An Intelligent Scanning Vehicle for Waste Collection Monitoring*

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Abstract. While many industries have adopted digital solutions to improve ecological footprints and optimize services, new technologies have not yet found broad acceptance in waste management. In addition, past efforts to motivate households to improve waste separation have shown limited success. To reduce greenhouse gas emissions as part of a greater plan for fighting climate change, institutions like the European Union (EU) undertake strong efforts. In this context, developing intelligent digital technologies for waste management helps to increase the recycling rate and as a consequence reduces greenhouse gas emissions. Within this work, we propose an innovative computer vision system that is able to assess the residential waste in real-time and deliver individual feedback to the households and waste management companies with the aim of increasing recycling rates and thus reducing emissions. It consists of two core components: A compact scanning hardware designed specifically for rugged environments like the innards of a garbage truck and an intelligent software that applies a convolutional neural network (CNN) to automatically identify the composition of the waste which was dumped into the truck and subsequently delivers the results to a web portal for further analysis and communication. We show that our system can impact household separation behavior and result in higher recycling rates leading to noticeable reduction of CO_2 emissions in the long term.

Keywords: convolutional neural networks · deep learning · computer vision · cloud computing · circular economy

1 Introduction

The world faces many ecological and economical challenges due to the steadily increasing global demand of resources, a process often referred to as the great acceleration [1]. Besides groundwater and air pollution the main issue is greenhouse gas emissions, among which carbon dioxide (CO_2) makes up the vast majority. Parts of this emissions are caused by household waste management, where waste

* Powered by Austrian Climate- and Energy Fund - Project *DigiColl (877638)*.

must be transported, separated or incinerated. Each of these actions incurs considerable amounts of emissions. To reduce emissions and pollution in general, in 2015 the UN introduced the Agenda 2030 for Sustainable Development [2], where 17 global goals were defined, among them *paying special attention to air quality and municipal and other waste management* (Goal 11). One main pillar in waste management to increase recycling quotes is waste avoidance, with the aim of eliminating waste by keeping materials in use. This systematic approach is commonly referred to as circular economy. In that respect, several international efforts have been made [3–6]. More recently the European Green Deal [7] was announced, with ambitious goals like reduction of emissions by 40% until 2030 and to 0% until 2050.

One aspect in above programs is transforming local communities and the waste management industries for the digital era. The availability of cheap devices and sensors allows for broad deployment in urban areas and leads to so called smart cities. In this context, opportunities for Internet-of-Things (IoT) enabled waste management arise [8, 9], mostly targeting the inefficiencies in transport and disposal in a general approach. A complementary and more specific approach

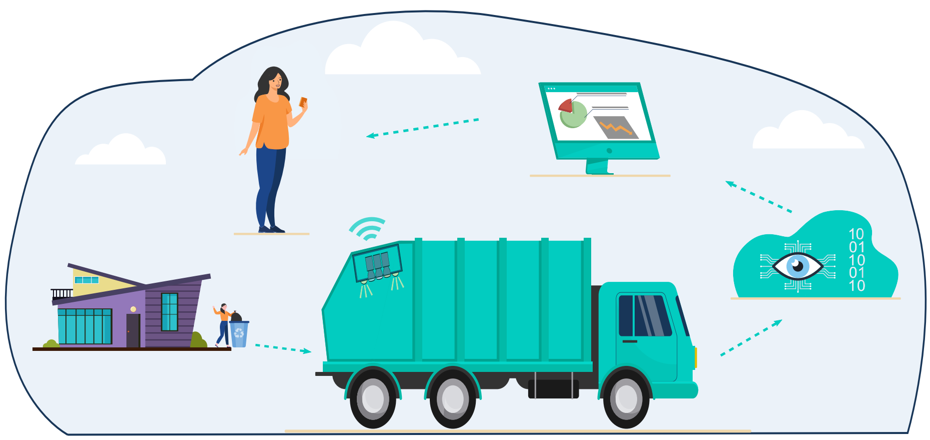

Fig. 1. System overview. In the center of the waste monitoring system is the intelligent garbage truck that is equipped with a complex hardware set combined within a compact and sealed casing. The truck acquires images and sends them for processing to the cloud using a GSM module. After that, the AI model classifies the waste and calculates a waste distribution that is sent to the customer web portal, where the information is communicated to single households. (This figure has been created using and modifying resources from https://www.freepik.com/pch-vector.)

