j|}{|D|} H(D_j) = -\sum_{j=1}^{m} \frac{|D_j|}{|D|} \sum_{k=1}^{K} \frac{|D_{j,k}|}{|D_j|} \log_2 \frac{|D_{j,k}|}{|D_j|}$$

16

| CK | It is the number of samples that belong to CK data sets. K is the number of categories in category C. M is the number of attributes of attribute A. | Dj | is the number of samples in the subset Dj. The number of samples of the subset Dj of CK.

The higher the information value obtained by the characteristic attribute A, the more impact on the final classification results of the students' graduation warning research, and the greater the importance in the classification. Calculate the information value obtained by each attribute according to the formula, and then get the weight value of each feature attribute. The formula is as follows:

$$W_t = \frac{\operatorname{Gain}(A_t)}{\sum_{i=1}^{n} \operatorname{Gain}(A_i)}$$

17

When the classification results of the two classification models are merged, the test sample is calculated based on the accuracy rate of the two models in the accuracy of the data set and the post -test probability of the two models and the corresponding post -verification probability of the two models. The category tag is the classification result when the highest probability is.

3.3 Overall model parameter selection

The accuracy of the test concentration is shown in Fig. 1. In the experimental results of the first 100 bytes, N is 60 is the local maximum value. The selection of the selection algorithm consistent with the results is added to the input feature vector of the deep learning model.

Since the model adopts a two-stage identification method, the final output depends on the fusion probability estimation of the unencrypted part and the encrypted part. The output weight of the encryption module is: ρ, The output ratio of the unencrypted module is 1- ρ. According to the results of the adjustment algorithm, the parameters ρ 0.77. Table 1 shows the differences ρ model recognition performance of the test data under the value.

Table 1
Different ρ Table of identification performance under value

P	0.6	0.65	0.7	0.77	0.8	0.85
Accuracy	92.64%	93.16%	94.55%	96.50%	95.87%	96.08%
Recall rate	91.85%	92.73%	93.96%	96.27%	95.81%	95.96%

4. Design And Implementation Of Computer System

4.1 System infrastructure design

According to the system function analysis, this article designed a functional module of the high -vocational care course based on machine learning video systems. The system consists of video demand modules, management modules, interactive modules and record modules (Fig. 2).

4.2 Learning early warning system module design

The overall business process of the system is divided into two paths, as shown in Fig. 3, which represents the overall process from early warning data pre-processing to training tuning, and finally to the front -end display.

The purpose of the final model is to learn early warning, so it is not enough to predict the results. This work needs to know the current warning level of students, divided into red warning (R), yellow warning (Y), and green warning (G), depending on the warning, depending on the warning The level is divided into three levels, and the division rules are shown in Table 2. Teachers can target students at different levels of early warning and learning according to the final warning learning level provided by early models.

Table 2
Learning early warning level table

Warning level	Red warning (R)	Yellow Warning (Y)	Green warning (G)
Level meaning	Such students have great learning difficulties and poor grades	Such students have greater learning difficulties, and their grades are average	Such students have less learning difficulties and good grades
Scope of predictive results	[0,69]	[70,85]	[86,100]
Degree of early warning	It requires a larger help and supplement	Need medium help supplements	It requires a smaller help and supplement

4.3 System simulation results analysis

Compared with the results of the simple Bayesian classification model and the Bagging-C4.5 classification model. The result is shown in Table 3:

Table 3
Graduation situation prediction model performance evaluation results

-	WNB			Bagging-C4.5			Combined model		
	Accuracy (%)	Recall (%)	Precision (%)	Accuracy (%)	Recall (%)	Precision (%)	Accuracy (%)	Recall (%)	Precision (%)
Under the first grade	75.1	69.6	77.5	73.5	65.1	76.4	82.4	84.1	80.8
Grade in the second grade	76.3	73.6	77.8	76.3	70.0	79.8	83.4	84.4	82.8
Under the second grade	76.1	75.3	77.5	76.8	76.8	77.8	84.1	84.8	83.7

Oracle11 database server resource usage is shown in Fig. 4:

The usage of web server resources is shown in Fig. 5.

4.4 Learning improvement effect test

As show in Table 4, of which cooperative learning and thinking the scores of political information literacy have been significantly improved.

