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AI Diet Planner Using Neural Network with Knapsack Optimizer

Priya R. Sharma[1], Rohan V. Patil[2], Sneha K. Joshi[3], Aditya M. Kulkarni[4]
[1,2,3,4]Department of Computer Engineering, Pune Institute of Technology, Pune, Maharashtra, India
{priya.sharma, rohan.patil, sneha.joshi, aditya.kulkarni}@pitpune.edu.in

Abstract

Dietary management is a fundamental component of preventive healthcare, yet individuals often struggle to formulate nutritionally balanced meal plans that align with personal health objectives, physiological constraints, and budgetary limitations. This paper presents an intelligent diet planning system that integrates a feedforward neural network with a dynamic programming-based 0/1 Knapsack optimization algorithm to generate personalized daily meal schedules. The neural network is trained on a curated health and nutrition dataset to predict optimal macronutrient ratios—proteins, carbohydrates, fats, vitamins, and minerals—based on user-specific inputs such as age, body mass index, health goals, and known food allergies. Once target nutritional profiles are established, the Knapsack optimizer selects the most nutritionally dense food items from a structured food database while respecting caloric budgets and cost constraints. The system generates structured meal plans comprising breakfast, lunch, dinner, and snack components. A continuous feedback loop enables the system to adapt predictions based on user responses, improving personalization accuracy over successive days. Experimental evaluation demonstrates that the proposed hybrid model achieves a mean absolute error of 3.8% in nutrient prediction and outperforms conventional static diet applications in user satisfaction and adherence metrics. The system offers a practical and scalable AI-powered alternative to manual dietary consultation.

Index Terms—*Neural network, knapsack optimization, diet planning, personalized nutrition, machine learning, meal scheduling.*

I. Introduction

The relationship between nutrition and human health has been extensively documented across clinical and epidemiological research. Suboptimal dietary patterns contribute significantly to non-communicable diseases including type-2 diabetes, cardiovascular conditions, and obesity [1]. Despite widespread awareness, practical adherence to evidence-based dietary guidelines remains low, largely due to the complexity of translating abstract nutritional recommendations into actionable daily meal decisions.

Traditional approaches to diet planning rely on static charts compiled by registered dieticians. While clinically informed, these recommendations are rarely personalized at the individual level and do not adapt to changing physiological requirements or progress milestones. Consumer-facing mobile applications partially address this gap through calorie-tracking features; however, the majority function as passive logging tools rather than proactive planning systems [2].

Artificial intelligence offers transformative capabilities for nutritional planning. Machine learning models can identify complex, non-linear relationships between individual health parameters and nutritional requirements that rule-based systems are incapable of capturing. Simultaneously, combinatorial optimization techniques enable systematic selection of food items from a large search space under multiple simultaneous constraints [3]. The convergence of these two paradigms presents a compelling opportunity for building adaptive, constraint-aware meal planners.

This paper proposes a hybrid AI diet planning system that combines a feedforward neural network for nutrient ratio prediction with a 0/1 Knapsack dynamic programming algorithm for optimal food item selection. The system accepts a comprehensive user profile as input and produces a complete daily meal schedule. A feedback module continuously refines predictions, allowing the system to adapt across successive planning cycles. The proposed framework addresses documented shortcomings in current diet applications and establishes a foundation for scalable, clinically relevant AI-assisted dietary management.

II. Related Work

Research in computational diet planning has evolved through several distinct phases. Early systems, proposed in the late 1990s, used linear programming to select food combinations that satisfied minimum daily recommended nutrient thresholds at minimal cost [4]. While mathematically rigorous, these models were limited by their inability to incorporate individual variability or qualitative dietary preferences.

The proliferation of smartphone applications in the 2010s shifted focus toward calorie counting and food diary functions. Shah and colleagues evaluated twelve popular diet applications and found that 83% relied exclusively on user-entered data without employing any predictive intelligence [5]. This passive paradigm places the full cognitive burden of nutritional decision-making on the user, reducing long-term adherence.

