Recipe Recommendation System Using Machine Learning Techniques

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Abstract: Personalized recommendation systems have become essential in various domains, especially in health and food-related applications. This paper presents the development of a web-based recipe recommendation system using Flask, designed to provide users with personalized recipe suggestions based on their dietary preferences and nutritional requirements. The system utilizes a cosine similarity algorithm to compare ingredients across recipes, ensuring that the recommendations are relevant and tailored to the user's needs. Additionally, users can submit feedback on recipes they try, which helps refine future suggestions. Key features of the system include user registration, login, profile management, feedback submission, and a dynamic recommendation engine that evolves based on user inputs. The system leverages data preprocessing and machine learning techniques to enhance the recommendation accuracy, providing a seamless and interactive user experience. Results demonstrate the application's ability to offer personalized culinary experiences, promoting healthier eating habits and recipe discovery.

Keywords: Personalized Recommendation System, Recipe Recommendations, Flask Web Application, Dietary Preferences, Cosine Similarity, User Feedback, Machine Learning, Nutritional Requirements, Health and Wellness, User Experience.

I. INTRODUCTION

The growing need for personalized services has significantly influenced the development of recommendation systems across various domains, including food and health. In particular, recipe recommendation systems have emerged as a promising tool for aiding individuals in making healthier, more informed food choices based on their specific dietary needs, preferences, and health goals. Such systems leverage vast amounts of data from user interactions, dietary requirements, and food preferences to generate tailored recipe suggestions. The idea of using personalized recommendations to enhance user experience in the food domain has gained traction due to the increasing awareness of the importance of nutrition and healthy eating habits.

This paper presents the development of a web-based recipe recommendation system built using Flask, a lightweight Python web framework. The system offers personalized recipe suggestions based on factors such as ingredients, nutritional content, user preferences, and dietary restrictions. The recommendation engine utilizes cosine similarity to compare ingredient lists from various recipes, ensuring that users receive suggestions that are more aligned with their tastes and health needs. In addition to personalized recommendations, the system incorporates a feedback mechanism that allows users to rate recipes, further refining and enhancing the accuracy of future suggestions.

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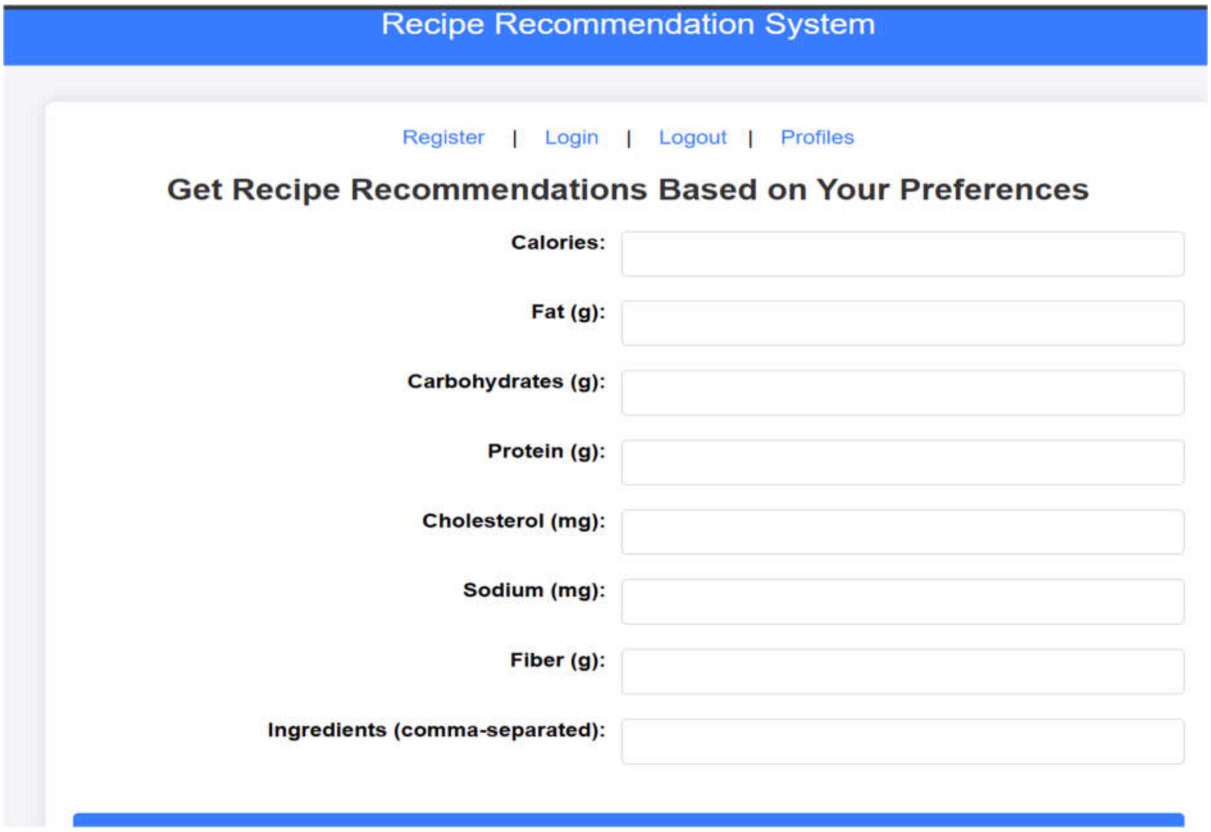

