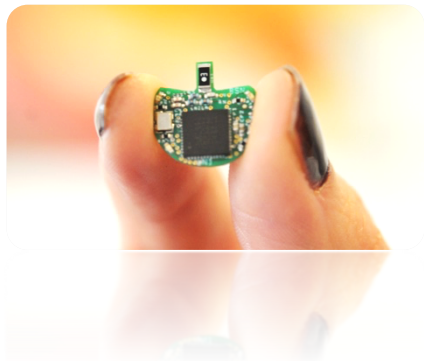




An innovative passive dietary monitoring system



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The Hamlyn Centre

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Dietary Assessment

- 24hr recall
- Food Frequency Questionnaire (FFQ)
- Weighed food record
- Urine biomarkers
- Blood biomarkers
- Doubly labelled water



An innovative passive dietary monitoring system

There is currently no accurate measurement of dietary intake. All current methodologies of assessing food intake have inaccuracy rates of 30-70%. Yet accurate assessment of nutritional intake is a prerequisite to define the nutritional status, nutritional needs of a population and to monitor the effectiveness of public health interventions to maintain nutritional health. To this end, it is necessary to develop tools that facilitate accurate assessment of nutritional intake in populations without affecting their normal routines. Existing dietary assessment methods are labour-intensive, expensive, and do not report nutritional intake accurately or social hierarchy of food intake. To address this gap in dietetics, the Bill and Melinda Gates Foundation funded project “An Innovative passive dietary monitoring system” aims to develop a passive dietary monitoring system for people living in Low-or-Middle Income Countries (LMICs) which does not rely on individual participation to record intake. This project focuses on both urban and rural areas in two African countries, Uganda and Ghana. To capture individual dietary intake, wearable camera technologies and fixed cameras are integrated into the system for capturing food preparation and eating activities in kitchens and dining areas. Extensive studies and field trials are being carried out in home settings in Uganda and Ghana.

