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Research Article

Personalized Recommendation Method of Sports Online Video Teaching Resources Based on Multiuser Characteristics

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Aiming at the problems of poor precision, low recall rate, and large recommendation time overhead in the personalized recommendation of sports online video teaching resources, this paper designs a personalized recommendation method for sports online video teaching resources based on multi-user characteristics. The area where the collected sports online video teaching resources are collected is fixed, and the confidence space for data collection is determined. The components of each clustering point are determined by the k-means clustering algorithm, and the data collection is completed continuously iteratively. The similar data in the data segments is removed with the help of cosine similarity, and the video segment data in the sports online video teaching resources with high similarity is removed for further data normalization. According to the multi-user feature analysis, the video teaching resource data that the user is interested in is matched, and the matching weight is calculated. In this paper, a personalized recommendation model of sports online video teaching resources is constructed by the recurrent convolutional neural networks (RCNN) method, and the personalized recommendation of video teaching resources is realized. The experimental results show that the mining accuracy of this method is about 96%, the highest recall rate can reach 98%, and its data recommendation time overhead is less than 1.3 s. This method effectively improves the effect of sports online video teaching resources.

1. Introduction

With the continuous change and development of educational thought, educational idea, teaching mode and teaching means, curriculum, and teaching reform are an important content of teacher education reform [1]. Video media plays a more and more important role in the process of multimedia teaching network. PE teachers cannot fully meet the needs of students according to book knowledge and their own technical skills. Combining the characteristics of PE teaching and the advantages of multimedia video teaching, it is of great significance to improve the quality of PE teaching. Physical education teaching usually involves a lot of action demonstration and model, if only rely on teachers repeated practice, not only difficult to achieve the desired results but also lack of effective attraction. As a result, the emergence of online video teaching resources for the sport has broken this limitation [2]. Sports online teaching video in essence is to make full use of internet resources through the use of diverse forms of resources bearing sports teaching content and make full use of the characteristics of sports video, such as real-time, diversity, fast update, and interactive features to promote teacher-student interaction, stimulate students' interest in learning, promote self-assessment, and improve the efficiency of sports teaching [3, 4]. It is an important way to promote the development of physical education in colleges and universities to integrate these advantages into the process of physical education video teaching, enrich the resources of physical education courses in colleges and universities, and construct modern physical education video teaching mode [5]. But with the changing needs of users, how to recommend sports online video teaching resources to users quickly and meet the needs of users has become a hot issue in this field.

Reference [6] presents a video recommendation algorithm based on the knowledge inference of Knowledge Atlas. This algorithm introduces knowledge graph inference into collaborative filtering. The multipath relationship between entities is mined by a path sorting algorithm, and all entity relationships are embedded in the semantic space with low dimensions. This method makes up for the shortcomings of the insufficiency of the recommendation algorithm for collaborative filtering and solves the problem of data sparsity to some extent. However, the proposed method has some shortcomings in the feature extraction of the recommended resource data and the analysis of user requirements, so it needs further improvement. Reference [7] proposes a video recommendation algorithm for multidimensional feature filtering. The algorithm extracts video features from user behavior and video tags. Then the similarity analysis is carried out, and the similarity is weighted to obtain the similar video candidate set. Based on the data set of MovieLens, the proposed video recommendation algorithm is implemented in python 3. This method considers the similarity between videos from several dimensions and cooperates with large-scale matrix decomposition technology to alleviate the problem of high sparsity of data sets. But this method has the problem of complex operation process, and the recommended time cost is high.

In view of the problems existing in the above methods, this paper designs a personalized recommendation method of sports online video teaching resources based on multi-user characteristics, which can improve the accuracy of personalized recommendation of sports online video teaching resources. The main technical route of this paper is as follows:

Step 1: the area where the collected sports online video teaching resources are collected is fixed, and the confidence space for data collection is determined. The sports online video teaching resource data in this range is converted into a standard deviation, and the component of each clustering point is determined by the k-means clustering algorithm to complete the data collection.

Step 2: remove similar data in data segments with the help of cosine similarity. The video clip data in the video teaching resources with high similarity is removed, and the data is normalized to improve the efficiency of resource recommendation.

