International Journal of Emerging Research in Science, Engineering, and Management
Vol. 1, Issue 6, pp.44-54, December 2025.
www.ijersem.com eISSN- 3107-9075

AI-based Food Recognition and Nutrient Prediction

[1]A. Surekha, [2]P Aswini, [3]M Shavan Kumar, [4]V Manisha, [5]V Nagendra Reddy, [6]B Nithin Kumar Reddy

Department of CSE, Siddartha Institute of Science and Technology, Puttur, India.
[1]surekhavitw530@gmail.com, [2]aswinisistk06@gmail.com, [3]shavank289@gmail.com, [4]venkateswarlumanisha@gmail.com, [5]visvanagendra@gmail.com, [6]nithinkumarreddy1730@gmail.com

Abstract: Accurate food recognition and nutrient estimation are critical for practical dietary assessment, health monitoring, and personalized nutrition management. Traditional calorie tracking methods rely heavily on manual input and self-reporting, which are often inaccurate, time-consuming, and inconsistent. Existing AI-based food recognition systems primarily rely on basic convolutional neural networks and two-dimensional image analysis, limiting their ability to identify complex, mixed, and regional dishes and failing to estimate portion sizes accurately. These limitations significantly reduce their practical applicability, particularly for diverse cuisines such as Indian food. To address these challenges, this project presents Nutri Vision, an AI-driven framework for food recognition, portion size estimation, nutrient prediction, and personalized dietary guidance. The proposed system integrates advanced deep learning models including YOLOv8, Vision Transformers, and Region-Based Convolutional Neural Networks to accurately detect and classify multiple food items from a single image. Portion size estimation is achieved using pixel-to-gram conversion and depth-aware analysis, enabling reliable calorie and nutrient computation through integrated food databases. Furthermore, machine-learning-based decision models are employed to generate personalized diet recommendations and healthier food alternatives based on users' goals and health conditions. The system delivers real-time, culturally adaptive, and scalable nutrition insights with high accuracy, making it suitable for applications in healthcare, fitness management, and nutrition research.

Keywords: Artificial Intelligence, Calorie Estimation, Food Recognition, Nutrient Prediction, Vision Transformers

1 INTRODUCTION

Recent advances in artificial intelligence (AI) and deep learning have significantly transformed food analysis by enabling automated food recognition and nutrient estimation from images. Conventional dietary assessment methods, such as manual food logging and self-reported intake, are often inaccurate and inconsistent due to reliance on users and estimation errors. To overcome these limitations, AI-based food recognition systems have been increasingly adopted to provide objective and scalable nutritional assessment solutions [1]. Deep learning models, particularly convolutional neural networks and vision-based architectures, have demonstrated strong performance in food category recognition and nutrient prediction. Studies show that these models can effectively learn visual features from food images and map them to nutritional information using integrated food databases. However, most existing systems are trained on limited datasets and primarily focus on western or straightforward food categories, making them less effective for complex and regional cuisines [2]. Accurate estimation of portion sizes remains a critical challenge in image-based nutrition analysis. Many current approaches rely solely on two-dimensional image analysis, which fails to capture food volume and depth, leading to significant errors in calorie estimation [3]. Recent research emphasizes integrating advanced computer vision techniques and intelligent models to improve the accuracy and overall reliability of nutrient prediction systems.

In addition to food recognition and calorie estimation, personalized nutrition has gained increasing attention in recent years. AI-driven decision models and intelligent recommendation systems enable personalized dietary guidance tailored to individual health conditions, dietary habits, and nutritional goals. Such systems have shown strong potential in healthcare and fitness applications by supporting personalized and data-driven dietary decision-making [4]. Motivated by these research advances, this project proposes Nutri Vision, an AI-based framework for food recognition, portion-size estimation, nutrient prediction, and personalized dietary guidance. The system integrates advanced object detection models, vision transformers, and machine learning-based recommendation techniques to deliver accurate, culturally adaptive, and real-time nutrition insights.

2 Literature Survey

The integration of artificial intelligence with advanced analytical techniques has significantly improved food component analysis and nutritional assessment. Cao *et al.* proposed a synergistic approach that combines AI with Nuclear Magnetic Resonance (NMR) spectroscopy to enhance the identification of food components. Their study demonstrated that AI-driven pattern recognition improves the accuracy and efficiency of nutrient profiling, enabling reliable analysis of complex food matrices [1].

As intelligent food systems evolve, Yakoubi introduced an Industry 5.0 paradigm emphasizing human-centered and AI-enabled food manufacturing. The study focused on AI-based digitization of nano-scale smart nutrient carriers, highlighting the role of intelligent systems in personalized nutrition and sustainable food production. This work underlines the importance of adaptive and human-centric AI models in next-generation nutrition technologies [2]. Zheng *et al.* conducted a comprehensive scoping review on artificial intelligence applications for measuring food and nutrient intake. Their findings show that AI-based dietary assessment tools reduce human bias and manual errors compared to traditional self-reporting methods. However, the study also identified challenges related to dataset diversity, mixed-meal recognition, and deployment in real-world conditions [3].

