BACS2003

ARTIFICIAL INTELLIGENCE

202501 Session, Year 2024/25

Assignment Documentation

Project Title: Food Recommender System
Programme: RSDY2S3
Tutorial Group: 5
Tutor: Ms. Mahani Binti Syed Ahmad

Team members' data

No	Student Name	Student ID	Module In Charge
1	Lim Jun Wei	24WMR09078	Hybrid Model Development + TF-IDF (Keyword Search-Based Recommendations)

2	**Chia Ming Yi**	**24WMR09040**	**KNN Content-Based Filtering (Nutrition & Time Preferences Recommendation)**
3	**Ong Yi Xin**	**24WMR09097**	**SVD Collaborative Filtering (User Review-Based Recommendations)**

Table Content

1. Introduction

1.1. Problem Background

As time goes by, various styles of cuisines have emerged. However, this **abundance of choices** also makes people confused when **faced** with a **multitude of complex cuisines**. Like strolling through a night market, each stall attracts attention and each cuisine is mouth-watering, but due to portion sizes and health concerns, people are forced to make choices. However, a problem that people often face is the fear that the food they choose will not fulfill their expectations.

In addition, improved quality of life has made people more health-conscious, and healthy eating is an effective way to achieve this goal. However, on the road to healthy eating, people **need to familiarize** themselves with the **nutritional properties** of each food or ingredient, but not everyone possesses extensive and accurate knowledge in this area.

What's more, some food enthusiasts want to **try different regional** or specialty cuisines, and they **don't know where to start**. The information available on the Internet is too general to recommend foods that suit individual needs. As a result, they are left to the trial-and-error method, which greatly dampens enthusiasm for food.

To solve these problems, AI food recommendation systems have been created. These systems provide **personalized food recommendations** by analyzing the user's health needs, dietary preferences and behavior. They not only help people choose healthy food, but also provide appropriate suggestions based on individual tastes and nutritional needs, thus enhancing the dining experience and health.

In addition, AI systems can **update and learn from user preferences** in real time, ensuring that recommendations are always in line with users' needs. By utilizing big data and machine learning algorithms, the AI food recommendation system can help people find the most suitable option for them among the rich food choices, reduce the cost and time of trial and error, and enhance their passion and satisfaction for food.

1.2. Objectives/Aims

As the saying goes, "Food is what people eat." In developing the food recommendation AI system, our core goal is to **provide personalized** and **accurate food recommendations**. By analyzing the user's health needs, dietary preferences and behavioral habits, the AI system is able to intelligently **match the right food**. For example, when users want to try salty and spicy flavors but can't get started, the AI can recommend the dish that best meets their needs based on their preferences and past choices, making the choice easier and more convenient.

In addition, we want to **reduce users' trial-and-error costs and time**. While traditional dietary choices often rely on personal experience or a lot of trial and error, our AI system is able to continuously optimize the recommendations through real-time learning and data updates. The AI not only adjusts the recommendations based on the user's feedback, but also predicts the foods that may be of interest, thus reducing the time and effort invested by the user in finding the right dining options.

Another important goal for us is to **enhance the dining experience and health** of our users. Through personalized recommendations, AI not only helps users discover delicious and healthy food, but also guides them to make choices that better meet their nutritional needs. In this way, users can not only enjoy the food, but also develop more scientific and rational eating habits, realizing both health and taste.

1.3. Motivation

As the diversity and complexity of global food culture continue to expand, individuals are increasingly faced with the challenge of making daily food choices that align with both their personal taste and health goals. With so many types of cuisines, ingredients, and nutritional styles to choose from, many users experience hesitation, indecision, or even frustration during mealtime. While the availability of food information online has increased, most suggestions remain generic and are not adapted to the needs of specific individuals. In this context, a personalized, intelligent food recommendation system can bring meaningful support to users in their daily decision-making.

Our AI-based food recommendation system is designed to directly address this gap. It focuses on **delivering personalized food suggestions** by analyzing three core aspects: the user's identity, their previous reviews, and their selected nutritional preferences. These inputs allow the system to form a **dynamic understanding** of each user's unique behavior, such as what kinds of food they have enjoyed in the past, what health-related choices they have made, and what dietary priorities they care about. The system does not simply match users with popular items. Instead, it learns continuously from their actions and feedback to refine its recommendations over time.

This system also provides **clear social value**. As modern health concerns such as obesity, heart disease, and diabetes become more common, individuals are increasingly encouraged to pay attention to what they eat. However, maintaining a balanced and healthy diet is not always easy, especially when users lack sufficient nutritional knowledge or find it hard to discover meals that are both healthy and enjoyable. By offering suggestions that are tailored to both taste and health needs, our system empowers users to make smarter decisions that support their physical well-being.

From a commercialization perspective, this system can be **adapted** for use in **wellness-focused mobile applications**, **nutrition tracking tools**, or **personalized health recommendation**

platforms. Developers and businesses in the health-tech sector can integrate the system to enhance user engagement by offering intelligent meal suggestions that reflect individual goals and preferences. By providing users with value through customization, such systems can increase retention, improve satisfaction, and offer insights into dietary behavior for future product improvement.

Our AI food recommendation system is designed to turn the often confusing process of deciding **what to eat** and **how to eat into a smooth, intelligent, and personalized experience**. By analyzing user identity, past reviews, and nutrition level choices, the system provides relevant, adaptive, and meaningful food recommendations. It helps users save time, reduce decision fatigue, and move toward healthier and more satisfying eating habits. This approach has the potential to redefine the relationship between people and food, using AI to bring both convenience and care into everyday eating decisions.

2. Research Background

2.1. Background of the applications

Personalized recommender systems have been widely used in fields like e-commerce and entertainment. In the food domain, however, many systems still **depend on static**, **content-based** or **popularity-driven algorithms** that fail to consider individual dietary goals, health profiles, or changing preferences. This limits their usefulness, especially as users increasingly seek recommendations tailored to both taste and well-being (Zhang et al., 2025).

Recent research has explored collaborative filtering, matrix factorization, and deep learning for meal recommendations. While effective to a degree, these methods often face cold-start issues and lack adaptability to nuanced goals such as sugar reduction, vegetarianism, or culinary exploration (Ju et al., 2022). Some systems incorporate nutritional data, but usually through fixed dietary labels (e.g., “low carb”), offering limited insight into users’ evolving needs and emotional relationships with food (Zhang et al., 2024).

Our system addresses these gaps by combining user identity, review history, and nutrition-level preferences to offer dynamic, personalized food recommendations. This user-centered approach enables the system to learn from feedback and adapt to changes in behavior over time.

Unlike many commercial applications tied to restaurant data, our system focuses solely on helping individuals discover food aligned with their health and lifestyle—offering both flexibility and deeper personalization. It advances current research by applying machine learning not just for item matching but for behavior-aware, adaptive learning that remains underexplored in non-commercial food systems (Chen et al., 2021).

By bridging technical and practical gaps, this project contributes to both the recommender system literature and real-world healthy decision-making.

