Detecting and Classifying Waste Bin Garbage Levels Along Transit Bus Routes

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***Abstract*— Waste bins assist in preventing the spread of trash by serving as central locations where people can discard their garbage. In recent years, researchers have explored using computers to monitor waste bin garbage levels and eliminate the need for human monitoring. Both Internet of Things (IoT) and computer vision technologies have been exploited to accomplish this task. However, IoT approaches require devices to be attached to waste bins which can be costly and time-consuming, and most computer vision methods have not been analyzed in real-world settings. In this paper, we present a waste bin detection and classification system designed for transit buses that utilizes already installed bus cameras to observe the bins. This application is needed because waste bin monitoring systems that rely on humans are ineffective for transportation companies whose bins are spread across large geographical areas. We label bus camera data to create a dataset used to train and evaluate our detection and classification models. Our results show that we can reliably detect waste bins of interest. Moving forward, we plan to complete our system's pipeline and deploy it on a transit bus to evaluate its live-action performance.**

***Index Terms*— Computer Vision for Transportation, Intelligent Transportation Systems, Object Detection, Segmentation and Categorization**

Fig. 1. Examples of an empty (left) and a full (right) waste bin found at different bus stops.

I. INTRODUCTION

It is estimated that the world produces approximately two billion metric tons of trash annually [1]. High levels of municipal solid waste resulting from the consumption of goods, high standards of living, and population growth threaten to pollute the planet if not properly handled [2]. Therefore, it is crucial that communities utilize trash disposal methods, such as using waste bins, to reduce the amount of new garbage introduced to the environment. Today, most waste bins are monitored by humans to determine when they must be emptied. However, this method is inefficient as it becomes increasingly time consuming and tedious for individuals to check on all waste bins when additional ones are deployed. This is especially problematic in cities where waste bins are commonly located on every block. As cities continue to grow and expand, officials will need to develop new methods of monitoring and determining when waste bins located along streets need to be emptied to help reduce the spread of garbage.

We propose accomplishing this job by using the cameras found on public transportation vehicles to monitor street waste bins. In particular, transit buses are well equipped for this task as many have exterior cameras for security purposes and drive along streets picking up and dropping off individuals at bus stops. Additionally, since most bus routes are traversed multiple times throughout the day, waste bins along these routes can be continually monitored. Utilizing buses for this task also benefits the transit companies as they are often responsible for maintaining the waste bins along their routes and therefore an automated monitoring system would reduce their operation costs.

In this paper, we present a waste bin detector that will eventually be deployed onto the *BusEdge* [3] system and used in a garbage level classification pipeline designed to determine when waste bins along bus routes need to be emptied. Using recorded videos captured by a bus's camera while traveling along its route from Washington, PA to Pittsburgh, PA, we create and label datasets using CVAT [4]. We develop a RetinaNet [5] detector model created using the detectron2 framework [6] and train on our custom dataset. The detector's success is measured using average precision and recall metrics to determine if the detector can consistently identify waste bins of interest. Based on the collected results, our detector can detect the waste bins we are most interested in with reasonable success. Even though we developed this detector for transit buses, it can easily be deployed on other mobile or fixed cameras that observe waste bins.

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Fig. 2. A transit bus similar to the one above was used to collect our training data. Likewise, our finished pipeline will be deployed onto such a bus.

Once completed, a pipeline containing our trained model will be deployed on a transit bus to evaluate its live-action performance. Video frames captured by the bus's camera will be passed to the pipeline using Robot Operating System (ROS) [7]. Waste bin detection using a light-weight model will take place on the bus, and all images with detections will be sent to a cloudlet server to be processed once more by an increased performance detector. Once the system is confident that a waste bin has been detected, the classifier will determine if the bin must be emptied or needs to be attended to. Whenever a waste bin is identified as needing to be emptied, a notification will be generated and sent out to the appropriate parties.

The structure of this paper is as follows: In Section II, a literature review is given on previous works surrounding detecting waste bins and monitoring their garbage levels. Section III provides an overview of the proposed system. The conducted experiments are described in Section IV, and their results presented in Section V. Lastly, a conclusion is provided in Section VI and future works are discussed.

II. RELATED WORK

A. Waste Bin Detection and Garbage Level Classification

Over the years, researchers have proposed using different techniques to create autonomous waste bin garbage level monitoring systems [8]–[11]. Existing works can be divided into two groups based on the underlying technologies: Internet of Things (IoT) and computer vision.

