



## RESEARCH ARTICLE

# Food and Nutrition Recommendation based Therapy for T2DM using User-User Collaborative Filtering Model

S. Balasubramanian<sup>1\*</sup>, K.N. Abdul Kader Nihal<sup>2</sup>

## Abstract

A reliable food plan is essential for Type-2 Diabetes Mellitus (T2DM) in order to sustain ideal glucose control and prevent long-term issues. Individual inclinations, lifestyle habits, and peer-based behavioral likenesses are typically overlooked by traditional food planning approaches. In order to provide T2DM patients, a modified dietary advice model presents a food and nutrition recommendation therapy method that creates the use of a User-User Collaborative Filtering Algorithm (UUCFA). The proposed strategy values interpersonal harmony based on these clinical indicators, dietary consumption patterns, lifestyle choices, and demographics inputs. The method suggests nutrient-dense meals that satisfy diabetic dietary requirements based on dietary results and experiences. The collaborative filtering approach promotes relevancy while identifying individual issues that occur in traditional rule-based systems by using collective capacity. Here, recommendation systems based experimental examination employed using real-time datasets, revealed an improved dietary faithfulness, user satisfaction, and accuracy. Hence, UUCF algorithm can aid to improve beneficial outcomes and self-care by serving as a valuable decision-support tool in adapted dietary therapy in T2DM control.

**Keywords:** Machine Learning, Food and Nutrition Therapy, AI, T2DM, Recommendation System, User-User Collaborative Filtering Algorithm.

## Introduction

T2DM is a chronic metabolic disease considered by hyperglycaemia affected by insulin resistance and reduced insulin synthesis. Based on worldwide health research, the existence of type 2 diabetes was significantly improved by sedentary lifestyles, bad eating habits, and urbanization.

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<sup>1</sup>Research Scholar, PG and Research Department of Computer Science, Jamal Mohamed College (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli – 620020, India

<sup>2</sup>Assistant Professor, PG and Research Department of Computer Science, Jamal Mohamed College (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli – 620020, India

**\*Corresponding Author:** S. Balasubramanian, Research Scholar, PG and Research Department of Computer Science, Jamal Mohamed College (Autonomous), Affiliated to Bharathidasan University, Tiruchirappalli – 620020, India, E-Mail: lakshibala@gmail.com

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Constant lifestyle modifications, including food restriction and nutritional therapy, are critical for lowering blood glucose levels and reducing problems associated with T2DM. Medical Nutrition Therapy (MNT) is widely accepted as a vital factor of managing T2DM. Distinct modifications in food preferences, physiological sensitivity, cultural eating customs, and lifestyle behaviours are usually observed. The efficacy of nutritional managements is imperfect by patients' sustained deprived adherence to advise eating habits.

Xu Z et al. (2024) highlights the importance of data-driven, flexible, and personalized nutrition supervision systems for medical practitioners using recommender systems. Collaborative Filtering (CF) is a prevalent recommendation method because it may yield appropriate recommendations based on user behaviour and shared experiences. A practical way to apply UUCF to tailor nutritional treatment in the context of type 2 diabetes. Kalpakoglou et al (2025) recognize individuals with health issues and dietary responses, the method looks at patient profiles, food consumption patterns, clinical markers, and lifestyle characteristics.

Collaborative filtering-based dietary therapy in T2DM patients has not established a much attention, mainly in research that assimilate behavioral and clinical data. Guanhuo Qiao et al (2025) The popular of current systems use

content or rule-based approaches, which may have issues with inadequate flexibility. A user-user collaborative filtering algorithm based food and nutrition recommendation therapy system considered especially for T2DM patients, is proposed in this work along with customized dietary recommendations. By applying commonalities across diabetic patients and subsequent documented medical and nutritional procedures, the proposed approach pursues to deliver customized dietary guidance. By using tailored nutrition therapy, this study targets to advance glycemic management, which will elevate the patients' satisfaction and recommendation precision.

