ZeroWaste Dataset: Towards Automated Waste Recycling

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Abstract

Less than 35% of recyclable waste is being actually recycled in the US [1], which leads to increased soil and sea pollution and is one of the major concerns of environmental researchers as well as the common public. At the heart of the problem is the inefficiencies of the waste sorting process (separating paper, plastic, metal, glass, etc.) due to the extremely complex and cluttered nature of the waste stream. Automated waste detection strategies have a great potential to enable more efficient, reliable and safer waste sorting practices, but the literature lacks comprehensive datasets and methodology for the industrial waste sorting solutions. In this paper, we take a step towards computer-aided waste detection and present the first in-the-wild industrial-grade waste detection and segmentation dataset, ZeroWaste. This dataset contains over 1800 fully segmented video frames collected from a real waste sorting plant along with waste material labels for training and evaluation of the segmentation methods, as well as over 6000 unlabeled frames that can be further used for semi-supervised and self-supervised learning techniques. ZeroWaste also provides frames of the conveyor belt before and after the sorting process, comprising a novel setup that can be used for weakly-supervised segmentation. We present baselines for fully-, semi- and weakly-supervised segmentation methods. Our experimental results demonstrate that state-of-the-art segmentation methods struggle to correctly detect and classify target objects which suggests the challenging nature of our proposed in-the-wild dataset. We believe that ZeroWaste will catalyze research in object detection and semantic segmentation in extreme clutter as well as applications in the recycling domain. Our project page can be found at http://ai.bu.edu/zerowaste/.

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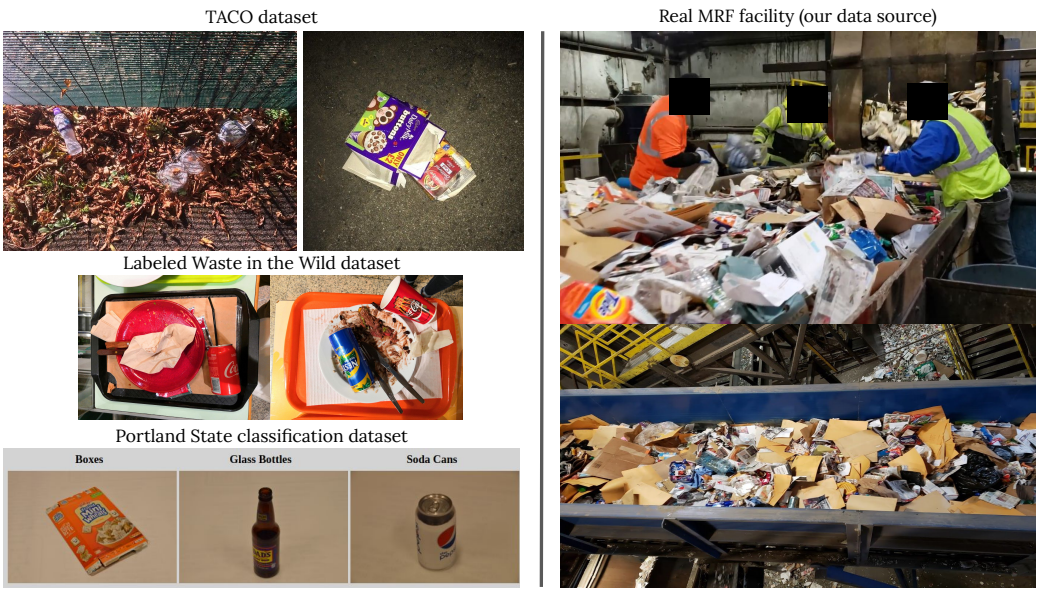

Figure 1: **Left:** examples of the existing waste detection and classification datasets (top to bottom): Trash Annotation in Context (TACO) [2], Labeled Waste in the Wild [3], Portland State University Recycling [4] datasets. **Right:** footage of the waste sorting process at a real Materials Recovery Facilities (MRF). The domain shift between the simplified datasets with solid background and little to no clutter and the real images of the conveyor belt from the MRF makes it impossible to use models trained on these datasets for automated detection on real waste processing plants. In this paper, we propose a new `ZeroWaste` dataset collected from a real waste sorting plant. Our dataset includes a set of densely annotated frames for training and evaluation of the detection and segmentation models, as well as a large number of unlabeled frames for semi- and self-supervised learning methods. We also include frames of the conveyor belt before and after manual collection of foreground objects to facilitate research on weakly supervised detection and segmentation. Please see Figure 2 for the illustration of our `ZeroWaste` dataset.

1 Introduction

As the world population grows and gets increasingly urbanized, waste production is estimated to reach 2.6 billion tonnes a year in 2030, an increase from its current level of around 2.1 billion tonnes [5]. Efficient recycling strategies are critical to reduce the devastating environmental effects of rising waste production. Materials Recovery Facilities (MRFs) are at the center of the recycling process. These facilities are where the collected recyclable waste is sorted into separate bales of plastic, paper, metal and glass. The accuracy of the sorting directly determines the quality of the recycled material; for high-quality, commercially viable recycling, the contamination levels (anything but the desired material) need to be less than a few percent of the bale. Even though the MRFs utilize a large number of machinery alongside manual labor [6], the extremely cluttered nature of the waste stream makes automated waste detection (*i.e.* detection of waste objects that should be removed from the conveyor belt) very challenging to achieve, and the recycling rates as well as the profit margins stay at undesirably low levels (e.g. less than 35% of the recyclable waste actually got recycled in the United States in 2018 [1]). Another crucial aspect of manual waste sorting is the safety of the workers that risk their lives daily picking up unsanitary objects (*e.g.* medical needles).

Recent advances in object classification and segmentation provide a great potential to make the recycling process more efficient, more profitable and safer for the workers. Accurate waste classification and detection algorithms have a potential to enable new sorting machinery (e.g. waste sorting robots), improve the performance of existing machinery (e.g. optical sorters [6]), and allow automatic quality control of the MRFs' output. Unfortunately, the research community is lacking the gold-standard in-the-wild datasets to train and evaluate the classification and segmentation algorithms for industrial waste sorting. While several companies do development on this subject (e.g. [7, 8, 9]), they keep their dataset private, and the few existing open-source datasets [2, 3, 4, 10] are very limited in data amount and/or generated in uncluttered environments, not representing the complexity of the domain (see Figure 1). In this paper, we propose a first large-scale in-the-wild waste detection dataset `ZeroWaste` that is specifically designed for the industrial waste detection. `ZeroWaste` is a dataset that is fundamentally different from the popular detection and segmentation benchmarks: high level

Figure 2: Examples of images (**left**) and the corresponding polygon annotation (**right**) of the proposed `ZeroWaste` dataset. At the end of this conveyor belt, only paper objects must remain. Therefore, we annotated the objects of four material types that should be removed from the conveyor belt as foreground: soft plastic, rigid plastic, cardboard and metal. The background includes the conveyor belt and paper objects. Severe clutter and occlusions, high variability of the foreground object shapes and textures, as well as severe deformations of objects usually not present in other segmentation datasets, make this domain very challenging for object detection. More examples of our annotated data can be found in Section B.3 of the Appendix (*best viewed in color*).

of clutter, visual diversity of the foreground and background objects that are often severely deformed, as well as a fine-grained difference between the object classes (*e.g.* brown paper vs. cardboard, soft vs. rigid plastic) – all these aspects pose a unique challenge for the automated vision. We envision that our open-access dataset will enable computer vision and robotics communities to develop more robust and data-efficient algorithms for object detection, robotic grasping and other related problems.

