FruitPunch AI

ReefSupport

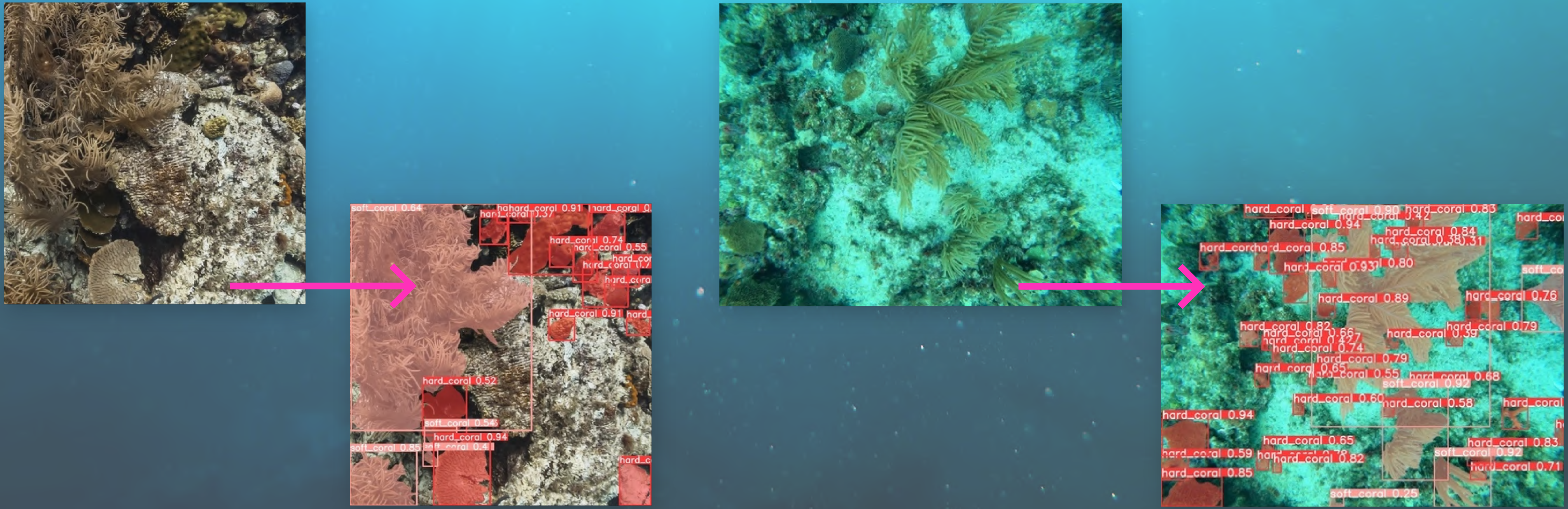
AI FOR CORAL REEF

Supervised - YOLO

Try Pitch

Agenda

1. The challenge
2. YOLOv8
3. Data
   a. Overview and identified issues
   b. Preprocessing
   c. Modeling
4. Results
5. Future work
6. Conclusions



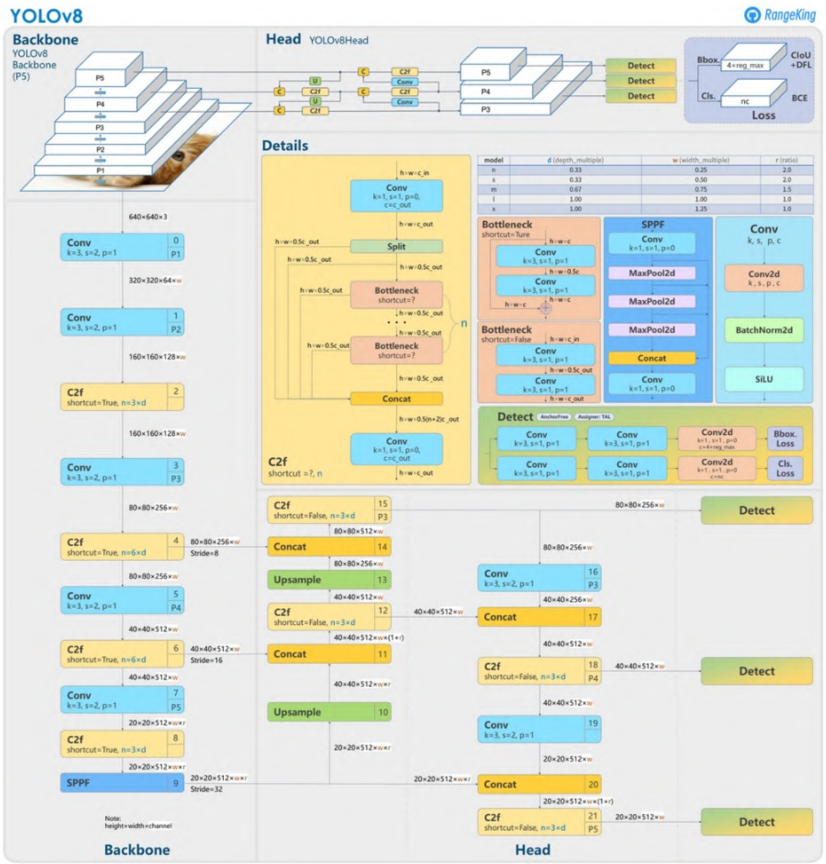
The challenge

Automate the image segmentation process for underwater imagery - focusing on accurately distinguishing between **hard** and **soft** corals.

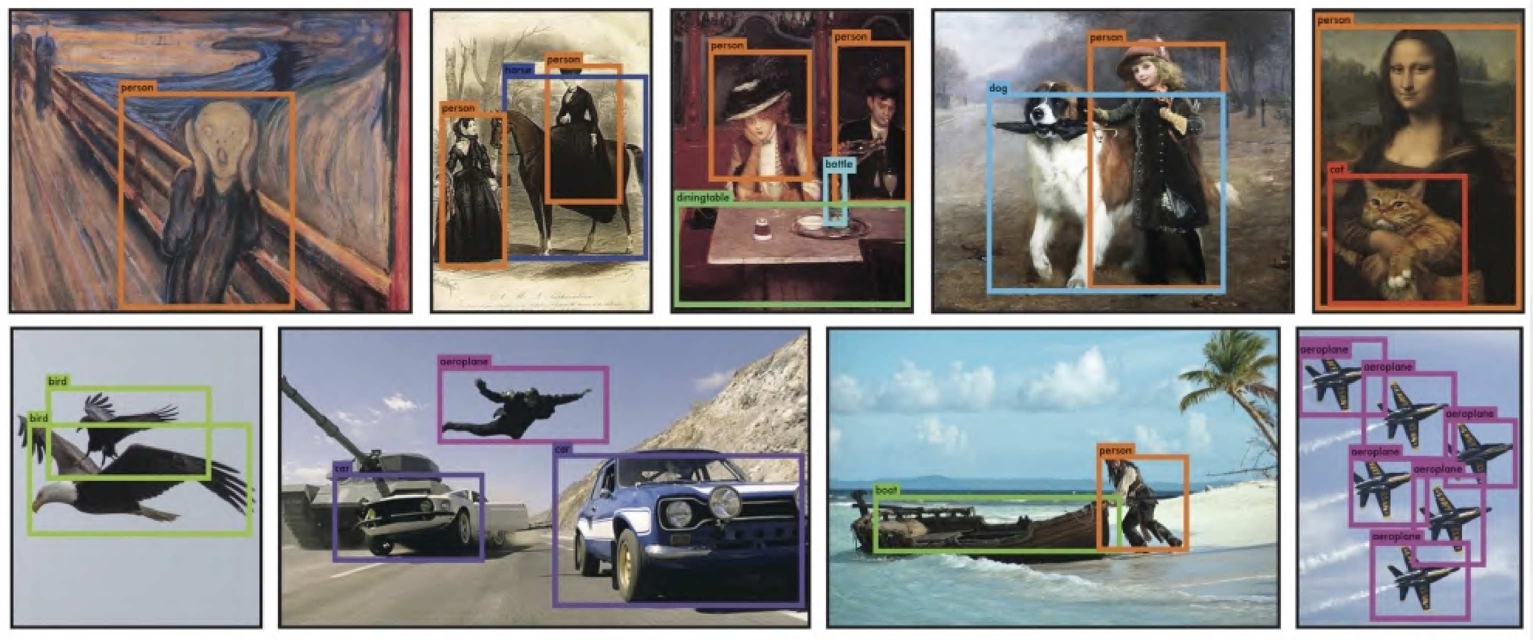
A crucial application for the developed model lies in estimating the **benthic coverage of coral groups**.

