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Machine Learning Approach for Smart Food Recommendation System

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Abstract : This paper introduces a smart food recommendation system that uses machine learning and user health profiling to suggest meals tailored to individual dietary needs. By considering factors such as age, weight, health conditions, and nutritional goals, the system offers food recommendations that promote well-being. It combines intelligent filtering techniques to align suggestions with both health requirements and user preferences. Unlike conventional systems, it learns from user interactions to refine its results over time.

***IndexTerms* – Recommendation system, Machine learning, Health profile.**

I. Introduction

In today's digital age, recommendation systems have become essential tools for simplifying decision-making and enhancing user experience across various platforms. These systems help users discover relevant content or products by analyzing large volumes of data and identifying meaningful patterns. Building upon this foundation, food recommendation systems have emerged as a specialized application area, uniquely positioned at the intersection of technology, health, and lifestyle. Unlike traditional recommender systems that focus mainly on media or retail, food recommendation systems must address multifaceted challenges such as dietary restrictions, cultural preferences, time-based needs, and most importantly, health conditions. These systems not only aim to match a user's taste preferences but also incorporate nutritional content, health goals, ingredient availability, and even emotional or contextual cues (e.g., mood, time of day).

Most food recommendation systems rely on general filters such as popularity, ratings, and proximity to suggest food items or restaurants. However, these filters do not take into account the specific needs and health requirements of individual users [1-2]. In the proposed work, filtration begins with user-provided health information such as age, weight, height, and known medical conditions. Based on this, to determine dietary requirements like calorie limits, nutrient ratios, or dietary restrictions (e.g., low-carb, high-protein, sugar-free). The system then filters out foods or meals that don't align with these health constraints [3].

Once health-related filtering is done, the system applies additional layers of intelligent filtering to refine the suggestions. This includes collaborative filtering to recommend meals preferred by users with similar health and taste profiles, and content-based filtering to suggest foods with ingredients and nutritional values matching the user's history or preferences. To enhance personalization, knowledge-based filtering integrates explicit dietary rules, while a hybrid approach ensures that the final recommendations balance both user preferences and health needs effectively [4-5]. The result is a dynamic, layered filtering system that adapts to the individual on multiple levels.

II. Literature review

Muhib Anwar Lambay and S. Pakkir Mohideen [1] presents a hybrid framework for generating healthy diet recommendations by combining Machine Learning (ML), Natural Language Processing (NLP), and Big Data Analytics. Recognizing the crucial impact of diet on human health, the authors propose an intelligent recommender system that analyzes large-scale food and user data to offer personalized dietary suggestions. The system, known as the Intelligent Recommender for Healthy Diet (IR-HD), uses a hybrid algorithm that integrates collaborative filtering techniques and matrix-based computations to predict user preferences. The data is structured into two key matrices: the user-food matrix and the rating matrix, which are then used to compute similarity between users and food items based on health and taste preferences.

In an innovative step toward personalized and health-focused dietary recommendations, authored by Sajad A et.al. [6] presents a hybrid framework that leverages time-aware community detection and reliability measurement for smarter food suggestion systems. The proposed system addresses the challenges in existing food recommender systems that often fail to incorporate users' evolving preferences and health concerns. The authors emphasize that user preferences toward food can change over time due to lifestyle shifts, dietary goals, or seasonal patterns. Therefore, they introduce a dynamic recommendation model that adjusts recommendations by learning from user's recent behaviors and their community memberships over time.

The framework is divided into three main components: community detection, preference modeling, and health-aware recommendation. In the first stage, a time-aware community detection algorithm groups users into communities based on their temporal interaction patterns and food preferences. This allows the system to detect dynamic communities that better reflect current user interests rather than relying solely on historical data. In the second stage, the model uses deep learning to model user preferences based on these detected communities. The authors apply graph neural networks to capture the evolving relationships among users and between users and food items. The preference model then learns the embedding of users and items in a latent space, considering both personal interactions and community dynamics.