Our contributions can be summarized as follows:

1. We propose the first fully-annotated `ZeroWaste-`f dataset specifically designed for industrial waste object detection. The proposed `ZeroWaste-`f dataset contains video frames from a real MRF conveyor belt densely annotated with instance segmentation and proposes a challenging real-life computer vision problem of detecting highly deformable objects in severely cluttered scenes. In addition to the fully annotated frames from `ZeroWaste-`f set, we include the unlabeled `ZeroWaste-`s set for semi-supervised learning.
2. We introduce a novel before-after data collection setup and propose the `ZeroWaste-`w dataset for binary classification of frames before and after the collection of target objects. This binary classification setup allows much cheaper data annotation and allows further development of weakly supervised segmentation and detection methods.
3. We implement the fully-supervised detection and segmentation baselines for the `ZeroWaste-`f dataset and semi- and weakly-supervised baselines for `ZeroWaste-`s and `ZeroWaste-`w datasets. Our experimental results show that popular detection and segmentation methods struggle to generalize to our proposed data, which indicates a challenging nature of our in-the-wild dataset and suggests that more robust and data-efficient methods must be developed to solve the waste detection problem.

2 Related Work

Detection and Segmentation Datasets Many datasets for image segmentation have been proposed with the goal of densely recognizing general objects and "stuff" in image scenes like street view [11, 12, 13], natural scenes [14, 15, 16, 17, 18], and indoor spaces [19, 20, 21]. Yet, few of them have

been designed for the more challenging vision task required in automated waste recycling, aiming to densely identify and segment deformable recyclable materials, many of which look very similar to each other, from a highly cluttered background [6]. Several related datasets have been proposed that contain only image-level labels. For example, *Portland State University Recycling* [4] consists of 11500 labeled images of five common recyclable types: box-board, glass bottles, soda cans, crushed soda cans and plastic bottles. Similarly, *Stanford TrashNet* [10] presents 400 images containing a single waste object from six predefined classes. Though beneficial for image-level classification in well-defined conditions, images of in these two datasets have very simple background and do not apply to waste object localization. To enable localization tasks, *Labeled Waste in the Wild* [3] annotated bounding boxes for objects of 20 classes in 1002 food tray photos. *Annotation in Context (TACO)* [2] went one step further by densely annotating 60 litter objects from 1500 images. Yet TACO contains deliberately collected outdoor scenes with one or a few foreground objects that are rarely occluded, which makes it less practical for materials recovery scenarios. In contrast, our `ZeroWaste` was collected from the front lines of a waste sorting plant where the collected objects are frequently severely deformed and occluded, which makes both detection and segmentation a significantly more challenging and practical task.

Detection and Segmentation Methods Image segmentation is an essential component in robotic systems like automated waste sorters [6], as it partitions images into multiple regions or objects suitable for grasping. Image segmentation can be formulated as a task that classifies each pixel into a set of labels [22]. Recent semantic segmentation models [23, 24, 25, 26] have achieved state-of-the-art performance for recognizing general object/stuff classes from natural scene images. Instance segmentation [27, 28, 29, 30] works by further consider instance identity for objects. Representative frameworks like MaskRCNN [31] effectively detect objects in images and simultaneously generate high-quality masks, which enables efficient interaction between robots and target objects. Yet due to their data-hungry nature, these methods rely on large volumes of annotated data for training, which can be challenging and expensive, especially in specialized application scenarios [32]. Recycling annotation in particular requires expert labelers and is thus even more costly. Semi-supervised segmentation methods have been proposed to address such limitations by jointly learning from both annotated and unannotated images [33, 34, 35, 36, 37, 38]. Weakly-supervised segmentation methods exploit annotations that are even easier to obtain, e.g. image-level tags [39, 40, 41]. These methods typically utilize class activation maps (CAM) [42] to select the most discriminative regions, which are later used as pixel-level supervision for segmentation networks [43, 44, 45]. All these advanced segmentation models are trained on general-purpose data, and applying them to waste sorting scenarios presents challenges like domain shift. To study the effectiveness of existing models and enable further improvement for the waste sorting task, we test our proposed `ZeroWaste` with previous state-of-the-art methods and report their performance as baselines.

3 `ZeroWaste` Dataset

In this section, we describe our `ZeroWaste-`*`f`* dataset for fully supervised detection and evaluation, unlabeled `ZeroWaste-`*`s`* data for semi-supervised learning and `ZeroWaste-w` dataset of images before and after the removal of target objects for weakly supervised detection. The datasets are licensed under the Creative Commons Attribution-NonCommercial 4.0 International License [46]. The MRF at which the data was collected agreed to release the data for any non-commercial purposes and decided to remain unacknowledged.

Data Collecion and Pre-processing The data was collected from a high-quality paper conveyor of a single stream recycling facility in Massachusetts. The sorting operation on this conveyor aims to keep high quality paper and consider anything else as contaminants including non-paper items (*e.g.* metal, plastic, brown paper, cardboard, boxboard). We collected data during the regular operation of the MRF using two compact recording installations at the start and end of the conveyor belt (see Fig. 3, right), that is, footage is captured simultaneously both at the unsorted and sorted sections of the same conveyor. The recording apparatus is designed to fit the constraints of the facility: In order not to disrupt the MRF operation and be able to work in confined spaces available near the conveyor the recording platform needs to be compact, non-intrusive (to the workers), and portable (easy to move, battery-powered). Note that the cameras are not directly mounted on the conveyor but to a stand-alone platform, to reduce vibrations transmitted to the cameras. Additional considerations are

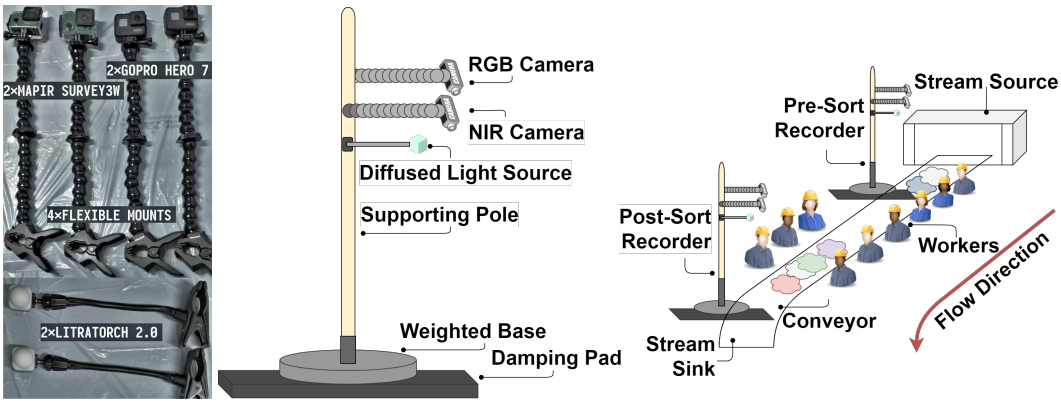

Figure 3: The footage recording setup is designed to fit the constraints of the facility environment. **Left:** The specific cameras and lamps used. **Center:** Assembly of each recording apparatus. **Right:** Layout of the recording setup in the recycling environment.

made (see Figure 3, center): (1) Damping pads are installed to counter the ground vibrations of the heavy machinery and reduce vibrations on the camera even further; (2) Weighted bases lower the center of mass to keep the apparatus stable.

