YOLO와 SAM을 활용한 해양 쓰레기 탐지 및 Pseudo Segmentation

2024.06.11

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Outline

- 1. Introduction
- 2. Method
- 3. Experiments
- 4. Results



Background

해양쓰레기 문제, 얼마나 심각하며 어떻게 해결할 수 있 을까

[인터뷰] 김경신 한국해양수산개발원 연구원

2021.06.28 | 정책브리핑 김차경

[사설] 늘어나는 해양 폐기물을 방치하면 안되는 이유

울산매일 │ ② 승인 2024.05.15 18:22 │ □ 15면

환경·자연

"전세계 바다에 떠다니는 미세플라스틱 무려 230만톤"

2023.03.09 17:25



Background

해양 생태계



- 서식지 파괴
- 종의 감소

생물의 다양성 감소

경제



- 관광업의 경제적 비용 증가
- 수산업 생산의 비효율성

경제적 손실



Background

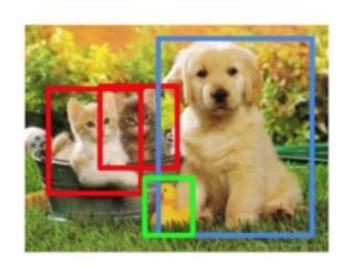


직접 탐지에 한계점

- 넓은 해양지역
- 조도가 낮은 심해환경

Background

Object Detection







Instance Segmentation



CAT, DOG, DUCK

Background



이미지



Background

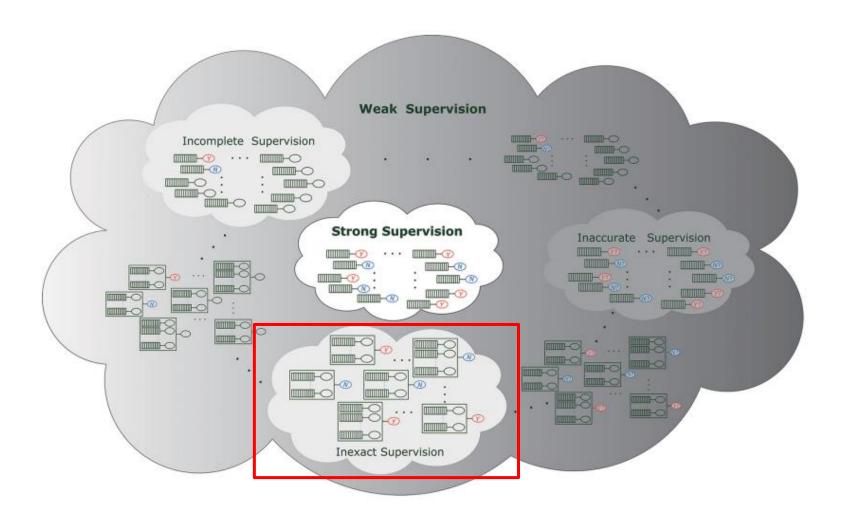
	등급 1 (첫 50,000개) 1000개당 가격	등급 2 (다음 950,000개) 1000개당 가격	
bounding box	63\$	49\$	
segmentation	870\$	850\$	

	Label당 제안되는 요금		
bounding box	0.036\$		
segmentation	0.84\$		

구글 Al Platform 아마존



Background



Weakly supervised learning

Background

Object Detection



YOLO(You Only Look Once)

Segmentation



SAM(Segment Anything Model)



Research Objectives

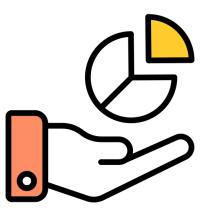
해양 쓰레기 탐지 모니터링



데이터 구축 비용 절감



Weakly supervised learning 기여





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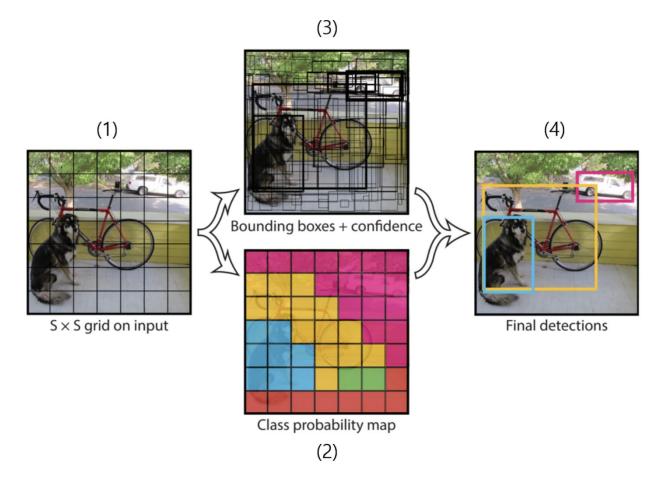


