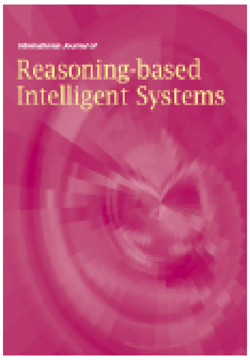

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A recognition method of learning behaviour in online classroom based on feature data mining

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A recognition method of learning behaviour in online classroom based on feature data mining

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Abstract: In order to effectively ensure the recognition effect of online classroom learning behaviour and improve the accuracy and efficiency of online classroom learning behaviour recognition, an online classroom learning behaviour recognition method based on feature data mining is proposed. This paper analyses the concept and process of feature data mining, and extracts the characteristics of learning behaviour data in online classroom. Principal component analysis was used to pre-process the characteristics of learning behaviour data in online classroom. Using the method of feature data mining, this paper constructs the recognition model of learning behaviour in online classroom to realise the recognition of learning behaviour in online classroom. The experimental results show that the proposed method has a good effect on the recognition of learning behaviour in the online classroom, and can effectively improve the accuracy and efficiency of the recognition of learning behaviour in the online classroom.

Keywords: feature data mining; principal component analysis; online classroom; learning behaviour; behaviour recognition.

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1 Introduction

At present, the development concept of the integration of teaching, management and service promotes the reform of education towards informatisation, personalisation and intelligence. With the support of human-computer interaction, cloud computing, big data, internet of things, computer vision and other information technologies, realise the reform of talent training mode and teaching methods of modernisation of teaching environment, personalised distribution of teaching resources, quality management of teaching process, accuracy of teaching quality evaluation and informatisation of educational decision support (Agarwal et al., 2021; Zheng et al., 2021; Chen et al., 2020). Classroom teaching is the top priority of education. Students' classroom behaviour is directly related to the quality of education and teaching. In the traditional teaching process, teachers only rely on the feedback obtained from the observation and analysis of students' behaviour in the teaching process to evaluate the teaching situation and students' learning efficiency. This process is not combined with the analysis of teachers' teaching behaviour, which has the defects of incomplete information acquisition, poor evaluation timeliness and insufficient reliability, unable to truly and accurately reflect the students' learning situation, which affects the teaching quality (Bao and Yu, 2021; Ning and Dehao, 2020). How to capture the classroom state of all students in an all-round way, analyse and obtain complete and effective classroom feedback, and improve teaching quality has always been a difficult problem in classroom teaching research.

At present, scholars in related fields have carried out research on learning behaviour recognition. Tba et al. (2021) proposed a method for classroom student behaviour recognition using VGG-16 deep transfer learning. Methods based on automatic facial expression recognition to capture and summarise students' behaviour in the classroom. In order to improve the students' ability to recognise the behaviour of video sequences, based on the method of deep transfer learning, the model is pre-trained on the facial expression dataset, and the students' behaviour is classified through the transfer model. This method can ensure that students' behaviour classification is more reasonable. Zhang et al. (2021) proposes an online classroom learning behaviour recognition method based on soft transfer and progressive learning, which collects student behaviours in digital image sequences, determines normal and abnormal behaviours of online classroom learning through feature difference measurement function, monitors online classroom learning behaviour by using learner supervisor learning mechanism, and segments student behaviour contour by using adjacent selection, According to the artificial neural network to realise the student recognition of classroom behaviour, this method has high efficiency of learning behaviour recognition, but the recognition accuracy is low. Guo et al. (2021) proposed a network classroom behaviour recognition method driven by deep learning model, and designed a three-dimensional convolutional neural network according to the classroom teaching scene. Taking dynamics as the main feature, this paper identifies teachers' classroom behaviour. The Yolo-v5 model is constructed through the improved loss function, and the multi-objective is the main feature to realise the recognition of students' classroom behaviour. This method can improve the recognition accuracy, but the recognition efficiency is low.

Aiming at the above problems, this paper proposes an online classroom learning behaviour recognition method based on feature data mining. Learning behaviour data features by extracting online classrooms. The principal component analysis method was used to pre-process the characteristics of online classroom learning behaviour data. Using the method of feature data mining, a recognition model of online classroom learning behaviour is constructed. The recognition effect of this method is good, and it can effectively recognise the accuracy and efficiency. The specific research ideas of this paper are as follows:

Firstly, the concept and process of feature data mining are analysed to extract the characteristics of learning behaviour data in online classroom. Secondly, the principal component analysis method is used to pre-process the characteristics of learning behaviour data in online classroom.

