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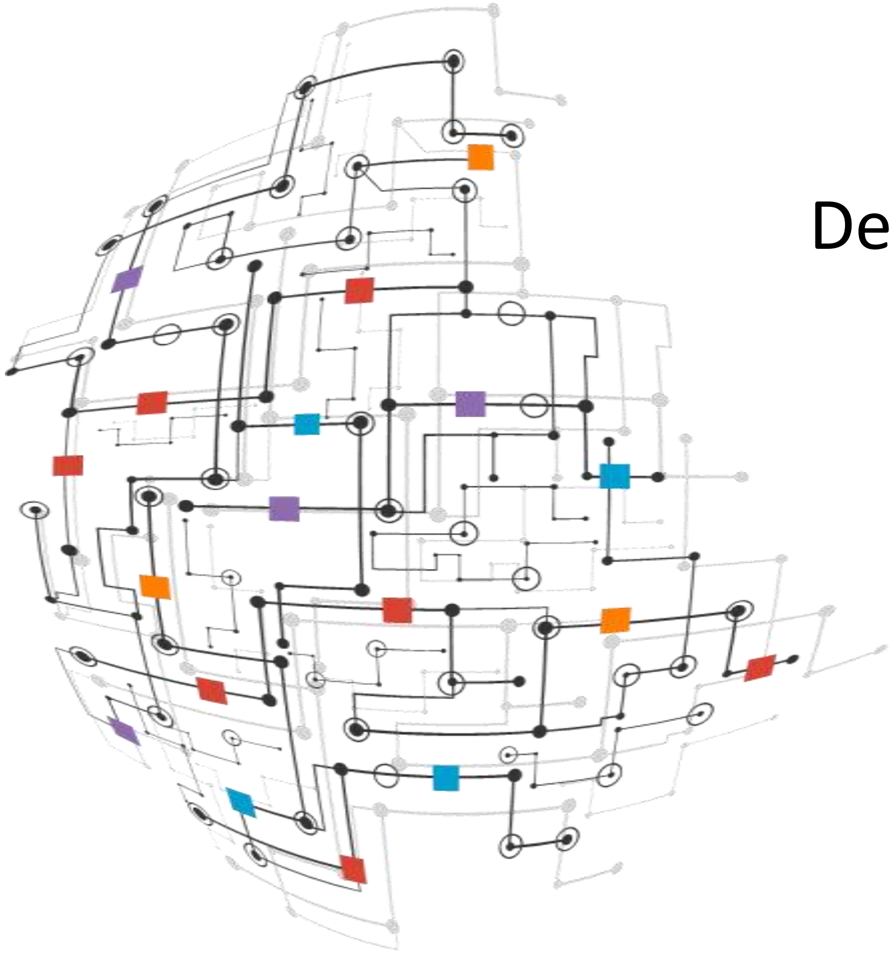

Deep Learning-Based Food Identification and Calorie Estimation System

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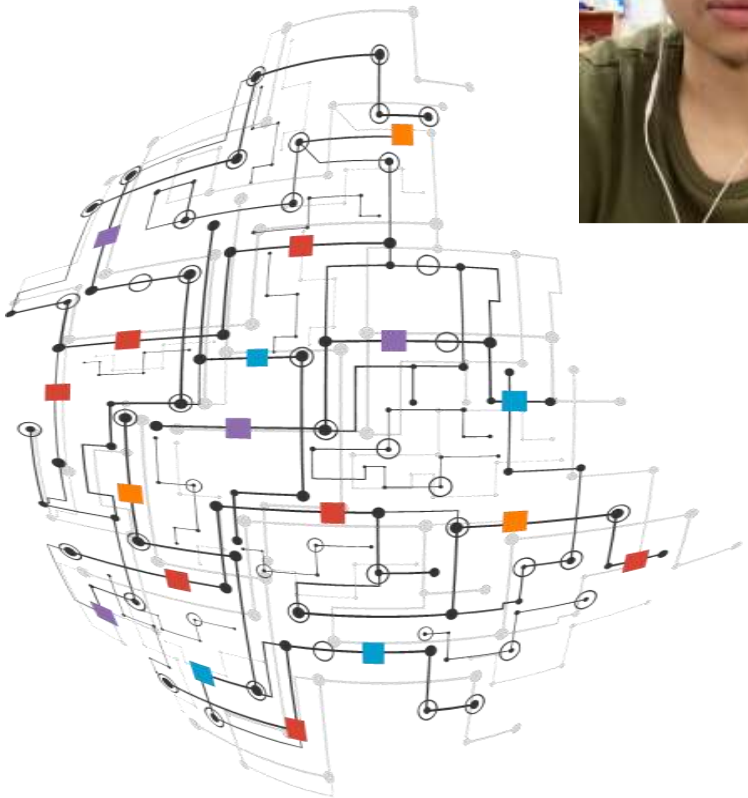

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Education

- M.S. Major in Graduate Institute of Automation Technology, National Taipei University of Technology, 2022

Research

- Network theory and application
- Algorithm
- Big data analysis
- Artificial intelligence(Deep Learning)

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Introduction

Goals	Contributions
• Train a YOLO model for food. • Maximize usage data. • Calorie Estimation.	• More than 90% recognition rate can be obtained. • Calorie estimation error is less than 10%.

