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Food Calorie Detection by Image Processing and Diet Assistant

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Abstract

Maintaining a healthy lifestyle requires accurate monitoring of food intake, but traditional calorie tracking methods such as manual logging and food charts are time-consuming and error-prone. This project presents an automated food calorie detection and diet assistant system that leverages computer vision, deep learning, and image processing to estimate calorie content directly from food images. The system captures both top and side views of meals with a reference object for precise size and volume estimation. Faster R-CNN with region proposal networks is used for food detection and classification, while segmentation methods such as GrabCut and Watershed ensure accurate extraction of food objects. The estimated volume is converted into mass using density values and mapped to calorie and nutritional data from trusted databases such as USDA, FooDD, and UECFOOD-256. A lightweight web-based application enables real-time calorie analysis without relying on external servers, ensuring efficiency and accessibility.This system reduces human error, provides instant results, and improves usability compared to traditional methods. Despite challenges like overlapping food items, varied lighting conditions, and the need for wider database coverage, the project demonstrates strong potential in personalized nutrition management. Future enhancements may include recipe suggestions, integration with wearable health devices, and AI-driven dietary recommendations. By combining accuracy, automation, and user-friendliness, this system supports informed dietary decisions, promotes healthy eating habits, and contributes to preventive healthcare and wellness.

1.INTRODUCTION

In today's busy lifestyle, following a healthy diet has become increasingly difficult. Most people eat without fully realizing the nutritional value of their meals, which often results in imbalanced diets and health issues such as obesity, diabetes, and heart-related problems. Although calorie and nutrient tracking can improve awareness, traditional methods like manually entering food details into apps are time-consuming, error-prone, and hard to continue over the long term. This creates a strong need for a smart, automated system that makes nutrition tracking simple, accurate, and convenient.The project "Food Recognition and Diet Assistant Web Application" is designed to meet this need by using artificial intelligence, computer vision, and deep learning. Built with Flask, PyTorch, and a ResNet-18 model**,** the system allows users to upload images of fruits or vegetables, which are then automatically identified by the model. Each recognized food item is linked to its nutritional profile per gram—covering calories, carbohydrates, proteins, fats, and fiber—so users instantly get precise dietary details. The system also includes a personalized diet planner**,** where users can enter information such as age, gender, weight, height, activity level, and dietary goals. Using the Basal Metabolic Rate (BMR) formula along with activity multipliers, the application generates customized diet plans that support goals like weight loss, maintenance, or muscle gain.With a clean and user-friendly interface built using HTML, CSS, and Flask templates**,** the application ensures smooth interaction and accessibility for all types of users. By automating food recognition and diet planning, it removes the hassle of manual logging, reduces errors, and provides quick and reliable nutritional insights. While the current system focuses on fruits and vegetables, it is scalable and can be expanded to cover more food categories, regional cuisines, multi-dish recognition, and even integration with wearable health devices in the future.Ultimately, this project bridges the gap between food consumption and health awareness**.** It shows how technology can transform everyday eating habits by making nutrition tracking effortless, accurate, and practical. More than just counting calories, it empowers users to make informed choices, encourages healthier lifestyles, and contributes to better long-term well-being.