In the context of sustainable agri-food systems, Nath *et al.* reviewed recent advances in AI technologies applied to food quality assessment, nutrient prediction, and supply chain optimization [4]. Their work emphasized that machine learning and deep learning models contribute to both nutritional accuracy and environmental sustainability, reinforcing the relevance of AI in modern food systems [4]. Extending nutrient monitoring to agricultural applications, Bharti *et al.* explored nano-biosensors for real-time tracking of plant nutrient levels [5]. Their research demonstrated that intelligent sensing technologies combined with AI enable precise nutrient monitoring. Although focused on agriculture, the study suggests that similar AI-assisted techniques can enhance nutrient estimation in consumer-level food analysis systems. Explainability has become a critical requirement in AI-driven nutrition systems, particularly in healthcare applications. Di Martino *et al.* proposed explainable AI models for malnutrition risk prediction using mobile health and clinical data [6]. Their work highlighted the importance of transparency and interpretability in AI systems to improve trust, usability, and clinical decision-making.

Deep learning approaches have shown strong performance in food image recognition tasks. Zhang *et al.* investigated deep learning models for food category recognition and reported significant improvements in classification accuracy over traditional image processing methods. Their findings confirm that deep neural architectures are effective for recognizing visually complex food items [7]. The real-world applicability of AI-based food recognition systems has also been evaluated. Lozano *et al.* validated an AI-based mobile application that identifies food items and estimates energy intake [8]. While promising results were achieved under controlled conditions, the study reported reduced performance in real-world scenarios involving poor lighting, occlusion, and complex food presentations [9]. Ingredient-level nutrient estimation has been explored to improve nutritional accuracy [10]. Ma *et al.* demonstrated that deep learning models can accurately predict food categories and nutrient values from ingredient lists [11]. Their work suggests that integrating ingredient-level analysis with visual recognition can significantly improve the accuracy of nutrient prediction. Early studies on mobile-based food recognition systems were conducted by Knez and Šajn, who evaluated food object recognition using mobile devices [12]. Their study identified limitations related to computational efficiency, dataset constraints, and reduced recognition accuracy in real-world environments. These findings highlight the need for robust, scalable, and adaptive AI-based food recognition frameworks

3 Problem Statement

Accurate dietary assessment is essential for effective nutrition monitoring, disease prevention, and personalized health management. However, existing food recognition and calorie estimation systems predominantly rely on manual food logging or fundamental image-based analysis, both of which are prone to inaccuracies and user dependence. Conventional methods fail to provide reliable nutrient estimates due to subjective portion-size reporting, inconsistent food descriptions, and limited user compliance. Most current AI-based food recognition systems utilize standard convolutional neural networks trained on generic datasets. These systems struggle to accurately recognize complex, mixed, and culturally diverse dishes, particularly regional foods with similar visual characteristics and hidden ingredients such as oils, spices, and condiments. Additionally, many approaches rely solely on two-dimensional image analysis, lacking depth and volume information, leading to significant errors in portion size and calorie estimation.

Furthermore, existing solutions provide limited or no personalized dietary guidance. While some applications estimate calorie intake, they do not consider individual user profiles, health conditions, dietary preferences, or nutritional goals. The absence of adaptive learning and explainable recommendation mechanisms reduces their effectiveness in healthcare and fitness applications. Real-time performance, scalability, and robustness under varying lighting and environmental conditions also remain significant challenges. Therefore, there is a critical need for an intelligent, automated, and scalable nutrition analysis system that accurately recognizes complex food items, estimates portion sizes and nutrient content, and delivers personalized dietary recommendations. Such a system must integrate advanced deep learning techniques, reliable portion-estimation methods, and machine-learning-based decision models to support accurate, real-time, and culturally adaptive dietary assessment.

4 PROPOSED SYSTEM

The proposed Nutri Vision system is an intelligent AI-based framework for automated food recognition, portion-size estimation, nutrient prediction, and personalized dietary recommendations. The methodology integrates advanced deep learning models for visual analysis, computer vision techniques for portion estimation, and machine learning algorithms for nutrition-based decision making. The system aims to provide accurate, real-time, and culturally adaptive nutrition insights from food images.

4.1 System Overview

The proposed system follows a modular architecture comprising image acquisition, preprocessing, food recognition, portion-size estimation, nutrient prediction, and personalized diet recommendation modules. Food images captured using a mobile or web-based interface are processed through deep learning models to identify multiple food items on a single plate. Detected food items are then analyzed for portion size, calorie content, and nutritional composition using integrated food databases.

