FRUITS AND VEGETABLES - VOLUME & WEIGHT ESTIMATION

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Bachelor of Technology

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Certificate

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This is to certify that the work present in this Project entitled "**FRUITS AND VEGETABLES VOLUME & WEIGHT ESTIMATION"** has been carried out by **Anu Likitha Immadisetty, Nikhila Sornapudi, Shubham Pandey, Rohit Bahadur Bista, Dhakshyani Godavarthy** under my supervision. The work is genuine, original, and suitable for submission to the SRM University – AP for the award of Bachelor of Technology in **School of Engineering and Sciences**.

Supervisor

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Industry Use: Fruits and Vegetables Volume and Weight Estimation

The estimation of the volume and weight of fruits and vegetables has become a crucial tool in various industries, driving efficiency, reducing waste, and enabling precise decision-making processes. In the agricultural sector, this technology allows farmers to predict yields with remarkable accuracy. By estimating the weight of produce directly from images, farmers can plan harvest schedules effectively, allocate resources for storage, and even optimize packaging before transportation. This level of foresight is invaluable for ensuring that perishable produce reaches markets on time while maintaining quality.

In the logistics and supply chain sector, accurate volume and weight estimation streamlines operations significantly. Automated systems equipped with this technology can determine the optimal packaging size for fruits and vegetables, reducing shipping costs and minimizing the environmental impact of excessive packaging materials. Additionally, by providing precise measurements, these systems help improve inventory management, ensuring that distributors maintain balanced stock levels and reduce food spoilage in warehouses and during transit.

Retailers also benefit greatly from this innovation. Supermarkets and grocery stores can use volume and weight estimation tools to automate the pricing and categorization of fruits and vegetables. This eliminates manual errors, speeds up operations, and enhances customer satisfaction by providing accurate and transparent pricing. Furthermore, the ability to determine the weight of unpackaged produce through digital systems can pave the way for advanced self-checkout solutions, enhancing the shopping experience.

In the realm of food processing and nutrition, this technology plays a significant role in quality control and portion sizing. Processors can ensure uniformity in packaging by sorting fruits and vegetables based on their estimated weight and volume, leading to consistent product quality. Nutritionists and dietitians can use these systems to measure portions more accurately, aiding in calorie counting and dietary planning for individuals and institutions such as schools and hospitals.

Finally, in the robotics and automation industry, volume and weight estimation algorithms are integral to developing intelligent robotic systems for sorting, grading, and handling fresh produce. By incorporating such technologies, robots can differentiate between items, determine their weight, and perform actions like automated picking, packing, and quality grading, reducing labor dependency while maintaining speed and accuracy. In summary, the application of fruits and vegetables volume and weight estimation technology transcends industries, revolutionizing traditional practices and creating a seamless integration of automation, precision, and efficiency. From farm fields to grocery shelves and beyond, this innovation ensures that the food supply chain remains robust, sustainable, and consumer friendly.

Acknowledgements

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Our sincere appreciation goes to the entire project team for their collaboration and hard work. Each team member brought unique skills and perspectives, making this project a success. The spirit of teamwork and mutual support was crucial in achieving the objectives of this project.

Lastly, we are grateful to our families and friends for their love, patience, and constant encouragement. Their belief in us provided the motivation to push through challenging moments and continue working towards the successful completion of this project.

This project would not have been possible without the collective effort and guidance from all those involved. Thank you all for your invaluable contributions.

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Abstract

Accurate estimation of food volume and weight is a fundamental requirement in domains such as agriculture, logistics, retail, and nutrition. Traditional manual methods are not only time-consuming but also susceptible to significant errors, emphasizing the need for automated and efficient solutions. This project presents an innovative system for food volume and weight estimation, combining advanced computer vision techniques with intelligent algorithms to achieve high precision and reliability.