2.LITERATURE SURVEY

The food calorie detection and dietary monitoring hasreceived increasing research attention due to the rising prevalence of obesity, diabetes, and diet-related diseases. Traditional calorie tracking methods, such as manual logging and dietary surveys, are time-consuming, error-prone, and inconvenient for users. To address these challenges, researchers have explored AI-driven approaches that leverage image processing, machine learning, and deep learning to automate food recognition and calorie estimation.One of the earliest approaches focused on using image processing techniques to capture food items from multiple angles. Reference objects such as coins, plates, or cards were included in the image to provide scale for volume estimation. Geometric modeling and segmentation algorithms were used to isolate food items from the background and estimate their size and weight. These values were then mapped to nutritional databases to calculate calories, proteins, fats, and carbohydrates. Although effective, these methods often struggled with mixed dishes, visually similar foods, and variations in cooking methods, which alter density and caloric values.To overcome these issues, researchers began adopting deep learning models for food recognition and calorie estimation. Faster R-CNN, a region-based convolutional neural network, has been widely applied for detecting and classifying food items within images. Combined with GrabCut segmentation, Faster R-CNN provides accurate isolation of food from its surroundings, significantly improving classification and calorie estimation. This approach ensures higher precision compared to traditional feature-based methods.Another important advancement came from the use of multi-dish calorie estimation techniques. Many meals consist of multiple items on a single plate, making calorie estimation complex. Studies applied Faster R-CNN and similar object detection models to separately detect and analyze each food item in an image. By estimating the calorie content of each dish individually, the overall accuracy of dietary monitoring was greatly enhanced. Challenges such as food overlap, occlusion, and complex plating remain, but deep learning has proven highly effective in handling these cases compared to older methods.To support the training and evaluation of deep learning systems, specialized datasets have been developed. The FooDD dataset provides more than 3,000 images of single and mixed food items captured under different lighting conditions, angles, and devices. It also includes calibration cues, such as a user's thumb, to assist in size and volume estimation. This dataset has played an important role in improving the robustness and adaptability of food detection models, ensuring they can perform well in real-world scenarios where conditions vary significantly.Beyond visual recognition, some studies have introduced context-aware calorie estimation. For instance, calorie values of foods are not determined solely by their appearance—cooking methods and ingredients play a crucial role. A grilled chicken dish and a fried chicken dish look similar but differ significantly in caloric content. To address this, researchers proposed integrating ingredient detection and cooking method recognition into calorie estimation systems. By combining visual features with nutritional knowledge bases, these models achieved more accurate and realistic calorie predictions.Lightweight and real-time solutions have also been proposed to ensure usability on mobile devices. Traditional deep learning models often needed high mathematical computation power and server support. To address this, researchers developed lightweight CNN models optimized for mobile phones, reducing the number of trainable parameters while maintaining high accuracy. These models support real-time food recognition and calorie estimation, enabling users to instantly monitor their meals without depending on cloud servers. This approach also addresses privacy concerns and is particularly useful in remote areas where internet access is limited.Another line of research explored YOLO (You Only Look Once) for food detection. YOLO-based systems are capable of identifying food items in real-time with high precision and recall. They map detected foods to standardized nutritional databases, such as FatSecret, to estimate calorie content per unit serving. YOLO's strength lies in its high-speed detection capability, making it suitable for applications that require quick and accurate food recognition. Performance evaluations reported high precision and F1-scores, reinforcing YOLO's potential in calorie estimation applications. In conclusion, the reviewed works collectively highlight that AI-powered food calorie detection is moving toward lightweight, realtme, mobile-friendly, and context-aware systems. These innovations not only automate dietary tracking but also make nutrition monitoring more accurate, accessible, and personalized. With continued advancements in deep learning, computer vision, and mobile computing, such systems hold great promise in promoting healthier lifestyles, assisting dietitians, and reducing the global burden of diet-related diseases.

The proposed model is validated through

extensive experiments and comparative analysis with existing deep learning architectures. Results indicate that the lightweight CNN model outperforms conventional approaches in terms of speed, accuracy, and energy efficiency, making it highly suitable for mobile-based dietary monitoring applications. One of the significant contributions of this research is the ability to process food images in real-time, enabling users to instantly estimate the caloric content of their meals without manual intervention. This advancement is particularly beneficial for health-conscious individuals, dietitians, and patients with dietary restrictions, as it provides instant insights into nutritional intake, helping them make informed dietary choices.

3. EXISTING SYSTEM

At present, most calorie tracking systems work either through manual food logging apps (such as MyFitnessPal or HealthifyMe) or through relatively simple image recognition models developed in earlier studies. These applications generally rely on classifying food images and then linking them to a static nutritional database for calorie estimation. A few advanced frameworks, like Im2Calories and Nutrition5k, leverage deep learning and larger datasets to boost recognition accuracy and, in some cases, even attempt portion estimation using depth sensors. However, the majority of mobile-based diet apps still depend largely on user input, barcode scanning, or preloaded menus, rather than offering a fully automated image-driven calorie detection experience.