We used the GoPro Hero 7 for RGB footage, and we additionally collected the the near-infrared (NIR) footage simultaneously with the RGB footage using the MAPIR Survey3W NIR camera for the future work (specifically, it captures at a wavelength of 850 nm). The cameras in their encasings meet both the portability and ruggedness requirements. To maintain consistent lighting, two LitraTorch 2.0 portable lamps are installed with a light diffuser. This softens the light and spreads it more evenly in the scene. Both cameras were installed at around 100 cm above the conveyor, and the light sources at around 80 cm. Sequences of twelve videos of total length of 95 minutes and 14 seconds with FPS 120 and size 1920×1080 were collected and processed. The preprocessing of the collected data involved the following steps:

1. Rotation and cropping. The frames were rotated so that the conveyor belt is parallel to the frame borders and cropped to remove the regions outside the conveyor belt. We ensured that any personal information or identifiable footage of the workers at the conveyor belt was excluded from our data.
2. Optical distortion. We removed the distortion [47] using the OpenCV [48] library to compensate for the fish-eye effect caused by the proximity of the cameras to the conveyor belt.
3. Deblurring. We used the SRN-Deblur [49] method to remove motion blur resulting from the fast-moving conveyor belt. According to our visual inspection, SRN-Deblur achieves satisfactory deblurring and does not introduce the undesired artifacts that usually appear when classical deconvolution-based methods are used.
4. Subsampling. We sampled every tenth frame from the video to avoid redundancy.

The illustration of the original frames shot at the beginning of the conveyor belt and the corresponding preprocessing results can be found on Figure 8 in Section B.3 of the Appendix.

Densely Annotated `ZeroWaste-f` and Unlabeled `ZeroWaste-s` Datasets The fully annotated `ZeroWaste-f` dataset consists of 1874 frames sampled from the processed videos and the corresponding ground truth polygon segmentation. We used the open-source CVAT [50] annotation toolkit to manually collect the polygon annotations of objects of four material types: cardboard, soft plastic, rigid plastic and metal. We chose this set of class labels following the MRF's guidelines for the workers to collect cardboard, plastic and metal into separate bins, as well as the fact that grasping of rigid and non-rigid objects might require the use of fundamentally different kinds of robotic systems. The polygon annotation was performed according to the following set of rules:

1. Objects of four material types were annotated as foreground: cardboard (including parcel packages, boxboard such as cereal boxes and other carton food packaging), soft plastic (*e.g.* plastic bags, wraps), rigid plastic (*e.g.* food containers, plastic bottles) and metal (*e.g.* metal cans). Paper objects were treated as background.

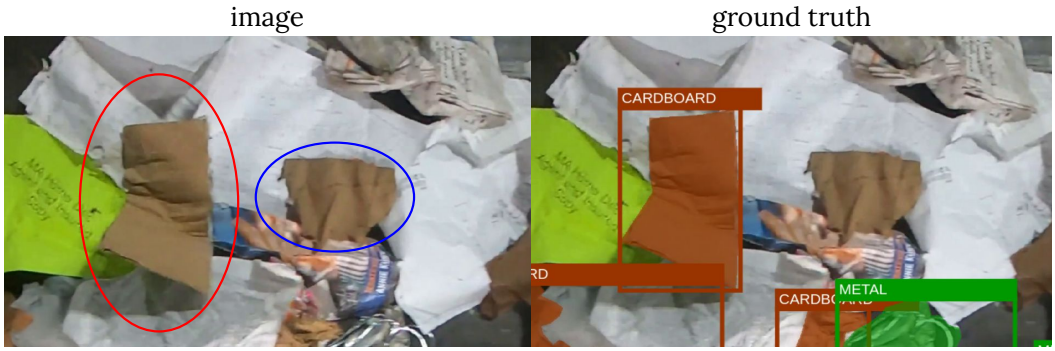

Figure 4: **Left:** example of an image from `ZeroWaste-f` dataset. **Right:** the corresponding ground truth instance segmentation. Expert training and common sense knowledge are required to distinguish between the cardboard object on the left (red circle) and the brown paper on the right (blue circle), as they are visually very similar but differ in thickness and rigidity (*best viewed in color*).

Split	#Images	*Carboard*	*Soft Plastic*	*Rigid Plastic*	*Metal*	#Objects
Train	1245	4038	1550	460	114	6162
Validation	312	795	310	195	24	1324
Test	317	1216	466	242	53	1977
Unlabeled	6212	-	-	-	-	-
Total	8086	6049	2326	897	191	9463

Table 1: Statistics of the training, validation and test splits of our `ZeroWaste-f` dataset *w.r.t.* the number of labeled objects, and the additional unlabeled `ZeroWaste-s` set of images for semi-supervised learning.

2. The entire object must be within the corresponding polygon.
3. If an object is partially occluded and separate parts are visible, we annotated them as separate objects.

Each annotated video frame was validated by an independent reviewer to pass the standards above (see Figure 2). Both the annotation and the review process were performed by the students and researchers with a computer science background specifically trained to perform the annotation. We did not delegate the annotation to the crowd-sourcing platforms, such as Amazon Mechanical Turk [51], due to the complexity of the domain that requires expert knowledge to be able to detect and correctly classify the foreground objects (see the illustration on Figure 4). The estimated average cost of the annotation and review is about 12.5 minutes per frame. The dataset was split into training, validation and test splits and stored in the widely used MS COCO [18] format for object detection and segmentation using the open-source Voxel51 toolkit [52]. Please refer to Table 1 for more details about the class-wise statistics of all splits. In addition to the fully annotated `ZeroWaste-f` examples, we provide 6212 unlabeled images that can be used to refine the detection using semi-supervised or self-supervised learning methods. We refer to this unlabeled set of images as `ZeroWaste-s` data later on in this paper.

`ZeroWaste-w` Dataset for Binary Classification We leverage the videos taken of the conveyor belt before and after the removal of the foreground objects to create a weakly-supervised `ZeroWaste-w` dataset. This dataset contains 1202 frames with the foreground objects (*before* class) and 1208 frames without the foreground objects (*after* class). One advantage of such a setup is that it is relatively cheap to acquire the ground truth labels (only an image-level inspection is required to ensure there are no false negatives in the *after* class subset). The `ZeroWaste-w` dataset is specifically collected to be used in the weakly-supervised setup and is meant to provide an alternative and more data-efficient solution to the problem. The ground truth instance segmentation is available for all images of the *before* class as it overlaps with the `ZeroWaste-f` dataset. Please see Figure 5 for an illustration of the `ZeroWaste-w` examples.

Figure 5: We installed two stationary cameras above the conveyor belt: one at the beginning of the line and another one at the end. At this particular conveyor belt, workers are asked to remove objects of any material other than paper, such as cardboard, plastic and metal. Therefore, the footage collected from the beginning of the line contains the "foreground" objects that need to be removed, and the frames from the end of the conveyor belt are supposed to only contain the "background" paper objects. We used this setup as a foundation of our `ZeroWaste-w` dataset.

4 Experiments

In this section, we provide baseline results for our proposed `ZeroWaste` dataset. We perform fully supervised instance and semantic segmentation on `ZeroWaste-f` using the most widely used Mask R-CNN [31] and DeepLabV3+ [53] respectively. We also perform fully- and semi-supervised semantic segmentation on `ZeroWaste-s` using the CCT [33] method, and report the initial segmentation quality of CAMs produced by a classifier trained on `ZeroWaste-w` dataset as a weakly-supervised baseline. The implementation of our experiments and the detailed description of the experimental setup are available at https://github.com/dbash/zerowaste.

4.1 Object Detection

Experiments with COCO-pretrained Networks It has been shown that pretraining the model on a large-scale dataset, such as MS COCO [18], improves generalization and helps to prevent severe overfitting in case when the target dataset is relatively small [54, 55, 56]. Therefore, in our first experiments, we used the initialized the model with weights learned on COCO and further finetuned it with our `ZeroWaste-f` dataset. We used a standard implementation of the popular Mask R-CNN with ResNet-50 [57] backbone provided in the popular Detectron2 [58] library in all of the experiments. The model was finetuned for 40000 iterations on the training set of our `ZeroWaste-f` dataset on a single Geforce GTX 1080 GPU with batch size 8. To compensate for a relatively small number examples in the training set and to avoid overfitting, we leveraged heavy data augmentation, including random rotation and cropping, adjustment of brightness and hue, *etc.* We report the experimental results in Table 2 (COCO $\rightarrow$ `ZeroWaste` section). A more detailed description of the results can be found in Section B.1 of Appendix.