is to target households to reduce the fraction of burned residential waste and keep valuable resources in the loop. This leads not only to less emissions but also lower costs for communities, giving monetary incentives to the households and communities as main target groups. Especially households play a critical role in increasing recycling quotes, as sorting the mixed residual waste later at the sorting plants is very inefficient and too expensive compared to burning the waste or landfilling. To achieve higher separation quotes, the awareness in households must be raised - a task that did not succeed in previous attempts, as they were either not targeted enough or required too much effort to reach a critical mass of households. One main factor that influences household waste separation is the individuals attitude [10], therefore constant qualified feedback is required to keep the individuals in the loop and raise the overall participation and engagement of citizens. With this feedback positive separation habits should be strengthened, especially in regards to the most problematic contaminants like batteries or plastics. There is common agreement that plastics and microplastics pose the biggest threat to our environment, polluting agricultural soil and marine ecosystems. After the import stop announced by China and Hong Kong in 2018 - who prior to that had imported over 70% of the worldwide share since 1992 [11], the problem of plastic recycling intensifies. In this concern, the EU has launched the European Strategy for Plastics in a Circular Economy [12] to achieve higher plastic waste recycling rates. The European targets for 2035 include a recycling rate of 75% for plastic waste and 65% for municipal waste, while limiting landfill to 10% at maximum [5]. As of now, while some countries like Austria, Belgium, Denmark, Germany, Luxembourg, Netherlands and Sweden are close to this target, the average of the EU-28 states remains at only 46.8% of recycled or composted municipal waste [13]. This reflects the different waste management strategies within the EU, where mostly in eastern countries incineration and landfilling dominate. The average EU recycling rate is comparable to the rate of the USA, as of now only few countries worldwide like Korea accomplish a higher rate of around 70% [14].

The proposed system focuses on the household level to target the recycling problem in an efficient and intelligent manner by automating the waste collection monitoring and providing real-time individual feedback. This is accomplished with an intelligent garbage truck that automatically acquires a set of images from the vehicle interior directly after waste containers are dumped inside. An RGB image is complemented with a multispectral image that delivers information up to near-infrared wavelengths (useful for organic waste) and depth information (useful for discrimination based on surface properties). The images are analyzed with artificial intelligence methods and the results are submitted to a web portal, where feedback is generated and passed on to the households. This feedback loop improves the waste separation habits, leads to increased recycling quotes and subsequently to reduced emissions. The proposed system is scalable and designed with cost efficiency in mind, to allow for broad and quick roll-out to communities for better waste management.

While there exist highly sophisticated computer vision supported systems in waste separation facilities, they not only come at a very high price, making them infeasible for deployment in large quantities, but also miss the link to single households. Only with the evaluation of every single garbage container directly at the source, i.e., after it is dumped into the garbage truck, the connection between household and separation habits can be made, which is essential for qualified feedback and change in behavior. Our intelligent vehicle enables exactly this:

Providing the households individual feedback with the aim of behavior change at large scale.