2.2. Analysis of selected tool with any other relevant tools

Tools comparison	**Remark**	**Jupyter Notebook**	**Streamlit**	**scikit-learn**
Type of license and open source	State all types of license	Modified BSD License	Apache License 2.0 (Open Source)	BSD 3-Clause License (Open Source)

license				
Year founded	When is this tool being introduced?	2014	2019	2007
Founding company	Owner	Project Jupyter (originally IPython project)	Streamlite Inc. (acquired by Snowflake)	David Cournapeau (community-driven)
License Pricing	Compare the prices if the license is used for development and business / commercialization	Free and open-source	Free and open-source	Free and open-source
Supported features	What features that it offer?	Interactive code execution, inline visualizations, markdown, easy debugging and data exploration	UI for data apps, interactive widgets, real-time updates and Python-based	Machine learning algorithms: regression, classification, clustering, preprocessing
Common applications	In what areas this tool is usually used?	Data science, machine learning model development and data visualization	Data apps, dashboards, machine learning model demos	Machine Learning and Data Science projects
Customer support	How the customer support is given, e.g. proprietary, online community, etc.	It has large community support, GitHub issues, Stack Overflow and official	Community-based, GitHub issues and paid support via Snowflake	Community-driven such as StackOverflow and GitHub

		documentation		
Limitations	The drawbacks of the software	Not suitable for production deployment, it has limited UI control and risk of executing cells out-of-order causing hidden state confusion.	Limited advanced UI control, it requires certain level of Python knowledge	It does not support deep learning, only supports traditional machine learning

2.3. Justify why the selected tool is suitable

Jupyter Notebook

Jupyter Notebook is mainly used in this project for data cleaning, data exploration, model training, testing and model building (Project Jupyter Documentation — Jupyter Documentation 4.1.1 Alpha Documentation, n.d.). It provides a platform for implementing the code for achieving those purposes. Meanwhile, it allows for quick experimentation with code via supporting interactive code execution and data visualization (10 Reasons Why Data Scientists Love Jupyter Notebooks, n.d.). Thus, it leads to an efficient code development with easy debugging and high readability. By collaborating with other libraries, it can help for processing different datasets and building the food recommendation algorithm models. In overall, it is a crucial tool for developing the models for building the food recommender system.

Streamlit

Streamlit takes an important role in creating the web application for the food recommender system. Even though Jupyter Notebook has built different models for recommending the food based on different criterias, it is still important to integrate those models and other Python scripts into an interactive web application (Streamlit Docs, n.d.). It allows the users to interact with the recommender system by typing the food keywords, selecting their user id and filtering the food nutrition criterias. So, the recommendation features in the model can be triggered effectively to find out and visualize the food recommendation for the users. Since it does not require the knowledge of web frameworks, it is suitable for quick demonstration and testing because the user interface can be built rapidly and updated without restarting the application (GeeksforGeeks, 2023).

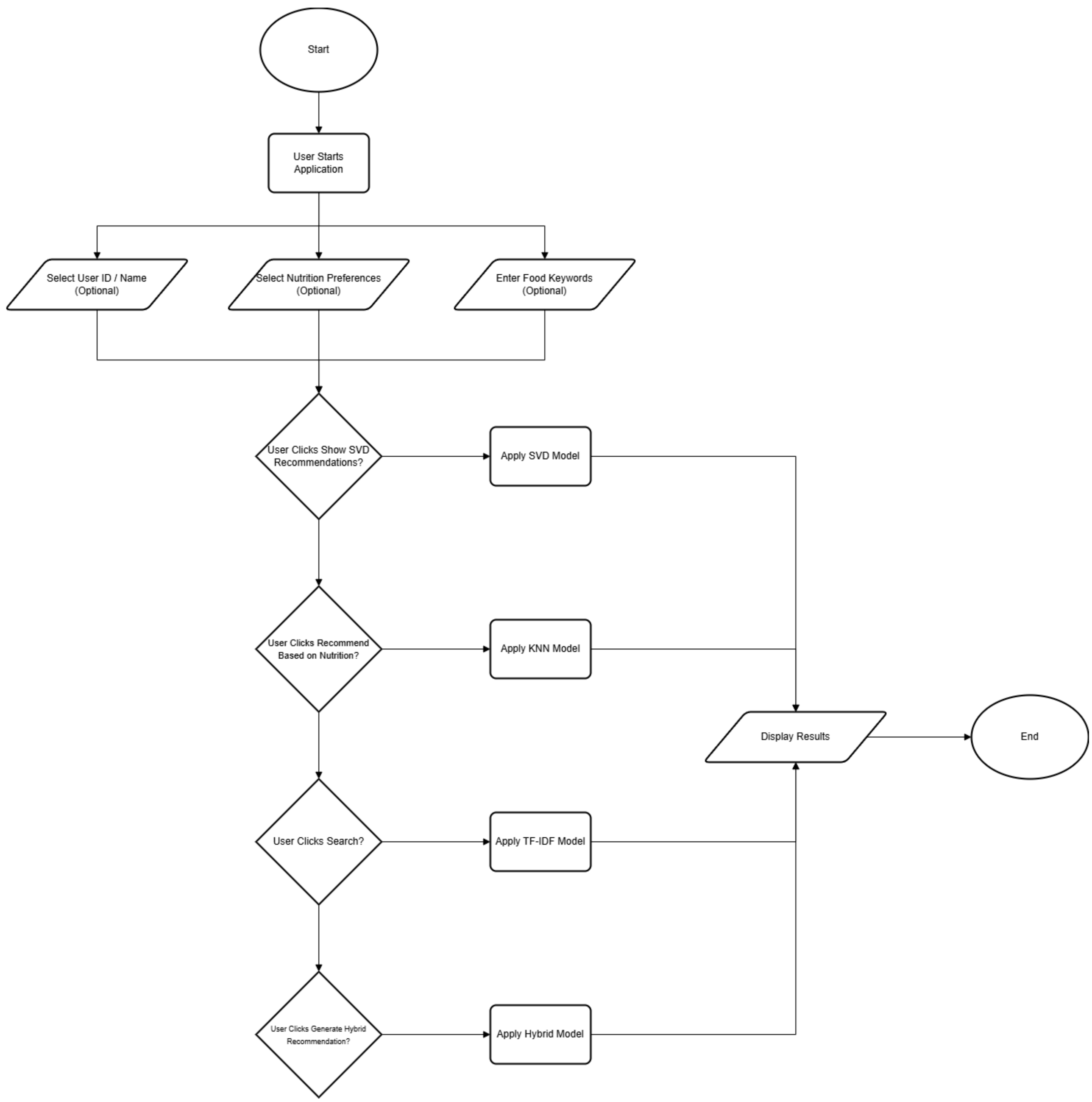
Scikit-learn

Scikit-learn is mainly taking part in the development of K-Nearest Neighbors (KNN) model for nutrition-based food recommendation and preprocessing tasks such as clustering (1.6. Nearest Neighbors, n.d.). It is an important tool for implementing machine learning algorithms with consistent APIs. It also comes with preprocessing tools such as scaling, clustering and classification which are ideal for transforming nutrition data into meaningful categories by different levels (Scikit-learn: Machine Learning in Python — Scikit-learn 1.6.1 Documentation, n.d.). Moreover, it also provides fast model development and testing with evaluation tools and metrics.

3. Methodology

3.1. System flowchart/activity diagram

System Flowchart for Food Recommendation Web Application



3.2. Description of dataset

The source of the dataset is obtained from Food.com - Recipes and Reviews in Kaggle platform. (Alvin, 2020) There are two dataset files being applied in the food recommender system which are recipes.csv and reviews.csv. Both datasets contain information about the food recipes, reviews and nutritional details and are linked together using RecipeId.