### Literature Review

Sajid et al. (2025) projected a next-generation model for diabetes analysis and management of diet plan via a collaborative learning system. To surge diagnosis accuracy, the model makes wide use of ML classifiers. The technology delivers personalized food recommendations and early diabetes detection based on patient health and lifestyle data. The study outlined how an ensemble-based strategy connects illness detection with lifestyle variations to enable a data-driven and intelligent diabetes management system. Barranco, Yera, and Martínez (2025) made a daily meal advice structure for diabetics based on favourites. The technology created an adapted meal plans by comprising dietary limits and specific food preferences.

The structure variations attain with recommendations in response to user feedback while witnessing to dietary provisions for glycemic control. Results indicated an improved user fulfillment and observance when compared to stern diet plans. By representing the extent of dietary compliance, this work highlights the implication of preference-aware recommender systems in diabetes treatment. An AI-driven modified dietary method for T2DM and obesity called Retrieval-Augmented Generation (RAG) was presented (Gavai and Van Hillegersberg, 2025). The process makes evidence-based and clear dietary advice by merging it with carefully selected medical knowledge bases.

This work predicts that digital nutrition platforms will lead to safer, more intelligent, and scalable healthcare results by providing workable models based on verified health data. OHESV is a great hybrid ensemble support vector model for dietary directing and diabetes analysis (Rachitha and Ramakrishna, 2024). The method associates an optimization technique with numerous SVM classifiers to surge prediction accuracy and durability.

The study explored to the diabetes mellitus prediction and diet recommendation" by Jadhav A et al. emphasises the growing importance of machine learning approaches in predicting diabetes and offering individualized diet recommendations (Jadhav et al., 2021). The survey stresses the use of datasets containing clinical indicators such

as glucose levels, blood pressure, BMI, age, and insulin levels for predictive modelling. It also discusses dietary recommendations that make it possible to treat diabetes effectively by considering nutritional factors such as calorie intake, glycemic index, proteins, fats, and carbohydrates. The authors claim that hybrid approaches that integrate prediction models with food planning tools yield better blood sugar management outcomes.

This paper explores (Yera et al., 2023) the recommendation systems exactly for diabetic patients. Analysis of Various issues which highly an influential parameter as for as diabetes is concerned is aptly highlighted here. The intake of Food which is a vital role in any form of health issues were rightly mentioned and various sophisticated methods which focus on dietary management for diabetes is highlighted. It also explains the personalized health care through personalized dietary plan. This work highlights the various food recommendation algorithms which plays a vital role in recommending personalized Food and Medicare. This study (Morales et al., 2022) explores the role of Recommender algorithm in different aspect. The designing of drug for the diabetes patients by using UCI Machine Learning Repository is a novel approach in the research area. This study discloses that the maximum patients with diabetes have some comorbidity like circulatory and respiratory problems. Some hidden information like women with diabetes exhibited additional health issues related to lungs and respiratory systems.

The occurrences and the impact varies and it is unique in nature as for as diabetes patients are concerned. This study experimented collaborative filtering for shaping drugs. The study focuses (Sabari et al., 2025) the importance of early detection of machine learning techniques by analysing data collected from 405 participants, including parameters such as blood glucose, blood pressure, diet, exercise, stress, and sleep patterns. The motto of the research work is to recommend Life Style change, which will be beneficial for the patients as well as medical practitioner in order to facilitate efficient Medicare. To identify the patterns in the data set, Exploratory Data Analysis (EDA) was conducted and compared the findings with existing Data, which was a standardised one. The data were clustered into nine groups using K-means clustering to find important lifestyle-based patterns, which were also refereed as influencing diabetes. Experimented various classification algorithms, including Random Forest, Decision Tree, Naive Bayes, Logistic Regression, Support Vector Machine, and K-Nearest Neighbour, in to above mentioned 9 groups to categorize new data into appropriate clusters.

