International Conference on Multidisciplinary Perspectives in Advanced Computing and Technology (IMPACT 2026)
G. B. Pant University of Agriculture and Technology, Uttarakhand, India. Jan. 10-11, 2026

AI-Based Personalized Nutrition and Diet Planner

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Abstract

In this fast-paced world, maintaining a healthy, balanced diet is difficult. Most diet apps today offer generic meal plans that are not specific to a person's body composition, allergies, health conditions, and fitness objectives. This results in poor outcomes and poor compliance with nutritional diets. The AI-Based Personalized Nutrition & Diet Planner attempts to remedy this issue using Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision to build personalized diet plans from user data. The program evaluates age, weight, height, fitness aims, dietary options, allergies, medical conditions, and even DNA reports (in case they're available) in order to devise a personalized diet plan. The app also includes Computer Vision-based food recognition, enabling users to scan dishes and receive instant calorie and nutrient analysis. It also connects with fitness trackers and health apps to track daily activity and modify meal plans accordingly. The intention behind this project is to have an intelligent, automatic, and accessible solution towards optimal nutrition. By providing immediate monitoring, artificial intelligence diet advice, and wear-and-tear-free integration, the system would be able to guide users in the direction of health goals optimally.

Keywords: Artificial Intelligence, Machine Learning, Computer Vision, food recognition

1. Introduction

In today's hectic, technological age, it is becoming increasingly difficult to eat healthily and maintain a balanced diet. Irregular lifestyles, irregular eating patterns, and the ubiquity of processed foods have led to unhealthy eating habits among individuals. Although there are several diet and nutrition apps available, most offer standard meal plans that do not account for an individual's specific health conditions, dietary limitations, body type, or fitness needs. These non-specific suggestions tend to result in unsatisfactory outcomes, poor compliance, and, at times, even health hazards [14]. Recent developments in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision (CV) open the doors for redefining the approach to personalized diet planning. With these technologies, dietary advice can be made adaptive, data-driven, and context-sensitive, thereby better catering to individual requirements [1][2]. Personalized nutrition means adjusting diet recommendations on various parameters like age, weight, height, fitness objectives, allergies, medical conditions, lifestyle habits, and, where possible, genetic data [4].

This study suggests the creation of an AI-based personalised nutrition & Diet Planner that not just creates personalised meal plans from rich user profiles but also integrates Computer vision-based food recognition to offer real-time calorie and nutrient analysis. The system integrates with wearable activity trackers and health apps to adjust dietary suggestions in real time based on current activity levels, ensuring nutritional advice is current and goal-relevant [1][2][4]. The goal of this project is to develop an intelligent, automated, and user-friendly solution that improves diet compliance, aids in long-term health progress, and prevents inaccuracies and the inconvenience of manual tracking techniques. By integrating real-time surveillance, AI-based analytics, and easy connectivity with health ecosystems, this system will lead users toward better nutrition and overall wellness [14].

2. Literature Survey

A.   Personalized Nutrition and Diet Planning

Classic diet apps like MyFitnessPal, HealthifyMe, and Lose It! primarily focus on calorie counting and generic meal planning. Though these sites provide general customization based on user-input preferences, they do not dynamically adjust meal plans for changing health data or include high-end biometric inputs like DNA profiles or metabolic rate. Research, such as that from Celis-Morales et al., has established that customized dietary advice on the basis of genetic and lifestyle information improves compliance and health outcomes over standardized planning. Yet, the application of these results in consumer technology is still limited [1][2][3].

B.   Artificial Intelligence in Nutrition and Health

AI and ML methods have exhibited strong promise for automating and individualizing diet suggestions. Machine learning models, like decision trees, random forests, and deep neural networks, have been applied to forecast ideal nutrition programs by analyzing large amounts of user health parameters [11]. For example, illustrated that nutritional modeling based on data can better align diet with personal needs. Further, recommendation algorithms powered by AI have seen extensive adoption in e-commerce and media but have yet to be exploited in health-oriented use cases, where real-time responsiveness matters.

