HydraML: Automated Assessment of Coral Bleaching With Deep CNNs

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Abstract

Coral Reefs are one of the most diverse ecosystems on our planet. However, due to the rise in global temperatures and various other threats, there has been over a 40% loss of coral reefs over the last 30 years alone.

Monitoring of the health of coral reef ecosystems is critical for providing a deeper understanding of the ecology of these systems to form a scientific foundation for informing crucial management recommendations. However, monitoring of coral reef bleaching is currently a time-consuming, expensive, and laborious process.

In this study, we curated a novel dataset of coral images in collaboration with the Stanford Palumbi Lab, and trained CNNs for coral object detection and classification to measure bleaching scores.

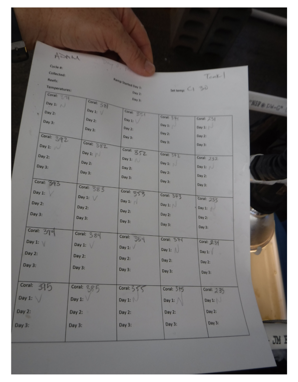
Background

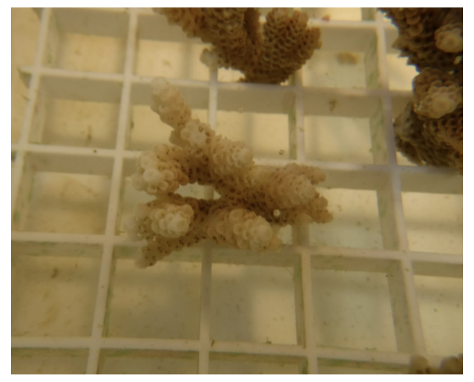
Though coral reefs occupy less than 1% of the world's ocean floor, they are home to over 25% of all marine life. From fixing nitrogen and carbon to protecting coastlines from tropical storms, coral reefs are crucial to our global ecosystem. The annual global economic value of coral reefs is estimated to be nearly $9.9 trillion USD. However, due to the rise in global temperatures and various other threats, there has been over a 40% loss of coral reefs over the last 30 years alone. As sea temperatures rise, coral bleaching occurs as coral turns white when expelling zooxanthellae, a symbiotic algae, from their tissue.

Healthy coral (left) vs. bleached coral (right)

The monitoring of coral reef health is crucial to enabling improved decision making to protect one of the world's most endangered ecosystems. However, current techniques to monitor coral are tedious and laborious. Current best practices use color cards to manually determine bleaching, and involve subjective judgements which don't scale to large datasets.

Challenges





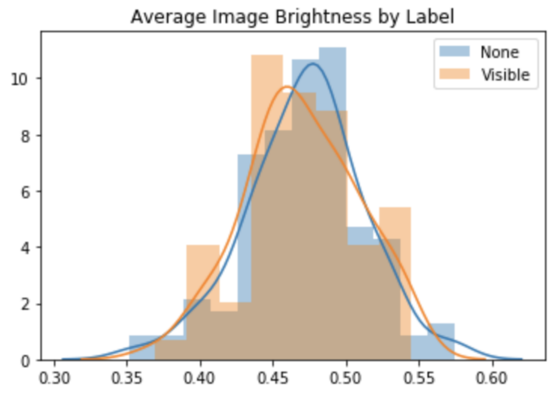
Currently, there is no standardized protocol for gathering data for the evaluation of coral reef monitoring, making data curation was the most challenging part of our project. Our images were presented in a variety of lighting conditions, backgrounds, and orientations, and in-picture locations. Additionally, the photos are out-of-water coral samples, which is hard to generalize to in-water or multicolored coral images. We manually labelled over 400 images.

Methodology

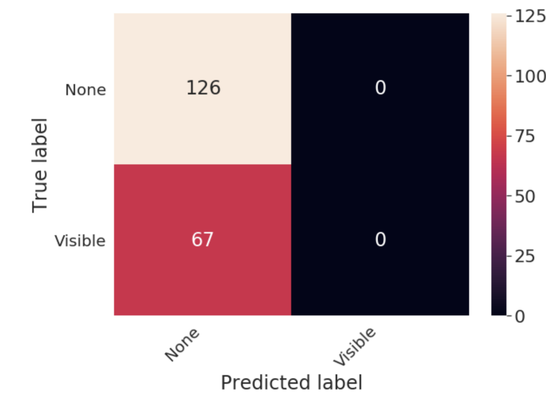
Baseline

The automated baseline takes the pixel-wise average brightness across each image, using this data point as the sole feature. We built a linear regression classifier to categorize the bleaching state of each sample. Through this approach, we achieved a 66% accuracy.