Experiments with TACO-pretrained Mask RCNN In the next set of experiments, we utilize the TACO dataset for waste detection in the outdoor scenes distributed under Attribution 4.0 International (CC BY 4.0) license. We trained Mask R-CNN for 40000 epochs on the modified TACO dataset with the material-based labels (cardboard, soft plastic, rigid plastic, metal and other) initialized with weights from MS COCO. We then finetuned the model on the training set of `ZeroWaste-f` data and report the results in Table B.1 (TACO$\rightarrow$ `ZeroWaste` section).

Results The experimental results with Mask RCNN indicate severe overfitting to the training data, hence the model fails to generalize to the unseen examples. The model pretrained on the TACO dataset performs poorly on both TACO and `ZeroWaste-f` datasets, which shows that, despite its remarkable efficiency on the large-scale datasets with natural scenes, such as MS COCO or Pascal VOC [59], Mask RCNN cannot generalize to our relatively small, extremely cluttered data with very diverse deformable objects. Recalling the history of success with other complex segmentation and detection datasets (*e.g.* from mIoU 57% in 2015 [60] to 84% in 2020 [61] on CityScapes [11], or from 51.6% in 2014 [62] to 90% in 2020 [63] on PASCAL VOC 2012 [59]), and knowing that the task *can* be solved by humans with a little training, we believe that the computer vision community will eventually come up with efficient methods for this challenging task.

	TACO → ZeroWaste			**COCO → ZeroWaste**		
	AP	AP50	AP75	AP	AP50	AP75
Train	39.11	54.77	44.58	62.55	81.59	71.59
Validation	15.86	28.83	16.37	14.99	23.62	16.09
Test	14.55	25.9	14.81	14.79	25.94	14.82

Table 2: Instance segmentation results of Mask R-CNN pretrained on TACO dataset (**left**) and MS COCO dataset (**right**).The model pretrained on MS COCO overfits to the training split, while pretraining on TACO dataset significantly reduces overfitting but does not yield a significant improvement in detection accuracy on the validation and test sets. Please refer to Tables 4 in the Appendix for class-wise results.

4.2 Semantic Segmentation

Fully supervised experiments We used the state-of-the-art DeeplabV3+ model as a fully-supervised semantic segmentation baseline for our dataset. DeeplabV3+ is an efficient segmentation model that combines the atrous convolutions to extract the features in multiple scales, and an encoder-decoder paradigm to gradually sharpen the object boundary using the intermediate features. As in the detection experiments, we used a standard implementation of DeeplabV3+ from Detectron2 library. We used the model with ResNet-101 backbone with three 3×3 convolutions instead of the first 7×7 convolution that was pretrained on Cityscapes dataset [11]. We froze the first three stages of the backbone (convolution and two first residual block groups) and finetuned the model on the training set of `ZeroWaste-f` for 10000 iterations with starting learning rate 0.01 and batch size 40 on a single GPU RTX A6000 which took approximately 14 hours. As in the previous experiments, we augmented the data extensively to prevent overfitting. The results of our experiments on all `ZeroWaste-f` splits can be found on the Table 3.

Semi-supervised experiments For a semi-supervised segmentation baseline, we used an official implementation of Cross-Consistency Training CCT [33] method. CCT uses a shared encoder and several auxiliary decoders each of which performs various augmentations, such as spatial dropout, random noise, cutout of object regions *etc.* , and a cross-entropy-based loss to force the unlabeled predictions to be consistent across all decoders. Since CCT uses a different backbone architecture from DeeplabV3+, we first trained CCT on the labeled `ZeroWaste-f` data only for comparison with the semi-supervised setting. We used the same default hyperparameters reported in the paper for both supervised and semi-supervised experiments (the exact configuration can be found in our project). We report the mean Intersection over Union (mIoU) as well as mean pixel accuracy for both setups in Table 3, and more details can be found in Section B.2 of the Appendix.

Weakly-supervised baseline As a baseline for weakly-supervised segmentation, we trained a binary classifier on the before and after collection frames of the `ZeroWaste-w` dataset. We used a standard Pytorch [64] implementation of ResNet50 [57] pretrained on ImageNet [65] for our classifier, and trained it for 5 epochs with learning rate 5×10^{-4} using the binary cross-entropy loss. The resulting classifier obtained over 98% accuracy on the test set. We then used RISE [66], a black-box saliency generating technique, to extract the class activation maps (CAMs). RISE masks the input image with a set of random binary masks and returns the linear combination of the resulting CAMs weighted with the corresponding masks. The maps generated by RISE are then normalized and thresholded with 0.621 that results in highest mIoU on the training set. For comparison, we computed the mean pixel accuracy and mIoU on randomly generated masks with the probability of each pixel belonging to the foreground class equal to the average fraction of the foreground pixels in the `ZeroWaste-w` dataset

	Supervision	Train		Validation		Test	
		mIoU	Pixel Acc.	mIoU	Pixel Acc.	mIoU	Pixel Acc.
Random	none	7.2	74.7	7.2	75.3	8.4	71.8
CAM	weak	15.7	43.9	16.3	47.5	18.6	43.2
CCT semi	semi	61.2	97.4	29.40	83.3	30.0	83.6
CCT	full	65.38	97.9	29.80	83.4	29.20	81.2
DeeplabV3+	full	88.5	98.19	40.16	91.23	39.06	88.47

Table 3: Results of CAMs produced by RISE [66] with a binary classifier trained on `ZeroWaste-w` before and after frames, CCT [33] trained only using the `ZeroWaste-f` , CCT trained with `ZeroWaste-f` and `ZeroWaste-s` , and DeepLabV3+ [53] on our `ZeroWaste-f` dataset. Results indicate that 1) severe overfitting occurs in the supervised scenario; 2) unlabeled `ZeroWaste-s` images do not significantly improve the segmentation quality of CCT and 3) the binary classifier trained on `ZeroWaste-w` provides plausible localization guidance that that can serve as cues for weakly-supervised segmentation. Please refer to Tables 7 and 8 for class-wise segmentation results and Figure 7 in the Appendix for confusion matrices on all splits.

14.9% and report these results in Table 3. The visualization of the resulting CAMs can be found in Figure 9 in Section B.3 of the Appendix.

Results Experimental results in Table 3 indicate that our `ZeroWaste` dataset proposes a challenging semantic segmentation task with an unusual for the standard segmentation datasets level of clutter, diversity of the foreground objects and, at the same time, their visual similarity with the background objects (all methods often tend to mistake the paper objects for cardboard and vice versa, and have a hard time distinguishing between soft and rigid plastic objects). The semi-supervised learning results indicate that the unlabeled examples from the `ZeroWaste-s` subset do not significantly help CCT improve the overall segmentation quality. As seen from the class-wise segmentation results on Table 8 in Section B.2 of Appendix, additional training of CCT with unlabeled data results in higher segmentation accuracy of the most frequent classes (*e.g.* cardboard and background), but degrades the performance on the objects of the rare classes (*e.g.* metal). Additionally, the binary classification results show that a simple CAM-based approach with cheap `ZeroWaste-w` data provides meaningful localization cues that can be further used for weakly- and semi-supervised segmentation.

5 Impact and Limitations of `ZeroWaste`

Machine Learning Research `ZeroWaste` provides a gold standard for the evaluation of different waste sorting methods. It will catalyze research in the areas of fully, semi, and weakly supervised segmentation, data-efficient learning and domain adaptation. Our dataset provides a real-world application that is significantly more challenging than the previously used benchmarks for these tasks.

Robotics Research This dataset will enable the development of robotic manipulation algorithms for waste sorting. It will facilitate research in object picking algorithms that can work with extremely cluttered scenes using realistic segmentation polygons. Integrating high-level reasoning about object classes and properties (e.g. hard/soft materials) to the picking algorithm will provide novel research avenues and can significantly boost the picking accuracy.

