

Article

Dynamic Personalized Recipe Recommendations Based on Facial Health Recognition

Yecheng Lao ¹, Chang Su ^{1,2,*} , Bolin Chen ¹, Yong Li ¹, Jia Shi ¹ and Haoming Fang ¹

¹ School of Advanced Manufacturing, Guangdong University of Technology, Jieyang 510006, China; 3121009315@mail2.gdut.edu.cn (Y.L.); 3121009461@mail2.gdut.edu.cn (B.C.); 3222009237@mail2.gdut.edu.cn (Y.L.); 3221009101@mail2.gdut.edu.cn (J.S.); 3122009283@mail2.gdut.edu.cn (H.F.)

² Guangdong Provincial Laboratory of Chemistry, Fine Chemical Engineering Jieyang Center Guangdong, Jieyang 522091, China

* Correspondence: gduisc@gdut.edu.cn

Abstract: Nowadays, the demand for more personalized healthy food recipes is increasing over time, but traditional personalized recipe recommendation systems often tend to overlook the differences that exist in different users' health conditions. This paper aims to address the issue by proposing an innovative personalized health recipe recommendation framework. This framework is based on different health needs, aiming to address users with different health conditions. More explicitly, the hybrid recommendation algorithm based on facial health recognition is designed to recommend the most suitable recipes for the user by taking into account the user's health status and preferences. In addition, the fitness factor will adjust the recommendation results to best meet the user's taste preferences and health goals. Experimental results and user research results show that the recommendation results of this framework are more accurate compared to existing systems, and therefore, users are more satisfied.

Keywords: personalized recipe recommendation; health status; facial health recommendation; hybrid recommendation algorithm; suitability factor



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1. Introduction

In recent years, with the continuous improvement of life quality, individuals' dietary requirements and health awareness have undergone positive changes. Personalized recipes are highly favored compared with traditional universal recipes, as they cater to individual dietary preferences and incorporate considerations for improving individuals' overall health. With the advancement of recommendation systems and internet technology, 'Personalized Recipe Recommendation' (hereinafter PRR) has become simpler and more convenient. However, traditional PRR has some limitations, such as being unable to solve the recommendation problem for new users effectively. Zhang Zy [1], proposed a method based on the meta-learning policy model that recommends the TOP-N developers [2] who are most likely to be successful in this context, but due to the inaccuracy of the description information, the recommendation performance of this model may not be ideal.

Most of the existing personalized recipe recommendation systems make recommendations based on the users' historical choices, but their physical health statuses are also an important consideration for personalized recipes, and their physical status is always changing. Therefore, traditional PRR cannot adequately address user needs. More recently, some scientific research results have shown that personalized meal plans can be provided based on an individual's current health status, thereby achieving a dynamic PRR that is determined by the user's health status. Li Ying [3] built a user-dynamic intelligent healthy diet recommendation system, which improved the accuracy of recommendations and increased user satisfaction. In addition, the basic principle of traditional Chinese medicine in understanding and treating diseases is based on syndrome differentiation and

treatment, in which inspection plays an important role in syndrome differentiation and treatment. Inspection involves analyzing the patient's physical health by observing the patient's overall or local acne, facial expression, morphological changes, etc. [4].

At the same time, accurate matches for user recommendations may not always be the most suitable ones. Traditional personalized recipe recommendation systems may not consider differences in users' medical conditions but they might recommend similar types of recipes. However, users with milder conditions may prioritize taste rather than effectiveness when it comes to food consumption. Therefore, different levels of severity in medical conditions require differentiated recommendations.

To address the above problem, we propose a novel framework for detecting the user's health status. The user's health status will then be used to tailor personalized facial health-based recipe recommendations (hereafter HFRR) for the user. In the design of this paper, the aim is to make the recommendation results more suitable for the user rather than catering to the user's preferences. We use facial recognition to detect the user's health status, and then derive the recommendation results through a hybrid recommendation algorithm based on content and collaborative filtering. Then we set the suitability factor representing the weight according to the degree of the user's health status, and adjust the recommendation results dynamically, so as to derive personalized healthy recipe recommendation results that are more suitable for the user. We then established a framework for the correspondence between facial symptoms and internal organs based on the principle that local lesions may cause systemic pathological reactions, and pathological changes in the whole body will also be manifested locally in Chinese medicine diagnostics. In this framework, we consider the user's facial skin recognition as a process of organ disease judgement. The factors and mechanisms in this process are used to guide our feature set construction and recipe recommendation model development.

In short, the research presented in this paper contributes in four ways. First, we develop a model that analyzes physical health status by recognizing the facial state of a user; second, we propose a hybrid recommendation algorithm that combines word frequency and inverse document frequency-based content recommendation and collaborative filtering based on a hidden semantic model in a cascade approach, which greatly alleviates the problems of cold-start and data sparsity of traditional recommendation algorithms; third, we construct a framework for recommending recipes based on the user's health status and preference needs; fourth, we propose a mechanism for adjusting the recommendation results by a fitness factor to derive recipes that are most suitable for the user's current state.

