THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Monitoring Food Waste in Restaurants Using Computer Vision and Data Visualization

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Outline

1. Introduction
2. Related Work
3. Contribution
4. Methods
5. Results
6. Conclusion

Background: Global Food Waste Situation

- Data by United Nations (UN) and other [3,4,5,6,7,8,9]:
- Globally, one-third of food produced annually -> wasted or lost
    - Lack of food for malnourished and poor population
- Majority disposed at landfills
    - Emits greenhouse gases -> Environmental damage
    - Representing food waste as a nation -> 3rd largest emitter
- UN's Aims: By 2030, eliminate food waste by half
- **One Major source**: Unfinished food at restaurants
    - **Solution**: Monitoring food waste in restaurants using technology

Food Waste Monitoring

Problem: Food waste due to unfinished food at restaurants

Solution: Monitoring food waste in restaurants to provide data-based actions for its reduction (a part of the Smart Dining Halls project at HKUST)

Steps:

- Technology: Videos -> Images -> Models for dish and quantity -> Dashboard -> Actions
- **End-users:** Restaurant managers
- Facilitators: Model developers and Data analysts.

Challenges

1. Customers’ privacy and large storage
2. Identifying food waste vs food
3. Labeling and testing
   a. Efficient approach for dish labeling
   b. Changes in restaurant serving style/menu
4. Analyzing large amount of restaurant’s data
5. Real world accurate solutions

Related Work

Overview

- Computer Vision for dish and quantity estimation
  - Food
  - Food Waste
- Visualizing Model's Predictions
- Active Learning
- Food waste data visualization

Related Work

Computer Vision for Food analysis

- Popular Datasets:
    - Food-101 [32]: 96.2%
    - ChineseFoodNet 208 [33]
    - Recipe1M+ [34]
- Limitations: Differences in classifying food vs food waste
    - Mixing of food items
    - Quantity variation: none to full
    - Occlusion with other items

Related Work

Computer Vision for Food Waste Analysis

- Eg1: Deep Learning for Classifying Food Waste [15]
- Eg2: A Weakly Supervised Convolutional Network for Change Segmentation and Classification [14]
- Limitations
  - Missing dish selection approach
  - Unstructured approach, no hierarchy
  - Unaddressed long term adaptability
  - Missing diagnosis of model predictions via a VA system
  - Unclear plans for transferability/generality

Related Work

Visual Analytics systems for visualizing Model's Predictions, in other scenarios

- Eg 1: A survey of visual analytics techniques for machine learning [13]
- Eg 2: Human-in-the-loop extraction of interpretable concepts in deep learning models [31]
- Usefulness
  - We learnt from their approaches
  - We surveyed our users to design suitable VA system

Related Work

Active Learning, in other scenarios

- Eg 1: Active learning literature survey [11]
- Eg 2: From theories to queries: Active learning in practice [12]
- Usefulness
  - We learnt from their approaches
  - We surveyed our users to design suitable active learning approaches

Related Work

Food waste data visualization

- Ex: Start digital tracking of food waste [35]
- Limitations
  - Designed for the particular scenario
    - of restaurant staff inputting each tray's information
  - Too time consuming and infeasible
    - in restaurants with lots of customers
- Addressed by
  - We automate the tray information extraction via computer vision
    - No input needed by restaurant staff
  - We conducted surveys with our users to design dashboards

Related Work

No existing works in restaurant food waste monitoring that:

- Utilizes **active learning** for efficiency and accounts for the limits of machine and human in dish classification
- Provides approaches for **maintainability** of dish classification solutions
  - Even with **changes** in restaurants serving style/menu
- Provides a comprehensive **dashboard** for data analysis
- Provides easily extendable strategies for other restaurants

Contribution

Scenario: For food waste monitoring in restaurants

- Theoretical:
  - Proposed a System Pipeline
  - (Main) Proposed a novel Dish Classification approach using Active Learning
  - Proposed categories based approach for Quantity Classification
- Practical: Solutions created and evaluated for LG1 Canteen at HKUST, over a year
- Deep learning Models: Tray image Detection, Dish and Quantity Classification
- Empirical: Interviews with End-users and Domain experts
- Techniques, Algorithms and Systems:
  - Novel Dish Classification technique, Visual analytics (VA) system and Dashboards

Main Contribution

Scenario: For food waste monitoring in restaurants

- Proposed and evaluated a **novel Dish classification approach** using **Active Learning**
  - Includes supportive Iterative process with Hierarchy of dishes and a Visual analytics system
- Expected benefits:
  - Human + Machine collaboration
    - For efficient and optimal dish classification
  - Helps in long term maintainability
    - Of Dish classification solutions
  - Easily transferable
    - To other restaurants

Methods and Results

Overview: Scenario of LG1 Canteen

- System pipeline
- Tray image extraction
- Dish classification
  - Active learning approach: Iteration, Hierarchy, VA system
  - Models
- Quantity classification
  - Categories
  - Models
- Dashboards: Prototype and Final

Preliminary surveys

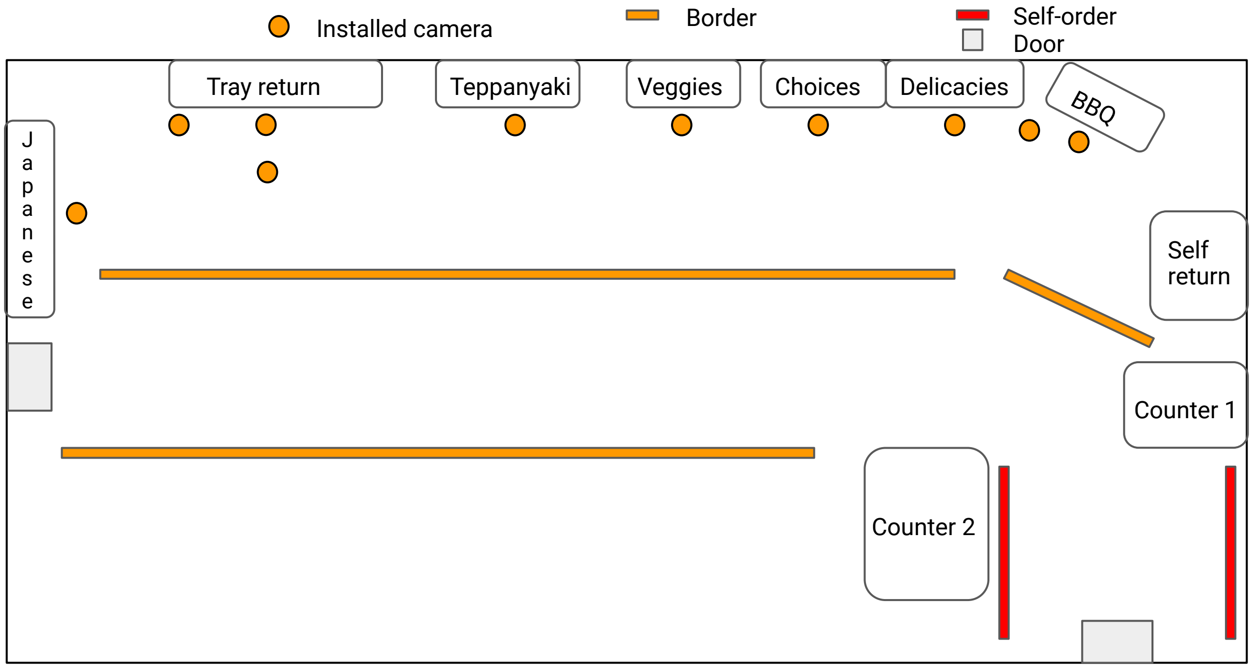
- In 2021, before designing dashboards
- Surveys regarding food waste at HKUST
  - 4 Restaurant managers
    - Situation, concerns, current steps for reduction, interests in automatic monitoring systems via dashboard
    - All managers were interested in the above, were supportive and wanted to learn more
  - 60 restaurant customers (39M, 21F)
    - Majority were students at HKUST and regularly ate at on-campus restaurants
    - Primary reasons for unfinished meals:
      - Rice is over served
      - Set isn't well balanced
      - Taste is not optimal
  - Conclusion:
    - Serving size is an important factor
    - A food waste monitoring system is needed
      - automates the estimation of dish and quantity
      - a dashboard to ease data analysis

