Smart Compost Bin for Measurement of Consumer Food Waste

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ABSTRACT

The rising amounts of food waste across the world is a severe environmental, social, and economic catastrophe. The majority of food waste occurs at the consumer level, yet we have no reliable means to quantify this waste. A lack of publicly available image datasets of commingled food waste has prohibited researchers from leveraging advances in computer vision for the task of automatic food waste measurement. We present an AI-assisted compost bin that automatically measures kitchen compost waste by collecting 2D, 3D, and thermal images alongside measurements of temperature, humidity, pressure, and volatile organic compounds. The compost bin utilizes speech recognition technology that allows users to verbally describe the items they deposit. We provide a companion mobile app that tasks a subset of volunteer users to draw boundaries around individual discarded food items in order to generate high-quality segmentation masks of food items present in the image. We will deploy this device in a forthcoming field study to curate a large and novel dataset of commingled food waste. This dataset will enable computer vision researchers to train intelligent models capable of quantifying and measuring food waste without the need of costly, labor-intensive human subject studies. Additionally, we train a preliminary food image segmentation model using existing datasets of images of uneaten food items, and evaluate it on images taken by our compost bin to demonstrate the critical need for a large, high-quality dataset of commingled compost waste.

CCS CONCEPTS

• **Computing methodologies** → **Image and video acquisition**; • **Hardware** → *Sensors and actuators*; • **Applied computing** → *Consumer products*; **Annotation**.

KEYWORDS

artificial intelligence, consumer compost, computer vision, food waste, smart technology

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1 INTRODUCTION

Food waste is a dire crisis that threatens health security, environmental sustainability, and economic stability across the world. Around 1.3 billion tons of food is wasted globally each year, representing economic losses of over $1 trillion [12]. The problems of food waste and food insecurity are intrinsically linked. Every year 783 million people battle hunger [13]. Yet, food waste squanders production from around 30% of agricultural land [13]. Food imports in high-income countries worsen food waste and loss which harms the environment in exporting countries [15]. Our food system is responsible for one-third of global greenhouse gas emissions [26], of which wasted food accounts for 10% [13]. The majority of food loss occurs at the retail and consumer level [12], and individual households account for 61% of all food waste [14]. This amounts to an annual loss of 81 kilograms per household [13]. Because there is no established way to systematically and accurately measure food waste, this gross inefficacy continues to worsen each year.

1.1 Motivation

Current approaches to measuring food waste are time-consuming, burdensome, and prone to human error. These difficulties hinder attempts to systemically measure consumer food waste. Human subject studies carry a high labor and economic cost leading to a severe lack of data. Furthermore, only 20% of the studies are based on direct measurements of food waste [39]. Reported rates of food waste are highly variable among studies [9] and are neither replicable nor comparable [1]. A lack of data is the foremost barrier to reducing food waste, and such data is largely absent at both national and international levels [3]. Moreover, the situation is likely far worse than we estimate. Studies tend to overestimate rates of consumption, and generally food loss waste is significantly underestimated [35]. One major reason why this data is not available is because approaches to measuring waste are inconsistent and the measurements themselves vary between studies [14].

1.2 Contributions

To close this gap, we propose an AI-assisted device that accurately quantifies commingled food waste. We design a smart compost bin to collect and measure food waste in home consumer kitchens. This device records waste disposals to create an accurate and systematic log of discarded waste. We design our approach with consideration to current household compost products so that consumers who already compost should not need to change their behavior.

We present a food waste data labeling workflow with the goal of limiting the annotation burden on the user. Our device supports applications and visualization tools that will provide data-driven and personalized interventions to empower individuals to reflect upon and change their food waste habits.

2 MEASURING FOOD WASTE

Presently, rates of food waste among various studies are highly variable [9] and these studies disproportionately sample affluent regions [39]. Although there have been attempts to analyze behavioral attitudes towards food loss by demographics and socioeconomic factors [27], there has been little attention to the demographic breakdown of participants in waste measure studies apart from high-level differences between country or household income [9].

It is critical that studies analyze the specific types of food wasted, not just the total quantities, in order to develop strategies to encourage the reduction of food waste [37]. Furthermore, because food waste decomposes, it is important to measure food waste at the time of disposal, rather than analyses at later points in time [10]. To understand food loss, we desperately need more data produced from direct and immediate measurements of food waste.

