Eindhoven University of Technology (TU/e)
Mathematics & Computer Science

Pixel-Level Segmentation for Quantifying Coral Bleaching & Health States

Capstone Data Challenge - JBG060

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Contents

1 Context, Problem Background, and Motivation

Coral reefs support nearly a quarter of all marine species, covering only 1% of the ocean floor, and protect coastal economies worth tens of billions of dollars annually. Yet rising sea temperatures, pollution, and overfishing are causing large-scale coral bleaching, threatening reef biodiversity and livelihoods (NOAA, n.d.). Traditional monitoring (manual photo analysis) by divers is slow, subjective, and limited in geographic scope (Reef Support, n.d.). Figure 1 shows a comparison between a healthy, bleached, and dead coral, which is the basic differentiation this research is built on.

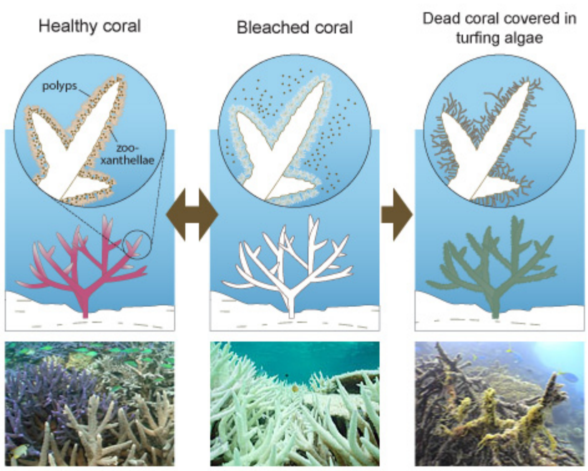

Figure 1: Healthy/Bleached/Dead coral (Valinsky, 2015)

Automated image-based assessment offers a scalable alternative. Most existing approaches focus on classifying whether an image contains bleached coral, but they overlook spatial detail and local variability in health. Pixel-level segmentation can capture the fine structure of coral colonies and distinguish gradients of bleaching within a single frame.

This project aims to move beyond binary detection of bleaching toward quantitative coral health estimation. Building on Reef Support's Open Coral AI initiative, we combine semantic segmentation with interpretable texture and morphological features derived from coral masks. These features, such as surface roughness, entropy, and brightness distribution, enable the derivation of a continuous health score based on what the literature states is healthy and what is not. The goal is to aid Reef Support by researching the extent to which a health score for coral can be quantified and all pixel values can be exploited.

2 Business and Data Understanding

2.1 Stakeholders and Requirements

The primary stakeholder, Reef Support, develops AI-based tools for reef monitoring and restoration. Their field partners collect hundreds of underwater photographs per site, which must be processed into live-coral-cover and bleaching metrics. Manual annotation of each frame can take hours and is prone to inconsistency between experts.

Reef Support's operational goal is to generate rapid bleaching alerts and quantitative health summaries from new survey batches with minimal human intervention. The model must generalize across camera types, lighting conditions, and geographic sites, while producing interpretable outputs that non-technical users can trust.

2.2 Datasets

The training data combine multiple reef image datasets to achieve site diversity and mask consistency. The primary sources include CoralSeg (4900 annotated coral–background pairs) and Reef Support's Benthic datasets (3300 images across eight sites such as Seaview, Seaflower, and Tayrona). Each sample includes an RGB image and a corresponding binary coral mask.

Masks were standardized to a single

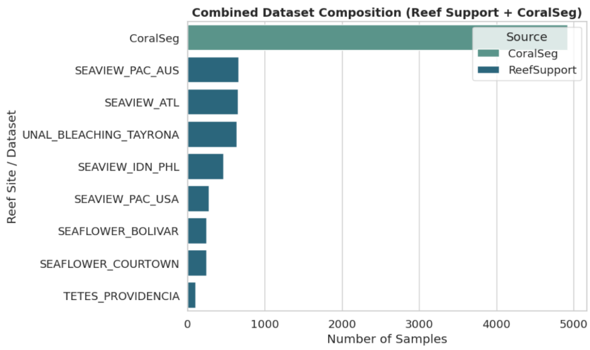

Figure 2: Project Data Composition (Visualizations Notebook).

