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Healthy Food Recommendation System Using LLM

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Abstract

Healthy eating plays an important role in preventing chronic diseases and maintaining overall well-being. However, many individuals experience difficulties in selecting foods that match their nutritional needs, health conditions, and dietary goals. This study proposes a Healthy Food Recommendation System that utilizes the QWEN Large Language Model (LLM) to provide personalized food recommendations through an interactive conversational interface. The system integrates user profile information, nutritional intake tracking, and artificial intelligence-based consultation to support informed dietary decision-making. This paper applies a user-centered approach that combines nutritional monitoring and LLM-driven recommendation generation. The system records daily calorie, protein, carbohydrate, and fat consumption while allowing users to consult an AI-powered Chat Coach for personalized dietary guidance. To evaluate system reliability, we conducted negative testing on four critical functional components, including authentication validation, user profile validation, nutritional data validation, and AI query restriction validation. The experimental results demonstrate that the proposed system successfully handled all invalid scenarios and achieved a 100% pass rate across all test cases. These findings indicate that the proposed system maintains data integrity, enforces functional requirements, and provides reliable user interactions. The integration of QWEN LLM further enhances the system by delivering personalized and context-aware food recommendations. Therefore, the proposed approach offers a practical solution for intelligent dietary assistance and healthy lifestyle management.

Keywords:
Healthy Food, Recommendation System, LLM, Dietary.

1. Introduction

The increasing prevalence of chronic diseases, unhealthy eating habits, and nutritional imbalance creates a growing demand for intelligent food recommendation systems. Many individuals struggle to select appropriate foods that align with their health conditions, dietary restrictions, and nutritional requirements. Conventional recommendation systems often rely on static nutritional databases or simple collaborative filtering techniques that fail to consider dynamic user preferences and health contexts. Recent advances in artificial intelligence, particularly deep learning, provide new opportunities to develop personalized dietary recommendation systems that can analyze complex relationships among food attributes, user behavior, nutritional values, and health conditions. Consequently, researchers increasingly explore deep learning approaches to improve recommendation accuracy and support healthier food choices. [1], [6], [9], [11], [17]

Food recommendation differs significantly from traditional recommendation domains such as movies or books because food preferences frequently change according to time, location, emotional state, physical condition, and nutritional needs. Existing systems often neglect these contextual factors, resulting in recommendations that lack relevance and personalization. To address this limitation, several studies introduce context-aware and time-aware recommendation frameworks. Boddupally et al. propose a time-aware food recommender system that integrates graph clustering and deep learning to model changing

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user preferences over time. Similarly, MenuAI utilizes transformer-based architectures to combine contextual information and nutritional requirements when recommending restaurant dishes. These studies demonstrate that incorporating temporal and contextual information can significantly enhance recommendation quality and user satisfaction. [1], [9], [19]

The rapid development of computer vision technologies further transforms food recommendation research. Traditional systems depend heavily on manually entered dietary information, which often introduces user burden and reporting errors. Recent studies employ image recognition models to automatically identify foods and estimate nutritional content from images. Cheng et al. develop a multimodal nutritional advisory system that combines food recognition, volume estimation, and dietary recommendation. Gopinath et al. propose a glycemic-index-based recommendation framework that identifies foods through image classification and generates healthier alternatives for diabetic patients. These advancements reduce the need for manual input while improving the practicality of real-world dietary monitoring systems. [2], [6], [12]

Personalized nutrition represents another major research direction in intelligent food recommendation systems. Different individuals require different dietary plans according to age, gender, health status, disease history, and lifestyle patterns. Researchers increasingly integrate health information into recommendation models to provide customized dietary guidance. Saravanan et al. utilize smartwatch and barcode data to generate personalized dietary recommendations for diabetic patients. Valluru et al. develop a deep learning framework for menstrual nutrition recommendations using optimized feature selection techniques. Lawdi and Boonnam also demonstrate that machine learning algorithms can effectively support dietary interventions for managing non-communicable diseases. These studies highlight the importance of combining health-related data with recommendation algorithms to achieve meaningful personalization. [8], [17], [20]