Fig: 1 Recipe Recommendation Based on nutritional Information and Ingredients

The **index page** of the Recipe Recommendation System is the starting point for users to personalize their recipe suggestions based on specific dietary preferences. Upon visiting the page, users are prompted to input key nutritional information such as calorie count, fat, carbohydrates, protein, cholesterol, sodium, fiber, and preferred ingredients. This allows the system to generate personalized recipe recommendations tailored to individual health goals. The page features a clean and intuitive design with easy-to-use forms where users can enter their preferences. A navigation header includes links for registration, login, logout, and profile access, while flash messages provide real-time feedback about actions like successful registration or errors. The form submission triggers the system to display recipes that meet the nutritional criteria provided by the user.

After submitting their nutritional preferences and ingredients on the index page, users are presented with personalized recipe recommendations on a results page. This page displays a curated list of recipes that align with the user's specified health goals and dietary requirements, such as calorie count, fat, carbohydrates, protein, cholesterol, sodium, fiber, and preferred ingredients. Each recommended recipe includes details such as the recipe name, a brief description, an image of the dish, and any health benefits associated with the ingredients.

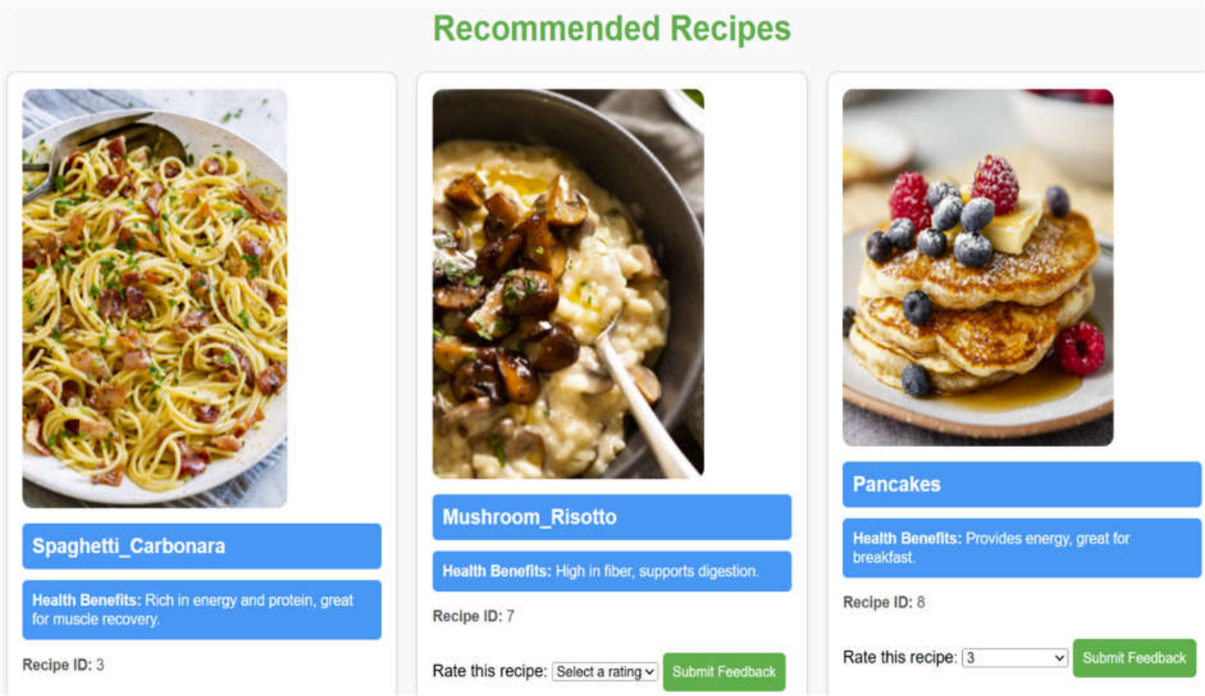

Fig.2 Recommended recipes based on nutritional information and ingredients

The result page of the Recipe Recommendation System displays personalized recipe recommendations based on the user's dietary preferences. After the user inputs their desired nutritional criteria, such as calories, fat, carbohydrates, protein, cholesterol, sodium, fiber, and ingredients, the system uses a recommendation algorithm to filter and rank recipes accordingly.The system leverages multiple algorithms for this purpose. Collaborative filtering is one approach that recommends recipes based on the preferences of other users with similar dietary habits. Content-based filtering, on the other hand, compares the user's input (nutritional content and ingredients) to the recipe database, suggesting recipes with the closest match.