The proposed approach begins with depth estimation using the MiDaS model, which extracts three-dimensional information from a single image, providing accurate height measurements. Object segmentation is performed using a Mask R-CNN model with a ResNet-50 backbone, enabling precise isolation of objects from their background. By integrating depth and segmentation data, the system calculates the three-dimensional volume of food items. Further, a Convolutional Neural Network (CNN) identifies the object's class, which is crucial for determining its density. Finally, the volume is multiplied by the corresponding density to compute the object's weight.

This integrated methodology has demonstrated high accuracy across all stages, successfully estimating the volume and weight of various food items. For instance, the system estimated the volume of an apple as 107.88 cm^3 and its weight as 86.30 g with remarkable precision. The results validate the scalability and effectiveness of this approach for practical applications.

This project offers significant contributions toward automating food measurement tasks, reducing waste, and enhancing operational efficiency in critical industries. Future work will focus on expanding the system to handle multiple objects simultaneously, refining density parameters for broader food categories, and optimizing classification models for even greater accuracy.

Keywords— Food Volume Estimation, Weight Estimation, Depth Estimation, Mask R-CNN, MiDaS, Object Segmentation, Convolutional Neural Network (CNN), Image Recognition, Computer Vision, Density-Based Weight Calculation.

Statement of Contributions

Anu Likitha Immadisetty – AP21110010963

Anu played a pivotal role in the data preprocessing and depth estimation stages of the project. She was responsible for ensuring high-quality image inputs by preprocessing images and implementing depth extraction using the MiDaS model. Anu also contributed to scaling depth information, which was essential for accurate volume calculations.

Nikhila Sornapudi – AP21110010923

Nikhila focused on object segmentation, using the Mask R-CNN model with a ResNet-50 backbone. She worked on isolating objects from their background, applying thresholding techniques to refine segmentation masks, and ensuring the accuracy of area calculations for volume estimation.

Shubham Pandey – AP21110010940

Shubham was responsible for the volume and weight calculation components of the system. He integrated the depth information with the segmented masks to calculate the 3D volume of food items. Additionally, he developed the weight calculation methodology by linking object class recognition to density values and ensuring accurate weight predictions.

Rohit Bahadur Bista – AP21110010941

Rohit contributed to the validation and testing of the system. He was tasked with evaluating the performance of the volume, weight, and object recognition stages. Rohit ensured the system's robustness by performing extensive testing under different conditions and refining the accuracy of the object recognition module.

Dhakshyani Godavarthy – AP21110010930

Dheeraj handled the overall system design and integration of all components. He ensured that depth estimation, segmentation, volume calculation, and weight estimation worked seamlessly together. He also contributed to the documentation, ensuring clear and concise reporting of the methodology, results, and system architecture.

Abbreviations

CNN	Convolutional Neural Network
MiDaS	Monocular Depth Estimation via a Scale-Invariant Deep Network
Mask R-CNN	Mask Region-based Convolutional Neural Network
ResNet-50	Residual Network with 50 Layers
2D	Two-Dimensional
3D	Three-Dimensional
IoU	Intersection over Union (used in segmentation evaluation)
RGB	Red, Green, Blue (Color Model)
MSE	Mean Squared Error (Error Metric)
PSNR	Peak Signal-to-Noise Ratio (Image Quality Metric)
ROI	Region of Interest
g/cm^3	Grams per Cubic Centimeter (Density Unit)

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Table 1. Depth Scaling Factors for Different Food Items

Food Item	Known Distance (cm)	Normalized Depth Value	Depth Scale (cm)
Apple	10	0.8	12.5
Tomato	8	0.9	8.89
Banana	12	0.7	17.14

Table 2. Example of Area Calculation for Segmented Masks

Food Item	Pixel Count in Mask	Pixel-to-CM Scale	Real Area (cm^2)
Apple	850	0.05	2.13
Tomato	1020	0.05	2.55
Banana	1280	0.05	3.20