C.   Computer Vision for Food Recognition

Advances in computer vision have enabled automatic identification of foods and the estimation of nutrient content from images. Datasets like Food-101 and UECFOOD-256 have made it possible to train convolutional neural networks (CNNs) and transfer learning models like MobileNet and YOLO for precise food categorization. Im2Calories has demonstrated that image-based calorie estimation can result in a substantial reduction in user burden compared to manual logging [5][6]. Despite this, difficulties such as estimating food portions, combining meals, and changing lighting conditions continue to limit accuracy in real-world settings [7][8][11][12].

D.   Gaps in Existing Solutions

Feature Although there are many reported breakthroughs in computer vision and AI-based healthcare applications in the literature, the industry still lacks unified solutions that integrate personalized diet planning, real-time monitoring of health data, and automatic food identification into one cohesive platform [7][8]. Even most solutions address these elements in silos, leading to disjointed user interactions [5][6]. Moreover, few solutions use genetic information and medical history in adaptive diets, even though research suggests its significance in personal healthcare [11][12].

3. Methodology

1.   System Architecture and Design

The system is architected as a modular, scalable platform to support the complexity of multiple, disparate data streams and sophisticated computational models. This supports the independent development and maintenance of each part of the system, which is essential for a system that includes real-time data from wearables, sophisticated computer vision, and machine learning models that require continuous revision. This architecture forms the basis for designing a high-class, AI-driven nutrition platform that can learn and adjust in real time and continuously learn from user input [5][6][7][8][11][12].

1.1   High-Level Conceptual Architecture

The architecture features a core AI-Powered Recommendation Engine as its central pillar. The engine is flanked by important modules and data sources. The Data Ingestion Layer is tasked with gathering and preprocessing data from all user inputs [5][6]. The Computer Vision (CV) Module performs image-based food recognition and portion size estimation. The Integration

Hub enables safe calling of external APIs from wearables and health apps. The user profiles, large nutrition database, and historical logs are all saved in a central Database. The system is accessed by the user through a User Interface (UI), which displays the individualized diet plans and monitors progress. A modular structure is a strategic imperative for the project's long-term viability and responsiveness, as it avoids single points of failure and enables computationally intensive modules, such as computer vision or the AI engine, to scale independently [7][8][11][12].

1.2   Data Flow Diagram (DFD)

The functioning of the system can be mapped by data flow diagram that shows the process of data moving from collection to output. User inputs, such as biometrics, health conditions, and preferences, are processed alongside wearable device data. The complete data is then input into the AI-Powered Recommendation Engine. At the same time, the CV Module processes images of food to provide calorie and nutrient details, which are incorporated into the user's daily log. The engine combines all these streams of data to create a dynamic and customized diet plan. The system also features a critical feedback loop whereby user behavior, for example, meal tracking and progress monitoring, is constantly provided back to the AI engine to improve subsequent recommendations. This process of ongoing learning, as shown in Figures 1and 2, is necessary to develop a hyper-personalised system [1][2][4][9][10].
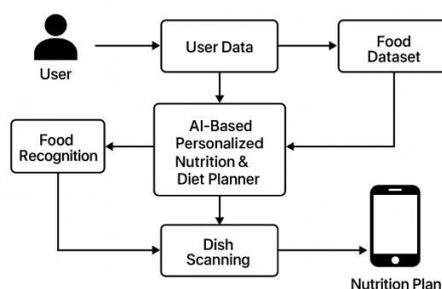