The emergence of multimodal learning significantly improves the capability of recommendation systems to understand food-related information. Modern systems process diverse data sources such as images, nutritional databases, ingredient lists, text descriptions, and user preferences simultaneously. Koreddi et al. introduce a multimodal framework that integrates computer vision, natural language processing, knowledge graphs, and transformer models for recipe recommendation. Ingredient detection systems developed by D. P. et al. and visual ingredient prediction models proposed by Theera-Ampornpunt and Treepong further demonstrate the effectiveness of image-based ingredient understanding. These approaches enable recommendation systems to capture richer semantic information and generate more accurate recommendations. [10], [15], [18]

Recent studies also reveal the growing role of advanced deep learning architectures in enhancing recommendation performance. Transformer models, graph neural networks, reinforcement learning, and multimodal neural networks demonstrate superior capability in learning complex user-food relationships. MenuAI employs transformer-based ranking models to recommend restaurant dishes according to nutritional goals. Tellechea et al. investigate reinforcement learning for population-level food recommendation and show that adaptive recommendation policies can effectively model user preferences. Meanwhile, recipe recommendation research increasingly incorporates graph neural networks and LLMs to generate more personalized and context-aware outputs. These developments indicate a shift from conventional recommendation methods toward more intelligent and adaptive deep learning frameworks. [9], [10], [19], [21]

Despite significant progress, several challenges remain unresolved. Many food recommendation systems focus primarily on recommendation accuracy while overlooking explainability, nutritional safety, long-term health impact, and user trust. Data scarcity, class imbalance, incomplete nutritional information, and limited multimodal datasets also affect model performance. Furthermore, many existing studies evaluate their models using laboratory datasets rather than real-world environments. Research on automated nutrient deficiency detection and nutritional advisory systems indicates that integrating multiple data modalities remains technically challenging. Consequently, developing robust, interpretable, and scalable recommendation systems continues to be an important research objective. [2], [16], [18], [21]

The success of deep learning in related domains further supports its application in food recommendation systems. Studies in agriculture demonstrate that deep learning can achieve high performance in disease classification, treatment recommendation, crop recommendation, and nutrient analysis. AgroSense integrates image-based soil classification with nutrient profiling to recommend crops accurately. Similar success appears in plant disease detection and treatment recommendation systems that employ convolutional neural networks and multimodal learning frameworks. These findings suggest that deep learning effectively captures complex relationships among heterogeneous data sources and can be extended to food recommendation tasks. Therefore, further research is needed to develop integrated food recommendation systems that combine nutritional knowledge, user health profiles, contextual information, and multimodal deep learning techniques to deliver accurate, personalized, and health-oriented recommendations. [3], [5], [7], [13], [14].

2. Related Works

Recent studies investigated the application of deep learning to personalized food recommendation systems. Boddupally et al. [1] developed a time-aware food recommender system that combined deep learning with graph clustering techniques. Their model captured changes in user preferences over time and improved recommendation relevance. The study demonstrated better performance than conventional recommendation approaches when evaluated using real-world datasets. However, the system primarily focused on temporal preference modeling and did not incorporate nutritional information, health conditions, or food image analysis. This limitation reduced its applicability in personalized healthcare and dietary management scenarios.

Researchers also explored contextual and nutrition-aware recommendation frameworks. Ju et al. [9] proposed MenuAI, a restaurant food recommendation system that employed optical character recognition and transformer-based learning-to-rank models. The system extracted menu information from images and ranked food items according to nutritional requirements. The study successfully integrated contextual information and dietary preferences into the recommendation process. Nevertheless, the framework relied heavily on menu text extraction and restaurant environments. It provided limited support for home-based dietary planning and direct food recognition from food images. Similar limitations appeared in the recipe recommendation survey conducted by B. M. et al. [21], which highlighted the growing importance of personalization but lacked implementation details for real-world healthcare applications.

