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Research Article

Analysis of College Art Teaching System under the Background of Video Big Data Technology

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Art teaching needs not only learning art knowledge but also a lot of practice and aesthetic appreciation. However, traditional teaching methods cannot provide students with a large number of relevant learning materials, which is not conducive to improving students' classroom enthusiasm. This paper presents the design and implementation of college art teaching system based on video big data technology and combines video recommendation algorithm with the Django teaching video website. The system analyzes the preference needs according to the behavior data of students watching videos and recommends videos for students. At the same time, the system can also evaluate the quality of the video content according to the behavior of students watching videos, reverse classify the video, and then optimize the recommendation results. The video recommendation algorithm model based on user behavior is better than the traditional collaborative filtering recommendation algorithm and fully connected neural network collaborative filtering algorithm. It can reduce the range of users who need similarity calculation and improve the accuracy of recommendation algorithm. The experimental results show that the fully connected neural network collaborative filtering algorithm has good recommendation performance and stability, can reduce the computational complexity, and can improve the recommendation accuracy. The teaching technology integrated through the Internet can greatly improve students' enthusiasm for art teaching.

1. Introduction

Video as an information carrier can not only convey information intuitively and effectively but also contain rich informative content. The development of Internet technology provides a favorable way and method for video transmission. With the surge in the number of videos that people can obtain, it has gradually become the focus of research to obtain the required videos quickly and effectively in a short time. With the rise of virtual reality industry, animation industry, and video game industry, college art courses pay more attention to the cultivation and teaching of students' art technology and technical art needs to carry out corresponding practice on the basis of art knowledge and theory and pursue the effective combination of disciplines and skills [1, 2]. At the same time, college art teaching will also enhance students' employment skills, which means that college students need to learn not only art courses but also other related technologies and knowledge [3]. However, traditional art teaching in colleges and universities pays more attention to the study of basic art knowledge and skills and has less experience in the application of art skills and integration with other disciplines [4]. Relatively simple and traditional art teaching methods cannot improve students' enthusiasm and autonomy in class [5]. In addition, college students have relatively more time to spend on their own outside the classroom. When they practice and study art skills on their own, they often encounter doubts but they are unable to obtain relevant materials or relevant professional teachers to solve their doubts in a short time, which makes students feel frustrated and reduces the enthusiasm and effectiveness of students' independent learning outside the classroom [6, 7].

It provides new solutions to the problems existing in art teaching in colleges and universities. The combination of big data technology and cloud computing can not only collect massive data with scattered sources and diversified formats but also has a fast access speed. It can conduct association analysis on the data and find new valuable knowledge, so as to create new value and improve new ability [8, 9]. Video recommendation technology based on big data can provide massive teaching information data for art teaching in colleges and universities, enrich teaching, provide the effectiveness and practicability of teaching, and enable students to constantly find their own problems in video learning, so as to improve their art skills and abilities [10]. Therefore, some scholars propose to build a corresponding video recommendation to provide users with corresponding services according to users' needs, preferences, and viewing intentions [11]. Based on this, some scholars take the resource access time and frequency in the platform as feature points to build a video recommendation algorithm based on user behavior analysis [12]. Other scholars put forward the method of optimizing the player progress bar according to the user's behavior of watching video and the problems arising in the process, so as to more intuitively and effectively show the whole process of learners watching videos [13]. Some scholars pointed out that the similarity of the video content they watch can be analyzed according to the user preference and the similarity of watching video behavior, and the video can be divided into similar recommendation sets based on this classification [14]. Some scholars have introduced the deep learning method into the video recommendation algorithm model, obtained the semantic features of video vectors contained in the user's viewing video history through the deep learning network, and analyzed the user's preferences and video recommendation [15, 16]. Other scholars optimized the weight increment and user aggregation similarity based on the collaborative filtering recommendation algorithm, which improved the accuracy and effectiveness of the algorithm recommendation video [17]. At present, collaborative filtering algorithm and its improved algorithm have become the main application promotion algorithm of various social platforms and video platforms. It can effectively make corresponding recommendations according to users' preferences, but at the same time, it also has problems such as insufficient data mining of users' preferences and cold start of recommendations, which need to be further optimized and solved [18].

College students can effectively and quickly select learning videos through big data. They need to search and obtain videos according to the keywords provided by teachers. In order to better improve the efficiency of students obtaining learning videos, this paper proposes the college art teaching system based on video big data technology; that is, Django's teaching video website introduces fuzzy algorithm and big data video recommendation algorithm to build the college art teaching system. The second part is the personalized video recommendation algorithm based on user behavior in college art teaching system. The third part is the experimental results and analysis of the application of personalized video recommendation algorithm based on user behavior in the college art teaching system.

