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Dietary Intake Monitoring System Based on Food Image Recognition

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Abstract: *The accurate recognition and nutritional assessment of food items have become crucial in addressing dietary management and health monitoring. While deep learning-based food image recognition has advanced significantly, existing models often fail to generalize across diverse cuisines, particularly Indian dishes with complex presentations. The lack of culturally inclusive datasets further limits the performance of these models. This study evaluates YOLOv8 for food recognition, highlighting its strengths and challenges when applied to Indian cuisine. Data augmentation, Synthetic Data Generation, and 3D reconstruction techniques were explored. The findings indicate that integrating stereo vision and depth estimation can significantly enhance volume measurement accuracy. This paper provides a comprehensive review of food image recognition methodologies focused primarily on Indian Cuisines and suggests improvements for real-world applications.*

Keywords: YOLOv8, computer vision, food recognition, nutrition, dietary assessment system, data augmentation, synthetic data generation, 3D reconstruction, artificial intelligence

I. INTRODUCTION

It is now becoming a need to monitor and keep track of nutritional intake for an individual along with the increasing awareness of diet and health. Traditional methods like manual food tracking, self-reporting is often prone to error as well as time consuming. These methods are influenced by user bias, failing to provide real-time, precise nutritional insights essential for informed dietary decisions. The demand for technological solutions that simplify food tracking and nutrition estimation has never been higher, particularly with the increase in chronic diseases like obesity, diabetes, and cardiovascular disorders, which are directly impacted by dietary habits. Despite existing advancements, current algorithms like YOLOv8 face significant challenges when applied to culturally diverse cuisines such as Indian dishes, which are complex in presentation and often include overlapping or irregularly shaped food items. Furthermore, the lack of standardized datasets capturing Maharashtrian or other regional cuisines further limits the algorithm's ability to deliver accurate recognition and nutritional estimation results.

Advancements in artificial intelligence (AI) and computer vision have opened the door to automated dietary monitoring systems. These systems utilize AI-powered food image recognition to identify and categorize food items from photos, estimate portion sizes, and calculate nutritional content in real-time. They not only decrease reliance on manual food logging but also offer accurate and scalable solutions for personalized nutrition management. By integrating machine learning models and extensive food datasets, it is now possible to automate the analysis of various meals, providing users with instant feedback on their nutritional intake.

This review paper seeks to explore the cutting-edge technologies utilized in dietary monitoring systems, focusing on food image recognition and nutrition estimation. It will examine current methodologies, from deep learning-based food classification to 3D reconstruction techniques for volume estimation [11], and evaluate the advantages and limitations of existing systems. Additionally, the paper will suggest future research directions, emphasizing how these technologies can be further improved and integrated into seamless, real-time dietary monitoring solutions to encourage healthier lifestyles.

II. MOTIVATION

Accurate dietary monitoring is essential for maintaining health, managing chronic diseases, and making informed food choices. Traditional food tracking methods, such as manual logging and self-reported intake, are time-consuming, errorprone, and inconvenient, leading to poor adherence. With advancements in AI and Computer Vision, food image recognition offers an automated, efficient, and user-friendly solution for tracking dietary intake. This project aims to develop an AI-driven system that simplifies food logging, improves accuracy, and enhances user engagement, making nutrition tracking more accessible and effective. With advancements in AI and Computer Vision, food image recognition offers an automated, efficient, and accurate solution. By allowing users to capture meal images, AI models can identify food items, estimate portions, and provide real-time nutritional analysis, reducing manual effort. This project aims to develop a user-friendly, AI-driven dietary monitoring system that enhances accuracy, integrates with health apps, and encourages healthier eating habits. It addresses the growing need for personalized nutrition tracking, disease management, and data-driven dietary recommendations, making nutrition monitoring more accessible and effective.

Objectives

Develop a food image recognition system using YOLOv8, optimized for Indian cuisine.

- Integrate stereo vision and depth estimation for accurate portion and volume analysis.
- Apply synthetic data generation and augmentation to improve recognition robustness.
- Provide real-time nutrition feedback based on food classification and quantity.
- Design a user-friendly mobile interface for capturing food images and displaying nutritional data.

III. LITERATURE REVIEW

The field of food image recognition has advanced significantly, introducing various innovative approaches to improve dietary assessment and classification. For example, one study focused on Mediterranean cuisine employed pre-trained convolutional neural networks (CNNs) for food classification alongside stereovision techniques to reconstruct 3D food volumes from dual images. This system reported an 83.8% accuracy for top-1 classification and a mean absolute percentage error of 10.5% in volume estimation [5]. Another example, the Deep NOVA system, emphasized the classification of food healthiness based on processing levels rather than calorie estimation. Utilizing a customized YOLOv3 model for food detection and MobileNetV2 for classification, it categorized foods into four NOVA groups, ranging from unprocessed to ultra-processed items, thus offering a fresh approach beyond traditional methods [6].

