Monitoring Food Waste in Restaurants Using Computer Vision and Data Visualization

by

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This is to certify that I have examined the above M.Phil. thesis

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25 August 2022

DEDICATION

To My Family
and
My Friends

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ABSTRACT

Food waste is a significant problem in the modern world, as about one-third of the food produced for human consumption gets wasted annually. A significant and reducible portion of food waste comes from restaurants due to unfinished food. This thesis aims to identify and solve the challenges in monitoring food waste in an on-campus restaurant to help restaurant managers make data-driven decisions toward its reduction. This research took over a year, during which, from 10 cameras, we collected a total of around 22000 hours (55 TB) of videos. Due to the enormous magnitude of video data, manual analysis was infeasible. Thus, deep learning approaches were needed to process the video data and extract food waste information computationally. Also, a data visualization dashboard was needed to help summarize the information and quickly discover valuable insights.

We used computer vision and data visualization tools to build deep learning models to extract food tray images from camera videos, classify dishes and quantities of food waste from those images, and creating dashboards for data analysis. We designed an active learning approach to create models for efficient dish classification and built a visual analytics (VA) system to monitor the model's performance over several months. The best dish classification model achieved 91.2% accuracy for eight cate-

gories of dishes.

During our research, we conducted several surveys and interviews with end-users and domain experts to gather requirements and test the usefulness of deep learning models, the VA system, and dashboards. The data analysts were satisfied with the design of the final dashboard, and the model developers were satisfied with the models for tray image extraction, dish classification, VA system, and prototype for quantity classification. However, quantity classification needs deeper exploration. The approaches from this research can be extended to many restaurants worldwide to reduce food waste.

CHAPTER 1

INTRODUCTION

1.1 Food Waste Problem

Food waste is a severe problem in modern society. Annually, about 1.3 billion tons of food is wasted, which accounts for approximately one-third of all food available for human consumption [3]. The current food crisis threat is compounded by failures in balancing food distribution and is estimated to the worst in about 50 years, according to the United Nations (UN) [4]. Climate experts say that if we represent food waste as a nation, it would be the third-largest emitter of greenhouse gases. Due to this, by 2030, the UN's environment program aims to eliminate food waste by half [3]. By reducing food waste, we can perhaps reduce the environmental damage and help feed the hungry, and malnourished populations [5].

Unfinished food in restaurants is one of the more significant sources of food waste [5, 6], apart from terrible weather, over-producing, transportation loss, and more. While many efforts have been devoted to managing food items on the production side [7], we identify opportunities to reduce food waste from the consumption side, beyond simply relying on the self-reflection of customers [8] or sending food waste for recycling [9]. Our work helps reduce unfinished food at the restaurant level by identifying and solving challenges in monitoring restaurant food waste.

1.2 Objectives

This thesis identifies the following objectives:

1. Develop an automated system to collect restaurant food tray images daily for at least six months.

2. Create a structured solution using deep learning to identify the wasted dishes from restaurant food trays.

3. Find approaches for monitoring and maintaining restaurant food tray's dish classification models over several months.

4. Develop deep learning models to estimate the quantities of food waste in a restaurant's food trays.

5. Design a suitable dashboard for data analysts to analyze restaurant food waste situations regarding dishes and quantities.

1.3 Challenges

Privacy and Storage: With the advancement in cameras, large storage disks, and computer vision, it is possible to record videos of food trays in restaurants. However, recording videos presents privacy concerns for customers present in those videos. Moreover, storing videos is space expensive. One can solve the privacy issue by finding a technique to convert video data into images that do not retain customers' identifiable information. Since images are less space expensive than videos, the storage issue can also be solved.

Food vs. Food waste: One can label data and build computer vision models to automatically analyze the videos or images for dish identification and quantity estimation of food. However, doing the same for food waste is challenging for machines and humans. The reasons are: the quantity of food wasted can vary, causing irregular shapes; mixing of food items could have occurred, or different dishes could have similar ingredients.

Recently, some researchers have made attempts via computer vision [10] towards food waste monitoring; however, their identified dishes are limited, and the approaches are unstructured. Moreover, little effort has been made to adapt the solution to other restaurants and when the restaurant's menu changes. This thesis presents structured approaches to food waste dish classification in restaurants.

Labeling and Testing: While developing a real-world solution for model developers, there is a limited monetary budget and time availability for data labeling. Also, testing the model in the real world is essential. Thus, an iterative method can help in spending as little labeling effort as possible and can also help to test the solution in the real world. In Active learning, model developers first identify a small subset of the data, label it, then train machine learning models and diagnose their performance. This process helps create a benchmark by identifying where models work well or fail. Then, some steps can be taken to improve model performance, such as updating the training data by merging classes, going into fine-grained categories, or labeling more data [11, 12]. A visual analytics system tailored to the problem and the approach is beneficial for testing the models on unlabeled data [13]. In this thesis, we have utilized active learning, a visual analytics system, and some new food waste dish classification approaches.

Number of dishes to identify: For classifying food waste by dishes in restaurants, simply trying to identify every dish from the menu may not work due to the similarities in food waste of several dishes. Moreover, it is very time-consuming to label images of each dish for creating a training dataset. Thus, simply picking some dishes from a restaurant is an unstructured approach.

With recent research in computer vision techniques to classify food waste, there are still opportunities for providing structured solutions [14, 15]. To the best of our knowledge, our work is the first to provide an iterative approach for identifying dishes from food waste trays in a hierarchy scheme and provide a visual system for model developers to supplement the scheme. The visual system can also help identify when food waste data changes with changes in the menu, requiring updating the dish and classification models. Our iterative hierarchy approach and the visual analytics system can also be applied to other restaurants. It also saves the labeling time and cost, as the labels are created by actively testing the machine learning models.

Data analysis: Raw data cannot be used directly, and data visualization techniques are essential for analysis. Making a data analysis dashboard suitable for the restaurant scenario is challenging. Several factors must be considered: data available, accuracy, appropriate visualizations, number of visualizations, and more, depending on the dashboard user. This thesis identifies and attempts to solve such issues by constructing a dashboard after several iterations of user surveys and design improvements.

Case study: We conducted a case study on an on-campus restaurant to evaluate our methods and show their usefulness. We also conducted expert evaluations to identify the advantages of our methods and areas for improvement.

1.4 Contributions

Overall, our contributions are:

1. We propose a system pipeline for food waste monitoring in restaurants.
2. We propose a novel structured approach using active learning for the dish classification of food waste in restaurants.
3. We train deep learning models to extract food tray images from videos and perform dish and quantity classification of food waste at an on-campus restaurant in our case study.
4. We design and build a data visualization dashboard via several iterations and feedback from restaurant managers, data analysts, and visualization researchers.
5. We conduct a real-world case study and interviews with end-users and domain experts to show the utility of our techniques.
6. We address issues in food waste monitoring such as privacy, model performance, reasons for failures, creating solutions for other restaurants or users, and ability to scale and generalize the solutions.

CHAPTER 2

PRELIMINARIES

This chapter presents preliminary information that is useful for understanding this thesis.

2.1 Deep Learning for Object Recognition

The task of object recognition in images or videos involves two components: object detection and object classification. By analyzing the research in this field, we have identified several popular models, see section 2.3, for such tasks by picking the top-performing models on well-recognized data sets in the field of computer vision [16].

2.1.1 Images

Using deep learning to classify objects in images is gaining popularity. Some simple data sets are MNIST handwritten digit recognition [17], and Cats vs. Dogs [18]. Some popular data sets used as a benchmark of model performances are ImageNet [16, 19] and CIFAR-10 [20].

2.1.2 Videos

Many researchers use deep learning to detect objects in videos. Since videos consist of several image frames, those images can be searched for objects. Since processing all the frames in the video can increase the computational capacity and time needed, one helpful technique is to skip a consistent number of frames while performing object recognition. Everyday object recognition tasks include identifying cars and their number plates in videos from road CCTV cameras [21] and identifying objects on the road for autonomous driving vehicles [22].

2.2 Transfer Learning via ImageNet

One of the largest and most famous data sets in visual object recognition research is ImageNet [16, 19]. It serves as a benchmark in image classification and object detection. Training models on the ImageNet dataset allows them to look for and identify several essential features while learning object classification. Thus, computer vision models are often first trained on the ImageNet data set, then stored for download and quick usage by training them (fine-tuning) again on the training data for the actual task. This way, the pre-trained models need less training time for the main task. This method often provides better results than directly training models on the final data and labels [23].

2.3 Models for Computer Vision

Based on the performance in the most popular benchmark data sets, several top-performing models are available for object recognition in images and videos. Here we discuss some of them.

2.3.1 Simple CNN

Several models can be constructed using Convolutional Neural Networks (CNN), varying the number of convolutional layers with their activation, max pooling, flattening, and fully connected layers. These are some of the most utilized neural networks for computer vision deep learning. They are generally utilized to experiment with several parameters to determine which setup might work best for the task. Moreover, these models serve as a benchmark for comparing the performances of more advanced models. In some cases, where the task is unique, these models can even give a comparable performance to more advanced models pre-trained on other data sets [24].

2.3.2 VGG

A famous convolutional neural network known for its simplicity and focus on increasing the depth of CNN is VGG (Visual Geometry Group). It consists of 3 * 3 filters, pooling layers, and a fully connected layer. There are two standard VGG networks named VGG-16 and VGG-19, which consist of 16, and 19 convolutional layers [25], respectively.

2.3.3 Inception V3

Inception V3 is based on CNN and is 48 layers deep. It has an accuracy of over 78% in the ImageNet dataset and is thus very popular for image classification [26]. It has also given great accuracy on other data sets, for example, Retinal OCT Disease Classification [27].

2.3.4 ResNet and ResNet-50

One of the popular models based on deeper convolutional layers using residual layers is ResNet. Using residual layers allows utilizing learning from other data and using more layers than models such as VGG. There are several variations of ResNet based on their number of layers. ResNet-50 consists of 50 layers using residual blocks and is often used in everyday object recognition tasks [28].

2.3.5 MobileNet V2

This famous CNN architecture seeks to perform well on mobile devices. It contains an initial fully convolution layer with 32 filters, followed by 19 residual bottleneck layers. It has often been used in computer vision by pre-training on the ImageNet data set and then training again (with corrected labels) for the specific task. [29]

2.4 Data Visualization and Analysis

2.4.1 Tools

Several charts are available to create data visualizations for conducting analysis. Some simple charts include bar/column charts, stacked/grouped variations of bar/column charts, pie charts, and heatmap charts. Many tools are available for creating dashboards, such as Microsoft Excel, Tableau, PowerBI, Python programming language, and Web-based tools [30]. The easiest and quickest tools are Microsoft Excel, Tableau, and PowerBI. However, their disadvantage is their limited customization depending on the inbuilt features of the software used. To create web-based interactive visualizations, either Python programming language or tools such as HTML, CSS, JavaScript (including libraries), and frameworks (React.js, Vue.js, and more) can be used. The benefit of web-based visualizations is that the user can fully customize them as per their needs; however, their disadvantage is that they can take time to create.

Deep learning users generally utilize Python programming language and thus prefer it for making visualizations and dashboards. Data analysts mostly use Excel, PowerBI, and Tableau. More advanced analysts use Web-based interactive dashboards using either Python or web development tools [30]. In this thesis, we have utilized a variety of data visualization tools to create solutions for data analysis.

2.4.2 Visualizing Model's Predictions

In Machine learning, due to the limited size of the test data, real-world open ended testing on a large amount of data is essential. Machine learning users have created several dashboards to visualize model predictions for this task. These dashboards range from simple to highly advanced/detailed, depending on their purpose [31]. Usually, they include several charts to provide a summary of the predictions per class, and an image explorer view to explore the predictions with their corresponding images. This helps in verifying if the model is performing well in the real-world. In this thesis, we have utilized some of these useful approaches for creating a suitable visual analytics system, surveyed our users for gathering design requirements and conducted its evaluation.

CHAPTER 3

RELATED WORK

3.1 Food Waste Analysis

With the advances in deep learning technology, many researchers have proposed food classification solutions based on deep neural networks and large-scale food datasets, including Food-101 [32], Food2K [33], ChineseFoodNet [34] and Recipe1M+ [35]. However, less focus has been given to classifying food **waste**. Food waste of the same dish can vary in shape, quantity, and color. Therefore, when the food is finished, the food waste tray can be challenging to classify by dish. Hence, there are several opportunities for research on food waste classification by dish.

Recently, some particular works have been using deep learning to classify food waste [14, 15]. However, they do not explain how they selected those categories, how they can discover more classes, or how to go deeper into the food constituents of the current ones. We follow a structured approach toward the types of food waste classification in our work. We apply an active learning approach using iteration and hierarchy to identify groups and then subgroups of dishes to classify food waste. The benefit of our work is the ease of transferability of our structured approaches to other application scenarios (*e.g.* other restaurants). However, the data and models from one restaurant may not be transferable to another due to the differences in food served and containers. Another benefit is that we utilize the models early to generate a coarse prediction for the next model. Also, we can identify and diagnose our model's limits in classifying food waste and take action accordingly.