The rest of this paper is organized as follows. In Section 2, we summarize the research on the latest related work in facial detection of health status and recommendation. Inspired by the findings of related scholars, we present our novel framework design in Section 3. Then, we test and evaluate our proposed novel framework in Section 4. Finally, Section 5 summarizes our study and maps out our future research directions.

2. Related Work

In this section, we first summarize relevant facial skin recognition health state models, which are the basis for further research, using their health status as our recommended input. We then review existing methods for facial state characterization of health states, which is a prerequisite for PRR. Finally, we analyze the latest research on PRR to guide our design.

2.1. Health Model of Facial Features

A suitable facial feature health model is an important factor in the accurate representation of embedded health information and additional recipe recommendations. Existing facial feature health information can be divided into two categories, namely facial feature recognition models and acne feature recognition models.

In the complexion feature recognition model, the complexion is divided into four categories: red, yellow, white, and black according to the theory of traditional Chinese medicine. Sun Haoxian [5] uses deep learning methods to achieve key point identification

and automatic segmentation of areas of interest in facial images. Based on different features, a variety of machine learning methods are used to classify and identify the extracted facial features. These characteristics can reflect the functional status of various tissues and organs throughout the body. In the acne feature recognition model, a framework of correspondence between facial diseases and internal organs is established based on facial examination in “Diagnostics of Traditional Chinese Medicine”. Wang Wei used linear interpolation to downsample the image and used the MTCNN-ERT algorithm to align the facial key points, extract the area of interest, and segment the facial area.

2.2. Extraction of Health Condition Features

Accurate feature description is a requirement for high-performance analysis. In user health status analysis, accurate feature description needs to be connected with an appropriate health model. Wang Wei [6] advocated using image recognition technology to analyze and identify whether acne is present and the amount of acne in each area of the face, and experimental results have proven that this method is convenient and effective. To reflect the characteristics of health conditions more accurately, it is not only necessary to consider the presence or absence of organ diseases, but also the severity of the disease. Zhang Zhe [7] used multispectral image analysis and spectral inversion algorithms to obtain reflectance spectral line information. Based on the collected data, a support vector machine classification model can be established to classify facial acne of different levels of severity, thereby reflecting the severity of visceral diseases.

2.3. Personalized Recipe Recommendation Based on Health Conditions

Traditional personalized recipe recommendation systems draw on recommendation methods from the e-commerce field, including content-based, collaborative filtering [8], and hybrid recommendation algorithms. Collaborative filtering [9] is based on historical user behavior data to calculate the similarity between users or recipes and recommend favorite recipes to other users. In recent years, many scholars have proposed improved algorithmic systems, such as collaborative filtering (Latent Factor Model, LFM) based on latent semantic models, which can use a large amount of user historical behavior data to improve recommendation accuracy. However, due to its reliance on historical behavioral data, LFM suffers from a cold start problem. The content-based recommendation algorithm recommends similar recipes to users by analyzing the characteristics of the recipes and the user's interests. A commonly used content-based recommendation algorithm is TF-IDF [10] (Term Frequency-Inverse Document Frequency), which is based on content. It then calculates the weight based on the frequency of occurrence and importance in the entire corpus. Since it does not rely on the behavioural data of other users, it can solve the cold-start problem of recommendation difficulties due to the lack of sufficient personalized information during the initial phase of the system or when targeting new users. The hybrid recommendation algorithm combines the advantages of multiple recommendation algorithms to optimize accuracy and recommendation effects. Therefore, this paper adopts a hybrid recommendation algorithm [11] combining TF-IDF and LFM in a cascade manner.

According to research in relevant literature, this system uses a hybrid recommendation algorithm [12] that combines user facial acne recognition, analysis of the type and severity level of the symptoms, and TF-IDF and LFM (Latent Factor Model) techniques for recommendation.

3. Research Methods

In this section, we first present the design of a comprehensive framework aimed at addressing the challenge of personalized recipe recommendation. Subsequently, the construction of a hybrid recommendation algorithm is detailed, including the fusion of word frequency and inverse document frequency-based content recommendation with latent semantic model-based collaborative filtering. Finally, we propose a tuning mechanism for appropriate factors to ensure that the recommendation results better satisfy users' needs.

3.1. Framework Design

We propose a recipe recommendation framework based on facial health, which includes three key steps: assessing the user's facial health status and taste needs, using the TF-IDF algorithm to profile users and recipes, and designing a system based on similarity and recommended models for LFM. The innovation of our design is the introduction of a "suitability factor" as a bias parameter to adjust the weight of efficacy and taste in the recommendation model. The suitability factors can be set manually or can be fed through automatically from the available data. Its purpose is to adjust the output results of the recommendation model according to the degree of deviation between the user's current health status and the focus of the recommended recipes to meet the user's needs. The recipe recommendation framework based on facial health recognition is shown in Figure 1.