2.1 Measuring Commercial Food Waste

Given the economic incentive, restaurants and commercial kitchens make substantial efforts to mitigate waste [22]. Researchers measuring food waste in commercial kitchens have explored a number of indirect and direct approaches. Supermarkets, restaurants, and cafes maintain extensive records of their purchases and sales, and together these records provide indirect estimates of food waste. Staff in restaurants and cafeterias may use clear trash cans or manually dig through the trash. This view may provide staff an informal understanding of which food items their customers are not eating and inform them to adjust portion sizes or menu choices.

In research studies attempting to directly measure post-consumer food waste, restaurants may sort trash and food waste into different colored trash bins [8, 22] or task a human observer to monitor the trash can and record all waste as it is disposed [8]. In other approaches, commercial kitchens have weighed kitchen scraps before disposal [34], measured the waste each customer leaves on their plate [36], and captured images of customer plate waste [6].

All of these systems are manual, based on sampling, and do not solve the underlying data problem. Furthermore, these approaches are reactive and tend to fail when the kitchen is busy. Most importantly, they do not create a mechanism for real-time intervention.

2.2 Measuring Consumer Food Waste

To attempt to track food waste at home, researchers have employed a variety of strategies, including surveys [33], food journals [28], and mobile apps [7]. Some of these methods, such as surveys, are informal and ask people to estimate the amount of food waste in their household. Other methods are more direct, tasking participants to keep a record of the specific amounts and types of food waste in a journal. Some of these studies provide scales and task users to directly weigh their food waste. In efforts to increase reliability of measurements, researchers may also collect refuse from homes to manually sort, log, and weigh discarded food [31].

However, all of these methods are based on human action and are costly, inaccurate, and time-consuming. A meta-analysis of 332 studies measuring food waste found that measurements were highly variable among studies and across methods [9]. Fundamentally, these measurement approaches do not provide a holistic view of food waste [21] nor do they solve the underlying data problem. Furthermore, these approaches fail to guide consumer behavior.

2.3 Use of Technology

Computer vision (CV) is a field within artificial intelligence (AI) that designs algorithms to identify objects in images and videos, with broad applications across engineering, medicine, and robotics. Although researchers in CV have given some limited attention to detection of food items, these tasks usually focus on detection of foods in the production chain or at the plate level before consumption [38]. Most food datasets contain images of food before consumption [23, 25, 38]. However, partially eaten, rotten, or discarded food looks fundamentally different than food before consumption [6].

Although computer vision systems have attempted to automatically quantify nutritional information from images of meals served at restaurants [23], the problem of identifying food waste from image data has not been well studied [6]. Although a few private companies have investigated food waste in commercial kitchens, there have been no prior efforts to use technology to measure food waste in consumer kitchens. And because public datasets of images of food waste do not exist, machine learning researchers are limited in their approaches to tackle this problem with computer vision.

In addition to the identification of food items, AI has been employed in other areas related to waste management (see review [11]). For example, systems of sensors can be used to measure the fill level of dumpsters in order to notify municipal waste management companies when it is time to empty them [17]. Smart technologies have been deployed to monitor and detect the concentration of odor in wastewater systems [5] and to measure various bioprocesses related to food waste (see review [32]). CV systems can be used to automatically sort recyclables [19] and to quantify and predict the amount of solid waste generated across different parts of a municipal waste collection system [18]. Furthermore, the use of digital technologies to improve efficiency in supply chains has been shown to lead to measurable reductions in food waste [30].

3 SMART COMPOST BIN

To facilitate the development of a large, high-quality household food waste dataset, we design a smart compost bin – an AI-assisted data collection device designed for residential consumer use. This device collects 2D, 3D, and thermal images, as well as environmental data using sensors integrated throughout the compost bin. Study participants annotate their disposals verbally, and we transcribe this speech to provide annotations for a novel food waste dataset.