Many previous works have used segmentation for the dish and quantity classification of food waste [14, 15]. In theory, the results of segmentation are better than that of classification. However, preparing data for segmentation is expensive in terms of labeling labor. Classification might also offer good results. Thus, we only use classification in this project for dish identification and quantity estimation, as it allows us to efficiently utilize the iterative hierarchical approach toward dish classification of food waste. It also allows us to quickly go deeper into the dish categories from the hierarchy. Simultaneously, we spend less time labeling a new category in classification than we would have in segmentation.

Moreover, since the conditions in a restaurant change with time, such as the dishes served, how they appear, and their serving containers, updating the models for food waste classification might be needed. Using classification ensures that the time needed to label data is always less than that of segmentation. However, we should note that we used the segmentation approach for extracting food tray images from the restaurant's camera videos, as classification would not work.

3.2 Active Learning

In the real world, labeling the entire data may not be feasible. Thus, one should prioritize the data to be labeled to have the most significant impact on training a supervised model. This process is known as Active learning [11, 12]. For example, several restaurants often serve thousands of meal trays daily and about two million a year, thus making the data large; a restaurant can also have about ten primary and 40 total dishes; therefore, priority in labeling is also needed. In Machine learning, one needs to label hundreds of images per category for good results. If we select 40 dishes and label 300 images per dish, we need to label 12000 images. The two factors of the number of images to label and the number of categories play a role in the time taken and cost of the labeling process.

Moreover, recognizing the dish in each food waste tray is impossible even for humans due to the similarities between dishes. Thus, accurately labeling all the dishes from the menu might not be possible. Therefore, this process can be very time-consuming and may not work well. A grouping of similar dishes into one labeling class can be beneficial. Thus, we propose an iterative process of:

1. Creating a hierarchy for labeling dishes by main categories (and subcategories in the subsequent iterations).

2. Labeling data and training the machine learning models.

3. Testing the models on extensive data using a visual analytics system.

4. Updating the hierarchy based on the inferred limits of machine learning and human abilities in dish classification.

5. Repeat steps 1-4 until a satisfactory result of dish classification is achieved.

3.3 Visualizing Model Predictions

Inspecting model predictions on large amounts of data in the real world is crucial. Based on our case study, the models may be trained with a few thousands of images in the food waste scenario, but they will predict dishes for over two million images in a year. Thus, many things can go wrong, with limitations in the training data, restaurant menu changes, and other external factors. Exploring the model predictions without an interactive system can be ineffective and challenging. In other areas, researchers have proposed several visualization systems for model and data iteration [13, 31]. However, there are a lack of visualization systems for helping developers in the model creating and diagnosis phase for dish classification of food waste. Moreover, the visualization systems by other researchers may not be directly applicable to the food waste scenario.

In this thesis, we present a visual analytics system after developers' interviews, which helps the developers monitor the predictions by the model, compare them across days, and visually inspect the failed scenarios. This way, our visual analytics system supplements our iterative approach to dish classification using hierarchy.

3.4 Food Waste Data Visualization

Throughout history, data visualization has served as a vital tool to facilitate the analysis of large amounts of data to discover valuable and actionable insights. There are some tools available for restaurant scenarios that involve the staff manually inputting the food information and weights and then generating several data visualizations [36]. However, depending on the rush at the restaurant, the restaurant staff has a limited amount of time to regularly input this information for each food tray. Moreover, for restaurants where a large number of customers visit, there might be no time available for the staff for manual input of information. Thus, there are limited data visualization tools available for restaurant scenarios that offer a comprehensive analysis of food waste data in terms of dish and quantity without requiring the restaurant staff to enter information for each food tray. To solve this problem, we conduct surveys and interviews with restaurant managers, data analysts, and visualization researchers to gather their requirements to design and create data visualization dashboards. We also create models for dish and quantity classification of food waste. Our approaches can be modified and automated. The design of the final dashboard can be utilized directly or with modifications for food waste monitoring in restaurants.

CHAPTER 4

METHODS

4.1 Data and Approaches

4.1.1 Data Description

At an on-campus restaurant, LG 1 Canteen, of the Hong Kong University of Science and Technology, we installed ten cameras to accumulate videos of food trays of when the customers collect them before eating and then return them after eating. Before eating, the customers collect trays with food from the six available counters. The food trays collected by customers before eating do not have food waste. After eating, the customers return the food trays with food waste in the tray return area. The counters have seven cameras at the top, which allow us to track the food trays of customers before eating, get a good idea of the food items served, and help recognize the food waste items. The tray return area has three cameras (placed at different angles) at the top, allowing us to track almost all the food waste trays returned by the customers.

Generally, each day the restaurant is open for about 12 hours. Each video is 208 seconds long (144 MB), with 3840*2160 resolution and 15 frames per second (FPS). Thus, each video consists of about 3120 high-resolution frames with many details. From 10 cameras in the counters and tray return area, the video content of a day would be 120 hours long (300 GB). In the overall duration of this research, which is over a year, the video data approximates 43800 hours (109 TB). At the start of the research, there were some issues of data loss when the automated video downloading code failed on several occasions. Later this problem was solved. Thus, we effectively gathered approximately 22000 hours (55 TB) of video data. Due to the enormous data size, it is impossible to be directly inspected by humans and needs machine learning techniques for extracting the relevant images of food trays.

Moreover, storing such large data is expensive. The privacy of users is also a concern while storing video data. Thus, our solution is to utilize machine learning to extract the relevant food tray images and store them instead of the videos. This solution will save storage space and ensure the customers' privacy.

4.1.2 Data Modeling and Processing

Tray Image Extractor

We trained a machine learning model, utilizing YOLO V3 architecture (you only look once) [37, 38] that can detect all the food trays from an image, and wrote a code to crop and then extract those detected tray images. At first, we passed each frame in the video through the tray image extractor code, but the process was very time-consuming and provided too many images of the same tray as people walked toward the return area to return the food trays. We added a method to skip 15 frames (1 second) by default to save computational time and space. When the code encounters a food tray, it slows down to only skip 5 (1/3 of a second); this ensures that the tray image extractor can also collect images of other trays in the frame.

We hosted the tray extractor system on a server that allows continuous recording of the videos during the restaurant's opening time and processes them to extract the tray images. We used the cron job scheduler [39] to automate the processing of the videos to extract the tray images and then delete the processed videos. The processing happens in the order of download and starts as soon as the first video gets downloaded. This way, the server does not need to wait for all videos to download before processing them. In a 24-hour cycle, the system automatically completes recording and downloading videos, processing them for extracting food tray images, then deleting the processed day's worth of videos.

After processing one day's videos, we get the images of trays extracted from those videos. Then, we delete the videos (300 GB) and only keep the extracted tray images (6 GB) for that day. This method saves the storage capacity needed, from 55 TB for video data to just about 1 TB for image data, for the entire research period of over a year, as videos are much more space expensive than images. Overall, storing the extracted food tray images instead of the videos reduces the storage needed to only 1.8%. Theoretically, a simple two terabytes (TB) solid-state drive (SSD) is sufficient to store a year's images and allow fast processing of a day's videos. At most, an SSD of four terabytes of storage is more than enough to account for the possibility of duplicate image data, assuming, at the worst, there is an average of three duplicate images per unique tray.

Source of Tray Image Extractor

In the Smart Dining Halls project's pilot run, which happened before this research started, several previous members were involved in this project [2]. They helped in creating the models for extracting tray images from videos. In this thesis, we improvised that code regarding time and space. Since the pipeline code and docker environment created by the previous members had several bugs making it inoperational and flaws making it ineffective, our research created a new pipeline code and docker environment.

The principle of the new pipeline is described above in "Tray Image Extractor" regarding the downloading and processing of the videos to obtain food tray images.

Handling Tray Images

Since we collected about three to ten images of the same tray, the next step is to decide which image is the best. We observed that the glass usually occludes the images collected last for a tray at the food counter or by another tray on top of it. Due to this, an appropriate step is to take the first image of each tray and discard the remaining images. This process further reduces the space cost from about 6GB to about 2GB for one day's images. Thus, reducing about 1 TB to just approximately 350 GB for over a year's research duration. The 350 GB of images are enough to observe food and analyze food waste from the extracted tray images. The food waste data comes only from the tray return area, from three cameras of ten. The remaining food data (non-waste), from seven cameras of ten, is helpful for humans to learn about the food served and then label the food waste data accordingly. We could label a small subset from this data and train machine learning models to classify the food tray images by dish and quantity.

4.1.3 Active Learning Approach for Dish Classification

Food vs. Food Waste

The dish classification of food waste differs from the dish classification of food before eating. The main problems in food waste identification by humans that we observed in this research are the small resolution of food waste and similarities in food waste for

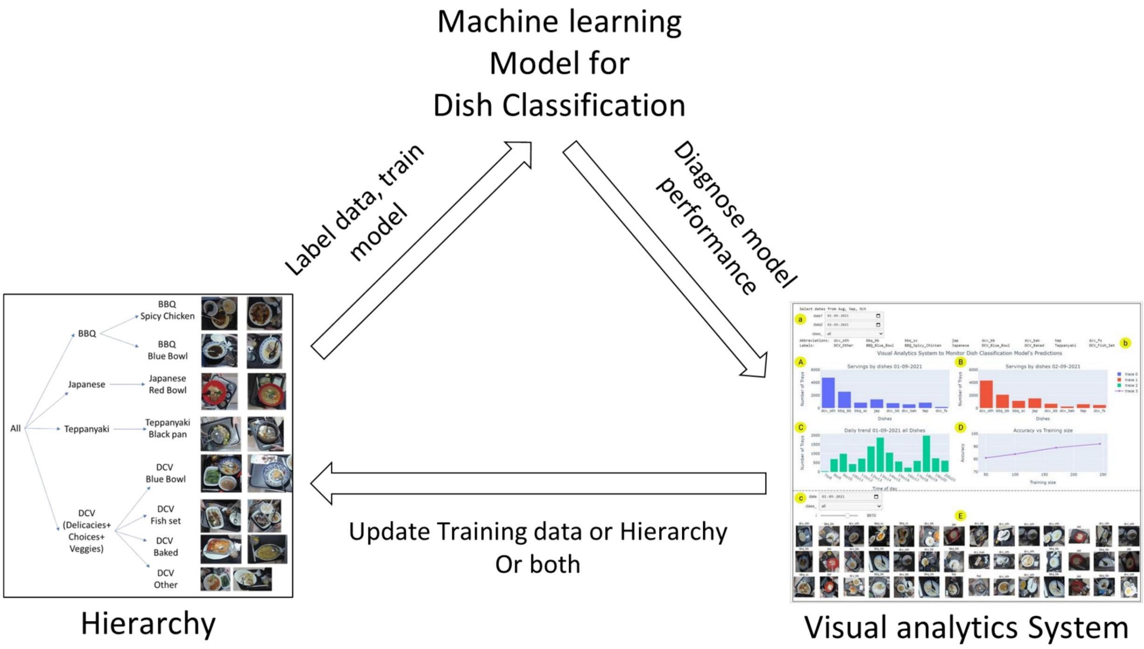

Figure 4.1: **Proposed Iterative Approach for Dish Classification Using Active Learning**: A loop of creating a hierarchy of dishes via groups and subgroups, then labeling the data for training machine learning models for dish classification, then extensively diagnosing the model performance via a visual analytics system.

different dishes due to changes in shapes, quantity, color, occlusion, and mixing of food items. Thus, identifying the dish is challenging even for human beings. Due to this, we cannot directly use all dishes from the restaurant's menu. We created an approach to explore the limits of machine learning by first focusing on classification via a small set of categories called main groups. This approach is a part of active learning. After doing so, we identified additional subgroups utilizing the fail cases of models and the restaurant menu. Later, we used the predictions from the model developed for main groups' dish classification to ease the labeling of subgroups. This process also helped us save on the labeling effort.

Approach Towards Dish Classification

It is crucial to consider how many images to label and the number of classes. The former can be decided by tracking the performance of machine learning models for different training sizes to decide on a suitable training size. The latter is a part of the active learning approach: an iterative process using hierarchy for dish classification and a visual analytics system to facilitate hierarchy creation.

One crucial considerations in recognizing food waste in a restaurant is maintaining the dish classification models for several months or even years in the future. When a restaurant's menu or serving containers change, the models might need to be updated. However, tracking their performance is difficult. Moreover, labeling several months of data to train machine learning models is too expensive. Thus, only a small subset of data can be labeled, such as a few hours or days. We can select this data from a month, then test it for several months to see if the model works for the overall period of interest. Another important consideration is that humans may be unable to label hundreds of food waste images of every dish from the restaurant's menu. Often, when dishes have similar ingredients or when there is no food waste, the images of food waste trays may be indistinguishable. Another note is that labeling costs are proportional to the number of classes. Thus, in our approach, we utilize the feedback from the human labeling team, iteratively train machine learning models for more classes using hierarchy and test the limits of machine learning.

In this thesis, we provide an active-learning-based iterative hierarchical approach to the dish classification of food waste. Fig 4.1 shows the loop of creating a hierarchy, labeling data, and creating machine learning models for dish classification, diagnosing their performance extensively via a Visual analytics system and utilizing that to update the hierarchy or training data. The images used for hierarchy 6.1 and visual analytics system 4.3 here present a snapshot of the systems we created in our case study, mentioned in section 6.1: Use Case.