Deep Learning Technologies Used

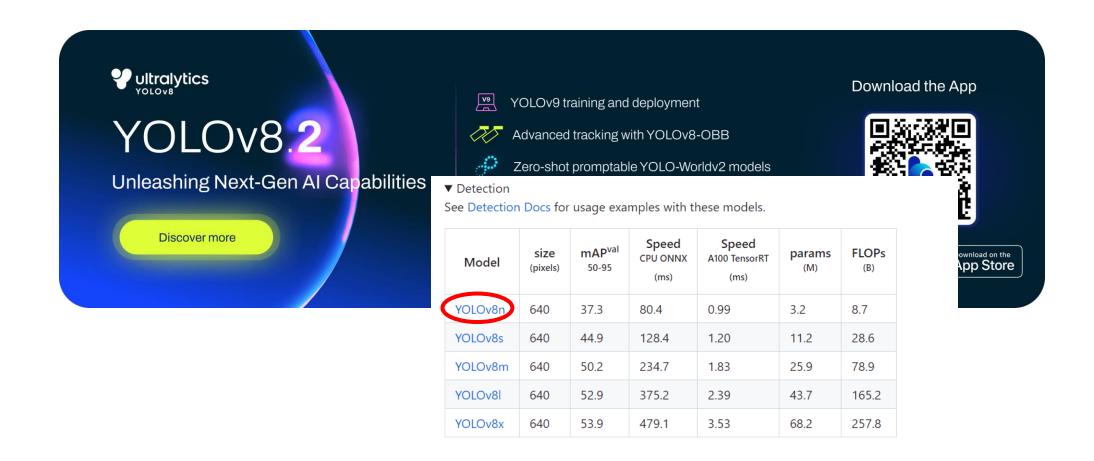
- YOLO(You Only Look Once)
- SAM(Segment Anything Model)
- Sea-thru



YOLO(You Only Look Once)



YOLO(You Only Look Once)

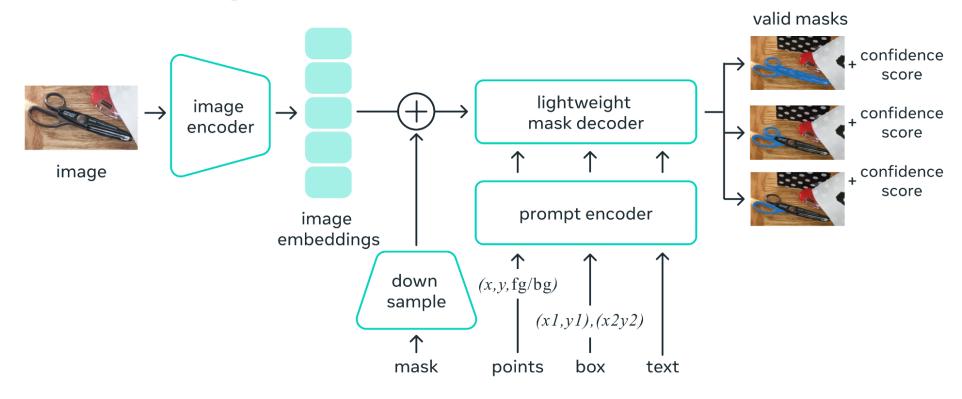


SAM(Segment Anything Model)

