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Nutri AI: Intelligent Food Recognition System

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Abstract: In recent years, unhealthy eating habits and improper nutritional intake have become major global concerns, leading to serious health conditions such as obesity, diabetes, cardiovascular diseases, and thyroid disorders. Monitoring daily calorie intake and maintaining a balanced diet are essential for preventing these issues. However, traditional dietary tracking methods rely heavily on manual food logging and estimation, which are often inaccurate, time-consuming, and inconvenient for users.To address these challenges, this project proposes an AI-based intelligent food recognition system named Nutri AI. The system automatically identifies food items from images using deep learning techniques and estimates ingredient-level calorie values, even for mixed food items. The proposed system utilizes Convolutional Neural Networks (CNN) for feature extraction and classification, enabling accurate recognition of food items based on visual characteristics such as color, texture, and shape. Additionally, the system provides personalized dietary recommendations based on user-specific health parameters such as Body Mass Index (BMI), making it a health-aware solution. By integrating computer vision, deep learning, and nutritional science, the proposed system enhances the accuracy and efficiency of dietary monitoring while reducing manual effort. Overall, this system aims to promote healthier eating habits and support users in maintaining a balanced lifestyle through intelligent automation.

Keywords: Food Recognition, Deep Learning, CNN, Calorie Estimation, Nutrition Analysis, BMI

I.INTRODUCTION

A healthy diet plays a crucial role in maintaining physical and mental well-being. However, modern lifestyles, busy schedules, and increased availability of fast food have led to unhealthy eating patterns. These habits significantly contribute to the rise of lifestyle diseases such as obesity, diabetes, hypertension, and thyroid disorders. Monitoring food intake and calorie consumption is essential to prevent these health issues and maintain overall wellness. Traditional methods of diet tracking involve manually recording food items and estimating calorie values using fixed tables or mobile applications. These methods are not only time-consuming but also prone to human error due to incorrect portion estimation and inconsistent data entry. Furthermore, most existing diet applications lack personalization and do not provide recommendations based on individual health conditions With advancements in artificial intelligence, particularly in computer vision and deep learning, automated food recognition systems have gained significant attention. These systems can analyze food images and identify items without requiring manual input. Convolutional Neural Networks (CNN) have proven to be highly effective in image classification tasks, making them suitable for food recognition applications.This project introduces Nutri AI, an intelligent food recognition system that leverages deep learning techniques to automate food identification and calorie estimation. The system also provides personalized dietary suggestions based on BMI, making it a comprehensive solution for nutrition monitoring. By reducing manual effort and improving accuracy, the proposed system aims to support healthier lifestyle choices.

II.RELATED WORK

Aibota Sanatbyek et al. (2025) proposed a multitask deep learning model for food recognition and portion estimation using a CNN-based architecture. The model improved efficiency and accuracy compared to single-task models but faced challenges when dealing with mixed food items and dataset generalization.

Zhao et al. (2025) conducted a comprehensive review of machine vision applications in food computing. Their study highlighted the advancements in food recognition systems but also emphasized challenges such as real-world variability, lighting conditions, and differences in food presentation.

Dalakleidi et al. (2022) performed a systematic review of AI-based food recognition systems for dietary assessment. The study identified key limitations, including difficulties in portion size estimation and handling complex mixed dishes.
Knez and Sajin (2020) developed a mobile-based food recognition system using image processing techniques. While the system demonstrated feasibility, its accuracy was limited when dealing with complex and diverse food items.

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Hokuto Kagaya, Kiyoharu Aizawa, and Makoto Ogawa (2014) were among the early researchers who applied CNN for food detection and recognition. Their work demonstrated that CNN-based models outperform traditional machine learning techniques such as Support Vector Machines in terms of accuracy and feature extraction.

Chang Liu, Yu Cao, Yan Luo, Guanling Chen, and Yunsheng Ma (2016) introduced the DeepFood system, which uses deep learning for dietary assessment through food image analysis. Their system aimed to improve calorie estimation accuracy using mobile-based food image recognition.

ArXiv Paritosh Pandey, Akella Deepthi, and Bappaditya Mandal (2017) proposed FoodNet, an ensemble deep learning model that combines multiple CNN architectures to improve classification performance. Their approach demonstrated better accuracy compared to single CNN models by leveraging feature fusion techniques.

