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Food Calories Estimation Using Depth Prediction And Fusion

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Abstract: Calorie estimation is crucial for dietary tracking and health management. This work presents a novel method that combines depth prediction and feature fusion to improve estimation accuracy. In order to accurately estimate the volume of food items, deep learning algorithms are used to forecast depth information. To enhance calorie computation, the retrieved depth, RGB, and texture data are subsequently combined utilizing sophisticated aggregation techniques. The suggested technique gets over the drawbacks of conventional 2D-based methods by utilizing RGB-D pictures, which results in more precise calorie and portion size estimation. According to experimental results, this technology performs better than traditional approaches and achieves a higher level of precision in calorie measurement.In real-time applications, robustness and efficiency are guaranteed by the combination of machine learning and multimodal data fusion. Prior research has confirmed the benefits of using depth information for volume estimate and demonstrated the efficacy of depth-based methods in food analysis. This approach may find use in healthcare, automated nutrition monitoring, and customized diet management programs. This method helps create intelligent health-monitoring tools that help users maintain balanced eating habits by increasing the accuracy of calorie calculation.

Keywords: Deep learning, CNN,Graph Neural Networks, food calorie estimation, depth prediction, feature fusion, RGB-D pictures, nutritional analysis, multimodal data fusion, machine learning, food volume estimation, real-time applications, dietary tracking, healthcare, and AI-driven models.

I. INTRODUCTION

For nutritional monitoring, nutrition tracking, and medical applications, precise food calorie calculation is crucial. Because self-reported food diaries and other traditional methods are frequently inaccurate and inefficient, automated systems are a useful substitute [1]. Food calorie estimation has greatly improved recently because to developments in deep learning and computer vision, with depth prediction and fusion approaches being essential for increasing accuracy [2]. These methods enable accurate food volume estimation by combining RGB and depth data, which results in more trustworthy nutritional analysis [3], [4].When compared to 2D photos, depth-based methods improve volume estimate by providing three-dimensional (3D) representations of food items, which has led to their popularity [5].

Convolutional Neural Networks (CNNs) have been shown in studies to efficiently extract visual information from RGB and depth images, which helps with calorie estimation [6].By utilizing feature interactions across modalities, a hybrid strategy that incorporates CNNs and Graph Neural Networks (GNNs) has demonstrated higher performance in calorie estimation [8], [9].

The efficiency and accuracy of food volume estimation have increased due to the further refinement of feature extraction through the combination of RGB-D pictures with AI-driven models [10]. By more precisely capturing the shape of food items, depth sensors—like time-of-flight cameras and structured light—improve calorie estimation [11], [12]. By photographing food from several perspectives, multi-view depth estimation has also been investigated as a way to lower volume prediction mistakes [13].

Current research highlights the value of real-time food calorie estimation for dietary planning, exercise, and healthcare applications [14], [15]. In order to increase automated food calorie estimation systems' accuracy and dependability and guarantee better use in practical situations, this study investigates depth-based fusion techniques [16].

II. RELATED WORK

In the developing subject of automated food calorie estimate, numerous models and methods have been put forth to improve efficiency and accuracy [1]. For accurate meal volume estimation, image-based algorithms must be used because traditional methods that depend on manual input are prone to inaccuracies [2]. Food calorie calculation has significantly improved with deep learning-based approaches, especially those that combine RGB and depth data [3].

Because CNNs can capture spatial and temporal dependencies in food images, they have been widely used for food volume estimate [4]. CNNs in particular have shown excellent performance in enhancing estimation accuracy by extracting features from food photos [5]. Furthermore, by utilizing temporal dependencies, hybrid algorithms that integrate CNNs have improved calorie prediction methods [6]. Techniques for depth prediction and fusion have been crucial in improving calorie estimating algorithms' accuracy [7]. Researchers have enhanced meal volume estimate by integrating RGB-D photos, which lessens the drawbacks of single-image methods [8]. More thorough feature extraction is made possible by combining RGB and depth data, which improves efficiency in real-time applications [9].

In order to improve the accuracy of food dimensions, a number of studies have looked into the use of 3D reconstruction techniques for food volume estimation [10]. In order to improve feature representation, Graph Neural Networks (GNNs) have also been investigated for modeling spatial dependencies in food photos [11]. By improving feature extraction procedures, the combination of GNNs and CNNs has further optimized calorie estimation models [12].In food calorie estimate, hybrid deep learning methods that combine several modalities have done better than traditional machine learning approaches [13]. Better contextual interpretation of food image data is now possible thanks to the introduction of transformer-based architectures [14]. These models improve prediction accuracy by using self-attention mechanisms to pick up on fine details in food photos [15].

