An Image Analysis of Coastal Debris Detection
-Detection of microplastics using deep learning-

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Abstract

To address the issue of litter drifting ashore, this study developed a deep learning-based microplastic detection system. The system employed yolov7 [1] as its deep learning network, complemented by SAHI (Slicing Aided Hyper Inference) [2] as an additional vision library. yolov7 is renowned for its efficacy in real-time object detection. Our experimental framework involved four tests, utilizing two variations of yolov7 - the standard model and yolov7-e6e - in conjunction with SAHI. The effectiveness of each test was quantified using metrics such as Intersection over Union (IoU), Precision, Recall, F-measure, and Detection Time in seconds. For our dataset, we gathered images from actual cleanup locations, such as Hokuto Mizukumi Park. The model's discriminator underwent 700 training iterations, with a learning rate set at 0.001. Experimental results showed that it detects fairly small microplastics.

Keywords: Deep learning, Object detection, YOLOv7

1. Introduction

Drifted litter has become widespread throughout Japan. In many regions, the composition of this litter, based on volume, weight, and count, is predominantly artificial rather than natural. Plastic litter does not decompose naturally and, due to the influence of ultraviolet rays and waves, breaks down into microplastics that drift in the ocean. They are then washed up on the sandy beaches. Microplastics, which may contain harmful substances from the time of product manufacturing or accumulate other toxicants, such as polychlorinated biphenyls, during their drift, can be ingested by marine life, potentially causing adverse effects. These microplastics, with a size of less than 5mm, make them difficult to visually detect on the sand.

A significant amount of waste washes up on the coasts of Japan. Among this, small items like microplastics, often buried in the sand, are difficult to detect by the current survey methods. Furthermore, some coastal areas, which are undeveloped or have wave-dissipating blocks, are difficult to access, making it impossible to undertake surveys there. To solve the problem of beached waste, a wide range of data is needed. However, the regular and systematic collection of data on the waste in various places is challenging with the present means of survey.

In this study, we aimed to realize labor-saving in beached waste surveys by using deep learning for image-based waste detection. Particularly, we focused on the challenge of detecting microplastics, extremely small items, previously undetected in other studies. To achieve this, we used deep learning to create a dataset with coastal images and utilized it for both training the detection model and validating its effectiveness. Fig.1 presents an image sample from the dataset. This research was conducted with a specific focus on a single-detection model, solely for microplastics.

Fig.1 Examples Dataset

2. Methodology

2.1. *Composition of YOLOv7*

In this study, we employed the deep learning model known as YOLOv7. YOLOv7 is an object detection algorithm that operates at a higher speed than the existing YOLO series. As shown in Fig.2 on the MS COCO dataset, it achieves an AP value that significantly surpasses the existing YOLO series. There are several models within YOLOv7, and for our research, we used the base model, YOLOv7 (plain), and YOLOv7-E6E. Each model has a three-stage pyramid structure, generating multiple feature maps through repeated upsampling and downsampling. Ultimately, three of these feature maps are used for estimation. The base model, YOLOv7 (plain), uses a network composed of multiple convolutional layers known as ELAN. Additionally, YOLOv7-E6E employs an expanded version of the ELAN network, called E-ELAN. The structures of ELAN and E-ELAN are shown in Fig.3

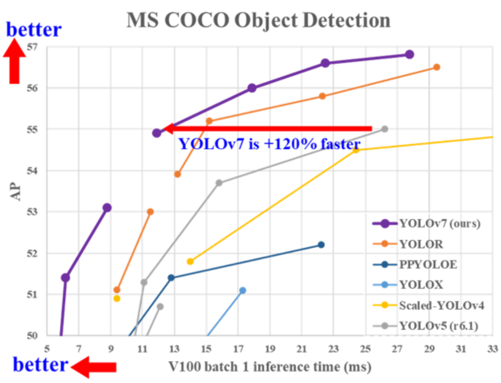

Fig.2 Comparison of YOLOv7 with other real-time object detectors

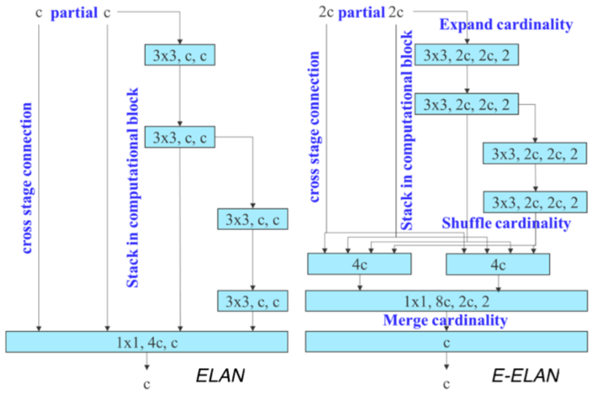

Fig.3 ELAN, E-ELAN Structure

2.2. *SAHI(Slicing Aided Hyper Inference)*

SAHI is a lightweight vision library for large-scale object detection and instance segmentation. As illustrated in Fig.4, it divides the input image into small rectangles. The model then performs an evaluation on each segmented image and finally merges and outputs the detection results. While SAHI can be applied to any deep learning model in principle, it has the limitation that the estimation time increases linearly, as it conducts the task on each of the segmented images.