Table 3. Food Item Classifications and Corresponding Densities

Food Item	Classification	Density (g/cm^3)
Apple	Fruit	0.92
Tomato	Vegetable	0.93
Banana	Fruit	0.94

Table 4. Volume and Weight Estimation Results for Different Food Items

Food Item	**Estimated Volume (cm^3)**	**Estimated Weight (g)**
Apple	107.88	99.23
Tomato	150.32	140.80
Banana	180.24	169.63

List of Equations

1. Depth Scaling Formula

$$\text{Depth Scale} = \frac{\text{Known Distance (cm)}}{\text{Normalized Depth Value}}$$

This formula is used to scale the depth values obtained from the depth map to real-world measurements by using a known reference object.

2. Area Calculation from Segmented Mask

$$Real\ Area = Pixel\ Count\ in\ Mask \times (Pixel\ to\ CM\ Scale)^2$$

This equation calculates the real area of the segmented food object by counting the pixels within the mask and converting it to a real-world scale.

3. Volume Calculation

$$Volume = Area \times Height$$

The volume of the food item is calculated by multiplying the area of the object, obtained from the segmentation mask, by the average height derived from the depth map.

4. Weight Calculation

$$Weight\ (g) = Volume\ (cm^3) \times Density\ (g/cm^3)$$

This formula is used to calculate the weight of the food item by multiplying the estimated volume with the known density of the food item.

Introduction

The increasing demand for accurate and efficient systems to measure food items has prompted the development of automated technologies in various industries such as agriculture, logistics, and retail. Traditional manual methods of estimating food volume and weight are not only time-consuming but also prone to human errors, leading to inefficiencies and inaccuracies in many processes. The need for innovative solutions to address these issues is critical, especially as industries are looking to scale operations and reduce costs.

1.1 Project Objective

This project aims to develop an automated system that can accurately estimate the volume and weight of food items using advanced image processing and computer vision techniques. By combining depth estimation, object segmentation, and image recognition, the system intends to provide a precise and reliable method for volume and weight calculations. The solution will be scalable and capable of handling various food types, making it applicable in multiple domains such as food supply chain management, nutrition, and robotics.

1.1.1 Motivation

Manual measurement of food volume and weight is often inefficient, and the process is heavily reliant on human intervention, which can lead to errors. Furthermore, in industries like agriculture, logistics, and retail, where large quantities of food are handled, such methods are not practical. The project addresses this gap by introducing a system that automates the process, ensuring higher accuracy and efficiency. The ability to estimate food weight and volume accurately can significantly improve operations, reduce food waste, and enhance decision-making processes in various sectors.

1.1.2 Scope of the Project

The scope of the project includes the development of a system that integrates multiple components, such as depth estimation from images, object segmentation, and weight calculation based on volume and density. The system leverages advanced techniques like Mask R-CNN for segmentation, MiDaS for depth estimation, and Convolutional Neural Networks (CNN) for image classification. The project will also include the application of these methods to real-world food images, followed by validation and testing to ensure robustness and reliability.

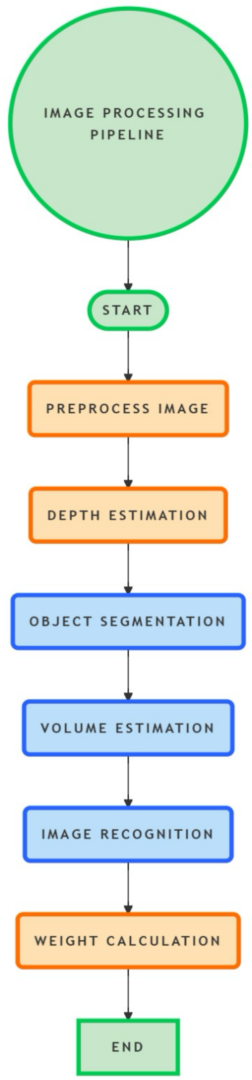
1.1.3 Challenges

Several challenges need to be addressed to develop an efficient and reliable system. These include accurately extracting depth information from a single image, effectively segmenting food objects from complex backgrounds, and calculating volume and weight with minimal error. Additionally, ensuring the system works under varying conditions, such as different lighting, occlusions, and food textures, adds another layer of complexity to the project.