YOLOv8

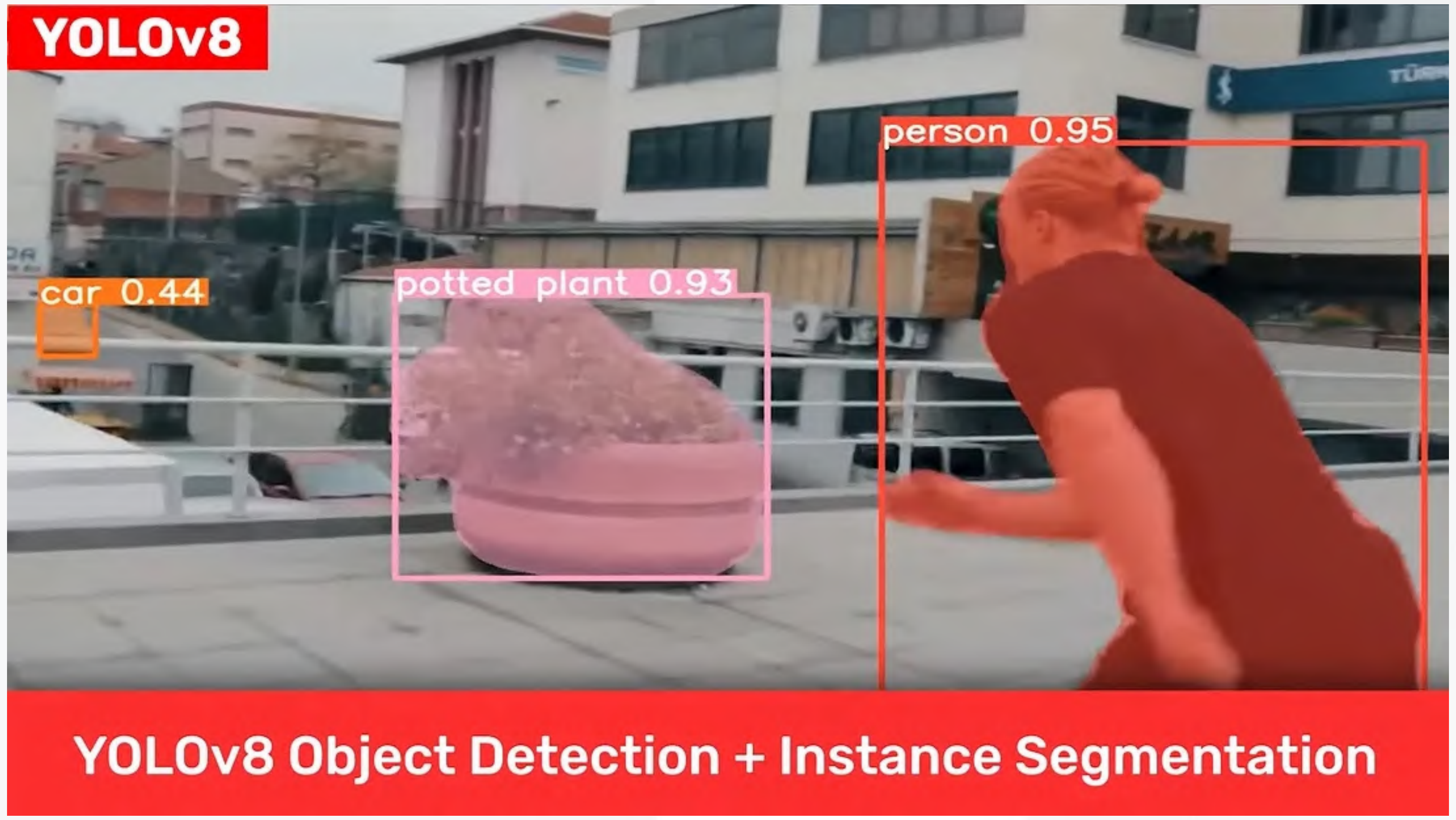
YOLOv8 (You Only Look Once version 8) is originally an object detection model used in computer vision. YOLOv8 is part of the YOLO series (You Only Look Once), which is known for its real-time object detection capabilities.



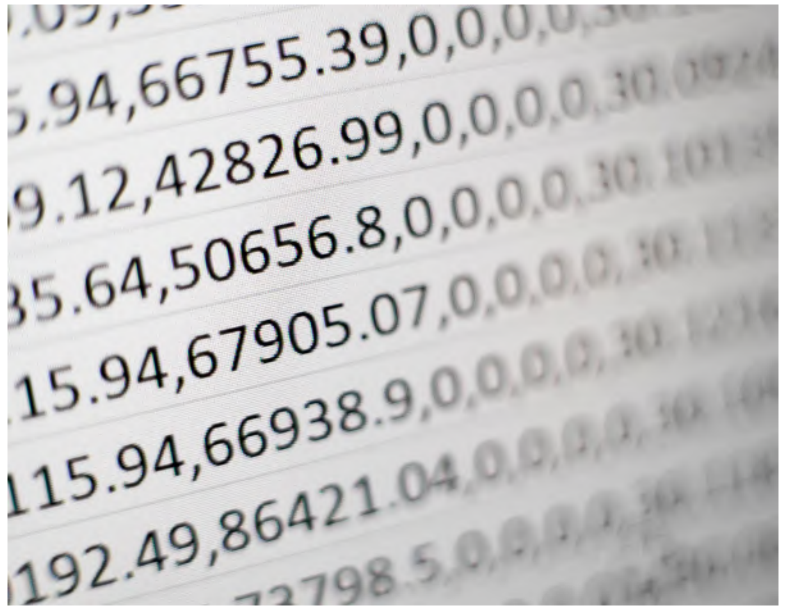
YOLOv8 network architecture



Real Time object detection algorithm



Instance segmentation - Pretrained on the COCO-SEG dataset



Overview

Composition of the provided datasets

Data issues

Empty masks, mismatch labels, low dense label quality, variable image sizes, data leaks, etc.

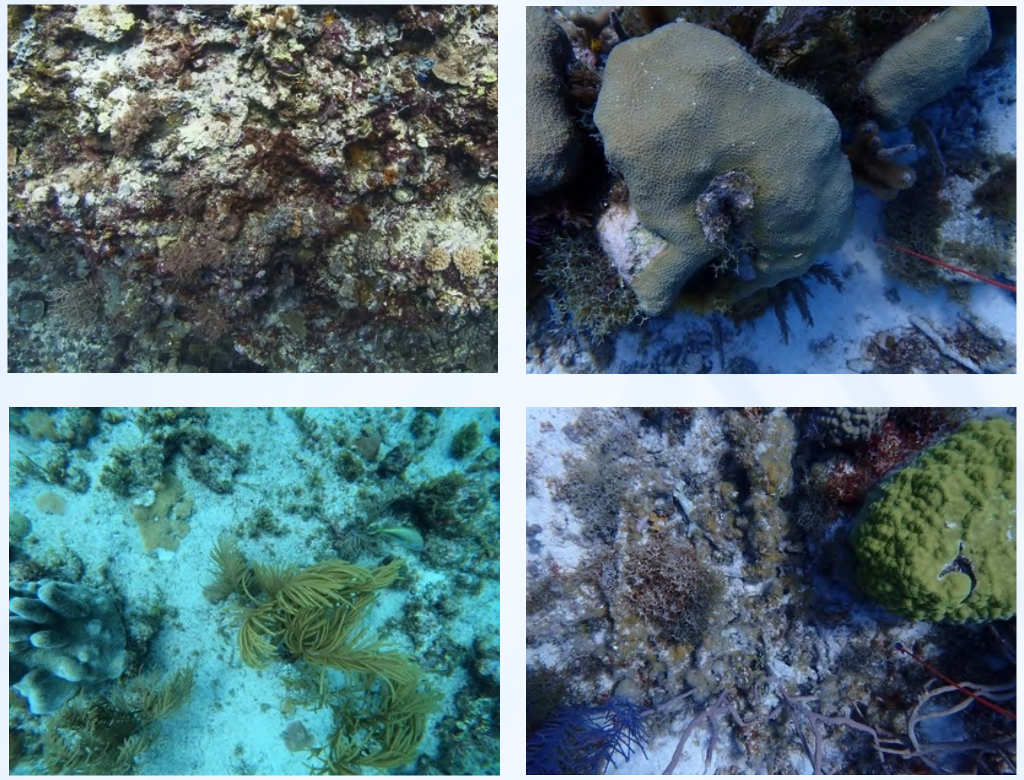
Data preprocessing

PyTorch YOLOv8 TXT format

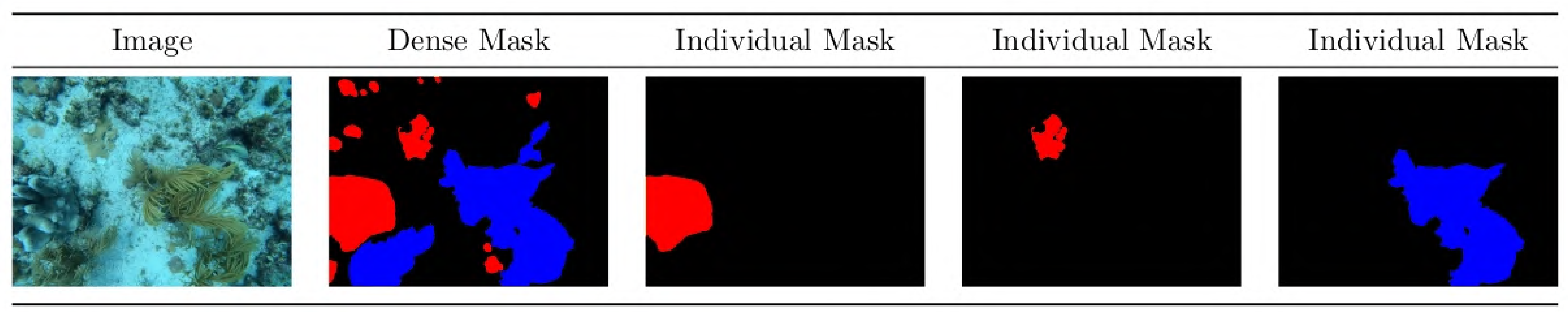
Data Modeling

Evaluation metrics. Train/val/test splits. Hyperparameters.

