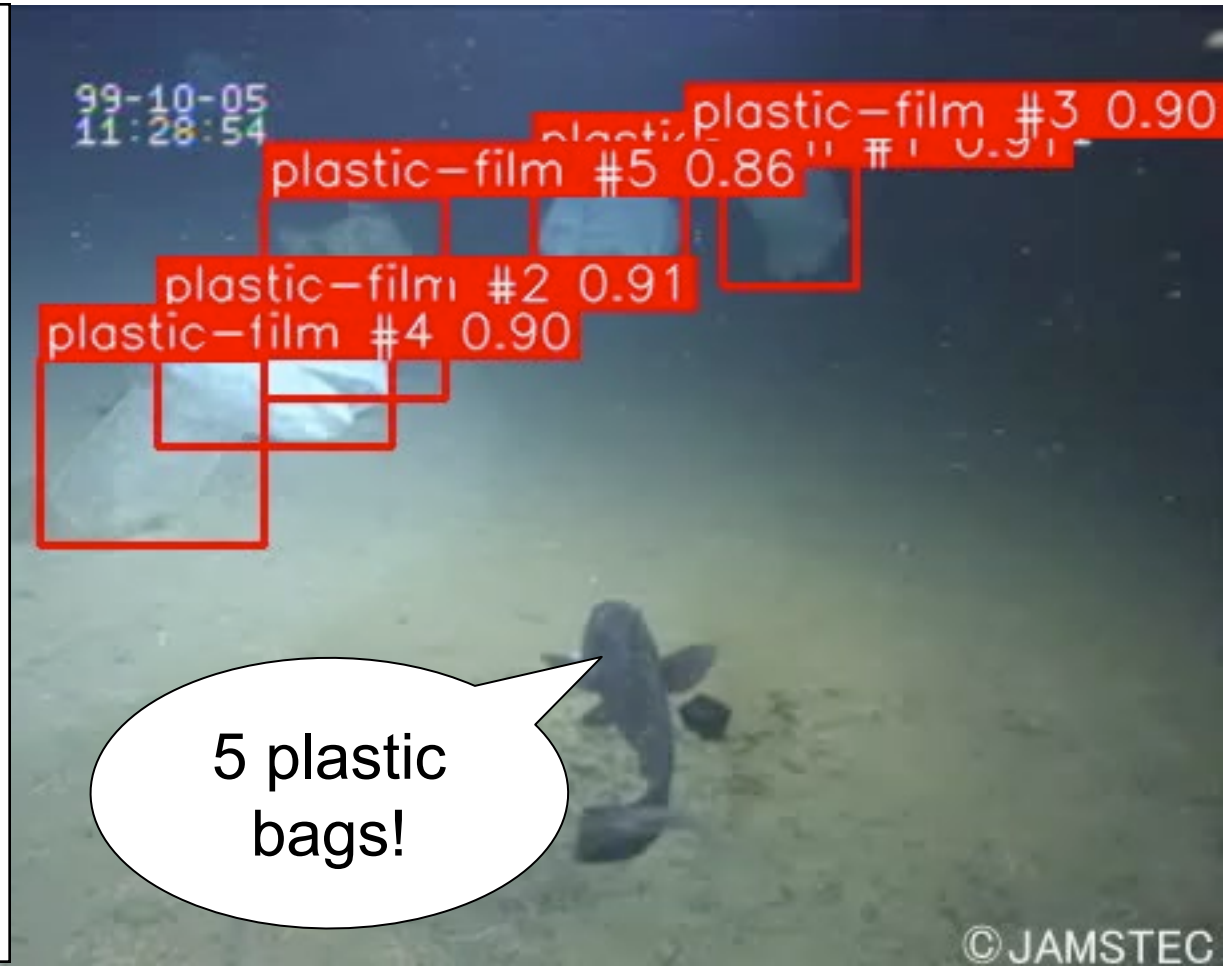
Development of an AI System for Quantifying Deep-Seafloor Plastic and Macrolitter



Ryota Nakajima, Takaki Nishio
H. Saito, S. Kawahara, D. Matsuoka

JAMSTEC 国立研究開発法人 海洋研究開発機構
Japan Agency for Marine-Earth Science and Technology

Challenges in seafloor litter monitoring



Problems:

