Coral Grief: Machine Learning on Crowd-sourced Data to Highlight an Ecological Crisis

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The research described herein utilized publicly available images from a variety of sources purely for educational and informational purposes. All sources have been credited as references. There is no risk to any living organism in this research. All work is performed digitally.

Introduction

Coral Reefs: Coral reefs are the most biodiverse marine environments housing millions of organisms across thousands of species within just 1% of the Earth's surface[1] (Figure 1). In fact, the largest living earth-bound organism is a coral reef itself, the Great Barrier Reef[2]. In addition to sustaining life, coral reefs protect coastal areas from tidal waves and erosion. Healthy reefs absorb 97% of a wave's energy, which buffers shorelines from currents, waves, and storms, thereby mitigating loss of life and property damage[1]. In addition to providing tremendous ecological benefits, coral reefs support the millions of people that rely on them for food and to draw tourists (over 70 million trips made annually), making these fragile and beautiful organisms a powerful engine of coastal and marine tourism. In one estimate[3], the net annual benefit of the world's coral reefs is approximately $30 billion in the forms of tourism, recreation, coastal protection, fisheries and biodiversity.

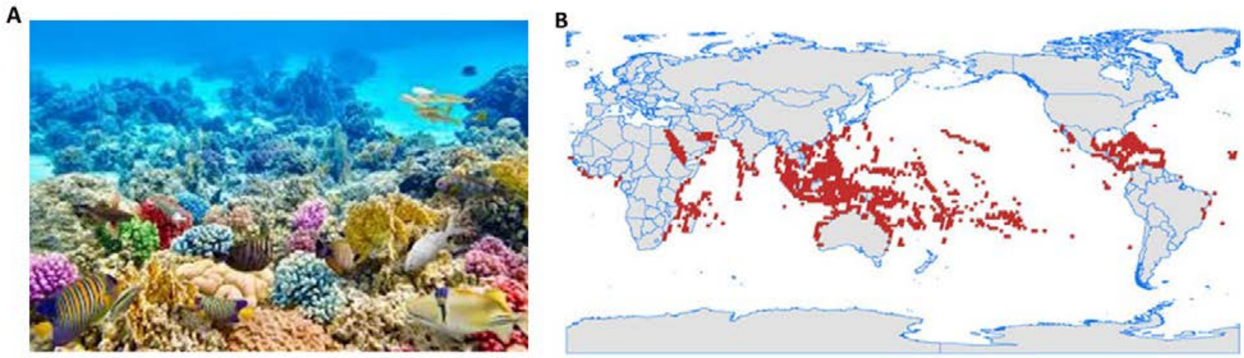


Figure 1. Corals and Global Coral Reef Cover: A. Coral foliage with vivid colors[4]. B. Over 1700 images (red boxes) from the Landsat 7 spacecraft were collected for the Millennium Coral Reef Mapping Project showing distribution of reefs across our world[5].

Coral Health: Corals and coral reefs are experiencing an unprecedented threat. Climate change is the biggest threat to the world's coral reefs, causing mass bleaching (Figure 2). Coral bleaching occurs when coral polyps expel algae that live inside their tissues[6]. Normally, coral polyps live in an endosymbiotic relationship with these algae, which are crucial for the health of the coral and the reef. The algae provides up to 90 percent of the coral's energy. Bleached corals continue to live but begin to starve after bleaching.

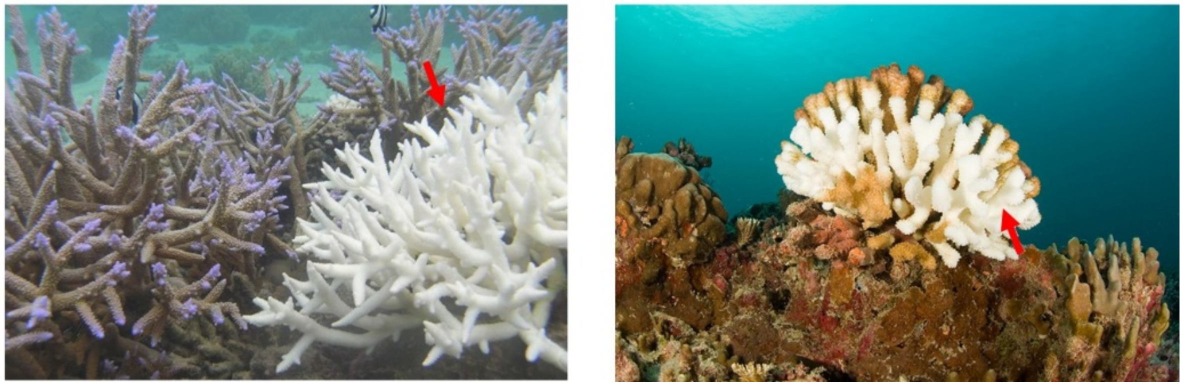
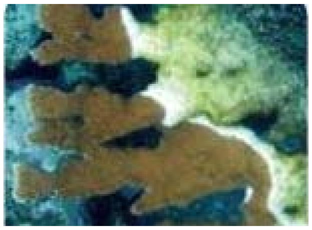


Figure 2. Coral Bleaching. A. Completely bleached coral (red arrow) amidst other corals[7]. B. Coral undergoing bleaching (red arrow)[8].

