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A Multi-Criteria Food and Restaurant Recommendation System

Maroua Chemlal
(LabSTIC Laboratory, Department of Computer Science, 8 Mai 1945 University. P.O. Box 401, Guelma 24000, Algeria
https://orcid.org/0009-0002-4156-4016, chemlal.maroua@univ-guelma.dz)

Amina Zedadra
(LabSTIC Laboratory, Department of Computer Science, 8 Mai 1945 University. P.O. Box 401, Guelma 24000, Algeria
https://orcid.org/0000-0002-5915-9986, zedadra.amina@univ-guelma.dz)

Ouarda Zedadra
(LabSTIC Laboratory, Department of Computer Science, 8 Mai 1945 University. P.O. Box 401, Guelma 24000, Algeria
https://orcid.org/0000-0002-7991-0677, zedadra.ouarda@univ-guelma.dz)

Antonio Guerrieri
(CNR - National Research Council of Italy, Institute for High Performance Computing and Networking (ICAR), Via P. Bucci 7-11C - 87036 Rende(CS), Italy
https://orcid.org/0000-0003-1469-9484, antonio.guerrieri@icar.cnr.it)

Med Nadjib Kouahla
(LabSTIC Laboratory, Department of Computer Science, 8 Mai 1945 University. P.O. Box 401, Guelma 24000, Algeria
https://orcid.org/0000-0003-1240-9156, kouahla.nadjib@univ-guelma.dz)

Abstract: Recommendation systems have been developed to address the immense volume of information accessible on the Internet. These systems employ filtering methodologies and customize their recommendations by drawing insights from user profiles, ultimately enhancing the relevance and utility of their suggestions. In this paper, we present our system called Smart Food and Restaurant Advisor based on nutritional needs and user profiling (SFRA); a multi-criteria food and restaurant recommendation system designed to prioritize personalized and health-conscious selections. This system uses user profiling to offer customized recommendations that cater to individual preferences, requirements, and geographic locations. Our primary objective is to enhance users' decision-making processes by promoting healthier and more refined lifestyle choices. The results of the proposed system demonstrate that it is well-suited for promoting a healthier lifestyle while offering comprehensive coverage of users' practices and preferences.

Keywords: Recommendation system, user profiling, Machine learning, Multi-criteria methods, Big data analytic, Food and restaurant recommendation, personalized recommendations
Categories: H.3.1, H.3.2, H.3.3, H.3.7, H.5.1
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1 Introduction

The proliferation of the Internet and the exponential growth of digital content have inundated users with an overwhelming volume of information to navigate. In response, recommendation systems have emerged as an indispensable technology, pivotal in guiding users toward highly relevant content that aligns with their unique preferences and interests. These systems significantly enhance the user experience and engagement on the internet by facilitating the discovery of new content, products, and services tailored to individual tastes and preferences. Beyond their role in content discovery, recommendation systems have found versatile applications across various domains, including tourism, transportation, e-commerce, healthcare, and dining, offering personalized recommendations to users in each context. In tourism, algorithms offer real-time personalized recommendations based on tourists' preferences and location. In transportation, automated parking systems promote road safety and provide data for local authorities. In news recommendations, social data from online communities improves accuracy and diversity. While, in nutrition, context-aware systems use sentiment analysis to extract food preferences from user comments. Health-aware recommendation systems employ collaborative filtering and content-based modeling to provide personalized, health-conscious food suggestions.

The escalating rates of obesity and associated health concerns underscore the urgency of solutions promoting healthier nutrition. Recommendation systems are actively tackling this challenge by delivering precise, individualized recommendations that cater to dietary requirements and preferences. These systems hold promise for enhancing user experiences and benefiting society across various domains. In this paper, we propose a recommendation system that takes into account user profiles, encompassing dietary needs, preferences, and locations, to generate personalized recommendations aligned with individual health objectives. The system employs advanced decision-making mechanisms, specifically the TOPSIS algorithm and Analytic Hierarchy Process (AHP), to assess and rank food and restaurant options based on factors like nutritional value, ingredients, and other pertinent criteria.

The rest of the paper is organized as follows: in Section 2 we present an overview and a comparison of related works on food recommendation systems and we give a brief description of the algorithms used in our filtering and recommendation system. In Section 3 we present the architecture, detailing the components of the proposed system and the used algorithms. In Section 4 we present the used datasets, experiments, results and discussions. Finally, in Section 5 concludes the research and outlines potential future directions.

2 Related Works and Background Algorithms

We present in this Section a summary of recent and relevant related works on food recommendation systems (Section 2.1). Then, we present a brief description of the algorithms used in our filtering and recommendation system (Section 2.2).

2.1 Related works

Food recommendation systems are unique because they take into consideration the individual's health, dietary preferences, and well-being. As a result, the recommended content is personalized, and must cater to a variety of individual needs and requirements. In this context, we reviewed papers related to food and restaurant recommendations. In particular, we subdivided the reviewed works into three Sections. In the first one, we considered food recommendation-related works; and in the second one, we considered healthy food recommendation-related works; and, in the last one, we considered restaurant recommendation systems. After that, we present a qualitative comparison of the reviewed related works (**Table 1**).

2.1.1 Food Recommendation Systems:

In this section we present several food recommendation systems.

Rostami et al. [Rostami et al., 2022] proposed a novel time-aware food recommender system based on deep learning and graph clustering that involves two phases: food content-based recommendation and user-based recommendation. In the first step, they used Graph clustering. While they used a deep-learning based approach to cluster both users and food items in the second step. Furthermore, the proposal takes into account users' similarities as well as foods' similarities based on their ingredients, while taking into consideration time factors and user's community aspects. The authors compared their model to the newest proposed food recommender system (Graph Convolutional Network (FGCN), Hierarchical Attention based Food Recommendation (HAFR) and Latent Dirichlet Allocation (LDA)) to evaluate their system. The experimental results indicated that the developed food recommender system achieved the best performance.

Agapito et al. [Agapito et al., 2016] developed a system called DIETOS (DIET Regulator System) that provides personalized nutritional recommendations to improve the quality of life and manage diet-related chronic diseases. The system creates a health profile using real-time questionnaires prepared by medical doctors and personalized to each user's health status and chronic diseases. The authors used a catalog of typical Calabrian foods compiled by nutritionists to create recommendations. Medical staff tested the system prototype, which shows its potential for managing and improving the nutritional intake of individuals with diet-related chronic diseases.

Huang et al. [Huang et al., 2017] described the process of building a recommendation system for grocery and gourmet foods using people's opinions from Amazon.com. The system predicts a user's likelihood of liking a food item by learning their taste and the product's features. The authors used several predictive models, including linear regression, baseline factor, bias SVD, and SVD++. The models were trained on various datasets, and their performance was evaluated using MSE. The results suggest that linear regression is suitable for inexperienced users, and the latent factor model, especially the SVD++ model, is most suitable for users who frequently rate products.

Khan et al.[Khan et al., 2019] proposed a personalized, health-aware recipe recommendation system using Ensemble Topic Modelling (EnsTM) based Feature Identification techniques for user-modeling and recipe recommendation. They implemented three different EnsTM based personalized FRS: a Food Feature-based Recommender (FFbR), a Weighted Food Feature-based Recommender (WFFbR), and a Food Feature-based Collaborative Filtering (FFbCF). To test their strategies, they developed a website and conducted a study with 48 users from different backgrounds. They used a smaller recipe-corpus of 92,539 recipes with valid images as the primary data-set, and extracted 288 features and their corresponding significance scores from a corpus of 230,876 recipes to reduce computational complexity. The results showed interesting associations between health groups and features. Overall, the proposed system has the potential to improve personalized recipe recommendations and promote healthier eating habits.

Pecune et al. [Pecune et al., 2020a] developed a system called Cora, which is a conversational system that recommends recipes based on user profiles. It aims to build rapport with users and deliver personalized recommendations. Additionally, the system investigates how conversational skills and interaction modes impact users' perception of the system and intention to cook recommended recipes. Using a conversational approach, Cora provides a more engaging and interactive experience for users.

Pecune et al. [Pecune et al., 2020b] presented a recommendation system that considers both user preferences and recipe healthiness. They collected 13,515 recipes from allrecipes.com using a web crawler and used collaborative filtering (CF) and user feedback to rank recipes based on preferences. Three algorithms (Alternating Least Squares (ALS), Bayesian Personalized Ranking (BPR) and Logistic Matrix Factorization (LMF)) were tested, and ALS was found to be the best-performing. The system identified two independent variables: the recommendation algorithm and whether the recipe card displays a healthiness tag. Results showed that the system's ability to combine healthiness with personalization depends on users' eating preferences. Overall, this system can help users make healthier food choices while still accommodating their taste preferences.

Ge et al. [Ge et al., 2015] presented a recommendation system that considered the user's preference and health requirements by including calorie balance. It was developed on the Android platform. The authors conducted a questionnaire about users' opinions on recipe recommendations. In the survey were involved 20 subjects from different countries such as Italy, Germany, France, China, USA, Spain and India. Their ages ranged from 22-50 years old, 65% of them male and 35% female. The obtained results show that means 95% of the surveyed users want to adapt their tastes in order to obtain healthy food recommendations. For this reason, they used an algorithm that extends matrix factorization by including additional parameters used for modeling the dependencies between assigned tags and ratings. Moreover, the user profile data is used to estimate the daily calories that the user needs, the rating of users, the preferences of users and feedback. After experimentation, application users commented that the quality of the recommendations is high and the system is easy to use.

