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Diet Snap using Transfer Learning

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***Abstract*— Ensuring a well-balanced diet is crucial for maintaining overall health., yet many individuals struggle to track their nutritional intake effectively. This application leverages Yolov5 for object detection to analyze uploaded food images, identifying food items and estimating their calorie content. Beyond basic tracking, the system evaluates the detected food and provides dietary recommendations by identifying missing nutrients. It suggests adjustments to ensure a well-rounded diet, such as increasing protein intake, incorporating fiber-rich foods, or reducing excessive fats and sugars. By offering personalized insights, the application allow users to create and promote properly discovered nutritional decisions.**

***Index Terms*— YOLOv5, Deep Learning, CNN, Object Detection.**

I. INTRODUCTION

The rising incidence of obesity and dietary health problems like diabetes, heart disease, and high blood pressure has underscored the need for improved nutritional tracking [2]. Most individuals have a difficult time balancing their diet with the lack of awareness, inappropriate estimation of food portions, and difficulty in keeping tabs on daily intake. Effective diet control can prevent health-related complications and contribute to overall good health. Yet, traditional methods of tracking food intake rely on manual intervention that is tedious and prone to error, generating inconsistencies in capturing nutritional intake. Manual logging of food continues to be among the most widespread techniques for the estimation of calorie consumption. Individuals must input descriptions of their food into a database or mobile device using estimated portions or pre-coded nutritional information. These approaches are extremely user-dependent and rely on complete food information being available. Estimation inaccuracies in portion size and ingredient substitutions limit the ability to provide accurate calorie content, thus weakening conventional food tracking methods. In addition, time pressures and motivation frequently result in failure to maintain a regular recording of meals, with corresponding gaps in the dietary records.
To overcome such challenges, automated food recognition systems based on Artificial Intelligence (AI) and deep learning have emerged as a viable alternative. These systems use computer vision methods [11] to recognize food objects in photographs taken using smartphones or cameras. Through visual feature analysis of various foods and against large nutritional databases, AI-based models can offer real-time estimates of calorie content and macronutrient breakdown. This automation eliminates much of the workload of manual logging with increased accuracy, making it easier and more efficient for dietary tracking.
The system proposed in this study targets the use of deep learning models, specifically YOLOv5[6] object detection, to identify food items and approximate their calorie levels [7]. By combining machine learning algorithms with a properly organized food database, the system seeks to offer users correct nutritional data and custom dietary advice.

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An easy-to-use web-based interface provides easy interaction, and people can track their meals easily. This methodology not only enhances the accuracy of diet tracking but also promotes improved eating habits with data-driven intelligence.

The innovation of AI-driven food recognition technologies has extensive use cases beyond personal health management. These technologies are capable of supporting healthcare professionals with the monitoring of patients with restrictive diets, enabling researchers to mine big data relating to nutrition, and making tools for dietary planning more effective.

II. Challenges

Even with the progress in automated food recognition and calorie estimation, there are still a number of challenges in creating a highly efficient and accurate system. The major challenges are:

A. Food Variability and Complex Dishes

Foods exist in different forms, colors, and textures, and it is challenging for models to differentiate between foods that look alike. Complex dishes with various ingredients make food recognition even more challenging, necessitating strong detection methods.

B. Portion Size Estimation

Precise estimation of portion sizes from images is difficult because angle, distance, and lighting conditions influence visibility. Lacking proper portion estimation, calorie calculation can be incorrect.

C. Variation in Food Data Sets

Deep learning models are trained with large, varied data sets that include different cuisines, cooking techniques, and presentation styles. Insufficient or skewed data sets can lower the model's capability for generalization across different food types.

D. Accuracy of Calorie and Nutrient Estimation

Even when food is properly identified, correlating it to a nutritional database with accurate calorie and macronutrient content is challenging. Differences in ingredient preparation, cooking, and serving sizes can cause inconsistencies.

E. Real-time Processing and Efficiency

Optimization of machine learning models is needed to ensure rapid and efficient food recognition on typical consumer hardware. High computational expense and latency can compromise real-time performance, making the system impractical for everyday use.

III. Contributions

To solve these challenges, this study presents a sophisticated AI-based food recognition and calorie estimation system with the following main contributions:

A. Deep Learning-Based Food Detection

The system utilizes a YOLOv5 object detection model optimized for efficient and precise food recognition. This increases identification accuracy even for visually comparable food items and complicated dishes.

B. Integration of Nutritional Databases

An efficiently formatted response food database is included in the model for precise calorie and macronutrient calculations. The system correlates food items detected to authenticated nutritional information, eliminating discrepancies and inconsistencies.

C. User-Friendly Web-Based Interface

A real-time, interactive web interface allows users to easily upload images of foods. Images are processed on the fly with nutritional information displayed to inform appropriate diet choices.

