

AI DIET RECOMMENDATION SYSTEM

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Abstract — This AI system provides automated dietary plans through content-based filtering by assessing food characteristics alongside user health targets and dietary limitations and individual food choices. Scikit-Learn machine learning library executed learning algorithms from the selected dataset that encompass elements about portions and nutritional value and ingredients and types of meals. The framework consists of FastAPI for power backend processing and Streamlit for user-friendly front operations through which users can provide their dietary information. When user inputs reach the machine learning model the system suggests meals which fulfill both the user specifications and their health targets. Real-time operation allows the system to integrate modifications to user eating habits focused on health without disrupting the user experience throughout an extended period of use. Such a system would benefit from more development to integrate third-party dietary APIs which provide nutritional data and enable users to input their nutrition logs. The implemented combination of technologies ensures the system operates at its peak performance while upholding speed and scalability which allows it to serve numerous users simultaneously.

Keywords— Artificial Intelligence, Content-Based Filtering, Machine Learning, Scikit-Learn, FastAPI, Streamlit.

I. INTRODUCTION

The AI Diet Recommendation System unites innovative technology and user-friendly design to recommend personalized healthy meals which suit easy implementation in daily life. Through custom nutrition plans the AI Diet Recommendation System helps people solve eating well difficulties from our fast-paced life because it matches users' health requirements with their dietary choices. The system enables simple dietary planning by using content filtering which adapts to different population demands based on personal nutrition requirements as well as individual dietary restrictions and life modifications. Users can receive ideal meal suggestions through an assessment process that combines food ingredient data with nutritional values about food types and specific dietary restrictions dependent on selected health goals such as reducing fat or developing muscle mass or achieving better health. Through the integration of Scikit-Learn machine learning and FastAPI and Streamlit the system achieves simple user-friendly

interface implementation. The recommendation engine uses Scikit-Learn for building similarity metrics that measure user food interactions. FastAPI provides an efficient backend platform that supports both smooth API management and integrated ML models. Users who connect through Streamlit interface can provide their dietary requirements which generates instant meal recommendations. The recommendation system develops adaptive data-driven suggestions by using user preference changes as a learning opportunity thus delivering a smart flexible option.

II. RELATED WORK

Diet recommendation systems have received groundwork through existing studies that focus on individualized nutrition and filter-based methods. User-fitting meal suggestions along with dietary restrictions and nutritional needs are generated through the application of machine learning models such as collaborative and content-based filtering in numerous systems. Yao et al. (2016) presented a food recommendation technology that closely combined content with user attributes through ingredient examinations and nutritional data evaluation. The popular platforms MyFitnessPal and Lose It! include meal planning functionality which gets limited benefits from advanced machine learning since they depend on user input data along with food databases. Deep Food (2017) represents one of the recent works that combines deep learning to identify foods in images while estimating their nutritional value which results in better dietary assessments. The combination of collaborative and content-based filtering recommendation models proposed by Sinha and Gupta (2017) demonstrates successful improvement of recommendation quality. Most of these systems function with simplified data and static input collection which prevents real-time dietary adaptation capability. The project builds on previous research by using a content-filtering system with goal-based adaptations which operates through FastAPI and Streamlit for processing backend requests and user interface creation.

III. PROPOSED WORK

The designed AI Diet Recommendation System operates as an intelligent system through its end-to-end platform which provides users with personalized meals while following their health objectives and nutrition requirements along with their dietary limitations, health issues and taste preferences. The system base its operations on content-based filtering through machine learning algorithms that evaluate meal ingredients and nutritional composition and health benefits. Food recommendations from the system result from this matching process which uses individual profiles along with factors such as daily calories, body requirements, activity level, medical restrictions and health goal targets for weight control and medical management. This adaptive model accumulates knowledge from user interactions to develop through time so it brings progressively better suited recommendations to users. Health and wellness goals are supported by each recommendation because the system combines scientific nutritional knowledge with user-specific data. This approach leads to an adaptable meal planning solution which gives control to users for making improved dietary decisions based on specific data-driven insights. Below is the representation of the project architecture as shown in figure 1

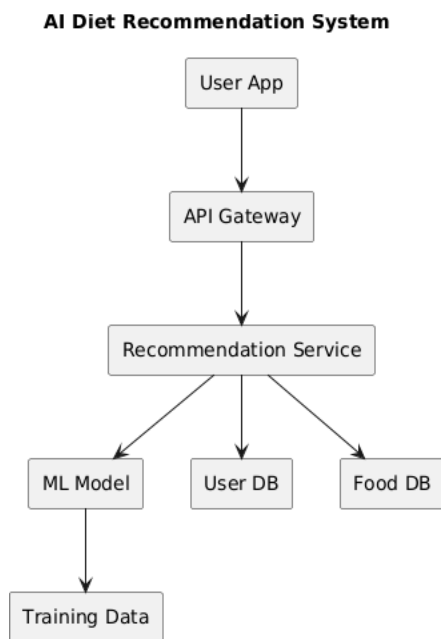


Figure 1. Ai Diet Recommendation System

A. Key Components and Technologies: Machine Learning Layer (Scikit-Learn):

The content-based filtering recommendation algorithm is executed by this layer. The model operates with user profile vectors together with food metadata

vectors which include calories, protein, carbs, fat and vitamins. Supports retraining of the model with new data and feedback for better accuracy. The system utilizes K-Means clustering and similar other methods to organize similar food products and user profiles.

