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Research Article

Coastal Litter Detection through Image Analysis-Employing Deep Learning to Identify Microplastics-

Yuto Okawachi[1], Shintaro Ogawa[1], Takamasa Hayashi[1], Tan Chi Jie[1], Janthori Titan[1], Eiji Hayashi[1], Ayumu Tominaga[2], Satoko Seino[3]

[1]*Department of Mechanical Information Science and Technology, Kyushu Institute of Technology, 680-4, Kawazu, Iizuka-City, Fukuoka, 820-8502, Japan*
[2]*Department of Creative Engineering Robotics and Mechatronics Course, National Institute of Technology Kitakyushu Colllege, 5-20-1 Shii, Kokuraminamiku, Kitakyushu, Fukuoka, 802-0985, Japan*
[3]*Graduate School of Engineering, Kyushu University 744 Motooka, Nishiku, Fukuoka city, Fukuoka, 819-0395, Japan*

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ABSTRACT

The challenge of coastal litter accumulation led to the creation of a detection system powered by deep learning, aimed at identifying microplastics. The system harnessed the yolov7 [1] deep learning architecture, known for its proficiency in real-time object detection, and integrated the SAHI (Slicing Aided Hyper Inference) [2] vision library to augment its capabilities. Within the scope of our study, we conducted four separate evaluations using two versions of yolov7—the base model and the advanced yolov7-e6e—alongside SAHI. The performance of each setup was measured against a set of metrics, including Intersection over Union (IoU), Precision, Recall, F-measure, and Detection Time, recorded in seconds. The dataset for the study was composed of images sourced from real-world beach clean-up sites, including Hokuto Mizukumi Park. The detection algorithm was subjected to 700 rounds of training, with an initial learning rate of 0.001. Our findings indicated that the system was adept at identifying relatively small microplastics.

1. Introduction

Litter drift has become a pervasive issue across Japan, with a significant portion of this litter, in terms of volume, weight, and quantity, being synthetic rather than organic. Plastics, which do not break down in nature, fragment into microplastics under the action of UV radiation and wave motion, subsequently adrift in marine environments before accumulating on beaches. Microplastics can carry hazardous chemicals incorporated during manufacturing or may adsorb dangerous substances like PCBs (polychlorinated biphenyls) while adrift, posing a risk to aquatic life if consumed. Due to their diminutive size, under 5mm, spotting these microplastics on beaches becomes a challenge.

Japan's shores are inundated with debris, including minuscule particles like microplastics that easily blend into the sand, rendering them nearly invisible to current detection methodologies. Moreover, the exploration of remote or technologically reinforced coastlines, characterized by the presence of wave-breakers, presents substantial logistical challenges, hindering survey efforts. Addressing the accumulation of coastal debris necessitates comprehensive data collection, a task that proves to be formidable using conventional survey techniques.

This research proposes a novel approach to streamline the survey process of coastal debris through the application of deep learning in the analysis of imagery for debris identification. A focal point of our investigation was the adept detection of microplastics—particles so small they have eluded detection in prior examinations. By harnessing deep learning to generate a coastal imagery dataset, we facilitated the development and subsequent validation of a model dedicated to detecting these particles. An exemplar from our dataset, depicted in Fig. 1, illustrates the type of imagery analyzed. The study prioritizes the development of a dedicated model for the detection of microplastics, showcasing its potential for Specialized application.

Corresponding author E-mail: ookawachi.yuuto693@mail.kyutech.jp, tominaga@kct.ac.jp, haya@mse.kyutech.ac.jp URL: http://www.kyutech.ac.jp/

Fig. 1 Examples Dataset

2. Methodology

2.1. *Composition of YOLOv7*

In this investigation, the YOLOv7 deep learning model was utilized. This model represents an evolution of the YOLO (You Only Look Once) family, providing a significant increase in processing speed for object detection tasks. As demonstrated in Fig. 2, when applied to the MS COCO dataset, YOLOv7 outperforms previous iterations of the YOLO series in terms of Average Precision (AP) values. Our study made use of two specific variants within the YOLOv7 suite: the standard YOLOv7, referred to as YOLOv7 (plain), and an enhanced version, YOLOv7-E6E. Both models employ a tri-level pyramid architecture that generates a variety of feature maps by alternating between upsampling and downsampling processes. For object prediction tasks, three distinct feature maps from this architecture are utilized. The YOLOv7 (plain) is constructed using a series of convolutional layers named ELAN, while YOLOv7-E6E incorporates a more advanced network structure, designated as E-ELAN. The configurations of the ELAN and E-ELAN networks are depicted in Fig. 3.