The leading cause of coral bleaching is rising water temperatures. Mass bleaching, covering hundreds of miles or more, is driven by prolonged anomalously warm ocean temperatures. In 2016, heat stress encompassed 51 percent of coral reefs globally[1]. The first mass bleaching (85 percent bleached) of the northern and far-northern Great Barrier Reef killed 29 percent of the reef's shallow water corals. Bleaching also occurred in much of the western Indian Ocean, including 69 percent to 99 percent of corals bleached and 50 percent dead in the Seychelles. The third global bleaching event, from 2014 to 2017, brought mass bleaching-level heat stress to more than 75 percent of global reefs; nearly 30 percent also suffered mortality level stress. This bleaching event was the longest, most widespread, and most destructive on record. In addition to warming oceans, impact from land-based sources of pollution—including coastal development, deforestation, agricultural runoff, and oil, and chemical spills—can impede coral growth and reproduction, disrupt overall ecological function, and cause disease and mortality in sensitive species. It is now well accepted that many serious coral reef ecosystem stressors originate from land-based sources, most notably toxicants, sediments, and nutrients Under the Endangered Species Act, 22 coral species are currently listed as threatened, and 3 are listed as endangered[9]. With more than 40% of the world's live coral cover lost in the last three decades, the number of people adversely impacted—500 million—is 35 percent more than the entire population of the United States[1].

Corals also face a plethora of other issues including disease and predation. The most common coral diseases (Figure 3) globally include black-, yellow-, and white band disease, dark spot disease, white plague, and white pox[10]. Many of these diseases are direct results of human actions: white pox is linked to the pollution of the oceans with human fecal matter and white plague has viral and bacterial origins that could be traced to humans and that thrive on coral already vulnerable from bleaching[11,12]. Dark spot disease is characterized by patchs or brown or purple tissue on the surface of the coral and is attributed to endolithic fungi that calcify the coral[13]. The spread of these fungi will be exacerbated by the warming of the oceans, placing further strain on coral reefs[14]. The banded diseases are attributed to bacteria which flourish in warmer waters[15] as well as algal overgrowths that occur when the ocean heats and general environmental stressors such as pollution[16].

Coral Disease	*Sample Image*
Black Band Disease	
Dark Spot Disease	
White Band Disease	
White Plague	
White Pox	

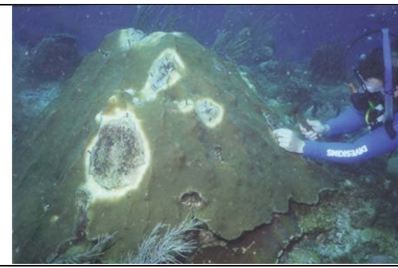
Yellow Band Disease	

Figure 3. Common Coral Diseases. Corals are susceptible to a number of diseases. These images formed part of the disease training set.

Conservation Efforts: Global efforts including the XL Caitlin Seaview Survey[17], the Allen Coral Atlas[18] and CORALNET[19] are using satellite-based images of the coral benthic cover, i.e. top view of the coral canopy, to both create a coral map and assess coral health in terms of the percentage of live coral. While this is currently being done by human experts, it is both laborious and expensive. Only recently researchers unveiled a Machine Learning (ML) process trained to analyze coral reef images[17-19]. It is 900X more rapid than the traditional method but just as accurate. Automating this process allows for the analysis of the millions of images of reefs taken each year by satellites. Currently the ML-based process is being employed to analyzing identify types of coral within a reef, other reef invertebrates, and to analyze the extent of the benthic cover[9-11]. However, assessment of the benthic cover alone or coral variety within a reef alone, other combination, is insufficient to fully diagnose the extent of reef disease. Satellite imagery might show healthy coral tentacle tops with the bleach appearing from bottom-up[20] (Figure 4), and may not detect the small lesions characteristic of yellow band disease or white pox. While there is tremendous cause for concern, there is much more need for action. The Tutuila airport reef project has demonstrated that coral bleaching is indeed reversible[21]. The University of California, Davis – Mars Symbioscience demonstrated that coral reefs can be rehabilitated[22]. In fact, removal of stressors allows bleaching to reverse. Black-band disease can be successfully treated[23].

Figure 4. Bottom-up Coral Bleaching. An orange monti bleaching from the bottom up (red arrow). The upper aspect of the tentacles appears relatively healthy[12].