Additional advancements include a privacy-preserving dietary monitoring system that transformed egocentric images into text-based descriptions, though it faced limitations in accurately estimating food volumes due to restricted image data [2]. Frank Po Wen Lo and colleagues reviewed food classification and volume estimation techniques, identifying the effectiveness of deep learning, particularly CNNs, while highlighting the challenges of 2D imaging and referencebased volume estimation in managing irregular food shapes [3]. Meanwhile, Smith et al. proposed using 3D image projection to estimate food volume. Their method, however, required manual mesh placement, which hindered full automation and accuracy [1]. Sultana et al. explored the use of generative adversarial networks (GANs) for creating 3D reconstructions, showing promise as an alternative to reference objects for more precise nutritional estimation, but requiring controlled conditions for effective application [4].

Although these studies demonstrate progress, key challenges remain unaddressed. Many approaches still rely on 2D images and manual interventions, reducing their practicality in dynamic real-world settings. Common limitations include difficulties in accounting for irregularly shaped items or overlapping portions, as well as inefficiencies introduced by text-based outputs or manual adjustments. Emerging approaches, such as stereo vision and multi-view imaging, offer promise but often require controlled environments to function optimally. While systems like Deep NOVA add value by focusing on food healthiness, they overlook critical aspects like portion sizes and overall nutritional balance.

From a technical perspective, developments in deep learning, stereovision, and geometry-based modelling hold the potential to resolve these constraints. For instance, EfficientNetB2 has demonstrated the effectiveness of transfer learning and augmentation in enhancing classification outcomes, while YOLOv3 has proven highly effective for real-time object detection in varied conditions. Combining these methods with depth estimation or techniques such as Structure from Motion (SfM) could facilitate more precise and scalable volume estimation. Future studies should aim to incorporate larger and more culturally diverse datasets to improve model generalizability across food types and cuisines.

Building on earlier research, [7] created a system that combines segmentation and classification for nutritional monitoring, applying it to Brazilian cuisine. This approach stands out for its use of advanced segmentation algorithms, particularly within mobile applications for dietary monitoring. [8] delves into food category recognition using deep learning models, highlighting how methods such as data augmentation and transfer learning enhance generalization across varied food datasets. Semi-supervised learning is also highlighted as a promising technique for scenarios with limited labelled data, offering potential for more scalable solutions. Lastly, [9] introduced an automatic calorie estimation system for smartphones, which innovatively uses reference objects to estimate food volumes, circumventing the need for depth cameras. However, this method still faces challenges when dealing with irregularly shaped or overlapping foods.

The literature on food image recognition underscores significant progress in both classification and volume estimation, particularly through deep learning and computer vision. Techniques like CNNs and YOLOv3 have achieved high accuracy in food classification, while stereo vision and 3D reconstruction have enhanced volume estimation. However, the continued reliance on 2D images and reference objects limits their practicality in real-world applications. While innovations like Deep NOVA provide a qualitative dimension by focusing on food healthiness, challenges remain in addressing irregular food shapes, overlapping portions, and achieving full automation. Emerging technologies like GANs for 3D reconstruction and more efficient transfer learning models show promise in overcoming these limitations. Future research should focus on integrating these advanced models with larger, more diverse datasets to improve scalability, aiming for more accurate and automated dietary assessment system. Many systems still rely on traditional 2D imaging and manual inputs for volume estimation, which limit scalability and automation. For instance, Smith et al. [1] used 3D projection with manual mesh transformations but faced high error rates (up to 60%) for irregular shapes. Similarly, Sultana et al. [4] explored GANs for food geometry estimation, which showed potential but required controlled imaging environments. Despite progress in multi-view geometry and stereo vision, practical implementation remains constrained by dataset variability and algorithmic inefficiencies.

IV. SYSTEM ARCHITECTURE

1. Image Acquisition Layer

Captures meal images using a smartphone camera

Optional stereo imaging (dual-angle capture) for volume estimation

User inputs for meal type or manual correction (if necessary)

2. Preprocessing Layer

Applies noise reduction, normalization, and contrast enhancement

Generates synthetic images through rotation, scaling, and color shifts

3. Detection & Classification Layer

YOLOv8 model trained on Indian food datasets

Identifies food categories and segments mixed dishes

Assigns labels and confidence scores to detected items

4. Volume Estimation Layer

Uses stereo vision and depth mapping to estimate portion size

Calculates volume using 3D reconstruction algorithms

5. Nutrition Analysis Layer

Maps recognized items and estimated volume to nutritional databases

Computes calorie, protein, fat, carbohydrate, and micronutrient values

6. User Interface Layer

Mobile application for real-time food logging and nutrition display
Provides summaries, history logs, and dietary trends
Enables feedback or corrections for user involvement

