AI-Based Personalized Diet Recommendation System

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Abstract—The increasing prevalence of lifestyle diseases such as diabetes, obesity, and food intolerances has created an urgent need for intelligent, condition-specific dietary guidance. Existing diet recommendation platforms focus primarily on calorie tracking and generic meal plans, failing to address the unique nutritional requirements and medical restrictions of individual users. This paper presents an AI-based personalized diet recommendation system that integrates user health data with curated nutritional and recipe datasets to generate condition-specific meal plans, ingredient substitutions, and detailed nutrition analysis. The proposed system employs a three-tier client-server architecture with a Next.js frontend, a Python-based backend, and a machine learning recommendation engine using content-based filtering and Decision Tree classification. Datasets from the USDA FoodData Central and Food.com repositories are used to match recipes with user-defined health conditions and dietary restrictions through a rule-based constraint layer. Experimental evaluation demonstrates the system's ability to produce accurate, personalized recommendations while maintaining scalability for future integration with advanced machine learning models and real-time data sources.

Keywords—*diet recommendation, artificial intelligence, machine learning, Decision Tree, personalized nutrition, health conditions, content-based filtering, Next.js, USDA FoodData*

I. INTRODUCTION

The global rise of chronic lifestyle diseases, including type 2 diabetes, cardiovascular disease, and obesity, has intensified the demand for accessible, personalized nutritional guidance. Diet plays a critical role in both the prevention and management of such conditions; however, designing an appropriate diet plan requires detailed knowledge of individual health status, food preferences, cultural restrictions, and nutrient composition. This complexity has historically limited effective diet management to clinical settings under the supervision of trained dietitians.

The proliferation of digital health applications has introduced a range of automated diet-tracking tools. Platforms such as MyFitnessPal and HealthifyMe have achieved widespread adoption by offering calorie logging and nutrient summaries. Nevertheless, these systems share a fundamental limitation: they do not generate condition-aware dietary guidance. A diabetic user and a healthy user may receive identical or minimally differentiated meal suggestions, overlooking critical glycaemic index thresholds, sodium limits, or allergen avoidance requirements.

Artificial Intelligence (AI) and Machine Learning (ML) techniques have demonstrated significant potential in overcoming these limitations. Content-based filtering, rule-based expert systems, and supervised classifiers can be combined to match user-specific health profiles with appropriately filtered recipe databases. This paper presents the design, architecture, and preliminary evaluation of an AI-based personalized diet recommendation system that integrates structured health input collection, ML-driven recommendation, and nutritional analysis into a single cohesive platform.

The remainder of this paper is organized as follows. Section II reviews related work. Section III presents the proposed system architecture and modules. Section IV describes the methodology and algorithms employed. Section V outlines implementation details. Section VI discusses results and evaluation. Section VII concludes the paper and outlines directions for future work.

II. RELATED WORK

Prior research has approached diet recommendation from several perspectives, including rule-based expert systems, collaborative filtering, content-based filtering, and hybrid methods.

Papastratis et al. [1] proposed a variational autoencoder (VAE) and gated recurrent unit (GRU) architecture for weekly meal plan generation, incorporating energy optimization and ingredient substitution. While nutrient accuracy was commendable, the high computational complexity and dependence on large curated datasets limit real-world scalability.

Dong et al. [2] developed a hybrid recommendation approach coupling constraint-based and preference-based methods with disease-specific knowledge graphs for conditions such as diabetes and hypertension. However, the study lacks long-term clinical evaluation and real-world deployment evidence.

A machine learning-based food recommendation system targeting health conditions [3] generated diet plans matched to nutritional needs but offered limited personalization depth and no recipe-level adaptive recommendations. Similarly, a BMI-based ML classification system [4] demonstrated that user input accuracy remains a critical constraint on recommendation quality.

III. PROPOSED SYSTEM

A. System Overview

The proposed system collects user health data and dietary preferences, applies a rule-based constraint layer to enforce medical dietary restrictions, and then invokes an ML recommendation engine to suggest suitable recipes. Personalized meal plans are generated from the filtered recipe set, accompanied by nutritional breakdowns derived from the USDA FoodData Central dataset and optional ingredient substitutions for restricted items.

B. System Architecture

The system employs a three-tier client-server architecture comprising a Presentation Layer, an Application Layer, and a Data Layer.

The Presentation Layer is implemented using Next.js and React, providing an interactive user dashboard. The Application Layer consists of a Python backend that exposes RESTful API endpoints, coordinating between the frontend and the ML recommendation engine. The Data Layer stores and indexes two primary datasets: the USDA FoodData Central CSV and the Food.com Recipes CSV.

C. System Modules

The system is decomposed into eight functional modules:

1) User Input Module: Collects demographic and clinical data including age, weight, height, diagnosed health conditions, dietary preferences, and food restrictions.

2) User Profile Module: Persists and manages the user health profile, enabling session continuity and historical tracking.

3) Recommendation Engine Module: Generates personalized recipe suggestions by combining content-based filtering with a Decision Tree classifier trained on labelled health-condition recipe associations.

4) Meal Plan Generator Module: Assembles daily and weekly meal plans from the recommended recipe pool, balancing macronutrient targets across breakfast, lunch, dinner, and snack slots.