Table 4
Test group Video Teaching Autonomous Learning Power Comparison (x + S)

Project	Before(n = 47)	After(n = 47)
Political Political Study Motor	33.24 ± 3.72	34.90 ± 4.20
Self -management ability	29.27 ± 3.62	30.68 ± 4.08
Ability to learn and cooperate	16.79 ± 1.76	19.04 ± 2.24
Ideological and political information quality	19.04 ± 1.98	20.72 ± 2.65
Total score	98.34 ± 9.15	105.34 ± 10.61

Comparing the scores of the total self -learning ability and four dimensions before and after traditional ideological and political teaching, after statistical inspection, the difference is not statistically significant, P > 0.05, (as show in Table 5).

Table 5
Comparison of autonomous learning ability before and after traditional teaching (x + S)

Project	Before(n = 47)	After(n = 47)
Political Political Study Motor	32.44 ± 3.65	32.04 ± 4.48
Self -management ability	28.24 ± 2.97	29.07 ± 4.28
Ability to learn and cooperate	16.38 ± 1.81	16.36 ± 2.48
Ideological and political information quality	18.71 ± 2.74	19.45 ± 2.09
Total score	95.78 ± 8.78	96.92 ± 9.79

5. The Application Research Of The Multimedia Video System In Political Teaching

5.1 The application effect of high -vocational political teaching in video systems

This article is to verify whether the political teaching system of high -vocational nursing courses based on the video system can achieve the expected effect, and the verification effect of the system needs to be analyzed. The ultimate purpose of the analysis is to check the performance of the system and whether it can meet the needs of users, and debug and change the system according to the results to provide users with more benefits.

Table 6
About students' attitudes to political education for video systems

Students' attitude towards the video system	Proportion
Strongly Agree	36.4%
Agree	47.5%
Disagree	16.1%

5.2 Promotion strategies of political teaching in higher vocational nursing courses

Then it is the system construction of the "network classroom" of Ideological and political courses in higher vocational colleges. First, the network teaching platform of interactive learning and management is selected. After the online teaching platform is determined, online courses can be built by themselves, or the existing course resources of the platform can be used to build online classroom teaching of Ideological and political courses in the school through the mixed teaching mode of "MOOC resources + smart classroom campus + offline", and organize real-time testing, selection, question and answer, discussion, examination and other teaching activities. And manage, detect and evaluate the whole learning process. The online classroom construction of political courses should be based on the principles of simplicity, practicality, convenience and stability, and effectively ensure the development of teaching quality.

Then, to effectively change the "practice classroom" of Ideological courses, we need to develop and improve the existing teaching system. The practice platform relies on multimedia technology, database, network communication, virtual simulation and other technologies, carefully designs and deeply develops cultural resources, and organizes students to implement network expansion guidance. Through the construction of such a practical three-dimensional classroom with standardized management, rich content and diverse forms, we can promote its integration with the traditional classroom and the network classroom, so as to realize the unity of knowledge and action.

6. Conclusion

The political teaching system of higher vocational nursing course based on "video machine learning system" is different from the traditional teaching concept of "teaching" and "learning". The system combines online teaching, video teaching and classroom teaching. While helping students learn knowledge, it emphasizes the empowerment of students, so that students can use practical skills while learning new knowledge and cultivate political literacy. Through the active application and practice of teaching, the political teaching of nursing courses in higher vocational colleges has effectively promoted the reform of classroom teaching, improved the teaching quality and efficiency.

Declarations

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Conflict of interest

The authors declare that they have no conflict of interests

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Data Availability

Data will be made available on request.

