Application of Food Nutrient Composition Analysis and Computer Algorithm in Nutrition Recommendation System

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Abstract: This paper studies the application of food nutrition composition and computer algorithm in nutrition recommendation system, and uses the Apriori algorithm in computer algorithm to optimize the nutrition recommendation results. In the process of research, this paper designs a nutritional recommendation computer algorithm based on Apriori, further improves it, and then realizes a nutritional recommendation system based on food nutrient analysis and Apriori algorithm based on the integration of various components. In addition, the system is used for practical applications. According to the experimental data, the recommended combination of high protein and low fat has met the needs of 85% of users, and the recommended combination of high fiber and low carb water can effectively help control blood sugar. Comprehensive analysis shows that the system can provide accurate dietary recommendations based on in-depth nutritional analysis to improve the health of users.

1 INTRODUCTION

In recent years, due to the enhancement of Chinese people's health awareness, personalized nutrition recommendations have become a research hotspot. There are researchers who can solve the problem of personalized meal recommendations based on manual calculations, but these methods are inefficient and cannot meet individual needs (Beecher, 2024). Some researchers also use statistical methods, such as simple regression analysis, to make nutritional recommendations, but their ability to analyze complex nutrient combinations is limited (Beltramo, and Bast, et al. 2023). In addition, some traditional rule-based systems can provide some recommendations, but they cannot be adjusted in time according to the dynamic needs of users (Dunlop, and Cunningham, et al. 2025). In this paper, computer algorithms, especially Apriori association rule mining, are used to analyze the nutritional composition of food and make personalized recommendations (Lara-Arevalo, and Laar, et al. 2024). The algorithm can efficiently process large-scale nutrition data and further generate accurate recommendations based on individual needs (Marchese, and Hendrie, et al. 2024). This round mainly analyzes the relationship between the enhancement of people's health awareness and the demand for personalized nutrition recommendation, and puts forward the shortcomings of data statistical methods and rule-based traditional systems in the pertinence of nutrition recommendation, and at the same time, introduces the value of food nutrition composition analysis and computer algorithm in nutrition recommendation, and then determines the research on the system.

2 RELATED WORKS

2.1 Advantages of Computer Algorithms

In the food nutrient analysis and nutrition recommendation system, computer algorithms are extremely crucial. Based on accurate data processing and efficient computer technology, the system can quickly parse huge nutrient data sets (Martins, and Magnusson, et al. 2023). Computer algorithms provide the basis for the calculation and analysis of complex food nutrients and related data, and effectively improve the accuracy and efficiency of

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nutrient composition analysis and prediction based on mechanism optimization and machine learning methods (Pickford, and McCormack, et al. 2022). In recommendation systems, common algorithms include regression analysis, clustering algorithms, and association rule mining, which are conducive to discovering hidden patterns in food nutrition content data and generating targeted recommendations. The introduction of computer algorithms, especially those based on data mining, has greatly improved the ability of the system to process large-scale complex data on food nutrition content (Silveira, and Valler, et al. 2024). These algorithms can accurately predict the nutritional composition of food based on the user's historical data, and have certain learning and optimization capabilities. Based on continuous updates and adjustments, the system can revise the mechanism according to real-time data to ensure the dynamic update and optimization of recommendation results. This ability to self-regulate makes the application of computer algorithms in nutritional recommendation systems extremely critical (Svarc, and Jensen, et al. 2022).

2.2 Apriori Algorithm Can be Used for Estimation of the Frequency of Occurrence of Nutrient Combinations

Among many computer algorithms, Apriori algorithm is an important association rule mining algorithm, which can find frequent item sets from large data sets and generate association rules based on these item sets. It is based on a recursive approach to find frequently occurring combinations in the data, such as the nutritional composition of a food, and then identify effective recommendation patterns (Víquez, and Morales, et al. 2022). The algorithm first defines the degree of support, which is mainly used to measure the frequency of occurrence of one nutrient combination , and the confidence level, which measures the probability of another ingredient appearing when there is a particular nutrient combination. In the nutrition recommendation system, the Apriori algorithm provides data support for personalized dietary recommendations based on the screening of high-support and high-confidence combinations of nutrients. Compared to other traditional algorithms, the Apriori algorithm can efficiently process multi-dimensional data and generate personalized nutrition recommendations for users. The advantage is that it can mine high-value correlation information from the big data set, and use this information to optimize the recommendation mechanism of the system.