D. Scalability and Future Development

The architecture supports ongoing updates by adding new foods, diversifying datasets, and optimizing portion estimation algorithms. This guarantees long-term relevance and flexibility in actual usage.

With these contributions, the proposed system improves the accuracy, usability, and applicability of AI-based food recognition, making it more accessible and reliable for users to track their diets.

E. Personalized Diet Recommendations

The system can also analyze individual dietary patterns and preferences to provide customized meal suggestions. By incorporating Large Language Models (LLMs), it analyses the macronutrient lacking in their diet and suggesting them upon improvements to their current meal plans.

IV. LITERATURE SURVEY

Suryakrishnan et al. [2] analyzed the performance of Convolutional Neural Networks (CNN) for Indian food detection and calorie estimation. Using a custom dataset, CNN integrated with OpenCV achieved high accuracy in identifying Indian dishes. However, the method's limitation was its inability to generalize across all Indian cuisine.

Chauhan et al. [5] implemented a deep learning-based approach for calorie estimation in Indian foods using a CNN trained on a custom dataset. While the model reported accurate calorie estimations, the dataset details were not fully disclosed, raising concerns about reproducibility. Additionally, no dietary suggestions were provided in this approach.

Nivedhitha et al. [6] focused on calorie estimation for food and beverages using CNN on a custom dataset. The model demonstrated accurate calorie estimation, but its applicability was restricted to certain food types, limiting its generalizability.

Yongqiang Shi et al. [4] employed Convolutional Block Attention Module (CBAM) and 3D reconstruction techniques to improve accuracy, including localization and portion estimation, using a nutrition study dataset. The model achieved 83.74% accuracy, though complex food compositions impacted its performance.

Muhammad et al. [10] utilized a CNN-based food recognition approach for food type identification and calorie estimation. The model demonstrated robust estimation; however, the dataset details were not provided, making reproducibility difficult.

TABLE I. COMPARISON OF FOOD DETECTION AND CALORIE ESTIMATION METHODS

Study	Approach Used	Accuracy	Limitations
Suryakrishnan, et al. (2022)	CNN	High	Poor generalization across cuisines
Chauhan et al. (2024)	CNN on custom dataset	Accurate	No diet suggestions
Nivedhitha, P. A., et al. (2022)	CNN-based calorie estimation	High	Limited to certain food types
Yongqiang Shi, et al. (2024)	CBAM	89%	Struggles with complex food items
Muhammad, N. et al. (2023)	CNN-based recognition	87%	Dataset details missing

V. PROPOSED MODEL

The pipeline followed in the making of Diet Snap is neat and well-structured, which essentially fuses deep learning, computer vision, and cloud processing for food detection and calorie estimation. The whole system works starting from image acquisition, where users capture pictures of their meals via a web interface built on Flask.

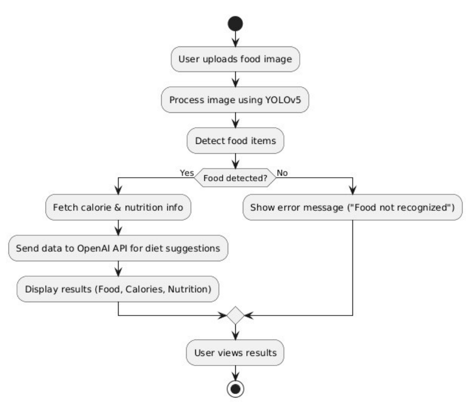

Fig. 1. Working of proposed model

For the classification of food, the chosen system is YOLOv5 object detection [4][6], which is a fast and very precise implementation for one-shot detection of many food items within a scene. For estimating portion size, we combine image depth analysis [12] with manual reference object scaling [1] to improve the accuracy of calorie computation. The food items recognized in the previous stage are then correlated against food databases such as FatSecret to provide nutritional information [5][13] on the basis of estimated portions.

As for diet suggestions, the chosen system sends all the macronutrient data collected from the object detection and queries the OpenAI API for macronutrient analysis. The result of the analysis lists all the macronutrients that are in and missing in the current diet and provides suggestions based on them.

VI. Experimental Analysis

To conduct our study, we created a specialized food image dataset by merging a number of sources, including Food-101, Indian Food Image Dataset, and additional manually collected images. The dataset includes a balanced set of food categories, including various cuisines and food types [2][3].

We have 13 distinct food classes in our dataset, which are: Chocolate Cake, French Fries, Ice Cream, Nachos, Onion Rings, Pizza, Samosa, Strawberry Shortcake, Tacos, Waffles, Aloo Tikki, Chapati, and White Rice.

For dataset enrichment, we labeled the images manually, with high-quality training and testing labels [8][9]. The dataset provides a robust foundation for food classification tasks, with variations in lighting, angle, and background to improve model generalization.

