Coral Segmentation from Point Labels to Dense Segmentation Masks

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Introduction

Coral reefs, covering less than 1% of the ocean floor while supporting over 25% of marine species, face severe threats from climate change, with potential losses of up to 90% by 2050. Traditional coral monitoring relies on labor-intensive manual image annotation.
Our goal is to aid the AI for Coral Reefs Challenge by improving coral monitoring through automated image segmentation. While original model generates dense segmentation masks from sparse labels, improvements in its quality and accuracy are needed. This research explores pre-processing, SAM (Segment Anything Model) variants, and post-processing techniques to enhance the segmentation process.

Business Understanding

ReefSupport is a conservation organization that relies on advanced AI models to improve the accuracy and efficiency of coral reef monitoring, helping them streamline environmental assessments and better protect marine ecosystems.

Approach

We explored different variants of SAM to generate dense segmentation masks from sparse point labels. Pre-processing techniques are applied to enhance quality of images before segmentation. Post-processing techniques are employed to remove noise from generated masks and ensure more precise segmentation outputs.

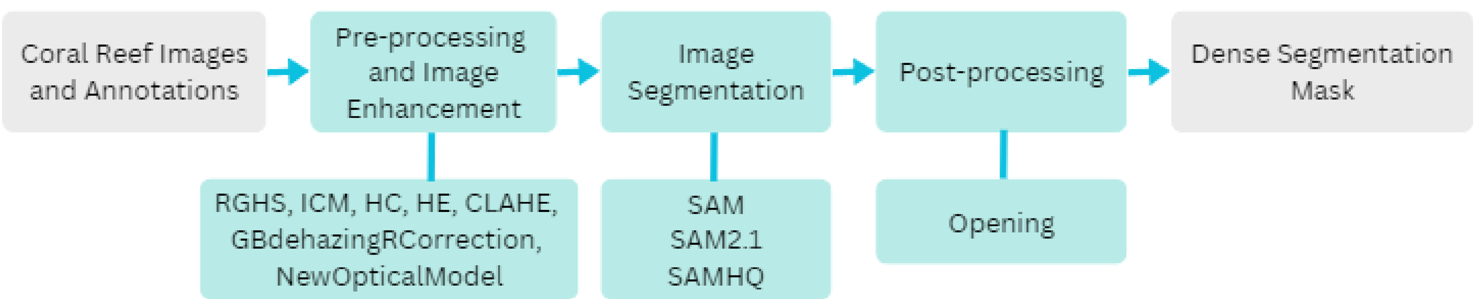


Figure 1. Diagrammatic Representation of approach carried out

Evaluation Method

The performance of model was evaluated using 63 images from the SEAVIEW_ATL region. To ensure a representative sample, we tried to select an equal proportion of images based on number of point labels per image. 30 images each with 50 and 100 point labels were chosen, while only 3 images with 150 point labels were available and were included in the evaluation.
The accuracy of model was accessed by comparing the predicted pixel classes in the generated masks with the actual pixel classes in the dense segmentation masks provided by Reef Support.

References

[1] Yan Wang, Wei Song, Giancarlo Fortino, Li-Zhe Qi, Wenqiang Zhang, and Antonio Liotta.
An experimental-based review of image enhancement and image restoration methods for underwater imaging.
IEEE Access, 7:140233–140251, 2019.

Data Understanding

1. The datasets used in this research were provided by ReefSupport, which includes Point Label Dataset with 11,387 sparsely annotated images and Mask Label Dataset with dense segmentation masks used for training and evaluation.
2. The dataset consists of low-quality images, introducing challenges like noise and poor contrast, complicating the segmentation task.

Results: Comparison of SAM variants

SAM-HQ (base) performed better with 98.20%, 47.42% and 44.74% of pixels correctly classified as Others, Hard and Soft Coral respectively.