BILL &
MELINDA
GATES
foundation



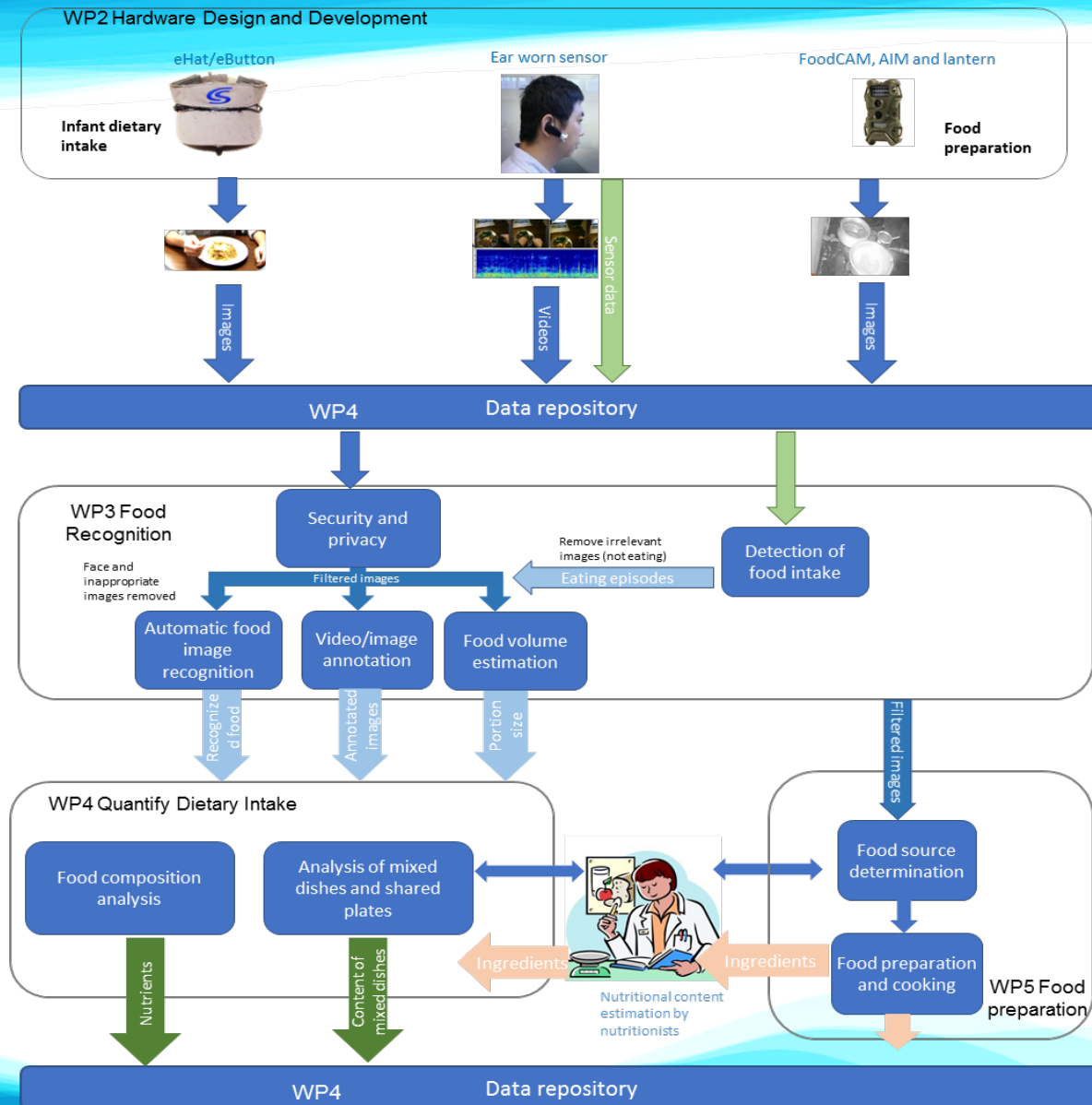
THE UNIVERSITY OF
ALABAMA

BOSTON
UNIVERSITY



Baylor
College of
Medicine

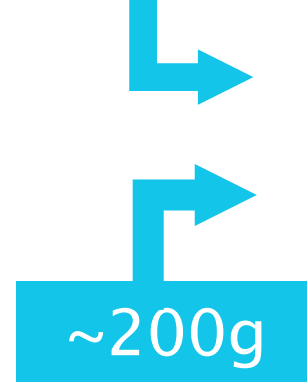
Project overview



Nutrition intake estimate



Jackfruit



USDA National Nutrient Database

Nutrient	
Water (g)	146.92
Energy (kcal)	190
Protein (g)	3.44
Fat (g)	1.28
Carbohydrate (g)	46.5
Fiber (g)	3
Sugars (g)	38.16
Calcium (mg)	48
Iron (mg)	0.46
Magnesium (mg)	58
Phosphorus (mg)	42
Potassium (mg)	896
Sodium (mg)	4
Vitamin C (mg)	27.4

e-Button & e-Hat



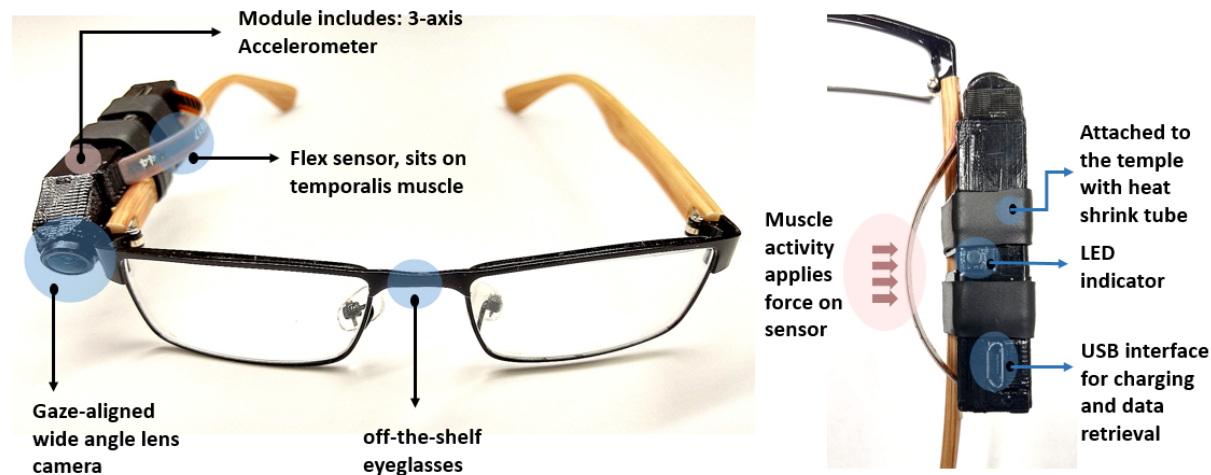
Sun, M., Fernstrom, J.D., Jia, W., Hackworth, S.A., Yao, N., Li, Y., Li, C., Fernstrom, M.H. and Scabassi, R.J., 2010. A wearable electronic system for objective dietary assessment. *Journal of the American Dietetic Association*, 110(1), pp.45-47



Automatic Ingestion Monitor

AIM is a wearable device that:

