A Personalized Restaurant Recommendation System Using ML-TOPSIS Approach

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Abstract. Recommendation systems represent complex algorithms that direct the user to interesting resources within the vast data space available on the Internet, taking into account his personal information, preferences, etc. Machine learning and multi-criteria methods have brought about significant development in recommendation systems, providing personalized and accurate solutions for recommending products or services, etc. However, the problem that machine learning models face is that they tend to lack robustness and accuracy if they lack features that help personalize recommendations. In this paper, we address this problem by proposing a new system known as ML-TOPSIS (Machine Learning and Preference Ranking Technique by Similarity to Ideal Solution) for personalized restaurant recommendations based on health, location, and ratings. The primary goal of this system is to develop an application that attempts to provide food from restaurants that matches a person's health status using the multi-criteria TOPSIS method, as well as their geographic location and similar ratings using machine learning algorithms based on collaborative filtering. By considering the nutritional requirements of individuals, especially for individuals suffering from obesity and diabetes. The results of the proposed system show that it helps users find restaurants according to their needs and aspirations to provide better suggestions.

Keywords: Recommender System · Machine Learning · Food and Restaurant Recommendation · locations, Nutrition, multi-criteria methods, machine learning.

1 Introduction

Recommender systems are vital tools for enhancing user experiences by offering personalized and relevant information. These intelligent tools employ sophisticated algorithms and techniques to analyze user preferences, historical behavior, and contextual data, with the goal of providing personalized suggestions and recommendations. Previous studies have demonstrated the high effectiveness of recommendation systems in efficiently enhancing users discover relevant and valuable information. These systems analyze users data and preferences in order

C. A. Kerrache et al. (eds.), *Proceedings of the International Conference on Emerging Intelligent Systems for Sustainable Development (ICEIS 2024)*, Advances in Intelligent Systems Research 184,
https://doi.org/10.2991/978-94-6463-496-9_21

to match users with suitable products, services, or content, leading to increased customer satisfaction and engagement [1]. This article introduces a hybrid recommendation system that enhances food and restaurant recommendations by providing users with personalized suggestions based on their physique profile and preferences. In the first stage the system use various decision mechanisms, including the topsis algorithm, which is defined as the technique of ranking user-specific attributes by similarity to target, is a multi-criteria decision analysis method. In which a group of alternatives is compared based on an initially defined criterion. They are used in many areas, especially commercial ones, to make decisions about products that have several characteristics, that is, to make an analytical decision based on the data collected [3]. In order to create a user profile that takes into account their nutritional needs for protein, carbohydrates, and calories.In addition, in the filtering stage we utilized machine-learning algorithms such as Singular Value Decomposition (SVD), Non-negative Matrix Factorization (NMF), and SlopeOne to obtain appropriate recommendations. This recommendation system relies on user's ratings . Additionally, it leverages the user's Geo-localization information to generate recommendation results. Machine learning algorithms are employed to implement these recommendations. In the case study, we used Restaurants dataset to recommend a restaurant that matches the user's location. The results demonstrate the effectiveness of the proposed system in suggesting personalized and suitable restaurants for each users. To build our recommendation system, we created a user model that allows us to decide which features to include in the system. These characteristics are presented through three profiles: demographic profile, preference profile, and location profile. Following this modeling, we recommend restaurants according to the user's health status and location, which facilitates smart navigation in the city in order to find the closest restaurants in terms of distance, and according to the reviews of the people closest to him, which allows knowing the most similar and convenient restaurants with regard to these ratings. The results are then integrated into our system to improve suggestions based on the user profile.
In the rest of the paper, Section 2 presents into prior research on food and restaurant recommendation systems. Following this, Section 3 elucidates the proposed approach and architecture, outlining the constituent components and algorithms employed. In Section 4, the experimental outcomes, encompassing system implementation, dataset utilization, and results discussion, are expounded upon. Finally, Section 5 concludes the research and presents the future directions for work.

2 Related Works

In recent years, many recent studies have focused on suggesting innovative approaches to recommending appropriate foods and restaurants. Where they contributed to the development of the individual's life, luxurious and healthy, by improving the food choices of individuals.Our review categorizes related works into three sections: Machine Learning-Based Recommendation Systems (Section

2.1), Health-Aware Recommendation Systems (Section 2.2), Personalized Recommender Systems (Section 2.3).

