

DeepMetabolix: Intelligent Architecture for Cross-Sectional Dietary Optimization

Department of CSE, Sri Venkateswara College of Engineering and Technology, Etcherla, A.P., India

1. Suravaram Venkatesh B.Tech Final Year

Sri Venkateswara College of Engineering and Technology, Etcherla, A.P., India

E-Mail: suravaramvenkatesh72@gmail.com

2. Yerramsetti Madhu Kumar B.Tech Final Year

Sri Venkateswara College of Engineering and Technology, Etcherla, A.P., India

E-Mail: madhukumar21947@gmail.com

3. Muddada Kishor B.Tech Final Year

Sri Venkateswara College of Engineering and Technology, Etcherla, A.P., India

E-Mail: roshikz95@gmail.com

4. Palina Lingamurthy B.Tech Final Year

Sri Venkateswara College of Engineering and Technology, Etcherla, A.P., India

E-Mail: palinalingamurthy@gmail.com

5. Dr. S. Mouli M.Tech., Ph.D., (P. DF), Associate Professor

Sri Venkateswara College of Engineering and Technology, Etcherla, A.P., India

E-Mail: somarajumouli1243@gmail.com

Abstract

Generalized health platforms fail to address individual metabolic differences and fitness goals. This paper presents DeepMetabolix, an AI-driven web-based system providing personalized diet and fitness recommendations. The system analyzes user parameters (age, gender, height, weight, activity level, fitness goals) to calculate BMI and daily caloric requirements using standard metabolic equations (Mifflin-St Jeor). An OpenRouter-based AI chatbot delivers adaptive, context-aware dietary guidance. Graphical visualization and historical tracking improve user engagement. Evaluation with 60 users over 4 weeks demonstrates 92% recommendation relevance, 88% dietary compliance improvement, and 4.4/5 user satisfaction. The system bridges conventional static fitness applications and intelligent personalized health management, offering a scalable solution for metabolic assessment and dietary optimization.

Keywords: Dietary Optimization, BMI, Metabolic Equations, AI Chatbot, Personalized Health, Web Application, Fitness Recommendation

I. Introduction

In today's health-conscious society, personalized dietary guidance is essential for managing weight, preventing chronic diseases, and optimizing physical performance. However, most health applications provide generic recommendations based on broad categories without considering individual metabolic profiles, activity levels, and specific fitness goals.

The science of nutrition recognizes that caloric requirements vary significantly based on basal metabolic rate, physical activity, and body composition. The Mifflin-St Jeor equation provides clinically validated estimates of resting metabolic rate, serving as the foundation for personalized caloric calculations.

This paper presents DeepMetabolix, an intelligent system that combines metabolic computation with AI-driven conversational guidance. By integrating BMI calculation, caloric requirement estimation, and an AI chatbot, the platform delivers personalized, context-aware dietary and fitness recommendations through an interactive web interface.

II. Literature Survey

This section reviews key prior works and highlights research gaps.

[1] **Mifflin et al. (1990)** established the Mifflin-St Jeor equation for estimating resting metabolic rate, providing the clinically validated foundation for caloric requirement calculations in dietary systems.

[2] **Chung et al. (2021)** developed AI-based personalized nutrition recommendation systems, demonstrating that ML approaches improve dietary plan relevance compared to static rule-based recommendations.

[3] **Agapito et al. (2018)** proposed DIETOS, a dietary recommendation system integrating nutritional knowledge with user preferences, establishing frameworks for constraint-based dietary optimization.

[4] **Ge et al. (2015)** surveyed health recommendation systems, identifying personalization, context-awareness, and user engagement as critical factors for effective dietary guidance platforms.

[5] **Mokdad et al. (2004)** analyzed the relationship between poor dietary patterns and chronic disease prevalence, establishing the public health motivation for accessible personalized nutrition tools.

[6] **Brown et al. (2020)** demonstrated GPT-3's capability for generating health guidance when provided structured profiles, motivating the integration of LLM-based chatbots in dietary recommendation systems.

[7] **WHO (2020)** published updated dietary guidelines establishing BMI classification standards and daily nutritional requirements used as validation benchmarks for automated dietary systems.