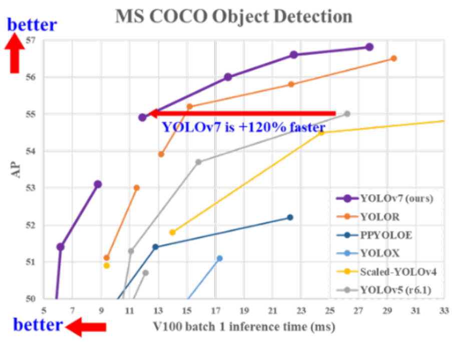

Fig. 2 Comparison of YOLOv7 with other real-time object detectors

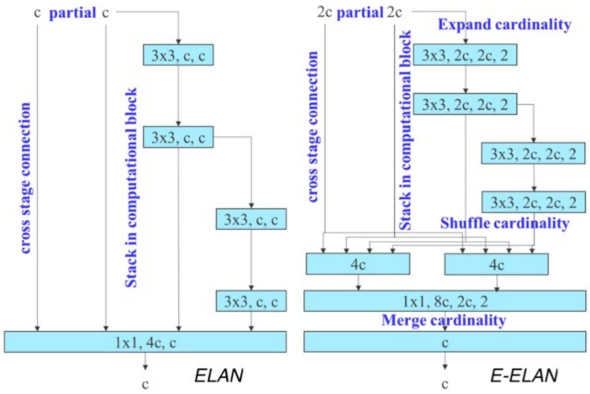

Fig. 3 ELAN, E-ELAN Structure

2.2. *SAHI(Slicing Aided Hyper Inference)*

SAHI is a streamlined vision toolkit designed for executing large-scale object detection and instance segmentation tasks with efficiency. Demonstrated in Fig. 4, the technique processes an input image by partitioning it into a series of smaller, manageable rectangles. The model assesses each of these individual sections in sequence and then compiles the results, producing a consolidated output of the detection findings. Although SAHI is compatible with a variety of deep learning models, it does face a constraint in that the time required for estimation proportionally increases with the number of image segments being analyzed.

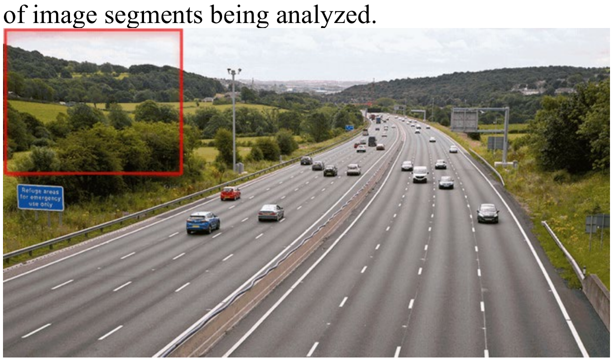

Fig. 4 Image segmentation image using SAHI

2.3. *Dataset creation*

This research utilized a dataset generated from photographs captured at actual beach cleaning sites, including Hokuto Miukumi Park, with a focus on microplastics interspersed in the sand. To enhance the model's ability to distinguish microplastics from other common beach detritus such as shells and stones, the dataset was supplemented with images exclusively featuring these items. The singular category labeled and identified within this dataset was microplastics. From an initial collection of 534 photographs, the dataset was expanded to encompass 1,376 images by applying a brightness filter to augment the dataset for training and testing purposes. This expanded set was allocated as follows: 977 images for the training set, 291 for the final test set, and 108 for a general test set.

2.4. *Identifier creation and evaluation methods*

In this study, the detection system was refined through 700 iterations of training with the assembled dataset. The models were fine-tuned with an emphasis on maximizing the combined weighted values of Average Precision (AP) and mean Average Precision (mAP), using a weighting ratio of 1:9 to guide the optimization process during training. The investigative procedures incorporated two variants of YOLOv7—YOLOv7 (plain) and YOLOv7-E6E—alongside the application of SAHI. The efficacy of the detection system was appraised by setting a threshold for the Intersection over Union (IoU) metric at above 0.65. Comparative analysis was carried out, focusing on metrics such as precision, recall, F1-score, and the duration of estimation. The F-score, which balances precision and recall through their harmonic mean, along with the estimation time—the interval required for the model to process an input image and generate an output—were central to the performance evaluation. The calculations for precision, recall, and the F-score are delineated in equations (1) through (4), and the corresponding confusion matrix is delineated in Table 1

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

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

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

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

Table1. Confusion Matrix

		Predictions	
		Positive	Negative
Actual Result	Positive	True Positive	False Negative
	Negative	False Positive	True Negative