Step 3: according to the multi-user feature analysis, the sports online video teaching resource data that the user is interested in is effectively matched, and the matching weight is calculated to improve the resource recommendation accuracy. Using the RCNN method, a personalized recommendation model for sports online video teaching resources is constructed to realize the personalized recommendation method of resources.

2. Materials and Methods

2.1. Data Collection of Sports Online Video Teaching Resources. In the recommendation of sports online video teaching resources, it is necessary to obtain the detailed description of sports online video teaching resources. There are two ways to obtain video information: manual acquisition and automatic acquisition. Due to the rapid increase in the number of videos, the cost of obtaining video data manually is too high, and obtaining video data automatically through web crawlers has become an effective solution. In the actual data acquisition process, the combination of manual acquisition and automatic acquisition is usually adopted [8]. That is, large-scale data is automatically processed by web crawlers. For video data that cannot be obtained automatically, a manual search is used to supplement and improve video data. Therefore, in order to realize the effective recommendation of sports online video teaching resources, we first collect the data of sports online video teaching resources [9]. The collected sports online video teaching resource data is taken as the important data of this paper, which lays the foundation for the follow-up research. The data acquisition process of sports online video teaching resources is shown in Figure 1:

According to the above designed data collection process of sports online video teaching resources, this paper fixes the collection area of sports online video teaching resources, and determines the reliability of data collection of sports online video teaching resources through the confidence interval [10]. The confidence interval ϕ is

$$\phi = \left[\mathrm{y} - \mathrm{a}_i \frac{\sqrt{c}}{m}\right](\mathrm{n}-1)\mathrm{a}_i + y, \tag{1}$$

where y is the mean, a is the confidence of $n-1$, $\overline{y}$ is the mean risk, $\sqrt{c}$ is the root mean square deviation, n represents the sample size, and a_i represents the constant.

After determining the confidence space range of sports online video teaching resource data collection, convert the sports online video teaching resource data in this range into a standard deviation, which is helpful to extract the sports online video teaching resource data at the same time, determine the average value of each sports online video teaching resource data, and determine the standard deviation of the data from all sports online video teaching resource data at each distance [11]. The standard deviation of sports online video teaching resource data is

$$B_i = S\left(\frac{\mu}{\sqrt{\tau^2}}\right)y. \tag{2}$$

Among them, B_i represents the standard deviation result of sports online video teaching resource data, S represents the confidence coefficient, μ represents sports online video teaching resource data arbitrarily within this range, and τ represents the standard deviation coefficient.

After standardizing the sports online video teaching resource data, the K-means clustering method is used to collect the sports online video teaching resource data. The K-means clustering algorithm determines K clustering points by minimizing the objective function and iteratively updating the objective to achieve local optimal clustering. The algorithm determines the component of each cluster point through multiple clustering operations and calculating the Euclidean distance between research objects, and continuously iterates to complete the collection of online video teaching resource data of sports [12].

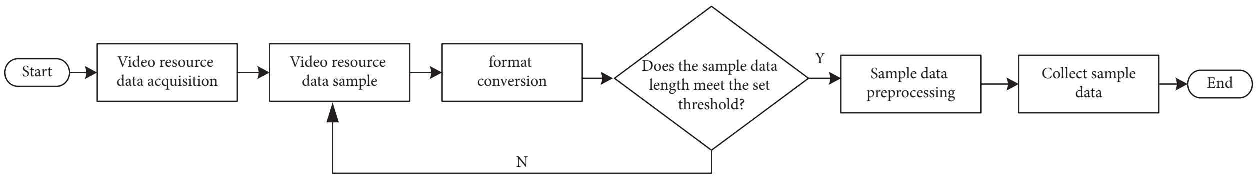

FIGURE 1: Data collection process of sports online video teaching resources.

Set up k clusters in the collected sports online video teaching resource data, set the training sample set as $\{b_1, b_2 \ldots b_n\}$, and the centroid of k clusters is determined as

$$V = \{v_1, v_2, \ldots v_n \in E\}. \tag{3}$$

Among them, $(v_1, v_2, \ldots v_n)$ represents different centroid values, and E represents the centroid selection range.

