Evaluation model of college students' online learning level difference based on support vector machine

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Abstract: There are some problems in the evaluation of online learning level differences among college students, such as low accuracy and long evaluation time. This paper proposes a new research method by extracting online learning behaviour characteristics to determine behaviour evaluation indexes and evaluation standards. The depth of the residual neural network method is used to remove interference index. Using the Lagrange multiplier method, the evaluation problem is transformed into a dual problem. The nonlinear transformation causes us to strive for the optimal classification plane. Difference in evaluation data was accessed by using big data technology, through the normalised processing the data, in order to obtain the optimal classification function. Finally, the final evaluation results are obtained, and the online learning evaluation level differences are completed. Through comparison, the accuracy of this method is 97%, and the time cost of assessment is always less than 9.5 ms.

Keywords: support vector machine; online learning; difference evaluation; behaviour characteristics.

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1 Introduction

Network platform is the most important tool for online learning. Most schools have their own online learning platform for students to use anytime, anywhere (Chen et al., 2018). Its main feature is to carry out learning activities in a remote way, and students can choose courses, teaching materials, homework organisation, organisation, test at any time, etc., which results in communication defects between teachers and students, lack of humanisation, poor practicality, lack of adaptability, and limited training resources, thereby leading to a large number of network dropouts with poor academic performance (Cui et al., 2019; Kuang et al., 2020; Lyons-Warren et al., 2016), which has caused many researchers' attention.

Hedtrich and Graulich (2018) proposed a learning engagement evaluation model of distance learners based on LMS data. The evaluation model analyses the degree of students' online learning engagement, takes the students' learning persistence as the characteristic variable, uses the data recorded by the learning management system to automatically detect the degree of their engagement, defines the four dimensions of the students' basic learning system, analyses the influencing factors of the students' learning level in online learning, and adopts the multi-level regression analysis method to construct The evaluation model of distance learners' total learning investment is established. However, there are few factors such as the online learning model which cannot fully analyse the students' learning performance.

Deng et al. (2016) proposed the design of online learning performance evaluation model based on mobile internet. The model first analyses the differences of students' performance in the process of online learning, evaluates the effect, records the behaviour performance of each course in their learning, collects the data of students' online learning, and constructs the evaluation model through self-learning, self-management and other factors. The model can effectively analyse the performance of students' online learning, but it cannot accurately evaluate students' real learning situation only by their performance.

Wong et al. (2018) shows the transition from face-to-face learning to blended learning by adding a parallel online group, which shows the synergy of blended learning and online learning in interactive level, enrolment rate, student satisfaction, dropout rate and final grade. Application design: new devices, online resources and other supporting materials allow students to choose their preferred learning style: asynchronous (lecture capture) or synchronous (face-to-face or live lecture). These changes have increased enrolment and student satisfaction, and reduced dropout rates. There was no significant difference between the mixed group and the online group. However, the research object of this method has some limitations and is not suitable for general application.

Based on this, the paper proposes a model of online learning level difference evaluation though SVM. This technical route is as follows:

1 To research the behaviour of learner, determines the evaluation index and evaluation standard, uses the method of deep residual neural network to delete the interference index, and constructs the evaluation model of college students' online learning level difference.

2 Analysing the basic principle of support vector machine learning algorithm, to change the evaluation phenomenon, sets this corresponding constraint conditions, through transformation of dimension space, realises this evaluation improvement of students' Online learning level difference.

3 The difference evaluation data of online learning level is obtained through big data technology, and the obtained data are trained and divided.

Through normalisation processing of the above data, the key students' online learning level indicators are input to obtain the final evaluation results, and the students' online learning level difference evaluation is completed.

2 Evaluation of online learning behaviour

Teaching evaluation should be carried out in accordance with the scientific process, and should be professional. For ensure a quality, though the analysis behaviour characteristics, this evaluation process is designed and the differences are studied, which provides a basis for teachers to supervise, manage and guide students' online activities more effectively.

2.1 Analysis on behavioural characteristics of online learning for college students

Online learning has the characteristics of digital resources, autonomy, cooperation and complementarity. Therefore, online learning also has corresponding behaviour characteristics.

In the process of online learning, students need a certain knowledge base to study in virtual learning environment, and analyse the characteristics of students' operation skill foundation, cognitive ability, emotional attitude and values.