2. Design of the College Art Teaching System Based on Video Big Data Technology

Art teaching not only needs theoretical learning but also needs a lot of practical practice. The art teaching system based on video big data technology can not only provide students with video learning materials but also provide teachers with a large number of classroom video big data teaching materials to assist teachers to complete the purpose of art teaching [19]. Due to the number of videos and their unfamiliarity with big data systems, they will feel frustrated and confused in the learning process. Therefore, teachers need to teach students the corresponding basic art technology in the initial stage and guide students to complete art learning tasks by using video big data through keywords [20]. At present, the recommendation algorithms used by many video websites will take the user's history, collection behavior, and evaluation as the basis of characteristic behavior analysis and make corresponding video recommendation. However, such recommendation algorithms have a large amount of calculation and relatively low recommendation efficiency, which cannot meet the needs of students in the learning process. In this paper, the college art video big data technology introduces the big data video recommendation algorithm into the teaching video website based on Django. Shown in Figure 1 is the recommendation function flow chart of the college art teaching system based on video big data technology.

It can be seen from Figure 1 that the recommendation principle of the art teaching system is to collect the user's behavior and corresponding behavior time in the process of watching the video and preprocess the collected data. At the same time, we must count and analyze the times of fast forward and backward and the playing time ratio of the video in the user's behavior and build the user's BP model. Then, the gradient division method is used to give different feature interval weights according to the data characteristics, and the user's interest, preference, and demand are analyzed on the basis of data mining based on the results of users' video watching hobby determined by the fuzzy comprehensive evaluation method [21]. Finally, the C&S model clusters all users and divides them into different groups, finds nonoverlapping videos for users with higher similarity in the group through the Jaccard coefficient, and forms the search results to a top-N recommendation set.

The college art video big data technology mainly has the functions of video uploading, online viewing, video recommendation, and so on, which provides students in the region with relevant video learning content to learn after class. In addition, it also includes different types of videos such as music, movies, and news, which improves the diversity of video types and enriches the width of extracurricular life and knowledge available to college students. Due to the relatively small mobility of students in colleges and universities, students cannot log in with the IP address

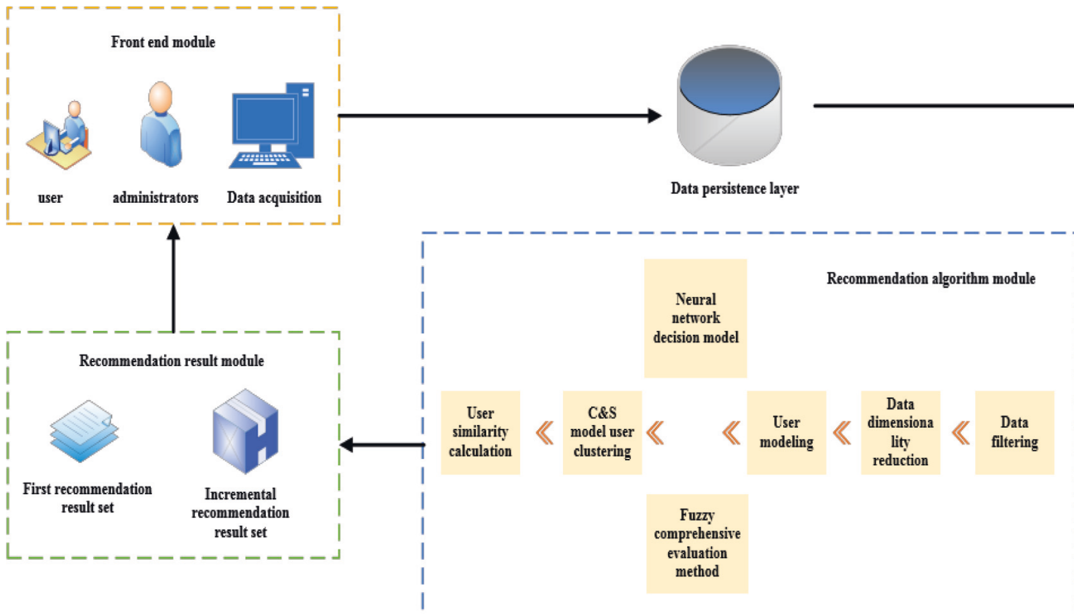

Figure 1: Recommendation function flow chart of the college art teaching system based on video big data technology.

as the user ID, but the system will record the students' behavior in the system and collect the corresponding data. Through the analysis of the recommendation algorithm, the videos that students may like are recommended to the students' client.

3. Personalized Video Recommendation Algorithm Based on User Behavior in the College Art Teaching System

Django is a free and open-source web framework developed in Python. It covers almost all aspects of web applications and can be used to quickly build high-performance and elegant websites. Django provides many modules often used in website background development, so that developers can focus on business departments. The demand for recommendation algorithms and retrieval efficiency in different fields are also increasing [22]. With its strong self-learning ability, calculation, and data ability, the deep neural network shows obvious advantages in the process of user modeling and feature extraction, abstraction, classification, and prediction of massive data. Therefore, the personalized video recommendation algorithm based on user behavior determines the degree of system user preference through fuzzy comprehensive evaluation method and deep neural network judgment method.