The overall methodology focuses on:

- Automated multi-food recognition from a single image
- Accurate portion size estimation using vision-based techniques
- Reliable calorie and nutrient prediction
- Personalized dietary recommendations based on user profiles

The complete system workflow is illustrated in the block diagram shown in Fig. 1.

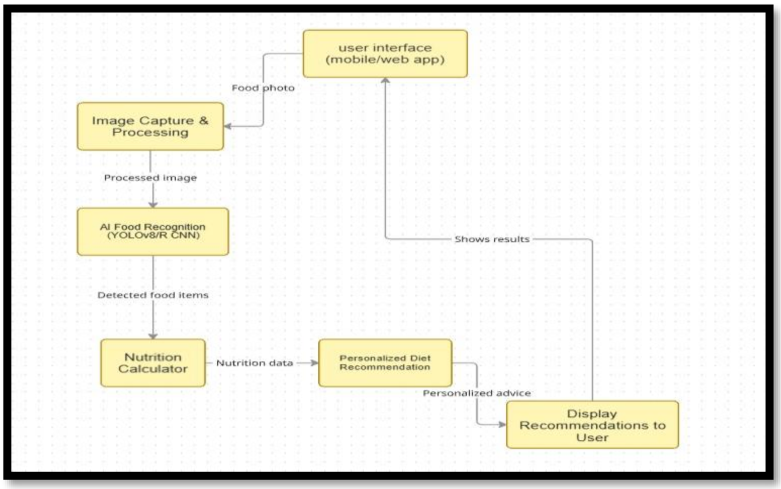

Fig. 1. block diagram

4.2 Image Acquisition and Preprocessing

Food images are captured using a smartphone or camera under normal lighting conditions. The acquired images are resized and normalized to match the input dimensions required by the deep learning models. Image preprocessing techniques such as noise reduction, contrast enhancement, and color normalization are applied to improve visual quality and robustness under varying environmental conditions.

4.3 Food Recognition Using Deep Learning Models

Food recognition is performed using advanced object detection and classification models such as YOLOv8, Vision Transformers (ViT), and Region-Based Convolutional Neural Networks (R-CNN). These models enable accurate detection and classification of multiple food items from a single image, including complex and mixed dishes. For each detected food item, bounding boxes are generated, and classification confidence scores are computed. YOLOv8 enables real-time detection with high precision, while Vision Transformers improve contextual understanding by modeling global dependencies across image patches.

4.4 Portion Size Estimation

Accurate portion-size estimation is achieved through pixel-to-gram conversion and depth-aware analysis. The detected food region area in pixels is converted into real-world measurements using calibration factors. The volume of the food item is estimated as:

$$V = A \times H$$

where:
V= Estimated food volume
A= Area of detected food region
H= Estimated height or depth of the food
The food weight is then calculated as:

$$W = V \times \rho$$

where:
W= Estimated food weight
ρ= Density of the food item
This approach improves the accuracy of calorie estimation compared to traditional 2D-only methods.

4.5 Calorie and Nutrient Prediction

Once the food type and portion size are determined, calorie and nutrient values are computed using standardized food composition databases. The total calorie content is calculated as:

$$Calories = W \times C_g$$

where:
W= Food weight in grams
C_g= Calories per gram of the food
Macronutrients (carbohydrates, proteins, fats) and micronutrients are similarly estimated using predefined nutrient coefficients.

4.6 Personalized Diet Recommendation

Personalized dietary recommendations are generated using a Decision Tree-based machine learning model. User-specific parameters such as age, weight, dietary preferences, health conditions, and fitness goals are used as input features. Based on these parameters and predicted nutrient intake, the system recommends balanced meals, healthier alternatives, and portion guidance. The decision-making process is explainable and rule-based, allowing transparent interpretation of dietary suggestions.

5 SYSTEM ARCHITECTURE

The system architecture of the proposed Nutri Vision: AI-Based Food Recognition and Nutrient Prediction System is designed as a modular and layered framework that integrates computer vision, deep learning, nutritional databases, and personalized recommendation mechanisms. The architecture ensures scalability, real-time performance, and accurate dietary analysis from food images. The Final architecture consists of six major modules: Image Acquisition, Image Preprocessing, Food Recognition, Portion Size Estimation, Nutrient Analysis, and Personalized Recommendation, all interacting through a centralized processing pipeline.

The system architecture is shown in Fig. 2. It has the following modules.