IoT methods address the waste level monitoring problem by attaching IoT sensors to the waste bins [8], [9]. These sensors monitor the fullness of waste bins and report back to central monitoring systems. Different types of sensors can be utilized to determine how full the bins are. For example, Y. Zhao et al. [8] developed sensors that monitor how full waste bins are by sensing changes in the bins' motor-induced vibrations. Alternatively, the sensors presented by S. J. Ramson et al. [9] rely on ultrasonic waves to detect what garbage level has been reached within the bins.

While IoT sensors have proven to be effective at monitoring waste levels and are commercially available, they are not without their faults. Each waste bin requires its own sensor, making such an approach expensive when install these IoT devices to a large number of bins. Additionally, as noted by Y. Zhao et al. [8], sensors can become damaged or knocked off after deployment. This greatly increases the difficulty of maintaining such a system as someone must be prepared to replace the sensors when necessary.

Computer vision algorithms have also been explored to monitor the garbage level in waste bins [10], [11]. Such algorithms are developed by extracting a set of key features from images in a training dataset that are then used to train a classifier. In [10], M. A. Hannan et al. propose two waste level classifiers that extract the gray level aura matrix of an images before using a multilayer perceptron or K-nearest neighbor classifier to determine how full the waste bin is. F. Aziz et al. [11] take a different approach. First, the waste bin opening is located using the Canny Edge Operator followed by applying the Hough transform. A Gabor filter is then applied to the image to extract additional properties. Using the collected features, F. Aziz et al. then pass them to a support vector machine or multilayer perceptron classifier that will place the image into one of three classes: empty, partially full, or full [11].

As was the case with the IoT approaches, computer vision algorithms still need to be improved and further explored before they can be fully exploited for garbage level monitoring. Such algorithms require large amounts of training data to properly and reliably function as intended. Creating appropriate datasets using real-world data is a time consuming and often costly endeavor. To our knowledge, no such datasets are publicly available for detecting waste bins and classifying them based on their garbage levels. While both [10] and [11] show promising results, these algorithms were trained and evaluated using artificial datasets. As a result, there is no guarantee that these approaches will work in real-world environments, and so their performance is still largely unknown from a practical application standpoint.

B. Deep Learning

In more recent years, computer vision research has heavily shifted to using deep learning methods. Within the area of waste management, many researchers have successfully utilized deep learning algorithms to detect, segment, or classify garbage and garbage-related objects in a wide arrangement of environments [12]–[15]. Deep learning techniques are also readily available to researchers through the use of frameworks such as detectron2 [6]. One advantage of using these frameworks is that they often provide common models that are already pre-trained using popular datasets such as ImageNet [16] and COCO [17] and therefore only need to be fine-tuned.

Today, there exists many different object detection models including RetinaNet [5], Faster R-CNN [18], R-FCN [19], SSD [20], and YOLO [21]. Convolutional neural networks (CNNs) approaches such as these have been shown to produce high performing models for various object detection tasks [22]. When selecting which architecture to use,

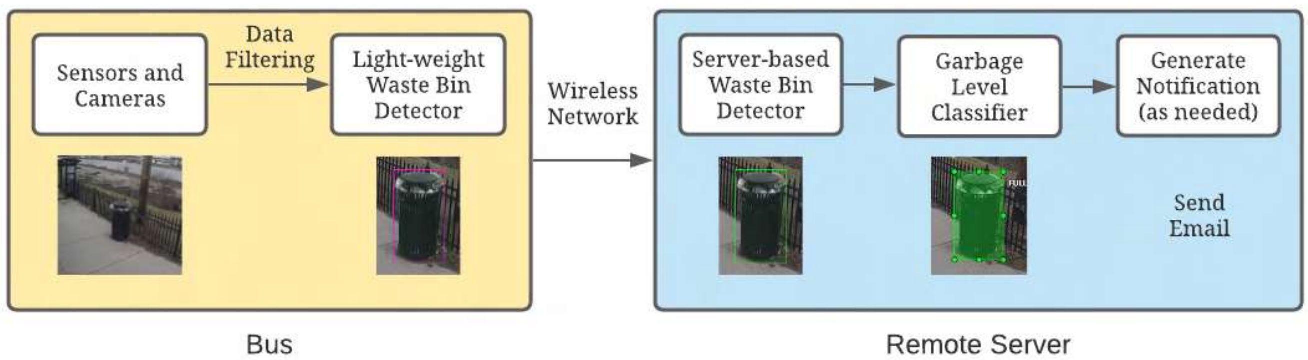

Fig. 3. Waste bin detection and classification pipeline.

researchers need to take into account model accuracy and available resources as different approaches balance these requirements differently and often put a heavier emphasis on one over the other. Additionally, feature extractor methods such as ResNet50 [23] and MobileNet_V1 [24] can be used to further improve the performance of object detection models.