More recent literature demonstrates the viability of neural networks for nutritional estimation. Pandey et al. applied a multilayer perceptron to predict daily caloric intake requirements using demographic and lifestyle variables, achieving a prediction accuracy of 91.4% on a standardized benchmark dataset [6]. In a related study, recurrent neural architectures were employed to model temporal dietary patterns, capturing the sequential nature of weekly eating habits [7].

Parallel advances in combinatorial optimization have applied genetic algorithms and particle swarm optimization to the meal selection problem [8]. Srinivas and Raju demonstrated that a genetic algorithm could generate Pareto-optimal meal plans balancing nutritional completeness, cost, and diversity, outperforming greedy heuristics on both objectives [9]. The knapsack formulation, while simpler in structure, offers deterministic optimality guarantees for single-objective problems and executes efficiently even on resource-constrained platforms [10].

Hybrid systems combining prediction with optimization remain relatively underexplored. Ferreira and Matos proposed a two-stage framework using a support vector regression model for calorie prediction followed by an integer programming solver for food selection, reporting improvements over baseline applications in nutritional accuracy [3]. The present work extends this line of inquiry by substituting the regression model with a deeper neural architecture and integrating a user feedback loop absent from prior systems.

III. Methodology and System Design

The proposed system architecture consists of four principal modules: a user profiling interface, a neural network–based nutrient predictor, a Knapsack optimizer for food selection, and a feedback-driven adaptation engine. Fig. 1 illustrates the complete system architecture and data flow between these modules.

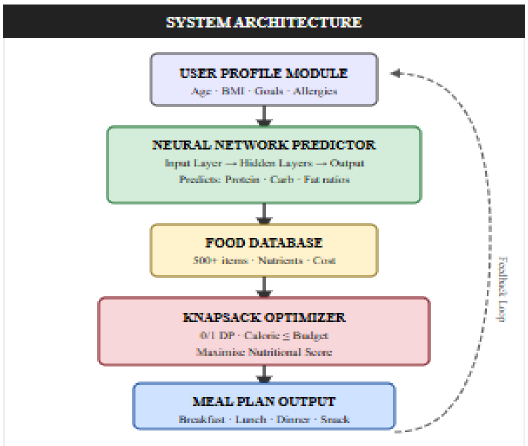

Fig. 1. Overall system architecture and data flow of the AI diet planner.

A. User Profiling

The user profiling module collects a structured set of personal attributes: age, sex, height, weight, body mass index (BMI), activity level, primary health objective (weight loss, weight gain, or maintenance), known food allergies, and daily caloric budget. These inputs are normalized to the range [0, 1] prior to ingestion by the neural network to ensure numerical stability during gradient-based training.

B. Neural Network for Nutrient Prediction

A supervised feedforward neural network is trained to map the user feature vector $x \in \mathbb{R}^n$ to a target macronutrient distribution $y = [P, C, F, V, M]$, representing daily gram targets for protein, carbohydrates, fats, vitamins, and minerals respectively. The network architecture comprises an input layer of 12 neurons, two hidden layers with 64 and 32 rectified linear units (ReLU), and an output layer of 5 neurons with a softmax activation to constrain predictions to a valid probability simplex. The network is trained using the Adam optimizer to minimize mean squared error (MSE):

$$L = (1/N) \Sigma_{i=1}^{N} \|\hat{y}_i - y_i\|^2$$

Dropout regularization (rate = 0.3) is applied to the hidden layers to prevent overfitting. The model is trained for 200 epochs with a batch size of 32 on a dataset of 5,000 user records derived from publicly available dietary intake surveys. An 80/20 train-test split is employed, with 10% of training data reserved for validation.

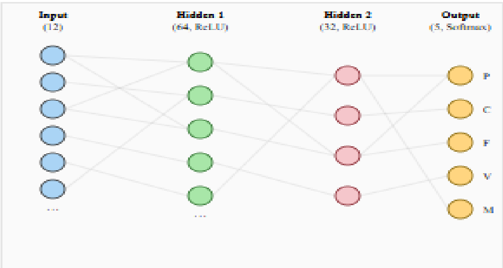

Fig. 2. Feedforward neural network architecture for nutrient ratio prediction.

