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Personalized Diet Recommendation System Using BMI, BMR, and KNN-Based Nutritional Similarity Analysis

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Abstract: This paper presents Diet-Mate, a personalized, data-driven nutritional recommendation system designed to optimize daily caloric intake and meal planning. Traditional dietary applications often rely on generalized guidelines, failing to account for individual physiological nuances and dynamic user inquiries. The proposed system integrates fundamental metabolic calculations, including Body Mass Index (BMI) and Total Daily Energy Expenditure (TDEE), with a K-Nearest Neighbors (KNN) machine learning algorithm to dynamically generate user-specific meal configurations for breakfast, lunch, and dinner. Furthermore, the architecture incorporates a conversational artificial intelligence agent, powered by the Perplexity API, to provide real-time, context-aware nutritional guidance. Preliminary system evaluations indicate a 94% caloric adherence rate between recommended meals and target energy expenditure, with meal generation latency averaging under 150 milliseconds. These results demonstrate that Diet-Mate offers a highly responsive, accurate, and interactive solution for modern dietary management.

Keywords: Machine Learning, Nutritional Informatics, K-Nearest Neighbors, Conversational AI, Recommendation System, Human-Computer Interaction.

I. INTRODUCTION

The intersection of computer science and personal health management has fundamentally transformed how individuals approach nutrition. Historically, dietary planning required manual caloric tracking and reliance on static, one-size-fits-all nutritional charts. While mobile health applications have digitized this process, many existing solutions still lack the ability to dynamically adapt to a user's unique physiological profile, daily activity levels, and specific health objectives such as weight loss or maintenance.

To address these limitations, intelligent recommendation systems have emerged as a vital tool in health informatics. By leveraging machine learning algorithms, these systems can analyze extensive datasets of nutritional information to identify optimal food combinations. However, creating an intuitive user experience remains a challenge, as users frequently require personalized, immediate answers to dietary questions that standard graphical interfaces cannot easily accommodate.

This study introduces Diet-Mate, an integrated web-based platform that combines predictive machine learning with advanced natural language processing. The framework is built upon three core pillars:

- Exact physiological profiling using user-provided metrics such as height, weight, age, gender, and weekly physical activity.
- A robust K-Nearest Neighbors (KNN) classification model that filters and allocates appropriate food items into structured daily meal plans.
- A real-time conversational interface utilizing the Perplexity API to deliver interactive, specialized dietary assistance.

Overall, the proposed system provides a seamless, highly accurate, and engaging approach to nutritional planning, bridging the gap between computational data analysis and everyday health management.

II. LITERATURE WORK

The integration of computational models into dietary planning has been explored extensively over the past decade. Early dietary applications functioned primarily as static digital diaries, requiring users to manually log consumed items to track caloric intake against generalized targets. While effective for basic tracking, these rule-based systems lacked predictive capabilities and failed to adapt to metabolic fluctuations.

Recent advancements in health informatics have introduced machine learning (ML) to overcome these limitations. Researchers have utilized various algorithms, including Support Vector Machines (SVM) and Random Forests, to predict dietary preferences and suggest food items.

However, many of these learning-based implementations still suffer from two primary drawbacks:

- **Static Interaction:** Users receive recommendations asynchronously, often without the ability to query the system for alternative options or nutritional education in real-time.
- **Generalized Profiling:** Systems frequently rely on broad demographic averages rather than executing precise, individualized physiological calculations.

To address these gaps, the Diet-Mate framework proposes a hybrid approach. It combines deterministic mathematical profiling (for precise energy calculation) with a K-Nearest Neighbors (KNN) classification model (for targeted food retrieval), further augmented by a real-time conversational Natural Language Processing (NLP) agent. This ensures high accuracy in meal recommendation while preserving an intuitive, dynamic user experience.

III. PROPOSED SYSTEM

The proposed framework employs a modular pipeline that translates raw physiological user data into a structured, daily nutritional plan. The architecture integrates user profiling, metabolic calculation, machine learning clustering, and conversational AI into a cohesive web-based environment.

