A Personalized Recommendation Method for Online Painting Education Courseware Based on Hyperheuristic Algorithm

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Abstract. Aiming at the problem of high similarity in online education courseware for painting, which leads to poor recommendation effectiveness. In order to optimize the recommendation effect of online education courseware for painting and improve the effectiveness of online education for painting, a personalized recommendation method for online education courseware for painting based on hyper heuristic algorithm is proposed. This paper introduces the calculation of keyword weight of personalized recommendation, the calculation of similarity of online painting education courseware, the calculation of user similarity, and the Committed step of the calculation of similarity between users and online painting education courseware. The Ant colony optimization algorithms in the super heuristic algorithm is used to design the personalized recommendation process and complete the theoretical research on personalized recommendation of online painting education courseware. The experimental results indicate that this method the average accuracy of this method is 91% with interest and 86% with no interest. When the number of people in the same period increases to 1000, the growth rate of system throughput slows down and the growth rate is relatively small. This method can recommend high-quality online education courseware for painting, which helps improve the learning experience and effectiveness of users for online education courseware for painting.

Keywords: Hyperheuristic Algorithm · Online Education · Painting Courses · Courseware Recommendation · Personalized Recommendation · Ant Colony

1 Introduction

Currently, online education has become one of the important ways for people to learn, and online education for painting is also showing a thriving trend. However, online education is mostly based on universal curriculum settings, lacking personalized recommendations tailored to individual differences among learners [2], resulting in low learning outcomes and inability to fully explore learning potential. Therefore, how to achieve personalized recommendation for online painting education courseware has important research value.

Reference [3] designed a personalized learning resource recommendation system that includes user profiles. The system consists of a data layer, a data analysis layer,

L. Yun et al. (Eds.): ADHIP 2023, LNICST 549, pp. 210–223, 2024.
https://doi.org/10.1007/978-3-031-50549-2_15

and a recommendation computing layer. Among them, the recommendation computing layer discovers users' learning behavior patterns through similarity analysis and clustering algorithms, uses TF-IDF method to mine users' resource preferences, and provides personalized learning suggestions based on this. Reference [4] proposed a personalized recommendation algorithm for network information that integrates LDA and attention. Using the LDA model to induce the distribution of topics and words in documents, introducing HowNet to process word semantics and calculate semantic similarity between them. Adopting attention mechanism to achieve personalized recommendation of online information. Reference [5] extracts biological gene fragments, social gene fragments, and behavioral gene fragments from user online learning information, calculates the proportion of each gene fragment using the CRITIC weight method, and constructs a user's social media gene map to help users quickly obtain personalized online education services.

The learners of online painting education have a diverse group, with differences in learning interests, painting abilities, and learning habits. Therefore, it is not possible to simply recommend universal painting textbooks, but rather to have a deep understanding of students' personalized needs in order to better recommend textbooks that are suitable for them. At the same time, personalized recommendations can improve students' online learning enthusiasm and learning effectiveness. By analyzing students' learning data, establishing personalized learning models, and recommending targeted painting textbooks, it can meet students' learning needs, stimulate their interest in learning, and improve their learning enthusiasm. At the same time, personalized learning recommendations can better improve learning outcomes, maximize students' learning abilities, and truly achieve personalized customization in online painting education. In summary, based on the personalized needs of students, this article proposes a personalized recommendation method for online painting education courseware based on hyper heuristic algorithm.

2 Personalized Recommendations

Extract courseware keywords based on online education courseware for painting, sort them according to keyword frequency, and obtain different keyword weights for online education courseware for painting. Use the obtained weights to calculate the similarity of online education courseware for painting. Based on this, a personalized recommendation process for online painting education courseware is designed using hyper heuristic algorithms.