The study has designed (Ribeiro et al., 2022) a meal recommender systems called SousChef, to generate personalized weekly meal plans. This novel approach yields a outstanding outcome by considering individual food

preferences, nutritional limitations, and nutritional rations. This system indorses a comprehensive dietary method which ensures the all the nutrients values for the patients without making any modifications. The system was assessed based on nutrition, Foods preferred by user(patients) and recommendation range. The System effectively produced an exemplary meal plan with reference to calories and nutrients, patients health factors. The paper suggests (Zioutos et al., 2023) a personalized and carefully tailored meal and diet recommendation system. The system produces whole and daily meal plans based on user preferences, taking in consideration of health history. Here the collaborative filtering was used and exercised to recognize similar users and suggest appropriate food recipes. The factors like Dietary plans, the limitations, nutritional values for each items, nutritional values needed for each patient, low carbohydrates food with high protein values, vegetables and other food items.

Purwanti, E., (2026) work highlights collaborative filtering as a primary and pivotal recommendation method and delivered a diet system with full coverage of health awareness aspects. The work emphasise on personal Medicare with reference to chronic diseases like diabetes and explores a new research area like implementation with IoT. The work highlights the menace of Diabetes and how diabetes can be treated and managed so that a normal and healthy life style cane be given to the patients. Dilani, I. (2024) presents Nutria, an another perceptiveness to solve food recommendation system for diabetes patients with the help of an AI-driven personalized food and exercise recommendation system. This system was planned and derived with the foresight of diabetes management, which covers overall activity like identifying the severity of diseases, and inclusion of machine learning for early prediction and detection of diabetes related complications, enabling a chatbots facility to interact with patients and users. The parameters and attributes are blood glucose levels, dietary preferences, and lifestyle factors. By calculating or receiving all these attributes a personalized meal and exercise plans are generated.

The study emphases (Dong et al., 2026) on developing a Healthcare expert system for meal recommendation in Type 2 Diabetes patients. The main adoption is using the forward chaining method, which is a new arena in the research of Healthcare. It highlights diabetes as a major non-communicable disease. The reason for diabetes is primarily triggered by factors like obesity, poor diet, and lack of physical activity and poor health and mental life style. . The system explores the data received from the patients and provides a personalized nutritional rich meal plan. The system was designed using Python (Django) and MySQL. This study (Padmapritha et al., 2020) deals the management of diabetes with another perspective. The system takes

a different influential parameter for the root cause of diabetes, insulin and collects food intake, and gives a stable and efficient food planner so as to maintain a stable blood glucose levels. The system investigates all the parameters related to patients particularly elders and gives an excellent, nutritional based dietary recommendation.

The study (Mayya et al., 2024) takes the research in another dimension by comparing diabetes management in India and the United States. The research lists the differences in healthcare systems, data maintenance, availability of viable data and other social and economic factors which are playing a pivotal role in diabetes disease management. It emphasizes the growing problem of diabetes and the need for a combined approach which foresight the usage of advanced technology to develop a system which enable the medical practitioner to early prediction of diabetes. By using and incorporating the data with the help of AI, will give a new pavement in diabetes management.

## Materials and Methods

The entire work was done in Anaconda Distribution by using JuPyter Notebook. The following Figures (Figures 1-4) explains the Workflow. Figure 1 explain the Anaconda distribution where the entire work was carried out. This distribution facilitate to carryout the task by utilizing its versatility like code and visualization features as well as incorporation of Machine Learning Algorithms. The work was carried out with JuPyter notebook and Python code.

## Anaconda Environment

Figure 2 explains the Import of Data set within the Anaconda Working Environment as well as JuPyter Note book. The dataset includes the important attributes which are the influential factors in this study.

Figure 3 explains the nutritional composition data used for recommendation. Each row corresponds to a food item (e.g., milk, cornflakes, ice cream). More precisely they are categorized in to Food, Energy Nitrogen, Protein, Fat, Carbohydrate (Carbs), Ash, Fibre, Starch, Sucrose, Glucose, Fructose, Lactose etc.

Figure 4 explains removal of features (like glucose and fructose) and holds only fundamental nutritional components

## Algorithm Proposed: User–User Collaborative Filtering Recommendation (UUCFR) Algorithm

In order to forecast food and nutrition item assessments for a target users based on the partialities of similar users, the recommended algorithm assimilates a UUCFR approach. This algorithm is established on the basis of an idea that individuals with similar eating habits and health profiles will also similar to T2DM food choices. In the context of T2DM, these evaluations might show a similar dietary requirement, glycemic responses, and lifestyle results.