For hierarchy, first, we identify k main groups of dishes from the restaurant's menu or the restaurant's serving style (such as separate counters). Then, we label n number of images for each k leading group, picking the same number for each group, ensuring that the model learns how to properly classify each group. We also note the feedback from the human labeling team during the labeling on the ease or difficulties in identifying and distinguishing between classes. We then split the labeled data into training, validation, and testing data. Then, we train machine learning models on the training data while checking their performance on the validation data.

We test the performance of the machine learning models on the testing data and select the four top-performing model architectures for comparison in the remainder of the iterations. We identify the best machine learning architecture and only focus on its diagnosis, as long as it significantly outperforms the other architectures. Then we extensively diagnose the best machine learning model's performance on several months' data. We utilize a visual analytics system to make this process easier. Upon inspecting the model's predictions, we pay attention to the model's fail cases, which provide information on creating subgroups of dishes for the next step in the hierarchy or adjusting the main groups. We also learned that merging some main groups is needed due to the poor performance of machine learning algorithms in distinguishing between them. We verify this with humans to see if humans also face a similar issue or outperform the machines. This approach helps us decide when to go deeper into classifying a dish or merge one dish category with another. Section 6.1.1 with Fig. 6.1, will offer examples for further clarity.

Now, after taking the necessary steps, we go to labeling data for the subgroups of dishes. Before doing so, we utilize the data we have already labeled for the main groups and the machine learning model's predictions on several months of data to ease the labeling process of subgroups of dishes.

Then, we split the data of subgroups into train, test, and validate. We train machine learning models and see how well they can classify food waste into subgroups of dishes. This is an iterative active machine learning process, where we add/remove classes, label data, train, and test machine learning models. Overall, using this process, we can obtain a hierarchy of primary groups and subgroups of dishes that the machine learning algorithms can classify. The utilization of a visual analytics system supports model developers in diagnosing the model predictions on a large amount of data in a structured manner, as the number of images can reach two million over a year of data.

We can save data labeling efforts by the iterative process, Fig. 4.1, and discover the limits of humans and machine learning for this problem. This way, we do not need to individually identify every dish from the restaurant's menu. We can focus on collectively identifying several dishes using groups, where the union of the groups covers all the dishes on the menu. By checking the model predictions over several months, we can make the necessary adjustments to the hierarchy and provide adaptable long-term solutions to the dish classification of food waste in restaurants.

4.1.4 Quantity Classification of Food Waste

Several approaches are available to classify the quantity of food waste, such as classification into groups or percentage estimation of food waste. This thesis offers a simple quantity classification solution for food waste in the scenario from the use case, section 6.1. We used random selection via python programming to extract about ten thousand images of food waste trays from the first week of August 2021. About 6000 images were identified as suitable and diverse for data labeling and training machine learning models. Then, we labeled these images into two main classes: "Almost empty" and "Has waste (not empty)." Then, we trained several machine learning algorithms for this task, utilizing state-of-art architectures pre-trained on ImageNet dataset [40] then fine-tuned on the training data. We also implemented variations of a simple CNN architecture to set a benchmark for performance comparison. MobileNet V2 [41] architecture provided the best accuracy for the two classes.

We expanded the categories for quantity classification into three sub-classes "Almost empty," "Some waste," and "Lots of waste." Objectively, the "Almost empty" category means less than 10% food waste, the "Some waste" category means between 10% to 40% food waste, and the "Lots of waste" category means more than 40% food waste. Here the food waste percentages are estimated concerning the possible amount of food served, determined based on our experience of eating at the restaurants frequently for several years. The values are only for reference, as the percentage of meals wasted can have a margin of error. The best accuracy for the three classes was achieved by MobileNet V2 [41] architecture upon labeling the data, training models, and testing. This way, a suitable method to classify the quantity of food waste was obtained. For a deeper exploration of quantity classification, the "Lots of waste" class can be split into two classes, supposedly "Significant waste" and "Mostly waste," representing 40% to 70% and more than 70% food waste in food trays. However, this thesis focuses mainly on the dish classification part, and quantity classification is thus only explored for these three classes. The results are covered in section 6.1.4.

4.1.5 Models for Dish and Quantity Classification

We created dish and quantity classification models using their corresponding training data; however, we used similar techniques. We utilized several state-of-the-art model architectures in image classification for creating models for dish and quantity classification of food waste. The examples include VGG-16, VGG-19 [25], Inception V3 [26], MobileNet V2 [41], and Resnet 50 [42]. We also created a simple CNN architecture to serve as a benchmark. We utilized transfer learning for training models for dish and quantity classification. The models other than the simple CNN were firstly pre-trained on the ImageNet dataset [40], then their weights were frozen, and additional dense layers were added. Then the updated models were trained on the training data (fine-tuning) for dish and quantity classification of food waste.

4.1.6 Usage

By applying the dish and quantity classification models, we can obtain the food waste information of a restaurant. The restaurant managers can use the end summary of the food waste information to make data-driven actions for its reduction. One of such actions can be the adjustment of the serving size. For example, they can reduce the serving sizes of the dish with the majority of (normalized) food waste. Since we tailor our system for the long term, the model developers can also track the restaurant managers' actions' effectiveness and provide them with updates on food waste trends. Our iterative hierarchical approach, 4.1, and visual analytics system (covered in section 4.3, Fig. 4.3) can help the model developers create and improve models for dish classification of food waste.

4.2 Pipeline Overview

Fig. 4.2 demonstrates the whole pipeline of our proposed system for monitoring food waste in restaurants. It starts with getting videos from cameras and applying a deep learning model to extract food **waste** (after eating) tray images. We also use it to extract food tray images during food serving (before eating) for later diagnosis upon need, such as while figuring out uneaten dishes from food waste during the labeling. We pass the food waste tray images through machine learning models for dish and quantity classification. After applying the models to several months or years of data, we get a food waste summary at the restaurant. Then data analysts can perform data analysis to detect food waste trends, create actionable insights and forward the insights to the restaurant managers, who can take data-based food waste reduction actions. Moreover, using this pipeline, the results of managerial actions can be tracked and utilized for further adjustments in serving food at the restaurant.

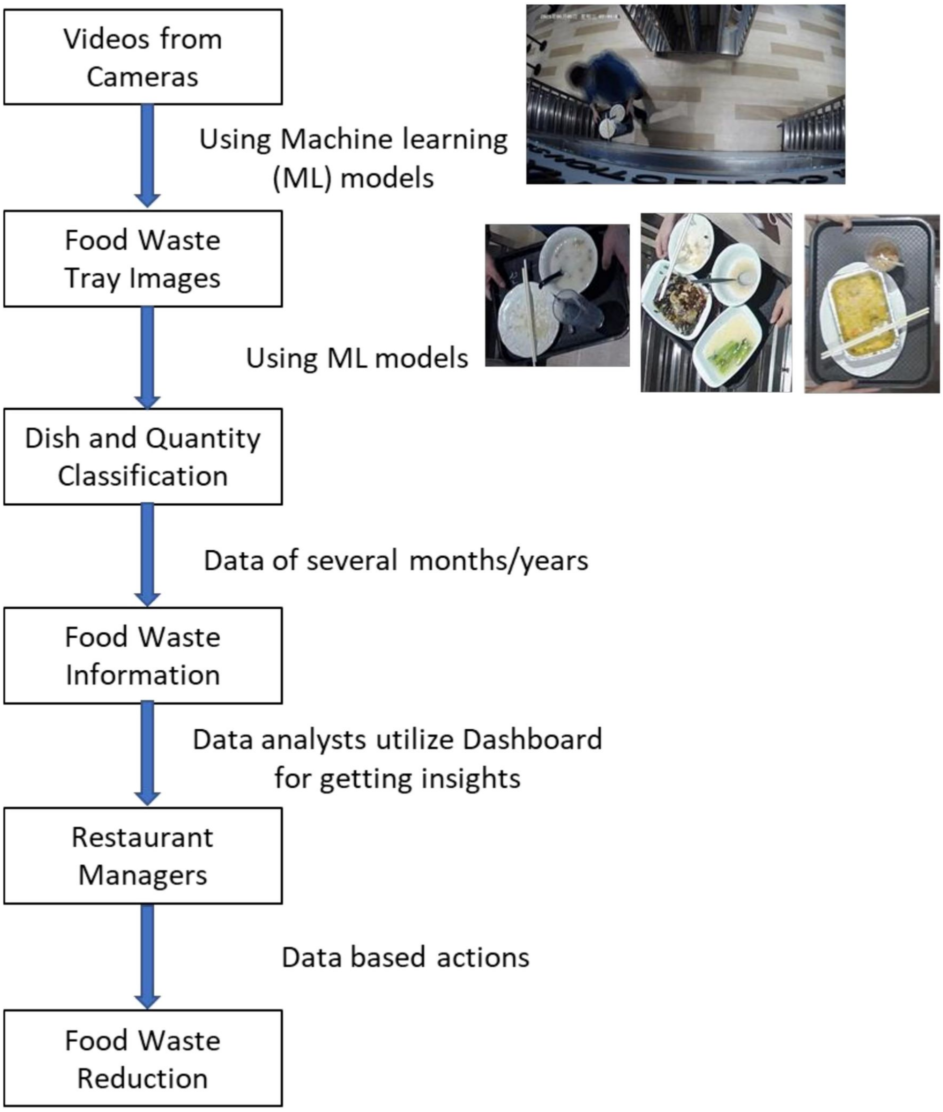

Figure 4.2: **Pipeline**: From cameras at the restaurant to getting food waste data and making decisions about food waste reduction

4.3 Visual Analytics System

4.3.1 Design Requirements

The model developers working on dish classifying food waste were the end-users of the Visual analytics system. The expected usage is to use the system to extensively inspect the model's predictions on several months of data. We first interviewed two end-users (U1 and U2) over two months to understand their problems due to the lack of a Visual analytics system. The problems were mainly due to the absence of an effective tool for inspecting model performance over several months of data, with useful

Figure 4.3: **The Visual Analytics (VA) System:** It consists of 4 views, Summary & Comparison view, Evolution view, Training size vs. Accuracy view, Image view. The purpose is to help model developers inspect the model's predictions on several months of food waste data.

options of summary, filter, and details explorer. These interviews helped us understand the system we could provide for solving those problems. We interviewed those end-users further to gather their requirements for the system. We also followed Shneiderman's mantra of presenting the overview first, then providing options for zoom and filter for getting the details on demand [43]. The design requirements were:

1. **R1 Obtain a quantitative summary of the model's predictions for a selected day.** Users were highly interested in obtaining a summary for a selected day to identify abnormal patterns in the dish classification by the model. This information could be useful for finding failed cases of the model due to the changes in data such as the restaurant's menu, cooking style, and serving style, including containers.

2. **R2 Compare the model's predictions quantitatively for different selected days.** Users were interested in comparing the trends of different days for further diagnosis of the model and changes in data.

3. **R3 Obtain any trends in waste throughout the selected day and dish.** Users wanted to observe the trend of dishes throughout the day for further inspection of the model and data when needed.

4. **R4 Explore the images with the model's predictions for the selected day and dish.** Users were interested in going deeper into the model's predictions than just a summary by directly exploring the images of the selected day. They also wanted to filter the predictions by dish for a detailed look at the model's performance on dish classification. This analysis would help them identify the errors in dish classification for improvements of the models.

4.3.2 Design Rationales

While designing our proposed Visual analytics system, we followed two design rationales:

- **Intuitive encoding and design.** Machine learning model developers are the end-users of our Visual analytics system, who may be familiar with data visualization but generally lack any understanding of advanced visualization techniques. Therefore, the use of simple visual designs is preferred for easier understanding.

- **Multi-scale visual exploration** There can be a variety and immensity of dish information in food waste tray images extracted from videos. Providing an overview initially and details on demand allows a fast and detailed understanding of the dish classification of food waste by machine learning models.

4.3.3 Design

The Visual analytics system, Fig 4.3, is composed of 2 parts, the charts part (top) and the images part (bottom), with their separate filters for ease of usage. Part (b) is a shared legend for getting the labels from abbreviations. The abbreviations were used due to limited space while representing the dish classes. The four views in the Visual analytics system are:

Summary & Comparison View: It contains 2 bar charts (A&B) that provide the summary of the number of predicted dish classes by the model for different days, allowing a side-by-side comparison. It helps in identifying and comparing the trends of dishes on different days. They help find patterns and abnormalities in dishes returned, which are the first step in recognizing if the models are not performing well or the patterns in the data have changed, indicating changes in a restaurant menu or customer's preferences. These features help in maintaining models for several months.

Day Trend View: It contains 1 bar chart (C) that provides the trends of the number of food waste trays observed for the selected dish (class_ in (a)) throughout the selected day (date1 in (a)). It shows the trends for all dishes by default, and a dish can be selected from the class filter. This chart can help further inspect dish trends for a day to find abnormalities, thus supplementing the Summary & Comparison View.

Accuracy vs. Training size View: It contains a line chart (D) that provides the accuracy trends for the average training size of each dish class. This chart helps the model developer factor in the effects of training size while making decisions for improving the model performance or updating the hierarchy.

Image Explorer View: It provides the images with their predicted dishes (E) for the model developer to inspect the dish classification models and is the most critical view for the developer for a detailed inspection of model predictions. By default, it shows the images of all the classes. In this view, the developer can filter the images by date or class (c). They can also use the slider to go through the images as they choose (c). These features help the model developer explore the model's successful, failed, and in-between cases to find possible reasons behind a models' poor performance and make decisions on subsequent actions to improve the model performance, such as updating the hierarchy or the training data.