Phanich et al. [Phanich et al., 2010] presented a Food Recommendation System (FRS) that focuses on providing proper substitutes for diabetic patients by utilizing food clustering analysis. The system employs Self-Organizing Map (SOM) and K-means clustering to cluster foods based on the similarity of eight essential nutrients for diabetic patients. The dataset is divided into Normal Food group (NF), Limited Food group (LF), and Avoidable Food group (AF) based on expert nutritionist opinions. The system's accuracy was evaluated using a questionnaire completed by invited nutritionists, and the results show that the FRS is accurate for users with a degree of 4 out of 5. Overall, the system shows potential for assisting diabetic patients in making healthier food choices.

Dhyani and Ojha. [Dhyani and Ojha, 2021] proposed a technique to recommend a dish to restaurant based on two factors such as their user's taste and location. Wherefore, Collaborative Filtering, Content-Based Filtering and Hybrid frameworks are used to recommend the dish. A hybrid recommendation model was created by using two approaches in a sequential order i.e., Content-Based Filtering and Collaborative Filtering. In Content-based approach, they used the cosine similarities function to find the similar dish for the dishes that the user preferred. In the Collaborative approach, they used the Pearson correlation function by visualizing the old rating history of the user and finding the most similar dish. In order to evaluate the performance of the method that is based on user Satisfaction, 20 users were invited to participate by using the application for 2 days. The top 10 dishes were recommended by using a hybrid approach and they were asked to rate their satisfaction from 0 to 5 (feedback screen). The result shows that 70% of the user has given a rating of 3 out of 5 which is positive feedback.

Sreenivasa et al.[Sreenivasa et al., 2022] present a model for the meal plan according to the individual's health and preference with filtered recipes and proper scheduling as per his/her daily requirements. The proposed approach uses technologies: ReactJS, MongoDB, NodeJS, ExpressJS (MERN) and is based on users' profiles, which consists of the user's personal information including their height, age, gender to calculate BMI and BMR. Furthermore, they established a web application where a customer delivered the products. Wherefore, they used database that contains information about recommended diet plans from certified nutritionists and health advisers. Also, the system monitor the nutritional recommendation, the health and discipline of the users.

Metwally et al. [Metwally et al., 2021] proposed a method to identify food preferences from food logs that use embeddings. The system uses an available dataset, the U.S. Department of Agriculture's Food and Nutrient Database for Dietary Studies (FNDDS), and the Workflow of the food preference-learning algorithm. The main steps of the algorithm are: preprocessing food logs through an NLP module, generating embedding vectors for food logs and database entries by using k-Nearest Neighbors classification, computing vector similarities, and using these similarities to identify commonly eaten foods.

2.1.2 Healthy Food recommendation systems:

In this section we present some healthy food recommendation systems:

Iwendi et al. [Iwendi et al., 2020] proposed a framework focused on implementing both machine and deep learning algorithms like Logistic Regression, Naive Bayes, Recurrent Neural Networks (RNN), Multilayer Perceptron (MLP), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM). In order to integrate a wide-ranging nutritional theory with the IoT system to recommend a specific nutritional model of patient or user. They used health-based medical dataset and other features such as age, gender, weight, calories, etc. The medical dataset was collected by using the IoT and the cloud and consists of 30 patients' data with 13 features of different diseases and 1000 products, where each product has 8 features set. The authors tested 1000 products on different disease patients. In order to know which feature has more impact in the dataset they used random forest classifier. The result of this work proved that LSTM technique performs better than other with respect to forecasting accuracy, recall, precision, and F1 measures, with 97.74% accuracy.

Sowah et al. [Sowah et al., 2020] proposed a system for tracking the activity of diabetic patients. Moreover, the system handles the factors that affect the health of people with diabetes by combining multiple artificial intelligence algorithms. In the first step, they build a TensorFlow neural network model for food classification. In the second step, they used the K-Nearest Neighbor (KNN) algorithm to recommend meals, and they used cognitive sciences to build a diabetes question-and-answer chatbot. Moreover, they utilized user geolocation and generated PDFs of recorded blood sugar readings. Furthermore, the model-learned features of the images fed from local Ghanaian dishes with specific nutritional value and essence in managing diabetics and provided accurate image classification with given labels. The food recognition model evaluated with cross-entropy metrics that support validation using Neural networks with a backpropagation algorithm. The results show that the food recognition and classification model achieved over 95% accuracy levels for specific calorie intakes.

Ünal and Çilgin. [Ceyda and ÇILGIN, 2022] proposed a web-based expert system in the field of nutrition. The authors developed application consisting of two phases. The first phase is an inference engine a rule-based system using the Prolog, which includes rules created from various nutritional values for Turkish food habits, BMI (Body Mass Index) and the number of calories to take daily. While, the second phase is a Web-based interface used by dietitians rather than the use of patients to determine the nutrition program/meal planning, and for the patients in the processes of maintaining and monitoring it. Furthermore, the important features of the problem determined the information obtained through interviews with two different dietitian' experts. However, the inference engine offers the appropriate food combinations for the expert's use instantly via the backtracking method.

Nallarasan et al. [Nallarasan et al., 2020a] proposed a program that recommends suitable food for people. In order to reach this goal, they use and analyze three attributes of food nutrition details, which are a person's physical details to calculate the Body Mass Index (BMI) and time (Breakfast, Lunch or Dinner), and tracking the user's interests. In addition, the items recommended are defined into three categories: Weight Loss, Weight Gain and Healthy category. Further, the authors used Machine Learning Algorithms K-Means Clustering for clustering the data, and Random Forest Classification to classify according to the categories listed. They used a dataset, which is a collection of various food items verified from various official food calorie websites. This latter contains 90 unique items with 16 attributes such as calories, fat etc.

Princy et al. [Princy et al., 2021] proposed a healthy diet for women, using recommendation system based on two methods, which are content-based filtering and collaborative filtering to overcome the chronic diseases related to them. Furthermore, this food recommendation system takes into consideration several features: users' tastes, eating habits, and nutritional requirements. Also, it provided alternatives of multiple choices of food to take nutrition foods. This food recommendation system helps to know the user about the healthy eating habits and to be aware of the healthy meals that they need to consume for their health.

Sambola et al. [Mckensy-Sambola et al., 2021] present a recommendation engine capable of identifying the different levels of obesity in users and providing dietary strategies to treat them. They proposed a knowledge-based diet recommendation system that infers the suitable diets given the user's data such as (height, weight, and BMI) and returns a set of recipes that adapted with to those diets' composition details. In addition, Semantic technologies are integrated in this work to provide a formal representation that enables accurately defining concepts such as food allergies, ingredients, recipes, and diets. The knowledge base and the underlying ontology schema were developed by adopting the Linked Data best practices (https://www.w3.org/TR/ld-bp/). To test this model the authors used a real set of individuals. Then, a panel of advisors evaluated each individual record and recommended the appropriate diets from those included in the ontology. In addition, the proposed system provides diet recommendations for each individual, which are compared with those proposed by the advisors, reaching a mean accuracy of 87%.

Alain Starke et al. [Trattner et al., 2021] proposed a novel metric called 'The Cholesterol Factor' to limit fat, based on nutritional guidelines from the Norwegian Directorate of Health to balance the accuracy and health of recipe recommendations through linear re-weighting in post-filtering. They assessed the accuracy of three recipe recommendation approaches: collaborative filtering (CF), content-based (CB), and hybrid. The authors evaluated these approaches offline. Moreover, they employed a dataset that comprised 1,031 unique recipes from the website Allrecipes.com, in which a CF-based

SVD method outperformed content-based and hybrid methods. Then, they used their Cholesterol Factor in the approach (CF; Matrix Factorization SVD) to post-filter the predicted recommendation set on both accuracy and health. Although, they found that increasing the healthiness of a recommended recipe set came at the cost of Precision and Recall metrics, only putting little weight (10-15%) on their Cholesterol Factor significantly improved the healthiness of a recommendation set with minimal accuracy losses.

Subramaniyaswamy et al. [Subramaniyaswamy et al., 2019] presented ProTrip, which is a health-centric tourism recommendation system based on hybrid filtering mechanisms along with intelligent recommendation models. It is based on an ontology-based framework used semantically manipulates the health and nutrition information and exploits a hybrid filtering mechanism. In order to improve the inquiry and to represent the recuperated data to be steady with the client's requirements, nutrition and health-oriented profile have been taken into consideration. Additionally, they have considered specific climatic conditions.

Chaturvedi et al. [Chaturvedi et al.,] proposed a novel system that estimates the nutritional ingredients of the food by analyzing the image of food items, that are used in the healthcare sector. For the accuracy of the result of nutritional components, the system employed different deep learning models. They used a dataset generated by using web scrapping for various categories of food items. The proposed system has been implemented as an Android application. By using a deep learning algorithm called CNN, the Concerned MASK R CNN algorithm is used on top of CNN. By masking the particular region of the photo, it extracts the information about the marked segment. In order to inform the user about a specific food, he/she takes a picture of this food and the APP will make an API call to the server and, after receiving the response from the server the app will provide information about the food. After training these networks the authors exported to models. These models feed with the test dataset therefore predicts the probability of how similar the photo matches with trained data.