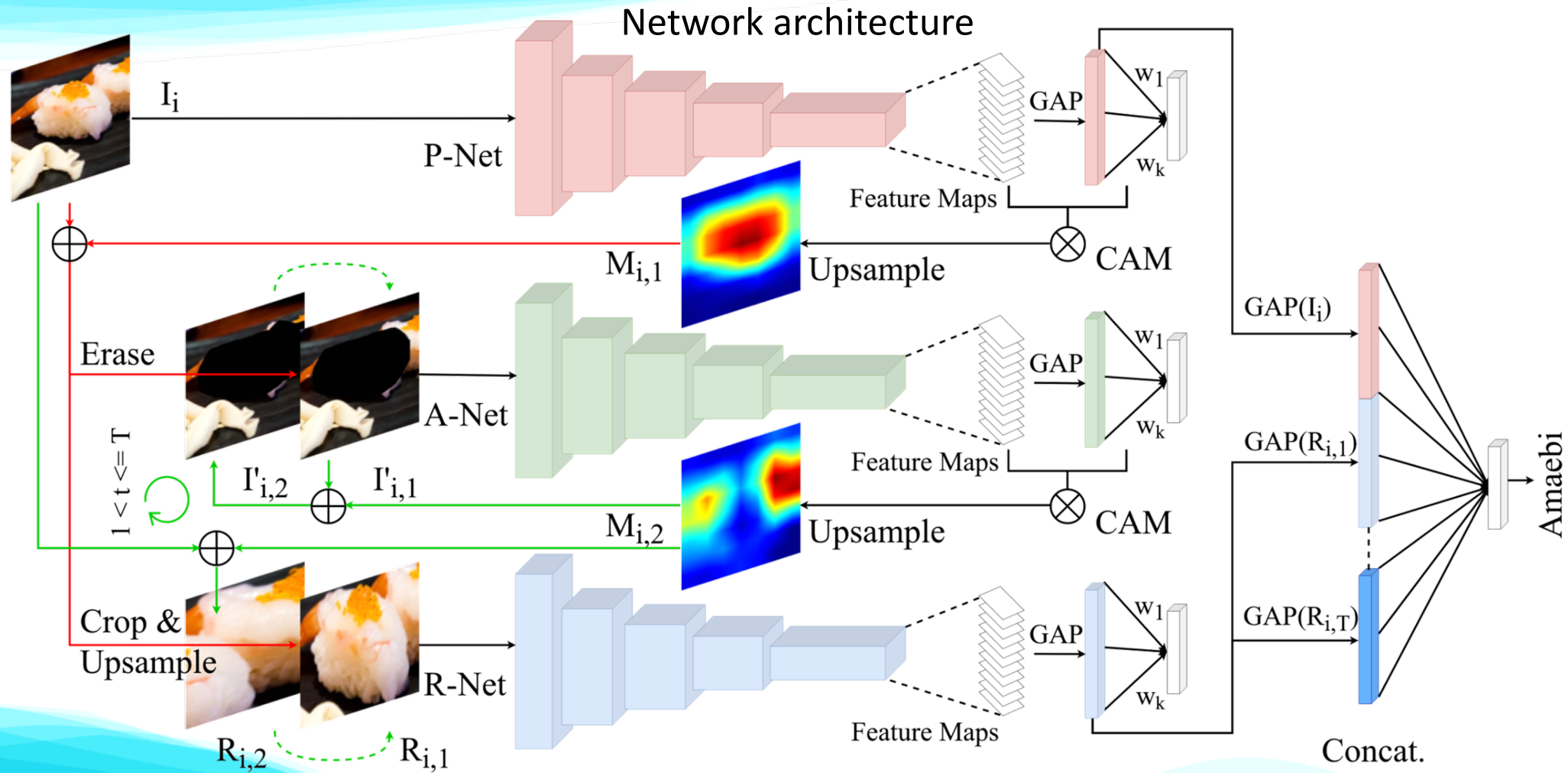
- Fully passive, does not require user actions beyond wearing
- Objectively measures when, what, how much and how we eat



Food Recognition



Food Recognition



Food Datasets

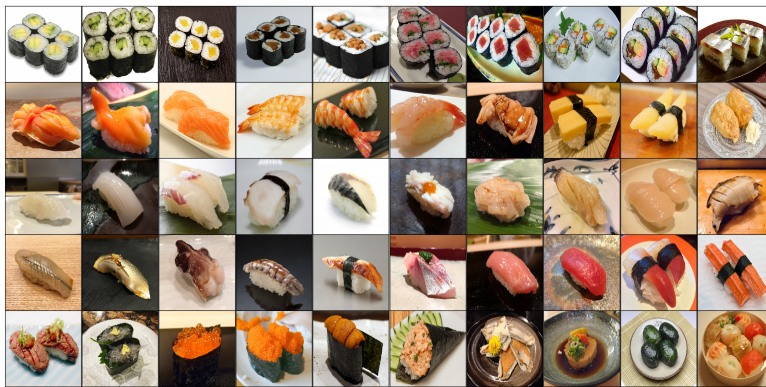
The proposed approach was tested on **two** large-scale publicly available food datasets and **one** newly proposed fine-grained food dataset.

publicly available food datasets:

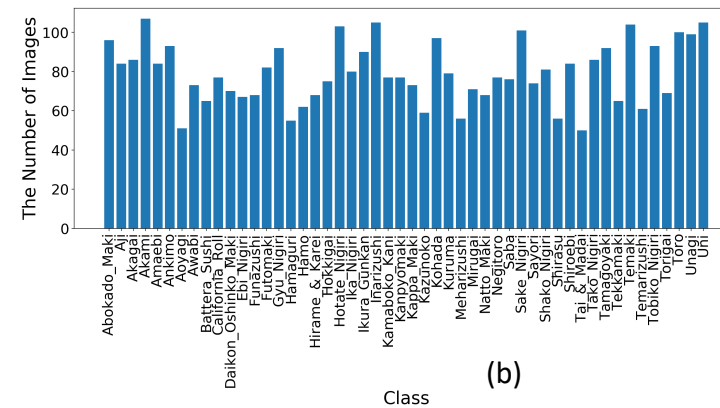
- * Food-101 ^[1]: **101** common food categories and **101,000** food images in total;
- * Vireo-172 ^[2]: **172** Chinese food categories and **110,241** food images in total.

food dataset proposed by this paper:

- * Sushi-50: **50** different sushi categories and **3,963** images in total.



(a)



(b)

(a) One sample of each category in Sushi-50. (b) The number of images of each category in Sushi-50.