To increase estimation precision, attention processes have been incorporated into food calorie estimating models to concentrate on key image regions [16]. By anticipating depth maps and improving volume computation, depth-aware CNNs have been suggested as a way to improve single-image calorie prediction [17].In order to properly integrate visual and depth cues and improve calorie prediction performance, multimodal fusion approaches have been investigated [18].

Large-scale food calorie estimation applications can be supported by cloud-based frameworks that guarantee scalability and real-time processing [19]. In order to efficiently manage large food image datasets and lower computational overhead, distributed computing techniques have been used [20]. Furthermore, real-time food calorie calculation on mobile devices has been made easier with the use of edge computing systems [21].

To help users keep track of their food intake, real-time food calorie estimating algorithms have been incorporated into healthcare applications [22]. Users may now instantly estimate the number of calories in food photos thanks to the integration of AI-driven food tracking technologies into smartphone applications [23]. Real-time calorie estimation on devices with limited resources is now much more feasible thanks to the creation of lightweight deep learning models [24].

Lastly, data augmentation approaches have been adopted to increase model generalization in food calorie estimation due to data scarcity [25]. Food photographs have been synthesized using generative models, such GANs, which improve model performance and enrich datasets. The potential for extremely precise and effective food calorie prediction systems is highlighted by the ongoing developments in deep learning and multimodal data fusion.

III. SELECTED METHODOLOGY

Depth prediction and fusion techniques offer a powerful approach to improving food calorie estimation by enhancing the accuracy of volume and portion size measurements. Depth prediction involves capturing three-dimensional information of food items through depth sensors, such as stereo cameras or LiDAR. Unlike conventional 2D images, which only provide surface information, depth data includes crucial spatial details about the food's shape, volume, and structure, offering a more comprehensive understanding of the food item. This capability is vital for estimating the true portion size, which directly impacts the accuracy of caloric calculations.

In food calorie estimation, depth prediction helps address challenges like irregular food shapes, varying textures, and inconsistent portions that can lead to errors in traditional methods. By providing depth information, it allows systems to calculate the exact volume of food, an essential factor in determining calorie content. For example, a piece of fruit or a bowl of soup can be measured more precisely by understanding its 3D volume rather than relying on visual cues alone.

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Fusion refers to the integration of depth data with other modalities, such as image-based recognition, to improve overall estimation accuracy. Visual recognition models can identify and classify food items, while depth data enhances the system's understanding of the food's spatial properties. When these data sources are fused, the system can more accurately assess both the type of food and its portion size, leading to more reliable calorie predictions. This fusion technique significantly reduces errors caused by inconsistent food appearances, such as overlapping items or foods with complex textures.

Together, depth prediction and fusion offer a robust solution for food calorie estimation, enabling more precise, real-time dietary tracking and personalized nutrition planning. This approach enhances the overall reliability and usability of automated food recognition systems.

