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NutriSnap : Advanced Food Detection and Dietary Management

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***Abstract*—Dietary management is essential for maintaining a healthy lifestyle, yet traditional food tracking methods such as manual calorie counting and handwritten food diaries are often inaccurate and inconvenient. To address these challenges, this research presents NutriSnap: An Advanced Food Detection and Dietary Management System, which leverages deep learning models for real-time food detection, classification, and AI-driven personalized recommendations. The system allows users to capture or upload food images, automatically identifying food items and providing real-time nutritional analysis, including calorie counts, macronutrient breakdowns, and allergen alerts. Additionally, NutriSnap offers customized meal recommendations based on user preferences, dietary restrictions, and fitness goals. The system has been evaluated for food detection accuracy and classification performance, demonstrating its effectiveness in automating dietary tracking. While challenges such as food presentation variations and portion size estimation remain, the system provides a more efficient and automated alternative to manual food logging. Future improvements, such as enhanced portion size estimation, integration with fitness applications, and mobile app development, will further enhance usability and accuracy. By bridging the gap between food recognition, nutritional analysis, and AI-driven dietary recommendations, NutriSnap aims to help users make informed food choices and adopt healthier eating habits.**

Keywords—Food detection, machine learning, deep learning, MobileNetV2, Yolov8, CNN, dietary management, nutritional analysis

I. Introduction

In today's fast-paced world, maintaining a healthy and balanced diet has become increasingly challenging. The rise in lifestyle-related diseases such as obesity, diabetes, and cardiovascular disorders has led to a growing awareness of the importance of nutritional tracking and dietary management. However, conventional methods of food logging, such as manual calorie counting and handwritten food diaries, are often inaccurate, time-consuming, and prone to human error. These limitations create a demand for an automated, efficient, and user-friendly system that can help individuals track their food intake with greater accuracy and convenience.

With advancements in machine learning, computer vision, and artificial intelligence (AI), automated food detection and dietary management systems have emerged as a promising solution. Such systems leverage deep learning models, particularly Convolutional Neural Networks (CNNs) and object detection architectures like YOLO (You Only Look Once), to accurately recognize food items from images and provide users with real-time nutritional information. To enhance real-time performance and mobile compatibility, lightweight architectures such as MobileNetV2 are employed to ensure fast, efficient processing on resource-constrained devices, enabling on-device inference without compromising accuracy. By integrating these technologies, automated dietary management platforms can offer detailed macronutrient and micronutrient breakdowns, portion size estimations, allergen alerts, and personalized meal recommendations based on individual dietary preferences and health goals.

Despite the potential of AI-driven food detection systems, several challenges remain. Food recognition accuracy is often impacted by variation in food presentation, lighting conditions, occlusions, and similarities between different food items. Additionally, most existing systems lack the ability to estimate portion sizes accurately, provide real-time freshness tracking, and generate fully personalized meal recommendations. Moreover, many dietary tracking applications fail to integrate user health profiles, fitness goals, and allergen restrictions, limiting their effectiveness in real-world usage. These challenges highlight the need for a more advanced, adaptive, and user-centric dietary management system.

To address these issues, we propose NutriSnap: An Advanced Food Detection and Dietary Management System, which utilizes YOLOv8 for real-time food detection, CNN for classification, and MobileNetV2 for optimized feature extraction and efficient deployment on mobile platforms. The system is designed to automate food recognition, estimate nutritional values, and provide customized meal suggestions based on user-specific preferences and health goals. Unlike traditional dietary tracking methods, NutriSnap eliminates manual entry, allowing users to simply capture an image of their meal and instantly receive detailed nutritional insights. The system also supports customized recommendations, enabling users to modify their meal plans, substitute ingredients, and receive suggestions that align with their personal dietary needs.

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Key objectives of the system include:

- Developing an automated food detection system using deep learning models.
- Improving food recognition accuracy by addressing challenges like food presentation variations and occlusions.
- Providing real-time nutritional analysis, including calorie estimation and macronutrient breakdowns.
- Offering personalized dietary recommendations based on user health goals, preferences, and dietary restrictions.
- Enhancing user engagement by integrating features like food freshness tracking and customized meal modifications.