Proposal

Novel Approach to Diagnose Coral Bleaching and Disease: Diagnosis triggers treatment. Hundreds of thousands of photographs routinely obtained and being obtained by professional and amateur scuba divers, and other deep-sea forays, represent a warehouse of untapped information that can speak to coral health across the globe. An approach coupling ML with crowd-sourced images will be used to complement existing efforts to identify the extent of worldwide coral bleaching and coral diseases. Analyzing images uploaded by users across the globe for evidence of bleaching or disease by traditional methods would be a Herculean task. By contrast, ML could be deployed to detect and identify disease in corals by first training the machines on an annotated set of images. As described below, a Convolutional Neural Network (CNN)[24] has now been trained on images of corals with varying degrees of health in order to create a model that can identify disease. The overarching deliverable is an ML-based platform that will be used to analyze incoming crowd-sourced images of corals along with location of these corals. Heightened public awareness can translate to increased data, more awareness and intensified conservation efforts. The data collected could be integrated into the National Oceanographic and Atmospheric Administration's (NOAA's) Deep Sea Coral Data Portal (DSCDP)[25], which houses images of and information about coral found around the world. This technology can also be used in citizen science projects such as the Great Reef Census[26], which asks volunteers to upload 10 photos of their diving site. This coral health database can be rapidly used to identify trends in health of different reefs and anticipate outbreaks. Based on these trends, resources for treatment of the diseases can be allocated, protection zones can be set up, and local awareness can be raised to lower risk factors.

Materials and Methods

1) An ML algorithm was selected to deploy for the model. Literature[27] indicates that a CNN has a high Mathew's Correlation Coefficient (MCC), which is a performance parameter that assesses classifiers, as compared to other algorithms that were applied to coral images The Mask Region CNN algorithm is an open source CNN that has been successfully used in the analysis of nuclei in microscope images, detection of sports fields in satellite images, and other object detection and segmentation projects. While a CNN is mainly for image classification, a R-CNN, with the R standing for region, is for object detection. A typical CNN can only tell you the class of the objects but not where they are located. The Mask R-CNN refers to the masks that are generated above the classified regions of interest when the model gives its output.
2) The algorithm's source code was modified to best suit the specific qualities of the dataset. This included adding and changing the classes and their names and making the algorithm compatible with the data annotation platform (Figure 5). An initial learning rate was selected that was updated as training progressed to make the process more effective and tailored to the data.
3) Images were obtained to train and test the algorithm. The accuracy of the labeling of the health of the coral in these images was ensured by collecting them from reliable research projects such as the XL Catlin Seaview Survey and other sources[10-19]. Three hundred and thirty-five images containing hundreds of instances of each type of disease and bleaching were represented.
4) A platform was selected on which to annotate these images. Labelbox[28] is one of many such platforms including LabelMe and the VGG Image Annotator which allow users to upload datasets, create classes and segmentation types with which to label images. For this purpose, the segmentation polygon tool was deemed best suited to create masks of the coral that follow the outline of the coral itself as well as the disease lesions. These masks are what the computer will learn from and then emulate.
5) The images were classified into in two groups, one for training and one for testing. The setup for both groups was identical in terms of classes and annotation type, but the data were split between the two, 80-20 training to validation, which the Pareto Principle[29] indicates is an ideal split for midsize data sets. The classes that images could be classified into were: healthy, bleached, black band disease, dark spot disease, white syndromes, and yellow band disease. White syndromes encompass white band disease, white plague, and white pox, mentioned in the introduction, which can visually take on the same appearance but affect different species of coral and are often linked to the *Vibrio* bacteria[30]. The platform generated a Java Script Object Notation (JSON) format that contains image paths and the annotations for each image. JSONs are readable by humans and computers alike, making them a viable method for providing data to a model. This JSON was used by the Mask R-CNN algorithm to train and validate the images.
6) An Amazon Web Services (AWS) Elastic Compute Cloud (EC2) instance was started to train the model in. These instances are remote computers dedicated to only the customer's purpose and therefore are able to carry out heavy training in a timely manner. Using one that has TensorFlow graphics processing unit (GPU) capabilities increases computing power. When used in conjunction with a computer's central processing unit (CPU), GPU can make training more efficient. The training and validation images, the JSON files, and the code were transferred to the instance and the model was trained within a powershell.
7) Logs created during the training were saved. Each subsequent training session began from the last log such that the model did not have to relearn but rather built up from memory, the essence of the neural network.
8) The progress of the training was monitored using Tensorboard (see 9) and the most recent logs. Once the box and class losses for training and validation neared 0 and accuracy approached 1, training was stopped. Overfitting was avoided by using image augmentation in the code and by not overtraining; signs of rapid descent to near zero loss were monitored.
9) Tensorboard, a feature of Tensorflow, was used to visualize the progress of ML. By inputting the most recent log to Tensorboard, the platform graphed the accuracy and loss rates for the training

and validation data sets over time for class loss as well as box loss. The goal for the losses is to be as close to 0 without overfitting the model, which would mean that the program has learned to recognize the classes but only as they appear in the training images rather than being able to be deployed successfully on new images, and the goal for the accuracies to be as close to one as possible without overfitting. Class accuracy reflects how well the model is able to categorize what it sees into the provided classes based on the class annotations made by the researcher on the datasets. Box accuracy reflects how well the program is able to pinpoint the location and boundaries of the object in the image, or in other words, how well it can segment the images. Tensorboard can be used to decide when to stop training as well as if learning rates need to be changed. If the loss or accuracy rates are stagnant, it can indicate the program has been caught in the loss landscape and needs a new learning rate to ascend out of the loss landscape. Once the model is actually in use, the confidence level it displays can be a useful measure of how well the program is performing. Within the code, the researcher can set a minimum confidence threshold in order for the model to display its results; results below that threshold will be ignored. If confidence is consistently low, it can indicate that more training needs to be done with a wider set of images, perhaps for a specific disease if that is what shows low confidence most often.

