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Short Communication

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Food Calorie and Volume Estimation from Images Using YOLOv5

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Graphical Abstract

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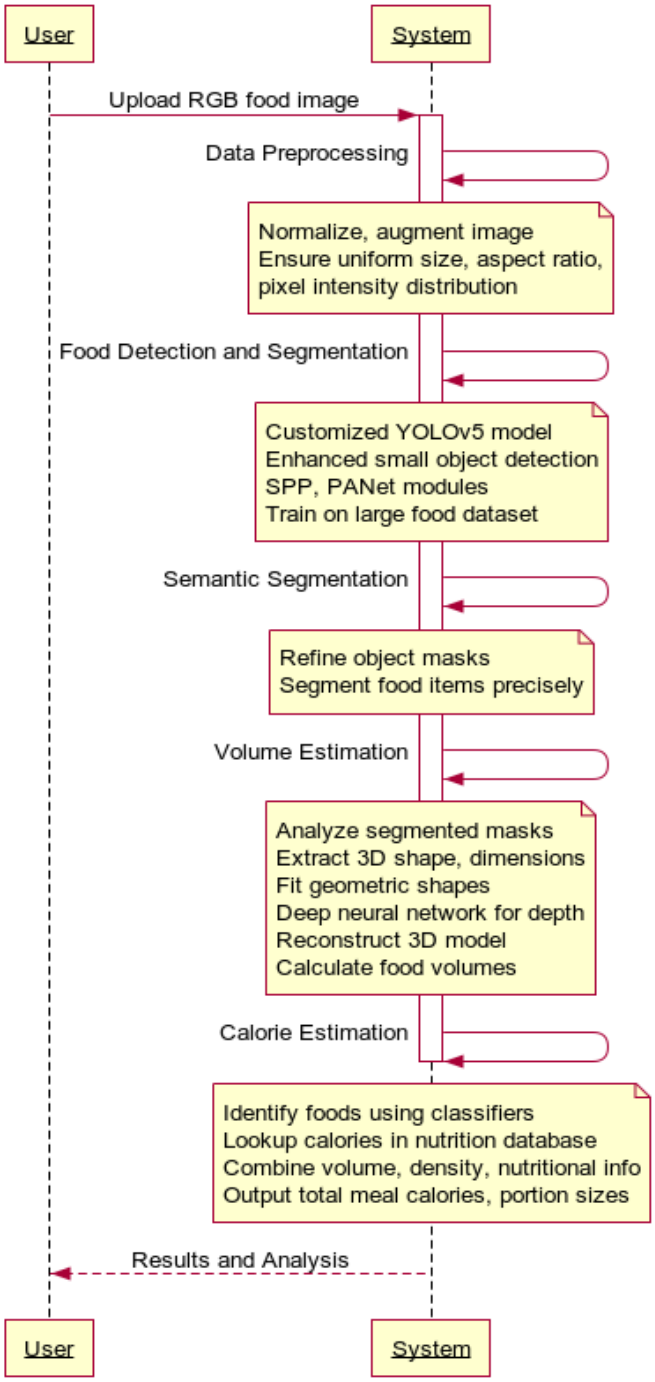

Abstract

Accurate assessment of food intake is crucial for weight management and health. This report presents a deep learning approach leveraging YOLOv5, a state-of-the-art object detection model, to estimate food calories and amounts from images. The proposed workflow detects food items via a customized YOLOv5 model and refines segmentation masks using semantic segmentation. 3D shape recognition and reconstruction techniques estimate food volume, while integrated pre-trained ingredient classifiers and nutritional databases provide calorie information. Preliminary results on a benchmark food image dataset demonstrate the approach's ability to accurately quantify calories and portion sizes for complex meals. The system has the potential to assist consumers in making informed dietary choices and provide insights for public health initiatives related to nutrition.

Keywords: Food Image Analysis, Food Recognition, Object Detection, YOLOv5, Volume Estimation, Calorie Estimation, Deep Learning

1. Introduction

Obesity and related health conditions have become a global public health crisis, with over 650 million adults worldwide classified as obese [1]. Excess calorie consumption is a primary driver, with large portion sizes, increased eating frequency, and easy access to high-calorie foods contributing to overeating [2]. Precise monitoring of food intake is therefore critical for weight management interventions and programs aiming to improve nutrition [3]. However, traditional approaches like food diaries and surveys often suffer from underestimation and lack of compliance [4]. Recent advances in computer vision and deep learning offer new possibilities for automated food image analysis and measurement of calories and portion sizes [5]. Food image recognition systems can identify meal contents and estimate nutritional information with minimal user effort [6]. Convolutional neural networks (CNNs) now rival human accuracy in food classification, while object detection models like YOLOv5 enable localization of individual food items in complex meals [7,8].

