Polymer Flake Detection Through Hyperspectral Imaging

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Introduction

- Worldwide less than 10 percent of all plastic ever produced has been recycled.
- Considering that the end-of-waste of plastics is a real threat for the environment, it is urgent to take up this challenge in the next decades.
- Since not all plastics are recyclable the sorting process is very important.
- The goal of this research is to determine if we can apply object detection and classification on Hyperspectral Images using Convolutional Neural Networks (CNNs) to aid in the sorting process.

Materials and Methods

- The dataset is generated using a Specim FX17 NIR camera.
- The dataset consists of 32 images of PET, PP, PS, PE, PLA and PVC plastic flakes.
- The images are annotated using LabelImg open-source software.
- Three CNNs are trained and tested: Yolov3, EfficientDet, Faster-RCNN.
- The networks are modified to accept and process Hyperspectral Images, see Figure 2.

Abstract

While the amount of disposed plastic waste is constantly increasing, the issue of recycling plastics largely remains an open problem. To improve the sorting process this research looks at the possibility to apply object detection and classification on hyperspectral images. Our experiments showed promising results which lead us to conclude that CNNs are perfectly capable of detecting and classifying polymer flakes in hyperspectral images.

Figure 1. The Camera setup with a conveyor belt underneath. The conveyor belt moves the flakes underneath the camera while it generates the image.

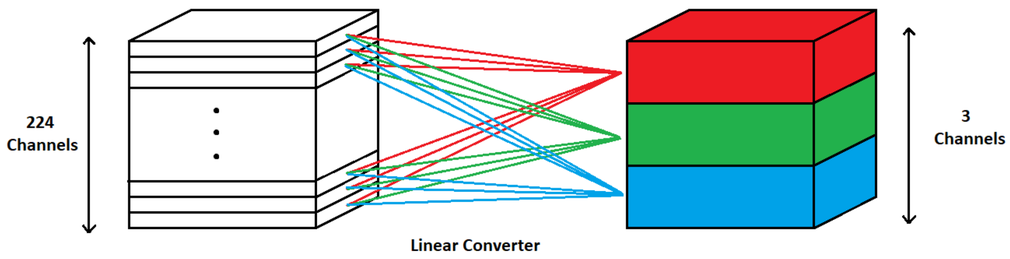

Figure 2. Illustration of the modification to the CNNs. A layer, the linear converter, was added to the networks to convert the 224 channeled hyperspectral data to 3 channeled data.

Each image in the dataset gets annotated. To the right you can see this process. Each flake gets a bounding box with a label indicating which polymer it is made of also called a class. In total there are six different classes, one for each polymer. The networks will use this information to teach themselves how to classify and localize polymer flakes in images.

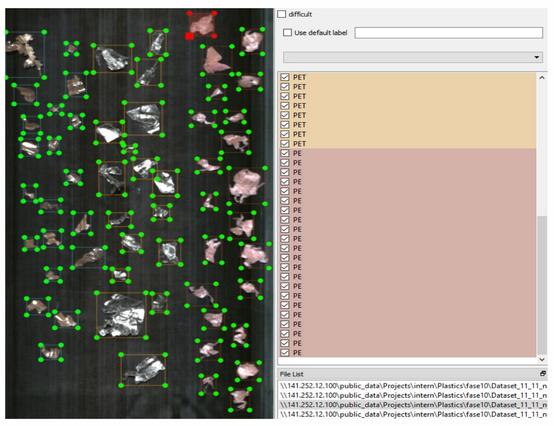

Figure 3. An image of the dataset being annotated. Each polymer flake gets its own bounding-box.