2 Related Work

Coordinators in charge of waste management make continuous attempts to improve waste separation quotes. On one hand, they try to improve efficiency of the waste collection process itself, e.g. they focus on routing optimization [15–17] or waste quantity prediction [18–20]. Some approaches build on the use of IoT devices, e.g. for measuring fill levels [21, 22] or weight and volume [23] of garbage bins. On the other hand, recent measurements taken in smart cities to reduce waste management emissions usually also involve the citizens and households. It was shown that putting containers for recyclables closer to households [24] has an impact on household level and can lead to better waste separation. An incentives system where waste pickup fees were reduced in exchange for better separation also prove effective [25]. Other than with structural improvements or incentives/penalties we involve households in a more direct fashion where they get instant feedback to raise awareness for their own recycling behavior. A scalable feedback approach cannot be based on manual monitoring, which is why our approach includes the use of an intelligent waste recognition module based on modern computer vision techniques. This computer vision method enables to extract information from waste images. Computer vision was previously dominated by handcrafted methods to extract the most distinct features from an image for content evaluation. Within the last decade Convolutional Neural Networks (CNN) replaced those handcrafted methods and showed astonishing performances over a variety of computer vision tasks. These networks no longer require manual design of features but instead learn to extract them from given data, where each data point (image) is associated with one or more labels. Since the introduction of AlexNet [26] research shifted from handcrafted feature design to network architecture design. Many CNN architectures have been proposed for a multitude of tasks like image classification, object detection or image segmentation. In this work we focus on the task of semantic image segmentation, where the CNN assigns a label to every single image pixel. Contrary to image classification, where the image is assigned a single label or object detection methods that locate objects in the image using bounding boxes (Fast R-CNN [27], Faster R-CNN [28], SSD [29], ...) or polygons (Mask R-CNN [30], ...), semantic segmentation allows for a much more detailed image analysis.

The few currently available computer vision approaches for waste recognition are often employed to decide in a binary fashion, if an image contains waste or not. Authors in [31] use a CNN to detect waste in urban images, binary classification of organic vs. recyclable waste is applied in [32]. Other works try to detect general waste classes like bags, bins or blobs from video streams [33]. Some works try to extract information about the waste composition directly from images. While not automated, in [34] authors estimate the physical composition of mixed waste using image based material analysis. Other approaches involve machine learning methods for classification of construction and demolition waste [35], classification of different plastic bottle types on a conveyor belt [36] or multi-class detection of single waste items [37]. Similar to our approach of classifying not only single objects but a mixture, authors in [38] use as sliding-window approach with a CNN classifier to generate waste label points in the image as input for a Gaussian clustering process. However they show results on simulated piles where objects do not overlap and are only partly identified, an oversimplified and unrealistic setting considering real world waste scenarios. As in our case, authors in [39] apply pixelwise segmentation, but only use two labels (waste and non-waste). Our approach in contrast classifies every single pixel of an real waste image into several classes and produces a much more detailed analysis of the composition. To the best of our knowledge, the only previous approach incorporating computer vision technology directly into waste vehicles is a road sweeper applying computer vision to control brushes, as a result saving electricity and reducing wearout [40].

3 Intelligent Waste Recognition System

At the heart of the proposed intelligent waste recognition system is the garbage truck, as shown in Figure 1. The truck is equipped with a compact hardware housing that contains multiple cameras, illumination, a GPS device, a GSM router and an industrial PC for image acquisition. This acquisition system is mounted on the ceiling of the lifting unit on the rear of the truck and immediately starts the recording sequence after a garbage container was lifted and emptied to the hopper. The resulting dataset consists of images from different sensors and a GPS position. As soon as the acquisition finishes, the GSM module starts transferring the dataset to the cloud, where the different modalities are preprocessed into one image stack, which is passed on to an AI based image recognition system that automatically assesses the waste composition. The results are then delivered to a web portal that sends feedback via a SMS gateway to the households. In addition, authorized community waste management personnel can use the web portal to monitor separation status for whole streets, districts or communities.

