Detecting Plastic in Rivers

Ankush Gajanan Arudkar

1 Problem Statement

Plastic pollution is a significant threat to the Earth's ecosystem (Ritchie 2021), particularly when it reaches the oceans via rivers. Detecting and preventing plastics from entering oceans is more manageable within river environments. This project aimed to identify floating plastics in river images to combat oceanic plastic pollution. The goal was to enhance the YOLOv5 (Jocher et al. 2021) baseline's detection accuracy for plastic bottles, which was initially around 5Two datasets, Trash Annotated in Context (Proença and Simoes 2020) and KILI Plastic in Rivers (Dullin 2022), were utilized for training, validation, and testing. Additionally, the Plastic Bottles in Rivers dataset assessed the model's generalizability. The model utilized 5759 images with 15185 annotations of labelled trash.

Figure 1: Detected floating plastic in test images using YOLOv5 and FastSAM+CNN approaches

The project comprised two main stages: object detection and binary classification (floating plastic vs. background). The first approach involved training YOLOv5 nano and small models, integrating object detection and classification into a single step. The second approach employed Fast Segment Anything Model (Zhao et al. 2023) for image segmentation, followed by detecting floating plastics in the segmented objects. Upon evaluation, the first approach demonstrated better performance on training and validation sets. However, the second approach exhibited greater versatility, successfully detecting plastic in diverse environmental conditions achieving a recall of nearly 51

2 Analysis and Visualisation

The KILI datasets contained bounding box annotations for four waste categories, while the TACO datasets included 60 distinct waste categories. As demonstrated in the class distribution depicted in the Figure 2, we observed a significant class label imbalance, with plastic bottles and bags comprising the majority of annotations.

As depicted in Figure 3, the images exhibited significant variation in size due to being sourced from crowds. Given our decision to employ neural networks for training, it became necessary to standardize the images based on the respective approaches before initiating the training process.

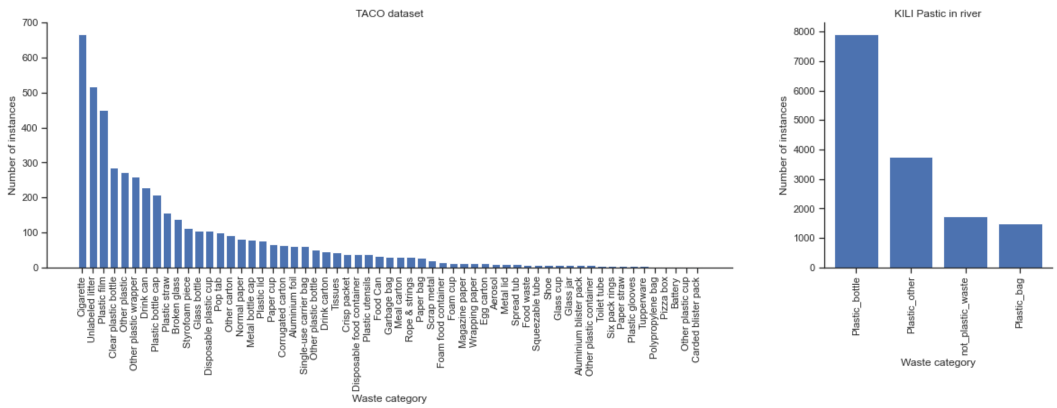

Figure 2: Histograms of waste category labels present in raw TACO (left) and KILI (right) datasets

