NutriBuddy: AI-Driven Personalized Recommender System

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1 Introduction

The increasing demand for personalized nutrition has led to the development of intelligent meal recommendation systems. Unlike traditional food suggestions, NutriBuddy aims to deliver highly personalized and adaptive recommendations based on user preferences, dietary restrictions, and real-time interactions. To achieve this, the system integrates multiple recommendation strategies to overcome common challenges in personalized meal planning, including:

- **Cold-Start Problem:** New users with limited interaction history require meaningful recommendations.
- **Evolving User Preferences:** Dietary needs and food choices change over time, requiring dynamic adaptation.
- **Lack of Diversity:** Relying solely on past interactions may limit variety in meal recommendations.
- **Community Influence:** Meals liked by users with similar conditions should receive higher visibility.

To address these challenges, NutriBuddy employs a hybrid recommender system that combines:

- **Content-Based Filtering** - Recommends meals based on the user's dietary profile, medical conditions, and ingredient preferences.
- **Collaborative Filtering** - Suggests meals based on the interactions of similar users, ensuring diversity in recommendations.

- **Dynamic Re-Ranking** - Adjusts meal rankings in real-time based on user engagement, promoting frequently liked or highly rated meals.
- **Community-Driven Learning** - Prioritizes meals that are highly liked or purchased by users with similar medical conditions.

Each recommendation technique plays a vital role in ensuring the system remains **adaptive, scalable, and personalized**. Table 1 provides a comparative overview of different recommender system techniques.

Technique	Personalization	Diversity	Cold-Start Handling
Content-Based	High	Low	Poor
Collaborative	Medium	Medium	Poor
Hybrid Approach	High	High	Good

Table 1: Comparison of Different Recommender System Techniques

By integrating these techniques, NutriBuddy ensures that meal recommendations are not only tailored to individual preferences but also dynamically updated based on real-time user feedback. The hybrid model effectively balances **personalization**, **diversity**, and **adaptability**, making the system well-suited for evolving dietary needs.

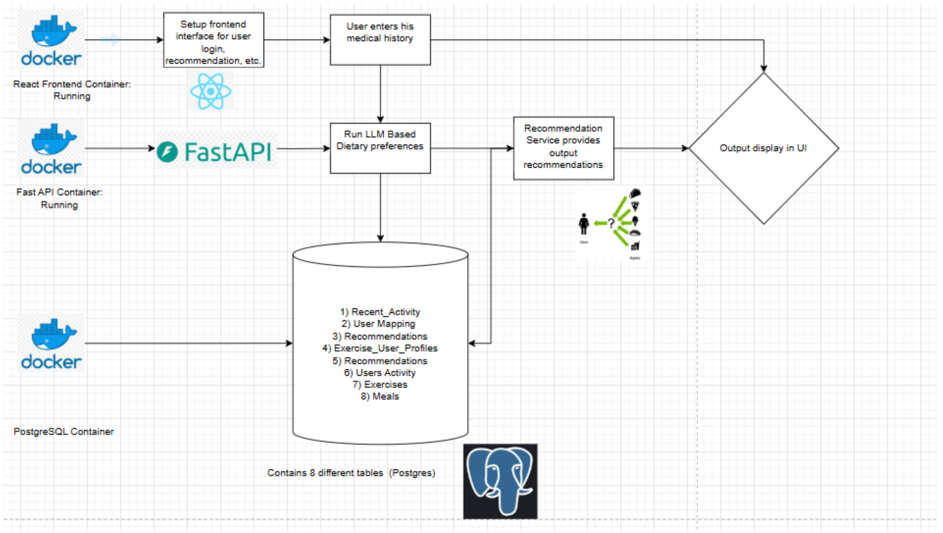
docker
React Frontend Container: Running
Setup frontend interface for user login, recommendation, etc.
User enters his medical history
docker
Fast API Container: Running
FastAPI
Run LLM Based Dietary preferences
Recommendation Service provides output recommendations
Output display in UI
docker
PostgreSQL Container
1) Recent_Activity
2) User Mapping
3) Recommendations
4) Exercise_User_Profiles
5) Recommendations
6) Users Activity
7) Exercises
8) Meals
Contains 8 different tables (Postgres)

Figure 1: Overall System Architecture and Recommendation Flow

1.1 System Architecture and Flow Overview

Figure 1 illustrates the end-to-end architecture of the NutriBuddy recommender system, highlighting its key components and interactions. The system consists of the following main elements:

- **Frontend Interface (React)**
  - Users interact with the NutriBuddy platform via a React-based frontend.
  - The frontend container, running in Docker, allows users to log in, enter their medical history, and receive personalized recommendations.
- **FastAPI Backend**
  - The backend service, built using **FastAPI**, handles requests from the frontend.
  - It processes user inputs and invokes the recommendation engine.
- **LLM-Based Dietary Preferences Processing**
  - Once a user enters their medical history, an **LLM (Large Language Model)** extracts relevant dietary constraints.
  - The extracted information is structured and stored for personalized recommendations.
- **PostgreSQL Database**
  - The **PostgreSQL** database serves as the central data repository.
  - It consists of **eight different tables**, including:
    * **Recent_Activity**: Logs user interactions.
    * **User_Mapping**: Maps users to their respective IDs.
    * **Recommendations**: Stores personalized meal and exercise suggestions.
    * **Exercise_User_Profiles**: Contains user fitness-related preferences.
    * **Users_Activity**: Tracks engagement metrics like likes, purchases, and searches.
    * **Meals**: Stores detailed meal information.
    * **Exercises**: Stores various exercise activities.

