Final Project:

Fridge Inventory Monitor

Nurdin Hossain, Mohan Liu, Joyce Yang, Rachel Yu

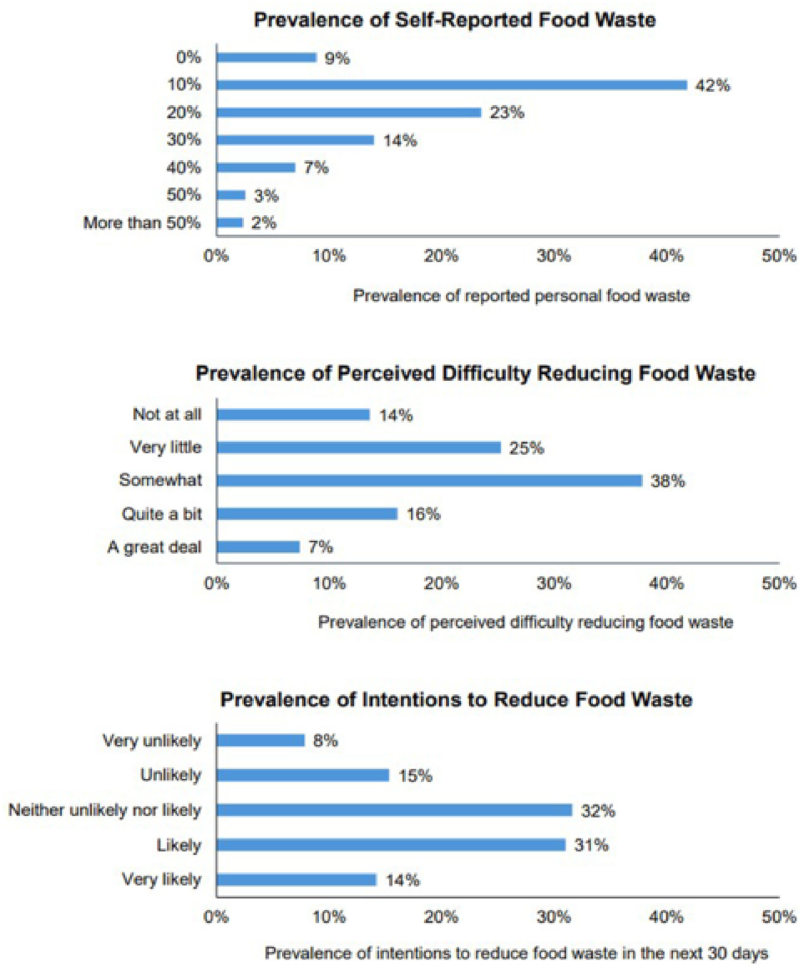
Motivation

- Busy college students with stocked fridges/pantries
- Molding/rotting food is a big health risk
- Waste of food = waste of money

We hope to develop a fridge monitor for food spoilage, generating available recipes, and providing macros for a balanced diet-all through machine learning!

Background

- The world wasted **1.05 billion metric tons** of food in 2022
    - More than **1 billion meals** wasted each day
- Food loss/waste = **10%** of global **greenhouse gas emissions**
- **60%** of food waste happens at **household level (us!)**
- In the United States, nearly 31% of total food production, valued at **$382 billion**, is wasted annually.
- In a study of young adults in the US,
    - 26% of participants reported high food waste (≥30% of food wasted)
    - 77% reported concern with food waste
    - **less than half** of the participants (45%) reported being likely to reduce their food waste in the next month.