Based on the centroid of the above-mentioned sports online video teaching resource data, it is collected with the help of the K-means clustering algorithm, and the following results are obtained:

$$P = \sum_{i=1}^{n} \eta_i \|p_i - x_i\|, \tag{4}$$

in the formula, P represents the target function of the cluster center distance of sports online video teaching resource data, p_i represents the eigenvalue of the i th sports online video teaching resource data, and x_i represents the i th data of sports online video teaching resource data cluster center η_i represents the cluster weight value.

In the data collection of sports online video teaching resources, fix the collection area of sports online video teaching resources, determine the confidence space of data collection, convert the sports online video teaching resources data in this range into a standard deviation, determine the component of each cluster point through the K-means clustering algorithm, and continuously iterate to complete the data collection of sports online video teaching resources.

2.2. Data Preprocessing of Sports Online Video Teaching Resources. Based on the above collection of sports online video teaching resource data, in order to realize the effective recommendation of sports online video teaching resource data, the data preprocessing stage mainly includes three steps: sorting out the amount of data, video segment segmentation, and proposing the main frame [13]. In this paper, the video clip data in the collected sports online video teaching resources are expressed as follows:

$$\varpi = \frac{1}{h_i} \sum_{i=1}^{n} d_i. \tag{5}$$

Among them, h_i represents the video fragments in online video teaching resources and d_i represents the duration of video resources.

According to the video segment data in the determined sports online video teaching resources, similar video data segments are effectively preprocessed. This paper uses cosine similarity to remove similar data in data segments, and its calculation formula is

$$\xi_{(x_i, y_i)} = \frac{\left|\xi(x_i) \cap \xi(x_j)\right|}{\left|\xi(x_i) \cup \xi(x_j)\right|}, \tag{6}$$

where $\xi_{(x_i, y_i)}$ represents the degree of similarity between video data x_i and y_i, and $\xi(x_i)$ is a collection of items during the interaction of video data fragments.

According to the similarity determined above, the data with the highest similarity of video segment data in sports online video teaching resources is removed [14], reducing the complexity of data search in subsequent recommendations, and the following results are obtained:

$$Q(x_i, y_i) = \sum_{x_i, y_i}^{n} q(x_i, y_i) \frac{q(x_i, y_i)}{n}, \tag{7}$$

where $Q(x_i, y_i)$ represents the final collected video data collected without similar data fragments.

On this basis, the video segment data from the online sports video teaching resources with high similarity were further normalized, and the normalized data were used as the video fragment data in the online sports video teaching resources of this study. Suppose that the eigenvalues of video segment data in sports online video teaching resources are scaled to the [0, 1] interval, and that the N sample feature data are represented as

$$F = \left[f^{(1)}, \ldots f^{(N)}\right] \in R^d, \tag{8}$$

where represents a d-dimensional vector, and the video segment data in all sports online video teaching resources are normalized to obtain:

$$f^{(n)} = \frac{f_i^{(n)} - \min_n f_i^{(n)}}{\max_n\left(f_i^{(n)}\right) - \min_n f_i^{(n)}}, \tag{9}$$

where max() and min() represent the minimum and maximum values in all sample data.

In the data preprocessing of sports online video teaching resources, the similar data in the data segment is removed with the help of cosine similarity, and the video segment data in the sports online video teaching resources with high similarity is further normalized, and the normalized data is used as the video segment data in the sports online video teaching resources of this study.

2.3. Personalized Recommendation Method of Sports Online Video Teaching Resources Based on Multiuser Characteristics. According to the above determined sports online video teaching resource data, this paper analyzes the multi-user characteristics and effectively matches the sports online video teaching resource data interested by users according to the multi-user characteristic analysis, so as to realize the design of personalized recommendation method of sports online video teaching resources based on multi-user characteristics.