3.1 Design

To annotate a large amount of food waste, we will distribute our compost bin to volunteer households. These participants will use this bin in their day-to-day compost disposal. We design our bin with convenience and similarity to existing compost solutions in mind in order to reduce annotator fatigue [16] and encourage user adoption. With the goal of enabling a wide-scale data collection study, we design for the following usability considerations:

Device Sanitation: The device should be easy to clean to prevent the buildup of decaying organic material. We provide a removable, dishwasher-safe internal polycarbonate bucket to house the composted items which allows convenient dishwasher cleaning.

Device Operation: To streamline the operation of the device, we integrate a spring-loaded hinge and an ergonomic latch which can be actuated even when the users hands are occupied while cooking.

Odor Management: We implement a passive air filtration system which uses carbon pellets to prevent the buildup of condensation or foul odors in the device. The lid seals against the outer bucket using a rubber gasket in order to prevent odor emission.

Ease of Use: We strive to make the data collection non-intrusive and hands-free to reduce annotator fatigue. The user is prompted to describe newly deposited items after an image is taken. A microphone records this speech description, which we then automatically transcribe to generate a food item label (see Section 3.2.2).

3.1.1 Components. The primary manufactured components of this compost bin consist of the main body and a hinged lid (see Figure 1). The main structure houses the chamber for disposed food items, as well as the embedded processor and weight scale. The majority of the device's sensors (see Section 3.1.2) are housed in the lid, which is connected to the main compartment by a spring-loaded hinge.

In the lid, a depth-imaging camera and thermal imaging sensor are mounted facing into the bin, allowing images of the disposed food waste to be captured when the lid is closed. The bucket interior is lit using a set of diffused WS2812B LEDs, to control lighting conditions while imaging. These sensors are protected from condensation using a polycarbonate protective layer for the depth camera, and an IR-transmissive polymer covering the infrared thermal sensor.

To gain insights about the contents of the compost bin, we integrate sensors to measure weight and gas levels. A metal-oxide gas sensor in the lid detects changes in volatile organic compound concentration inside the bucket, as well as the ambient humidity and temperature of the surroundings. The base of the device is designed such that force is distributed through a single-point load cell, allowing the calculation of the mass for each food item deposited.

The device is constructed primarily using 3D-printed components, reducing total manufacturing cost for low-volume production runs compared to traditional plastics manufacturing methods. We use Polylactic Acid (PLA) and Polyethylene Terepthalate Glycol (PETG) for our materials. Including the processor, sensors, and all other hardware, each compost bin costs $468 to produce.

3.1.2 Sensors. Our device contains an array of sensors (see Table 1) to support the collection of multimodal data characterizing the food waste. An Intel RealSense D401 stereoscopic camera is used for capturing images, and we reconstruct a 3D point cloud using Intel RealSense software[1]. This low-profile stereoscopic camera operates at a minimum depth of 7cm, allowing it to be used effectively at the ranges between the lid and base of the compost bin. This camera system has a dedicated coprocessor for camera synchronization, reducing the total overhead on our main processor.

Using this data, we intend to train a computer vision model for instance segmentation on post-consumer food images (see 3.3). A MLX90640 IR thermal imaging sensor is also integrated next to our optical sensor, to record a heatmap within the compost bin. We anticipate that recently disposed items may have a different temperature than the surrounding compost items, which may enable automatic image segmentation and classification in cases where RGB color data is insufficient to differentiate compost items.

We incorporate a Bosch BME688 gas sensor to measure the total volatile organic compound (VOC) concentration inside the bin, as well as to measure ambient temperature and humidity. This sensor measures changes in resistance across a metal oxide plate in response to higher VOC concentrations. Using the Bosch BSEC library[2], we convert these resistance values into total VOC and CO2 concentration measurements. A load cell in the bottom of the device measures the total weight of the compost bin during every detection, from which we derive the mass of each compost item.

These sensors are integrated into the compost bin lid using a custom printed circuit board, enabling standardized and repeatable assembly. A 40-pin FPC data link connects the Raspberry Pi 5 microcontroller to the sensors in the lid.

3.2 Data Pipeline

We develop an integrated data pipeline to enable the autonomous collection of data from a distributed network of smart compost bins (see Figure 2). Our approach consists of on-device driver software, a centralized database server for data aggregation, and a mobile smartphone app to assist users operating the compost bin and provide a robust workflow for segmentation annotation.