2.1 Keyword Weight Calculation

Obtain keyword weights through the TF-IDF algorithm [6]. TF and IDF represent word frequency and reverse word frequency, respectively, reflecting the importance of keywords in online painting education courseware and the general importance of words. Assuming F and K respectively represent the number of all extracted keywords and the number of times keywords appear in the designated online education courseware for painting, the calculation result of word frequency TF is shown in formula (1):

$$\mathrm{TF} = \frac{K/F}{N} \tag{1}$$

Assuming K and N respectively represent the number of online education courseware containing a certain keyword and the total number of all online education courseware containing a certain keyword, the IDF calculation result can be obtained as shown in formula (2):

$$\mathrm{IDF} = \lg \frac{N}{|K+1|} \tag{2}$$

Obtain the final TF-IDF calculation result, that is, the keyword weight of the online education courseware for painting, as shown in formula (3):

$$\text{TF-IDF} = \mathrm{TF} \times \mathrm{IDF} \tag{3}$$

2.2 Calculation of Similarity in Online Education Courseware for Painting

If the number of common keywords in the online education courseware i and j for painting is t, the similarity calculation results of the two online education courseware for painting can be obtained as shown in formula (4):

$$\mathrm{sim}(i,j) = \text{TF-IDF}_{\max} \sum_{i,j=1}^{t} W_i \times W_j \tag{4}$$

Among them, W represents the keyword weight.

2.3 User Similarity Calculation

Calculate the total similarity of users by calculating their attribute similarity and user activity similarity.

(1) User attribute similarity

Let C_i represent the numerical attribute similarity between users obtained based on the values of different user attribute intervals [7]. The calculation result of user attribute similarity is shown in formula (5):

$$\mathrm{sim}_{num} = \mathrm{sim}(i,j) \sum_{i=1}^{n} C_i \tag{5}$$

The text type attributes of users are taken as 1 and 0 respectively when they are the same or different. By accumulating the similarity sim_t of each user's text type attribute, the calculation result of user attribute similarity is shown in formula (6):

$$\mathrm{sim}_{att} = \mathrm{sim}_{num} + \mathrm{sim}_t \tag{6}$$

From the above formula, it can be seen that user similarity increases with the increase of sim_{att} value, otherwise it is the opposite.

(2) User activity similarity

By obtaining the similarity sim_{act} of user activity through dynamic information of users, assuming that the number of common keywords between user U_i and user U_j is t, sim_{act} can be obtained as shown in formula (7):

$$\mathrm{sim}_{act} = \frac{1}{\sum_{i,j=1}^{t} W_i \times W_j} \tag{7}$$

The similarity of user activity is higher when the sim_{act} value is higher, otherwise the opposite is true.

(3) User similarity

Linear weighted user attribute similarity and active similarity are used to obtain the final user similarity, as shown in formula (8):

$$\mathrm{sim}_{A,B} = \mathrm{sim}_{att} + \mathrm{sim}_{act} \tag{8}$$

2.4 Similarity Between Users and Online Education Courseware for Painting

Assuming that the number of common keywords between user U_i and online education courseware j for painting is t, the similarity between user U_i and online education courseware for painting can be obtained as shown in formula (9):

$$\mathrm{sim}_{U_i} = \mathrm{sim}_{A,B} \sum_{i=1}^{t} W_i \times W_j \tag{9}$$

The similarity between users and online education courseware for painting is higher when the sim_{U_i} value is higher, otherwise the opposite is true.

2.5 Personalized Recommendation Based on Ant Colony Algorithm

The hyper heuristic algorithm based on meta heuristic algorithm adopts the existing meta heuristic algorithm (as a high-level strategy) to select LLH. This kind of super heuristic algorithm can be divided into Tabu search [8], genetic algorithm [9], genetic programming, ant colony algorithm, etc. Among them, the ant colony algorithm [10] is used for personalized recommendation. The pheromone mechanism of the ant colony when searching for food is used to express the preference of users for online painting education courseware, which can better consider the diversity and personality of users, so as to improve the coverage and personalization of recommendations. Therefore, this article utilizes ant colony algorithm to achieve personalized recommendation of online painting education courseware.

Based on the specific values of the similarity between users and online education courseware for painting obtained above, the picking probability and abandonment probability for influencing factors are obtained as formula (10):

$$\begin{cases} p_1 = \left[\lambda_2/\mathrm{sim}_{U_i}(\lambda_1 + \lambda_2)\right] \\ p_2 = 1 - p_1 \end{cases} \tag{10}$$

In the formula: p_1 represents the probability of picking up; p_2 represents the probability of abandonment; λ_1 represents the degree of correlation between shallow impact data; λ_2 represents the degree of correlation between deep impact data. In order to ensure recommendation efficiency, based on this, a personalized recommendation ant colony optimization control model for painting online education courseware is constructed as formula (11):

$$A = P + \frac{p_2(w + y)}{G} \tag{11}$$

Among them, P represents the optimization extremum for personalized recommendation of online education courseware for painting, G represents the optimal solution for personalized recommendation of online education courseware for painting, and w and y represent the gradient global extremum and individual extremum obtained for personalized recommendation of online education courseware for painting in each iteration. The ant colony optimization result for personalized recommendation of painting online education courseware is formula (12):

$$Z = A\left[v(\tau + 1) + p(\tau + 1)\right] \tag{12}$$

Among them, $v(\tau + 1)$ and $p(\tau + 1)$ are the efficiency parameters for personalized recommendation of online education courseware for painting recommended by the ant colony in the next moment.