Results

- The proposed method achieves **the current best** accuracy on all three food datasets

Table 1: Comparison with other methods on the three food datasets chosen

Method	Top-1 (%)
RFDC [1]	50.76
DCNN-FOOD [3]	70.41
DeepFood [4]	77.4
Inception V3 [5]	88.28
DLA (CVPR2018) [6]	90.0
WISeR (WACV2018) [7]	90.27
DSTL (CVPR2018) [8]	90.4
Ours	90.4

Food-101




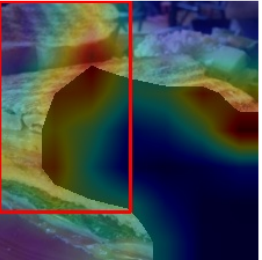

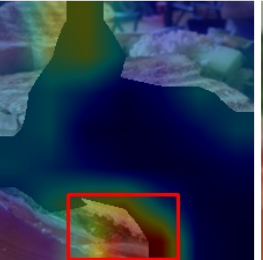



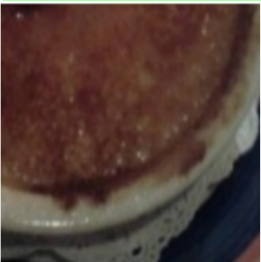
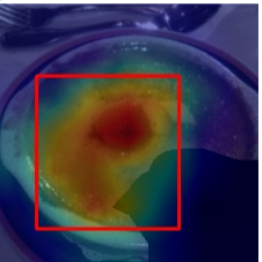
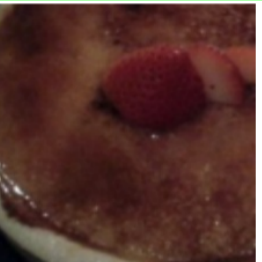
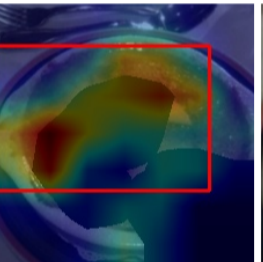
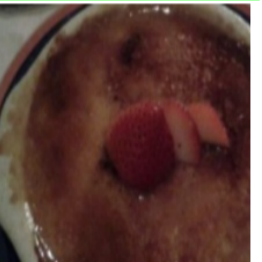
Method	Top-1 (%)
VGG [9]	80.41
Arch-D [2]	82.06
Ours	90.2

Vireo-172

Method	Top-1 (%)
ResNet-101 [10]	90.0
Ours	92.0

Sushi-50

Results

	Input Img. I_i / Pred.	$M_{i,1}$	$R_{i,1}$ / Pred.	$M_{i,2}$	$R_{i,2}$ / Pred.	$M_{i,3}$	$R_{i,3}$ / Pred.
Food-101	 grilled cheese sandwich		 club sandwich		 club sandwich		 club sandwich
	 pancakes		 creme brulee		 creme brulee		 creme brulee

GT:

club sandwich

Concat. Pred.:

club sandwich

GT:

creme brulee

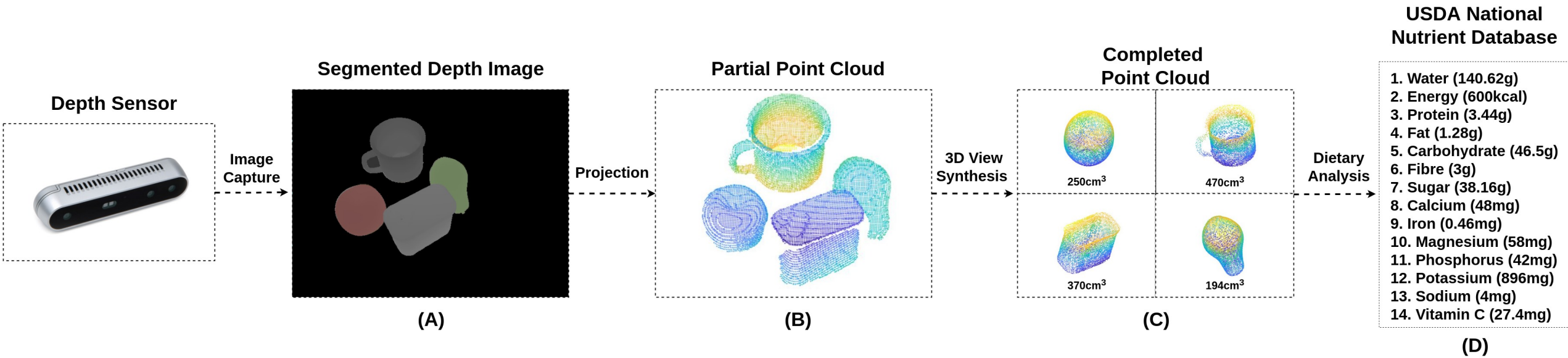
Concat. Pred.:

creme brulee

Portion size estimate



Volume Estimation - deep learning view synthesis



Volume Estimation

Detailed information

- A stereo or depth sensor is required to capture an image from any convenient viewing angle and position.
- Each food item is segmented out through a segmentation method.
- The depth image is converted from image coordinate to camera coordinate so that the partial point cloud of each food item
- Point completion network is applied.