4 Hardware Design

To reduce maintenance of the involved hardware parts, a robust custom designed stainless steel box with glass windows was built. This ensures that all parts can be mounted in a rigid fashion and image acquisition is reliable. The housing and all plugs must be protected against water damage during regular cleaning with a high-pressure cleaner. Furthermore, in case of unexpected problems the box can be quickly replaced and analyzed while operation can be continued. Inside the box is a multispectral snapshot camera that records 9 channels between 550nm and 830nm wavelength, a RGB camera and a dual monochrome camera stereo setup for depth. For a broad acceptance of the system in the market a convincing cost effectiveness is needed. The combination of a high resolution RGB camera, covering the visible range of wavelengths with a snapshot VISNIR multispectral camera is a good approach to get the maximum information gain [41]. As most multispectral cameras, especially if they include the short-wave infrared (SWIR) range, are far too expensive for mass deployment and a pushbroom scanning approach is not applicable in the truck setup, we opted for the proposed setup which allowed a fast realization and a field test with a higher number of installed systems. For a constant illumination covering all necessary wavelengths, several halogen floodlights are placed inside the box. To prevent cooling problems of the system and to extend the service life of the lamps, each of them is switched on only with a short pre-glow time for the exposures. To operate such systems in trucks with a power supply providing voltage peaks from nominal 24V up to 40V requires special solutions, since the intensity and wavelength distribution of the lamps is highly influenced by the supply voltage. In addition, switching on multiple lamps at the same time produces voltage drops, which causes the controlling PC to reboot. The rationale for using lamps, even though they are complicated to handle, was that at the time of the project start no sufficiently powerful multispectral LED illuminators covering the VISNIR range were available at affordable prices. The recording process is controlled by an industrial PC unit with a passive cooling system. A GSM module is connected to the PC for data transfers into the cloud. A systemic overview of the hardware composition is shown in Figure 2, where also the power and trigger signals coming from the vehicle are depicted.

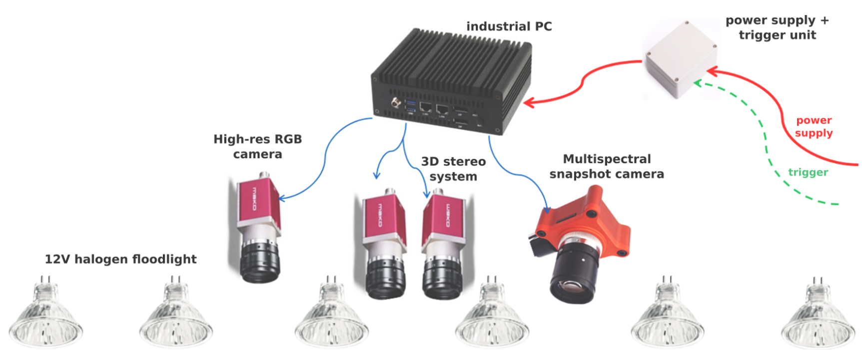

Fig. 2. Hardware overview. The hardware system consists of a stereo system, RGB and multispectral cameras, halogen floodlights and an industrial PC. The trigger signal and power supply are provided by the garbage truck.

5 Software Design

Upon arrival in the cloud, the data goes through a two-step procedure. First, the preprocessing instance takes all modalities, registers them so that pixels from different sensors are located at the same position and forwards them to the intelligent waste segmentation instance. In the second step, a convolutional neural network assigns a class to each pixel and outputs a class distribution over all pixels, where the background is ignored. This evaluation is then sent to the households along with a customized feedback. In the following, we describe the steps in more detail.

5.1 Data Preprocessing

The utilized sensors yield different data types which must be aggregated into one data stack per recording. First, the image modalities (3 RGB channels, 1 depth channel and 9 multispectral channels) are registered, warped and resized. For the RGB and multispectral images, an automated white balance correction to account for illumination changes is applied. The outcome of this preprocessing procedure is the input for the subsequent intelligent waste segmentation task.

5.2 Intelligent Waste Segmentation

To automatically extract the composition of waste from images a computer vision method is applied that generates waste composition statistics from waste images. Our model is a slightly modified DeepLabv3 [42] version that allows us to use the different modalities within the framework without adding too much computational overhead. We therefore apply early fusion on the different image modalities (RGB, multispectral, depth) through a compression layer and leave the remaining network architecture unchanged. To counter dataset imbalance, we additionally apply Focal Loss [43]. Successful CNN model training typically requires hundreds or thousands manually annotated images, which is often problematic as it is cost- and labor-intensive. To reduce the labeling effort and save resources, we adopt an intelligent prelabeling system. We train a segmentation network on a limited amount of data, e.g. a few dozen images. This network produces rough labels at first, that are further refined and corrected by human annotators. This is an iterative process, as the new human labels are then used for network retraining and the retrained network yields improved labels for the human annotators. Waste management in Europe is small-structured with many divergent separation guidelines, we identified the 6 main classes emerging from those guidelines for evaluation in our approach. For regional requirements, a finer differentiation might be needed. The results of the intelligent waste segmentation model are submitted to the web portal for analysis and communication.