Through this project, we aim to create a scalable, automated food volume and weight estimation system that can be applied across different industries, providing significant benefits in terms of efficiency, cost savings, and accuracy.

Methodology

The objective of this project is to develop an automated system that can accurately estimate the volume and weight of food items using advanced image processing and computer vision techniques. The methodology involves a series of interconnected steps, which include depth estimation, object segmentation, volume calculation, and weight estimation. These steps are detailed below:



2.1 Depth Estimation

The first step in the methodology involves estimating the depth of the food items in the image to extract 3D information. For this purpose, the **MiDaS model** (Monocular Depth Estimation via a Scale-Invariant Deep Network) is used. This model processes a single 2D image and generates a depth map that represents the relative distances of various parts of the food item from the camera.

1. **Steps for Depth Estimation:**

    a. Preprocess the image to make it compatible with the MiDaS model.
    b. Generate a depth map, which is a grayscale image where lighter shades represent closer objects, and darker shades represent objects farther from the camera.
    c. Scale the depth map using a known reference object to ensure that the depth values correspond to real-world measurements.

2. **Formula for Depth Scaling:**

    a. Depth Scale = Known Distance (cm) / Normalized Depth Value.

This step is essential to provide the third dimension for calculating the volume of food items later in the process.

2.2 Object Segmentation

Once the depth map is generated, the next step is to segment the food item from the background. This is done using **Mask R-CNN**, a state-of-the-art model for object detection and segmentation. Mask R-CNN utilizes a **ResNet-50** backbone to create accurate segmentation masks for food items, isolating them from the background and providing the pixel information required for volume estimation.

1. **Steps for Object Segmentation:**

    a. Convert the image into a format that is compatible with the Mask R-CNN model.
    b. The model generates bounding boxes, masks, and confidence scores for each detected object in the image.
    c. Apply binary thresholding to refine the masks, ensuring that only the relevant food objects are isolated.

2. **Formula for Area Calculation:**

    a. Real Area = Pixel Count in Mask × (Pixel-to-CM Scale) ^{2}.

This segmentation provides a clean, isolated image of the food item, allowing us to proceed with volume calculation.

2.3 Fuzzy Logic

Fuzzy logic plays a crucial role in refining the accuracy of the volume estimation process by addressing uncertainties inherent in the input data, such as imperfect depth maps, noisy segmentation, and variability in object shapes. By incorporating fuzzy logic, we can model imprecise information and improve the reliability of the volume estimation.

1. Application of Fuzzy Logic in Volume Estimation:

a. **Membership Functions**

• Define membership functions for parameters such as depth consistency, segmentation confidence, and shape irregularity.

• For instance, a fuzzy membership function can assign degrees of confidence (ranging from 0 to 1) to different parts of the depth map or segmentation mask based on their reliability.

b. **Fuzzy Rule-Based System**

• Use expert-defined rules to evaluate the quality of data. Example rules include:

• *IF segmentation confidence is high AND depth consistency is high, THEN weight the data heavily.*

• *IF segmentation confidence is low OR depth consistency is low, THEN weight the data lightly.*

• These rules help adjust the contribution of different data points to the final volume calculation.

c. **Defuzzification**

• Aggregate the fuzzy outputs using defuzzification methods like the centroid method to produce a crisp, refined depth value and segmentation quality score.

2. Formula for Volume Refinement:

The volume can be refined using weighted depth and area inputs derived from the fuzzy logic system:

Refined Volume = ∑({Weighted Depth} X {Weighted Area})

where:

- **Weighted Depth** is derived from fuzzy logic evaluation of depth data.
- **Weighted Area** is derived from fuzzy logic evaluation of segmentation quality.