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Figures

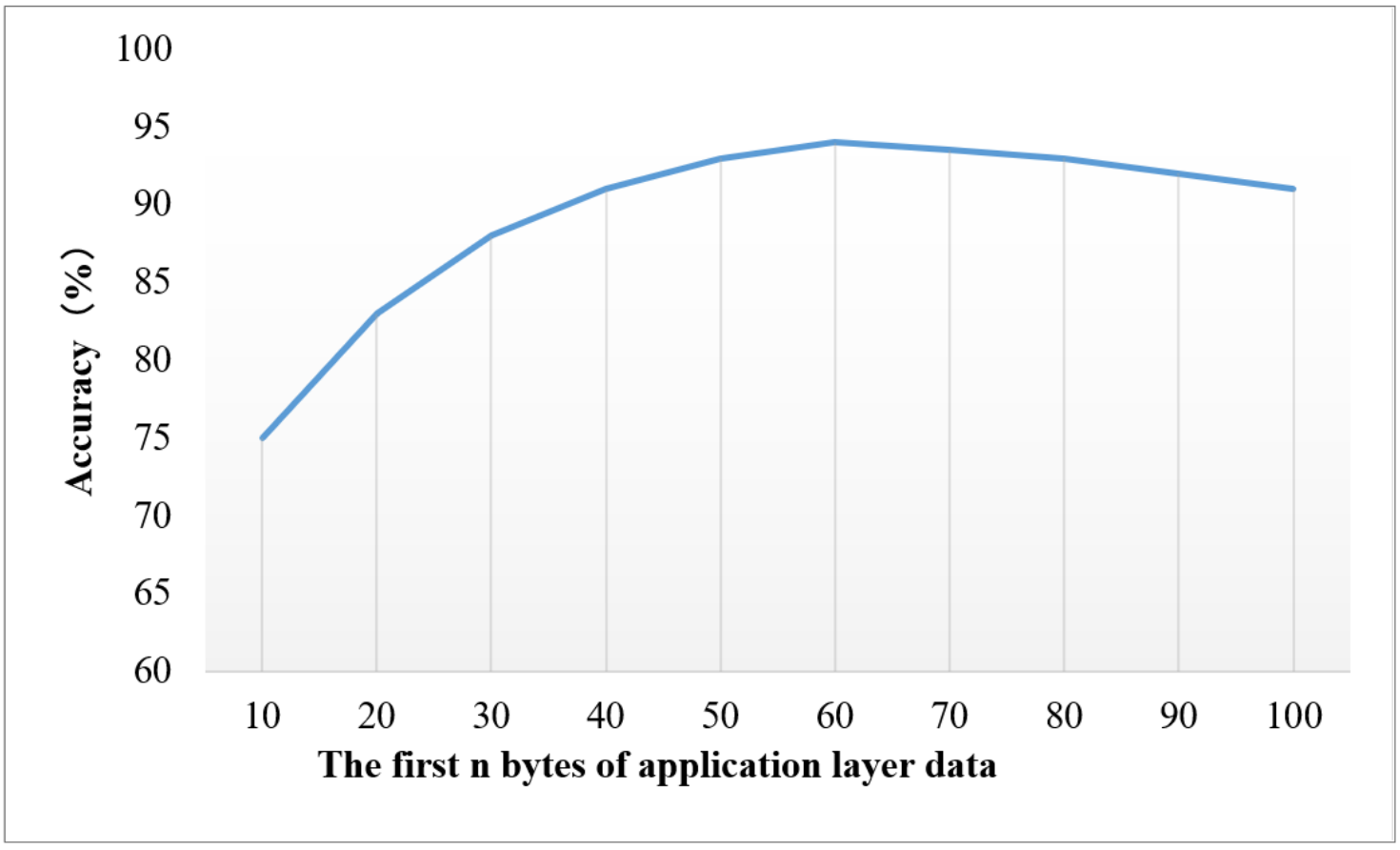

Figure 1