First of all, according to the historical behavior records of multiple users, that is, the online teaching video of sports and sports online resources, the multi-user collection is U, and the data set of the online sports video teaching resources is I. The nodes in the multi-user feature binary graph are composed of user nodes and video nodes, and an edge is established between the multi-user and the video data. At this time, the identification relationship between the multi-user features and the video data is shown in Figure 2:

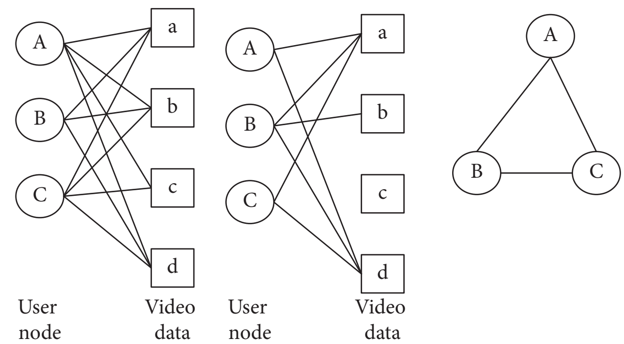

Figure 2: Schematic diagram of the matching relationship between multi-user features and video resource data.

As can be seen in Figure 2, there is not only a correspondence between multi-user features and video data. In video websites, a large number of users play video, a small number of likes, and a very small number of comments. Obviously, a very small amount of comment behavior is more about user interest. This algorithm integrates the multiple behaviors of all users successively, in the form of $(B_1, B_2 ... B_N)$, at this time, the weight between the behavioral characteristics of the multiple users and the video data is determined according to the multiple characteristics of the user. Calculating the proportion of multi-user features gives

$$g_i = wk_i \sum_{i=1}^{N} k_i B_N, \tag{10}$$

where w represents the execution behavior present in the multi-user feature, and k_i represents the weight size of the multiple user corresponding to the video data. At this point, the multi-user feature-Sports Video Data "graph is an undirected dichotomous graph used to continue to build edges between multi-user and users in order to identify and strengthen the connection between those users with similar interests.

In the personalized recommendation of sports online video teaching resources, after determining the multi-user characteristics, in order to realize the personalized recommendation, we need to design the personalized recommendation algorithm according to the user's interest. According to the obtained user interest representation sequence, the probability of users clicking on the new micro video is predicted.

The PE teaching video can be represented by a D-dimensional vector, recorded here as $D(x)$. Using the attention model to aggregate the sequence of user interest representations gives

$$l(x) = g_i(\varepsilon u_i + \varepsilon x_i + b_3), \tag{11}$$

where u_i represents the parameters to be learned. ε represents the activation function. The resulting attention scores, normalized by softmax to $\varepsilon(x_i)$.

The long- and short-term dynamic characterization vector of interest is obtained by modeling the user behavior sequence. To further capture the static user interest representation, an embedded vector representation t is learned for each user, and then the user interest representation vectors z and F predict the degree of interest that the video is interested by the user and get

$$\widetilde{y} = MLP[t; z; F] \tag{12}$$

among them, $[MLP]$ represents a multi-layer perceptron.

According to the multi-user characteristics and user interest function determined above, a training network structure is constructed by training multi-user characteristic data and online physical education teaching resource data. The loss function of the data after training is as follows:

$$LOSS(x) = -\widetilde{y}\lg y(1 - l(x)). \tag{13}$$

Among them, y represents the real label between the multi-user and the video data.

Finally, according to the data after training, this paper realizes the design of personalized recommendation algorithm of sports online video teaching resources based on multi-user characteristics with the help of RCNN model [15, 16]. The RCNN model is a milestone in applying CNN methods to object detection problems. The model uses the good feature extraction and classification performance of CNN to realize the transformation of the target detection problem through the Region Proposal method. It has higher detection accuracy, and its training can be updated to the entire network. Its training is single-stage or single-channel, and uses a multi-stage task loss. The network structure diagram of RCNN model is shown in Figure 3.

After the convolutional network passes through the fully connected layer, it is not directly to the softmax function layer (namely, the classification layer), but directly to the increased recurrent neural network layer. The Relu function is used as a nonlinear mapping function in the network. In this network structure, a video frame X that represents the video data is initialized. The main image is then extracted from the resulting video frame X, and the video resources are feature extracted using a convolutional operator. The pooling operator is used to convert it into low-dimensional feature information σ_a, which σ_a is output through the full connection layer, and the multi-user features are