Lo et al. [Lo et al., 2008] proposed a new Curative Food Service (CFS) recommendation system in the semantic web, which is the designed Situation-aware Curative Food Service Recommendation System (SCFSRS). The latter is a five-tier system composed of the Mobile Users (MUs), UDDI Registries (UDDIRs), CFSPs, Curative Food Services Server (CFSS), and a Database Server (DS). It combines the technical application of the SOA, OWL-S, and semantic web on the information system through the communication networks including the internet and 3G/GPRS/GSM mobile networks.

Toledo et al. [Toledo et al., 2019] proposed a general framework for daily meal plan recommendations that takes into account both nutritional and preference-aware information. It incorporates a MCDA approach for filtering out inappropriate foods and an optimization-based stage for generating a daily meal plan that satisfies the user's nutritional requirements while recommending highly preferred foods that haven't been consumed recently. The system also includes a pre-filtering phase that uses AHPSort to filter out foods unsuitable for the user's characteristics. The authors conducted a case study to test the system's performance, demonstrating its potential for personalized meal planning.

Chavan et al. [Chavan et al., 2021] built a hybrid model for recipe recommendations using big datasets. The contribution of this research is offering recommendations for food recipes focused on the features of ingredients, cooking method, calories and diet labels. The experimental evaluation showed that the results obtained from the hybrid recommendation system, which combined content from individual recipes, individual recipe preferences and content rated by the group were more efficient in terms of recommendations due to the simple fact that it considers user preferences and calorie restrictions.

Gorbonos et al. [Gorbonos et al., 2018] proposed a novel algorithm called NutRec. The latter is based on machine learning techniques in order to model interactions between the ingredients and their proportions within recipes for offering suitable recommendations for healthy recipes. The authors used a neural network-based (NN-based) model to capture the characteristics of ingredient quantities using an iterative process with nutritional compatibility considered at each step. The datasets used in this work are composed of real-world online recipes collected from two major food websites, namely Allrecipes.com and Yummly.com. The method generates a set of ingredients and respective amounts. After that, the authors matched this pseudo-recipe with recipes in their dataset to find similar recommendations.

Pawar et al. [Pawar et al., 2021] present a disease-based food recommendation system called NutriCure which takes into consideration users' health-related data with their preferences and their needs to provide a diet plan, which consists of various nutrients, minerals and vitamins. In this proposal, they used two approaches. In the first one, they used the KNN algorithm for generating recommendations with a dataset that they are generated on healthy and nutrient-rich foods from different websites that by using Web Scraping. In the second one, they focused on the users' disease information and the users' vegetarian or non-vegetarian preferences. In addition, they filtered the recipes by setting specific parameters. In order to test their approach, they generated 100 demo users, and this testing was useful for validating the efficiency of NutriCure's recommendations.

2.1.3 Restaurant recommendation systems

In this section we present several restaurant recommendation systems:

Gupta et al.[Gupta et al., 2021] proposed a model that recommends food based on the users' current mood from top-rated restaurants. they took data on Zomato and food choices for attributes like cuisines, location, mood, nutrition, gender etc. To locate the restaurants based on the location of the user, which are grouped by using the K-Means Algorithm and this model is connected to the web application that is developed by Flask. The application uses content-based filtering and collaborative filtering methods to recommend food and restaurants. In addition, the customers select their current mood from various moods displayed on the screen of the application. The total number restaurants recommended to a customer are 9, and the top 3 represent the best recommendations. Finally, they got the desired output of recommending types of foods by entering users' moods and location.

Park et al.[Park et al., 2008] proposed a restaurant recommendation system that considers the preferences of group users in a mobile environment. The process is divided into four steps: context-log collection, preference modeling of individual users using Bayesian network, and using AHP (Analytic Hierarchy Process) of multi-criteria decision-making to integrate the preference of individual users for recommend information to group users.

Martínez et al.[Martinez et al., 2009] present a geo-referenced hybrid recommendation system for restaurants called REJA, based on collaborative and knowledge-based, that provides recommendations in any required situation by the users besides. It provides information referred to by Google Maps. This system is composed of a collaborative system that uses the collaborative filtering engine CoFE (http://eecs.oregonstate.edu/iis/CoFE/) and a knowledge-based model which uses information users' needs that is gathered as an incomplete preference relation (users' knowledge) and knowledge that the restaurants in the database (catalog Knowledge). The knowledge-based system computes the recommendations by means of a case-based reasoning method. The system ranks the set of restaurants to the quality of service and provides the top ten to the user.

Sawant and Pai.[Sawant and Pai, 2013] present a recommendation system for Yelp users in application to food choices by applying learning algorithms to develop a predictive model of customers' restaurant ratings. The authors used Yelp's dataset. In addition, they extracted collaborative and content-based features to identify customer and restaurant profiles. Besides, they implemented algorithms on their dataset such as singular value decomposition, the hybrid cascade of K-nearest neighbor clustering, weighted bi-partite graph projection, and several other learning algorithms.

Domain	Ref	Aim(s)	Technique(s) Recommendation Systems	Algorithm(s)	Dataset	Developed System	Features Used
Food	[Rostami et al., 2022]	A novel hybrid food recommender system that addresses previous shortcomings by incorporating food ingredients, time stamp, cold start users and cold start foods, and user community.	Content based	-Graph clustering. -deep-learning.	Allrecipes .com	Time-aware food recommender system based on Deep Learning and Graph Clustering (TDLGC)	-Ratings food items. -User's preference.
	[Agapito et al., 2016]	Individualized Nutritional recommendation according to the health profile.	/	Algorithm1	-Calabrian POD foods. -Health Calabrian Food Database.	DIETOS: DIET-Organizer System	-Health status. -Eventual chronic diseases.
	[Huang et al., 2017]	Build a recommender system for grocery and gourmet food based on people's reviews on amazon.com	/	-Linear Regression.-basic latent factor.-Bias-SVD -SVD++.	Amazon website (dataset provided by Julian McAuleyon)	Food recommender system on Amazon	-User's taste. -product's features. -reviews.
	[Khan et al., 2019]	User modeling for personalized recipe recommendation according to nutritional preference	-Collaborative filtering. -Hybrid recommendation.	-a Topic-Term Weight Matrix. -FFbR, WFFbR, FFbCF algorithms	Recipe corpus	a personalized health-aware recipe recommendation.	-User preference. -Food features -Social and cultural groups

Table 1 : *Related works of Food, healthy food and restaurant recommendation systems*

Food	[Pecune et al., 2020c]	Developed a conversational system to implement a recipe recommender system based on users' perception and their intention to cook	Conversational system	-Natural Language Understanding(NLU). -Dialog Manager(DM). -Natural Language Generation(NLG) module.	healthiness-fillingness food (https:// spoonacular .com/food-api)	Cora	-User profile (eating habits, needs). -The emotion -ingredient
	[Pecune et al., 2020b]	Developed a recommender system for healthy and personalized recipe recommendations	Collaborative filtering	Alternating Least Squares(ALS). -Bayesian PersonalizedRanking(BPR). -Logistic Matrix Factorization(LMF).	allrecipes .com	A Recommender System for Healthy and Personalized Recipe Recommendations	-Users' preferences. -Feedback.
	[Ge et al., 2015]	Develop a recipe recommender system which take into consideration users preference and users health	/	matrix factorization	/	Health-aware Food Recommender System	-User personal -activities - calories -User preferences -Health requirement
	[Dhyani and Ojha, 2021]	suggested a dish along with the location of close by restaurant where the dish is available.	Hybrid filtering	-Similarity Matrix. -correlation function.	ZOMATO website	A food recommendation approach that will take flavor	-flavor -location -Preference -dish profile -restaurant ratings -ingredients -feedback
	[Sreenivasa et al., 2022]	generated a meal plan every day and satisfying his/her daily nutritional requirements.	-based filtering	/	/	genereted Data personalized meal plans.	-height. -weight. -Age. -Sex. -preference. -BMI. -BMR. -ingredient.