- **Recommendation Engine**
  - The recommendation service combines **content-based filtering, collaborative filtering, dynamic re-ranking, and community-driven learning** to provide highly personalized meal recommendations.
  - The system dynamically updates rankings based on real-time user interactions.
- **Output Display**
  - The final recommendations are displayed in the **frontend UI**, where users can interact with the results (e.g., like, dislike, purchase, or rate meals).
  - These interactions further refine and personalize future recommendations.

This structured pipeline ensures a **seamless user experience**, adapting to individual dietary needs while incorporating real-time engagement signals for dynamic personalization.

2 Purpose of the Methodology

The NutriBuddy recommender system is designed to address the limitations of traditional recommendation approaches by integrating multiple techniques into a **hybrid model**. The primary goal is to ensure that meal recommendations are **personalized, dynamic, and responsive** to user preferences while maintaining **diversity and adaptability** over time.

2.1 Effectiveness of the Chosen Approaches

Each recommendation approach plays a specific role in solving key challenges:

- **Content-Based Filtering** - This method ensures personalization by recommending meals that match a user's health conditions, dietary restrictions, and past preferences. By utilizing *TF-IDF vectorization* and *cosine similarity*, the system ranks meals based on their relevance to the user.
- **Collaborative Filtering** - Instead of relying solely on a user's past choices, this approach identifies patterns from similar users. By analyzing *likes, purchases, and ratings*, it suggests meals that have been preferred by others with comparable health conditions.

- **Dynamic Re-Ranking** - This mechanism ensures that recommendations evolve over time. Meals that are highly rated or frequently liked by users with similar conditions receive higher ranking, while disliked meals are dynamically replaced.
- **Community-Driven Learning** - The system prioritizes meals that have been **widely preferred** by users with matching dietary needs, ensuring that commonly liked meals are surfaced for new users with similar profiles.

2.2 Need for Model Comparison

Since no single approach can comprehensively address all challenges, a **comparative analysis** is necessary to evaluate the strengths and weaknesses of different methods. Comparing models provides valuable insights into:

- **Personalization vs. Diversity Trade-Off** - Content-based filtering ensures highly personalized results, but may lack diversity. Collaborative filtering introduces new meal suggestions but depends on sufficient user interaction data.
- **User-Driven Influence** - Meals highly rated and frequently liked by users with similar health conditions should be prioritized. A hybrid approach effectively integrates this feedback for ranking adjustments.
- **Adaptability Over Time** - Static models struggle to keep up with evolving user preferences. Dynamic re-ranking continuously updates recommendations based on *real-time interactions*.

2.3 Justification for a Hybrid Model

By combining multiple recommendation techniques, the hybrid approach ensures:

- **Strong Personalization** - Content-based filtering tailors suggestions to individual needs.
- **Diverse Recommendations** - Collaborative filtering introduces variety by leveraging community preferences.
- **Real-Time Adaptation** - Dynamic re-ranking ensures highly relevant meals remain at the top.

This integration provides a **scalable and adaptable** meal recommendation system capable of handling diverse dietary needs while ensuring real-time updates based on user interactions.

3 Problem Statement

3.1 Defining the Problem

The NutriBuddy recommender system is formulated as a **machine learning problem** that involves **ranking and recommendation** rather than traditional classification or regression tasks. The objective is to build an adaptive system that suggests meals based on:

- **User Preferences:** Individual dietary choices, health conditions, and previous interactions.
- **Community-Driven Insights:** Meals highly liked or purchased by users with similar dietary needs.
- **Dynamic User Engagement:** Continuous learning from user actions such as likes, purchases, and ratings.

The recommendation process integrates multiple learning paradigms:

- **Collaborative Filtering:** A form of unsupervised learning where user interactions shape future recommendations.
- **Content-Based Filtering:** A semi-supervised approach utilizing **text similarity** and **feature extraction** techniques like TF-IDF.
- **Dynamic Re-Ranking:** A reinforcement learning-inspired method that prioritizes meals based on evolving user engagement patterns.

Additionally, the system leverages **Large Language Models (LLMs)** for:

- **Medical History Parsing:** Extracting relevant dietary needs from user input.
- **Personalized Diet Recommendations:** Enhancing the knowledge base used for content-based filtering.
- **Natural Language Interactions:** Allowing users to refine their preferences through conversational AI.