Limitations and Future Directions Despite the fact that `ZeroWaste` is to the date the largest public dataset for waste detection and segmentation, it is still smaller than the standard large-scale benchmarks due to the fact that the annotation process for this domain is very expensive. For this reason, state-of-the-art detection and segmentation methods tend to overfit to the training data and therefore do not generalize well to the unseen examples. As future work, we plan to increase the diversity of our dataset by using synthetic-to-real domain adaptation and other data augmentation techniques. Another important future direction is to utilize visual signals of other modalities, *e.g.* near infrared footage that can be especially useful for distinguishing different material types.

Societal Impact This paper is a part of a collaboration project that investigates the implications of deploying new AI and Robotics algorithms to MRFs [67]. We believe that human-robot collaboration is essential for more efficient computer-aided recycling, quality control of the sorting process, as well as in establishing safer work conditions for the MRF workers (*e.g.* by detecting dangerous waste items, such as sharp or explosive objects). This dataset can potentially be used to develop fully-automated MRFs with waste sorting robots, which may compromise the financial security of the MRF workers.

However, after consulting with experts, we found that such fully-automated solutions would be far from sufficient to meet the contamination levels required in recycling, especially considering the complex, cluttered and varying nature of the waste stream. Given that only a small portion of the recyclable waste is currently getting recycled, achieving an efficient human-robot collaboration has a potential to solve the pressing problem of water and soil pollution.

6 Conclusion

This work introduces the largest public dataset for waste detection. `ZeroWaste` is designed as a benchmark for training and evaluation of fully, weakly, and semi-supervised detection and segmentation methods, and can be directly used for a broader category of tasks including transfer learning, domain adaptation and label-efficient learning. We provide baseline results for the most popular fully, weakly, semi-supervised, and transfer learning techniques. Our results show that current state-of-the-art detection and segmentation methods cannot efficiently handle this complex in-the-wild domain. We anticipate that our dataset will motivate the computer vision community to develop more data-efficient methods applicable to a wider range of real-world problems.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] Please see Section 4
   (c) Did you discuss any potential negative societal impacts of your work? [Yes] Please refer to the Section 5
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [N/A] No theoretical results
   (b) Did you include complete proofs of all theoretical results? [N/A] No theoretical results
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] See Section 3 for our data URL and 4 containing the link to our Github project containing the code for all the experiments
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See Section 4 as well as the configuration logs for all of our experiments on our project page
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See Section 4
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes] see Sections 2 and 4
   (b) Did you mention the license of the assets? [Yes]
   (c) Did you include any new assets either in the supplemental material or as a URL? [Yes] project URL in Section 4 and link to the dataset in Section 3
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes] mentioned tMRF's consent in Section 3
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] mentioned that we removed the identifiable information in Section 3
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [Yes] provided the annotation guidelines in Section 3
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [Yes] We included this information to the Datasheet.

A Additional Information for the Reviewers

A.1 Author Responsibility Statement

The authors of this paper confirm that they bear all responsibility in case of violation of rights. The proposed ZeroWaste data will be released under the Creative Commons Attribution-NonCommercial 4.0 International License upon acceptance.

A.2 Data Hosting and Maintenance Plan

For this submission, reviewers can download our data on the FTP server hosted by Boston University (please see the URL provided with the submission).

Upon publication, our dataset will be stored in Zenodo data repository (https://zenodo.org/) and will be accessible upon request according to the dataset license. The ZeroWaste dataset page on Zenodo is: https://doi.org/10.5281/zenodo.4899927. All the consecutive versions of the dataset will also be published on Zenodo that provides a persistent versioned mirror of the uploaded data.

A.3 Links to the Data

The main project page can be found here: http://ai.bu.edu/zerowaste/. The ZeroWaste-*f* is stored in the MS COCO format and can be read using the standard tools, such as Pycocotools. Additionally, we host a web-server for the visualization of our dataset: http://emmy.bu.edu:5000/. Please see Figure 6 to learn how to use the visualization tool.

The code and configurations used in our experiments can be found here: https://github.com/dbash/zerowaste.

DOI: 10.5281/zenodo.4899927

Link to metadata: https://zenodo.org/record/4899927/export/schemaorg_jsonld#.YLpUHTdKhhE

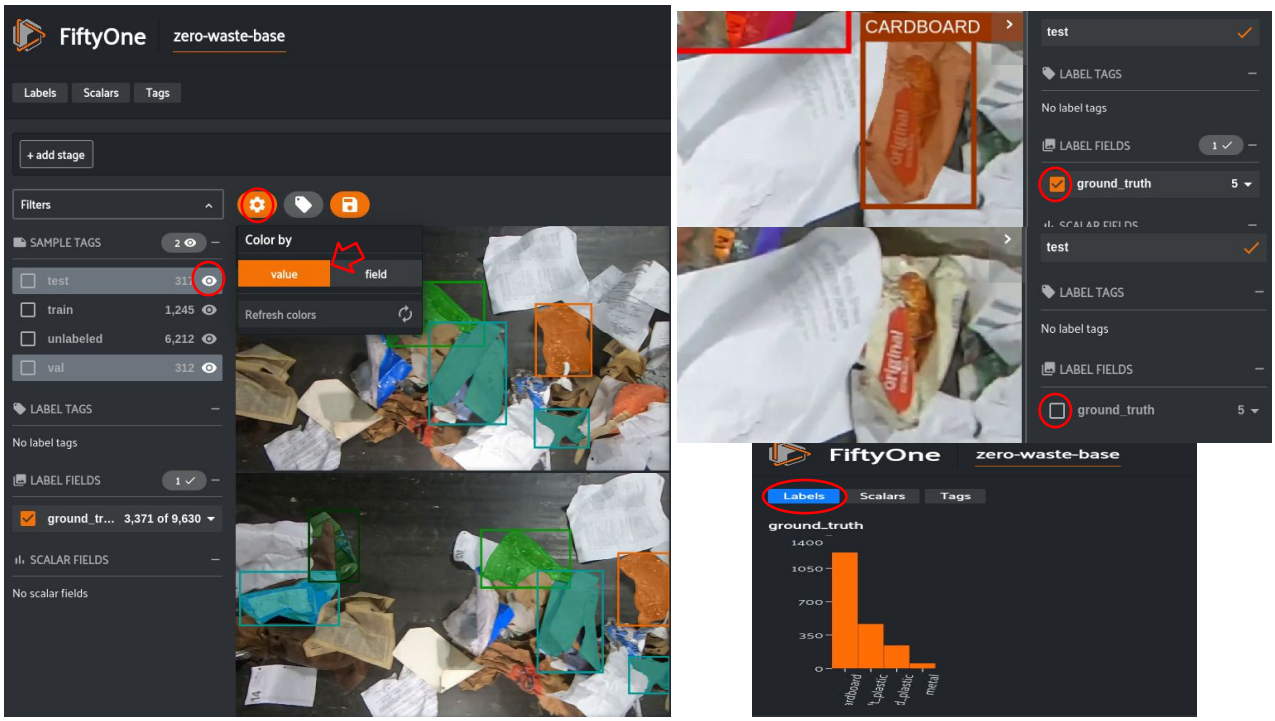


Figure 6: **Left:** To see examples from a particular split (*e.g.* test), please click the eye icon on the left sidebar of the corresponding split. To make the annotations appear in different colors depending on the class label, please select the "Color by value" option. **Right:** In order to show or hide the annotations, please select the "ground truth" option on the right sidebar after clicking on the particular image. Selecting "Labels" option in the top left corner of the page will show the class-wise statistics in the selected split. For more information, please refer to the official guide of Voxel FiftyOne.