The fuzzy comprehensive evaluation method is a quantitative evaluation method for the factors with a fuzzy boundary according to the membership function. In the set P, the membership function corresponds to the mapping relationship of its subset. The membership degree of element x and sets is expressed by $\varphi_p(x)$ value, as shown in

$$\varphi_p(x) = \begin{cases} 1, & x \in P, \\ 0, & x \notin P, \end{cases} \tag{1}$$

where $\varphi_p(x) \in [0,1]$ is a membership function with [0, 1] value, and its mathematical expression is shown in

$$f = \begin{cases} 0, x \leq a, \\ \dfrac{x-a}{c-a}, a \leq x \leq c, \\ \dfrac{b-x}{b-c}, c \leq x \leq b, \\ 0, x \geq b. \end{cases} \tag{2}$$

The Key of Fuzzy Comprehensive Function. Generally, the membership function can be determined by fuzzy statistics, intuitive statistics, and binary comparison ranking method. The fuzzy statistical method is based on a large number of random experiments and statistical analysis to obtain an elastic boundary of the elements in the objective universe, namely, $x_0 \in P$. Its calculation formula is shown in

$$\text{membership of } x_0 \text{ to } P = \lim_{m \longrightarrow \infty} \frac{\text{times of } x_0 \in P}{m}. \tag{3}$$

The number of tests is expressed as m, and with the increase in its number, the membership function with gradually stable membership degree can be obtained.

The fully connected neural network is often used in other fields. Its hidden layer has at least one layer of neuron perceptron, and all neurons in each layer are connected to each neuron in the previous layer. The formed network is often used in two or more classifiers. Let the input of the fully connected neural network be expressed as X_1, X_2 and the hidden layer as a_n, b_n. After the feature learning of multiple hidden layers, the features are obtained and output as sample set classification. The n weight of the m element in the P layer is expressed as $W_{mn}^{(p)}(p,m,n = 1,2,3,\ldots,N)$, and the bias term is expressed as Z_n and $n = 1,2,3,\ldots,N$. Then, order of $X = [X_1, X_2]$, $W^{(1)} = \begin{pmatrix} W_{11}^{(1)} & W_{12}^{(1)} & W_{13}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} & W_{23}^{(1)} \end{pmatrix}$, and $Z^{(1)} = (Z_1, Z_2, Z_3)$ are shown in

$$a^{(1)} = X \cdot W^{(1)} + Z^{(1)}. \tag{4}$$

If $a^{(1)} = [a_1, a_2, a_3]$, $W^{(2)} = \begin{pmatrix} W_{11}^{(2)} & W_{12}^{(2)} & W_{13}^{(2)} \\ W_{21}^{(2)} & W_{22}^{(2)} & W_{23}^{(2)} \\ W_{31}^{(2)} & W_{32}^{(2)} & W_{33}^{(2)} \end{pmatrix}$, and $Z^{(2)} = (Z_1, Z_2, Z_3)$, we can obtain

$$b^{(2)} = a^{(1)} \cdot W^{(2)} + Z^{(2)}. \tag{5}$$

If $b^{(2)} = [b_1, b_2, b_3]$, $W^{(3)} = \begin{pmatrix} W_{11}^{(3)} \\ W_{21}^{(3)} \\ W_{31}^{(3)} \end{pmatrix}$ and $Z^{(3)} = (Z_1, Z_2, Z_3)$, we can obtain

$$Y = b^{(2)} \cdot W^{(3)} + Z^{(3)}. \tag{6}$$

Generally, if the error obtained in the training process of neural network is not small enough, it will produce fitting phenomenon, so as to reduce the classification accuracy of neural network. The solutions are as follows:simplify the model and deal with overfitting. The first thought is to reduce the complexity of the model. The training method of neural network model generally uses the iterative method (such as gradient descent) to train the model. If there is a big gap between the training set and the test set, the neural network will also produce the fitting phenomenon, so as to reduce its generalization ability. In order to avoid the above situation, the overfitting phenomenon of neural network model can be avoided by weight attenuation and dropout method. Among them, weight attenuation is to reduce the complexity of the corresponding network by reducing the weight value, so as to achieve a better effect of data fitting. As shown in formula (7), after the regularization term is added to the cost function, it can reduce the probability of overfitting of neural network to a certain extent:

$$C = -\frac{1}{m}\sum_{i=1}^{m} \ln \frac{e^{W_{Z_i}^T x_i + b_{Z_i}}}{\sum_{j=1}^{n} e^{W_{Z_j}^T x_i + b_{Z_j}}} + \frac{\lambda}{2n}\sum_{\omega} \omega^2. \tag{7}$$

The regularization term is the sum of squares of all parameters ω, the sample size of the training set is expressed as n, and the weight attenuation coefficient is expressed as $\lambda/2$.

