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MyAiPlate: A Mobile Application for Personalized Nutrition Using YOLOv8 Food Recognition and a Hybrid LSTM-DQN Model for Real-Time Meal Plan Adaptation

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***Abstract*— Keeping a balanced and individualized diet plays an important role in the prevention of chronic diseases as well as in maintaining optimal wellness. The accurate monitoring of daily calorie consumption and abiding by the restrictions of certain diets is key to achieving good health. Nevertheless, existing dieting apps are not dynamic enough; they only serve as online diaries incapable of adjusting according to the behaviour of the user. A multi-model machine learning architecture was developed for the MyAiPlate application to address this gap. A YOLOv8 object detection model, fine-tuned on a real-world dataset of 1,169 labelled food images, was implemented to visually recognize food items and estimate caloric intake from user-captured images. The proposed machine learning components were rigorously evaluated for performance and user safety. The YOLOv8 food recognition model was validated using unseen, real-world meal images. On the held-out validation set the model achieved 95.16% precision, 94.42% recall, 97.51% mAP@50, and 75.57% mAP@50-95. In addition to encouraging user participation, feedback was provided through a conversational interface within the application. Traditional diet tracking tools do not have a conversational approach and cannot answer specific user inquiries in a context-aware manner. An AI Nutrition Chatbot was implemented using Large Language Models (LLMs) based on transformers from OpenRouter, which offered real-time, context-aware, personalized nutritional advice based on meal entries. The conversational interface was tested using 50 queries, including 25 challenging nutritional queries and 25 common diet prompts to ensure that the LLM could deliver reliable results without hallucinations.**

***Keywords*— Personalized Nutrition, Machine Learning, Object Detection, YOLOv8, Large Language Models**

I. INTRODUCTION

In the current world, people rely on the internet for every activity they perform. Therefore, recommender systems for various activities such as music, movies, shopping, food and books are highly evolving and used by people because it is efficient and helps them to reduce their workload and time [1]. Food recommendation systems play a major role in assisting the users to adapt to a healthier lifestyle and reduce the risk of getting diseases [2]. These food recommendation systems often put users into groups and recommend food and diet based on that. For example, if the user is a vegetarian, the system recommends vegetarian based food based [3]. This is a major problem because the other aspects of the users such as health concerns and allergies are not considered in the diet recommendation.

Due to the busy lives led by people in the current world, health is given minimum priority as people run behind success, fame and money. Improper nutrition and consuming too much processed and unhealthy food is the main cause of various diseases [4]. According to a study done in 2016 with 5,558 Brazilian people, it was discovered that people who consumed more ultra processed food showed a higher risk of death due to ischemic heart disease [5]. The increasing prevalence of diet-related diseases such as obesity, diabetes, and cardiovascular conditions highlights the urgent need for smarter health management tools. However, making healthy meal plans is not easy or convenient because it must consider the health concerns, dietary preferences, BMI, allergies and tastes of the user. Currently, there is a lack of systems which recommend meal plans dynamically according to the evolving user needs and changes. When the user's health concerns, dietary preferences, and tastes evolve, the system cannot adjust meal plans accordingly [6]. This is a major problem.

II. RELATED WORK

In recent years, personalized nutrition has emerged as a major trend in health management due to understanding among people that everyone is unique. This is supported by advancements in artificial intelligence, mobile health technologies, and data analytics. Personalized nutrition refers to tailoring dietary recommendations to an individual's biological characteristics, lifestyle, preferences, allergies, BMI and health goals. Unlike generalized dietary plans, which often overlook individual metabolic and behavioral differences and provide meal plans according to specific groups, personalized nutrition ensures that meal plans align with specific needs such as weight management, allergy avoidance, and nutrient balance. Traditional personal dietary recommendations frequently fail to achieve sustainable results because it assumes a “one-size-fits-all” model that does not consider genetic variation, activity levels, and environmental influences. It is often designed to target disease prevention or management [7].