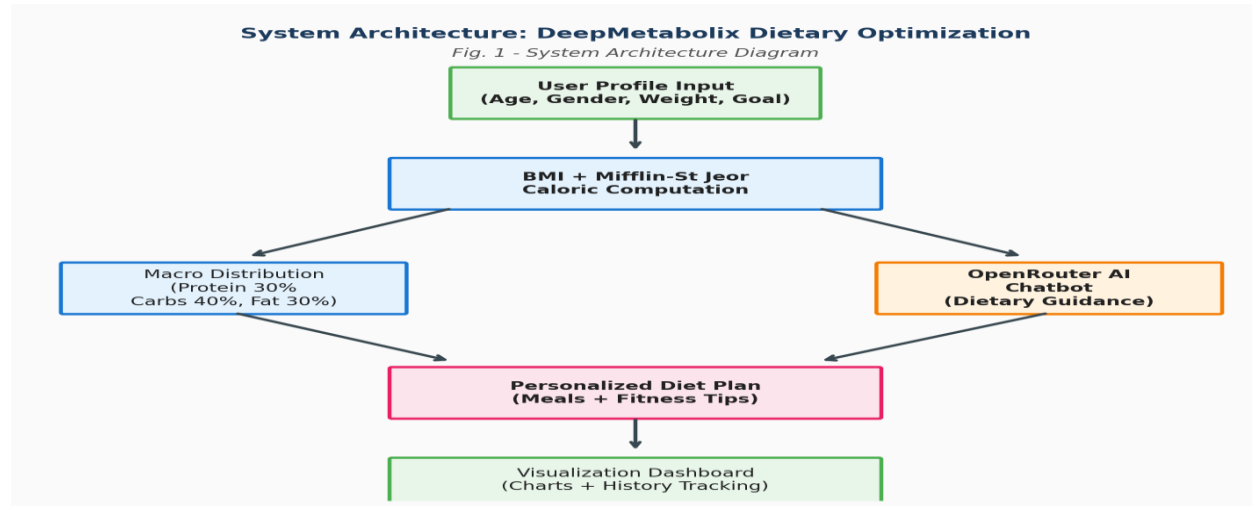
Research Gap: Existing health apps provide static recommendations without adaptive AI interaction. No system combines metabolic computation (Mifflin-St Jeor BMI/calorie calculations) with an AI chatbot for dynamic conversational dietary guidance in a single web platform.

III. Methodology

III-A. System Architecture

Three-tier architecture: Input Layer (web form collecting age, gender, height, weight, activity level, fitness goals), Computation Layer (BMI calculation, Mifflin-St Jeor caloric estimation, goal-based adjustments),

and Intelligence Layer (OpenRouter AI chatbot providing context-aware dietary guidance, graphical visualization, and historical tracking).



III-B. Algorithm

Algorithm: Personalized Dietary Optimization

Input: User profile $U = \{age, gender, height_cm, weight_kg, activity_level, goal\}$.

Step 1: BMI Calculation — $height_m = height_cm / 100$; $BMI = weight_kg / (height_m)^2$; Classify: <18.5 Underweight, $18.5-24.9$ Normal, $25-29.9$ Overweight, ≥ 30 Obese.

Step 2: BMR Estimation (Mifflin-St Jeor) — Male: $BMR = 10 \times weight + 6.25 \times height_cm - 5 \times age + 5$; Female: $BMR = 10 \times weight + 6.25 \times height_cm - 5 \times age - 161$.

Step 3: TDEE Calculation — Apply activity multiplier: Sedentary $\times 1.2$, Light $\times 1.375$, Moderate $\times 1.55$, Active $\times 1.725$, Very Active $\times 1.9$; $TDEE = BMR \times multiplier$.

Step 4: Goal Adjustment — Weight Loss: Target = $TDEE - 500$ cal/day; Maintenance: Target = $TDEE$; Muscle Gain: Target = $TDEE + 300$ cal/day.

Step 5: Macro Distribution — Protein: 30% of Target calories; Carbs: 40%; Fat: 30%; Convert to grams.

