CENTER FOR BIOTECH DATA SCIENCE CENTER FOR FOOD CHEMISTRY AND TECHNOLOGY

Developing a Segmentation Model for Microscopic Images of Microplastics Isolated from Clams

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MICROPLASTIC (MP) – CHARACTERIZATION



Туре
Macroplastic
Mesoplastic
Microplastic
- Large MP
- Small MP

Nanoplastic



J. Li et al., "Using mussel as a global bioindicator of coastal microplastic pollution," Environ. Pollut., vol. 244, pp. 522–533, 2019. Arthur, C., Baker, J. & Bamford, H. Proceedings of the International Research Workshop on the Occurrence, Effects, and Fate of Microplastic Marine Debris. Sept 9-11, 2008. 530 (2009)



Size

- > 5 cm
- 5 cm 5 mm

5 mm - 0.1 μm

5 mm - 1 mm

1 mm - 0.1 μm

< 0.1 µm

MICROPLASTIC CONCENTRATION IN FOOD

MP derived from plastics



Ingestion by marine biota



Concentration by food chain



MP monitoring via Manila clams **Needs 8 phases**



National Oceanic and Atmospheric Administration. Microplastic Fact sheet. Available at: https://marinedebris.noaa.gov/info/plastic.html.



Concentration by food chain



3

WET LAB PHASE (PHASE 1 – 4)















DRY LAB PHASE (PHASE 5 – 8)











Counting and measuring













P6: High-resolution fluorescent image (stitched together)



P7: Binarized image (ground truth mask)



GLOBAL CAMPUS

Magnified image

Ground truth

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Original image









Prata, J. C., Reis, V., Matos, J. T., da Costa, J. P., Duarte, A. C., & Rocha-Santos, T. (2019). A new approach for routine quantification of microplastics using Nile Red and automated software (MP-VAT). Science of The Total Environment, 690, 1277-1283.



GLOBAL CAMPUS

Takes 10 – 30 min for labeling

Binarized image

DEEP SEGMENTATION MODEL







Original image





Binarized image



 99 fluorescent microscopy images and corresponding masks - resolution: 1280×960 - 7140×5424

- Use of a sliding window, cropping, and random selection to generate 100,000 patches with a resolution of 256×256
 - organized into 5 datasets of 20,000 patches
 - 4 datasets for 4-fold cross-validation
 - I dataset for testing



DEEP SEGMENTATION MODEL

- Use of U-Net (pre-trained on ImageNet)
 - initially developed for biomedical image segmentation
 - now often used in other domains



QUANTITATIVE RESULTS







TP: # of true positives TN: # of true negatives FP: # of false positives FN: # of false negatives

QUANTITATIVE RESULTS



MP-VAT



(1) high number of true negatives (background pixels can be predicted well)(2) reduced number of false positives

U-Net

QUALITATIVE RESULTS (HALO DETECTION)

MP-VAT



white and black pixels: correctly predicted red pixels: false positives green pixels: false negatives 16



U-Net



QUALITATIVE RESULTS (NOISE REMOVAL)

MP-VAT







white and black pixels: correctly predicted red pixels: false positives green pixels: false negatives 17



U-Net



QUALITATIVE RESULTS (LOSS FUNCTIONS)





U-Net (1) BCE with logits loss and SGD

U-Net (2) Dice loss and Adam







U-Net (3) BCE with dice loss and Adam

BCE: Binary cross-entropy



- MP monitoring using marine biota (i.e., Manila clams)
- MP detection in microscopic images
 - MP-VAT (manual intervention, prone to errors)
 - U-Net (deep learning, highly automated)
- Better results in terms of false positive detection ($F_{0.5}$, precision)
- Alternative to already existing methods



FUTURE WORK

Model improvement

- reduction of false positives
- comparison to other segmentation models
- optimization of hyperparameter values (vs. default ones)

- Better accessibility & usefulness
 - GUI interface or ImageJ macro
 - integration of support for counting and finding size and shape



Thank you for your attention! Any questions?

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