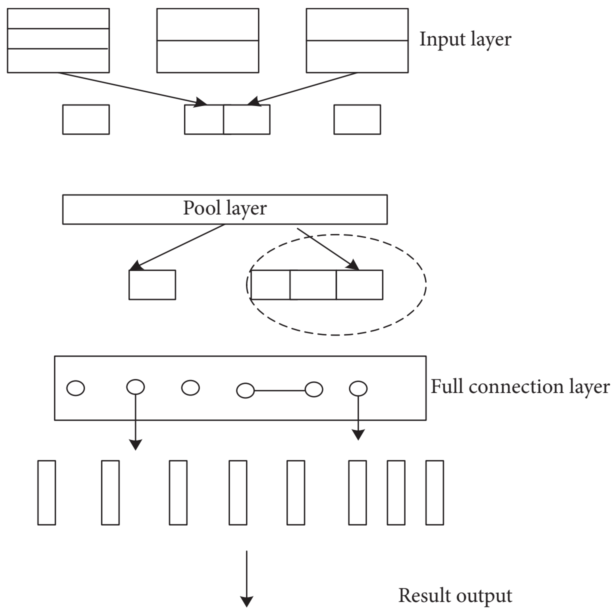

Figure 3: Network structure diagram of the RCNN model.

$$\sigma_a = f(\sigma_{a-1} \times w_a + s_a). \quad (14)$$

In the full connection layer, the output of the full connection layer can be weighted and summed through the input layer and obtained through the activation function. The obtained sports online teaching video data results are as follows:

$$w_a = f(\sigma_a + b_a) \sum_{i=1}^{N} u_i \sigma_a. \quad (15)$$

Finally, build the matching model between multi-user characteristics and sports online video teaching resources, that is, design the personalized recommendation model of sports online video teaching resources, and get:

$$\delta_j^i = w_a \times y_i(k) + b_a. \quad (16)$$

Among them, δ_j^i represents the final personalized recommendation result and $y_i(k)$ represents the personalized factor recommended by the model.

The personalized recommendation process of sports online video teaching resources based on multi-user characteristics is shown in Figure 4.

3. Results and Discussion

3.1. Design of Experimental Scheme. In order to verify the effectiveness of the proposed method, a simulation experiment is carried out. The experiment is carried out on MATLAB version 7.2, and its running memory is 32 GB. Due to the large amount of data in the experiment, the experimental statistical tool is SPSS13 0 to make effective statistics on the data and results in the experiment. In this paper, the reliability coefficient is set to be greater than 0.95, and the standard deviation coefficient is set to 1.5. The test data in the experiment comes from the professional physical education resource database. 5000 pieces of sports video teaching resource data in the database are selected as the training sample set, and the selected sample data are Yuchul and Shi. The level of data meets the requirements of the experiment. The specific test data contents are shown in Table 1.

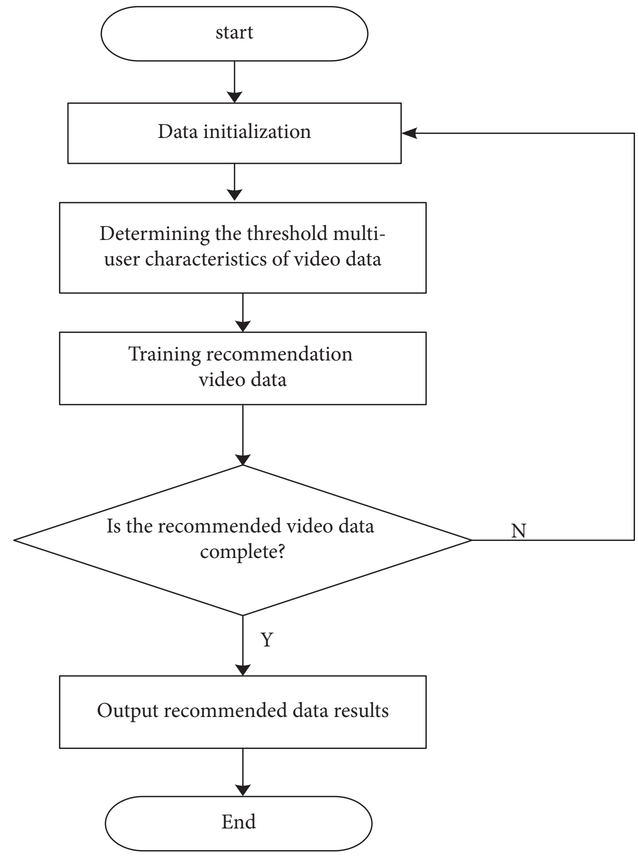

Figure 4: Personalized recommendation process of sports online video teaching resources based on multi-user characteristics.