B Appendix

B.1 Mask R-CNN experiments

Please see Table 4 for a detailed results of the experiments with Mask RCNN pretrained with COCO, and Tables 6 and 5 for the TACO-pretraining results. The pretreining results on TACO dataset with `ZeroWaste` labels can be found in Table 4.

	AP *Cardboard*	AP *Soft Plastic*	AP *Rigid Plastic*	AP *Metal*	Total AP
Train	47.34	36.76	23.05	62.73	42.47
Validation	23.43	22.39	8.60	1.96	14.09
Test	28.33	13.17	17.45	0.01	14.74

Table 4: Class-wise average precision results of a COCO-pretrained Mask R-CNN on our `ZeroWaste-f` dataset.

	AP *Cardboard*	AP *Soft Plastic*	AP *Rigid Plastic*	AP *Metal*	Total AP
Train	41.60	34.00	20.21	60.14	39.12
Validation	27.28	23.37	6.37	6.43	15.86
Test	26.42	14.52	17.19	0.06	14.55

Table 5: Class-wise average precision results of a TACO-pretrained Mask R-CNN on our `ZeroWaste-f` dataset.

	AP *Cardboard*	AP *S. Plastic*	AP *R. Plastic*	AP *Metal*	AP *Other*	Total AP	AP50	AP75
Train	21.90	20.02	20.47	31.93	4.23	19.71	27.86	20.94
Test	5.12	14.96	11.90	5.79	2.91	8.14	13.25	8.55

Table 6: Class-wise average precision results of a COCO-pretrained Mask R-CNN on the TACO-zerowaste dataset.

B.2 Segmentation experiments

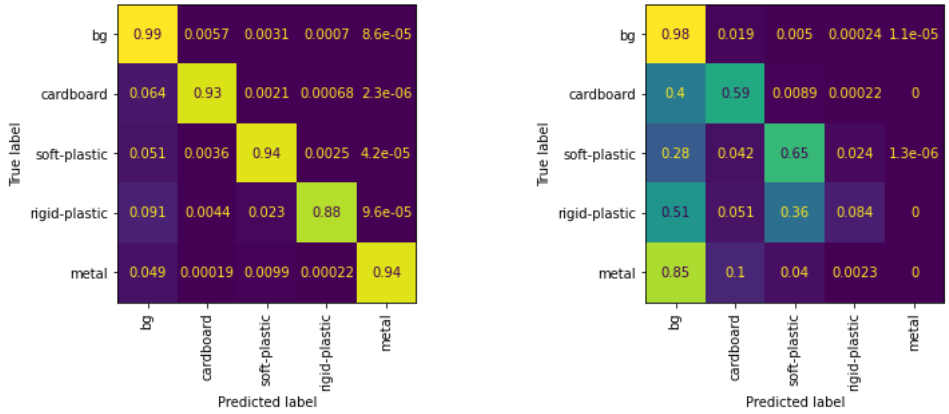
Table 7 shows the segmentation results of DeeplabV3+ for each class in `ZeroWaste` dataset. The confusion matrices of DeeplabV3+ for each split can be found on Figure 7. Please see the examples of the CCT pretdicitons in supervised and semi-supervised settings on Figure 12. Detailed DeeplabV3+ and CCT results can be found on Tables 7 and 8 respectively.

	Train			**Validation**			**Test**		
	IoU	Precision	Recall	IoU	Precision	Recall	IoU	Precision	Recall
Background	98.0	98.9	99.0	91.6	93.7	97.6	88.8	91.8	96.4
Cardboard	88.6	94.6	93.3	47.7	70.7	59.4	47.7	73.6	57.5
Soft plastic	88.6	93.6	94.2	53.8	75.1	65.5	47.3	63.1	65.3
Rigid plastic	80.3	89.9	88.2	7.8	50.7	8.4	11.4	46.4	13.1
Metal	87.1	92.2	94.0	0.0	0.0	0.0	0.1	4.7	0.2
mean	88.5	93.9	93.8	40.2	58.0	46.2	39.1	55.9	46.5

Table 7: Experimental results of DeepLabV3+ [53] on our `ZeroWaste-f` dataset.

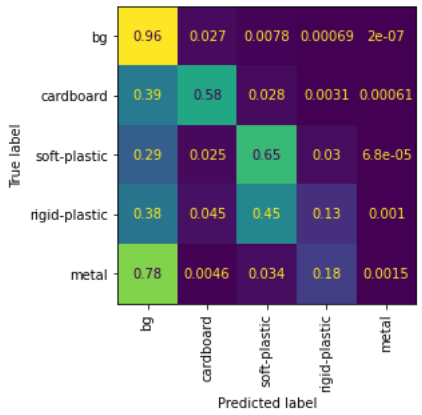
	Background	*Cardboard*	*S. plastic*	*R. Plastic*	*Metal*	**mIoU**	**Pixel Acc.**
supervised	81.7	39.8	22.6	0.4	0.04	28.9	81.2
semi-supervised	83.3	40.3	23.2	0.0	0.0	29.4	83.6

Table 8: Class-wise mIoU results of CCT on the test set of `ZeroWaste-f`. Results indicate that, while training with additional unlabeled examples slightly improves the segmentation accuracy of the most frequent classes (background and cardboard), it also results in the model misclassifying objects of the rare classes (metal).



(a) Train

(b) Val



(c) Test

Figure 7: Confiusion matrices of Deeplabv3+ on train, validation and test splits of `ZeroWaste-f`.

B.3 More data examples

The example of a frame from ZeroWaste before and after processing as described in Section 3 can be found on Figure 8. The examples of frames of ZeroWaste-*w* dataset of images *before* and *after* the collection of the foreground objects along with the RISE CAM results can be found on Figure 9.

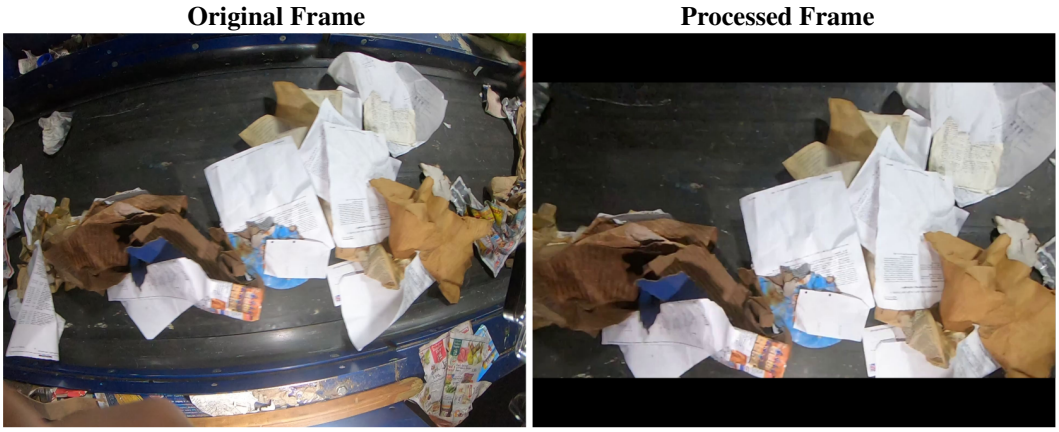


Figure 8: **Left:** sample video frame from ZeroWaste *before* collection of target objects to be removed from the conveyer belt. **Right:** the same video frame processed as described in section 3: fisheye effect removed, frame rotated to make the conveyor belt parallel to the image border, regions outside conveyor belt cropped out, motion blur removed.