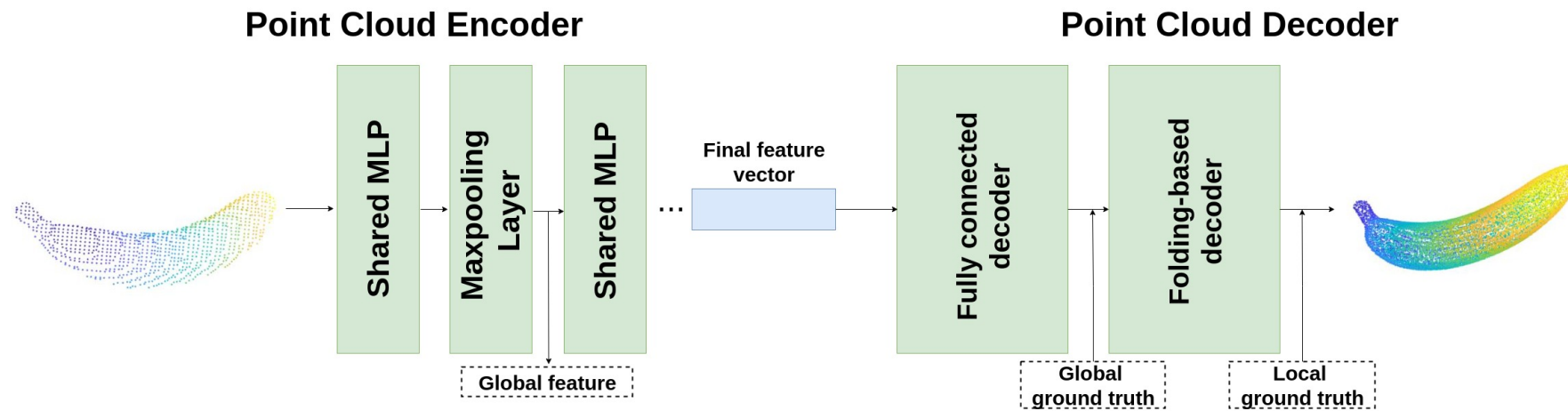
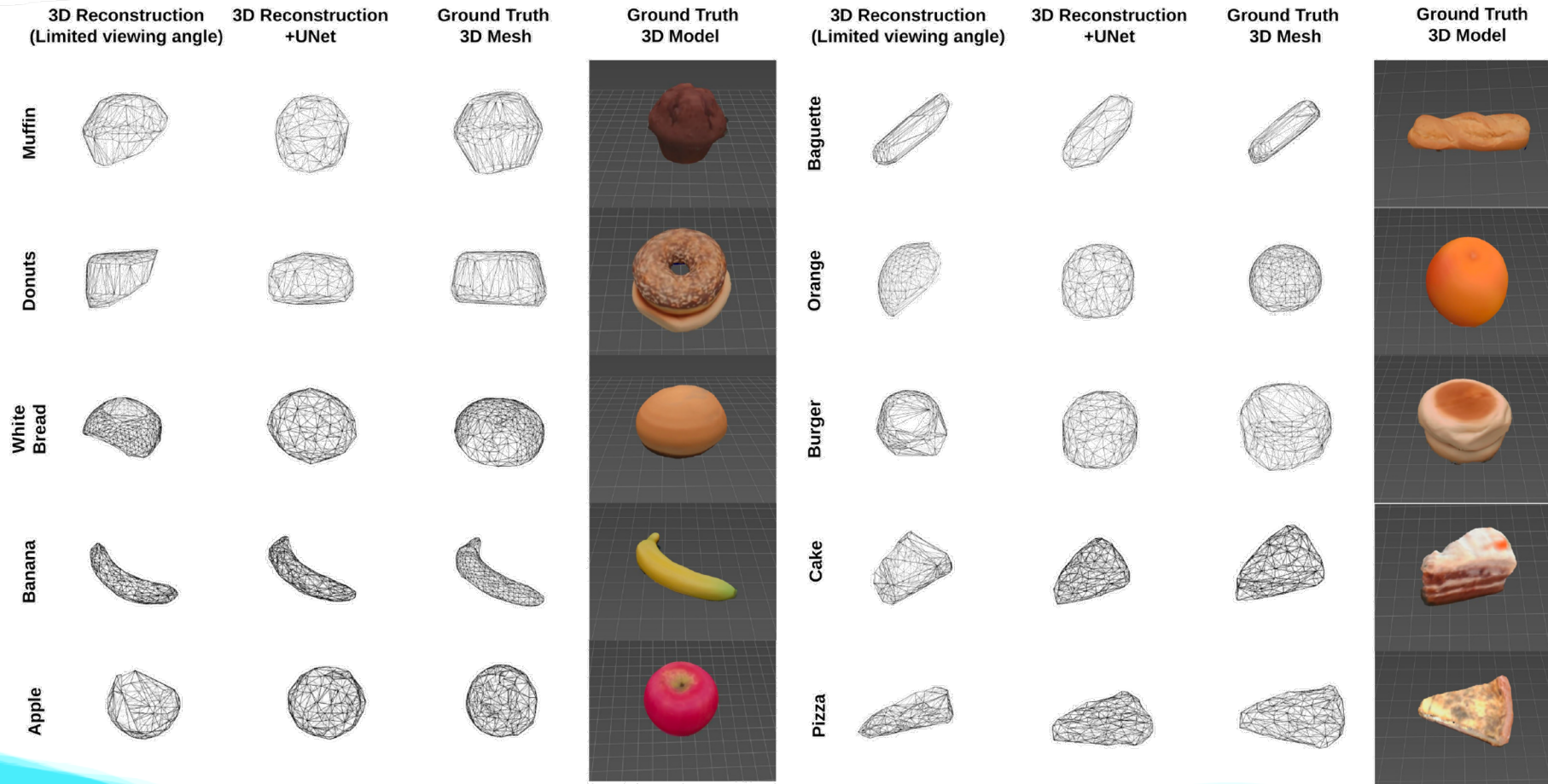
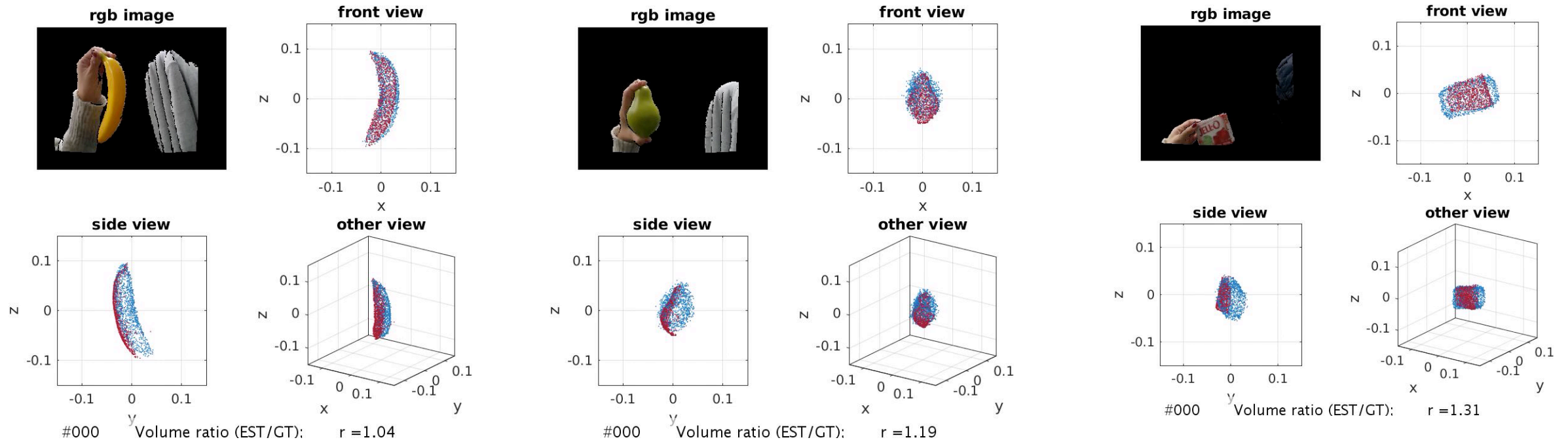