2.1 Machine Learning-Based Recommendation Systems:

Kim et al. [7] presented a context-aware model for personalized item recommendations in healthcare services. By leveraging contextual information, such as health conditions and preferences, the model delivers tailored recommendations to users. In addition to enhance the effectiveness and relevance of item suggestions, improving the overall healthcare service experience for individuals.

sun et al. [11] proposed a restaurant recommendation system based on users' tasks, their friends' preferences, and commuting patterns, using matrix factorization to obtain a personalized restaurant recommendation for users. Moreover, they took the data from yelp.com, which covers the Manhattan area. They also collected a complete snapshot, including users' profile, user ratings, users' friends list, and restaurant profile, from Yelp. The total number of restaurants is 7115. In order to check out the performance of this model.

chen et al. [4] proposed a personal expert recommendation system for good nutrition. Which is based on inferring the relationship between nutrients and genes, by using a machine learning model called a deep neural network sush as a recommendation system with a genetic algorithm.

Kouahla et al.[8]presented a recommendation system based on leveraging sentiment analysis, user preferences, and ratings to enhance point-of-interest (POI) recommendations. By incorporating the LightGCN model, Yelp's data sets experiment validates the effectiveness of their approach, improving point-of-interest suggestions for users, closely aligned with their preferences and interests.

2.2 Health-Aware Recommendation Systems:

Trattner and Elsweiler [14] provided personalized recommendations that aligned with the user's nutritional needs, and promoted healthy eating habits. They explore approaches that integrate aspects of nutrition directly into the recommendation process. As this system is based on identifying the user's calorie requirements and comparing them with the calorie content of different foods or recipes.

Alian et al. [2] presented a personalized recommendation system that caters to the needs of American Indians in managing diabetes. It acknowledges the distinct challenges and cultural factors relevant to this population. By harnessing machine learning and individual health data, the system delivers customized dietary recommendations, enabling enhanced blood sugar regulation and overall health improvement.

Zhang et al. [17] proposed an intelligent system based on fuzzy inference that recommends food based on an individual's health status and personal activities. Where he recommends a diet plan and treatment mechanisms in real time. They developed a platform to conduct experiments to verify performance. The results showed the effort of the dietitian and also showed that the proposed method works effectively.

Wang et al.[15] developed a healthy food recommendation model called Market2Dish. People can use Market2Dish to discover personalized foods and maintain a healthy lifestyle by using market ingredients mapping to healthy dishes eaten at home. This system profiles the user's health by capturing health-related textual information from social networks.

2.3 Personalized Recommender Systems:

Yang et al. [16] presented Yum-Me, which is a personalized nutrient-based meal recommender system. Yum-Me utilizes individual nutrient requirements to generate personalized meal recommendations. By considering nutritional needs and preferences.

Rehman et al. [10] presented Diet-Right, which is an intelligent food recommendation system.it utilizes users' pathological reports and an ant colony algorithm to generate optimal food lists. By considering user preferences, health conditions, and nutritional requirements.

Trang Tran et al. [13]provided a comprehensive look at healthy food recommendation systems, and explore their role in suggesting nutritious food choices. Which covers different filters, including content-based, collaborative filtering, and mixed methods.

Rachitha et al. [9] presented a personalized food recommendation system for people with diabetes, optimizing glycemic control, nutritional balance, and individual preferences. By taking advantage of advanced technologies, using MWSMO, which is a multi-purpose advanced algorithm for optimizing whale slime molds integrated with GAN model.

Fakhri et al.[5] built a recommendation system that can recommend the restaurant in the Bandung area. In addition to relying on restaurant reviews from other users. They used a user-based hybrid filtering method to personally recommend a restaurant. Ln addition, applied two similarities, that is, user rating similarity and user attribute similarity, to find the proximity between users. They used a survey of users who gave a rating of the restaurant they visited as a data set.

Tabassum et al. [12] presented an intelligent nutrition diet recommender system specifically designed for diabetic patients. This approach is based on fuzzy logic to determine individual dietary requirements at the micro and macro nutrient levels considering factors such as blood sugar control, nutritional balance, and individual preferences.