Each recipe is presented in a visually appealing card format with key details, such as health benefits, which are derived from analyzing the nutritional content of the ingredients. Users are also encouraged to rate the recipes, and this feedback is incorporated into the recommendation system to refine future suggestions. The entire process is dynamic and adaptive, meaning that as the user interacts with the system—by providing ratings and feedback—the recipe recommendations become more personalized and accurate over time. This combination of user input, sophisticated algorithms, and ongoing feedback makes the recipe discovery process tailored to individual health goals and dietary preferences.

II. RECIPE RECOMMENDATION APPROACHES

A literature survey is a systematic review of existing research and publications related to a specific topic. It provides an overview of the key theories, methodologies, findings, and gaps in the field. The purpose of a literature survey is to summarize and analyze previous studies, offering insights into what has been done, what challenges remain, and how the current research can build upon existing knowledge. The following are the different works carried out in the given area. Each paper is discussed with methods, advantages, drawbacks and brief methodology.

2.1 "Ingredient Detection and Recipe Recommendation Using Deep Learning"

They developed a system for food ingredient recognition and recipe recommendation, combining deep learning and machine learning techniques. They used a Convolutional Neural Network (CNN) model, specifically the ResNet50 architecture, to classify 32 different food ingredients from a custom dataset. This CNN model was trained on a collection of images, enabling the system to accurately recognize various ingredients based on their visual features. After detecting the ingredients in the images, the system employed a recommendation algorithm to suggest relevant recipes.

2.2 "Optimization Framework for Flavour and Nutrition Balanced Recipe: A Data Driven Approach"

Food has been playing a major part of human civilization as not only being a physiological need, but being a major factor for defining the culture and society. The choice of the food is mainly depended on both flavour and nutrient but the biasness towards to the flavour factor has lead the human to effect badly on their healthier lifestyle. Recipe recommendation literature typically considers either flavour or nutrient factor. Various flavour traits are also preventing the promotion of healthy foods while maintaining the pliability.