Interactions: The charts part (top) consists of date filters (date1 and date2) and class filter (class_)(a). Selecting values of these filters updates the charts in the numbers part (top). The images part (bottom) consists of a date filter (date), class filter (class_), and a slider (i) (c). Updating values of these filters updates the charts in the images part (bottom). The slider helps to go over the entire images of the data based on the selected filters.

4.3.4 Implementation

The system users are deep learning model developers for computer vision applications and regularly utilize Python programming language [44] to develop models. We had different options for the implementation of the Visual Analytics (VA) system, such as using web development tools (HTML, CSS, JavaScript, Frameworks) or using Python data visualization libraries (Jupyter widgets, Matplotlib and Plotly). Since we want the VA system to be easily understandable and modifiable by the model developers in the future, we decided to select Python for its implementation. We implemented the VA system on a Jupyter Notebook [45], using the Jupyter Widgets [46], Matplotlib [47], and Plotly [48] libraries in Python. The backbone utilizes Pandas [49] and Plotly libraries for loading data and showing images. Due to the simplicity of Jupyter notebooks, the users can easily modify the dashboard or create other visualizations if they choose. Thus this Visual analytics system is helpful in the long run.

CHAPTER 5

DASHBOARDS

From Dec 2020 to Aug 2021, before developing our models for Dish and Quantity classification, as mentioned in chapter 4, we utilized models created by previous Smart Dining Halls project members [2] to obtain food waste data. The data was only partially accurate but provided us with an understanding of the format of food waste data for designing a dashboard for its analysis. We implemented two dashboards, a prototype and the final, to be used by data analysts to summarize the essential findings and report them to the restaurant manager for making data-based decisions to reduce food waste. A crucial observation is that even though we utilized models by previous members to get the data for building these dashboards, we can still utilize our dashboards' designs now and in the future. These dashboards can be updated to represent the current data based on the models we developed during this thesis research, mentioned in chapters 4 and 6. This way, the design of the final dashboard retains its usefulness.

Dashboard 1, Fig. 5.1, is a prototype of dashboard 2, Fig. 5.2. Based on the feedback we obtained on dashboard 1, we formulated the goals and improved the design principles for dashboard 2. Thus, dashboard 2 is the final dashboard of ours to be used by data analysts to find insights and convey their findings to the restaurant managers.

5.1 Dashboard 1

5.1.1 Source

First, we utilized our tray image extractor, created in the first half of 2021, to get images of food waste trays from the restaurant's videos. This part works accurately. Then, we applied the models developed by previous members, specifically Team 2's final year project [2], to these images to get food waste data. These models are based upon image segmentation to first detect the containers in the tray, then the food items in that container. The information on food waste is based on the food waste by dish (container) and quantity (estimated pixels). However, just getting the food waste information per image was not enough for analysis. We aggregated the data to summarize it by the hour as that information is suitable for the managers.

We observed that the models by the previous members estimate the pixels of the various food components, dishes (containers), and trays from the food tray images. To measure food waste per container in percentages, we divided the sum of estimated food components pixels by the estimated container pixels. To measure food waste per tray in percentages, we took the weighted average (using container pixels) of the percentage of food waste per container for each tray. The inaccuracies magnified their combined error in categorizing containers and food components. Upon diagnosing the model performances of models by previous members, we identified several inaccuracies, such as the misidentification of containers or food components by class or quantity.

Regarding containers misidentified by class, assuming correct segmentation, the classified results are inaccurate by about 50%. Since the class estimation was incorrect, the quantity estimation also failed for individual classes. However, the quantity estimation for **overall food waste per tray** still proved to be about 70% accurate. Owing to this, we decided mainly to use these models to get data for the design creation of dashboards but not to rely on the data obtained entirely. The amount of trays and overall food wasted per tray is more reliable than the individual food waste per container or food type. Later, in Aug 2021, we started creating our models, mentioned in chapters 4 and 6, to obtain more accurate data in dish and quantity classification.

5.1.2 Design Objectives and Tasks

Food waste monitoring and analysis are essential for reducing food waste on the consumption side. "Smart Restaurant Dashboard (dashboard 1)," Fig.5.1, utilizes food waste data to create a visualization dashboard to keep track of and analyze food waste at the restaurant. Our first contribution here is the formulation of the design objectives and user tasks for this purpose.

To derive design objectives for a "Smart Restaurant Dashboard," Fig.5.1, we initially conducted multiple group discussions with visualization researchers and collected feedback from restaurant managers and customers.

In our discussions with visualization researchers, we iterated over the visualization tasks, the process of data exploration, the design prototype, and the feedback.

During our discussions with four restaurant managers, we asked them about the food waste situation in their restaurants, their concerns about food waste, steps for reducing food waste at their restaurants, interests in an automatic food waste monitoring system via a visualization dashboard, and its features. All the managers showed an interest in utilizing a visualization dashboard for monitoring and analyzing food waste and wanted to learn more about it.

We conducted discussions with 60 restaurant customers (39 male and 21 female) of on-campus restaurants at The Hong Kong University of Science and Technology. The majority of the respondents were students studying on campus. We asked them about the possible reasons for people not finishing their meals. Although nearly 90% percent of the customers know the portion of meals they want or need, about half of the respondents suggested that the rice served is too much, and the most frequent leftover is rice. Moreover, about one-third of the respondents suggested that the set is poorly balanced. Therefore, serving size is critical in reducing food waste from these results.

Our discussions led to the following design objectives regarding providing a summary of food waste data for managers from overview to details.

O1. Analyze the consumption time series in different granularity. In the context of campus restaurants, the timescales include day, month, and some arbitrary time ranges.

O2. Understand the waste/empty plate ratio and detailed food waste distribution from the component and dish aspects.

O3. Gain an overview of the percentage of meals wasted in the population.

Accordingly, we list the tasks for the visualization system to support below.

T1. Filter time to see trend, seasonality, and anomaly points under different timescales.

T2. Provide a faceted distribution of food waste in terms of food and dish categories, with their estimated quantities.

T3. Show the consumption distribution in the crowd.

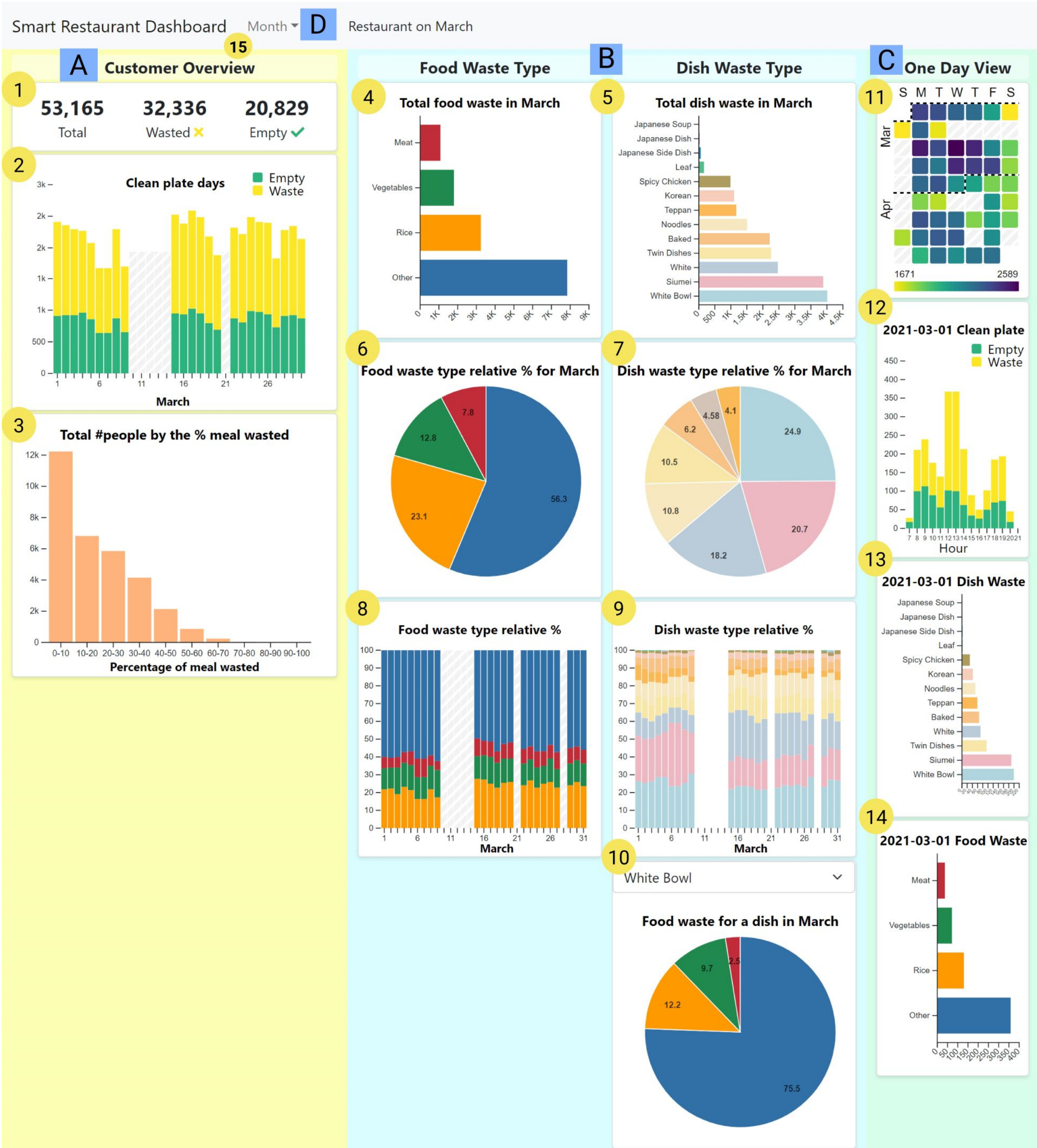

Figure 5.1: **Smart Restaurant Dashboard (Dashboard 1)**: A visual interface prototype for restaurant managers to monitor food waste in their restaurant, and make data-based decisions for its reduction.

5.1.3 Visualization Design and System

This section describes the visual encoding of the "Smart Restaurant Dashboard" shown in Fig.5.1 and their interactions. The interface is composed of Customer Overview (A), Food and Dish Overview (B), One Day View (C), and Monthly Filters (D). We carefully decided the order and position of these components for a better understanding by the user of the data on food waste.

Since the restaurant managers may not be well versed in visualization, we decided to use commonly known charts, such as bar charts, stacked bar charts, pie charts, a calendar-based heat map chart, and more. Hovering over their elements in each visualization chart gives more detailed information about them. The charts representing different kinds of food waste distributions, such as clean plate, food type, dish type, percentage of meal wasted, and calendar, have been given distinct color schemes and tones to avoid confusion. However, similar charts have been given the same color scheme for easy understanding, removing the need for a legend in each chart. The user can refer to similar charts with a legend or hover over the chart's elements for details.

We created stacked bar charts to show data throughout the month or day due to the percentage nature of their distribution values, where the missing bars represent that the data of that day is missing. Similarly, we created bar charts to show the overall data for a month or day. We also created pie charts to show percentage data, averaged over a month.

Customer Overview (A)

This part has three visual elements of the text (1), stacked bar chart (2), and histogram (3). They are all based on the data of a month. The default month is March, from the two available months of March and April. The purpose of this layout is to show the basic trends of customers finishing their meals for the selected period and monitor it across different months.

- Text (1) shows the summarized information about food trays returned by the customers.
- Stacked bar chart (2) shows the clean plate days, which is the distribution of trays.

- Histogram (3) shows the summarized distribution of the total number (#) of people by estimated percentage (%) of meals wasted.

Food and Dish Overview (B)

This part has seven visual elements including bar charts (4 and 5), pie charts (6 and 7), stacked bar charts (8 and 9), and a pie chart with a drop-down menu (10), all based on the data of a month. The default month is March, from the two available months of March and April.

The purpose of this layout is to show the distribution of the food waste in the restaurant by its four most common food components, i.e., "Rice," "Vegetables," "Meat," and "Others,"; and the thirteen most common dish types, i.e., "White Bowl," "Siumei," "White (white plates)," "Noodles," "Twin Dishes," "Baked," "Teppan," "Korean," "Spicy Chicken," "Leaf," "Japanese Dish," "Japanese Side Dish," and "Japanese Soup." "White" and "White Bowl" refer to the food served on white plates and bowls. "Siumei" refers to the Chinese barbecue types of dishes. This layout can help the manager to adjust the serving size of the most wasted food and dish items and monitor the changes.

- Bar charts (4 and 5) show the total food and dish waste distribution for four food component types and 13 dish types.
- Stacked bar charts (8 and 9) show the relative percentage distribution of food waste in 4 food component types and 13 dish types.
- A pie chart with a drop-down menu (10) shows the averaged food waste distribution by food component type for the dish selected using the drop-down menu.

One Day View (C)

This part has four visual elements of a calendar heat map chart (11), a stacked bar chart (12), and bar charts (13 and 14), all based on daily data. The default day is 1st March, with options for several days in March and April. The purpose of this layout is to show the food waste data for the selected day in the calendar chart and to help detect unusual days.