The presented related works advancements in recommendation systems tailored to diverse user needs, especially focusing on health and dietary considerations. Trattner and Elsweiler integrate nutritional aspects into recommendations, promoting healthy eating habits by aligning with users' calorie requirements. Alian et al. address the specific needs of American Indians in managing diabetes with customized dietary recommendations. Zhang et al. propose an intelligent system offering real-time diet plans based on health status and activities, while

Wang et al. develop Market2Dish for personalized healthy food recommendations. In the domain of hybrid recommendation systems, Yang et al. introduce Yum-Me for personalized nutrient-based meal recommendations, and Rehman et al. present Diet-Right, considering user preferences, health conditions, and nutritional requirements. Trang Tran et al. provide a comprehensive overview of healthy food recommendation systems, while Rachitha et al. optimize glycemic control and nutritional balance for people with diabetes. Fakhri et al. focus on restaurant recommendations using hybrid filtering methods, and Tabassum et al. offer an intelligent diet recommender for diabetic patients. Together, these works contribute to enhancing user well-being through personalized recommendation systems.

ML-TOPSIS recommender system for personalized restaurant recommendations, leveraging Machine Learning and TOPSIS methodology. ML-TOPSIS integrates health, location, and ratings to match users with suitable food options, prioritizing nutritional needs, particularly for those with obesity and diabetes. Its goal is to provide tailored restaurant suggestions based on individual health status and preferences.

3 The proposed Approach

In our proposed system, we takes into account user profiles, including the user's specific nutritional needs, ratings restaurants and current location, to generate personalized recommendations aligned with the user's well-being. The system uses advanced recommendation mechanisms, specifically machine learning algorithms, to evaluate and rank restaurant options based on factors such as user ratings and other relevant criteria. This approach aims at recommending list of food and restaurant based on the user's specific nutritional needs, especially for people with diabetes and obesity. The process consists of two main steps: user profiling and filtering. In the build user profiling stage, various personal, physical and health data are collected, such as age, height, weight, diabetes or not. These details are used to calculate key metrics such as body mass index (BMI), BMI category, basal metabolic rate (BMR), total daily energy expenditure (TDEE), and daily value calories [6]. These calculations provide insight into the user's body composition, energy requirements, and daily caloric intake, in which the multi-criteria TOPSIS method is used. The user's nutritional needs, order food and restaurant choices. The TOPSIS method takes into account multiple parameters such as fat, carbohydrate, protein and calories, i.e. the nutritional requirements of the user. The approach calculates a TOPSIS score and then ranks the available food choices. The second stage involves the filtering process, in which recommendations are tailored to the user's Ratings and location. After the Topsis method reduces the food that an individual can eat, the system selects the restaurants that have this food, taking into account the reviews of users who are similar to it. This entails offering restaurant recommendations that align with the user's ratings, leveraging machine learning algorithms such as Singular Value Decomposition (SVD), Non-negative Matrix Factorization (NMF), and

Slope One. These algorithms analyze the user's past ratings and behaviors to generate personalized recommendations that are geographically relevant, thus enhancing the overall user experience. Then, a web site is developed to evaluate this proposed system. In the case study, we used dataset restaurant to recommend a restaurant that matches the user's context. The results demonstrate the effectiveness of the proposed system in suggesting personalized and suitable restaurants for each users. Figure 1 presents the proposed system architecture.