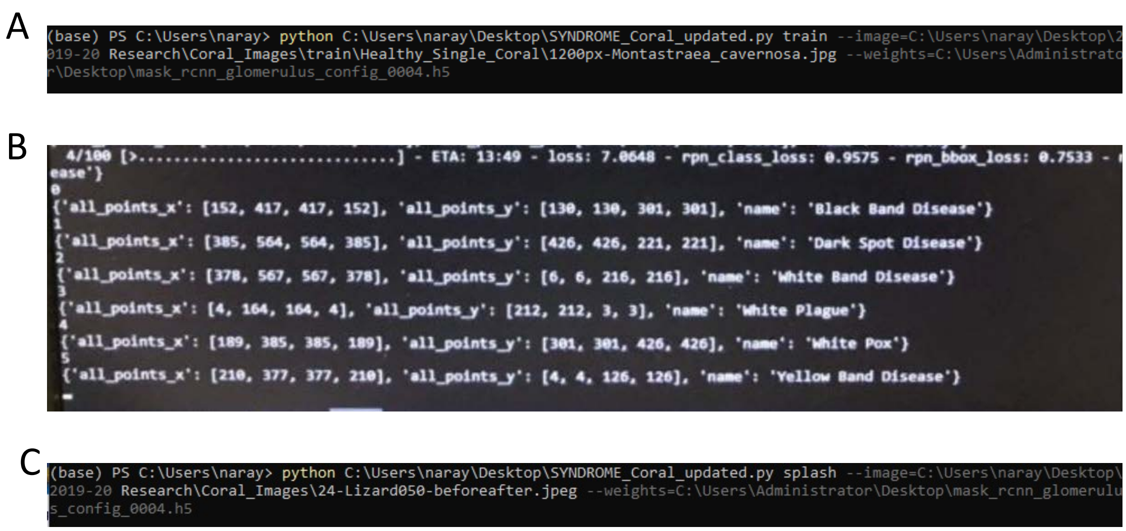


Figure 5. Machine Learning. A. Training command prompt for the model inside a powershell with the algorithm’s code, the training and validation image folder, and the latest log to work off of. B. Powershell display during training. The accuracies and losses early on are displayed as well as annotation data from the JSON file under each image number. C. Splash command prompt in the powershell for deployment of the model on a sample image.

Results

The training set forms a major component of any ML-driven exercise. A dataset was produced featuring annotations of healthy and unhealthy corals broken up between different classes depending on the condition of the coral (Figure 6). Descriptions from the image sources were used to judge the condition of each coral.