Table 1 : *Related works of Food, healthy food and restaurant recommendation systems*

Food	[Metwally et al., 2021]	Generated healthy and realistic meal recommendations That feature ingredients that the user commonly consumes.	/	K-Nearest Neighbors	U.S. Department of Agriculture's Food and Nutrient Database for Dietary Studies (FNDDS).	System identifies food preferences by identifying foods that are eaten frequently	-Food logs. -food name. -Food categories.
Healthy Food	[Subramaniyaswamy et al., 2019]	Suggest the food availability through considering climate attributes based on user's personal choice and nutritive value.	Hybrid filtering	Ontological knowledge base	-India's city climate data. -nutritional dataset with recipe info. -user dataset collected	ProTrip.	-Basic profile. -Medical info. -Food place. -User preferences
	[Iwendi et al., 2020]	Proposed an IoT system to recommend a specific nutritional model of patient or user. They used health base medical dataset and other features such as age, gender, weight, calories, etc.	/	machine and deep learning (logistic regression, naive bayes, RNN, MLP, GRU and LSTM)	medical dataset collected through the internet and hospitals	IoMT-Assisted Patient Diet Recommendation System Through Machine Learning Model.	-Medical data -Age -Gender -Weight -Calories
	[Sowah et al., 2020]	Designed and developed diabetes management system based on machine learning techniques	Knowledge-based approach	Machine learning (KNN)	food images dataset -Obtained patient and nutrition data from University of Ghana and MyFitnessPal database.	Diabetes Management System Using Machine Learning.	user activity -user geolocation -blood sugar
	[Ceyda and ÇILGIN, 2022]	Developed a system aims at: - helping the dietitian in the process of determining the nutrition program/meal planning - and for the patients in the processes of maintaining and monitoring it	Content-based.	Backtracking	Generated	a web-based expert system in the field of nutrition with a rule-based system approach.	-Ages -genders -heights -weights -calories -carbohydrates -proteins -fats

Table 1 : *Related works of Food, healthy food and restaurant recommendation systems*

Healthy Food	[Nallarasan et al., 2020b]	to develop a program that recommends diet to the people.	Content-based.	Machine Learning (ML),k-Means Clustering, Random Forest	Generated	The Diet Recommendation System.	-age -height -weight -vegetarian or non-vegetarian -Carbohydras -Fats -Nutrients
	[Princy et al., 2021]	Identified the different levels of overweight and obesity in users and providing dietary strategies to mitigate them.	An ontology	Semantic technologies - Reasoning techniques - iterative method	-Allrecipes.com -kaggle.com -dataset generated by Palechor and Manotas	A knowledge-based diet recommendation system.	User's profile(weight, age, height,..) -BMR -BMI -Blood Pressure (BP). -Ingredients nutritional.
	[Mckensy-Sambola et al., 2021]	Identifying and mitigating overweight/obesity levels with personalized dietary strategies, including medical condition-specific suggestions for users' dietary restrictions.	An ontology	Semantic technologies - Reasoning techniques	-Allrecipes.com -kaggle.com -dataset generated by Palechor and Manotas	A knowledge-based diet recommendation system.	-User's profile. -BMR. -BMI. - Blood Pressure. -Ingredients nutritional.
	[Trattner et al., 2021]	Recommend relevant recipes that avoid nutrients that contribute to high levels of cholesterol, increased the healthiness of recipe recommendations.	- collaborative filtering -content-based -hybrid methods	Matrix Factorization and SVD	Allrecipes.com	A novel metric called 'The Cholesterol Facto.	-Cholesterol Factor. -nutrient. -caloric.
	[Lo et al., 2008]	Recommendation of therapeutic food services aware of the condition	Content-based Filtering	-Ontology -LSA -knn -TF-IDF	Collected Data from several web sites, books, and papers which are all provided by dietitians or doctors	Situation-aware Curative Food Service Recommendation System.	- Class food. -medical requirements. - expert's suggestions.

Table 1 : *Related works of Food, healthy food and restaurant recommendation systems*

Healthy Food	[Chaturvedi et al.,]	explored the variety of food and get to know their nutritional value to recommend certain food, towards fitness and creating awareness among people for eating healthy.	/	Deep learning	Created Data	Food Recognition and Nutrition Estimation Using Deep Learning.	-ingredients -location -nutritional information
	[Toledo et al., 2019]	Develop a food recommender system based on nutritional information and user preferences.	Content based	Multi-criteria (AHPSort)	Generated Data	Daily meal plan recommendations.	-User information personally. -User preferences
	[Chavan et al., 2021]	Develop a recommendation model that provides individuals with more healthy choices within the range of their tastes	Content-based, Collaborative filtering, Hybrid recommendation	VSM and SVD algorithm	-foodRecSys-V1 (Kaggle.com) -AllRecipes.com	/	-User information. -User's preferences. -Ingredients. -Cook Method. -Calories. -Diet Labels.
	[Gorbonos et al., 2018]	Developed system NutRec which utilizes machine learning techniques in order to model the interactions between ingredients and their proportions within recipes for the purpose of offering suitable recommendations	/	Machine learning (neural networks, matrix factorization)	-Allrecipes.com -Yummly.com	NutRec: Nutrition Oriented Online Recipe Recommender.	-Ingredients. -recipe.
	[Pawar et al., 2021]	Provided a personalized diet plan consisting of the desired nutrients for maintaining health and enhancing immunity by curing the diseases.	Hybrid filtering	KNN algorithm	Data Collected	Nutricure: A Disease-Based Food Recommender System.	-User's health profile. -User preferences.
Restaurant	[Gupta et al., 2021]	Suggested food based on user's mood from top-rated restaurants for best quality.	-Content-based. -collaborative filtering.	K-Means Algorithm	- Zomato -Food choices.	Mood Based Food Recommendation System.	-Mood. -location. -interest. -rating. -cost. -user personal.

Table 1 : *Related works of Food, healthy food and restaurant recommendation systems*

Restaurant	[Park et al., 2008]	To model the preference of individual user and integrated the results of group users to apply it to restaurant recommendation for group users.	Content based filtering - Collaborative filtering	Bayesian . -AHP.	Data collected (restaurants Located in Seoul, Korea)	Restaurant Recommendation for Group of People in Mobile Environments.	-Preferences (mood, price, distance, seat, parking Restaurant type). -context log (temperature, weather, season, period, latitude, longitude, user request, time). -User profile.
	[Martinez et al., 2009]	Provided successful recommendations to users about the existing restaurants in any required situation by the users/customers.	Hybrid recommender	-KNN -matrix similarity	Database (restaurants of province of Jaén).	Reja: a georeferenced hybrid recommender system for restaurants.	-rating -user profile (needs, preference, knowledge, catalogue Knowledge) -Location
	[Sawant and Pai, 2013]	builder a recommendation system that will enable to make sophisticated food recommendations for Yelp users	- Collaborative filtering -content based filtering	maching Learning algorithms (Svd, knn, k-means,..)	Yelp Dataset	Yelp Food Recommendation System	-Preferences. - personalities.

Table 1 : Related works of Food, healthy food and restaurant recommendation systems

From **Table 1**, we can conclude some important points:

- The vast array of dishes and meals today necessitates effective recommendation systems. Such systems can greatly impact user preferences and steer their choices towards particular services. The reviewed papers feature promising studies in the realm of food delivery and restaurant recommendations. A notable reference is Gupta et al.'s work [Gupta et al., 2021], which lays the foundation for exploring the connection between user well-being and health;
- Researchers have ventured into various methods to construct recommendations, including standard collaborative filtering and content-based algorithms (Dhyani and Ojha.[Dhyani and Ojha, 2021]);
- More innovative approaches such as latent space textures, self-organizing maps, and graph-based techniques have been explored. Notably, some researchers have experimented with linear programming, genetic algorithms, and Bayesian methods;
- A primary driving factor behind these approaches is the richness of recipe ingredients. Recipes detail individual ingredients, creating a context where ingredients interact

harmoniously. The intricacies of recipes extend beyond ingredients, encompassing cooking methods, preparation times, sequences, cuisines, and other relevant factors. This extensive yet intricate metadata offers a wealth of information for recommendation systems;

- The used datasets are allrecipes.com, Yelp, Yummly, and food.com, e (Alain Starke et al.[Trattner et al., 2021], Chaturvedi et al.[Chaturvedi et al.,]);
- A significant gap identified in the existing literature pertains to the integration of health and well-being considerations into dietary recommendations. While people do seek out healthy food choices for everyday consumption, there's a notable absence of studies that offer a holistic approach, considering individual health preferences and locations;
- Some studies touch upon dietary recommendations that involve designing multiple daily menus to address patient monotony, but a comprehensive framework aligning health and preference is lacking;
- Finally, the research surrounding food recommendations is vast and multifaceted. While challenges persist in terms of data sparsity and cultural diversity, there's an exciting opportunity to further develop recommendation systems that prioritize both user health and preferences, bridging the gap between culinary delight and well-being.

2.2 Algorithms Used in our Filtering and Recommendation System

There are several multi-criteria decision analysis (MCDA) methods that are commonly used across various applications to help decision-makers evaluate and compare alternatives based on multiple criteria, facilitating informed and well-balanced decision-making. Here are the most common MCDA methods and their applications:

1. **Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)**
   TOPSIS is relies on the principle that the optimal choice should exhibit the shortest Euclidean distance to the ideal solution and the greatest distance from the negative ideal solution. The "ideal solution" represents a theoretical scenario where all the attributes achieve their maximum values, while the "negative ideal solution" embodies the opposite, with attributes at their minimum values. As a result, TOPSIS provides a solution that excels by being both closest to the ideal and farthest from the undesirable extreme, ensuring a balanced and robust selection process for decision-makers [Gavade, 2014]. This approach promotes a well-rounded assessment of alternatives in multi-criteria decision-making scenarios, which is applied in fields like environmental management, transportation planning, financial portfolio optimization, healthcare, transportation and logistics, investment decision-making and finance [Forouzandeh et al., 2022].

