Detecting Bioplastic Objects Using Instance Segmentation and Hyperspectral Imaging

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Summer 2020

Introduction

- A world without plastic is unimaginable. Advantages of plastic, being lightweight and durable, also make plastics a significant environmental hazard.
- Bioplastics play an important role in solving the plastic pollution problem. They are made from renewable resources, biodegradable or both.
- Correctly and quickly sorting different plastic types is imperative for increasing the worldwide plastic recycling rate.
- The main goal of this research is to determine to what extent object detection can be used to sort various (bio)plastics.

Materials and Methods

- The dataset consists of 30 images of PET, PP and PE plastic flakes.
- Preprocessing : flat-field correction & HHSI algorithm.
- Deep learning: instance segmentation network Mask R-CNN.
- Dimensionality reduction using a convolutional layer.
- Statistical tests: Shapiro-Wilk test for normality of data & Mann-Whitney U test for comparing distributions of two groups.

Abstract

Pollution by plastic waste is a growing problem. To improve plastic sorting, this study explores the use of instance segmentation model Mask R-CNN with hyperspectral images of PET, PP and PE. Image dimensionality is reduced by an added convolutional layer. A mask mAP (IoU of 0.5:0.5) of 0.8261 is achieved. Adding a 2nd layer does not change the results. Relevance of hyperspectral bands in the reduction process appears related to average relative reflectance.

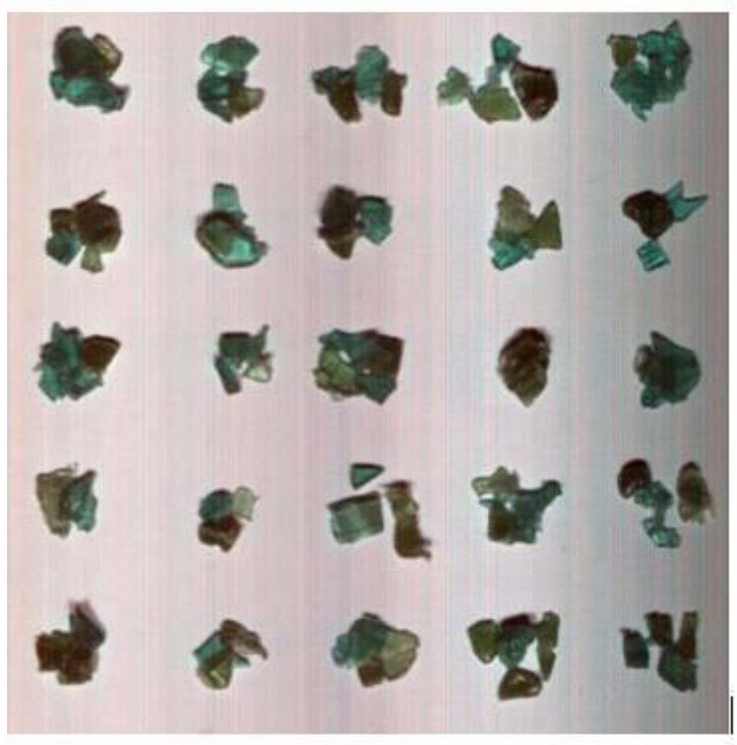

Figure 1. Example of an image taken by FX17. It contains 25 heaps of polymer flakes. Every heap is considered an object. This image is split into 25 input images for Mask R-CNN.