Then, using the method of feature data mining, this paper constructs the learning behaviour recognition model of online classroom to realise the learning behaviour recognition of online classroom.

Finally, the effectiveness of this method is verified by recognition accuracy and recognition accuracy, and a conclusion is drawn.

2 Feature data mining technology

2.1 The concept of feature data mining

Feature data mining is the process of extracting potential and valuable knowledge from a large amount of data. Feature data mining brings together achievements from various disciplines such as machine learning, pattern recognition, databases, statistics, artificial intelligence, and management information systems (Guo et al., 2021; Afonso et al., 2019; Safarnejad et al., 2021). The interdisciplinary integration and mutual promotion have enabled this new discipline to flourish and have begun to take shape. The main tasks of feature data mining are association analysis, cluster analysis, classification, prediction, time series pattern and deviation analysis.

2.2 The process of feature data mining

The process of feature data mining can be divided into the following steps:

1 Understand the requirements: Understand the application solution goals and requirements from the application point of view, convert them into data mining problem definitions, and design a preliminary plan outline to achieve the goals.

2 Collect data: Collect preliminary data, and carry out data description, data exploration and data quality verification.

3 Preparing data: Constructing the initial raw data into a dataset that is finally suitable for processing by modelling tools. Including table, record and attribute selection, data transformation and data cleaning, etc.

4 Modelling: Select and apply various modelling techniques and optimise their parameters.

5 Model evaluation: Conduct a more thorough evaluation of the model, and check each step of building the model to confirm whether it really achieves the intended application purpose.

6 Model deployment: Organise and represent the acquired knowledge in a usable way. Implement a repeatable data mining process.

3 Recognition method of learning behaviour in online classroom based on feature data mining

3.1 Feature extraction of learning behaviour data in online classroom

In order to effectively realise the recognition of online classroom learning behaviour based on feature data mining, firstly, the data features of online classroom learning behaviour are extracted. The optimal solution of the data characteristics of learning behaviour in online classroom is defined:

$$Q_m = Q_{m-1} \times W_m \tag{1}$$

In equation (1), W_m represents the characteristic initial value of the learning behaviour data in the online classroom, and Q_{m-1} represents the weight of the learning behaviour data in the online classroom. When constructing a neural network (Zhou et al., 2021; Ke et al., 2021) for the number of samples of learning behaviour data in an online classroom, the position of the n neuron in m+1 can be expressed as:

$$W_n(m+1) = \frac{W_n(m)}{W_b(m)} + \alpha \times W_n(m) \tag{2}$$

In equation (2), $W_n(m)$ represents the input data for feature extraction of online classroom learning behaviour data, α represents the location of online classroom learning behaviour data, and $W_b(m)$ represents the output data for online classroom learning behaviour data feature extraction.

If the online classroom learning behaviour data vector set contains v sample data, then the fuzzy mean vector of the sample β_i is:

$$\beta_i = (\beta_{i1}, \beta_{i2}, ..., \beta_{iv})^T \tag{3}$$

According to the confidence of the online classroom learning behaviour data, the centre vector of the c behaviour data of the online classroom learning behaviour data is obtained, and the training data feature extraction expression of the online classroom learning behaviour data can be obtained as follows:

$$E = \{\gamma_{cm} \mid c = 1, 2, ..., R\} \tag{4}$$

In equation (4), R represents the distribution characteristics of online classroom learning behaviour data, and γ_{cm} represents the distribution characteristics set of online classroom learning behaviour data. In order to reflect the diversity characteristics of online classroom learning behaviour data, the extraction expression of the characteristics of the online classroom learning behaviour data sample set can be obtained as follows:

$$Y(E,U) = \sum\nolimits_{m=1,c=1}^{n} \gamma_{cm} \times \varepsilon \times \left(\frac{\delta_{cm}}{\beta_i}\right) \tag{5}$$