- Calendar heatmap chart (11) shows the total number of trays throughout all days and is linked to the remaining charts in this section C. When a day in the calendar is selected, it updates all charts in layout C to show the visualization of data of the selected day. Non-colored rectangles represent missing days.

- Stacked bar chart (12) shows the clean plate hours and is similar to chart (2). However chart (12) shows trends over a day, whereas chart (2) over a month.
- Bar charts (13 and 14) show the total dish and food waste and are similar to charts (5 and 4). However, charts (13 and 14) show average trends for a day, whereas charts (5 and 4) show average trends for a month.

Monthly filters (D)

This part has a filter option to select the time range for the charts, such as the drop-down option (15) for selecting the month as either March or April.

5.1.4 User Study

To evaluate our system, we conducted a user study with one restaurant manager of LG 1 Canteen with over ten years of working experience in the catering industry.

Firstly, we introduced the visualization system and then asked the manager to give an overall rating to the system from some perspectives on a 5-point Likert scale, where 1 to 5 denote the ratings from worst to best. In other words, the rating denotes the score out of 5, the worst is the least score 1 and the best is the full score 5. The manager rated the interface of our visualization dashboard, Fig.5.1: aesthetics as 4, intuitiveness as 3, and the usefulness of getting insights as 4. The manager was generally satisfied with the dashboard and agreed that it facilitates decision-making on food waste intervention.

Secondly, to test whether our design can effectively deliver insights to our intended user, we asked the manager to perform four assignments in half an hour.

A1. Identify the dish type with the most food waste (T2).

A2. Find the food type with the most food waste (T2).

A3. Decide on adjusting the quantity of some dishes components (T1, T2, T3).

A4. Name days with unusual patterns (T1, T2).

The manager was able to complete A1, A2, and A4. Regarding A4, the manager noted that the new menu in March seemed quite popular among the restaurant's customers. There were fewer returned trays at the beginning of April due to the 6-days Easter holiday on campus. It should be noted that the tray image extractor code and overall food waste quantity estimation per tray works considerably accurately. Thus, the data for the total number of trays, divided into empty trays and waste trays, is also accurate. However, in a follow-up interview, the manager expressed concerns that hindered the decision, as in A3. It was slightly difficult for the manager to understand the logic behind the linkage between the charts and thus spent some time figuring it out. In addition, due to the inherent challenge for the classifier to distinguish bone, straw, and tissue paper from wasted food, the manager is slightly skeptical of the given results and would like to learn more about these types of irreducible wastes. Lastly, the system only accounts for returned food trays, but the takeaway meals take up a portion of the total restaurant food waste, which is also of some interest to the manager.

From our surveys with the restaurant manager, we learned that customers could ask for less rice at the time of order and enjoy a discount on their meal. We suggest flipping "opt-in" to "opt-out," i.e., offering less rice by default while paying the discounted meal price and providing customers the option to ask for more rice and accordingly get charged for the same amount of the original discount. Thus, in addition to monitoring food waste, our research might also be helpful from the nudging perspective [50].

The design of the visualization system was somewhat helpful to the restaurant manager learn more about the food waste situation in their restaurant. Specific improvements can be made based on user feedback, such as improving the interpretability of the linkage between the visualized data and the actual food waste behaviors. Additionally, the models for dish and quantity classification can be improved. If the goal is to create dashboards for direct viewing by restaurant managers, the dashboards need to be much simpler. Otherwise, there is another option of adding an intermediary to conduct analysis and report to the managers.

Overall, we observed that restaurant managers could find the abundance of information in the dashboards challenging to comprehend. Thus data analysts should be added as an intermediary to analyze the data using dashboards and then communicate their insights to the managers for decision making. Utilizing the restaurant manager's feedback, we started creating the final dashboard, Dashboard 2, Fig.5.2, which we will discuss in the next section.

Regarding creating better dish and quantity classification models, we will discuss our models in chapters 4 and 6.

5.2 Dashboard 2

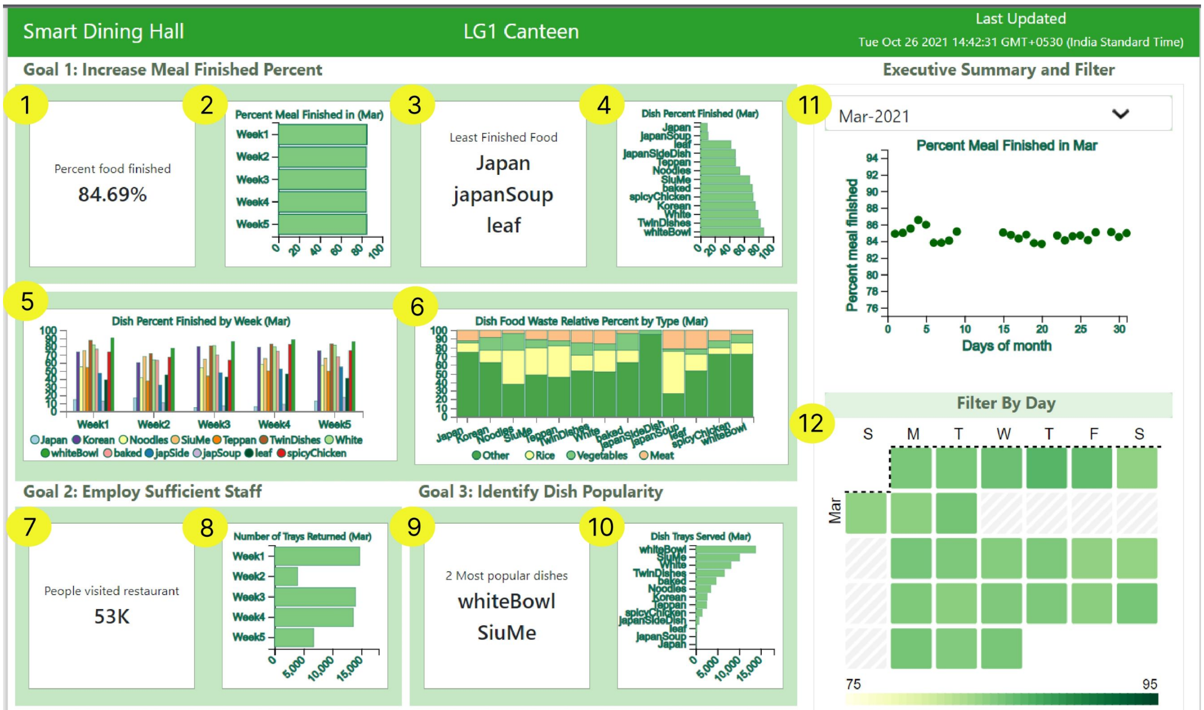

Figure 5.2: **Smart Dining Hall Dashboard (Dashboard 2)**: A visual interface for data analysts to monitor food waste in the restaurant and provide suggestions for data-based actions to restaurant managers for its reduction.

We utilized the feedback on Dashboard 1, Fig.5.1, and the design principles from "The Big Book of Dashboards" [51] to create Dashboard 2, Fig.5.2.

5.2.1 Design Principles

Some design principles we learned from the examples and theory of "The Big Book of Dashboards" [51] are:

- **Design on a grid** to keep the dashboard neat and organized. Ex: The grid on graph paper.
- **Divide** the dashboard sections into **goals and executive summary**.

- **Avoid clutter** such as overuse of colors, lines, and other shapes that overlap. Thus, we predominantly used green color (to represent our goal of sustainability and environmental conservation) on a white background in our Dashboard 2, Fig.5.2, and limited overusing colors. We only used other colors when necessary. This method contrasts sharply with Dashboard 1, Fig.5.1, which often uses several colors very often. Instead of using overly complex charts, such as combining a line and bar chart in one chart, we used more straightforward charts to reduce clutter.

- **Color**: We followed the categorical color scheme for representing different dishes in the grouped column chart and for different food components in the stack column chart for easier identification without the textual information, thus saving space. In the bar charts, we used the same green color since the text provides the information of the bars. We followed a sequential color scheme in the calendar-based heatmap as the color represents the percentage value, a number, in the order from low to high.

- **Font size**: We used three main sizes of fonts: small, medium, and large, as advised in the book. The sizes can consist of sub-sizes with minor differences for enhancing the user's experience.

- **Collaboration for feedback and improvement**: In several stages of Dashboard 2, Fig.5.2 and feedback on its precursor, Dashboard 1, Fig.5.1, we collaborated with the restaurant manager, data analysts, and visualization experts for iterative improvements in the design of Dashboard 2, Fig.5.2.

5.2.2 Source

The data source is the same as Dashboard 1, Fig. 5.1. However, we apply more data transformations to get the percentage of meals finished for different dishes and their food components. Specifically, we normalized the data for different containers and food types by utilizing the percentage of meals finished making fairer comparisons. The reason of focusing on "percentage meal finished" instead of "percentage meal wasted" is the positive outlook of the former, which is preferred by restaurant managers based on our interviews.

5.2.3 Design Objectives and Tasks

We collected feedback on Dashboard 1, Fig. 5.1, from 6 visualization experts, one restaurant manager from LG 1, and 3 IEEE VIS reviewers via short paper submission. We present a summary of the feedback here, which we utilized to form the basis for Dashboard 2, Fig.5.2, a huge improvement over Dashboard 1, Fig. 5.1:

- **Proportion of charts**: The disproportionate size of charts in the first dashboard.
- **Spacing in the dashboard**: The extra space at the bottom left of dashboard 1 needs to be removed.
- **Normalizing food waste** and using the percentage of food waste or food finished.
- Goal-oriented visualizations, **show data on various levels**: month, week, and day. Add filters correspondingly.
- **Simplify the identification of trends**: Percentage of food finished, least finished food, number of people visiting restaurants, and most popular dishes.
- **Visual appeal**: The number of colors used needs to be reduced.
- Use **rectangular grids** to divide sections and charts properly.

To derive design objectives for "Smart Dining Hall," i.e., Dashboard 2, Fig.5.2, we conducted multiple group discussions with visualization researchers and data analysts. In our discussions with two visualization researchers, we iterated over the visualization tasks, the process of data exploration, the design prototype, and feedback. During our discussions with 3 data analysts, we asked them about their evaluation of Dashboard 1, Fig. 5.1 and other ideas of things of interest for creating Dashboard 2, Fig.5.2. Our discussions led to the following design objectives regarding providing trends of food waste data for data analysts from overview to details.

O1. Analyze the consumption time series in different granularities. In the context of campus restaurants, the timescales include day, week, and month.

O2. Gain insights into the percentage meal finished trends of different dishes.

O3. Gain an estimate of the crowd in the restaurant.

O4. Gain an insight into the popularity of several dishes.

In accordance, tasks for the visualization system to support are listed below.

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 components.

T3. Provide the estimation of the crowd at the restaurant.

T4. Provide the popularity distribution of dish category.

5.2.4 Visualization Design and System

This section describes the visual encoding of the "Smart Dining Hall (Dashboard 2)" interface shown in Fig. 5.2 and their interactions. The interface is composed of Goal 1: Increased Meal Finished Percent (A), Goal 2: Employ Sufficient Staff (B), Goal 3: Identify Dish Popularity (C), and Executive Summary and Filter (D). We carefully decided the order and position of these components considering users' cognitive load and a better understanding of the data on food waste. The users are data analysts who are responsible to utilize dashboard for analyzing food waste trends and reporting the insights to restaurant managers.

To facilitate the quick overlook of trends, we decided to use big numbers, and to support more profound analysis, we used commonly known charts, such as bar charts, stacked column charts, grouped chart, line chart, calendar-based heat map chart, and more. The food components and dishes (containers) shown on dashboard 2, Fig. 5.2, follow the same convention as on dashboard 1, Fig. 5.1.

Hovering over their elements in all visualization charts gives more detailed information about them. The color green is predominantly used in the dashboard, representing sustainability and the environment. Most trends represent the percentage of meals finished, representing the charts positively instead of using the percentage of wasted trends, which has a negative outlook.

The big numbers are used to summarize the most useful trends of the detailed trends represented through bar charts. They ease the cognitive overload of the user by helping them to focus on the essential summary.

The line chart and calendar-based heatmap present trends across the month and provide an essential overview. Any missing days are due to the missing data.

Goal 1: Increase in Percentage of Finished Meals (A)

This goal is essential to the dashboard for a deeper analysis of food waste trends over a month. It consists of 6 visual elements of the large text (1), bar chart (2), another large text (3), another bar chart (4), grouped column chart (5), and stacked column chart (6). These elements are initially based on a month's data. The default month is March, from the two available months of March and April. By selecting a day in the calendar-based heatmap (12), these elements will update to show the data of the selected day.

The purpose of this layout is to show the summarized, detailed trends of the percentage of meals finished by customers concerning dishes and their food components for the selected period and monitor it across different months by their weeks, with options to see trends across different days by the hour.

- **Large text (1)**: Shows the average percentage of food finished in the selected month or day.
- **Bar chart (2)**: Shows the average percentage of food finished across the weeks in the selected month or the hours in the selected day.
- **Large text (3)**: Shows the top 3 least finished dishes, in the order of least finished dish at the top.
- **Bar chart (4)**: Shows the trend of the percentage of dish finished for 13 dishes across the selected month or day. It is in ascending order of average percentage dish finished for the selected period.
- **Grouped Column chart (5)**: Shows the trend of the percentage of dishes finished for 13 dishes across the (usually) 5 weeks of the selected month or five-time slots of the selected day. This helps to see the trends in a dish of interest across different weeks (selected month) or time slots (selected day) and compare it with other dishes. The overall benefit can be to identify the patterns in the food waste by dish across different periods and make appropriate adjustments to the serving sizes of dishes according to their patterns.