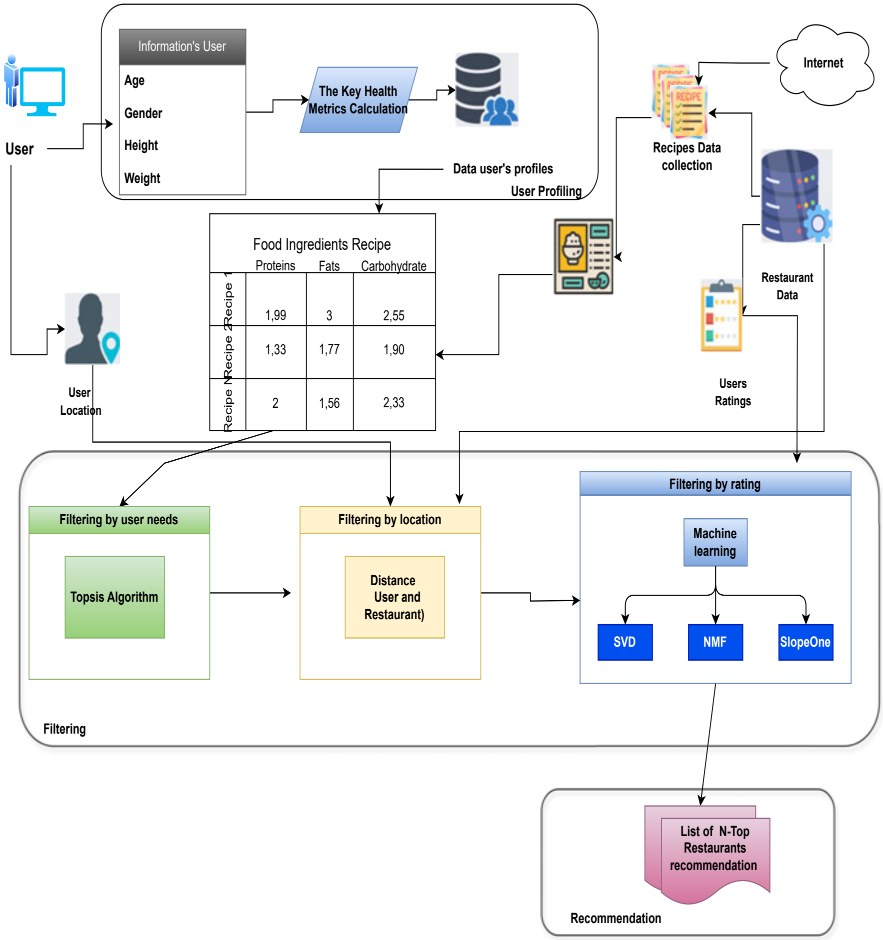

Fig. 1. System architecture

3.1 User Profiling

During the registration process, users provide essential information such as age, gender, weight, and height. This data is then used to calculate key metrics that form the basis of the user profile. Here's a detailed breakdown of the process from National Library of Medicine - National Institutes of Health:

- **Body Mass Index (BMI)**:
  $\text{BMI} = \frac{\text{weight (kg)}}{\text{height (m)}^2}$
- **Basal Metabolic Rate (BMR)**:
  - For Men: $\text{BMR} = 88.362 + (13.397 \times \text{weight (kg)}) + (4.799 \times \text{height (cm)}) - (5.677 \times \text{age})$
  - For Women: $\text{BMR} = 447.593 + (9.247 \times \text{weight (kg)}) + (3.098 \times \text{height (cm)}) - (4.330 \times \text{age})$
- BMR represents the number of calories the body needs at rest to maintain vital functions.
- **Total Daily Energy Expenditure (TDEE)**:
  $\text{TDEE} = \text{BMR} \times \text{Activity Level}$
- Activity levels range from sedentary to very active, with corresponding multipliers. TDEE indicates the total calories needed per day based on the user's activity level.

This data forms the initial user profile, addressing the 'cold start' problem by enabling tailored recommendations from the outset. By considering personal, physical, and nutritional factors, the user profile serves as the foundation for personalized recommendations, aiming to offer a concise yet precise description of the user.

3.2 Filtering

The filtering process composed of three main phases. Firstly, the TOPSIS method evaluates food options based on nutritional parameters, providing personalized recommendations aligned with the user's dietary needs (Point 1 in the following). Secondly, location-based filtering determines the proximity of restaurants to the user, enhancing practicality in dining choices (Point 2, below) . Finally, collaborative filtering with machine learning algorithms refines recommendations by analyzing user ratings (Point 3, below), ensuring precision and relevance in suggestion generation.

Filtering by User Needs based on TOPSIS Method In the filtering phase, we employ calculations to gain insight into the user's body composition, energy requirements, and daily caloric intake. This is achieved through the utilization of the multi-criteria Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method. The TOPSIS method takes into account various parameters such as fat, carbohydrate, protein, and calories, which are essential components in assessing the nutritional needs of the user for ordering food and restaurant choices. By evaluating these factors comprehensively, TOPSIS calculates a score for each food option, considering its nutritional composition in relation to the user's requirements. This process ensures a thorough assessment of the nutritional compatibility and suitability of each food option for the user, allowing for personalized recommendations that align closely with their dietary preferences and health goals.

