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Meal Planning Applications: A Comprehensive Review of Technologies, Trends and Challenges

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***Abstract*—Examining studies on personalized meal suggestion systems, this study aims to address the growing concern about harmful eating practices. The studies investigate a range of methodologies, such as collaborative filtering for personalized meal plans, frameworks for daily meal plan recommendations, interactive diet consultants for balanced food recommendations, social-affective computing for food preference recognition, meal planning systems that take user preferences and nutrient content into account, and health-aware food recommendation systems. The review's analysis of these studies attempts to advance knowledge of the function that personalized nutrition plays in encouraging better eating practices and enhancing public health.**

***Index Terms*—Health, planning, recommendations, diet, food, system, model, meal, collaborative filtering**

I. Introduction

Food suggestion seeks to offer consumers a customized list of food items based on ratings. The relevance of food recommender systems for healthy living has recently drawn increased attention. The majority of research studies now conducted in the food domain focus on recommendations that indicate suitable food items for individual customers based on their preferences or health concerns. Additionally, these systems offer features to monitor healthy consumption and persuade users to make positive dietary changes.

Systems that recommend food items based on certain eating habits or features are known as food recommendation systems [1]. The way users interact with the system determines these preferences. Food items can be advised by retrieving current items or creating new ones based on the learned choices. Typically, the food recommendation system receives input data and matches it against an item database. A subjective review is used to assess the recommendation. The general architecture is shown in Fig. 1.

Food recommendation systems can be roughly classified into two basic groups at the highest level: implicit and explicit suggestions. The most typical category is the first one. User-provided preferences are used for implicit recommendations. These characteristics are processed in a way that makes them similar to food products. They include contextual information, historical data, and recipe ratings. Following the acquisition of a similarity metric, the user is shown comparable food products. This implicit advice is intrinsically individualized because it takes into account the preferences of the user [2].

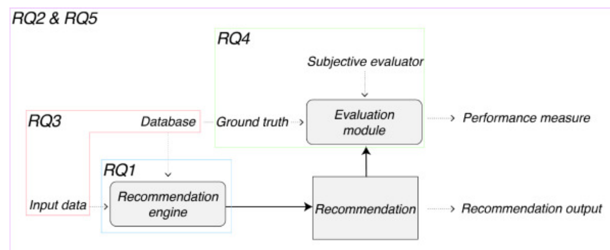

Fig. 1. The general architecture used in Food recommendation systems. The RQs are linked to the relevant aspects of the system [2].

When proposing food products, the second category of Food recommendation systems just considers the qualities of the food items. This method involves explicitly providing these attributes to the system via a query. Understanding user preferences is not required because all the information needed to make a recommendation is provided. The technology can either develop new food products or retrieve similar ones based on user preferences. While user preferences can be taken into account, some solutions do not require customization. Should that be the case, several users utilizing the same query would get different suggestions.

II. Related Works

In contemporary society, various options are available to prevent negative consequences, including advice from the attending physician, such as a nutritionist or cardiologist, as well as applications with an emphasis on smart technologies that make people's life less complicated. The most often seen free resources on the Internet are calculators, questionnaires, food nutrient information system, and tracking tools. These apps can be summarized as store and track what you eat and graph for reviewing a user's goal. However, none of the aforementioned tools or apps can give a user a personal guidance about diet management. [3]. Here are some solutions that were provided in the previous publications:

SmartDiet [3] is a system that uses geographic coordinates from the user's mobile device to negotiate with food vendors near the user's current location regarding available meals and nutrition details. The acquired information is passed on to the next component, after which the user will receive a list of possible foods and establishments. In the next stage, users can interact with the algorithm to tailor the proposed foods to their specific needs. In the final step, the suggested system will update the limits to generate a customized diet plan based on the user's preferences.

Islam et al. evaluate an affective behavior-based personalized nutrition recommendation and menu planning (AMRP) system [4] and propose the collection of brain signal (EEG) and survey data from people. The survey data contained replies to questions concerning how participants reacted when they saw photos of food. Their computing system is focused on raw signal capture, preprocessing, and efficiency calculations. Dietary suggestions include the top five foods based on feelings. The menu planning method proposes meals for breakfast, lunch, dinner, and snacks. The decision to arrange a meal is based on both the nutritional worth and effectiveness of the various foods. To conclude, the proposed AMRP system consists of three major modules: affective computing, nutritional guidance, and diet planning.