5.3 Result Analysis and Communication

To close the loop to households, the customized feedback is generated from the web portal. Along with information about the recycling progress over time, the users receive detailed information about their waste compositions. This shows them which contaminants were wrongly placed in the waste bin and influences their future behavior.

6 Results

We verify both our intelligent CNN based waste segmentation model and the overall system impact. For the first part, to evaluate the performances of our CNN model, we curated a dataset of waste images and annotated them by hand as human groundtruth. The dataset contains the dominant 6 waste categories *organic*, *garbage_bag*, *paper*, *PET*, *plastic* and *residual*. We also add a *background* class for the garbage truck and an *ignore* class to mark image areas that cannot be identified and are left out during training. Our labeled dataset consists of 3107 images, where 2908 are used for training, 60 for model validation and 139 for evaluation of the final models. A big challenge is the small proportion of waste in relation to background as well as the imbalance in image area proportions for different classes (see Table 1 for details). We train several CNN models and

Table 1. Training and test dataset overview: 2908 and 139 images were used for training and testing the CNN models. Strong class imbalances makes waste segmentation a very hard task, as some classes only cover 2% or less image area on average.

class	img count	img area (mean±std) [%]	img area range [%]
background	2908/2908	71.67 ± 9.77	$0.61 - 93.86$
ignore	1882/2908	2.68 ± 5.65	$0.00 - 67.06$
organic	956/2908	1.79 ± 4.27	$0.00 - 39.39$
garbage_bag	2364/2908	6.92 ± 5.42	$0.00 - 49.07$
paper	2449/2908	2.04 ± 2.39	$0.00 - 18.85$
pet	1787/2908	0.62 ± 0.77	$0.00 - 9.67$
plastic	2844/2908	6.57 ± 5.33	$0.00 - 33.91$
residual	2908/2908	11.85 ± 5.29	$5.02 - 58.13$

a) train

background	139/139	68.85 ± 10.21	$39.03 - 100.00$
ignore	72/139	1.78 ± 2.16	$0.00 - 10.21$
organic	96/139	19.84 ± 16.05	$0.03 - 58.46$
garbage_bag	93/139	6.39 ± 5.31	$0.05 - 23.51$
paper	82/139	3.10 ± 2.83	$0.04 - 13.99$
pet	59/139	0.87 ± 0.89	$0.08 - 4.77$
plastic	90/139	6.46 ± 5.08	$0.05 - 32.46$
residual	112/139	7.30 ± 6.47	$0.00 - 35.78$

b) test

evaluate them on the held-out test dataset. To evaluate the difference between groundtruth (manual labels) and predictions (CNN output), we use two established metrics, accuracy (ACC) and Intersection-over-Union (IOU) scores and report mean/std over all images. The accuracy measures the amount of correctly labeled pixels, while the IOU measures how good the groundtruth and prediction areas overlap. Typically a score of 0.5 (50%) or higher is considered a good score. Evaluation results can be seen in Table 2. It is obvious, that the model perfectly learns to separate waste from the truck interior (*background* class). For the waste categories, results differ from 35% to 68% accuracy. This is due to the fact, that some classes are quite underrepresented in the training set (see Table 1) with *organic*, *paper* and *pet* covering 2% or less of the image area on average. A second issue is the subjective labeling due to the challenging nature of the data, where errors in the CNN predictions are often discussable. While the scores due to imperfect CNN segmentation masks are not optimal yet, it is often sufficient to find only parts of the contaminants for a qualitative feedback. If we weight the results with the image area proportions the different classes cover on average, the results are much better - the accuracy increases from 53.36% to 82.77%, the IOU from 43.84% to 77.22% (weighted average marked with * in Table 2). To get a better intuition for the numbers we show some qualitative results in Table 3. Due to the similar surface it is sometimes hard for the network to distinguish between *plastic* (yellow) and *garbage_bag* (light pink). Also, *pet* (turquoise) is a class with typically very small items where every inexact segmentation has large impact on the overall scores. On the other hand, our trained model is often able to spot contaminants that the human annotators missed during the labeling procedure. For example, in the lower right sample in Table 3 the CNN model correctly predicts organic waste (green) opposed to the annotated residual waste (grey) in the groundtruth.