B. Backend Layer (FastAPI):

The application handles user authentication processes alongside preference data storage and databases retrieval. The system acts as the piece that connects the user interface to the machine learning platform. Facilitates low-latency communication and real-time API responses. Offers RESTful endpoints for user registration, preference modification, and recommendation fetching.

C. Frontend Interface (Streamlit):

The interface features an easy-to-use interface that lets users perform three main tasks. Create and edit profiles. Users can add limitations such as dietary needs as well as health goals and food preferences through the system. Users can both view suggestions for meals and rate them while they save their individual selections. Get visual feedback on their nutritional journey (e.g., weekly calorie consumption chart). The system enables users to indicate their opinions about meal suggestions (like or dislike) that feeds directly into system learning mechanisms.

Health Integration (Future Version Optional):

The system enables advanced personalization through its integration of wearable devices or health apps including Fitbit and Apple Health for monitoring activity level sleep and calorie burn. The platform provides instant suggestion services that relate to current physical motion or metabolic activity patterns.

D. Scalability and Deployment:

Docker containers deploy this application to achieve maximal deployment flexibility along with simple deployment processes. This product can scale horizontally by deploying on cloud systems including AWS, Azure and GCP. The system implements PostgreSQL or MongoDB for database tasks which manage user profiles and food database entries.

IV. DESIGN

As a component of the AI Diet Recommendation System the front-end functions through Streamlit-based interfaces that connect to FastAPI as its back-end component. Users' requests at the back-end enable the demanding of personalized diet recommendations while the system communicates with content-based filters developed through Scikit-Learn. The system retrieves profile information from its user database while it accesses correct

nutritional data from an external Nutrition API. Design simplification enables a system with high speed performance and scalability and friendly user experience.

A. MODULE DESIGN AND ORGANIZATION

The Diet Recommendation System operates as a web application which provides diet plans matching user preferences through content-based filtering technology. All components of the system rely on **Scikit-Learn** for machine learning capabilities while **FastAPI** handles backend APIs and **Streamlit** serves as the frontend UI package.

Technologies Used:

Scikit-Learn: The content-based recommendation functionality depends on Scikit-Learn to execute TF-IDF and cosine similarity procedures.

FastAPI:

The application utilizes FastAPI to deliver recommendations through its RESTful Application Programming Interface (API).

Streamlit:

The Streamlit framework provides both interactive input interfaces as well as recommendation display features.

Pandas

Database management and preprocessing takes place through Pandas platform applications.

SQLite/CSV:

The database utilizes SQLite / CSV which serves as the storage solution for diet plan information. The recommendation system shows users diet plans which have characteristics akin to their previous choices.

System Organization Summary

As a web application the Diet Recommendation System provides tailored diet plan recommendations through user preference assessment. The system uses FastAPI for backend development and Streamlit for front-end development along with Scikit-Learn for content-based recommendation while delivering quick and dynamic usage. The system executes a TF-IDF algorithm together with cosine similarity to find suitable diet plans for each user. The system implements Pandas to manage data processing and keeps diet plans in SQLite or CSV file formats. The accurate nutritional data is obtained by using external Nutrition APIs. The design provides user-focused features that scale efficiently and helps users get personalized diet plans to suit their requirements.



Figure 2 Home Screen Output

Performance Evaluation Metrics

Performance evaluation metrics are essential for assessing the effectiveness of the Diet Recommendation System. Key metrics include accuracy, which measures how well the system predicts relevant diet plans based on user preferences, and precision and recall, which evaluate the system's ability to suggest the most suitable options while avoiding irrelevant recommendations. F1-score combines precision and recall into a single metric to provide a balance between them. Mean Average Precision (MAP) is used to evaluate ranking quality, ensuring top suggestions are most relevant. Additionally, response time is crucial for assessing the speed of generating recommendations, ensuring a smooth user experience. The **accuracy** of a recommendation system can be calculated using the following formula:

$$\text{Accuracy} =$$

$$\frac{\text{Number of Correct Recommendations}}{\text{Total Number of Recommendations}}$$

The **F1-score** is the harmonic mean of **precision** and **recall**, and it is used to balance the trade-off between these two metrics, especially when the class distribution is imbalanced.