Acknowledgements

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Experiments and Results

- 1st experiment: We changed the classes of all the flakes to just 'Flake' in order to test if the networks were able to detect just the flakes in the images.
- 2nd: We trained and tested the networks on a small dataset to see if they were able to detect and classify the six classes of polymer flakes. They performed worse then on just flakes, this needed to be improved upon.
- 3rd: We trained and tested the networks on the whole dataset to see if they would perform better when given more images, this improved the performance of the networks.
- 4th: We tested if the networks performed better when given augmented data such as flipped and rotated images, this significantly improved the results.
- 5th: We tested if modifying parameters of the scheduler of the networks such as learning rate and patience would improve the results, this gave the best performance boost.
- The best results were achieved by combining the findings of experiment 3, 4 and 5.

Metrics per network	YOLO-V3	EfficientDet
Precision	0.53	0.53
Recall	0.42	0.43
F1-score	0.46	0.47
mAP	0.23	0.32
False Discovery Rate	0.88	0.47

Table 1. Metrics per network after experiment 4.

Metrics per network	YOLO-V3	EfficientDet
Precision	0.68	0.65
Recall	0.60	0.70
F1-score	0.63	0.68
mAP	0.47	0.61
False Discovery Rate	0.32	0.35

Table 2. Metrics per network after experiment 5.

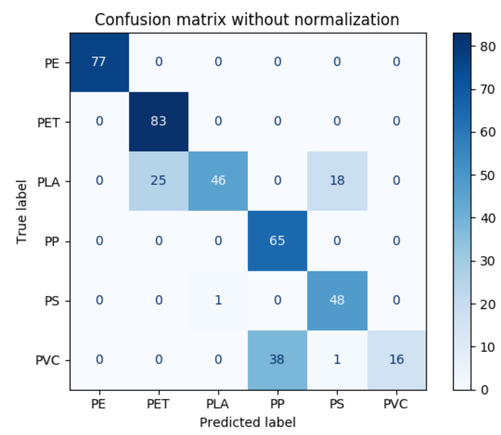

Table 3. Confusion matrix for the flakes detected with YOLO-V3 network after experiment 5.

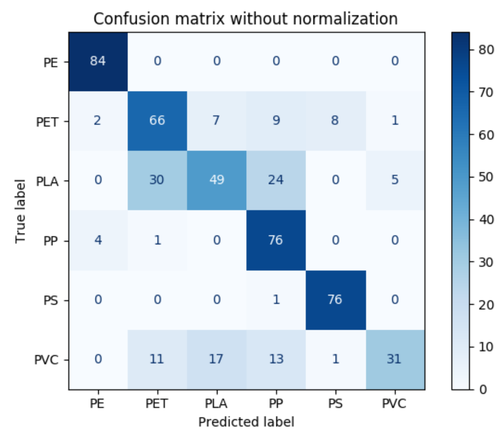

Table 4. Confusion matrix for the flakes detected with EfficientDet network after experiment 5.

Figure 4. Final results of YOLO-V3 on a test image.

Figure 5. Final results of EfficientDet on a test image.

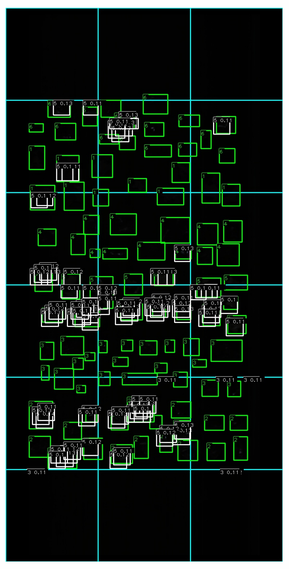

Figure 6. Final results of Faster-RCNN on a test image.

Conclusions

- By adapting existing object detection CNNs with an input layer that converts n-amount of inputs to 3 inputs gives the possibility to process hypercubes.
- Adding data augmentation improved the results on all three models.
- The CNN's perform better when given more data.
- The EfficientDet model performs as the best model among the three.
- The YOLO-V3 model performs as the best classifying model among the three.
- Plastic flake localization and classification through hyperspectral imaging can be a promising addition to any plastic sorting process that works with flakes when researched and refined further.