Timeline

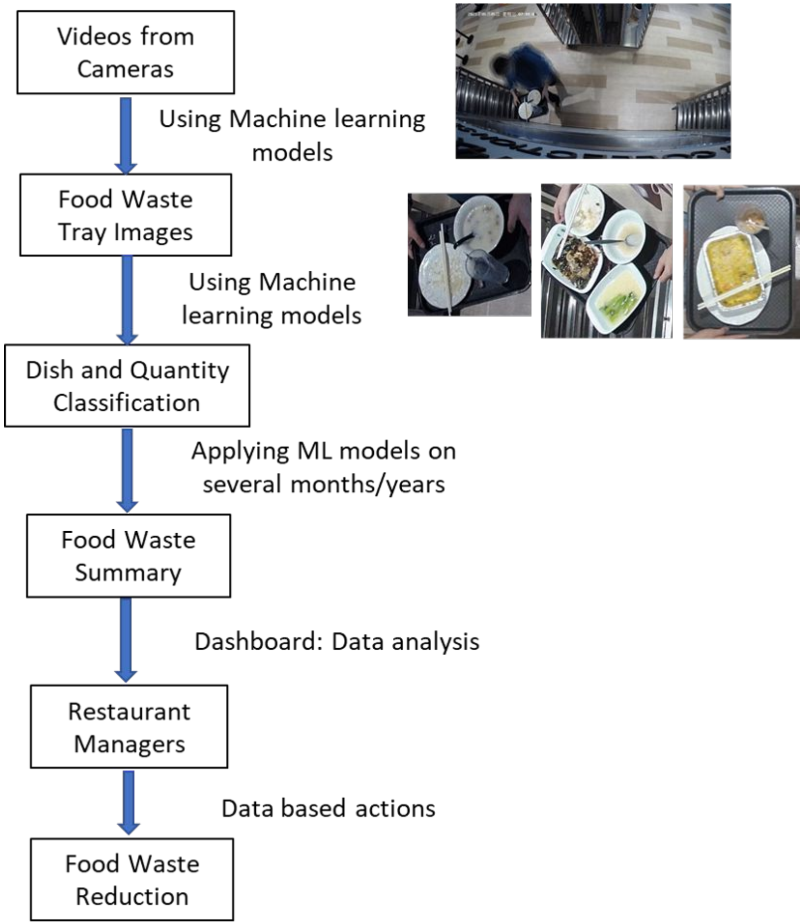
- Before Dec 2020: Pilot run, Previous members [2]
  - Cameras installation, initial tray images extraction technique
  - Inaccurate segmentation-based models by for dish and quantity estimation
- Dec 2020-Dec 2021: Majority of this thesis research
  - From Dec 2020: Improvements in Video recording and created Tray image extractor system
  - By Jun 2021: Dashboard Prototype and evaluation, Short paper submission
  - By Oct 2021: Dashboard Final and evaluation
  - By Dec 2021: Deep learning models implemented, VA system implemented, Evaluation, Full paper submission
- After Dec 2021: Improvements
  - Model improvements
  - Thesis writing

LG1 Canteen

- When cameras installed
  - Installed 10 cameras -> 3 at return area, 7 for 6 serving counters
  - Cover the food tray before eating and after eating
    - Both needed to form an understanding of food served and food waste



System Pipeline



Tray image extraction from videos

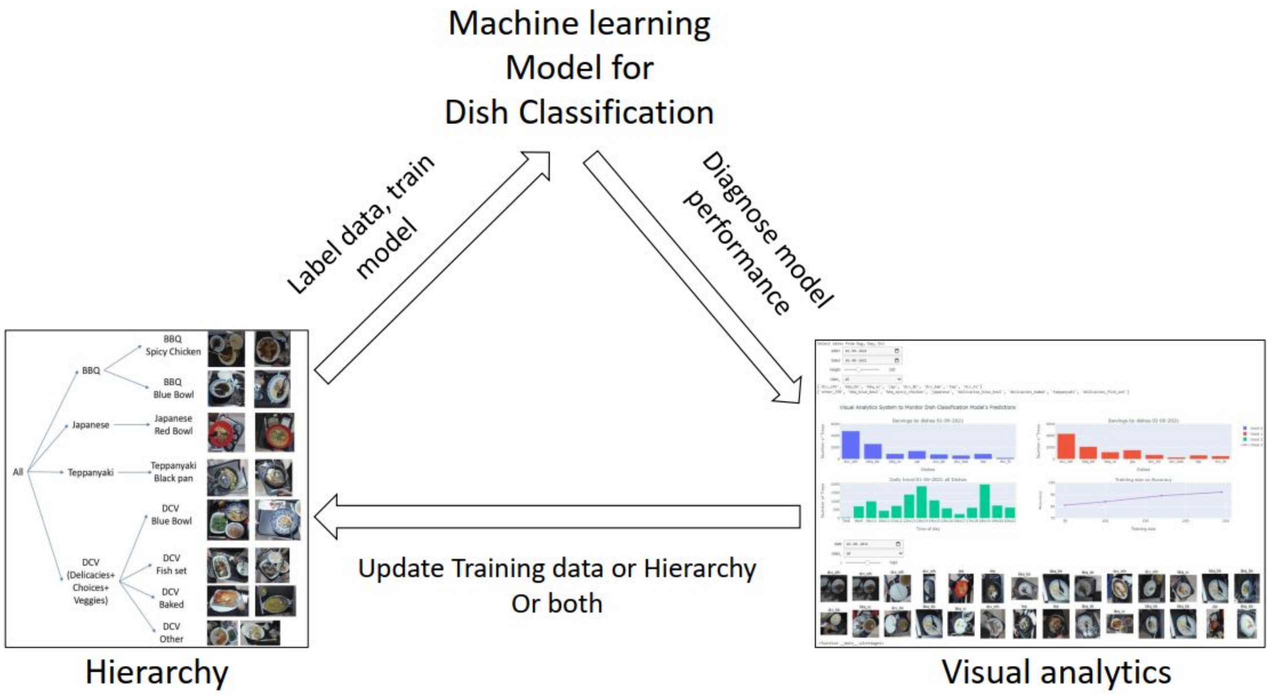
- Daily
  - 10 cameras operating 12 hours each
  - Total 300 GB of videos/day ~ 109 TB/year
- Algorithm: Yolo V3
  - Object detection of food trays and crops tray images
    - Initial code based on pilot study
  - We improved their code in processing time
    - Instead of processing each frame
      - Generally, skip 15 frames (1s). When encounter a tray, skip only 5 frames (0.33s)
    - Pick the 1st image of same tray among several to prevent occlusion
- Net data:
  - Only store tray images (2-3 GB/day) instead of videos (300 GB/day)
    - Reduces storage cost to < 1%
    - Protects customers' privacy

