

Abstract:

Malnutrition is a major health challenge in many low- and middle-income countries (LMICs). Accurate dietary intake assessment is important to reduce malnutrition. However, existing dietary assessment tools require access to a computer/smartphone, limiting their deployment in resource-poor LMICs.

Method 1: Passive Dietary monitoring

- Using low-cost **wearable cameras** in measuring dietary intake through passive dietary monitoring method (i.e., AI-based).
- Raw videos** are fed into our proposed model.
- Consumed **food recognition** and **bite counting** can be inferred to provide guidance to dietitians for dietary assessment.

Method 2: Image Captioning



The subject is eating **rice with egg stew with the family**, and the **bowl is half empty**

- Food categories
- Eating alone/with others
- A rough portion size

- A novel **captioning model** is also designed to generate the captions for the dietary images.

- Advantages:
 - Preserve the subject's privacy
 - Reduce workload (i.e., frames with eating episodes can be obtained easily)
 - Can generate a nutrient intake report with consumed food type, eating duration, and rough volume.

Examples

Up-Down: the subject is eating jollof rice
Att2in: the subject is eating jollof rice
M² Transformer: the subject is eating jollof rice
GL-Transformer: the subject is eating jollof rice, and more than half of the bowl is empty
GL-Transformer: the subject is eating jollof rice, and only less than half is left in the bowl
GT: the subject is eating jollof rice, and there isn't much left in the bowl

Up-Down: the subject is processing fish in the kitchen
Att2in: the subject is having a meal
M² Transformer: the subject is eating akple and okra stew
GL-Transformer: the subject is eating akple and okra stew with the children
GL-Transformer: the subject is processing some green vegetables
GT: the subject is processing some green vegetables

Qiu, Jianing, Frank P-W. Lo, Xiao Gu, Modou L. Jobarteh, Wenyan Jia, Tom Baranowski, Matilda Steiner-Asiedu et al. "Egocentric Image Captioning for Privacy-Preserved Passive Dietary Intake Monitoring." *arXiv preprint arXiv:2107.00372* (2021).

Passive dietary monitoring

Ground Truth Estimation

	0: chicken 1: water 2: rice 3: takuan 4: celery 5: green_bean	0: water 1: rice 2: takuan 3: celery 5: pork_ribs
	0: water 1: prawn 2: mussel 3: pasta 4: squid 5: tomato_sauce	0: water 1: mussel 2: pasta 3: tomato_sauce
	0: chicken 1: water 2: broccoli 3: rice 4: carrot 5: teriyaki_sauce	0: water 1: rice 2: carrot 3: teriyaki_sauce
	0: chicken 1: rice 2: tofu 3: miso_soup 4: tomato 5: sushi_vegetable 6: soy_sauce 7: lettuce	0: rice 1: salmon 2: sushi_vegetable 3: soy_sauce 4: lettuce

Fig 1. Recognized food items (ingredients and drinks)

potato	chicken	beef	soda	water	orange_juice
red_wine	champagne	green_onion	seaweed	dumpling	broccoli
napa_cabbage	chili_pepper	rice	chicken_katsu	curry	pickled_radish

Fig 2. 66 unique food items labelled in the dataset

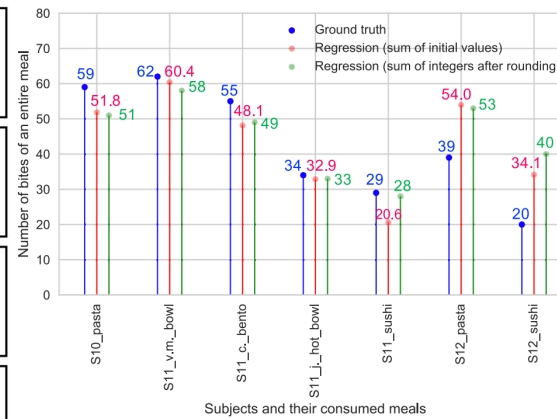


Fig 3. Qualitative results of bite counting

Results:

ACC in Food Recognition (Board Categories): 97.55%
ACC in Food Recognition (Fine Categories): 54.77
Error in bite count (Mean square error): 0.312

Qiu, Jianing, et al. "Counting bites and recognizing consumed food from videos for passive dietary monitoring." *IEEE Journal of Biomedical and Health Informatics* 25.5 (2020): 1471-1482.