Overall, the literature consistently demonstrates that adaptive, AI-powered meal planning systems outperform static approaches. However, a critical gap remains: no existing system integrates real-time within-day calorie redistribution, allergy constraint enforcement, and adherence prediction within a single unified application, which is the combination this study aims to deliver. Although numerous diet-related mobile applications exist, most of them are static in nature, providing meal recommendations that remain unchanged regardless of actual consumption patterns. The existing apps rely heavily on manual input and do not automatically update plans based on user behavior. While existing diet tracking apps are effective in monitoring consumption, they lack the ability to respond to real-time deviations. For example, when users exceed their lunch calorie goals, these apps fail to readjust dinner recommendations accordingly [8].

Furthermore, few studies have explored integrating AI models with contextual user data such as allergies, preferences, and emotional states, all of which significantly influence eating behavior. Another limitation in current research is the absence of systems capable of predicting adherence probability, that is, the likelihood that a user will follow a given meal plan. Incorporating machine learning models that learn from user compliance patterns could greatly improve long-term engagement.

III. Research Gap and Objectives

Recent work has begun to explore dynamic, adaptive food and meal recommendation. Amiri et al. demonstrated the effectiveness of flexible, real-time adaptive meal plans over static ones [6]. Similarly, Huynh and Hoang demonstrated the feasibility of AI-assisted adaptive recalculation of meal plans for conditions such as gestational diabetes [9]. While both studies demonstrate that adaptive meal recommendation is feasible, neither integrates real-time within-day calorie redistribution based on logged intake, allergy constraint enforcement, and image-based food recognition within a single unified mobile application, which remains the specific gap this study addresses.

Thus, this study aims to address these research gaps by developing a machine learning–driven, adaptive meal planning application that continuously updates calorie distribution and food recommendations according to user intake, preferences, and health goals. The system will go beyond basic calorie counting and serve as a personalized dietary assistant capable of learning and evolving with the user's habits.

General diet plans and diet recommendation applications fail to consider dynamically evolving user needs such as allergies, health concerns and dietary preferences which makes it difficult to find accurate, flexible and personalized diets for individuals who are highly health conscious. MyAiPlate aims to solve this problem by generating personalized meal plans using AI. The app considers the user's BMI, dietary preferences, allergies, fitness goals, and daily calorie needs to recommend suitable meals for breakfast, lunch, dinner, and snacks. The system automatically adjusts remaining meals if a user consumes extra calories earlier in the day, ensuring that the total daily calorie intake remains balanced.

The core objectives of this study are to evaluate existing diet planning systems and identify their limitations in personalization and adaptability; to develop an effective mechanism for capturing real-time user data, including BMI, allergies, preferences, and meal logs; to design and implement a mobile application that delivers dynamic dietary recommendations and intelligently adjusts caloric intake based on user behavior; and to assess and select suitable machine learning models for accurate prediction and adaptation of personalized meal plans. The application is intended to be used as an assistant to maintain a healthy lifestyle. It is not meant to be used as a replacement for any medical advice or diagnosis.

Stated explicitly, the objectives of this study are: (1) to design a hybrid LSTM-DQN reinforcement learning model capable of adapting future meal recommendations based on a user's logged intake and remaining calorie budget; (2) to fine-tune a YOLOv8 food-recognition model for automatic calorie estimation from meal images; (3) to evaluate both models quantitatively, including reward-based training analysis and before/after adaptation testing; and (4) to integrate these components into a single mobile application supporting real-time personalized nutrition guidance.

IV. Methodology

A. Research Approach

MyAiPlate is a mobile application that uses a machine learning technique to provide a solution to the problem of current static meal planning applications. It collects user profile information such as age, gender, height, weight, activity level, and dietary preferences and goals. It then calculates a daily meal plan based on user profile information using BMI and BMR calculations. Based on this calculation, it creates a meal plan consisting of breakfast, lunch, dinner, and snacks. The system leverages a hybrid pipeline combining an LSTM sequence encoder with a Deep Q-Network (DQN) to evaluate user habits alongside demographic states.

B. Research Design

The key aspect of MyAiPlate is its “Dynamic Adjustment Engine.” Once actual food consumed is logged into the program through various means like manual input, barcode recognition, and AI image recognition, it checks for actual and planned calories consumed per meal. Once it identifies a variance in consumed calories, it will redistribute the available calorific allowance for the day for future meals. This way, it will not let users stray from their calorific goals even if there is a deviation in calorific intake at noon. There are two actors in the system: User and Admin.