1 Basic operation skills. Learners should have certain computer skills such as registration, login, games, browsing the web, editing text and so on. At present, students have mastered the basic operation skills required by online learning.

2 Cognitive ability. College students have shown a mature aspect in their intellectual development and various thinking abilities. At the same time, it also has certain dialectical thinking, which enhances the independence of thinking.

3 Emotional values. Students have clear emotional values, strong sense of belief and social participation, strong self-discipline ability, gradually stable personality, and improve the ability of self-regulation.

2.2 Evaluation model of students' line learning level difference

Firstly, the evaluation criteria with online learning level were determined. In this process, because online learning is online teaching through the internet, teachers cannot directly observe or understand the learning situation of students. Therefore, in the evaluation, the specific significance and requirements of each index should be properly explained, that is, the evaluation description and criteria of each evaluation index. The description with evaluation standard evaluation index are arranged in Table 1.

Table 1 Evaluation indicators of online learning behaviour

Evaluating indicator		*Indicator note*	*Evaluation criteria*
Primary indicators	*Secondary indicators*		
Knowledge acquisition	Course video viewing integrity	Students' viewing time ÷ original duration × 100%	0%–100%
	Reading completion of course materials	Do students read the course materials	0%–100%
	Assignments and quizzes	fraction	Percentage system
Collaboration and exchange	Put questions	questions	0–10
	Publish discussion	discussions	0–10
	Reply to discussion	replies	0–10
Learning attitude	Course visit	visits	0–10
	Number of assignments and tests completed	Times of completion	/
	Bad class record	'0'or '1'	Abnormal operation

In the determined evaluation index of students' online behaviour, the index to be measured shall be given priority treatment. The first level index is the total index of online behaviour evaluation, and the second level index is the detailed content of the first level index. In the determination of indicators, it is necessary to delete the non key indicators and indicators with less influence. Though deep residual neural network to delete these indicators with interference. The deep residual network is composed of residual blocks, which are expressed as follows:

$$\begin{aligned} p_i &= a(w_i) + B(w_i, u_i) \\ w_{i+1} &= \varphi(p_i) \end{aligned} \tag{1}$$

In the formula, B represents the residual function u_i, represents the weight matrix w_i, P_i represents the input and output of the deep residual network α, represents the input index weight value of student difference evaluation.

In the difference index of students' online learning level, all indicators are input into the network α. If the weight of this input evaluation index value is greater than the set weight, this value is taken as a measurement parameters. If this value was less than a set value, it will be deleted. The calculation of the evaluation weight is obtained by formula (2).

$$B(w_i, u_i) = u_i \cdot \varphi[A(u_i\,') \cdot \varphi A(w_i\,')] \tag{2}$$

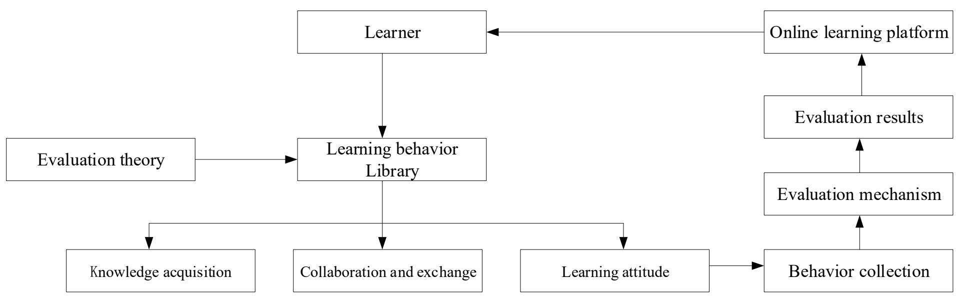
where φ, is a convolution numerical value in the network.

The analysis of the evaluation index of online learning behaviour in Figure 1, the structure real time model with difference evaluation is constructed, as shown in Figure 1.

Figure 1 shows the evaluation model, which reflects this process for to certain extent. And because the comprehensive evaluation model based on vector tools can effectively avoid the subjective factors of artificial evaluation and scoring (Martínez et al., 2020), the index system is trained and optimised, and new optimisation processing is carried out on the basis of the existing rating model, which avoids the uncertainty caused by the constraints of human factors, material resources and time, and improves the evaluation efficiency.