In equation (5), ε represents the characteristic sampling data of online classroom learning behaviour data, and δ_{cm} represents the amplitude of the online classroom learning behaviour data characteristic. The least squares method is used to represent the data vector of the learning behaviour data in the online classroom, namely:

$$\delta_{cm} = W_b(m) \times \|W_m - U\| \tag{6}$$

Assume that s_e represents the training sample set of the entire online classroom learning behaviour data, $\in$ represents the new online classroom learning behaviour data sample set after training using the feature data mining algorithm, d_c represents the sample attribute of the online classroom learning behaviour data, and θ represents the online classroom information thresholds for learning behavioural data. The following formula can be used to obtain the information threshold for the division of the online classroom learning behaviour data sample set $\in$ corresponding to the attribute a:

$$P_n = \frac{a \times \in}{s_e} \times \frac{d_c \times \theta}{f_d} \tag{7}$$

In equation (7), f_d represents the total number of datasets of learning behaviour data in the entire online classroom. Assuming that g_{cm} represents the dataset divided by online classroom learning behaviour data attributes, the following formula can be used to complete the extraction of online classroom learning behaviour data features:

$$P_w = \frac{\in \times g_{cm}}{Y(E,U)} \times \beta_i \tag{8}$$

According to the above calculation steps, the feature extraction of online classroom learning behaviour data is realised.

3.2 Pre-processing of learning behaviour data characteristics in online classroom

Due to the diversity of the characteristics of the above-mentioned extracted learning behaviour data in the online classroom, the amount of calculation in the actual identification process is huge. In order to effectively reduce the complexity of online classroom learning behaviour recognition, it is necessary to reduce the amount of calculation as much as possible. The principal component analysis processing of online classroom learning behaviour data can extract concise and complete information about the characteristics of online classroom learning behaviour data.

The main idea of principal component analysis is to transform a large amount of data into a multivariate statistical analysis method with complete information but greatly reduced quantity, which is specifically reflected in that all data are transformed into low-dimensional space through mapping, and a small amount of data is used to replace the highly representative original data. At present, this method is the most commonly used method for feature extraction (Xu et al., 2020; Li et al., 2021; Zuo et al., 2020).

Assuming that the number of online classroom learning behaviour data samples is k, and each sample needs to be processed by principal component analysis, the set expression of the characteristic variables of the online classroom learning behaviour data of each sample is:

$$H = \{h_1, h_2, ..., h_k\} \tag{9}$$

In equation (9), H represents the eigenvalue variable of the online classroom learning behaviour data sample, and k represents the feature quantity of the online classroom learning behaviour data. Then, the calculation formula of the mean value of the online classroom learning behaviour data sample is obtained as follows:

$$l_j = \frac{1}{k} \sum\nolimits_{i=1}^{k} l_{ij} \tag{10}$$

In equation (10), l_{ij} represents the mean vector of data samples of online classroom learning behaviour. Then the formula for calculating the standard deviation of the online classroom learning behaviour data sample is:

$$z_j = \sqrt{\frac{1}{k} \sum\nolimits_{i=1}^{k} (l_j - l_{ij})^2} \tag{11}$$

The characteristic variable expression after standardising the online classroom learning behaviour data is:

$$l_{ij} = \frac{l_j - l_{ij}}{z_j} \tag{12}$$

In equation (12), i and j represent constant terms. According to the above formula, the calculation formula of the correlation matrix of online classroom learning behaviour data samples is deduced, and its expression is:

$$X = \frac{1}{k} \times H^T \times H \tag{13}$$

By decomposing the matrix X, the eigenvalues of the data related to the online classroom learning behaviour are obtained, and the eigenvalues of the online classroom learning behaviour data are sorted to obtain the cumulative contribution rate of the principal components of the eigenvalues of each online classroom learning behaviour data, and its expression is:

$$C = \sum_{i=1}^{q} \omega_i \Big/ \sum_{i=1}^{w} \omega_i \tag{14}$$

In equation (14), q represents the number of eigenvalues of online classroom learning behaviour data for calculation of cumulative contribution rate, w represents the total number of eigenvalues of online classroom learning behaviour data, and ω_i represents the parameter in the calculation of cumulative contribution rate.

Improve the cumulative contribution rate of the ranking eigenvalues to obtain the eigenvalues that meet the requirements of the cumulative contribution rate, and use the corresponding online classroom learning behaviour data eigenvectors to generate the load matrix φ. Finally, using the load matrix and the characteristic variables of the online classroom learning behaviour data, the dimensionality reduction and simplified online classroom learning behaviour dataset is obtained, and its expression is:

$$V = \varphi \times C \tag{15}$$

Through the above steps, the pre-processing of the characteristics of the learning behaviour data in the online classroom is completed.