Table 2. Results of our CNN model. Weighted results are marked with $^{\mathbf{w}}$, see text for details.

class	**ACC**	**IOU**
background	98.35 ± 3.62	96.03 ± 5.15
organic	56.86 ± 35.91	53.24 ± 33.64
garbage_bag	68.42 ± 28.26	54.66 ± 26.24
paper	50.36 ± 28.77	40.13 ± 24.69
pet	35.61 ± 25.80	27.56 ± 20.60
plastic	49.97 ± 22.05	38.81 ± 18.80
residual	67.26 ± 26.01	40.32 ± 22.71
average	$\mathbf{53.36 \pm 26.55}$	$\mathbf{43.84 \pm 25.41}$
average$^{\mathbf{w}}$	$\mathbf{82.77 \pm 14.06}$	$\mathbf{77.22 \pm 13.93}$

Table 3. Qualitative results of our intelligent waste segmentation. Left: Input (RGB only for visualization), middle: CNN prediction, right: groundtruth labels. Best viewed digitally.

For the overall system evaluation, we monitored around 40 households over a period of 14 months. As Figure 3 shows, the immediate household feedback improves separation rates by around 30% with ups and downs indicating seasonal fluctuations like increased organic waste around public holidays and reduced contaminants after improving communication strategies. An exact quantitative evaluation of resulting reductions in waste management costs and CO_2 emissions is part of an ongoing project. There are multiple dependencies on the collection area that must be taken into account (urban/rural, household income, education level, age structure, ...) to quantify the outcome of increased environmental awareness and separation behavior as result of our user-centric feedback component.

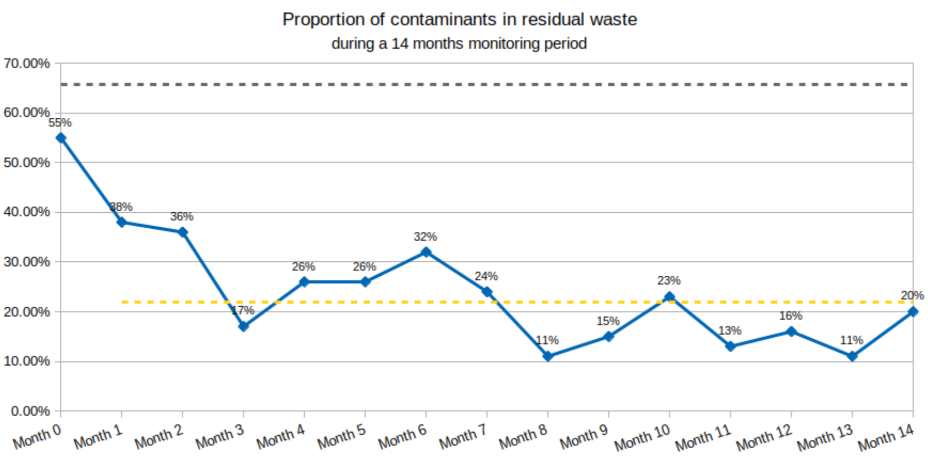

Fig. 3. Proportion of contaminants in residual waste over time. Households were monitored to evaluate the feedback impact. After communication start, the proportion went from 55% to 38% (blue line), showing the raised awareness. During the next year, it averaged at around 22% with seasonal fluctuations due to holidays etc. (yellow dashed line). The dashed grey line shows a nationwide average for comparison.

7 Conclusion

In this paper, we present an intelligent system for waste collection monitoring that enables communities for the first time to involve single households in the waste management process. The real-time feedback allows the households to reflect on habits that might harm the common goal of reducing CO_2 emissions and a functioning circular economy.

At this stage the proposed system is designed after European waste management systems but adaptation for other parts of the world should be straightforward, as the collection of household waste is one of the main tasks in communities worldwide. In near future we plan to further enhance the hardware within the garbage vehicles by using edge computing devices to reduce the amount of transferred data and incorporate fast LED illumination for faster acquisition times.

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