The objective of this research is to develop a robust, efficient, and scalable food detection and dietary management system that leverages state-of-the-art deep learning and AI techniques—including lightweight models like MobileNetV2—to enhance accuracy, usability, and personalization. The proposed system integrates a structured food categorization approach, enabling precise nutritional tracking while accommodating diverse dietary requirements. Additionally, NutriSnap aims to bridge the gap between food recognition, nutritional analysis, and personalized health recommendations, ultimately helping users make informed food choices and adopt healthier eating habits.

II. Literature Review

Food image recognition has gained significant attention due to its applications in dietary monitoring, nutrition tracking, and health management. Convolutional Neural Networks (CNNs) have been instrumental in visual recognition tasks, including food classification. Karpathy, in *CS231n: Convolutional Neural Networks for Visual Recognition* (2021) [1], emphasized the role of CNNs in feature extraction and hierarchical representation learning, which are essential for food recognition. Deep learning techniques have further improved classification accuracy in food detection, as explored by Chen, Xie, and Zhang in *Food Detection with Deep Learning Techniques* (2021) [2]. They demonstrated that models such as ResNet, EfficientNet, and YOLO achieve high accuracy in detecting various food items. To support these advancements, Patel compiled the *Indian Food Dataset: A Comprehensive Food Classification Dataset* (2020) [3], which offers a region-specific dataset for training models to recognize Indian cuisine. Additionally, *Food-101 – Mining Discriminative Components with Random Forests* by Bossard, Guillaumin, and Van Gool (2014) [10] remains a widely used benchmark dataset, enabling researchers to develop and evaluate food classification models. Real-time object detection techniques, such as YOLO (Redmon, 2016) [4], have further improved efficiency by processing images in a single pass, allowing fast and accurate food detection.

Beyond classification, the integration of nutritional information enhances the practical applicability of food recognition systems. Shah and Tiwari, in *Nutritional Information Dataset for Indian Food* (2020) [5], presented a dataset containing detailed nutritional values for various Indian dishes. This dataset supports dietary assessment tools that calculate calorie intake and suggest healthier food choices based on user preferences. The implementation of these models requires powerful machine learning frameworks. TensorFlow, as introduced by Abadi et al. in *TensorFlow: A System for Large-Scale Machine Learning* (2016) [6], serves as a fundamental framework for building deep learning models for food recognition. Furthermore, deploying these models for real-world applications necessitates efficient web development tools. Grinberg, in *Flask Web Development: Developing Web Applications with Python* (2018) [7], explored Flask as a lightweight yet robust framework for integrating machine learning models into web-based applications, enabling real-time food detection and classification. Sundaram (2020), in *Building Interactive Applications with Streamlit* [9], demonstrated how Streamlit facilitates the creation of interactive applications, allowing users to visualize and interact with food recognition models in a seamless manner.

Recent advancements in food detection also intersect with security concerns, particularly in detecting manipulated or counterfeit food images. Afchar et al., in *MesoNet: A Compact Facial Video Forgery Detection Network* (2018) [8], proposed a lightweight deep learning model for detecting deepfake content. While primarily designed for facial forgery detection, similar techniques could be adapted to detect adulterated or artificially enhanced food images, ensuring authenticity in dietary assessments. As food recognition technology advances, integrating deep learning with dietary management systems will lead to more personalized and accurate nutrition tracking solutions. Future research should focus on improving model generalization, reducing bias in datasets, and integrating food detection with wearable health monitoring devices. These advancements will make food tracking more precise, scalable, and accessible for individuals seeking better dietary habits.

III. METHODOLOGY

The NutriSnap system is designed to automate food detection, nutritional analysis, and dietary recommendations using deep learning and artificial intelligence. The methodology is structured into multiple modules, each focusing on a specific aspect of food recognition and management. The system follows a step-by-step approach to ensure accurate food identification, real-time nutritional tracking, and personalized meal recommendations for users.