Dish classification
Previous Approach

- Previous members
  - (Esp. FYP Team 2) from Pilot run of Smart Dining Halls
- Dish identification
  - Used segmentation to identify dish categories
  - Real world accuracy around 50%
    - Assuming correct segmentation, still several misclassifications
    - 13 Dish categories (10 main)
    - 4 Food constituents categories: Rice, Vegetables, Meat, and Other
      - Ineffective since dishes vary and have more ingredients
- Quantity estimation
  - Used segmentation to estimate quantity
    - of food waste, container, tray in pixels
  - We converted pixels into approximate % food waste per container:
    - Generally: Highly inaccurate due to failures in dish identification
    - Total food waste in tray: 70% accuracy

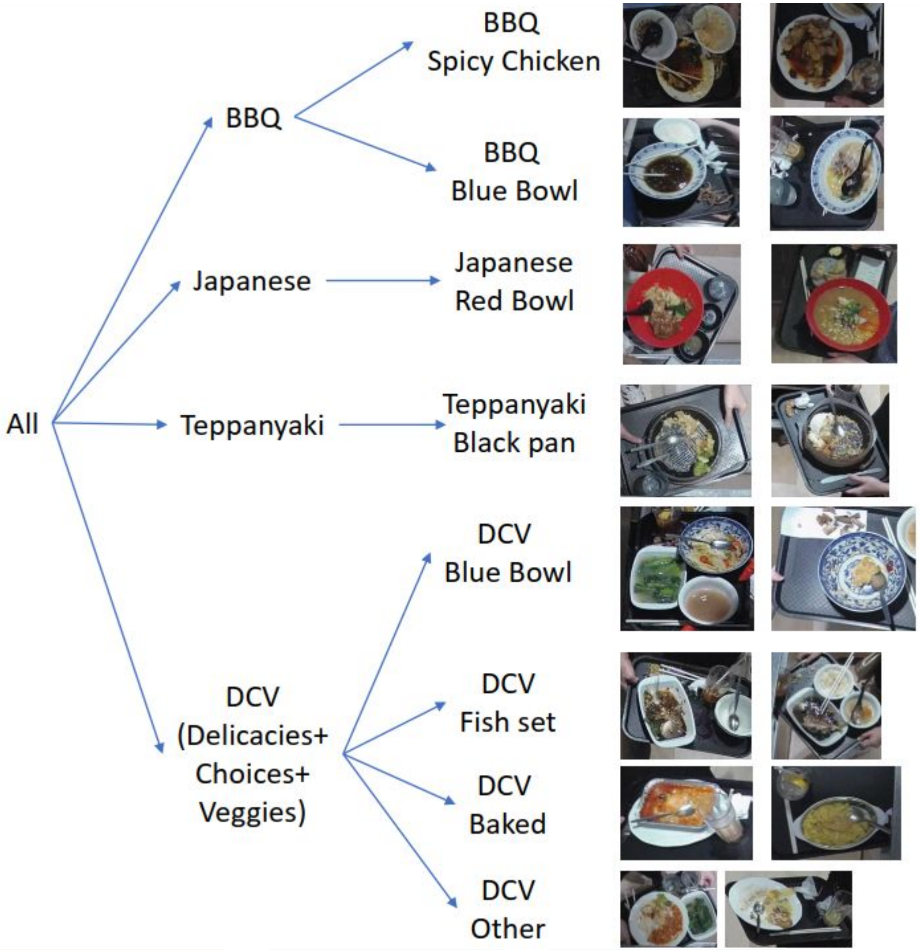
Dish classification
Our Approach

- **Group by Counter Model**
    - **Iterative process for dish classification**
        - Active ML: label most important data utilizing human and machine limitations
    - Hierarchy:
        - All -> Counters -> Dishes



Dish classification: Hierarchy

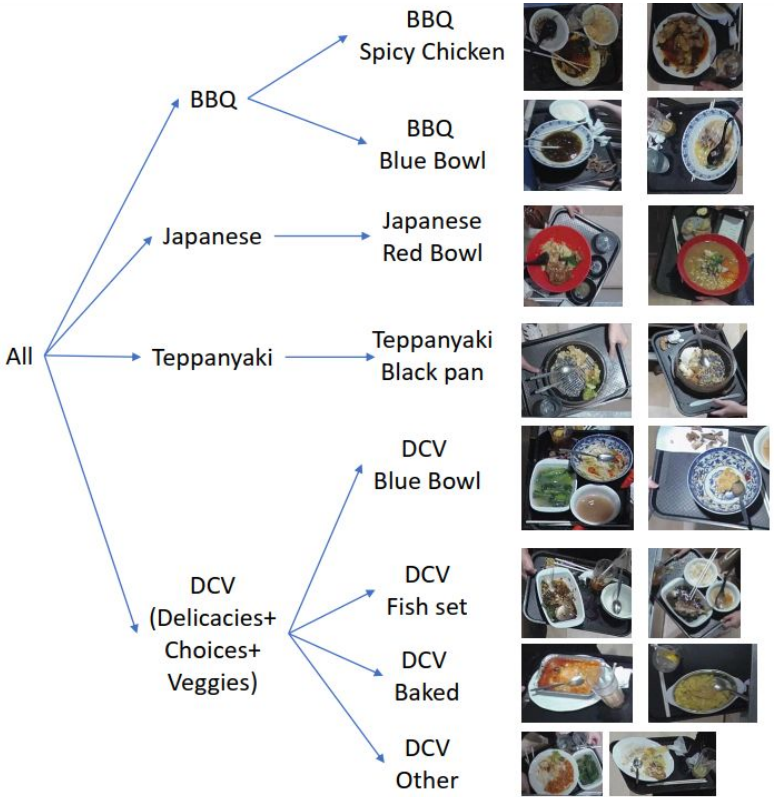
- **Final Group by Counter Model**
  - **8 dish categories, 4 groups**
  - Training Set
    - 2800 food waste images (after eating) for training & testing, from Aug & Sep 2021
    - 350 per dish
  - Model architectures:
    - Mobilenet V2, Inception V3, VGG-16, VGG-19, Resnet 50, Simple CNN (benchmark)
    - Pre-trained on Imagenet weights, frozen layers and fine-tuned
  - Best Testing Result (Accuracy) Mobilenet V2
    - **Acc: 91.2%,**
    - **F1 scores from 86% to 98% for 8 categories**