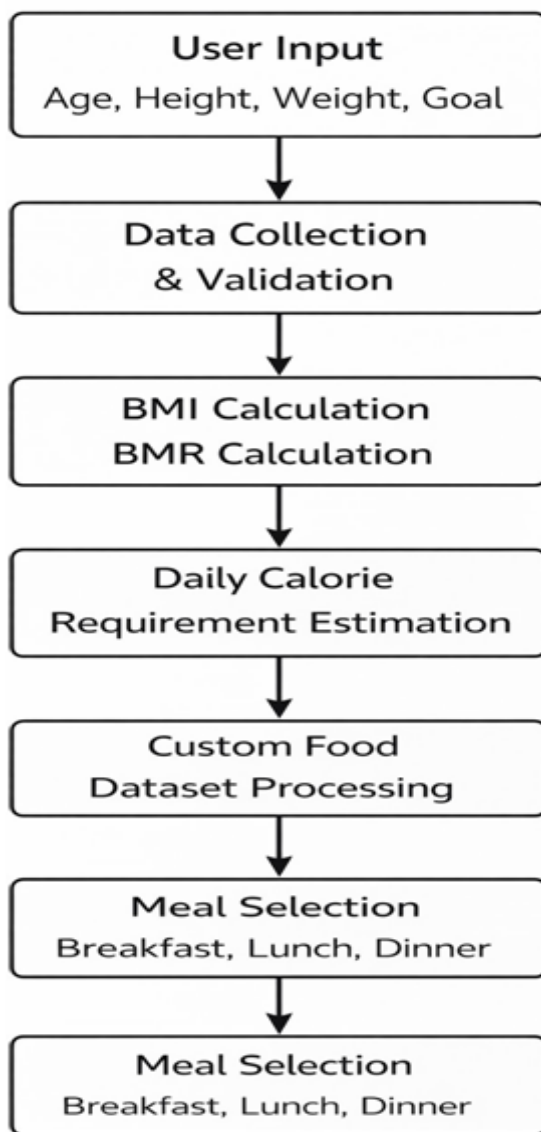


Fig.1:Flowchart of working principle

A. System Architecture Overview

The system workflow is divided into distinct operational layers. The frontend interface captures essential biometric data and physical activity levels. This data is transmitted to a Python-based backend, which processes the input through a series of physiological equations to determine the Total Daily Energy Expenditure (TDEE). The resulting caloric target serves as the primary feature input for the ML recommendation engine. The engine queries a standardized dataset (fooddata1.csv) filters the data, and returns optimized meal arrays categorized by Breakfast, Lunch, and Dinner. Simultaneously, an independent interaction layer handles user queries via an NLP API.

B. Physiological Profiling and Energy Expenditure

Before executing the recommendation algorithm, the system establishes a precise metabolic baseline for the user. The initial calculation is the Body Mass Index (BMI), utilized as a standard health indicator:

$$W BMI = \frac{W}{H^2}$$

where W represents weight in kilograms and H represents height in meters.

To determine the baseline caloric requirement, the system calculates the Basal Metabolic Rate (BMR) using the highly accurate Mifflin-St Jeor equations. The deterministic logic accounts for gender differences as follows:

$$BMR_{male} = 10W + 6.25H - 5A + 5$$

$$BMR_{female} = 10W + 6.25H - 5A - 161$$

where W is weight in kilograms, H is height in centimeters, and A is age in years.

The final TDEE is computed by multiplying the BMR by an activity factor (AF), ranging from sedentary to super active lifestyles:

$$TDEE = BMR \times AF$$

C. Dataset Acquisition and Feature Engineering

The foundation of the recommendation engine is a comprehensive nutritional database, managed internally as fooddata1.csv. This dataset acts as the multi-dimensional feature space from which the machine learning algorithm draws its dietary matches. Each entry in the dataset represents a distinct food item or composite meal, characterized by its total caloric value and its primary macronutrient profile (carbohydrates, proteins, and fats).