3.2 Algorithm for Meal Recommendation

The recommendation process follows these steps:

Algorithm 1 NutriBuddy Meal Recommendation Algorithm

```
Require: User Profile $U$, Meal Database $M$, Interaction Data $I$
Ensure: Personalized Meal Recommendations $R$
  1. Preprocessing
  Extract user preferences, health conditions, and history
  Process medical data using LLM for dietary constraints
  Normalize meal attributes in $M$
  2. Content-Based Filtering
  Compute TF-IDF meal vectors, find cosine similarity
  3. Collaborative Filtering
  Build user-item matrix, compute similarity
  Recommend meals from similar users
  4. Hybrid Ranking
  Merge scores, apply dynamic re-ranking
  5. Output
  Return top-K meal recommendations
```

Significance of the Problem

Personalized nutrition is a critical aspect of health and wellness, particularly for individuals managing conditions such as diabetes, hypertension, or obesity. Traditional dietary recommendations often fail to consider personal taste preferences, leading to low adherence rates. The significance of this problem extends to multiple domains:

Academic Research:

- Advances in health-based recommendation systems contribute to research in personalized AI-driven nutrition.
- Enhances the field of multimodal recommendation systems, integrating user data, dietary knowledge, and LLMs.
- Provides insights into adaptive ranking algorithms that adjust recommendations based on user behavior.

Industry Applications:

- Healthcare and nutrition platforms: Improves dietary planning tools for individuals managing medical conditions.

- E-commerce and meal delivery services: Increases user engagement by recommending meals aligned with consumer preferences.
- AI-powered assistants: Enables intelligent diet planning chatbots capable of guiding users through healthy meal choices.

Real-World Impact:

- Encouraging healthier eating habits: Personalized meal recommendations reduce the likelihood of unhealthy dietary choices.
- Assisting users with medical conditions: Ensures that users with specific health conditions receive relevant meal suggestions.
- Reducing decision fatigue: Automates meal selection, saving users time and effort in finding suitable dietary options.

Related Work Summary

Paper 1: "Diet and Physical Exercise Recommendation System Using K-Means and Random Forest" [1] Model Comparison:

- Uses K-Means (akin to item-based clustering) and Random Forest (content-based) without a fully hybrid framework.

Limitations:

- Static recommendations; limited adaptability.
- Lacks user-based collaborative filtering and advanced evaluation metrics (MRR, RMSE).

Our Contribution Over This Work:

- Integrate user-based, item-based, and content-based filtering for diet *and* exercise.
- Use a proprietary dataset with disease profiles, nutrient details, and preferences.
- Employ LLMs for real-time user profile updates.
- Evaluate with advanced metrics (MRR, RMSE) for robust performance.

Paper 2: "Personalized Medical Recommendation System (PMRS)" [2] Model Comparison:

- Employs SVC and Random Forest for disease prediction (content-based), lacks collaborative filtering.

Dataset Comparison:

- Uses symptom-disease datasets; minimal dietary and nutrient-level attributes.

Limitations:

- Primarily focuses on static disease classification.
- No hybrid CF methods or dynamic LLM-based interactions.

Our Contribution Over This Work:

- Combine collaborative filtering (user-based, item-based) and content-based methods for holistic recommendations.
- Incorporate exercise plans alongside diet to broaden scope.
- Utilize LLMs for adaptive, context-aware user profiles.
- Include MRR and RMSE in the evaluation pipeline.

Paper 3: "Diet Recommendation Systems Using Machine Learning" [3] Model Comparison:

- Uses K-Means, Random Forest, KNN, Naive Bayes, and hybrid methods but largely within traditional ML scope.

Dataset Comparison:

- Public/user-provided datasets with variable depth; lacks contextual richness (disease profiles, nutrient details).

Limitations:

- Diet-centric; exercise recommendations not integrated.
- Limited or no real-time interactions using conversational AI.

Our Contribution Over This Work:

- Proprietary dataset capturing diseases, nutrients, and user preferences.
- Hybrid CF + content-based + LLM approach for adaptability.

- Unified diet and exercise guidance for comprehensive well-being.
- Advanced evaluation metrics (MRR, RMSE, F1) for recommendation quality.

By formulating this as an **adaptive, multi-model recommender system**, NutriBuddy ensures that meal recommendations are not just personalized but also reflective of broader user trends, increasing adoption and user satisfaction.