The increasing need for personalized food suggestions has led to the development of an Intelligent Time-Aware Food Recommender system by Minakshi Panwar et.al. [2] which presents a smart model that recommends food based on user preferences and time of day using machine learning. This system aims to intelligently suggest healthy food items to users by incorporating multiple factors including the user's age, food preferences in terms of calorie needs, and the time of day or week. The system introduces a two-stage computation process—first generating a User Identity Document (UID) based on user age and dietary preferences, and second, using this UID along with the time of day to predict a food rating score (PFR). An additional factor is applied for weekends to reflect potential changes in food behavior. These computed ratings are then used to generate personalized food recommendations. The proposed framework consists of several components: data collection, preprocessing, feature engineering, model training using SVM, and recommendation generation. The UID is calculated with weighted contributions from age and user calorie preferences, and the PFR is computed using both UID and the time of day. The SVM model is trained with these features and used to predict suitable food items for users.

In a work on Personalized healthy and sustainable grocery product recommendations by Laura Z.H. Jansen and K. E. Bennin [4] a novel recommender system that uniquely combines consumer preferences with product health and sustainability factors to deliver truly personalized grocery suggestions is proposed. Unlike traditional recommender systems that focus solely on customer purchase history to increase satisfaction and sales, this study aims to promote healthier and more environmentally sustainable food choices without compromising user satisfaction. The system was built to consider attributes such as nutritional quality (based on NutriScore) and sustainability markers (like EU organic labels) while still aligning with individual purchase behavior. The approach seeks to provide a balance between maintaining user preferences and nudging consumers toward better food decisions.

A groundbreaking methodological framework that enables recommender systems to integrate data from multiple heterogeneous sources is introduced by Federica Cena et.al. [7] paving the way for more accurate and comprehensive recommendations. Unlike traditional recommender systems that rely heavily on user ratings or purchase histories within a single domain, this research emphasizes the importance of modeling users in a more comprehensive and realistic way. The core idea is that effective recommendations—especially in domains such as food and health—must reflect the complexity of human decision-making, which is influenced not just by preferences, but also by emotional states, health conditions, social context, long-term goals, and environmental factors. To enable such “holistic” recommendations, the framework proposes the use of Holistic User Models (HUMs), which gather and organize data from sources like social networks, mobile apps, wearable devices, and sensor data to create detailed, multifaceted representations of individuals.

Mehrdad Rostami et.al. [3] presents an innovative approach to food recommendation through their Time-Aware Deep Learning and Graph Clustering (TDLGC) model, addressing the shortcomings of traditional systems by factoring in temporal patterns and complex user-item relationships. The primary aim is to deliver more accurate and personalized food suggestions by considering multiple real-world factors influencing eating behavior. TDLGC uses a hybrid approach combining deep learning and graph clustering to improve recommendation quality, especially in the presence of cold-start problems and dynamic user preferences. By integrating collaborative filtering, content-based filtering, and social trust analysis, the TDLGC system provides highly adaptive and accurate food recommendations. Its ability to capture ingredient-level details and user social dynamics enables it to effectively handle both cold-start users and items, setting it apart from traditional recommender models.

A comprehensively personalized food recommender system introduced by Saeed Hamdollahi Oskouei and Mahdi Hashemzadeh [8] named as FoodRecNet uses a deep learning system designed to deliver personalized and health-aware meal recommendations tailored to individual dietary needs and preferences. Unlike traditional recommendation systems that mainly rely on collaborative or content-based filtering, FoodRecNet integrates a wide range of user and food-related features textual, visual, and numerical to generate more accurate and relevant recommendations. A major limitation of existing models is their lack of attention to health factors such as allergies, dietary restrictions, and nutritional balance. FoodRecNet addresses this gap by incorporating user demographics, health conditions, dietary preferences, cultural or religious restrictions, and both short-term and long-term preferences into the recommendation process.

III. SYSTEM ARCHITECTURE

The proposed food recommendation system includes a user interface and a machine learning-based recommendation engine. The different components and entities involved in the system are illustrated in Figure 1. The proposed system consists of different modules as explained below.

