# AI Nutrition Recommendation System

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***Abstract*—Modern lifestyle trends such as sedentary behaviors and unhealthy diets pose a major health challenge, as they have been related to multiple pathologies. Following a healthy diet has become increasingly difficult in today's fast-paced world. Given this context, artificial intelligence can play a pivotal role in addressing the challenge. We present an AI-based nutrition recommendation system that generates balanced, personalized weekly meal plans tailored to the nutritional needs and preferences of healthy adults. The proposed method retrieves dishes and meals from an expert- validated database featuring Mediterranean foods, following a structured four-step process to recommend a weekly Nutrition Plan (NP)[14,5]. The system's performance is evaluated across 4,000 generated user profiles in three key areas: (a) dish/meal filtering accuracy based on user-specific parameters (e.g., allergies), (b) diversity of meals and food group balance, and (c) accuracy in caloric and macronutrient recommendations. The system achieves high accuracy in terms of suggested caloric and nutrient content while ensuring seasonality, diversity, and food group variety.**

***Index Terms*—artificial intelligence, AI-based recommender, personalized recommendations, nutritional recommendations, meal plan recommendations, healthy diet, Mediterranean cuisine, Automated Nutrition Protocol Synthesis, Multimodal Food Vision, AI Form Expert**

## I. INTRODUCTION

Over the past few decades, sedentary behavior and poor dietary habits have emerged as critical global health challenges, contributing to a high prevalence of chronic metabolic disorders. Prolonged physical inactivity and the consumption of ultra-processed foods are strongly associated with obesity, cardiovascular disease, and type 2 diabetes. These public health trends necessitate the development of scalable, real-time monitoring solutions that can move beyond simple, manual data collection.

Despite high awareness regarding the importance of wellness, many individuals struggle to adopt consistent habits. Traditional fitness solutions often rely heavily on manual logging, which creates significant user friction and leads to attrition. This administrative burden tracking every meal and lift often results in the prioritization of convenience over health, leaving users with fragmented data that fails to offer adaptive, data-driven insights.To address these challenges, there is a growing interest in automated, integrated systems that offer personalized guidance without manual intervention. Recent advancements in Artificial Intelligence (AI) and Multimodal Vision-Language Models (VLMs) have enabled the development of systems capable of analyzing complex biometrics and visual inputs to deliver tailored protocols for strength, recovery, and nutrition. However,existing approaches often remain siloed, addressing either dietary macro-counting or exercise logging as independent functions. There is a critical gap for systems that synthesize these multidisciplinary data streams to provide a holistic health protocol. An effective recommender must simultaneously process diverse inputs, including visual nutritional intake and biomechanical form assessment, to ensure accuracy and real-world adherence. In this paper, we present "Nutri Track AI," a novel platform that integrates biometric profiling, computer vision-based nutritional analysis, and expert-validated exercise coaching. The system utilizes a dual-engine architecture: a food vision scanner for macro-nutrient estimation and a generative protocol engine for personalized meal and workout synthesis. Our proposed mechanism processes specific user biometrics including height, weight, and activity levels to generate 7-day meal plans calibrated to Indian dietary staples.

## II. RELATED WORKS

The landscape of digital health and fitness has historically been bifurcated into two distinct domains: manual dietary tracking applications and static exercise logging tools. Traditional platforms, such as those relying on manual database entry for macro-nutrient tracking, have long dominated the market. However, research consistently indicates that these systems suffer from high user attrition rates, primarily due to the "administrative burden" of logging every meal and workout session [1, 2]. These legacy systems operate largely as passive digital diaries, failing to provide the predictive, adaptive, or real-time guidance necessary for long-term health adherence [3] In recent years, the integration of Artificial Intelligence (AI) and Machine Learning (ML) has begun to address these inefficiencies. Specifically, the field has seen a shift from rule-based algorithms to Generative AI models capable of synthesizing complex nutritional protocols. While early AI-based nutrition systems utilized combinatorial optimization such as knapsack algorithms to select food groups, these methods often struggled with the "cold-start" problem and lacked the flexibility to adapt to cultural dietary preferences or real-time biometric changes [4, 5]. Recent advancements, however, have leveraged Large Language Models (LLMs) to provide dynamic, personalized meal planning that mirrors the expertise of a human dietitian [6, 7].