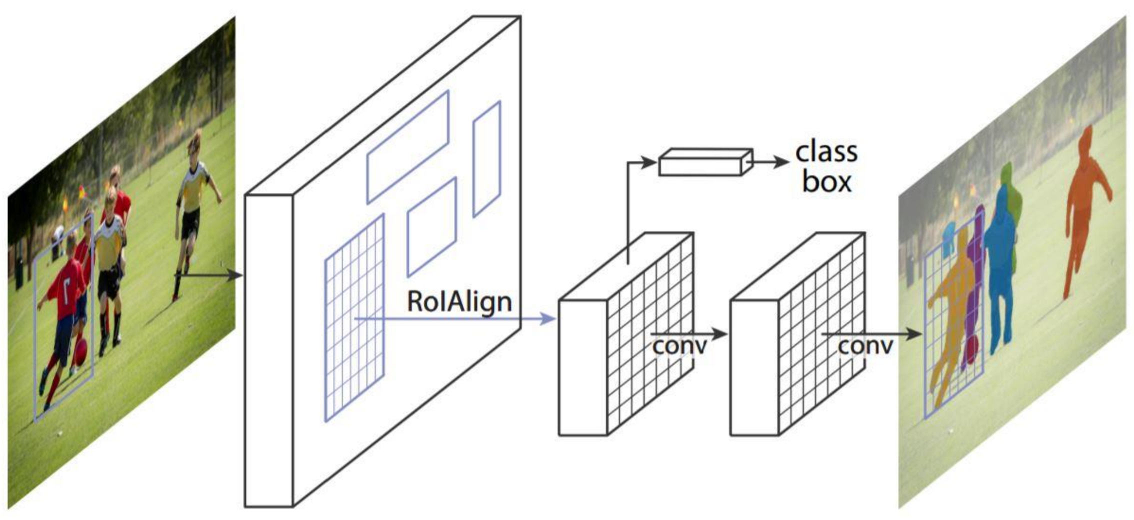

Figure 2. The Mask R-CNN model for instance segmentation. It has a two-stage pipeline with an RPN (Region Proposal Network) in the first stage. The second stage consists of classification and bounding box regression and, in parallel, production of a binary mask for each RoI.

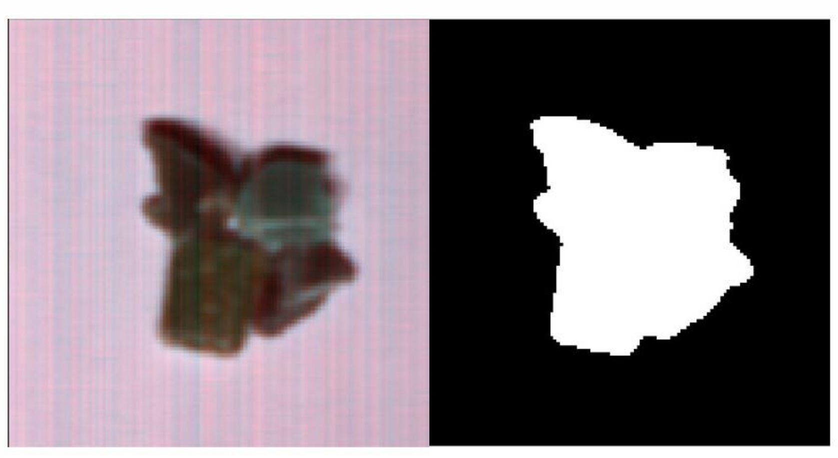

Figure 3. Example of an image and its ground truth mask. The models performance is determined by comparing the predicted mask with this ground truth mask.

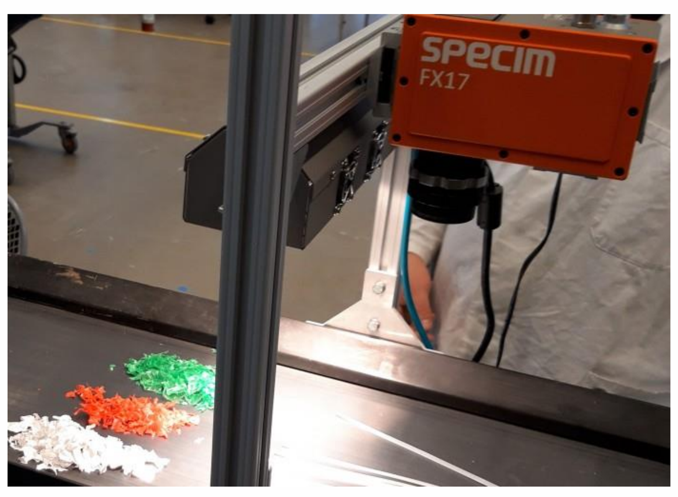

Figure 4. Setup Specim FX17: The plastic samples are moved underneath the hyperspectral camera via a conveyor belt.