Dropout reduces the overfitting phenomenon by randomly stopping half of the neurons, as shown in Figure 2.

When calculating the similarity between users, between users and projects, and between projects, the calculation methods of similarity include cosine similarity, editing distance, and Jaccard similarity [20]. Cosine similarity measures the degree of similarity based on the cosine value of the angle between the two vectors. The greater the value, the higher the degree of preference similarity between users. The calculation formula is shown in

$$\cos\theta = \frac{\sum_{i=1}^{n} (X_i * Y_i)}{\sqrt{\sum_{i=1}^{n} (X_i)^2} * \sqrt{\sum_{i=1}^{n} (Y_i)^2}}. \tag{8}$$

We also obtain

$$\text{Edit}[i,j] = \begin{cases} 0, & i = 0, j = 0, \\ j, & i = 0, j > 0, \\ i, & i > 0, j = 0, \\ \min(\text{edit}[i-1][j] + 1, \text{edit}[i][j-1] + 1, \text{edit}[i-1][j-1] + N), & i > 0, \quad j > 0. \end{cases} \tag{9}$$

Here, the mark of effective times of substitution is expressed as N.

Jaccard similarity is a memory calculation of the similarity between two texts. The larger the value, the higher the similarity between two users. The calculation formula is shown in

$$J(A,B) = \frac{\sum_i \min(X_i, Y_i)}{\sum_i \max(X_i, Y_i)}, \; J(A,B) \in [0,1]. \tag{10}$$

The college art teaching system provides students with video resources for self-help learning art knowledge, and students' behavior of watching relevant videos can also reflect the content quality of the video. Especially with the increase of video resources and the number of students, the quality of video content has a great impact on students' activity in the platform. Therefore, in order to continuously improve, it is very important to understand students' behavior and preferences, which is also conducive to improving the quality of the video content.

The video content quality evaluation model based on students' behavior proposed in this paper is to extract students' behavior characteristics and viewing history when watching video, then use fully connected neural network to judge students' preference for video, analyze students' needs and interests, and finally count students' preference data for video content for comprehensive evaluation.

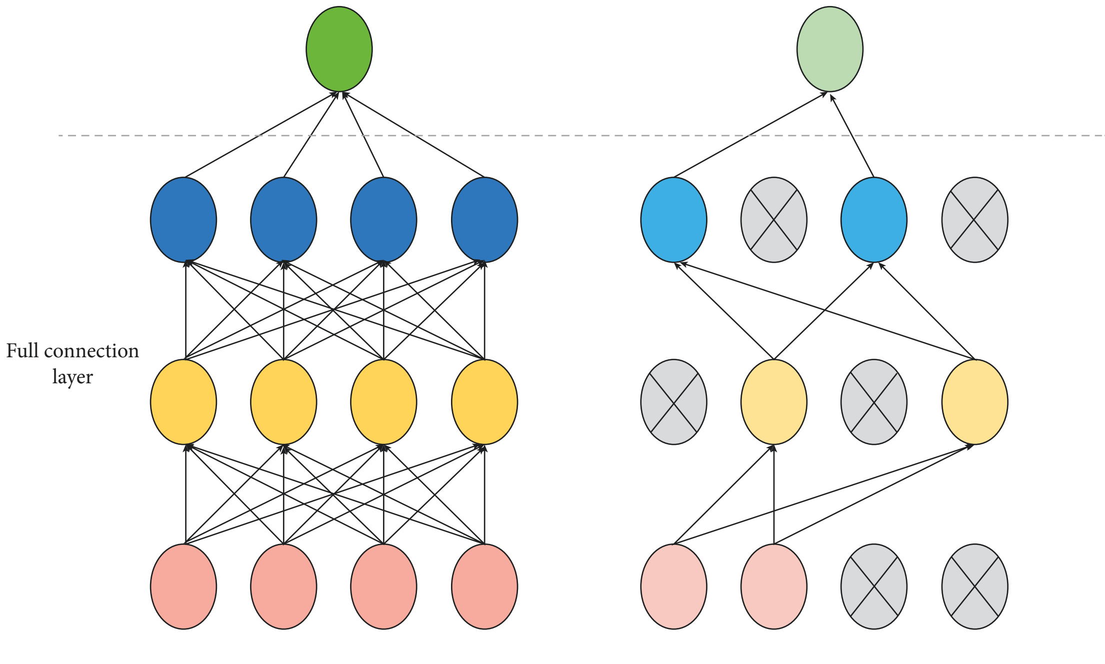

Figure 2: Schematic diagram of the dropout working principle.

According to formula (11), data preprocessing is carried out for the playback duration ratio of students watching video. If the playback duration ratio is less than 0.3, it is regarded as invalid and filtered data.

$$\partial = \frac{T_i}{T}, \tag{11}$$

where the playing duration ratio is expressed as ∂, the duration of students watching i video is expressed as T_i, and the total duration of the video is expressed as T.