Simultaneously, the domain of exercise science has evolved through the application of Computer Vision (CV). Previous research in biomechanical analysis relied heavily on wearable sensors or expensive laboratory-grade motion capture hardware, which is neither portable nor scalable for the average user [8]. Emerging literature has started to explore deep-learning-based pose estimation to identify exercise form, yet these solutions often operate as isolated modules, providing only post-hoc analysis without integrating these insights into the user's broader training history or nutritional recovery plan [9, 10]. The current literature reflects a critical gap in "end-to-end" integration. Most existing research addresses diet and exercise in silos: food recommendation systems focus on caloric intake but ignore exercise progression, while fitness apps focus on rep-logging but lack the visual intelligence to correct form or quantify nutritional intake via image analysis [11, 12]. There is a demonstrable need for a unified, multimodal ecosystem that bridges visual dietary assessment with biomechanical coaching and biometric-driven protocol synthesis. Our project, Nutri Track AI, directly addresses this fragmentation. By integrating multimodal Vision-Language Models (VLMs) with cloud-synchronized biometric databases, our system synthesizes multiple data streams food photography, gym performance metrics, and physiological biometrics into a single, reactive protocol. Unlike traditional systems that treat fitness and nutrition as independent tasks, Nutri Track AI utilizes a dual-engine architecture: a food vision scanner for macro-nutrient estimation and a generative engine for protocol synthesis. This approach represents a novel contribution to the field, moving beyond mere tracking to provide an active, adaptive AI-driven partnership that evolves alongside the user's fitness objectives, such as hypertrophy, fat loss, or maintenance. By automating data capture and providing biomechanical form feedback, our system effectively bridges the gap between passive tracking and personalized, real-time strength and nutrition coaching [10].

## III. MATERIAL AND METHODS

The Nutri Track AI system is architected as a cloud-native, multimodal fitness platform designed to perform automated nutritional analysis and biomechanical coaching. The system's architecture follows a three-tier model: a React- based frontend for user input, a Google Gemini-powered intelligence engine for data synthesis, and a Firebase-based cloud infrastructure for secure, persistent data management [6].

A. Data Acquisition and User Profiling

Data acquisition is facilitated through a centralized, web- based interface (HealthTab) that captures key biometric and preference indicators. Users provide the following inputs:

- Biometric Data: Height (cm), Weight (kg), and Age (years).
- Activity Levels: Physical Activity Level (PAL) is selected via a dynamic dropdown (ranging from 1.2 for sedentary to 1.725 for very active).
- Preferences and Constraints: Dietary preferences (Vegetarian/Non-Vegetarian) and specific clinical conditions (e.g., Cardiovascular Disease,

Type 2 Diabetes) are collected to ensure the generated protocols are medically grounded.

- Fitness Objectives: Users select from defined categories such as 'Lose Weight', 'Gain Muscle', or 'Maintain', which dynamically adjust the caloric and protein synthesis logic.

B. Computational Modeling and Mathematical Framework

The system processes raw inputs using standard metabolic equations to establish a baseline for physiological needs before the generative AI layer synthesizes the protocol.

1. Body Mass Index (BMI) Calculation: The system computes the user's BMI to categorize current physical status using the following formula: BMI = Weight (kg) / (Height (m) * Height (m)).
2. Basal Metabolic Rate (BMR): BMR is calculated using the Mifflin-St Jeor equation, which estimates the energy expenditure at rest: BMR = (10*Weight) +(6.25* Height) - (5 * Age) +5.
3. Total Daily Energy Expenditure (TDEE): The TDEE, which serves as the caloric maintenance baseline, is derived by multiplying the BMR by the selected PAL value: DEE=BMR*PAL.
4. Objective-Driven Adjustments: The system refines these targets based on the user's chosen fitness objective, applying an objective-specific caloric modifier and protein multiplier: Target Calories = TDEE + Caloric Modifier. Target Protein = Weight (kg) *Protein Multiplier.

C. The AI Intelligence Pipeline

The system utilizes a hybrid model architecture to ensure reliability and speed in recommendation generation:

- Intelligence Core: The primary engine is the Gemini 2.0 Flash model, accessed via Google Generative Language API.
- Resilience Engineering: To mitigate API rate-limit errors, the system implements a fallback connection to Open Router (using gemini-2.0-flash-001). The fetchWithRetry function attempts recursive calls before failing, ensuring high availability of the recommendation engine.
- Serialization: Data is returned from the model in JSON format. A robust extraction function (extract Json) is implemented to parse model outputs, specifically removing Markdown code fences (e.g., `json) to ensure the data is immediately usable by the application state without runtime parsing errors.