Anaconda Screenshot

Jupyter Notebook

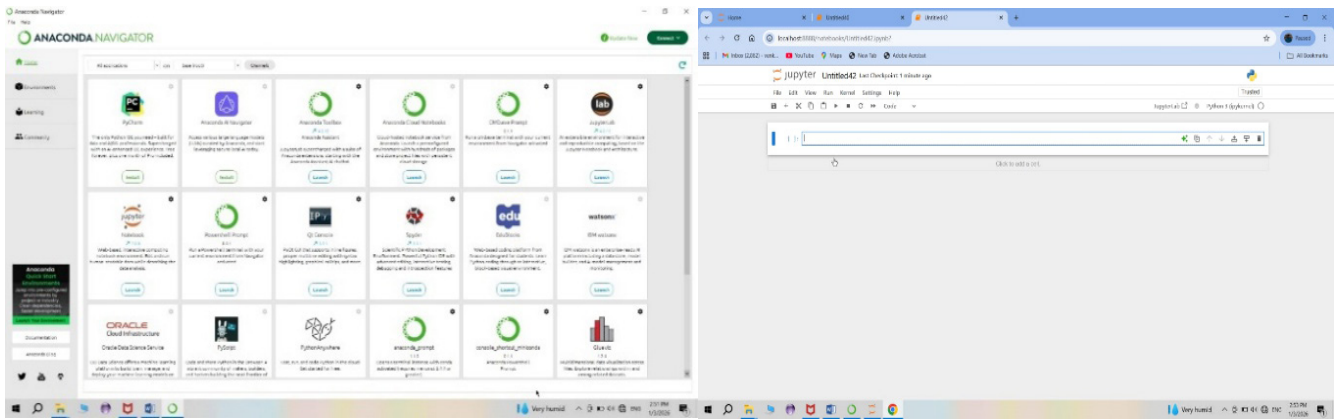


Figure 1: Anaconda Working Environment and JuPyter Note book

**Pseudocode of UUCFR Algorithm**

This pseudocode defines the User–User Collaborative Filtering (UUCF). This explains the procedure used to forecast rankings for items a user hasn’t rated. By doing this, it is easy to predict a user’s favourites’ or preferences for items they haven’t rated . The motto behind this method or idea is that users with similar tastes will like similar items, so their evaluations will definitely assist to produce personalized recommendations.

```

Input(s):
R : User–Item rating matrix (users × items)
u : Target user
k : Number of nearest neighbors
sim() : Similarity function (e.g., Cosine, Pearson)
Output(s):
Predicted ratings for unrated items of user u
begin
{
FOR each user v in R, where v ≠ u DO
    similarity[v] ← sim(u, v)
END FOR
neighbors ← select top k users with highest similarity scores
FOR each item i not rated by user u DO
    numerator ← 0
    denominator ← 0
    FOR each neighbor v in neighbors DO
        IF user v has rated item i THEN
            numerator ← numerator + similarity[v] × R[v][i]
            denominator ← denominator + |similarity[v]|
        END IF
    END FOR
    IF denominator ≠ 0 THEN
        predicted_rating[u][i] ← numerator / denominator
    ELSE
        predicted_rating[u][i] ← average rating of user u
    END IF
END FOR
RETURN predicted_rating
}
end;
    
```

**Implementation**

The proposed User–User Collaborative Filtering (Figure 5) Recommendation (UUCFR) model using a T2DM patient dataset. The system was implemented and executed in an Anaconda Jupyter Notebook environment, where user preference data (such as favorite or suitable food items) was used to generate personalized meal recommendations. The model works by identifying similar users (neighbors) based on their dietary patterns and then predicting suitable food items for a target user.