3.2.1 Device Firmware. Our Raspberry Pi 5 processor communicates with the BME688 gas sensor, NAU7802 load cell amplifier, MLX90640 thermal camera, and lighting devices over I^2C, while the D401 camera and audio subsystem are integrated over USB. We design a multithreaded, event-based firmware architecture to reduce the total runtime of our detection routine. This system asynchronously processes speech transcription and file uploads in the background to improve device responsiveness for the end user.

The compost bin detects when the user has closed the lid using a magnetic hall effect sensor. After capturing images and reading from each sensor, the device prompts the user to verbally describe the disposed food waste. The user's response is recorded, and this speech audio is transcribed to provide a text annotation for the captured image (see Section 3.2.2). The image files, topological map, sensor data, and transcribed audio label are posted to a remote database server using a secure encrypted network protocol.

3.2.2 Automatic Speech Recognition. Traditionally, annotating a large image dataset requires a separate annotation study, leveraging crowdsourced annotators to identify and label objects in each image. To improve the efficiency of our data collection process, we collect and annotate data simultaneously, leveraging the collaboration of volunteer study participants. We automatically convert speech audio provided by our users to a text label using `Whisper` [29], a state-of-the-art automatic speech recognition (ASR) model.

[1]https://github.com/IntelRealSense/librealsense

[2]https://www.bosch-sensortec.com/software-tools/software/bme688-software/

Figure 1: Images of the Smart Compost Bin (left-to-right): lid closed, lid open, inside bin, rear, bottom.

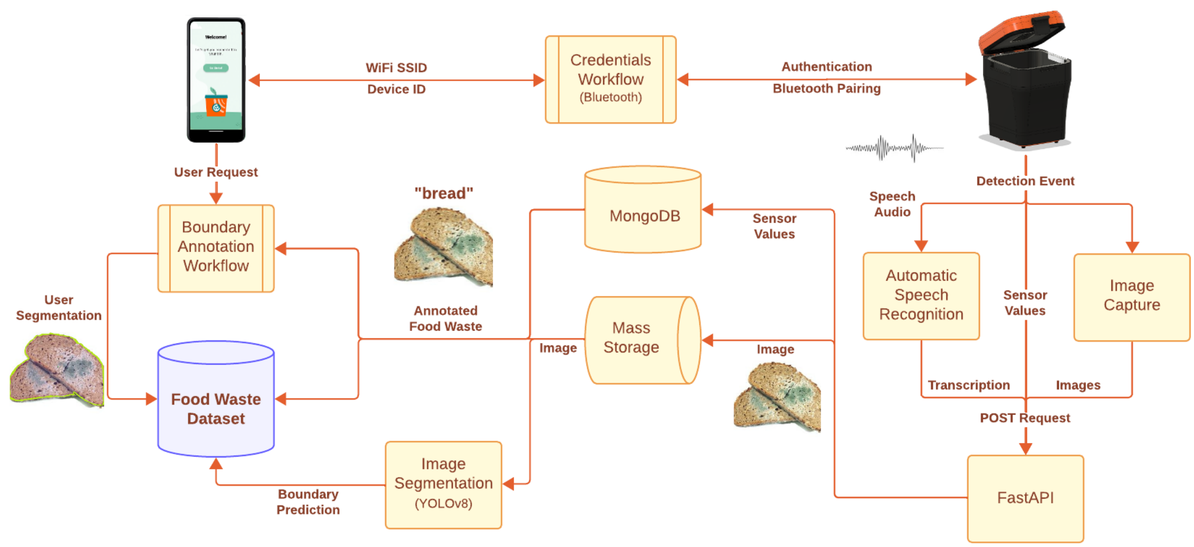

Figure 2: System diagram detailing the data pipeline of our smart bin system.