3. Results and Discussion

Fig.5 Example of detection results

Table2. Performance metrics by model pairing

Model	Precision	Recall	F-score	Time of Estimation
YOLOv7	0.771	0.679	0.722	0.157
YOLOv7 + SAHI	0.801	0.671	0.73	1.63
YOLOv7-E6E	0.836	0.571	0.679	0.216
YOLOv7-E6E + SAHI	0.832	0.765	0.753	2.91

Fig. 5 showcases the detector's capability to pinpoint even diminutive microplastics and effectively discern them from similarly shaped stones, avoiding false positives. The integration of SAHI with both YOLOv7 models enhanced precision across most evaluated metrics, except for the time taken for estimation. Notably, when paired with the YOLOv7-E6E model, SAHI substantially boosted the recall metric by about 0.2, signifying an enhancement in the model's ability to identify microplastics when supplemented with SAHI. This improvement, however, came with the trade-off of a tenfold increase in the time required for estimation.

Despite the promising ability of the detection system to accurately identify microplastics, as evidenced by its performance, the precision and recall rates reported in Table 2 were suboptimal. One potential factor contributing to this could be the inherent quality of the dataset. Since the annotations within the dataset were manually generated, and items not clearly identifiable as debris were omitted from labeling, this practice might have led to the identification of previously unlabeled microplastics, thus affecting the precision rate. The issue with recall might stem from the model's inability to detect microplastics that share a visual similarity with stones or shells. The photographs in the dataset were taken using an iPhone at high resolutions, such as 3024 × 4032. To lessen the computational demand during the experiment, the images were downsized to 1280 × 1280 before being fed into the model, which could hinder the recognition of smaller items. Remedying these limitations could entail labeling even the smallest detectable objects and enriching the training dataset with more varied representations of materials like stones and shells. Fine-tuning model hyperparameters, for example, batch size, may also lead to improved accuracy. The longer estimation times associated with the use of SAHI might be alleviated through the adoption of software solutions like TensorR [3], designed to expedite deep learning inference processes.

4. Conclusion

In our validation trial, we engineered a detection system utilizing the YOLOv7 model specifically to recognize microplastics. We measured the detector's precision through a quartet of metrics: precision, recall, F1-score, and the time required for estimation. The findings indicate that the detector operates with an accuracy level that is deemed adequate for practical applications. It is posited that refining the approach to annotation and tweaking the model's hyperparameters might pave the way to enhancing the model's detection accuracy.

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Authors Introduction

Mr. Yuto Okawachi

He received his Bachelor's degree in Engineering in 2023 from intelligent and Control Systems, Kyushu Institute of technology in Japan. He is currently a Master student in Kyushu Institute of Technology and conducts research at Hayashi Laboratory.

Mr. Shintaro Ogawa

He received his Bachelor's degree in Engineering in 2022 from intelligent and Control Systems, Kyushu Institute of technology in Japan. He is currently a Master student in Kyushu Institute of Technology and conducts research at Hayashi Laboratory.

Mr. Takamasa Hayashi

He received his Bachelor's degree in Engineering in 2023 from intelligent and Control Systems, Kyushu Institute of technology in Japan. He is currently a Master student in Kyushu Institute of Technology and conducts research at Hayashi Laboratory.

Mr. Tan Chi Jie

He received his Master of Creative Informatics from the Department of Computer Science and Systems Engineering, Kyushu Institute of Technology, Japan in 2023. He is currently a Doctoral student at Kyushu Institute of Technology and conducts research at Hayashi Laboratory.

Mr. Janthori Titan

He received his Bachelor of Engineering in Robotic Engineering and Automation System from the Department of Production Engineering, Faculty of Engineering, King Mongkut's University of Technology North Bangkok in 2022. He is currently a Master student at Kyushu Institute of Technology and conducts research at Hayashi Laboratory.

Dr. Ayumu Tominaga

He is a professor in Department of Creative Engineering Robotics and Mechatronics Course at National Institute of Technology Kitakyushu College. He received the Ph.D. (Dr. Eng.) degree from Kyushu Institute of Technology in 2021. His research interests include Intelligent mechanics, Mechanical systems and Perceptual information processing.

Dr. Eiji Hayashi

He is a professor in the Department of Intelligent and Control Systems at Kyushu Institute of Technology. He received the Ph.D. (Dr. Eng.) degree from Waseda University in 1996. His research interests include Intelligent mechanics, Mechanical systems and Percentual information processing. He is a member of The Institute of Electrical and Electronics Engineers (IEEE) and The Japan Society of Mechanical Engineers (JSME).

Dr. Satoko Seino

She is an associate professor in Graduate School of Engineering, Kyushu university. She received the Ph.D. (Eng.) from Kyushu University. Her research interests include coastal and riverine environmental conservation.