Dataset Structures

- recipes.csv
    - This dataset is mainly focusing on collecting the information about various food recipes such as the name, ingredients, nutritional information, cooking time and other relevant details. The number of record rows in the dataset is 522568.
    - Data dictionary:

Column Name	Description	Type
RecipeId	A unique identifier for each recipe.	Integer
Name	The name of the recipe.	String
AuthorId	The unique identifier for the author who submitted the recipe.	Integer
AuthorName	The name of the author who submitted the recipe.	String
CookTime	The time required to cook the recipe.	ISO 8601 standard for durations
PrepTime	The time required to prepare the recipe.	ISO 8601 standard for durations
TotalTime	The total time required to make the recipe, which is the sum of CookTime and PrepTime.	ISO 8601 standard for durations
DatePublished	The date and time when the recipe was published.	ISO 8601 standard for date and time representation

Description	A brief description of the recipe which may provide an overview or key highlights.	String
Images	A list of links associated with the recipe.	R language vector
RecipeCategory	The category or type of recipe.	String
Keywords	Keywords related to the recipe that help users find it through search or filtering.	R language vector
RecipeIngredientQuantities	The quantities or weights of ingredients required for the recipe.	R language vector
RecipeIngredientParts	Describes the ingredients used which are associated with the column RecipeIngredientQuantities in the recipe.	R language vector
AggregatedRating	The average rating of the recipe, calculated from all the user ratings.	Float
ReviewCount	The total number of reviews submitted for the recipe.	Integer
Calories	The total calorie content per serving for the recipe.	Float
FatContent	The amount of fat per serving in the recipe.	Float
SaturatedFatContent	The amount of saturated fat per serving in the recipe.	Float
CholesterolContent	The amount of cholesterol per serving	Float

	in the recipe.	
SodiumContent	The amount of sodium per serving in the recipe.	Float
CarbohydrateContent	The amount of carbohydrates per serving in the recipe.	Float
FiberContent	The amount of dietary fiber per serving in the recipe.	Float
SugarContent	The amount of sugar per serving in the recipe.	Float
ProteinContent	The amount of protein per serving in the recipe.	Float
RecipeServings	The number of servings the recipe yields.	Float
RecipeYield	The output or yield of the recipe (e.g., amount of dish prepared).	String
RecipeInstructions	Step-by-step instructions for preparing the recipe.	R language vector

- reviews.csv
    - This dataset contains user-generated reviews for recipes. Each row represents one review written by a user about a specific recipe. This dataset is associated with the recipes.csv using the RecipeId column.
    - Data Dictionary:

Column Name	Description	Type
ReviewId	A unique identifier for each review.	Integer
RecipeId	The identifier of the recipe being reviewed	Integer
AuthorId	The unique identifier of the user who submitted the review	Integer

AuthorName	The name of the author who wrote the review.	String
Rating	The numeric rating given to the recipe on a scale of 1 to 5 stars.	Integer
Review	The written text content of the user's review describing their opinion.	String
DateSubmitted	The date the review was originally submitted.	ISO 8601 standard for date and time representation
DateModified	The date the review was last edited or updated by the user.	ISO 8601 standard for date and time representation

3.3. Description of algorithm(s)

Collaborative Filtering (SVD - Singular Value Decomposition)

Since the dataset has provided the information about various authors' reviews on different recipes with ratings, the Singular Value Decomposition (SVD) can be applied on the reviews.csv dataset for **recommending recipes based on user's past reviews and ratings**. This algorithm will identify the patterns in how authors rate the recipes and predict unknown ratings by factoring the user-recipe interaction matrix into hidden features. Via transforming the trained model of SVD into a .pkl file, it can be **implemented in the web application for interactive user-based recommendation**. Users can select the specific user via selecting or entering the user's ID or name. Then, they can click on the submit button to trigger the SVD recommendation function to recommend appropriate foods in which the users may be interested.

Content-Based Filtering - K-Nearest Neighbors (KNN)

In order to recommend users' preferable foods based on their desired nutrition content or cooking time, K-Nearest Neighbors (KNN) can be applied to the nutrition-related and cooking time related columns in recipes.csv. For example, Calories, FatContent, FibreContent, SugarContent, PrepTime and so on. Via **grouping the recipes based on nutritional similarity using clustering**, the KNN-model can **find the closest recipes to that profile after users selected their favourable level of nutrition and time required**. Thus, the health-conscious or dietary users can easily get their suitable recipes by selecting preferences.

Data Preprocessing Techniques

Data preprocessing is one of the crucial steps to be taken for ensuring the consistency, quality, integrity and readiness of a dataset. This is useful for increasing the effectiveness and efficiency of model training. There are some missing values in some columns in the dataset obtained so it is necessary to handle the missing value gracefully via suitable methodologies. In this project, the **rows with missing values in the critical column will be removed** such as the image column. This is because the image column is essential for ensuring the consistency of web application recommendation output result representation. Besides, there are many column values which are applied in different formats. It will significantly affect the data exploration and model training process in the later stages. Thus, **standardization should be applied on those column values to maintain the readability** when it comes to data exploration and model training. For example, the TotalTime column values are applying the ISO 8601 standard form for durations (combine numerical and alphabetical characters) which may not be appropriate or readable for the analysis process. Thus, a conversion will be implemented to convert the values into the minutes integer to ensure an ideal readability. Not only that, there are many nutritional values which are too scattered in each row even though the values are precise. The over-scattered nutritional values may lead to difficulties or lower performance for model training of recommending food based on nutrition preferences. Thus, a **normalization method is used to scale the nutritional values** before feeding into models like KNN to prevent large numbers from skewing distance calculations.

Hybrid Recommendation Strategy

Hybrid recommendation is a strategy which allows the food recommender system to **recommend foods based on different criterias and models such as SVD and KNN models**. Via combining both collaborative and content-based approaches, a more balanced and relevant food recommendation can be made for the users. In the system, the **SVD model will be used for recommending food to users based on specific user's past reviews and ratings** while **KNN model will be used for recommending food to users based on their selected nutritional and time preferences**. At the same time, the **food searching feature is also implemented using TF-IDF for providing a more flexible way for users to find foods**. By combining 3 of them together into hybrid recommendations, users can search the food keywords in which they may want, select their user identity and select the nutritional level and time level for finding the most suitable food for fulfilling their needs.

3.4. Proposed test plan/hypothesis

Hypothesis

1. H1: The SVD collaborative filtering model will successfully recommend recipes that align with a user's past preferences based on review ratings.
2. H2: The KNN model will recommend nutritionally suitable recipes based on selected nutrition and time preferences.
3. H3: The TF-IDF search will accurately retrieve recipes that contain the user-entered keywords.
4. H4: The hybrid recommendation system will produce more relevant and satisfying recommendations than using any single method alone.

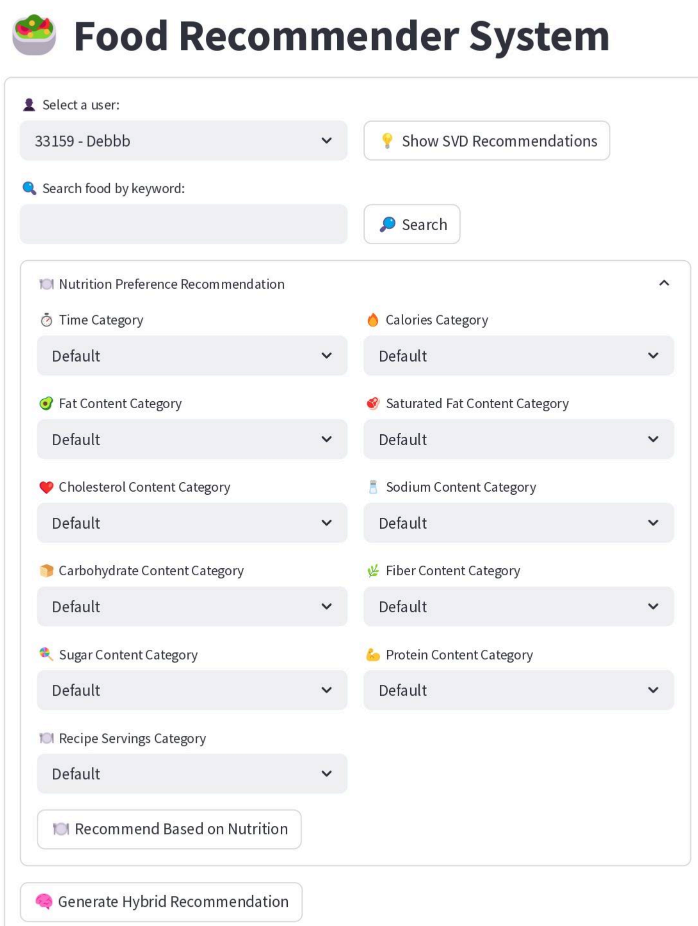
Test Plan

Test Case	Description	Input	Expected Output	Evaluation Criteria
TC01	Test SVD Recommendations	User ID / Name	List of recommended recipes	Relevance to past reviews
TC02	Test KNN Nutrition Filter	Nutrition and time preferences	List of recommended recipes	Match to preferences
TC03	Test Keyword Search	Food keyword	Recipes containing keyword	Keyword relevance
TC04	Test Hybrid Recommendation	User ID + Preferences + Keywords	Combined recommended list	Relevance and personalization

