Enhanced Food Detection & Nutritional Inference System

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ABSTRACT

Food recognition from images is a challenging problem because many food items appear visually similar and often contain multiple ingredients. Lighting conditions, camera angles, and presentation styles further complicate the task. This project proposes an Enhanced Food Detection and Nutritional Inference System that uses artificial intelligence to detect food items from images and estimate their nutritional values.

The system integrates computer vision models, vision–language reasoning techniques, and a structured nutrition database to generate nutritional information automatically. The workflow includes image preprocessing, food detection, food identification using AI reasoning, and mapping the detected food items to a nutritional database. The final system provides nutritional insights such as calories and macronutrients to help users better understand their dietary intake.

I. INTRODUCTION / BACKGROUND

Maintaining a healthy diet is an important part of preventing lifestyle diseases such as obesity and diabetes. Many individuals attempt to monitor their daily nutritional intake, but manually calculating calories and nutrients can be difficult and time-consuming.

Recent advancements in artificial intelligence and computer vision have enabled automated systems capable of recognizing objects in images. Food recognition systems use machine learning models to classify food items and estimate nutritional content.

This project introduces an Enhanced Food Detection and Nutritional Inference System that combines object detection models, vision-language reasoning, and nutritional databases to automatically analyze food images and generate nutritional information.

II. PROBLEM STATEMENT

Food images often contain multiple items or mixed dishes, making accurate identification difficult. Many food categories share similar visual characteristics, which increases the complexity of classification tasks. Variations in lighting, camera angles, and presentation styles also reduce the accuracy of detection models.

Traditional food recognition systems often struggle with real-world images due to these challenges. Therefore, an intelligent system is required to detect food items accurately and estimate their nutritional values automatically.

This project addresses these challenges by building a machine learning pipeline capable of detecting food items from images and linking them with nutritional data.

III. STAGE 2 – DATA COLLECTION AND PREPROCESSING

Stage 2 focused on collecting datasets and preparing them for model training. The Food-101 dataset was used for food image classification and contains images across 101 food categories. The UEC-Food256 dataset was used for object detection because it includes bounding box annotations for multiple food items.

Nutritional data was obtained from the USDA FoodData Central database, which provides detailed information about calories, carbohydrates, proteins, and fats.

During preprocessing, duplicate images and unnecessary samples were removed. Image formats and sizes were standardized to ensure consistent input. Corrupted images and incomplete samples were eliminated to improve dataset quality.

IV. STAGE 3 – EXPLORATORY DATA ANALYSIS

Stage 3 involved conducting Exploratory Data Analysis to understand dataset characteristics and identify patterns. The distribution of food categories was analyzed to detect class imbalance across datasets.

Sample images were inspected to evaluate variations in lighting, resolution, and presentation style. These variations may influence model performance.

Further analysis was conducted on nutritional data to examine relationships between calories and macronutrients. The analysis showed that calories strongly correlate with carbohydrates and fats, while protein contributes significantly to overall nutritional value.

V. STAGE 4 – FEATURE ENGINEERING AND FEATURE SELECTION

Stage 4 focused on improving dataset quality through feature engineering and feature selection. Image preprocessing techniques were applied to enhance input quality.

Contrast enhancement was performed using CLAHE to improve image clarity. Image resolution and color distribution were normalized to create consistent inputs for model training.

Feature scaling was applied by normalizing pixel values and standardizing image sizes. These steps helped reduce variations caused by lighting conditions and camera devices.

VI. STAGE 5 – MODEL DEVELOPMENT AND TRAINING

Stage 5 involved developing the food detection and identification models. The cleaned dataset was used to train deep learning models capable of detecting food items from images.

The Segment Anything Model (SAM) was used for object detection and localization. Bounding box annotations from the UEC-Food256 dataset helped detect multiple food items in a single image.

Vision-language reasoning models such as Gemini API, GPT-4o, and Qwen-VLM were integrated to improve food identification accuracy. Detected food items were then mapped to a nutrition database stored in SQLite.

The backend system was implemented using FastAPI to support efficient data processing and integration.

VII. STAGE 6 – MODEL ASSESSMENT AND PERFORMANCE ADJUSTMENT

Stage 6 focused on evaluating the reliability of the developed system and improving its performance. Detection accuracy was used to measure the correctness of food identification.

Precision and Recall metrics were used to evaluate classification reliability. Mean Average Precision (MAP) was used to assess object detection performance.

Cross-validation was performed to ensure the model performs consistently on unseen data. Hyperparameter tuning was also conducted to optimize learning rates, training epochs, and detection thresholds.

VIII. EXPECTED OUTCOMES

The expected outcome of this project is the development of a reliable system capable of detecting food items from images and estimating their nutritional values automatically. The system will provide nutritional insights such as calories, proteins, carbohydrates, and fats.

The project demonstrates the practical application of artificial intelligence in dietary monitoring and healthcare applications. It can help users understand the nutritional composition of their meals and support healthier lifestyle choices.

IX. PROJECT TIMELINE

The project followed a structured development timeline consisting of multiple stages.

Week	Planned Activity
Week 2	Data collection and preprocessing
Week 3	Exploratory Data Analysis and visualization
Week 4	Feature engineering and feature selection
Week 5	Model development and training
Week 6	Model assessment and performance adjustment
Week 7	Final report preparation and system integration

X. CONCLUSION

This project developed an AI-based system for detecting food items and estimating their nutritional values from images. The system integrates computer vision models, vision-language reasoning, and nutritional databases to provide automated dietary insights.

Through systematic stages including data preprocessing, exploratory analysis, feature engineering, model development, and evaluation, a reliable food detection pipeline was created.

Future improvements may include expanding the training dataset, improving portion size estimation, and integrating real-time detection capabilities for mobile applications.

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