3.3 Identification method of learning behaviour in online classroom

On the basis of pre-processing the characteristics of online classroom learning behaviour data, the feature data mining method is used to construct the online classroom learning behaviour recognition function to realise the online classroom learning behaviour recognition. In this paper, we use the method of feature data mining to obtain the relevance of online classroom learning behaviour. The specific methods are as follows:

Suppose the k^{th} person in the image has two key points j_1 and j_2 on the same limb c, point $\boldsymbol{P}$ is a point on limb c, $L^*_{c,k}(\boldsymbol{P})$ represents the unit vector of j_1 pointing to j_2, and other points are zero vectors, such as equation (16)

$$L^*_{c,k}(\boldsymbol{P}) = \begin{cases} v, & p \textit{ is on the limb } C \textit{ of individual } k \\ 0, & \textit{other} \end{cases} \tag{16}$$

If there are overlapping limbs, that is, there will be multiple PAF vectors for a pixel, sum them and divide by the number of overlapping limbs n_c, as shown in equation (17).

$$S^*_c(\boldsymbol{p}) = \frac{1}{n_c(\boldsymbol{P})} \sum_k L^*_{c,k}(\boldsymbol{P}) \tag{17}$$

The characteristic map is sent to the confidence map generation module. The architecture of this module is consistent with that of the PAFS generation module. The difference is that in addition to the characteristic diagram and the output of the previous stage, the input of the confidence graph module also considers the PAFS output of the previous module, providing context for the current stage, and solving the problem of lack of global context information during key point detection. Another difference is that the loss function is different. The formula of the confidence graph generation module is as shown in equation (18).

$$S^t = \rho^t\left(F, L^{T_p}, S^{t-1}\right), \forall T_p < t \le T_p + T_C \tag{18}$$

Among them, ρ^t refers to the neural network at stage t, and T_C refers to the number of stages of the total confidence map.

The formula for generating the total confidence map is shown in equation (19), which generates a single person confidence map and takes the maximum confidence map after aggregation.

$$S^*_{j,k}(p) = exp\left(-\frac{\left\|p - x_{j,k}\right\|_2^2}{\delta^2}\right) \tag{19}$$

$$S^*_j(p) = max_k S^*_{j,k}(p) \tag{20}$$

where $x_{j,k}$ represents the position of the j^{th} key point of the k^{th} person in the real image, and p represents the coordinates of pixel points, δ used to control peak propagation The module calculates the integral of PAF along the line of candidate key points to measure the relationship between the two key points of student behaviour. Such as equations (21), (22):

$$E = \int_{u=0}^{u=1} L_c(p(u)) \cdot \frac{d_{j_2} - d_{j_1}}{\left\|d_{j_2} - d_{j_1}\right\|_2} du \tag{21}$$

$$p(u) = (1-u)d_{j_1} + ud_{j_2} \tag{22}$$

Among them, d_{j_1} and d_{j_2} are candidate key points, and $p(u)$ represents the position of key points. The larger the correlation confidence E, the greater the connection between the two key points. At this time, the calculated correlation confidence is the correlation degree of online classroom learning behaviour. Learning behaviour recognition is realised according to the relevance of learning behaviour in online classroom.

Assuming that the input transmission volume of the online classroom learning behaviour data is B, and the output transmission volume is F, using the feature data mining method to train the extracted online classroom learning behaviour data features, and pre-process the online classroom learning behaviour data features, we can get the information value of the online classroom learning behaviour data:

$$\tau(F,B)=\sigma(F,B)\log\frac{\sigma(F)\times\sigma(B)}{\rho(F,B)} \tag{23}$$

In equation (16), $\sigma(F)$ and $\sigma(B)$ represent the probability density of online classroom learning behaviour data F and B, $\sigma(F,B)$ represents the combined online classroom learning behaviour data probability density, and $\rho(F,B)$ represents the online classroom learning behaviour data entropy value (Yu et al., 2021; Mou et al., 2020; Guo and Wang, 2021). Using equation (17), calculate the distance between the minimum information value and the maximum information value of the latent variable of the learning behaviour data in the online classroom:

$$J_s=\frac{\pi_{max}-\pi_{min}}{\mu} \tag{24}$$

In equation (17), π_{max} and π_{min} represent the variable values of all potential online classroom learning behaviour data, and π represents the variance contribution rate of all the extracted online classroom learning behaviour data. Select the potential online classroom learning behaviour data threshold π_τ, and use equation (18) to calculate:

$$\pi_\tau=\frac{\vartheta}{\mu}\times\left(\pi_{max}-\pi_{min}\right) \tag{25}$$