Based on the probability of picking up, factors that can improve the efficiency of the enterprise are obtained. Let the ant colony be ant_M, and the number of ants in this algorithm is M. The location of each ant is a m-dimensional vector that can be represented as $ant_\rho(t)$, where $1 \leq \rho \leq M$ and ρ are natural numbers. Make the ant colony search from any position, i.e. assign an initial value to $ant_{\rho 1}(t), ant_{\rho 2}(t), \ldots, ant_{\rho n}(t)$; Then allow ants to freely search within the set range, allowing the $ant_\rho(t)$ value to continuously change during n iteration until clustering is completed. The clustering process of this factor can be divided into four stages as shown in Fig. 1.

Based on the above clustering process, a clustering model for personalized recommendation of painting online education courseware is constructed, and the output is formula (13):

$$B = f(z) + Z[\varphi + h(u)] \tag{13}$$

Among them, $f(z)$ represents the rating value of personalized recommendation for online education courseware, φ is the hierarchical scheduling model parameter for personalized recommendation output of online education courseware, and $h(u)$ is the feature information that is beneficial for detection.

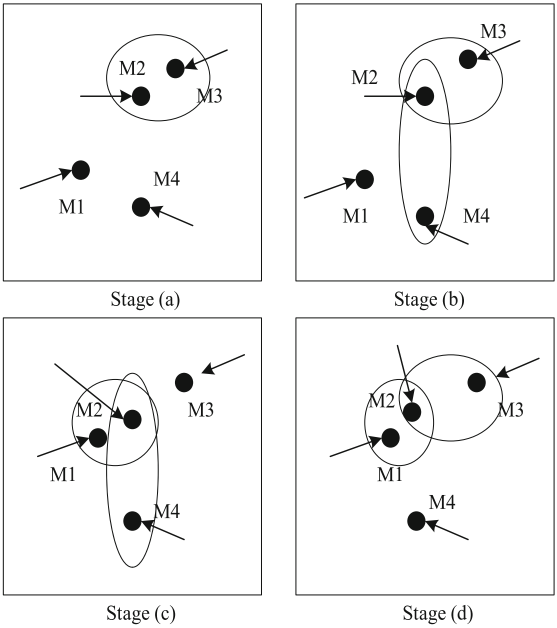


Fig. 1. Clustering process

By using the method of weighted sum per pixel, an adaptive adjustment formula for personalized recommendation of painting online education courseware is obtained as shown in formula (14):

$$R = B|W_{\min} + W_{\max}| \tag{14}$$

Among them, $[W_{\min}, W_{\max}]$ is the distribution range of top-down paths in ant colony optimization, generally taken as [0.5, 0.6]. Based on the above analysis, the algorithm implementation process for personalized recommendation of online education courseware for painting is shown in Fig. 2.

Step 1: Initialize ant colony information;
Step 2: $i = 1$, and select the i-th ant;
Step 3: Solve the ant route;
Step 4: Bring the results of the solution into the global ant colony;
Step 5: Solution optimization. After optimization, proceed to step 6. If not optimized, return to step 4;
Step 6: Update global ant colony information, $i = i + 1$;
Step 7: Whether to traverse all ants, if not, return to Step 3; If yes, output personalized recommendation results for online education courseware on painting.

3 Experimental Testing

3.1 Experimental Setup

The experimental platform parameters are shown in Table 1.