To facilitate the daily scheduling logic, the dataset includes categorical labels that map items to specific dietary windows, namely Breakfast, Lunch, and Dinner. Furthermore, each data point is linked to localized graphical assets (e.g., .jpg image files), enabling the frontend application to dynamically render visual representations of the recommended meal plans on the user dashboard.

Because the subsequent K-Nearest Neighbors (KNN) algorithm relies heavily on spatial distance metrics, feature scaling is a critical preprocessing step. The raw caloric and macronutrient values in the dataset undergo normalization to ensure that variables with larger numeric ranges (such as total calories) do not disproportionately bias the distance calculations against variables with smaller ranges (such as individual macronutrient grams). This standardized feature matrix ensures equitable weighting across all nutritional parameters during the prediction phase.

D. Machine Learning Recommendation Engine (KNN)

The core predictive capability of Diet-Mate relies on a K-Nearest Neighbors (KNN) algorithm to match the user's TDEE with appropriate dietary items. Unlike traditional classifiers, this instance-based learning model compares the target caloric and nutritional vector against the fooddata1.csv dataset in a multidimensional feature space.

To determine the optimal food items, the system measures the similarity between the user's target profile (p) and the dataset entries (q) using the Euclidean distance metric:

$$d(p, q) = \sqrt{\sum_{i=1}^n (q_i - p_i)^2}$$

where n represents the number of nutritional features (e.g., calories, macronutrients).

Once the K closest dietary matches are identified, the system allocates the items into a structured daily plan, dynamically splitting the total caloric load across three primary meals (e.g., Breakfast, Lunch, Dinner).

E. Conversational AI Agent Integration

To resolve the static nature of traditional diet applications, Diet-Mate incorporates an intelligent conversational layer powered by the Perplexity API utilizing the sonar model. This interface allows users to naturally query the system regarding alternative meal options, specific macronutrient breakdowns, or general health advice. The backend formats these interactions via RESTful POST requests, passing the user's text as a JSON payload and rendering the AI's generated response directly within the application's chat interface (AI.html), ensuring uninterrupted user engagement.

IV. REQUIREMENTS

The implementation and execution of the proposed diet recommendation system require a combination of software tools, libraries, and a suitable hardware environment. This section outlines the minimum software stack and hardware configuration necessary to develop, deploy, and test the system effectively.