Hardware

Raspberry Pi	Item
CPU	ARM Cortex-A72 (ARMv8) 1.5GHz
GPU	H.265 (4Kp60), H.264 (1080p60 / 1080p30)，OpenGL ES 3.0
Memory	2/4/8 GB (LPDDR4-3200)
USB	USB 3.0 *2、USB 2.0 *2

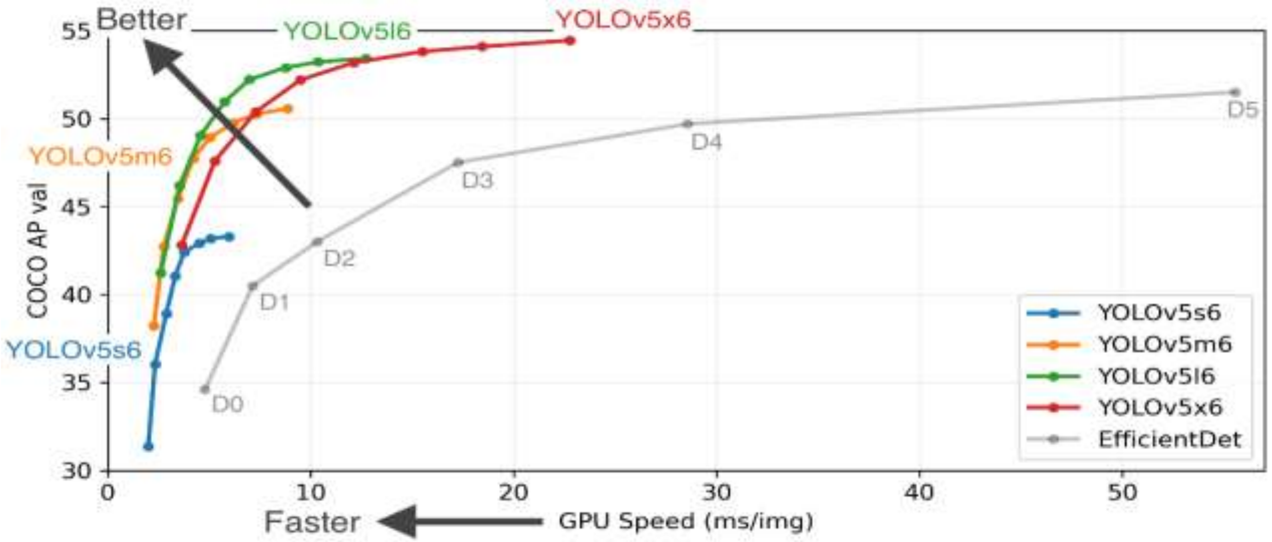
Depth Camera	Item
RGB FOV(H×V)	69°×42°(±1°)
Depth resolution	1280×720
RGB resolution	1920×1080
Min depth distance	0.105m
Max depth distance	10m

Data Acquisition

- In this work, a food dataset named Food-101 is used, which contains a large number of images.
- The pictures collected by myself, a total of 400 photos in 4 categories, including: rice, eggs, shrimp, broccoli, etc.
- Collect as many pictures of different angles and light as possible.

Yolo v5

- The YOLO (YouOnly Look Once) algorithm was originally proposed by Joseph Redmon.
- In YOLO v5, its author Glenn Jocher gave a total of four versions of the target detection network, divided into Yolov5s, Yolov5m, Yolov5l, Yolov5x. Compared with YOLO v4, YOLO v5 will reduce the size Reduced by 90%.
- On Tesla P100 YOLO v5 claims that it can achieve 140FPS fast detection, YOLO v4 The results are obtained at 50FPS, but the accuracy of the two is almost the same.



Volume Estimation

- Using yolov5 label the food type and record the coordinates.

- Depth images of pre- and post-meal food are recorded, and the depth difference for each pixel on the image is calculated. The depth difference of each point is the height of the actual height.