2. **Analytic Hierarchy Process (AHP)**
   The Analytic Hierarchy Process (AHP), pioneered by Saaty, is a renowned technique for tackling complex decision-making challenges. AHP employs a hierarchical structure, breaking down decisions into objectives, criteria, and alternatives, accommodating as many levels as necessary to capture the nuances of each situation. Its key strengths lie in its ability to handle subjective judgments, accommodate multiple decision-makers, and provide measures of preference consistency [Chen et al., 2010]. AHP stands out as the favored method for decision-making due to its alignment with human thought processes. It excels in handling tangible and intangible attributes, making it particularly valuable when subjective judgments from diverse individuals

play a pivotal role in the decision-making journey, which is used in diverse domains such as project selection, supplier evaluation, site selection, and healthcare decision-making. It's particularly suitable when decision-makers need to prioritize criteria and alternatives hierarchically [Mashal et al., 2020].

3 The proposed System: Smart Food and Restaurant Advisor

In this Section, we proposed a new food and restaurant recommendation system called Smart Food and Restaurant Advisor (SFRA). This latter is based on individual's profile including dietary needs, preferences, and geographic location. It consists of two main processes: (1) user profiling (Point 1 in the following) and (2) filtering and recommendation (Point 2, below). The used database contains a wide range of users' features such as demographic and physical features, and their preferences for restaurants. These features form the basis for the filtering process in addition to a database of restaurants and databases of recipes provided by these restaurants, where the food was divided into categories.

Figure 1 shows the global architecture of the proposed system. We present below a description of such architecture.

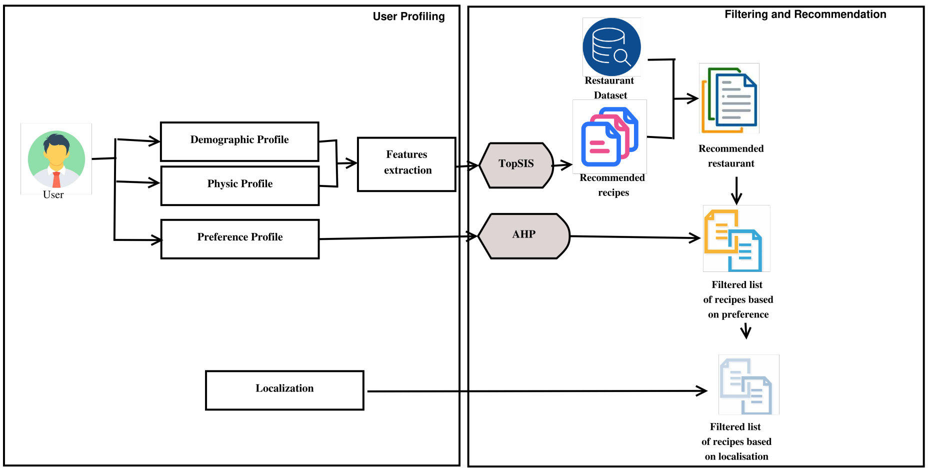


Figure 1: SFRA global architecture

1. **User profiling**

   In this process, we create a comprehensive user profile by taking into account various features such as demographic and physical information, preferences and geographic location. This detailed profile is the foundation for the personal recommendation process. The user profiling approach aims to provide a rough but accurate description of the user. We provide a detailed explanation of the different components of this step below:

- Features extraction: Features extraction is important for enhancing the algorithm's ability to process and interpret data, ultimately leading to more accurate and insightful results. In the following, we are explaining all the steps used for the Features Extraction.
  (a) The first step towards using a dataset is to prepare and improve it for analysis;
  (b) Generating user profiles based on their relevant needs by collecting and analyzing user information such as physical and demographic.(e.g. "height in meters", "weight in kilograms", "age in years", "gender", and "activity". User activity levels can be divided into five categories, namely, "stable", "slightly active", "moderately active", "very active" and "extremely active". The Harris-Benedict equation is used to estimate an individual's basal metabolic rate (BMR). This estimated BMR value multiplied by a number corresponding to the user's activity level provides the approximate daily caloric intake to maintain current body weight. To calculate the female or male basal metabolic rate, the Harris Benedict equation 1 [Luy and Dampil, 2018] is used. This step extracts the following information from the demographic profile and the physical profile (see figure 2):
     - Demographic profile: The user's demographic profile includes basic information such as ID user, age, etc. This information acts as an initial user profile, particularly when no other data is available. This helps address the challenge of the 'cold start' problem, ensuring that appropriate recommendations can be given to the user based on the available data.
     - Physical profile: The user's physical profile includes basic information such as gender, weight and height.To ensure that recipe recommendations are in line with the user's nutritional needs, the recipe is selected based on several criteria, including protein, fat, calories, Carbohydrates etc. To create a profile of their dietary needs, this information is then used to select food found in restaurants using the Topsis multi-criteria method.

     We used demographic profile (such as age) and physical profile (such as gender, weight, height) to calculate metrics like: (1) BMI using equation 1, (2) BMR male and BMR female using equation 2 and equation 3, and (3) TDEE using equation 4. These metrics are crucial for assessing user nutritional requirements where they serve as the foundation for determining the ideal proportions of fat, protein, and carbohydrates tailored to each user's dietary needs. By analyzing these factors, we can recommend personalized food choices, aligning with individual health goals and optimizing nutritional intake. This approach empowers users to make informed decisions about their diets, promoting overall well-being and balanced nutrition.

$$BMI = (weight(g)/1000)/(height(cm)/100)^2 \tag{1}$$

$$\begin{aligned}\text{BMR (male)} = 66 + (6.3 * \text{weight\_lbs}) + (12.9 * \text{height\_inches}) \\ +(6.8 * \text{age})\end{aligned} \tag{2}$$

$$\begin{aligned}\mathrm{B}MR(female) = 66.5 + (4.3 * \mathrm{w}eight_lbs) + (4.7* \\ \mathrm{h}eight_inches) + (4.7 * age)\end{aligned} \tag{3}$$

$$TDEE = BMR * activity_multipliers[activity] \quad (4)$$

- BMI Category Calculator: The function takes a person's BMI value as input and returns a string representing their BMI category, based on the following categories: Underweight: BMI less than 18.5, Normal weight: BMI between 18.5 and 24.9, Overweight: BMI between 25 and 29.9, and Obese: BMI 30 or greater
- Weight for Normal BMI Range Calculator: The function takes a person's height (in meters) and BMI value as inputs and returns the minimum and maximum weight required to be in the normal BMI range, as well as a suggested goal (loss, gain, or stable) to achieve that range. The suggested goal is based on the following: If the person's BMI is above the normal range, the goal is to lose weight, if the person's BMI is below the normal range, the goal is to gain weight, if the person's BMI is already in the normal range, the goal is to maintain their weight.
- Daily Caloric Needs Calculator: The function takes a person's weight (in kg) and a period (in days) as inputs and returns the daily value of calories required to either lose or gain weight during that period. The calculation is based on the following: to lose weight, the person must consume fewer calories than they burn. To gain weight, the person must consume more calories than they burn.
- TDEE Goal Calculator: The function takes a person's TDEE (Total Daily Energy Expenditure), a goal (lose, gain, or maintain weight), and a daily caloric value as inputs, and returns the TDEE goal value depending on the given goal. The calculation is based on the following: to lose weight, the TDEE goal value is TDEE minus the daily caloric value; to gain weight, the TDEE goal value is TDEE plus the daily caloric value; to maintain weight, the TDEE goal value is equal to the TDEE.

The relationship between the BMR and the activity level of the user is illustrated in Table 2. The approximate daily caloric and protein intake to maintain an individual's current weight is a product of BMR for lifestyle factors.

(c) Normalize the data set by inputting the number of columns, weights, and the number of columns with missing values (NaN).

(d) TOPSIS function takes the food and client data, the number of columns that are not used (NaN), and a parameter called 'diabetic' as input. This function first normalizes the food data set using the client data and then calculates the positive and negative values based on the impact parameter. The Topsis score and ranking are then calculated for each row in the data set.

(e) Finally, The top 10 recommended restaurants.

– Preference profile: User preference profile. To ensure restaurant recommendations align with user preferences, each restaurant is evaluated based on several

Lifestyle	Multiplication Factor	Calorie Intake (approx.)
Sedentary	1.2	BMR * 1.2
Lightly Active	1.375	BMR * 1.375
Moderately Active	1.55	BMR * 1.55
Very Active	1.725	BMR * 1.725
Extra Active	1.9	BMR * 1.9

Table 2: Calorie intake based on Basal Metabolic Rate [Luy and Dampil, 2018]

criteria, including cost, dress preference, ambiance, transportation, and more. To create a preference profile, this information is then used to rate restaurants using the AHP multi-criteria method. AHP is a decision-making technique that identifies criteria and choices that are traditionally difficult to measure with hard numbers. It helps determine which criteria are most important to the user and ranks restaurants accordingly, providing personalized recommendations that align best with their values. Overall, this personalized approach to restaurant recommendations improves user satisfaction and helps them find restaurants that meet their specific preferences and needs.

– Localization: The user's location (the latitude and longitude coordinates, see figure 2). This information is used to suggest nearby restaurants that fit their preferences and dietary needs. By using this location data, we can provide more accurate and personalized recommendations for the user.