However, upon taking a closer look at the results, we discovered that the model simply predicted the majority class for every image because the average brightness across different categories of coral bleaching is nearly the same, as seen in the histogram below. Thus, the baseline model was not able to achieve high levels of accuracy.



Brightness Distribution by Bleaching Category

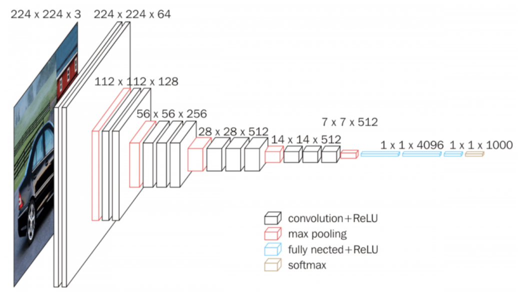


Confusion Matrix for Baseline Predictions

Deep CNN Model

Data Preprocessing
To preprocess our data, we first crop all the images and interpolate them to 1000 by 1000 pixels, and then normalize the RGB values in each image. Additionally, we augment our data to increase the effective size of our dataset and prevent overfitting; specifically, we randomly rotate, shear, flip, and edit the brightness of each image.

Architecture
We used deep CNNs to assess coral bleaching. As a first pass, we used VGG-16 as an image classification model to classify the bleaching category of coral samples, where the coral sample dominates the majority of the image. In the future, we will use RetinaNet as an object detection model to identify the bleaching categories for each coral sample in images with multiple samples.



VGG Network Architecture

Training
The performance of the CNN will be assessed by a categorical crossentropy loss function, given by

$$L(p_{c_{true}}) = -\log(p_{c_{true}})$$

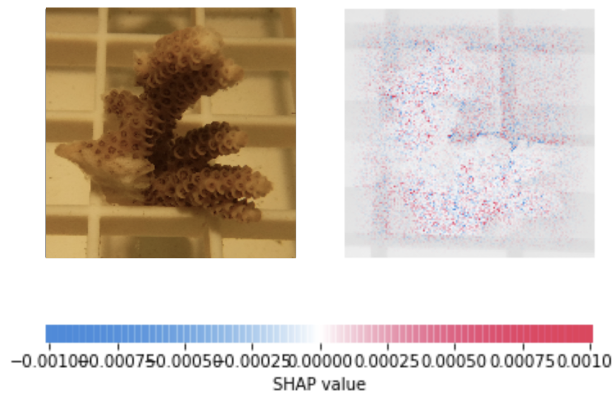
for a single sample, or

$$L(y) = -\frac{1}{N}\sum_{i=1}^{N} \log p_{model}[y_i \in C_i]$$

for a batch size of N, where C_i is the correct class.

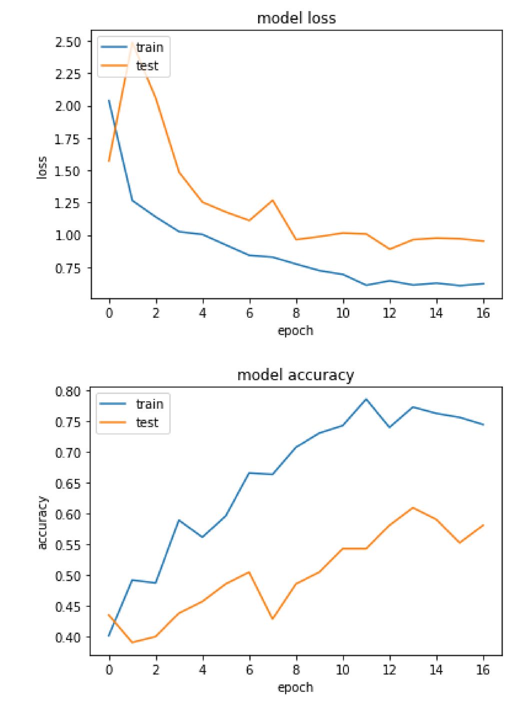
Example
As a concrete example, consider the image to the right. This is an image with the label *M*; we manually cropped this image, mapped it to its corresponding label in our CSV, and then put it in our validation dataset file heirarchy in an ingestible form. We then normalized the image RGB and resampled to 1000x1000 pixels, but did no further data augmentation.