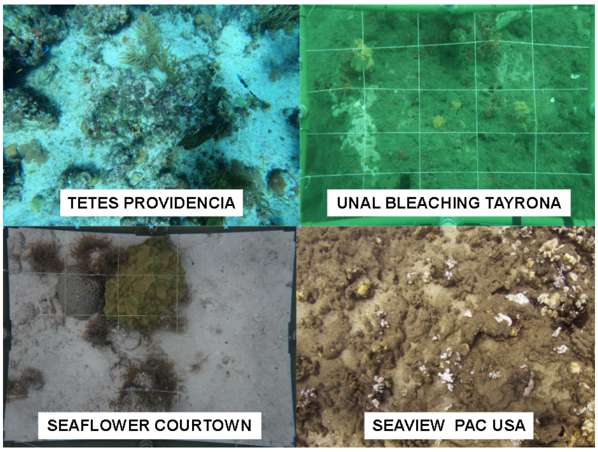

Figure 3: General water/vision difference across different sites.

coral-vs-non-coral format and resampled to 256x256 px, since testing showed that reducing size barely affected precision compared to the computational speed gained. This allows for a uniform segmentation pipeline that is independent of the original labeling schemas. Additional datasets, such as CoralScapes and CoralSCOP, can be integrated, however, permission to use must be requested and justified and at the time of writing this it has not been approved.

2.3 Data Properties and Risks

The datasets differ in water depth, camera calibration, and illumination, producing significant color-cast and contrast variation. Coral morphology also varies across regions, leading to domain shifts between training and test sites. Label uncertainty is present in the weakest bleaching areas, where color boundaries are ambiguous. To mitigate these risks, preprocessing included histogram equalization, mask validation, and site-stratified splitting to prevent leakage between train and validation sets, since different sites, as shown in figure 3, has a general color, turbidity or tone that can be identified in most of its images.

3 Research Objective

The primary objective of this project is to develop a segmentation-based data pipeline that can isolate coral regions from underwater imagery and quantitatively assess their condition through interpretable image-derived features. Instead of producing a single "health score" of uncertain validity, the study aims to identify and characterize specific and researched morphological and textural indicators that correlate with coral health status across sites.

Concretely, the project pursues three measurable goals:

1. Train a robust segmentation model to separate coral from background, evaluated primarily through the Intersection-over-Union (IoU) metric.

2. Extract post-processed features (color, brightness, texture, and morphological shape descriptors) from the segmented coral regions, and statistically analyze their interrelationships and site-level variability.

3. Investigate to what extent combinations of these features can predict or differentiate bleaching severity, and outline how they could be aggregated into a future continuous health index grounded in literature and domain expertise.

4 Approach

The analysis follows a two-stage pipeline: (1) segmentation to isolate coral regions, and (2) post-processing to derive and analyze quantitative features describing coral health. This modular design allows separating generalizable computer-vision learning (stage 1) from site-specific ecological interpretation (stage 2), aligning with Reef Support's need for scalable yet interpretable analytics.

4.1 4.1 Data Processing Pipeline

The raw data came from heterogeneous sources, images from eight reef sites, captured with different cameras, depths, and lighting. To ensure comparability, preprocessing aimed to reduce non-biological variance while retaining color and texture cues linked to bleaching.

Steps and motivation:

- *Resolution normalization (*256×256*)*: balances computational efficiency and morphological detail. Pilot tests showed negligible loss in segmentation IoU below this size.

- *Histogram equalization and white balancing*: mitigates underwater color cast caused by wavelength absorption at depth; this step standardizes illumination and preserves true color contrast between coral and background.

- *Mask validation*: removes samples with <5% coral coverage or corrupted masks, preventing training bias toward background-dominant images.

- *Site-stratified split*: ensures that images from the same reef site do not leak between training and validation sets, enabling an honest measure of site generalization.

The unified dataset contained **3,276 usable image–mask pairs**. A summary of coral coverage per site is shown in Figure 4, illustrating substantial inter-site variability that motivates robust domain handling.

Figure 4: Distribution of coral coverage per image across sites (placeholder).

[Optionally insert example before–after image showing color correction or mask overlay to visualize preprocessing impact.]