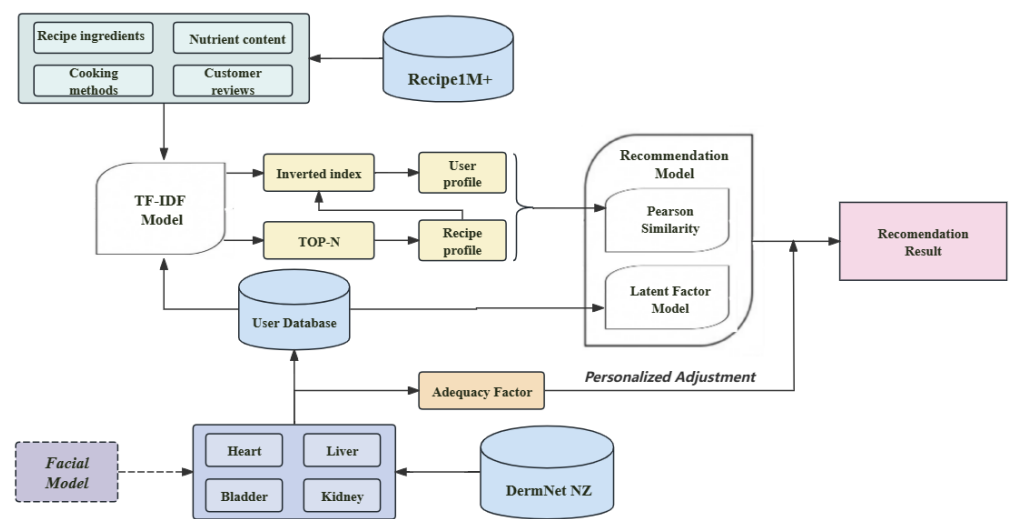


Figure 1. Health-based recipe recommendation framework.

3.2. User Health Status Identification

3.2.1. Health Monitoring Basis Based on Facial Skin Characteristics

This article focuses on facial skin as the research object of facial diagnosis. According to the Diagnostics of Traditional Chinese Medicine, it is believed that local lesions may cause systematic pathological reactions and systematic pathological changes will also be manifested locally. Facial observation can focus on features such as moles, spots, bumps, redness, and swelling, which are considered signs of potential pathology. By observing changes in these characteristics, we can initially judge the health status of the organs, thereby guiding subsequent diagnosis and treatment. It should be noted that in TCM theory, "zang-fu" not only refers to the actual organs but also includes the overall understanding of the body's physiological functions and pathological changes. Therefore, the zang-fu studied in this article are abstract concepts in traditional Chinese medicine theory, covering the overall condition of each part of the body. Figure 2 shows this article's research on the correspondence between facial acne and internal organs.

On the theoretical basis, we drew on Wang's [6] method for assessing health status based on face palpation and facial video. By systematically summarizing and analyzing the application of facial auscultation in Chinese medicine and facial video in heart rate estimation, we explored the potential and application value of these methods in assessing human health status. In terms of data analysis, Chen [13] used an epidemiological survey method to study 840 young students. The face was divided into five regions, and clinical symptoms and facial data were collected to determine the identification elements. It was concluded that there is a correspondence between facial regions and the five organs, which can be used as one of the objective bases for identification. In actual cases, Peng [14] explored the etiology and pathogenesis of acne through the local diagnosis of the face, considering the relevant

parts of the internal organs on the face, the characteristics of acne, and the accompanying symptoms. This approach was used for direct diagnosis and treatment of acne, resulting in satisfactory results. It also reflects the relevance of the health of the face to the internal organs. Based on the literature review, we invited industry experts to identify and supplement the information. After many discussions, we finally reached the following conclusion: there is a close relationship between facial acne and internal organs. We obtained a research diagram of the correspondence between facial diseases and internal organs, as shown in Figure 2.

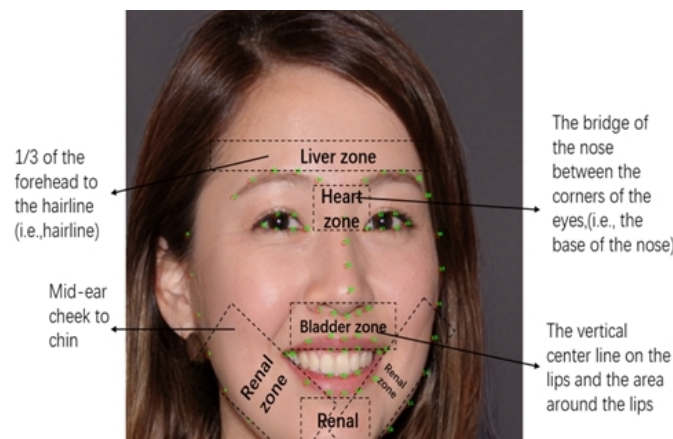


Figure 2. Correspondence diagram between facial acne and internal organs.

3.2.2. Analysis of the Degree of Facial Acne Based on Multispectral Imaging Technology

This recognition system builds a set of experimental devices based on multispectral cameras, which combine lighting conditions and multispectral cameras to record multispectral image information of patients in different condition levels and calibrate the target area of the collected images. Additionally, the spectral response function of the skin is obtained based on the unique physiological and optical characteristics of each individual. The SVM acne sample classification model is therefore established, and based on the differences in the spectral curves of the four levels of acne severity, the three- and four-level classification of acne can be effectively achieved.