2.3 "You Are What You Eat: Exploring Rich Recipe Information for Cross- Region Food Analysis"

Cuisine is a style of cooking and usually associated with a specific geographic region. Recipes from different cuisines shared on the web are an indicator of culinary cultures in different countries. Therefore, analysis of these recipes can lead to deep understanding of food from the cultural perspective. In this paper, we perform the first cross-region recipe analysis by jointly using the recipe ingredients, food images, and attributes such as the cuisine and course (e.g., main dish and dessert). For that solution, we propose a culinary culture analysis framework to discover the topics of ingredient bases and visualize them to enable various applications.

2.4 "Recipe Recommendation System Using TF-IDF"

They propose a Recipe Recommendation System that helps users find recipes based on the ingredients they have available. The system uses a dataset of Indian food recipes and implements a content-based recommendation approach using Term Frequency-Inverse Document Frequency (TF-IDF) and Cosine Similarity. Users can input available ingredients into the mobile app, which queries the recommendation system to suggest recipes that match those ingredients. The app also allows users to filter recipes based on course type, diet type (e.g., gluten-free or diabetic-friendly), and other preferences. The authors pre-process the dataset by cleaning and lemmatizing the ingredients to remove unnecessary information. They apply TF-IDF for encoding recipe ingredients and calculate recipe similarity using Cosine Similarity. The recommendation system is developed using Flask, and the mobile application is built with React Native.

2.5 "Automatic Generation of Recipe Recommendation Based On Outlier Analysis"

In this study they have developed a dietary recommendation system based on ontology and machine learning. The System Can Recommend recipes based on user's health conditions and preference. In this paper they added one class SVM based ODM and a RGM in our system. Therotically infinitly number of new recipes can be generated by using the RGM based on existing ones, and some of the generated recipes can be recommended to user if they can pass the evaluation of ODM.

2.6 "Recipe Recommendation System using Machine Learning Models"

The paper presents a Recipe Recommendation System that uses machine learning models to pair ingredients and suggest alternative ingredients, with a focus on Indian cuisine. It utilizes web scraping to collect recipe data from Yummly.com, which is then processed for analysis. The system employs TF-IDF (Term Frequency-Inverse Document Frequency) to assign weights to ingredients based on their flavor components, and cosine similarity to find matching pairs using a vector space model. For recommending alternative ingredients, the Word2Vec model is used to create vector spaces for ingredients, identifying those with similar contexts. The system aims to innovate new dishes by pairing ingredients from different cuisines and providing alternatives for unavailable ingredients, making it useful for culinary exploration and helping people with ingredient allergies.

2.7 "Recipe Recommendation System Based on Ingredients"

They developed a Recipe Recommendation System that provides personalized recipe suggestions based on the ingredients available to the user. The system utilizes advanced algorithms such as Non-Negative Matrix Factorization (NMF) for feature extraction and sentiment analysis to tailor recommendations according to user preferences and feedback. Built using Python, Flask, SKLearn, and MongoDB, the system offers a web-based interface for real-time recipe suggestions. It also incorporates feedback mechanisms to continuously refine and enhance the recommendation accuracy. The goal is to reduce food waste, inspire culinary creativity, and streamline meal planning for users.

2.8 "Indian Cuisine Recipe Recommendation based on Ingredients using Machine Learning Techniques"

They develop a recipe recommendation system that utilizes content-based filtering and collaborative filtering techniques to provide personalized food suggestions. The paper reviews various approaches, including a dietary recommendation system that uses ontology and machine learning to suggest recipes based on users' health conditions and preferences. They also explore the Yum-me system, which recommends healthy meals based on fine-grained user preferences. Additionally, they discuss an automatic method for generating recipe metadata based on users' moods. The authors propose a new approach that uses recipe ingredients for recommendation, along with an experimental setup to evaluate the system's effectiveness.