Figure: The network architecture of the point completion network

A Vision-based Dietary Assessment Approach using View Synthesis



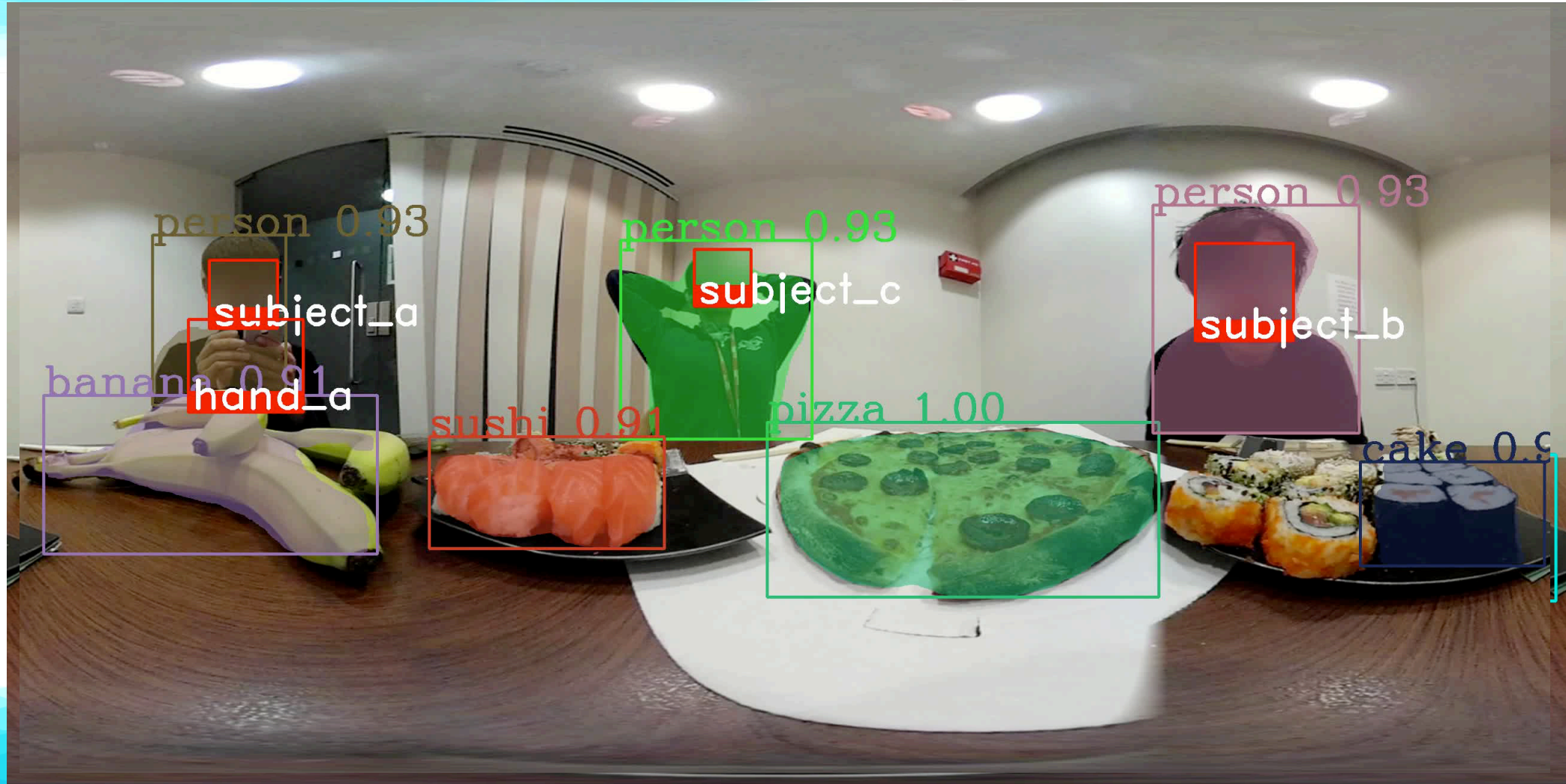
Volume Estimation in Real World Scenarios



