

Analysis of Histogram Asymmetry for Waste Recognition

Janusz Bobulski, Kamila Pasternak

Abstract—Despite many years of effort and research, the problem of waste management is still current. There is a lack of fast and effective algorithms for classifying individual waste fractions. Many programs and projects improve statistics on the percentage of waste recycled every year. In these efforts, it is worth using modern Computer Vision techniques supported by artificial intelligence. In the article, we present a method of identifying plastic waste based on the asymmetry analysis of the histogram of the image containing the waste. The method is simple but effective (94%), which allows it to be implemented on devices with low computing power, in particular on microcomputers. Such de-vices will be used both at home and in waste sorting plants.

Keywords—Computer vision, environmental protection, image processing, waste management.

I. INTRODUCTION

NOWADAYS, environmental protection is a very important issue. One of the most crucial methods that are used to protect the environment is recycling. Its main goal is to reduce the amount of waste stored in landfills and conservation of natural resources. The meaning of the term recycling is to recover raw materials by the transformation of substances or materials contained in waste in the production process to obtain the substance or material for the fate of primary or other purposes. It should be noticed that in many European countries waste segregation is done in households, i.e. at the begging of the recycling path. It means that people divide rubbish into groups such as metal, glass, plastic, paper, and organic waste on their own. Such an approach makes the usage of selective automatic techniques much easier than for municipal solid waste. However, a large part of the waste is still collected as mixed waste. Therefore, it is reasonable to strive for the effective reprocessing of waste materials. Due to this fact, an alternative to a manual-automatic way of the sorting process is highly needed. Thanks to the development of artificial intelligence, deep learning, and intelligent technologies it is possible to reduce the manpower and material resources that are required for the waste sorting process. Therefore, the main goal of this paper is to propose an efficient system for waste classification.

II. RELATED WORKS

Two different categories of research on waste classification methods can be found in the literature: traditional methods and

neural network methods. An exemplary traditional approach is applied in [1]. A Bayesian computational framework for material category recognition is presented and the augmented Latent Dirichlet Allocation (aL-DA) model which is proposed achieved a 44.6% of recognition rate. An existing manually engineering model and an improved conventional machine learning algorithm, a random forest classifier was used in [2] to obtain the best effect and improve the prediction quality of emptying of the recycling container. In [3] authors proposed the original graph structure of the network and mathematical statistics method to extract specific reasonableness. The results presented in this paper have a promotion effect on waste classification. It should be noticed that the traditional machine learning methods need the calibration of a large number of training data. Algorithms such as k-Nearest Neighbor (kNN), Random Forest (RF), etc. perform a huge amount of calculations and cannot fit the data and balance samples well. Therefore, it can seem that traditional machine learning technologies are not a suitable choice for waste classification. The advantage of neural network methods (specifically the Convolutional Neural Network) above the traditional machine learning approach is shown e.g. in [4]. An accuracy obtained using kNN, Support Vector Machine (SVM) and RF was 88%, 85%, and 80% respectively. Whereas, test accuracy of 93% and 91% were achieved using respectively a pre-trained VGG-16 CNN and AlexNet CNN. The comparison of results obtained with traditional and neural networks approaches can also be seen in [5].

There are much research works in the waste sorting area using neural networks methods in the literature. In 2016 in [6] the first important results in waste sorting using deep learning were obtained. In this paper, TrashNet - a database for municipal waste, has been developed. This database was used by authors to train two classifiers: SVM and CNN (Convolutional Neural Network) to classify images of waste into six categories: metal, paper, glass, plastic, trash, and cardboard. The former achieved an accuracy of 63%, the latter did not learn well (only 22% accuracy was achieved) because of the hyper-parameter setup. Following the results of [6], the same dataset was augmented in [7] and used to train Faster R-CNN which obtained a better mean average precision of 68.3%. Further research on the TrashNet (or TrashNet with some augmentation) dataset has provided better results. For example, in [8] a validation accuracy of 88.42% was achieved with VGG-19 CNN. The authors performed some adjustments to the

J. Bobulski is with Computer Science Department, Czestochowa University of Technology; Czestochowa, Poland (corresponding author, e-mail: janusz@icis.pcz.pl).