In the construction of students' online level difference evaluation model, we first analyse the characteristics, determine the measurement parameters and evaluation standard of online learning behaviour, and use the deep residual neural network method to delete the interference index. Complete the construction of online learning level difference evaluation model for college students. On this basis, the evaluation model is optimised to realise the design of online learning level difference evaluation model for college students.

Figure 1 Model of online learning behaviour difference evaluation



3 Optimising the evaluation model

For the above research, a difference evaluation model of online learning level of college students with support vector machine (Zhang et al., 2019, 2016), and the evaluation model of online learning level difference.

3.1 Support vector machine learning algorithm

SVM has certain advantages in obtaining global optimal solution of nonlinear problems and high-dimensional data problems, and is widely used in many evaluation problems. In the case of linearly separable (Jin et al., 2016; Huang et al., 2018; Nishitsuj and Exley, 2019). For n linearly separable observation samples (x_1, y_2), ···, (x_i, y_i), ···, (x_n, y_n), as shown in Figure 2.

According to the support vector machine learning algorithm shown in Figure 3, it is processed by a discriminating function. There are two types of education modes between the positions of solid points and hollow points. Let the equation of hyper plane be $\alpha x + b = 0$.

When α was a vector perpendicular to this hyper plane and b was a hyper plane make up. A hyper plane can be completely determined by its parameter (α, b). Define the conditions to meet:

$$\min \quad \left|\boldsymbol{\alpha} x_i + b\right| = 1, \tag{3}$$

The hyper plane calculated by formula (1) is a normal hyper plane, and the linearly separable sample set satisfies the following constraints:

$$y_i(\boldsymbol{\alpha} x_i + b) \geq 1, \quad i = 1, 2, \ldots, n \tag{4}$$

At this point, $\text{margin} = \frac{2}{|\boldsymbol{\alpha}|}$. The training samples are correctly separable, and the sample points satisfying $\omega x_i + b = 1$ have the minimum distance from the classification line. They determine the optimal classification line.

Figure 2 Schematic representation of the SVM learning algorithm

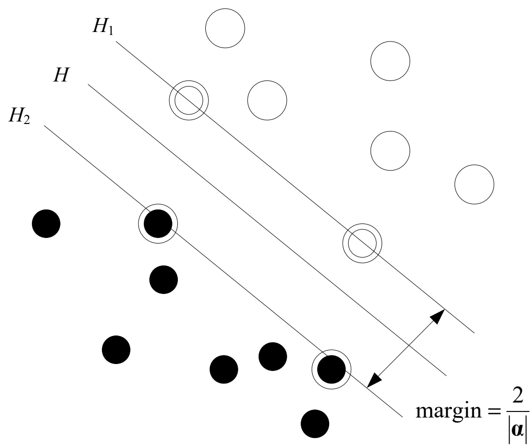
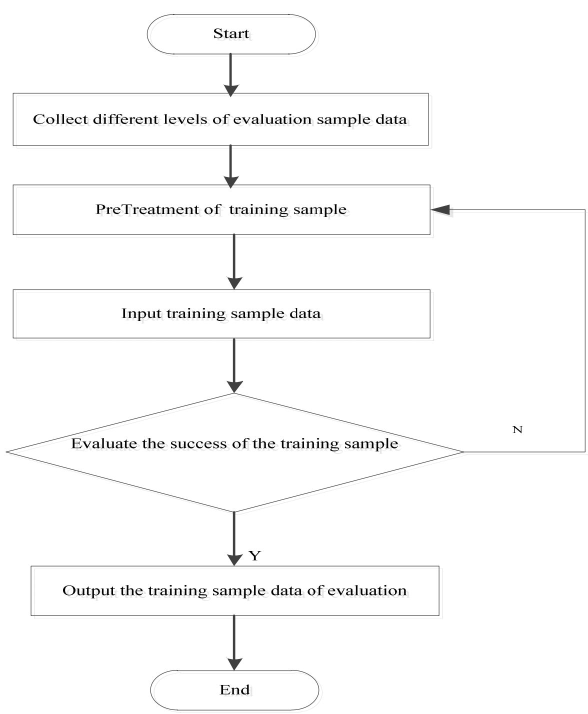


Figure 3 Flowchart for variance evaluation



By using Lagrange multiplier optimisation method, the above problems are transformed into dual problems, that is, there are constraints:

$$\begin{cases} \sum_{i=1}^{n} y_i \beta_i & i = 1, 2, \ldots, n \\ \beta_i \geq 0 \end{cases} \tag{5}$$

Based on formula (3), gets the maximum value of the function for $\wp_i$:

$$W(\beta) = \sum_{i=1}^{n} \wp_i - 0.5 \sum_{i,j} \wp_i \wp_j y_i y_j \left(x_i x_j \right) \tag{6}$$

In the case of non-separable linearity, many relaxation variables and penalty coefficients can be added to the condition to reduce the restriction and obtain a generalised linear classification.