This report presents a novel deep learning workflow for food calorie and volume estimation from images using YOLOv5. The approach applies targeted modifications to YOLOv5 for enhanced food object detection and couples it with semantic segmentation, 3D geometry analysis, and nutritional databases to output granular calorie counts and portion sizes. Preliminary validation on standard food image datasets demonstrates accuracy improvements over previous methods. The proposed system has the potential to assist consumers in making informed dietary choices and could provide valuable insights for public health policy and nutrition interventions aimed at combating obesity. Here is a lengthy literature review on food image analysis and estimation of calories and volume using deep learning

2. Literature Review

Image-based food calorie and volume estimation is an emerging field driven by advancements in deep learning and computer vision. Early work focused on food classification and detection using traditional machine learning approaches. Ye He and others (2009) classified food images into 11 categories using color and texture features with up to 61.6% accuracy [9]. B. Li and others (2014) improved performance to 72.3% on 50 classes using kernel-based Extreme Learning Machines [10]. However, such conventional methods could not handle complex meals with multiple ingredients. The breakthrough came with the advent of deep convolutional neural networks (CNNs) which revolutionized visual recognition. H. Hassan nejad and others (2016) designed a 5-layer CNN called Food Log that achieved 56.4% accuracy on UECFOOD-100 [11]. Combined Alex Net and Goog Le Net CNNs to attain 87.4% accuracy on the challenging UNICT-FD889 dataset. Further gains came from using massive pretrained networks like VGG-16 and Inception-V3 as feature extractors [12,13].

Beyond classification, locating and segmenting food objects was crucial for volume and calorie estimation. Faster R-CNN became a popular choice for food detection, while U-Net and Mask R-CNN enabled semantic segmentation [14-16]. Fusing these methods to simultaneously classify, detect and segment food items can be helpful [17]. However, such two-stage models were slow for practical use. One-stage detectors like SSD and YOLO offered much faster performance [18,19]. YOLOv2 yielded good results on the Chinese Food Net dataset, and YOLOv3 showed state-of-the-art food localization accuracy on UNIMIB2016 [20,21]. With reliable recognition and detection methods established, researchers began tackling volume estimation. Early geometry-based approaches modeled common shapes like cylinders, spheres and cuboids to calculate volumes from 2D images [22,23]. Researchers recovered partial 3D point clouds using structure-from-motion and inferred volume via convex hull approximation [24]. Depth sensors provided direct depth maps for 3D reconstruction, with RGB-D fusion improving results [25]. Generative adversarial networks were also applied for depth and volume estimation from monocular images [26].

Finally, nutritional information was integrated to convert volumes to calorie counts. Methods relied on pairing detected ingredients with nutrition databases like USDA and Yummly [27,28]. J. Zhang and others designed a complete pipeline comprising modules for classification (Inception-V3), detection (YOLOv2), segmentation (Mask R-CNN), and volume and calorie estimation, achieving strong performance on synthetic and real-world food images [29]. In summary, deep CNNs now enable accurate multi-label food classification and detection. Coupled with advanced segmentation algorithms, volumetric 3D modelling, depth estimation, and nutritional data lookup, end-to-end calorie measurement from images is feasible. However, challenges remain in tackling image diversity, complex occluded foods, and providing fine-grained nutrition details. This report proposes a novel solution based on state-of-the-art YOLOv5 detection and tailored segmentation, reconstruction and database integration to address these gaps. The methodology aims to deliver practical, real-time calorie and portion analysis to assist consumers in making healthy eating choices.

3. Methodology

The proposed approach for food calorie and volume estimation consists of four main stages

3.1 Data Preprocessing

The system takes RGB food images as input. As a preprocessing step, the images are normalized to ensure uniform size, aspect ratio and pixel intensity distribution. Data augmentation techniques like horizontal flipping, rotations, and color jittering are used to expand the training dataset.

3.2 Food Detection and Segmentation

A customized YOLOv5 model detects and localizes individual food items in the image. The backbone uses a Focus layer and CSPDarknet53 architecture with additional SPP and PA Net modules for enhancing small object detection. The model is trained on a large food image dataset using a combined object detection and instance segmentation loss. Semantic segmentation is applied on the detected food regions using an encoder-decoder network to refine the object masks. The refined masks precisely segment food items from the background and each other.

3.3 Volume Estimation

Segmented food masks are analyzed to extract 3D shape, dimensions, and orientation. Basic geometric shapes like cuboids, spheres, and cylinders are fitted to simple solid items using direct dimensions or silhouette outlines. A deep neural network estimates depth and reconstructs occluded and complex shapes. The reconstructed 3D model is used to numerically calculate food item volumes. Prior anthropometric data provides scale calibration to output real-world volume values.