Based on the above experimental environment and experimental parameter settings, the proposed method, the method in literature [6], and the method in literature [7] are compared to highlight the advantages of this method. In the experiment, the proposed method, literature [6] method and literature [7] method are mainly used to recommend 200 different users for the selected sample data. According to different user characteristics, the accuracy, recall rate and recommendation time overhead in the personalized recommendation of sports online video teaching resources are determined.

4. Analysis of Experimental Results

In the experiment, we first analyzed the proposed method, literature [6] method, and literature [7] method, selected any 2000 pieces of data in the training video data set, recommended these data to 200 users in this experiment, set the user characteristics of these 200 users before the beginning of the experiment, determined the required data according to their preferences, and counted the accuracy of the data

TABLE 1: Test data.

Parameter	Data
Sample data/GB	2
Multi-user data feature/bar	3000
Sample collection interval/s	10
Recommended times/times	100–200
Number of experimental users/person	200

recommended by the proposed method, literature [6] method and literature [7] method. The results obtained are shown in Figure 5.

By analyzing the data in Figure 5, it can be seen that with the continuous change of sample data, there are some differences in the accuracy of sample data recommendation by using the methods in this paper, literature [6] and literature [7]. When the sample data is 600, the mining accuracy of this method is about 97%, that of literature [6] method is about 81%, and that of literature [7] method is about 52%. When the sample data is 1200, the mining accuracy of this method is about 96%, that of literature [6] method is about 85%, and that of literature [7] method is about 59%. Comparing the three methods, it can be seen that the recommendation accuracy of this method is the highest. This is because this method extracts multi-user features in recommendation and matches video data according to user features to improve the recommendation accuracy. Because the method in this paper effectively matches the sports online video teaching resource data that users are interested in based on multi-user feature analysis and calculates the matching weight. This method can improve the resource recommendation accuracy.

In the experiment, the recall rate of sample data recommended by this method, literature [6] method and literature [7] method is analyzed. The results are shown in Figure 6:

By analyzing the experimental results in Figure 6, it can be seen that with the continuous change of recall times, there are some differences in the recall rate when recommending sample data by using the methods in this paper, literature [6] and literature [7]. Among them, the recall rate of sample data recommended by this method is large and tends to be stable. Although the recall rate of sample data recommended by literature [6] method and literature [7] method is also within a reasonable range, there are certain fluctuations. It can be seen that this method is more stable and can realize personalized recommendation.

In order to further verify the effectiveness of the proposed method, the time cost of this method, literature [6] method and literature [7] method in data recommendation is experimentally analyzed. The results are shown in Table 2.

By analyzing the data in Table 2, it can be seen that under the same experimental conditions, there are certain differences in the time-consuming of using the three methods to recommend the sample data. When the number of iterations is 30, the recommended time overhead of the method in this paper is about 1.28 s, the recommended time overhead of the method in literature [6] is about 2.49 s, and the recommended time overhead of the method in literature [7] is

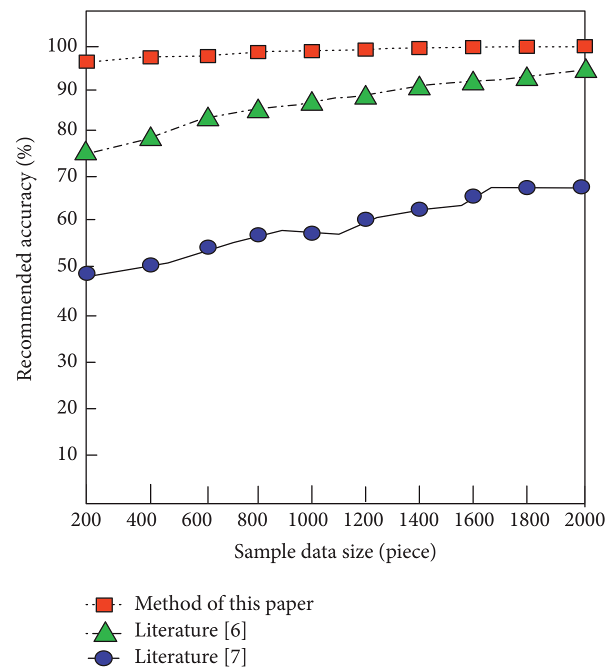

FIGURE 5: Analysis of recommendation accuracy of sports video resource data with different recommendation methods.