C. System Design and Architecture

The overall structure of the system, and the way the user, meal-log, food-recognition and chatbot inputs feed into the Dynamic Adjustment Engine, are shown in Fig. 1 and Fig. 2.

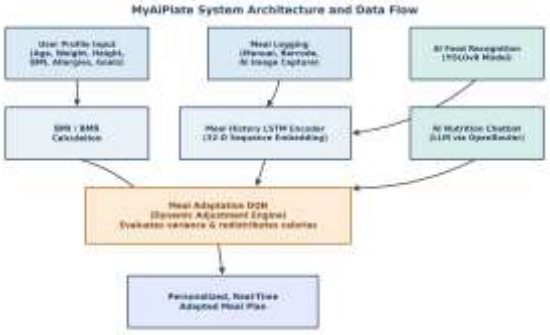


Fig. 1. System architecture and data flow of MyAiPlate, showing how user, meal-log, food-recognition, and chatbot inputs feed the LSTM/DQN Dynamic Adjustment Engine to produce the personalized meal plan.

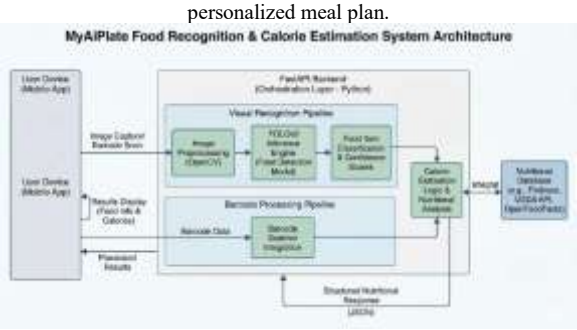


Fig. 2. Architecture diagram for AI processing – MyAiPlate Mobile Application

D. Model Architecture and Components

Meal History LSTM Encoder (MealHistoryLSTMEncoder): Type: Recurrent Neural Network (LSTM Layer). Function: Encodes a 5-step time-series sequence representing a user's chronological eating choices for a given meal category. Input Features: 5 dimensions per timestep, mapping Calories, Eaten food list and meal type. Hidden Representation: Outputs a 32-dimensional sequential feature embedding extracted from the final LSTM hidden state.

Meal Adaptation DQN (MealAdaptationDQN): Type: Feedforward Multi-Layer Perceptron (MLP) acting as a Deep Q-Network. Input Layer: Concatenates the 32-dimensional history vector with a 6-dimensional static feature vector detailing user demographics (Age, Weight, Height, BMI, Gender, and Activity Level) to create a 38-dimensional layer. Hidden Layers: Configured with two linear layers driven by ReLU activation functions: Fully Connected Layer 1 inputs 38 units and outputs 64 units; Fully Connected Layer 2 inputs 64 units and outputs 32 units. Output Head: A final linear projection layer calculating unique Q-values across 15 discrete actions, which map directly to a catalog of 15 targeted recipes (divided evenly among Breakfast, Lunch, and Dinner options).

The meal adaptation approach described above is referred to in this paper as a Hybrid LSTM-DQN Reinforcement Learning Model for Personalized Meal Adaptation. The architecture was designed specifically for this study by combining two established techniques, namely an LSTM for sequence-based meal-history representation, and a Deep Q-Network for reward-based meal-recommendation selection, inspired by standard LSTM sequence modelling and DQN reinforcement-learning approaches, then adapted to the meal-adaptation problem.

E. Machine Learning Methodology and Training Phases

The model undergoes an integrated, two-stage optimization cycle:

Phase 1: Supervised Pre-Training (Behavioral Cloning). Goal: Train the network to replicate meal patterns recorded in the synthetic logs. Loss Function: CrossEntropyLoss used to address classification selection. Optimization: Handled via the Adam optimizer set to a learning rate of 2e-3.