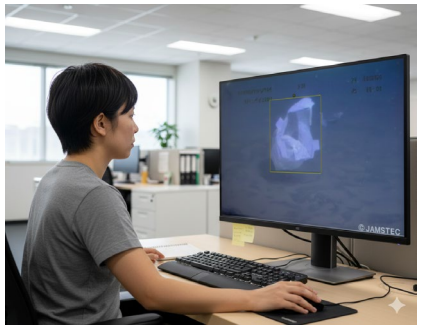
- Damage to seafloor ecosystems
- Low collection efficiency



- Non-destructive
- Direct observation of litter

Hanke et al. 2025

Manual video analysis



Time-consuming

- Identification
- Classification
- Counting



100 hours of footage
= 1 month of manual analysis

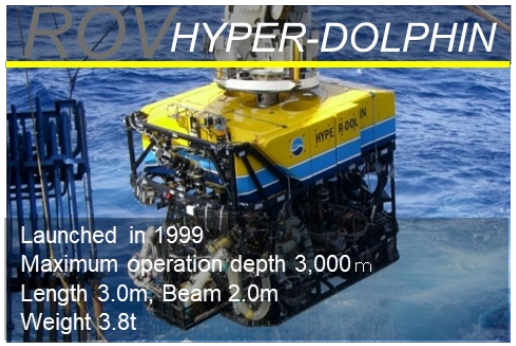
Limits large-scale and long-term monitoring