4. Result

4.1. Results

Test Case TC01: SVD Recommendations

<table>
<tr><td>Input</td><td>Choose 'User ID 33159 - Debb' in the user dropdown list and click on the button 'Show SVD Recommendation'.</td></tr>
<tr><td>Expected Output</td><td>10 recipe suggestions are displayed based on selected user past reviews.</td></tr>
<tr><td>Actual Output</td><td>
</td></tr>
</table>

🎯 Recommendations for 33159 - Debbb:

🍽️ Mozzarella, Tomato and Basil Salad

Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 54

📜 Ingredients:

👩‍🍳 Instructions:

🗣️ User Reviews:

European | < 15 Mins | No Cook | Easy

🍽️ Olive Garden Zuppa Toscana



Rating: ★★★★★ (5.0/5)

Total Reviews: 96

Ingredients:

Instructions:

User Reviews:

Potato Poultry Vegetable Meat European Spicy < 60 Mins

🍽️ Calzones



Rating: ★★★★★ (5.0/5)

Total Reviews: 62

🧾 Ingredients:

👨‍🍳 Instructions:

🗣️ User Reviews:

Kid Friendly | Weeknight | Oven | < 4 Hours | Easy

🍽️ Crisp Lemon Calf Liver

Rating: ★★★★★ (5.0/5)

Total Reviews: 19

🧾 Ingredients:

👨‍🍳 Instructions:

🗣️ User Reviews:

Beef Organ Meats | Beef Liver | Poultry | Meat | Canadian | Kid Friendly | < 30 Mins | Stove Top | Easy

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🍽️ Braised Red Cabbage with Red Onion and Apples

Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 30

🧾 Ingredients:

👩‍🍳 Instructions:

🗣️ User Reviews:

Fruit | Vegetable | Canadian | Low Protein | Low Cholesterol | Kid Friendly | Kosher | Potluck | Christmas | Thanksgiving | Weeknight | Stove Top | < 4 Hours | Easy | Inexpensive

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🍽️ Mom's Gingersnaps

 

Rating: ★★★★★ (5.0/5)

Total Reviews: 22

🧾 Ingredients:

🧑‍🍳 Instructions:

🗣️ User Reviews:

Lunch/Snacks | Cookie & Brownie | Kid Friendly | < 30 Mins | Oven | Easy | Inexpensive

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🍽️ Uncle Bill's Broccoli Soup


Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 25

Ingredients:

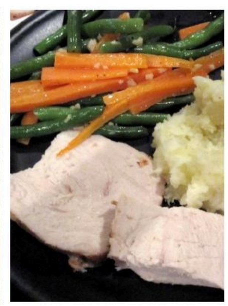
Instructions:

User Reviews:

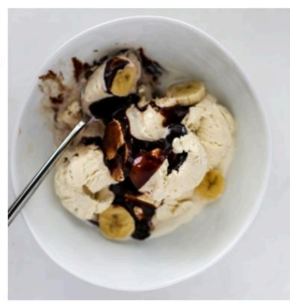
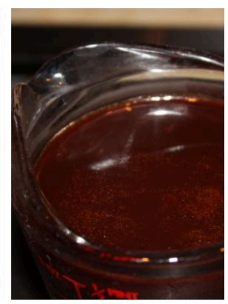
Canadian | Low Protein | < 60 Mins