Vandersip et. al.,

Related Work

- **Lee et. al., 2021 - Smart Refrigerator Inventory Management Using Convolutional Neural Networks**
    - Utilized wide angle cameras + training set of fridge items with different levels of occlusion/hand placement to train convolutional neural network for object detection

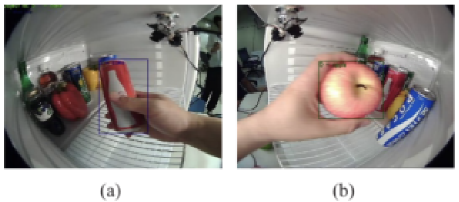


Figure 1. Images selected from multiple cameras as training data (a) image of an object in right hand captured by the left camera (b) image of an object in left hand captured by the right camera

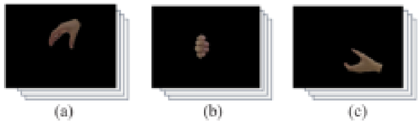


Figure 2. Segmented hand type (a) Up-hand (b) Middle-hand (c) Down-hand

- **Pachon et. al., 2018 - Product Detection System for Home Refrigerators implemented through a Region-based Convolutional Neural Network**
    - Used pattern-recognition by R-CNN trained on image data to implement a product detection system in a refrigerator able to detect missing items from the total set of objects.

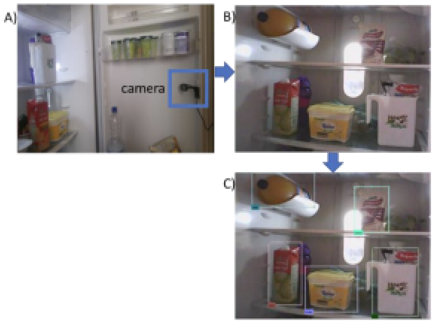


Figure 6. Work environment with the camera in the fridge.

Claim/Target Task

We aim to:

- Monitor the contents of a refrigerator for food spoilage
- Generate recipes based on ingredient availability and prioritize foods that might expire soon
- Supplement recipe information with macros for a balanced diet

Ultimately, we hope to reduce food waste and make it easier to track perishable items in a fridge in addition to supporting balanced meals.

Proposed Solution

We propose to:

- Design a camera-based system for monitoring and remembering food stored and retrieved from the fridge
- Develop a computer vision algorithm for identifying various classes of food with high accuracy
- Design a user interface to make this food data (including food age and expiration dates) known to the user

How our solution is innovative:

- All in one fridge monitoring app with features such as expiration tracking, recipe recommendations, and nutrition macros.

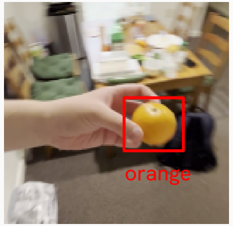
Implementation

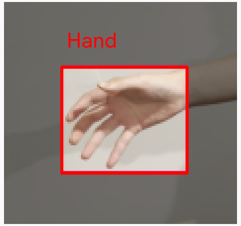
- Dataset Creation
  - Roboflow for image annotation
- Technical Aspects
  - Hardware:
    - Camera in fridge corner → computer → locally hosted web app
  - Computer vision pipeline:
    1. Image capture at fridge open/close
    2. Image preprocessing
    3. CNN object detection → model architecture based off research paper
    4. Database update
    5. User interface update
  - Database:
    - timestamp, category, expiration date