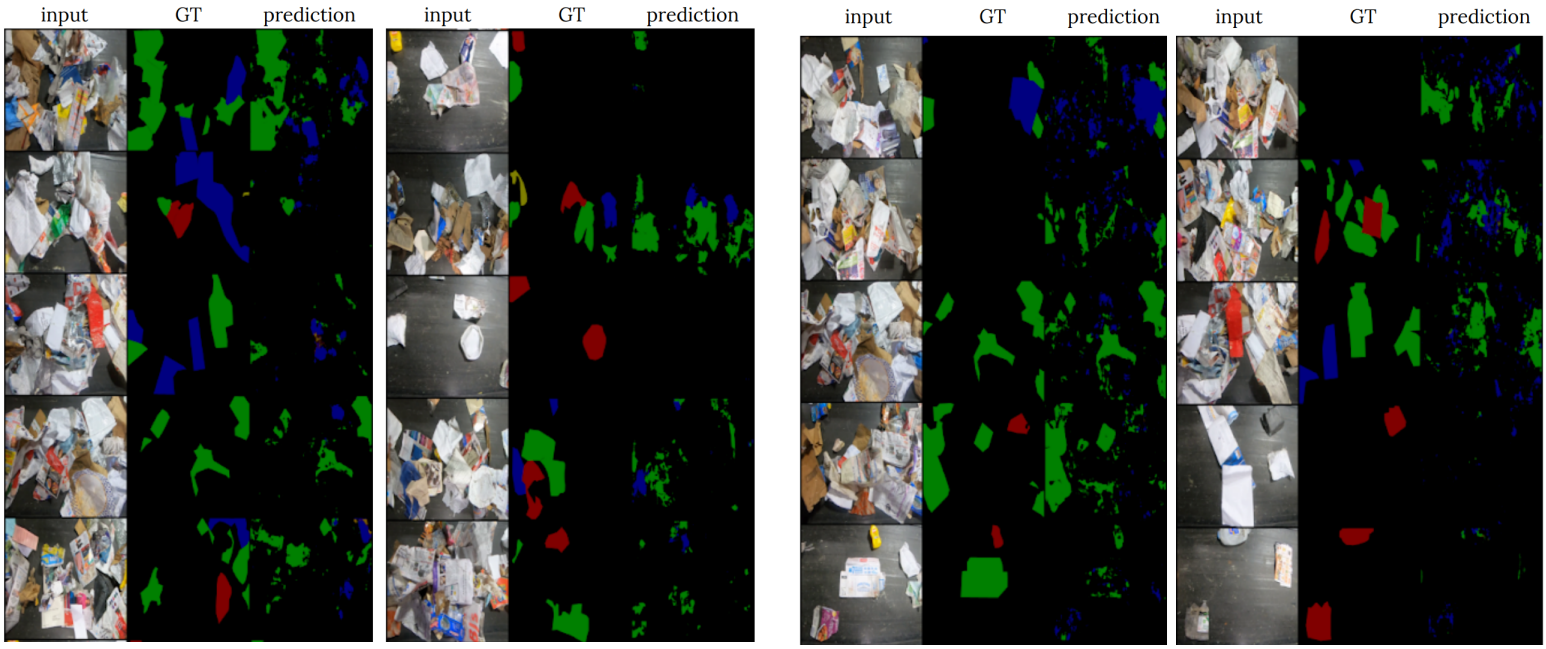
(a)

(b)

Figure 9: Examples of `ZeroWaste-w` data. **Left** examples of *After* collection frame. **Middle:** ground truth segmentation of the *Before* class example. **Right:** the corresponding CAM produced by RISE using a ResNet50 binary classifier trained on `ZeroWaste-w` data.
More examples of the fully annotated `ZeroWaste-f` dataset can be found on Figures 10 and 11. The illustration of the results of CCT in the semi-supervised and fully-supervised settings are shown on Figures 12a and 12b respectively.

Figure 10: Examples of images (**left**) and the corresponding polygon annotation (**right**) of the proposed `ZeroWaste` dataset.

Figure 11: Examples of images (**left**) and the corresponding polygon annotation (**right**) of the proposed `ZeroWaste` dataset.



(a) Semi-supervised results

(b) Supervised results

Figure 12: Examples of predictions of the semi-supervised (**a**) and supervised (**b**) versions of the CCT method on the images from the validation set.

C ZeroWasteDataset Datasheet

C.1 Motivation

- **For what purpose was the dataset created?** The ZeroWaste dataset was created for the development and evaluation of detection algorithms for industrial waste sorting. While some efforts have been made by the computer vision community to create some data specifically targeted towards automated waste classification [4, 10] and detection [2, 3], the available data is very limited to the simplistic scenario of a constant background and little to no clutter. ZeroWaste fills this gap and introduces set of densely labeled frames of a conveyor belt from a real Materials Recovery Facility (MRF) that is specifically designed for the industrial waste sorting. We hope that our open-access dataset will push both the computer vision and the robotics communities towards more robust and data-efficient algorithms for object detection, robotic grasping and many other related problems.
- **Who created the dataset?** The dataset was collected by the Robotics Lab at Worcester Polytechnic Institute, namely James Akl and Fadi Alladkani under supervision of Professor Berk Calli, and processed and tested by the Image and Video Computing Lab at Boston University, namely: Dina Bashkirova, Ziliang Zhu and Ping Hu under supervision of Professor Kate Saenko, Professor Sarah Adel Bargal and Dr. Vitaly Ablavsky.
- **Who funded the creation of the dataset?** This paper is a part of an NSF-funded [67] collaboration project that investigates the implications of new AI and Robotics technology to MRFs and the recycling process.

C.2 Composition

- **What do the instances that comprise the dataset represent (e.g., documents, photos, people, countries)?** The dataset consists of a set of RGB frames from video data collected at the conveyor belt dedicated to sorting paper from objects of other material types in an MRF in Massachusetts. The polygon annotation of the objects that should be removed from the conveyor belt (objects of four classes: cardboard, soft plastic, rigid plastic and metal) are stored in JSON format according to the MS COCO [18] standard.
- **How many instances are there in total?** The fully annotated ZeroWaste-*f* dataset with polygon annotations contains 1874 images total: 1245 in the training split, 312 in the validation split and 317 images in the test split. The unlabeled ZeroWaste-*s* dataset contains 6212 images. The binary classification ZeroWaste-*w* dataset contains 1202 frames containing target objects (*before* class) and 1208 frames without the foreground objects (*after* class).
- **Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set?** The dataset contains a small fraction of the frames originally collected: we sampled every 10th frame from the beginning of the original 120 FPS videos for the ZeroWaste-*f* subset and every 30th frame for the ZeroWaste-*s* subset. The frames of *before* class are a subset of frames from ZeroWaste-*f* with at least one foreground object. Frames from *after* class are taken from the video after collection and are filtered so that they only contain frames with no foreground objects sampled 1 in 20.
- **What data does each instance consist of?** Each image from the ZeroWaste-*f* and ZeroWaste-*s* datasets is a frame from a video shot at the beginning of the conveyor belt (before collection). These frames contain one or multiple foreground objects (objects that must be removed from the belt, in this case anything but paper).
- **Is there a label or target associated with each instance?** Each frame from ZeroWaste-*f* is associated with a set of polygons (one for each foreground object) labeled with one of four class labels: cardboard, soft plastic, rigid plastic and metal. All polygons are stored in a single JSON file in the standard MS COCO format. Additionally, for each frame in ZeroWaste-*f* we include a semantic segmentation map with each pixel assigned the corresponding class label index as in MS COCO.
- **Is any information missing from individual instances?** There are no polygon annotations for the paper objects in this dataset since paper objects are considered background (they should stay on the belt).