C. Vehicle Edge Computing

As the automotive industry works to develop connected vehicle systems, edge computing will play a crucial role in balancing the need for real-time computing within vehicles while allowing for some tasks to be offloaded to remote servers [25]. While vehicle edge computer poses many challenges, researchers such as X. Xu et al. [26] are working to ensure that edge computing transmitting tasks can take place without compromising the safety or functionality of vehicles. One example of a system that utilizes vehicle edge computing is proposed by C. Ye [3]. The system, referred to as *BusEdge*, runs on public transit buses and provides a platform for applications to access bus data in real-time such as camera video streams and the bus's latitude and longitude coordinates.

III. SYSTEM OVERVIEW

In this section, we discuss the components that make up our proposed system which was inspired by the pipeline proposed in [3]. Fig. 3 visualizes how the individual pieces are connected and provides an example of the output or triggered response after each segment is finished running.

Fig. 4. Hardware components located on the bus (from left to right: onboard computer, exterior camera, GPS and network antenna).

A. Bus Sensors and Data Pre-Processing

The transit bus is equipped with a series of sensors including multiple exterior cameras and a global positioning system (GPS). The sensors communicate with the bus's onboard computer using ROS [7] through individual topic publish-subscription channels between each sensor and the computer. For our application, we utilize the exterior camera on the right side of the bus angled towards the front of the bus and the GPS. Latitude and longitude coordinates are encoded into the individual frames from the camera's video stream. These images are then continually processed through a filter before being sent to the onboard waste bin detector. This filter removes frames so that the overall frames-per-second rate is lowered to ensure that the light-weight detector can process new frames in real-time without creating a bottleneck. Several components belonging to the bus's hardware system can be seen in Fig. 4.

B. Waste Bin Detection

Within the pipeline, there are two main constraints we must address relating to the transit bus. The first is that the bus is only equipped with a basic computer system that has limited memory and no graphics processing unit. As a result, the applications running on the bus must require only minimal resources. The second limitation with using the bus is that there only exists a finite amount of bandwidth to be used when communicating between the bus's onboard system and the cloudlet server. Even after undergoing pre-processing, it is infeasible to transfer all the data collected by the bus's sensors to the cloudlet. Therefore, we need to further reduce the number of video frames by using a model to identify the frames of interest within the waste bin detection task.

To resolve these constraints, we propose the use of two waste bin detection models within our pipeline. The transit bus's onboard computer will run a lightweight model, such as an SSD [20], to detect waste bins as the bus drives past them. While this simpler detector will have a lower performance compared to models that consist of more complex neural networks, it will significantly reduce the overhead on the bus's internal system. Additionally, this model can be tuned to be more lenient in identifying waste bins even if it results in more false positives as these instances will be eliminated later on the servers where more computational power is available. Since most waste bins of interest appear in multiple frames, this detector will also have multiple chances to identify instances as the bus drives past them. Once this model detects a waste bin instance in the current frame, the system will send it to the cloudlet through the edge network.

Once the cloudlet server receives a frame from the bus, it will pass the image to another detection model which has more computing resources at its disposal. This detector will use a more complex architecture, such as RetinaNet [5], therefore enabling it to better recognize waste bins when compared against the bus's lightweight model. Additionally, once a waste bin is detected by the cloudlet model, it will crop the region containing the bin from the original frame before passing it to the garbage level classifier. This functionality eliminates the need for the classifier to locate the waste bin of interest before assigning it to a class.

C. Garbage Level Classification

The final model within the pipeline will be the classifier used to determine if a detected waste bin needs to be emptied. To reduce the number of classes within the model, all waste bins with no visible trash will be considered not full and any bin with visible trash will be classified as full regardless of how much trash is present. Additionally, the classifier will also determine if there are any garbage bags surrounding the waste bins as this signals that someone still needs to attend these bins. Similar to the second detector, the garbage level classifier will use a model that focuses on performance such as a RetinaNet [5] or Faster R-CNN [18]. When a full waste bin is detected, the information will be passed to the last component within the pipeline responsible for notifying the appropriate parties.