In "FOOD AND RESTAURANT" the recommended items are the foods available on the restaurant menus from restaurants dataset. They are classified into different categories based on their nutritional components, in order to recommend them to users according to their daily nutritional needs. The categories used in this recommendation system are listed in Table 1.

Table 1. Food categories in " FOOD and RESTAURANT"

Number	Category of Food
1	Beverages
2	Entrees
3	Pizza
4	Sandwiches
5	Burgers
6	Salads
7	Appetizers and Sides
8	Baked Goods
9	Desserts
10	Soup
11	Toppings and Ingredients
12	Fried Potatoes

Filtering by Location In addition to assessing nutritional aspects, the system calculates the distance between the user's location and various restaurants. This distance calculation is crucial for determining the proximity of restaurants to the user, thereby influencing the recommendation process. By incorporating location-based information, the system can offer suggestions that are geographically convenient for the user, enhancing the overall user experience and ensuring practicality in their dining choices.

Filtering by Rating based on machine learning techniques In this filtering process, ML-TOPSIS employs collaborative filtering to enhance user experience. Initially, it computes the similarity between user location and potential restaurants, integrating factors like distance and proximity. Subsequently, machine learning algorithms such as Singular Value Decomposition (SVD), Nonnegative Matrix Factorization (NMF), and Slope One refine recommendations based on the user's historical ratings. By analyzing past ratings, these algorithms generate personalized suggestions, ensuring precision and relevance. Collaborative filtering aims to predict user ratings by leveraging ratings from other users. Matrix decomposition, a common technique in collaborative filtering, distinguishes items and users through factor vectors derived from item classification patterns. This involves decomposing the user and restaurant classification matrix into two parts. For example, ML-TOPSIS applies three matrix factorization-based algorithms—NMF, SVD, and Slope One—tailored to accommodate implicit feedback, such as information from other users' rating histories. This approach enhances recommendation accuracy by considering both explicit and implicit user preferences, resulting in refined and personalized restaurant suggestions. "FOOD and RESTAURANT" recommend food based on the user's nutritional needs According to the food category that the user prefers.

3.3 Recommendation

In "Food and Restaurants", restaurants are recommended based on the food available and location, in addition to user ratings through which the user's rating is predicted and converted into a real rating. We were able to recommend based on collaborative filtering technology.

Algorithm 1 presents the main steps of Restaurant Recommendation System.

Algorithm 1 Restaurant Recommendation Algorithm

1: Calculate Normalized Matrix and Weighted Normalize Matrix
2: Determine the impact based on the value of *diabetic*:
3: **if** *diabetic* == 'yes' **then**
4:     $impact \leftarrow ['-','+','+']$
5: **else**
6:     $impact \leftarrow ['+','+','+']$
7: **end if**
8: Calculate positive and negative values
9: Calculate Topsis Score and Ranking
10: Sort the list of food and select the top 10 rows
11: Predict user ratings with machine learning algorithms using Singular Value Decomposition (SVD), Non-negative Matrix Factorization (NMF), and Slope One
12: Split the data into training and testing sets to evaluate the performance of the algorithms
13: Train each selected algorithm (SVD, NMF, Slope One) on the training data
14: Aggregate predicted ratings to generate a ranked list of recommended restaurants for each user
15: Evaluate the trained models using metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE)
16: Return the *top_list_10* list of restaurants

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4 Experimental Results

To handle the computational requirements for modeling large datasets, we used Google Colab to take advantage of shared resources and ensure consistent performance. All algorithms have been implemented in Python using popular libraries such as NumPy and pandas. PyCharm was used as an integrated development environment (IDE) for managing and deploying packages, and additional libraries including arbitrary math and os.path were used. A website is created using the Laravel framework and JavaScript.
To develop a restaurant recommendation system, the user's favorite food category and user needs are taken into accoun. which provides various datasets for academic, non-commercial purposes. These datasets include information such as user reviews, business details, ratings, and more.