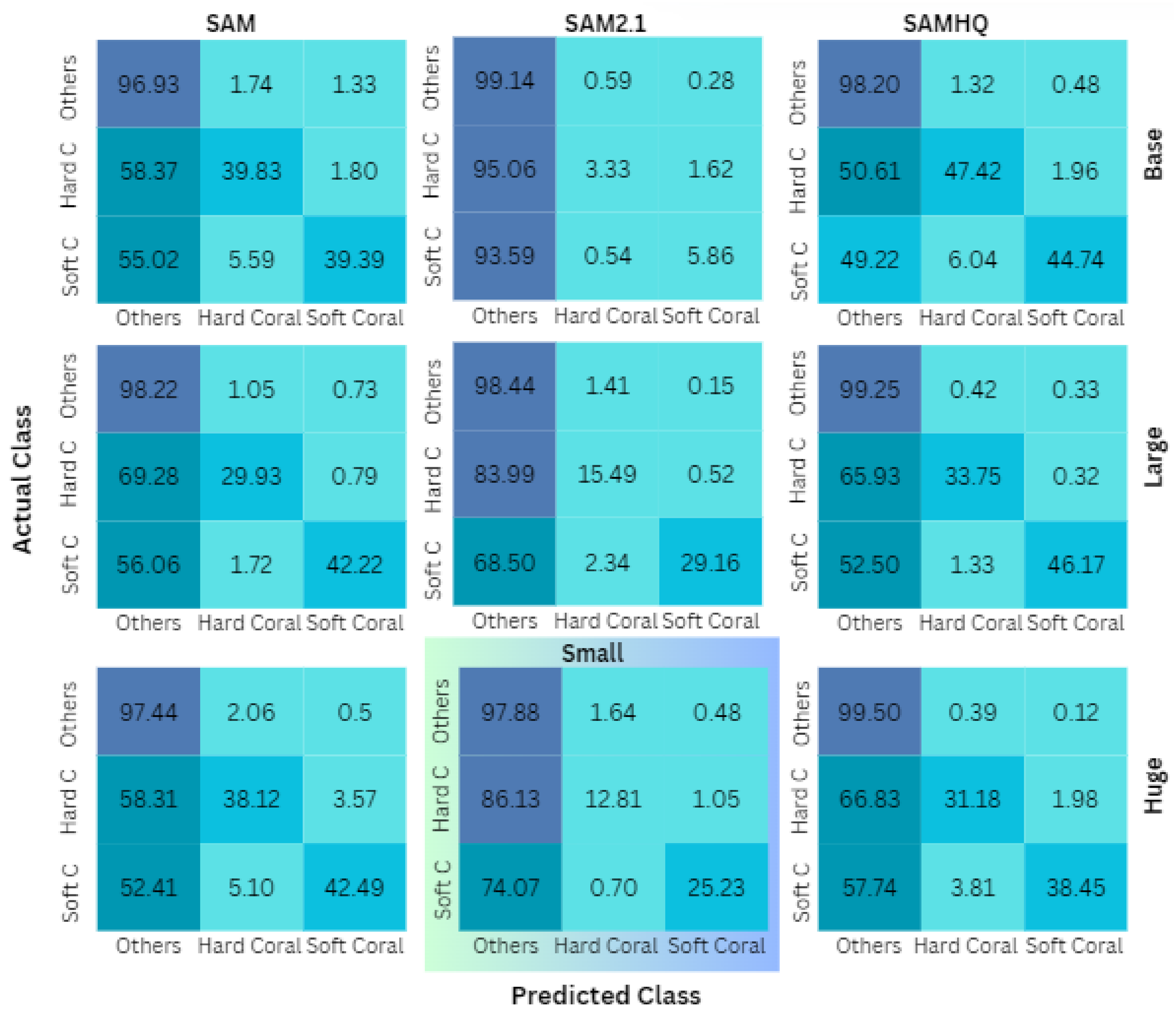


Figure 2. Accuracy of different variants of SAM

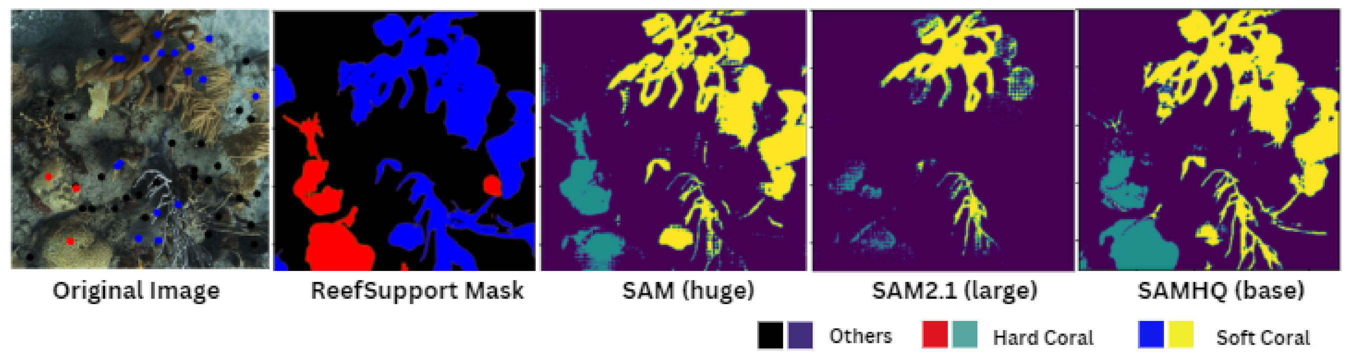


Figure 3. Mask generated by SAM variants for image: 25016137702

Interpretation and Critical Reflection

1. SAM, SAM2.1 and SAM-HQ can be used to generate dense segmentation mask from sparse point labels.
2. SAM-HQ (base) outperformed SAM and SAM2.1, mainly for background regions. All models struggled with coral specific regions, where accuracy remained below 50%, suggesting its reliability for general segmentation but less effectiveness for complex coral regions.
3. Pre-processing did not improve performance of SAM, likely due to model being pre-trained on general datasets and not fine-tuned for coral-specific tasks. Post-processing using opening helped in noise reduction, but optimal kernel size selection is crucial.

Research Questions