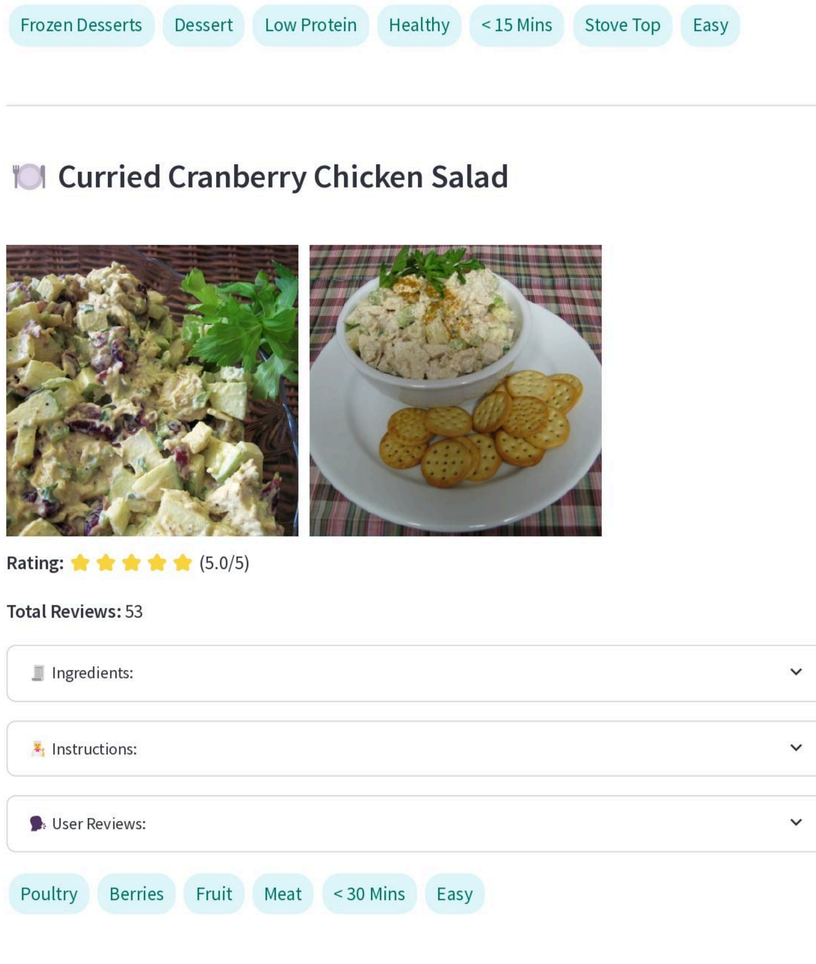
Supreme Garlic Mashed Potatoes



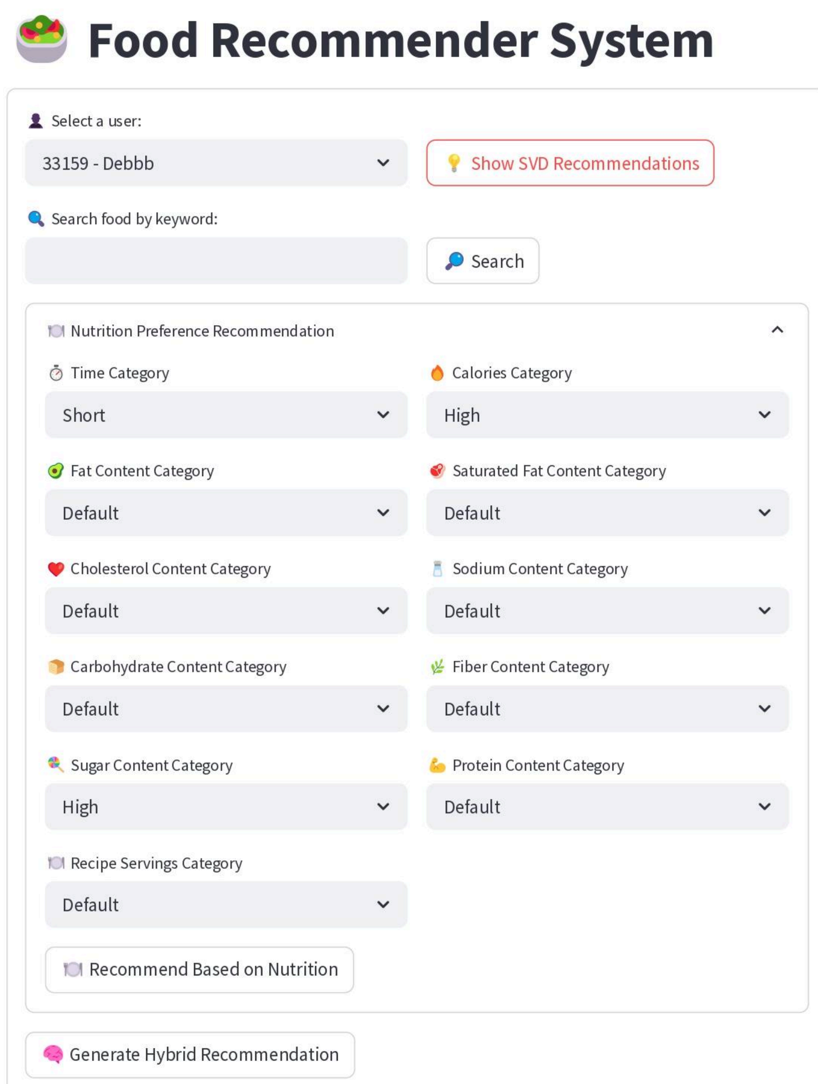


Rating: ⭐⭐⭐⭐⭐ (5.0/5)

	Total Reviews: 74 🧾 Ingredients: 🧑‍🍳 Instructions: 🗣️ User Reviews: Vegetable · Low Protein · Kid Friendly · Thanksgiving · < 30 Mins · Stove Top · Easy · Inexpensive 🍽️ **Lee Lee's Famous Chocolate Sauce for Ice Cream**    **Rating:** ⭐⭐⭐⭐⭐ (5.0/5) **Total Reviews:** 163 🧾 Ingredients: 🧑‍🍳 Instructions: 🗣️ User Reviews:

	
Analysis	10 recommended recipes which have highly rating by users or similar users are displayed using SVD model recommendations. Since the recommendations are aligned well with user preferences, the result supports H1.

Test Case TC02: Test KNN Nutrition Filter

Input	Select 'Short' in Time Category dropdown list, 'High' in Calories Category and 'High' in Sugar Content Category. Then, click on 'Recommend Based on Nutrition' button.
Expected Output	10 recipe suggestions are displayed based on nutrition and time categories level selected.
Actual Output	

🥗 Nutrition-based Recommendations for Your Nutrition Preferences:

🍽️ Chicken Breast Stuffed With Pineapple Stuffing

Rating: ⭐⭐⭐⭐⭐ (4.5/5)

Total Reviews: 1

🧾 Ingredients:

👨‍🍳 Instructions:

🗣️ User Reviews:

Chicken | Poultry | Meat | Savory | < 60 Mins | Beginner Cook | Easy | Inexpensive

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🍽️ Tropical Silverbeet (Chard) Phyllo

 

Rating: ⭐⭐⭐⭐☆ (3.8/5)

Total Reviews: 1

🧾 Ingredients:

👩‍🍳 Instructions:

🗣️ User Reviews:

Pineapple Chard Tropical Fruits Greens Fruit Vegetable Australian Brunch < 60 Mins

---

🍽️ Curried Pasta Salad With Chicken

  

Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 5

🧾 Ingredients:

👨‍🍳 Instructions:

🗣️ User Reviews:

Asian | Potluck | Weeknight | < 60 Mins

🍽️ Corn Casserole/Pudding

  

Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 6

📜 Ingredients:

👨‍🍳 Instructions:

🗣️ User Reviews:

Vegetable Christmas Thanksgiving < 60 Mins Easy

🍽️ Banana Blintz Loaf



Rating: ⭐⭐⭐☆☆ (3.1/5)

Total Reviews: 3

📜 Ingredients:

👨‍🍳 Instructions:

🗣️ User Reviews:

Cheese Tropical Fruits Fruit Kosher Sweet Brunch < 60 Mins Small Appliance

---

🍽️ Roast Chicken with Lemon and Figs

 

Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 4

📜 Ingredients:

🧑‍🍳 Instructions:

🗣️ User Reviews:

Chicken Lemon Poultry Citrus Fruit Meat < 60 Mins Oven Beginner Cook Easy

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🍽️ Easy Cheesy Sloppy Joes


Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 3

🧾 Ingredients:

🧑‍🍳 Instructions:

🗣️ User Reviews:

< 4 Hours   Easy

🍽️ Lemon Poppy Seed Quick Bread



Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 7

🧾 Ingredients:

👨‍🍳 Instructions:

🗣️ User Reviews:

Breads | Grains | Fruit | Kid Friendly | Potluck | Weeknight | Oven | < 4 Hours | Easy | Inexpensive

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🍽️ Kugelhopf

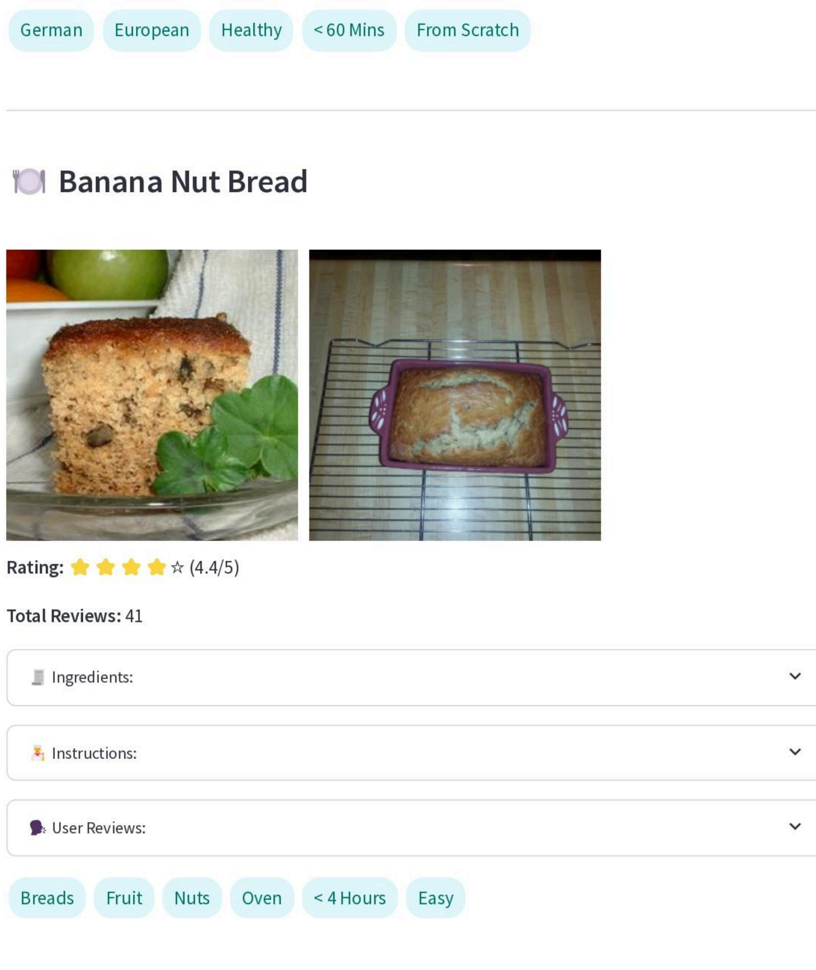
Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 1

🧾 Ingredients:

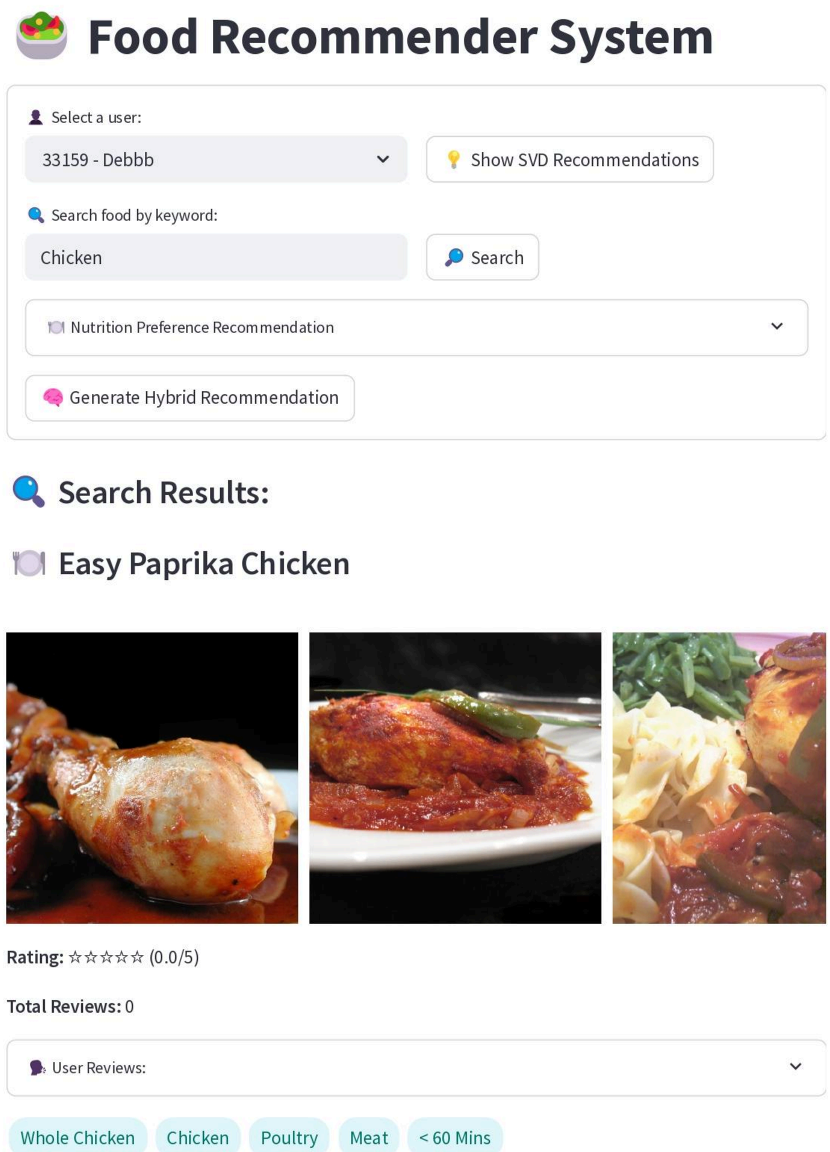
👨‍🍳 Instructions:

🗣️ User Reviews:

	
Analysis	The KNN model has returned 10 recommended recipes that matched the nutrition and time profile. The result support H2 as the recommendations are suitable in terms of nutrition and time category levels.

Test Case TC03: Test Keyword Search

Input	Enter 'Chicken' in the food keyword search bar and click on 'Search'

<table>
<tr><td></td><td>button.</td></tr>
<tr><td>Expected Output</td><td>10 recipe suggestions are displayed where their name or keywords contain the word "Chicken".</td></tr>
<tr><td>Actual Output</td><td>


</td></tr>
</table>

🍽️ Chicken Soup and Homemade Noodles

Rating: ☆☆☆☆☆ (0.0/5)

Total Reviews: 0

🗣️ User Reviews:

Whole Chicken | Chicken | Poultry | Meat | < 4 Hours

🍽️ Easy Chicken Curry

Rating: ☆☆☆☆☆ (0.0/5)

Total Reviews: 0

🗣 User Reviews:

Whole Chicken | Chicken | Poultry | Meat | < 30 Mins | Easy

🍽️ The Easiest Chicken and Noodles Recipe Ever


Rating: ☆☆☆☆☆ (0.0/5)

Total Reviews: 0

🗣 User Reviews:

Whole Chicken | Chicken | Poultry | Meat | < 4 Hours | Easy

🍽️ Chicken Lime Vegetable Soup

Rating: ☆☆☆☆☆ (0.0/5)

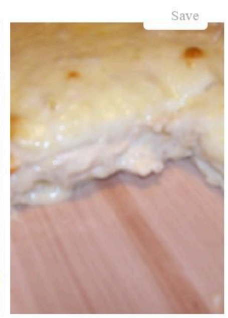
Total Reviews: 0

🗣 User Reviews:

Whole Chicken | Chicken | Poultry | Vegetable | Meat | < 4 Hours

---

🍽 Sour Cream Chicken Enchilada Casserole

Rating: ☆☆☆☆☆ (0.0/5)

Total Reviews: 0

🗣 User Reviews:

Whole Chicken | Chicken | Poultry | Meat | < 60 Mins | Oven | Easy

---

🍽️ Chicken Enchilada Salad

Rating: ☆☆☆☆☆ (0.0/5)

Total Reviews: 0

🗣️ User Reviews:

Whole Chicken | Chicken | Poultry | Meat | < 15 Mins | Easy | Inexpensive

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🍽️ Barefoot Contessa Chicken Bouillabaisse

Rating: ☆☆☆☆☆ (0.0/5)

Total Reviews: 0

🗣 User Reviews:

Whole Chicken · Chicken · Poultry · Meat · European · < 4 Hours

---

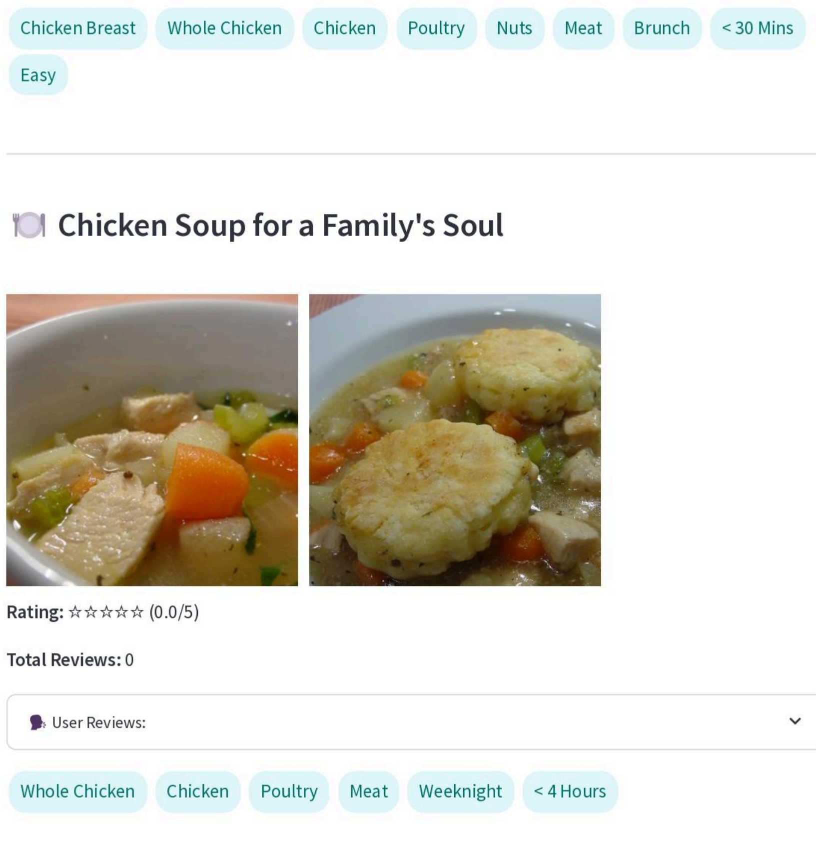
🍽️ Italian Chicken Salad

Rating: ☆☆☆☆☆ (0.0/5)