2.9 "Machine Learning Based Food Recipe Recommendation System"

They propose a comparative study of two collaborative filtering approaches—item-based and user-based—to recommend recipes based on user preferences in the form of ratings. The item-based approach utilizes similarity measures such as Tanimoto Coefficient and Log Likelihood to compute the similarity between recipes. The user-based approach, on the other hand, calculates similarity using Euclidean Distance and Pearson Correlation, incorporating fixed-size and threshold-based neighborhood methods. The results show that the user-based approach outperforms the item-based approach, providing more accurate recommendations, especially with larger datasets like the Allrecipes dataset.

3.0 "A Recommender System for Healthy Food Choices: Building a Hybrid Model for Recipe Recommendations using Big Data Sets"

They develop a hybrid recommender system for healthy food choices, combining content-based and collaborative filtering models to offer personalized recipe recommendations. This system analyzes user preferences, dietary needs, and health-related factors to suggest recipes that promote healthier eating habits. By leveraging Big Data, the system processes vast amounts of online recipe information to provide tailored suggestions, addressing the challenge of information overload. The hybrid approach enhances the accuracy of recommendations by considering both individual tastes and community preferences. Additionally, they explore ingredient substitution techniques to recommend healthier alternatives for recipes with low nutritional value.

III. METHODOLOGY

Recipe recommendation system is built around the principles of data processing, machine learning, and user interaction. The methodology section explains the approaches, techniques, and algorithms used to construct and implement the system, with particular emphasis on data collection, processing, recommendation algorithms, user authentication, feedback handling, and interface design. The overall goal is to provide an intuitive, dynamic, and personalized experience for the users based on their dietary preferences and tastes.

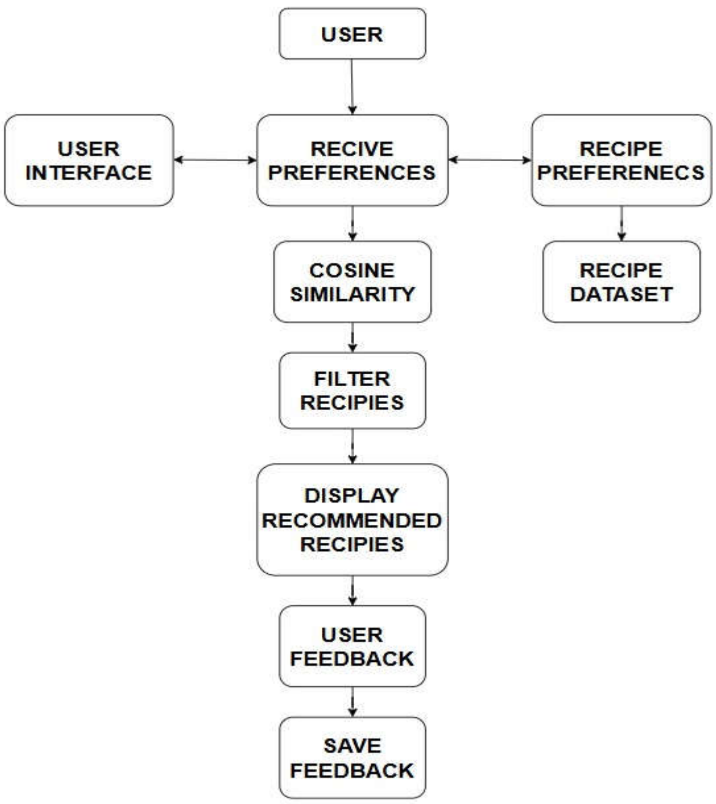

Fig 3: Data flows through the user interaction

The system begins by collecting data from various sources, including recipe information, user details, and feedback. The recipe data is stored in a CSV file (recipes.csv), which contains essential information about each recipe, such as ingredients, nutritional values (calories, fat, protein), and health benefits. The user data is kept in another CSV file (users.csv), which includes usernames, hashed passwords (for security), and optional profile images. Additionally, the system gathers feedback data from users, including ratings and comments on recipes, which are stored in feedback.csv. This feedback is essential for refining and improving the recommendation system based on user preferences. After collecting the data, preprocessing steps are performed to ensure its quality. Cleaning is conducted to handle missing or invalid entries, ensuring the dataset is complete and reliable. Feature engineering is then applied, particularly to the ingredients field. Using scikit-learn's CountVectorizer, ingredients are tokenized to create a vector representation. This vectorization is crucial for calculating the similarity between recipes, as it enables the system to compare recipes based on the ingredients used, forming the foundation for the recommendation system.