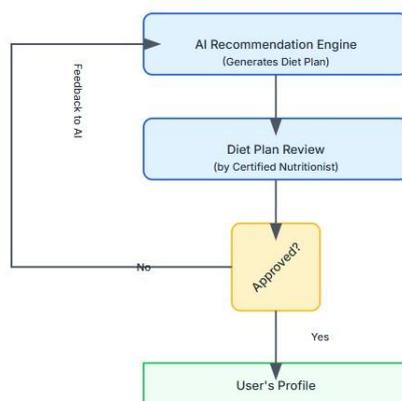**Figure 1:** Data Flow Diagram

Figure 2: Nutritionist Approval Flowchart

1.3 Technology Stack Foundations
The platform will be built on a robust technology stack to ensure scalability, security, and performance. Cloud infrastructure (e.g., AWS, Azure) will handle the computational power

needed for training and deploying deep learning models. A properly secured relational or NoSQL database can store large amounts of user data, a comprehensive food and nutrient database, and machine learning model parameters. Security and privacy will be paramount concerns, with the system designed from the ground up to be compliant with data protection regulations such as the Health Insurance Portability and Accountability Act (HIPAA), particularly given the sensitive nature of the health data being handled.

2. Data Collection and User Profiling Module

The success of the system's personalization depends on both the quality and the scope of the data gathered. This module's task is to ingest diverse sets of user data and build a rich, combined profile that underlies all the recommendations.

2.1. Refined Data Inputs

Information is gathered from various sources to provide a multi-dimensional picture of the user. The inputs are grouped for the sake of clarity:

- Biometric and Demographic Information: These involve basic metrics like age, sex, height, weight, BMI, and percentage body fat. More advanced metrics such as Resting Metabolic Rate (RMR) are also included in order to make caloric intake recommendations sensitive to a person's individual metabolic changes.

- Lifestyle and Behavioral Data: Physical activity level (sedentary, moderate, active), work schedule, and sleep patterns are gathered. Dietary preferences (vegan, keto, gluten-free, low-FODMAP) and food cravings are other important inputs.

- Clinical and Health Information: The system supports a comprehensive medical history, such as allergies, intolerances, and ongoing conditions such as diabetes or hypertension. Blood tests biomarkers like Hemoglobin A1C (HbA1c), lipid panels (Total Cholesterol, LDL, HDL), and inflammatory markers are essential for understanding metabolic health and risk of disease [2].

- Advanced Omics Data: The platform is built to ingest and analyze advanced data sources, including DNA reports and microbiome analysis. The integration of genetic variations, i.e., Single Nucleotide Polymorphisms (SNPs), enables the platform to comprehend individual metabolic requirements and health condition predispositions, making it possible to employ predictive and preventative nutrition as opposed to a strictly reactive model.

2.2. Secure Data Ingestion and Preprocessing

Data ingestion is handled through dynamic onboarding forms and a smooth integration hub that links to relevant wearables and health apps. An important data preprocessing pipeline maintains the integrity and usability of this heterogeneous data. The pipeline is used for cleaning, normalizing, and feature engineering of the data. For instance, to filter out data quality issues, any weight records that change by more than 5% over a 7-day rolling window are removed as outliers. The causal nature of drawing on advanced data sources is a major one: a genetic predisposition to illnesses such as celiac disease or diabetes can be identified early, enabling the system to actively suggest a personalised diet before clinical manifestations or adverse health effects. This places the app above the level of a mere calorie tracker to a highly advanced, forward-thinking health aid [13], as shown in Table 1.

Table 1: User Data Collection and Feature Matrix

Data Point	Source(s)	Primary Use Case in the System
Age, Gender, Height, Weight	Self-reported, wearable	Self-reported, wearable BMR calculation, BMI, and initial meal plan generation
Physical	Self-reported,	Daily Energy Expenditure (DEE) calculation, dynamic

Activity Level	wearable	adjustment
BMI, Body Fat %, RMR	Self-reported, wearable, calculated	Caloric intake recommendations, disease risk assessment
Dietary Preferences	Self-reported	Initial meal plan filtering (e.g., keto, vegan)
Allergies, Medical History	Self-reported	Filtering out allergenic or contraindicated food items
Blood Biomarkers (HbA1c, Lipids)	Self-reported (lab reports)	Diabetes management, cardiovascular risk assessment
Genetic Data (SNPs)	Uploaded DNA report	Predictive analysis for metabolic needs and disease predispositions
Gut Microbiome Data	Uploaded report	Advanced personalized dietary advice, identifying food interactions

3. AI-Powered Personalization and Recommendation Engine

This component is the essence of the system's intellectual property. It takes the integrated user profile and creates a dynamic, personalized meal plan. The system uses a rich combination of machine learning algorithms to provide not just accurate but also extremely engaging and relevant recommendations to the user [1][2][4][9][10].

