Deep Learning-Based Microplastic Detection Water Systems

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Introduction:

Microplastics pose a significant threat to marine ecosystems, infiltrating water systems and impacting aquatic life and human health. Traditional methods of detecting and quantifying these pollutants are often labor-intensive and rely heavily on specialized equipment, limiting their accessibility for researchers and environmental agencies. Our deep learning-based methodology aims to revolutionize microplastic monitoring, providing an efficient and scalable tool that enhances environmental management and fosters the protection of vulnerable aquatic ecosystems.

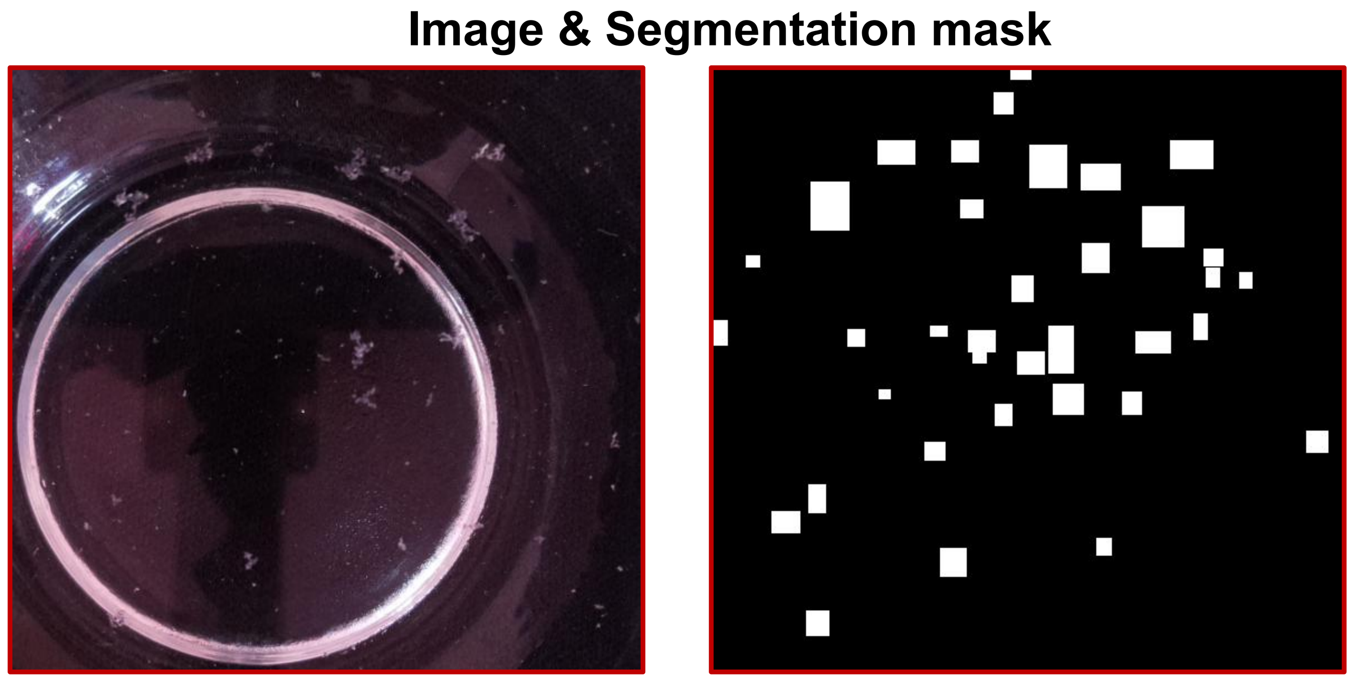
Objective:

Our goal is to develop a deep learning-based methodology for the accurate detection and quantification of microplastics in water systems using the Microplastic Dataset for Computer Vision. This approach aims to enhance environmental monitoring by providing an efficient, accessible tool for researchers and agencies, replacing traditional labor-intensive methods. Ultimately, it will facilitate scalable analysis of microplastic pollution, supporting better environmental management and protecting aquatic ecosystems and human health.