The system facilitates user registration and authentication to provide personalized recommendations and allow users to save their feedback. The methodology begins with password hashing, ensuring that user passwords are never stored in plain text. Instead, passwords are securely hashed using the werkzeug.security library, which protects user credentials from potential security breaches. Session management is also implemented, where a session is initiated upon a successful login. This session helps maintain the user's state, allowing them to interact with the system and access personalized content without needing to log in repeatedly. Additionally, the system allows users to upload a profile image during the registration process. If a user chooses to upload an image, it is stored in a dedicated folder on the server, and the file path is recorded in the users.csv file. This allows the system to display the user's profile image when they interact with the application.

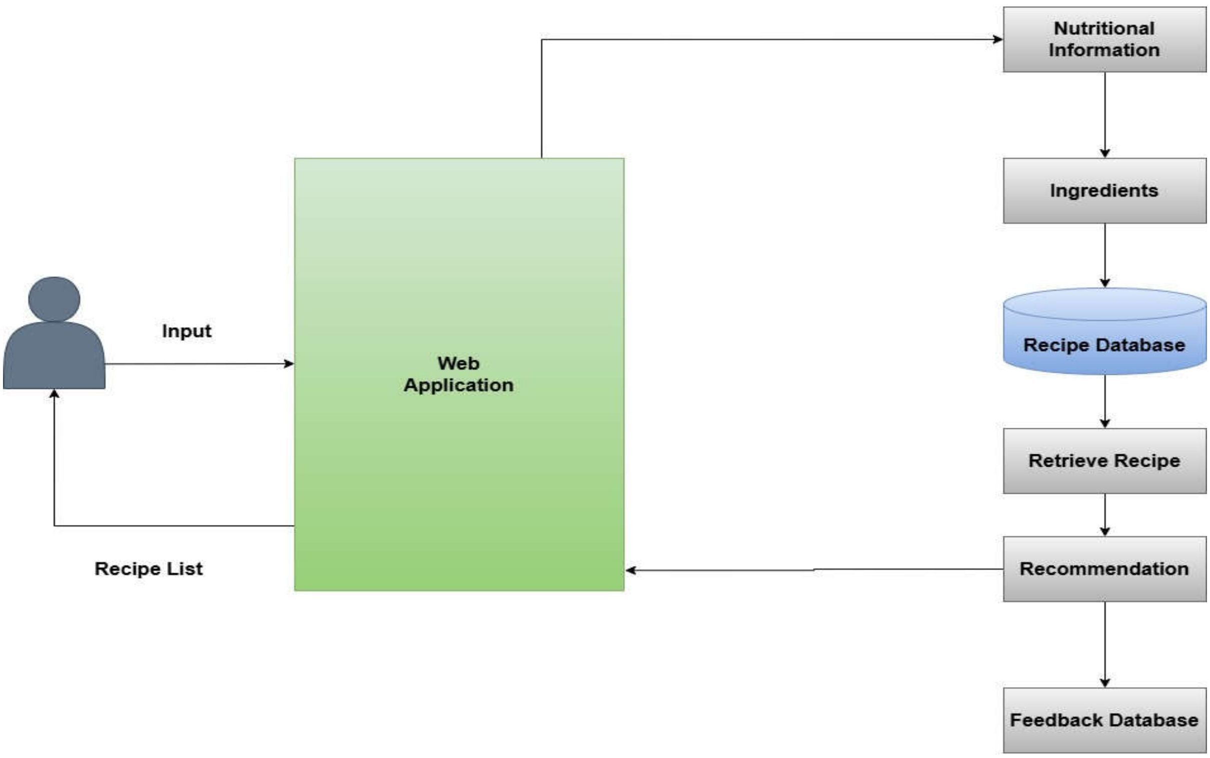

Fig.4: System Architecture

Recipe Recommendation Algorithm, which utilizes a content-based filtering approach. This method compares the user's input preferences—such as calorie count, fat content, protein, and other nutritional values—with the ingredients and nutritional information of recipes in the database. The process begins with user input, where the user specifies their dietary preferences. Based on these parameters, the system filters out recipes that do not meet the user's nutritional requirements. After this, the system applies cosine similarity to compare the ingredients of the filtered recipes with the user's preferred ingredients. Using scikit-learn's CountVectorizer, the system tokenizes and vectorizes the list of ingredients, allowing for a comparison of similarities between the user's preferences and recipe ingredients. Once the relevant recipes are filtered and ranked based on similarity, the system generates recommendations by selecting the top recipes that best match the user's dietary constraints and ingredient preferences. Additionally, health benefits associated with each recipe are taken into account and can be highlighted in the recommendations to inform the user about the nutritional advantages of specific recipes. The recommendations are, therefore, influenced by both the user's nutritional input and the similarity between the ingredients of the recipes. Lastly, feedback collection and aggregation play a crucial role, as users are encouraged to rate the recipes, which helps refine and improve the recommendation system over time.

Content-Based Filtering:

Content-based filtering is a recommendation system technique that suggests items based on the features of the items themselves and a user's past preferences. In the context of a recipe recommendation system, it works by analyzing the nutritional values and ingredients of recipes that a user has interacted with or shown interest in. When a user provides dietary preferences (such as specific ingredients or nutritional requirements), the system filters recipes from the database that match these criteria. The key idea is to recommend items that are similar in content to what the user has previously liked or shown interest in, rather than relying on the preferences of other users.