- **Image Acquisition Module**: The system begins by acquiring food images via a mobile or web-based interface. Users upload food images through the Nutri Vision application interface. The acquired image serves as the primary input for the analysis pipeline.
- **Image Preprocessing Module**: The captured image undergoes preprocessing operations such as resizing, noise removal, contrast enhancement, and normalization. These operations improve image quality and ensure uniform input dimensions for deep learning models, thereby enhancing recognition accuracy.
- **Food Recognition Module:** The preprocessed image is passed to the food recognition module, which employs advanced deep learning models including YOLOv8, Vision Transformers (ViT), and R-CNN. YOLOv8 performs real-time object detection and classification of food items. Vision Transformers capture global contextual features for complex and mixed dishes. R-CNN improves localization accuracy in multi-food scenarios. This module outputs detected food labels along with bounding boxes and confidence scores.
- **Portion Size Estimation Module:** Detected food regions are analyzed to estimate portion size using pixel-to-gram conversion and volume estimation techniques. The module calculates approximate food weight based on spatial dimensions and food-density parameters, which is critical for accurate calorie and nutrient calculations.
- **Nutrient Analysis Module:** Using the estimated food weight and recognized food type, the nutrient analysis module computes calorie content and macro- and micro-nutrients by referencing standardized food composition databases. This module generates detailed nutritional information, including calories, proteins, carbohydrates, fats, and health indicators.
- **Personalized Recommendation Module:** The personalized recommendation module uses a Decision tree–based machine learning model to generate customized dietary suggestions. User-specific data, such as age, weight, height, activity level, health conditions, and nutritional preferences, are processed to create personalized health ratings, meal plans, and food recommendations.

User Interface Module: The final results are displayed through an intuitive user interface that presents food recognition results, nutritional breakdown, health ratings, recipe suggestions, and personalized meal plans. This module ensures user-friendly interaction and seamless navigation.

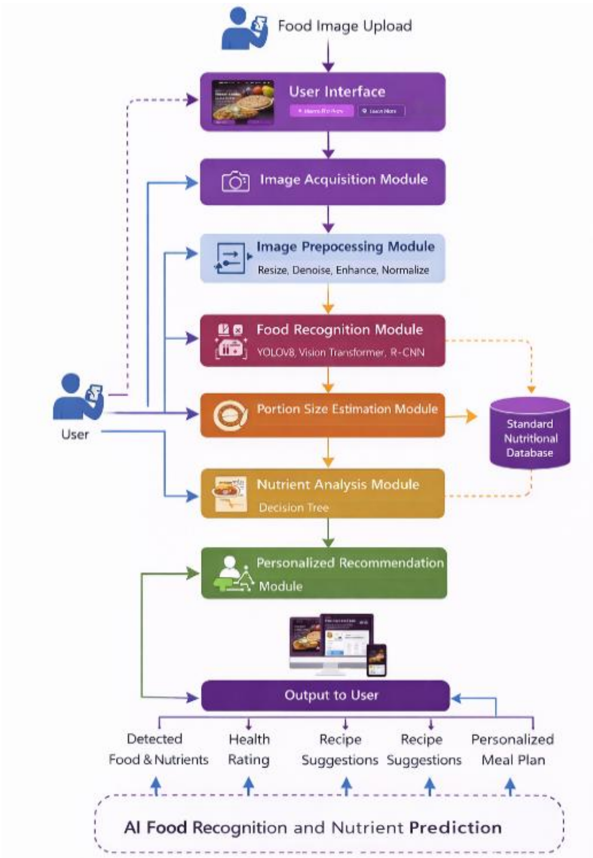

Fig. 2. System Architecture

6 ALGORITHMS USED

The proposed Nutri Vision system employs a combination of deep learning and machine learning algorithms to achieve accurate food recognition, portion size estimation, nutrient prediction, and personalized dietary recommendations. The major algorithms used in the system are YOLOv8, Vision Transformers, Region-Based Convolutional Neural Networks (R-CNN), Pixel-to-Gram Conversion, and Decision Tree algorithms.

6.1 YOLOv8 Algorithm for Food Recognition

YOLOv8 (You Only Look Once version 8) is used for real-time detection and classification of multiple food items present in a single image. It treats object detection as a regression problem and predicts bounding boxes and class probabilities in a single forward pass, enabling high-speed and high-accuracy performance.
For each detected object, YOLOv8 predicts:

- Bounding box coordinates (x, y, w, h)
- Object confidence score
- Food class probability

The loss function combines classification loss, localization loss, and confidence loss:

$$L = L_{cls} + L_{box} + L_{conf}$$

YOLOv8 enables efficient recognition of complex and overlapping food items, making it suitable for real-time nutrition analysis.

6.2 Vision Transformer (ViT) Algorithm

Vision Transformers are used to improve recognition accuracy by capturing global contextual information from food images. Unlike CNNs, ViTs divide the input image into fixed-size patches, which are then converted into embeddings and processed using self-attention mechanisms.