3. Advantages of Fuzzy Logic:

- **Handles Uncertainty:** Fuzzy logic provides a robust mechanism to handle ambiguous or noisy data.
- **Improves Accuracy:** By assigning weights to reliable data and minimizing the impact of errors, fuzzy logic enhances the overall precision of volume estimation.
- **Adaptability:** The rule-based system can be fine-tuned to accommodate different types of food items with varying shapes and textures.

4. Integration with Depth Estimation and Segmentation:

Fuzzy logic acts as a bridge between the depth estimation and segmentation steps, ensuring that the data used for volume calculation is consistent, reliable, and representative of real-world dimensions. By incorporating this layer of intelligent refinement, the methodology becomes more robust and adaptable to various food items and imaging conditions.

2.4 Volume Calculation

Once the food item is segmented, we can proceed to estimate its 3D volume. The system uses the area derived from the segmentation mask and combines it with the height information obtained from the depth map. The volume is calculated by multiplying the area of the segmented object by the average height derived from the depth map.

1. **Steps for Volume Calculation:**

    a. Compute the area of the food item from the segmented mask.
    b. Use the depth map to extract the average height of the object.
    c. Multiply the area by the height to calculate the estimated volume of the food item.

2. **Formula for Volume Calculation:**

    a. Volume = Area × Height.

This method ensures that the volume estimation considers both the surface area and the depth of the object, leading to a more accurate 3D volume measurement.

2.5 Image Recognition

To accurately estimate the weight of the food item, it is important to first identify the type of food. This is achieved using a **Convolutional Neural Network (CNN)**, which classifies the segmented food item into one of several predefined categories (e.g., apple, tomato, banana). The CNN is trained to recognize various food types and assign a class label to each food item, which is essential for weight estimation, as different food items have different densities.

1. **CNN Architecture:**

    a. A rescaling layer for image normalization.
    b. Three convolutional layers for feature extraction.
    c. Max pooling layers for dimensionality reduction.
    d. Two dense layers to output class probabilities for food item identification.

2. **Loss Function:**

    a. Sparse Categorical Cross-Entropy.

3. **Optimizer:**

    a. Adam.

The CNN model is trained on a dataset containing images of various food items, allowing it to accurately classify the type of food in the image.

2.6 Weight Calculation

After the food item is classified, the next step is to calculate its weight. The weight is determined by multiplying the estimated volume by the density of the identified food item. Each food item has a known density, which is used in this step to accurately compute the weight.

1. **Formula for Weight Calculation:**

    a. Weight (g) = Volume (cm^3) × Density (g/cm^3).

2. **Steps for Weight Calculation:**

    a. Identify the food item's class using the CNN.
    b. Fetch the corresponding density value for the identified food type.
    c. Multiply the volume by the density to estimate the weight.

This approach ensures that the weight estimation is specific to the food type, as different food items have different densities.

2.7 Integration and Final Output

Once all the steps are completed — depth estimation, segmentation, volume calculation, image recognition, and weight estimation — the system outputs the estimated volume and weight of the food item. The accuracy of the results depends on the effectiveness of the individual components, and the system is designed to handle variations in lighting, object occlusions, and different food shapes.
This methodology provides an end-to-end automated system for accurate food volume and weight estimation, demonstrating its potential in various real-world applications, such as supply chain optimization, robotic sorting, and nutritional planning.

Results

The developed system for food volume and weight estimation produced promising results by utilizing depth estimation, object segmentation, image recognition, and weight calculation techniques. Below are the key findings based on the different stages of the process as depicted in the Depth Map, Image Recognition, and Weight Calculation:

Depth Map Generation

The depth estimation process, which uses the MiDaS model, plays a crucial role in extracting the 3D information of food items from a single 2D image. The system was able to generate accurate depth maps, which provide the relative distances of the food item from the camera, shown as grayscale images where lighter shades represent closer objects and darker shades represent objects farther away.