3 METHODS

3.1 The Structure of Each Component of the Nutrition Recommendation System

The research in this paper needs to construct a nutritional recommendation system, which includes six components, each of which has its own content that needs to be responsible. Specifically, the task of the data collection component is to collect data related to the user's food nutrients, such as the user's dietary history, physical fitness information, nutritional needs, etc. The widget is based on an interface to obtain the nutritional content data of food products, and then maintain the integrity and accuracy of the data. In addition, the widget interfaces with external databases, allowing the latest food data to be updated in real time. The task of the data preprocessing component is to clean, standardize and structure food nutrition data to ensure that the data format is uniform. Data preprocessing mainly focuses on the processing of missing values, outliers and standardized nutrient composition data. It is also possible to select key food ingredients relevant to nutritional analysis based on feature extraction, preparing them for subsequent analysis. The task of the Association Rule Mining component is to apply the Apriori algorithm to perform frequent itemset mining and association rule generation. It can be based on a set minimum level of support and confidence to provide insight into potential associations between food nutrients. Another task is to export the association rules of nutrients to provide stable, reliable, and comprehensive data support for personalized recommendations. The task of the recommendation engine component is to apply the mined association rules to generate nutritional recommendations according to the user's individual needs. The recommendation engine provides users with suitable food recommendations based on the user's health goals, such as the user's fat loss goals, muscle gain goals, etc. It can adjust the recommended regimen in real-time to meet the different dietary needs of users. The task of the User Feedback widget is to collect user feedback on the recommendation results and apply their feedback to system optimization. Users can provide feedback on recommended foods based on ratings, evaluations, etc. User feedback data is fed into the Associated Rule widget to improve recommendation accuracy and user experience. The task of the system management component is to manage and monitor the system as a whole, such as algorithm tuning, data update, user management, etc. It ensures the stable operation of the system and monitors the system performance, such as recommendation accuracy, user satisfaction, etc. The system administrator can adjust the system parameters based on this widget to further optimize the functionality of the system.

3.2 Mining of Frequent Itemsets and Design of Computer Algorithms for Nutritional Recommendations

In the frequent itemset mining stage, the algorithm mechanism needs to mine the frequent component combinations from a large number of food nutrient data. The nutritional content of each food, such as proteins, fats, carbohydrates, vitamins, minerals, etc., can be considered as an item. Apriori taps into these frequent combinations of nutrients by progressively filtering out the most supportive items. See Eq. (1) for this.

$$\mathrm{Support}(X) = \frac{|T(X)|}{|T|} \tag{1}$$

In this formula, $\mathrm{Support}(X)$ refers to the degree of support of item X, which is the frequency of occurrence of the nutrient item set in all foods. $|T(X)|$ Refers to the number of transactions that contain item set X, in this case the number of foods containing a specific combination of nutrients. $|T|$ Refers to the total number of transactions, which is the total number of all food samples. Based on this formula, it is possible to calculate the degree of support for each nutrient combination and identify the nutrient combinations that occur frequently. For example, if the combination of high protein and high fiber is more supportive, it proves that this combination is frequent in many foods and can be used as a basis for nutritional recommendations.

After you've identified a frequent itemset, the next step is to build an association rule. Association rules are used to explore potential relationships between nutrients, such as whether a food containing one ingredient is often accompanied by another. The strength of this relationship is measured based on the calculation confidence, for which see Eq. (2).

$$\mathrm{Confidence}(X \Rightarrow Y) = \frac{\mathrm{Support}(X \cup Y)}{\mathrm{Support}(X)} \tag{2}$$

In this formula, $\mathrm{Confidence}(X \Rightarrow Y)$ refers to the probability that a food containing X is another nutrient at the same time Y given a combination of nutrients. $\mathrm{Support}(X \cup Y)$ Refers to X Y is the proportion of food products that contain both and in the data. $\mathrm{Support}(X \cup Y)$ Refers to the support of the itemset X. Is based on the calculation confidence, it is possible to identify strong associations between nutrients, such as certain high-protein foods that are often found to be present with low-fat nutrients, and corresponding association rules can be generated for nutrition recommendations.