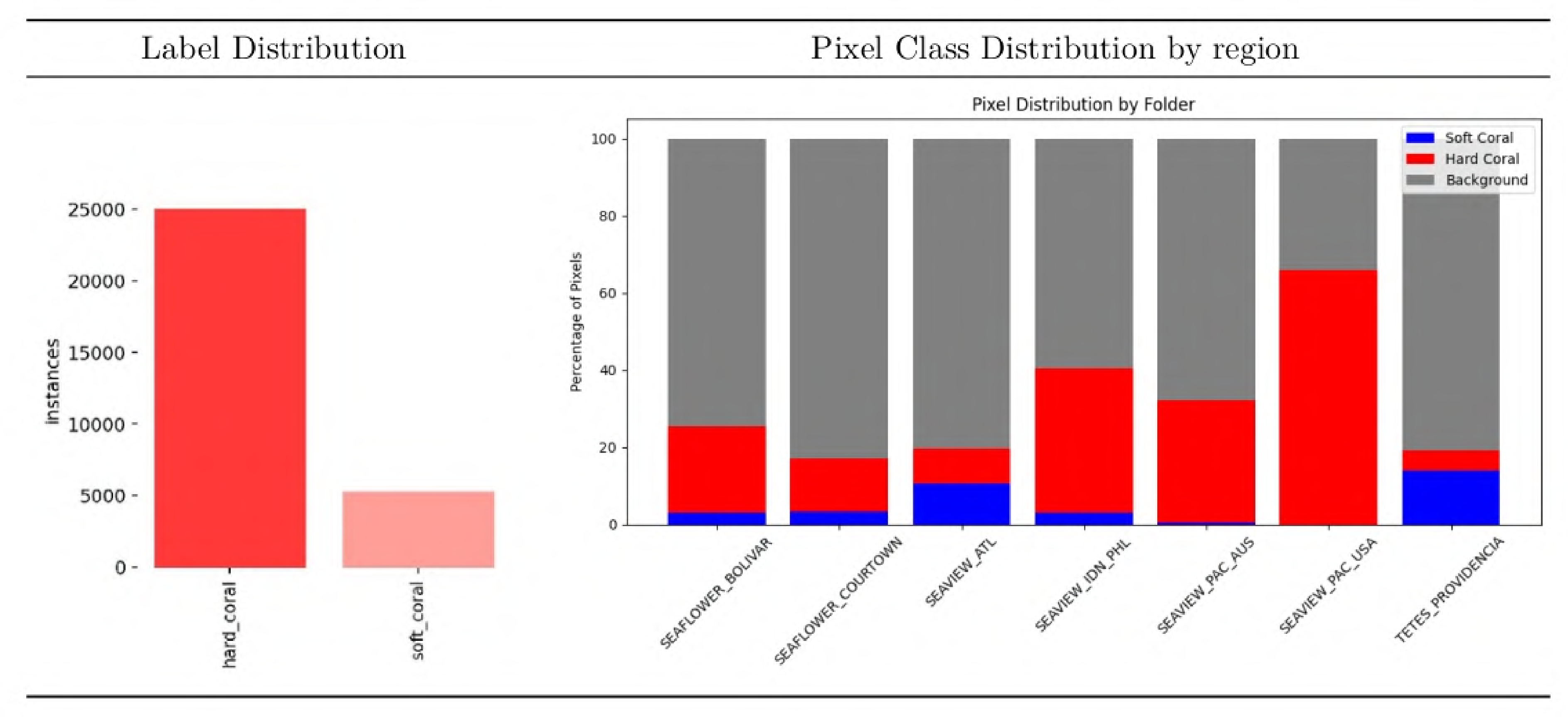
DATA OVERVIEW



Random Sample from the ReefSupport dataset



Each image is associated with a dense stitched mask made of all the individual coral instance



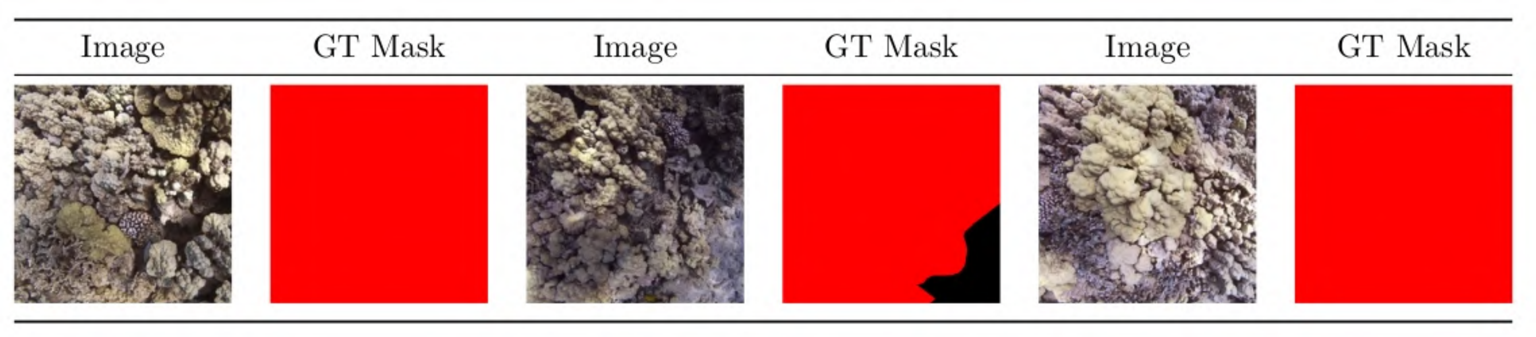
2 classes: hard/soft coral with data imbalance

7 different regions across the world, with different distributions

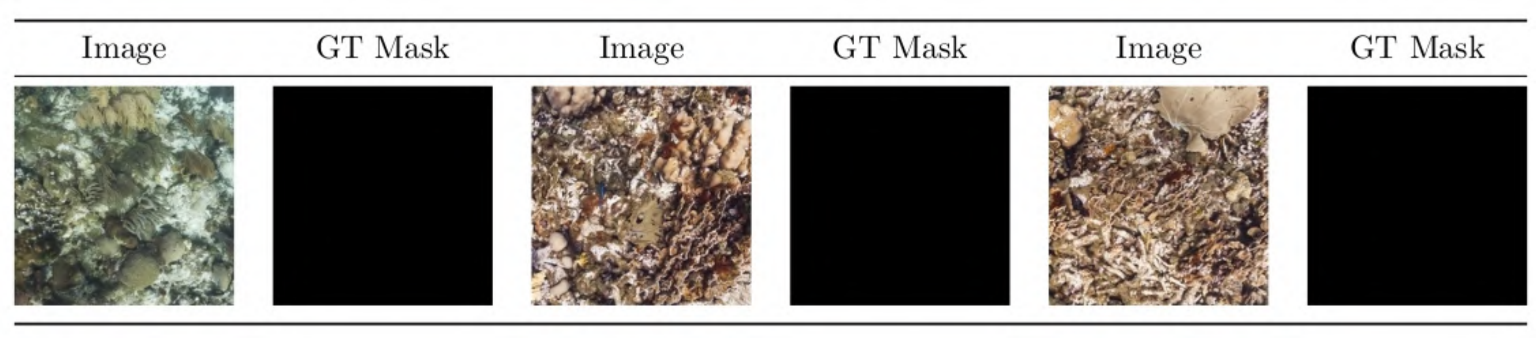
3299 images provided/**1742** usable for training

DATA ISSUES

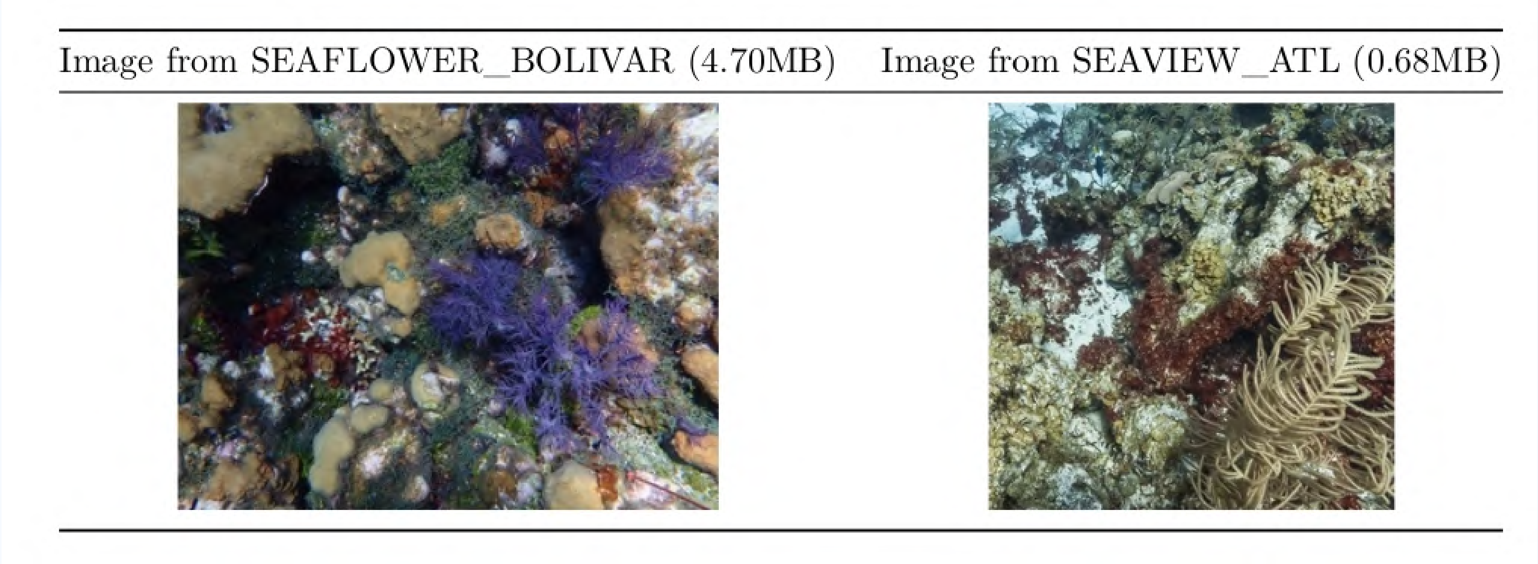
Dataset	Region	# dense labels	# usable dense labels	Reasons
SEAFLOWER	BOLIVAR	246	245	labels mismatch
SEAFLOWER	COURTOWN	241	241	
SEAVIEW	ATL	705	**330**	empty masks + labels_mismatch
SEAVIEW	IDN_PHL	466	**237**	empty masks + labels mismatch
SEAVIEW	PAC_AUS	808	**584**	empty masks + labels mismatch
SEAVIEW	PAC_USA	728	**0**	low quality labelling
TETES	PROVIDENCIA	105	***105***	data leakage
ALL	ALL	**3299**	**1742**	