3.3. Content Recommendation Algorithm Based on TF-IDF

The content-based recommendation algorithm was the most widely used in the early days of recommendation systems. The main idea behind it is to form a portrait based on the relevant characteristics of users and items, and then measure their similarity. Finally, the TOP-N items with the highest similarity are obtained as the recommendation results for the corresponding users. Its main structure is shown in Figure 3.

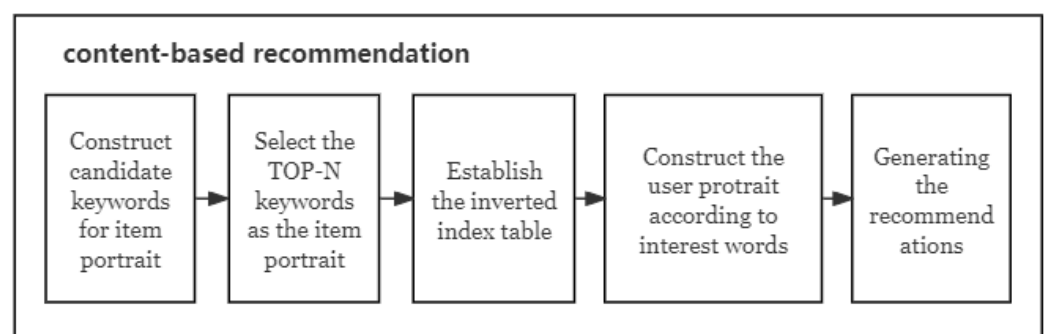


Figure 3. Content-based recommendation algorithm structure.

We construct candidate keywords for the recipe image based on the taste, nutritional attributes, and other characteristics of the recipe. We use TF-IDF to calculate the weight value of candidate keywords:

$$TF(t, d) = \frac{n_{t,d}}{\sum_k n_{k,d}} \quad (1)$$

$$IDF_t = \log\left(\frac{N}{n_t + 1}\right) \quad (2)$$

$$W(d, t) = TF(t, d) * IDF_t \quad (3)$$

Here, $TF(t, d)$ is the word frequency of word t appearing in the document, while IDF_t represents the inverse document frequency, which is the number of times the word appears in the text. $\sum_k n_{k,d}$ is the sum of the number of times all words appear in the text, N is the total number of documents in the vocabulary database, n_t is the word for the number of documents in the database in which the word appears [15] and $W(d, t)$ is the calculated weight of the candidate keyword in the text.

Additionally, we use the weight values calculated by TF-IDF to select the TOP-N candidate keywords to create a portrait of the recipe. We also build an inverted index list based on recipe portrait keywords to allow users to provide feedback on interest items when logging into the system and collect user interest words. We then use TF-IDF to calculate the weight of user interest words, select the corresponding TOP-N candidate keywords, and combine user attributes to construct user portraits. Similarity calculation is performed based on user portraits and recipe portraits. Many calculation methods can be applied in this case. Pearson similarity [16] considers the degree of linear correlation between variables and can also consider the length of the vector. Therefore, the Pearson similarity is selected as the similarity calculation method:

$$P(A, B) = \frac{\sum_{i=1}^n (A_i - \bar{A})(B_i - \bar{B})}{\sqrt{\sum_{i=1}^n (A_i - \bar{A})^2} \sqrt{\sum_{i=1}^n (B_i - \bar{B})^2}} \quad (4)$$

Finally, the calculated TOP-N items with the highest similarity are output as recommendation results for users.

3.4. Collaborative Filtering Recommendation Algorithm Based on LFM

The recommendation algorithm based on collaborative filtering is currently the most widely used. Its basic idea is to discover user preferences by mining user historical data and predict the products that users may prefer for recommendation. This article uses a model-based recommendation algorithm and applies the LFM model (latent factor model, latent semantic model) proposed by Y Koren, R Bell [17], etc. to predict and recommend user preferences. This model is closely related to singular value decomposition (SVD). This is a mature technique for identifying latent semantic factors in information retrieval, and its structure is shown in Figure 4.

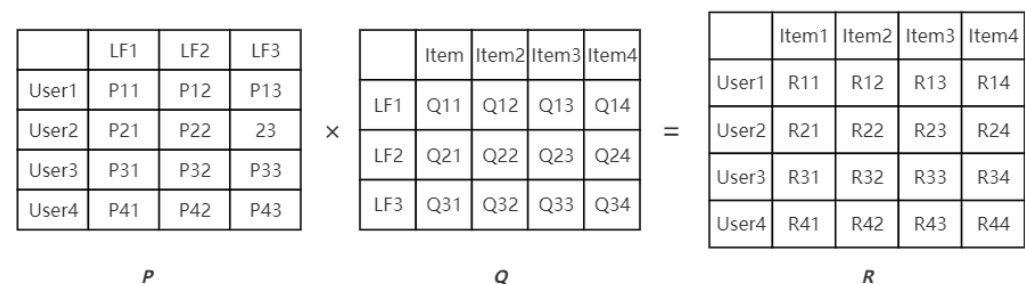


Figure 4. Recommendation algorithm structure diagram based on LFM.