Introduction | Related Work | Contribution | **Methods** | Evaluation | Conclusion

Dish classification: Hierarchy

- **Iterative Process: Group by Counter Model**
  - 1st, only selected 4 counters:
    - BBQ, Japanese, Delicacies, Choices
    - Found out that food waste from Delicacies and Choices is very similar.
    - Also, model failed a lot in distinguishing between Blue bowl of BBQ and Delicacies
  - 2nd, updated hierarchy
    - Merged Delicacies and Choices into DC
    - Split BBQ into BBQ Blue Bowl and BBQ Spicy chicken, as only these 2 main dishes
    - Split DC into DC blue bowl and DC other
  - 3rd, added Veggies counter
    - since similar food waste to DC, merged into DCV
    - Splitted the DCV into more dishes, popular ones
  - 4th, added Teppanyaki counter when reopened
  - Finally, all 6 counters, and 8 dish categories covering all dishes



Dish classification: VA system

VA system to monitor data and ML models

- Preliminary interviews: 2 model developers
- Design requirements
  - R1. Obtain a quantitative summary of the model's predictions for a selected day
  - R2. Compare the model's predictions quantitatively for different selected days
  - R3. Obtain any trends in waste throughout the selected day and dish
  - R4. Explore the images with the model's predictions for the selected day and dish

Dish classification: VA system

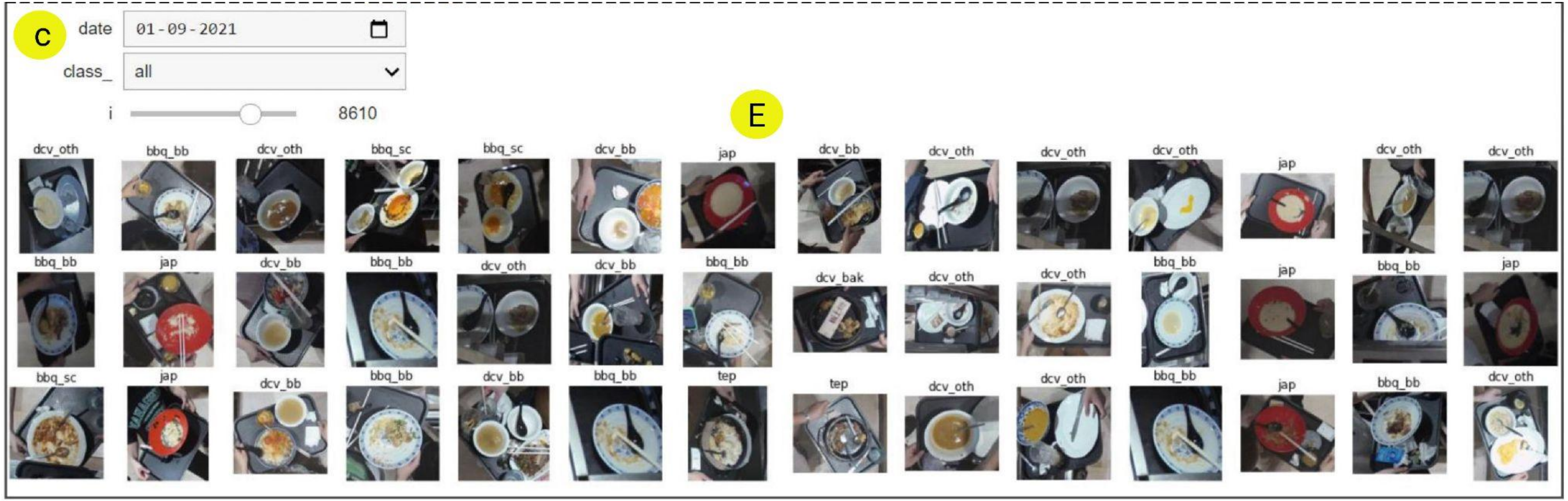
- VA system to monitor data and ML models
  - Real-world performance
  - Over several months/years
  - Compare daily trends
  - Inspect images with predictions
    - Find fail cases
  - Implemented via Jupyter notebooks
    - Allowing easy modification by model developers

Dish classification: VA system

- VA system (Part 1): Trend analyzer
  - a. Filters
    - 2 dates and dish class
  - b. Legend
    - for dish classes
  - A and B: Servings
    - by dishes for the selected 2 dates
    - for side by side comparison
  - C: Day’s Trend
    - for the selected dish class
  - D: Accuracy vs Training size

Dish classification: VA system

- **VA system (Part 2): Images explorer**
  - c. Filters for date & dish class, Slider to go through all images
  - E. Images with labels predicted by models



Quantity Classification

- This thesis models based on classification
  - **2 classes: Almost empty, Has waste**
  - **3 classes: Almost empty, Some waste, Lots of waste**
  - Initial results during this research were bad. New rules created. New results significant improvement:
    - 2 classes: 78.6% -> 90.1%
    - 3 classes: 67.3% -> 80.5%
  - New strict rules for labeling:
    - Statistical meaning of the 3 classes
      - Almost empty (< 10% waste)
      - Some waste (10% to 40% waste)
      - Lots of waste (> 40% waste)
    - Dish wise criteria for the classes

Unfinished soup often misclassified as empty

Leftover sauce often misclassified as waste

Quantity Classification


Almost empty


Some waste


Lots of waste

- New labeling rules
  a. General statistical meaning: Total reducible food waste percent
     - Almost empty (< 10%), Some waste (10% to 40%), Lots of waste (> 40%)
  b. Almost empty class: Irreducible food waste like bones, tissues, very small quantities of soup or sauce or meat skin
  c. If significant amount of soup is wasted
     - No other solid waste -> Some waste class
     - Some other solid waste: Summing at least about 40% -> Lots of waste class
  d. BBQ Spicy Chicken dish:
     - If only bones and a significant amount of sauce are wasted with almost negligible amount of chicken or rice waste -> Some waste class
  e. DCV Fish Set dish:
     - If only bones and a minor portion of fish skin is wasted, with significant amount of soup waste -> Some waste class
  f. Pay close attention to white plates: as white rice might be present and might have been easily missed

Quantity Classification

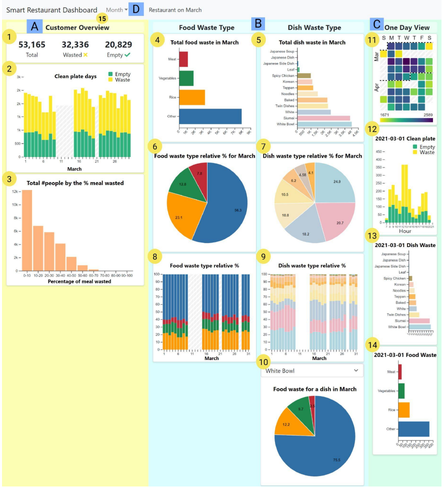
- Models
  - Training Set: about 6000 images of food waste
  - Model architectures: Mobilenet V2, Inception V3, VGG-19, Resnet 50, Simple CNN
    - Trained on Imagenet weights, then froze their layers, then fine-tuned
  - Best Testing Result (Accuracy):
    - **Mobilenet V2: 80.1% for 3 classes and 90.5% for 2 classes**
  - Future Improvement
    - Add more images of fail cases in next training data
    - Utilize Group by counter models for in-depth error analysis
  - Future steps:
    - More classes of has waste