Low dense labels quality in SEAVIEW_PAC_USA



Empty masks



Variable image sizes and quality

DATA ISSUES

Dataset	Region	# dense labels	# usable dense labels	Reasons
SEAFLOWER	BOLIVAR	246	245	labels mismatch
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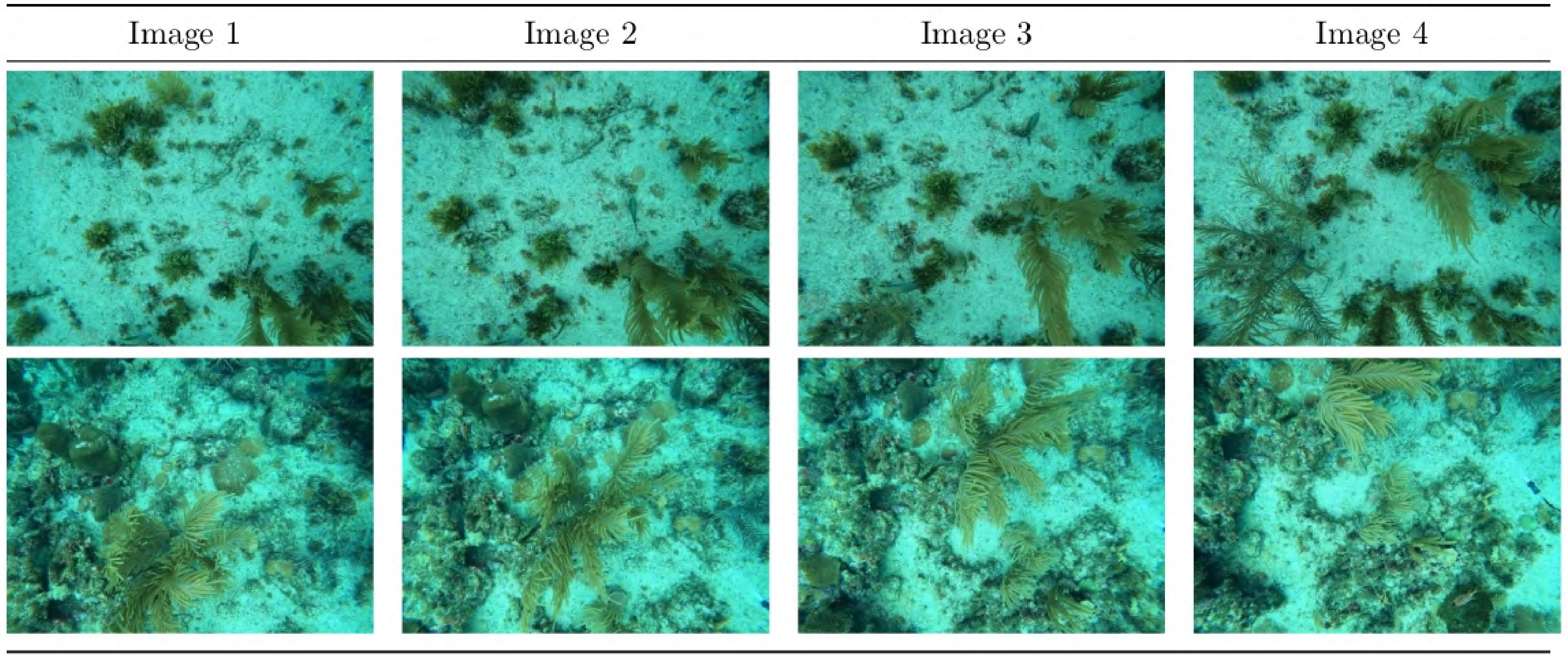
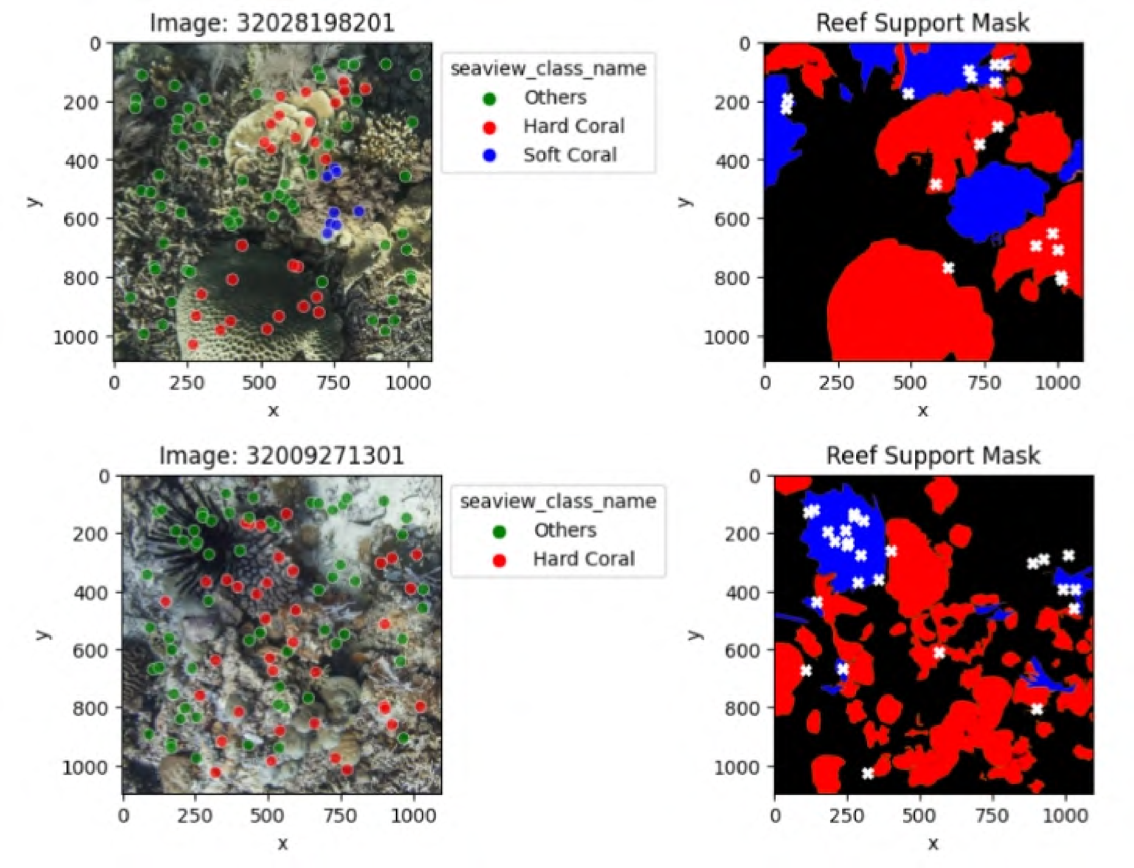
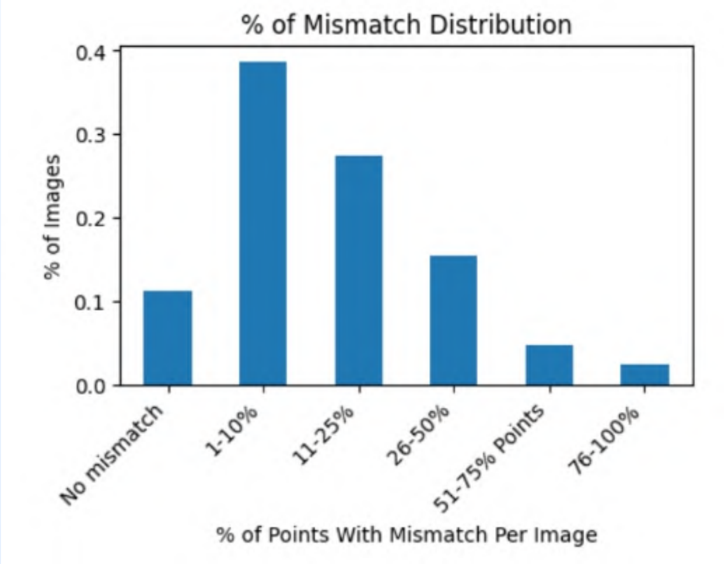
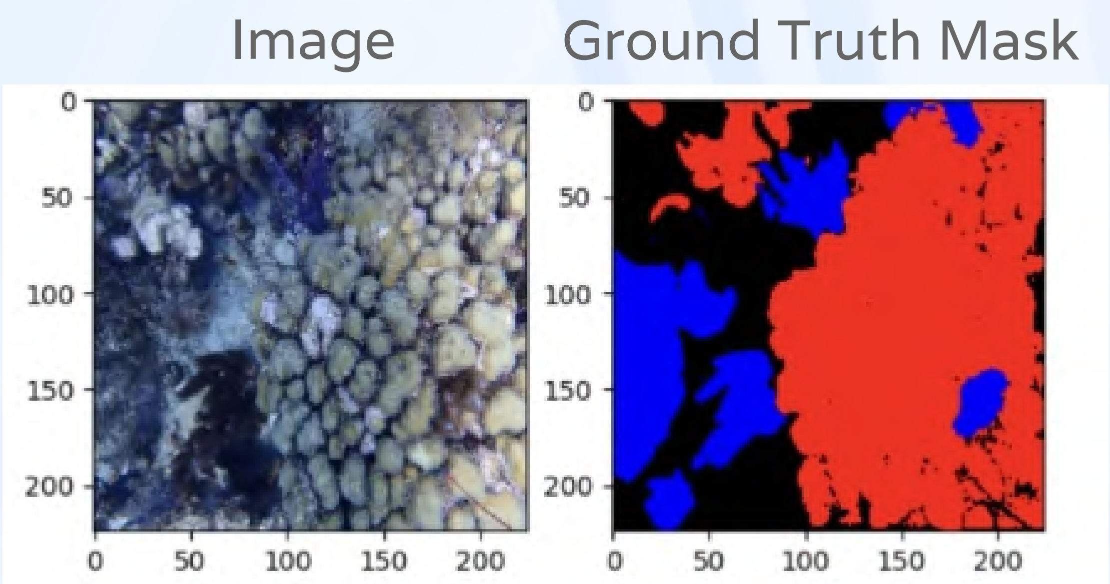