D. Full Waste Bin Response

The last piece of our proposed pipeline is responsible for informing the transit bus company or associated party that there is a waste bin that needs to be attended to. After receiving a full classification instance, this system component will decode the GPS location associated with the instance to determine if the detected and classified waste bin is within the jurisdiction of the overseeing parties. Once this information is confirmed, an automatic email containing the image associated with the full instance and its GPS location will be sent to the necessary individuals. Additionally, this information will be used to update an interactive webpage that maps out the bus route so that the locations of all full waste bins can be found in one centralized location. The webpage will also contain the images of the full instances so that the involved party members can confirm that the bins are truly full before sending someone to collect the garbage in the event that a false positive occurred.

IV. EXPERIMENTATION

A. Dataset

To evaluate the performance of our models, we created custom datasets using recorded video streams obtained during normal operations. Annotations were manually added to the datasets through the use of CVAT [4]. Bounding boxes were placed over instances of waste bins in the detection dataset, and three classes were identified for the classification dataset: full, not full, and garbage bag besides a waste bin. For training purposes, both datasets were split by a 60-20-20 ratio for the training, validation, and test sets, respectively. All images used in the training set were taken from the same date. The images used in the validation and test sets come from the same run taken at a different date than the training set, although images are only used in one set and not the other. Tables I and II provide the distribution of samples in each subset. For grouping purposes, small refers to a bounding box area less than 1,024 pixels, medium refers to a bounding box area between 1,024 and 9,216 pixels, and large refers to a bounding box area greater than 9,216 pixels. Our datasets are publicly available and can be accessed through the kraggle website [27], [28].

TABLE I
DETECTION DATASET - WASTE BIN DISTRIBUTION AMONGST THE TRAINING, VALIDATION, AND TEST SETS

Bounding Box Size	Training	Validation	Test
Small	818	268	268
Medium	604	247	247
Large	141	72	71
All Sizes	1563	587	586

TABLE II
CLASSIFICATION DATASET - CLASS DISTRIBUTIONS AMONGST THE TRAINING, VALIDATION, AND TEST SETS

Class	Bounding Box Size	Training	Validation	Test
Not Full Waste Bins	Small	767	265	268
	Medium	518	241	239
	Large	116	65	66
	All Sizes	1401	571	573
Full Waste Bins	Small	53	2	1
	Medium	87	7	6
	Large	26	7	5
	All Sizes	166	16	12
Garbage Bags	Small	54	31	31
	Medium	61	42	47
	Large	19	6	4
	All Sizes	134	79	82

B. *Model Training and Evaluation*

Within the scope of this paper, two experiments will be analyzed. The first evaluates the performance of a RetinaNet [5] waste bin detector similar to the final detector model that will run on the cloudlet server. The second experiment provides a proof-of-concept test to determine if a single model can be used to both detect and classify full waste bins. Our selected model for this proof-of-concept experiment is a RetinaNet [5] multi-class detector. Both models are created using the detectron2 framework and start with pre-trained RetinaNets [5] that are then trained on their respective datasets as previously described. Each model is trained for 20,000 iterations on the training dataset with periodic evaluations on the validation set every 1,000 iterations. After the training procedure is completed, both models are evaluated on their respective test sets using the standard detectron2 COCO evaluator and their metric scores are recorded. These results are presented in the following section.

V. RESULTS

A. *Server-Based Waste Bin Detector*

After training our waste bin detector as defined in the previous section, our model achieves an overall average precision of 44.2% as computed by the detectron2 COCO evaluator when assessed on the test set. This score increases to 67.4% when the Intersection over Union (IoU) metric is restricted to 0.5. Additionally, the model yields an average recall of 56.9%. However, we see that these scores increase when we restrict the evaluation to take into account different bounding box area sizes of detected waste bins. For example, our model reaches an average precision of 57.3% and an average recall of 67.1% when detecting medium-sized waste bins. These scores further increase to AP = 74.8% and AR = 79.2% when only considering the large-sized waste bin detections. Figs. 5 and 6 show the precision-recall curves for the medium and large-sized waste bins. Based on the results, there is still room for improvement in training the server-based waste bin detector. However, the average precision and recall metrics for large-sized waste bins confirm that our current detector can reasonably identify bins of interest since most fall under the large-sized category in at least one video frame. This is further supported by the precision-recall curve for large-sized waste bins.