K. Pasternak is with Computer Science Department, Czestochowa University of Technology; Czestochowa, Poland (e-mail: kamila.pasternak@pcz.pl).

hyper-parameters, architecture, and classification on the fully connected layers. A precision of 84.2% and a recall of 87.8% were obtained in [9] using a Faster R-CNN based on InceptionV2 and pre-trained on the MSCOCO dataset. In [10] several different deep CNN architectures were experimented with; for example, DenseNet121 with a test accuracy of 95% and Inception-ResNetV2 with a test accuracy of 87%. In the same research, the novel architecture specific to the recycling material dataset, RecycleNet, was proposed and it obtained a test accuracy of 81%. In [11], the results showed a test accuracy of 87% using a 50-layer residual network (ResNet50) as the extractor with an SVM classifier. A very high accuracy (98.7%) was achieved in [5] by using MobileNetV2 for feature extraction and an SVM classifier. In [12] several types of CNN are applied to municipal waste identification. Two types of object detectors are studied in this paper: Single Shot Detectors (SSD) which are fast and able to detect large objects and Regional Proposal Network (RPN) which is very good at identifying small objects but it is slower than SSD networks. The highest accuracy (97.63%) was obtained with SSD MobileNetV2. The RPN model - faster R-CNN architecture based on Inception-ResNet achieved 95.76% of accuracy.

As it can be seen, the TrashNet dataset (and/or its augmentation) is widely common in literature [4]-[12]. However, there are also authors which used their dataset in research. For example, in [13], the Labeled Waste in the Wild dataset is proposed and used for training the Faster R-CNN which obtained 86% of the mean average precision. Reference [14] is research that used a custom garbage dataset for training a multilayer hybrid deep learning model (MLH) for waste classification. In this paper, it can be seen that the MLH approach can achieve higher classification performance than the CNN-only model. The accuracies of 98.2% and 91.6% are obtained with MLH under two different testing scenarios. A multilayer hybrid convolution neural network as a waste classification method is also proposed in [15]. This research is based on the TrashNet dataset. An accuracy that was obtained in this research equals 92.6%. Another interesting research can be found in [16]. A deep neural network based on Faster R-CNN to detect coastal waste was proposed in this paper. The authors created a new waste object dataset named IST-Waste. A model presented in [16] obtained 83% of the mean average precision.

III. MATERIALS AND METHODS

In many countries, pre-sorting of garbage already occurs at home, but not all. Therefore, in some sorting plants, it is necessary to use sorting to divide into individual fractions. It is a time-consuming and costly job. That is why automatic sorting systems are appearing more and more often. We propose a simple method based on the analysis of the histogram of the photo containing the waste. The camera will be placed on a transmission belt with the captured photo being sent to a computer for analysis and decision making. Then the rubbish is directed to the appropriate container with the help of a mechanical arm. Another way to use the proposed method is a portable microcomputer telling the employee what type of

waste it is. The basic assumption when developing the algorithm was that it should be simple and fast so that it could be used in the sorting plant in real-time.

First, we load the image and then we use the cascading object detector which uses the Viola-Jones algorithm to detect plastic waste in the digital image. In the preliminary tests, we adapted the detector to our task, teaching it to detect garbage in images from the database used in the experiment. After detecting the object, the ROI (region of interest) is extracted from the RGB image. In the next step, we compute a histogram for each R, G and B component of that part of the image. The histogram is then analyzed by comparing the sums of the ranges of the starting (A) and ending (B) parts of histograms. For example, we add the first hundred and last hundred elements of the histogram together and compare the two sums. In the case of plastic, the first sum will be higher, while in the case of other opaque materials, the second sum will be higher (Figs. 2 and 3). In the last phase, a decision is made to classify the facility as Plastic or not Plastic.