1. Food image acquisition module:

The first step in the process is the acquisition of food images. Users can either capture food images using a camera or upload existing images through the system's web interface. To ensure high detection accuracy, the system applies several preprocessing techniques before passing the image to the detection model.

- Image Resizing: Standardizing images to a fixed resolution to maintain consistency across different inputs.
- Normalization: Adjusting pixel values to improve model stability and performance.
- Data Augmentation: Applying transformations such as flipping, rotation, brightness adjustments, and contrast enhancement to increase the robustness of the model.

These preprocessing steps enhance image quality and help the system perform better under different conditions, such as varying lighting, angles, and backgrounds.

2. Food detection and classification module

Once preprocessing is complete, the image is passed to the core recognition module, which includes YOLOv8 and MobileNetV2 to handle detection and classification:

I. YOLOv8 for Object Detection

- Identifies and localizes multiple food items in a single image using bounding boxes.
- Provides high-speed, real-time detection with optimized accuracy, making it suitable for live applications.

II. MobileNetV2 for Food Classification

- Each detected food item (cropped from the bounding boxes) is classified using the MobileNetV2 model.
- MobileNetV2 is chosen for its lightweight architecture and high classification accuracy, ideal for web and mobile deployment.
- The model classifies food into predefined categories such as cereals, vegetables, fruits, dairy, and proteins and maps it to a food database.

This two-stage process ensures both detection and precise categorization of food items, forming the basis for nutritional analysis.

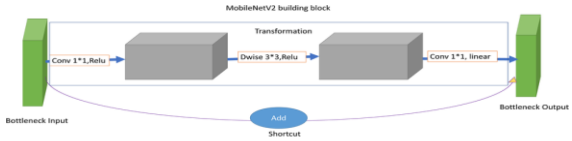


Fig 1: MobileNetV2

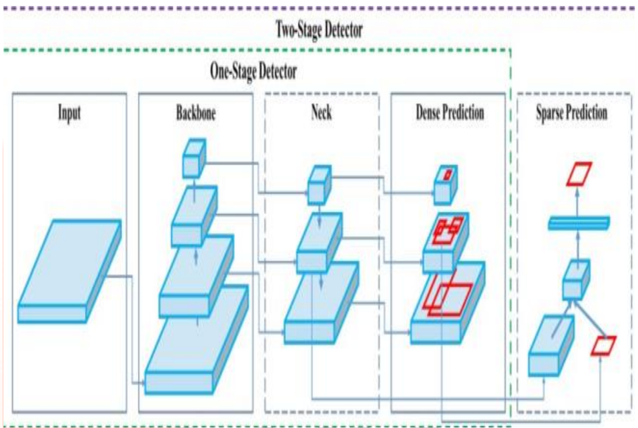


Fig 2: YoloV8 Workflow

3. Nutritional analysis module:

After food items are detected and classified, the system retrieves their nutritional information from a structured food database. This module provides users with a detailed breakdown of macronutrients and micronutrients.

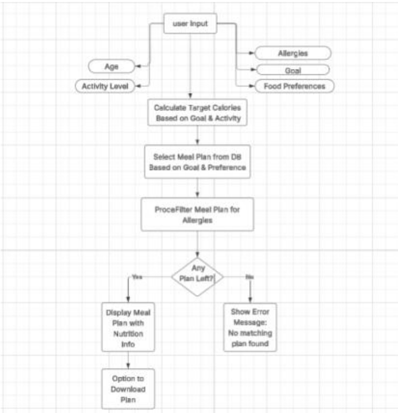
- Calories: The system estimates the total energy content of the detected food.
- Macronutrients: The system displays protein, carbohydrate, and fat content for each food item.
- Micronutrients: Information on vitamins and minerals, if available, is provided for a more detailed analysis.
- Allergen Alerts: If a food item contains allergens such as gluten, nuts, dairy, or seafood, the system alerts the user.