The system developed by Aberg [5] demonstrates and evaluates several aspects of meal planning. It takes into account dietary constraints, such as allergies or other medical conditions, nutritional content, such as fat and protein levels, preparation time, and cooking difficulties. It additionally considers factors such as the cost of products, their availability at home, differences in components and meal categories when compared to other dishes in the plan, and user-rated taste preferences.

SHARE System [6]. The system discussed in the study utilizes user ratings, medical history, and a database of recipes as its primary inputs. It incorporates a knowledge-based component that focuses on nutrients relevant to chronic diseases. The system combines collaborative and content-based filtering techniques with the consideration of nutrients related to chronic illnesses to generate a personalized weekly nutrition plan. This plan is then dynamically adjusted based on the user's preferences. Collaborative filtering is employed to provide recommendations to individual users based on their ratings and those of similar users. To address the specific health needs of each user, the system includes personalization features that take into account the user's medical history. Users have the flexibility to create weekly meal plans for any desired duration. Furthermore, the system allows people to actively participate in shaping the recommendations by providing feedback in real time. Another notable feature is the ability for users to request additional information about any recommended recipe, such as the type of food, number of ingredients, and nutritional value. This functionality enables users to better understand why a recipe was suggested, and determine if it aligns with their dietary requirements and preferences.

III. METHODOLOGY

A. Healthy and Time-Aware Food Recommender System (HTFRS) [7]

A new nutritional hybrid recommendation system has been created that takes advantage of both collaborative filtering and content-based models. HTFRS lists favorite dishes using the user's similarities and product groups. Since each user's preferences, diet, lifestyle, and eating habits may change over time, HTFRS takes into account the temporary effects of historical ratings in the process of calculating user similarity. HTFRS contains two main steps:

1) Time-aware collaborative filtering
2) The food-ingredients-based prediction rating

The first stage involves calculating the user-to-user similarity matrix, considering the rating's timestamp. The collaborative filtering-based approach predicts user ratings based on similarity and prior ratings. In the second stage, foods are categorized as nodes in an attributed social network. Each node's attributes indicate its constituents. Next, the food-to-food similarity matrix is created using the social network representation. A novel attributed community-detection method categorizes the initial foods. The produced food clusters are then used to forecast ratings for non-rated foods. Finally, the top-N healthy foods are recommended through collaborative filtering, food ingredient-based prediction, and nutrition facts after these two steps.

The main task of a collaborative filtering-based recommender system is to identify users that have similar preferences in food. The model suggests products to active users by the result of similar user ratings. This phase of the proposed model utilizes the user-food rating matrix to estimate user-to-user similarity.

Classic recommender systems face the cold-start and data-sparsity issue, where certain items do not have past ratings. Newly added foods may not be suggested due to the cold-start problem, leaving them "cold" indefinitely. Hybrid recommendations combine content-based and collaborative filtering techniques to address the item's cold start and data sparsity issues. Content recommendation systems use item clustering algorithms to deliver exact recommendations and address this issue. In this study, a meal clustering strategy to increase the final suggestion performance was presented. For this purpose, a new attributed community-detection algorithm for food clustering based on ingredients was created.

The provided approach evaluates the usefulness of food products based on the content of trace elements in them. Macronutrients such as fats, proteins, and carbohydrates are essential for energy production and survival. A balanced diet containing these trace elements helps to promote health and life expectancy. The ideal range of food macronutrients of dietary recommendations is shown in Table 1.