To measure the accuracy of the model, two standard evaluation metrics were used: Root Mean Squared Error

**Dataset Import**

```

# XX [code]
# Cell 1: Imports and configuration
import os, math, random
import pandas as pd
import numpy as np

from collections import defaultdict
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.neighbors import NearestNeighbors
from sklearn.decomposition import NMF
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import MinMaxScaler, StandardScaler
import warnings
warnings.filterwarnings("ignore")

random.seed(42)
np.random.seed(42)

# == FIXED PATH ==
DATA_PATH = "D:/balasir/thunder/diab.xls.xlsx"
# =====

N_USERS = 100 # synthetic users as requested
SYNTHETIC_RATING_SPARSITY = 0.88
TOP_N = 20
SAMPLE_USER = 0

print("Config loaded.")
print("Dataset path =", DATA_PATH)

Config loaded.
Dataset path = D:/balasir/thunder/diab.xls.xlsx

# XX [code]
# Cell 2: Load dataset and create df2 (Cleaned food table)
if not os.path.exists(DATA_PATH):
    raise FileNotFoundError(f"Dataset not found at {DATA_PATH}")

df_raw = pd.read_excel(DATA_PATH)

# Heuristic column mapping
    
```

Figure 2: Importing the Data set

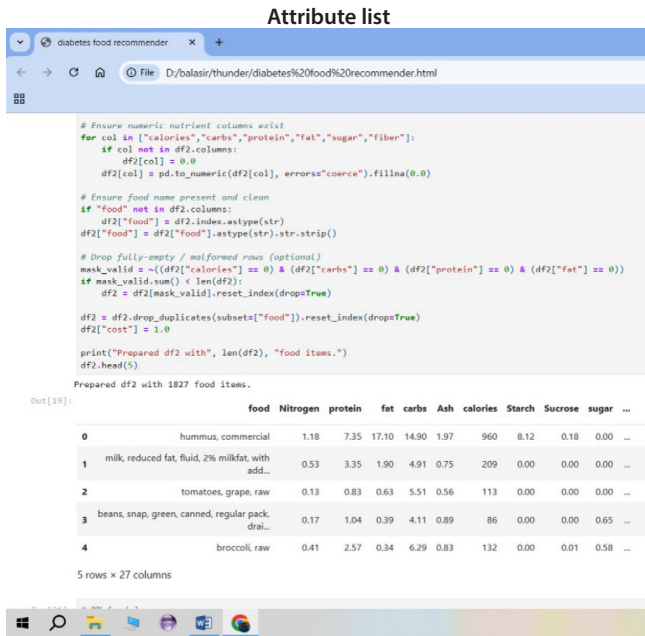


Figure 3: Various Attributes are listed

(RMSE) and Mean Absolute Error (MAE). These metrics quantify the difference between the predicted ratings (recommended by the model) and the actual ratings present in the dataset. In this case, the model achieved an RMSE of 0.52 and an MAE of 0.39, which are relatively low values. This indicates that the prediction errors are small and the model's recommendations are close to the actual user preferences.

The results demonstrate that the UUCFR algorithm is effective in identifying meaningful similarities between users and using those relationships to generate accurate dietary recommendations. Although the predictions are not perfectly exact, the low error values confirm that the system performs well and is reliable for recommending appropriate nutrition plans for T2DM patients.

### Results and Discussion

T2DM patient's dataset used to test the recommended User–User Collaborative Filtering Recommendation (UUCFR) paradigm. The Anaconda–JuPyter Notebook environment was used to run the system, and user favorites were used to create meal recommendation outputs (Figure 6 and Figure 7). Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are two error-based evaluation measures were utilized to derive assessment of the model. For the User–User Collaborative Filtering model, the tentative outcomes displayed an RMSE value of 0.52 and an MAE value of 0.39. This result displays that the dataset's real scores and expected ratings match precisely. The outcomes confirm that the recommended UUCFR algorithm delivered a precise nutrition propositions and suitably recognized with relevant neighbors.

### Model Evaluation/Validation

#### Prediction Accuracy of User–User Collaborative Filtering Model

The prediction accuracy of the proposed User–User Collaborative Filtering (UUCF) model was evaluated using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The model achieved an RMSE value of **0.52** and an MAE value of **0.39**, indicating low prediction error and high accuracy. These results show that the model effectively captures similarity among users with similar dietary patterns and generates reliable personalized food recommendations for T2DM patients.