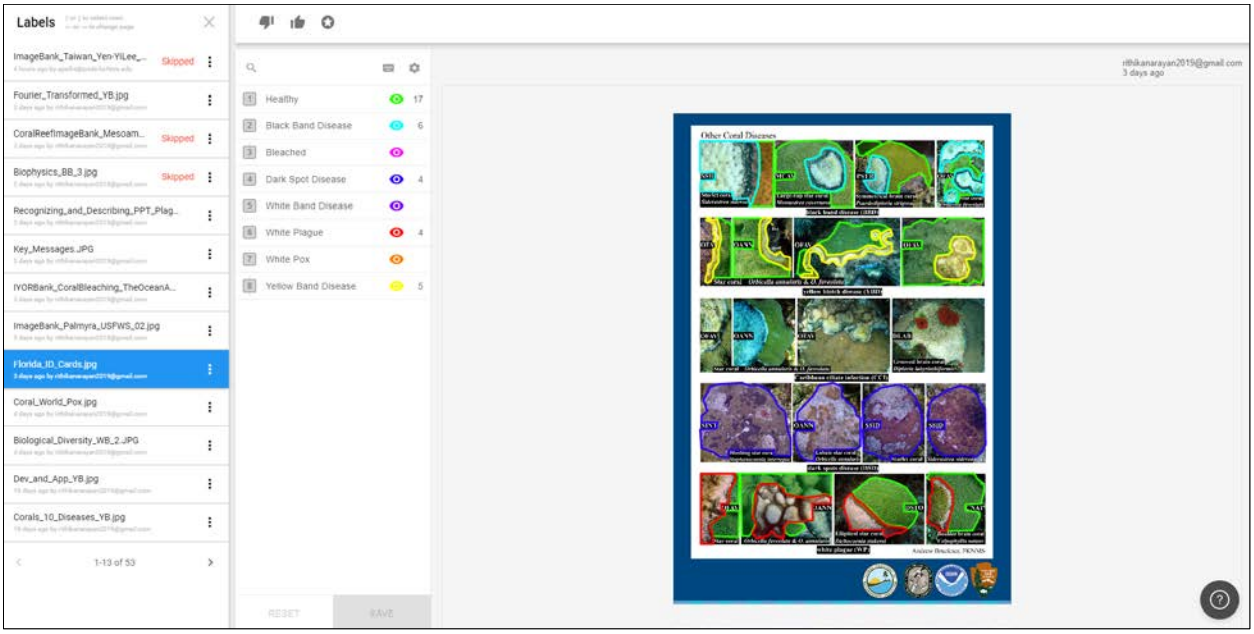


Figure 6. Annotation within Training Set: Example of image data annotated in Labelbox and used for model-training. Healthy and diseased corals were annotated with different colors using the polygonal selection tool. The above image shows annotations for black band disease, yellow band disease, dark spot disease, and white plague as well as the surrounding healthy tissue. The annotations are stored in the JSON file for the model to learn.

The model was trained on this dataset for ~283 epochs with heavy image augmentation to prevent overfitting and loss values eventually approached zero as shown by the Tensorboard plots (Figure 7). All losses have been minimized - segmentation loss has approached 0.136, binding-box loss has approached 0.013, and class loss has approached .003. Peaks in the loss indicate a change in learning rate or the addition of image augmentation by the researcher.

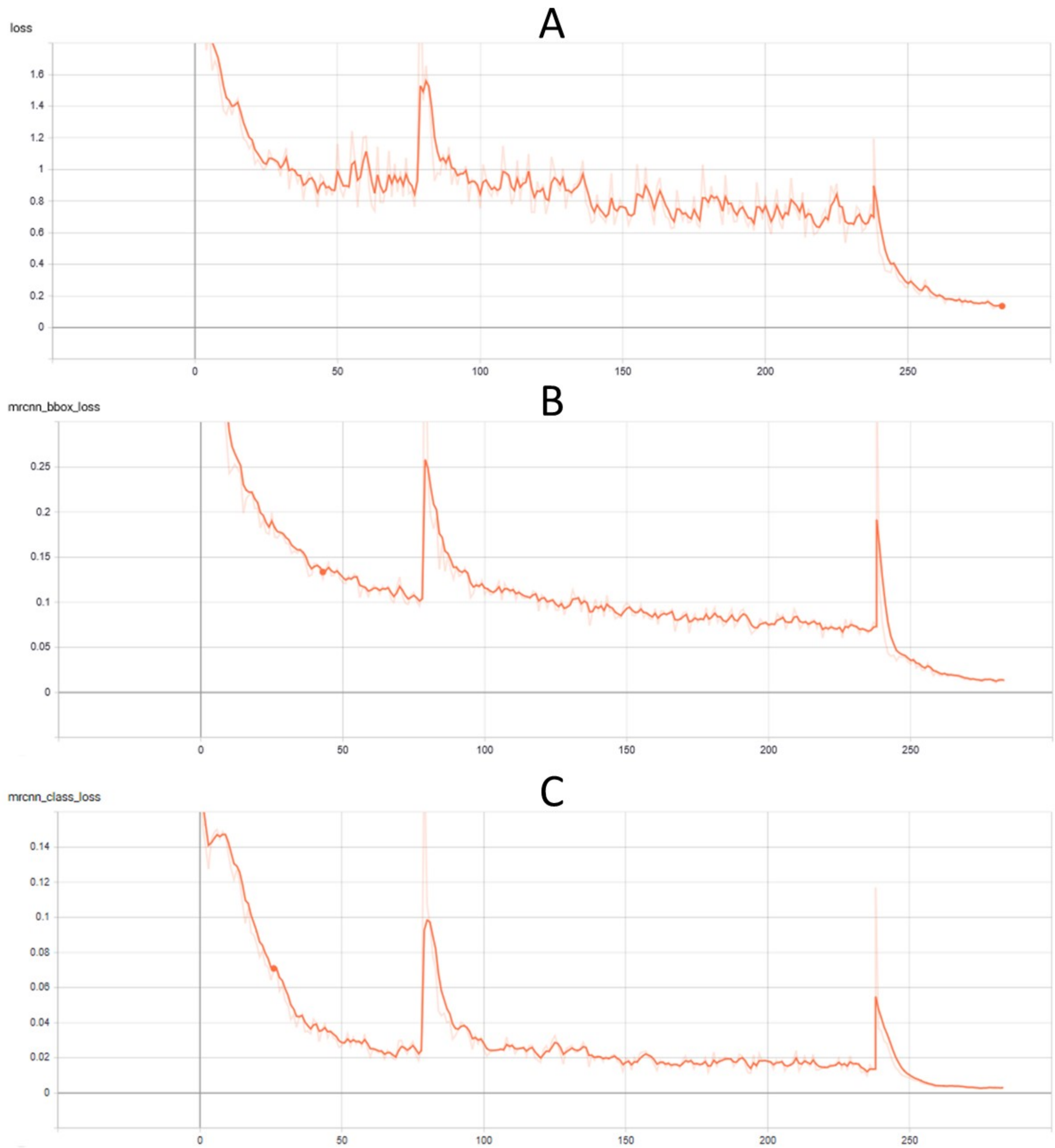


Figure 7. Tensorboard Loss Statistics following Model Training: Loss is defined as the difference between the results of the ground-truth "user" annotation training data and the model's prediction attempt. Pictured here: segmentation loss (A), binding-box loss (B), and class loss (C). Segmentation and binding-box identifies coral features while class loss predicts which class those features belong to healthy or diseased coral.