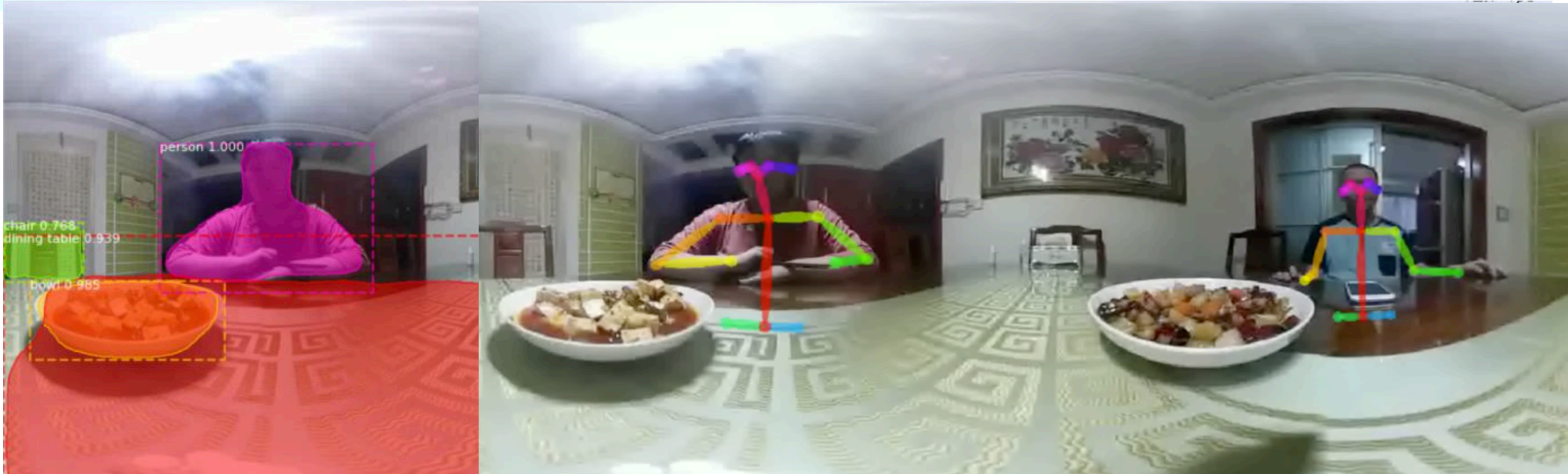
Communal eating/ Shared plate



Communal eating/Shared plate



Communal eating/Shared plate



Studies



Studies

- Study 1: Laboratory validation of food intake estimation devices
- Study 2: Acceptability and feasibility in the field
 - Phase 1: Household food behavior
 - Phase 2: Pre-field test data gathering prior to the preliminary field test:
 - Acceptability of the devices
 - Preliminary field test for acceptability, reliability and performance of recording devices
- Study 3: Field validation studies in Uganda and Ghana
 - Phase 1: Preliminary field data (~4 households at each site (~ 16 in total) lasting one day)
 - Phase 2: System validation in target populations (in ~22 households at each site (~88 in total) lasting three consecutive days)

Study 1: Laboratory validation of food intake estimation devices

Imperial College
London

Food images captured by eButton



Food images captured by Glass-worn device



in households in Ghana

- Identify and solve field related challenges To assess the feasibility, acceptability and general performance of devices
- Completeness of data collection
 - Clarity of food related images



Phase 2 of Study 2

- Feasibility of passive devices in dietary assessment
 - Consent and device demonstration
 - Day 1 - Introduction and demonstration of devices to households
 - Day 2- Devices worn and installed for data collection
 - Day 3 - Independent field assistant conducted device assessment
 - 24-hour dietary recall
 - Day 4 - Repeat of Day 2 activities
 - 24-hour dietary recall
 - Weighed food intake