Experiments and Results

- **Baseline experiment:** 20 runs of 100 epochs of Mask R-CNN.
- 24 images used in training set and 6 images in testing set.

	mAP instance segmentation		mAP bounding box	
	average	standard deviation	average	standard deviation
IoU: 0.5:0.95	0.7057	0.2562	0.6718	0.2208
IoU: 0.50	0.8863	0.1986	0.9222	0.1411
IoU: 0.75	0.8154	0.3306	0.7676	0.3619
Without outliers:				
IoU: 0.5:0.95	0.8261	0.0597	0.7724	0.0836
IoU: 0.50	0.9741	0.0495	0.9741	0.0495
IoU: 0.75	0.9741	0.0495	0.9351	0.1275

Table 1. Average results of baseline experiment. mAP stands for mean Average Precision.

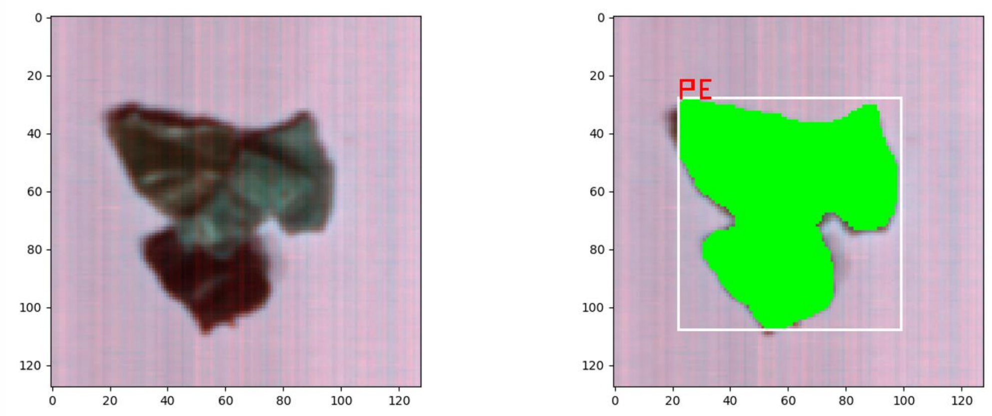

Figure 5. Example of original image (left) and its predicted bounding box, class and mask (right).

- **2nd experiment**: Comparison of baseline experiment with 20 runs of the model with extra convolutional layer for dimensionality reduction.
- Performed Mann-Whitney U test: p-value of 0.350. → the null hypothesis is accepted: the distributions of the two groups are the same.
- **3rd experiment**: Determining the relative importance of hyperspectral bands in dimensionality reduction process.
- The importance of the bands is visually compared to the average relative reflectance graph.