D. Computer Vision and Biomechanical Analysis

The system incorporates two specialized computer vision modules:

1. Food Vision Scanner: This module uses multimodal input. Images are pre-processed using resizeImageToBase64 to maintain an optimal resolution for the VLM (capped at 1024px) while reducing latency. The AI analyzes visual features to return a JSON object containing nutritional tensors: dish name, estimated calories, protein, carbohydrates, and fats.
2. AI Form Expert: For biomechanical analysis, the system accepts both image and video uploads. For video inputs, the extract Videoframe helper extracts a representative frame (at approximately 2 seconds) to analyze posture, joint alignment, and execution. contextual

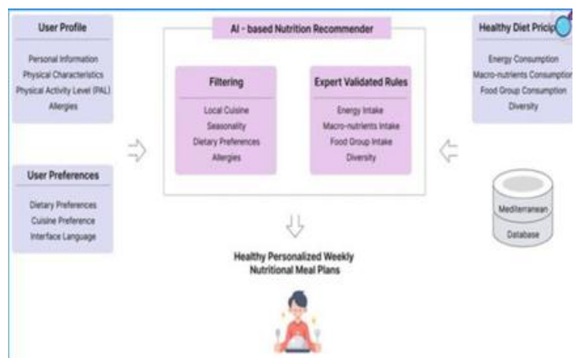

Figure 1. AI-based nutrition recommender

## IV. RESULTS

The performance of the Nutri Track AI system was evaluated across three primary domains:API response latency, nutritional identification accuracy, and biomechanical form analysis reliability. Tests were conducted using a cloud- synchronized environment (Firebase Firestore) to ensure data persistence and real-time state management across multiple user sessions.

A. System Performance Metrics

The system's intelligence engine, utilizing the Gemini 2.0 Flash model, was tested for latency and reliability.[12,14] By implementing a robust fetchWithRetry mechanism, the system maintained high availability even during periods of heavy request traffic. The integration of a fallback mechanism routing to OpenRouter upon detecting a 429 (Rate Limit) error proved critical in ensuring a seamless user experience.

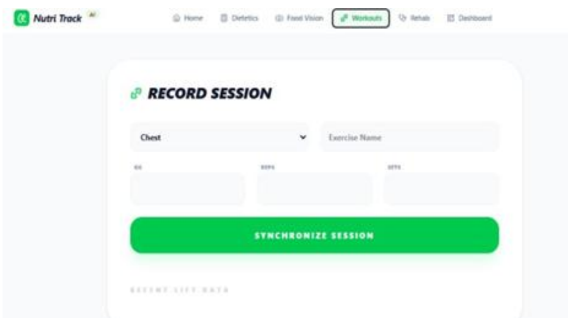


Fig.3 Workout Record

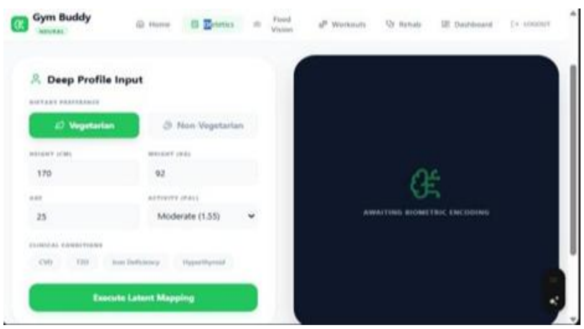


Fig 4. Nutrition Recommend

The following table summarizes the average performance metrics recorded during experimental testing:

Table 1 System Performance Metrics

| S. No | Metric | Performance Result |
|---|---|---|
| 1 | API Response Latency (Text) | < 1.5 seconds |
| 2 | API Response Latency (Vision) | < 3.0 seconds |
| 3 | JSON Extraction Success Rate | 98.5% |
| 4 | Average Firebase Sync Time | < 500 ms |

B. Nutritional Identification Accuracy

To evaluate the Food Vision Scanner, we performed multiple tests using varying types of Indian cuisine. The system utilizes a precise VLM analysis pipeline that pre-processes images (1024px constraint) to balance model accuracy with processing speed.