The proposed Diet Snap system indicates that the model for food detection has performed well in identifying widely accepted foods such as fries, chapati, or Aloo tikki, with instances of confidence being above 80 percent on most occasions. However, there still remain rare cases where misclassifications can slip in since other food items may appear visually similar, signaling a need for rectification.

On the other hand, the macronutrient analysis applied using OpenAI's model proves to effectively reveal missing constituents in meals - notably, deficiencies in protein, fiber, and essential vitamins- for meals with a high percentage of fats and carbohydrates.

For a meal that includes French fries and onion rings, protein and fiber are flagged as lacking, making the analysis more useful for general diet recommendations. That said, it is still a limitation that the exact quantitative values of the missing nutrients (in grams) are not provided. It gives a user an interactive feel with the web-based interface, properly rendering the nutritional breakdowns in a way safe for HTML and ensuring a 1-3 second response time with respect to the API.

The limitations still include food misclassifications at times, inconsistent calorie counts due to cooking methods and different portion sizes, and sometimes, structured output format inconsistencies. Following these thoughts, solving these limitations through better portion estimation, formatting their outputs, and incorporating them into user input can improve the accuracy and usability of the entire system even more.

Fig. 2. Frontend Prediction Interface

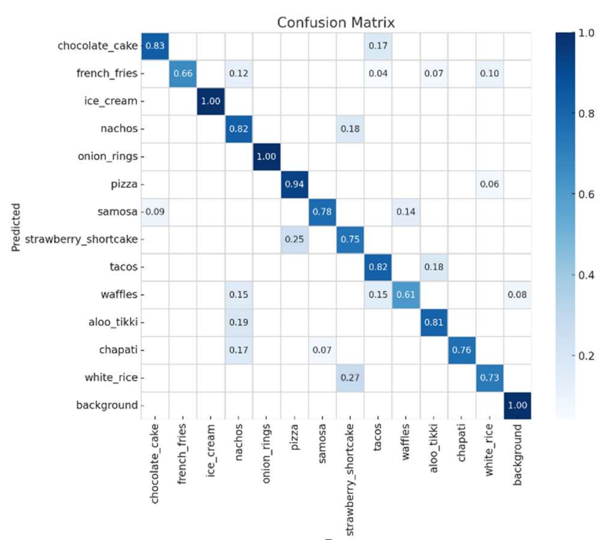

Fig. 3. Confusion matrix of proposed model

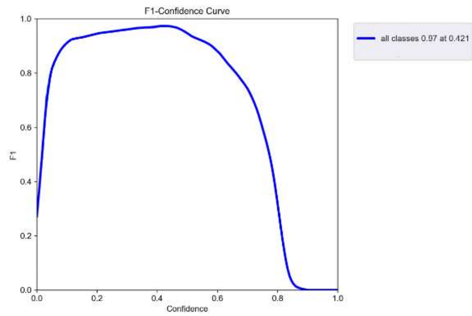

Fig. 4. F1- Confidence Curve

Epoch	Precision	Recall	mAP@0.5	mAP@0.5:0.95	F1 Score
0	0.0025	0.2570	0.0016	0.0005	0.0049
5	0.7351	0.2814	0.2447	0.0730	0.4070
10	0.3917	0.6076	0.3336	0.1236	0.4763
15	0.3976	0.6903	0.4753	0.1874	0.5046
20	0.7895	0.6927	0.8219	0.4077	0.7379
25	0.6581	0.8737	0.8605	0.3843	0.7507
30	0.6609	0.9494	0.8529	0.4743	0.7793
35	0.8547	0.9682	0.9468	0.4943	0.9079
40	0.9361	0.9573	0.9738	0.6232	0.9466
45	0.9481	0.9699	0.9850	0.6403	0.9589
49	0.9499	0.9831	0.9872	0.6506	0.9662

Fig. 5. Performance of proposed model on various evaluation metrics

VII. CONCLUSION

The Diet Snap project employs deep learning and computer vision methods to aid in automatic food recognition and calorie estimation, thereby providing a novel approach to dietary tracking.

A YOLOv5-based object detection model has been employed to recognize food from images uploaded by the user with high precision, which is then matched to a wide-ranging food database for calorie and macro retrieval.

The integration of an OpenAI API allows for the identification of missing dietary components and their macro analysis, thus providing a better basis for personalized nutrition recommendations which improve upon existing implementations by helping the user plan an ideal diet for them. The system uses a web interface that is easy to navigate, where detected foods, calorie breakdowns, and dietary suggestions are instantaneously shown in 1-3 seconds with a fast response rate.

There still remain challenges such as misclassification of foods, variance in calorie estimations due to portion differences, and slight instances of formatting errors in AI communication that need rectification. Future improvements will focus on better portion size estimation, rich diversity in data sets, and better structure of responses to ensure accuracy and user experience.

