

DETECTING FOODS AT A CAFETERIA NEAR YOU

- Autonomously logging cafeteria food consumption provides the opportunity to reduce both malnutrition and food waste. According to the Agency for Healthcare Research and Quality, malnutrition in the United States affects more than 30% of hospitalized patients. Furthermore, patients with malnutrition are 50% more likely to be readmitted to the hospital within 100 days than those without malnutrition [1].
- As for food waste, in the United States, an estimated 31% of the available food supply went uneaten in 2010, which represents 133 billion pounds of food [2].



Figure 1: Food Detection Device

- Imagine an automated food computer vision system that notifies a nurse when a patient is at risk for malnutrition. Or imagine a system that uses food waste monitoring and makes suggestions to the head chef. In this project, I lay the foundation for this vision. I create a baseline food detection model that I hope can be used to track nutritional intake in hospitals, schools, and correctional facilities.



MALNUTRITION & FOOD WASTE COMPUTER VISION PROJECT

Does machine learning have the potential to change cafeterias for the better?

DATA SCIENCE METHODS

I first assembled an American cafeteria food dataset of annotated meal images comprised from publicly available datasets [3] and [4]. Dataset [3] consists of 100 primarily Japanese food categories, from which I selected 12. Dataset [4] consists of 73 primarily Italian foods, which I also selected 12 foods from. Out of those two sets of 12, I merged 6 from each together since they were the same foods. The result is a dataset of **3839 images with n=18 classes**.

To detect food items, I implemented the state-of-the-art **YOLOR model** [5] that detects objects by class and localizes them with bounding boxes. I specified the model's input and output image size as 1280x1280 pixels. Then, I **trained for 300 epochs** with a batch size of 8 images, using the default YOLOR-P6.

The model detects **18 food items** with **0.917 overall mAP@0.5 IoU*** and 0.721 overall mAP@0.95 IoU on held-out test data.