4.2 4.2 Segmentation Model

A **U-Net** architecture with an **EfficientNet-B0 encoder** was chosen for its balance between parameter efficiency and spatial accuracy on limited data. The model was trained with a combined *Binary Cross-Entropy + Dice loss*, which stabilizes convergence under severe class imbalance (few coral pixels relative to background). Optimization used Adam with cyclical learning rate scheduling to enhance generalization.

Evaluation metric: Since segmentation aims to maximize spatial overlap rather than discrete classification, performance was assessed via *Mean Intersection-over-Union (mIoU)* and *Dice coefficient*. These metrics quantify how accurately coral areas are reproduced pixel-wise, directly matching the project's objective of reliable mask extraction.

Training ran for 50 epochs on Google Colab (T4 GPU, mixed precision). The best model achieved **val mIoU = 0.xx** (*to be filled in*) on unseen sites.

`placeholder_masks.png`

Figure 5: Example of segmentation predictions vs. ground-truth masks across sites (placeholder).

Qualitative inspection revealed strong performance on well-lit, shallow images and lower IoU in turbid or low-contrast scenes, consistent with known underwater vision limitations.

4.3 4.3 Post-processing and Feature Extraction

Once coral regions were isolated, we computed a suite of features grouped into three interpretable categories (Table 1).

Table 1: Summary of extracted feature families.

Feature type	Description / ecological relevanc
Color / Brightness	Mean and variance of RGB + HSV ch ies for pigment concentration and blea
Texture	Laplacian variance (sharpness), LB GLCM contrast, Shannon entropy, ca complexity and tissue microstructure
Morphology	Coral area ratio, perimeter-area ra fractal dimension, approximate colon tion or rugosity.

Feature computation was implemented in `OpenCV` and `scikit-image`, applied only within coral masks to avoid background contamination.

To inspect distribution patterns, we visualized per-site histograms (Figure 6) and boxplots comparing variance in brightness and entropy. For example, higher brightness variance correlated visually with paler, bleached corals.

Pairwise correlations (Figure 7) showed strong association among Laplacian, LBP, and GLCM-based features ($r > 0.9$), indicating redundancy among texture descriptors. This justifies dimensionality-reduction steps introduced later.

4.4 4.4 Statistical Modeling and Interpretation

To interpret how features vary across reef sites and potential bleaching gradients, we performed:

- **Principal Component Analysis (PCA)**: reduces correlated features into orthogonal axes summarizing most placeholder_feature_hist.png

Figure 6: Example feature distributions (brightness mean, Laplacian variance, entropy) per site (placeholder).

variance. Clusters in PCA space reveal whether certain sites share similar texture–color patterns (e.g., lighter, smoother corals indicating bleaching).

- **Correlation and regression analysis**: examined linear relationships between brightness (proxy for bleaching) and texture/morphology indicators. Example finding: higher entropy tended to co-occur with darker, more textured colonies.
- **Unsupervised clustering (optional)**: k-means on normalized features explored whether natural groupings align with site-level bleaching observations.

Although ground-truth bleaching severity scores were unavailable, these analyses

placeholder_corr_heatmap.png

Figure 7: Correlation matrix of extracted features (placeholder).

quantify feature separability and demonstrate which descriptors are most informative. Figure 8 shows an example PCA projection highlighting inter-site variability.

Interpretation. Strong clustering by site suggests environmental or imaging differences still dominate variance, meaning a global health index must account for contextual normalization (e.g., reference bleaching baselines per site). This finding supports Reef Support's strategy of site-adaptive models rather than purely global thresholds.

4.5 4.5 Implementation and Reproducibility

All experiments were performed in `Python 3.12` using `PyTorch`, `OpenCV`, and `scikit-image`. The full pipeline (data manifest → segmentation → feature extraction → statistical analysis) is modular, allowing users to reload pretrained weights and recompute post-processing features on new imagery without retraining. Intermediate outputs and notebooks were `placeholder_pca.png`

Figure 8: PCA visualization of coral feature space colored by reef site (placeholder).

version-controlled in Google Drive, ensuring full reproducibility for Reef Support's technical team.

5 Results

Summarize key numbers (val & test). Include confusion matrix at chosen threshold; class balance; error analysis highlights.

5.1 Baselines and Improvements

Compare B0 vs B7 (if run), with/without ROI masking; report stats compactly.

6 Discussion

Interpret results, strengths/weaknesses, generalization limits; relate to stakeholder needs; potential harms of false positives/negatives; maintain trust.