3.1. Hybrid Recommendation System

In order to achieve maximum accuracy and user satisfaction, the system utilizes a hybrid model of recommendation. Content-Based Filtering: The first meal plan is created from an in-depth examination of the user's profile. A typical user with high blood glucose levels, for example, will be given a diet high in fiber and complex carbohydrates, a choice informed by their clinical information. This method guarantees the first set of recommendations is precisely tailored to the user's medical conditions and expressed preferences [2]. Collaborative Filtering: When the user interacts with the app by logging meals and providing preferences, the system becomes aware of these actions. It subsequently leverages this data to identify other similar users with the same behavior and preferences and suggests recipes or meal plans they have liked. This approach addresses the "cold start" issue for new users, enabling it to make well-informed recommendations before the user has a substantial interaction history in the app.

3.2. Large Language Models (LLMs) and Machine Learning (ML) Algorithms

The personalization engine is driven by a mix of LLMs and traditional ML algorithms to accomplish its objectives. The centre meal plan generation draws on a Large Language Model (LLM) to build structured, detailed, and readable meal plans. The model will implement a Retrieval-Augmented Generation (RAG) method to retrieve real-time, accurate nutritional information from a handpicked database (e.g., USDA) to avoid inaccuracies arising from the LLM's training data. Moreover, traditional ML algorithms like multilayer perceptrons (MLPs) and reinforcement learning are employed for predictive analysis. These models learn to predict physiological responses to various foods and dynamically adapt recommendations based on a

user's progress and evolving habits over time. This real-time adaptation is a prime reason why the diet regimen remains up-to-date and effective.

3.3. Dynamic Plan Adjustment

A key aspect of the system is its ability to modify diet plans in real time. The hub gathers real-time data from wearables, including steps taken per day, heart rate, and workouts. This information is utilized to determine a user's Daily Energy Expenditure (DEE) including exercising calories burned and Non-Exercise Activity Thermogenesis (NEAT) [2][3][13]. The system's dynamic algorithm then adjusts the daily macronutrient and caloric targets to align with the user's real-life activity level. As an example, a user who has an exceptionally active day with a high step total will have their daily calorie goal increased to accommodate the higher energy output. This creates a reactive feedback loop that keeps the plan on track with the user's physiological demands and serves as an influential psychological stimulus, overcoming the ubiquitous issue of noncompliance with rigid, one-size-fits-all diets.   As in Figure 3: AI-Powered Recommendation Engine Flowchart [1][2][4][9][10].
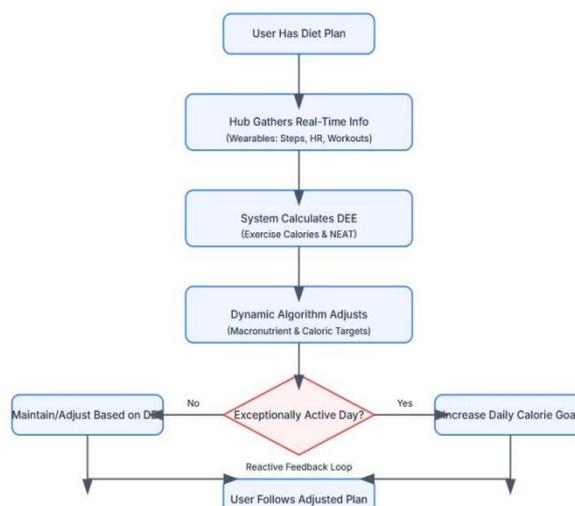

Figure 3: AI-Powered Recommendation Engine Flowchart

4.   Computer Vision Module for Food Recognition

This module provides a key user-facing feature: the automatic logging of meals and nutritional information from a single image. The accuracy and reliability of this component are foundational to the entire system's effectiveness and trustworthiness [5][6][7][8][11][12].