Several studies focused on image-based food understanding to improve recommendation accuracy. Cheng et al. [2] proposed a multimodal nutritional advisory system that combined food classification, volume estimation, nutritional analysis, and dietary recommendation. The framework utilized a fine-tuned CLIP model and a LLM to generate personalized dietary advice. The study demonstrated the effectiveness of multimodal learning in dietary assessment. Similarly, Gopinath et al. [6] developed a glycemic-index-based food recommendation system that identified foods from images and suggested healthier alternatives for diabetic patients. Although both studies achieved promising results, they primarily emphasized nutritional assessment rather than comprehensive recommendation strategies that considered broader user preferences and behavioral factors.

Personalized nutrition recommendation emerged as another important research direction. Saravanan et al. [17] designed a dietary recommendation framework for diabetic patients using smartwatch and barcode data. The system employed neural networks to estimate glycemic risk levels and recommend suitable food products. Valluru et al. [20] proposed an optimized deep learning framework for menstrual nutrition recommendation using Opposition Learning-Based Red Panda Optimization. Their model improved prediction accuracy while reducing computational complexity. These studies demonstrated the value of integrating health-related information into recommendation systems. However, both frameworks targeted specific health conditions and lacked generalization across diverse user populations and dietary requirements.

Researchers also investigated multimodal recipe recommendation systems. Koreddi et al. [10] introduced a framework that integrated computer vision, natural language processing, knowledge graphs, graph neural networks, and transformer models. Their system performed ingredient detection, recipe generation, and personalized recommendation within a unified architecture. Similarly, D. P. et al. [15] utilized YOLOv8 for ingredient recognition and machine learning algorithms for recipe recommendation. Both studies achieved high prediction performance and demonstrated the benefits of combining image analysis with recommendation models. However, their systems focused primarily on recipe generation and ingredient matching. They paid less attention to nutritional optimization and health-aware personalization.

Recent studies further explored advanced machine learning and reinforcement learning approaches for recommendation tasks. Lawdi and Boonnam [11] compared several machine learning algorithms for personalized food recommendation in non-communicable disease management. Their results showed that Random Forest achieved the highest predictive accuracy among evaluated methods. Tellechea et al. [19] investigated reinforcement learning for population-level food recommendation and demonstrated that adaptive recommendation policies could effectively model dietary preferences. These studies improved understanding of recommendation strategies. Nevertheless, they relied largely on structured datasets and did not fully exploit multimodal information such as images, ingredient compositions, and contextual user behavior.

Several supporting studies examined nutritional assessment and food ingredient understanding using deep learning. Rojanaphan [16] reviewed automated nutrient deficiency detection systems that integrated food images, dietary records, biomarkers, and natural language processing techniques. The study emphasized the importance of multimodal data integration in nutrition science. Theera-Ampornpunt and Treepong [18] proposed a direct F-score optimization framework for visual ingredient prediction and achieved significant improvements on the Recipe1M dataset. These findings demonstrated the growing capability of deep learning models to extract meaningful nutritional information from visual content. However, the studies mainly addressed classification and prediction tasks rather than end-to-end recommendation generation.

Deep learning applications in agriculture also provided valuable insights for recommendation system development. Pandey et al. [14] introduced AgroSense, which integrated soil image analysis and nutrient profiling for crop recommendation. Chelamala et al. [3], Farande et al. [5], Hemkumar et al. [7], and Joseph and Srinitya [8] developed disease detection and treatment recommendation systems using convolutional neural networks and deep learning frameworks. These studies achieved high classification accuracy and demonstrated the effectiveness of combining image recognition with recommendation engines. Although their application domains differed from food recommendation, they confirmed that deep learning models effectively processed heterogeneous data and generated decision-support recommendations. These findings suggested that similar multimodal approaches could enhance future food recommendation systems by integrating user profiles, nutritional information, visual food data, and contextual factors into a unified recommendation framework.