To find the optimal classification surface. The nonlinear problem is solved by the inner product operation of the function in the original space. Therefore, assuming that the kernel function satisfying Mercer condition is $K(x_i, x_j)$, to individe classification could obtained by nonlinear transformation without increasing is

$$f(x) = \text{sgn}(\boldsymbol{\alpha} x + b) = \frac{\sum_{i=1} \wp_i^* y_i K\left(x_i, x_j\right) + b^*}{n} \tag{7}$$

By analysing support vector machine algorithm, the evaluation problem was change to deal with by Lagrange multiplier, and the corresponding constraints are setup. For to individe surface with obtain this optimal classification function, the evaluation optimisation of students' online learning level difference is realised.

3.2 Construction of online learning level difference evaluation system

The specific process of constructing the online learning level difference evaluation model of support vector machine (Tang et al., 2020; Wang et al., 2020) is as follows:

1 Using big data method to collect online learning level difference evaluation data, according to the proportion of 1:2, randomly divided into training samples and prediction samples.

2 Normalise the collected samples and prediction data, and delete the wrong data:

$$G = \frac{u_i - u_{\min}}{u_{\max} - u_{\min}} \tag{8}$$

where $u_{\max}$ and $u_{\min}$ are the maximum and minimum values of collected data, u_i is the value before preprocessing, and G is the value before preprocessing.

Represents the value after preprocessing.

3 Determine the content of input and output objects, and construct the evaluation model of online learning level difference.

4 Evaluate the test samples in the online learning level difference evaluation model, and get the prediction results.

5 Comparative analysis, observation and prediction.

The specific model is described as follows.

Let D be the set of students, L be the set of difference evaluation indexes, the corresponding eigenvector in L is marked as $\overrightarrow{f_j}$, and $H = h_{ij}$ is the evaluation result. Thus, by evaluating the existing learning data, we can understand the evaluation results of the j^{th} student, that is, predict $h_{i(j+1)}$ by $\left(\overrightarrow{f_j},\ h_{ij}\right)$, and get the flow chart of difference evaluation, as shown in Figure 3:

On the basis of support vector machine, the difference evaluation data of online learning level is obtained by big data technology, and the obtained data are trained and divided. Through normalisation processing of the above data, the key students' online learning level indicators are input to obtain the final evaluation results, and the students' online learning level difference evaluation is completed.

4 Experimental

The verification method was to calculate this online learning level difference evaluation model of college students, output the evaluation results, and compare whether the calculation results are consistent with the final examination scores.

4.1 Experimental environment and parameters

In order to verify the validity of the proposed model, a simulation experiment is carried out. The experiment is realised by MATLAB SVM Tool box software. By SPSS 10.0, the data of soft armour statistical experiment, the operating system of the experiment is WINDOW 8,CPU 3.6. GHz.

According to the difference evaluation process of support vector machine, the data of 20 courses were counted and calculated, with a total of 4,006 groups of data. From 20 randomly selected courses, take the same course as an example. There are 198 learners in this course. After normalisation and preprocessing by formula (9), partial data of online learning process scores are obtained, as shown in Table 2.

4.2 Experimental indicators and programs

According to the model, the evaluation index factor set is determined:

$$\begin{aligned} &U = \begin{pmatrix} U_1 \\ U_2 \\ U_3 \end{pmatrix} \\ &U_1 = U_{11}, U_{12}, U_{13} \\ &U_2 = U_{21}, U_{22}, U_{23} \\ &U_3 = U_{31}, U_{32}, U_{33} \end{aligned} \tag{9}$$

Table 2 Demonstration chart of score calculation for online learning process (part of data)