In equation (18), ϑ represents the variance contribution rate of feature extraction from online classroom learning behaviour data. Based on the online classroom learning behaviour data threshold π_τ, using the feature data mining algorithm, initialise the online classroom learning behaviour data parameters, and obtain the probability matrix of the online classroom learning behaviour data extraction results:

$$F_G=\frac{\{\zeta_J\mp\zeta\}}{\eta}\otimes V_B\frac{\phi\times\Psi}{\kappa} \tag{26}$$

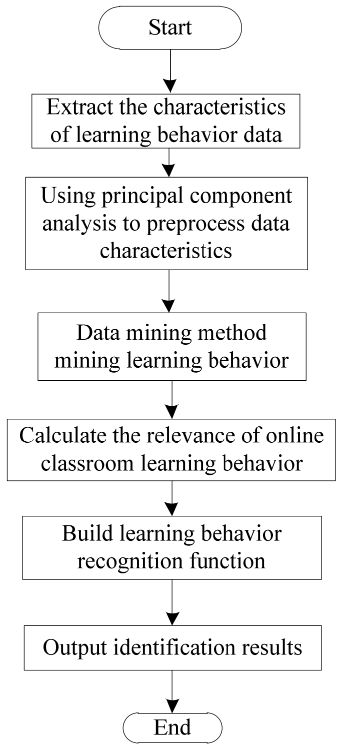
In equation (19), η is the probability that the online classroom learning behaviour data is transferred from state ζ to ζ_J, V_B is the probability matrix representing the online classroom learning behaviour data, κ is the probability matrix of the online classroom learning behaviour data state in the transition process, ϕ is the probability of a random observation Ψ. Taking the feature vector of online classroom learning behaviour data recognition as the input of the feature data mining algorithm, the online classroom learning behaviour recognition model is constructed and expressed as:

$$F_H=\frac{H_G\otimes G_C}{S_T\times G_D}\mp\frac{J_Y}{F_G}\oplus Z_Y \tag{27}$$

In equation (20), S_T is the attribute feature of online classroom learning behaviour data, G_C is the state observation value obtained by feature data mining, and H_G is the posterior probability corresponding to the recognition result of online classroom learning behaviour data. G_D is the correlation degree of the time length of online classroom learning behaviour data identification, J_Y is the verification probability of online classroom learning behaviour data identification, and Z_Y is the optimal solution of the results of online classroom learning behaviour data extraction.

The above-mentioned feature data mining algorithm is used to construct an online classroom learning behaviour identification model, which realises the identification of online classroom learning behaviour. It is online classroom learning behaviour recognition process is shown in Figure 1.

Figure 1 Flow chart of learning behaviour recognition in online classroom



4 Experimental simulation and analysis

4.1 Setting up the experimental environment

In order to verify the effectiveness of the learning behaviour recognition method in the online classroom based on feature data mining, the learning behaviour recognition experiments were carried out on the public dataset BUHMAP-DB and the custom online classroom dataset KCRD respectively. The computer used in this experiment is a Veriton M275 computer, the operating system is Windows 7 32-bit SP1, the programming environment is Microsoft Visual Studio 2010 and MATLAB R2010b, and the software used includes Open CV 2.4.3 and Qt 4.8.4. 2500 online classroom learning behaviour data are randomly selected from the four datasets in Table 1, and the effectiveness of the proposed method is verified by comparing the method in Tba et al. (2021), the method in Zhang et al. (2021) and the proposed method.

Table 1 relevant parameters of validated dataset

Dataset	*Type*	*Data volume/GB*
BNU-LCSAD	int	1000
The KTH dataset	float	896
The IXMAS dataset	long	1109
SBBRD	int	658

4.2 Experimental index

4.2.1 The better the recognition effect

In order to verify the effectiveness of the proposed method in network classroom learning behaviour recognition, the recognition rate was taken as an evaluation index. The higher the recognition rate is, the better the recognition effect is. Its calculation formula is as follows:

$$S_B = \frac{S_G}{S_Z} \times 100\% \tag{28}$$

In equation (28), S_G refers to the number of all recognised network classroom learning behaviour data, and the number of network classroom learning behaviour data to be recognised.