Limitations of the Existing System

- **High Manual Effort** – Many current systems require users to type in food names, choose portion sizes, or select from lists, which is both time-consuming and prone to mistakes.
- **Accuracy Issues in Real Use** – Food recognition tends to fail when images are captured in poor lighting, from unusual angles, or when multiple food items appear in the same plate.
- **Inadequate Portion Size Detection** – Since most models rely on flat 2D images, they struggle to accurately estimate the quantity of food without depth or reference scaling.
- **Restricted Datasets** – Available public datasets such as Food-101 or UECFOOD cover only limited cuisines, making models biased and less reliable for diverse cultural foods.
- **Single-item Recognition Bias** – Many existing approaches work well for one main dish but fail when faced with **mixed meals** like Indian thalis, curries, or buffet plates.
- **Generalized Calorie Estimates** – Calorie values are often based on standard averages and do not consider variations in **cooking methods, recipes, or portion differences**.
- **No Personalization** – While most systems provide calorie counts, very few offer **tailored diet plans** that adapt to a user's health goals, activity level, or restrictions.

- **Hardware Dependence** – Advanced models that use depth or multiple camera inputs are impractical for daily smartphone users.

- **Limited Practical Application** – Many of these systems remain **research prototypes** and are not fully developed into reliable, user-friendly apps for everyday monitoring.Cultural Gaps – Since most datasets are built around Western or East Asian cuisines, foods from diverse regions (e.g., Indian local dishes) often get misclassified.

4.PROPOSED SYSTEM

The developed system is designed as an intelligent food recognition and calorie estimation assistant**,** with an initial focus on fruits and vegetables. Unlike the older methods that depend on manual input or partially automated tools, this system applies deep learning models to analyze food images and instantly provide their nutritional information on a per-gram basis**.**What makes the system more powerful is its integration with a personalized diet recommendation engine, which adapts suggestions according to a user's Basal Metabolic Rate (BMR), activity level, and specific health objectives**.** Instead of users struggling with menus or calorie charts, they can simply upload or capture a food image through a clean and easy-to-use interface to receive instant results. The larger vision is to minimize human effort, improve calorie estimation accuracy, and create a smarter, more engaging platform for diet management**.**

Advantages:

- **Automated Food Tracking** – Removes the hassle of manual logging, barcode scanning, or searching menus, making food tracking effortless.
- **Higher Accuracy** – Deep learning ensures more consistent recognition even under varied lighting, angles, or backgrounds.
- **Precise Per-gram Insights** – Goes beyond generic averages by calculating nutritional values based on weight for better precision.
- **Personalized Recommendations** – Adapts calorie and diet plans to individual needs by considering BMR, activity, and health goals.
- **Simple User Interface** – Designed with ease of use in mind so that anyone, regardless of technical background, can use it comfortably.
- **Instant Feedback** – Provides quick recognition and nutritional breakdown in real time, boosting practical usefulness.
- **Expandable Design** – Can later support cooked dishes, beverages, and mixed meals, making the system more versatile.
- **Encourages Health Awareness** – Helps users become more conscious of food intaking and its nutritional value, supporting healthier habits.
- **Culturally Inclusive** – Future enhancements can incorporate foods from different regions, minimizing bias toward limited cuisines.
- **Future Integration Ready** – Can be linked with mobile apps, smart wearables, or healthcare systems to generate a complete digital health ecosystem.

Fig: Proposed System

5.IMPLEMENTATIONS

1. Environment Setup

To begin, the project requires Python 3.10. Several key libraries are installed to support different parts of the application. PyTorch and Torchvision are used for building and training the deep learning model, while Flask powers the web interface. Pillow (PIL) handles image processing tasks, and standard utilities such as os and numpy help with file management and numerical operations. For efficient model training, a GPU-enabled system is recommended, though smaller datasets can also be handled using a CPU. The project is organized in a structured way, with separate folders for training and validation images, templates for HTML pages, a location to store uploaded images, the trained model weights, and a text file containing class labels.