1. How can dense segmentation masks be generated from sparse point labels using different variants of SAM?
2. How do different segmentation methods, compare in terms of accuracy when applied to coral reef images, especially in the presence of lower-quality images?
3. What potential improvements can pre and post-processing bring to models when applied to coral reef monitoring?

Results: Pre-processing and Post-processing

The percentage of pixels correctly classified across all categories seems to be similar with or without pre-processing.
Morphological operation like opening helped to reduce noise in generated masks while preserving larger structures. Using small kernel was not fruitful to remove noise, while using large kernel removed noise along with some required pixels.

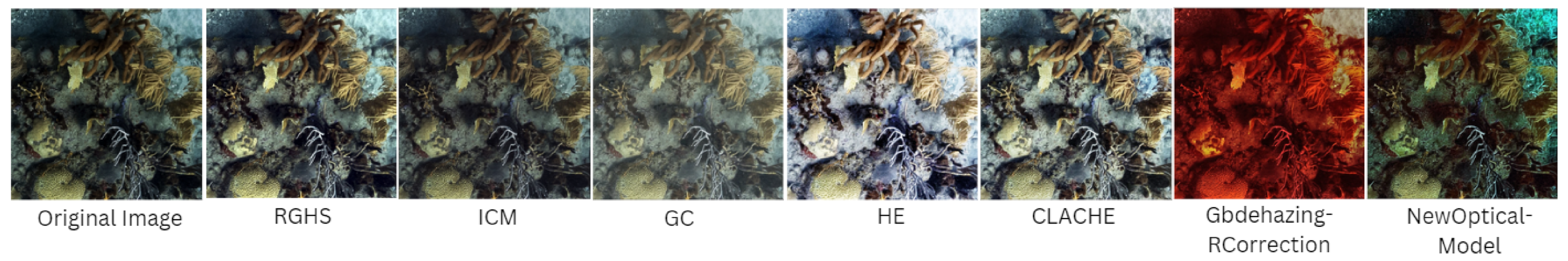
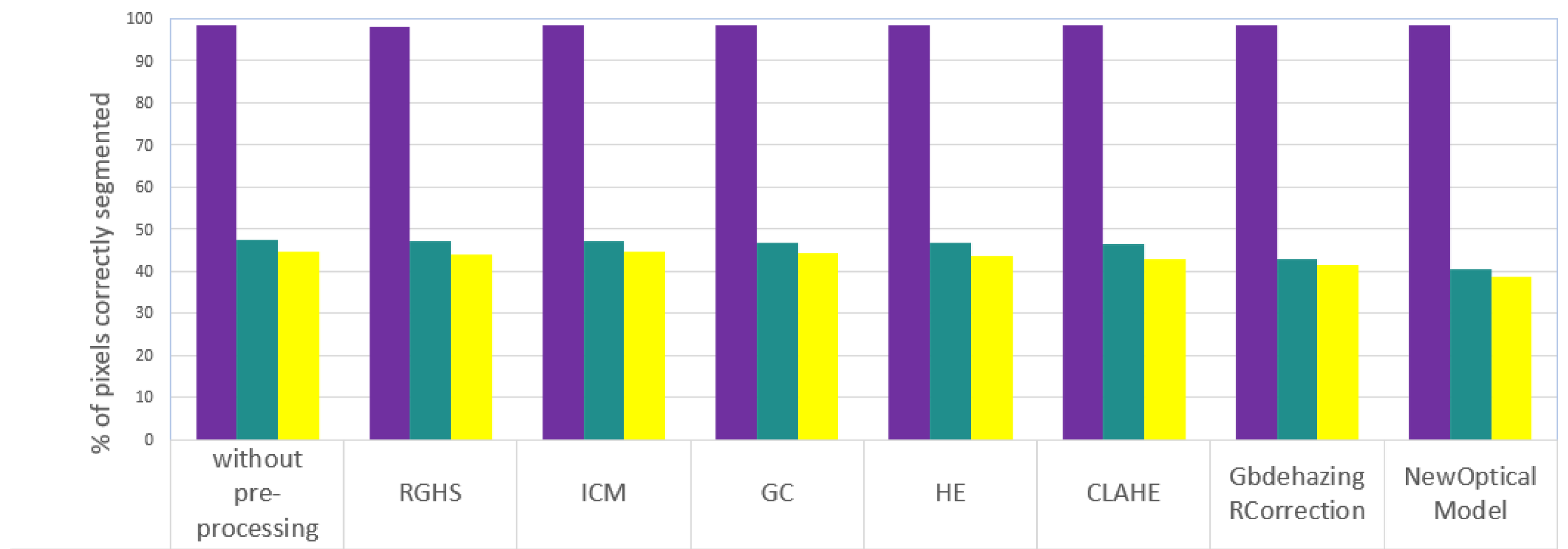