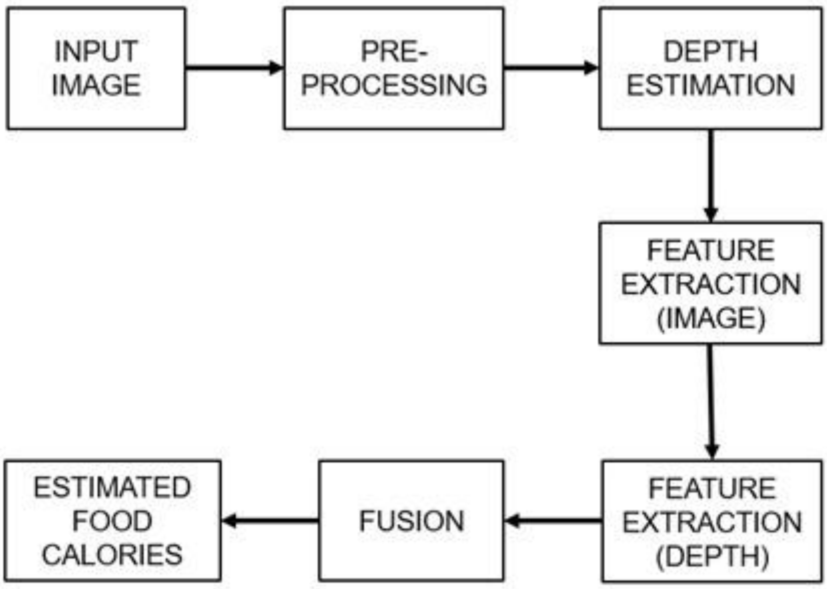

Fig. 1 Block diagram

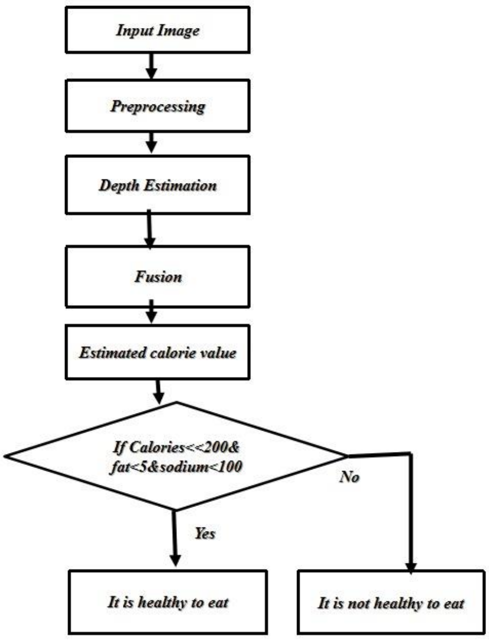

Fig. 2 Flow chart

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Steps:

1. Data Collection: Gather a large dataset of food images with corresponding nutrition information and depth data.
2. Data Preprocessing: Clean, annotate, and preprocess the data for training.
3. Depth Prediction: Train a deep learning model (e.g., CNN) to predict depth from food images.
4. Sensor Fusion: Integrate depth data with other sensor data (e.g., weight, volume) to improve accuracy.
5. Nutrition Estimation: Train a separate deep learning model to estimate nutrition from the fused data.
6. Model Evaluation: Test and evaluate the performance of both models.
7. Integration: Integrate the depth prediction and nutrition estimation models into a single system.
8. Testing and Validation: Conduct thorough testing and validation of the system.

Food	Calories	Protein (g)	Carbs (g)	Fat (g)	Sugar (g)	Sodium (mg)
Apple	95	0.3	25	0.2	19	2
Banana	105	1.3	27	0.3	14	1
Orange	62	1.2	15	0.2	12	0
Pizza	285	12	36	10	4	640
Burger	354	17	29	20	9	500
Rice	206	4.3	45	0.4	0.1	1
Pasta	221	8	43	1.3	2	5
Chicken	165	31	0	3.6	0	74
Fish	208	20	0	13	0	59

Fig. 3 Nutritional Information of Various Foods

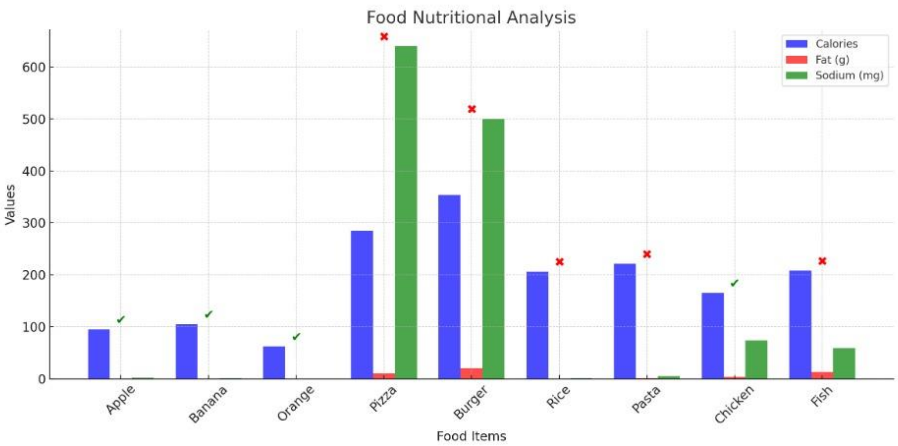

Fig. 4 Comparative Nutritional Analysis of Various Foods

IV. RESULT AND DISCUSSIONS

Food calorie estimation using depth prediction and fusion is an innovative method that combines depth sensing technologies and computer vision to improve calorie accuracy. Depth prediction allows for precise measurement of food volume, surface area, and shape, which are critical for estimating calorie content as they directly relate to portion size. By integrating visual data, which provides texture, color, and shape details, with depth data, the system can effectively identify and distinguish between different food types, even in cluttered or complex settings. Once the food is recognized and a 3D model is created, algorithms estimate its volume and compare it to a database of foods with known calorie densities, providing more accurate calorie estimations than traditional 2D image-based methods. The fusion of depth and visual data enhances the system's ability to handle overlapping foods and irregular shapes, offering a precise, user-friendly solution for dietary tracking, health monitoring, and automated food logging, ultimately supporting healthier eating habits.