4.2.2 Recognition accuracy

The accuracy of the proposed method was further verified, and the recognition accuracy was taken as an evaluation index. The higher the recognition accuracy is, the higher the recognition accuracy is. Its calculation formula is as follows:

$$Z_Q = \frac{J_S}{S_Z} \times 100\% \tag{29}$$

In equation (29), J_S refers to the number of correctly identified network classroom learning behaviour data.

4.2.3 Identification time

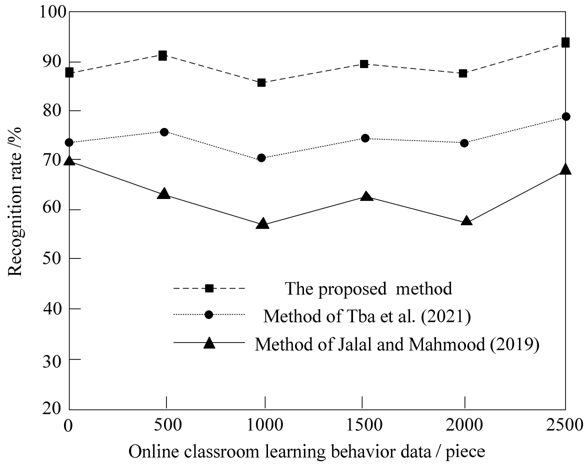
Take the identification time as the evaluation index. The shorter the recognition time, the higher the efficiency of online classroom learning behaviour recognition.

4.3 Experimental results

4.3.1 Analysis of the effect of online classroom learning behaviour recognition

In order to verify the recognition effect of network classroom learning behaviour of the proposed method, the recognition rate was taken as an evaluation index and compared with the method in Tba et al. (2021), and Zhang et al. (2021) and the proposed method. The recognition rate of network classroom learning behaviour of different methods was obtained, as shown in Figure 2.

Figure 2 Recognition rates of learning behaviours in online classrooms with different methods



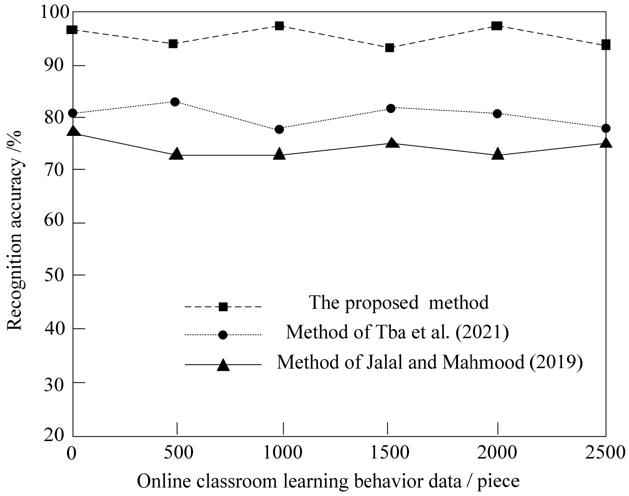
According to Figure 2, when there are 500 online classroom learning behaviour data, the average online classroom learning behaviour recognition rate of Tba et al. (2021) method is 76.5%, the average online classroom learning behaviour recognition rate of Zhang et al. (2021) method is 63.2%, and the average online classroom learning behaviour recognition rate of the proposed method is as high as 92.1%.When there are 2500 online classroom learning behaviour data, the average online classroom learning behaviour recognition rate of Tba et al. (2021) method is 78.6%, and the average online classroom learning behaviour recognition rate of r Zhang et al. (2021) method is 68.2%. The average recognition rate of online classroom learning behaviour of the proposed method is as high as 93.0%.It can be seen that the recognition rate of online classroom learning behaviour of the proposed method is high, indicating that the recognition effect of online classroom learning behaviour of the proposed method is good.

4.3.2 Analysis of accuracy of learning behaviour recognition in online classroom

The accuracy of online classroom learning behaviour recognition of the proposed method was further verified. The methods in Tba et al. (2021), and Zhang et al. (2021) and the proposed method were respectively compared to obtain the accuracy of online classroom learning behaviour recognition of different methods, as shown in Figure 3.