5) Nutrition Analysis Module: Computes per-recipe and per-day nutritional summaries using the USDA FoodData dataset, including calories, macronutrients, vitamins, and minerals.

6) Ingredient Substitution Module: Identifies restricted ingredients in recommended recipes and proposes nutritionally comparable alternatives.

7) Database Module: Stores and indexes the recipe, ingredient, and nutrition data to support efficient query processing.

8) Frontend Dashboard Module: Renders recommendations, meal plans, nutritional details, and substitutions in an accessible user interface.

IV. METHODOLOGY

A. Data Sources

Two publicly available datasets are utilized. The USDA FoodData Central dataset [7] provides standardized nutritional composition data for over 600,000 food items, serving as the authoritative source for macro- and micronutrient calculations. The Food.com Recipes dataset [8] contains approximately 180,000 recipes with ingredient lists, preparation steps, tags, and user ratings, forming the recipe recommendation pool.

B. Data Preprocessing

Raw datasets are preprocessed using Pandas and NumPy. Recipe records are cleaned to remove entries with missing nutritional tags or malformed ingredient lists. Nutritional values are normalized to a standard serving size of 100 g. User-input health conditions are mapped to a predefined set of dietary constraint rules.

C. Rule-Based Constraint Layer

A rule-based filtering stage enforces medical dietary restrictions prior to ML-based ranking. Rules are defined for a set of conditions including diabetes (low glycaemic index, reduced sugar), lactose intolerance (no dairy), gluten sensitivity (gluten-free ingredients), hypertension (low sodium), and obesity (calorie-controlled). Recipes violating any applicable constraint are excluded from the candidate set.

D. Machine Learning Recommendation Engine

Candidate recipes surviving the constraint filter are ranked using content-based filtering augmented with a Decision Tree classifier [5, 6]. Feature vectors are constructed from normalized nutritional attributes and recipe category tags. The Decision Tree, trained on a labelled dataset of health-condition-to-recipe suitability mappings, predicts a suitability score for each candidate recipe. Top-ranked recipes are selected for meal plan construction.

E. Algorithm Summary

The end-to-end recommendation pipeline proceeds as follows:

Step 1 — User Input: Collect health conditions, dietary preferences, and restrictions.
Step 2 — Preprocessing: Map inputs to nutritional constraint rules and normalize parameters.
Step 3 — Dataset Filtering: Exclude non-compliant recipes using the rule-based constraint layer.
Step 4 — ML Ranking: Apply Decision Tree classifier to score remaining candidates.
Step 5 — Ingredient Substitution: Flag and replace any restricted ingredients in selected recipes.
Step 6 — Nutrition Calculation: Compute per-meal and per-day nutritional totals using USDA data.
Step 7 — Meal Plan Assembly: Arrange top recipes into a structured daily or weekly meal plan.
Step 8 — Display: Return results to the frontend dashboard for user review.

V. IMPLEMENTATION

A. Technology Stack

The frontend is built with Next.js 14 [9] and React, providing server-side rendering and optimized component delivery. The backend is implemented in Python 3.11, exposing a RESTful API layer that interfaces with the ML engine and datasets. Machine learning components leverage scikit-learn for Decision Tree training and inference, while Pandas and NumPy handle data ingestion and preprocessing. VS Code was used as the primary development environment.

B. Development Phases

Development was organized into eight phases: (1) requirements analysis, (2) dataset acquisition, (3) system design, (4) backend and ML engine development, (5) frontend development, (6) backend-frontend integration via REST APIs, (7) testing and debugging, and (8) deployment and documentation. This phased approach ensured systematic validation at each stage before integration.

VI. RESULTS AND DISCUSSION

The system successfully generates personalized recipe recommendations and meal plans for users with specified health conditions. For a test case involving a diabetic user with lactose intolerance, the constraint layer correctly excluded high-sugar and dairy-containing recipes, and the Decision Tree classifier ranked low-glycaemic, plant-based options at the top of the candidate list.

Nutritional analysis confirmed that generated meal plans met condition-appropriate macronutrient targets in over 90% of test cases. Ingredient substitutions were successfully identified for all flagged restricted items across evaluation scenarios.

The frontend dashboard rendered recommendations, nutritional breakdowns, and substitution suggestions in a clear, user-accessible layout. System response times for recommendation generation averaged under three seconds for standard user profiles on the evaluation hardware.

Comparative analysis against existing systems confirms that the proposed system uniquely combines condition-specific rule filtering with ML-based ranking and integrated substitution guidance within a single platform, addressing key limitations identified in the literature survey.

VII. CONCLUSION

This paper presented an AI-based personalized diet recommendation system designed to address the limitations of generic diet platforms for users with specific health conditions. By integrating a rule-based medical constraint layer with Decision Tree-based content filtering and nutrition analysis drawn from standardized datasets, the system generates condition-specific meal plans and ingredient substitutions in a scalable, user-friendly platform.

Future work will extend the system with advanced deep learning recommendation models, real-time nutritional data integration, longitudinal user health tracking, and clinical validation studies to assess dietary outcome improvements over extended usage periods.

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