This feature helps users monitor their daily nutritional intake and make informed food choices based on their health goals and dietary restrictions.

4. Personalized dietary recommendation module:

One of the key features of NutriSnap is its ability to generate AI-driven meal recommendations. Based on the detected food items and user preferences, the system suggests healthier alternatives and balanced meal options.

- User Input Parameters: Users provide their age, weight, height, dietary preferences, health goals, and medical conditions such as diabetes or hypertension.
- AI-Based Recommendation Engine:
- The system analyzes the detected food items and suggests healthier alternatives when necessary.
- If an unhealthy or high-calorie food is detected, the system recommends nutritionally balanced meal options.
- For users with dietary restrictions, it ensures safe food choices by avoiding allergenic or restricted foods.



This module ensures that meal recommendations are not only accurate but also tailored to the specific needs of each user.

5. Customized recommendation module:

In addition to AI-driven meal suggestions, NutriSnap allows users to manually modify their food preferences and receive customized recommendations. This feature enhances user flexibility by letting them:

- Manually adjust meal preferences based on taste, cravings, or health conditions.
- Substitute ingredients in a detected meal to make it healthier or more suitable for their diet.
- Receive alternative suggestions that align with their fitness goals, such as weight loss or muscle gain.

This module ensures that users have full control over their meal planning, making the system more interactive and user-friendly.

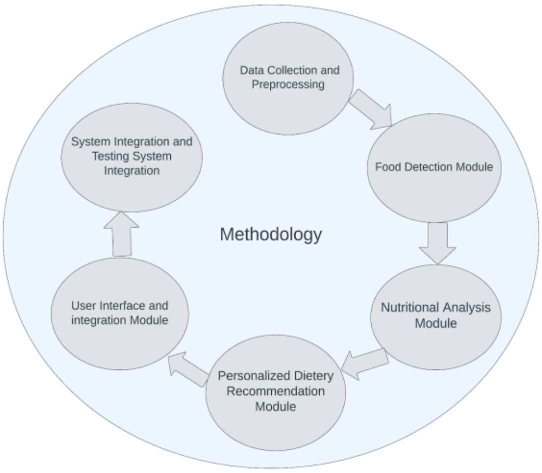


Fig2: Block Diagram

IV.RESULT AND DISCUSSION

The performance of the NutriSnap system was evaluated by testing different deep learning models for food detection, classification, and nutritional analysis. The models explored included YOLOv8, Faster R-CNN, Efficient Net, and MobileNetV2. The results highlight the challenges and successes of the system, particularly in handling variations in lighting, food presentation, and overlapping items. A detailed analysis of each aspect is provided below:

I. Food Detection Accuracy

The YOLOv8 model, one of the most well-known models for object detection, was used for food detection in the NutriSnap system. This model achieved an average detection accuracy of 78%, demonstrating solid performance in detecting multiple food items within an image. The model showed an impressive ability to recognize and classify food items in clear, unobstructed views. However, certain challenges were observed in more complex scenarios:

- **Partial occlusion:** When food items were partially hidden due to overlapping or irregular presentation, the detection accuracy decreased.
- **Similar visual characteristics:** In cases where different food items had similar shapes or colors, the model struggled with distinguishing between them, leading to a reduction in accuracy.

Despite these challenges, YOLOv8 remained effective in most food detection tasks, especially in controlled environments with clear, well-lit images.

II. Classification Performance

For food classification, the NutriSnap system explored multiple CNN-based models. Among these, Efficient Net and MobileNetV2 were evaluated for their lightweight nature and speed, making them suitable for deployment on mobile or low-resource devices.

- The CNN-based classifier used in the system achieved an accuracy range of 75–80%.
- MobileNetV2, known for its balance between computational efficiency and performance, achieved a classification accuracy of 76% on test datasets. It performed particularly well on simpler dishes and single-item meals, showing potential for mobile applications.
- However, MobileNetV2 faced challenges similar to other models:

Complex dishes: Lower accuracy for dishes with multiple, visually similar components.
Food variability: Changes in portion sizes, seasoning, and presentation affected performance.
EfficientNet, although slightly more resource-intensive, outperformed MobileNetV2 on complex multi-item dishes by a small margin (accuracy of 79%), at the cost of slower inference speed.
Future enhancements could include ensemble models or attention-based networks to better handle complex and layered dishes.