4.1. Deep Learning Architecture for Food Recognition

The food recognition system is built upon a deep learning model, specifically a Convolutional Neural Network (CNN), which is a proven method for image classification and object detection tasks [5][6][7][8][11][12]. To gain high performance, the system employs transfer learning. This entails starting with pre-trained CNN models (e.g., VGG16, ResNet50, InceptionV3) trained on large, general-purpose image datasets. They are subsequently fine-tuned on food-specific datasets, including Food-101 and UECFOOD256, to fine-tune their performance for food identification. The application of these big, publicly available datasets guarantees that the models are trained on a large set of food images with good diversity, thereby increasing their ability to generalize to new, previously unseen foods.

4.2. Portion Size and Calorie Estimation

Once a food product is recognized, the system will then correctly approximate its portion size to determine its nutritional value [6][7][8][11][12]. This is a multi-step process. The system uses

a deep learning-based approach to infer the 3D volume of the food from a single 2D image. This may involve using known objects in the image, such as a plate or a fork, as a scale reference. Alternatively, it might utilize state-of-the-art monocular depth estimation models (e.g., MiDaS) to learn depth information, which is essential to estimate volume from a single image without the need for multiple views or specialized sensors. After estimating the portion size, the system correlates the detected food item and portion size with a rich nutritional database (e.g., USDA) to estimate total calories, macronutrients, and micronutrients. The success of the AI-based recommendation engine relies on the precision of this module [1][2][4][9][10].Any food classification or estimation of portion size error will result in incorrect calorie counts, which in turn will generate poor diet recommendations and destroy user trust, as shown in Figure 3 [6][7][8][11][12].
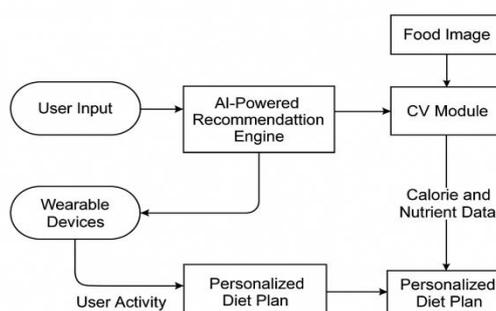

Figure 4: Computer Vision Module Flowchart

5. Integration with Wearables and Health APIs

Smooth interfacing with external health data sources is essential to deliver dynamic and personalized feedback. This module describes the technical and architectural strategy for linking the app to the user's larger health ecosystem [13].

5.1. Integration Hub Architecture

The system's Integration Hub is architected to interface with popular health platforms and wearable devices through their respective APIs. This hub will deal with the complexity of data authentication, parsing, and normalization across multiple sources, like Apple Health, Google Fit, Fitbit, and Garmin. One strategic consideration is the adoption of a single health data API, like Rook, that abstracts away specific integrations and provides normalized, clean data across more than 300 wearables. This is a huge time and resource savings for developers, enabling the team to concentrate on the addition of core features instead of the maintenance of fragmented integrations [13].

5.2. Dynamic Calorie and Nutrient Adjustment Algorithm

The information gathered from wearables, such as daily steps, heart rate, and intensity of workouts, is utilized to dynamically modify the user's nutritional targets. This establishes a robust, real-time feedback loop [6][7][8][11][12]. For instance, a user's daily calorie allowance may automatically be boosted to offset a high-energy gym session, rewarding their effort and maintaining their diet plan in sync with their true physiological requirements. This helps shift the system away from a rigid planner and toward a dynamic "digital coach," a key element in enhancing user engagement and, by consequence, healthy outcomes [13].The cause-and-effect is self-evident: real-time activity data from a wearable initiates a dynamic goal adjustment, instilling a sense of progress and agency, which results in higher user engagement and compliance [14].