After the rules are generated, the associated rules are filtered and refined. Lift is a key indicator of the strength of association rules, which measures the actual relevance of a combination of nutritional recommendations. For this, see Eq. (3).

$$\mathrm{Lift}(X \Rightarrow Y) = \frac{\mathrm{Confidence}(X \Rightarrow Y)}{\mathrm{Support}(Y)} \tag{3}$$

In this formula, $\mathrm{Lift}(X \Rightarrow Y)$ refers to the degree of lift, which represents X Y is the actual correlation between and . $\mathrm{Confidence}(X \Rightarrow Y)$ Refers to the confidence level of the rule. $\mathrm{Support}(Y)$ Refers to the degree of support of item (Y), which is the proportion of nutrients in a food Y. If the lift is greater than 1, there is a strong positive correlation between the two nutrients and can be used for nutritional recommendations. For example, if the system finds that a high-protein food is often accompanied by a low-fat ingredient and has a high degree of lifting, it can consider this combination as part of the recommendation.

3.3 Further Improvement of The Computer Algorithm for Nutritional Recommendation

At this stage, the system generates and optimizes association rules based on frequent scans of nutrient data. Specifically, it is necessary to optimize the support, confidence, and promotion thresholds of rules to ensure that the rules generated by the system have high relevance and reliability. Training on multiple food samples allows the system to find high-frequency and high-confidence nutrient combinations to improve the accuracy of recommendations. For example, the system will generate personalized nutrition recommendations based on the user's dietary history, recommending high-fiber foods to supplement the user's daily missing nutrients.

In order to improve the efficiency and accuracy of the mechanism, the generated association rules should be pruned in the optimization stage. Rule pruning is based on setting minimum confidence and lift thresholds to remove redundant, meaningless rules. For example, some rules have a higher confidence level of less than 1, indicating that the nutrient content of these rules is not strongly correlated. For this, see Eq. (4).

$$\mathrm{Prune}(\mathrm{X} \Rightarrow \mathrm{Y}) = \{ \mathit{1} \quad \mathit{if}\, \mathrm{Confidence}(\mathrm{X} \Rightarrow \mathrm{Y}) \geq \tau \backslash \mathit{0} \quad \mathit{otherwise} \tag{4}$$

In this formula, the τ is pruning threshold is the minimum confidence level that is set. Based on pruning, it can reduce useless association rules and improve the computational efficiency of the nutrition recommendation mechanism. For example, the system can delete food combinations with low confidence and weak relevance, and retain rules that are beneficial to the user's health.

Rule merging is another important step in improving the mechanism, based on the expansion and merging of similar rules, the system can generate more flexible and diverse nutrition recommendations. For example, two similar combinations of nutrients can be combined into a new, more extensive recommendation rule, allowing users to have a more diverse nutritional choice. See Eq. (5) for this.

$$\mathrm{Combine}(\mathrm{X}_{\mathit{1}} \Rightarrow \mathrm{Y}, \mathrm{X}_{\mathit{2}} \Rightarrow \mathrm{Y}) = \mathrm{X}_{\mathit{1}} \cup \mathrm{X}_{\mathit{2}} \Rightarrow \mathrm{Y} \tag{5}$$

In this formula, X_{1}, X_{2} refers to a combination of different nutrient ingredients that can be combined to generate a new rule. Based on the consolidation of rules, the system will increase the flexibility of recommendations and provide comprehensive nutritional recommendations based on the combination of nutrients in different foods.

In the process of improving the mechanism, it is also necessary to evaluate the mechanism so that the generated association rules and recommendation results can meet the expected accuracy and user satisfaction. Commonly used evaluation metrics are accuracy, recall, and F1 score. See Eq. (6) for this.

$$\mathrm{F}\mathit{1} = \mathit{2} \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{1}$$

In this formula, $\mathrm{Precision}$ refers to the precision rate, which indicates the correct proportion of the recommended nutrient content. Recall refers to the recall rate, which is the proportion of the nutrient that the system correctly recommends in the user's actual needs.

Based on the evaluation of the accuracy and recommendation effect of the system, the parameters of the mechanism can be further optimized, and the overall performance of the system can be improved based on this. For example, if the system finds that certain recommended rules have low F1 scores, they will need to be readjusted.