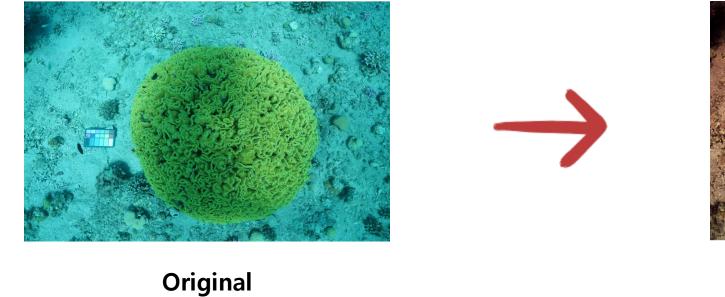


SAM(Segment Anything Model)

Universal segmentation model



Sea-thru





Sea-thru

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Experiments

Dataset

- Al-Hub 해양 침적 쓰레기 이미지
- 소나 이미지 46,000장, 수중 촬영 이미지 18,000장
- 객체 여러 개 또는 미존재 제거 → 12,000장 사용
- Train, val, test = 7:1:2

Experiments

YOLO

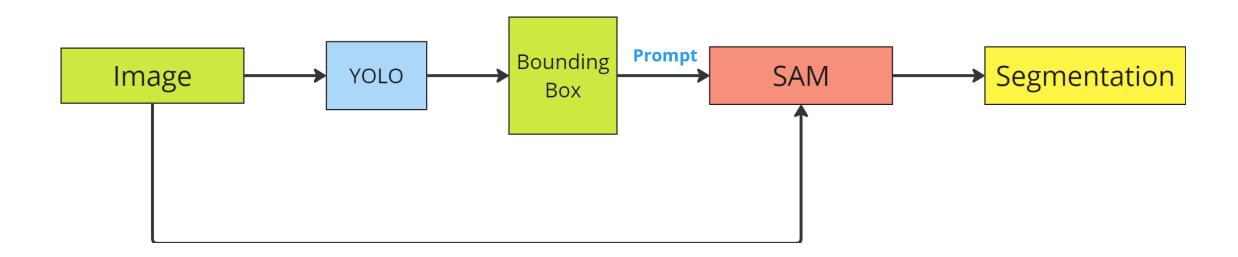
- COCO pre-trained YOLOv8n
- Batch size: 128, Input size: 512
- AdamW(lr: 0.001111, momentum: 0.9), epoch: 50

SAM

- Pre-trained ViT-H
- Input size: 512
- Prompt : bounding box

Experiments

Pipeline



Outline

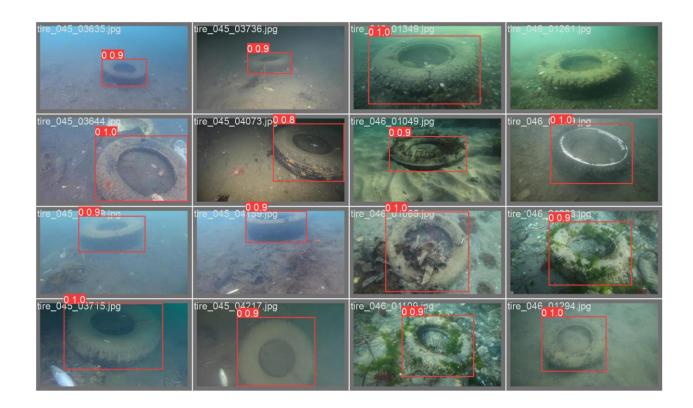
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YOLO

- Train보다 test 성능 우수
- Overfitting x, 일반화 성능

	precision	recall	f1	mAP50	mAP50-95
train	0.86	0.68	0.74	0.73	0.61
test	0.91	0.69	0.73	0.76	0.62



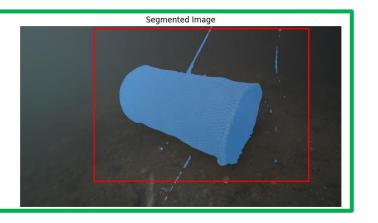
SAM

- Ground Truth bbox, prediction bbox 비교
- Prediciton에서 더 좋은 segmentation



Ground Truth





Prediction



Pseudo label

• SAM Inference time: 0.05s

• 수작업 labeling : 10~30m

• 약 10,000배 시간 단축

Average Inference Time: 0.0532 seconds

Labeling cost & time 감소



■ 기대 효과 – 해양 환경 보호

- YOLO, SAM을 통한 해저 쓰레기 탐지
- 해양 생태계 유지 및 보호
- Segmentation을 통한 쓰레기 크기, 밀도 추정 → 처리 우선순위, 수색 시간 감소