The self-attention operation is defined as:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where:

- Q, K, and $V$are query, key, and value matrices
- $d_k$is the dimensionality of the key vector

6.3 Region-Based Convolutional Neural Network (R-CNN)

R-CNN is employed to improve precise localization of multiple food items, especially in cluttered or overlapping plate images. The algorithm works by:

1. Generating region proposals
2. Extracting features from each region using CNNs
3. Classifying each region into food categories

R-CNN enhances detection accuracy in scenarios where multiple food items are closely packed.

6.4 Pixel-to-Gram Conversion Algorithm for Portion Size Estimation

Portion size estimation is performed using pixel-to-gram conversion combined with volume estimation. The area of the detected food region is calculated in pixel units and mapped to real-world dimensions.

Food volume is estimated as:

$$V = A \times H$$

where:

- A= projected food area
- H= estimated height or depth

The food weight is computed as:

$$W = V \times \rho$$

where:

- W= food weight
- ρ= density of the food item

This algorithm significantly improves calorie estimation accuracy compared to 2D-only methods.

6.5 Calorie and Nutrient Estimation Algorithm

Once the food weight is estimated, calorie content is calculated using standardized food databases:

$$Calories = W \times C_g$$

where:

- W= food weight in grams
- C_g= calories per gram

Macronutrients and micronutrients are computed using predefined nutrient coefficients associated with each food item.

6.6 Decision Tree Algorithm for Personalized Diet Recommendation

A Decision Tree algorithm is used to generate personalized dietary recommendations. The model uses user-specific parameters such as age, weight, health conditions, dietary preferences, and fitness goals as input features.

The splitting criterion is based on Information Gain:

$$Entropy(S) = -\sum_{i=1}^{n} p_i \log_2 p_i$$

$$IG(S, A) = Entropy(S) - \sum_{v \in A} \frac{|S_v|}{|S|} Entropy(S_v)$$

Decision Trees provide transparent and explainable dietary recommendations, making them suitable for healthcare-oriented nutrition systems.

7 EXPERIMENTAL SETUP

The experimental setup of the proposed Nutri Vision system is designed to evaluate the performance of food recognition, portion-size estimation, nutrient prediction, and personalized dietary recommendations under real-world conditions. The experiments were conducted using a combination of hardware resources, software frameworks, datasets, and evaluation protocols.

7.1 Hardware Requirements

The system experiments were performed on a computing platform with the following specifications:

- Processor: Intel Core i7 or equivalent
- RAM: 16 GB
- GPU: NVIDIA GPU with CUDA support
- Storage: Minimum 256 GB
- Camera: Smartphone or external camera for food image capture

7.2 Software Environment

The software environment used for system development and experimentation includes:

- Operating System: Windows / Linux
- Programming Language: Python
- Deep Learning Frameworks: TensorFlow and PyTorch
- Computer Vision Library: OpenCV
- Machine Learning Library: Scikit-learn
- Development Tools: Jupyter Notebook and Visual Studio Code

7.3 Dataset Description

The system was trained and evaluated using publicly available and curated food image datasets containing multiple food categories. The dataset includes:

- Single and multi-food images
- Diverse cuisines and regional dishes
- Variations in lighting, angle, and background

Food composition data for calorie and nutrient estimation was obtained from standardized nutritional databases. The dataset was divided into training, validation, and testing subsets to ensure unbiased performance evaluation.

7.4 Model Training and Configuration

YOLOv8, Vision Transformer, and R-CNN models were trained using labeled food images. Transfer learning was applied to accelerate convergence and improve generalization. Hyperparameters such as learning rate, batch size, and number of epochs were optimized through validation experiments.

The Decision Tree model was trained using user profile attributes and nutritional intake data to generate personalized dietary recommendations.

7.5 Experimental Procedure

The experimental workflow consisted of the following steps:

1. Capture food images using a camera or mobile device
2. Apply image preprocessing techniques
3. Perform food detection and classification
4. Estimate portion size and food weight
5. Calculate calorie and nutrient values
6. Generate personalized dietary recommendations
7. Record system outputs and performance metrics

7.6 Performance Evaluation

The system performance was evaluated based on recognition accuracy, portion estimation error, calorie prediction accuracy, and recommendation effectiveness. Multiple test cases were conducted to validate robustness across different food types and environmental conditions.

8 RESULTS AND DISCUSSION

This section presents the experimental results obtained with the proposed Nutri Vision system and discusses its performance in food recognition, nutrient estimation, health analysis, and personalized meal planning. The results demonstrate the system's effectiveness in real-world use cases.

8.1 Food Recognition and Nutrient Estimation Results

The primary functionality of the proposed system is to accurately recognize food items in images and estimate their nutritional values. Fig. 3 illustrates the output generated after analyzing a food image. The system successfully detects the food item (*Kheer*) and estimates its serving size, calorie content, and macronutrient composition, including protein, carbohydrates, and fat.