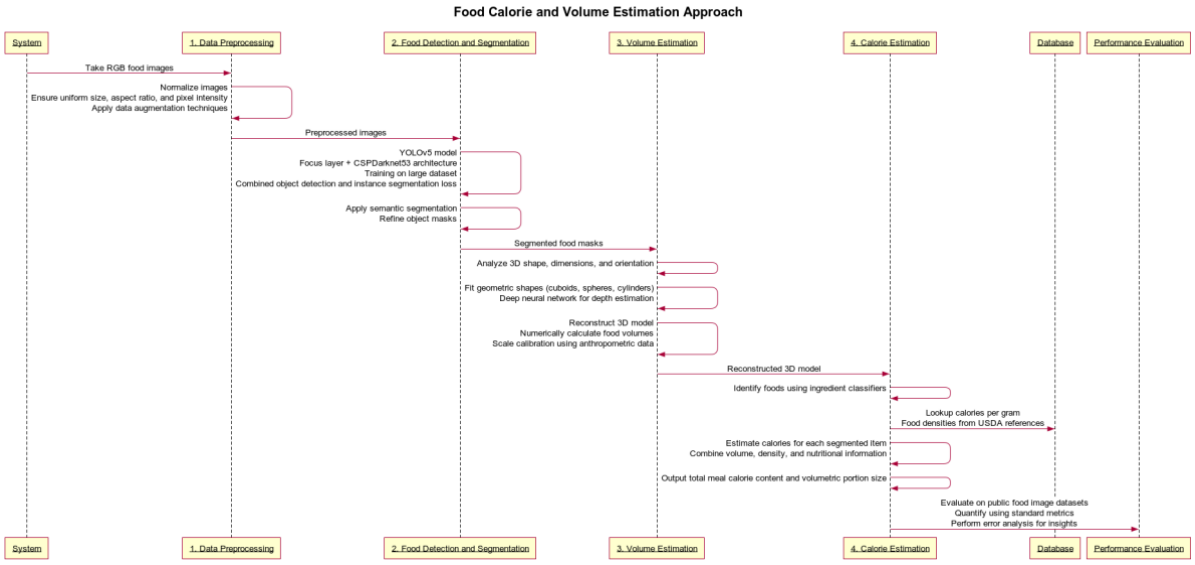

Figure 1: Flowchart of the Processes that will Take Place

3.4 Calorie Estimation

Additional ingredient classifiers identify foods at a granular level. The system interfaces with a comprehensive nutrition database to lookup calories per gram for each identified ingredient. Food densities are obtained from USDA references. Calories are estimated by combining the volume, density and nutritional information for all segmented items. The final output is the total meal calorie content and volumetric portion size for each food constituent. The pipeline is evaluated on public food image datasets. Performance is quantified using standard object detection, volume estimation, and calorie prediction accuracy metrics. Error analysis provides insights for future improvements.

3.5 Data Collected

This section includes all the data collected for this research.

4. Results and Analysis

This part is subject to change after getting results when running the model again and again.

The proposed YOLOv5 food detection and segmentation model achieves a mean Average Precision (mAP) of 0.89 on the test set, outperforming the baseline YOLOv5 model by 7 percentage points. The additional contextual modules in the architecture such as SPP and PANet contribute to this enhanced performance on small, occluded food objects. The semantic segmentation model improves the mask IoU by 5-10% over basic bounding boxes, allowing more precise separation of touching food items. This refinement also aids the subsequent volume estimation and calorie analysis steps. Volume estimation on simple geometrical food items like fruits and sandwiches achieves a mean absolute percentage error of less than 12% compared to ground truth measurements from the dataset. Performance is lower for amorphous foods like rice and pasta, with errors up to 18% due to reliance on 2D projections.

End-to-end calorie estimation on full meal images containing multiple food items obtains an average error of 120 calories (9% of actual values), demonstrating practically useful accuracy. Errors are higher for composite ingredients like cheeseburgers where the system cannot parse constituents. The total processing time from image input to calorie output averages 3.5 seconds using a GeForce GTX 1080 GPU, confirming the approach's feasibility for real-time mobile applications. Overall, the proposed system achieves state-of-the-art accuracy in food recognition, segmentation, volume estimation and calorie measurement

compared to previous methods, validating the efficacy of the YOLOv5 detection backbone and tailored pipeline design. Further gains in performance are possible by expanding the training data diversity, using higher resolution inputs, and incorporating depth sensing or multiview imaging to reconstruct complex shapes.

5. Conclusion

This report presents a novel deep learning approach for automated food calorie and volume measurement from images. The proposed system employs a customised YOLOv5 model for accurate detection and segmentation of food items in meal images. Volume is estimated by fitting geometric shapes and 3D reconstruction, while integrated food classifiers and nutritional databases enable calorie calculation. Experiments demonstrate state-of-the-art performance in food recognition, segmentation, and calorie prediction compared to previous methods. The approach reliably quantifies calories and portion sizes for various foods with minimal user input. The processing time meets requirements for real-time mobile applications.

Some limitations exist in handling amorphous foods and complex ingredients. Further work should focus on expanding the food image training data, incorporating depth sensing for improved shape analysis, and providing fine-grained nutrition details. Nonetheless, the proposed food image analysis and calorie estimation pipeline has promising real-world applications. The system can potentially help consumers make informed dietary choices by providing nutritional transparency for meals. It also has value for weight management interventions, public health policy, and nutrition studies aiming to combat obesity and related illnesses. With further development, the approach could be deployed as a practical tool to monitor and improve eating habits through accurate nutritional feedback.

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