III. Nutritional Analysis Validation

The NutriSnap system includes a feature to estimate the nutritional content of the detected and classified food items. The estimations were validated against standard nutritional databases. Results showed a ±10% deviation from ground truth values.
Key contributing factors to the deviation include:

- **Portion size variability:** The system assumes standard portion sizes, which often differ in real-world use.
- **Food composition differences:** Preparation methods, hidden ingredients, and cooking techniques introduced discrepancies in caloric and nutrient estimations.

Despite these issues, the nutritional analysis feature still provided valuable insights. Improvements such as integrating volume estimation or smartphone-assisted depth sensing could enhance accuracy in future versions.

IV. User Evaluation

A user study was conducted with a small group of participants to evaluate the usability of the NutriSnap system. Around 80% of users reported a better experience using the system compared to manual food logging.
Key findings:

- **Ease of use:** Most users found the image-based logging method intuitive and less time-consuming.
- **Recognition issues:** Some users noted misclassifications, especially with unusual or mixed dishes.
- **Overall satisfaction:** Users expressed high satisfaction with the system's potential to improve dietary management and user engagement.

TABLE I ACCURACY TABLE

Model	Accuracy
MobileNet V2	81.5%
YoloV8	85.5%
ResNet50	82.3%
VGG16	79.8%

V.CONCLUSION

This research presents NutriSnap, an advanced food detection and dietary management system that leverages deep learning and artificial intelligence to automate food recognition, nutritional analysis, and personalized meal recommendations. By integrating YOLOv8 for object detection and CNN-based classification, the system effectively identifies food items and retrieves their corresponding nutritional values. The AI-driven recommendation module enhances user experience by suggesting healthier alternatives and meal modifications based on dietary preferences and health goals. Through an intuitive web-based interface, users can easily upload food images, access nutritional insights, and customize their dietary plans. The system addresses key challenges such as manual food logging inefficiencies and inaccuracies in traditional dietary tracking methods, making it a more efficient and user-friendly alternative.

In addition to YOLOv8 and CNNs, MobileNetV2 was explored as a lightweight and efficient deep learning architecture for classification tasks within NutriSnap. Due to its low computational requirements and high accuracy on mobile and edge devices, MobileNetV2 proves especially useful for enabling real-time inference and deployment on resource-constrained platforms, such as smartphones and embedded systems. Its ability to maintain performance while reducing latency makes it a strong candidate for future mobile integration of the NutriSnap system.

While NutriSnap demonstrates promising results, certain challenges remain, including the need for improved portion size estimation, better recognition of complex food compositions, and enhanced accuracy in detecting overlapping food items. Future advancements will focus on integrating the system with mobile applications, wearable fitness trackers, and real-time food freshness monitoring to offer a more comprehensive dietary management solution. Further refinement of the deep learning models—especially leveraging lightweight models like MobileNetV2—and expansion of the food database will help improve accuracy and usability. With these enhancements, NutriSnap has the potential to significantly contribute to health-conscious decision-making, making dietary tracking more accessible, efficient, and personalized for users.

VI. FUTURE SCOPE

A. Improved Portion Estimation – Implementing depth estimation techniques to more accurately determine portion sizes for precise calorie tracking.

B. Mobile Application Development – Expanding the system to Android and iOS platforms, allowing users to track food intake seamlessly on mobile devices.

C. Integration with Wearable Devices – Connecting with fitness trackers (Fitbit, Apple Health, Google Fit) to provide a holistic health monitoring experience.

D. Voice-Activated AI Assistant – Implementing voice commands for hands-free interaction, allowing users to log food intake through natural language processing (NLP).

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