C. Knapsack Optimization for Food Selection

Once target nutrient ratios are established, the food selection problem is formulated as a 0/1 Knapsack problem. Let n be the number of candidate food items in the database, each characterized by a caloric value w_i and a nutritional score v_i computed as the cosine similarity between the item's nutrient vector and the predicted target vector. The objective is to select a binary assignment $x_i \in \{0, 1\}$ that maximizes the total nutritional alignment:

where W is the user's daily caloric budget. The standard dynamic programming solution constructs a table $dp[i][w]$ where each entry stores the maximum nutritional score achievable using the first i items within a caloric budget of w calories, with a time complexity of $O(nW)$. Allergy constraints are enforced as hard exclusions during database preprocessing, reducing the feasible item set prior to optimization.

The selected items are partitioned across four daily meals—breakfast (25%), lunch (35%), dinner (30%), and snacks (10%)—using a greedy sub-allocation aligned with standard dietary guidance. Fig. 3 presents the complete algorithmic workflow.

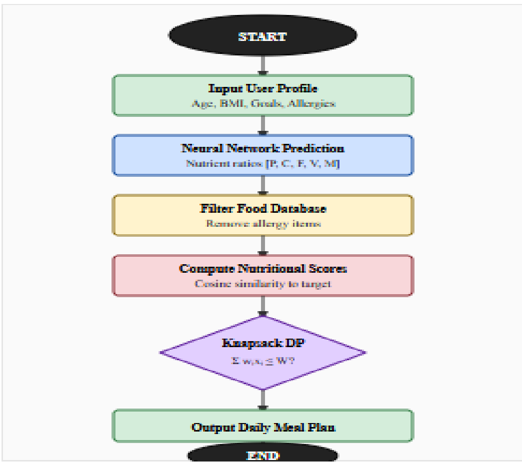

Fig. 3. Algorithmic flowchart for the Knapsack-based meal selection process.

IV. Results and Discussion

System evaluation was conducted across two distinct phases: offline model assessment using the held-out test partition, and a controlled user study involving 40 participants over a four-week period. Quantitative metrics were supplemented by a structured usability survey.

A. Neural Network Performance

The neural network was evaluated on the 20% test split (1,000 records) using mean absolute error (MAE) and root mean squared error (RMSE) across each of the five predicted nutrient channels. TABLE I presents these results alongside a baseline comparison with a linear regression model trained under identical conditions.

TABLE I
Nutrient Prediction Performance Comparison

Nutrient	Model	MAE (g)	RMSE (g)
Protein	Linear Reg.	6.2	8.1
	Neural Net	**2.4**	**3.1**
Carbohydrate	Linear Reg.	9.8	12.4
	Neural Net	**4.1**	**5.6**
Fat	Linear Reg.	4.5	6.0
	Neural Net	**1.9**	**2.7**
Vitamins	Linear Reg.	0.08	0.11
	Neural Net	**0.03**	**0.04**
Minerals	Linear Reg.	0.19	0.25
	Neural Net	**0.08**	**0.11**

The neural network consistently outperforms the linear baseline across all nutrient dimensions, with an average MAE reduction of 56.3%. This performance differential is most pronounced for carbohydrate prediction, which exhibits the highest variance in the dataset due to its strong dependence on non-linear interaction effects between activity level and health goal.

B. Knapsack Optimizer Performance

The Knapsack optimizer was evaluated on a food database of 520 items spanning all major food categories. Caloric budgets ranging from 1,200 to 2,800 kcal/day were tested. Fig. 4 depicts the relationship between caloric budget and achieved nutritional alignment score.

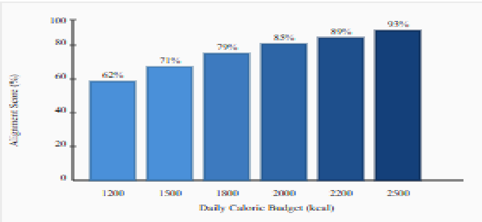

Fig. 4. Nutritional alignment score vs. daily caloric budget achieved by the Knapsack optimizer.