5.3. Data Security and Compliance

With the extremely sensitive nature of healthcare data, the platform is designed to be HIPAA compliant. This entails rigorous data encryption in transit and at rest, secure API access, and explicit user consent for data sharing. Respect for privacy is critical in establishing and maintaining user trust, a critical requirement for long-term interaction with any digital health platform [14].

1. Research and Evaluation Framework

To ensure the validity of the system's effectiveness and ascertain its worth in a scientific setting, an official research protocol is suggested. This framework extends beyond basic technical measures to quantify measurable health results and usage.

6.1. Study Design: Randomized Controlled Trial (RCT)

The most critical way to assess a digital health intervention is a randomized controlled trial (RCT). We suggest a parallel-group, home-based RCT with the following elements: Participants: The research will enroll a range of adults who fulfill certain inclusion criteria, for example, being between 18 and 70 years old with a BMI of between 25 and 60 kg/m. Those with eating disorders or already strict dieters will be excluded to maintain an appropriate study population. Intervention Group: The participants of this group will be provided with unrestricted access to the AI-Based Personalized Nutrition & Diet Planner and asked to adhere to the suggestions [1][2][4]. Control Group: Subjects in this arm will be given general, non-individualized nutrition recommendations (e.g., USDA Dietary Guidelines for Americans) without access to the app.

6.2. Primary Outcome Measures

The assessment will employ a mix of objective and subjective criteria to provide a comprehensive overview of the system's impact.

- Primary Outcomes: These are objective, measurable physiological changes that demonstrate the system's effectiveness. They include weight change (both in kilograms and as a percentage) and changes in blood biomarker levels for LDL-C, triglycerides, and HbA1c. The utility of personalization is established by quantifying these targeted biomarkers, which are the direct targets of the system's personalized recommendations.

- Secondary Outcomes: These are measurements of behavioral and psychological responses. They involve modification in waist circumference, food craving, and subjective hunger ratings, which are measured by standardized questionnaires (such as the Three-Factor Eating Questionnaire). User-assessed general health status will also be monitored.

- Engagement Measures: As a means of understanding the connection between app use and health outcomes, we will monitor in-app activity, which is considered to be any action within the app on a daily basis (e.g., food logging, weight tracking). In existing studies, a definite dose-response relationship has already been identified between app use and weight loss, as shown in Table 2.

Table 2: Proposed Outcome Measures and Evaluation Metrics

Category	Specific Metric	Measurement Method	Time Frame
Primary Outcomes	Weight Change (kg, %)	In-app logs	12, 26, 52 weeks
	LDL-C & Triglycerides	Fasted blood draws	Baseline to 12 weeks

	HbA1c (if applicable)	Blood draw	Baseline to 12 weeks
Secondary Outcomes	Waist Circumference (cm)	Anthropometric measurements	Baseline to 12 weeks
	Food Cravings Score	33-item Food Craving Inventory	Baseline to 12 weeks
	Hunger Score	14-item Hunger subscale of TFEQ	Baseline to 12 weeks
Technical Metrics	Food Recognition Accuracy	Precision, Recall, F1 score	Continuous
	Calorie Estimation Error	Root-mean-square error (RMSE)	Continuous
	LLM Caloric Adherence	Percentage Error, MAE	Continuous
User Metrics	In-app Activity	Logged actions/day	Continuous
	User Satisfaction	Qualitative surveys	Baseline, 12 weeks

6.3. Assessment of System Performance

In addition to the clinical performance, an intense technical assessment of the system's main components is required. The accuracy of the food recognition module will be quantified in terms of standard measures such as precision, recall, accuracy, and F1 score. The estimation of the portion size and calories will be assessed in terms of the Root-Mean-Square Error (RMSE) for measuring the error in prediction. Lastly, the performance of the LLM-driven recommendation engine will be measured in terms of how well it follows user-specified caloric goals, using percentage error and Mean Absolute Error (MAE), as well as response time in delivering meal plans [5][6][7][8][11][12].