Implementation - Product Demo

Implementation - Code Demo

Data Summary

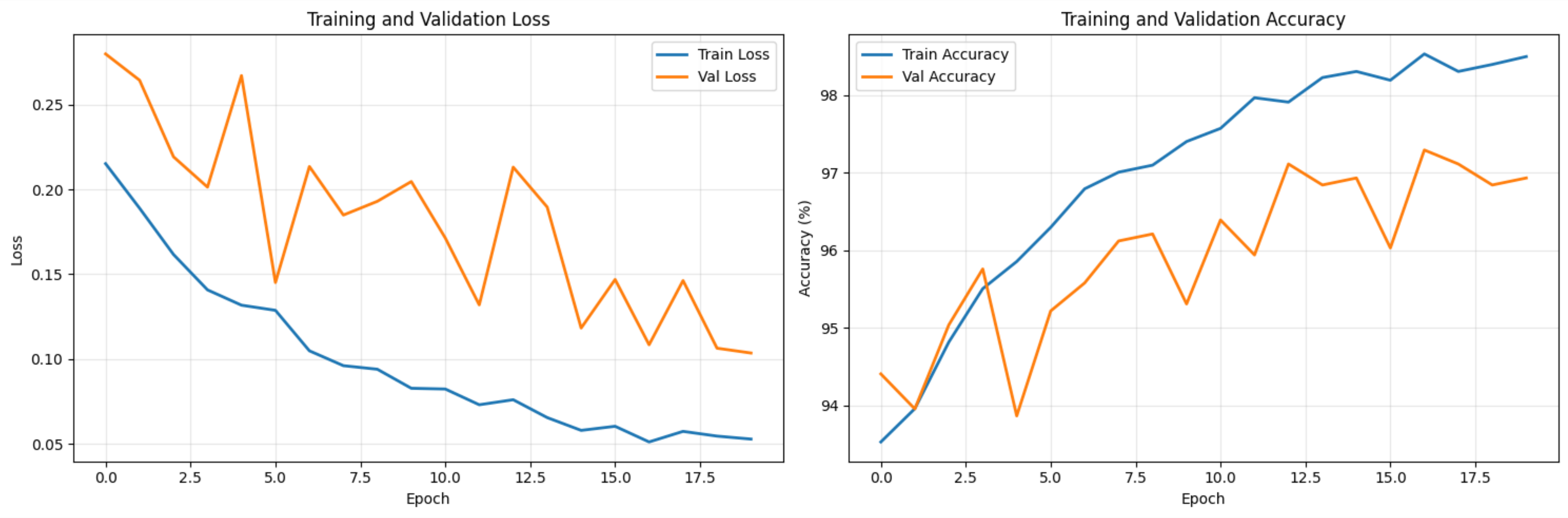




- Training dataset composition:
    a. Food classes tailored to college students' needs
        - ~11k bounding-box crops from labeled images
        - Labeled using Roboflow (YOLOv5 format)
        - Categories include: Hand, Asian pear, Orange, Tomato, Cucumber, Eggs, Leafy green, Sauce, Soda, Leftovers
    b. Various hand positioning, lighting angles, occlusion levels
- Data pre-processing
    a. Train/Test/Validation data split: 80%/10%/10%
        - ~8800 train, ~1100 test, ~1100 validation
    b. Transformations:
        - Training:
            - Resized to 32x32, data augmentations, normalized
        - Validation/test:
            - Resized to 32x32, normalized

Experimental Results

Training vs Validation Loss/Accuracy Curves:



Experimental Results

Per-Class Accuracy and Classification Report:

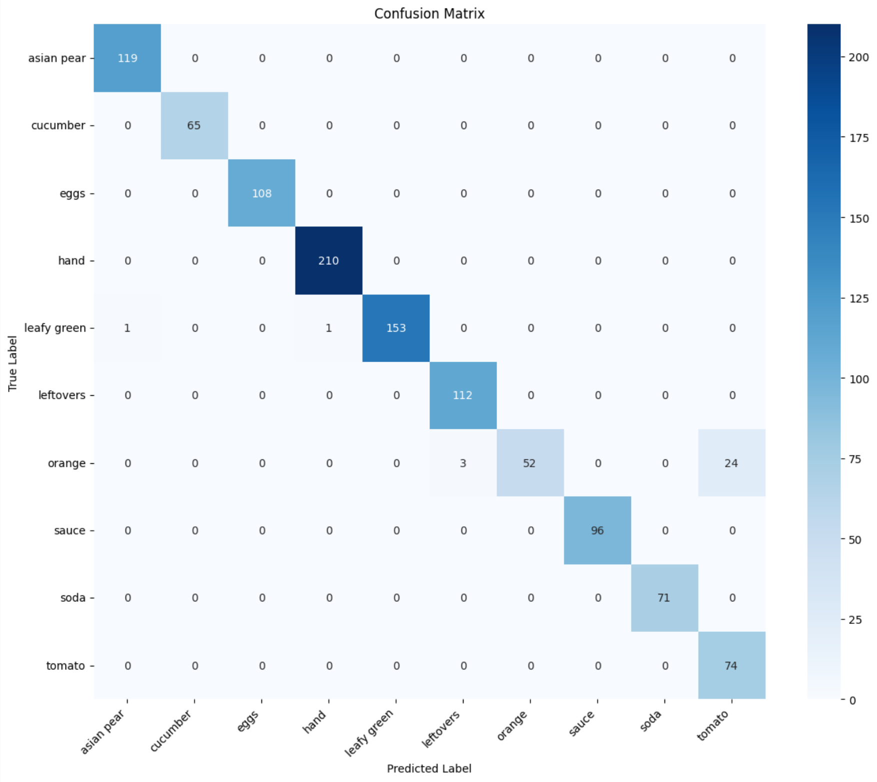
```
Per-Class Accuracy:
----------------------------------------
asian pear      : 100.00% (119/119)
cucumber        : 100.00% (65/65)
eggs            : 100.00% (108/108)
hand            : 100.00% (210/210)
leafy green     :  98.71% (153/155)
leftovers       : 100.00% (112/112)
orange          :  65.82% (52/79)
sauce           : 100.00% (96/96)
soda            : 100.00% (71/71)
tomato          : 100.00% (74/74)
```

```
classification report:
              precision    recall  f1-score   support

  asian pear       0.99      1.00      1.00       119
    cucumber       1.00      1.00      1.00        65
        eggs       1.00      1.00      1.00       108
        hand       1.00      1.00      1.00       210
 leafy green       1.00      0.99      0.99       155
   leftovers       0.97      1.00      0.99       112
      orange       1.00      0.66      0.79        79
       sauce       1.00      1.00      1.00        96
        soda       1.00      1.00      1.00        71
      tomato       0.76      1.00      0.86        74

    accuracy                           0.97      1089
   macro avg       0.97      0.96      0.96      1089
weighted avg       0.98      0.97      0.97      1089
```

Experimental Analysis

In general, the model was able to successfully label objects from the camera input, consistently performing at over 98% accuracy for all classes, with the exception of orange.

The orange class performance (65% accuracy) is an outlier, and points to difficulty distinguishing between oranges and tomatoes as over 33% of oranges were misclassified as tomatoes (via the Confusion Matrix)–likely due to insufficient training and image data for the orange class.



Conclusion & Future Work

In conclusion, we successfully developed a computer vision algorithm (custom CNN) for identifying various classes of food with high accuracy and designed a user interface to make this food data (including expiration dates and recipe recommendations based on fridge inventory) known to the user.

In the future, we may aim to train on more data and have more specific, detailed classifications for food items, expiration details, and tailored recipe information.

Additionally, we may consider a more rigorous method of composing the training data, which involves automatically joining various hand and object masks together, as to reduce the workload on the team.

References

- https://www.cnn.com/2024/03/27/climate/un-food-waste-one-billion-meals-intl
- https://www.wfp.org/stories/5-facts-about-food-waste-and-hunger
- https://www.sciencedirect.com/science/article/pii/S2475299125030033
- https://ieeexplore.ieee.org/document/9458527
- https://www.researchgate.net/publication/326271885_Product_Detection_System_for_Home_Refrigerators_implemented_though_a_Region-based_Convolutional_Neural_Network

Contributions

- Joyce:
  - Data Annotation, Model Architecture, Frontend Functionality
- Rachel:
  - Data Annotation, Data Export/Pipeline, Model Architecture, Model training
- Nurdin:
  - Data Annotation, Validation database structure, Hardware, Object detection software, Integration to Database
- Mohan:
  - Data annotation, front end styling/display, data export and validation