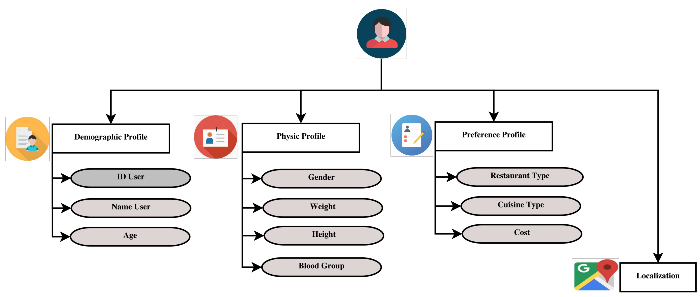


Figure 2: User profiling

2. **Filtering and recommendation**
 Filtering takes into account the user's nutritional needs, preferences and location. This system filters foods and restaurants based on the user's nutritional needs through a database of restaurants and recipes. The filter selects the categories that have a high degree of similarity to the user profile for each category. Our approach provides

highly personalized recommendations to users looking for food options that match their nutritional needs. More in particular, our recommendations give advice about food and restaurants based on the user's nutritional needs, preferences, and location.

- Recommended food: the recommended items are food items that are available on the menus of the restaurants. These food items are categorized 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 bread, main-dish, side-dish, world-cuisine, desserts, breakfast-and-brunch, salad, soups-stews-and-chili, meat-and-poultry, drinks, appetizers-and-snacks, beans and lentils, restaurant foods, beverages, dairy and egg products, meats, vegetables, fish, breadsm cereals, fastfood, grains, beverages, seafood, fried potatoes, desserts, entrees, salads, baked goods.
- Recommended restaurant: The recommended restaurant includes different attributes. These attributes include the type of food available, the ingredients used in each food item, as well as the restaurant's geographic location (defined by latitude and longitude). In addition, it takes into account the unique features of each restaurant, such as the price of the restaurant, and other factors that align with user preferences.

3.1 Localisation Restaurant Recommendation Filtering Algorithm

Previous filtering techniques do not include the opinions of all users when recommending items, and are therefore limited to making recommendations at the expense of their dietary needs and preferences. So we wanted to add information about the domain the user is in. The idea behind combining different recommendation techniques is that the resulting algorithm will provide more accurate and effective recommendations.

We proposed a Localization Restaurant Recommendation Filtering Algorithm (LR-RFA) in the SFRA system. It is a combination of the TOPSIS algorithm and the preference-based recommendation filtering algorithm presented in Section 2.2. This integration enables the SFRA system to compare user preferences and restaurant features, thus enhancing the accuracy and relevance of the recommendations. In addition, based on the user's context, such as their location, we further enhance our recommendations by incorporating contextual information into the recommendation algorithm. By analyzing the users' location data, we can recommend restaurants that are near to the users' current location. This provides a more personalized and convenient experience for the user, as they are more likely to visit a restaurant that is in close proximity to their current location. We generate restaurant recommendations for users based on their dietary needs and preferences, in addition to their current location. Furthermore, the SFRA system takes into account the user's health condition, particularly whether they have diabetes or not, and recommends food options that are suitable for their condition.

The recommendation process involves selecting top dishes in a preferred food category using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). TOPSIS ranks alternatives based on their similarity to an ideal solution and dissimilarity to a negative ideal solution. The normalized decision matrix A is created, where rows represent dishes and columns represent nutritional attributes. Mathematically. The positive ideal solution (PIS) and negative ideal solution (NIS) are calculated based on the user's dietary needs. The TOPSIS score for each dish is computed using the Euclidean distance from PIS and NIS. The top-ranked dishes are selected for recommendation.
User preferences are compared using the Analytic Hierarchy Process (AHP), a multi-criteria decision-making technique. AHP involves pairwise comparisons of criteria to determine their relative importance. The comparison matrix C is created, where C_{ij} represents the preference of criterion i over criterion j. The matrix is normalized to obtain

the priority vector w, representing the weights of each criterion. The final comparison result is a hierarchy tree with the criteria and their weights.
Similar to user preference comparison, restaurant comparison also uses AHP. Criteria include restaurant type, cuisine type, and cost. Each criterion has its own comparison matrix and priority vector. Weights are assigned to each criterion based on its importance in the recommendation process. The comparison matrices are combined into a hierarchy tree for restaurant comparison.

3.1.1 TOPSIS Method

The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method is a multi-criteria decision-making technique used to assist users in selecting the most suitable food options based on their dietary needs, which are influenced by factors such as BMI (Body Mass Index), BMR (Basal Metabolic Rate), and TDEE (Total Daily Energy Expenditure).

Firstly, the criteria for evaluation are identified, each representing a different aspect or dimension of the decision problem. These criteria include factors such as Fat, Carbohydrates, and Protein.

A. Decision Matrix Formation:

The decision matrix X is constructed with m rows representing alternative food options and n columns representing nutritional criteria such as fat (F), carbohydrates (C), and protein (P) content. Each element x_{ij} in the matrix denotes the quantity of the j^{th} nutrient ($j = 1, 2, 3$) in the i^{th} food option.

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ x_{21} & x_{22} & x_{23} \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{m3} \end{bmatrix}$$

B. Normalization of Data

To standardize the data and ensure comparability across different criteria, each element in the decision matrix is normalized using the formula:

$$x_{ij}^{*} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^{2}}} \tag{5}$$

This normalization process eliminates disparities arising from variations in measurement units and scales.
Following normalization, the ideal best and ideal worst alternatives are determined for each criterion. The ideal best represents the maximum desired value for each criterion,

while the ideal worst represents the minimum desired value. These ideal solutions serve as reference points for evaluating the alternatives:

$$A_j^+ = \max(r_{ij}), \quad A_j^- = \min(r_{ij})$$

where A_j^+ and A_j^- are the ideal best and worst values for criterion j

C. Identification of Ideal Solutions

Positive and negative ideal solutions (PIS and NIS) are determined based on the user's dietary preferences and restrictions. For instance, if the user aims to minimize fat intake and maximize protein consumption, low values represent the PIS for fat (F^+) and NIS for protein (P^-).

$$\text{PIS: } (F^+, C^+, P^+) \quad \text{NIS: } (F^-, C^-, P^-)$$

D. Calculation of Distances

Euclidean distances D_i^+ and D_i^- are computed to quantify the similarity of each food option to the ideal solutions. These distances are calculated using the formulas:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(x_{ij}^* - p_j^*)^2} \tag{6}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(x_{ij}^* - n_j^*)^2} \tag{7}$$

E. Evaluation of Relative Closeness:

The relative closeness C_i of each food option to the ideal solutions is determined using the formula:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{8}$$

A higher C_i indicates greater suitability of the food option for the user's dietary needs.

F. Ranking of Food Options

Food options are ranked based on their relative closeness scores, with higher scores indicating better alignment with the user's dietary preferences. In case of ties, additional criteria or user preferences can be considered for resolution.

$$\text{Ranking: } Food_1 > Food_2 > \cdots > Food_m$$

3.1.2 Analytic Hierarchy Process (AHP) for Restaurant Selection

The Analytic Hierarchy Process (AHP) is a decision-making framework developed by Thomas Saaty in the 1970s. It is a structured technique that helps individuals or groups make complex decisions by breaking them down into a hierarchy of criteria and alternatives, and then systematically evaluating and comparing these elements based on their relative importance or preference [Saaty, 1987].

A. Pairwise Comparison

We begin by constructing a pairwise comparison matrix C for the criteria C_1, C_2, and C_3. The user provides judgments on the relative importance of each criterion compared to the others. Let c_{ij} represent the user's judgment of the importance of criterion i compared to criterion j. The matrix C is a square matrix where c_{ij} represents the importance of criterion i relative to criterion j.

B. Pairwise Comparison Matrix

The pairwise comparison matrix C is structured as follows:

$$C = \begin{bmatrix} 1 & c_{12} & c_{13} \\ \frac{1}{c_{12}} & 1 & c_{23} \\ \frac{1}{c_{13}} & \frac{1}{c_{23}} & 1 \end{bmatrix}$$

Entries on the diagonal are always 1 because each criterion is equally important to itself. The elements above the diagonal (c_{ij}) represent the user's judgments, while those below ($\frac{1}{c_{ij}}$) are reciprocals of the corresponding judgments.

C. Eigenvalue Calculation

Next, we calculate the principal eigenvector of the matrix C to obtain the relative weights of the criteria. Let w represent the eigenvector associated with the largest eigenvalue of C.

D. Normalization

We normalize the eigenvector w to ensure its components sum to 1. The normalized eigenvector w' is obtained by dividing each element of w by the sum of all elements of w. This ensures that the weights of the criteria are proportional and can be interpreted as probabilities.

E. Aggregation of Weights for Restaurants

For each restaurant r, we calculate an aggregated score S_r based on its attributes and the normalized weights w'. Let A_r represent the attributes of restaurant r for criteria C_1, C_2, and C_3. The aggregated score S_r is calculated as:

$$S_r = w'_1 \cdot A_{r1} + w'_2 \cdot A_{r2} + w'_3 \cdot A_{r3} \tag{9}$$

This equation represents a weighted sum of the attributes of each restaurant, where the weights are determined by the normalized eigenvector w'.