After that, the data dimension of the filtered data is reduced and transformed into independent data and each data set contains the relevant data statistics of students watching a video. The playback duration ratio, fast forward, and backward times in the relevant data will be divided into four intervals for labeling. These data will become the input of the video content quality evaluation model after processing, and its output is the video content quality evaluation level. The weighted average of the evaluation of all students watching the unified video is calculated, and the result is the neutralization evaluation of the video content quality:

$$\overline{a} = \frac{X_A f_A + X_B f_B + X_C f_C + X_D f_D}{X_A + X_B + X_C + X_D}. \tag{12}$$

Here, the total number of people corresponding to grade i is expressed as X_i, its score is expressed as f_i, and the comprehensive score of the video content quality is expressed as $\overline{a}$.

In the parameters of constructing the fully connected neural network model, the output vector is expressed as y, the hidden layer is expressed as a_i, the weight matrix of the i layer is expressed as W_i and $i = 1, 2, 3, \ldots, n-1$, and its offset is expressed as Z_i, which can be obtained as shown in

$$a_i = \begin{cases} W_i x + Z_i, & i = 1, \\ f\left(W_i a_{i-1} + Z_i\right), & i = 2, 3, \ldots, n-1, \end{cases} \tag{13}$$

$$y = f\left(W_i a_{i-1} + Z_i\right). \tag{14}$$

The activation function is expressed as $f(x)$ and $i = n$ in formula (14). The output layer classifier is softmax, and the extracted data features are used as classifier input for classification and detection, which can achieve the purpose of video content quality evaluation. The rules are shown in

$$f(x) = \begin{cases} x, & x > 0, \\ 0, & x < 0. \end{cases} \tag{15}$$

4. Experimental Results of Personalized Video Recommendation Algorithm Based on User Behavior in the College Art Teaching System

In this paper, the dropout method is used to randomly select neurons to disconnect the connection between them in the training process of the system model and only let the other neurons continue to work. At the same time, there is also a certain probability that the neuron activation value does not work, does not participate in the calculation, and does not update the weight in the training, which can reduce the probability of the overfitting phenomenon. Let the probability of selecting neurons in the system model in this experiment be 0.75. The parameters directly affecting the accuracy and loss rate of the video content quality evaluation module in the college art teaching system model include the number of fully connected neural network layers and learning rates. In order to obtain the best parameters, the relationship experiment

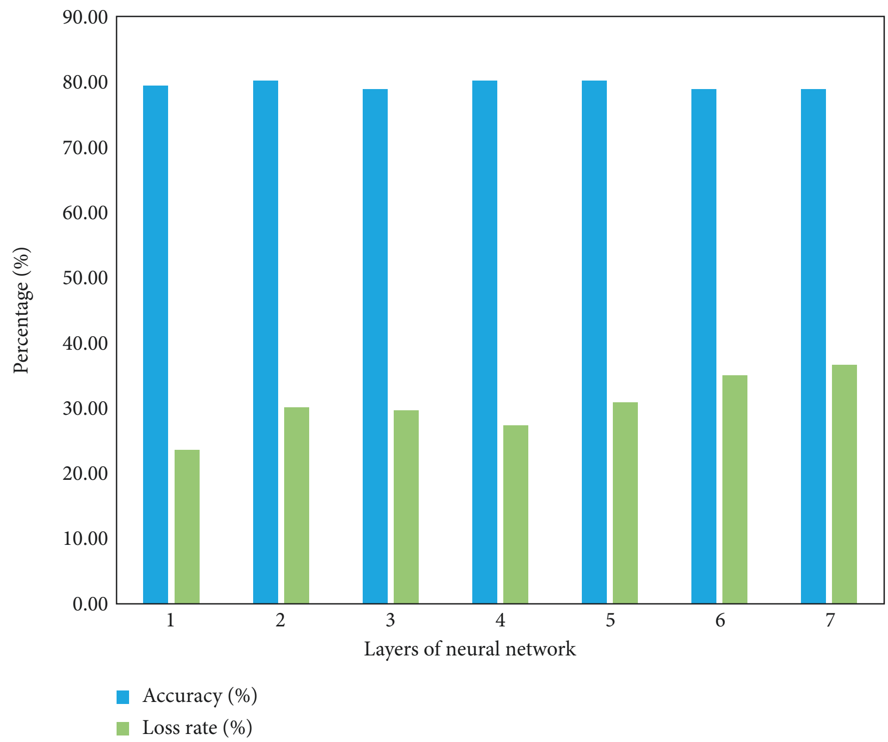

Figure 3: Experimental results of the network efficiency relationship.