III.PROPOSED METHODOLOGY

The proposed Nutri AI system is designed to provide an automated and intelligent solution for food recognition and calorie estimation. Initially, a large dataset of food images is collected from various sources, including real-world images and publicly available datasets. The collected images undergo preprocessing steps such as resizing, normalization, noise removal, and data augmentation to improve image quality and ensure uniformity. The preprocessed dataset is divided into training and validation sets. The training dataset is used to train the deep learning model, while the validation dataset is used to evaluate performance and prevent overfitting. The system employs a Convolutional Neural Network (CNN) architecture for feature extraction and classification. The CNN model extracts important features such as color patterns, textures, and shapes from food images, enabling accurate identification of food items. Once the model is trained, it can classify food images and estimate calorie values, including ingredient-level analysis for mixed foods. Additionally, the system calculates the user's BMI and provides personalized dietary recommendations based on health conditions. The integration of deep learning and nutritional analysis makes the system efficient, accurate, and user-friendly.

IV.SYSTEM DESIGN AND IMPLEMENTATION DETAILS

IV.1 Dataset Collection Module

In this module, a large dataset of food images is collected from different sources such as online repositories and real-world environments. The dataset includes various types of food items, including simple and mixed dishes. Proper labeling is performed to ensure accurate classification. A diverse dataset helps improve the model's ability to generalize across different food categories.

IV.2 Image Preprocessing Module

Image preprocessing is essential to improve data quality. The collected images may vary in size, resolution, brightness, and noise levels. Preprocessing techniques such as resizing, normalization, noise removal, and contrast enhancement are applied to standardize the images. Data augmentation techniques such as rotation, flipping, and scaling are also used to increase dataset diversity and improve model robustness.

IV.3 Feature Extraction Module

The system uses Convolutional Neural Networks (CNN) to extract meaningful features from food images. CNN automatically learns features such as edges, textures, shapes, and color patterns. These features are essential for distinguishing between different food items and improving classification accuracy.

IV.4 Model Training Module

The CNN model is trained using the prepared dataset. The dataset is split into training and validation sets to monitor performance during training. Optimization techniques such as learning rate adjustment and regularization are applied to improve accuracy and prevent overfitting. The trained model learns to recognize patterns associated with different food categories.

IV.5 Food Recognition and Calorie Estimation Module

This module uses the trained model to classify food images and estimate calorie values. The system can identify individual food items as well as mixed dishes. Ingredient-level calorie estimation is performed to provide more accurate nutritional information. The output includes food name, calorie count, and nutritional details.

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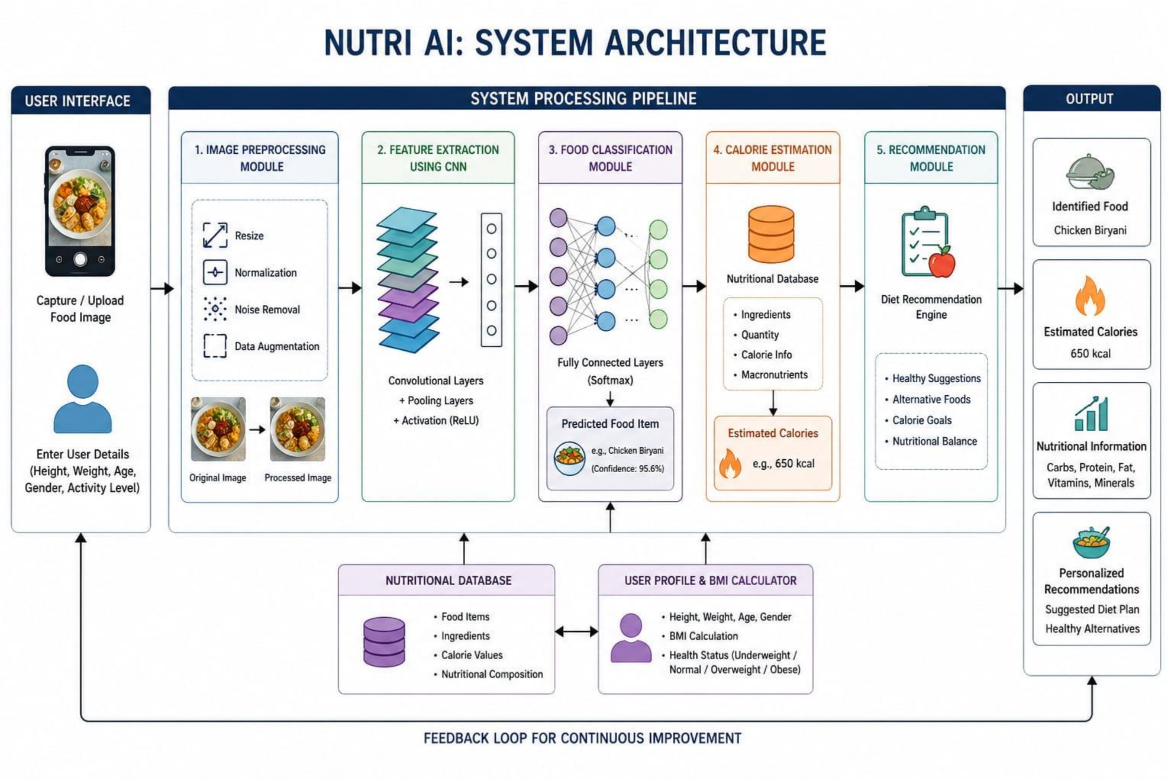
IV.6 Recommendation Module