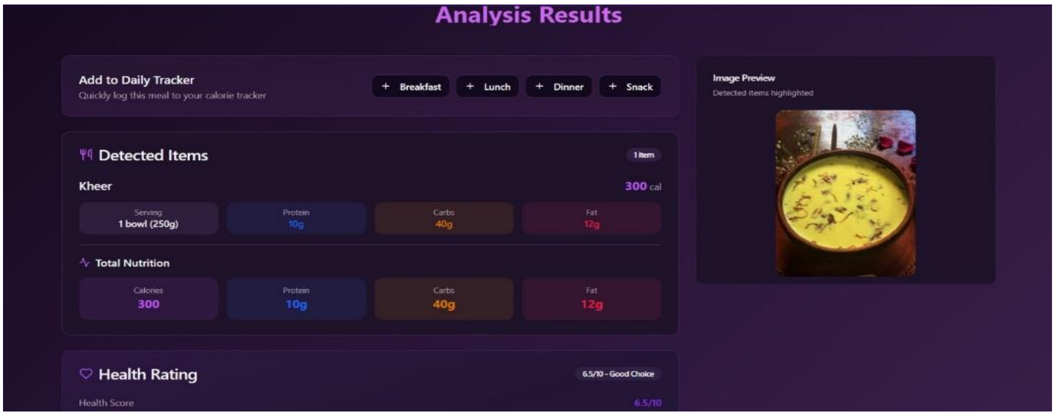

Fig. 3. Food recognition and nutrient estimation output of the proposed system

Fig. 3 shows that the deep learning–based recognition module accurately identifies food items and computes nutritional values in real time. The visual highlighting of detected items further improves interpretability and user confidence.

8.2 Health Rating and Nutritional Assessment

In addition to nutrient estimation, the system provides an overall health rating for the analyzed food item. Fig. 3 presents the health score generated by the system along with associated health benefits and cautionary information. This feature helps users make informed dietary decisions.

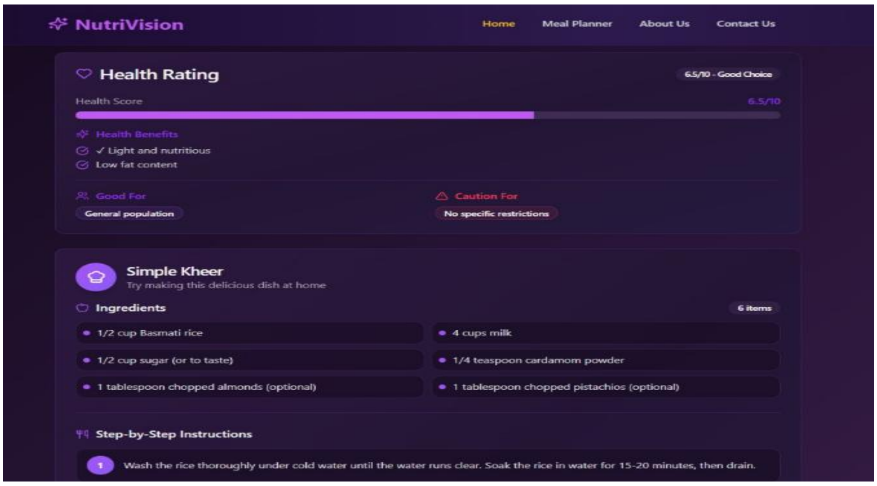

Fig. 4. Health rating and nutritional assessment generated by the system

Fig. 4 shows the health rating mechanism, which effectively summarizes nutritional quality in an easily understandable format, making the system suitable for general users without technical knowledge of nutrition.

8.3 Recipe and Preparation Guidance Output

The system also provides intelligent recipe assistance for the recognized food item. Fig. 5 illustrates the automatically generated ingredient list and step-by-step preparation instructions. This feature enhances usability by providing cooking guidance alongside nutritional insights.