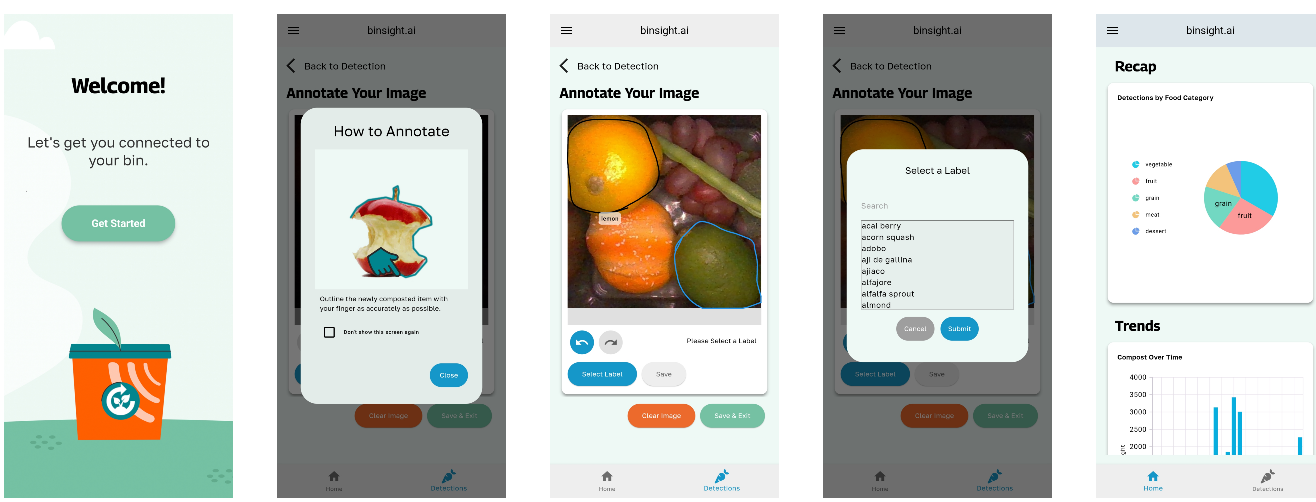

Figure 3: Demonstration of the smart compost bin mobile app and annotation routine.

Table 1: List of electronics and sensors included in the design.

Component	Part	Purpose
Processor	Raspberry Pi 5 4GB	Communicates with sensors; uploads to database.
Camera	Intel RealSense D401	Takes 2D and 3D image.
Thermal camera	110° MLX90640 IR Matrix	Generates thermal image and heatmap.
Gas sensor	Bosch BME688	Measures temperature, humidity, tVOC, and pressure.
Hall Effect	Melexis US5881LUA	Detects when the lid is opened and closed.
Microphone and DAC	Waveshare USB Sound Card	Records speech audio, prompts user.
Load cell amplifier	NAU7802 24-bit ADC	Measures value from load cell.
Load cell	10kg Single-Point (C3 Grade)	Measures mass of food items.

Whisper is a large transformer model containing over 74 million parameters. Such a model is typically unsuitable for deployment on a low-power ARM processor such as the Raspberry Pi 5 powering the smart compost bin. To improve transcription speed, we use `whisper.cpp`[3], a re-implementation of Whisper designed for efficient CPU inference. Additionally, we apply 5-bit quantization to this model to further accelerate ASR runtime performance.

3.2.3 Database Backend. Once the device completes a detection routine, the sensor readings, topological map, images, speech audio, and transcribed image label are uploaded to our database server. We use FastAPI[4] as our web server, routing inbound HTTP traffic from client devices and handling form validation. Multimedia data is saved to disk, while sensor readings and metadata are written to a MongoDB non-relational database instance. Images are associated with each database record using file paths, allowing efficient and optimized record querying without compromising write operation performance for record insertion operations.

3.2.4 Mobile app. To serve as the user interface to the smart compost bin, we developed a cross-platform mobile application (see Figure 3). This app tracks usage and informs users about their composting habits. When a new user opens the app for the first time, it guides them through a one-time setup process, using a Bluetooth pairing routine to connect the compost bin to the user's Wi-Fi network. Once connected, the app provides a data-driven dashboard that tracks that user's composting habits.

Each time the user opens the app, it downloads any recent images of the user's compost from our database server. For each new image, the app tasks the user to draw an outline around each compost item in the image using their touchscreen. We save this boundary annotation alongside the transcribed categorical label to our database. These boundaries will allow us to train a robust semi-supervised segmentation model to automatically detect food waste. We will deploy this app for our initial field study to construct a dataset of labeled and manually segmented examples. This dataset will support the training of our food waste recognition model, and future versions of this application will perform food waste detection automatically, without requiring user input (see Section 3.3).