Initially, and as expected, model accuracy was poor (Figure 8). Each box represents a class prediction by the model with the predicted class and confidence level noted in the upper lefthand corner. Initially, confidence levels were low - 0.373 for example – and the confidence threshold was increased to 0.8 in order to display only predictions that the model was confident of.

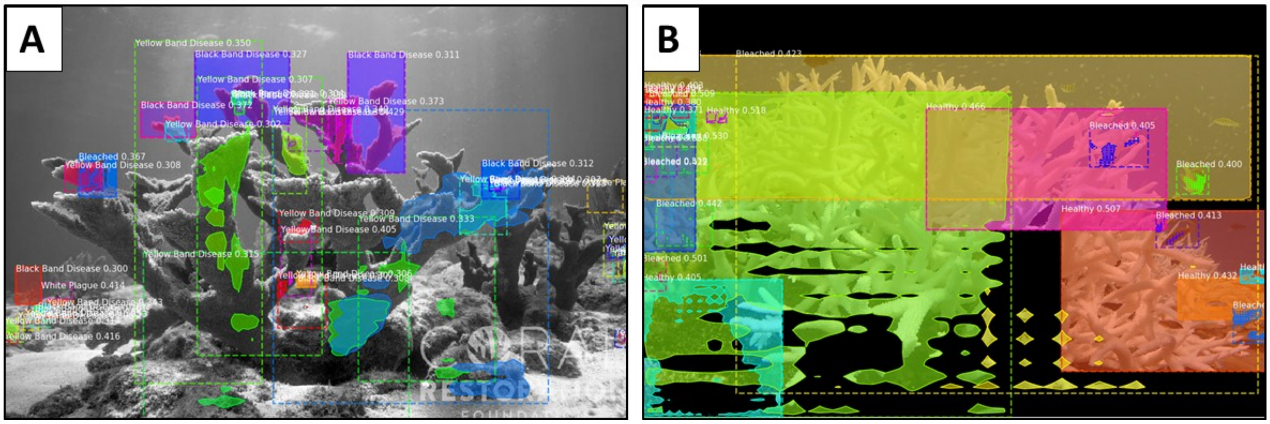


Figure 8. Early Model Predictions: Some coral features are picked out (A), but overall features (B) are poorly segmented and poorly identified.

The ML model improved as training progressed until producing more accurate predictions of coral detection and class separation (Figures 9 and 10). Black areas are those that the model recognizes as background.

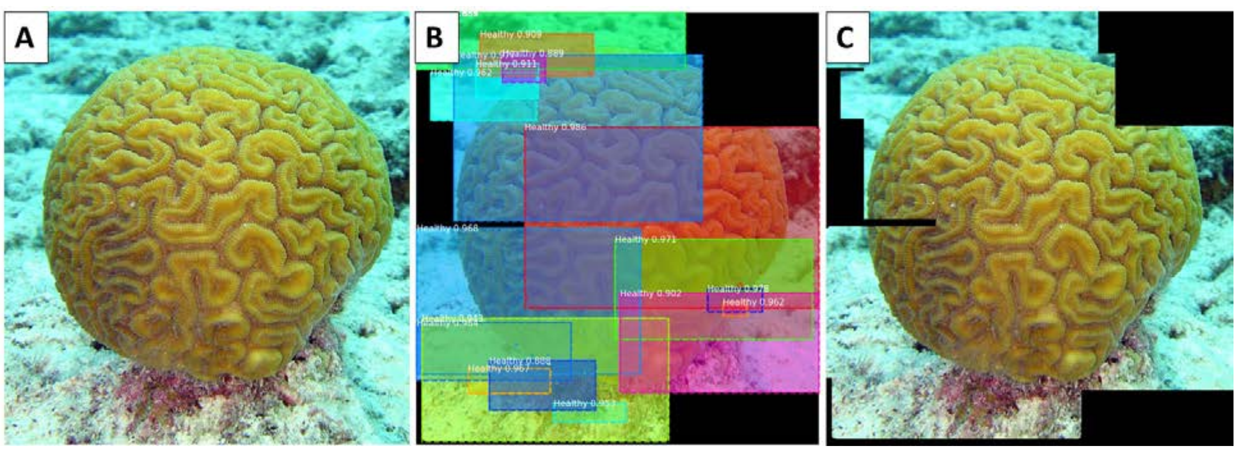


Figure 9. Healthy Coral Detection: Model detection of healthy coral. Images of healthy coral (A) are analyzed with the model which makes predictions (B) breaking the image down into segmented regions that the computer recognizes as healthy coral (visualized in C).