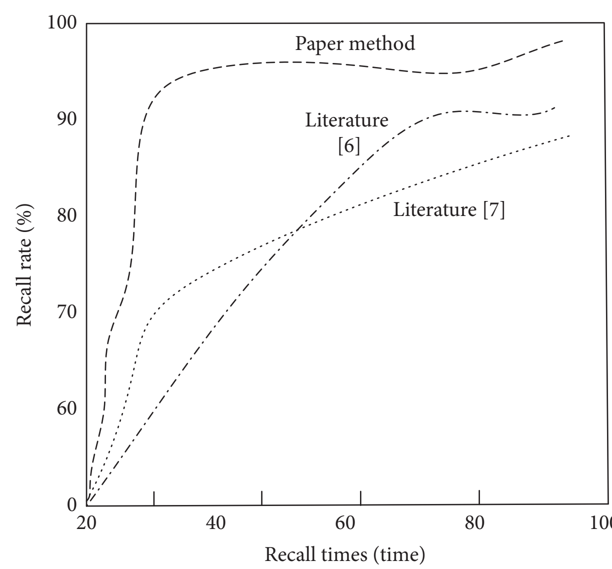

FIGURE 6: Analysis of recall rate of recommended data of different recommendation methods.

about 2.32 s; When the number of iterations is 60, the recommended time overhead of the method in this paper is about 1.22 s, the recommended time overhead of the method in literature [6] is about 2.82 s, and the recommended time overhead of the method in literature [7] is about 2.88 s. When the number of iterations is 100, the recommended time overhead of the method in this paper is about 1.22 s, the recommended time overhead of the method in literature [6] is about 2.85 s, and the recommended time overhead of the method in literature [7] is about 2.85 s. In contrast, the

Table 2: Data recommended time overhead for different recommended methods (s).

Number of iterations/times	The method of this paper	Literature [6] methods	Literature [7] methods
10	1.25	2.35	2.59
20	1.26	2.56	2.66
30	1.28	2.49	2.32
40	1.19	2.27	2.43
50	1.30	2.69	2.54
60	1.22	2.82	2.88
70	1.22	2.93	2.77
80	1.24	3.22	2.56
90	1.20	2.94	2.69
100	1.22	2.85	2.48

recommendation time overhead of the proposed method is short, which verifies the effectiveness of the proposed method. Because the method in this paper removes the similar data in the data segment with the help of cosine similarity. The video clip data in the sports online video teaching resources with high similarity is removed for further data normalization, which improves the efficiency of resource recommendation.

5. Conclusions

Personalized recommendation of sports online video teaching resources is related to the quality of physical education. Therefore, in order to improve the effect of personalized recommendation of sports online video teaching resources, this paper designs a personalized recommendation method of sports online video teaching resources based on multi-user characteristics. Firstly, fix the collection area of sports online video teaching resources, determine the confidence space of data collection, convert the sports online video teaching resources data in this range into a standard deviation, determine the component of each cluster point through K-means clustering algorithm, and then remove the similar data in the data segment with the help of cosine similarity. The video segment data in the sports online video teaching resources with high similarity will be further normalized to complete the data preprocessing; According to the analysis of multi-user characteristics, the data of sports online video teaching resources that users are interested in are effectively matched, and the matching weight is calculated. Finally, the personalized recommendation model of sports online video teaching resources is constructed with the help of RCNN model to realize the design of personalized recommendation method of sports online video teaching resources based on multi-user characteristics. The data accuracy of the proposed method is higher than 95%, and the recall rate is high, the recommendation time is short, so it is feasible. In future research, we can analyze the semantic relationship in students' topic discussions by mining the relationship between a student's daily information, learning trajectory, classroom speech, and test score data. In this way, the dimension of resource recommendation can be increased, so as to increase the recommended range of video-related resources.

Data Availability

The authors confirm that the data supporting the findings of this study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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