Figure 4. Image pre-processed through different techniques



	without pre-processing	RGHS	ICM	GC	HE	CLAHE	Gbdehazing RCorrection	NewOptical Model
Others	98.2	98.15	98.2	98.25	98.29	98.21	98.26	98.4
Hard Coral	47.42	47.25	47.16	46.87	46.62	46.33	42.82	40.43
Soft Coral	44.74	43.89	44.56	44.41	43.72	42.91	41.42	38.51

Figure 5. Accuracy of SAM-HQ base model with pre-processing

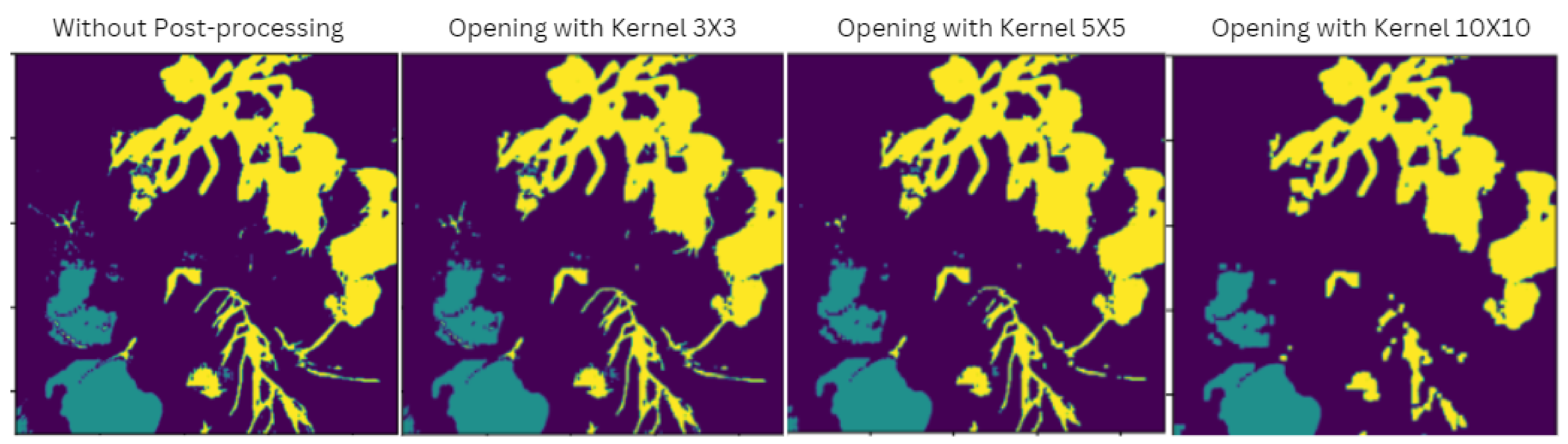


Figure 6. Post-processing through Morphological Operation (Opening)

Recommendations

1. Leveraging post-processing for refinement of dense mask generated is helpful. However, selection of optimum size of kernel is important.
2. Combining SAM with models specifically trained for coral reef classification could leverage segmentation strength of SAM.