Collaborative Filtering:

Collaborative filtering is a recommendation system technique that relies on user behavior and preferences to recommend items. Unlike content-based filtering, it doesn't require knowledge of item content but instead focuses on the interactions between users and items. Collaborative filtering can be divided into two types: user-based and item-based. In user-based collaborative filtering, the system recommends items based on the preferences of similar users. In item-based collaborative filtering, the system recommends items that are similar to those the user has previously liked. Collaborative filtering assumes that users who have agreed in the past will agree in the future on similar items.

Cosine Similarity:

Cosine similarity is a metric used to measure the similarity between two vectors. It is widely used in text mining, information retrieval, and recommendation systems. The cosine similarity score ranges from -1 to 1, where 1 indicates that two vectors are identical (i.e., they have the same direction), 0 means they are orthogonal (no similarity), and -1 means they are diametrically opposite. In a recommendation system, cosine similarity is used to measure the similarity between the user's preferences and the features of items, such as recipes. A higher cosine similarity score indicates that a recipe is more similar to the user's preferences, making it a better recommendation.

Count Vectorizer:

CountVectorizer is a tool provided by the scikit-learn library that converts a collection of text documents into a matrix of token counts. It is often used in text-based tasks like natural language processing (NLP) and recommendation systems to transform text (such as ingredients in recipes) into a numerical representation that can be analyzed. The CountVectorizer breaks down text into "tokens" (words or phrases) and counts the occurrence of each token. In a recipe recommendation system, the CountVectorizer can tokenize ingredients into vectors, where each element in the vector represents the frequency of a specific ingredient in a recipe. These numerical vectors are then used to compute similarities between recipes using methods like cosine similarity.

IV. CONCLUSION

In conclusion, the system effectively combines user preferences, recipe data, and a content-based filtering approach to recommend personalized recipes. By utilizing cosine similarity, it matches recipes based on nutritional values and preferred ingredients. User feedback helps refine these recommendations, creating an evolving and more accurate system over time. The design ensures a smooth user experience with secure authentication, data management, and easy recipe browsing. This approach provides users with meaningful, health-conscious suggestions tailored to their dietary needs.

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