Data Leaks in TETES_PROVIDENCIA

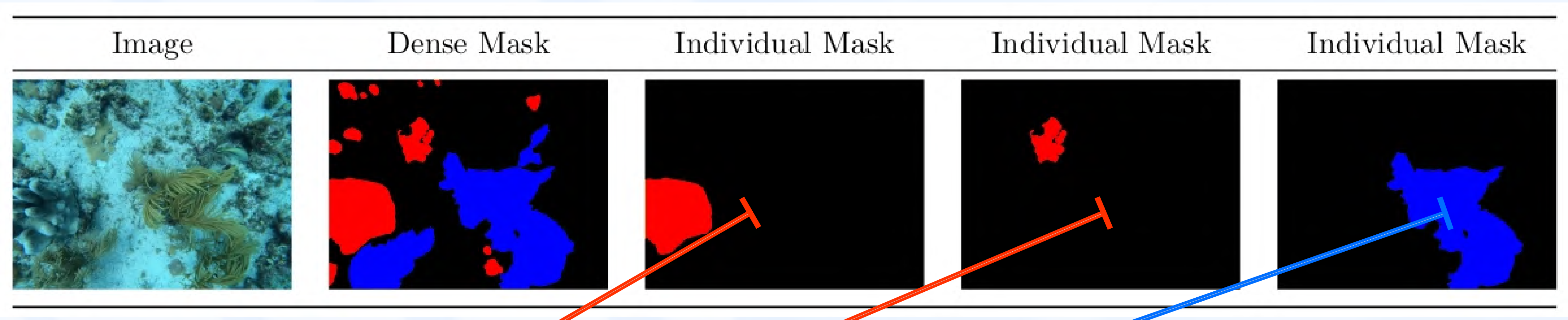




Label mismatches



Polygon contour for each coral instance



line 1
line 2
line 3

```
0 0.37744140625 0.2396240234375 0.37719726562
0 0.31005859375 0.8251953125 0.309814453125 0
1 0.0017509460449921875 0.9013671875 0.0015010
```

Label file required for each image to train YOLOv8

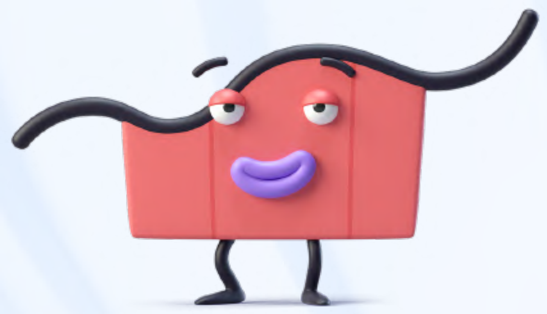
Try Pitch

DATA MODELING AND DATA AUGMENTATION

Evaluation Metrics

$$IoU = \frac{A \cap B}{A \cup B}$$

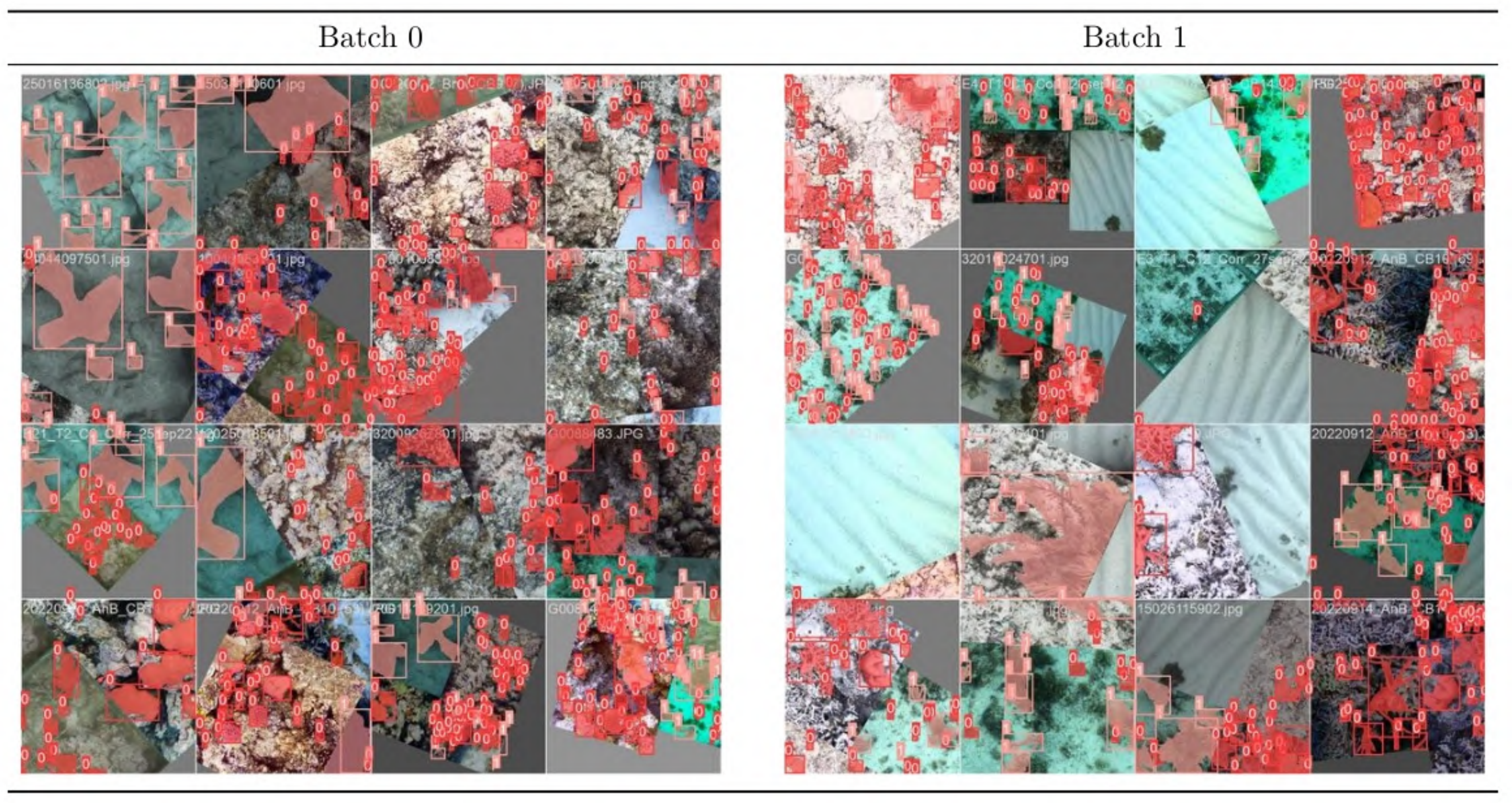
$$DiceCoefficient = \frac{2 \times TP}{2 \times TP + FP + FN}$$



YOLOv8 provides extra information such as **localization bounding boxes** which can be used to count instances in an image compared to a model that would only perform semantic segmentation. The selected metrics can’t report on the localization performance of YOLOv8 but **they allow us to compare with other models that perform semantic segmentation**.

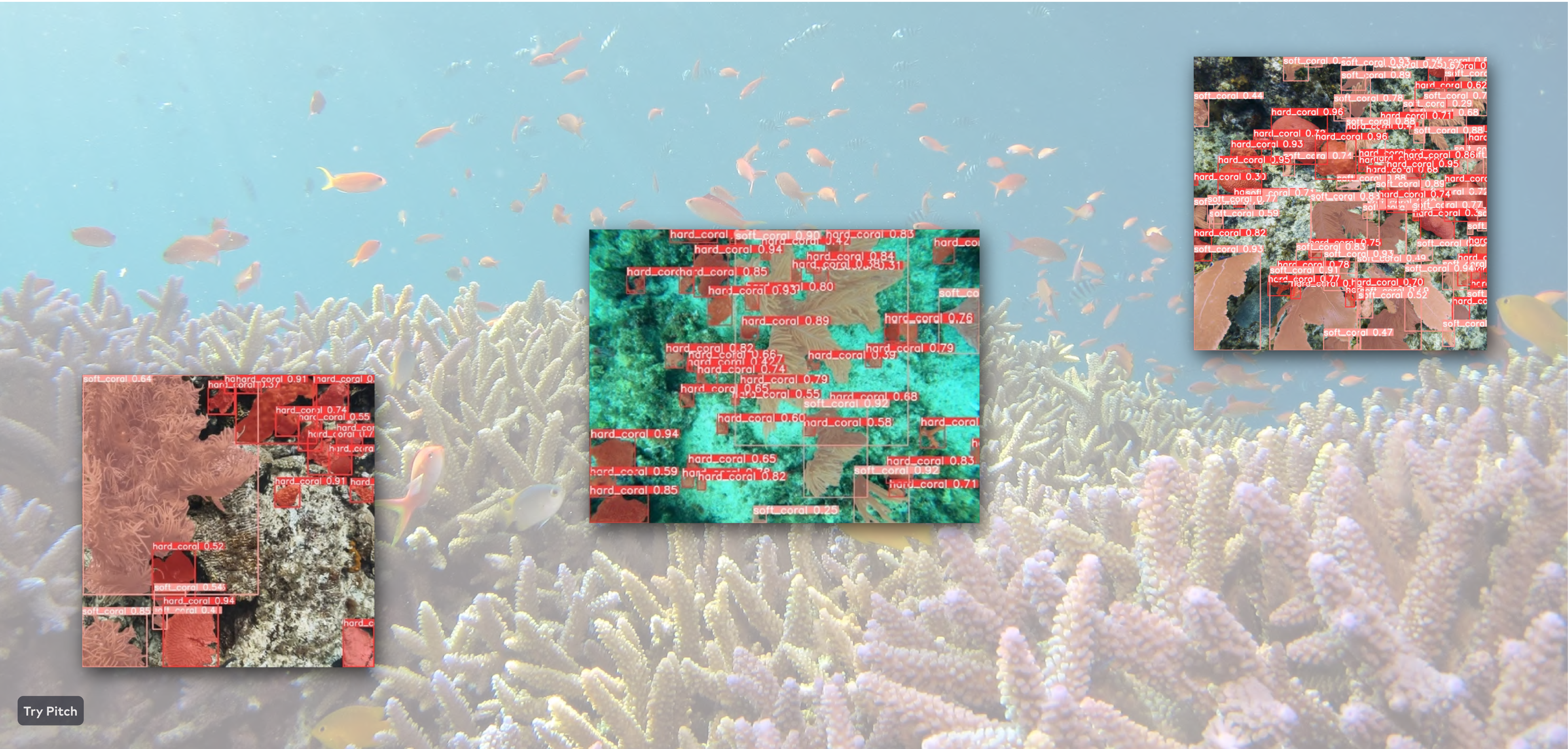
Dataset	Region	splits ratio	train	val	test	total
ALL	ALL	80/10/10	1392	173	177	1742
SEAFLOWER	BOLIVAR	80/10/10	196	24	25	245
SEAFLOWER	COURTOWN	80/10/10	192	24	25	241
SEAVIEW	ATL	80/10/10	264	33	33	330
SEAVIEW	IDN_PHL	80/10/10	189	24	24	237
SEAVIEW	PAC_AUS	80/10/10	467	58	59	584
TETES	PROVIDENCIA	80/10/10	84	10	11	105