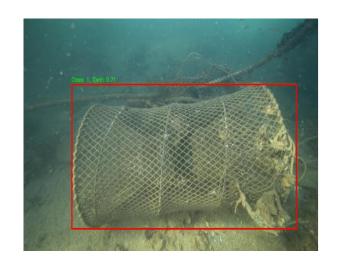


데이터 구축 비용 절감



Weakly supervised learning 기여





쓰레기 탐지



해양 생태계 보호



쓰레기 처리

■ 기대 효과 – 비용 절감

- AI 탐지 모델 → 인력 및 처리 비용 감소
- Ground Truth보다 더 정확한 bbox label
- Segmentation label 구축 비용 절감



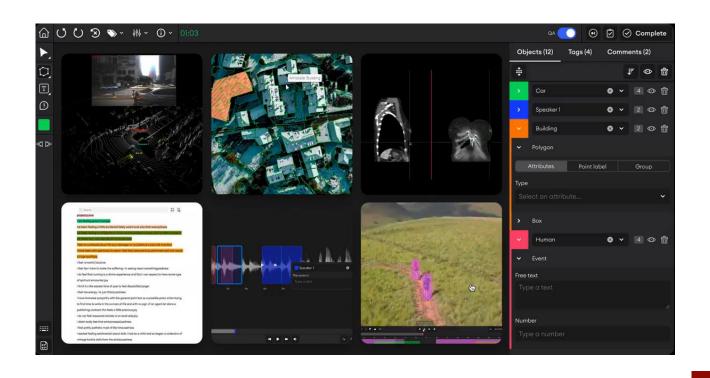
해양 쓰레기 탐지 모니터링





Weakly supervised learning 기여







■ 활용 분야

- 해양 쓰레기 탐지
 - 공공기관 및 민간 기업 활용
 - 해당 과정에서 데이터 축적 → 고도화된 모델 및 기술 개발
- 해양 쓰레기 연구
 - 해양 쓰레기 종류와 분포 분석
 - 수질 오염 원인 및 쓰레기 처리 방법에 도움
 - Weakly supervise learning에 기여

해양 쓰레기 탐지 모니터링

데이터 구축 비용 절감









Q & A 감사합니다!