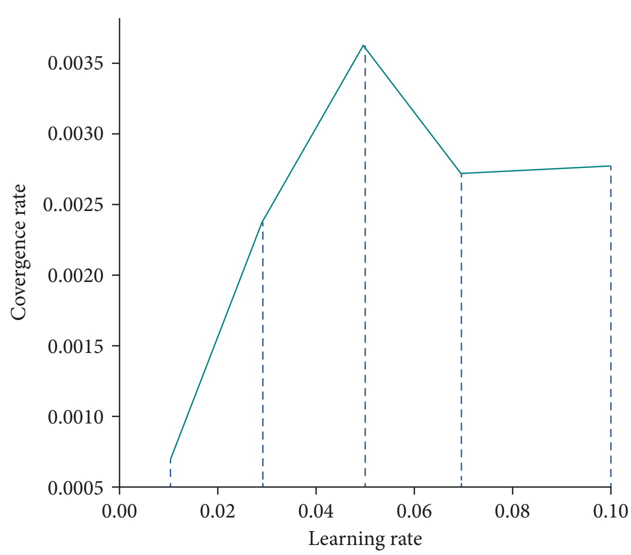

Figure 4: Convergence rate results of the model neural network under different learning rates.

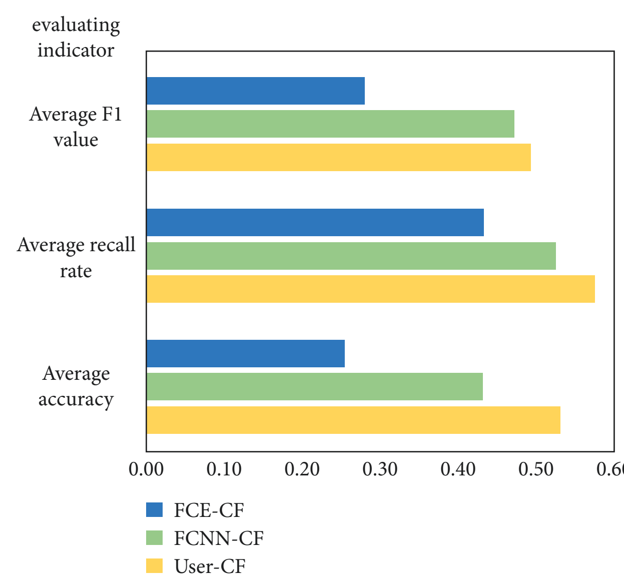

Figure 5: Comparison results of recommended evaluation indexes of three different algorithms.

between the number of model neuron layers and efficiency is carried out. The results are shown in Figure 3. When the number of hidden layers is four, the accuracy reaches the best, and then, the accuracy decreases. This is because when the number of hidden layers in the network is less than four, the number of hidden layers is too small, resulting in the overfitting phenomenon, which reduces the accuracy of the model. When the number of hidden layers is more than four, too many layers will increase the complexity of the model itself, resulting in underfitting.

Figure 4 shows the convergence rate results of the model neural network under different learning rates. The decisive factor of the gradient descent rate of neural network is the learning efficiency. When the learning efficiency is small, the gradient descent rate is slow; when the learning efficiency is high, the neural network presents an oscillatory convergence process. It can be seen from the results in the figure that the overall learning efficiency of the neural network shows a trend of increasing first and then decreasing. When the

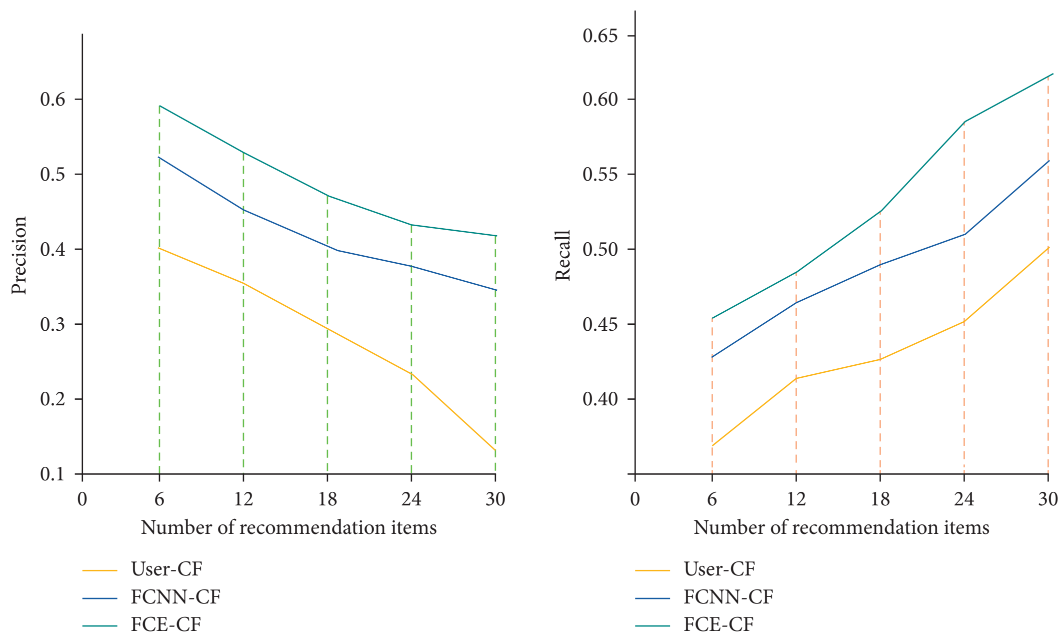

Figure 6: Experimental results of different number of recommended items with different recall and accuracy of three different algorithms.