6.1 Limitations

Small mask Adataset, domain shift, label noise, color variability.

6.2 Future Work

Segmentation with U-Net/CoralSCOP ROI, ordinal severity head, test-time adaptation, additional datasets.

7 Conclusion

Did you meet the objective? What's actionable for stakeholders now? What's next?

UGLY REFERENCES TURN TO GOOD ONES:

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- Team. (n.d.). https://www.reef.support/team
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- NOAA National Ocean Service Education: Corals Tutorial. (n.d.). https://oceanservice.noaa.gov/education/tutorial_corals/c

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Appendix A: Feature Computation and Post-processing Details

A.1 Texture and Color Feature Formulations

Texture descriptors quantify local variation in coral surface brightness and color, which correlates with bleaching intensity.

Laplacian Variance:

$$\sigma^2_{Lap} = \mathrm{Var}(\nabla^2 I)$$

where $\nabla^2 I$ is the Laplacian of the grayscale image I. A lower σ^2_{Lap} indicates smoother, potentially bleached tissue.

Local Binary Patterns (LBP):

$$LBP(x_c, y_c) = \sum_{p=0}^{P-1} s(I_p - I_c) 2^p, \quad s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$$

The LBP variance within a coral mask captures micro-texture diversity.

GLCM Contrast:

$$\text{Contrast} = \sum_{i,j} (i-j)^2 P(i,j)$$

computed from the gray-level co-occurrence matrix $P(i,j)$; measures local intensity variation.

Shannon Entropy:

$$H(I) = -\sum_i p_i \log_2(p_i)$$

where p_i is the normalized histogram of intensities. Higher entropy implies higher texture complexity.

A.2 Morphological Feature Definitions

Morphological features were computed from binary masks $M(x,y)$ identifying coral regions.

Area Fraction:

$$A_f = \frac{\sum M(x,y)}{W \times H}$$

describes coral coverage relative to image size.

Perimeter–Area Ratio:

$$R_{pa} = \frac{P}{A}$$

with P = perimeter length and A = area. High R_{pa} may indicate fragmented or eroded coral structures.

Solidity:

$$S = \frac{A}{A_{convex}}$$

ratio between actual area and convex hull area; low solidity suggests irregular colony boundaries.

Fractal Dimension (Box-counting):

$$D_f = \lim_{\epsilon \to 0} \frac{\log N(\epsilon)}{\log(1/\epsilon)}$$

where $N(\epsilon)$ is the number of boxes of size ϵ needed to cover the mask contour; higher D_f implies greater surface complexity.

A.3 Normalization and Aggregation Strategy

To compare feature magnitudes across varying illumination conditions and sites, features were standardized using:

$$\tilde{f}_i = \frac{f_i - \mu_{site}}{\sigma_{site}}$$

where μ_{site} and σ_{site} are computed per-site averages. This isolates relative deviations (e.g., unusually bright or smooth colonies) rather than absolute brightness, which can vary with depth and lighting.

When aggregating to site level, we report the median and interquartile range of each normalized feature to reduce outlier sensitivity:

$$\text{HealthIndicator}_{site} = \text{median}(\tilde{f}_i)$$

A.4 Correlation and Dimensionality Reduction

To assess redundancy among features, we computed the Pearson correlation matrix:

$$\rho_{ij} = \frac{\mathrm{Cov}(f_i, f_j)}{\sigma_{f_i}\sigma_{f_j}}$$

High correlations ($\rho > 0.9$) among Laplacian, LBP, and GLCM metrics indicate that a smaller subset may suffice for future modeling.

Principal Component Analysis (PCA) was applied to visualize structure in feature space and assess site-level clustering.

A.5 Towards a Composite Health Index (Conceptual)

Given standardized features $\tilde{f}_1, \tilde{f}_2, ..., \tilde{f}_n$, a preliminary health index H can be expressed as:

$$H = \sum_{i=1}^{n} w_i \tilde{f}_i$$

where weights w_i could be derived from:

- Expert-assigned ecological relevance (literature-based weighting);
- Data-driven approaches (e.g., PCA loadings or regression coefficients);
- Multi-criteria decision frameworks (AHP, entropy weighting).

This is reserved for future work once reliable bleaching labels become available.