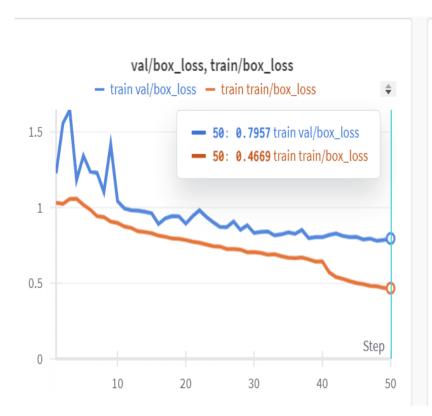
Sea-thru

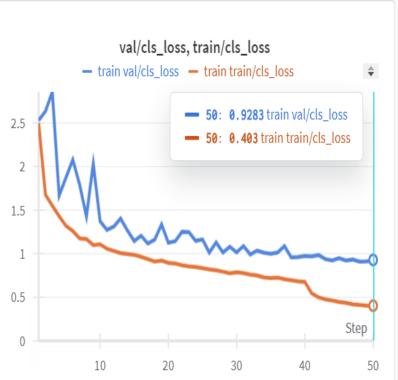


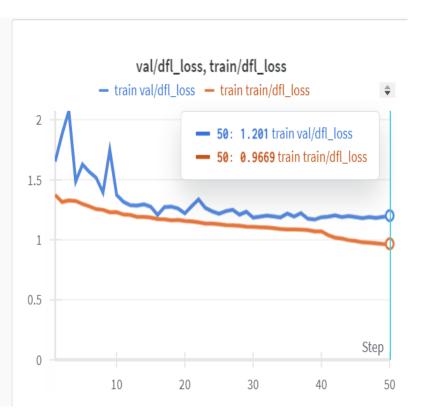




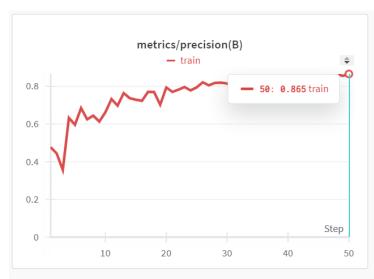
Train & validation loss

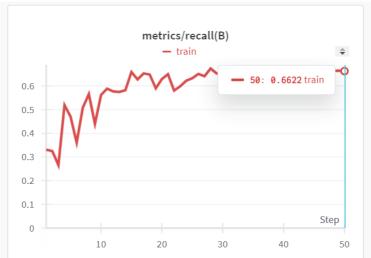


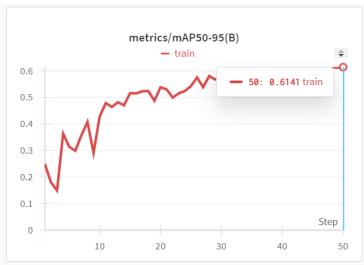


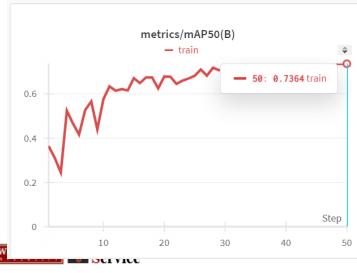


Training metric

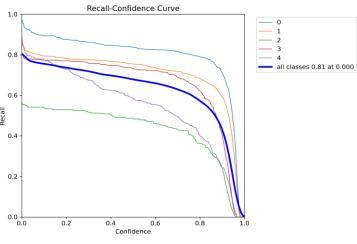




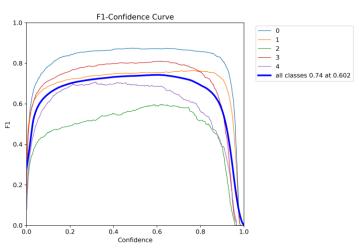




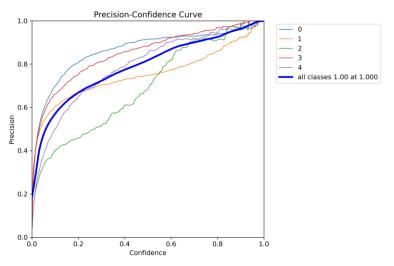
Training metric



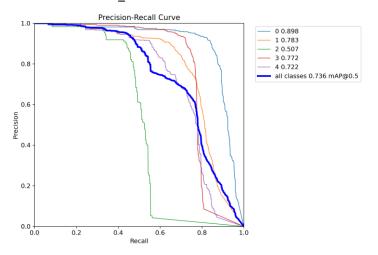
R_Curve



F1_Curve