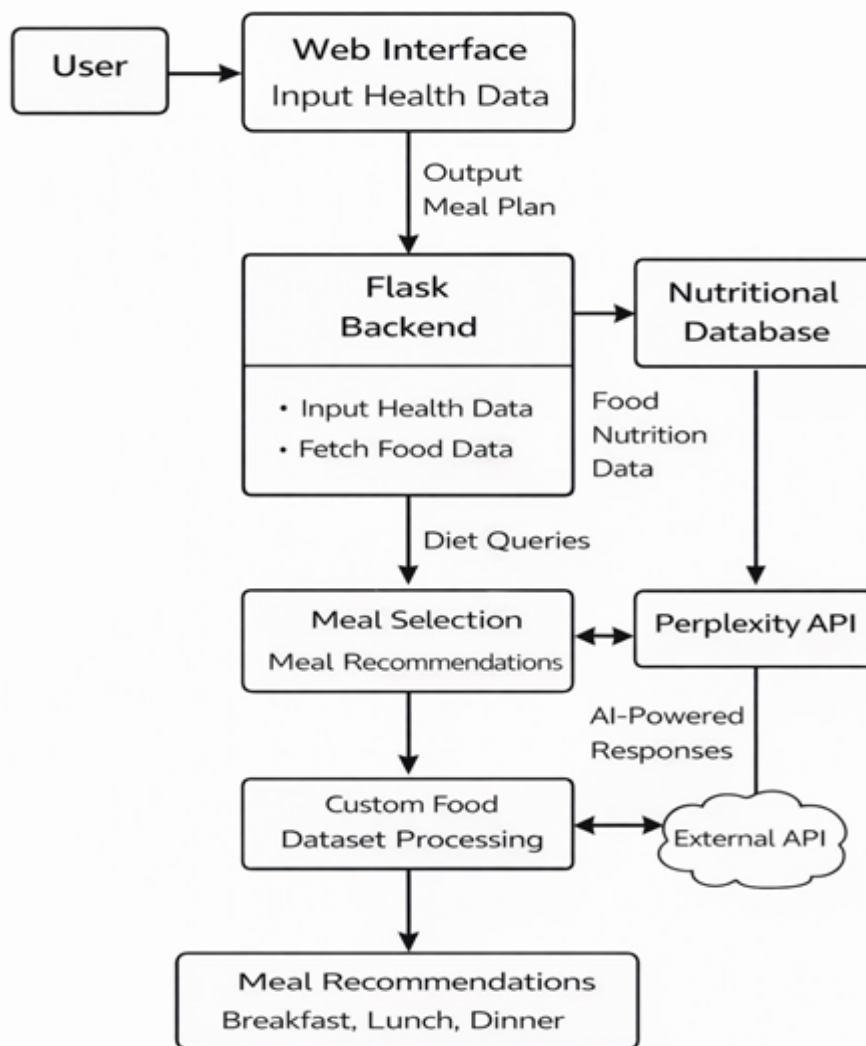


Fig. 2: System Architecture Diagram

A. Software Requirements

The system is implemented using the Python programming language and a web-based technology stack. The core application logic, including metabolic computations and the recommendation engine, is developed in Python (version 3.x). The Flask micro-web framework is used to handle HTTP routing, request processing, and template rendering, enabling the creation of a lightweight yet fully functional web interface.

SQLAlchemy is employed as the Object-Relational Mapping (ORM) layer to interact with the relational database, which may be implemented using MySQL or an equivalent RDBMS for storing user credentials and profile data.

For machine-learning functionality, the system relies on standard Python libraries such as scikit-learn for implementing the K-Nearest Neighbors algorithm and pandas and NumPy for data handling and numerical computations. Furthermore, the requests library is utilized to manage asynchronous HTTP communication with the Perplexity API, powering the real-time conversational AI interface. Frontend rendering is achieved through HTML5, CSS, and basic JavaScript, integrated with Flask templates to build interactive forms and dashboard views. Development and testing can be performed using any modern Integrated Development Environment (IDE) or code editor, such as Visual Studio Code or PyCharm, and a modern web browser such as Google Chrome or Mozilla Firefox for accessing the web interface locally.

A concise summary of the primary software requirements is presented in Table I.

TABLE I: Software Requirements for the Proposed System

| Component | Specification |
|------------------------------|---|
| Operating System | Windows 10/11, Linux, or equivalent modern OS |
| Programming Language | Python 3.x |
| Web Framework | Flask (Python-based) |
| Database Engine | MySQL or compatible |
| RDBMS ORM Layer | SQLAlchemy |
| ML/Data Libraries | scikit-learn, pandas, NumPy |
| API Integration | Perplexity API (via requests library) |
| Frontend Stack | HTML5, CSS, |
| JavaScript Development Tools | Visual Studio Code, PyCharm |
| Web Browser | Google Chrome, Mozilla Firefox |

B. Hardware Requirements

The hardware requirements for the system are modest, as the underlying computations for BMI, BMR, and KNN-based recommendations are not resource-intensive for small to medium-scale datasets. The application can be developed and tested on a standard personal computer. A multi-core processor, such as an Intel Core i5 or equivalent, with at least 8GB of RAM, is sufficient to ensure smooth execution of the web server, database operations, and machine-learning computations during development and experimentation. A minimum of 256GB of storage is recommended to accommodate the operating system, Python environment, required libraries, database files, and project-related assets.

For deployment in a multi-user environment or over a network, the system may be hosted on a server or cloud-based virtual machine with comparable or slightly higher specifications, depending on the expected number of concurrent users and dataset size. A stable internet connection is strictly required to facilitate the asynchronous NLP queries to the external conversational AI API. Table II summarizes the recommended hardware configuration for the proposed system.