Accuracy of different N values on the test set

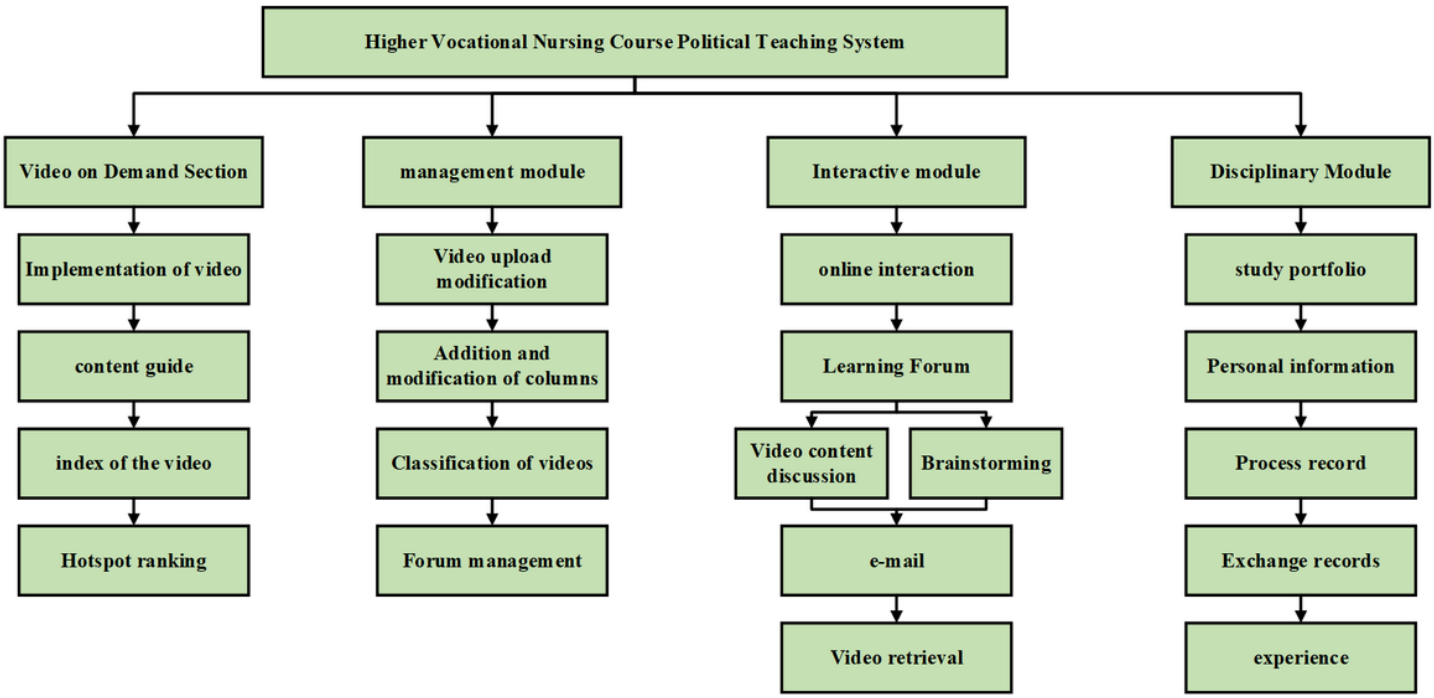

Figure 2

The module structure of the system