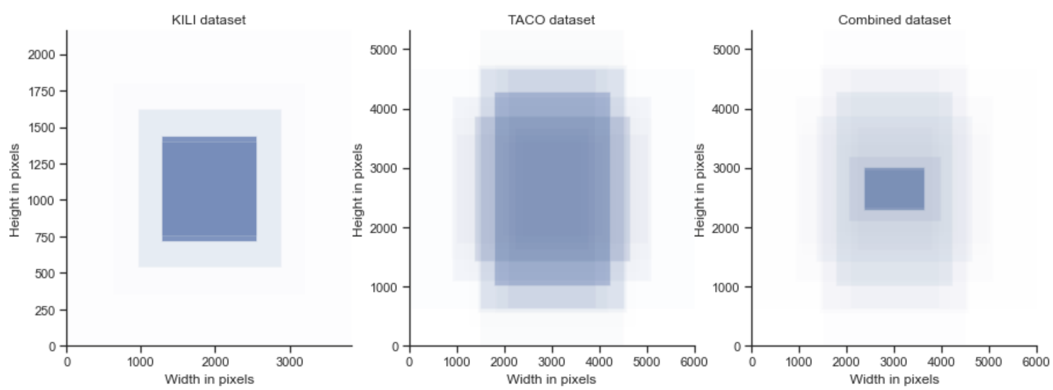

Figure 3: Density plots of various image sizes present in KILI, TACO and merged datasets

We evaluated four models using two distinct approaches. The first approach included YOLOv5 nano and YOLOv5 small, which integrated detection and classification stages. The second approach involved FastSAM, which utilized classifying CNNs leveraging segmentation capabilities for object detection. Loss curves and validation accuracy for the YOLOv5 models are illustrated in Figure 4, while the second approach is depicted in Figure 5.

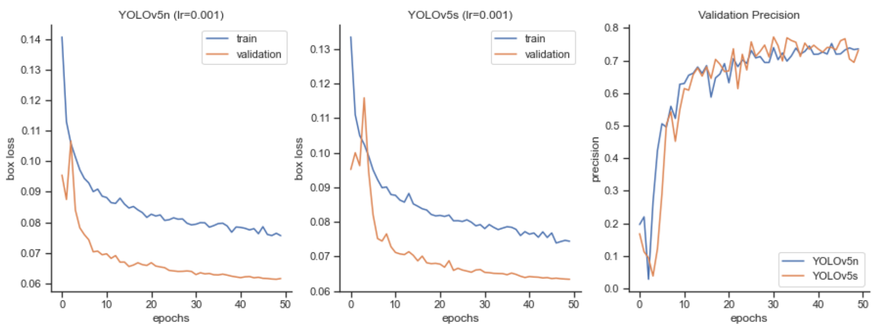

Figure 4: Learning and precision curves for YOLOv5 nano and small model with learning rate=0.001 and batch size 64, with other default configurations

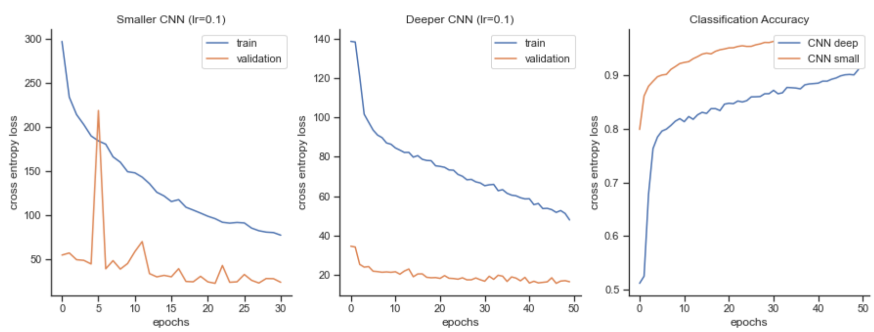

Figure 5: Cross entropy loss and accuracy curves for binary classification for shallow and deeper CNN. Due to different convergence each model was trained for different epochs

To assess the performance of the models, we computed precision, recall, and F1-scores on the testing dataset. Additionally, to gauge the applicability of the trained models beyond the training data, we employed a separate holdout dataset comprising generic images depicting floating plastics in rivers. The obtained results are presented in the Table 1.