7. Data Pre-Processing

Data pre-processing is a paramount step that ensures the AI-based diet recommendation system receives clean, regular, and interpretable input data. Given that the garnered data comes from various heterogeneous sources like user biometrics, images of foods, wearable devices, medical histories, and DNA reports, pre-processing pipelines work to normalize, validate, and convert raw inputs into a structured format amenable to downstream recommendation systems and machine learning [2][3].

1. Data Sources

The system feeds data from various streams, each adding distinct attributes to the user profile: User-Reported Inputs: Age, gender, height, weight, dietary habits, food allergies, medical conditions, and fitness objectives [2]. Wearables and Fitness Apps: Steps taken, heart rate, exercise logs, and calorie burn [13]. Computer Vision (Food Recognition): Food images are

scanned to estimate nutrient content (calories, macronutrients, and micronutrients) [5][6][7][8][11][12]. Medical & Genomic Data: Clinical history, DNA analysis, and disease markers [3][15]. Historical Logs: Past meal plans, adherence rates, weight history, and lifestyle compliance [14].
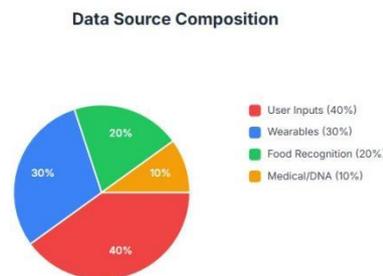

Figure 5: Data Source Composition

2. Pre-Processing Pipeline

The entire pipeline (Figure 5 and Figure 6) converts raw data into AI-friendly structured datasets via a series of cleaning, normalization, and feature engineering processes [2][3].
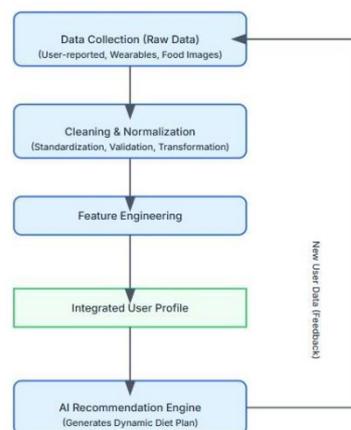

Figure 6: High-Level Data Pre-processing Pipeline

Step 1. Data Cleaning & Standardization

- Missing Value Handling: Imputation from historical values (e.g., missing weight records) or user requests for manual entry (e.g., unknown food items) [2][3].

- Outlier Removal: Elimination of impossible values (e.g., 50k steps/day, unreasonable heart rates).

- Normalization: Standardization of units (weight → kg, height → cm, calories → kcal, macronutrients → grams) [6][7][8][11][12].

- Encoding: Food preferences and allergies encoded as categorical/numeric values (e.g., vegetarian = 0, vegan = 1, keto = 2).
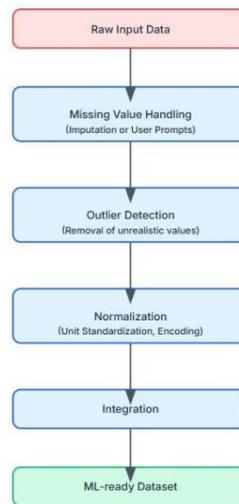
Figure 7: Data Cleaning Workflow Flowchart

Step 2. Data-Specific Pre-Processing

- Biometric & Demographic Data: Standardization, scaling, and encoding [2][3].

- Wearable/Sensor Data: Smoothing of time-series data, aggregation (hourly heart rate, daily steps), and unit harmonization between devices.