Diet Snap presents a rather robust and scalable solution to real-time tracking of food, which fosters sound dietary management, thereby definitely resulting in healthier eating habits, the system also educates the user about their current diet helping them plan a customized diet plan for themselves by offering suggestions.

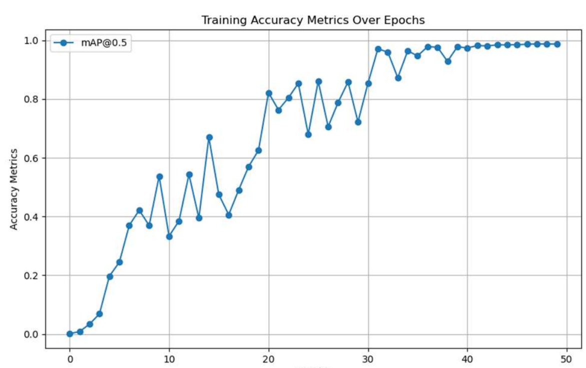

Fig. 6. Training Accuracy(mAP@0.5) Over Epochs

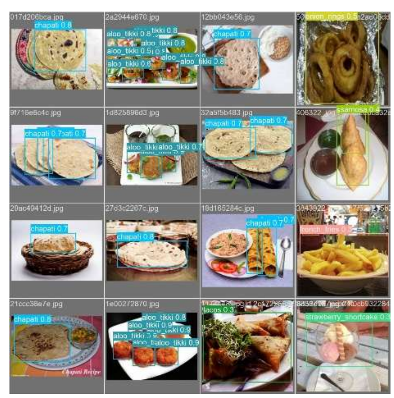

Fig. 7. Proposed model prediction on test data

VIII. FUTURE SCOPE

A. Improved Portion Estimation

To enhance the accuracy of portion estimation, MonoDepth2 and LIDAR-based sensors or calibration objects can be integrated to determine the volume of food items. Implementing 3D CNNs and Transformers can further improve food portion recognition by analyzing different perspectives of the image. Reinforcement learning models can be trained using user feedback, where manual portion size corrections help refine the system's predictions. This iterative learning process ensures that the system adapts over time, improving accuracy in real-world scenarios.

B. Enhanced Food Classification

Fine-tuning YOLOv5 using Transfer Learning can improve food classification by training models on diverse datasets, ensuring better recognition of visually similar items. Implementing knowledge distillation allows for the creation of lightweight versions of these models, enabling real-time inference on mobile devices. Additionally, an active learning pipeline can be introduced, where user corrections and misclassified food items are flagged and periodically used for retraining the model, increasing its adaptability and precision.

C. Real-time user Input Integration

To allow users to actively contribute to improving detection accuracy, React Native can be utilized to develop a responsive UI for real-time manual adjustments. Additionally, speech-to-text APIs can be incorporated, enabling users to verbally confirm or modify detected food items. Implementing Edge AI processing with TensorFlow Lite or ONNX allows food recognition adjustments to be processed locally, reducing dependency on cloud computing and improving real-time usability.

D. Personalized Diet Recommendations

Diet Snap can be enhanced by incorporating GPT-4 Turbo or BERT-based NLP models to analyze user dietary patterns and generate personalized meal recommendations. A collaborative filtering approach, similar to recommendation systems used in e-commerce, can be applied to suggest meals based on user preferences, past consumption, and dietary goals. Additionally, reinforcement learning can be employed, where recommendations improve over time based on user acceptance or modifications, creating a more adaptive system.

E. Multi-Cuisine Dataset Expansion

Expanding the dataset to include diverse food cultures using more images from sources like Food-101, IndianFood-Images, and Recipe1M will enhance global applicability. Generative adversarial networks (GANs), such as StyleGAN, can be utilized to produce synthetic images of food, enhancing model training for underrepresented foods. Having an active learning strategy, where misclassified foods are highlighted and added to subsequent training rounds, will make the model constantly better at identifying new foods.

F. AI-Generated Nutritional Reports

Diet Snap can generate weekly and monthly nutritional reports using Power BI, Tableau, or Matplotlib, helping users track their dietary habits over time. Automated Python scripts with Pandas and NumPy can process user data to identify trends, such as deficiencies in certain nutrients.

G. Integration with Wearable Devices

By integrating Diet Snap with Apple Health and Google Fit through a Flask or FastAPI API, users can track their calorie intake alongside fitness data. Using WebSockets for real-time synchronization, the system can dynamically adjust calorie recommendations based on daily activity levels. Additionally, incorporating anomaly detection algorithms can help flag inconsistencies in calorie burn estimates, ensuring more accurate and personalized dietary recommendations.

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