TABLE III
SERVER-BASED WASTE BIN DETECTOR METRICS

Bounding Box Size	Average Precision	Average Recall
All Sizes	44.2%	56.9%
Medium	57.3%	67.1%
Large	74.8%	79.2%

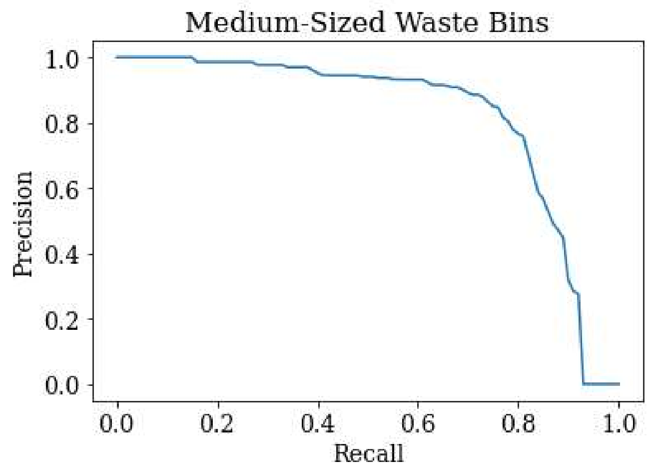

Fig. 5. Precision-recall curve for medium-sized waste bins (bounding box area is between 1,024 and 9,216 pixels).

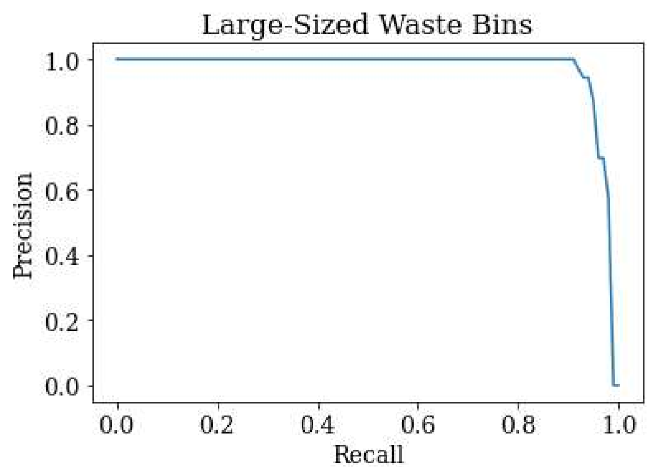

Fig. 6. Precision-recall curve for large-sized waste bins (bounding box area is greater than 9,216 pixels).

B. *Proof-of-Concept Waste Bin Multi-Class Detector*

After following the training procedure detailed in Section IV, our waste bin multi-class detector was evaluated using the classification test set. For each class, the average precision score was recorded. The model achieves an average precision of 45.3% for not-full waste bins, 7.0% for full waste bins, and 54.0% for garbage bags. These metrics signal that the multi-class detection approach is insufficient for completing our desired task. Moving forward, we will separate the detection and classification tasks from one another to determine if using separate but connected models improves the final classification performance.

VI. CONCLUSIONS

In this paper, we present a waste bin detection and garbage level classification system that can be installed onto public transit buses to monitor waste bins along bus routes. Our results support that we can train detection models to identify waste bins as the bus drives past them. In particular, our evaluated model frequently detects waste bins of interest since these instances are always medium or large-sized within the captured images. Additionally, important waste bin instances are usually captured in several frames, further increasing our system's capabilities of detecting all bins of interest. This paper also explores the possibility of using a single model to both detect and classify full waste bins. However, the results do not support that such a model can successfully accomplish this task.

A. Future Works

Before advancing with the development of our proposed pipeline, we will gather and label more bus data. While all parts of the system will benefit from having access to more training data, the classification of full waste bins will improve the most as our dataset currently has very few instances belonging to this class. The data will be collected along the same bus route using the same transit bus company to keep data collection consistent.

Upon completion of our pipeline, we will deploy the respective models onto the transit bus and cloudlet server to evaluate their performance in real-time. Once we have collected enough results after deployment, we will re-analyze our pipeline and make appropriate changes until it can detect and classify full waste bins with high consistency. We will then deploy the system onto other buses traveling along different routes within the same area to evaluate how the system performs in environments independent of the training data. We hope our work will inspire other researchers to develop similar useful systems that utilize public transportation to accomplish their tasks.

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