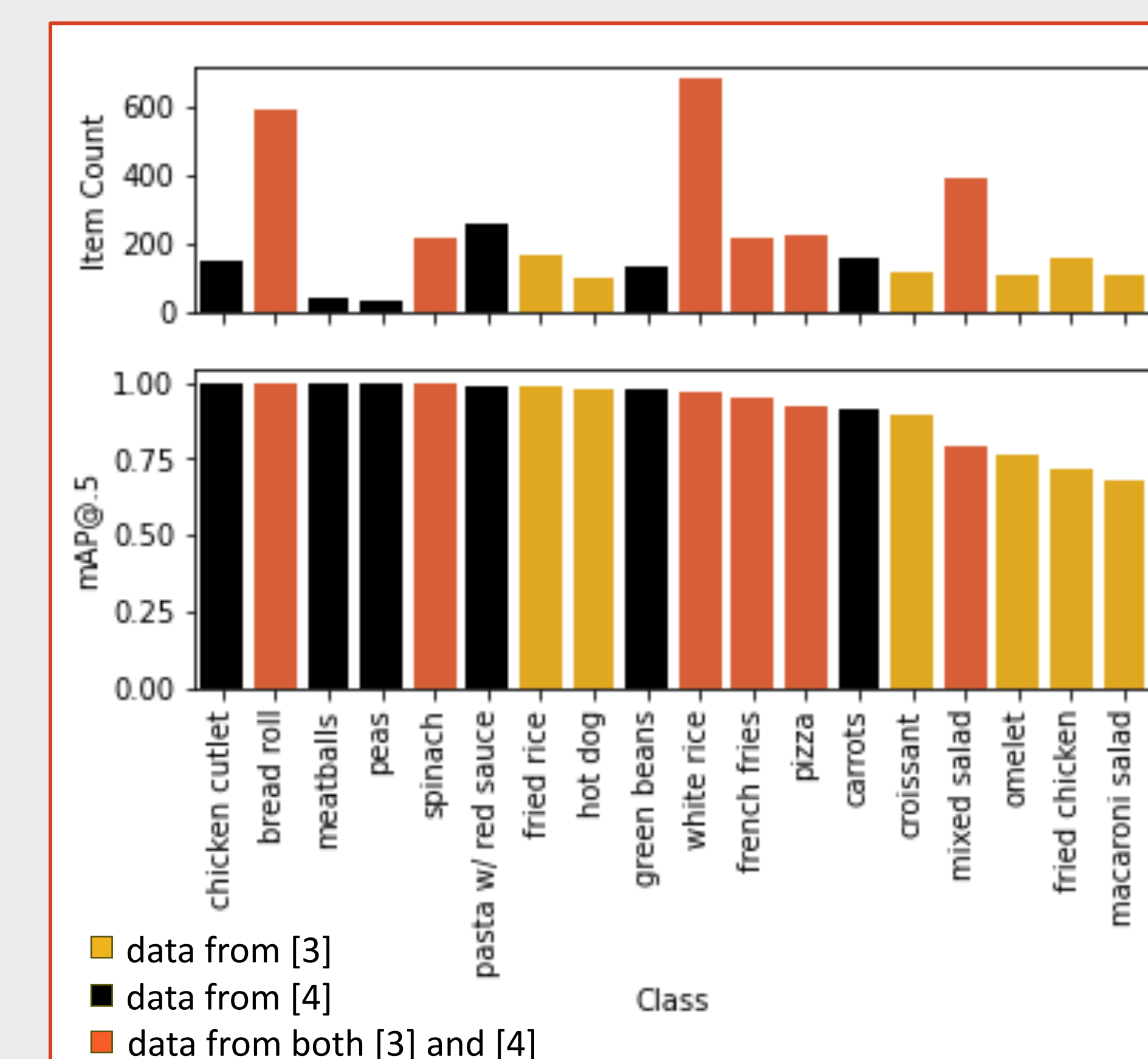


Figure 2: Food detection model results, colored by origin dataset

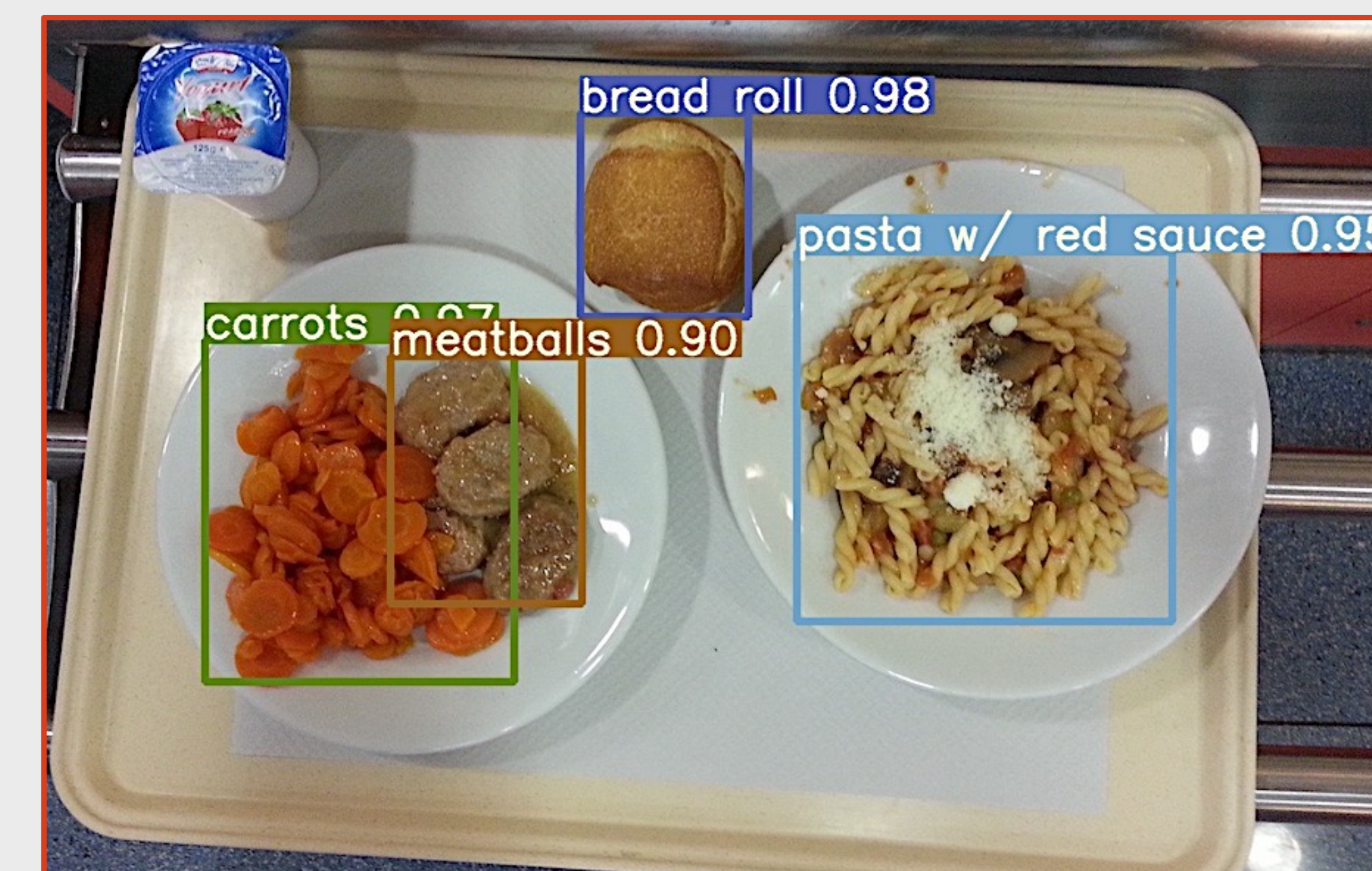


Figure 3: Example detection from my model

DATA COLLECTION PIPELINE

As seen in Figure 1, students in my lab constructed a food detection device that will take pictures and record the weight of food trays at cafeterias. To process the newly collected data, I developed a server with **Python3's FastAPI** to receive data from the device and store it in a **MySQL database**. The server not only allows for data collection needed for the development of more models, but it also runs image detections, as seen above in Figure 3.