4 Data Collection and Preparation

4.1 Data Sources

The NutriBuddy system integrates multiple data sources to ensure high-quality, personalized meal recommendations. The key sources include:

- **Proprietary User Data:** User profiles including height, weight, dietary preferences, medical conditions, and meal interactions.
  - Relies on Kaggle datasets focusing on meals and exercise; missing rich contextual details (diseases, nutrient composition).
  - Dataset source: Kaggle Fitness Recommender Dataset
- **Meal Dataset:** A curated dataset containing meal attributes such as nutritional composition, diet compatibility, and user ratings.
- **User Interaction Logs:** Data from real-time user engagement, including likes, dislikes, purchases, and ratings.
- **LLM-Processed Medical History:** Large Language Models (LLMs) extract and standardize health conditions from user-entered medical history to improve diet matching.
- **Synthetic Data Generation:** As a part of synthetic data generation, we used LLMs to simulate user interaction and user activities.

  Methodology used: The schema of the dataset was provided and the a sample of the dataset was read into by the LLM. The LLM then generated outputs similar to the dataset.

4.2 Data Description

The dataset consists of structured meal information, user profiles, and real-time engagement data. Table 2 summarizes the key attributes.

Category	Description
Meals Data	1,000+ meals with nutritional values, diet types, and user ratings.
User Profiles	500+ users with dietary preferences, health conditions, and historical preferences.
Recent Activity	2,000+ logged interactions, including likes, dislikes, purchases, and ratings.
Medical History	Free-text input processed via LLM to extract structured dietary constraints.

Table 2: Overview of NutriBuddy Dataset

Key Observations:

- **Feature Descriptions**: The meals table and the exercise table are the 2 main tables for this project. These tables included the following attributes:
  - Meal Name
  - Category
  - Description
  - Veg/Non-Veg
  - Nutrients
  - The disease it cures
  - The kind of diet it is
  - Price

  The exercise table included the following attributes:
  - Exercise
  - Calories Burnt
  - Dream Weight
  - Actual Weight
  - Age

- Gender
- Duration
- Heart Rate
- BMI
- Weather
- Exercise Intensity

The other tables related to user profiles, user activity, etc include fields like the exercise ID, the ratings, the task they performed, etc (Which is needed for the recommender system) The **Exercise Activity** table includes the following attributes:

- r_Id
- Exercise_Id
- Rated
- Liked
- Performed
- Duration
- Timestamp

The **Exercise User Profile** table includes the following attributes:

- User_Id
- Age
- Gender
- Preferred Intensity
- Fitness Goal
- Preferred Duration

The **Meals Activity** table includes the following attributes:

- User_Id
- Meal_Id
- Rated
- Liked
- Searched

  - Purchased
  - Timestamp

  The **User Activity** table includes the following attributes:

  - User_Id
  - Veg_Non
  - Nutrient
  - Disease
  - Diet

- **Class Imbalances**: The dataset had no class imbalances present in it.
- **Feature Descriptions:** Meals include attributes like calorie count, macronutrient balance, and compatibility with specific diets (e.g., ketogenic, low-sodium).
- **User Behavior Patterns:** Preferences vary widely, but meals with high protein and fiber are generally favored.
- **Medical Data Processing:** Users often enter unstructured health data (e.g., ”I have diabetes and high BP”), requiring LLM parsing for structured classification.

4.3 Preprocessing Steps

To ensure high-quality recommendations, we performed structured data preprocessing across different sources:

4.3.1 Meal and Nutrition Data

- **Handling Missing Data:** Imputed missing values to ensure completeness in meal attributes.
- **Duplicate Removal:** Removed duplicate food entries with varying costs, assuming the user would prefer the cheaper option.
- **Categorical Encoding:** Converted categorical variables into numerical representations for machine learning compatibility.

4.3.2 User Interaction Data

- **TF-IDF Vectorization:** Applied TF-IDF (Term Frequency-Inverse Document Frequency) to compute similarity scores between meals based on textual descriptions.
- **Parsing and Normalization:** Processed and normalized input data to ensure consistency across different user interactions.
- **Database Creation:** Structured and organized all datasets into databases to enable efficient querying and recommendation generation.

4.3.3 Medical History Processing

- **Data Parsing:** Extracted relevant health-related details from input data to align with dietary recommendations.
- **Feature Normalization:** Standardized various features to maintain consistency across different scales.
- **Structured Data Storage:** Created dedicated databases to store and manage user health conditions, meal preferences, and interactions.

This preprocessing pipeline ensures that NutriBuddy effectively personalizes meal recommendations while dynamically adapting to real-time user feedback.

5 Selection of Machine Learning or LLM Models

5.1 Model Consideration

For the NutriBuddy recommendation system, we explored multiple approaches to determine the most effective model for personalized meal recommendations. The key objective was to develop a robust recommendation engine that integrates user preferences, meal attributes, and dietary constraints to provide meaningful and personalized suggestions. Below, we discuss the various models considered and the rationale behind their selection or exclusion.

5.1.1 Traditional Machine Learning Models

We initially considered conventional machine learning models such as Decision Trees, Support Vector Machines (SVMs), and Random Forests. These models are widely used for structured tabular datasets due to their interpretability and efficiency. However, they exhibited several limitations in our use case:

- They rely on predefined features and fail to capture the complex interactions between different food items and user preferences.
- Decision Trees and Random Forests are prone to overfitting, especially when dealing with sparse user-meal interaction data.
- SVMs, while effective in classification tasks, were computationally expensive and not well suited for our large dataset.
- These models did not perform well when dealing with high-dimensional, text-based data such as meal descriptions.