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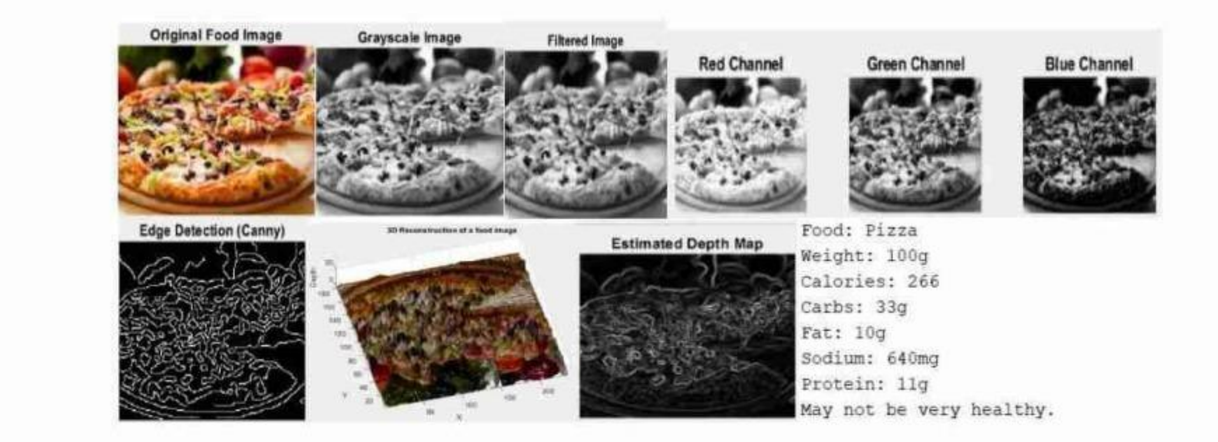

Fig. 5 Food Image Processing for Calorie Estimation

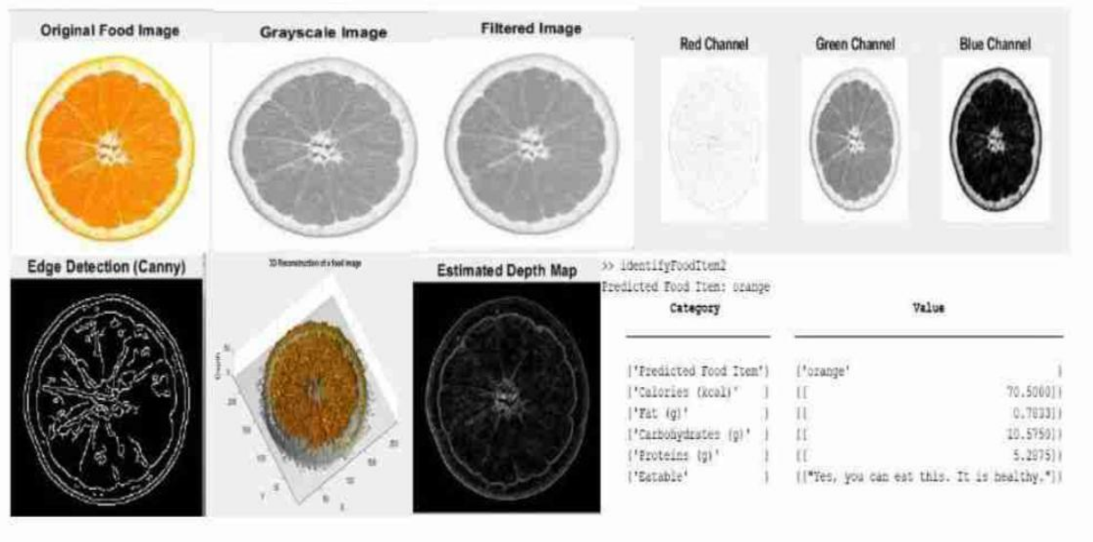

Fig. 6 Depth-Based Food Identification and Nutritional Analysis

Fig. 7 Automated Food Calorie and Nutrition Estimation

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V. CONCLUSION

One revolutionary development in nutrition tracking is the combination of depth prediction and fusion in food calorie estimation. This technology offers a more precise and dependable method of calculating food portions and calorie content by fusing depth data with food photos. Even though there are still issues with managing various food shapes and creating large databases, continuous improvements can greatly enhance dietary monitoring. This technology has the potential to completely transform personal health management as it becomes more widely available, making accurate and seamless calorie tracking possible. It might play a significant role in encouraging better eating practices and averting diet-related illnesses in the future.

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