AI-powered automated analysis
detection, classification, counting

Requires high-quality training data

JAMSTEC Extensive archives of dee-sea imagery







JAMSTEC's public image database

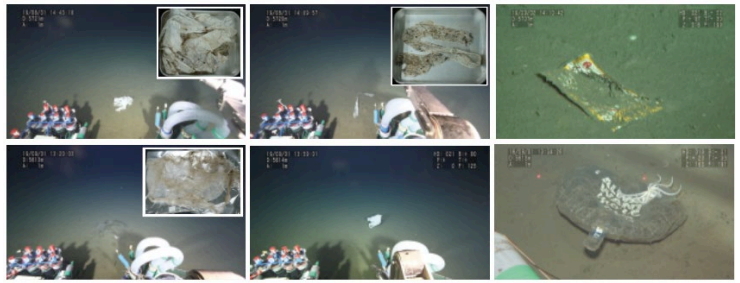


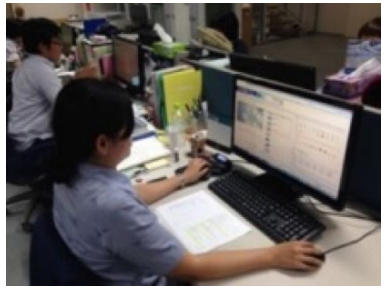


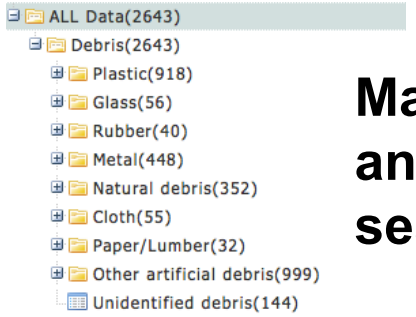
Deep-sea surveys since 1983

6,000+ deep-sea dives

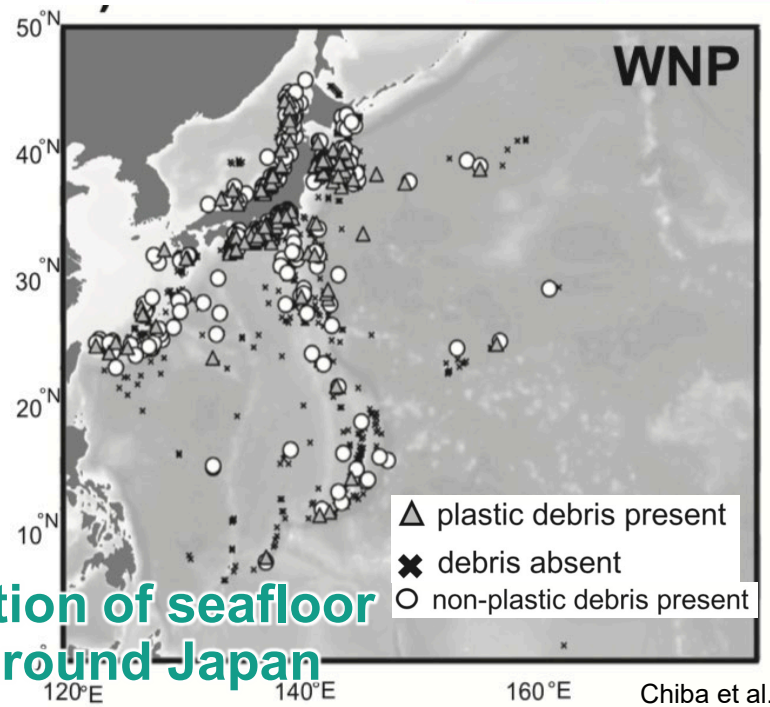








Manual identification and annotation of seafloor litter

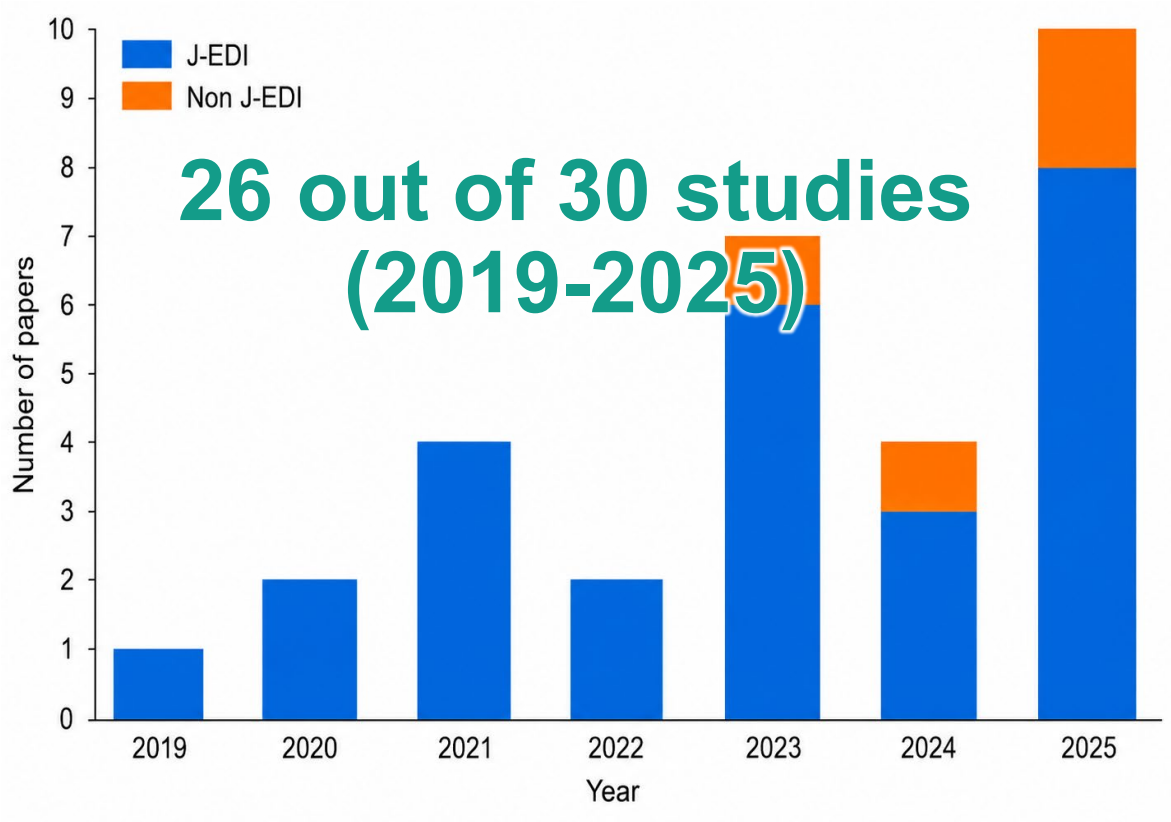


Distribution of seafloor litter around Japan

Chiba et al. 2018

Widely used for AI training in seafloor litter detection

87% used JAMSTEC images

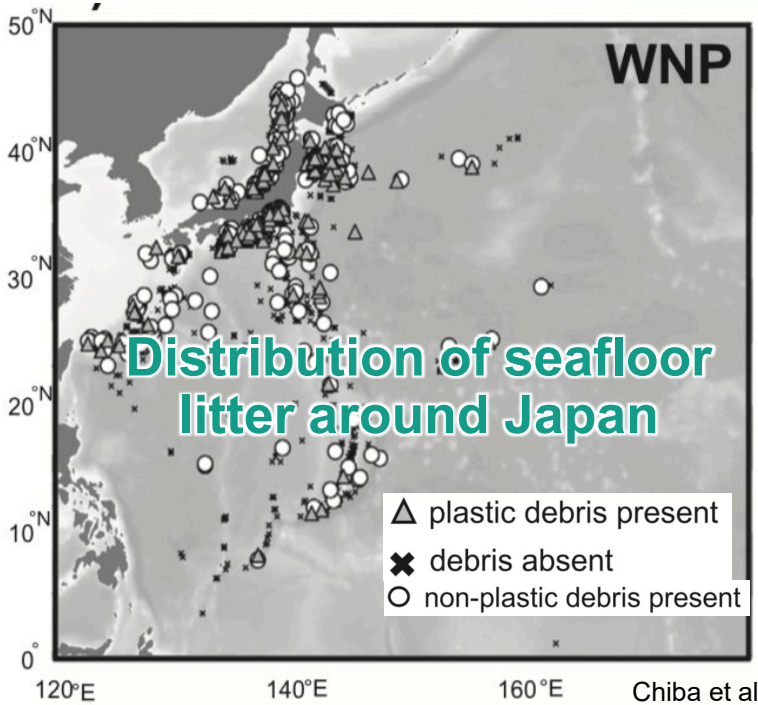


Growth in AI-based seafloor litter detection studies

JAMSTEC‘s public image database