Phase 2: Interactive Environment and RL DQN Fine-Tuning. Goal: Adaptive policy tuning inside a simulated user landscape (MealSpecificEnv) where dynamic constraints filter selections to accommodate varying target calorie bounds. Loss Function: MSELoss evaluating the Mean Squared Error between temporal difference predictions and expected target Bellman values. Optimization: Driven by the Adam optimizer at a learning rate of 1e-4 over 300 simulation episodes. Exploration Strategy: An epsilon-greedy strategy initializes epsilon at 0.35, applying a decay rate of 0.98 per episode down to a baseline exploration minimum of 0.05. Experience Replay: A customized ReplayBuffer with a localized memory threshold of 500 records draws random mini-batches of size 16 to untangle temporal correlation errors. Stabilization Head: A dedicated target network tracks policy updates and mirrors the underlying network weights every 5 episodes to stop output variance oscillations.

F. Data Collection and Sampling Method

Dataset Preparation: Organized the training data into proper directory structures with train/test splits, ensuring the dataset covers a diverse range of food categories.

The synthetic dataset was generated to simulate realistic user meal-history patterns, comprising 30 synthetic user profiles over 40 days, with three meal logs per user per day (breakfast, lunch, dinner), producing 3,600 total meal-log records and 3,150 meal-history training samples using a history window of 5 previous meals across a 15-option meal action space. Each profile included age, gender, height, weight, BMI, and activity level. Meal selections and ratings were generated using preference weights, so that preferred meals were more likely to receive higher ratings, and were validated at a prototype level by checking that meal categories, calorie ranges, and macronutrients followed reasonable eating-pattern assumptions.

G. Technology Stack

Frontend: React Native (JavaScript). Backend: Node.js, Laravel. Database: MySQL. AI Inference: TensorFlow Lite (on device) and SVM on the backend.

Food Recognition and Calorie Estimation System. Tech stack: YOLOv8, Python, OpenCV (for image processing), Fast API (Backend API routing).

The food-recognition component was fine-tuned from pretrained YOLOv8n weights rather than trained from scratch, using an image size of 640, 50 training epochs, and a batch size of 16. The dataset comprised approximately 1,169 images across the five food classes listed above, split approximately 70:20:10 into training (814 images), validation (233 images, 319 labelled instances), and test (122 images) sets.

AI Nutrition Chatbot. Tech stack: OpenRouter (for LLM API routing), Transformer-based LLMs, Fast API (Backend API routing).

H. Model Evaluation Methodology

Two evaluation procedures were used to assess the meal adaptation model. First, reward-per-episode values were recorded throughout the 300-episode DQN fine-tuning stage to monitor whether the model was learning to select meal actions that satisfied calorie and meal-type constraints. Second, before/after adaptation testing was conducted by simulating changes in a user's logged intake and observing whether the system's recommendation for the next meal changed accordingly, in comparison to a static, rule-based planner that does not recalculate meal targets after logged intake. The YOLOv8 food-recognition model was evaluated using standard object-detection validation metrics (precision, recall, mAP@50, and mAP@50-95) computed on a held-out validation set.

I. Ethical Clearance Statement

This study did not involve human participants, human data, or animal subjects. The MyAiPlate application was developed and evaluated using internally generated synthetic user profiles and synthetic meal-logging data, and the AI components were tested using publicly available and internally curated food-image datasets. Accordingly, formal ethical clearance from an institutional ethics committee or review board was not required for this study.

J. Informed Consent

Not applicable. This study did not involve human participants, and no personal or identifiable data were collected from any individual during the design, development, or testing of the MyAiPlate application.

V. Results and Discussion

The findings of this study support the initial hypothesis that a dynamic, machine learning-driven meal planning system can outperform static diet applications by adjusting recommendations in real time based on user intake and preferences. Comprehensive testing was conducted throughout the development process, including unit testing, integration testing, system testing, and user acceptance testing. The testing results demonstrated that the system functions reliably and meets the specified functional and non-functional requirements, and user feedback indicated that the application is easy to use, informative, and beneficial for meal planning and nutritional awareness.

The system achieved an overall pass rate of 75.08% across 44 test cases. The core objectives of the research were achieved: food detection, meal recommendation, and the AI chatbot were all rated as achieved, as illustrated in the system architecture and workflow diagrams below.