Train/Val/Test splits



Training Batch samples

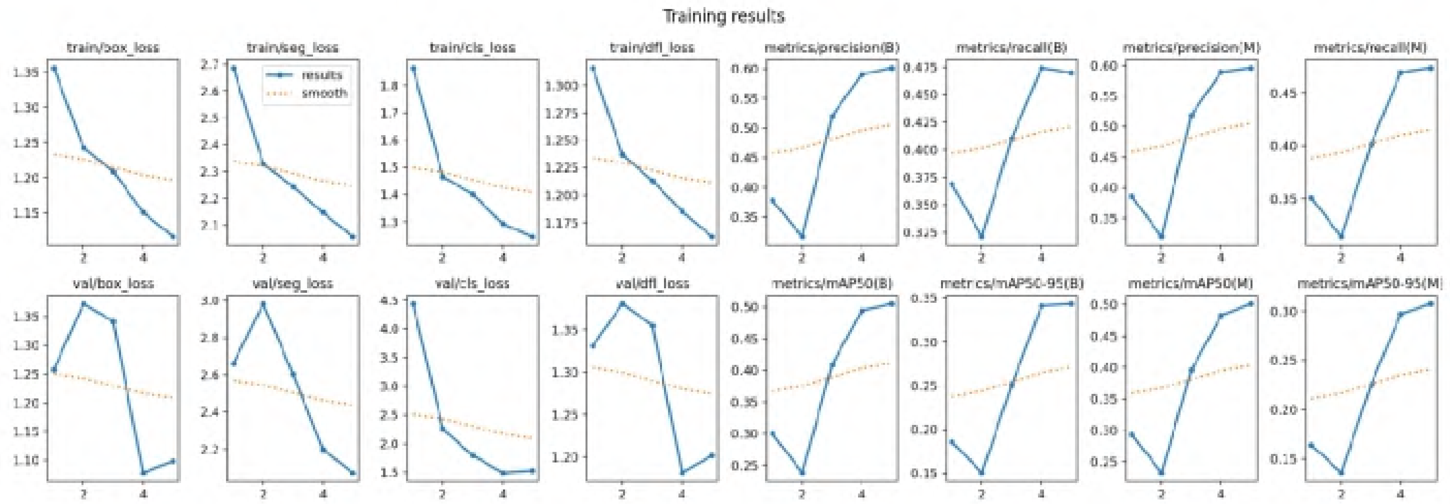
RESULTS

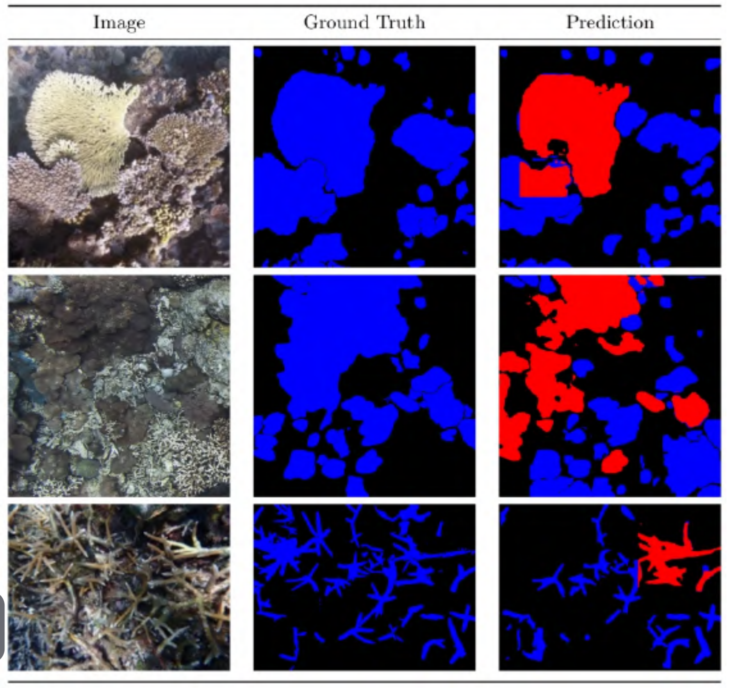


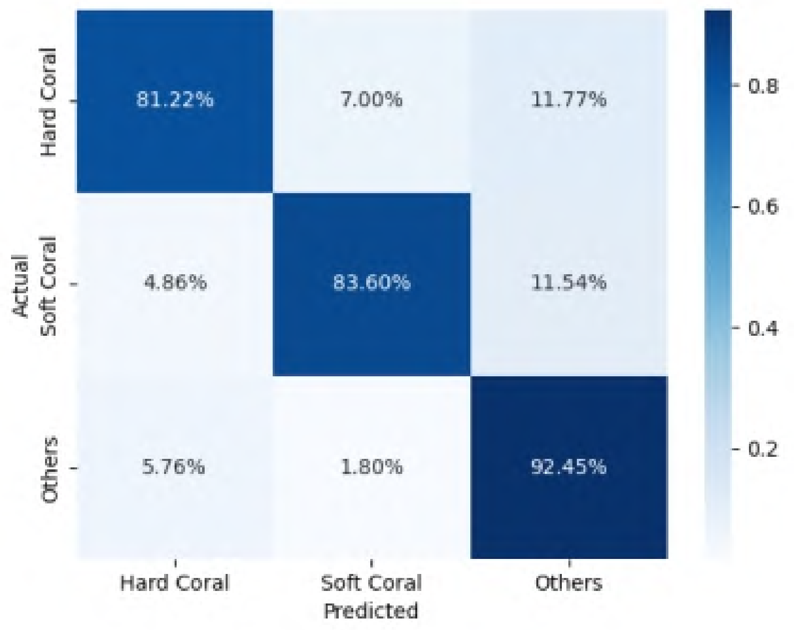
BASELINE

Hyperparameter Name	Hyperparameter Value
Model Size	m
data	All regions
epochs	5
imgsz	640
close_mosaic	10
degrees	0
flipud	0
translate	0.1

mIoU	IoU_hard	IoU_soft	IoU_other	mDice	Dice_hard	Dice_soft	Dice_other
0.70	0.64	0.58	0.89	0.82	0.78	0.73	0.94