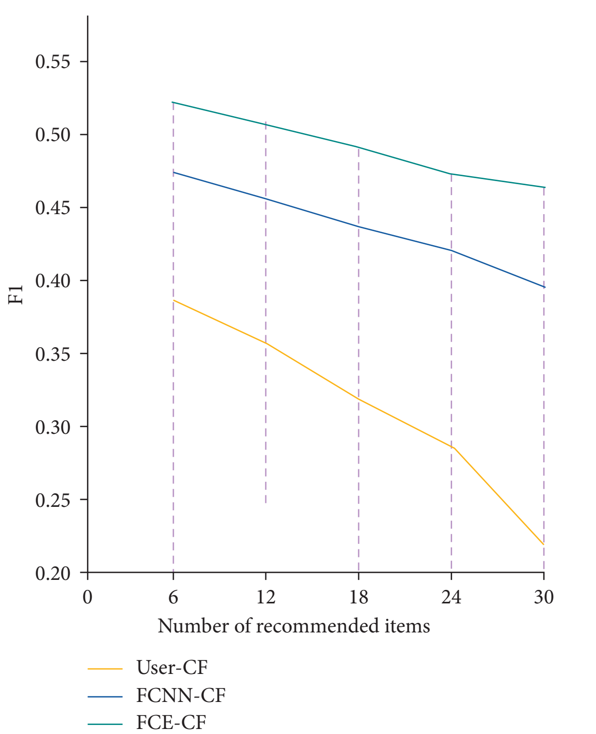

Figure 7: Experimental results of different number of recommended items of three different algorithms $F1$.

Figure 8: Comparison results of two test scores of two classes.

learning efficiency rate reaches 0.05, its convergence rate reaches the fastest.

In order to better study the performance of the personalized video recommendation algorithm based on user behavior, the traditional collaborative filtering recommendation algorithm and fully connected neural network collaborative filtering algorithm are selected for experimental comparison. The former is the analysis and recommendation based on the viewer's playback records, and the latter is based on the viewer's preference. The comparison experiment is the comparison of the recommendation results of three different algorithms on the same data, as shown in Figure 5, which shows that this algorithm has better performance and better results, recommended for users compared with the other two algorithms.

Its stability needs to be verified. Therefore, the stability experiment is to recommend different numbers of video

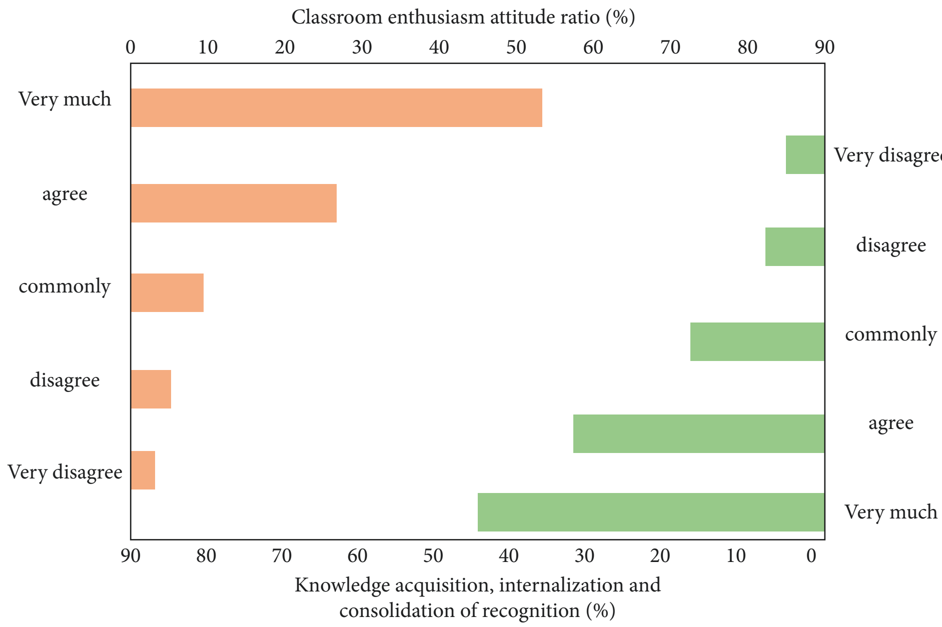

Figure 9: Evaluation results of the college art teaching system based on video big data technology by students in the experimental class.