B. A food recommender system considering nutritional information and user preferences [8].

The architecture consists of four levels for processing the information pipeline, which begins at the user information

TABLE I
DIETARY RECOMMENDATIONS ARE BASED ON THE PERCENTAGE OF ENERGY

Macronutrients	Percentage of energy contribution(%)
Protein	Min:10 - Max:15 - Average:12.5
Fat	Min:15 - Max:30 - Average:20
Carbohydrate	Min:55 - Max:75 - Average:65

level and ends when the final recommendation is generated. They are:

1) The information-gathering layer
2) The user profile dataset
3) The intelligent systems layer
4) An end-user interface

The information collection layer collects various nutrition-related data from users, including physiological indicators such as height, weight, heart rate, and calories burned, along with user-provided daily food intake and expert knowledge from product composition tables, using Internet of Things (IoT) sensor devices to continuously collect data to create comprehensive user profiles. The user profile dataset stores user-characterizing information from the information-gathering layer, serving as input for nutritional recommendation methods. The intelligent systems layer processes user profile information to create recommended meal plans using the knowledge of nutrition experts from the information collection layer. It includes three main components:

- defining the nutrition context;
- short-term intelligent models for making daily meal plans;
- long-term intelligent models for refining plans with weekly and monthly meal plans.

The end-user interface presents recommended nutrition plans and visualization of nutrient information and collects user feedback for continuous use in user profiling at the information processing level.

Thus, the characteristics of the products shown in Eq. 1 will be made up of the amount of nutrients that have been considered as key characteristics of the products. These nutrients are proteins, lipids, carbohydrates, cholesterol, sodium, and saturated fats.

$$a_k = (pro_k, lip_k, cb_k, ch_k, sod_k, sat_k) \tag{1}$$

TABLE II
CRITERIA FOR CHARACTERIZING FOODS

Term	Nutrient
pro_k	Amount of proteins of food k
lip_k	Amount of lipids of food k
cb_k	Amount of carbohydrates of food k
ch_k	Amount of cholesterol of food k
sod_k	Amount of sodium of food k
sat_k	Amount of saturated fats of food k

Fig. 2 provides an overview of the approach to making menu recommendations. This approach uses a menu query and a pre-filtered list of products as input and consists of three main steps: frequency-based menu generation (Step 1), probability-based menu refinement (Step 2), and limited frequency-based menu generation (Step 3).

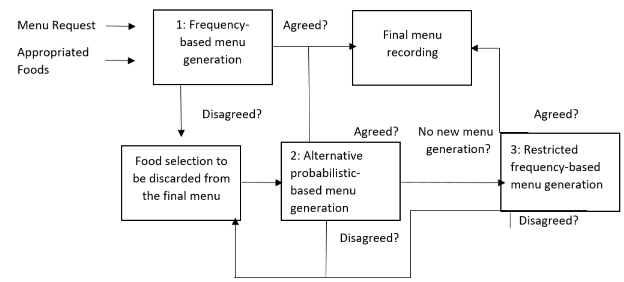

Fig. 2. General scheme of the menu recommendation approach

This general model is taken as the basis for the three necessary tasks of forming a meal plan (Fig. 2). Forming a menu based on frequency (Step 1 in Fig. 2) focused on offering products that were preferred in the past but have not been consumed recently. Refining the menu based on probabilities (Step 2 in Fig. 2). At this stage, it is first required that the user selects the products presented in the initial menu that will be finally consumed by the user (set ”agreed”), as well as products whose recommendations were not accepted by the user and, therefore, will be excluded from the final menu (set ”disagreed”). In these latter cases, the recommendation of alternative products is necessary. Therefore, this step includes two new constraints to the model presented in step 1, which ensure that all products are included in the ”agreed” set and that all products are excluded from the ”disagreed” list. Refinement of the menu based on a limited frequency (step 3 in Figure 3). This step is performed when refining the menu based on probability does not lead to any alternative menu. In such cases, the frequency-based menu is formed again, but taking into account two new restrictions that guarantee the inclusion of all products in the ”agreed” set and the exclusion of all products from the ”disagreed” set.

C. An Evaluation of a Meal Planning System: Ease of Use and Perceived Usefulness [9]

The factors influencing a person’s food choices have been studied to a fairly large extent in food science. This model is completely based on the user’s settings. The model was created not to predict the user’s choice of food, but to convince the user to choose the optimal food by weighing the relevant factors.

- Dietary restrictions, for example, ingredients that the user is allergic to or should not consume for other medical reasons.
- Nutritional value, for example, the amount of fat or protein contained in a recipe or required by the user.
- The cooking time of the dish.
- Preparation difficulty of a meal.