Chiba et al. 2018

Limitation of existing training datasets

Mostly large, clearly visible litter







AI trained on large-objects





Poor detection of small objects

Real surveys: wide-field imagery





Litter appears very small!



Need training images containing small litter objects

J-Litter: A new training dataset

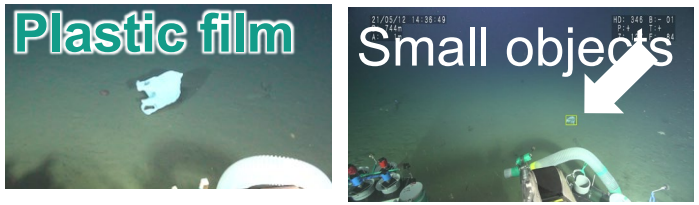
12,029 original images

Annotated dataset for AI training

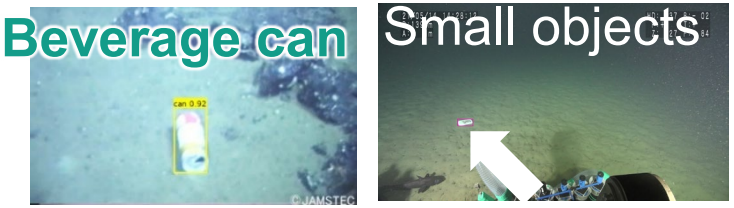
Litter category	Original images (Objects)
Plastic-film	2524 (2997)
Plastic-bottle	116 (137)
Beverage can	395 (429)
Other-metal	255 (260)
Others	907 (1061)
Background (no litter)	7832
Total	12029

Includes ~2000 images of small litter objects

Litter images







+

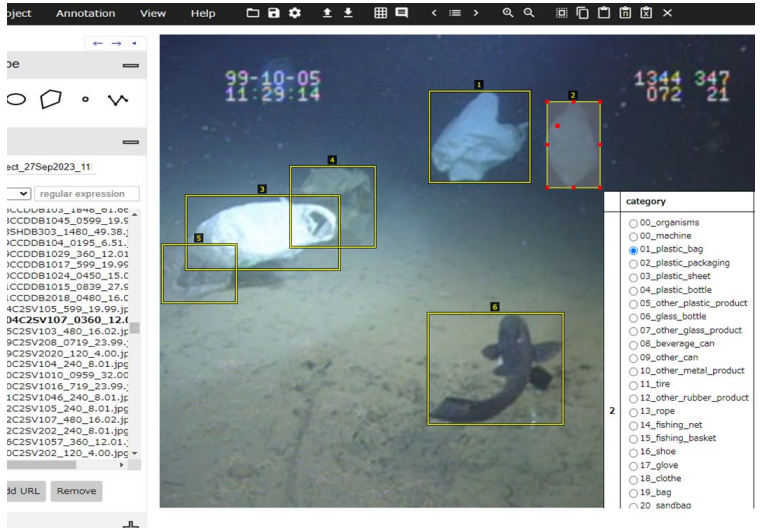
Background images (no litter)