4.1 Used Dataset

The restaurant dataset 'Zomato' used for recommendations includes 19 features and 9,543 rows detailing restaurant attributes and menus. It encompasses crucial data points like Restaurant ID, Name, Country Code, City, Address, Locality, Latitude, Cuisines, Average Cost for Two, Reservation Availability, Online Delivery, Delivery Options, Price Range, Overall Rating, Rating Color, Rating Text, and Votes, offering comprehensive insights for effective recommendation systems

4.2 Developed System

The developed system is a website which offer an interface specifically for individuals managing diabetes and obesity, facilitating their dining experiences by offering tailored food and restaurant suggestions aligned with their health requirements. It goes beyond computing personalized health metrics to accurately predict user ratings. In addition, it guarantees that users receive recommendations precisely tailored to their nutritional needs and health profiles, elevating their dining satisfaction and overall well-being. By ensuring personalized recommendations aligned with individual health requirements, the system enhances the user experience, promoting healthier dining choices and lifestyle habits. This tailored approach fosters a sense of satisfaction and well-being, empowering users to make informed decisions about their dining options.
The operational steps of the website are:

1. Users log in using their email and password.
2. After log in process, users are required to enter personal data such as age, gender, and health status.
3. The system calculates basic health metrics including body mass index (BMI), BMI category, basal metabolic rate (BMR), total daily energy expenditure (TDEE), and daily value calories.
4. Get his location from the GPS device.

5. Taking advantage of the data collected, our system creates personalized recommendations for suitable restaurants that match the user's needs, location and rating.
6. Recommendations take into account the global users profile.

Figure 2 shows the user registration interface of the web application.

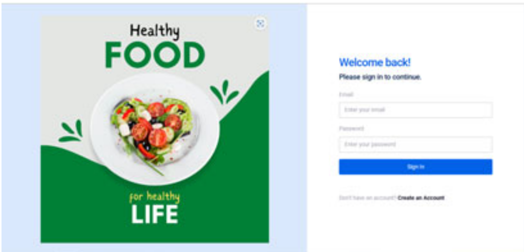

Fig. 2. System interface.

Figure 3 displays the users input form in which they can introduce their personal information.

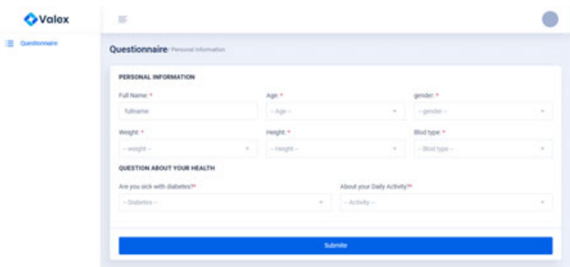

Fig. 3. Users input form.

Figure 4 illustrates the characteristics calculation of various health-related parameters based on the user's input.

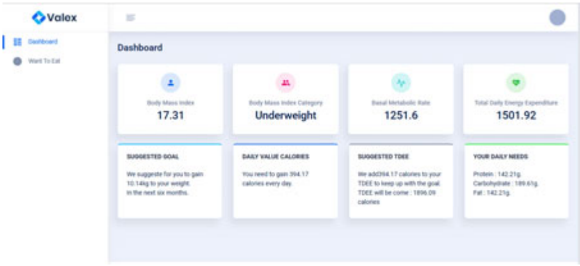

Fig. 4. Characteristics calculation of various health-related parameters based on the users input.

The results of recommending the top 10 food and restaurants are presented in Figure 5.

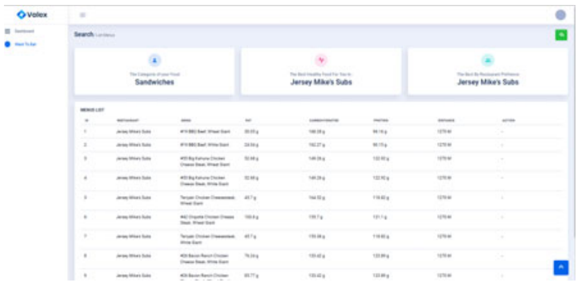

Fig. 5. Recommendation results of the Top 10 Food and Restaurants.

This web application provides users with a complete solution to improve their health and find suitable food and restaurant options.