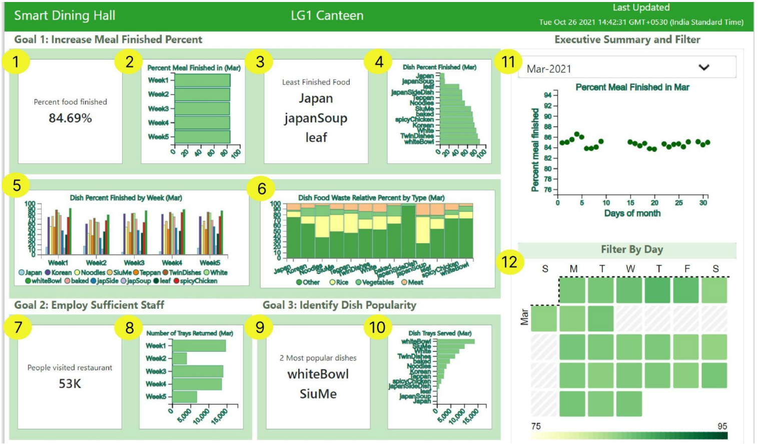
Comparison with previous members models

- Comparison with pilot study
  - FYP teams -> Team 2 created best models
    - Based on segmentation+classification from food trays images
    - Dish and ingredient
      - Fail for half of the identified dish categories: net acc. < 50%
      - Whereas, new model (this thesis): acc. > 90%
    - Quantity
      - Only measure pixels, no real world meaning. Total % waste acc. ~ 70%.
      - Whereas, new model (this thesis) as 3 classes with acc. ~ 80%, and 2 classes with acc. ~ 90%
  - Other disadvantages of previous models:
    - Time and cost expensive data labeling
    - Not maintainable or modifiable (bugs) over time
    - Missing labeling criteria, implementation code and training data
  - These disadvantages are solved by new models in this thesis.
  - The only benefit of previous models
    - To get mock data for designing dashboards, before creating models in this thesis
    - A benchmark of accuracy using segmentation, for dish and quantity models
    - Initial models for tray image extraction

Dashboards: Prototype and Final

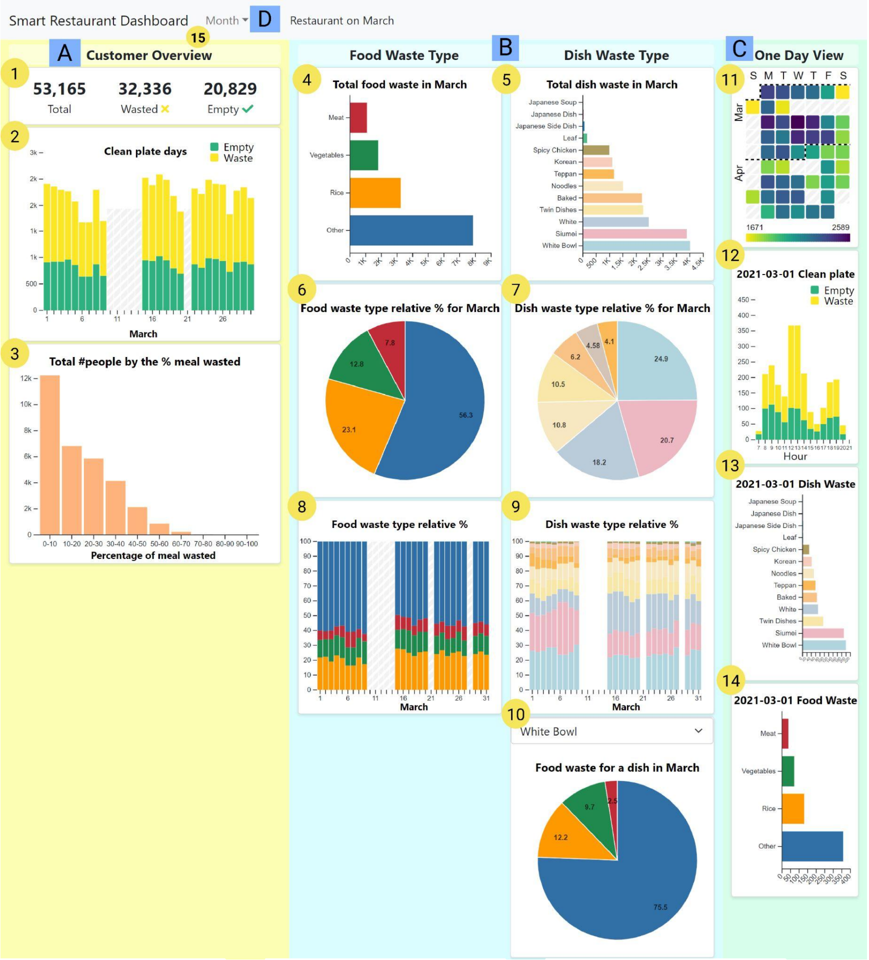
- Designed before Sep 2021
  - Before creating our models
- Data Source:
  - Data obtained by using models by previous members (FYP Team 2)
    - Inaccurate data, but useful for design
    - Later, we can use our models to get real data and realistic dashboards
  - We applied data processing to make it usable
    - Converted pixels of food waste and dishes into approximate percentage food finished
- Design requirements:
  - Surveyed restaurant managers
- Iterative design process
  - Discussions with Visualization researchers and data analysts
    - Gathering requirements: Before creation
    - Design Improvements: During creation
    - Evaluation: After creation