V. METHODOLOGY

A. Model Training & Data Handling

Dataset: Custom dataset featuring Indian dishes
Augmentation: Random flip, rotate, brightness/contrast variation
YOLOv8 Fine-tuning: Transfer learning from pre-trained weights
Metrics: Evaluated using mAP, IoU, F1-score

B. Depth Estimation

Stereo images processed to compute disparity and depth maps
Volume estimated using calibrated 3D reconstruction techniques

C. Nutritional Mapping

Uses Indian Food Composition Tables (IFCT)
Estimates nutrients based on label + volume
Flask backend maps food tags to nutritional values

D. Web Development

Backend: Flask (Python), handles model integration and API calls
Frontend: HTML & CSS for interactive web UI
Cloud Storage: AWS S3 for storing user-uploaded images and analysis logs
Security: User authentication and secure access to data via AWS

VI. RESULTS

Developing an accurate food recognition and nutrition estimation system for Indian cuisine faced challenges due to the lack of publicly available datasets. To address this, we generated a diverse dataset through data augmentation, applying transformations like rotation, cropping, brightness adjustments, and noise addition. Additionally, synthetic images were created using DALL·E 3 and SDXL to fill dataset gaps for traditional dishes like Puran Poli Thali. We then trained and compared YOLOv8 against YOLOv4, YOLOv3, Faster R-CNN, and R-CNN, evaluating factors such as training time, accuracy, and inference speed. YOLOv8 outperformed all models, achieving 87.2% MAP(Mean Average Precision) with 55 FPS(Frame per Second) and 18ms(milli-seconds) latency, making it significantly faster than Faster R-CNN while maintaining high accuracy. Unlike YOLOv4 and YOLOv3, which struggled with small and overlapping food items, YOLOv8's anchor-free architecture improved detection of intricate Indian meals. It also proved robust against varying lighting conditions and camera angles, making it the best choice for real-time food recognition applications.

Module	Metric	Result
Food Recognition	YOLOv8 mAP	91.3%
Volume Estimation	Accuracy (compared to ground truth)	88.6%
Nutrition Analysis	Calorie Estimation Error	±9.2%
Backend Performance	Flask API Avg. Response Time	< 1.5 sec
Cloud Storage	AWS Upload/Access Latency	< 1 sec
User Satisfaction	Survey Rating (out of 5)	4.4

Table 1: Performance Metrics of Model

VII. FUTURE SCOPE

Future advancements in food recognition systems can focus on dataset expansion, volume estimation, and improved classification accuracy. Current models rely on synthetic and augmented images, which may not fully capture real-world variations. Enhancing the dataset with real-world images from diverse environments, leveraging crowdsourcing, and applying domain adaptation techniques can improve generalization. Additionally, volume estimation remains a challenge, particularly for flat and liquid-based foods. This can be addressed using multi-view image analysis, 3D reconstruction techniques like Structure-from-Motion (SfM), and depth-aware models such as MiDaS to improve portion size predictions. Challenges related to model bias, misclassification, and real-time deployment also need attention. Similar-looking food items and mixed dishes often lead to misclassification, which can be mitigated through refined dataset labeling, multimodal learning, and transformer-based architectures like DETR and Swin Transformer. While YOLOv8 outperforms previous models, it struggles with small and occluded food items, which hybrid models and selfsupervised learning can help refine. Additionally, deploying models on edge devices requires optimization techniques such as quantization and pruning. Implementing real-time user feedback mechanisms can further enhance classification accuracy over time. Ethical considerations, including privacy concerns and dietary restrictions, should also be addressed by incorporating privacy-preserving AI techniques and personalized nutrition modules, ensuring a more user-centric experience.

VIII. CONCLUSION

This study highlights the capabilities and limitations of YOLOv8 for Indian food recognition and nutritional assessment. While the model excels in real-time object detection, its performance is affected by dataset biases, overlapping food items, and volume estimation challenges.

Enhancing food recognition systems requires addressing key challenges such as dataset limitations, volume estimation, model bias, real-time deployment, and ethical considerations. Expanding datasets with real-world images, refining classification techniques using transformer-based architectures, and integrating depth-aware models for portion estimation can significantly improve accuracy. Optimizing models for edge devices through quantization and pruning, along with implementing real-time user feedback, can enhance deployment efficiency. Additionally, incorporating privacy-preserving AI techniques and personalized nutrition modules ensures a more secure and user-centric approach. By addressing these areas, food recognition technology can become more accurate, efficient, and widely applicable across diverse real-world scenarios.

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