Students	*Course video viewing complete/%*	*Course material reading completion/%*	*Quality of assignments and tests/%*	*Number of questions/times*	*Number of launches/times*	*Number of responses/times*	*Number of course page visits/times*	*Completion of assignments and tests/%*	*Bad brush record*	*Final exam results/grade*
1	99.77	100	99.71	0	0	0	73	100	0	100
2	99.16	100	99.35	0	0	0	10	100	0	100
3	95.23	100	35.82	0	0	0	13	85.51	–1	98
4	95.81	100	89.36	0	0	0	94	100	0	100
5	97.58	100	100	0	0	0	170	100	0	100
6	99.30	100	99.03	0	0	0	85	100	0	100
7	98.98	100	99.35	0	0	0	19	100	0	100
8	97.11	100	98.99	0	0	0	13	100	–1	99
9	91.86	100	97.27	0	0	0	40	100	0	96
10	92.68	100	96.84	0	0	0	38	100	0	100

Among them, U_1 is knowledge acquisition, U_2 is collaborative communication, U_3 is learning attitude, U_{11}, U_{12}, U_{13} are three indicators of knowledge acquisition, U_{21}, U_{22}, U_{23} are three indicators of collaborative communication, U_{31}, U_{32}, U_{33} are three indicators of learning attitude.

Comments collection:

$$V = \begin{pmatrix} 95 \\ 85 \\ 75 \\ 65 \\ 55 \end{pmatrix} \tag{10}$$

Among them, the data in formula (10) represent excellent, good, medium, pass and fail respectively.

Index weight set:

$$A = (0.583,\ 0.126,\ 0.151)$$
$$A1 = (0.228,\ 0.108,\ 0.648)$$
$$A2 = (0.633,\ 0.261,\ 0.106)$$
$$A3 = (0.230,\ 0.648,\ 0.122)$$

To sum up, the analysis of the evaluation index system and index weight shows that there is a nonlinear relationship between the evaluation index and the evaluation result, and the evaluation result shows multi classification. Therefore, this paper uses MATLAB SVM toolbox to realise multi classification support vector machine, and selects Gaussian kernel function of formula (7) as kernel function to determine parameters and in RBF. Finally, and are determined, and the prediction accuracy of the four datasets is compared, as shown in Table 3.

Table 3 Changes in accuracy with parameter C and γ

C value	*γvalue*	*Accuracy/%*
26	0.015	91.2078
26	0.035	93.1055
27	0.067	93.4687
28	0.0733	97.6567
…	…	…
29	0.089	94.4585

Based on the data in Table 3, the sample labels and attributes in the data dataset are visualised, and the results of visual comparison are shown in Figure 4.

Based on the visualisation result chart in Figure 5, in MATLAB environment, the one to one multi classification method integrated in MATLAB SVM toolbox software is used for sample training. To prediction sample though contrast sample, and accuracy of evaluation result is obtained:

Figure 4 Visualisation of test dataset (see online version for colours)