Algorithm:

- load the photo I;
- detect the object D on I;
- select the area I2 from I containing object D;
- calculate the histogram of I2 for each RGB component separately;
- select ranges A and B;
- calculate the sum of elements range A and B;
- compare sums;
- decide: Plastic/not Plastic

In Figs. 1 and 2 we can see the calculated histograms for the plastic object (Fig. 2) and not plastic (Fig. 1). We use the equation:

$$H_k \sum_{k=0}^{255} I2(i, j)_k \quad (1)$$

A. TrashBox Dataset

We use the TrashBox dataset for waste classification in the experiment [17]. Images do not contain detection annotations provided in the repository and contain 17785 waste object images scraped from the website. We use 5000 random images from all categories. Image parameters were as follows:

- size 512 x 384 pixels
- color depth 24 bits
- resolution 96 dpi
- format jpg.

Waste categories are as follows:

- Trash waste: random; the number of images: 2010.
- Plastic: Bags, Bottles, Containers, Cups; the number of images: 2669.
- Paper: Tetra Pak, News Papers, Paper Cups, Paper Tissues; the number of images: 2695.
- Metal: Beverage Cans, Scrap, Spray Cans, Food Grade Cans; the number of images: 2586.
- Glass: bottles; the number of images: 2528.
- Cardboard: the number of images: 2414.

Hardware used in experiment: Processor Intel Core i7 - 10700F – 8 core, RAM 16 GB, NVIDIA GeForce RTX 2080 Ti

– 8GB GDDR6 197, HDD SSD 1TB.

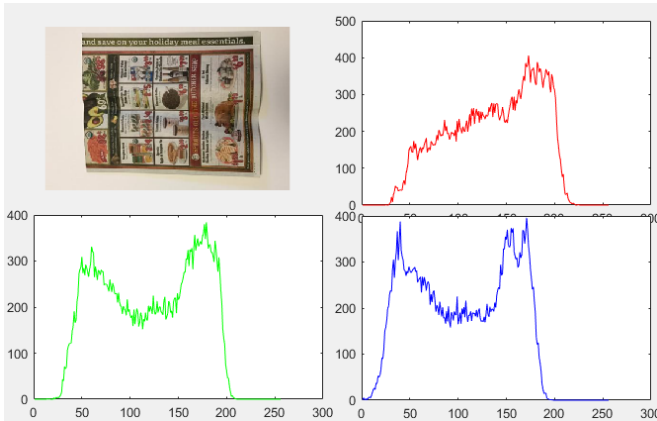


Fig. 1 Histogram of the not plastic object

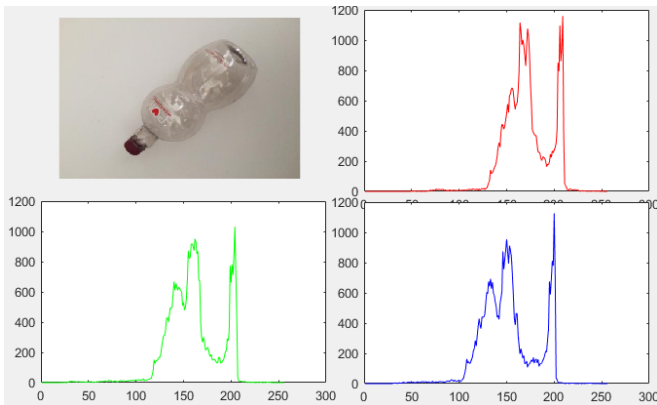


Fig. 2 Histogram of the plastic object

IV. RESULTS AND DISCUSSION

Table I presents the results of the main experiment. The object recognition task was tested depending on the ranges of the histogram (Fig. 3). When analyzing the results, we can see that the selection of the element ranges from the histogram has a significant impact on the recognition results. A simple symmetrical split in half produces weaker results, as do selecting 100 extreme elements at each end. The best results were obtained for asymmetric sizes of ranges A and B and their asymmetrical position. In addition, it is also recommended to select the range from the so-called overlap, that is, that they partially overlap.

Table II shows the results of the second stage of the experiment, in which we tested the effectiveness of the method depending on the type of material from which the object in the garbage photo is made. We obtained the best results for mixed waste and plastic. We got the worst level of identification for metal. The reason for this may be the properties of the metal in the form of light reflections. Regardless, we got a good average recognition rate of 94%.