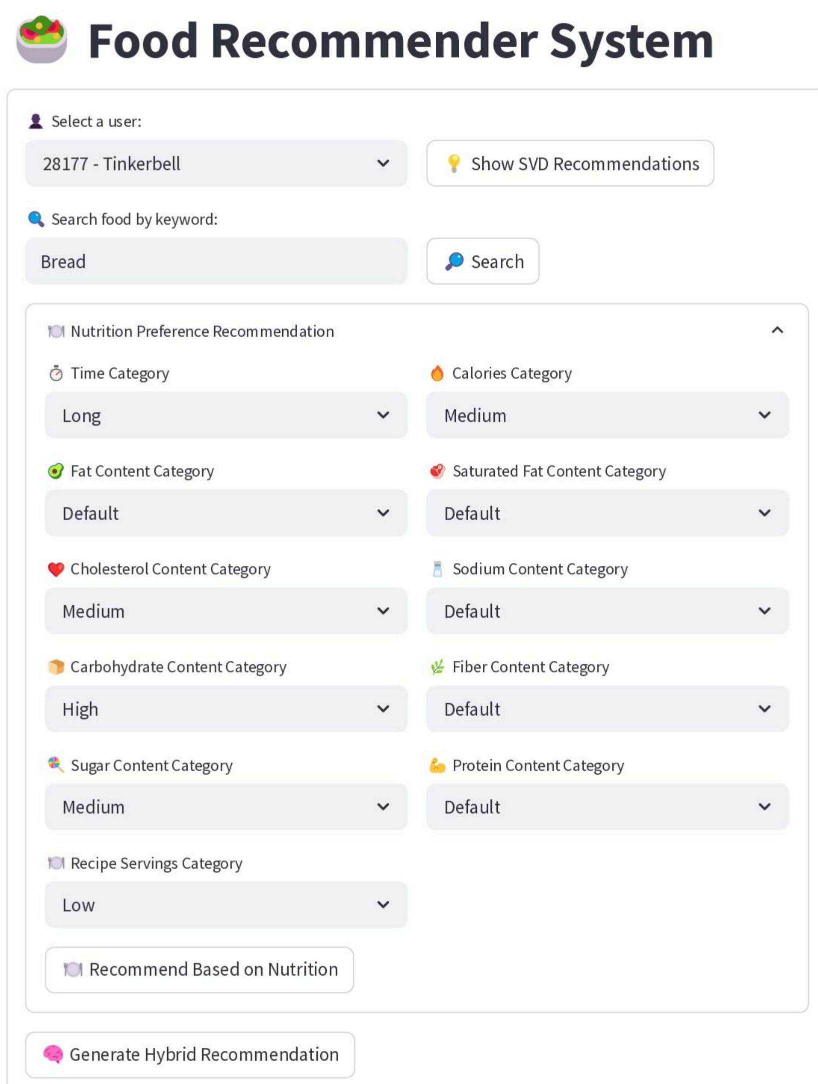
Total Reviews: 0

🗣 User Reviews:

	
Analysis	TF-IDF retrieved 10 recommended recipes which are matched with the keywords 'Chicken' input. The result supports H3 as the searching feature is working as expected.

Test Case TC04: Test Hybrid Recommendation

Input	Select '28177 - TinkerBell' in user dropdown list, enter 'Bread' into the keyword search bar, select 'Long' in Time Category, 'Medium' in

	Calories Category, 'Medium' in Cholesterol Content Category, 'High' in Carbohydrate Content Category, 'Medium' in Sugar Content Category and 'Low' in Recipe Servings Category. Then, click on 'Generate Hybrid Recommendation' button.
Expected Output	10 recipe suggestions are displayed based on the past reviews made by '28177 - TinkerBel', the keyword 'Bread' entered in the search bar, and the nutrition and time preferences selected.
Actual Output	

🧠 Hybrid Recommendation Results:

🍽️ Irresistible Peanut Butter Cookies

Rating: ⭐⭐⭐⭐☆ (4.4/5)

Total Reviews: 72

📜 Ingredients:

👨‍🍳 Instructions:

🗣️ User Reviews:

Dessert | Cookie & Brownie | Fruit | Nuts | < 30 Mins | Oven

🍽️ Best Banana Bread

Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 2273

🧾 Ingredients:

👨‍🍳 Instructions:

🗣️ User Reviews:

Breads | Fruit | Oven | < 4 Hours

🍽️ Meatball Soup

Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 35

🧾 Ingredients:

👩‍🍳 Instructions:

🗣️ User Reviews:

< 60 Mins | Easy

🍽️ Pumpkin Chocolate Chip Muffins

Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 151

🧾 Ingredients:

👩‍🍳 Instructions:

🗣️ User Reviews:

Breads | < 30 Mins | Oven

🍽️ Best Ever Meatloaf

Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 62

📜 Ingredients:

🧑‍🍳 Instructions:

🗣️ User Reviews:

Cheese | Meat | Kid Friendly | Spring | Winter | Weeknight | Oven | < 4 Hours

🍽️ Oyster Stuffing



Rating: ⭐⭐⭐⭐☆ (4.4/5)

Total Reviews: 12

📜 Ingredients:

👩‍🍳 Instructions:

🗣️ User Reviews:

< 30 Mins | Oven | Oysters

🍽️ Chicken, Broccoli and Rice Casserole

Rating: ⭐⭐⭐⭐☆ (4.4/5)

Total Reviews: 71

🧾 Ingredients:

👩‍🍳 Instructions:

🗣️ User Reviews:

Lunch/Snacks | Chicken Breast | Chicken | Poultry | Rice | Cheese | Vegetable | Meat | Kid Friendly | Potluck | < 60 Mins | Oven | Easy

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🍽️ Great Grains Oatmeal Muffins

Rating: ⭐⭐⭐⭐☆ (4.4/5)

Total Reviews: 13

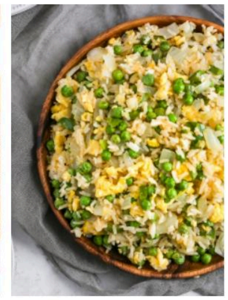
🧾 Ingredients:

👩‍🍳 Instructions:

🗣️ User Reviews:

Breads < 60 Mins Oven

🍽️ Fried Rice



Rating: ⭐⭐⭐⭐⭐ (5.0/5)

Total Reviews: 248

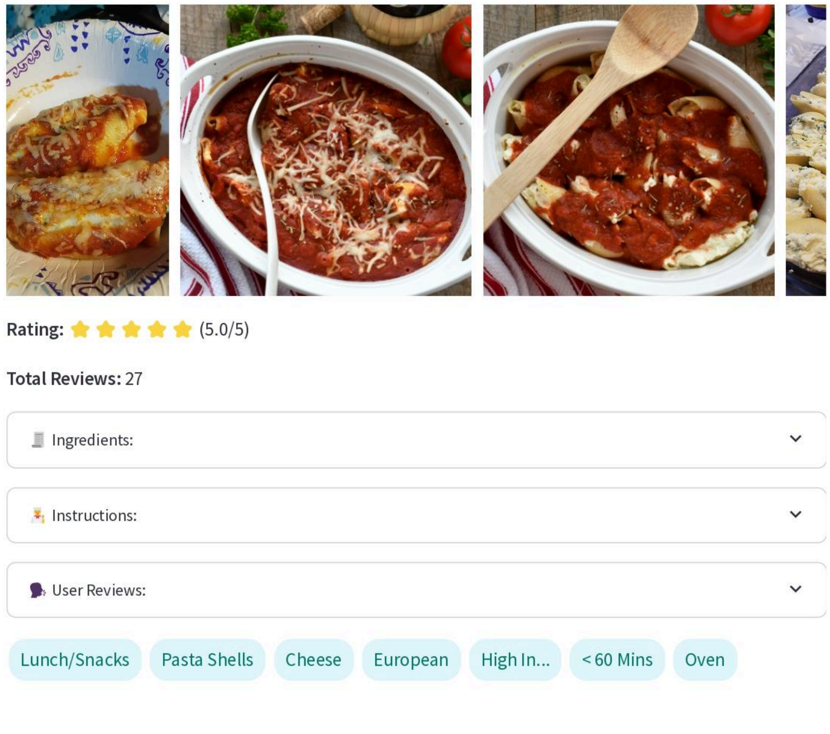
📄 Ingredients:

👩‍🍳 Instructions:

🗣️ User Reviews:

Pork Poultry Rice Meat Chinese Asian Healthy < 30 Mins Stove Top Easy

🍽️ Cheese Stuffed Shells

	
Analysis	The hybrid model has combined 3 types of requirements (SVD, KNN, TF-IDF) equally to recommend the 10 recipes which can fulfil all the requirements stated as far as possible. The result supports H4 as the hybrid model produced a refined list that was more relevant and diverse.