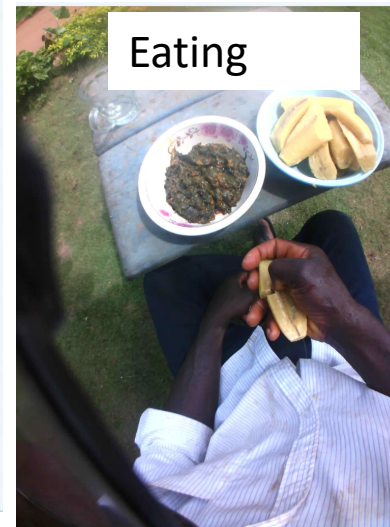
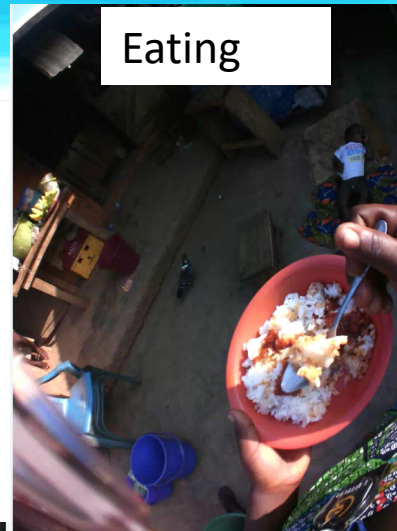
Study 2: Data collected in Ghana

- Examples of eButton images (containing foods)



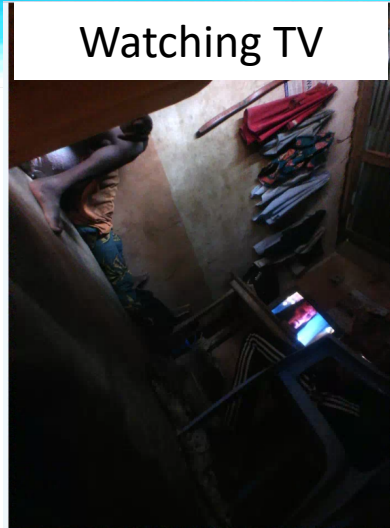
Study 2:

(Sample Images
captured by)
AIM





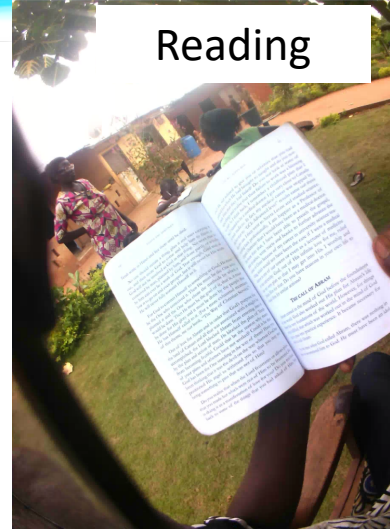
Blowing a
Balloon!



Watching TV



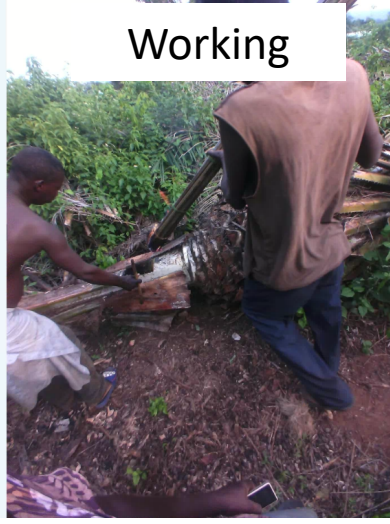
Shopping



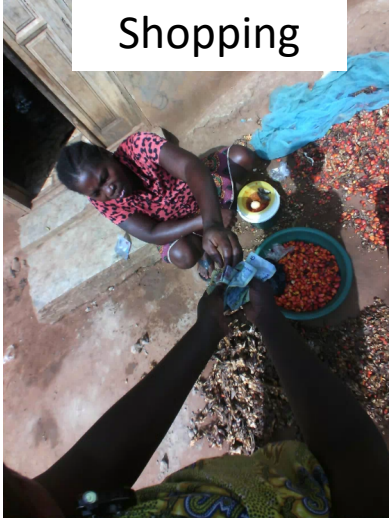
Reading



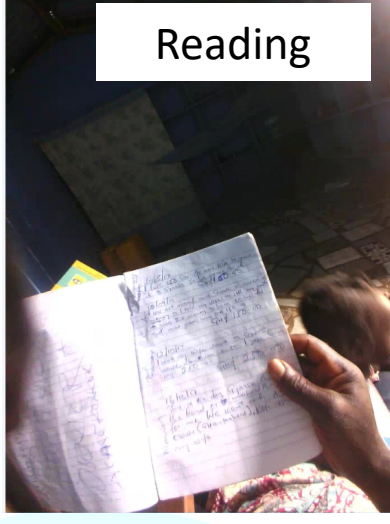
Hanging out
with friends!



Working



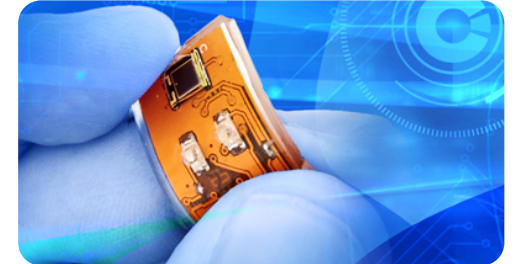
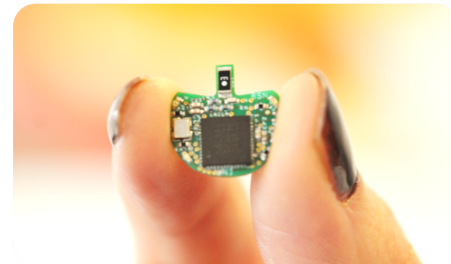
Shopping



Reading

Challenges

- Ethics
- Device issues
- Wearability
- Image and lighting
- User compliance
- Vast amount of data
- COVID-19



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