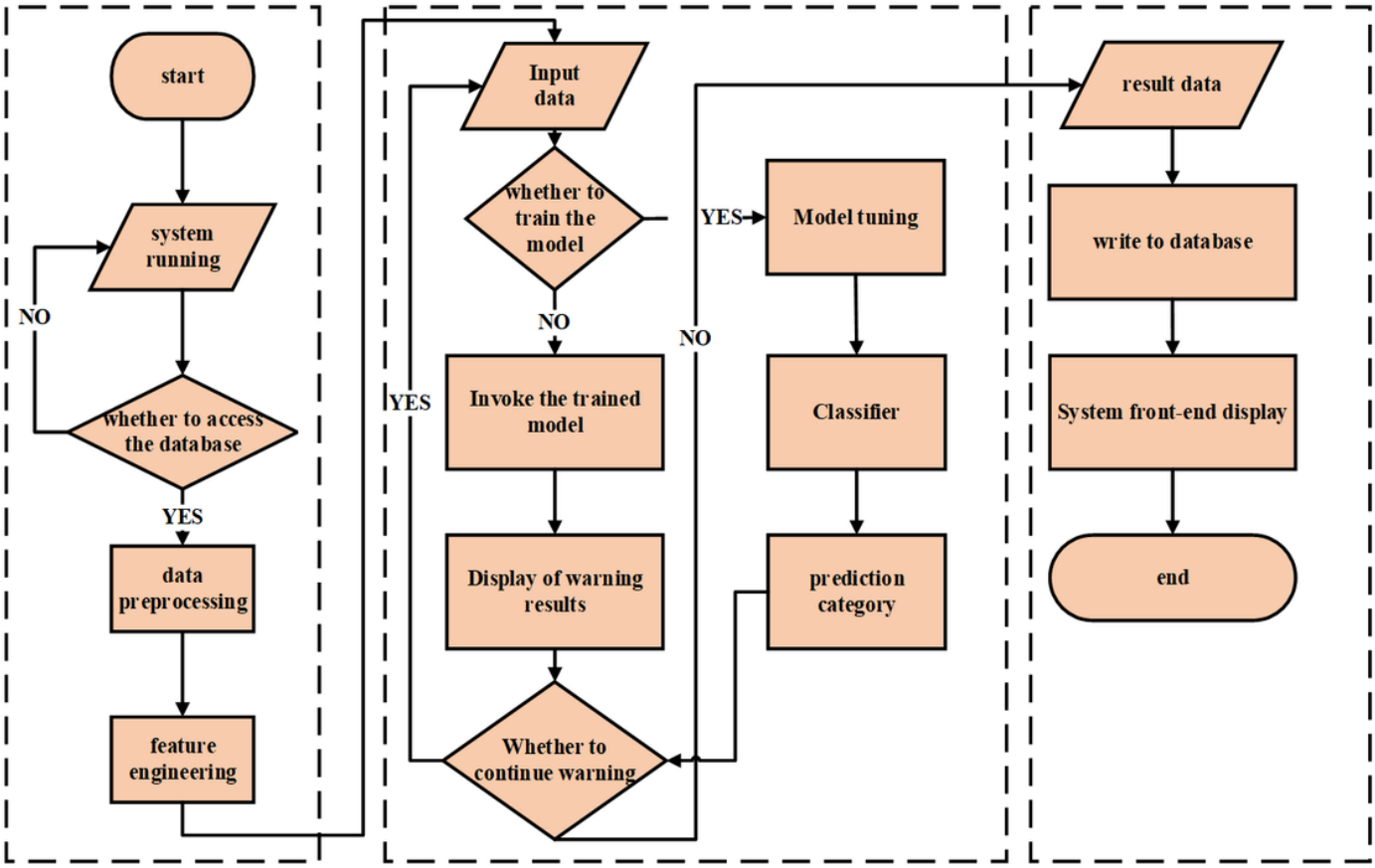

Figure 3

The overall business flowchart of the system

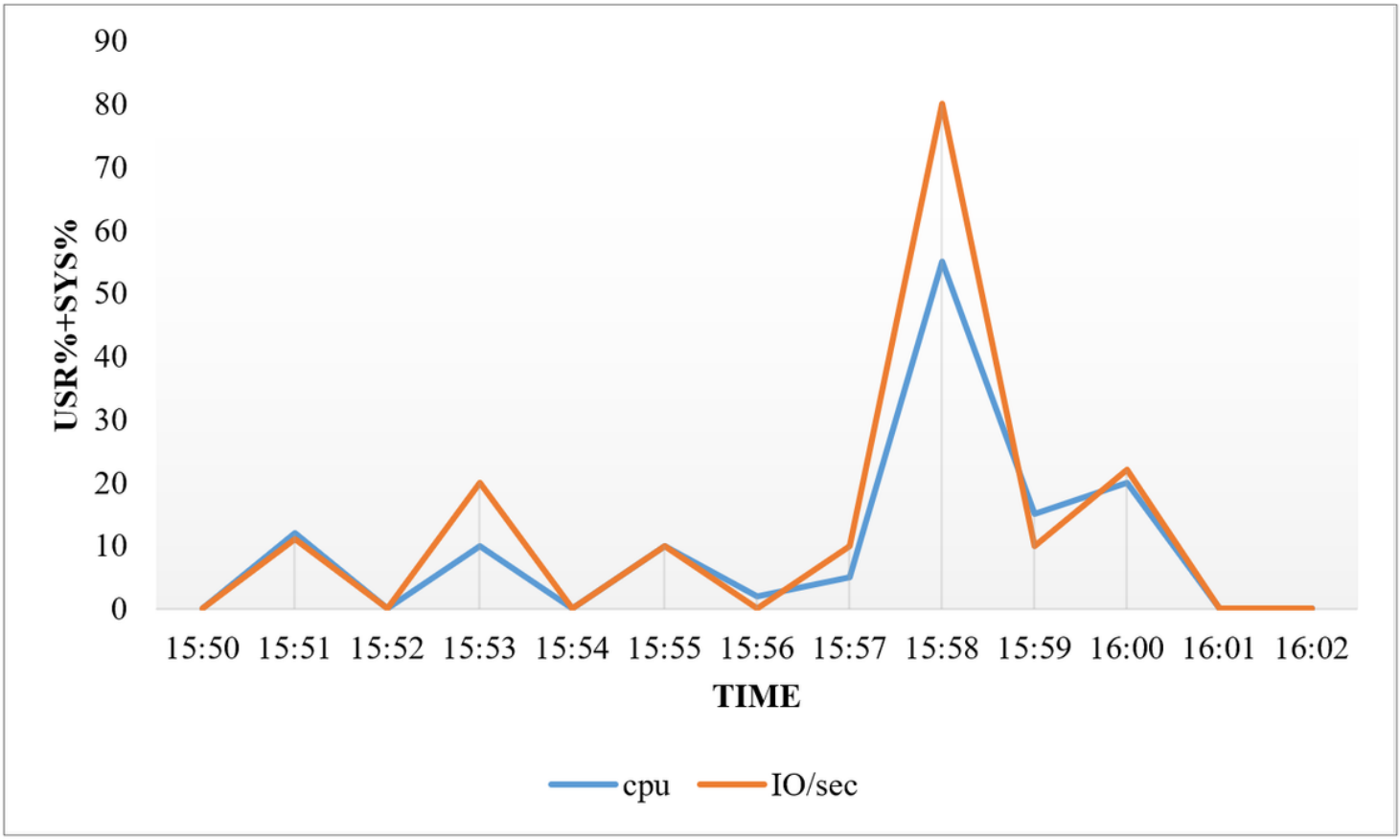

Figure 4