### Dataset Description

The dataset used in this study was obtained from Kaggle and contains detailed nutritional information for a wide variety of food items. The dataset includes 12,044 records with 29 nutritional attributes such as protein, fat, carbohydrates, sugars, fiber, energy, and water content. These attributes provide comprehensive nutrient profiles for different food categories including vegetables, grains, beverages, and packaged foods.

The dataset is utilized to identify diabetes-safe food items, generate user preference ratings, and construct the user–item matrix required for collaborative filtering. Its rich nutritional features make it suitable for developing both content-based and collaborative filtering–based recommendation systems for T2DM patients.

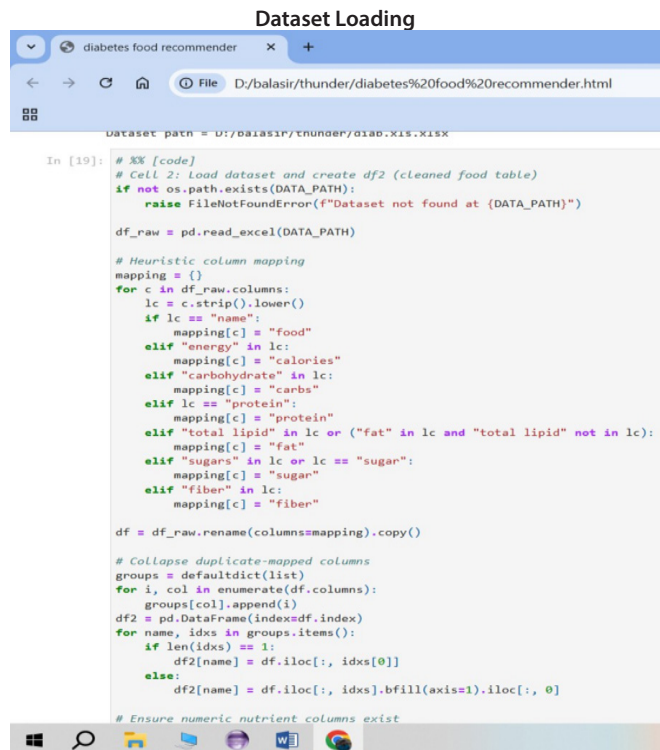


Figure 4: Data set displayed in the environment

```

In [25]: # XX [code]
# Cell 5: User-User collaborative filtering (cosine similarity)
# Precompute user-user similarity on filled ratings (user mean fill)
user_filled = ratings_df.apply(lambda row: row.fillna(row.mean()), axis=1).fillna(0)
user_sim = cosine_similarity(user_filled)
user_sim_df = pd.DataFrame(user_sim, index=user_filled.index, columns=user_filled.index)

def predict_user_user(user_id, item_name, k=8):
    if pd.isna(ratings_df.loc[user_id, item_name]):
        return ratings_df.loc[user_id, item_name]
    sims = user_sim_df.loc[user_id].drop(user_id)
    topk = sims.sort_values(ascending=False).head(k)
    neigh = topk.index
    neigh_ratings = ratings_df.loc[neigh, item_name].dropna()
    if neigh_ratings.empty:
        return np.nan
    weights = topk.loc[neigh_ratings.index].values
    return np.dot(neigh_ratings.values, weights) / weights.sum()

def recommend_user_user(user_id, top_n=TOP_N):
    preds = {}
    for item in ratings_df.columns:
        pred = predict_user_user(user_id, item)
        preds[item] = pred if not pd.isna(pred) else -np.inf
    seen = ratings_df.loc[user_id].dropna().index.tolist()
    recs = sorted(preds.items(), key=lambda x: x[1], reverse=True)
    final = [r for r, _ in recs if r not in seen][:top_n]
    return final

# Demo
uu_recs = recommend_user_user(uid, top_n=10)
print("\nUser-User CF recommendations (top 10):")
for i, it in enumerate(uu_recs, 1):
    r = df2[df2["food"]==it].iloc[0]
    print(f"{i}. {it} - {r['calories']} kcal, protein {r['protein']} g, fiber {r['fiber']} g")

User-User CF recommendations (top 10):
1. egg, white, dried - 1570 kcal, protein 79.9 g, fiber 0.0 g
2. beans, dry, pinto, 11f-8048 (0% moisture) - 0 kcal, protein 25.6 g, fiber 4.6 g