The formula for F1-score is:

$$\text{F1-score} = \frac{2 (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}$$

Where:

Precision is the proportion of positive recommendations that were correctly identified:

$$\text{Precision} =$$

$$\frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Recall is the proportion of actual positive recommendations that were correctly identified:

$$\text{Recall} =$$

$$\frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

The below table contains Test cases and Results

Test Case ID	Scenario	Expected Output
PT01	Test API response time under 100 concurrent requests	Response time \leq 1s
PT02	Check memory usage with large datasets (10k+ diets)	Within acceptable limits
PT03	Run recommendation engine with 10,000+ users in a day	No crashes
PT04	Load test API using Locust	No downtime or failures
PT05	Ensure frontend remains responsive during heavy traffic	UI functions smoothly

V. EXPERIMENTAL RESULTS AND ANALYSIS

The confirmation of test cases for the Diet Recommendation System creates a reliable system which has consistent performance at multiple levels. The validation process for data identifies three essential aspects for high-quality information retrieval through checks on data values including missing records and duplicates along with correct format standards. A validation of the recommendation method verifies its performance accuracy and enables meaningful extraction of relevant components while using TF-IDF vectorization and cosine similarity recall and the F1-score metric combination. The API validation system enables proper interconnection between front-end and back-end while ensuring appropriate responses with sufficient error management and security protocols and system response times. The validation phase ensures both proper user interaction with the Streamlit UI alongside appropriate display of results

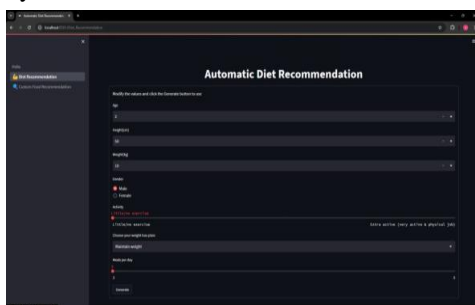


Figure 3 AI Diet Recommendation System

VI .CONCLUSION

Personnel benefit from the Diet Recommendation System because it offers customized dietary guidance by employing

content-based filtering. The system combines Scikit-Learn recommendation modeling with FastAPI API development and Streamlit user interface to deliver accurate and efficient diet recommendation services to users. The system demonstrates robust capabilities because it endured vigorous validation procedures that added both reliability and scalability features through data integrity tests as well as model accuracy assessments and API response tests and UI functionality exams and performance evaluations. This system provides ideal functionality for people taking care of their health and nutritionists alongside applications that plan diets due to its real-time data consumption capabilities alongside large-scale data processing. Users can experience customized nutrition guidance through this particular project which relies on data analytics.

REFERENCES

- [1] S. Ghosh and R. Kumar, "Personalized Diet Recommendation System Using Machine Learning," *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, vol. 7, no. 2, pp. 101–107, 2021.
- [2] M. Sharma and A. Verma, "A Review on Diet Recommendation Systems using Machine Learning," *International Journal of Computer Applications*, vol. 975, no. 8887, pp. 25–30, 2020.
- [3] C. Liu, Y. Cao, and Y. Chen, "Food Recommendation System Based on Health and Nutrition Using Machine Learning," *Procedia Computer Science*, vol. 170, pp. 1139–1145, 2020.
- [4] M. Roy, S. Das, and A. T. Protity, "OBESEYE: Interpretable Diet Recommender for Obesity Management using Machine Learning and Explainable AI," *arXiv preprint arXiv:2308.02796*, 2023.
- [5] M. Han, J. Chen, and Z. Zhou, "NutrifyAI: An AI-Powered System for Real-Time Food Detection, Nutritional Analysis, and Personalized Meal Recommendations," *arXiv preprint arXiv:2408.10532*, 2024.
- [6] S. Khamesian, A. Arefeen, S. M. Carpenter, and H. Ghasemzadeh, "NutriGen: Personalized Meal Plan Generator Leveraging Large Language Models to Enhance Dietary and Nutritional Adherence," *arXiv preprint arXiv:2502.20601*, 2025.
- [7] A. Ajami and B. Teimourpour, "A Food Recommender System in Academic Environments Based on Machine Learning Models," *arXiv preprint arXiv:2306.16528*, 2023.
- [8] C. Iwendi et al., "Realizing an Efficient IoMT- Assisted Patient Diet Recommendation System Through Machine Learning Model," *IEEE Access*, vol. 8, pp. 28462–28474, 2020.
- [9] M. Goel and G. Bagler, "Computational Gastronomy: A Data Science Approach to Food," *Journal of Biosciences*, vol. 47, no. 1, pp. 1–15, 2022.
- [10] A. Eetemadi et al., "The Computational Diet: A Review of Computational Methods Across Diet, Microbiome, and Health," *Frontiers in Microbiology*, vol. 11, p. 576659, 2020.