- **Are relationships between individual instances made explicit (e.g., users' movie ratings, social network links)?** Each frame is named in the following format: "X_frame_Y", where X is the number of the video (12 in total) the frame was taken from and Y is the frame number. Therefore, the dataset contains the information about the temporal relationship of between the frames.
- **Are there recommended data splits (e.g., training, development/validation, testing)** The `ZeroWaste-f` is split into training (1245 images), validation (312 images) and test (317) splits. We picked one sequence of 101 frames following some of the frames from the training set and two sequences of 101 images from the videos not present in the training set for the validation split, and added 10 more frames containing metal objects to compensate for the class imbalance. We chose three sequences of 101 frames that do not follow any of the frames from the training set as well as 10 frames containing metal objects to comprise the test set. We chose this setup so that all splits approximately follow the same class distribution, and to make the test split more challenging than the validation split by only containing the completely unseen data. We believe that the random sampling would not be the best choice for splitting of the frames since it would compromise the evaluation on the unseen data.
- **Are there any errors, sources of noise, or redundancies in the dataset?** The annotation was evaluated by a graduate student with common (non-expert) knowledge on the subject, and given the challenging setup it is possible that a few errors in the object labeling might occur, but the dataset has been thoroughly reviewed multiple times, so the label-level noise is possible but very rare.
- **Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)?** Yes, the dataset is self-contained and does not rely on any external resources.
- **Does the dataset contain data that might be considered confidential (e.g., data that is protected by legal privilege or by doctorpatient confidentiality, data that includes the content of individuals' non-public communications)?** No, all information that might compromise the private information about the MRF employees or other individuals was excluded from this dataset.
- **Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety?** No.
- **Does the dataset relate to people?** No.

C.3 Collection Process

- **How was the data associated with each instance acquired?** The each frame is associated with a frame from the raw RGB video collected at the MRF facility.
- **What mechanisms or procedures were used to collect the data (e.g., hardware apparatus or sensor, manual human curation, software program, software API)?** The recording apparatus is designed to fit the constraints of the facility: in order not to disrupt the MRF operation and be able to work in confined spaces available near the conveyor the recording platform needs to be compact, non-intrusive (to the workers), and portable (easy to move, battery-powered). Note that the cameras are not directly mounted on the conveyor but to a stand-alone platform, to reduce vibrations transmitted to the cameras. Additionally, (1) Damping pads are installed to counter the ground vibrations of the heavy machinery and reduce vibrations on the camera even further; (2) Weighted bases lower the center of mass to keep the apparatus stable. We used the GoPro Hero 7 for RGB footage, and we additionally collected the the near-infrared (NIR) footage simultaneously with the RGB footage using the MAPIR Survey3W NIR camera for the future work (specifically, it captures at a wavelength of 850 nm). The cameras in their encasings meet both the portability and ruggedness requirements. To maintain consistent lighting, two LitraTorch 2.0 portable lamps are installed with a light diffuser. This softens the light and spreads it more evenly in the scene. Both cameras were installed at around 100 cm above the conveyor, and the light sources at around 80 cm.
- **If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?** We deterministically

subsampled each tenth frame from the beginning of each of 12 small videos we collected for `ZeroWaste-f` dataset and every 30th frame starting after the `ZeroWaste-f` frames for the unlabeled `ZeroWaste-s` dataset. We sampled every 20th frame from the videos after *after* collection and left only the frames with no foreground objects.

- **Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?** The data collection was performed by the graduate students involved in the project. 75% of the annotations were acquired by a student researcher hired 20 hours/week for 20 USD per hour, and the rest of the data was annotated for free by the volunteering students at Boston University.
- **Over what timeframe was the data collected?** the raw video data was collected in October 2020 and processed and annotated during January 2020 - April 2021.
- **Were any ethical review processes conducted (e.g., by an institutional review board)?** No
- **Does the dataset relate to people?** No.

C.4 Preprocessing/cleaning/labeling

- **Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)?**
  1. Rotation and cropping. The frames were rotated so that the conveyor belt is parallel to the frame borders and cropped to remove the regions outside the conveyor belt. We ensured that any personal information or identifiable footage of the workers at the conveyor belt was excluded from our data.
  2. Camera calibration. We removed the distortion [47] using the OpenCV [48] library to compensate for fish-eye effect caused by the proximity of the cameras to the conveyor belt.
  3. Deblurring. We used SRN-Deblur [49] method to remove motion blur resulting from a fast-moving conveyor belt. According to our visual inspection, SRN-Deblur achieves satisfactory deblurring and does not introduce the undesired artifacts that usually appear when classical deconvolution-based methods are used.
  4. Subsampling. We sampled every tenth frame from the video to avoid redundancy.
- **Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)?** The raw data is stored internally on one of the machines at Boston University and can be sent upon request.
- **Is the software used to preprocess/clean/label the instances available?** we used the open-source OpenCV [48] tool for the data processing as well as the SRN [49] method (`https://github.com/jiangsutx/SRN-Deblur`) to remove motion blur.

C.5 Uses

- **Has the dataset been used for any tasks already?** We performed some initial experiments using `ZeroWaste` dataset on semantic segmentation and detection of the foreground objects. Namely, we ran a set of experiments with Mask RCNN [31] for supervised detection and transfer learning from the free-license TACO [3] dataset, DeeplabV3+ [53] for supervised semantic segmentation, and CCT [33] for semi-siupervised semantic segmentation. Additionally, we evaluated the accuracy of the class activation maps (CAMs) acquired by RISE [66] method and a ResNet50 [57] classifier trained on the `ZeroWaste-w` data for binary classification.
- **Is there a repository that links to any or all papers or systems that use the dataset?**
- **What (other) tasks could the dataset be used for?** This dataset can be used for training and evaluation of other detection and localization tasks, *e.g.* keypoint estimation, classification, as well as generative and domain adaptaion methods.
- **Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses?** No

- **Are there tasks for which the dataset should not be used?** Although this dataset may be used for the development of a fully automated waste sorting system, authors emphasize that it was not intended for that purpose. Our goal was to improve the efficiency and safety of the waste sorting process and not to fully replace the human workers by the robots.

C.6 Distribution

- **Will the dataset be distributed to third parties outside of the entity (e.g., company, institution, organization) on behalf of which the dataset was created?** Yes, the dataset will be in the open access online for non-commercial use.
- **How will the dataset will be distributed (e.g., tarball on website, API, GitHub)?** Upon publication, our dataset will be stored in Zenodo data repository (https://zenodo.org/) and will be accessible upon request according to the dataset license. The ZeroWaste dataset page on Zenodo is: https://doi.org/10.5281/zenodo.4899927.
- **When will the dataset be distributed?** the dataset will be opened upon acceptance by a peer-reviewed venue.
- **Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)?** The ZeroWaste dataset is licensed under the Creative Commons Attribution-NonCommercial 4.0 International License [46] (please see the terms at https://creativecommons.org/licenses/by-nc/4.0/).
- **Have any third parties imposed IP-based or other restrictions on the data associated with the instances?** No

C.7 Maintenance

- **Who is supporting/hosting/maintaining the dataset?** The dataset is hosted and maintained by the members of the Image and Video Computing Lab at Boston University. Zenodo repository guarantees persistent accessibility to all versions of the dataset.
- **How can the owner/curator/manager of the dataset be contacted (e.g., email address)?** The primary curators of the ZeroWaste dataset are Dina Bashkirova (dbash@bu.edu) and Kate Saenko (saenko@bu.edu).
- **Is there an erratum?** No
- **Will the dataset be updated (e.g., to correct labeling errors, add new instances, delete instances)?** The dataset will be updated upon request of the users or once the new version of the data is available. The information about the updates and corrections will be included to the project page (http://ai.bu.edu/zerowaste/). All dataset versions will be available for download at https://doi.org/10.5281/zenodo.4899927.
- **If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (e.g., were individuals in question told that their data would be retained for a fixed period of time and then deleted)?** The dataset is not related to people.
- **Will older versions of the dataset continue to be supported/hosted/maintained?** The older versions of the dataset will be available for download on the Zenodo page at any time.
- **If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so?** We welcome any initiatives form the research community. To propose an extension/correction of our dataset, please contact Dina Bashkirova (dbash@bu.edu) or Kate Saenko (saenko@bu.edu). All update requests will then undergo the appropriate review process prior to acceptance.