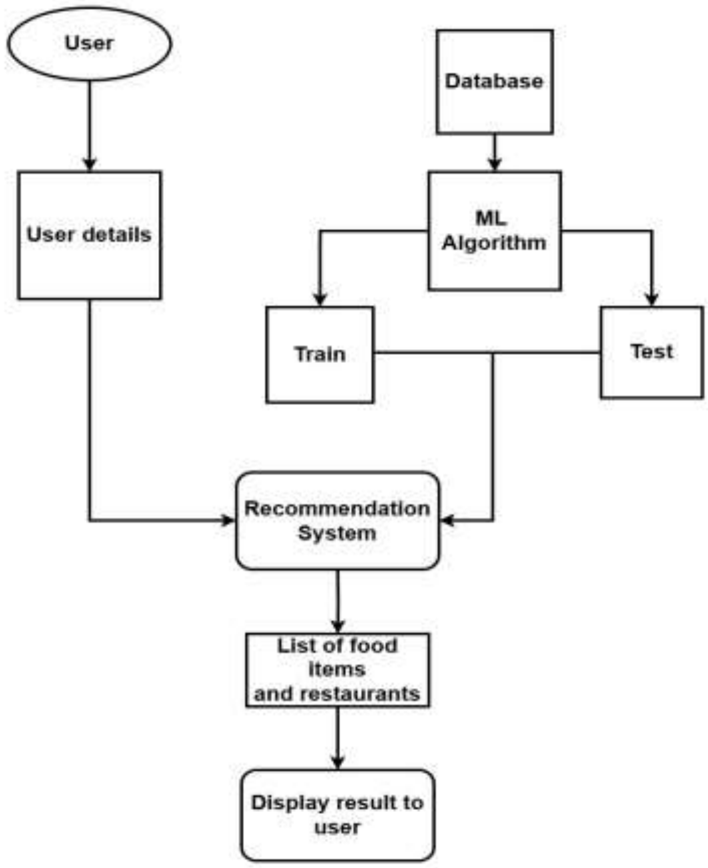

Figure 1: System Architecture

Data Collection and Preprocessing

The system begins with gathering data from three main sources: Food and Ingredients, Diet Plans, and Restaurants. These datasets form the foundation for health-based food and restaurant recommendations. Before being used, the data undergoes a cleaning and preprocessing phase, where inconsistencies, missing values, and duplicates are handled to ensure the data is well-structured and ready for further processing. This cleaned data is then ingested into a centralized database for structured storage and efficient querying .

User Interface, Input Handling, and Security

The frontend user interface acts as the primary interaction point between users and the system, requiring inputs such as Name, Date of Birth, Gender, Health Conditions, Email, Mobile Number, and Location. These details are critical for generating personalized recommendations and are securely stored in the User Database. The interface is designed to be intuitive, helping users easily provide relevant health-related information. To protect this sensitive data, the system incorporates robust authentication mechanisms, ensuring that only verified users can access or modify their information. Every interaction undergoes a verification process to maintain user privacy and preserve data integrity across the system.

API Management and Integration

The API Management Services module facilitates the communication between the frontend, backend, and databases. This module handles request/response cycles and ensures data flows securely and efficiently across different components. It also enables modular service interaction, so each unit can function independently while still contributing to the overall goal [9].

Data Storage and Management

The system architecture separates user data and food-related data into two different databases to enhance performance and manageability. The main database stores structured information derived from food ingredients, diet plans, and restaurant listings, while the user database maintains individual user profiles and historical interactions. This separation also supports scalability and modularity, allowing each component to be managed or scaled independently.

Backend Engine and Recommendation Core

The backend is powered by a Backend Engine responsible for coordinating all data-related tasks. Once the user submits their information, the backend retrieves relevant data from the databases according to the input. The engine uses Data Extraction Modules to fetch and organize information necessary for the recommendation logic. The engine is also responsible for executing algorithms and orchestrating API calls to generate personalized results.

Machine Learning-Based Filtering

At the core of the system's intelligence lies the K-Nearest Neighbors (KNN) algorithm, which is used to recommend food items and restaurants. A pre-trained database is used. The algorithm operates in two main stages.

- Filter by User and Food: Matches suitable food options based on user health profiles and dietary restrictions.
- Filter by Location, User, and Restaurants: Narrows down restaurant choices based on proximity, user preferences, and food compatibility.

These stages help the system personalize the output and ensure it aligns with both user needs and local availability.

III . FLOW CHART

The flowchart of the proposed system illustrates the sequence of steps in the food recommendation system, starting from user registration, authentication, data retrieval, processing, and generating personalized recommendations. It shows the interaction between users and the system's backend, which utilizes a KNN algorithm for recommendations, as depicted in Figure 2.