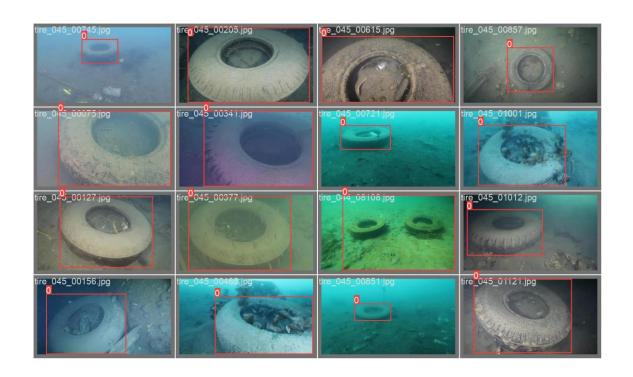


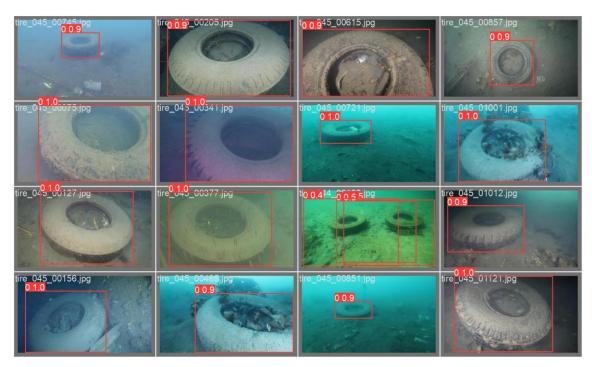
P_Curve



PR_Curve

Validation batch



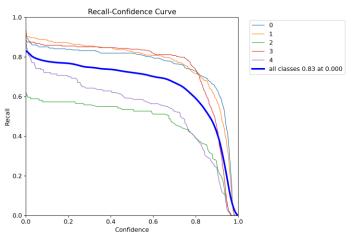


Ground Thrth

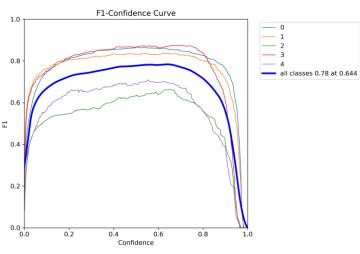
prediction



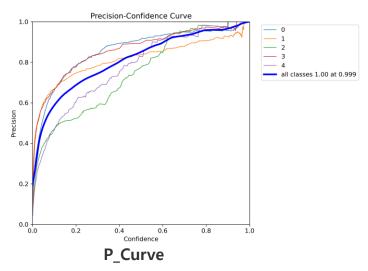
Test metric

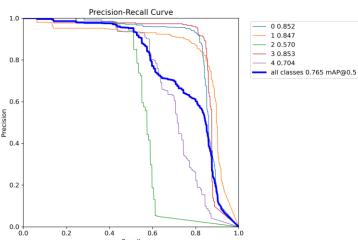


R_Curve

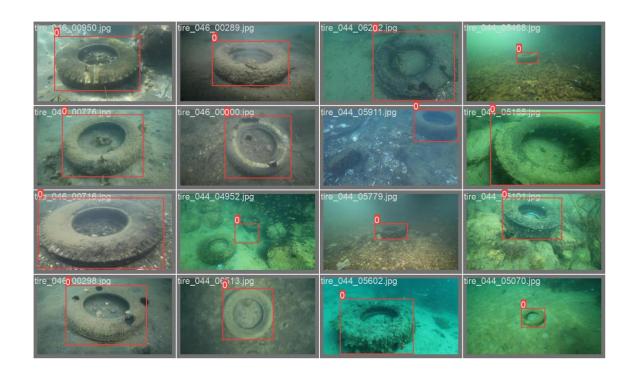


F1_Curve





Test batch

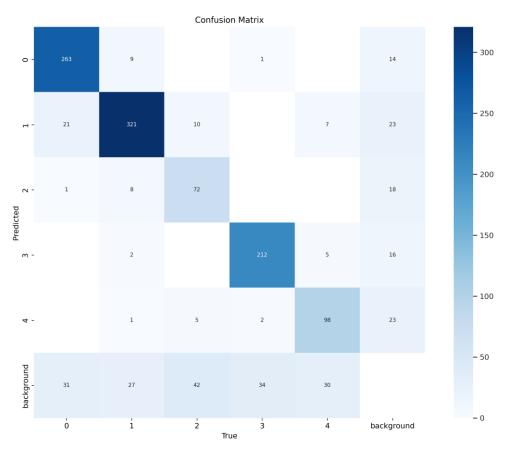




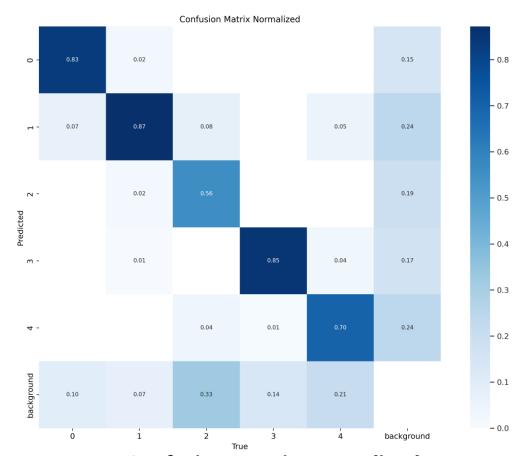
Ground Thrth

prediction

Test confusion matrix



Confusion matrix



Confusion matrix normalized