Table III shows a comparison of our method to other methods known today. Compared to the methods using artificial neural networks, and in particular convolutional networks (CNN), the method we propose is less effective. It is caused by lower

computational complexity, which is an advantage when we want to use a method on a mobile device or in real-time. However, compared to other methods using KNN, SVM or RF, the use of asymmetric histogram analysis gives better results.

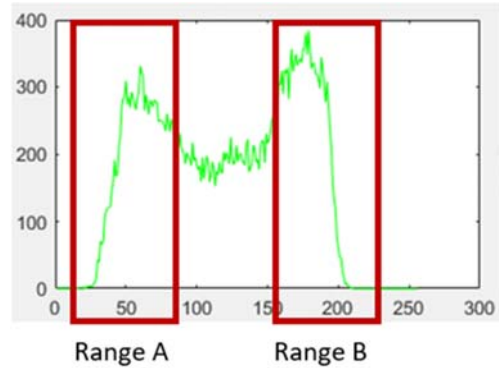


Fig. 3 Ranges of the histogram

Range A	Range B	Accuracy [%]
1-100	155-255	74
1-100	101-255	91
1-150	155-255	54
1-100	101-200	88
50-150	151-200	51
50-100	101-200	89
50-150	151-255	70
1-120	151-255	69
1-120	121-255	83
1-180	121-255	94

no	type	FRR	FAR	Accuracy [%]
1	carton	0	4	96
2	glass	0	8	92
3	metal	0	15	85
4	paper	0	6	94
5	plastic	0	2	98
6	trash	0	1	99
average		0	6	94

The analysis of the obtained results allows concluding that the idea of applying the asymmetric histogram analysis turned out to be correct and that the obtained results allow its implementation in real conditions.

V. CONCLUSIONS

The paper presents a method of recognizing domestic waste using computer vision techniques. We used a simple scheme to analyze the asymmetry of a histogram of a digital image containing a garbage object. The conducted research confirms that the use of simple image analysis techniques allows for the construction of effective methods of identifying or classifying objects. The method proved to be 94% effective, which is a satisfactory result and allows the method to be used in real systems, in particular on mobile microcomputers. Such

implementation allows for wide application and further work on the problem of waste management.

TABLE III
 COMPARISON TO OTHER METHODS

Research	Year	Dataset	Method	Accuracy [%]
[6]	2016	TrashNet	SVM CNN	63 (test accuracy) 22
[7]	2017	TrashNet	Faster R-CNN	68.3 (mAP)
[8]	2018	TrashNet	VGG-19 CNN	88.4 (validation accuracy)
[9]	2018	TrashNet	Faster R-CNN based on Inception V2 DenseNet211	84.2 (precision) 87.8 (recall) 95 (test accuracy)
[10]	2018	TrashNet	Inception-ResNetV2 RecycleNet Pre-trained VGG-16 CNN AlexNet CNN	87 (test accuracy) 81 (test accuracy) 93 91
[4]	2018	TrashNet	KNN RF SVM	88 85 80
[11]	2019	TrashNet	ResNet50 CNN with SVM Classifier	87
[5]	2020	TrashNet	MobileNetV2 MobileNetV2	98.7 97.6 (precision) 94.4 (recall)
[12]	2020	TrashNet	Faster R-CNN based on Inception ResNet	95.8 (precision) 94.4 (recall)
[13]	2019	LWW	Faster R-CNN	86 (mAP)
[14]	2018	Custom dataset	Multilayer Hybrid CNN (MHS)	98.2 (accuracy) 98.5 (precision) 99.3 (recall)
[15]	2021	TrashNet	Multilayer Hybrid CNN (MLH-CNN)	92.6
[16]	2021	IST-Waste	Faster R-CNN	83 (test mAP)
[18]	2021	Wadaba	CNN	74 (accuracy)
Our	2022	TrashNet	Histogram	94 (accuracy)

Despite the passage of many years of struggle with this problem, it is still current. Work on comprehensive waste management systems is still ongoing. New projects sponsored by global concerns are being launched to reduce the scale of the problem, but there is still a lot of work to be done. Therefore, research should still be conducted to develop effective methods to automate the recycling processes.