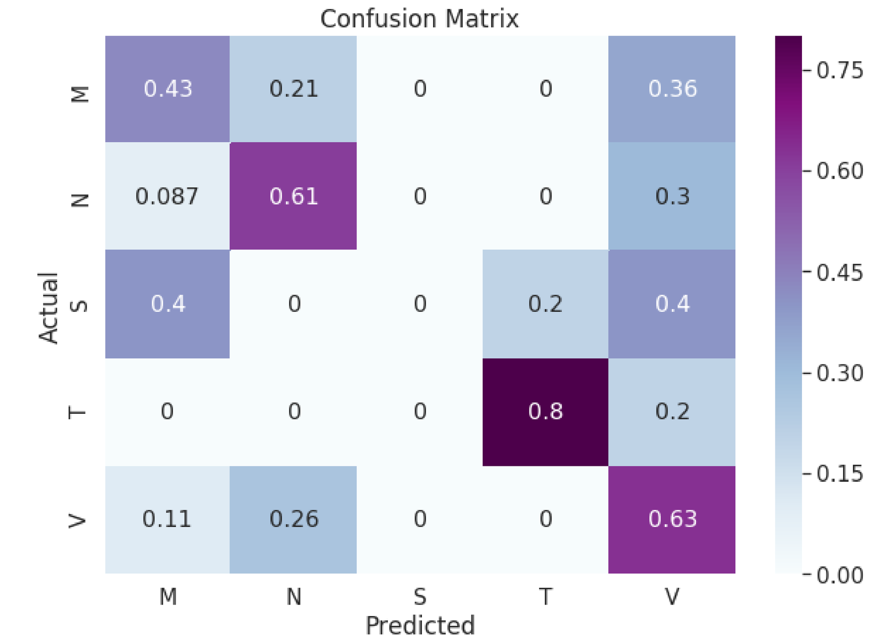
The model did a forward pass on the image, represented as a 1000 x 1000 x 3 array of RGB values, and produced the correct prediction, *M*. By calculating the gradient of the class scores with respect to the input pixels, we can visualize what the model was looking at when doing this prediction; here, we see the model is ignoring the background, and paying attention to the silhouette of the coral.



Interpreting a Single Example

Results and Analysis





Confusion Matrix for Deep CNN Predictions

The deep CNN model achieved 60% accuracy on the testing data when classifying coral into the five categories of bleaching, as broken down in the confusion matrix above. The model was best at classifying the bleaching category T, representing total bleaching, as this was the most visually obvious category. It predicted categories N (None) and V (Visible) with ~60% accuracy, and category M (Moderate) with only 43% accuracy.

Error Analysis

The model struggled most to predict category M (Moderate) bleaching, and only achieved 43% accuracy. When talking to Professor Steven Palumbi and PhD students in his lab, we learned that when students manually classify coral samples, they are inclined to label samples as moderate as it is the center of the categories. A large percentage of the photos were labelled moderate. The model predicted S (Severe) for 40% of M (Moderate) coral samples, as the S and M categories are closest to each other.

Additionally, because the original coral samples were labelled without a standardized protocol, there is a high level of noise amongst the data beyond our control. Due to human error, many coral samples may have been incorrectly classified in a neighboring category.

As a test, we ran our model on only categories T (Total) and N (None), and were able to achieve a high level of accuracy, as the two categories are on opposite sides of the spectrum.

To further improve our model, we are working to manually label more images that we can use for training. By increasing the number of photos that represent each category of bleaching, the accuracy of the model should improve.

Outreach and Social Impact

Throughout our project, we have reached out to experts in the coral industry to maximize the impact our project has. We have been in contact with Sustainable Travel International, the Tom Kat Center, NOAA (National Oceanic and Atmospheric Administration), and several other marine biology organizations. From the TomKat Center, we received a seed grant to continue our work. We also pitched our project at SENSA's Social Impact Night.