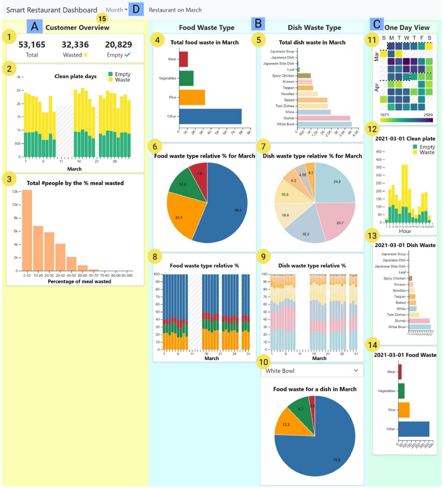
Dashboard Prototype

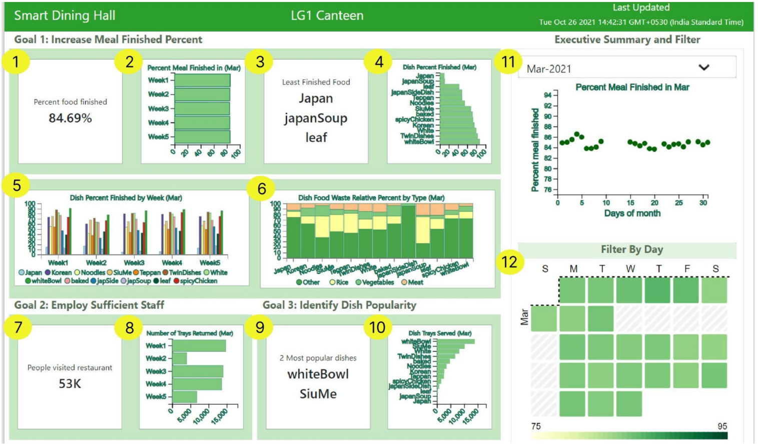
- Gathered requirements by surveying restaurant managers
  - Of several on-campus restaurants at HKUST
- [Link](): Best view at 75% zoom in Google chrome.
- Parts
  - Sections
    - Customer overview (A)
    - Food waste type (B)
    - Dish waste type (B)
    - One day view (C)
  - Filters
    - Monthly (D)
    - Daily (11)



Dashboard Final

- Based on feedback on Dashboard Prototype
  - LG1 Managers wanted
    - More intuitive dashboard using summary+filters
    - Easy to understand linkage
    - Trends by hour for several charts
  - Feedback by 3 data analysts
  - Feedback by visualization researchers
    - 6 on prototype, 2 iteratively for final dashboard
  - Feedback from 3 reviewers of IEEE VIS Short paper
- Design philosophy and improvements
  - The Big Book of Dashboards [50]
- Link: Best view at 75% zoom in Google chrome





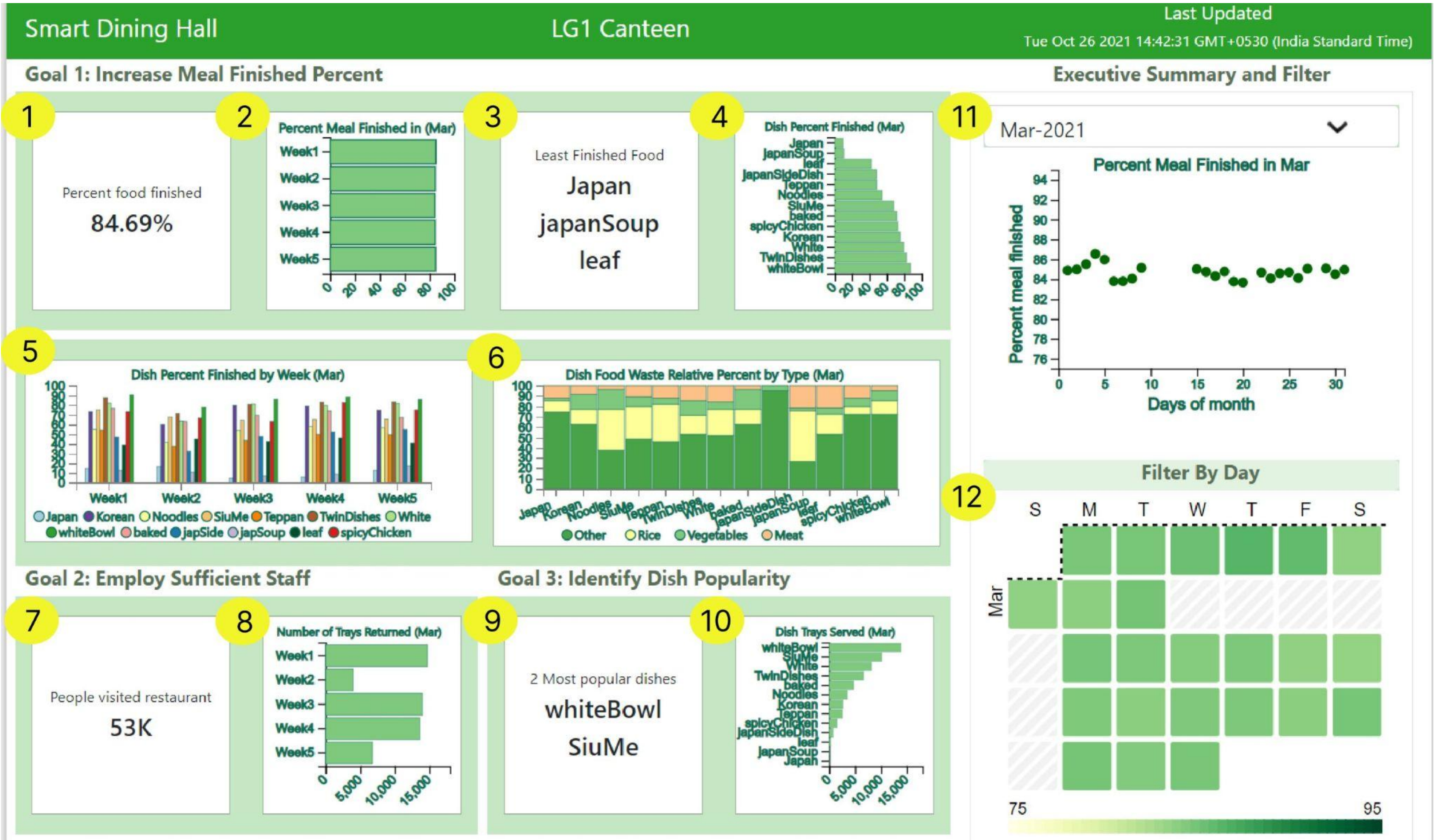
Dashboard Final

Design Objectives:

- O1. Analyze the consumption time series in different granularity
  - In the context of campus restaurants, the timescales include day, week, and month
- O2. Gain insights of the percentage meal finished trend of dishes
- O3. Gain an estimate of the crowd in the restaurant
- O4. Gain an insight into the popularity of several dishes

Design Tasks:

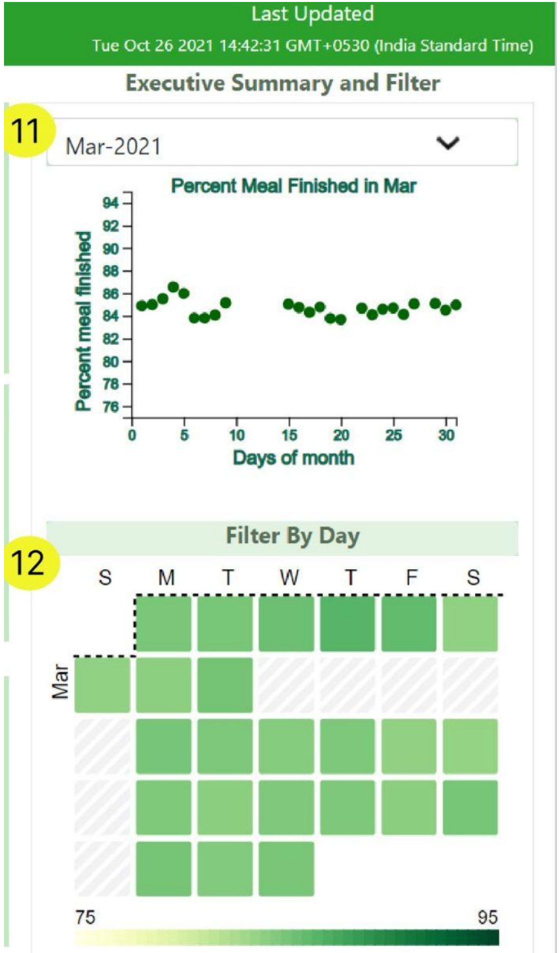
- T1. Filter time to see trend, seasonality, and anomaly points under different timescales
- T2. Provide the faceted distribution of the percentage of wasted food in terms of dish category and food ingredients.
- T3. Provide the estimation of the crowd at the restaurant
- T4. Provide the popularity distribution of dish category



