Coral Life Forms Detection for Analysis of Climate Change Impact on Coral Biodiversity

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Background & Problem Statement

- Coral reefs, often referred to as the "rainforests of the sea," are some of the most diverse ecosystems in the world. Thousands of species rely on reefs for survival. Millions of people all over the world also depend on coral reefs for food, protection and jobs. Unfortunately, these vital ecosystems are facing unprecedented threats due to climate change.

- National Oceanic and Atmospheric Administration (NOAA) stated that climate change will affect coral reef ecosystems, through sea level rise, changes to the frequency and intensity of tropical storms, and altered ocean circulation patterns. When combined, all of these impacts dramatically alter ecosystem function, as well as the goods and services coral reef ecosystems provide to people around the globe.

- Traditional methods of coral assessment, such as Line Intercept Transect (LIT) for identifying coral coverage, often face limitations in terms of scope and efficiency. These limitations are particularly evident in survey scalability and the constraints of human diving time. To bridge this gap, our project is dedicated to the utilization of automatic Coral Life Forms Detection for conducting a comprehensive analysis of coral coverage during site surveys by an underwater robot.

- By integrating cutting-edge detection techniques into an automated coral monitoring method using an underwater robot, our objective is to offer a more nuanced understanding of how climate change impacts various coral species, their distribution, and overall reef dynamics. This endeavor aims to empower researchers and conservationists to make decisions about further interventions more efficiently.

Objectives & Scope

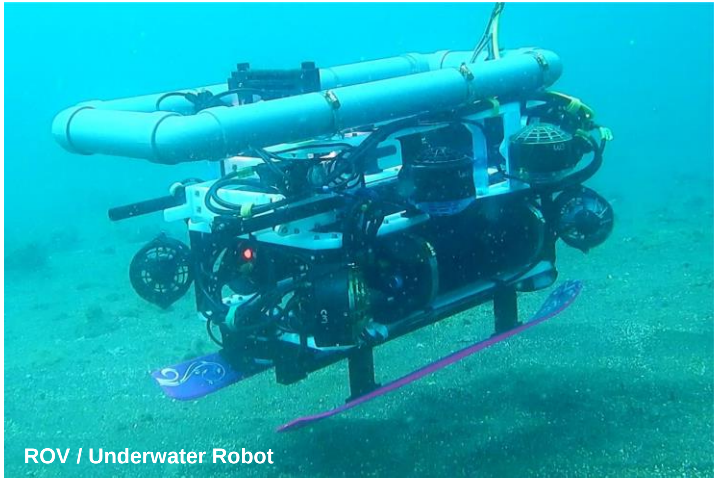
Objectives

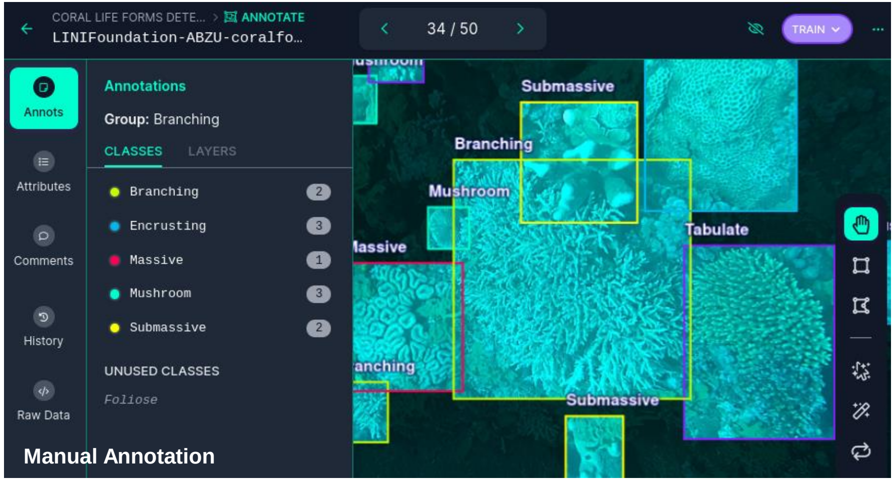
Develop deep learning models for identifying and analyzing coral life forms, focusing on seven main forms (Branching, Massive, Submassive, Foliose, Mushroom, Tabulate, Encrusting).