4.2. Discussion/Interpretation

In overall, the results from all 4 test cases are able to support the proposed hypotheses. Each individual model component can successfully provide the relevant recommendations based on the criterias chosen. For example, **SVD model** is able to **capture the user preferences based on collaborative filtering from review history**. **KNN models** can accurately **filter recipes based on nutritional and time preferences**. **TF-IDF** can **provide accurate food recommendation results which can fulfill the keyword search**. The **hybrid recommendation** is able to **enhance the personalization by combining SVD model, KNN model and TF-IDF**, this feature has led to a more relevant and diverse suggestions exploration.

For **Hypothesis H1** results, it has applied an **SVD model to recommend foods based on specific user's review history**. This model has effectively offered the recommendations which are suited to the users. However, this model would **require a large number and high quality of review data** to provide an accurate and reliable recommendation for different users. The larger the amount of review data by a user, the higher the reliability of the food recommendation results. Thus, this model may not perform well for new users who have only posted or even not post any reviews on food.

For **Hypothesis H2** results, it has applied **KNN model to gather the nutrition and time preferences decided by the users and recommend appropriate food based on those selected preferences**. This is very efficient for different types of users which have different tastes and wants on food to explore a list of suitable foods such as dietary users, diabetes users and users who have high blood pressure. Although this model is very suitable for different types of users to find out their favourite food, it may **require a large amount of foods which have various nutrition specifications** so that the KNN model is able to analyze enough food data and recommend the most suitable food to the users.

For **Hypothesis H3** results, it has applied **TF-IDF keyword search to help users to find out their wanted foods via directly searching the keywords entered by the users**. This can effectively allow users to easily access or find out their wanted food without using the characteristics which are ambiguous such as nutrition levels and time categories. This is suitable for the users who are certain with what food they want to eat. However, it **may return irrelevant results if the keyword is too generic or ambiguous or the dataset owned is not sufficient**.

For **Hypothesis H4** results, it has **combined three methodologies which are SVD model, KNN model and TF-IDF keyword search** to provide the best balance between personalization, diversity and flexibility. However, it might not be able to present the results that users really want since this hybrid recommendation focuses on deciding the balanced results between 3 results by SVD model, KNN model and TF-IDF keyword search.

Sometimes, **users may give different weightage for each result** so the hybrid recommendation may not be able to provide the results which fulfilled users' desired weightage.

Based on the overall results in the food recommender system, it has indicated some potential limitations. For the SVD model, the **cold start problem for new users may lead to inaccurate results** since new users might not have enough reviews data for being referred by the SVD model. For TF-IDF keyword search, it might **return unreliable results due to the generic and ambiguous keywords entered by users**. For hybrid recommendation, **different weightage desired on different models by different users may cause the unwanted results provided**.

In order to minimize or address the current issues, the system should **collect explicit user preferences during onboarding to assist in generating initial recommendations**. (Iain Brown PhD, 2024) Thus, the cold start issue for new users can be addressed and it can help SVD models to generate useful results via integrating with content-based filtering like the KNN model. Apart from that, the **system can be upgraded to semantic search models** such as Word2Vec or BERT for better understanding user intent. (Ankiit, 2022) So, the TF-IDF search relevance can be improved via applying the spell-checking, synonym detection and auto-suggestions feature. For addressing the problem of weightage sensitivity in hybrid models, the system can **design a slider for enabling users to manually adjust each model's weightage or implementing adaptive learning to track user interactions for weightage auto-tuning**. (Jannach et al., 2017) Thus, the hybrid recommendation can significantly maximize the reliability and accuracy of results when meeting ideal results desired by users.

From the aspects of implications, the food recommendation system may take a crucial role in real-world applications. It can act as a **useful tool for providing suggestions to users who have personalized health and diet planning**. (Qiao et al., 2025). Meanwhile, it can also help for **assisting users who have dietary restrictions** due to certain reasons such as congenital conditions or acquired diseases via **recommending the food based on their preferred nutrition levels**. Moreover, it is also able to **integrate or collaborate with other field related applications such as cooking apps, smart kitchens and health-monitoring tools**. (Rostami et al., 2023) This can effectively enhance the functionality of the integrated systems and improve the flexibility of users on exploring foods.

5. Discussion and Conclusion

5.1. Achievements

We have developed a food recommendation AI system that successfully achieves its core objective of **providing personalized, intelligent, and health-conscious food suggestions**. By applying Singular Value Decomposition (SVD) for collaborative filtering, the system effectively recommends dishes that **match the user's taste profile**, even when direct feedback is limited, and **helps** the user **discover options** such as salty or spicy foods based on prior behavior and preferences. Unlike traditional pure rating approaches, we **processed** the **text of users' reviews** to **gain insight** into their preferences. These numerical representations are then fed into the SVD model to generate more accurate latent factors for both the user and the food item, leading to smarter and more nuanced recommendations.

We also did this by using K-Nearest Neighbors (KNN) to recommend foods that **meet specific nutritional requirements**, further enhancing the system's ability to directly help users make informed, healthy choices. Not only that, the integration of TF-IDF and cosine similarity also allows users to **search for dishes using natural language**, thus returning highly relevant results and simplifying the decision-making process. Users no longer have to worry about using the system with a language barrier that makes it more difficult to use. In addition, we chose to use KMeans clustering in the preprocessing to **transform** the **raw nutritional data into intuitive categories**, which improves the interpretability and recommendation accuracy of the system.

In short, the system provides intelligent, data-driven recommendations based on a user's existing preferences and nutritional needs, significantly reducing trial-and-error efforts and decision-making time. It improves the convenience and enjoyment of food choices while guiding users to healthier, more balanced eating habits. Although the system currently operates on a static dataset, it provides a solid foundation for integrating real-time learning in the future. Overall, by providing a powerful, insightful, and user-centered food recommendation platform, the project has successfully achieved and even surpassed its initial goals.

5.2. Limitations and Future Works

While the food recommendation AI system is effective in achieving its core goals, there are some limitations that provide opportunities for future improvements. First, the system currently **relies on a static dataset**, which means it cannot adapt to real-time user feedback or changing preferences. Without dynamic learning, recommendations may become less accurate over time as user behavior changes. Second, while **comment text is incorporated** into the recommendation process, natural language understanding is still limited, especially when dealing with slang, typos, or multilingual input. The system can be enhanced in the future with **more advanced NLP models** such as converters or large-scale language models that can significantly improve text-based insights.

Additionally, nutrition-based recommendations via KNN work well, but currently do **not take** into **account user-specific health conditions** such as allergies, diabetes, or dietary restrictions, which may be critical for some users. **Introducing user profiles** containing health information in the future could make recommendations more personalized and secure. Additionally, while categorizing nutritional values into intuitive categories helps improve interpretability, it may **oversimplify complex dietary needs**. Finally, the system does not yet support continuous learning or online updates, which limits its adaptability.

In the future, integrating real-time feedback loops, enabling user-specific health profiles, incorporating richer contextual data such as time of day or location, and upgrading the NLP pipeline could greatly improve the system's intelligence, adaptability, and user satisfaction.

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