Methodology:

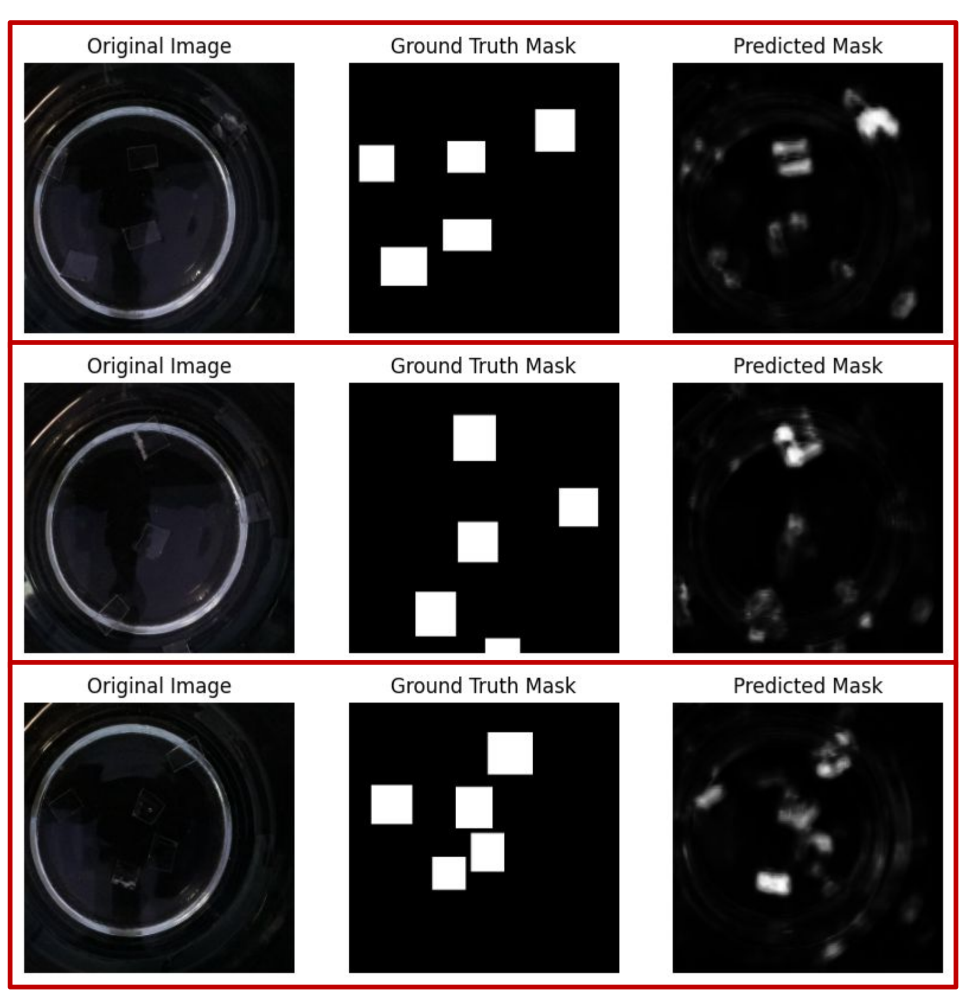
- Dataset Preparation: A microplastic dataset in COCO format was utilized, featuring annotated images with bounding boxes indicating microplastic locations. The bounding boxes, provided in the format (xmin, ymin, xmax, ymax), were converted into segmentation masks by filling each box with white pixels (255) on a blank mask. The dataset was then split into training, validation, and test sets for model training and evaluation.