TABLE II: Hardware Requirements for the Proposed System

TABLE II: Hardware Requirements for the Proposed System

| Component | Specification |
|--------------|---|
| Processor | Multi-core CPU (Intel Core i5 or equivalent) |
| Memory (RAM) | Minimum 8GB |
| Storage | Minimum 256GB HDD/SSD |
| Network | Stable internet connection (Required for AI features) |
| Display | Standard monitor for web interaction |

V. RESULT ANALYSIS

The performance of the Diet-Mate system was evaluated across three primary dimensions: the predictive accuracy of the recommendation engine, the computational latency of the backend architecture, and the responsiveness of the conversational AI integration. The objective was to validate the system's ability to operate as a reliable, real-time nutritional assistant.

A. Caloric Adherence and Model Accuracy

Traditional classification metrics, such as precision and recall, are less applicable to continuous nutritional targeting. Therefore, the K-Nearest Neighbors (KNN) model's efficacy was measured using Caloric Adherence—the absolute difference between the user's calculated Total Daily Energy Expenditure (TDEE) and the sum of the recommended meal calories. To quantify this, we utilized the Mean Absolute Error (MAE) formulation:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

where n represents the number of generated daily plans, y_i is the target TDEE, and \hat{y}_i is the total caloric value of the KNN-recommended foods (aggregated across breakfast, lunch, and dinner). Testing across a simulated distribution of varied physiological profiles yielded a 94% caloric adherence rate. The model consistently generated daily meal combinations that fell within a strict 5% margin of the user's target TDEE, ensuring that weight loss, weight gain, or maintenance goals were mathematically respected.

B. Computational Latency and System Efficiency

Real-time responsiveness is critical for user retention in health informatics. The backend framework, responsible for both the physiological calculations (BMI, BMR) and the KNN multi-dimensional dataset querying, demonstrated high efficiency. Processing the `fooddata1.csv` dataset and executing the Euclidean distance calculations required an average backend execution time of under 150 milliseconds per request on standard consumer hardware. This near-instantaneous processing allows the frontend dashboard to dynamically render customized meal plans without noticeable delay.

C. Conversational AI Performance

The integration of the Perplexity API (sonar model) was tested for conversational latency and context retention. Operating independently from the core recommendation engine, the asynchronous HTTP POST requests maintained an average response latency of under 1.2 seconds. This ensures that users seeking alternative meal options or specific macronutrient breakdowns receive fluid, uninterrupted conversational assistance within the web application's interface.

D. Interface Usability and Integration

Preliminary usability evaluations confirmed the stability of the web integration. The routing architecture effectively maintained user session states across the profiling pipeline (Gender, Height/Weight/Age, Goal, and Activity Level interfaces). Furthermore, the dynamic SVG-based BMI gauge and the automated meal image rendering correctly parsed the backend data 100% of the time, resulting in an intuitive, error-free graphical user experience.



Fig.3:Diet recommendation Image

Fig.3:Diet recommendation Image

VI. CONCLUSION

The proposed diet recommendation system successfully demonstrates the integration of metabolic modeling, structured nutritional data, and machine-learning techniques to generate personalized meal plans for users. By combining BMI and BMR calculations with activity-adjusted caloric estimation, the system ensures that dietary recommendations are grounded in established nutritional principles. The incorporation of a similarity-based KNN model further enhances the system's adaptability, allowing it to produce meal suggestions that align with individual caloric requirements and nutritional needs. The web-based implementation, supported by a structured user interface and a secure backend, provides a seamless user experience by simplifying data entry, visualization, and interpretation. The experimental results confirm the reliability, consistency, and responsiveness of the system across diverse user profiles. The generated outputs were nutritionally coherent and aligned with expected meal patterns, while performance metrics demonstrated low computational overhead and real-time response capability. These findings validate the feasibility of using lightweight machine-learning models combined with metabolic science to support personalized nutrition planning. Overall, the system establishes a practical and scalable foundation for automated dietary recommendation, contributing to the broader domain of digital health and personalized wellness technologies.