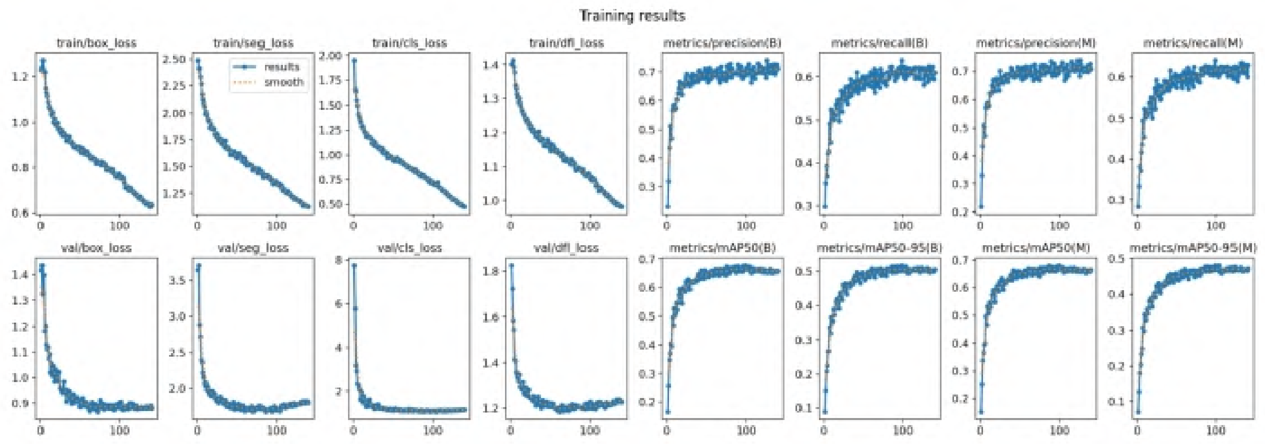


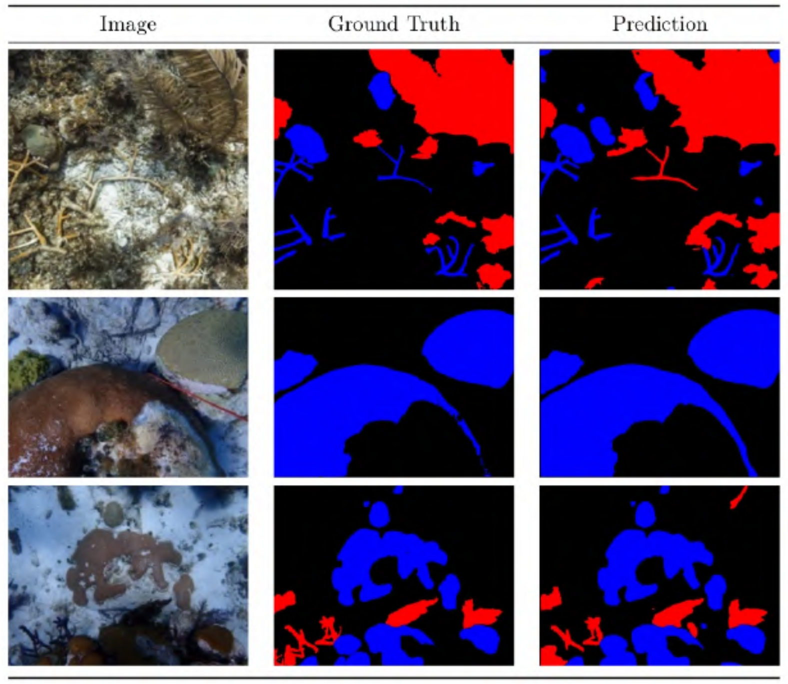


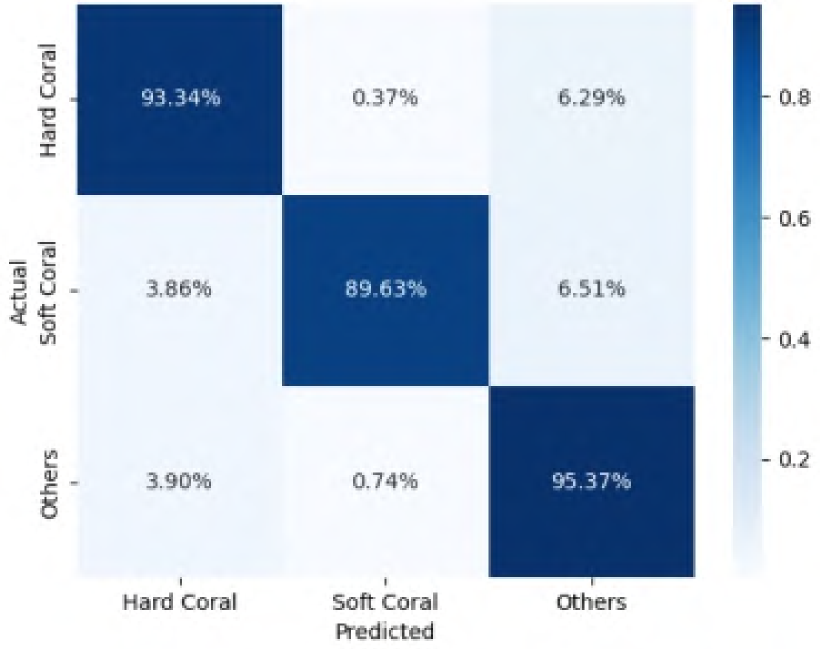
BEST MODELS

Hyperparameter Name	Hyperparameter Value
Model Size	x
data	All regions
epochs	140
imgsz	1024
close_mosaic	35
degrees	45
flipud	0.5
translate	0.2

model size	mIoU	IoU_hard	IoU_soft	IoU_other	mDice	Dice_hard	Dice_soft	Dice_other
x	**0.85**	0.79	**0.81**	**0.94**	**0.92**	0.88	**0.90**	0.97
l	**0.85**	**0.80**	**0.81**	**0.94**	**0.92**	**0.89**	**0.90**	0.97
m	**0.85**	**0.80**	0.80	**0.94**	**0.92**	**0.89**	0.89	0.97
s	0.84	0.78	0.80	0.93	0.91	0.88	0.89	**0.98**
n	0.83	0.77	0.80	0.93	0.91	0.87	0.89	0.97



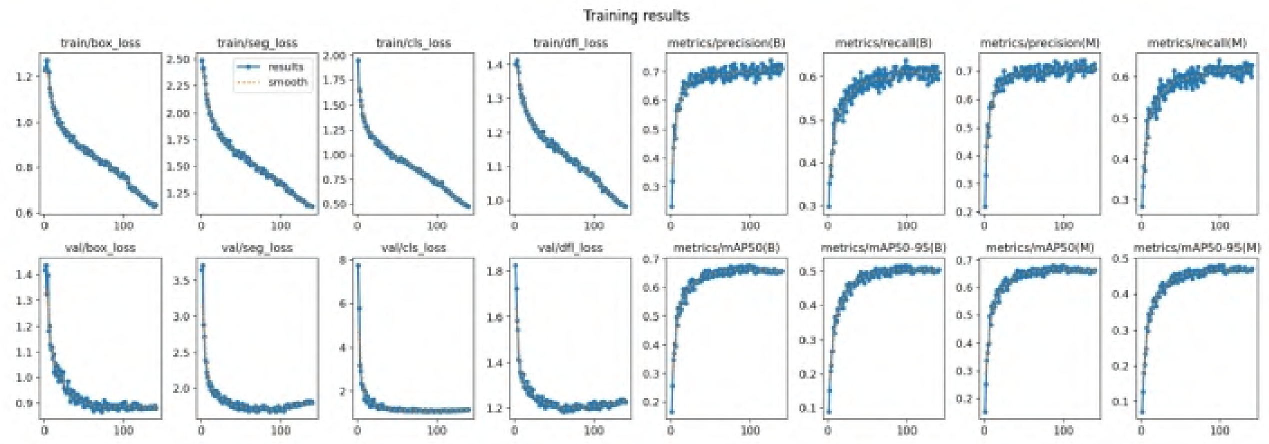


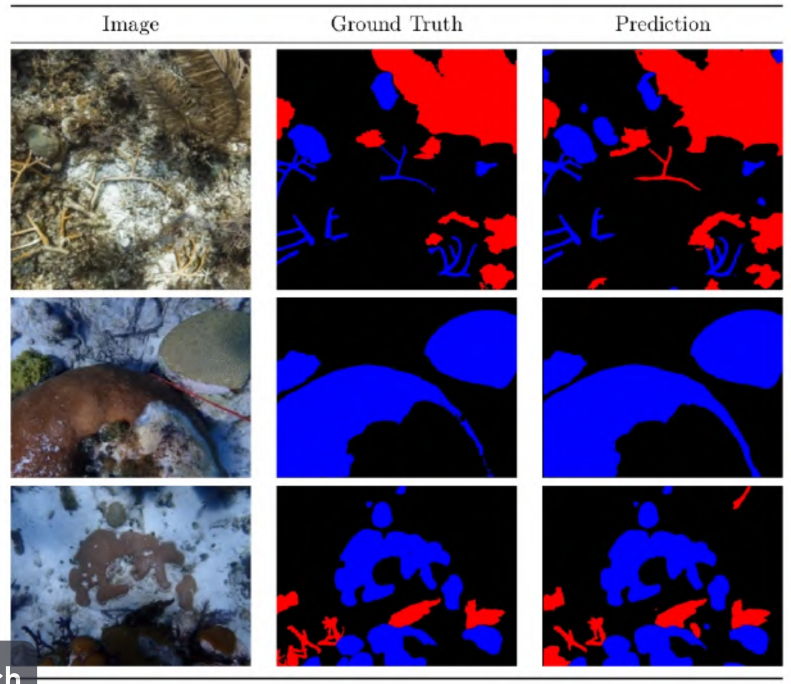


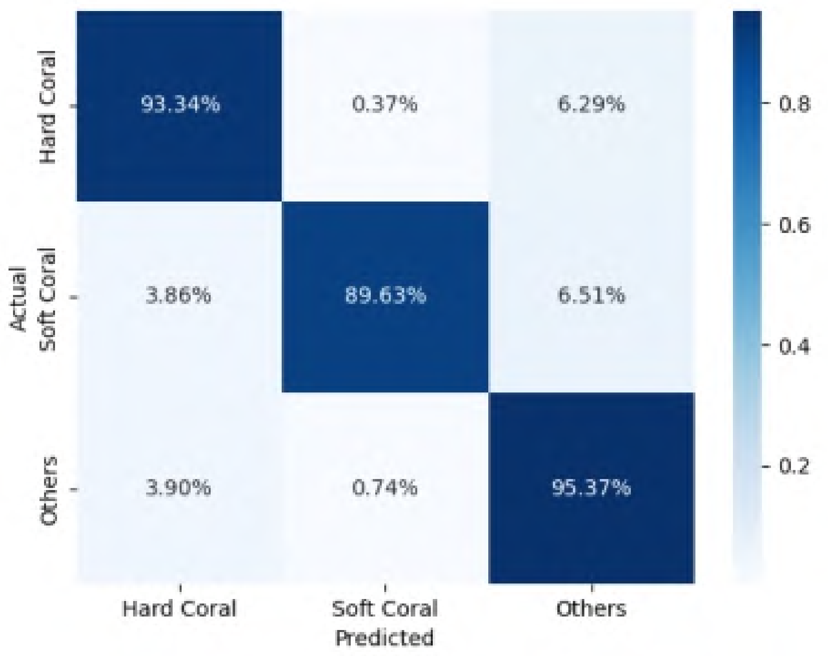
BEST MODEL BREAKDOWN

SEEING THE FULL PICTURE

model size	mIoU	IoU_hard	IoU_soft	IoU_other	mDice	Dice_hard	Dice_soft	Dice_other
x	**0.85**	0.79	**0.81**	**0.94**	**0.92**	0.88	**0.90**	0.97
l	**0.85**	**0.80**	**0.81**	**0.94**	**0.92**	**0.89**	**0.90**	0.97
m	**0.85**	**0.80**	0.80	**0.94**	**0.92**	**0.89**	0.89	0.97
s	0.84	0.78	0.80	0.93	0.91	0.88	0.89	**0.98**
n	0.83	0.77	0.80	0.93	0.91	0.87	0.89	0.97