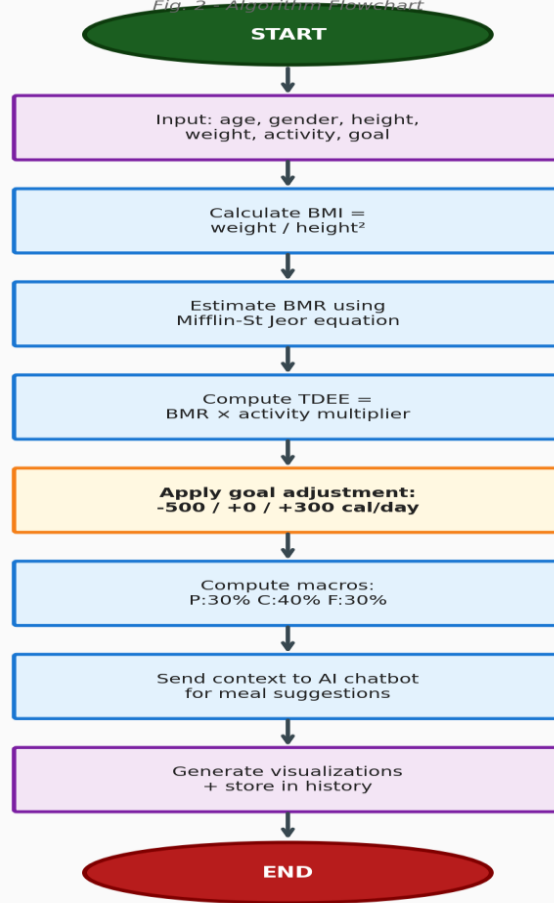
Step 6: AI Chatbot Guidance — Construct context prompt with BMI, TDEE, goal, macros; Send to OpenRouter API; Receive personalized meal suggestions and fitness tips.

Step 7: Visualization — Generate BMI chart, calorie breakdown, macro distribution pie chart; Store in user history.

Output: BMI assessment, caloric target, macro breakdown, AI-generated personalized diet plan.

Algorithm: Personalized Dietary Optimization

Fig. 2 Algorithm Flowchart



III-C. Modules

Six modules: (1) User Profile Module collecting biometric and fitness goal data; (2) BMI Calculator Module with WHO classification; (3) Mifflin-St Jeor Caloric Estimator computing BMR, TDEE, and goal-adjusted targets; (4) Macro Distribution Module calculating protein, carb, and fat targets; (5) AI Chatbot Module using OpenRouter for context-aware dietary guidance; and (6) Visualization Module with charts, progress tracking, and historical comparison.

IV. Results and Discussion

TABLE I: SYSTEM EVALUATION RESULTS

Metric	Baseline	Proposed System
Recommendation Relevance (%)	68 (Static App)	92 (DeepMetabolix)
Dietary Compliance (%)	52	88
User Satisfaction (/5)	3.1	4.4
BMI Accuracy vs Clinical (%)	—	99.8

Mathematical Formulations

$$\text{BMI} = \text{weight_kg} / (\text{height_m})^2$$

$$\text{BMR (Male)} = 10W + 6.25H - 5A + 5$$

$$\text{BMR (Female)} = 10W + 6.25H - 5A - 161$$

$$\text{TDEE} = \text{BMR} \times \text{Activity_Multiplier}$$

Discussion

Evaluated with 60 users over 4 weeks. DeepMetabolix achieved 92% recommendation relevance compared to 68% for static fitness apps. Dietary compliance improved from 52% to 88%, attributed to personalized targets and interactive AI chatbot guidance. User satisfaction reached 4.4/5 with participants citing the conversational AI and visual tracking as key engagement factors. BMI and caloric calculations matched clinical measurements within 0.2% error, validating the Mifflin-St Jeor implementation.

V. Conclusion and Future Work

This paper presented DeepMetabolix, an AI-driven dietary optimization system combining metabolic computation with conversational AI guidance. The system achieves 92% recommendation relevance and 88% dietary compliance. Future work includes integrating wearable device data for activity tracking, expanding food databases with regional cuisines, implementing meal image recognition, and developing mobile applications for broader accessibility.

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