Introduction | Related Work | Contribution | Methods | Evaluation | Conclusion

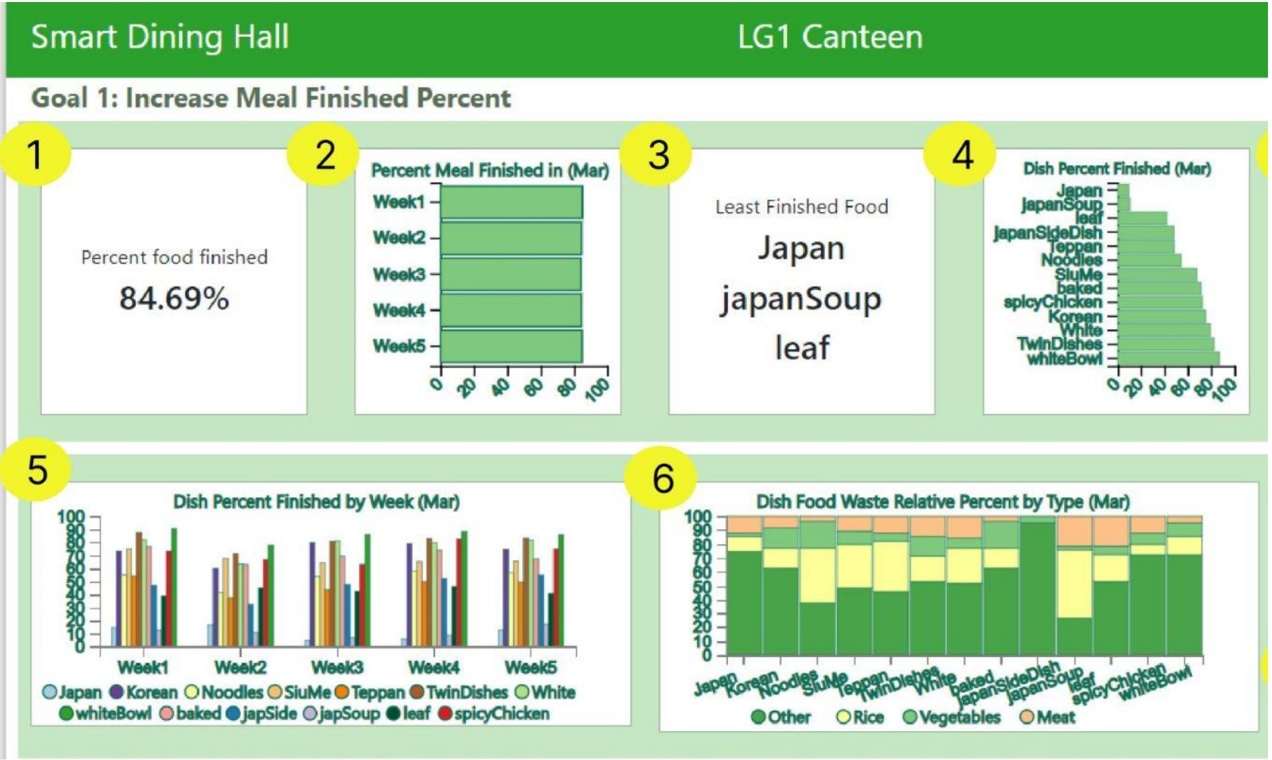
Dashboard Final

- Executive Summary and Filters
  - Filters:
    - Updates entire dashboard according to the selection
    - Drop-down menu (11): **selects month for monthly trends**
    - Calendar-based heatmap (12): **selects day for daily trends**
  - Trends summary % meal finished
    - Dotted Line chart (11): missing dots = missing data
    - Calendar-based heatmap (12): missing rectangles = missing data



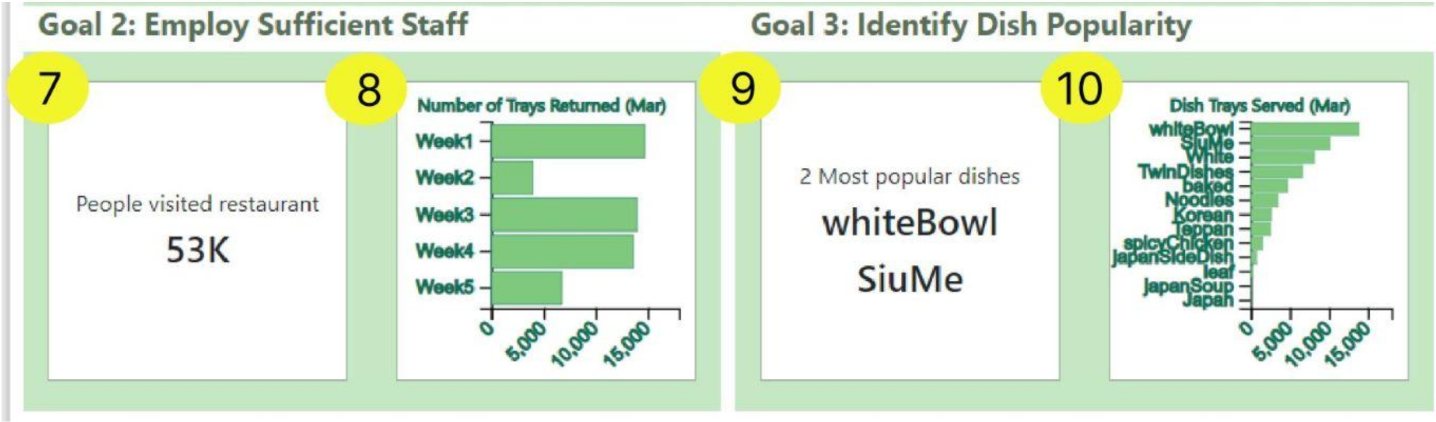
Dashboard Final

- Goal 1: Increase Meal Finished Percent
  - Most important goal
  - Trends by the selected month (drop down) or day (calendar)
  - Trends of % meal finished by
    - Average of Month/Day (1)
    - Week of month/Times in days (2, 5)
    - Dishes (3, 4)
    - Food ingredients (6)