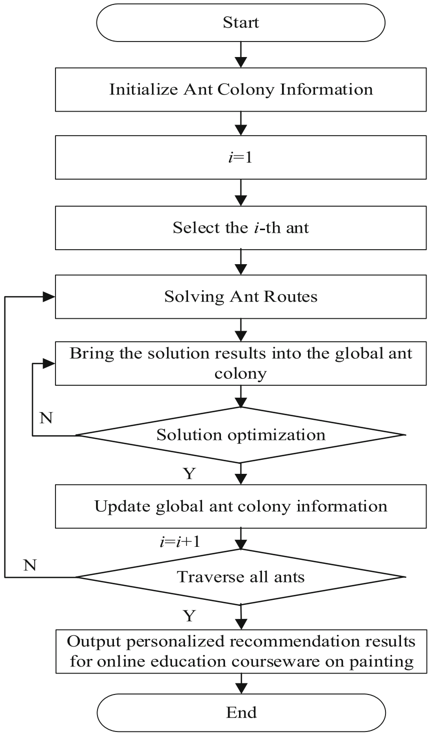


Fig. 2. Implementation process of recommendation algorithm

Table 1. Experimental Platform Parameters

Category	Parameter
Number of courses	100 painting courses
Course Type	Sketching, colors, characters, landscapes, still life, animals, etc.
Number of students	1000 students using the platform
Number of teachers	20 teachers provide painting courses and assessments
Evaluation method	After students submit their works, the teacher conducts a comprehensive evaluation, including grading and targeted suggestions

The dataset parameters are shown in Table 2.

Table 2. Dataset parameters

Category	Parameter
Dataset size	100000 images of painting works
Classification quantity	10 different painting categories, such as characters, landscapes, and imitations
Dataset Source	Obtained from 5 famous art museums and galleries
Annotation method	Include artist, work name, era, creative location, and painting style labels
Image feature dimension	RGB color feature dimension, edge feature dimension, texture feature dimension, etc.

Under the above preparation, the reference [3] method, the reference [5] method and the algorithm in this paper are respectively used for personalized recommendation of online painting education courseware. By comparing the indicator data of each algorithm, the effectiveness and feasibility of the algorithm in this paper are verified.

3.2 Result Analysis

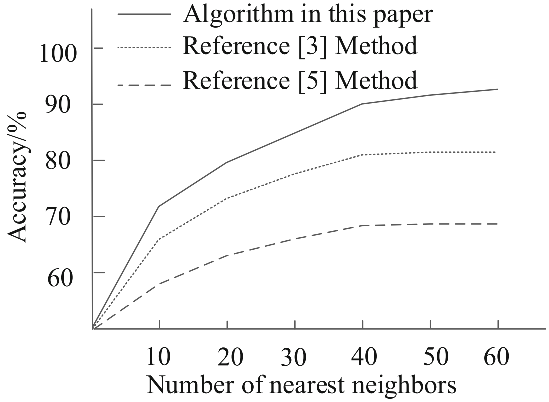
(1) Qualitative experiments

The experimental indicators include accuracy, recall, comprehensive average and average absolute error. The details are as follows:

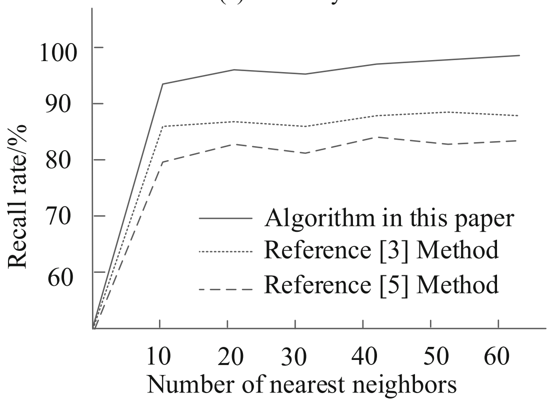
Precision refers to the ratio of the recommended number of correct online education courseware for painting recommended by the algorithm to the total number of online education courseware for painting that actual users are interested in. It is expressed as follows: Precision = recommended number of correct online education courseware for painting/recommended total number of online education courseware for painting. The higher the accuracy value, the higher the proportion of users who are interested in the painting online education courseware recommended by the recommendation algorithm.

Recall rate refers to the ratio between the recommended number of correct painting online education courseware by the algorithm and the total number of painting online education courseware of interest to the actual user. It is expressed as: Recall = recommended number of correct painting online education courseware/total number of painting online education courseware of interest to the actual user. The higher the recall rate, the more likely the recommendation algorithm can find the online education courseware of painting that users are interested in the F1 score, which combines accuracy and recall, is a harmonic mean expressed as F1 score = 2 * (Precision * Recall)/(Precision + Recall). The comprehensive average takes into account both accuracy and recall, and is a commonly used evaluation indicator.

