Polymer Semantic Segmentation with Hyperspectral Imaging and Artificial Neural Network

Performance of new neural networks HRNet and HRNet+OCR

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Introduction

- Polymers -- 350 million tones produced per year but only 20 % are recycled.
- Polymer sorting by combine hyperspectral imaging and artificial neural network.
- Already be able to classify normal polymers such as PE,PP,PET and PEF.
- New neural networks are needed to be integrated and tested.

Materials and Methods

- GenNet -- a modular neural network structure that can classify normal polymers.
- New neural network – HRNet and HRNet+OCR
- Two hyperspectral datasets – PET-PEF-CP-shaped and Plasitcs.
  - PET-PEF-CP-shaped dataset has six classes: PET, PEF, PET bottle, PEF bottle, 6% co-polymer and 11% co-polymer
  - Plasitcs dataset has four classes: PET, PEF, PP and PE
- Two preprocessing methods: Logarithmic Derivative and Hyper Hue

Abstract

To sort different types of polymers, a modular neural network structure GenNet which can classify normal polymers such as PET and PEF was developed. Two new neural networks HRNet+OCR which achieved the highest IOU value 84.5% on semantic segmentation of public dataset Cityscapes, and HRNet is integrated to GenNet. But HRNet and HRNet+OCR can't provide better performance than Deep Res U-Net. They confuse flakes and object made in the same material and the Adam Optimizer can improve the performance.

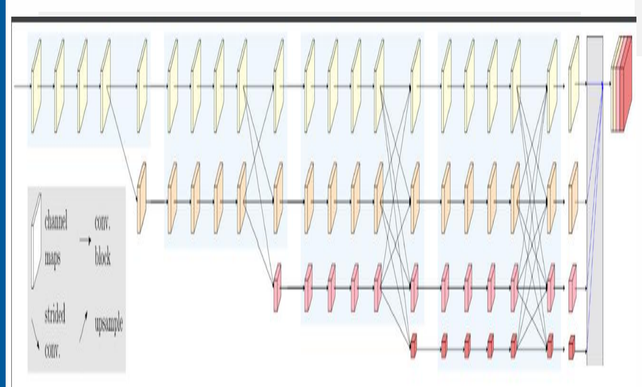

Figure 1. The structure of HRNet. HRNet will aggregate the output representations at four different resolutions, and then use a 1X1 convolutions to fuse these representations.

Materials and Methods

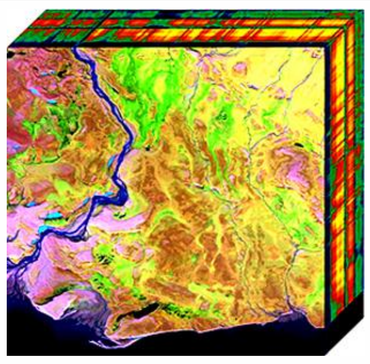

Figure 2. Hyperspectral data cube representation

Figure 3. Ground truth image of testing set of PET-PEF-CP-shaped dataset. The green class is PET, and the yellow class is PET bottle, the red class is PEF, the blue is PEF bottle, the white class is 6% co-polymer, and the orange class is 11% co-polymer.

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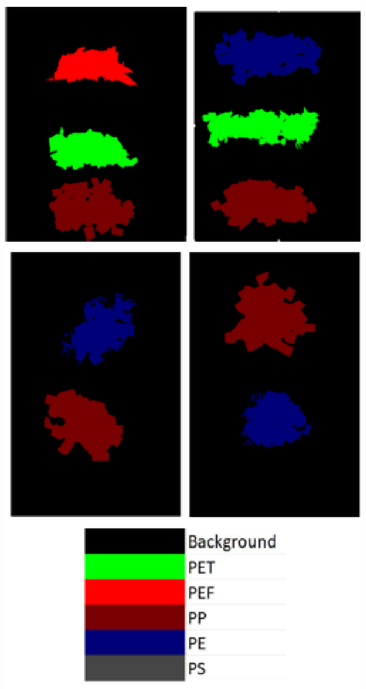

Figure 4. Ground truth image of the testing set of Plastics dataset and the color map of classes. The ground truth image and its label are the same as Plastics-hh, Plastics-hhi, Plastics-hhs datasets.