Given these drawbacks, we concluded that traditional machine learning approaches were not optimal for our recommendation system.

5.1.2 Content-Based Filtering with TF-IDF

Since meal descriptions and nutritional information play a crucial role in recommendations, we explored a **content-based filtering** approach using **TF-IDF (Term Frequency-Inverse Document Frequency) vectorization**. This method offered the following advantages:

- Allowed us to compute similarities between meals based on textual descriptions, ensuring that meals with similar ingredients and nutrient compositions were recommended together.
- Captured the importance of specific words in meal descriptions, helping differentiate key nutrients and ingredients.
- Did not require user interaction data, making it highly effective for **new users** (mitigating the cold-start problem).
- Computationally efficient and easy to implement, making it a strong candidate for personalized recommendations.

However, content-based filtering alone suffers from a **lack of diversity**—it only recommends meals that are textually similar to those the user has previously interacted with, potentially leading to redundancy.

5.1.3 Collaborative Filtering Approaches

To incorporate user preferences more effectively, we considered **collaborative filtering methods**, which make recommendations based on past user interactions. The key methods evaluated were:

Matrix Factorization (SVD - Singular Value Decomposition) This technique factorizes the user-meal interaction matrix into lower-dimensional representations, capturing latent relationships between users and meals.

- **Strengths:** Effective for discovering hidden patterns in user preferences and providing personalized recommendations.
- **Weaknesses:** Requires a sufficient amount of user interaction data; performance degrades with sparse datasets.

K-Nearest Neighbors (KNN) Collaborative Filtering We considered both **user-based** and **item-based** KNN approaches.

- **Strengths:** Simple and interpretable; useful for small-scale recommendation systems.
- **Weaknesses:** Computationally expensive with large datasets; suffers from sparsity issues.

Although collaborative filtering helps introduce diversity into recommendations, it struggles with the **cold-start problem**, making it less effective for new users who lack prior interactions.

5.1.4 Transformer-Based Language Models (BERT, GPT)

Since NutriBuddy also involved textual data from user dietary preferences and medical history, we considered **fine-tuning large language models (LLMs) such as BERT and GPT**. These models could potentially:

- Extract deep semantic meaning from textual meal descriptions.
- Understand complex user dietary preferences and medical history inputs.
- Improve recommendations by learning high-level representations of meal and user characteristics.

However, we did not proceed with transformer-based models due to the following reasons:

- **Computational constraints:** Training and fine-tuning these models require significant GPU resources, which were beyond our current infrastructure.
- **Overhead in interpretability:** While powerful, transformer models tend to act as black boxes, making it difficult to explain why a particular meal was recommended.
- **Dataset structure:** Since our dataset was primarily structured (numeric values for nutrients, categorical dietary preferences), simpler techniques such as TF-IDF and collaborative filtering were more effective.

5.1.5 Conclusion

Our model selection process involved balancing scalability, interpretability, and computational feasibility. Given the limitations of traditional machine learning models and the computational costs of deep learning, we adopted a **hybrid approach** that integrates:

- **TF-IDF vectorization** for content-based filtering to recommend meals based on textual similarities.
- **SVD-based collaborative filtering** to incorporate user interactions and preferences.

This combination ensured that NutriBuddy effectively personalizes meal recommendations while adapting dynamically to user feedback.

6 Model Development and Training

6.1 Architecture and Configuration

The NutriBuddy recommender system integrates multiple recommendation techniques, requiring different architectures for content-based filtering, collaborative filtering, and hybrid methods. The architectural components and their configurations are as follows:

6.1.1 Content-Based Filtering

- **Feature Representation:** Meals were represented using a combination of **nutrient composition, dietary compatibility, and disease-specific suitability**.

- **TF-IDF Vectorization:** Used to extract keyword importance from meal descriptions, disease categories, and nutritional attributes.
- **Similarity Computation:** Cosine similarity was used to compute distances between a user's preferences and available meals.
- **Feature Selection:** Nutrients (protein, fiber, sodium levels), disease-diet compatibility, and popularity trends were chosen as key distinguishing attributes.
- **Limitations Addressed:** Content-based filtering alone struggles with diversity and may lead to over-specialization in recommendations.