Based on user input such as height and weight, the system calculates BMI and provides personalized diet recommendations. The system suggests healthier food options and helps users maintain a balanced diet. This module makes the system health-aware and user-centric.

IV.6 System Architecture



The architecture of the proposed Nutri AI system begins with the user uploading a food image along with basic details such as height and weight. The input image is first passed through the preprocessing module, where operations like resizing, normalization, and noise removal are performed to improve image quality. The processed image is then fed into a Convolutional Neural Network (CNN) for feature extraction, where important visual features such as color, texture, and shape are identified. These features are used by the classification module to recognize the food item accurately. Once the food is identified, the system accesses a nutritional database to estimate calorie values and nutritional information. Simultaneously, the user details are used to calculate BMI and determine health status. Based on this information, the recommendation module generates personalized diet suggestions and healthy alternatives. Finally, the system provides output including identified food, estimated calories, nutritional details, and personalized recommendations, making the entire process automated, efficient, and user-friendly.

V.RESULT AND DISCUSSION

The proposed Nutri AI system demonstrates effective performance in recognizing food items and estimating calorie values. The use of CNN improves classification accuracy and enables the system to handle real-world food images. Compared to traditional manual methods, the system significantly reduces time and effort while improving accuracy. The system also provides personalized recommendations, which enhances its practical usability. Experimental results show that the system can effectively identify food items and provide reliable nutritional information, making it suitable for real-world applications.

VI.CONCLUSION

The proposed Nutri AI system can be further enhanced by using larger and more diverse datasets to improve accuracy and handle different types of food items, including complex mixed dishes. Advanced deep learning models such as transformer-based architectures can be implemented to improve feature extraction and classification performance. The

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system can also be extended to support real-time food recognition using mobile cameras, enabling users to instantly capture images and receive calorie estimations. Additionally, portion size estimation techniques can be incorporated to provide more accurate nutritional analysis. Integration with mobile applications, wearable devices, and healthcare systems can help in delivering personalized diet recommendations based on real-time health data. The system can also include multilingual support and voice interaction to improve usability. These improvements will make Nutri AI a more efficient, user-friendly, and intelligent solution for real-world dietary monitoring.

Future Directions

The proposed Nutri AI system can be further enhanced by using larger and more diverse datasets to improve accuracy and handle different types of food items, including complex mixed dishes. Advanced deep learning models such as transformer-based architectures can be implemented to improve feature extraction and classification performance. The system can also be extended to support real-time food recognition using mobile cameras, enabling users to instantly capture images and receive calorie estimations. Additionally, portion size estimation techniques can be incorporated to provide more accurate nutritional analysis. Integration with mobile applications, wearable devices, and healthcare systems can help in delivering personalized diet recommendations based on real-time health data. The system can also include multilingual support and voice interaction to improve usability. These improvements will make Nutri AI a more efficient, user-friendly, and intelligent solution for real-world dietary monitoring.

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