Scope

Explore YOLO state of the art object detection algorithm in developing deep learning model for coral life forms detection.

Data Collection


ROV / Underwater Robot



Manual Annotation

- The data is collected through video extraction recorded by a Remotely Operated Underwater Vehicle (ROV) conducting surveys of coral reefs at depths ranging from 8 to 15 meters underwater in the North Bali Sea.
- The extracted images then proceed to undergo manual annotation into seven distinct classes within Roboflow, enabling a detailed classification of coral life forms.

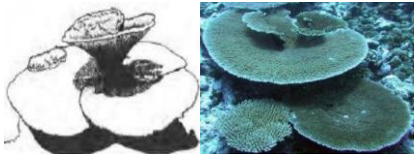
Data Understanding

Coral Branching

Coral structure resembles tree-like branches.

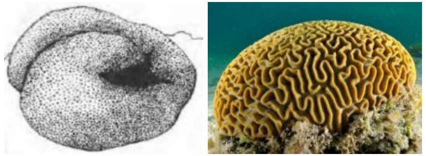
Coral Tabulate

Corals form flat, tabletop-like structures.



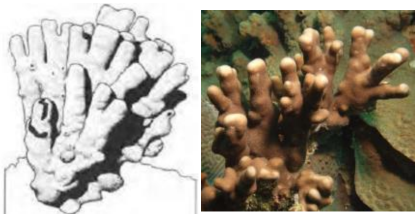
Coral Massive

Solid appearance with a rounded or boulder-like shape.



Coral Submassive

Combination of massive and branching structures. Rounded or columnar structures with irregular branching components.



Coral Mushroom

Mushroom-like appearance with a flattened, circular or oval shape and a central mouth.

Coral Foliose

Colonies form flattened, leaf-like structures, develop thin and plate-like formations that often create intricate and delicate appearances.

Coral Encrusting

Coral species where the colonies grow as thin layers, closely adhering to the substrate.

Data Preparation

Original

TRAIN SET 80%	VALID SET 10%	TEST SET 10%
264 Images	33 Images	33 Images

Preprocessing
Auto-Orient
Resize (640x640)

Augmentation
Flip (Horizontal, Vertical)
Grayscale (15%)
Hue (+/- 15°)

Augmented

TRAIN SET 92%	VALID SET 4%	TEST SET 4%
791 Images	33 Images	33 Images

Model Development

- Implementing **YOLO** *(You Only Look Once)* as a state-of-the-art real-time object detection system that stands out for its real-time capabilities, achieving high accuracy and speed by simultaneously predicting bounding boxes and class probabilities with a single neural network.

- Explore and examining the architectural variations of YOLOv3, YOLOv5, and YOLOv8 to optimize the accuracy and efficiency of the coral life form detection system.

  YOLO variation using ultralytics library:

  - YOLOv3
  - YOLOv3u
  - YOLOv5s
  - YOLOv5l
  - YOLOv5m
  - YOLOv8n
  - YOLOv8s
  - YOLOv8m
  - YOLO v8l
  - YOLOv8x

Training & Optimization

Hyperparameter

- Epoch :100
- Batch_size : 16
- Img_size : 416
- Learning Rate :
  - lr0 = 0.01
  - lrf = 0.0001
- Momentum: 0.937
- Weight Decay: 0.0005
- Optimizer : AdamW

YOLO Augmentation (Default)