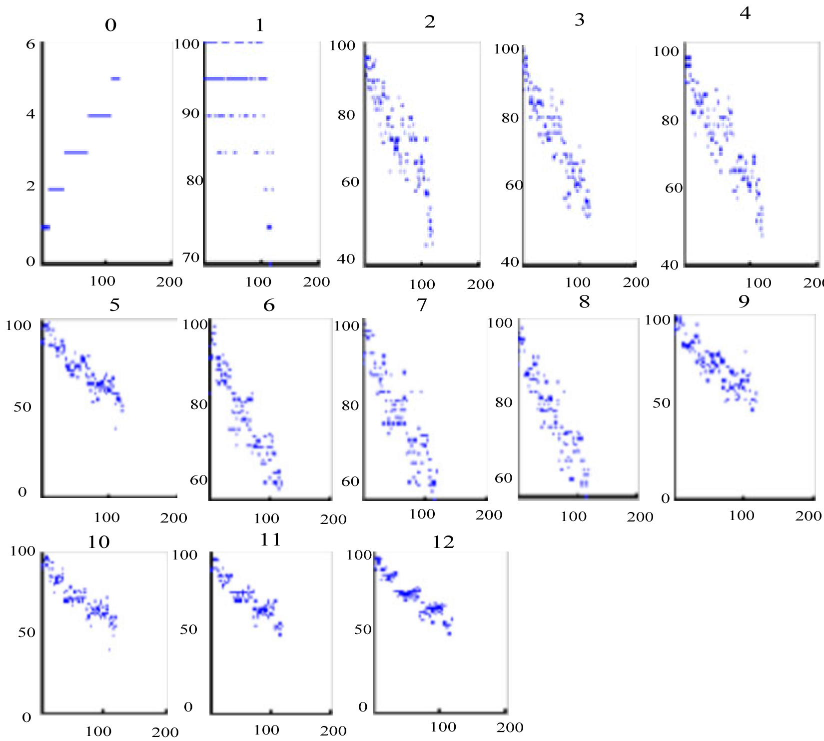
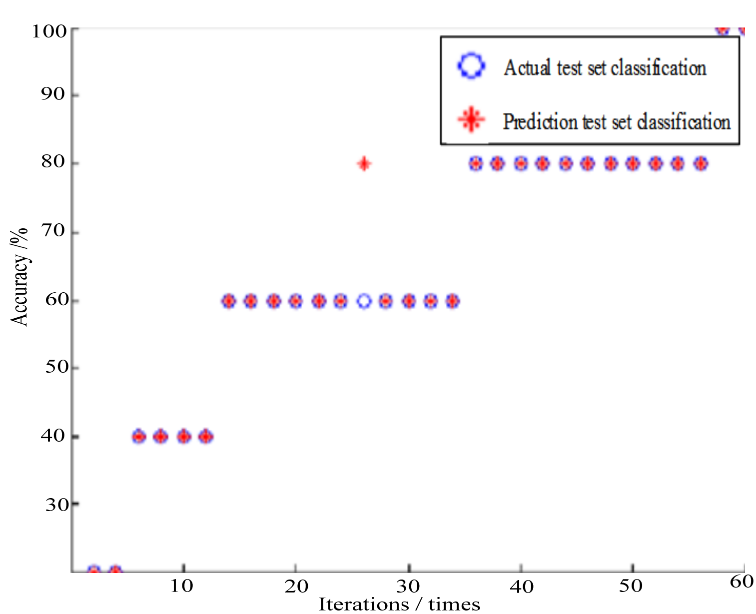


Figure 5 Comparison chart of data test set classification (see online version for colours)



As shown in Figure 5, the evaluation results of the online learning behaviour difference model of college students based on support vector machine are basically consistent with the actual evaluation results, which can well output the final learning results. Under the same data test set, the online learning behaviour data of college students are evaluated respectively with the BP neural network evaluation method in reference. The final evaluation results are shown in Table 4.

Table 4 Comparison of evaluation results

Evaluation object	*Evaluation method*	*Evaluation accuracy /%*
Date	Methods of this paper	97.97
	BP neural networks	95.96
Date1	Methods of this paper	98.73
	BP neural networks	96.47
Date2	Methods of this paper	98.98
	BP neural networks	94.96
Date3	Methods of this paper	97.25
	BP neural networks	93.83

As shown in Table 4, the prediction accuracy of this method is more than 97.25%, which is better than that of BP neural network. This is due to the reasonable classification of samples by using support vector machine algorithm.

In order to further verify the practicability of the method in this paper, the two methods are used to predict four datasets, and ten experiments are conducted on the datasets, and the average time consumption is obtained. The time cost comparison results are shown in Table 5.

Table 5 Comparison of time overhead

Evaluation object	*Evaluation method*	*Training time/ms*	*Test time/ms*
Date	Methods of this paper	23.9	6.5
	BP neural networks	27.0	9.0
Date1	Methods of this paper	23.8	7.3
	BP neural networks	28.03	9.2
Date2	Methods of this paper	24.33	7.1
	BP neural networks	27.87	9.5
Date3	Methods of this paper	24.78	6.8
	BP neural networks	27.34	9.5

It can be concluded from Table 5 that the BP neural network consumes a little longer time, but the time cost of this method in the classification process is less. This is because the method uses the support vector machine algorithm to reasonably classify the test data, which saves the prediction time and improves the evaluation efficiency.

5 Conclusions

The difference evaluation model of online learning level is designed. By extracting the characteristics of online learning behaviour of college students, the difference evaluation model of online learning level is constructed to realise the evaluation of online learning behaviour of college students; through the optimisation model of support vector machine learning algorithm, the difference evaluation system of online learning level of college students is designed, and the evaluation model of online learning level difference of college students is completed design. Compared with traditional methods, it has the following advantages:

1 The accuracy of the model is more than 97%, which has certain credibility.

2 The time cost of the model is less than 9.5 MS and the efficiency is high.

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