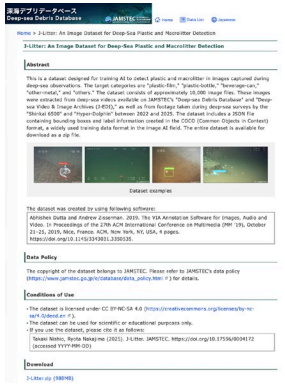
Seafloor features, organisms, vehicle components

Training AI what is NOT litter

Manual annotation



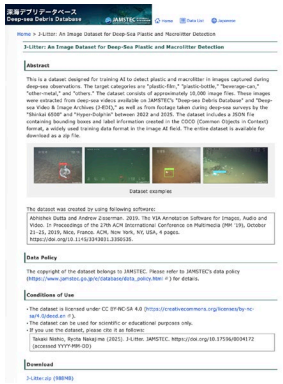
J-Litter Dataset Openly available!





Development of DeepLitterAI

J-Litter Dataset



12,029
original images

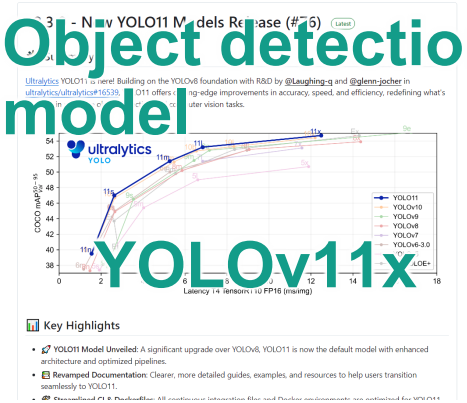
Annotated dataset for AI training

Category	Original images (Objects)	After augmentation of the training subset (60% of original images) (images/objects)
Plastic film	2524 (2997)	7358 (10629)
Plastic bottle	116 (137)	7615 (9373)
Beverage can	395 (429)	7579 (9642)
Other metal	255 (260)	8277 (8511)
Others	907 (1061)	3922 (9027)
Background	7832	24142
Total	12029	**52674**

Augmented training images **52,674**

Transfer learning with J-Litter

Object detection model

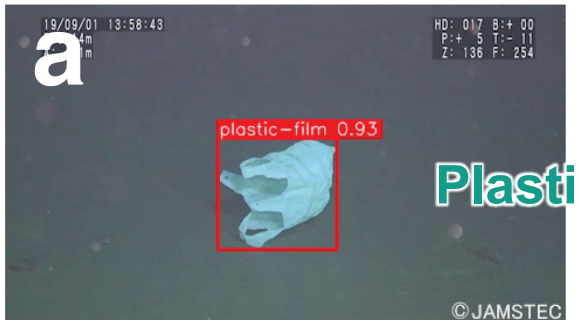


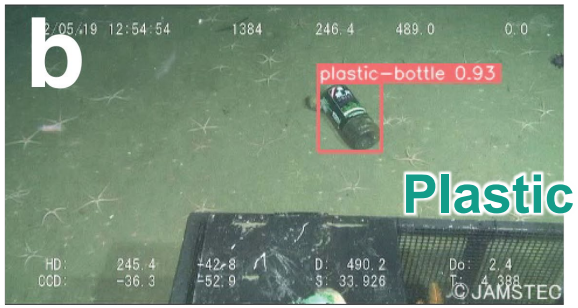
YOLOv11x

DeepLitterAI

Object detection performance of DeepLitterAI

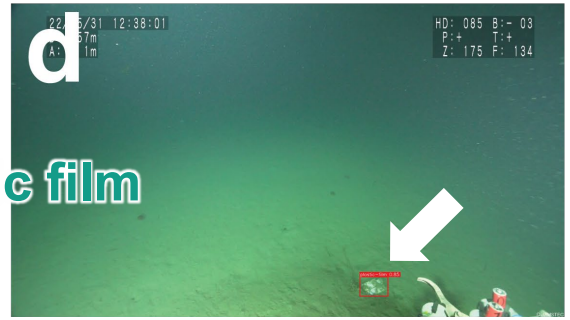
Large, clearly visible litter



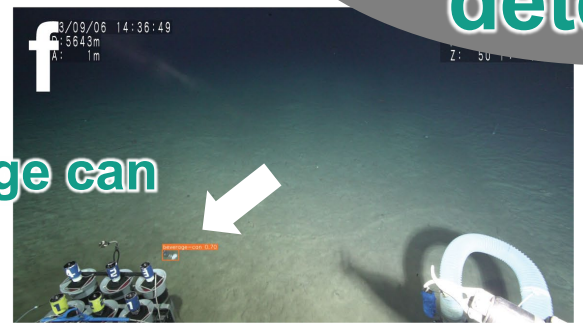




Small litter in wide-field images







Even small litter objects can be detected!