2. Dataset Preparation

The dataset comprises images of various fruits and vegetables, neatly organized into training and validation sets. Each class, such as apple, banana, or carrot, has its own folder to maintain clear labeling, which is essential for accurate model training. Before feeding the images to the model, they are resized to 224×224 pixels to maintain uniformity. Normalization is applied to standardize pixel values, ensuring faster convergence during training. To make the model robust, data augmentation techniques such as horizontal flips, rotations, and brightness adjustments are applied. Additionally, a custom image loader converts any transparent images to RGB, preventing errors during preprocessing and training.

3. Model Design

The application utilizes ResNet-18, a largely used pre-trained convolutional neural network known for its efficiency in image classification. The finally connected layer is replaced to match the exact number of food classes in the dataset. During training, CrossEntropyLoss is used as the loss function, and the Adam optimizer updates the model weights. Training occurs in batches of 16 images over 45 epochs, with the device automatically set to GPU if available. The training process continuously reports the loss and validation accuracy, allowing monitoring of performance. Once training is done, the model weights are saved as fruitveg_resnet18.pth for use in fututre in prediction tasks.

4. Web Application Using Flask

The web interface is built using Flask, providing a simple and responsive way for users to interact with the system. The homepage presents two main options: food prediction and diet planning. The /prediction route allows users to upload an image of a fruit or vegetable, and the system returns the predicted class along with its nutritional information. The frontend design is visually appealing, featuring gradients, shadows, and responsive layouts. The prediction page clearly shows the uploaded image and nutritional details, while the diet plan page displays the calculated calories and macronutrient distribution in a clean, readable format.

5. Food Prediction Workflow

When a user uploads a food image, it is first preprocessed by resizing, normalizing, and converting it into a tensor compatible with the model. The trained ResNet-18 model then predicts the food class. Once the class is identified, the system retrieves nutritional information such as calories, carbohydrates, protein, fat, and fiber from a pre-defined dictionary. The results, along with the uploaded image, are displayed on the webpage, giving the user both visual and nutritional feedback on the food item.

6. Diet Plan Calculation

The diet plan feature calculates the Basal Metabolic Rate (BMR) based on the user's age, weight, height, and gender. This BMR is adjusted using an activity factor that reflects the user's daily activity level. The calorie count is further modified depending on the user's goal, whether it is to lose, maintain, or gain weight. The system distributes calories among macronutrients, assigning 30% to protein, 40% to carbohydrates, and 30% to fats. Finally, the output provides the user with total calories and the grams of protein, carbs, and fats recommended for their personalized diet plan.

6. CONCLUSIONS

The Food & Diet Assistant is a comprehensive platform that combines the power of deep learning with modern web technologies to offer users an intuitive tool for recognizing fruits and vegetables and receiving personalized diet recommendations. By utilizing a pre-trained ResNet-18 model, the system achieves high accuracy in food classification, ensuring reliable identification of various fruits and vegetables. Alongside this, the diet planning module calculates daily caloric requirements and distributes macronutrients—proteins, carbohydrates, and fats—according to the user's age, weight, height, gender, activity level, and personal health goals.The application is designed with a responsive and user-friendly interface, making navigation between the food prediction and diet planning features smooth and straightforward. Visual feedback, clear layout, and interactive forms enhance the user experience, while robust backend processes ensure that uploaded images are handled correctly and predictions are returned efficiently. Error handling mechanisms further strengthen reliability by managing invalid inputs, non-image uploads, and edge cases gracefully.Extensive testing, including unit, functional, integration, UI, and performance tests, validates the system's accuracy, stability, and responsiveness across different scenarios. Users can confidently interact with the platform knowing that both predictions and diet calculations are dependable and informative.Overall, this project highlights the practical application of artificial intelligence in promoting healthier lifestyle choices. It bridges the gap between complex machine learning algorithms and accessible health tools for end-users. With further enhancements, such as expanding the dataset to cover more food items, incorporating portion sizes, suggesting meal combinations, or even integrating barcode scanning for packaged foods, this platform can evolve into a fully-featured nutritional assistant capable of guiding users toward well-balanced diets and improved overall health.

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