- The cost of the dish, i.e. the cost of the necessary ingredients.
- The availability of ingredients for a dish, for example, to what extent the necessary ingredients correspond to the ingredients available to the user at home.
- Changes regarding other dishes in the plan, in terms of the point of view of the ingredients used and the category of the dish.
- The taste of the user's dish, i.e. how the user evaluates the recipe on a taste scale.

The approach to making optimal nutrition plans according to the factors presented above uses methods to satisfy constraints. This model uses a specially developed XML-based recipe markup language, which allows us to present the necessary information about the contents of recipes in the database. The problem of matching constraints is modeled using a combination of weighted soft constraints and traditional hard constraints. In the approach, variables are used to describe various aspects of a recipe, such as time, cost, energy, protein, etc., and the variable domains consist of values found in the recipe database. To make sure that the solution has the appropriate recipe, an additional strict restriction is required. This restriction requires a full assignment of the variable so that it matches only existing recipes in the database.

Interaction Mechanism. The mechanism of interaction with the system is based on the principle that the proposed meal plans are always the result of an optimization process. This is done to ensure that the proposed meal plans do not override any strict restrictions and that the mild restrictions are respected to the maximum extent possible. This means that to clarify the proposed meal plan, the user must review the settings, clarify them, and then reschedule. There are no direct ways to change the proposed plans, for example, by dragging recipes between different proposed plans.

IV. Comparative Analysis

A. Review of Related Works

The related works (Fig. 3) highlight a variety of strategies meant to enhance eating habits using technology and personalized guidance.

№	Paper title	Dataset size	Acquisition method	Features	Model used
1	A novel healthy and time-aware food recommender system using attributed community detection	1. 45,630 foods 2. 178,265 foods	1. Allrecipes.com 2. Food.com	Protein, carbohydrate, fat	HAFR
2	A food recommender system considering nutritional information and user preferences	600+ foods	Nutritional recommendation	Personalized filtering technique	AHPSort
3	Healthy Personalized Recipe Recommendations for Weekly Meal Planning	2.774.676 recipes	1. Food.com 2. Osteoporosis Fast Facts	Type, number of ingredients, and nutritional value	MCDM method
4	An Evaluation of a Meal Planning System: Ease of Use and Perceived Usefulness	250 recipes	Existing recipes	Time, cost, energy, protein	Not Found
5	Human-Behavior-Based Personalized Meal Recommendation and Menu Planning Social System	A set of 40 images	1. EEG signals 2. Survey	Intuitive, culinary photos, and food ingredients	FoodDis
6	SmartDiet: A Personal Diet Consultant for Healthy Meal Planning	Not Found	1. USDA National Nutrient Database 2. FDA Taiwan 3. Menus on the Internet	Customized diet plan	Not Found

Fig. 3. Comparative Analysis of Related Works

Each work showcases a different method for approaching meal planning and recommendation systems, ranging from taking user feedback and emotional reactions into account to including nutritional data and resolving user interface (UI) issues. The approaches illustrate a wide range of tactics to improve customer satisfaction and engagement with meal planning systems, from collaborative filtering and optimization techniques to emotional computing and empirical user surveys.

B. Results and Discussions

The dataset used for our work was obtained from kaggle.com (https://www.kaggle.com/datasets/schemersays/food-recommendation-system/data) containing data related to the foods, ingredients, and cuisines involved. The dataset contains 400 entries on various food items, with key features including:

- Food ID: A unique identifier for each food item.
- Name: The name of the food item.
- C_Type: The category type, which includes various cuisines and food types.
- Veg_Non: Indicates whether the food is vegetarian or non-vegetarian.
- Describe: A textual description of the food item.

By integrating nutritional data into its recommendation algorithms, the project prioritizes health first, aiming to encourage a balanced and nutrient-dense diet.

```
Get_Recommendations('tricolour salad')
```

	Food_ID	index	Name	C_Type	Veg_Non	Describe	soup
0	126.0	125	andhra crab meat masala	Indian	non-veg	processed crab meat refined oil curry leaves g...	Indian non-veg processed crab meat refined oil...
1	75.0	74	detox haldi tea	Beverage	veg	haldi ginger black pepper honey water	Beverage veg haldi ginger black pepper honey w...
2	100.0	99	spicy chicken curry	Indian	non-veg	oil ghee onion paste garlic paste ginger paste...	Indian non-veg oil ghee onion paste garlic pas...
3	259.0	258	ragi coconut ladoo (laddu)	Dessert	veg	finger millet flour ragi jaggery peanuts cocon...	Dessert veg finger millet flour ragi jaggery p...
4	51.0	50	christmas chocolate fudge cookies	Dessert	veg	unsalted butter brown sugar chocolate chocolat...	Dessert veg unsalted butter brown sugar chocol...