- **Stacked Column chart (6)**: Shows the relative percentage of a dish by its food components for the 13 dishes and their 4 food components from the food waste. This allows the user to identify the food component that makes up the majority of the food waste in the dish of interest. They can also make an effective decision on reducing a food component's serving size to have the maximum impact on reducing the corresponding dish's food waste.

Goal 2: Employ Sufficient Staff (B)

This part has two visual elements of the large text (7) and a bar chart (8), all based on a month's data. The default month is March, from the two available months of March and April. By selecting a day in the calendar-based heatmap chart (12), these elements will display the data of the selected day.

The purpose of this layout is to show the crowd, that is, the approximate number of people at the restaurant, based on the returned trays, for a selected month or day. This can be used to determine the number of staff employed at the restaurant for different hours and days of the month. Utilizing this information will eventually lead to better customer service and ensure proper hygiene by regularly removing the trays returned and preventing too many food waste trays from piling up.

- **Large text (7)**: shows the approximate number of people who visited the restaurant, estimated using the number of trays returned, for the selected month or day.

- **Bar chart (8)**: shows the number of trays returned in the selected month by the weeks or the selected day by the hours. This helps to identify the restaurant crowd patterns across hours, days, and weeks. This can help restaurants to arrange sufficient staff to ensure the hygiene and cleanliness of the tray return area.

Goal 3: Identify Dish Popularity (C)

This part has two visual elements of a large text (9) and a bar chart (10), all initially based on monthly data. The default month is March, from the two available months of March and April. By selecting a day from a calendar-based heatmap (12), these elements will show the data of the selected day.

The purpose of this layout is to show the popularity of each dish. This layout can be used with charts (3) and (4) regarding the percent of meals finished by different dishes to determine the total food waste generated by different dishes. This information can be helpful in determining by reducing the serving size of which dishes would have the maximum impact on total food waste reduction in the restaurant.

- **Large text (9)**: shows the two most popular dishes at the restaurant on the selected day or month. Here popularity is calculated by arranging the number of orders in descending order. Thus high popularity means that the dish is ordered more than low popularity.
- **Bar chart (10)**: shows the popularity of dishes in terms of dishes served at the restaurant on the selected day or month. The dishes have been arranged in descending order of the number of trays served to quickly find the most and least popular and make a data-based comparison between them.

Executive Summary and Filters

This part has two visual elements, a drop-down menu coupled with a dot chart (11) and a calendar-based heatmap (12). The purpose of this layout is to present an executive summary of the selected month and select executive filters using either the drop-down menu (11) or by clicking on a day (rectangle) in the calendar (12).

- **Drop down filter and Dot chart (11)**: The drop-down filter is used to select the month, March, and April of 2021 in this case. By selecting a month, all the elements (1-12) get updated accordingly to present the data of the selected month. The dot chart shows the trend of the percentage of meals finished over the selected month concerning the days of the month. The dots represent the percentage of meals finished (vertical axis) corresponding to the day of the month (horizontal axis). In case of missing data on certain days, the dot chart does not have any dot for that day.
- **Calendar-based heatmap chart (12)**: It shows the percent meal finished trend over the selected month using a drop-down menu (11). The rectangles represent the days of the month. The distribution of days in the calendar form helps identify trends and patterns over different weeks and days of the week across a

month. Hovering over a rectangle representing a day shows the date information and the percentage of meals finished. When a rectangle representing a day is clicked upon, the charts in the dashboard (1-10) get updated to show the data of that selected day. The color scheme in the calendar is made using a sequential scale converting the percentage value from 75 to 95 (determined from data as min and max of percentage meal finished +- 5 points standard deviation, as it usually falls in the 80 to 90 range) from yellow to green color.

5.2.5 User Study

For the evaluation of our dashboard 2, Fig.5.2, we conducted a user study with three data analysts. We gave them the scenario of which they are responsible in terms of reporting the findings and suggesting actions to the restaurant manager for food waste reduction.

Firstly, we introduced the visualization system (dashboard 2), Fig.5.2, and then asked the data analysts to give an overall rating to the system from some perspectives on a 5-point Likert scale, where 1 to 5 denote the ratings from worst to best. On average, the analysts rated the interface of our visualization dashboard as follows: aesthetics as 4.33, intuitiveness as 4, and the usefulness of getting insights as 4.33. The analysts were generally satisfied with the dashboard and agreed that it facilitates decision-making on food waste intervention.

Secondly, to test whether our design can effectively deliver insights to our intended user, we further asked the analysts to subjectively answer five questions in half an hour, based on their analysis using the dashboard 2, Fig.5.2.

Q1. What is the average percentage trend of meals finished across different time ranges such as month, week, day? (T1, T2)

Q2. What is the average trend of least finished dish across different time ranges such as a month, week, or day? (T1, T2)

Q3. What is the relative proportion of the constituent food waste components 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)

Thirdly, we introduced dashboard 1, Fig.5.1, to the data analysts and asked them to comment on which dashboard they preferred.

The data analysts performed the analysis and answered all the questions successfully. They commented that the features of large text accompanying the corresponding chart are handy for quickly reviewing the trends. The calendar linkage is also helpful for switching from the default mode of months and weeks to days and hours for more detailed trend analysis. They also commented that dashboard 2, Fig.5.2, significantly improved over dashboard 1, Fig.5.1, in terms of aesthetics, clarity, and usability. Thus, they preferred to use dashboard 2, Fig.5.2, over dashboard 1, Fig.5.1.

Overall, the visualization system, Fig.5.2, achieved its objective of helping data analysts analyze the food waste situation in the restaurant. More user studies can be done to gain further insights into the system's usability.

5.2.6 Discussion

The final dashboard, Dashboard 2, Fig.5.2, called the "Smart Dining Halls" dashboard, helps analyze food waste trends. Based on our user studies with data analysts, it is useful in the restaurant scenario for analyzing food waste trends. Its design is currently based on the data obtained from the previous model. However, it can be updated for the current and future models. The dashboard's accuracy depends on the input data's accuracy, thus dependent on the accuracy of models. Overall, if we can provide accurate data as input and data analysts to perform analysis, dashboard 2, Fig.5.2, can help restaurant managers to obtain real food waste insights and take data-based actions for its reduction. Moreover, the design of dashboard 2, Fig.5.2, can be useful for other restaurants as well.

Since the dashboard 2 is designed for comprehensive analysis by data analysts, it may be difficult to understand directly by restaurant managers or customers, and simpler visualization interfaces can be designed for their usage scenarios, see section 6.3.7.

CHAPTER 6

RESULTS AND DISCUSSION

6.1 Use Case

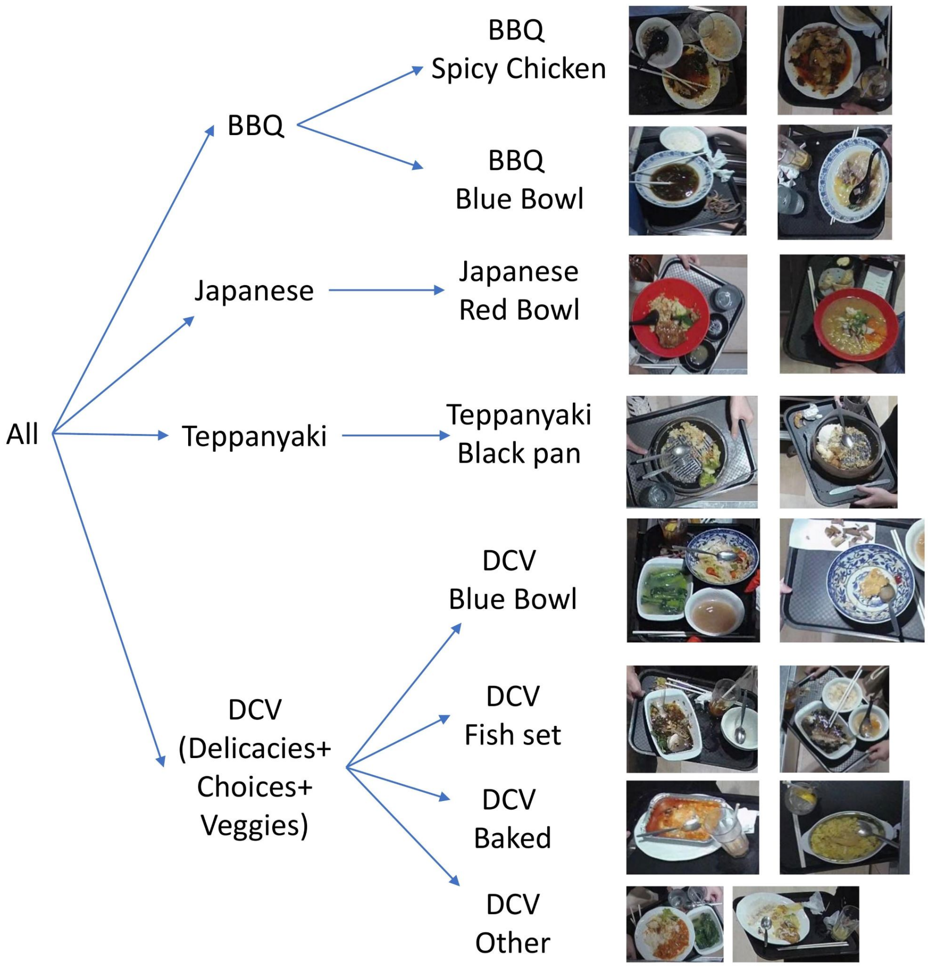

Figure 6.1: **Hierarchy of Dishes in Use Case:** The hierarchy example here is the final result of our case study at LG1 Canteen. It consists of 2 levels other than the root node. The root node consists of all dishes. The 1st level contains four groups of six counters. The 2nd level contains eight subgroups for dishes on those counters.

We conducted a real-world case study of our approach in an on-campus restaurant, LG 1 Canteen of HKUST, for over a year, from Dec 2020 to Dec 2021. We created a system for tray image extraction and the pipeline to automate it in the first half of 2021. In 2021, we processed about 55 TB of video data (22000 hours) from 10 cameras using our tray image extractor system. We created dashboards for food waste data analysis by the end of Sep 2021. From Aug 2021, we started creating dish and quantity classification models and a Visual analytics (VA) system for monitoring the performance of dish classification models. We evaluated our VA system and dish classification models on three months of data from August, September and October 2021, which consisted of about 567K food waste tray images. Later, we improved the quantity classification models. This section provides a detailed explanation of our processes and results.

6.1.1 Dish Classification

From the restaurant's serving style, we observed that they serve food via several different counters. Since it would be easier for the restaurant to adjust overall serving sizes at the counters, we decided to use counters as our main groups for dish classification (top level of hierarchy) instead of only following the main groups from the menu. The result of the hierarchy is in Fig 6.1 which contains helpful examples for understanding the dishes served on those counters.

In the majority of August 2021, the "Teppanyaki" counter was closed. Out of 5 counters available, namely "BBQ," "Delicacies," "Choices," "Veggies," and "Japanese," we first selected 4 of them (all except Veggies) as our main group to test the limits of machine learning in separating the food waste images from those counters, before adding the "Veggies" counter.

Then, we attempted to label the food waste data for these counters, and successfully labeled a total of around 1600 images. We observed that humans found distinguishing food waste images from the "Delicacies" and "Choices" counters challenging during the labeling process. We also reviewed the food served (before eating, not waste) from those two counters for further diagnosis. We found that the food waste from "Delicacies" and "Choices" looked strikingly similar due to the use of similar containers and items in the food served. We trained machine learning models on the labeled data and obtained the highest accuracy of about 67% using Mobilenet V2 architecture (Decreasing order of f1 scores: "Japanese," "BBQ," "Delicacies," and "Choices"). This accuracy was insufficient and we needed to conduct a more detailed analysis of the best model's predictions, for which we utilized our Visual analytics system, mentioned in section 4.3.

The models were trained were a simple CNN and several pre-trained models on ImageNet dataset [40] such as VGG-16, VGG-19, Inception V3, Mobilenet V2, and

Resnet 50. We fine-tuned the pre-trained models on our training data to learn dish classification. The best performing pre-trained models were VGG-19, Inception V3 and Mobilenet V2. We decided to keep these architectures along with the Simple CNN (benchmark) for further experiments and discard the remaining architectures. We also decided to mainly focus on the best architecture, Mobilenet V2, for diagnosis and improving model performances. Upon analyzing the test results and training data, we found it was not easy to distinguish between the "Delicacies" and "Choices." A similar observation was found for other selected models as well. Since the issue is also the training data, we merged these two categories into one, "Delicacies & Choices," in our next iteration. This way, we were testing the limits of humans to create a suitable hierarchy and pushing the limits of machine learning in the dish classification of food waste. We applied the model to predict the food waste images by dishes for the entire month of Aug '21.