Additionally, we provide an interactive analytics dashboard to inform users about their composting habits. This dashboard highlights common behavioral trends, including graphs illustrating their most frequently discarded food items. Our mobile app provides personalized analytics to the user to encourage informed decision-making that leads to reductions in their food waste footprint.

This app enables crowd-sourcing the laborious task of creating segmentation masks to label individual items present in commingled food waste images. We do not require our users to exhaustively annotate every item, instead relying on a limited number of fully annotated samples and a vast quantity of labeled but not segmented images collected from the compost bin, which will facilitate the training of a semi-supervised image segmentation model. By allowing users to freely engage with the compost bin without restricting use to specific items, we curate a large dataset representative of the types of food waste which users most frequently compost.

3.3 Image Segmentation

Our long-term goal is to provide a system that automatically quantifies food waste without relying on user annotation. Towards this objective, we produce a preliminary food item segmentation model. There are no available datasets of food waste images, and existing datasets only contain images of plated, pre-consumer food. Furthermore, modern computer vision models often require training very large datasets beyond the scale of current food image datasets and of our data collection study. To address these challenges, we first train an initial model for pre-consumer food recognition and apply it towards compost segmentation.

We select `YOLOv8-seg`[5], a popular object recognition model which achieves state-of-the-art accuracy and inference speed on many computer vision tasks [24]. `YOLOv8-seg` consists of three components: a `CSPDarknet53`[6] backbone for feature extraction, a convolutional network for object detection, and a series of fully connected layers for generating segmentation proposals from latent features. The model uses non-maximal suppression to select only the most probable detection for the segmentation mask prediction. A standard joint loss function is used, with a binary cross-entropy term for segmentation mask loss, a classification loss term, and a distributed focal loss term for bounding box accuracy. `YOLOv8-seg` is pretrained on the `COCO` dataset [20], a ubiquitous computer vision dataset containing over 200,000 labeled images. However, `COCO` only consists of 91 class labels, of which, only 10 are food items, which limits the food categories this pretrained model can detect.

[3]https://github.com/ggerganov/whisper.cpp
[4]https://fastapi.tiangolo.com/
[5]https://docs.ultralytics.com/tasks/segment/
[6]https://huggingface.co/docs/timm/en/models/csp-darknet

Table 2: List of datasets segmenting images of food.

Dataset	Source	Year	*n* images	*n* labels	*n* items
COCO	[20]	2017	328,000	91	2.5M
FoodSeg 103	[23]	2021	7,118	104	42,097
UECFoodPix	[25]	2020	10,000	103	36,929
Food201	[38]	2017	12,093	208	55,412

In the absence of large, annotated image datasets of food compost, we fine-tune our model on three pre-consumer food image datasets. We select FoodSeg103 [38], Food201 [23], and UECFoodPix [25], each of which contain segmentation mask annotations for images of food objects and meals (see Table 2). After combining similar classes, we find 322 unique food categories in our merged training dataset, with 29,211 images and 135,129 annotations. For each dataset, we randomly sample 80% of images for training, 10% for validation, and 10% for testing. We concatenate each split with the corresponding splits from the other datasets to form our merged fine-tuning set. After the model has been fine-tuned, we perform subset validation at each epoch, utilizing early stopping to select the checkpoint with the best performance while avoiding overfitting.

(a) Labels

(b) Predictions

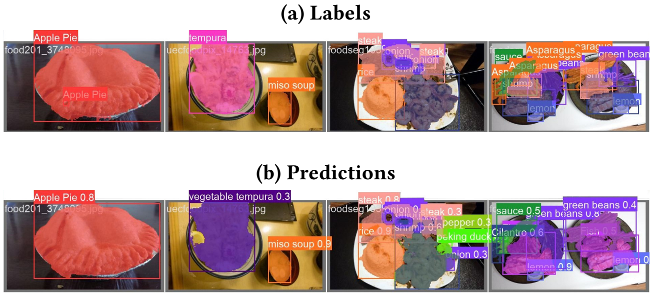

Figure 4: Examples of detections on food image test subset.