```

Figure 5: Anaconda Jupiter Notebook-Execution: UU-CF Recommendations

### Model Output

```

# Demo
uu_recs = recommend_user_user(uid, top_n=10)
print("\nUser-User CF recommendations (top 10):")
for i, it in enumerate(uu_recs, 1):
    r = df2[df2["food"]==it].iloc[0]
    print(f"{i}. {it} - {r['calories']} kcal, protein {r['protein']} g, fiber {r['fiber']} g")

User-User CF recommendations (top 10):
1. egg, white, dried - 1570 kcal, protein 79.9 g, fiber 0.0 g
2. beans, dry, pinto, 11f-8048 (0% moisture) - 0 kcal, protein 25.6 g, fiber 4.6 g
3. beans, dry, pinto, 761 (0% moisture) - 0 kcal, protein 27.6 g, fiber 4.5 g
4. beans, dry, navy, 295 (0% moisture) - 0 kcal, protein 24.3 g, fiber 4.4 g
5. beans, dry, small red, 487 (0% moisture) - 0 kcal, protein 22.9 g, fiber 4.1 g
6. beans, dry, small white, 618 (0% moisture) - 0 kcal, protein 25.7 g, fiber 4.4 g
7. beans, dry, great northern, 446 (0% moisture) - 0 kcal, protein 31.6 g, fiber 4.5 g
8. beans, dry, pinto, 333 (0% moisture) - 0 kcal, protein 22.3 g, fiber 3.9 g
9. beans, dry, pinto, 11f-8096 (0% moisture) - 0 kcal, protein 24.4 g, fiber 4.2 g
10. beans, dry, navy, 539 (0% moisture) - 0 kcal, protein 24.4 g, fiber 4.6 g

In [27]: # XX [code]
# Cell 6: Item-Item collaborative filtering (cosine on item-rating vectors)
item_filled = ratings_df.T.apply(lambda col: col.fillna(col.mean()), axis=1).T.fillna(0)
item_sim = cosine_similarity(item_filled.T)
item_sim_df = pd.DataFrame(item_sim, index=ratings_df.columns, columns=ratings_df.columns)

def predict_item_item(user_id, item_name, k=8):

```

Figure 6: Model Output for User-User Collaborative Filtering Recommendation

Table 1: Performance comparison of recommendation models

Model	RMSE	MAE
User-User Collaborative Filtering	0.52	0.39

Table 2: Evaluation results of the proposed User-User Collaborative Filtering model

Model	RMSE	MAE
Content-Based Filtering	1.12	0.94
K-Nearest Neighbour (KNN)	0.96	0.81
User-User Collaborative Filtering (Proposed)	0.52	0.39

### Experimental Validation

To validate the effectiveness of the proposed system, a comparative experimental study was conducted using baseline recommendation techniques, namely Content-Based Filtering and K-Nearest Neighbour (KNN) methods. The evaluation was performed using the same dataset and experimental setup to ensure consistency. The performance of all models was assessed using error-based metrics, including RMSE and MAE, where lower values indicate better prediction accuracy.