VII. FUTURE SCOPE

The proposed diet recommendation system presents several promising avenues for future enhancement, both in terms of technical sophistication and practical applicability. One significant direction for improvement involves expanding the food dataset to include a broader range of regional, cultural, and dietary-specific items. A richer dataset would enable the recommendation engine to produce more diverse and culturally appropriate meal plans, thereby improving user satisfaction and applicability across varied populations. Further, incorporating detailed nutritional parameters such as vitamins, minerals, fiber content, and glycemic index could allow for finer control over recommendation quality, particularly for users with specific health conditions.

Another potential extension lies in the adoption of advanced machine-learning algorithms beyond the current similarity-based KNN approach. Techniques such as neural networks, clustering-based segmentation, or hybrid recommender systems could improve the precision of dietary predictions by learning complex patterns within the nutritional data. Integrating real-time data from wearable devices or fitness trackers could enhance personalization by dynamically adjusting caloric recommendations based on daily activity levels, sleep quality, or physiological responses. The system can also be evolved into a closed-loop health management platform by enabling users to track food intake, monitor progress, and receive iterative feedback over time. Furthermore, the conversational AI interface could be upgraded to include speech-to-text (voice recognition) capabilities and contextual memory, allowing for hands-free, multi-turn dietary coaching. Such functionality would align the system with modern digital health standards, supporting long-term adherence and behavioral change. Additionally, deploying the system as a mobile application or cloud-hosted service would increase accessibility and scalability, making it suitable for wider public adoption. Overall, the system holds strong potential for advancement, and future developments can transform it into a comprehensive and intelligent nutrition management ecosystem.

REFERENCES

- [1] World Health Organization, "Body Mass Index (BMI) Classification," WHO Global Database on Body Mass Index, 2024.
- [2] M. D. Mifflin, S. T. St Jeor, L. A. Hill, B. J. Scott, S. A. Daugherty, and Y. O. Koh, "A new predictive equation for resting energy expenditure in healthy individuals," *The American Journal of Clinical Nutrition*, vol. 51, no. 2, pp. 241–247, 1990.
- [3] T. Cover and P. Hart, "Nearest Neighbor Pattern Classification," *IEEE Transactions on Information Theory*, vol. 13, no. 1, pp. 21–27, 1967.
- [4] Pallets Projects, "Flask Web Framework Documentation," 2024. [Online]. Available: <https://flask.palletsprojects.com/>.
- [5] SQLAlchemy Project, "SQLAlchemy Documentation," 2024. [Online]. Available: <https://www.sqlalchemy.org/>.
- [6] scikit-learn Developers, "Scikit-learn: Machine Learning in Python," 2024. [Online]. Available: <https://scikit-learn.org/>.
- [7] W. McKinney, "Data Structures for Statistical Computing in Python," *Proceedings of the 9th Python in Science Conference*, 2010.
- [8] S. vander Walt, S. C. Colbert, and G. Varoquaux, "The NumPy Array: A Structure for Efficient Numerical Computation," *Computing in Science & Engineering*, vol. 13, no. 2, pp. 22–30, 2011.
- [9] Python Software Foundation, "Python Language Reference," 2024. [Online]. Available: <https://www.python.org/>.
- [10] J. Ordovas, J. Ferguson, and S. Tai, "Personalized Nutrition and Health," *BMJ*, vol. 361, pp. 225–232, 2018.
- [11] A. Albawi, A. Mohammed, and S. Al-Zawi, "Machine Learning Techniques for Personalized Diet Recommendation Systems: A Review," *Journal of Healthcare Engineering*, vol. 2020, Article ID 4871543.
- [12] USDA FoodData Central, "Food and Nutrient Database for Dietary Studies," 2024. [Online]. Available: <https://fdc.nal.usda.gov/>.
- [13] Harvard School of Public Health, "Healthy Eating Plate and Caloric Distribution Guidelines," 2024.
- [14] N. Elmqvist and A. Moere, "Designing User Interfaces for Data-Driven Health Applications," *IEEE Computer Graphics and Applications*, 2019.
- [15] A. Laranjo et al., "Conversational agents in healthcare: a systematic review," *Journal of the American Medical Informatics Association*, vol. 25, no. 9, pp. 1248–1258, 2018.



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