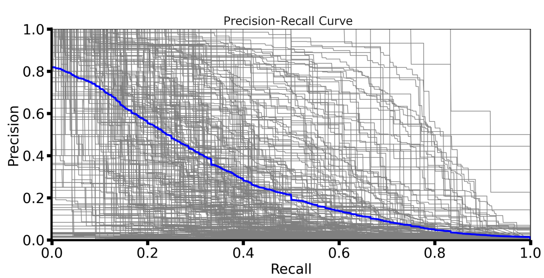

Figure 5: Precision-recall curve of Unified `YOLOv8l-seg` with an average 0.297 mAP@50 across the 322 food items.

We find that our fine-tuned `YOLOv8-seg` model demonstrates modest performance on food instance segmentation, achieving a mean average precision of 0.233 (see Table 3). Figure 5 shows the precision-recall curve for each of our 322 food classes. A subset of classes disproportionately affect model performance, which we assess to be the result of a class imbalance in our merged dataset. UECFoodPix and FoodSeg103 contain classes for food dishes (e.g., vegetable tempura *n*=12, eels-on-rice *n*=7), while Food201 is labeled with discrete food items. These food dish classes are underrepresented in our dataset. When evaluated on individual food datasets, we find that our model attains better performance on datasets with fewer classes such as UECFoodPix and FoodSeg103, and struggles with the granular and highly multilabel Food201 dataset. Despite these differences between datasets, `YOLOv8-seg` is still able to segment food items in a commingled image, such as a plate of food, as demonstrated in Figure 4.

Table 3: `YOLOv8` performance on food instance segmentation.

Dataset	Precision	Recall	mAP50	mAP50-95
Food201	0.317	0.173	0.152	0.103
FoodSeg103	0.432	0.334	0.315	0.253
UECFoodPix	0.700	0.481	0.505	0.430
Unified	0.518	0.284	0.297	0.233

We assess model performance on compost instance segmentation for food waste measurement. We manually label a small sample of 41 images with 97 food items taken during device development. Using our fine-tuned `YOLOv8-seg` model, we predict segmentation masks for each image (examples in Figure 6). Our model identifies 30 food items in total, of which four match ground truth annotations, achieving only an accuracy of 4% on our downstream task.

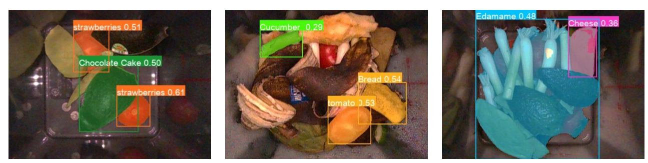

Figure 6: Examples of detections on compost bin images.

In many cases, our model fails to predict any of the food items in the image. We hypothesize this performance degradation reflects the fact that food compost instances are far out-of-distribution relative to images of uneaten food. Segmentation models use spatial features to detect the presence of an object in an image, and food compost innately has vastly different spatial properties than uneaten food. Using existing food segmentation datasets, we are unable to develop a model to automatically identify food waste items. However, this preliminary model provides a framework for the implementation of food instance segmentation models. These experiments underscore the need for a high-quality, large image dataset of annotated post-consumer food images to enable the development of a robust computer vision model for food waste detection.

4 USER STUDY

We will perform a pilot study to rigorously test our device, collect measurements, and assess the potential to scale this approach. We will deploy this study in consumer homes, manufacturing a device for *n*=50 participants for use over a one month period.

While many food waste studies seek a representative sample of participants to develop an understanding of food waste habits [39], we instead aim to produce a dataset of annotated images of food waste items with associated sensor readings. This pilot study informs us of the viability of the smart compost bin as a method for food waste monitoring and understanding, and informs us which types of data and features are relevant for the task of automatic food waste recognition. With these considerations in mind, we seek a convenience population, enrolling 50 volunteer households which already participate in existing municipal composting programs. In this study, we will ask each user to engage in their usual food waste composting habits and to annotate the resulting images.