Upon using the VA system to diagnose the Mobilenet V2 model predictions on data from August 2021, from the image explorer view (part E), we observed that the model had difficulty distinguishing between the blue bowls from "BBQ" and "Delicacies & Choices" counters. We gave this task to humans, and we found that initially, humans had some difficulties as well, but after some practice, they could easily distinguish between the blue bowls from these two counters. Thus, we decided to create subgroups of "BBQ Blue Bowl" and "Delicacies & Choices Blue Bowl" for the 2nd level of the hierarchy. We also found that the "BBQ" counter predominantly served another dish called spicy chicken; thus, we added it as a subgroup category, namely "BBQ Spicy Chicken." Since the Mobilenet V2 model performed exceptionally well in predicting "Japanese" dishes from the "Japanese" counter, which always used a red bowl, we added the "Japanese Red Bowl" directly as a subgroup, as no splitting seemed mandatory. For "Delicacies & Choices," they had a lot of food items other than the Blue Bowl; thus, we added them as "Delicacies & Choices Other." In this way, we updated the hierarchy with main groups of counters as the first level and subgroups of dishes as the second level.

Then, we labeled data for the second hierarchy level, the subgroups of dishes. We utilized the previous predictions by the Mobilenet V2 model on Aug data; this eased up the labeling process. Upon training the models on the subgroups and testing, we observed that the models provided an accuracy of 91% (with f1-scores from 86% to 99% for each category). Then we applied the Mobilenet V2 model on entire food waste images data from August 2021 and used the VA system to diagnose the model predictions. We observed some instances where the fish set from "Delicacies & Choices" was misclassified as spicy chicken from the "BBQ" counter. This was a minor issue, and we decided to address this later by creating a new subcategory for this dish. Our main priority was adding a "Veggies" counter dish as the main group we had left earlier.

Thus, we labeled some food waste data from the "Veggies" counter. Upon doing so, we realized that the food waste from "Veggies" is very similar to that from "Delicacies & Choices"; thus, it would be better to merge them as one main group and later use subgroups for the dishes that humans can distinguish.

We identified several abnormal patterns using the VA system to diagnose the Mobilenet V2 model's (trained on Aug '21 data) predictions on Sep '21 data. From the image explorer view (part E), we observed several black pans, which meant that the restaurant had reopened another counter called "Teppanyaki" towards the start of Sep '21. Thus, we added it as a main group and subgroup. We labeled its images for training data and trained a Mobilenet V2 model on the updated training data. Upon observing the predictions by the model, using the VA system, on September data, we found that the Baked dish from the "Delicacies & Choices & Veggies (DCV)" group was often misclassified in the "Teppanyaki." Thus, we added the dishes Baked and Fish set as two additional subcategories of the merged DCV group.

Overall, see Fig 6.1, in the 1st level of the hierarchy system, we created the four main groups of "BBQ," "Japanese," "Teppanyaki," and "Delicacies & Choices & Veggies (DCV)" for the six counters. In the 2nd level of the hierarchy system, we created the eight subgroups of "BBQ Blue Bowl," "BBQ Spicy Chicken," "Japanese," "Teppanyaki," "DCV Blue Bowl," "DCV Baked," "DCV Fish Set," and "DCV Other."

Then, we labeled the data for the new subgroups while utilizing the current model's predictions. This saved our labeling effort. Upon training and testing the final Mobilenet V2 model for the subgroups, we got an accuracy of 91.2%, with f1 scores ranging from 86% to 98%, see Tab 6.2. We also applied the Mobilenet V2 model to predict all the data from Aug '21 to Oct '21 (567K images), and we used the VA system to diagnose the results. There were still some instances of misclassification among the eight subgroups, but the overall performance was pretty good. Due to thus, we decided it would be our final hierarchy, Fig 6.1. The best model learned the four groups using the eight subgroups pretty well. Since these results were satisfactory, we decided to keep the obtained Mobilenet V2 as the final model for dish classification. The hierarchy can be expanded in the future by adding more dishes from the "DCV Other" category.

Our final labeled data had 2800 images, consisting of 350 images per category for the eight final dish categories (subgroups). We used 30% of this data (840 images chosen randomly) for testing, and the remaining for training and validation. The performance of the selected four models on our final hierarchy is shown in Tab.6.1. Overall, the Mobilenet V2 architecture-based model severely outperformed the other model architectures in our case study. One possible reason might be that among the models utilized here which were pre-trained on ImageNet dataset, Mobilenet V2 is better at learning from relatively small training data.

Table 6.1: Performance Metric of Best 4 Models in Food Waste Dish Classification

Model	Simple CNN	Inception V3	VGG-19	Mobilenet V2
Accuracy (%)	61.4	61.7	69.6	91.2
Cohen Kappa Score (%)	56.0	56.3	65.2	89.9

Table 6.2: Performance Metric of Mobilenet V2 Model in Food Waste Dish Classification

Class	Precision (%)	Recall (%)	F1-score (%)
BBQ Blue Bowl	98	88	92
BBQ Spicy Chicken	83	98	90
DCV Blue Bowl	92	80	86
DCV Fish Set	89	96	93
DCV Baked	95	84	89
DCV Other	99	92	95
Teppanyaki	97	99	98
Japanese	80	92	86
Weighted Average	92	91	91

6.1.2 Role of Containers

While labeling data and analyzing the models' predictions, we found that the containers can help quickly classify the dishes. For example, in our case study at LG 1 Canteen, the "Japanese" counter always comprised a specific kind of red bowl along with some other smaller containers. Thus, if we find that kind of red bowl from the food waste tray, it would likely be a "Japanese" counter dish. Even in our starting models, we found that the similarity between the "BBQ Blue Bowl" and "DCV Blue Bowl" containers was causing models to often misclassify them. It was also observed for human classification of dishes at first, but soon they learned to distinguish between them. When we trained models on separate data (classes separated) for these two types of blue bowls, they performed much better than before; however, there were still a relatively insignificant amount of incorrect classifications among these categories.

Overall, we found that the containers serving food can play an essential role in dish classification. This can help models when the containers are unique for each class or confuse models when the containers are similar in shape or type for different classes. This observation can be utilized by the managers, as they can ask their staff to utilize different containers for different dishes; this way, the models can perform better. This technique can be used for dishes of interest to classify them accurately. Alternatively, for dishes served the most, this technique can help reduce their food wastage, which can significantly reduce overall food wastage.

6.1.3 Transfer Learning From Food Served to Food Waste

We experimented with the transfer learning approach of training a model on food trays served (before eating) data and testing on the food waste trays (after eating) data. However, the performance was not optimal. Only for a small number of main groups did the model perform well (75% accuracy), but when we increased the main groups and the subgroups, the model failed miserably (less than 30% accuracy). Thus, we infer that food (trays served) data can help humans during data labeling of food waste. To a small extent labeled food data (before eating) can help deep learning models classify food waste, but it is much less helpful than directly training models on labeled food waste data. This finding further supports our observation that classifying food differs from classifying food waste.

6.1.4 Quantity Classification

Chapter 4 briefly mentioned our approach to the quantity classification of food waste. We labeled around 5.5K images for training. Initially, the results were unsatisfactory as we only obtained an accuracy of 67.3% for three sub-classes and 78.6% for two main classes. Due to our iterative process, we analyzed the predictions by the model for diagnosis. This made us realize that the problem was in data labeling, as dividing images into three classes is subjective and can lead to several inconsistencies. Thus, we created specific rules for dividing data into the three sub-classes. We re-labeled the data and also labeled a relatively small amount of additional data. This time the total labeled data had about 6K images. The new labeling rules were:

1. **"Almost empty" class**: This class is selected when the food wasted seems to be less than about 10% of the food served. However, the 10% food waste is counted only for eatable food items. Thus, we exclude irreducible or uneatable food items from our calculation. Some excluded items are bones, tissues, and minimal quantities of soup or sauce. Overall, if the edible food waste is less than 10%, then even if the inedible waste mentioned here is present, the food waste tray image will still be labeled as "Almost empty".

2. **If only a significant amount of soup is wasted**: with no visible solid eatable items in the waste, such as pasta, meat, rice, noodles, or other items, then the food waste tray is classified in the "Some waste" class and not in the "Lots of waste" class. This is done as most of the food trays with soup often have some other solid ingredient served along with them and the solid ingredient being wasted is more critical than the soup, as soup consists predominantly of water.

3. **If there is a significant amount of soup and some eatable solid ingredient wasted**, summing at least about 40% food waste: it shall be classified in the "Lots of waste" class. Note that inedible or irreducible solid waste, such as bones or tissues, is not considered enough to be in the "Lots of waste" class.

4. **For "BBQ Spicy Chicken" dish**: if only the sauce and chicken bones are wasted, with an almost negligible amount of rice or chicken, then it cannot be considered "Lots of waste." If a significant amount of sauce is wasted, then it would be moved to the "Some waste" class. If an insignificant amount of sauce is wasted, it would be moved to the "Almost empty" class.

5. **For "DCV Fish Set" dish**: If only fish bones and a minor portion of fish skin are wasted, with an almost negligible amount of rice or fish meat, then it cannot be considered as "Lots of waste." If a significant amount of soup is wasted, then move to the "Some waste" class. If not even a significant amount of soup is wasted, then move to the "Almost empty" class.

6. **Pay close attention to the white plates**, as white rice on white plates can be challenging to detect during data labeling.

The final data set constructed using the above rules had a total of 5951 images, with 2370 Almost empty, 1750 Some waste, and 1831 Lots of waste. Tab. 6.3 shows the results of our selected models on the final data set for quantity classification. Tab. 6.4 shows the performance of the Mobilenet V2 model for quantity classification on our final data set with three classes. Overall, Mobilenet V2 architecture-based model significantly outperformed VGG-19 and Inception V3. The performance by Simple CNN was better than the pre-trained VGG-19 and Inception V3, probably because the quantity classification task was more about learning from the food waste examples than learning general visual features learned by models pre-trained on ImageNet dataset. Still, Mobilenet V2 is our best model, as it gave an accuracy of 80.1% with three classes of almost empty, some waste, lots of waste, and 90.5% with two classes of almost empty or has waste. In the future, one more class can be added by breaking down the "Lots of waste" into two, as mentioned in section 4.1.4.

Table 6.3: Performance Metric of Best 4 Models in Food Waste Quantity Classification

Model	Simple CNN	Inception V3	VGG-19	Mobilenet V2
Accuracy (%) 2 classes	88.0	85.9	84.6	90.5
Accuracy (%) 3 classes	78.1	73.5	69.9	80.1
Cohen Kappa (%) 3 classes	66.5	59.2	54.2	68.7

Table 6.4: Performance Metric of Mobilenet V2 Model in Food Waste Quantity Classification

Class	Precision (%)	Recall (%)	F1-score (%)
Almost empty	92	85	88
Some waste	70	69	69
Lots of waste	76	84	80
Weighted Avg	81	80	80

6.2 Interviews and Feedback

We conducted semi-structured interviews with our target users to further evaluate our approach and get feedback. We interviewed two machine learning model developers on our system pipeline and the approaches towards dish and quantity classification, including the visual analytics system for dish classification. Each interview was semi-structured and lasted an hour. We also interviewed two data analysts responsible for the data analysis of dish and quantity trends and conveying this information as actionable insights to restaurant managers. These interviews were semi-structured and lasted half an hour each. The four participants were also members of the Smart Dining Halls project. We conducted preliminary surveys with four restaurant managers, from three different restaurants, on their interests in obtaining and utilizing food waste summaries for reducing food waste at their restaurants via an in-depth questionnaire created on Google forms and short 15 to 30-minute discussions. The managers have 5 to 20 years of experience in the catering industry.

Interviews with machine learning model developers: During our interviews with model developers on the hierarchical approach for dish classification, they found the approach helpful. It helps them simplify the dish classification problem by going deeper into the hierarchy when needed—at the same time, also allowing them to utilize the results at deeper levels for classifying dishes at upper levels of the hierarchy. They commented that selecting all the dishes for data labeling and model training will be time-consuming and ineffective without the hierarchy.

Considering the key steps of exploring the dish classification model's predictions and images with the Visual Analytics (VA) system, we designed the following tasks for their free exploration:

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 of three dishes and over three days diagnose how well the model performs (R4).

They were able to complete all the tasks successfully within 20 minutes. They found the visual designs appropriate and the system easy to use. They also agreed that the system could help them inspect the model's predictions over several months of data, identify failure cases, and make improvements. They shared that the system is a much better approach than just downloading some data and checking the model's predictions on it. The system helps them conveniently inspect the model's predictions for several months by picking any day of interest to them. Thus, it can help in maintaining models over several months. They also found the system useful for iteratively updating the hierarchy.

They found the accuracy vs. training size chart helpful but expressed concern that it may be useful as an additional feature but may not be most essential while diagnosing the model predictions due to its static nature. They offered a valuable suggestion to add a filter for confidence scores for quickly identifying incorrectly classified cases. However, they also expressed that the filter may not work well in the food waste scenario, but it can still be an option to experiment with in the future. They also offered other suggestions, such as adding a chart or method to compare trends of more than two days at once.

They were satisfied with our system pipeline and models for dish and quantity classification. For quantity classification, they suggested us to expand the three classes into four, to make our solutions more useful.