recommendations with the same interval, as shown in Figures 6 and 7. It can be seen from the overall results in the figure that the accuracy and $F1$ value of the three algorithms decrease, while the recall rate is the opposite. The initial accuracy of this algorithm can reach 0.59, which decreases to a minimum of 0.42 with the increase in the number of recommended items. Both the maximum and minimum accuracy are higher than the other two algorithms when the number of recommended items is the same. In terms of recall rates, the changed rates of the three algorithms are similar, but the recall rate of this algorithm is higher as a whole, which shows that this algorithm has better stability than the other two algorithms. In addition, the complexity of the three algorithms is different. Among them, the time complexity is almost square multiple than that of the other two algorithms. Compared with that, the algorithm in this paper can reduce the similarity range of users to be calculated, reduce the complexity of the calculation process, and improve the efficiency of system recommendation under the same data set.

To sum up, the personalized video recommendation algorithm model based on user behavior has better performance and stability, which can reduce the overfitting phenomenon of the system model, effectively reduce the user range to be calculated while reducing the computational complexity, and greatly improve the system recommendation efficiency. This provides a reliable and effective data basis for the comparative experiment of art teaching system in colleges and universities.

This paper selects two classes of the same grade and major in a university as the object of the comparative experiment of the college art teaching system. The number of the two classes is equal, one of which is the experimental class. In one semester, they study through the college art teaching system based on video big data technology; the other class is the comparison class, and its teaching and management methods remain unchanged. During the comparative experiment, the students in the two classes will be tested twice, one before the experiment and one after the experiment. As shown in Figure 8, the comparison results of two test scores of two classes are shown. As can be seen from the data in the figure, the test results before the experiment show that the scores of the two classes are not much different and there is no obvious difference, which can ensure the authenticity and reliability of the comparative experiment. After a semester, there is a clear gap between the second test results of the two classes. The data in the figure show that the number of excellent students in the experimental class has increased significantly, more than twice the number of excellent students in the first test, and the failure rate has also been reduced to 1%. In the test results of the comparison class, although the excellent rate has improved, the failure rate has not decreased significantly. This shows that the college art teaching system based on video big data technology can effectively help students improve the effect of art learning, promote students' enthusiasm to learn art skills after class, and improve students' ability of autonomous learning.

Figure 9 shows the evaluation results of the experimental class students on the college art teaching system based on video big data technology. It can be seen from the results in the figure that more than half of the students agree with the teaching system in helping students improve their enthusiasm in classroom art learning; while 9% of the students disagree. In the teaching system to help students acquire knowledge and internalize and consolidate it, 77% of the students agree, and only about 9% of the students disagree. This shows that most students recognize the college art teaching system based on video big data technology; that is, it can effectively improve students' art classroom enthusiasm, help students better understand and internalize the knowledge in art teaching, and finally achieve the purpose of greatly improving students' art performance and art skills. In addition, art needs a lot of practice, which is why students often encounter doubts about art skills and knowledge when practicing after class. The college art teaching system based on video big data technology can help students solve their doubts in a short time and improve their learning efficiency.

5. Conclusion

With the development of big data technology, video learning has gradually become a new way of learning, and obtaining the required video materials from massive videos in a short time has become the research focus of video big data technology. With the development of video games, animation, and other industries, the teaching of art in colleges and universities is also constantly reformed according to the needs of society, paying more attention to the application of students' art skills and the cultivation of employment skills. Students have relatively few opportunities to practice art skills and need to practice by themselves after class. This makes many students encounter confusion in the process of practice and cannot solve the content in a short time or obtain corresponding guidance, which increases students' learning frustration and strikes students' enthusiasm for autonomous learning. Big data video technology can solve these problems and enrich the means and content of teaching. This paper puts forward the design and implementation of the college art teaching system based on video big data technology, combines the video recommendation algorithm with the Django teaching video website, and analyzes the preference needs according to the behavior data of students watching videos, so as to recommend videos for students. At the same time, the system can also evaluate the quality of video content according to the behavior of students watching video, classify the video in reverse, and then optimize the recommendation results. The video recommendation algorithm model based on user behavior is better than the traditional collaborative filtering recommendation algorithm and fully connected neural network collaborative filtering algorithm. It can reduce the range of users who need similarity calculation and improve the accuracy of the recommendation algorithm at the same time. Through the comparative experiment of the two classes, it can be seen that the college art teaching system based on video big data technology can stimulate students' enthusiasm in the art classroom, help students effectively and significantly improve art grades and skills, increase students' enthusiasm for independent learning after class, provide students with corresponding learning services, and improve learning efficiency. However, this paper still has some limitations. There is no personalized video recommendation algorithm model based on user behavior, which needs to consider different user characteristics. This needs further analysis in future research works.

Data Availability

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

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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