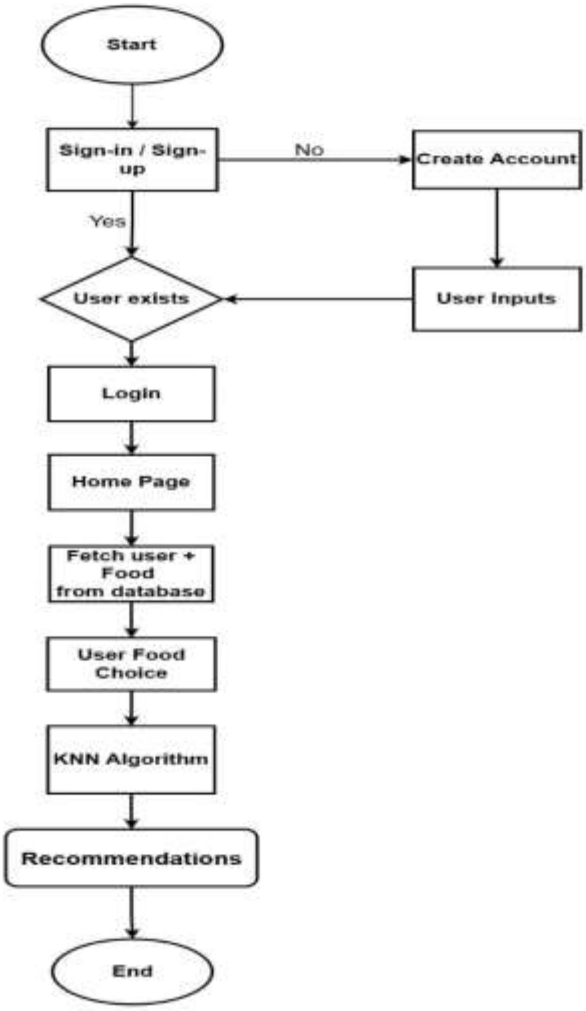

Figure 2: System Flow chart

1. **User Authentication**
During the user registration and authentication stage, the system prompts the individual to either sign up or sign in. If the user already exists in the system, they are directed to the login interface, where their credentials are verified. If the user is new, they proceed to the account creation process, where they are required to input essential personal information, including name, date of birth, gender, contact details, location, and relevant health conditions. This ensures the system has a comprehensive profile to generate accurate food recommendations tailored to the user's needs.
2. **Data Management**
The next step involves data management, where external data sources supply structured information about food items, ingredients, and restaurants. This data undergoes a cleaning and structuring process before being stored in a relational database management system. The use of an RDBMS ensures that data is efficiently organized and readily accessible for the recommendation engine.
3. **User Interaction Flow**
Once logged in, the user interacts with the system through an intuitive user interface. They are first directed to the home page, which serves as the primary dashboard for interaction. From here, users can explore different functionalities, including searching for food items. The "Search Food" feature allows users to browse through available food options and view relevant information aligned with their preferences and health profiles.
4. **KNN Algorithm**
In the backend, the system leverages the K-Nearest Neighbors (KNN) algorithm as its core recommendation engine. This algorithm analyzes the user's health conditions and input preferences, comparing them against the stored data. It filters and ranks food options based on their proximity to the user's profile using similarity measures. Simultaneously, the algorithm retrieves relevant data from the database to support real-time processing and decision-making.
5. **Food Suitability**
Following this, the system reaches a decision point where it evaluates the suitability of the selected food for the user. If the food is deemed appropriate based on the user's health profile, the system proceeds to the food ordering phase. If the

food is not suitable, the system triggers a recommendation alert that suggests healthier or more appropriate alternatives tailored to the users.

III . Conclusion

The growing importance and complexity of food recommendation systems, particularly in the context of health and personalized nutrition is reviewed. While existing systems often utilize collaborative, content-based, and hybrid filtering techniques to suggest meals or restaurants based on user preferences or historical interactions, and lack integration with user health profiles, dietary restrictions, and real-time nutritional assessments. This gap presents a strong motivation for developing an intelligent and health-aware food recommendation system that not only considers taste and convenience but also aligns with individual health needs. The proposed work, is focused on designing and implementing a machine learning–based system, such as one using the K-Nearest Neighbors (KNN) algorithm, to deliver personalized food suggestions tailored to specific user profiles.

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