According to Figure 3, when there are 500 online classroom learning behaviour data, the average online classroom learning behaviour recognition accuracy of Tba et al. (2021) method is 83.5%, the average online classroom learning behaviour recognition accuracy of Zhang et al. (2021) method is 72.6%, and the average online classroom learning behaviour recognition accuracy of the proposed method is as high as 93.2%.When there are 2,500 online classroom learning behaviour data, the average online classroom learning behaviour recognition accuracy of Tba et al. (2021) method is 81.4%, and the average online classroom learning behaviour recognition accuracy of Zhang et al. (2021) method is 77.9%. The average recognition rate of online learning methods is as high as 8.96%. Therefore, the proposed method has a high accuracy of online classroom learning behaviour recognition, and can effectively improve the accuracy of online classroom learning behaviour recognition.

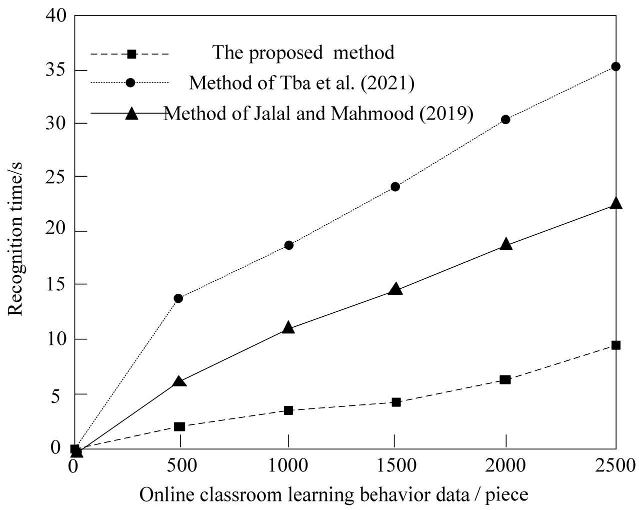
Figure 3 Correct rate of learning behaviour recognition in online classrooms with different methods



4.3.3 Efficiency analysis of learning behaviour recognition in online classroom

On this basis, the recognition efficiency of the proposed method in online classroom learning behaviour is further verified, and the recognition time is used as the evaluation index. The shorter the recognition time, the higher the recognition efficiency of the method in online classroom learning behaviour. The method of Tba et al. (2021), the method of Zhang et al. (2021) and the proposed method are used to compare, and the recognition time of online classroom learning behaviour of different methods is shown in Figure 4.

Figure 4 Correct rate of learning behaviour recognition in online classrooms with different methods



According to Figure 4, with the increase of online classroom learning behaviour data, the recognition time of online classroom learning behaviour of different methods increases. When the online classroom learning behaviour data is 2,500, the online classroom learning behaviour recognition time of Tba et al. (2021) method is 35.1s.The recognition time of learning behaviour in online classroom based on the method of Zhang et al. (2021) is 25.2s.while the online classroom learning behaviour recognition time of the proposed method is only 9.8s.It can be seen that the recognition time of learning behaviour in online classroom of the proposed method is short, which can effectively improve the recognition efficiency of learning behaviour in online classroom.

5 Conclusions

This paper puts forward the recognition method of online classroom learning behaviour based on feature data mining, analyses the concept and process of feature data mining, and extracts the data characteristics of online classroom learning behaviour. Principal component analysis was used to pre-process the characteristics of learning behaviour data in online classroom. Using the method of feature data mining, this paper constructs the recognition model of learning behaviour in online classroom to realise the recognition of learning behaviour in online classroom. The experimental results show that:

1 When the online classroom learning behaviour data is 2,500, the average online classroom learning behaviour recognition rate of the proposed method is as high as 90.1%. The online classroom learning behaviour recognition rate of the proposed method is high, indicating that the online classroom learning behaviour recognition effect of the proposed method is better.

2 When there are 2,500 online classroom learning behaviour data, the average accuracy of online classroom learning behaviour recognition of the proposed method is as high as 96.8%. The proposed method can effectively improve the accuracy of online classroom learning behaviour recognition.

3 When there are 2, 500 online classroom learning behaviour data, the recognition time of online classroom learning behaviour of the proposed method is only 9.8s.

However, this method does not consider the adaptability in different environments, and is only for simple environments. Therefore, in the following research, we will consider accurate behaviour recognition from complex environment, so as to further optimise the effect of behaviour data recognition.

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