Image & Segmentation mask



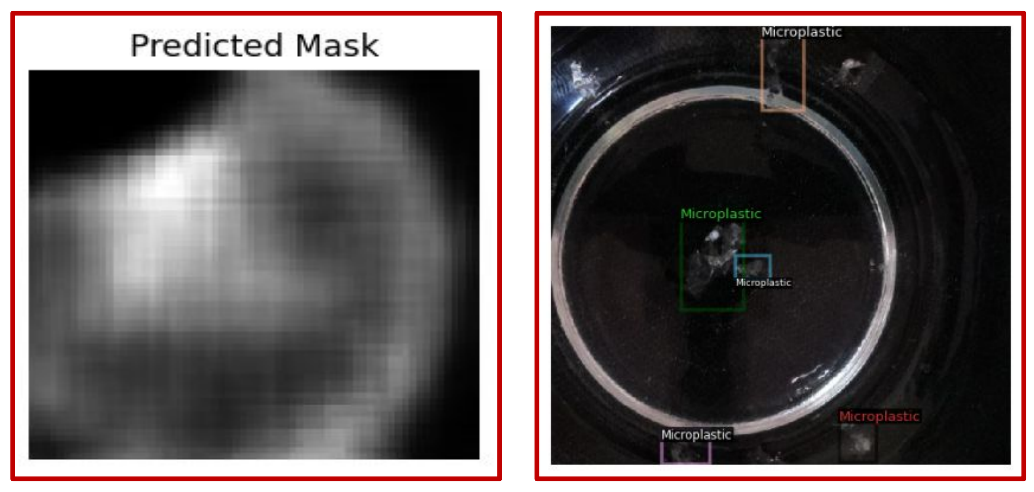
- Model Training and Comparison Study: Three models were trained and evaluated for microplastic detection and segmentation: Faster R-CNN, UNet, and ResNet50 with a custom decoder.
  - **Faster R-CNN**: Implemented using Detectron2, Faster R-CNN was pre-trained on the COCO dataset and fine-tuned with a ResNet50 backbone. It was trained for 2000 iterations with a batch size of 2, achieving effective object detection and segmentation for microplastics.
  - **UNet**: U-Net utilized a convolutional architecture for downsampling and transposed convolutions for upsampling, trained for 25 epochs with a batch size of 8. It employed binary cross-entropy loss and Adam optimizer, demonstrating strong performance in microplastic segmentation.

UNet Predictions



  - **ResNet50**: ResNet-50 was utilized as a pre-trained backbone with additional layers for segmentation tasks, fine-tuned while freezing the initial layers to enhance performance on the microplastic dataset.
  - **YOLOv8**: YOLOv8 achieved a mean Average Precision (mAP) of 78.4% at IoU=0.50 and 37.6% across IoU thresholds, with rapid inference of 0.7 milliseconds per image, making it ideal for real-time microplastic detection. The model was fine-tuned for 10 epochs with a batch size of 16 and an image size of 640 x 640 pixels.

Faster R-CNN & ReNet50 Predictions



The models were evaluated using accuracy, loss, and COCO-style Average Precision (AP) for bounding boxes and segmentation masks. Faster R-CNN achieved an AP of 30.5% at IoU=0.50:0.95 and 42.5% for medium-sized objects, indicating its effectiveness in microplastic detection. U-Net demonstrated strong segmentation performance with a validation accuracy of 96% and a loss of 0.12, while ResNet-50 achieved a validation accuracy of 95.8% and a loss of 0.13, comparable to U-Net. YOLOv8 excelled with a mean Average Precision (mAP) of 78.4% at IoU=0.50 and 37.6% across thresholds, alongside an impressive inference time of 0.7 milliseconds per image, making it ideal for real-time detection. These results collectively highlight the strengths and limitations of each model in microplastic detection and segmentation.

Result Comparison Table

Model	Task	AP (IoU=0.50:0.95)	AP50	AP75	Validation Loss	Validation Accuracy
Faster R-CNN	Object Detection	30.47%	68.37%	23.37%	-	-
U-Net	Semantic Segmentation	-	-	-	0.1161	96.03%
ResNet-50	Classification	-	-	-	0.2091	94.02%
YOLOv8	Object Detection	37.6%	78.4%	32.1%	-	-

Results:

- The performance of four models—Faster R-CNN, U-Net, ResNet-50, and YOLOv8—was evaluated for object detection, semantic segmentation, and classification tasks. **Faster R-CNN** achieved an Average Precision (AP) of 30.47% at IoU=0.50:0.95, with better performance for medium (42.47%) and large (65.12%) objects but lower for small ones (13.86%). **U-Net** excelled in semantic segmentation with a 96.03% accuracy and a loss of 0.1161, while **ResNet-50** yielded a 94.02% accuracy and a loss of 0.2091 for classification. **YOLOv8** demonstrated strong performance with an mAP50 of 78.4% and mAP50-95 of 37.6%, making it ideal for real-time microplastic detection due to its speed and precision.

Conclusion:

U-Net achieves a higher accuracy (96.03%) and lower validation loss (0.1161), indicating strong performance in recognizing and segmenting microplastics. U-Net is the more appropriate model for microplastic detection if your focus is on precisely identifying and segmenting microplastics at a pixel level.

Reference:

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2.Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In N. Navab, J. Hornegger, W. M. Wells, & A. F. Frangi (Eds.), Medical Image Computing and Computer-Assisted Intervention (MICCAI) 2015 (Vol. 9351, pp. 234–241). Springer, Cham. https://doi.org/10.1007/978-3-319-24574-4_28