- Medical History (Unstructured Text): Processed by Natural Language Processing (NLP) [2]:

  i. Tokenization and cleaning

  ii. Named Entity Recognition (NER) for diseases, drugs, and allergies

  iii. Relationship extraction (e.g., identifying a diagnosis with medication or food restriction)

- Genomic Data: Expert bioinformatics pre-processing [3][15]:

  i. Cleaning and removal of duplicates

  ii. Quality control (e.g., reliability of sequencing, quality of mapping)

  iii. Normalization to remove systematic bias

- Computer Vision (Food Recognition) as showing in Figure 8: [5][6][7][8][11][12]:

  i. Image standardization (resizing, normalization to RGB tensors)

  ii. Segmentation for portion estimation. As shown in Figure 9.

  iii. Nutrient mapping using deep learning that has been trained on food-specific data (e.g., Food-101, UECFOOD256)

Figure 8: Computer Vision Pre-Processing Diagram

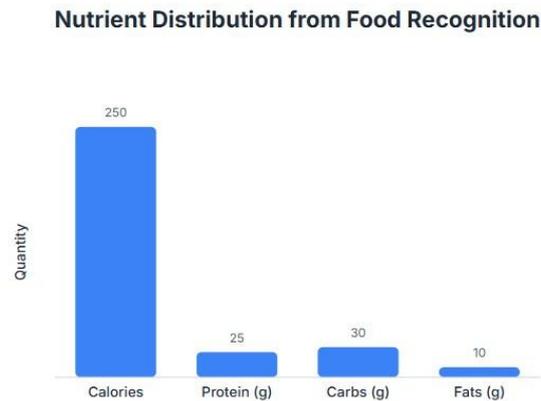**Nutrient Distribution from Food Recognition**

Figure 9: Nutrient Distribution from Food Recognition

- Historical Logs: Feature extraction, compliance score, and temporal aggregation to determine trends [14].

Step 3. Feature Engineering

- BMI (Body Mass Index):

$$BMI = \frac{\text{Weight (kg)}}{\text{Height (m)}^2}$$

- BMR (Basal Metabolic Rate) & DEE (Daily Energy Expenditure): Calculated from biometrics and activity logs.
- Nutritional Gap Analysis: Intake vs. requirement comparisons.
- Compliance Metrics: Extracted from past meal plan adherence [14].

Step 4. Data Integration

All processed data sets (biometric, genomic, wearable, food identification, and historical) are integrated into a single user health profile, which serves as the basis for the AI-powered recommendation engine [3][15].

8. Conclusion

In today's fast-paced lifestyle, it has become all the more difficult to achieve and sustain a healthy, balanced diet. Most diet apps available do not take into consideration the uniqueness of an individual, giving generalized advice without considering important factors like body type, allergies, medical conditions, and personal health objectives. This results in poor compliance and poor results most of the time. The designed AI-Based Personalized Nutrition & Diet Planner offers a revolutionary solution towards personalized healthcare management. Using Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision, the system consolidates various user data, such as biometrics, food preferences, medical history, wearable sensor data, and even genomic results, into one coherent framework. With advanced pre-processing, nutrient analysis, and intelligent feature engineering, the system is able to produce adaptive and dynamic diet recommendations that are personalized. The distinctive strength of this solution is its computer vision-based food identification, which enables real-time estimation of nutrients from scanned meals. In addition, compatibility with fitness trackers and health apps provides ongoing

International Conference on Multidisciplinary Perspectives in Advanced Computing and Technology (IMPACT 2026)

G. B. Pant University of Agriculture and Technology, Uttarakhand, India. Jan. 10-11, 2026

monitoring, and the feedback loop refines nutrition recommendations in sync with the user's changing lifestyle and health goals.

In the end, this study illustrates how the integration of AI-based personalization with real-time monitoring constitutes a comprehensive, intelligent, and accessible nutritional solution. This is not only more efficient in terms of user compliance and health improvement, but also opens the door to the future of precision nutrition and preventive medicine.

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