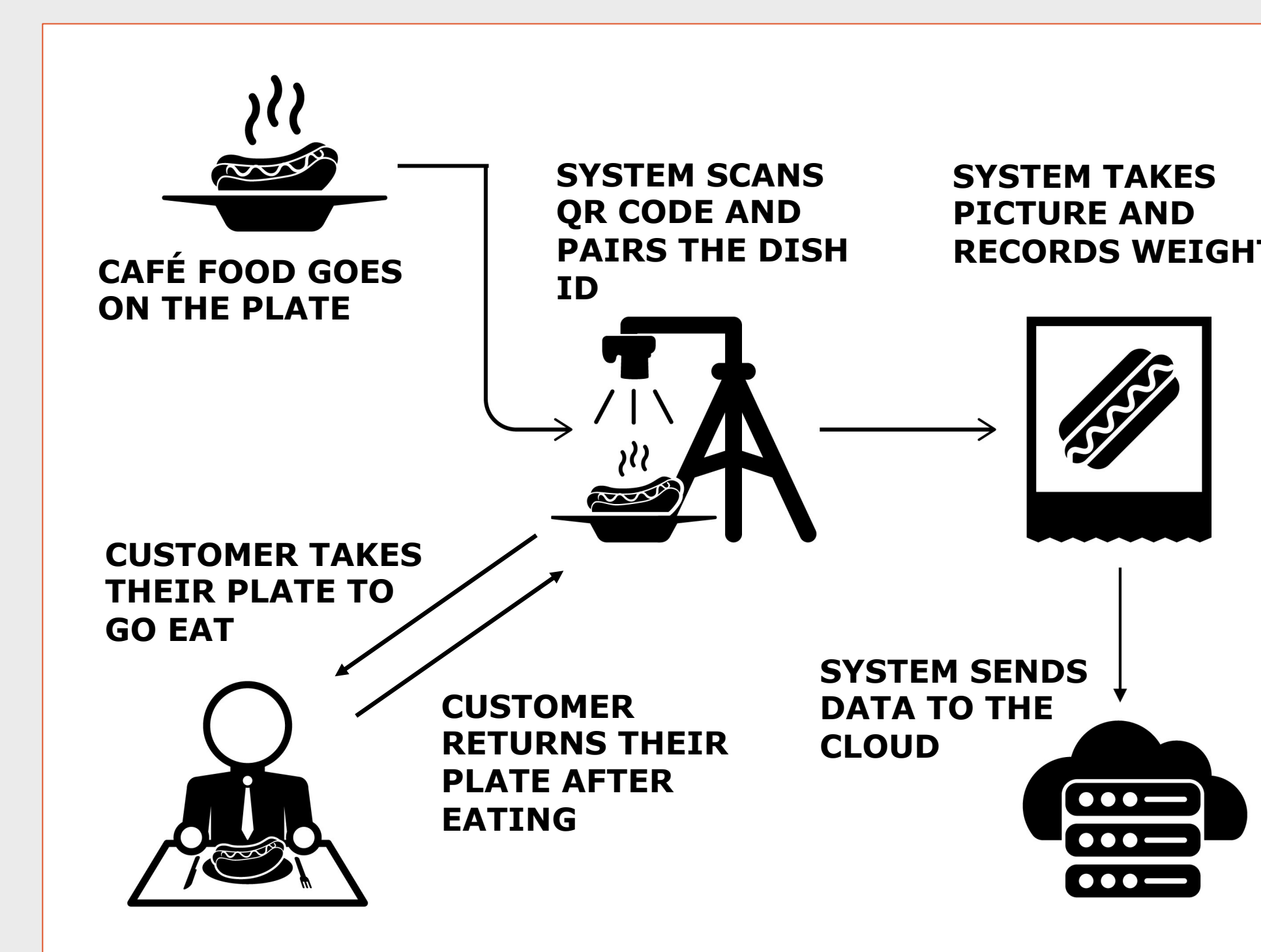


Figure 4: Diagram illustrating how cafeteria food data is collected from the consumer and processed

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- Student**
Matthew Morgan - morgamat@oregonstate.edu
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Associate Professor Patrick Donnelly - Patrick.Donnelly@osucascades.edu
- Matthew Morgan is a computer science student with a focus in data science. For the project, he prepared the dataset, trained the machine learning model, and wrote the code for the data collection pipeline.
- In the Spring of 2022, Matthew presented his research at both the National Conference for Undergraduate Research and the Stanford Undergraduate Research Conference.



Matthew Morgan

REFERENCES

- [1] K. R. Finger *et al.*, "All-Cause Readmissions Following Hospital Stays for Patients With Malnutrition, 2013," *Agency for Healthcare Research and Quality*. <https://hcup-us.ahrq.gov/reports/statbriefs/sb218-Malnutrition-Readmissions-2013.jsp>.
- [2] J. C. Buzby, H. Farah-Wells, and J. Hyman, "The estimated amount, value, and calories of postharvest food losses at the retail and consumer levels in the United States," *USDA-ERS Econ. Inf. Bull.*, no. 121, 2014.
- [3] Y. Matsuda, H. Hoashi, and K. Yanai, "Recognition of Multiple-Food Images by Detecting Candidate Regions," 2012.
- [4] G. Ciocca, P. Napolitano, and R. Schettini, "Food recognition: a new dataset, experiments and results," *IEEE J. Biomed. Health Inform.*, vol. 21, no. 3, pp. 588–598, 2017, doi: 10.1109/JBHI.2016.2636441.
- [5] C.-Y. Wang, I.-H. Yeh, and H.-Y. M. Liao, "You Only Learn One Representation: Unified Network for Multiple Tasks," *ArXiv Prepr. ArXiv210504206*, 2021.

* mAP@0.5 = mean average precision,
where $\text{true vs. pred. box intersection} / \text{union} > 0.5$