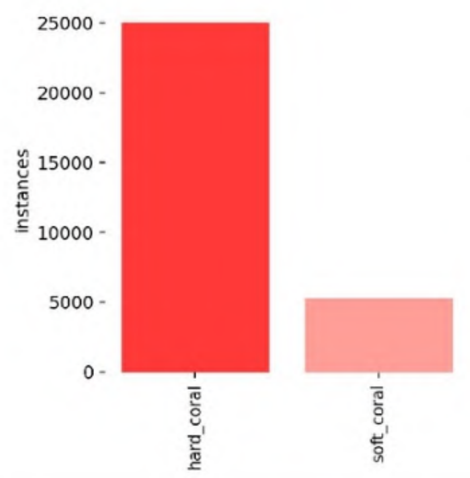
data	mIoU	IoU_hard	IoU_soft	IoU_other	mDice	Dice_hard	Dice_soft	Dice_other
all	**0.85**	0.80	0.81	0.94	0.92	0.89	0.90	0.97
sf_bol	0.80	**0.85**	0.63	0.93	0.89	0.92	0.77	0.97
sf_crt	0.72	0.70	0.54	0.94	0.83	0.82	0.70	0.97
sv_atl	0.78	0.63	0.78	0.92	0.87	0.78	0.87	0.96
sv_phl	**0.62**	0.75	**0.21**	0.91	0.72	0.86	0.34	0.95
sv_aus	0.69	0.76	0.38	0.92	0.79	0.86	0.55	0.96
tt_pro	**0.87**	0.77	**0.88**	0.96	0.93	0.87	0.94	0.98

Regional performances

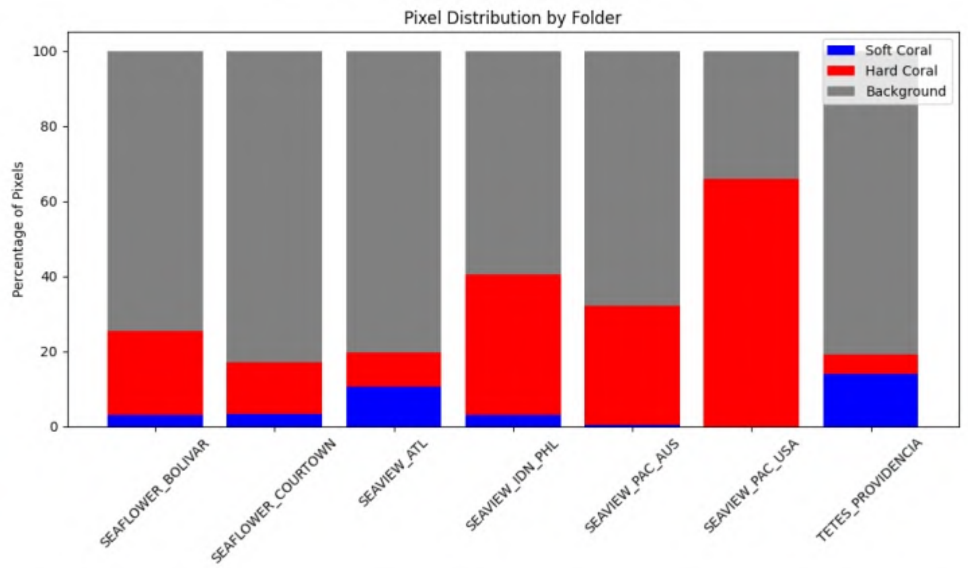
data	# images (test)	# pixels	weight (%)	mIoU	IoU_hard	IoU_soft	IoU_other
sf_bol	**25**	7056000000	**39.2**	0.80	**0.85**	0.63	0.93
sf_crt	25	1912699566	10.6	0.72	0.70	0.54	0.94
sv_atl	33	1136559093	6.3	0.78	0.63	0.78	0.92
sv_phl	**24**	866520651	**4.8**	**0.62**	0.75	**0.21**	0.91
sv_aus	59	1944497328	10.8	0.69	0.76	0.38	0.92
tt_pro	**11**	5079158784	**28.2**	**0.87**	0.77	**0.88**	0.96

Weights assigned to regions

Label Distribution



Pixel Class Distribution by region



GENERALIZATION TO UNSEEN REGIONS

HOW WELL DOES A MODEL TRAINED ON A SPECIFIC REGION GENERALIZE TO ANOTHER REGION?

model	data	mIoU	IoU_hard	IoU_soft	IoU_other	mDice	Dice_hard	Dice_soft	Dice_other
global	all	**0.85**	0.80	0.81	0.94	0.92	0.89	0.90	0.97
sv_atl	all	0.56	0.47	0.38	0.84	0.70	0.64	0.55	0.91
global	sf_bol	**0.80**	0.85	0.63	0.93	0.89	0.92	0.77	0.97
sv_atl	sf_bol	0.49	0.57	0.08	0.80	0.59	0.73	0.15	0.89
global	sf_crt	**0.72**	0.70	0.54	0.94	0.83	0.82	0.70	0.97
sv_atl	sf_crt	0.32	0.16	0.08	0.73	0.42	0.27	0.14	0.84
global	sv_atl	**0.78**	0.63	0.78	0.92	0.87	0.78	0.87	0.96
sv_atl	sv_atl	**0.78**	0.65	0.77	0.92	0.87	0.79	0.87	0.96
global	sv_phl	**0.62**	0.75	0.21	0.91	0.72	0.86	0.34	0.95
sv_atl	sv_phl	0.49	0.48	0.16	0.82	0.61	0.65	0.28	0.90
global	sv_aus	**0.69**	0.76	0.38	0.92	0.79	0.86	0.55	0.96
sv_atl	sv_aus	0.40	0.35	0.01	0.84	0.48	0.52	0.01	0.91
global	tt_pro	**0.87**	0.77	0.88	0.96	0.93	0.87	0.94	0.98
sv_atl	tt_pro	0.60	0.28	0.62	0.91	0.72	0.43	0.77	0.95

Comparison between the performance of the global model and the SEAVIEW_ATL specific model on the test sets from various regions.

While the region-specific model exhibits a respectable mIoU in most cases, indicating a degree of generalization to unseen regions, its performance falls considerably short of the global model trained on the entirety of these regions.

REGIONAL MODEL VS GLOBAL MODEL

DOES A REGION SPECIFIC MODEL OUTPERFORM A GLOBAL MODEL TRAINED ON ALL REGIONS?

model	data	mIoU	IoU_hard	IoU_soft	IoU_other	mDice	Dice_hard	Dice_soft	Dice_other
global	**all**	**0.85**	0.80	0.81	0.94	0.92	0.89	0.90	0.97
global	**sf_bol**	**0.80**	0.85	0.63	0.93	0.89	0.92	0.77	0.97
sf_bol	sf_bol	0.71	0.81	0.40	0.93	0.81	0.90	0.57	0.96
global	sf_crt	0.72	0.70	0.54	0.94	0.83	0.82	0.70	0.97
sf_crt	**sf_crt**	**0.74**	0.71	0.58	0.94	0.85	0.83	0.74	0.97
global	sv_atl	0.78	0.63	0.78	0.92	0.87	0.78	0.87	0.96
sv_atl	sv_atl	0.78	0.65	0.77	0.92	0.87	0.79	0.87	0.96
global	**sv_phl**	**0.62**	0.75	0.21	0.91	0.72	0.86	0.34	0.95
sv_phl	sv_phl	0.49	0.59	0.02	0.87	0.57	0.74	0.04	0.93
global	**sv_aus**	**0.69**	0.76	0.38	0.92	0.79	0.86	0.55	0.96
sv_aus	sv_aus	0.67	0.76	0.35	0.92	0.78	0.86	0.52	0.96
global	**tt_pro**	**0.87**	0.77	0.88	0.96	0.93	0.87	0.94	0.98
tt_pro	tt_pro	0.84	0.73	0.85	0.95	0.91	0.84	0.92	0.97

Exceptionally, the region-specific model for ***SEAFLOWER_COURTOWN*** exhibits superior performance on its designated test set, surpassing the global model by a marginal difference (**0.74** mIoU vs. **0.72** mIoU).

However, across all other instances, the global model, trained on the entirety of regions, consistently outperforms or equals the performance of region-specific models.

Future Work 

EXPAND TAXONOMIC SCOPE

Include additional benthic organisms and coral functional groups to provide a more comprehensive understanding of coral reef conditions.

CONTINUOUS MODEL RETRAINING

Implement a strategy for continuous model retraining as new data becomes available. This ensures the model’s ongoing improvement and adaptability over time.

UTILIZE PREDICTIONS FOR ANNOTATION

Utilize YOLOv8 predictions as a starting point for annotating new images and regions, streamlining the annotation process and promoting efficiency.

ESTABLISH A VIRTUOUS LOOP

Foster a virtuous loop where conservationists can enhance their underwater imagery analysis while concurrently contributing to the growth of the ReefSupport dataset.

EMBED SMALL FOOTPRINT MODELS

Explore the possibility of embedding small footprint YOLOv8 models onto underwater cameras to facilitate real-time analysis of coral reefs, providing timely insights into the
underwater ecosystem.

Conclusions

VALIDATED MODELING APPROACH

YOLOv8 is a highly suitable model benthic segmentation. Its exceptional performance, even on modest hardware configurations, positions it as an effective solution for resource-constrained environments

ONE MODEL TO RULE THEM ALL

A model trained on the full dataset performs better than regional models.

DATASET CURATION

Data issues in half of the annotated data in reefsupport, including problems such as data leakage, empty masks, label mismatches or poor annotations. Addressing these challenges through dataset curation has the potential to significantly enhance overall performance.

Questions?