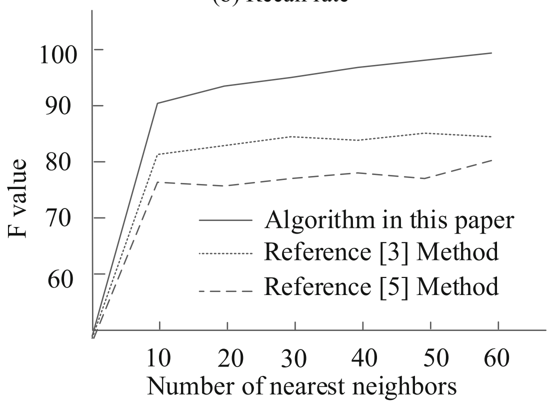
Average absolute error (MAE) refers to the average of the absolute value of the difference between the recommended value and the true value, which is expressed by the formula: MAE = (|recommended value - true value|)/number of samples. The smaller the average absolute error is, the smaller the error between the recommended value and the true value of the recommended algorithm is, and the more accurate the recommendation result is the comparison results of experimental data are shown in Fig. 3.



(a) Accuracy

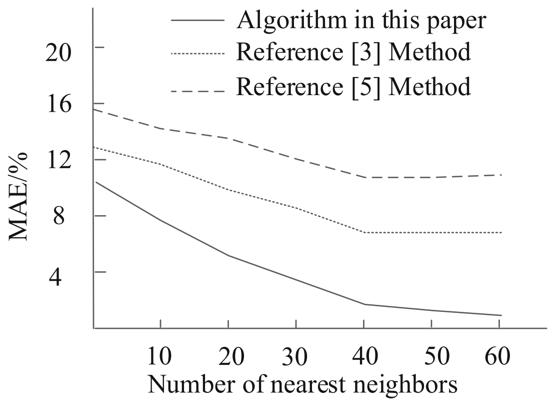


(b) Recall rate



(c) Comprehensive average

Fig. 3. Comparison of experimental data for performance indicators of various algorithms



(d) Average absolute error

Fig. 3. (*continued*)

From the curve trend in Fig. 3, it can be seen that compared to the methods in reference [3] and [5], the algorithm proposed in this paper has significant advantages. In Fig. 3 (a), the accuracy of each algorithm is directly proportional to the number of nearest neighbors. When the number of nearest neighbors reaches a certain value, the accuracy of the algorithm in this paper gradually stabilizes, but there is still a small increase in accuracy; From the comparison of recall rates shown in Fig. 3 (b), it can be seen that although the fluctuation of each algorithm is relatively small, the curve of the algorithm in this paper has always been at a high level, indicating that the algorithm has a high probability of recommending online education courseware for painting that users are interested in; According to the weighted harmonic average trend in Fig. 3 (c), it is found that the algorithm proposed in this paper has good comprehensive performance and relatively ideal recommendation performance; The average absolute error value of each algorithm in Fig. 3 (d) shows that the error of the algorithm recommendation results in this paper is small and has been declining, which has certain feasibility.

(2) Quantitative experiments

A personalized recommendation experiment was conducted on online education courseware for painting based on the browsing records of each user, and the experimental results are shown in Table 3.

From Table 3, it can be seen that the average accuracy rate for personalized recommendation of online education courseware in painting is 91%, while the average accuracy rate for non interest is 86%. This result fully demonstrates that the method proposed in this article can meet the demand for personalized recommendation of online education courseware in painting.

In addition to the above indicator tests, the LoadRunner load testing tool is used to predict the recommended performance of this method through the throughput test. The basic steps for testing are as follows:

(1) Setting up a testing environment: In order to conduct throughput testing, it is necessary to first establish a testing environment in which various actual operational

Table 3. Personalized Recommendation Results of Online Education Courseware for Painting

User	Items of interest			No interest items		
	Total	Correct number	Accuracy/%	Total	Correct number	Accuracy/%
A	345	304	88.1	248	205	82.6
B	321	301	93.7	565	515	91.1
C	357	312	87.3	350	289	82.5
D	435	398	91.4	198	158	79.8
E	305	268	87.8	352	308	87.5
F	387	362	93.5	201	169	84.1
G	369	329	89.1	358	323	90.2
H	325	303	93.2	265	231	87.2

situations can be simulated. This may require the use of special testing tools and software.