Fig. 4. Recommendations

The proposed food recommendation system uses a comprehensive methodology that includes exploratory data analysis (EDA), data preprocessing, visualization, and recommendation engine algorithms (Fig. 4). The system uses a wide range of data, including detailed food data, nutritional information, and user preferences. Through careful preprocessing, the project ensures data integrity and relevance using text cleaning and feature aggregation techniques. TF-IDF vectorization and cosine similarity provide the foundation of the recommendation logic, which is enhanced by a multi-feature approach that takes into account text descriptions, dietary preferences, and different types of cuisine.

```
[ ] df['C_Type'].unique()

array(['Healthy Food', 'Snack', 'Dessert', 'Japanese', 'Indian', 'French',
       'Mexican', 'Italian', 'Chinese', 'Beverage', 'Thai', 'Korean',
       ' Korean', 'Vietnames', 'Nepalese', 'Spanish'], dtype=object)
```

Fig. 5. C_Type

There are visualizations to explore the distribution of categories within the dataset, specifically looking at the 'C_Type'(Fig. 5) and 'Veg_Non' (Fig. 6) columns. This implies the dataset contains categorical information about the

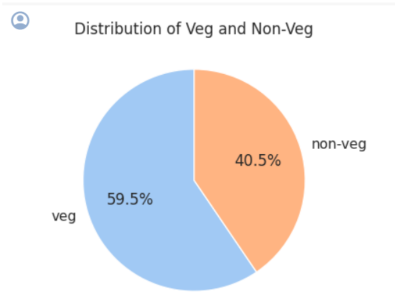

Fig. 6. Veg_Non

food items, such as their style of cuisine or dish and whether they are vegetarian or not.

TABLE III
USER FOOD RATING DATA

User_ID	Food_ID	Rating
99.0	65.0	7.0
99.0	22.0	1.0
100.0	24.0	10.0
100.0	233.0	10.0
100.0	29.0	7.0

The inclusion of ratings (Table 3) as a form of user feedback enhances user happiness and fosters confidence in the system's recommendations.

V. Limitations of Related Works

Individuals have various food preferences and dietary needs, making food advice and diet planning challenging. One of the drawbacks that might prevent certain suggested systems from providing personalized nutritional advice is their reliance on pre-existing algorithms and general dietary guidelines [3]. While systems aim to customize recommendations for every user, they might not account for slight variations in dietary preferences, health conditions, and metabolic profiles [10].

The second limitation identified in the sources is the lack of female participants in the studies, which raises doubts about the conclusions' applicability to female users. The matter is critical because it affects the validity as well as implementation of the system's findings and highlights the need for more inclusive research techniques in future investigations [5].

VI. Conclusion and Future Work

Food recommendation systems are critical in providing customers with individualized food choices based on a variety of recommendation approaches, algorithms, datasets, preprocessing methods, and data formats. These systems' quality and suggestions are assessed using a variety of metrics and evaluation approaches. These strategies help to control information overload by filtering away irrelevant material, hence improving the user experience. Food recommendation systems are projected to become increasingly important as recipe-sharing websites and recipes become more widely available. Despite their obvious advantages, there are implementation-specific limits that must be overcome before these systems may achieve their full potential.

This systematic review of the research on food recommendation systems examined all aspects of dietary guidelines. It provided a thorough overview of the methodology, data, evaluation, availability, and state-of-the-art meal recommendation systems. By examining the present landscape of food recommendation systems, this analysis offered insight on the field's challenges and prospects. Future study in this field could concentrate on increasing the accuracy and personalization of meal recommendations, as well as resolving privacy and security issues about user data. Overall, food recommendation systems have the potential to transform how individuals plan their meals and make dietary decisions, resulting in healthier lifestyles and better well-being.

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