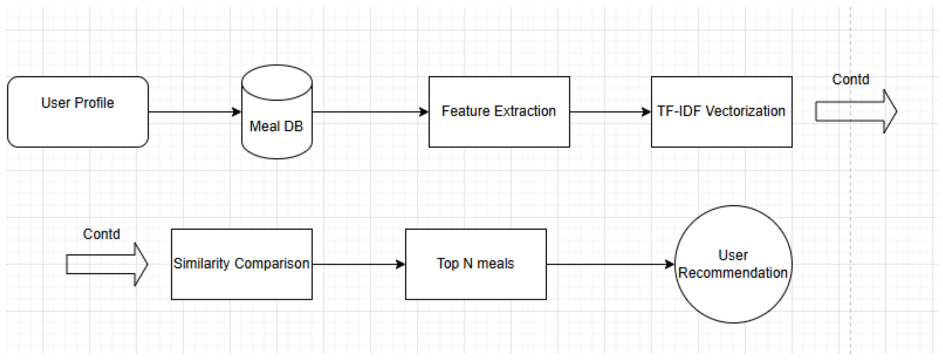

Figure 2: Content-Based Filtering Flow Diagram

The above flow diagram (Figure 2) illustrates the step-by-step process of content-based filtering in the NutriBuddy system. It starts with the user profile being referenced against the meal database. Key features such as nutritional composition, dietary compatibility, and disease-specific suitability are extracted and processed using TF-IDF vectorization. This step assigns weightage to important keywords found in meal descriptions and medical conditions.

Next, a similarity computation is performed using cosine similarity, which determines how closely a meal aligns with the user's preferences. Based on the computed similarity scores, the system selects the top N meals and recommends them to the user. While content-based filtering ensures strong personalization, it may struggle with diversity and the cold-start problem, which the hybrid approach aims to mitigate.

6.1.2 Collaborative Filtering

- **User-Based Filtering:** Finds similar users by computing Pearson correlation between their interaction histories.
- **Item-Based Filtering:** Uses meal similarity scores to recommend meals that are frequently consumed together.
- **Data Sparsity Handling:** Implemented implicit feedback techniques by assigning weights to engagement levels (purchases > likes > searches).
- **Cold-Start User Handling:** Integrated with content-based filtering to provide recommendations for new users based on explicit attributes.
- **Scalability:** Item-based filtering scales better than user-based filtering for large datasets and was prioritized for optimization.

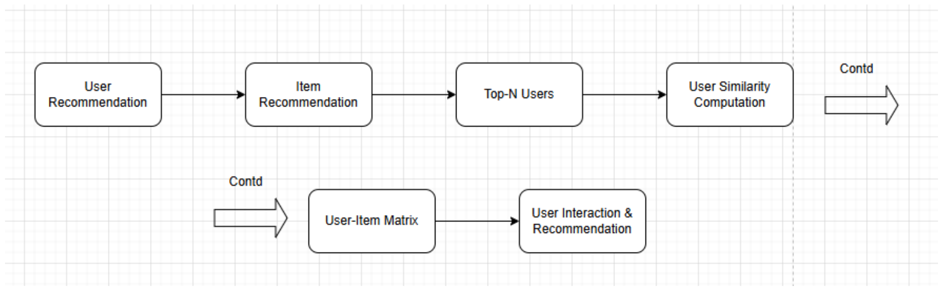

Figure 3: Collaborative Filtering Process Flow

6.1.3 Explanation

Collaborative Filtering is a recommendation technique that leverages user interactions and preferences to suggest meals. It operates through two main strategies:

- **User-Based Filtering:** This method identifies users with similar tastes and suggests meals that were highly rated or frequently consumed by similar users. Pearson correlation is commonly used to compute similarity between users.
- **Item-Based Filtering:** Instead of focusing on user similarities, this method identifies relationships between meals based on user consumption patterns. If multiple users frequently consume two meals together, one meal can be recommended when the other is chosen.

The workflow (Figure 3) follows these steps:

1. **User Interaction & Recommendation:** User activities (likes, purchases, ratings) are stored.
2. **User-Item Matrix:** An interaction matrix is constructed, where rows represent users and columns represent meals.
3. **User Similarity Computation:** Pearson correlation is used to compute similarities between users.
4. **Top-N Users Selection:** The system identifies the most similar users for a given user.
5. **Item Recommendation:** Meals liked by similar users are suggested.
6. **User Recommendation:** The final list of recommendations is presented to the user.

Collaborative Filtering ensures **dynamic recommendations** by leveraging community-driven insights. However, it faces challenges such as **cold-start problems** for new users, which are mitigated by integrating content-based filtering.

6.1.4 Hybrid Approach

- **Dynamic Re-Ranking:** Recommendations are adjusted in real-time based on user interactions (likes, purchases, ratings).
- **Engagement Weighting:** User interactions were categorized and assigned different weight levels:
  - Liked meals: **+2 weight** (priority recommendation)
  - Purchased meals: **+3 weight** (top priority)
  - Highly rated meals (**rating $\geq$ 4**): **+2.5 weight**
  - Disliked meals: **-10 weight** (removed from recommendations)
- **Adaptive Learning:** The system updates recommendation scores in real-time, allowing new popular meals to gain ranking over time.