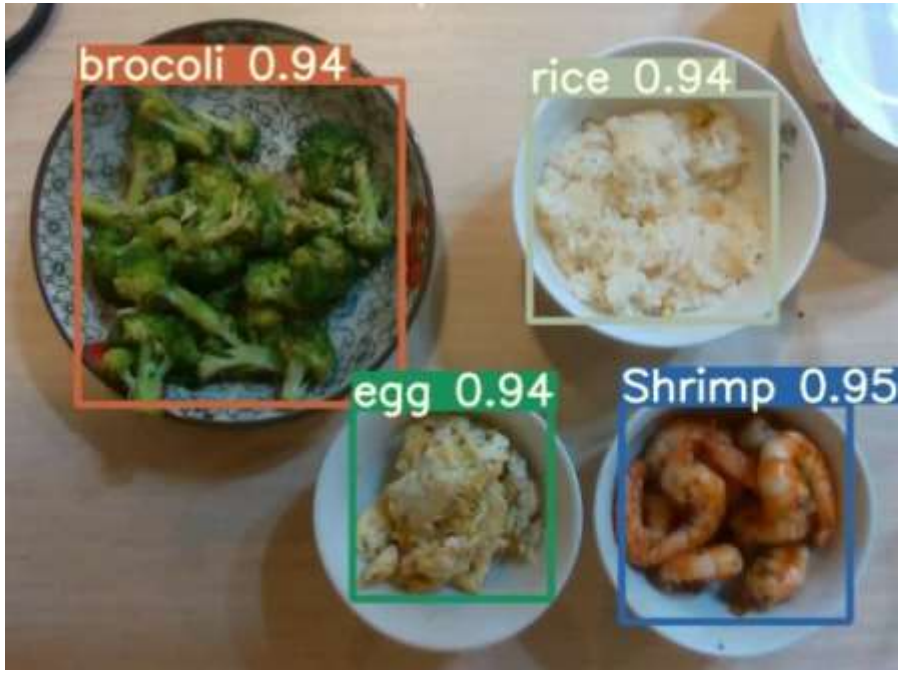
- The pixels go through linear regression to find the actual area of each pixel. Finally, sum and integrate all depth differences to get the true volume of the food.

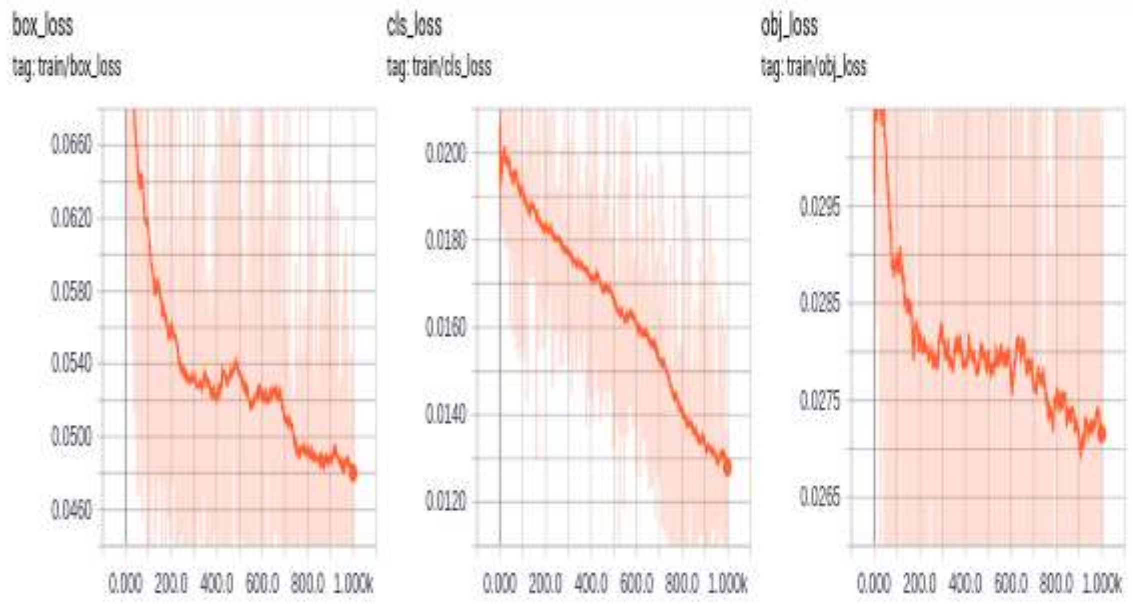
Calories Estimation

- For the convenience of calculation Calories of food, need to know the weight of the food, the density formula is used for Convert volume to weight, and density of each food obtained by the drainage method. Every food has one Density is different. Finally, convert calories and Get the three nutrients from food.

Image recognition Results

- We randomly select 10 images from the dataset and use our trained model to identify them with an average accuracy of over 90% for individual food items, The recognition rate of recognition is shown. The recognition rate is above 93%.
- The trained loss function is below 0.01.





Calorie Estimation Results

- This result is the same as the previous experiment, we randomly select 10 images from the dataset and use our model to estimate the calories of the food, record the real weight and the estimated weight, average all the recorded weights and calculate the error. has an error of less than 10%, which means that the calorie error will also be less than 10 calories.

Food	Data		
	Actual weight (g)	Estimated weight (g)	Error (%)
Rice	82.8	76.8	7.8
Egg	71	72.8	2.5
Broccoli	70.6	65.8	7.2
Shrimp	97.6	103.8	6.3

Conclusions

- Results show that it is feasible to use depth cameras for image recognition and calorie estimation.
- Uses a depth camera for image recognition and calorie estimation of the food, more than 90% recognition rate can be obtained.
- In most cases, while the heat estimation error is less than 10%.

Future Work

Experiment	Technology
• Increased experimental volume to increase experimental confidence.	• Increase the recognition rate and the types of recognition. • Reduce errors in calorie estimates.

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