The LFM algorithm is a recommendation algorithm based on matrix decomposition. It decomposes the high-dimensional user-item rating matrix into two matrices, maps users

and items to a low-dimensional space, and changes the potential semantic relationship between users and items in the subspace, thereby capturing the latent characteristics of user items for prediction and recommendation. The schematic diagram is shown in Figure 5.

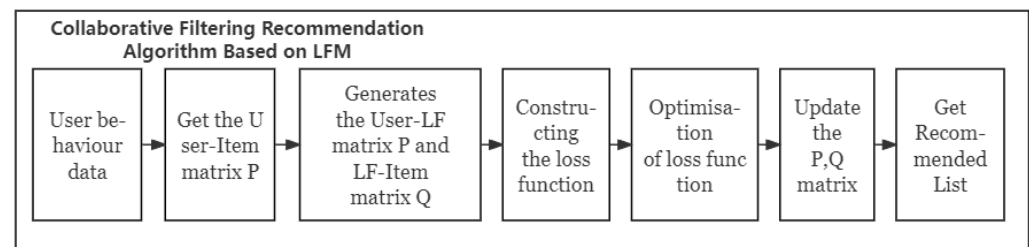


Figure 5. LFM algorithm principal diagram.

The P matrix is the User-LF (user-latent factor matrix). The Q matrix is the LF-Item (latent factor-item matrix), and the R matrix is the User-Item (user-item preference matrix) matrix. The core idea of the LFM model is to reduce the dimensionality of the R high-order matrix through matrix decomposition and decompose it into two matrices, P and Q. LFM associates items and users through implicit factors and calculates user's interest in item i:

$$R_{ui} = PQ \quad (5)$$

First, one needs to learn the training data set to obtain the P and Q matrices, restore the R matrix through calculation, predict the vacant values in the original data set, and fill them in. F is the number of hidden factors:

$$\hat{R}_{ui} = \sum_{f=1}^F P_{u,f} Q_{i,f} \quad (6)$$

$P_{(u,f)}$ and $Q_{(u,f)}$ represent the f-th eigenvalue of the eigenvector of user u and item i, respectively. User 1's predicted liking value for item 1 is as follows:

$$R_{11} = P_{11}Q_{11} + P_{12}Q_{12} + P_{13}Q_{31} \quad (7)$$

The way to learn the LFM model is to initialize the matrices P and Q, then solve for the minimization of the root mean square error (RMSE), and construct a minimization loss function to update the matrices P and Q. The loss function is defined as follows:

$$Cost = \sum_{u,i \in R} (R_{ui} - \hat{R}_{ui})^2 = \left(\sum_{u,i \in R} R_{ui} \sum_{f=1}^F P_{ui} Q_{if} \right)^2 \quad (8)$$

To avoid overfitting the loss function during the iterative solution process, regularization parameters can be added. At this time, the loss function becomes

$$Cost = \sum_{u,i \in R} (R_{ui} - \hat{R}_{ui})^2 = \left(\sum_{u,i \in R} R_{ui} \sum_{f=1}^F P_{ui} Q_{if} \right)^2 \quad (9)$$

Furthermore, the gradient descent method is used to optimize the loss function, which requires a partial derivative. The formula is as follows:

$$\frac{\partial}{\partial P_{u,f}} Cost = -2 \sum_{u,i \in R} (R_{ui} - \sum_{f=1}^F P_{u,f} Q_{i,f}) (-Q_{i,f}) + 2\lambda P_{u,f} \quad (10)$$

$$\frac{\partial}{\partial P_{f,i}} Cost = -2 \sum_{u,i \in R} (R_{ui} - \sum_{f=1}^F P_{u,f} Q_{i,f}) (-Q_{u,f}) + 2\lambda P_{u,f} \quad (11)$$

We iteratively calculate the update matrices P and Q to find the optimal P matrix and Q matrix:

$$P_{u,f} = P_{u,f} + \alpha \left[\left(R_{ui} - \sum_{f=1}^F P_{u,f} Q_{i,f} \right) Q_{i,f} - \lambda_1 P_{u,f} \right] \quad (12)$$

$$Q_{i,f} = Q_{i,f} + \alpha \left[\left(R_{ui} - \sum_{f=1}^F P_{u,f} Q_{i,f} \right) P_{u,f} - \lambda_2 Q_{i,f} \right] \quad (13)$$

Here, α is the learning rate, which represents the step size of iterative learning.

3.5. Recipe Recommendations Based on Facial Health

We use a hybrid recommendation algorithm based on content and collaborative filtering to implement recipe recommendations and design a recommendation model based on Pearson and the latent factor model (LFM) for recommendation.