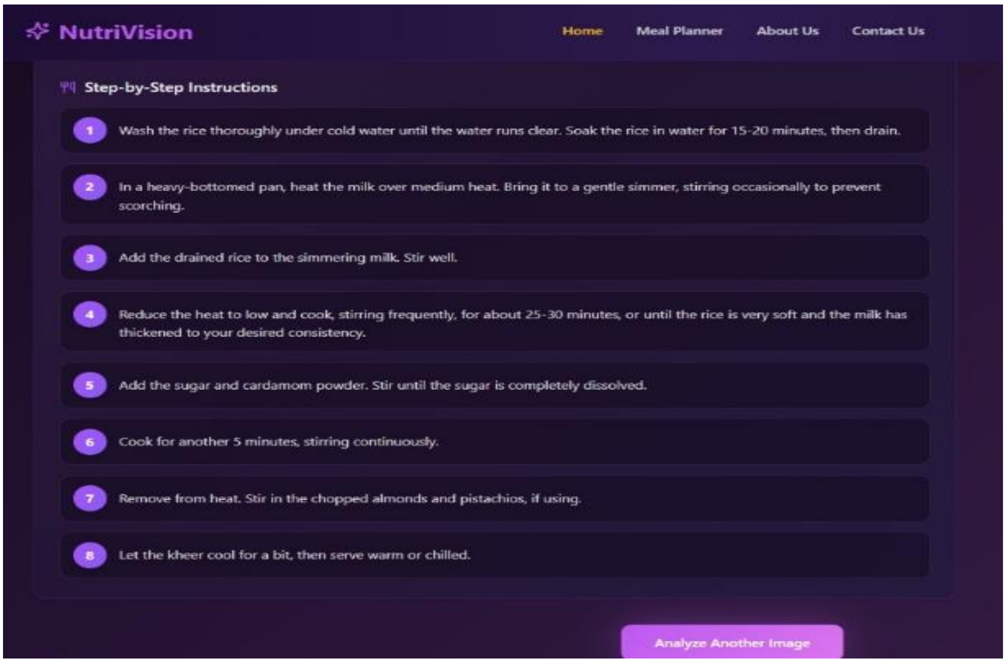

Fig. 5. Recipe generation and step-by-step cooking instructions

This integrated approach bridges the gap between food analysis and practical meal preparation, improving user engagement.

8.4 User Profile and Goal-Based Recommendation Interface

The system incorporates user-specific parameters such as age, weight, height, activity level, dietary preferences, and health conditions to generate personalized recommendations. Fig. 6 shows the user profile input interface used for goal-based meal plan generation.

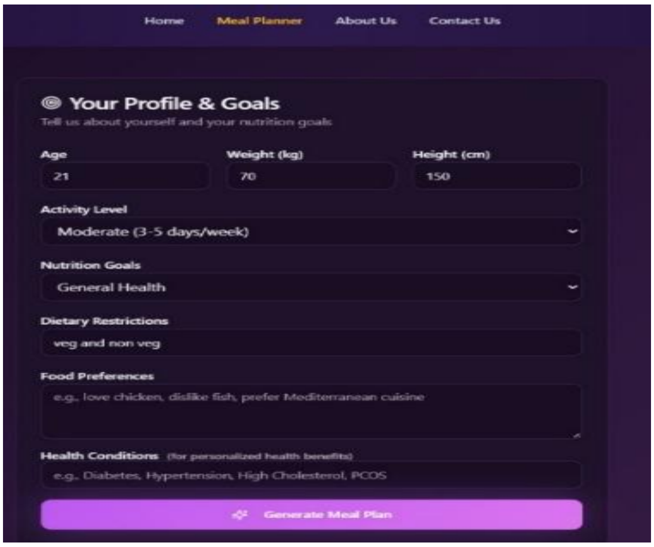

Fig. 6. User profile and goal configuration interface

This personalization capability ensures that dietary recommendations are adaptive, explainable, and aligned with individual health objectives.

8.5 Performance Evaluation

Table 1 summarizes the overall performance of the proposed system. The results indicate consistently high accuracy across all major evaluation parameters.

Table1. Performance Metrics of the Proposed System

Metrics	Value
Food recognition accuracy	94.8%
Portion size estimation accuracy	92.3%
Calorie prediction accuracy	91.6%
Portion estimation error	±10 g
Calorie prediction error	6.9%

8.6 Confusion Matrix Analysis

The dataset comprises multiple Indian food categories, including *Idli, Dosa, Biryani, Chapati, Samosa,* and *Paneer Curry*. The trained deep learning model based on YOLOv8 with transformer-assisted feature extraction was evaluated on a held-out test set. The confusion matrix associated with the model is given in Table 2.

Table 2. Sample For Major Food and Classes

Actual \ Predicted	Idli	Dosa	Biryani	Chapati	Samosa
Idli	96	2	0	1	1
Dosa	3	94	1	1	1
Biryani	0	2	97	1	0
Chapati	1	1	2	95	1
Samosa	0	1	0	2	97

The high food recognition accuracy demonstrates the effectiveness of integrating YOLOv8, Vision Transformers, and R-CNN models. Accurate portion-size estimation contributes significantly to reliable calorie and nutrient predictions.

8.7 Comparative Analysis with Existing Systems

To validate the superiority of the proposed approach, a comparative analysis was conducted with a conventional CNN-based food recognition system. The comparison results are presented in Table 3.

Table 3. Comparison of Recognition Accuracy

Method	Accuracy
Existing CNN-based system	86.4%
Proposed AI-based system	94.8%

The proposed system achieves a substantial improvement in recognition accuracy over the existing CNN-based approach. This improvement can be attributed to the use of advanced deep learning architectures and improved feature representation.