- Mosaic : 1.0
- Translate: 0.1
- Scale: 0.5
- fliplr: 0.5
- hsv_h (hue): 0.015
- hsv_s (saturation): 0.7
- hsv_v (value): 0.4

```
    Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
   99/100      1.97G      0.641     0.3743      0.855         70        416: 100% 50/50 [00:10<00:00,  4.67it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 2/2 [00:00<00:00,  3.41it/s]
                   all         33        316      0.749      0.654      0.703        0.5

    Epoch    GPU_mem   box_loss   cls_loss   dfl_loss  Instances       Size
  100/100      1.94G      0.637     0.3771     0.8552         80        416: 100% 50/50 [00:10<00:00,  4.67it/s]
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95): 100% 2/2 [00:00<00:00,  3.04it/s]
                   all         33        316      0.748      0.652      0.696      0.494
```

To evaluate the performance of our **YOLO** model, We utilized **evaluation metrics** such as Precision, Recall, mAP50, and mAP(50-95).

Precision:

- **Definition:** Precision measures the accuracy of positive predictions made by the model. It is the ratio of correctly predicted positive instances to the total instances predicted as positive.
- **Formula:** Precision = True Positives / (True Positives + False Positives)
- **Interpretation:** A high precision indicates that when the model predicts an object, it is likely to be correct.

Recall:

- **Definition:** Recall, also known as sensitivity or true positive rate, assesses the model's ability to capture all relevant instances of a class. It is the ratio of correctly predicted positive instances to the total actual positive instances.
- **Formula:** Recall = True Positives / (True Positives + False Negatives)
- **Interpretation:** A high recall value indicates that the model can effectively identify most of the true positive instances.

mAP50 (mean Average Precision at 50):

- **Definition:** mAP50 is the mean Average Precision calculated at an intersection over union (IoU) threshold of 50%. It represents the average precision across different confidence levels for predicted bounding boxes.
- **Interpretation:** mAP50 gives an overview of the model's performance at a standard IoU threshold, which is commonly set at 50%.

mAP(50-95) (mean Average Precision between 50 and 95):

- **Definition:** mAP(50-95) is the mean Average Precision calculated over a range of IoU thresholds, typically from 50% to 95%. It provides a more comprehensive evaluation of the model's accuracy at varying degrees of overlap between predicted and ground truth bounding boxes.
- **Interpretation:** mAP(50-95) offers insights into the model's robustness across a spectrum of IoU thresholds, accounting for different levels of object overlap.

Results

Validation Results from representatives of each version from YOLOv3, YOLOv5, and YOLOv8

Class	Images	Instances	Box(P	R	mAP50	mAP50-95):
all	33	288	0.816	0.778	0.81	0.644
Branching	33	59	0.749	0.81	0.826	0.587
Encrusting	33	47	0.881	0.787	0.807	0.631
Foliose	33	21	0.937	0.712	0.817	0.706
Massive	33	85	0.779	0.704	0.739	0.539
Mushroom	33	38	0.684	0.632	0.685	0.52
Submassive	33	16	0.896	0.938	0.921	0.796
Tabulate	33	22	0.785	0.864	0.878	0.729

YOLOv3u

Class	Images	Labels	P	R	mAP@.5	mAP@.5:.95:
all	33	316	0.711	0.499	0.562	0.31
Branching	33	93	0.663	0.591	0.643	0.323
Encrusting	33	50	0.714	0.4	0.496	0.246
Foliose	33	11	0.879	0.364	0.426	0.285
Massive	33	73	0.665	0.411	0.492	0.277
Mushroom	33	40	0.845	0.65	0.732	0.375
Submassive	33	18	0.759	0.722	0.756	0.467
Tabulate	33	31	0.45	0.355	0.39	0.195

YOLOv5s

Class	Images	Instances	Box(P	R	mAP50	mAP50-95):
all	33	288	0.859	0.779	0.829	0.637
Branching	33	59	0.869	0.831	0.866	0.603
Encrusting	33	47	0.857	0.745	0.8	0.628
Foliose	33	21	0.944	0.857	0.888	0.756
Massive	33	85	0.777	0.635	0.749	0.538
Mushroom	33	38	0.842	0.526	0.645	0.471
Submassive	33	16	0.888	0.994	0.973	0.809
Tabulate	33	22	0.837	0.864	0.882	0.656