3. Proposed Method

1. User Profile Representation

In this study, a user profile is represented as:

$$u = [a, w, h, p, c]$$

where a = age, w = weight, h = height, p = physical activity level, and c = health condition.

2. BMI Calculation

The system estimates the user's body mass index:

$$BMI = \frac{w}{h^2} \tag{1}$$

where w is in kilograms and h is in meters.

3. Nutritional Matching Score

For each food item f, the nutritional suitability score is computed as:

$$S_f = 1 - \frac{1}{m} \sum_{i=1}^{m} \left| \frac{R_i - N_{fi}}{R_i} \right| \tag{2}$$

where R_i is the recommended nutrient value and N_{fi} is the nutrient value of food f.

4. Health Penalty

Foods that violate health restrictions receive a penalty:

$$P_f = \sum_{j=1}^{k} \lambda_j v_j \tag{3}$$

where v_j indicates a violation and λ_j is the penalty weight.

5. Final Recommendation Score

The final ranking score is:

$$R_f = S_f - \alpha P_f \tag{4}$$

where α controls the influence of health penalties.

6. QWEN LLM Recommendation Generation

The top-ranked foods are provided to QWEN LLM:

$$Y = \text{QWEN}(u, F_{top}, N) \tag{5}$$

where u is the user profile, F_{top} is the set of top-ranked foods, and N is nutritional information.

The QWEN model generates personalized healthy food recommendations, explanations, and alternative food options in natural language.

This study employed a lightweight mathematical scoring mechanism before invoking the QWEN LLM. The nutritional suitability score measured the similarity between user nutritional requirements and food nutrient composition, while a health penalty reduced the scores of foods that violated medical or dietary restrictions. The final recommendation score was used to rank candidate foods, and the top-ranked foods were provided to QWEN LLM to generate personalized healthy food recommendations and explanations.

4. Result and Analysis

A. Functionality

Fig. 1 illustrates the main dashboard of the proposed Healthy Food Recommendation System. The Total Calories section summarizes the user's daily nutritional intake, including total calories, protein, carbohydrates, and fat, based on records entered through the Track feature. This information enables users to monitor their dietary consumption and evaluate their nutritional balance throughout the day. In addition, the Quick Actions section provides direct access to the system's primary functions, thereby improving navigation efficiency and enhancing the overall user experience.

The dashboard also integrates the Chat Coach feature, which serves as an interactive nutritional assistant powered by the QWEN LLM. Through this feature, users can engage in natural language conversations to obtain personalized food recommendations based on their health conditions, dietary goals, nutritional requirements, and food preferences. The Chat Coach analyzes user-provided information and generates tailored dietary suggestions, enabling users to make informed nutritional decisions in a more interactive and user-friendly manner.