3.4 Integration of the Various Components of the Nutrition Recommendation System

In this step, it is necessary to combine the various components of the nutrition recommendation system to ensure the smooth flow of data for food nutrition content analysis and achieve accurate personalized recommendations. To this end, the data acquisition component will obtain the user's dietary data and food nutrition content in real time from external databases and sensors, and these data will be comprehensively processed by the data preprocessing component to become data that is more in line with the system requirements. The processed data is transferred to the Association Rule Mining widget, which is tasked with analyzing the correlation of nutrients in food using the Apriori algorithm and generating frequent itemsets and association rules that meet the health needs of the user. These rules will be passed to the recommendation engine artifact to provide users with personalized nutrition recommendations. After that, the user feedback component will play an effective role, which will collect feedback data such as user satisfaction with the recommended food and the actual effect, and return all this information to the association rule mining model, and then realize the update of the rules and the optimization of one set. Then, the system management component will coordinate the operation of each component in a unified manner, and monitor the performance indicators of the system, such as recommendation accuracy, response speed and user satisfaction, which can ensure that the nutrition recommendation system continues to adapt to the needs of users. Based on this, the entire nutrition recommendation system can adjust the recommendation content in real time, and give more accurate and personalized nutritional analysis and recommendations.

4 RESULTS AND DISCUSSIONG

4.1 Background of the Case

In this application case, this paper uses a food nutrition analysis and nutrition recommendation system based on the Apriori algorithm to accurately analyze the nutritional needs of different user groups, such as athletes, diabetic patients, the elderly, and ordinary adults, to achieve personalized recommendations. According to their different nutritional needs, the system analyzes the most suitable combination from the nutrient content of the food and generates corresponding dietary recommendations. These combinations generally contain a variety of nutrients, such as proteins, fats, carbohydrates, etc., covering 4 types of foods with high nutrient content. For example, chicken breast contains 31.0g of protein, 3.6g of fat, etc.

Table 1: Food nutrient composition data

Name of the food	Protein (g)	Fat (g)	Carbohydrates (g)
Chicken Breast	31.0	3.6	0
Cauliflower	2.8	0.4	6
Brown Rice	3.5	1.0	22
Avocado	2.0	15.0	9

Table I shows the nutritional content data of the foods analyzed by the recommendation system, such as chicken breast is rich in protein, avocado is more fat, and brown rice is higher in carbohydrates, which provide the basis for the system's nutritional recommendations. The process of recommending nutritional components is shown in Figure 1.

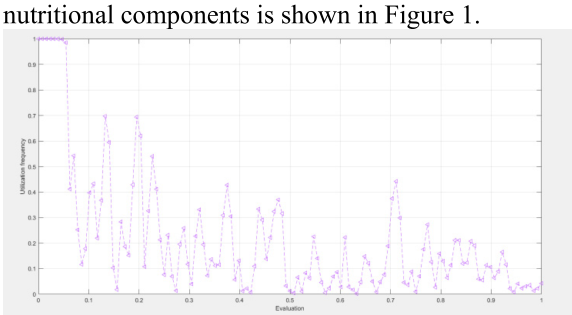

Figure 1: The process of recommending nutritional components.

4.2 The Recommended Effect of Nutritional Components

Table 2: Types of users and nutritional needs

User type	Protein requirement (g)	Carbohydrate requirement (g)	Fat requirement (g)
Jock	150	300	70
Diabetic	60	150	60
Senior Citizen	50	200	65
Ordinary Adults	70	250	75

Table 2 shows the daily nutritional requirements for different user types, such as athletes who need more protein and people with diabetes who need to limit carbohydrate intake. Based on these needs, the system generates personalized dietary recommendations， The distribution of nutrients is shown in Figure 2.

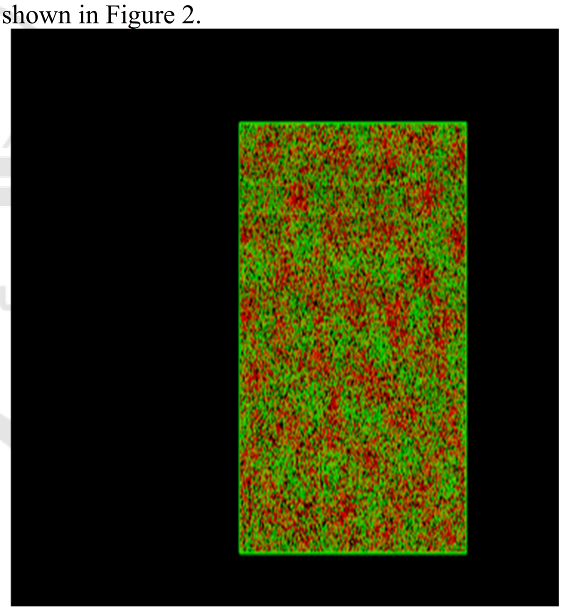

Figure 2: The distribution process of nutritional components.