Quantitative Model Evaluation. The following subsections report the quantitative evaluation of the two machine learning components underlying the Dynamic Adjustment Engine, namely the YOLOv8 food-recognition model and the hybrid LSTM-DQN meal adaptation model, in addition to the system-level test case results already summarized above.

YOLOv8 Food Recognition Evaluation. The fine-tuned YOLOv8n model was evaluated on a held-out validation set of 233 images (319 labelled food instances) across five food classes (Apple, Banana, Fried Chicken, Fried Egg, Rice), following a 70:20:10 train/validation/test split of a 1,169-image dataset. The model achieved 95.16% precision, 94.42% recall, 97.51% mAP@50, and 75.57% mAP@50-95 on the validation set (Table I). Per-class mAP@50-95 scores were: Apple 76.36%, Banana 72.32%, Fried Chicken 79.75%, Fried Egg 76.65%, and Rice 72.78% (Table II). These results indicate that the fine-tuned model generalized well across all five food classes, with Fried Chicken achieving the strongest per-class performance.

TABLE I. YOLOv8 Validation Metrics

Metric	Value
Precision	95.16%
Recall	94.42%
mAP@50	97.51%
mAP@50-95	75.57%

TABLE II. Per-Class mAP@50-95

Class	mAP@50-95
Apple	76.36%
Banana	72.32%
Fried Chicken	79.75%
Fried Egg	76.65%
Rice	72.78%

Meal Adaptation Model Evaluation (DQN Training). The DQN component of the meal adaptation model was fine-tuned for 300 episodes, with reward values recorded throughout training. The recorded reward rose from −3.00 at episode 20 to a peak of 1.27 at episode 160, before settling to a lower but still positive reward by episode 300 (Fig. 3). This progression indicates that the model learned to select meal actions that better satisfied the reward function's calorie and meal-type constraints, though the reward curve was not perfectly smooth, which is expected in a

small-scale reinforcement-learning simulation. The supervised behavioral-cloning pretraining stage, used to initialize the DQN before reinforcement-learning fine-tuning, reached a final CrossEntropyLoss of approximately 2.70 and a preference-prediction accuracy of approximately 7.90%. This accuracy is low in absolute terms, but is consistent with the difficulty of the 15-way meal-action classification task at this pretraining stage; the pretraining phase was intended only to initialize network weights, with the model's adaptive behaviour developed during the subsequent DQN reward-based fine-tuning stage rather than during pretraining.

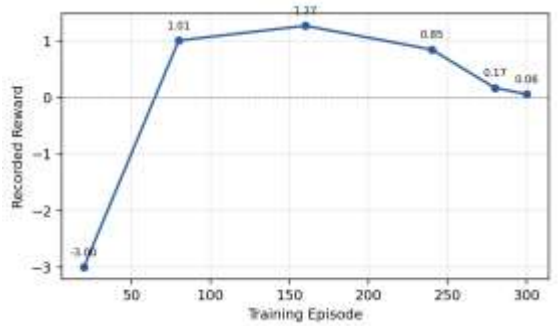


Fig. 3. DQN reward per episode during fine-tuning (episodes 20–300).

Before/After Adaptation Testing. To confirm that the system produces dynamic rather than static recommendations, before/after testing was conducted by comparing the model's output against a static, rule-based planner under identical conditions (Table III). In a static planner, meal targets remain fixed regardless of actual intake. Under the adaptive approach, when a user's logged lunch intake increased from an expected 667 kcal to an actual 900 kcal against a 2000 kcal daily target, the remaining calorie allowance fell to 211 kcal, and the system's dinner recommendation was reduced accordingly from 444 kcal to 211 kcal, a 233 kcal adjustment that a static planner would not have made. A second test simulated overeating at breakfast (1,100 kcal against an original 800 kcal target); the system proportionally reduced the remaining lunch, dinner, and snack targets from 600/400/200 kcal to 450/300/150 kcal to keep the user closer to the 2000 kcal daily goal. These results demonstrate that the model responds to logged user behaviour in real time, directly addressing the adaptive-recommendation capability that motivated this research.