First, we identify the user's facial health status, analyze it, and update the health information in the user database. Then, we determine whether the user appears again in the previous records or not. For new users, we adopt a content-based recommendation algorithm that models items and users using the TF-IDF method. We also solve the cold start problem and use Pearson similarity to recommend TOP-N recipes. For non-new users, we use the collaborative filtering recommendation algorithm based on LFM to recommend recipes. The flow chart is shown in Figure 6.

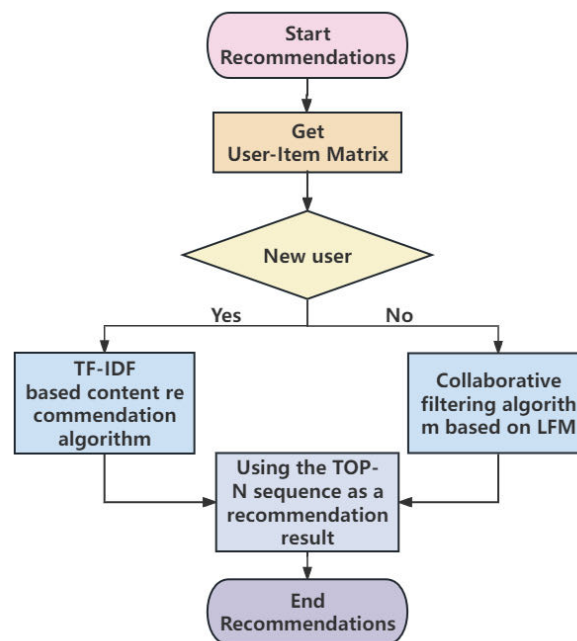


Figure 6. Hybrid recommendation algorithm flow chart.

Finally, in recipe recommendation, we introduce a bias parameter called “suitability factor” to adjust the recommendation results. Due to changes in facial health status, we adjust the focus of the recipes, including efficacy and taste, according to the user's health status. For example, when a user's health condition is poor, we will recommend recipes that focus more on efficacy. For other users, we may pay more attention to functional recipes that meet their taste preferences. This kind of personalized adjustment can meet the needs of different user groups. The pseudocode of the recipe recommendation framework based on facial health is shown in below Algorithm 1.

Algorithm 1: HFRR Algorithm

Input: FH = User's recent facial healthy condition;
 HR = healthy recipes for Recipe1M+;
 UserPreference = parameters calculated from User's historical data;
 User = New User OR Old User

Output: FR = Top-N recommended recipes

```

1 Function HFRR(FH,HR,UserPreference):
2   // Get Adequcy Factors
3   AdequcyFactor = GetAdequcyFactors(FH, UserPreference);
4   dislist = empty list;
5   for  $i \leftarrow 1$  to len(HR) do
6     if User = New User then
7       // Extract recipe features
8       KeyWord[i] = TF-IDF(HR[i]);
9       RecipeProfile = Top-N(KeyWord);
10      // Extract user features
11      Feedback = inverted-index(KeyWord);
12      InterestWord = TF-IDF(Feedback, UserPreference);
13      UserProfile = Top-N(InterestWord);
14      distance = dis(RecipeProfile, UserProfile);
15    else
16      distance = LFM(UserPreference, HR[i]);
17    dislist = add(dislist, distance);
18  topK = GetMinK(dislist);
19  R = GetResult(HR, topK);
20  FR = adjust(R, AdequcyFactor);
21  return FR;

```

4. System Evaluation

This section first describes the construction of our dataset, followed by a description of the evaluation criteria selected to reflect user needs and system performance. This is followed by a qualitative analysis of the recommendation results. Finally, the methodology and results of the user satisfaction study are explored to gain insights into the performance and user experience of recommender systems in real-world applications.

4.1. Construction of Data Set

To verify the effectiveness of our proposed new framework, we implemented three datasets.

The first dataset is used to train the health state model. We selected DermNet NZ's facial acne image dataset [18], which contains a wide range of dermatology images and other relevant information. Since facial acne is a common skin problem, its coverage in this dataset is high, which allows us to obtain a sufficient amount and diversity of acne image data from it. By segmenting the skin images and extracting the acne regions, we obtained a set of facial skin acne data. Using this dataset, we trained our health state model. The second dataset is used for feature extraction of recipes. We chose the public data set-Recipe1M+ [19] as it contains more than one million recipes, each of which includes multiple attributes and information, such as recipe title, ingredient list, cooking steps, and ingredient amounts. This detailed information allows us to conduct a comprehensive analysis of recipes and thus better understand culinary diversity. The third data set is used to determine the user's health status and dietary requirements. We conducted a user study by recruiting 50 participants, collected data on their facial health status in the past month, and understood their preferences for recipes. These data help us design personalized healthy diet plans and understand user preferences for different cuisines and ingredients.

Through these three datasets, we can verify the effectiveness of our proposed framework in health status model training, recipe feature extraction, and user needs analysis. These data provide us with a wealth of information that helps us better understand and apply knowledge in the areas of recipes and health.

4.2. Evaluation Criteria

The following three evaluation criteria are used for the recommendation results selected in this experiment.