ACKNOWLEDGMENT

This research was funded by the Minister of Science and Higher Education under the name "Regional Initiative of Excellence" in the years 2019 - 2022 project number 020/RID/2018/19 the amount of financing 12,000,000 PLN.

REFERENCES

[1] Lui, C.; Sharan, L.; Adelson, E.H. Rosenholtz, R. Exploring Features in a Bayesian framework for material recognition. In Proceedings of the 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, San Francisco, CA, USA; 239–246.

[2] Rutqvist, D.; Kleyko, D.; Blomstedt, F. An automated machine learning approach for smart waste management systems. *IEEE Trans. Ind. Inform*2020, 16, 384–392.

[3] Zheng, J.; Xu, M.; Cai, M.; Wang, Z.; Yang, M. Modeling group behaviour to study innovation diffusion based on cognition and network: An analysis for the garbage classification system in Shanghai, China. *Int. J. Environ. Res. Public Health*, 2019, 16, 3349.

[4] Costa, B.S.; Bernardes, A.C.; Pereira, J.V.; Zampa, V.H.; Pereira, V.A.; Matos, G.F.; Soares, E.A.; Soares, C.L.; Silva, A.F. Artificial

intelligence in automated sorting in trash recycling. In Proceedings of the Anais do XV Encontro Nacional de Inteligência Artificial e Computacional, São Paulo, Brazil, 22–25 October 2018; 198–205.

[5] Xu, X.; Qi, X.; Diao, X. Reach on Waste Classification and Identification by Transfer Learning and Lightweight Neural Network. Preprints 2020, 2, 327.

[6] Yang, M.; Thung, G. Classification of Trash for Recyclability Status. CS229 Project Report; Stanford University: Stanford, CA, USA, 2016.

[7] Awe, O.; Mengistu, R.; Sreedhar, V. Smart trash net: Waste localization and classification. arXiv 2017, preprint.

[8] Kennedy, T. OscarNet: Using Transfer Learning to Classify Disposable Waste; CS230 Report: Deep Learning; Stanford University: Stanford, CA, USA, 2018.

[9] Kulkarni, H.N.; Raman, N.K.S. Waste Object Detection and Classification; CS230 Report: Deep Learning; Stanford University: Stanford, CA, USA, 2018.

[10] Bircanoglu, C.; Atay, M.; Beser, F.; Genc, O.; Kizrak, M.A. RecycleNet: Intelligent Waste Sorting Using Deep Neural Networks. In Proceedings of the 2018 Innovations in Intelligent Systems and Applications (INISTA), Thessaloniki, Greece, 3–5 July 2018.

[11] Adedeji, O.; Wang, Z. Intelligent Waste Classification System Using Deep Learning Convolutional Neural Network. *Procedia Manuf.* 2019, 35, 607–612.

[12] Melinte, D.O.; Travediu, A-M; Dumitriu, D.N. Deep Convolutional Neural Networks Object Detector for Real-Time Waste Identification. *Applied Sciences*2020, 10(20):7301.

[13] Sousa, J.; Rebelo, A.; Cardoso, J.S. Automation of Waste Sorting with Deep Learning. In Proceedings of the 2019 XV Workshop de Visão Computacional (WVC), Sao Paulo, Brazil, 9–11 September 2019; 43–48.

[14] Chu, Y.; Huang, C.; Xie, X.; Tan, B.; Kamal, S.; Xiong, X. Multilayer Hybrid Deep-Learning Method for Waste Classification and Recycling. *Comput. Intell. Neurosci.*2018, 2018.

[15] Shi, C.; Tan, C.; Wang, T.; Wang, L. A Waste Classification Method Based on a Multilayer Hybrid Convolution Neural Network. *Appl. Sci.*2021, 11, 8572.

[16] Ren, C.; Jung, H.; Lee, S.; Jeong, D. Coastal Waste Detection Based on Deep Convolutional Neural Networks. *Sensors* 2021, 21, 7269.

[17] Kumsetty, N.; Nekkare, A. TrashBox database, doi: 10.5281/zenodo.1234.

[18] Bobulski, J.; Kubanek M. Deep Learning for Plastic Waste Classification System. *Applied Computational Intelligence and Soft Computing*, 2021, art. no. 6626948.