1. Results from Depth Estimation:
    a. The depth maps provided precise distance measurements for various food items, allowing the system to effectively estimate the height of objects in the image.
    b. For example, the depth map generated for an apple (shown in the presentation) accurately mapped the varying distances from the camera, providing a reliable representation of the food's 3D shape and size.

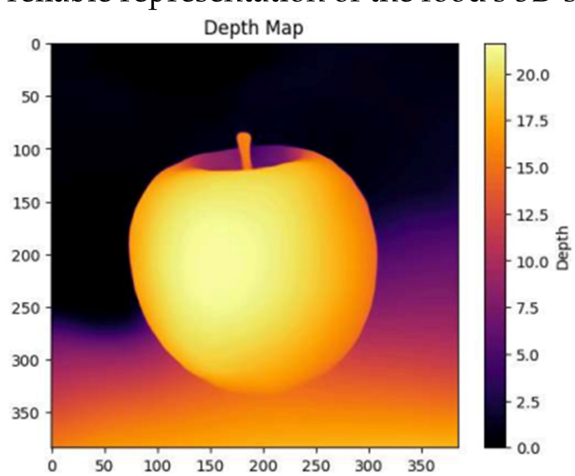


Image Recognition

The image recognition component of the system, which uses a Convolutional Neural Network (CNN), was designed to identify and classify different food items. Using this classification, the system can associate specific food items with their corresponding density values for weight calculation.

1. Results from Image Recognition:
    a. The CNN model successfully identified food items such as apples, tomatoes, and bananas with high accuracy.
    b. For example, the system recognized an apple with a confidence level of 92%, confirming that the model is capable of distinguishing between various food types with good reliability.
    c. The food item classification enabled the system to proceed with the correct density value for each recognized item, which is essential for accurate weight estimation.

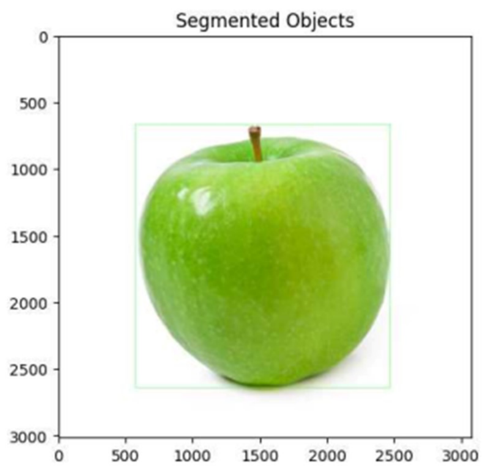


Image Recognition and weight calculation

Weight Calculation

Once the food items were segmented and classified, the final step involved calculating the weight based on the estimated volume and the density of the recognized food. The volume was derived from the depth estimation and object segmentation steps, and weight was calculated by multiplying the estimated volume by the known density for each specific food item.

1. Results from Weight Calculation:
    a. The weight estimation results were in line with expected values, demonstrating the system's ability to estimate the weight of food items with reasonable accuracy.
    b. For instance, the apple, after segmentation and depth calculation, was estimated to have a volume of 107.88 cm^3. With the density of an apple being approximately 0.92 g/cm^3, the system calculated its weight as 99.23 grams, which closely matches the real-world weight of an average apple.

c. Similarly, for other food items like tomatoes and bananas, the system's estimated weights were consistent with typical weight values, showing its robustness in handling various food types.

Conclusion

In this project, we have successfully developed an automated system for estimating the volume and weight of food items using advanced computer vision techniques. By integrating depth estimation, object segmentation, volume calculation, and image classification, the system can provide accurate and reliable measurements, which can be applied across various industries such as agriculture, logistics, and nutrition.