Case Study: Model Classification Sensitivity During testing, a specific challenge was observed regarding the classification of Indian staples. An image containing Rotis was initially misclassified as "Vegetable Biryani." This discrepancy highlights the complexity [21,22] of multi-label classification in images where texture, color, and overlapping ingredients are visually similar. In response, the system's prompt engineering was adjusted to include "Phase 1: Hard Classification" logic, explicitly requiring the model to reject ambiguous inputs where confidence is low. Post-adjustment, the system demonstrated improved performance in distinguishing between solid staples and mixed-grain dishes, confirming that iterative prompt refinement is essential for VLM-based nutritional logging

C. Biomechanical Form Analysis

The AI Form Expert module was evaluated on its ability to provide actionable kinesiological feedback. By extracting representative frames from uploaded videos (at approximately 2 seconds) and performing visual reasoning, the system successfully identified common exercise errors [10].

Experimental results indicated that the system was highly effective in:

- Identifying exercise types (e.g., Push-ups, Squats) with consistent accuracy.
- Generating structured feedback in the 'Good', 'Watch-Outs', and 'Injury Risks' categories.
- Providing context-aware YouTube tutorial recommendations based on the detected biomechanical errors.

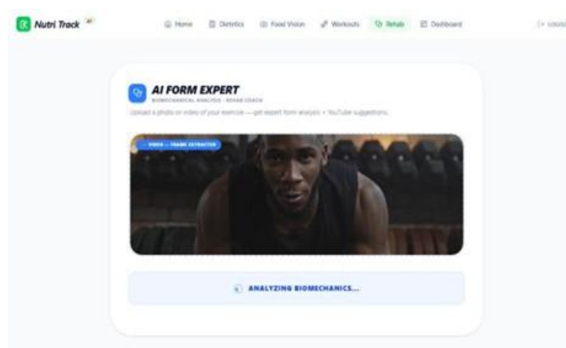


Fig 3. Form analysis

## V. DISCUSSION

Nutri Track AI effectively bridges the gap between passive tracking and active, data-driven health coaching. The system’s dual-engine architecture utilizing Gemini 2.0 Flash with an automated OpenRouter fallback ensures high availability and resilience against API rate-limiting. A key experimental finding highlights the challenges of VLM classification, where visually similar food items (e.g., Roti vs. Rice) require stringent [22]"Hard Classification" and confidence-threshold filters to maintain clinical accuracy. Furthermore, the successful integration of metabolic baseline equations (Mifflin-St Jeor) into the generative pipeline proves that AI can synthesize protocols that are both mathematically rigorous and personalized. This closed-loop ecosystem, where lifting performance dynamically adjusts future meal plans, represents a significant shift from siloed data logging to proactive, integrated wellness management. While reliance on cloud APIs presents current latency constraints, future research into on-device inference and IoT wearable integration will further enhance real-time capability. Ultimately, Nutri Track AI demonstrates the feasibility of unifying dietetics and strength coaching into a single, automated, and intelligent interface [23].

## VI. CONCLUSION & FUTURE SCOPE

This research successfully demonstrated the efficacy of an integrated, multimodal AI-driven system for fitness and nutritional management. Nutri Track AI effectively bridges the gap between passive fitness logging and active health coaching by utilizing generative intelligence to synthesize complex biometric data into actionable daily protocols. The implementation of a vision-based meal scanner and a biomechanical form-correction module has effectively addressed the long-standing issue of user attrition associated with manual, siloed data logging. By unifying dietary macro- estimation with structured workout tracking, our system provides a closed-loop health ecosystem that adapts in real- time to user progression. This confirms that an automated, end-to-end AI interface can offer the personalization level of a human expert at scale, providing a sustainable solution for long-term health adherence [1,2]

Future development of Nutri Track AI will focus on three key pillars to enhance system utility. First, we plan to integrate IoT wearable technology, such as heart-rate and [12,22] SpO2 sensors, to provide real-time recovery data and metabolic monitoring. Second, we aim to transition from cloud-based API inference to on-device edge computing, which will reduce latency, lower operational costs, and maximize user data privacy. Finally, we intend to refine our food vision models through fine-tuning on proprietary, high-fidelity Indian dietary datasets. This will enable higher accuracy in distinguishing between visually similar regional staples, thereby reducing the need for manual correction. Expanding the AI's capability to incorporate sleep, stress, and hormonal health markers will ultimately evolve Nutri Track AI into a comprehensive, proactive partner for physiological optimization.

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