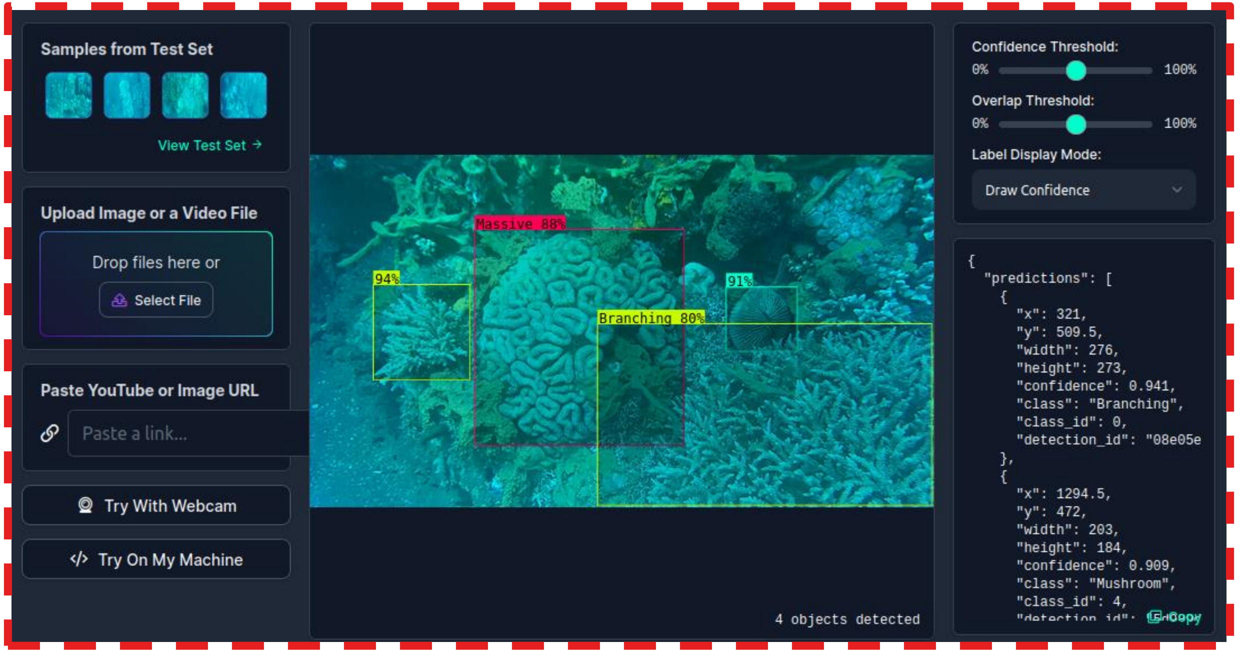
YOLOv8s

Overall Results Comparison

Model	epoch	Input size	Batch size	GPU	Precision	Recall	mAP50	mAP(50-95)	Inference time (ms)
YOLOv3	100	416	16	T4	0.784	0.664	0.715	0.55	±18
YOLOv3u	100	416	16	T4	0.816	0.778	0.810	0.644	±21
YOLOv5s	100	416	16	T4	0.755	0.510	0.562	0.310	±11
YOLOv5m	100	416	16	T4	0.707	0.500	0.562	0.308	±10
YOLOv5l	100	416	16	T4	0.742	0.706	0.687	0.582	±10
YOLOv8n	100	416	16	T4	0.840	0.625	0.750	0.538	±11
YOLOv8s	**100**	**416**	**16**	**T4**	**0.859**	**0.779**	**0.829**	**0.637**	**±11**
YOLOv8m	100	416	16	T4	0.877	0.748	0.820	0.631	±15
YOLOv8l	100	416	16	T4	0.843	0.768	0.828	0.660	±18
YOLOv8x	100	416	16	T4	0.801	0.695	0.782	0.535	±59