4.3 Results Discussion

To evaluate the performance of the proposed approach, we used the TOPSIS method. At the beginning we calculated the similarity scores between the recommended dishes and the nutritional needs of the user. The results showed that our algorithm showed an average similarity score of 0.87 for the top 10 recommended dishes. This indicates that our algorithm is effective in providing personalized food recommendations based on the user's dietary needs and health status. And we used error comparison and analysis tests using the two measures RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) for the evaluation of the final results of the prediction. These metrics provide quantitative measures of the differences between predicted ($\hat{y}_i$) and actual (y_i) values, offering insights into the performance of our recommendation system.

RMSE is calculated as the square root of the average of squared differences between predicted and actual values:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

MAE is calculated as the average of absolute differences between predicted and actual values:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Table 2 illustrates the result of our system.

Table 2. Evaluation Results.

Algorithms	**RMSE**	**MAE**
MLT-SVD	0.7048	0.5936
MLT-NMF	0.7429	0.5838
MLT-SlopOne	1.4150	1.2084

The results produced by the three algorithms relatively close, as shown in the table 2. Compared to other methods, the SVD algorithm gives the best results, with RMSE = 0.7048, MAE = 0.5936. To this end, we create a learning model based on this method that construct and provide RMSE and MAE values for the recommendation system. Figure 6depicts the performance comparison of recommendation algorithms (SVD, NMF, Slope One) based on RMSE and MAE metrics.

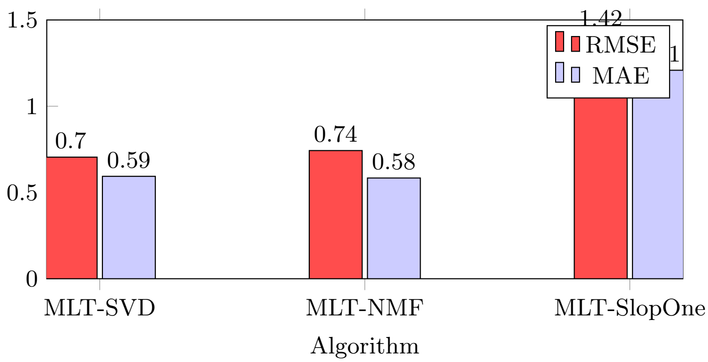

Fig. 6. Performance Comparison of Recommendation Algorithms

While our proposed approach demonstrates effectiveness in providing personalized food recommendations based on user-specific dietary needs and health status, several potential limitations should be considered, the accuracy and relevance of recommendations heavily depend on the availability and quality of user-provided data (e.g., age, weight, health conditions). Incomplete or inaccurate data may lead to less precise recommendations. In addition, Scaling the recommendation system to handle a large number of users and diverse dietary preferences can pose challenges. Processing large volumes of data in real-time to provide timely recommendations requires efficient algorithm design and computational resources. Moreover, Machine learning algorithms used in recommendation systems may inadvertently introduce biases, affecting the fairness and inclusivity of recommendations. Bias can arise from skewed training data or inherent algorithmic design choices.

5 Conclusion and Future Works

This paper presents a personalized approach to food and restaurant recommendations for individuals based on their health status, especially those with diabetes and obesity. We offer an innovative recommendation system designed to enhance the user experience by looking at individual profiles, calculating health metrics, and applying the TOPSIS method to generate personalized recommendations based on the user's current location and predictive rating using machine learning algorithms. This approach takes into account the user's diabetes status and optimal nutrient intake. It provides a user-friendly interface and requires users to enter relevant personal details. The system calculates the nutritional content. Overall, the program aims to support individuals in making healthy food choices when dining out. The system skillfully evaluates and prioritizes restaurant options based on multi-criteria, including user ratings and other relevant factors.Our approach effectively personalizes food recommendations but faces challenges: data accuracy influences precision, scaling for diverse users strains real-time processing, and algorithmic biases may affect recommendation fairness. As a future work, we want to develop a system which will consider individual dietary requirements, health goals, and medical guidelines, taking into account factors such as blood sugar control, portion sizes, nutrient composition, and overall calorie intake. Also, we plan to use machine learning algorithms to offer a real-time data analysis in order to provide provide an intelligent recommendations for diabetic and obese patients guiding them towards healthier food choices. we aim to foster a more holistic approach to personalized recommendation systems that prioritize accuracy, scalability, fairness, and user trust. This, in turn, can significantly impact user well-being by facilitating informed dietary choices and promoting healthier lifestyles.

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