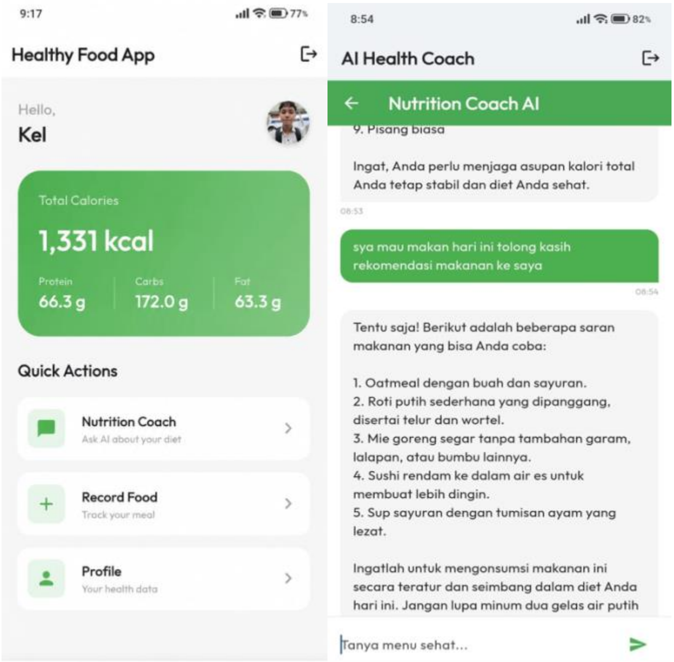

Fig. 1 Main dashboard of the proposed Healthy Food Recommendation

B. System Functionality and Negative Testing Results

Table 1 presents the results of negative testing conducted to evaluate the robustness of the proposed Healthy Food Recommendation System. The tests focused on invalid user inputs, incomplete data submissions, and misuse of the AI consultation feature. The system successfully detected and handled all invalid scenarios, resulting in a 100% pass rate.

Table 1. Negative Testing Results

No.	Test Scenario	Expected Result	Actual Result	Status
1	Login using an unregistered account or incorrect credentials	The system rejects access and displays an authentication error message.	The system displayed an alert indicating that the account credentials were invalid.	Pass
2	Register an account with missing mandatory physical attributes (e.g., weight or height)	The system prevents registration and requests complete user information.	Form validation blocked the registration process and highlighted the missing required fields.	Pass
3	Submit food tracking data with missing or invalid nutritional values (calories, protein, fat, or carbohydrates)	The system rejects the submission and requests valid nutritional values.	The system prevented data storage and displayed a validation warning to complete all nutritional fields correctly.	Pass
4	Submit prompts unrelated to food, nutrition, or dietary consultation through the AI assistant	The AI assistant restricts responses to nutrition-related topics only.	The AI assistant informed users that its functionality is limited to food, diet, and nutrition consultations.	Pass

The results indicate that the system effectively handled authentication errors, incomplete user profiles, invalid nutritional inputs, and inappropriate AI queries. All test cases produced the expected outcomes, demonstrating the reliability and robustness of the proposed system in preventing invalid operations and maintaining data integrity.
Negative Testing Results

Or for publication:

- X-axis: Test Status (Pass, Fail)
- Y-axis: Number of Test Cases
- Values: Pass = 4, Fail = 0

Table 2. Test Case Validation Coverage

Test Category	Result
Authentication Validation	Pass
User Profile Validation	Pass
Nutritional Data Validation	Pass
AI Query Restriction Validation	Pass

This can be visualized as a horizontal bar chart showing 100% success for each validation category. This graph is generally more informative for software engineering and AI system evaluation papers than a simple pass/fail chart because it demonstrates which functional modules were tested.

5. Conclusion

This paper developed and evaluated a Healthy Food Recommendation System that integrates nutritional tracking and an AI-powered consultation feature based on the QWEN LLM. We utilized user profile information, nutritional records, and natural language interactions to provide personalized dietary recommendations. The proposed system also incorporated input validation and access control mechanisms to ensure data quality and system reliability. The implementation demonstrated that the system could effectively support users in monitoring their nutritional intake while receiving personalized food recommendations through an interactive conversational interface.

The testing results confirmed the robustness of the proposed system. We conducted negative testing on four critical functional components, including authentication validation, user profile validation, nutritional data validation, and AI query restriction validation. All test cases achieved the expected outcomes, resulting in a 100% success rate. The system successfully rejected invalid login attempts, prevented incomplete user registrations, blocked incorrect nutritional data submissions, and restricted the AI assistant from responding to queries unrelated to food and nutrition. These findings indicate that the system effectively handled invalid operations and maintained data integrity throughout the user interaction process.

The results demonstrate that the proposed Healthy Food Recommendation System can provide reliable and secure dietary support while maintaining consistent system performance. We showed that the integration of QWEN LLM enhanced user engagement by enabling personalized and context-aware nutritional consultations. Furthermore, the successful validation of all tested functionalities confirms the practicality of the proposed approach for real-world deployment. Future work may incorporate additional health indicators, food image recognition, and adaptive recommendation algorithms to further improve recommendation accuracy and personalization capabilities.

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