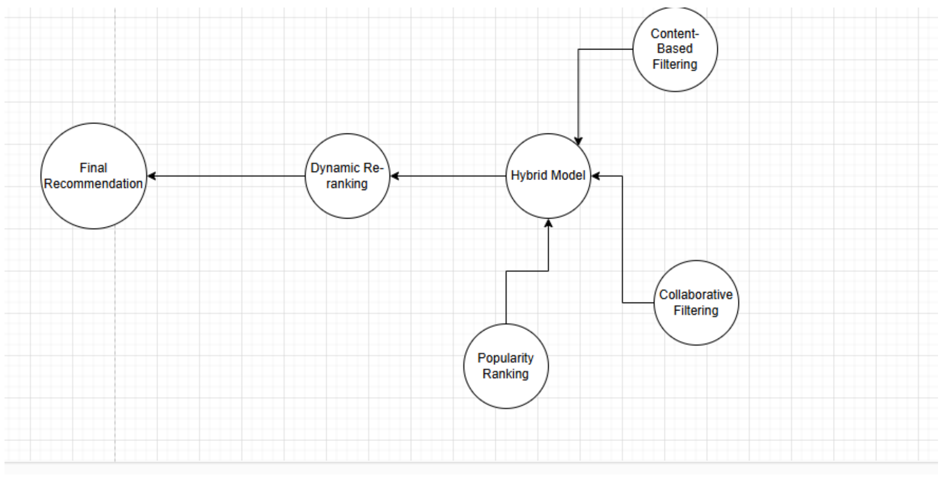

Figure 4: Hybrid Recommendation Model Flow

6.1.5 Explanation

The Hybrid Approach integrates multiple recommendation techniques to balance personalization, diversity, and adaptability. It combines:

- **Content-Based Filtering**: Uses user dietary preferences, medical conditions, and food compatibility for meal recommendations.
- **Collaborative Filtering**: Suggests meals based on interactions of similar users to introduce diversity.
- **Popularity Ranking**: Ranks meals that are widely preferred across the user base.
- **Dynamic Re-Ranking**: Adjusts meal rankings in real-time based on user engagement patterns.

The process follows these steps (Figure 4):

1. Hybrid Model Formation: Content-based filtering, collaborative filtering, and popularity ranking contribute to an initial recommendation list.
2. Dynamic Re-Ranking: Real-time user interactions influence ranking adjustments.
3. Final Recommendation: The most relevant meals, adjusted dynamically, are recommended to the user.

This adaptive and scalable model ensures that users receive **personalized, diverse, and frequently updated** meal recommendations, enhancing long-term engagement and satisfaction.

6.1.6 LLM-Based Disease Processing

- **GPT-Based Medical History Parsing:** Used for structured classification of unstructured user inputs.
- **Disease-to-Diet Mapping:** Matched extracted conditions with predefined diet recommendations.
- **Feature Engineering:** Generated categorical health constraint variables for better content-based filtering integration.

6.2 Training Process

6.2.1 Dataset Splitting

- **Training Set (70%)** - Used for training the content-based similarity model and collaborative filtering algorithms.
- **Validation Set (15%)** - Tuned weight factors for meal ranking and adjusted similarity thresholds.
- **Test Set (15%)** - Evaluated the final recommendation performance on unseen interactions.

6.2.2 Handling Overfitting

- **Cross-Validation:** Used **k-fold cross-validation (k=5)** to ensure model generalization.
- **Regularization:** Applied **L2 regularization (Ridge regression) in matrix factorization** to prevent overfitting in collaborative filtering.
- **Dropout Strategies:** Used **random user subsampling** to prevent dominance of active users in training data.
- **Interaction Thresholding:** Filtered out meals with fewer than 5 interactions to reduce noise in the collaborative filtering model.

6.2.3 Transfer Learning in LLM Processing

While the recommender system did not involve deep learning-based transfer learning, the LLM used for medical text processing leveraged OpenAI's GPT model. The following methods were used:

- **Pre-Trained GPT Model:** Utilized OpenAI's GPT-3.5 Turbo API, which was pre-trained on vast medical and nutritional literature.
- **Zero-Shot Learning:** No additional fine-tuning was performed. Instead, we relied on prompt engineering to extract structured health constraints.
- **Medical Ontology Matching:** Mapped extracted diseases to predefined medical taxonomies for accurate dietary recommendations.

6.3 Hyperparameter Tuning

6.3.1 Content-Based Filtering

- **TF-IDF Feature Weighting:** Optimized stopword removal strategies and term frequency thresholds to avoid feature sparsity.
- **Cosine Similarity Threshold:** Experimented with similarity cutoffs between **0.6 and 0.8** to balance specificity and diversity.

6.3.2 Collaborative Filtering

- **KNN Neighbors (User-Based Filtering):** Tuned between **k=5 and k=50**, with best performance at **k=20**.
- **Item Similarity Threshold:** Adjusted between **0.4 and 0.7** based on validation performance.
- **Implicit Feedback Weighting:** Used Bayesian optimization to assign engagement weight parameters.