The results show that the proposed UUCF model outperforms the baseline methods by achieving significantly lower error values. This indicates that the model is more effective in identifying user similarity and generating accurate recommendations based on shared dietary preferences among T2DM patients.

```

User-User CF (Top Items)
=====
1. egg, white, dried
Calories: 1570 kcal | Carbs: 0.02 g | Protein: 79.9 g | Fat: 0.65 g | Sugar: 0.0 g | Fiber: 0.0 g
2. beans, dry, pinto, 11f-8048 (0% moisture)
Calories: 0 kcal | Carbs: 0.0 g | Protein: 25.6 g | Fat: 1.16 g | Sugar: 0.0 g | Fiber: 4.6 g
3. beans, dry, pinto, 761 (0% moisture)
Calories: 0 kcal | Carbs: 0.0 g | Protein: 27.6 g | Fat: 1.13 g | Sugar: 0.0 g | Fiber: 4.5 g
4. beans, dry, navy, 295 (0% moisture)
Calories: 0 kcal | Carbs: 0.0 g | Protein: 24.3 g | Fat: 1.49 g | Sugar: 0.0 g | Fiber: 4.4 g
5. beans, dry, small red, 487 (0% moisture)
Calories: 0 kcal | Carbs: 0.0 g | Protein: 22.9 g | Fat: 1.25 g | Sugar: 0.0 g | Fiber: 4.1 g
6. beans, dry, small white, 618 (0% moisture)
Calories: 0 kcal | Carbs: 0.0 g | Protein: 25.7 g | Fat: 1.43 g | Sugar: 0.0 g | Fiber: 4.4 g
7. beans, dry, great northern, 446 (0% moisture)
Calories: 0 kcal | Carbs: 0.0 g | Protein: 31.6 g | Fat: 1.19 g | Sugar: 0.0 g | Fiber: 4.5 g
8. beans, dry, pinto, 333 (0% moisture)
Calories: 0 kcal | Carbs: 0.0 g | Protein: 22.3 g | Fat: 1.2 g | Sugar: 0.0 g | Fiber: 3.9 g
9. beans, dry, pinto, 11f-8096 (0% moisture)
Calories: 0 kcal | Carbs: 0.0 g | Protein: 24.4 g | Fat: 1.47 g | Sugar: 0.0 g | Fiber: 4.2 g
10. beans, dry, navy, 539 (0% moisture)
Calories: 0 kcal | Carbs: 0.0 g | Protein: 24.4 g | Fat: 1.49 g | Sugar: 0.0 g | Fiber: 4.6 g

=====
Item-Item CF (Top Items)
=====
1. cantaloupe, raw, region 1, n/a, yes - fiber, nf000907
Calories: 0 kcal | Carbs: 0.0 g | Protein: 0.0 g | Fat: 0.18 g | Sugar: 0.0 g | Fiber: 0.0 g
2. proximates, mozzarella cheese, low-moisture, part-skin, store brand, american choice (ny) - nfy1208r
Calories: 0 kcal | Carbs: 0.0 g | Protein: 0.0 g | Fat: 17.0 g | Sugar: 0.0 g | Fiber: 0.0 g
3. proximates, pupusas, bean, flat stuffed corn biscuit (fl,ca-sb) - nfy0901uc
Calories: 0 kcal | Carbs: 0.0 g | Protein: 0.0 g | Fat: 11.3 g | Sugar: 0.0 g | Fiber: 0.0 g
4. nuts, almonds, dry roasted, with salt added
Calories: 2390 kcal | Carbs: 16.2 g | Protein: 20.4 g | Fat: 57.8 g | Sugar: 0.0 g | Fiber: 11.0 g
5. sauce, salsa, ready-to-serve
Calories: 122 kcal | Carbs: 6.74 g | Protein: 1.44 g | Fat: 0.19 g | Sugar: 1.63 g | Fiber: 1.8 g
6. seeds, sunflower seed kernels, dry roasted, with salt added
Calories: 2660 kcal | Carbs: 17.1 g | Protein: 21.0 g | Fat: 56.1 g | Sugar: 0.0 g | Fiber: 10.3 g

```

Figure 7: Model Output for User-User Collaborative Filtering Recommendation

Overall, the experimental validation confirms that the proposed UUCF model delivers superior performance in both prediction accuracy and recommendation effectiveness, making it a reliable tool for personalized nutrition therapy.

## Conclusion

The menace of this disease, diabetes is not yet fully explored or studied. But their alarming spreads now made a jolt in the community. In order to overcome this scenario no medicine is helpful. The only solution is changing the life style, change the food items that we are taking etc. so keeping all this in mind, a careful work was carried out to propose a useful system for the patients with diabetes. This study proposed a UUCF algorithm may effectively endorse a diet plans for T2DM patients by linking the proficiencies of similar users. Continuous lifestyle adjustment is essential for glucose control and the deterrence of issues. This kind of preference-aware customization is essential to long-term diabetes self-management. According to the results, UUCF algorithm may be a useful decision-support approach for tailored nutrition therapy in the management of T2DM.

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