Experiments and Results

- Test the influence of different Optimizers Adam and SGD on HRNet and HRNet+OCR.
- Compare HRNet with Deep Res U Net and U Net++ on two datasets.
- Test the influence of different preprocessing methods Logarithmic Derivative and Hyper Hue on HRNet

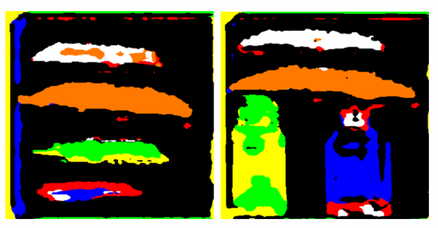

Figure 5. Prediction on PET-PEF-CP-shaped dataset from HRNet trained with SGD Optimizer.

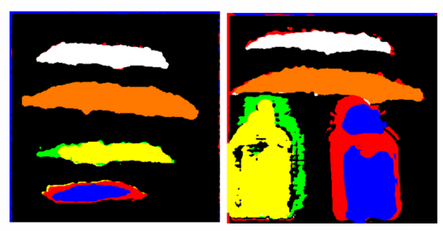

Figure 7. Prediction on PET-PEF-CP-shaped dataset from HRNet trained with Adam Optimizer.

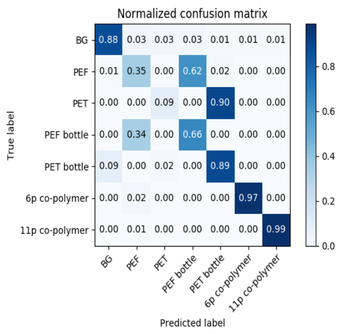

Figure 9. Confusion matrix of HRNet+OCR on PET-PEF-CP-shaped dataset

Experiments and Results

- Adam Optimizer will provide HRNet and HRNet+OCR a better performance.
- Deep Res U-Net provide the best performance on both Plastics and PET-PEF-CP-shaped datasets.
- Datasets preprocessed by Logarithmic Derivative achieved better performance from HRNet than Hyper-Hue.
- HRNet+OCR has a little better performance than HRNet when using Adam Optimizer.
- HRNet, HRNet+OCR and U Net++ have the same problem of confusing flakes and objects made in the same material

Backbone	Dataset	Optimizer	F1 score	Mean IOU
HRNet	PET-PEF-CP-shaped	Adam	0.63652	0.54901
		SGD	0.64417	0.51320
	Plastics	SGD	0.84169	0.74574
	Plastics-hh	SGD	0.59438	0.49066
	Plastics-hhi	SGD	0.72035	0.58397
	Plastics-hhs	SGD	0.67420	0.54386
Deep Res U-Net	PET-PEF-CP-shaped	SGD	**0.97260**	**0.94696**
	Plastics	SGD	**0.97626**	**0.95420**
U-Net++	PET-PEF-CP-shaped	SGD	0.80172	0.70572
	Plastics	SGD	0.95744	0.91966
HRNet+OCR	PET-PEF-CP-shaped	Adam	0.78055	0.67304
		SGD	**0.40651**	**0.18052**

Table 1. F1 score and Mean IOU from different neural network with different optimizers Adam and SGD on datasets PET-PEF-CP-shaped. Plastics-hh, Plastics-hhi and Plastics-hhs are raw Plastics dataset preprocessed by Hyper-Hue. Plastics-hhi was added withadditional intensity information and Plastics-hhs was added with additional saturation information.

Conclusions

- HRNet and HRNet+OCR can learning the hyperspectral data but may not be the best choice for learning hyperspectral data, and Deep Res U-Net is good at it.
- Logarithmic Derivative is more suitable to preprocess the hyperspectral data for training the HRNet and HRNet+OCR, and Intensity could be important information for HRNet and HRNet+OCR.
- HRNet, HRNet+OCR and U-Net++ prefer to learn two-dimensional features like colors, angles, and edges.
- The Choice of Optimizers has a great influence on HRNet and HRNet+OCR when learning hyperspectral data.
- HRNet+OCR and HRNet may be more suitable for normal RGB images.

Acknowledgements

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NHL STENDEN computer vision & data science

NHL STENDEN university of applied sciences

References

- Yijing Xie. Eli Nabavi Robert Bradford Shakeel R Saeed Sebastien Ourselin-Tom Vercauteren Jonathan Shapey. Intraoperative multispectral and hyperspectral label free imaging: A systematic review of in vivo clinical studies.
- Ke Sun, Bin Xiao, Dong Liu, and Jingdong Wang. Deep high-resolution representation learning for human pose estimation. In CVPR, 2019.
- Carlos Alejandro Guerrero Martinez. Polymer segmentation through hyper-spectral imaging and convolutional neural networks.
- Bart Riesebos. Pet and pef classification using hyper-spectral imaging and semantic segmentation networks.