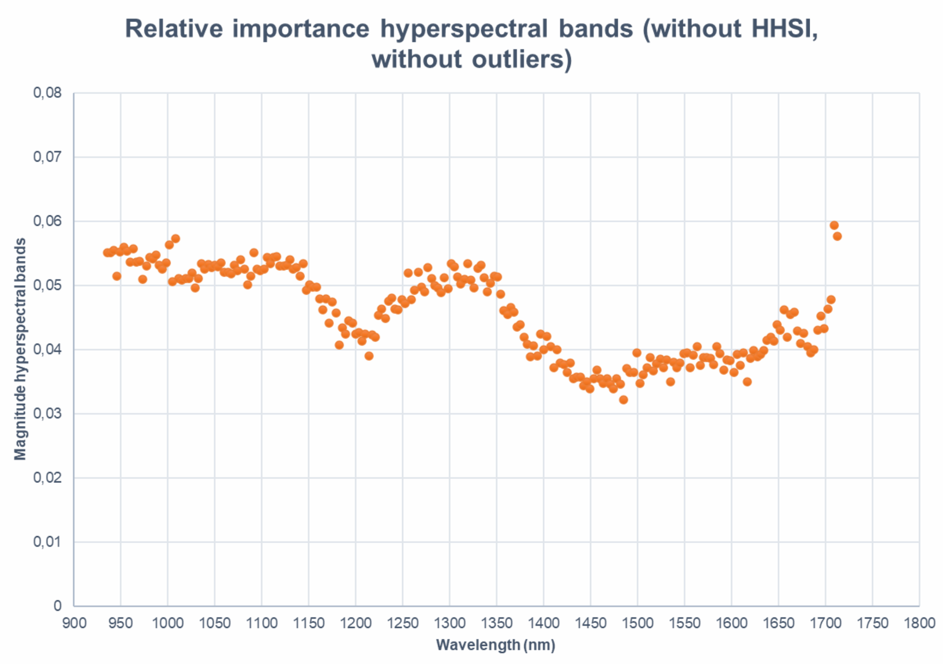

Figure 6. Relative importance of hyperspectral wavelengths for separating PE, PP and PET (without outliers).

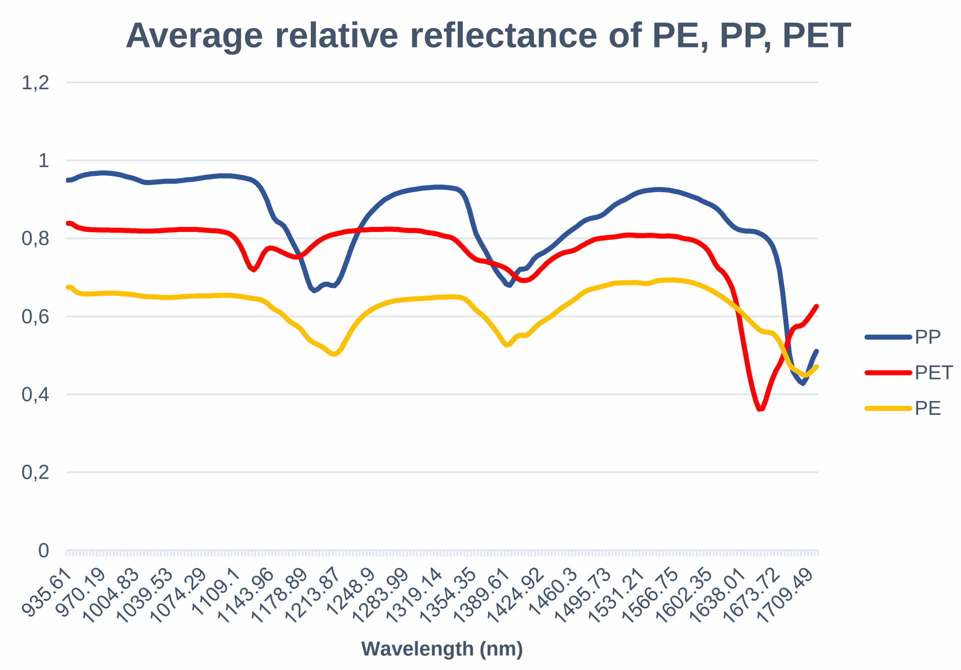

Figure 7. Average relative reflectance of PE, PP and PET.

Conclusions

- Mask R-CNN in combination with hyperspectral imaging and a convolutional layer for dimensionality reduction works well for detecting regular plastic flakes.
- Without outliers, a mask mAP of 0.8261 is achieved. Including outliers, a mask mAP of 0.7057 is achieved.
- Adding an extra convolutional layer for dimensionality reduction does not lead to significantly better results.
- The hyperspectral bands that show large differences in relative reflection appear to correspond with the hyperspectral bands that have the largest magnitude in the dimensionality reduction.

NHL STENDEN
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Acknowledgements

- This project is financially supported by the Innovatieprogramma Ultieme Kunststof Kringloop (UKK).
- This project is a collaboration between the Centre of Expertise in Computer Vision & Data Science and the Circular Plastics Professorship.

References

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