Detection performance (AP@0.5)

Litter category	Large-object test set	Realistic test set (small objects)
Plastic film	0.92	0.81
Plastic bottle	0.88	0.78
Beverage can	0.86	0.79
mAP@0.5	**0.89**	**0.80**

AP@0.5: Average precision at IoU = 0.5

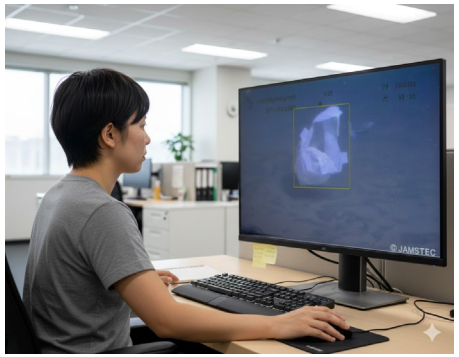
High detection performance for small litter

mAP@0.5 = 0.80

For three major litter categories under realistic survey conditions

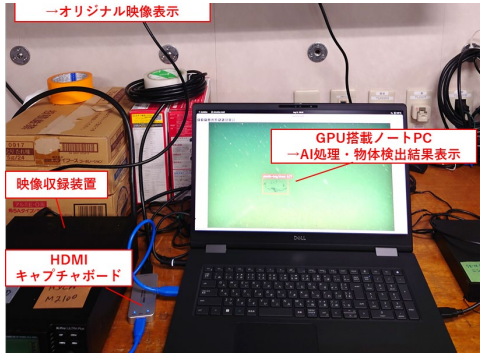
Human vs. AI: How accurately can AI count litter?

Human Researcher



VS

DeepLitterAI



Detection

▼

Classification

▼

Counting

▼

CSV output

CSV

Automatic CSV export

Field validation using 6 independent deep-sea survey videos

Survey	1	2	3	4	5	6
Area/Year	Sea of Japan/2024	Sea of Japan/2024	Sea of Japan/2024	Sea of Japan/2024	Kikai Basin/2023	Off Shimokita/2024
Video duration	2:02:16	1:21:03	1:01:03	1:46:08	1:42:21	5:05:28

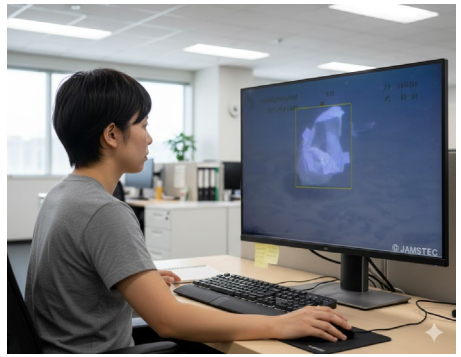
Object tracking（BoT-SORT）

Tracks individual litter items across video frames to reduce double counting



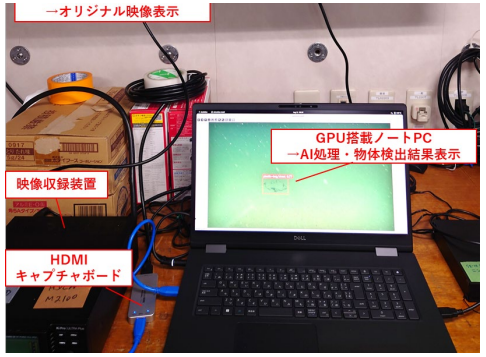
Human vs. AI: How accurately can AI count litter?