First, when the user discards food items in the bin, the device will prompt them to verbally describe the items they just added (e.g., "*two banana peels*", "*three eggshells*"). We collect open-vocabulary annotations which allow users to describe their food waste naturally rather than instructing them to match a specific category. In contrast to traditional food waste journal approaches, this allows users to quickly engage with the device's annotation routine with little disruption to their standard composting habits, which we expect to encourage user adoption of our device. We will use an automatic speech processing model to transcribe this speech annotation into a text label for the image. From this, we will leverage unsupervised natural language processing techniques to cluster the unstructured labels into a specific food waste category.

Second, we task the user to annotate the images of food waste using our companion mobile app. After a user discards an item, the image captured by the compost bin is displayed in the app, alongside the transcription of the description the user provided.

The user is instructed to draw an outline around each recently deposited food item. This boundary is converted to a segmentation mask and stored in our database. These segmentation masks will be used to train computer vision models to automatically identify and quantify food waste from image data. In future deployments of our compost bin, this boundary annotation workflow will not be required, and our application will simply provide users with analytics about their composting history and food waste habits.

For each food item disposed, we collect a precise weight measurement of the item. Although the item will rest on top of other compost, we use the difference between the previous measurement to calculate the specific weight of newly added items. As the bin fills with compost, participants may empty their indoor compost bin to their larger outside compost bin. Because we measure and log the total weight of waste in the bin every time the lid opens and closes, we easily detect and account for this event.

Because we model our kitchen compost bucket after those distributed by local waste utilities, we will measure all food intended for composting. In our community, customers may compost almost all food waste. This includes edible waste, such as meat, seafood, fruit, vegetables, dairy, baked goods, plate scrapings, and inedible waste, such as fruit and vegetable peels, coffee grinds, tea bags, egg shells, and bones. Our local composting program does not accept seafood shells nor oils and grease, and these inedible items will not be included in our measurement study. Yard waste is collected in an outside bin and does not factor into our study.

To understand the users participating in our study, we will survey each user before the start of the study. We will collect demographic information such as household size, ages, household income, self-described gender, and ethnicity. Additionally, we will survey users to document their purchase and dining habits, as well as their opinions, attitudes, and practices towards food waste.

5 DISCUSSION

Fundamentally, if we hope to reduce household food waste, we must find ways to induce behavioral changes in consumers [4]. These strategies include encouraging better meal planning, motivating more sustainable shopping routines, encouraging the purchase of less visually appealing produce, more efficient cooking and food storage routines, and better utilization of meal leftovers [2]. However, because we lack the means to accurately measure consumer food waste, we cannot implement tools that provide personalized analytics to encourage individuals to change their behaviors.

Currently there are no large-scale public datasets on residential commingled food refuse. The absence of such a dataset hinders the application of computer vision methods to the task of food waste recognition. To address this need, we present a smart compost bin that automatically weighs and images discarded food items. We provide a mobile application to enable crowd-sourced labeling of consumer compost waste. Following our forthcoming data collection study, we will collect these annotated images, alongside sensor readings, to publish a novel dataset of commingled food waste.

The automatic identification of food waste using artificial intelligence presents a number of unique challenges [23], such as ascertaining the quantity of discarded items, segmenting food item instances commingled in the refuse bin, differentiating between related forms of certain foods (e.g., apple slice vs. apple core), and recognizing a diverse set of class labels. Given these many challenges, it remains unclear which features will be most effective for classifying food waste. Our system senses various descriptors of the visual, physical, and chemical properties of a user's compost. From this highly multimodal data, we will be able to investigate which features are most descriptive for the task of food waste classification. This analysis will help inform the development of future cost-effective smart home devices for food waste monitoring.

Current state-of-the-art CV models require very large datasets to train accurate image segmentation models. We demonstrate the ability of a general object segmentation model, pretrained on both food and non-food items, to be adapted to the task of food item segmentation. In future work, we will utilize transfer learning using our novel food waste image dataset to fine-tune an instance segmentation model to the task of automatic food waste measurement. Such a model could be applicable across the entire food distribution network, including in the agriculture sector, at grocery stores and commercial kitchens, and in municipal waste processing programs.

Our goal is to create a large, high-quality dataset of images and sensor readings to be used to train computer vision models that automatically quantify consumer food waste. By designing a system to facilitate the collection of food waste data, we hope to provide the foundation for future technologies that result in meaningful, data-driven analytics, inspiring changes in consumer habits and attitudes towards food waste reduction.

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