Oracle11 database server resource usage

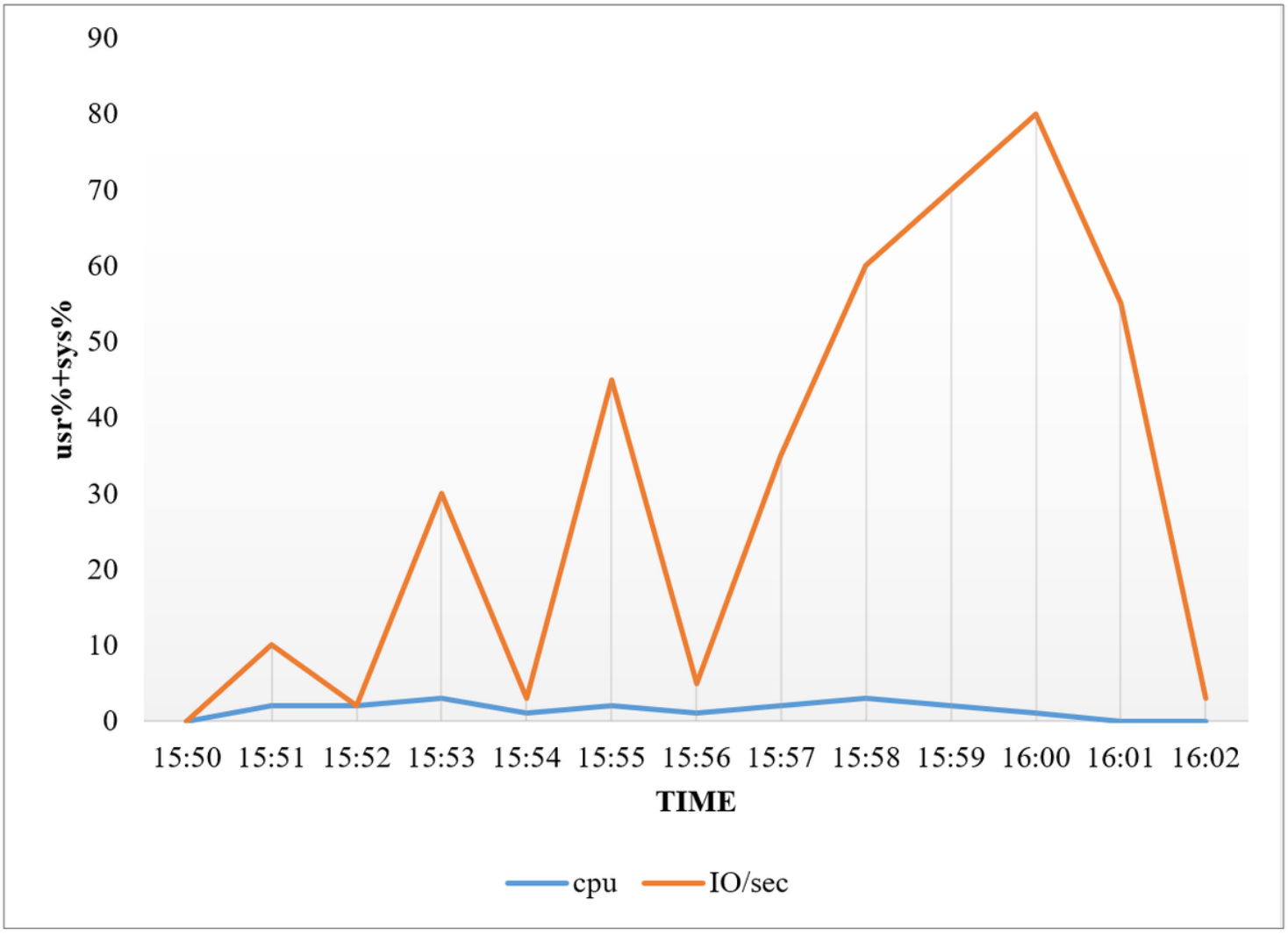

Figure 5

WEB server resource usage situation