Interviews with data analysts: During our interviews with data analysts, they shared that the information from the VA system can also help find and compare trends in dish servings, by the day and throughout the day. They shared the insight that they can add quantitative information on food waste to the VA system or modify the design of final dashboard 2 to create a dashboard and use it to find trends in food waste and share actionable insights with managers.

The data analysts also shared that using groups and subgroups can help make valuable suggestions to the restaurant managers on reducing food waste when combined with the quantity estimation methods. They also believe that the groups and subgroups can help restaurant managers easily make serving size adjustments instead of adjusting each dish in the restaurant. Since restaurants often need to serve food fast, making adjustments for each dish might be too difficult to implement in the real world. Thus the hierarchy can help to simplify this process.

Surveys with restaurant managers: We surveyed the managers before creating the dish classification models to gather information about the current steps in reducing food waste at their restaurants and their interest in our proposed solution. During our survey with restaurant managers, they all expressed concerns about the food waste situation at their restaurants. They were interested in taking steps for its reduction, as reducing the waste can benefit the environment and save the restaurants' money. They also shared that a summary of food waste trends by dish and quantity can be handy for taking data-based actions on reducing food waste, such as adjusting serving sizes and tracking the results of their actions. The managers said they do not need the techniques to be highly accurate but accurate enough to see the effects of their actions. They were also interested in seeing the images with models' predictions to increase their trust in the models. They expressed interest that once the solution is complete for one restaurant, it should be helpful to expand it to other branches of that restaurant.

We observed that they were interested in actionable insights for adjusting the serving sizes. Thus, after improving our quantity estimation method, the data predicted by our models can be added into a suitable modified version of dashboard 2. The data analysts can use this to summarize the trends and communicate their findings with the restaurant managers as actionable insights. Then the managers can utilize the insights to take practical actions toward reducing food waste. Alternatively, a simpler dashboard can be created for direct understanding by the restaurant managers.

Overall, our pipeline and approaches are practical and helpful in monitoring restaurants' food waste. However, the dashboard needs to be simplified and the quantity classification classes need to be expanded. Our techniques provide approaches and initial solutions for future researchers to conduct a deeper exploration of monitoring food waste in restaurants and creating ideal solutions.

6.3 Discussion and Limitations

6.3.1 Privacy Issue

Storing restaurant videos can raise concerns about the privacy of customers. To address this issue, we only store the tray images cropped and extracted from the videos and then delete the videos. The tray images do not contain identifying information about the customers. We restrict the access to tray images to only a handful of people involved in the project to increase privacy further.

6.3.2 Model Performance

In this thesis, we trained dish and quantity classification models on the data from an on-campus restaurant. We utilized the proposed iterative approach via hierarchy for dish classification of food waste and visual analytics system to inspect the model's predictions. Our primary focus was on the iterative hierarchical approach and visual analytics system for dish classification.

Our models for dish classification achieved an accuracy of 91.2% and quantity classification of 80.1%. The accuracy of dish classification is sufficient. Regarding dish classification, the accuracy is limited by the training data, which means the ability of humans to perform dish classification. In future, the hierarchy can be expanded horizontally by splitting the counter category into more dishes, and vertically by recognizing dish components. The accuracy of quantity classification can be improved by adding more training data with strict rules on dividing into classes.

The following are other techniques that can be experimented with to create better models.

1. Utilize other recent model architectures that are performing well in food classification challenges and datasets.

2. Utilize segmentation approach for food waste quantity estimation: During data labeling, for each food tray returned, mark the food waste boundaries in the food tray image, and assign an estimated percentage of food waste. Train segmentation-based machine learning model which learns to bound the parts of an image with food waste and estimate the percentage of food waste.

3. Utilize food datasets for pre-training the models, with or without the ImageNet dataset. If we use the ImageNet dataset for pre-training, we can still utilize other food datasets by training models on them after training on ImageNet. We can finally fine-tune them on the training data for the specific restaurant. Another approach is not to use ImageNet for pre-training and directly use the food data sets for pre-training models and then fine-tune them to the training data of the specific restaurant. When selecting a food dataset for transfer learning, the food dataset should contain items similar to the restaurant for which the models are being created; otherwise, if there are substantial differences between the datasets, then the transfer learning approach may not work. Some examples of useful data sets are Food-101 [32], ChineseFoodNet [34], and Food2K [33]. Among these, the Food2K dataset has two thousand categories, which is the largest in categories; hence, it might be the most useful.

6.3.3 Dish Classification Failure

We carefully explored the cases where dish classification fails. For different dishes, the cases where dish classification becomes very challenging for humans and machine learning models are (one or more occurring at once):

1. When containers have similar shapes or colors.
2. When there is almost no food waste.
3. When the constituent food items are similar or appear similar in color.
4. Imbalanced training data examples for different sub-classes of dishes.
5. When some dishes are not covered or have very limited instances in the training data.

6.3.4 Quantity Classification Failure

We utilized simple image classification by labeling about 6K returned (after eating) food tray images into "Almost empty," "Some waste," and "Lots of waste" classes for obtaining training and testing data. Our accuracy for the two main classes of almost empty and has waste is 90.5%, suitable for binary classification. For the three sub-classes, our accuracy of 80.1% is sufficient. However, to increase the sub-classes in the future, we must consider stricter data labeling rules and fail case analysis.

The common reasons for failures in quantity classification are:

1. Using categories for estimating food waste by quantity. This approach is more subjective than objective. In some cases, stricter rules might help in improving accuracy.
2. Cases where categories are indistinguishable. Even when humans cannot determine which category the image should fall into, the models are bound to fail.
3. When there are insufficient training examples of a dish.

6.3.5 Scalability and Generality

Our approaches can easily be scaled up for larger restaurants or more customers in a restaurant by adding GPUs for the deep learning model to process videos for extracting their tray images, which is the most computationally expensive part. Also, since our focus is on an iterative approach for dish classification while using a visual analytics system, our methods can be applied to other restaurants, and the hierarchy can be tailored to their menu or serving style (ex: counters). However, the models will need to be trained from scratch as our data is not transferable.

Our iterative approach using a hierarchy and visual analytic system can be applied to other scenarios where the classes are not fixed, and the limits of machine learning need to be explored. Our methods can be applied to several active learning scenarios and are not limited to food waste scenarios. However, when there is no fixed tray return area for food waste in restaurants, it cannot be easy to use the restaurant's videos directly. Some other innovative approaches may be needed. However, once the food waste images are obtained, our classification approaches for the dish can prove helpful.

An important point to be noted here is that the data from our study is not transferable. Each restaurant has its unique menu (dishes) and serving style (including containers), so the data from one restaurant is not helpful for another unless they have a very similar menu and serving styles. Due to this, our models for dish and quantity classification of food waste are non-transferable to other restaurants. Even if the pipeline technique is the same for new restaurants, it still needs to be installed from scratch, only retaining the methodology. The new restaurants' data collection, labeling, and model creation will take time as they have to be done from the start. The benefit of our work in this scenario is that it provides the steps to create solutions for a real restaurant via case study. To create solutions for another restaurant, the method we used for creating our solutions can be utilized. This is discussed in the next section 6.3.6.

6.3.6 Steps for Food Waste Estimation at Another Restaurant

First, check if the restaurant has a separate food tray return area. If it does not, then create such an area. The following steps are from our proposed system pipeline.

1. Install cameras at the tray return area to capture all the trays being returned by

customers after eating.

2. Install cameras at the food tray serving area to collect videos of food items served. These videos will help recognize the food waste from the returned trays and reduce confusion during data labeling. These videos will also help monitor the restaurant serving style, including containers and dishes, and help to adapt solutions to the changes.

3. Train machine learning models to detect the food trays from the restaurant camera videos. A similar model architecture to ours can be utilized, for example, Yolo V3 [37]. Implement code to automate downloading the videos, detecting their tray images using machine learning models, then cropping and storing those cropped images, and deleting the processed videos.

4. Automate the tray image extractor system and conduct its real-world testing.

5. Conduct a survey of the restaurant's menu, dishes available, and their components. Utilize the images extracted from videos and the menu information to determine an initial hierarchy for dish classification.

6. Utilize our proposed active learning process to create dish classification models efficiently. Please note that the methods from our restaurants are transferrable, but the data and models are not. The visual analytics system from our research is transferable for monitoring the dish classification model predictions. After creating dish classification models, evaluate their performance on data from different months.

7. Similarly, utilize our approaches in quantity classification of food waste to create suitable categories. Gather images for data labeling, as our data and models are not transferable. Then, train models for quantity classification of food waste and evaluate their performance by selecting data from different months. Improve the models by updating the category classification rules or adding more training data.

8. Now, the dish and quantity classification models are ready. Utilize them on several months of data to get food waste information from the restaurant.

9. Design suitable dashboards, or utilize our final dashboard's design for food waste data analysis. Conduct user studies for this task before creation for gathering re-

quirements, during creation for iterative improvements, and after creation for evaluation. Our dashboard is created for analysts to analyze data, summarize findings and report their insights to the restaurant managers. Due to the abundance of information on our final dashboard, they are not suitable for direct viewing by customers or managers. Thus, other simpler dashboards can be created for customers and managers, see section 6.3.7.

10. Using the dashboard for data analysis, data analysts can analyze the trends in food waste and suggest actions to managers for food waste reduction. Alternatively, simpler dashboards can be directly shown to the managers for taking data-based actions or to customers to raise their awareness.

11. For long-term validity of the approaches, monitor the trends in food waste using dashboards and model predictions for dish classification using our proposed visual analytics system.

6.3.7 Creating Dashboards for Restaurant Managers and Customers

The final dashboard design is created for analysts to analyze data, summarize their findings and report them to the restaurant managers. However, as the information on the final dashboard is shown aggregated in one view, it may not be understandable by the restaurant managers or customers who do not have prior experience in data analysis using visualizations. For example, suppose the final dashboard is shown directly, without including an intermediary to summarize its analysis, it might be ineffective for raising the awareness of customers or the restaurant managers, as the immensity of information might be too much for their cognitive load and understanding.

The steps to create a new dashboard, which is suitable for direct viewing by customers or the restaurant managers, can be:

1. Analyze dashboards in other scenarios where they are shown to the general public and have been successfully understood by the public. More specifically, where they are created for people who may not be well versed in data analysis via visualizations.

2. Limit the number of charts to show in a one-page view. Perhaps either by allowing scrolling the page to see the remaining charts or providing a slideshow

interface where each page or slide shows just a limited number of charts focusing on only one aspect of food waste.

3. Create several designs for the points mentioned above and conduct user studies with restaurant managers and customers to learn their preferences. Select the design or design combinations that are preferred the most by the aforementioned users.

4. Use an iterative process for improving the design, which involves conducting user studies on the improved designs for gathering feedback.

5. Implement the dashboard.

6. Conduct its evaluation to verify if it is suitable for the users.

CHAPTER 7

CONCLUSION

Reducing food waste is a significant challenge in the modern world. Solving that can minimize environmental harm and help feed the needy. In this thesis, we identified and attempted to resolve several challenges in a restaurant's food waste analysis. We conducted a case study at an on-campus restaurant, LG1 Canteen at The Hong Kong University of Science and Technology (HKUST), to verify our methods.

We followed our proposed system pipeline. First, we installed cameras at the restaurant to get videos, then created deep learning models to extract food tray images. Second, we only stored the cropped food tray images and discarded the videos to ensure customers' privacy. Third, we automated the tray image extraction to process the entire day's videos from 10 cameras in 24 hours. We also solved the problem of missing data due to unexpected interruptions. By storing the images and discarding the processed videos, we also saved a significant amount of storage needed for a year's worth of data. Fourth, by using active learning along with iteration and hierarchy, we solved the problem of dish classification of food waste. We experimented with different deep learning model architectures and utilized transfer learning with fine-tuning to obtain the best model, which gave an accuracy of 91.2% for eight dish categories and 92.4% for four main groups representing six counters in the restaurant during the case study. Moreover, we created a visual analytics (VA) system to monitor the model's performance across several months. We evaluated our dish classification models using the VA system on about 567K tray images of food waste from three months data.

Fifth, we solved the problem of quantity classification by creating deep learning models. Our best model for quantity classification of food waste gives an accuracy of 90.5% for two main classes and 80.1% for three sub-classes. We also presented suggestions for adding more classes in quantity classification via split. Sixth, we solved the problem of analyzing food waste data by building dashboards. We created a prototype version and its final dashboard for data analysts to conduct food waste data analysis. Seventh, we discussed several limitations of this thesis, steps for creating simpler dashboards for customers and managers, and steps for food waste estimation in other restaurants.

Our interviews and surveys with end-users and domain experts concluded that they were satisfied with our approaches. Our proposed pipeline and techniques are easily scalable and generalized. While this thesis presents an end-to-end approach for food waste monitoring at a restaurant, this work's primary novel contribution is the dish classification approach, which supports human and machine collaboration via iteration, hierarchy, active learning, and visual analytics. This approach can be applied to many restaurants for dish classification. Overall, this thesis achieved its objectives. In the future, more restaurants can use the methods from this thesis with suitable improvements and create solutions for food waste monitoring and reduction.

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List of Publications

- L. Y.-H. Lo, A. Gupta, K. Shigyo, A. Wu, E. Bertini, and H. Qu, "Misinformed by visualization: What do we learn from misinformative visualizations?" Computer Graphics Forum, vol. 41, no. 3, pp. 515–525, 2022. [52]