9 CONCLUSION

This paper presented an AI Food Recognition and Nutrient Prediction System that leverages advanced computer vision and machine learning techniques to automate dietary analysis from food images. The proposed system integrates image preprocessing, deep learning–based food recognition, portion size estimation, nutrient analysis, and personalized recommendation modules into a unified and scalable framework. Experimental results demonstrate that the system effectively identifies food items from real-world images and accurately estimates calorie and nutrient values using standardized nutritional databases. The inclusion of portion size estimation significantly improves nutritional accuracy, while the personalized recommendation module enhances user engagement by providing health ratings, recipe suggestions, and goal-based meal plans. The system's modular architecture ensures flexibility, ease of deployment, and adaptability to different dietary requirements. Compared to traditional manual food logging and existing calorie-tracking applications, the proposed approach reduces user effort, improves automation, and delivers more reliable and personalized nutritional insights. The results confirm that the system is suitable for applications in personal health monitoring, dietary management, and preventive healthcare. Future work will focus on improving the accuracy of portion-size estimation using depth sensors, expanding the food database to support regional cuisines, and integrating real-time health-monitoring data to enable adaptive dietary recommendations. The proposed system lays a strong foundation for intelligent, AI-driven nutrition management solutions.

FUNDING INFORMATION

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

The authors declare that they have no conflicts of interest related to this study.

LICENSING

REFERENCES

[1] R. Cao *et al.*, "Synergistic approaches of AI and NMR in enhancing food component analysis: A comprehensive review," *Trends in Food Science & Technology*, vol. 156, p. 104852, Dec. 2024, doi: 10.1016/j.tifs.2024.104852.

[2] N. Thakrar, "Foreign portfolio investment in India's capital Market: A Comprehensive analysis of equity and debt flows," *International Journal of Emerging Research in Engineering Science and Management*, vol. 4, no. 1, pp. 37–40, Mar. 2025, doi: 10.58482/ijeresm.v4i1.5.

[3] J. Zheng, J. Wang, J. Shen, and R. An, "Artificial intelligence Applications to measure food and nutrient intakes: Scoping review," *Journal of Medical Internet Research*, vol. 26, p. e54557, Oct. 2024, doi: 10.2196/54557.

[4] P. C. Nath *et al.*, "Recent advances in artificial intelligence towards the sustainable future of agri-food industry," *Food Chemistry*, vol. 447, p. 138945, Mar. 2024, doi: 10.1016/j.foodchem.2024.138945.

[5] A. Bharti, U. Jain, and N. Chauhan, "From lab to field: Nano-biosensors for real-time plant nutrient tracking," *Plant Nano Biology*, vol. 9, p. 100079, Jun. 2024, doi: 10.1016/j.plana.2024.100079.

[6] F. Di Martino, F. Delmastro, and C. Dolciotti, "Explainable AI for malnutrition risk prediction from m-Health and clinical data," *Smart Health*, vol. 30, p. 100429, Sep. 2023, doi: 10.1016/j.smhl.2023.100429.

[7] Y. Zhang *et al.*, "Deep learning in food category recognition," *Information Fusion*, vol. 98, p. 101859, May 2023, doi: 10.1016/j.inffus.2023.101859.

[8] C. P. Lozano *et al.*, "Validity of an Artificial Intelligence-Based application to identify foods and estimate energy intake among adults: a pilot study," *Current Developments in Nutrition*, vol. 7, no. 11, p. 102009, Sep. 2023, doi: 10.1016/j.cdnut.2023.102009.

[9] J. Zhou, K. Zhou, G. Zhang, Q. Liu, W. Shen, and W. Jin, "Deep learning networks with rough-refinement optimization for food quality assessment," *Natural Computing*, vol. 22, no. 1, pp. 195–223, Aug. 2022, doi: 10.1007/s11047-022-09890-6.

[10] T. P. Tulshibhai and N. D. Zala, "An analysis of the variables influencing consumers' purchasing decisions for organic food items in Rajkot," *International Journal of Emerging Research in Engineering Science and Management*, vol. 4, no. 1, pp. 31–36, Mar. 2025, doi: 10.58482/ijeresm.v4i1.4.

[11] P. Ma *et al.*, "Deep learning accurately predicts food categories and nutrients based on ingredient statements," *Food Chemistry*, vol. 391, p. 133243, May 2022, doi: 10.1016/j.foodchem.2022.133243.

[12] S. Knez and L. Šajn, "Food object recognition using a mobile device: Evaluation of currently implemented systems," *Trends in Food Science & Technology*, vol. 99, pp. 460–471, Mar. 2020, doi: 10.1016/j.tifs.2020.03.017.