Accuracy rate: represents the proportion of items that users like or are interested in among the TOP-N recommendation results. The calculation formula is as follows:

$$\text{Precision} = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |R(u)|} \quad (14)$$

Depicted in this equation are the total number of users, the recommendation result set generated for each user, and the user's actual behavior result set.

4.3. Analysis of Experimental Results

To verify the superiority of the hybrid recommendation algorithm based on content and collaborative filtering used in this experiment, a comparative experiment was conducted between the hybrid recommendation algorithm, the user-based collaborative filtering algorithm [20], and the item-based collaborative filtering algorithm [21]. The effectiveness of the given framework in health status model training, recipe feature extraction, and user demand analysis are calculated respectively. These data provide us with a wealth of information that helps us better understand and apply knowledge in the areas of recipes and health.

The recall rate indicates the proportion of items that the user likes or is interested in among the TOP-N recommendation results, compared to all the items that the user likes. The calculation formula is as follows:

$$\text{Recall} = \frac{\sum_{u \in U} |R(u) \cap T(u)|}{\sum_{u \in U} |T(u)|} \quad (15)$$

The coverage rate refers to the proportion of the TOP-N recommended results by the system to the entire recommended project set. This indicator reflects the recommendation system's ability to mine long-tail projects from the side. The calculation formula is as follows:

$$\text{Coverage} = \frac{|U_{\text{uff}} \cap R(u)|}{I} \quad (16)$$

Here, the total number of items is depicted.

When the recommended length N is 5, 10, 15, 20, 25, and 30, the accuracy, recall, and coverage rates of the three methods are shown in Tables 1–3. We then draw the change trend when the recommended length is 5, 10, 15, 20, 25, and 30, as shown in Figure 7a,c.

Table 1. Accuracy.

	%					
Algorithm	Top-5	Top-10	Top-15	Top-20	Top-25	Top-30
Mixed	64.25	52.78	50.86	43.77	36.94	35.14
User-based	46.22	40.50	31.98	28.97	25.41	23.42
Item-based	39.64	32.43	29.21	24.26	22.12	21.13

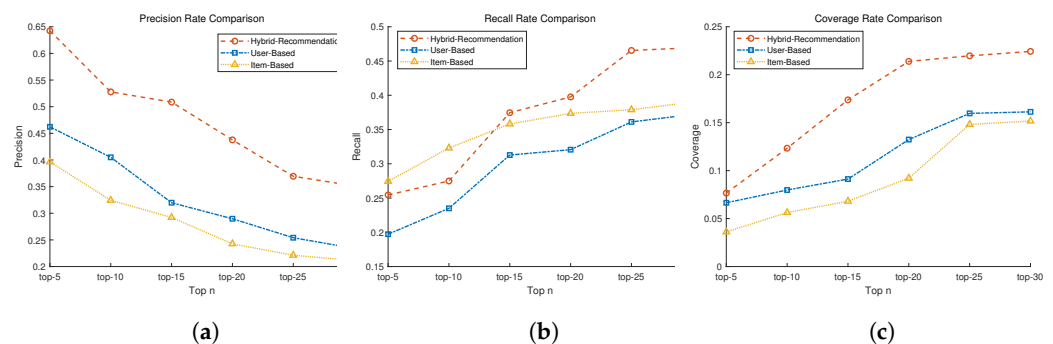
As can be seen from Table 1 and Figure 7a, the hybrid recommendation algorithm based on content and collaborative filtering used in this experiment has better accuracy than the user-based and item-based collaborative filtering algorithms in the listed situations. When the recommended length is greater than or equal to 25, the accuracy gradually tends to stabilize.

Table 2. Recall.

	%					
Algorithm	Top-5	Top-10	Top-15	Top-20	Top-25	Top-30
Mixed	25.35	27.49	37.46	39.76	46.54	46.94
User-based	19.72	23.50	31.28	32.06	36.11	37.20
Item-based	27.44	32.30	35.81	37.36	37.89	39.00

Table 3. Coverage.

	%					
Algorithm	Top-5	Top-10	Top-15	Top-20	Top-25	Top-30
Mixed	7.66	12.34	17.38	21.39	21.97	22.43
User-based	6.65	7.98	9.12	13.24	15.97	16.13
Item-based	3.61	5.63	6.81	9.21	14.82	15.17

**Figure 7.** Recommended Indicator. (a) Precision. (b) Recall. (c) Coverage.

As can be seen from Table 2 and Figure 7b, the recall rate of the hybrid recommendation algorithm used in this experiment gradually outperforms the user-based and item-based recommendation algorithms as the length of the recommendation queue increases. When the length reaches 15, the recall rate of the hybrid recommendation algorithm starts to be greater than that of the item-based recommendation algorithm.

As can be seen from Table 3 and Figure 7c, the coverage rate of the hybrid recommendation algorithm used in this experiment is also better than the other two algorithms. When the recommended length is greater than or equal to 25, the coverage rate gradually tends to get stabilized.

In summary, the hybrid recommendation algorithm based on content and collaborative filtering used in this experiment can not only solve the cold start problem, but also performs better than the traditional recommendation algorithm based on collaborative filtering. Moreover, it can better provide recommendation services to users.