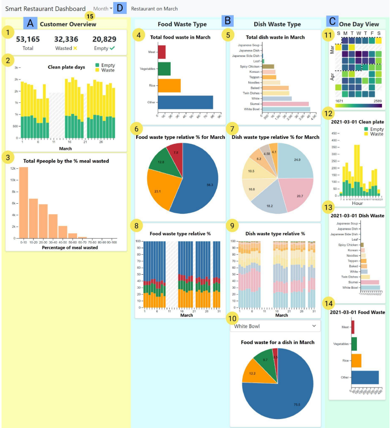
Dashboard Final

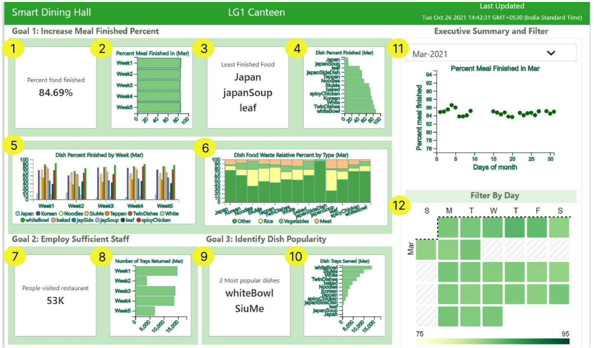
- Goal 2 (Employ Sufficient Staff)
  - Crowd at restaurant -> more staff for removing trays
- Goal 3 (Identify Dish Popularity)
  - Which dish is ordered most?
  - Combining with percentage of dish finished, can give total dish finished



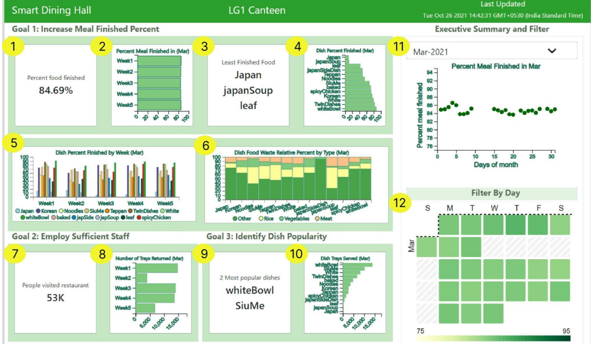
User studies: Dashboard

- Final dashboard was built using the feedback on the prototype:
  - By 6 visualization researchers
  - By 1 restaurant manager from LG1 Canteen, HKUST
  - By 3 paper reviewers at IEEE VIS
- Evaluation of Final Dashboard:
  - We interviewed **3 Data analysts**, 30 min each
    - **Scenario:** responsible to analyze restaurant's food waste using final dashboard, summarize it and report findings to the restaurant manager
  - Satisfied with the final dashboard design.
    - **Average of ratings (points out of 5): Aesthetics as 4.33, Intuitiveness as 4, Usefulness of getting insights as 4.33**
  - Able to complete all open ended tasks successfully.
  - Later, we also shared the prototype design with them for comparison
    - They preferred the final dashboard's design significantly over the prototype's





User studies: Dashboard



Open-ended questions during evaluation

- Q1. What is the average percentage meal finished trend across different time ranges such as month, week, day? (T1, T2)
- Q2. What is the average least dish finished trend across different time ranges such as a month, week, or day? (T1, T2)
- Q3. What is the relative proportion of the constituent food waste ingredients of the least finished dishes? (T1, T2)
- Q4. What is the general trend of several people coming to the restaurant across different time ranges, such as months, weeks, or days? (T1, T3)
- Q5. What is the general trend of restaurant dishes’ popularity across different time ranges, such as months, weeks, and days? (T1, T4)

User studies: Dish classification (inc. VA system)

- VA system: created to inspect model’s predictions in dish classification over several months
- Evaluation: We interviewed
  - 2 Machine Learning model developers (**End-users**): An hour each
- Tasks for VA system evaluation
  - T1. Describe the overall dish distribution for a day of interest (R3).
  - T2. Compare the overall dishes distribution for two days of interest (R2, R3).
  - T3. Select a dish and day of interest and explore the dish trends throughout the day (R3).
  - T4. Identify the appropriate training size for satisfactory accuracy.
  - T5. Inspect the model’s predictions with images for three dishes and over three days of interest to diagnose how well the model performs (R4).
- Comments by model developers
  - Successfully completed all 5 tasks in about 20 minutes on average per person.

User studies: Dish classification (inc. VA system)

- Comments by model developers (contd.)
  - Found the system very useful for deep inspection of model’s performance
  - Shared that the system is much effective than the alternative of randomly downloading a few days data and inspecting model’s performance manually on it
  - Found the iterative process of dish classification useful for efficiently creating models
- Limitations:
  - Although the D view (Accuracy vs Training size) is useful in model creation, it’s static nature makes it less essential during analysis

User studies: Models, System Pipeline

- Semi-structured interviews
  - 2 Model developers
  - About 30 min each
- Satisfied with
  - System pipeline/workflow
  - Tray image extraction model from videos, and its automation on server
  - Dish and Quantity classification models for food waste tray images
- Needs improvement
  - Quantity classification
    - Extend to 4 categories instead of 3, based on % wasted
      - Almost Empty (< 10% wasted)
      - Has Waste
        - Some waste (10% to 40%), **Significant waste (40% to 70%), Lots of waste (> 70%)**

Discussion

- Privacy and Storage
  - Solved. Automated to only store cropped tray images and delete videos
- Model performance
  - Dish works very well for the 8 categories.
  - Quantity works well for the 3 categories: one more category is needed
- Dish recognition
  - Great. Reasons for the minor inaccuracies: similarities in dishes/ingredients/containers, mixing
- Quantity classification
  - More categories can be added. Deeper analysis of misclassifications can be helpful
- Scalability
  - Easily scalable with addition of more GPUs
- Generality
  - Easily generalizable dish classification.
  - Also can transfer all techniques to restaurants with separate tray return area or after adding such area

Future steps

- Improve the quantity classification approach
  - 4 classes instead of 3
- Update final dashboard design
  - To accommodate new model results in dish and quantity classification
- Automate the entire proposed system pipeline
  - From camera videos to dashboards

Conclusion

- Thesis presented
  - Several approaches for analyzing food waste in restaurants
  - End to end solutions for a real-world restaurant via case study
    - System Pipeline
    - Automated: download videos, food tray image extraction from videos, store images and delete videos
    - Active learning: Iterative approach using hierarchy for dish classification
    - Dish and quantity classification models for food waste tray images
    - VA system for monitoring performance of dish classification model
    - Dashboard design for food waste data analysis
  - Surveys and interviews with domain experts and end users
  - Covered other issues
- Approaches can be extended to more restaurants on campus and throughout the world

Publications during MPhil

Conference: EuroVIS 2022 (Rome, Italy)

1. Leo Yu-Ho Lo, **Ayush Gupta**, Kento Shigyo, Aoyu Wu, Enrico Bertini, and Huamin Qu, "Misinformed by visualization: What do we learn from misinformative visualizations?" Computer Graphics Forum, vol. 41, no. 3, pp. 515–525, 2022. [Online]. Available: https://onlinelibrary.wiley.com/doi/abs/10.1111/cgf.14559

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Thank you!

Q&A