F. Recommendation Generation

Based on the aggregated scores S_r, we rank the restaurants and recommend the top-ranked ones to the user. The recommended restaurants are those that best align with the user's preferences for restaurant type, cuisine type, and cost, as reflected in the aggregated scores.

3.1.3 LRRFA: Localisation Restaurant Recommendation Filtering Algorithm Pseudo Code

The pseudo code of LRRFA is shown in Algorithm 1.

Algorithm 1 Localization Restaurant Recommendation Filtering

Input: $data_{users_{profile}}$, $data_{zomato}$, $data_{recipes}$
Output: Top restaurant recommendations for each user based on their preferences
Read $data_{users_{profile}}$, $data_{zomato}$, $data_{recipes}$
Normalize and calculate the weighted normalized matrix
Calculate positive and negative ideal solutions
Calculate the TOPSIS score and ranking for each food item
Create a data frame with relevant information
Collect user preferences and restaurant features data
Use the AHP algorithm to calculate feature importance
Generate a similarity matrix between restaurants
Filter restaurants by proximity
Rank remaining restaurants based on user preferences and location
Return the top recommended food and restaurants

4 Experiments, results and discussions

We present in this section the used datasets, the realized experiments, the results and some discussions. To handle the computational requirements of the dataset, we used Google Colab for research 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 math, random, and os.path were used.

4.1 Used Datasets

- **Data set 1:** We relied on an existing dataset called Covid-19 DataSet India [1]. Furthermore, each profile is completed by generating a random sequence of preferences for each user, in order to simulate the behavior of real users. To develop a personalized food recommendation system that takes into account a user's needs, preferences, and location. The dataset contains such as location, gender and age. Geographical details such as City, District, State, and State code were utilized to determine latitude and longitude coordinates for each user. Futhermore, some preferences are randomly generated such as type of cuisine, cost, etc. Also, height and weight are generated.

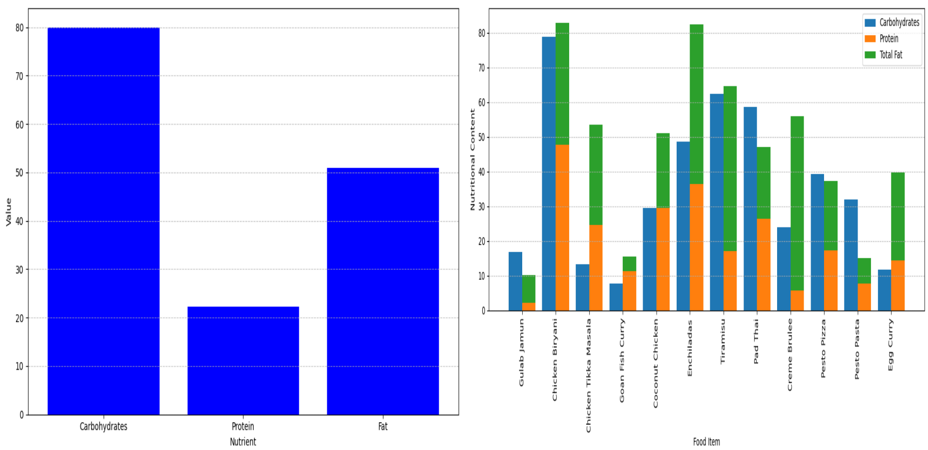
[1] https://www.kaggle.com/code/mkbond777/covid19-india/input

– **Dataset 2:** We used for restaurant recommendations a dataset called ’Zomato’ [2], which contains the restaurants’ features and even the foods that the restaurant provides is used. It consists of 19 features and 9,543 rows representing restaurants. It provides information such as: Restaurant ID, Restaurant Name, Country Code, City, Address, Locality, Area Verbosity, Latitude, Cuisines, Average Cost for Two, Has Table Reservation, Online Delivery, Delivery, Switch to Order List, Price Range, Overall Rating, Rating color, rating text, votes.
  The relationship between the Covid19-India dataset and the Zomato dataset lies in their shared geographical dimension: the addresses of users in the Covid19-India dataset and the addresses of restaurants in the Zomato dataset both pertain to locations within India. By leveraging the geographical details provided in both datasets, such as city, district, and state, it becomes possible to potentially correlate information between users’ locations and nearby restaurants, enabling analyses that explore the relationship between health patterns and dining preferences across different regions in India.

– **Dataset 3:** We employed a dataset that comprised 93 unique recipes provided by restaurants located in the Zomato dataset, which were obtained from the website Allrecipes.com, one of the largest recipe websites. Recipes were annotated with nutrient-specific metadata, including the contents in grams of specific elements (i.e., carbohydrates, (saturated) fat, fiber, protein, sugar), as well as a recipe’s caloric content.

4.2 Results

We present in this Section the results of the evaluation of the proposed system. Figure 3a shows the users’ nutritional needs graph. In particular, it displays three bars representing the users’ nutritional needs for carbohydrates, protein, and fat.



(a) Generic user ’u’ nutritional needs. *(b) Top food items recommendations.*

Figure 3: Top food items nutritional content.

[2] https://www.kaggle.com/code/yekahaaagayeham/zomato-eda-and-preprocessing-for-machine-learning

When examining the *user's nutritional needs plot*, we gain insight into the user's specified requirements for carbohydrates, protein, and fat. This offers a comprehensive understanding of the user's dietary needs. In the *Top Food Items Recommendation plot (see Figure 3b)*, we can make a direct comparison between the nutritional composition of the recommended food items and the user's dietary requirements. The information of user with ID 10744 are Weight: 70 kg, Height: 190 cm, Gender: Male and Age: 32 years. Figures 4a, 4b and 4c shows the results of the recommended recipes for Beverages, Appetizers-and-snacks and Entrees categories respectively.

```
Topsis Score: 0.005511067350991675 Rank: 10.0
This is the top list of: Beverages For user 10744.0
           recipe_name Total_Fat Carbohydrates  Protein
34              Mojito      0.02          2.46     0.09
37              Coffee      0.02           0.0     0.12
39                Beer       0.0          3.55     0.46
41            Espresso      0.18          1.67     0.12
42             Martini       0.0          0.15     0.07
43         Bloody Mary      0.23          3.16     0.64
46           Margarita      0.08         16.06     0.08
55       Hot Chocolate       2.5          37.0     2.00
60          Cappuccino       4.0          36.0     2.00
63  Chocolate Milkshake     13.0          79.0    10.00
---------------------------------------------------------
```

(a) Beverages category.

```
Topsis Score: 0 Rank: 1.0
This is the top list of: appetizers-and-snacks For user 10744.0
    recipe_name Total_Fat Carbohydrates  Protein
22  Onion Rings      22.6          29.1      3.3
---------------------------------------------------------
```

(b) Appetizers-and-snacks category.

```
Topsis Score: 0.3916703307942286 Rank: 3.0
This is the top list of: Entrees For user 10744.0
     recipe_name Total_Fat Carbohydrates  Protein
57  French Toast       8.0          30.0      8.0
61     Spaghetti       7.0          45.0      7.0
62     Pork Ribs      12.0           0.0     22.0
---------------------------------------------------------
```

(c) Entrees category.

Figure 4: Result of the recommended recipes.

Figure 5 shows five restaurants that have been recommended taking into consideration the user's preferences. This Figure illustrates the recommended restaurants, which are derived from the previously suggested food items (Figure 4). It considers the availability of these foods at various restaurants and further refines the user's preferences. The highest preference values are determined based on the initial set of recommended restaurants.

In Figure 6 and Figure 7, we present the results obtained by our proposed system. Figures 6 and 7 shows SFRA system and the recommended restaurants based on the group of restaurants recommended in the previous stage, as it takes into account the user's nutritional needs and preferences and then filters based on the user's location, so that the closest restaurant to the user that meets the user's preferences is obtained.