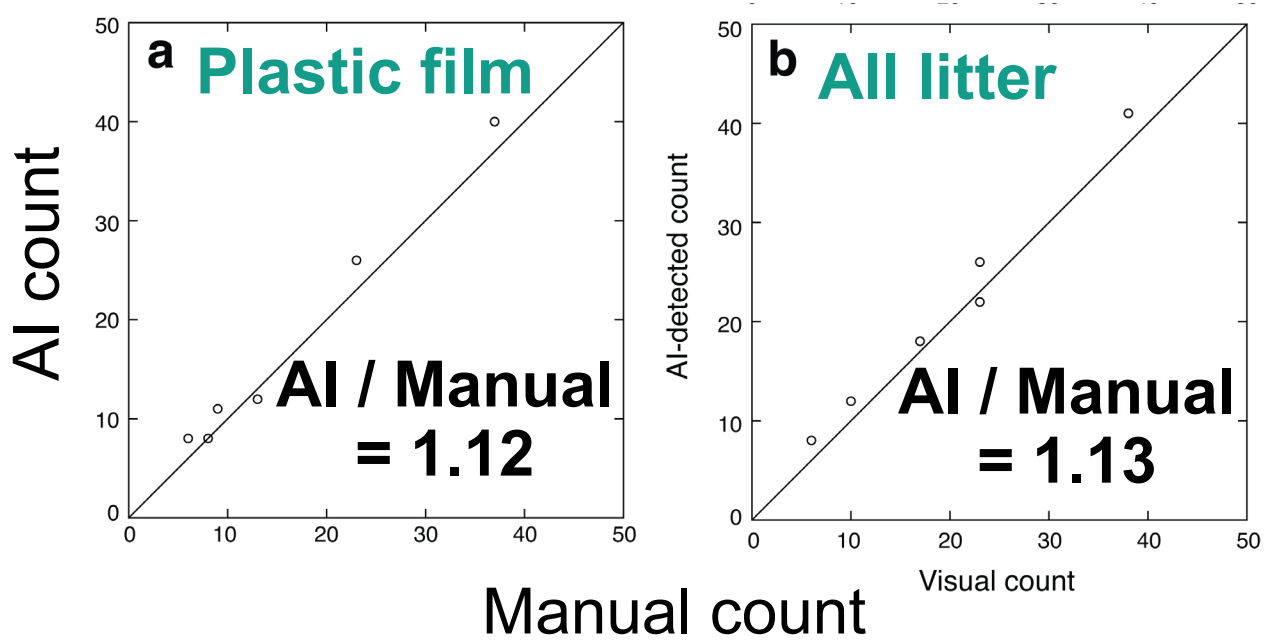
Human Researcher



VS

DeepLitterAI





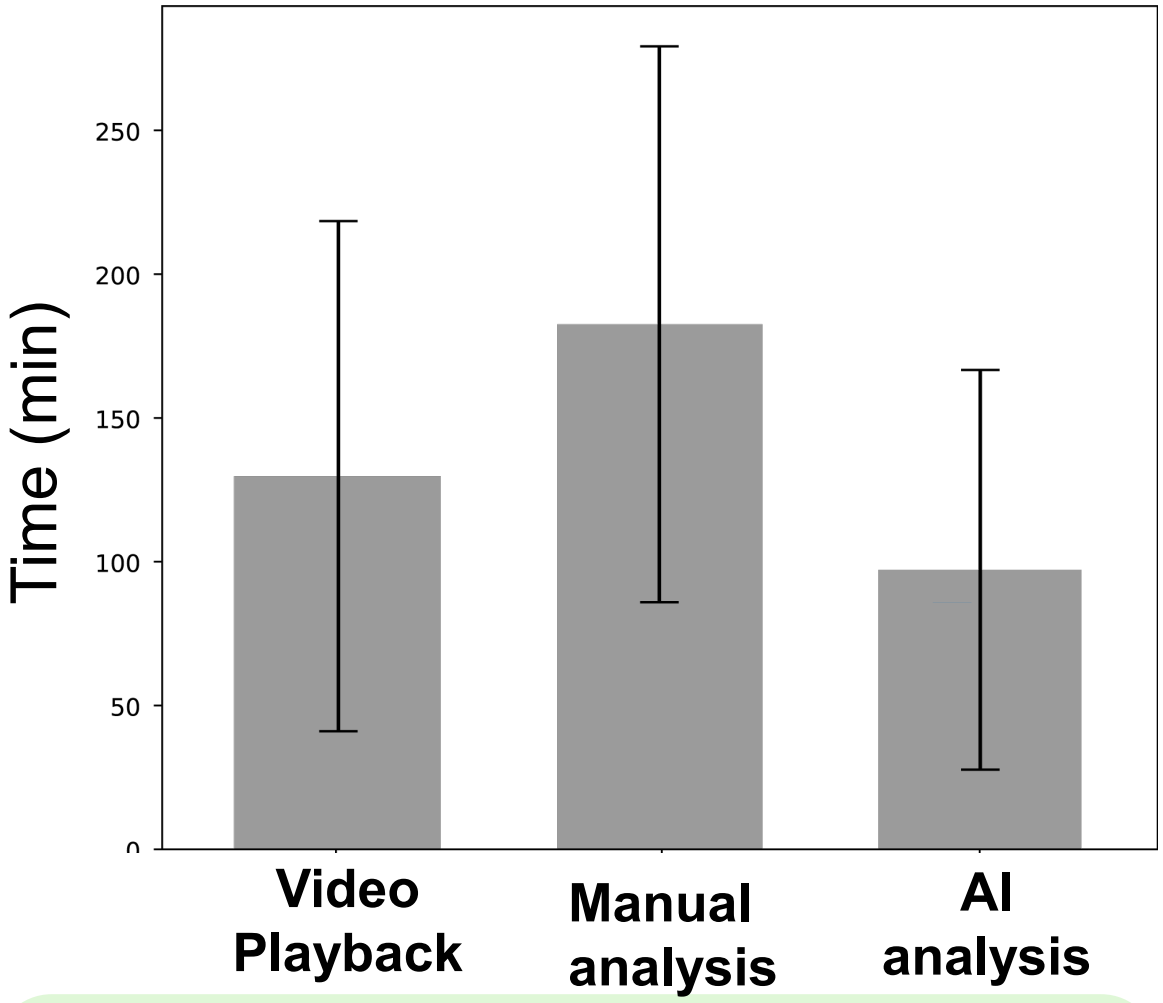
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Video duration	2:02:16	1:21:03	1:01:03	1:46:08	1:42:21	5:05:28