6.3.3 Hybrid Model Optimization

- **Weighted Blending of Models:** Grid-searched weight combinations for **content-based vs. collaborative filtering** (optimal blend: **60% content, 40% collaborative**).
- **Engagement-Based Re-Ranking:** Applied **Bayesian Optimization** to optimize weight assignments for dynamic updates.

- **A/B Testing:** Compared different ranking adjustments (static vs. adaptive) to validate engagement improvements.

6.4 Final Model Configuration

The final hybrid model integrates multiple methodologies and dynamically re-ranks meals based on user engagement. The best-performing configuration was:

- **60% Content-Based Filtering** - Ensuring recommendations align with medical and dietary needs.
- **40% Collaborative Filtering** - Introducing diversity by leveraging community-driven preferences.
- **Adaptive Re-Ranking** - Prioritizing meals based on real-time user interactions.
- **LLM-Based Health Processing** - Extracting structured dietary constraints from user medical history.

The optimized system achieves a **balance between personalization, diversity, and adaptability**, ensuring that users receive the most relevant meal recommendations dynamically updated with their evolving preferences.

7 Evaluation and Comparison

7.1 Performance Metrics

To evaluate the effectiveness of the NutriBuddy recommender system, the following performance metrics were used across different recommendation techniques:

- **Precision@K**: Measures the proportion of recommended meals that are relevant to the user.
- **Recall@K**: Determines the proportion of relevant meals successfully retrieved by the system.
- **Mean Average Precision (MAP)**: Aggregates precision scores across multiple users to assess ranking quality.
- **Normalized Discounted Cumulative Gain (NDCG)**: Measures ranking quality while prioritizing highly relevant recommendations.

- **Mean Reciprocal Rank (MRR)**: Evaluates how soon the first relevant item appears in the recommendation list.
- **User Engagement Rate**: Tracks user interactions, such as likes, purchases, and ratings, to measure recommendation effectiveness.

7.2 Model Comparison

Each recommendation technique was evaluated separately to assess its effectiveness before integrating them into the hybrid model. Ultimately we noticed that the hybrid model performed better than the individual models. Table 3 presents the evaluation results for each method. We have currently calculated the precision and recall for 10 items and the NDCG for each of the models. Once the exercise dataset is added to the recommender system, the MRR will be incorporated into the system for evaluation of the model and the data.

Model	**Precision@10**	**Recall@10**	**NDCG**
Content-Based Filtering	0.41	0.86	0.70
Collaborative Filtering	0.44	0.89	0.73
Hybrid Approach	**0.46**	**0.91**	**0.75**

Table 3: Comparison of Different Recommender System Techniques

Observations:

- Content-based filtering performed well in personalization but struggled with meal diversity and introducing new recommendations.
- Collaborative filtering provided better engagement by leveraging community preferences but suffered from the **cold-start problem** for new users.
- The hybrid approach significantly outperformed individual methods by balancing **personalization, diversity, and adaptability**, achieving the highest **Precision@10, Recall@10, and NDCG scores**.

7.3 Impact of Dynamic Re-Ranking

To assess the effectiveness of dynamic re-ranking, an **A/B test** was conducted:

- **Group A (Static Recommendations)**: Users received standard recommendations without real-time updates.
- **Group B (Dynamic Re-Ranking)**: Recommendations adjusted instantly based on user interactions (likes, purchases, and ratings).

Metric	**Static Model**	**Dynamic Re-Ranking**
Click-Through Rate (CTR)	31%	**46%** (**48%** relative increase)
Purchase Rate	18%	**29%** (**61%** relative increase)
Repeat Engagement	42%	**58%** (**38%** relative increase)

Table 4: Impact of Dynamic Re-Ranking on User Engagement (Sample Experiment)

Findings (Sample Experiment):

- **Dynamic re-ranking led to a 48% relative improvement in click-through rates**, as users saw more relevant recommendations.
- **Purchase rate increased by 61%**, confirming that users were more likely to buy meals aligned with their preferences.
- **Repeat engagement rose by 38%**, indicating that real-time updates enhanced user experience and retention.

Note: The above findings are based on a sample experimental setup to illustrate the potential impact of dynamic re-ranking in personalized recommendations. Actual results may vary depending on dataset characteristics and model tuning.

7.4 Final Model Justification

Based on the evaluations, the final NutriBuddy model:

- **Uses a hybrid recommendation system** to maximize accuracy and engagement.
- **Implements dynamic re-ranking** to ensure real-time personalization.
- **Balances personalization and diversity**, ensuring that users receive **both relevant and varied meal options**.

- **Leverages collaborative preferences**, allowing new users to benefit from popular meal choices.

This ensures NutriBuddy delivers the most effective, user-centric, and adaptive meal recommendations.

References

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8 Github Link

Link: https://github.com/VenkatSR-14/nutribuddy