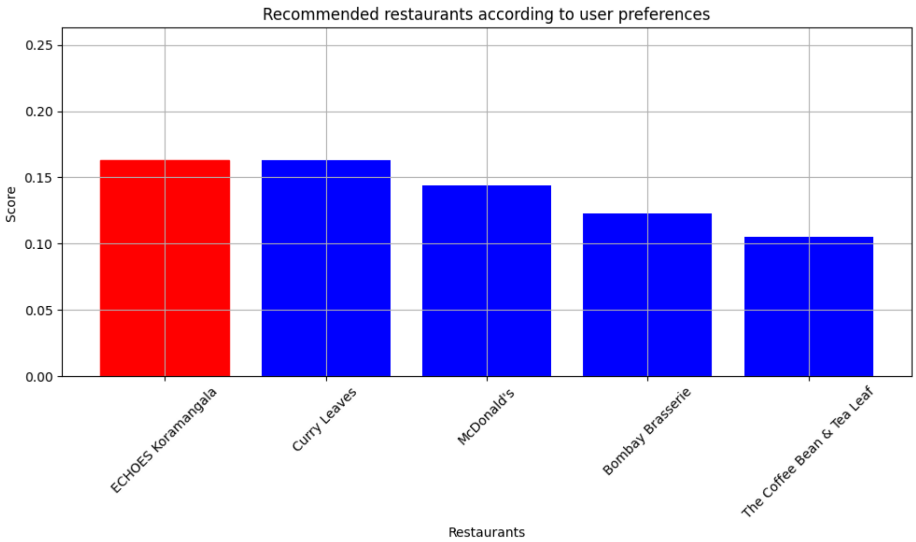


Figure 5: Graph of Preference-based Restaurant recommendation filtering

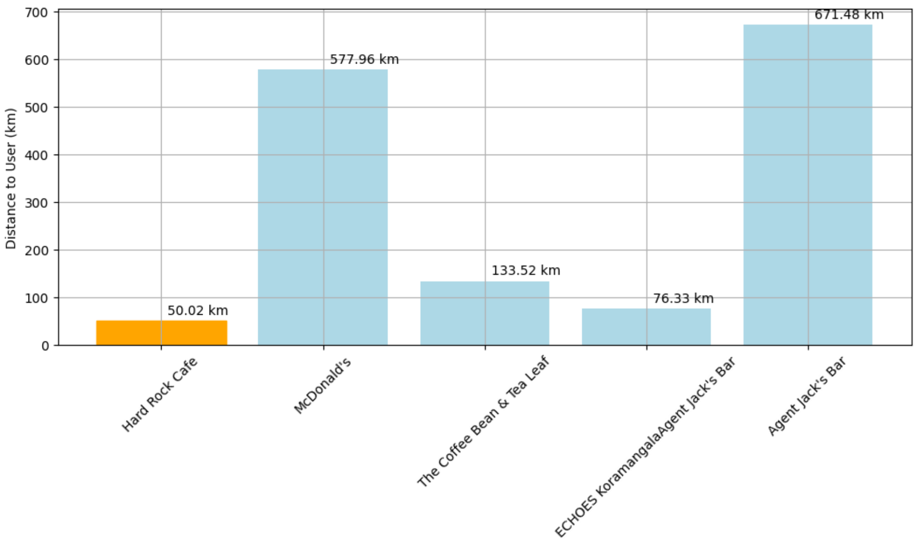


Figure 6: SFRA

```
Topsis Score: 0.005511067350991675 Rank: 10.0
This is the top list of: Beverages For user 10744.0
           recipe_name Total_Fat Carbohydrates  Protein
34              Mojito      0.02          2.46     0.09
37              Coffee      0.02           0.0     0.12
39                Beer       0.0          3.55     0.46
41            Espresso      0.18          1.67     0.12
42             Martini       0.0          0.15     0.07
43         Bloody Mary      0.23          3.16     0.64
46           Margarita      0.08         16.06     0.08
55       Hot Chocolate       2.5          37.0     2.00
60          Cappuccino       4.0          36.0     2.00
63  Chocolate Milkshake     13.0          79.0    10.00
------------------------------------------------------------

Restaurant recommendations :
Restaurant: ECHOES Koramangala, Restaurant ID: 18439634, Recipe 1: Chocolate Milkshake, Resto Type: Casual Dining, Cuisine Type: Chinese cuisines, Cost: Medi
Restaurant: McDonald's, Restaurant ID: 2400014, Recipe 2: Hot Chocolate, Resto Type: Fast Food, Cuisine Type: Fast Food and Burgers, Cost: Low, Distance to u
Restaurant: The Coffee Bean & Tea Leaf, Restaurant ID: 307370, Recipe 3: Cappuccino, Resto Type: Cafes and Bakeries, Cuisine Type: Cafe and Desserts, Cost: M
Restaurant: Agent Jack's Bar, Restaurant ID: 6507461, Recipe 4: Margarita, Resto Type: Fancy restaurant, Cuisine Type: Pizza and Italian cuisines, Cost: High
Restaurant: Hard Rock Cafe, Restaurant ID: 201531, Recipe 5: Bloody Mary, Resto Type: Casual Dining, Cuisine Type: nan, Cost: Low, Distance to user: nan km
Restaurant: Bombay Brasserie, Restaurant ID: 18407918, Recipe 6: Beer, Resto Type: Casual Dining, Cuisine Type: Indian cuisines, Cost: High, Distance to user
Restaurant: Curry Leaves, Restaurant ID: 1600007, Recipe 7: Mojito, Resto Type: Casual Dining, Cuisine Type: Chinese cuisines, Cost: Medium, Distance to user
Restaurant: The Coffee Bean & Tea Leaf, Restaurant ID: 307370, Recipe 8: Espresso, Resto Type: Cafes and Bakeries, Cuisine Type: Cafe and Desserts, Cost: Med
Restaurant: The Chocolate Room, Restaurant ID: 18217857, Recipe 9: Coffee, Resto Type: Fast Food, Cuisine Type: Cafe and Desserts, Cost: Medium, Distance to
Restaurant: Farzi Cafe, Restaurant ID: 18233284, Recipe 10: Martini, Resto Type: Casual Dining, Cuisine Type: nan, Cost: Low, Distance to user: nan km
------------------------------------------------------------
Recommended preference restaurants:
ECHOES Koramangala  Score: 0.164
Curry Leaves  Score: 0.164
McDonald's  Score: 0.156
Bombay Brasserie  Score: 0.125
The Coffee Bean & Tea Leaf  Score: 0.103
------------------------------------------------------------
### the best closet restaurants
Restaurant: ECHOES Koramangala, Restaurant ID: 18439634, Recipe 1: Chocolate Milkshake, Resto Type: Casual Dining, Cuisine Type: Chinese cuisines, Cost: Medi
Restaurant: McDonald's, Restaurant ID: 2400014, Recipe 2: Hot Chocolate, Resto Type: Fast Food, Cuisine Type: Fast Food and Burgers, Cost: Low, Distance to u
Restaurant: The Coffee Bean & Tea Leaf, Restaurant ID: 307370, Recipe 3: Cappuccino, Resto Type: Cafes and Bakeries, Cuisine Type: Cafe and Desserts, Cost: M
Restaurant: Agent Jack's Bar, Restaurant ID: 6507461, Recipe 4: Margarita, Resto Type: Fancy restaurant, Cuisine Type: Pizza and Italian cuisines, Cost: High
Restaurant: Hard Rock Cafe, Restaurant ID: 201531, Recipe 5: Bloody Mary, Resto Type: Casual Dining, Cuisine Type: nan, Cost: Low, Distance to user: nan km
```

Figure 7: Result of SFRA: Smart Food and Restaurant Advisor based on Nutritional Needs and User Profiling

The developed SFRA system is expected to contribute to the effective implementation of meal planning, especially in areas where there are not enough specialists, to speed up the remote follow-up of the nutrition program, and to carry out appropriate reviews in the nutrition program by acting as a decision support system for experts and so on. Enjoy eating restaurants and at the same time it applies to your nutritional needs. Although research in popular literature such as (Sambola et al. [Mckensy-Sambola et al., 2021], Princy et al. [Princy et al., 2021], Nallarasan et al. [Nallarasan et al., 2020b]) generally aims to create a healthy nutrition plan based on one's nutritional needs rather than on one's preferences and current location, so the main purpose of this research is to maintain health, enjoyment, and comfort. In addition, many of the developed systems are designed to plan healthy nutrition according to rules without taking into account the individual's preference of eating or place. Overall, there are studies (Martınez et al. [Martinez et al., 2009], Toledo et al. [Toledo et al., 2019], Gupta et al. [Gupta et al., 2021]) based on individual preferences only, such as his/her tastes and foods that he/she loves, or restaurants that he/she prefers, for example, in terms of price, and vice versa, that do not take into account his/her nutritional needs for the user.On the contrary, a person may get bored of the line because it does not contain the foods he/she loves, or he/she cannot eat in any restaurant he/she wants. On the contrary, the SFRA system that was created not only for healthy eating and food plans but also allows the individual to eat and enjoy in restaurants according to his/her preferences and location.

5 Conclusion

Smart food and restaurant recommendation systems have proven to be effective in providing personalized dining experiences by analyzing various factors such as dietary restrictions, nutritional needs, and cuisine preferences. These systems offer tailored recommendations that align with individual tastes and health goals, taking into account factors like location, price range, and user reviews. This empowers users to discover new culinary experiences while making informed choices that suit their unique preferences and dietary requirements. In this article, a recommendation system was presented with a focus on providing users with healthy food options based on their dietary needs and personalized restaurant suggestions according to their preferences and geographical location. The approach involves two phases: user profiling, where individual preferences and dietary information are gathered, and filtering, where the system applies advanced algorithms to generate relevant and personalized recommendations. Building on the success of this recommendation approach in the food and restaurant domain, the article proposes expanding its application beyond just food and restaurants. The goal is to offer personalized suggestions for various points of interest. By seamlessly integrating diverse information, such as categories, user preferences, location, and contextual factors, the system aims to deliver tailored recommendations in other domains as well.

Expanding our perspectives, we intend to apply this recommendation approach beyond food and restaurants, aiming to offer personalized suggestions for various points of interest. By seamlessly integrating diverse information such as categories, user preferences, location, and contextual factors.

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