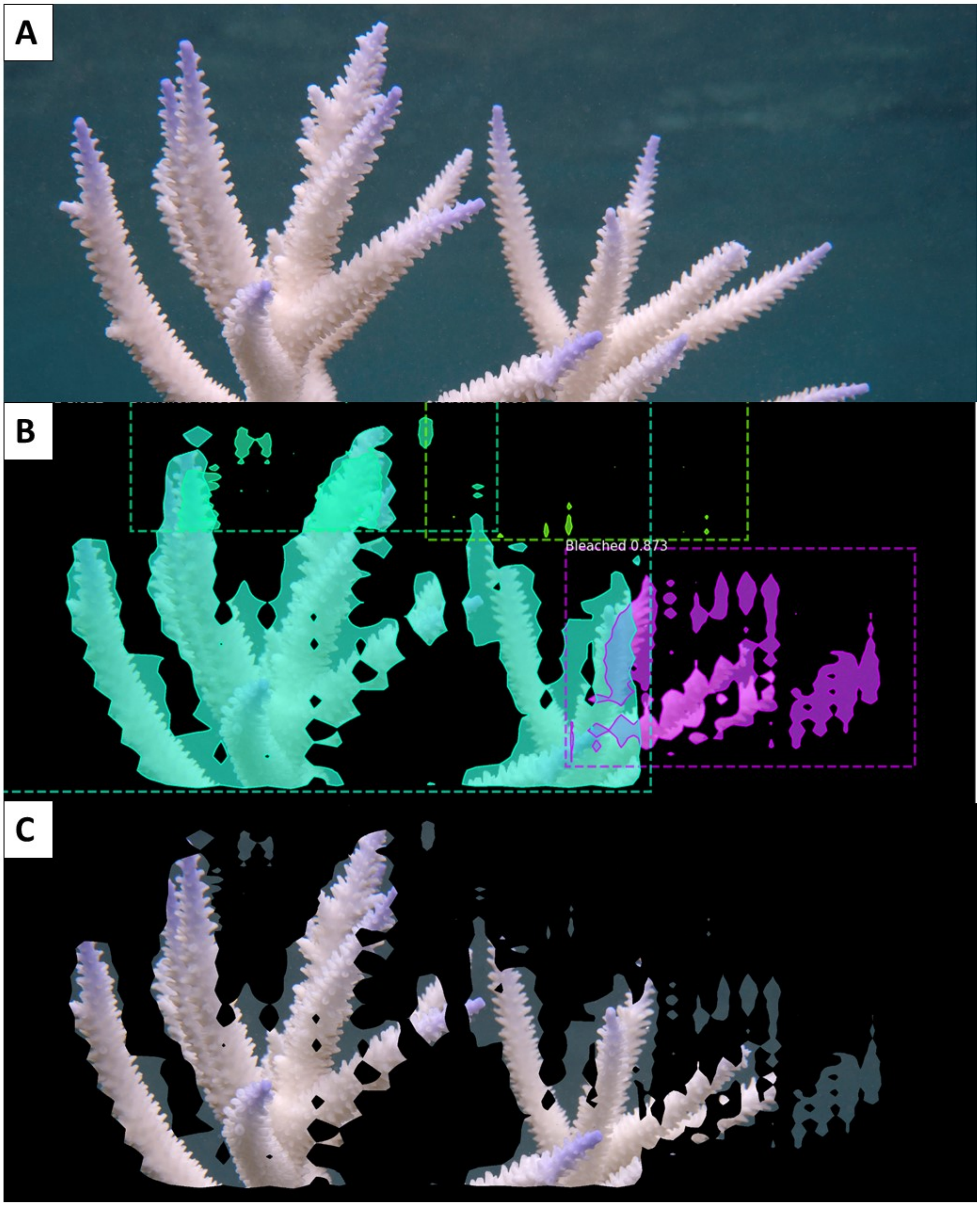


Figure 10. Bleached Coral Detection: Model detection of a bleached coral showcasing the developing segmentation capabilities of the model. Images of unhealthy coral (A) are analyzed with the model that makes predictions (B) breaking the image into segmented regions that the computer recognizes as bleached coral (visualized in C).

This ML-based algorithm can recognize the health class of the coral with 99.7% accuracy. This includes bleached corals and coral diseases such as black band and yellow band. The algorithm discriminates between bleaching and "white" disease but cannot at this point subclassify white diseases.

Discussion and Conclusion

The research presented herein couples crowd-sourced data with ML to provide a deliverable that complements existing strategies to diagnose the extent of coral bleaching and identify diseased corals.