4.4. User Satisfaction Research

In practical applications, the most accurate recommendation is not necessarily the most suitable recommendation for the user. As mentioned above, the purpose of our personalized recipe recommendation system based on the user's physical health status is to make the recommendation results more suitable for the user, rather than blindly catering to the user's preferences. Therefore, the advantages of our design cannot be achieved through the widely used methods mentioned above. To address this issue, we conducted a user satisfaction study and compared the performance of the following three recommendation methods:

- (R1) Completely random recipes.
- (R2) When using our HFRR model to recommend recipes, the suitability factors will be set based on the user's current health.
- (R3) When using our HFRR model to recommend recipes, suitability factors will be set according to user-defined needs.

The 50 volunteers in Section 4.1 also participated in the study, all of whom were university students with an average age of 21 years, of whom 28 were male and 22 were female. According to the users' dietary preferences, physical health status, and demand for personalized recipes, we divided them into experimental groups and control groups. Thirty of them were in the experimental group and the other twenty were in the control group. They did not know which group they were in. Users in the experimental group are recommended by R2 and R3, while users in the control group are recommended by R1.

In each test, users were asked to receive three recipe recommendations and fill out a six-question questionnaire (see Table 4 below). First, we asked participants about their overall satisfaction (Q1). Then, we measured user satisfaction (Q2 to Q4) in detail based on the components of quality, practicality, and dietary preferences. Finally, we asked specific questions about the health benefits of personalized recipes, which included measurements of current health status (Q5) and health-improving effects (Q6).

Table 4. Questionnaire.

Number	Question
Q1	Overall, are you satisfied with the results of the recommended recipes?
Q2	What do you think of the quality of the recommended recipes?
Q3	How well the recommended recipes meet your needs?
Q4	How well the recommended recipes match your dietary preferences?
Q5	How accurately do recommended recipes reflect your current health level?
Q6	How the recommended recipes will improve your health?

The questions mentioned in the table above were evaluated using a 5-point Likert scale. The results are shown in Figure 8. From Figure Q6, R2, and R3, we can observe the obvious advantages over R1, which means that the recipe recommendations provided by R2 and R3 have the function of improving the users' health statuses. Moreover, we can see that the results of R2 and R3 are also significantly better than R1 in terms of satisfaction and emotion measurement (Q1 to Q5). In terms of overall satisfaction and practicality, the R3 with user-defined settings performs better. This shows that suitability factors based on user-defined settings work better in the recommendations, but also shows that it is difficult to capture the differences in individual needs between each individual.

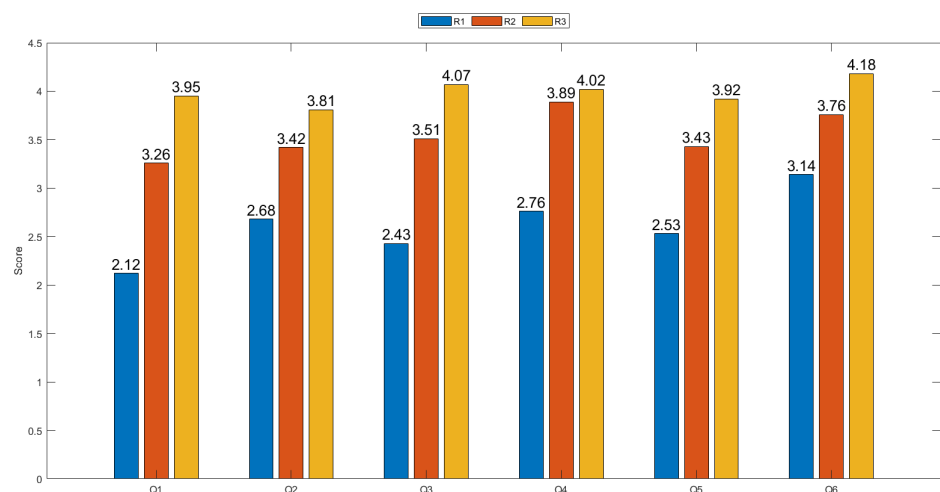


Figure 8. User satisfaction research results (Q1–Q6).

5. Conclusions

Overall, the research conducted in this article has four contributions. First, we built a model that can analyze physical health statuses by recognizing facial statuses. Second, we proposed a hybrid recommendation algorithm that effectively solves the cold start and data

sparsity problems in traditional recommendation algorithms by combining content recommendation based on word frequency and inverse document frequency with collaborative filtering based on latent semantic models. Third, we build a framework to recommend recipes based on the user's health status and dietary preference. Finally, we proposed a mechanism of appropriate factors to adjust the recommendation results to best suit the user's current status. While our research shows that personalized recipes can help improve users' health statuses, there is still a problem: suitability factors for physical health detected through facial health recognition are not as accurate and effective as user-defined suitability factors, indicating that users are satisfied with the recommendation results. Therefore, we hope to explore the theory of facial recognition analysis of health status in future research further and integrate recipe recommendations with users' characteristics to improve the performance of our recommendation framework and achieve more personalized recipe recommendations.

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