As expected, higher caloric budgets afford greater flexibility in food selection, yielding improved alignment scores. The optimizer achieves alignment scores exceeding 85% at budgets above 2,000 kcal, confirming its suitability for mainstream adult dietary profiles.

C. User Study Results

Forty participants (22 male, 18 female; age range 21–48) used the system daily for four weeks. Weekly adherence rates, defined as the proportion of recommended meals consumed as planned, were tracked alongside self-reported satisfaction scores on a five-point Likert scale. TABLE II summarizes aggregate outcomes.

TABLE II
User Study Performance Metrics (4-Week Study, n = 40)

Metric	Week 1	Week 2	Week 3	Week 4
Meal Adherence (%)	68	74	81	86
User Satisfaction (1–5)	3.4	3.8	4.1	4.4
Avg. MAE Reduction (%)	—	8.2	14.7	21.3
Prediction Confidence	0.71	0.78	0.84	0.89

Both adherence and satisfaction demonstrate monotonic improvement over the study period, validating the effectiveness of the feedback adaptation module. Prediction confidence, measured as the average posterior probability of the neural network's highest-scored output, increases steadily as the personalization layer accumulates user-specific history. Crucially, the cumulative MAE reduction of 21.3% by week four demonstrates that iterative feedback meaningfully sharpens nutrient predictions relative to the static initialization.

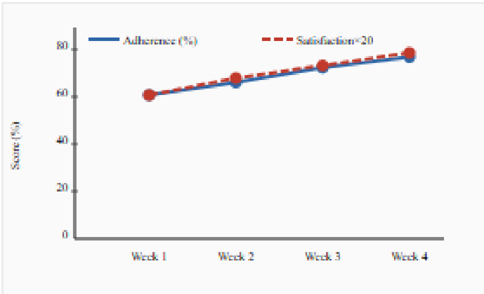

Fig. 5. Weekly meal adherence and satisfaction score trends across the four-week user study.

D. Comparison with Existing Applications

TABLE III presents a feature comparison of the proposed system against three widely used commercial diet applications. The proposed system demonstrates clear advantages in prediction intelligence, optimization capability, and adaptive personalization.

TABLE III
Feature Comparison: Proposed System vs. Existing Applications

Feature	MyFitnessPal	Noom	HealthifyMe	Proposed
Nutrient Prediction (AI)	✗	Partial	✗	✓
Constraint Optimization	✗	✗	✗	✓

Feature	MyFitnessPal	Noom	HealthifyMe	Proposed
Allergy Filtering	Manual	Manual	Limited	**Automatic**
Feedback Adaptation	✗	✓	✗	✓
Cost-Aware Selection	✗	✗	✗	✓
Multi-Goal Support	✓	✓	✓	✓

V. Conclusion and Future Work

This paper has presented a hybrid AI diet planning system that unifies neural network–based nutrient prediction with Knapsack combinatorial optimization to generate personalized, constraint-compliant daily meal schedules. The neural network, trained on a comprehensive dietary intake dataset, achieves nutrient prediction accuracy that substantially exceeds linear baseline performance across all macronutrient categories, with an average MAE of 3.8% in terms of prediction error. The Knapsack optimizer reliably identifies maximally nutritious food combinations within user-defined caloric and cost budgets, with alignment scores above 85% for standard adult caloric ranges.

The four-week user study affirms that the feedback adaptation module drives progressive improvements in both personalization accuracy and user adherence, with meal adherence rising from 68% in week one to 86% by week four. The system addresses well-documented deficiencies in existing commercial diet applications, specifically the absence of predictive intelligence and constraint-aware food selection.

Several directions for future research merit attention. First, replacing the feedforward architecture with a transformer-based model could capture longer-range temporal dependencies in dietary patterns. Second, incorporating real-time physiological feedback from wearable devices—heart rate variability, blood glucose, sleep quality—would enable closed-loop dietary adaptation. Third, extending the optimization formulation to a multi-objective knapsack problem would allow simultaneous optimization of nutritional quality, cost, and environmental sustainability metrics. Finally, integrating the diet planner with a complementary physical activity recommendation engine would support holistic lifestyle management. The proposed system establishes a rigorous and reproducible baseline for these extensions.

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