(2) Define test cases: Test cases are a sequence of actions that need to be executed during the testing process, including steps such as request, response, and validation. When defining test cases, it is necessary to consider parameters such as load, number of concurrent users, and data size.
(3) Testing: When conducting testing, it is necessary to execute defined test cases and record indicator data during the testing process, such as processing time, throughput, etc.
(4) Analysis of test results: After the test is completed, it is necessary to analyze the test results to evaluate the performance of the equipment or system. During the analysis process, various factors need to be considered, such as hardware, software, network environment, etc.

According to the above process, the number of simultaneous operation users in the simulation setting gradually increased from 100 to 1000. The performance test of the method in this paper, the method in Reference [3] and the method in Reference [5] was conducted through the throughput, and the results are shown in Table 4.

According to the statistical results in Table 4, it can be seen that the recommended users of the system, reference [3] method, and reference [5] method in this article increased from 100 to 1000 at the same time, and the throughput increased with the increase of the number of users. Among them, the methods in reference [3] and reference [5] have lower throughput. Due to the slow response of the methods in reference [3] and reference [5], the number of successful recommendations is relatively low. When the number of people in this method increases to 1000 during the same period, the growth rate of system throughput slows down, and the growth rate is relatively small. The system operation status remains stable and all users successfully complete the recommendation, without any system access failure or lag phenomenon. Therefore, it can be concluded that the recommendation performance of this method is good.

Table 4. Throughput testing

Number of simulated users/person	Algorithm in this paper/Mbps	Reference [3] Method/Mbps	Reference [5] Method/Mbps
100	17.72	14.22	15.62
200	21.26	17.76	19.16
300	26.50	23.12	24.51
400	29.56	26.06	27.46
500	33.88	30.38	31.78
600	38.02	34.52	35.92
700	41.38	37.88	39.28
800	45.92	42.42	43.82
900	49.54	46.04	47.44
	54.62	51.12	52.52

The similarity calculation ablation experiment is an experiment conducted on the influence of similarity calculation methods in the personalized recommendation system for online painting education courseware based on hyperheuristic algorithms. Set the similarity calculation method as an independent variable and set different experimental groups, each using a similarity calculation method. Use the correct number of courseware to evaluate the quality and effectiveness of recommendation results. The results are shown in Table 5.

Table 5. Experimental result

	Algorithm in this paper	Reference [3] Method	Reference [5] Method
Experimental courseware	368	368	368
Correct courseware	367	352	346
Accuracy	99.73%	95.65%	94.02%

From Table 5, it can be seen that the recommendation results analyzed using this method are significantly higher than those of traditional methods. The recommendation of the method in this article will not completely filter out bottlenecks, and this reason is due to the similarity calculation of online education courseware for painting.

4 Conclusion

Through the study of personalized recommendation methods for painting online education courseware based on hyper heuristic algorithms, the following conclusion has been drawn: personalized recommendation systems can greatly improve users' learning experience and effectiveness for painting online education courseware. Especially in the era of big data, recommendation algorithms can track user learning records and interest preferences, accurately recommend courseware and content suitable for users, avoid the shortcomings of traditional education methods, and improve the effectiveness of courseware and user satisfaction. Moreover, with the continuous optimization and update of recommendation algorithms, it can also help users discover interesting content that they have not discovered, enhance the fun of painting learning, and stimulate users' interest in learning. In summary, personalized recommendation systems will become one of the important methods for future education, which can help users comprehensively improve the learning effect and fun of painting education. With the rapid development of online education in painting, personalized recommendation systems have gradually become an important trend. In the coming years, personalized recommendation of online education courseware for painting will continue to maintain rapid development. Here are several possible research prospects:

(1) Multimodal recommendation system: Integrate multimedia resources in online education courseware for painting, and use multiple modal information such as voice, image, and text to design multimodal recommendation algorithms to improve recommendation effectiveness and user satisfaction.
(2) Recommendation system based on deep learning technology: Deep learning (AL) is currently one of the most promising research fields. Combining the characteristics of the painting field, through deep learning technology, more accurate and intelligent recommendation algorithms are established. For example, deep learning technology can be used to construct an image recognition system that accurately recognizes and analyzes the user's painting style to support recommendation algorithms.

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