3 Improvement of Situation

To combat marine plastic pollution, we introduced two methodologies for identifying floating plastics in rivers. As evident from the metrics, the second approach yielded a more versatile model capable of detecting plastic debris in non-standard images. Initiatives like The Ocean Cleanup (Slat 2019) could benefit from such systems to automate the detection of garbage patches on ocean surfaces.

The trained model could be deployed on centralized servers, receiving river surface image data. It would then process batches of images, annotating identified plastic items. With

Dataset	Model	Precision	Recall	F1-Score
Testing set	YOLOv5n	0.29	0.41	0.17
	YOLOv5s	0.30	0.43	0.18
	FastSAM+CNN1	0.15	0.42	0.11
	FastSAM+CNN2	0.153	0.39	0.10
Holdout dataset	YOLOv5n	0.57	0.05	0.09
	YOLOv5s	0.45	0.03	0.05
	FastSAM+CNN1	0.10	0.50	0.16
	FastSAM+CNN2	0.11	0.51	0.18

Table 1: Test metrics evaluated on testing set and holdout Plastic Bottles in Rivers dataset (mn-0 2021) to access general usability of models

location information from the images, the model could closely monitor the extent of plastic pollution in rivers, guiding cleaning and control efforts.

To enhance the model further, the amassed data could be employed to refine its training, making it better suited for its intended environments. Although the second approach managed to identify over half of the plastic waste in the holdout dataset, it did experience a high false positive rate. To mitigate this, we propose training the system as a batch online learning system. This approach would continuously learn from new data, becoming increasingly adept at the specific environments it operates in.

We suggest this method as a means to identify, track, and curtail plastic pollution in rivers, thereby contributing to the prevention of marine plastic contamination.

4 Conclusion and Future work

Detecting floating plastic in rivers poses significant challenges due to scene and image variations. We explored two distinct approaches: employing YOLOvx models and utilizing FastSAM+CNNs for the detection of floating plastics in river settings. Some results from images collected from Torrens River, Adelaide are shown in Figure 6.

The first approach exhibited better precision (57%) and minimal false positives when detecting plastics in familiar images. However, its adaptability to new, dissimilar images – which were not well-represented in the training set – was limited, leading to subpar performance on an independent test dataset.

Conversely, the second approach, relying on segmentation for object detection, displayed better adaptability (51% recall). Despite demonstrating efficacy in detecting floating plastics across diverse environments, this approach suffered from a higher incidence of false positives (11% precision).

In future, our focus lies in enhancing the second approach by mitigating false positives. As we recognize that image cropping for classification results in the loss of contextual information, we intend to implement contextual learning. This approach aims to comprehend the object's context, ultimately refining the classification accuracy of floating plastics.

Figure 6: Example images from River Torrens, Adelaide with detections from trained YOLOv5s and Fast SAM+CNN2 model, showing better generalization of second approach

References

mn-0, GitHub (2021). *GitHub - m0-n/Plastic-Bottles-Dataset: A dataset of 5,592 plastic bottles swimming in rivers and some attempts to build a model on that. — github.com.* `https://github.com/m0-n/Plastic-Bottles-Dataset`.

Dullin, Theo (2022). "Kili's Community Challenge - plastic in river dataset". In: *kili*. URL: `https://kili-technology.com/data-labeling/machine-learning/kili-s-community-challenge-plastic-in-river-dataset`.

Jocher, Glenn et al. (2021). "ultralytics/yolov5: v5. 0-YOLOv5-P6 1280 models, AWS, Supervise. ly and YouTube integrations". In: *Zenodo*.

Proença, Pedro F and Pedro Simoes (2020). "Taco: Trash annotations in context for litter detection". In: *arXiv preprint arXiv:2003.06975*.

Ritchie, Hannah (2021). "Where does the plastic in our oceans come from? — ourworldindata.org". In: [Accessed 12-Jun-2023].

Slat, Boyan (2019). "The Ocean Cleanup Project". In: [Accessed 12-Aug-2023].

Zhao, Xu et al. (2023). "Fast Segment Anything". In: *arXiv preprint arXiv:2306.12156*.