The nutritional analysis can be integrated with computers to better recommend ingredients.

4.3 The Overall Effectiveness of the Nutrient Recommendation System

A comprehensive analysis of the data in the above three tables shows that the system can be significantly applied to different user groups. Specifically, high-protein foods, such as chicken breast, are commonly used in athletes' dietary recommendations, with a 90% accuracy rate for systematically recommended protein intake. In addition, the system recommended a high-fiber, low-carbohydrate food combination for diabetic patients, as shown in Table 3.

Table 3: Association Rule Mining Results

Nutritional Composition Combination	Support	Confidence	Lift
High in protein, low in fat	0.52	0.80	1.25
High in fiber, low in carbs	0.43	0.75	1.30
High protein, high fiber	0.48	0.78	1.35
High in vitamin C	0.35	0.60	1.18

Table 3 shows that the nutritional recommendation system designed in this design has a high degree of support and confidence based on the combination of nutrients generated by association rule mining, such as the combination of high protein and low fat, so as to provide practical and efficient nutritional recommendations for athletes and weight control users with a support level of 0.43 and a confidence level of 0.75 to ensure effective blood glucose control. Moreover, dietary recommendations for the elderly and ordinary adults also show the effectiveness of the system, The analysis of nutritional components is shown in Figure 3.

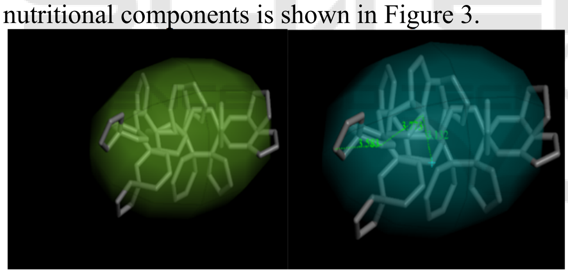

Figure 3: Analysis of nutritional components

From Figure 3, it can be seen that in the process of recommending nutritional components, the nutritional components are relatively reasonable and can meet the actual needs. The fat intake is systematically optimized to ensure that the daily fat intake is controlled within a healthy range. User feedback showed that the system-recommended food combinations were effective in improving the balance of nutrient intake, with 80% of users achieving significant improvements in weight control, blood sugar regulation, and overall health. Overall, the nutrition recommendation system is based on an in-depth analysis of the nutritional content of food to provide accurate and personalized nutrition recommendations for different user groups. Its powerful association rule mining and high-support and confidence combination recommendation can finally achieve the user's health goals, the final recommended nutritional composition is shown in Figure 4.

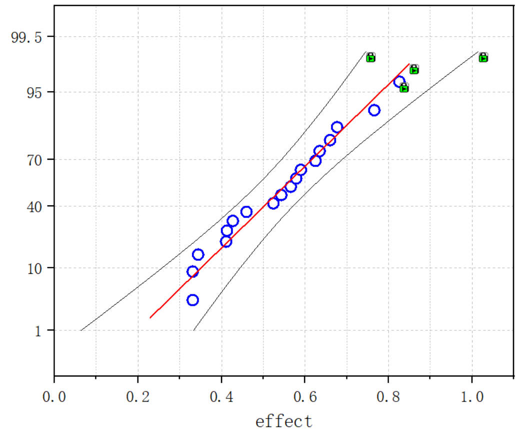

Figure 4: The final recommended nutritional content.

5 CONCLUSIONS

This paper verifies the efficient application of food nutrient analysis and computer algorithm in nutrition recommendation system. Based on the Apriori algorithm, the system can quickly and accurately analyze complex nutrient combinations in food and provide precise dietary recommendations based on user needs. The results show that the algorithm performs well in processing large-scale nutrition data and meeting personalized health needs, and provides strong technical support for the realization of personalized nutrition management. Moreover, the system is flexible enough to dynamically adjust based on user health feedback and continuously optimize recommendations. This shows that food nutrition analysis combined with computer algorithms can be widely used in the field of health management and improve the effect of personalized recommendation. The data content of this paper is still relatively limited, so it has certain limitations and needs to be further studied in the future.

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