TABLE III. BEFORE/AFTER ADAPTATION TEST EXAMPLES

Scenario	Before	After
Lunch 667→900 kcal: Dinner target	444 kcal	211 kcal
Breakfast 800→1100 kcal: Lunch target	600 kcal	450 kcal
Breakfast 800→1100 kcal: Dinner target	400 kcal	300 kcal
Breakfast 800→1100 kcal: Snack target	200 kcal	150 kcal

Modules with well-defined, structured inputs (Health Profile & BMI Calculation, Dashboard & Analytics, and the Backend API & MySQL Database) achieved a 100% pass rate, reflecting the deterministic nature of these components. In contrast, the Dynamic Calorie Adjustment module recorded the lowest pass rate (60.00%), and the AI Food Recognition and AI Nutrition Chatbot modules each recorded 75.00%. These lower rates are consistent with the challenges reported during development: dataset limitations arising from limited Sri Lankan food data, difficulty obtaining accurate nutritional data, the trade-off between speed and accuracy in AI model optimization, and difficulty maintaining chatbot context relevance. This suggests that the components relying on external or incomplete data sources, rather than deterministic logic, are the primary source of remaining system failures, and should be prioritized in future refinement.

These results relate directly to the research gap identified in the literature: prior systems have demonstrated adaptive or real-time meal planning individually, but no existing system was found to integrate real-time within-day calorie redistribution, allergy constraint enforcement, and adherence prediction within a single unified application. The successful implementation and testing of the Dynamic Adjustment Engine, alongside the AI-based food recognition and chatbot components, indicates that this combination is feasible within a single mobile application, supporting the direction proposed in prior work on adaptive, AI-powered meal planning over static approaches.

The findings should nonetheless be interpreted with some caution. The 60.00% pass rate for Dynamic Calorie Adjustment indicates that the core adaptive mechanism of the system requires further refinement before it can be considered fully reliable. In addition, the limitations identified during development (limited local food coverage, dependency on internet connectivity, and limited capacity for medical diagnosis) constrain the contexts in which the system can currently be deployed with confidence, particularly for users with region-specific diets or restricted connectivity.

A. Benefits of MyAiPlate

Personalized nutrition guidance; improved dietary awareness; automated meal planning; real-time food recognition. Overall, despite the limitations identified above, the results indicate that MyAiPlate achieves its stated objectives and provides evidence that adaptive, AI-driven meal planning offers benefits over static diet-tracking approaches, consistent with the broader trend reported in the personalized nutrition literature.

VI. CONCLUSION

This research successfully developed MyAiPlate, an AI-powered nutrition and meal planning application designed to help users make healthier dietary choices through personalized recommendations and intelligent nutritional guidance. The developed solution enables users to create and manage personal health profiles, generate customized meal plans, track daily nutritional intake, recognize food items using image-based food detection, and interact with an AI-powered nutrition chatbot.

Overall, the objectives defined at the beginning of the research were successfully achieved. The before/after adaptation tests reported in Section V provide direct evidence that dynamic dietary recommendation was achieved rather than only proposed: the Dynamic Adjustment Engine recalculated the remaining meal targets in response to logged intake, whereas a static planner would have left them unchanged. This extends the adaptive meal-planning approaches of Amiri et al. [6] and Huynh and Hoang [9] by combining within-day calorie redistribution with image-based food recognition inside a single mobile application, addressing the gap identified in [8]. The final product demonstrates the potential of artificial intelligence and machine learning technologies in supporting personalized nutrition management and promoting healthier eating habits. Future enhancements identified for the system include smartwatch and fitness tracker integration, voice assistant support, a grocery list generator, multi-language support, micronutrient optimization, health risk prediction, and wearable device integration.

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Conflict of Interest Statement. The authors declare that they have no conflict of interest.

Data Availability Statement. The synthetic datasets used to train and evaluate the machine learning components of this study (including the meal-logging sequences used for the LSTM/DQN models and the food-image dataset used to fine-tune the YOLOv8 model) were developed internally for this research. As they were generated specifically for this study and are not part of a public repository, they are not publicly available but can be made available by the corresponding author upon reasonable request.

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