Video Inference Result (YOLOv8s)

Real-world Application

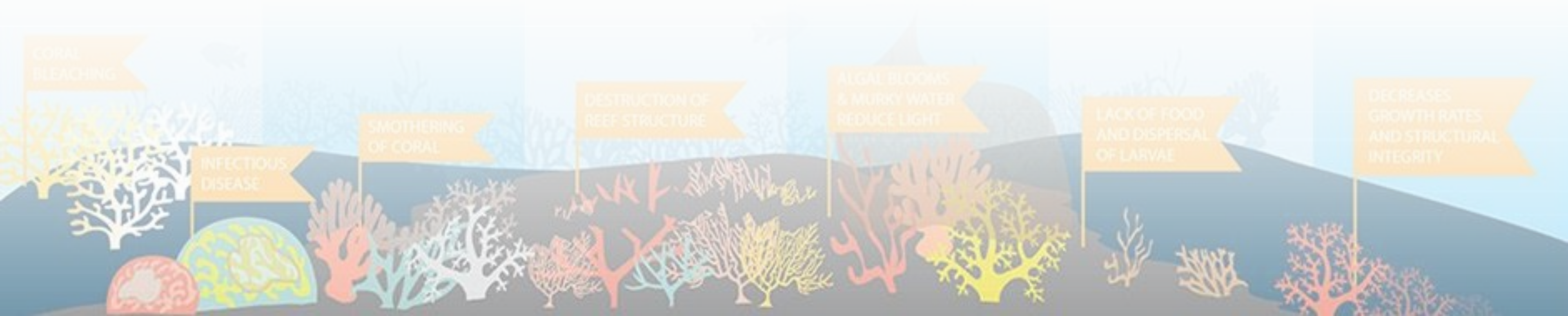


[Roboflow Web Deployment]

Conclusion

- Upon comparing the training results among YOLOv3, YOLOv5, and YOLOv8, it becomes evident, based on precision, recall, and mAP evaluation metrics, that YOLOv8 achieves the highest overall evaluation score when compared to the other YOLO variants.

- Considering the real-time deployment needs that necessitate fast inference times, we conclude that the YOLOv8s variation is the most optimal model for real-time deployment purposes. Where the overall score results on the evaluation metrics are among the highest. **(Precision: 0.859; Recall: 0.779; mAP50: 0.829; mAP (50-95): 0.637)**, and the inference time is one of the fastest, with a value of **11 milliseconds** (ms).

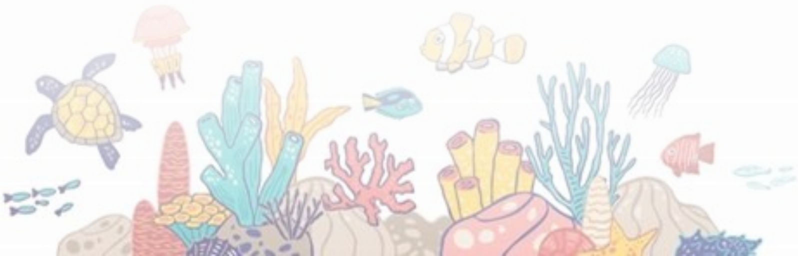


Future Improvement

- **Implement additional tracking and counting algorithms**
  This addition will enable the model not only to identify and classify coral life forms but also to quantify population sizes, offering deeper insights into ecosystem dynamics.

- **Integrating into Robot Operating System (ROS)**
  Integrate the coral detection system into the Robot Operating System (ROS) to facilitate real-time deployment using the underwater robot (ROV) in an actual coral reef ecosystem environment.

- **Carry out regular deployment in real time**
  This advancement aims to transition the model into continuous monitoring, providing instant insights for practical conservation applications.



ROS
Robot Operating System

Contact Us

Don’t hesitate to contact us for further inquiries or any collaborations.

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