AI-derived litter counts were comparable to manual counts

Mean F1 score = 0.77

Human vs. AI: How much faster is AI?



Survey	AI processing speed (fps)	Manual analysis Time / video duration	AI speed-up vs. manual
1	39.9	1.9	2.5
2	41.4	1.4	1.9
3	41.4	2.2	3.1
4	42.0	1.1	1.6
5	39.6	1.4	1.8
6	39.0	1.2	1.5
Average	**40.6 ± 1.2**	**1.5 ± 0.4**	**2.1 ± 0.6**

AI: 2.1x faster on average (up to 3.1x)

Example: 100 hours of survey footage

Manual ~1 month (Weekdays only)

DeepLitter AI ~2 days
(Continuous processing 24/7)

Take home message

DeepLitterAI



- Automated detection
- Classification
- Counting

Great precision,
Up to 3x faster!

CSV

Litter type
Number

Output

- Quantification (items/km²)
- Hotspot discovery
- Policy-making support

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DeepLitterAI: Automated detection and quantification of deep-sea benthic plastic and macrolitter with field validation in waters around Japan

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[a] Institute for Earth and Material Sciences (EMS), Japan Agency for Marine-Earth Science and Technology (JAMSTEC), 2-15 Natsushima, Yokosuka, Japan
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ARTICLE INFO

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Macrolitter
Artificial intelligence
Object detection
Automated monitoring
Japan

ABSTRACT

Deep-sea imagery is a non-destructive tool for monitoring seafloor litter, but manual inspection limits its scalability. DeepLitterAI, a YOLOv11x-based detector combined with BoT-SORT tracking, was developed to automatically detect and quantify deep-sea benthic macrolitter. The model was trained with J-Litter, a dataset of 12,029 annotated images extracted from footage acquired by the Japan Agency for Marine-Earth Science and Technology (JAMSTEC) between 1983 and 2025. J-Litter includes small litter objects and non-litter images. DeepLitterAI was compared with a model trained only on large, clearly visible litter to evaluate training-data bias. On realistic test images containing small objects, DeepLitterAI achieved average precision (AP), which summarizes precision-recall performance, of 0.79-0.81 and F_1 scores, defined as the harmonic mean of precision and recall, of 0.71-0.76 for plastic films, plastic bottles, and beverage cans (mean AP@0.5 = 0.80 and mean F_1 = 0.73), with AP values averaging 1.6-fold higher than those of the large-object model. In six independent survey videos acquired at depths of 860-5641 m, using manual inspection as the reference, DeepLitterAI achieved F_1 scores of 0.65-0.89, with a mean of 0.77 across categories. AI-derived total litter density averaged 1.1 times the manual estimate. AI analysis was 1.5-3.1 times faster than manual inspection, with a mean speed-up of 2.1-fold. Performance was robust to viewing angle, whereas false-negative rate increased to 25% under the highest synthetic turbidity condition. DeepLitterAI provides a scalable, non-destructive framework for standardized monitoring and mapping of deep-sea macrolitter.

DeepLitterAI

Next step

Expanding J-Litter with images from around the world

J-Litter ▶ G-Litter