Fig.4 Image segmentation image using SAHI

2.3. *Dataset creation*

The dataset used in this study was created using photographs taken at real-world beach cleanup locations, including Hokuto Miukumi Park. The main subject of the photographs was microplastics found on the sand. To enable the identification of these microplastics from other beach debris like shells and stones, we also included images of only shells and stones. The only class created was for microplastics. A total of 534 photographs were taken, and the number of images for training and final test datasets was tripled to 1,376 by using a brightness filter. These were then divided into 977 for training, 291 for final test dataset, and 108 for the general test dataset.

2.4. *Identifier creation and evaluation methods*

The identifier was trained 700 times using the created dataset. The study used models that were optimized to achieve the highest weighted sum of Average Precision (AP) and mean Average Precision (mAP) at a 1:9 ratio during the training. Experiments were conducted using two different types of YOLOv7 (plain) and YOLOv7-E6E, as well as SAHI. The evaluation of the detector's effectiveness was based on the range of the IoU value being over 0.65, and the results were compared in terms of precision, recall, F1-score, and time of estimation. The F1-score, representing the harmonic mean of precision and recall, and the time of estimation, which is the time taken for the model to read the input image and produce an output, were the main points of performance analysis. The formulas for precision, recall, and F-score are shown in equations (1) to (4). Additionally, the confusion matrix is presented in Table1

$$Precision = \frac{TruePositive}{TruePositive + FalseNegative} \quad (1)$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \quad (2)$$

$$F - score = \frac{2 * Precision * \ Recall}{Precision + Recall} \quad (3)$$

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union} \quad (4)$$

Table1. Confusion Matrix

		Predictions	
		Positive	Negative
Actual Results	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

3. Results and Discussion

Fig.5 Example of detection results

Table2. Score per model combination

Model	Precision	Recall	F-score	Time of estimation
Yolov7	0.771	0.679	0.722	0.157
Yolov7 + SAHI	0.801	0.671	0.730	1.63
YOLOv7-E6E	0.836	0.571	0.679	0.216
YOLOv7-E6E + SAHI	0.832	0.765	0.753	2.92

As observed in Fig.5, the detector can identify even very small microplastics. It also effectively prevents false detections of stones with similar shapes. Using SAHI with both models resulted in improved accuracy across all metrics except for estimation time. Specifically focusing on the YOLOv7-E6E model, the use of SAHI significantly increased the recall rate by nearly 0.2, demonstrating that the model becomes more robust in detecting microplastics with SAHI. However, the use of SAHI resulted in an estimation time that was approximately ten times longer.

The detection results demonstrate that the detector can accurately identify microplastics, indicating its practical viability. However, as indicated in Table2, high precision and recall rates were not achieved. A potential reason for this could be the dataset's quality. The annotations for the dataset were manually done, and objects not visually identifiable as trash were not labeled. The results show that the detector can identify microplastics that were too small to be labeled, leading to a lower precision rate. Regarding recall, the failure to detect microplastics resembling stones or shells in color resulted in lower accuracy. The dataset images were captured with an iPhone at resolutions like 3024 × 4032. To minimize the PC's load in the experiment, the input images for the model were resized to 1280 × 1280, making smaller objects even harder to recognize. Addressing these issues could involve labeling even smaller objects and increasing training data for items like stones and shells. Adjusting hyperparameters such as batch size might also enhance accuracy. The increased estimation time due to SAHI's use could be mitigated with software like TensorRT [3], which accelerates deep learning inference.

4. Conclusion

In a validation experiment, we developed a detector using YOLOv7 to identify microplastics and evaluated its accuracy. Accuracy was assessed using four metrics: precision, recall, F1-score, and estimation time. The results suggest that the detector achieves sufficiently accurate detection for practical use. It is suggested that modifying the annotation method and adjusting hyperparameters could lead to the development of a more accurate model.

Acknowledgements

This research was conducted at the Laboratory of Professor Hideharu Hayashi, Department of Intelligent Systems Engineering, Faculty of Information Engineering, Kyushu Institute of Technology. I am deeply grateful to Professor Hideharu Hayashi for his valuable opinions and guidance throughout the research. My heartfelt thanks also go to all members of the Hayashi Laboratory for their guidance in my daily research activities.

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