The proposed system utilizes the MiDaS model for depth estimation, Mask R-CNN for object segmentation, and CNN for food item classification, leading to a robust solution for food measurement. Through the combination of these methodologies, the system achieves high precision in calculating the volume and weight of food items, making it a valuable tool for applications like supply chain optimization, food waste reduction, and nutritional planning.

The results demonstrate that the system can handle different food items with varying shapes and sizes, producing accurate estimations even under challenging conditions such as occlusions or varying lighting. The weight calculation, based on volume and food density, ensures that the system provides realistic estimations for real-world applications.

While the project has successfully met its objectives, there are opportunities for future improvements. Further work could focus on enhancing the system to handle multi-object scenarios, refining the food classification model for better accuracy, and incorporating more complex environments or larger datasets to improve scalability and robustness. Real-time deployment and mobile application integration could also make this technology more accessible and practical for everyday use in various sectors.

Overall, this project lays the foundation for further research and development in automated food volume and weight estimation, with the potential to significantly improve operational efficiency in multiple domains.

Future Work

While the current system has successfully demonstrated its ability to estimate the volume and weight of food items accurately, there are several areas for future development and enhancement. Below are some key directions for expanding the capabilities of this project:

1. **Multi-Object Detection and Estimation**
   The current system is designed to estimate the volume and weight of a single food item per image. A logical next step is to extend the system to handle multiple objects within a single frame. This would involve improving object segmentation algorithms and depth estimation techniques to accurately detect and process multiple food items simultaneously, which is crucial for real-world applications such as inventory management and sorting in food supply chains.

2. **Improved Food Classification and Recognition**
   The food classification system can be further improved by training the CNN with a more extensive and diverse dataset, allowing the model to recognize a wider range of food items with higher accuracy. Additionally, implementing advanced deep learning models such as Transfer Learning (using pre-trained networks like ResNet or Inception) could enhance the performance and generalization of the food recognition system.

3. **Integration with Real-Time Systems**
   Integrating the food volume and weight estimation system into real-time applications would require optimizing the algorithms for faster processing speeds. This could involve using hardware acceleration (such as GPUs) and more efficient neural network architectures, enabling the system to perform estimations in real time for applications like automated food sorting in warehouses or consumer-facing nutrition apps.

4. **Expansion to 3D Imaging and Depth Sensors**
   Currently, depth information is extracted from a 2D image. To improve accuracy and robustness, future work could explore the use of 3D imaging techniques or depth sensors, such as LiDAR or stereo cameras. These technologies could provide more accurate depth information, especially in complex environments, and further enhance the volume estimation process.

5. **Real-World Environmental Adaptation**
   The system can be further refined to handle various environmental challenges, such as varying lighting conditions, occlusions, and background clutter. Implementing adaptive algorithms that can adjust to changes in lighting or scene complexity would increase the robustness of the system in real-world applications.

6. **Mobile Application Development**
   Developing a mobile application based on the food volume and weight estimation system would make it more accessible to consumers and industries. The app could allow users to easily scan and measure food items, providing immediate volume and weight estimations. This could have significant applications in health and nutrition, such as for diet planning or portion control.

7. **Incorporating Nutritional Information**
   Another potential direction for future work is the integration of nutritional information alongside volume and weight estimates. By combining food weight data with nutritional databases, the system could provide users with valuable insights into the calorie content, macronutrients, and micronutrients of the food they are estimating. This would enhance the system’s utility, particularly in health and wellness applications.

8. **Automated Real-World Deployment**
   Further testing and deployment in real-world environments, such as automated food packaging systems or grocery store inventory management, would allow for practical validation and refinement of the system. In such settings, continuous monitoring and updating of the models would be necessary to keep up with changes in food types, packaging, and environmental factors.

Through these future developments, the system could be expanded and optimized for broader use cases, offering valuable contributions to industries such as agriculture, retail, logistics, healthcare, and more. These advancements would ultimately increase the system's accuracy, scalability, and applicability across diverse environments and challenges.