Almost on a seasonal basis we are experiencing biosphere tipping points, ecomarkers of climate change, some reversible, others not. The cascade of changes sparked by global warming could threaten the future of humanity, say scientists[31] who warned that more than half of the climate tipping points identified a decade ago are now "active". Human footprints, including pollution and global warming, are starting to leave indelible marks on our fragile ecosystem. Coral bleaching is one such marker, perhaps less known, because of its sub aquatic existence. The corals that form the great reef ecosystems of tropical seas depend upon a symbiotic relationship with algae-like single-celled flagellate protozoa called zooxanthellae that live within their tissues and give the coral its coloration[6]. The zooxanthellae provide the coral with nutrients through photosynthesis, a crucial factor in the clear and nutrient-poor tropical waters. In exchange, the coral provide the zooxanthellae with the carbon dioxide and ammonium needed for photosynthesis. Negative environmental conditions thwart the coral's ability to provide for the zooxanthellae's needs. To ensure short-term survival, the coral-polyp then expels the zooxanthellae. This leads to a lighter or completely white appearance, hence the term "bleached". As the zooxanthellae provide up to 90 percent of the coral's energy needs through products of photosynthesis, after expelling, the coral may begin to starve. Coral can survive short-term disturbances, but if the conditions that lead to the expulsion of the zooxanthellae persist, the coral's chances of survival diminish. In order to recover from bleaching, the zooxanthellae have to re-enter the tissues of the coral polyps and restart photosynthesis to sustain the coral as a whole and the ecosystem that depends on it. If the coral polyps die of starvation after bleaching, they will decay. The hard coral species will then leave behind their calcium carbonate skeletons, which will be taken over by algae, effectively blocking coral re-growth[6]. Eventually, the coral skeletons will erode, causing the reef structure to collapse. Coral bleaching can be caused by a number of factors. While localized triggers lead to localized bleaching, the large-scale coral bleaching events of the recent years have been triggered by global warming. Under increased carbon dioxide concentration expected in the 21st century, corals are expected to becoming increasingly rare on reef systems. Coral reefs located in warm, shallow water with low water flow have been more affected than reefs located in areas with higher water flow. In the 2012–2040 period, coral reefs are expected to experience more frequent bleaching events. Fortunately, bleaching is reversible if the stressors are removed quickly[21,22].

Coral that are already compromised by bleaching are further damaged by dozens of bacterial and viral diseases that can be traced back to pollution or are exacerbated by warming oceans. Injured corals are most susceptible to black band disease, which can be carried through 1 meter of water or by fish. Although this disease was first identified in the Caribbean, within two decades it had spread through the Red Sea across the world to the Great Barrier Reef and to the Indo-Pacific, where it interferes with the structure of the reef during warm months[32]. Following the identification of black band disease in the 1970s, a multitude of other diseases were discovered such as dark spot disease, which causes tissue mortality in scleractinian corals and peaks during the warmest months; white band disease, which has put Caribbean acroporid corals on the critically endangered list and is spread by zooplankton through the water, resulting in death and exposure of the corals' white skeletons[34]; white plague, which attacks reefs from all directions - outside in, top down, and bottom up – traveling through the water and on predators or coral such as snails and is responsible for the decline of up to 40% of benthic cover in mass bleaching regions[36]; white pox, which put the common Caribbean *Acropora palmata* (elkhorn) coral on the Endangered Species Act and results from the transmission of bacteria through untreated human sewage as well as through non-affected coral species[37]; and yellow band disease, which began in the Caribbean and was first reported in the Pacific in 2008. Yellow band disease is associated with the death of the zooxanthellae that also causes bleaching, however in this case, *Vibrio* bacteria cause the death of these microorganisms[37]. Often, multiple diseases affect a single coral or colony at once, rapidly increasing the rate of mortality for the organisms and leading to structural collapse of the local ecosystem. Of the most common diseases affecting coral – black band, yellow band, dark spot, and white syndromes – only black band disease is treatable[23]. This makes it that much more important to contain and stop the spread of such diseases.

There is a global ongoing effort to harness satellite imagery to map benthic cover[17-19]. However, additional resources must be taken advantage of. Fortunately, there is a large crowd-sourced databank in the form of videos and photographs of corals and coral reefs across the globe. These up close and personal photographs hold valuable information on the health of the corals.

The research described herein utilizes a ML-based approach to diagnose coral bleaching based on these photographs. ML has precedent in diagnosis: the technology has revolutionized medicine. It routinely outperforms and outpaces human doctors in making MRI and radiograph diagnoses at a fraction of the cost, saving lives across the world.

Uploading of data, including images, onto "clouds" makes them available for use both remotely and continuously. ML approaches come with notable benefits including: increased efficiency allowing for larger sample analyses, the presence of a "trained expert" wherever there is a computer rather than relying on thinly spread marine biologists or medical doctors, the detection of patterns and correlations which would require a mass workforce working in unison for large amounts of time to replicate, and learning based on expert evaluations such as the annotation of coral images according to the descriptions from published marine biology and ecology manuscripts or the annotation of radiographs from radiologists present at the time of taking the radiograph.

The present research uses a supervised ML strategy for identification of bleached corals. Hundreds of images of healthy, bleached and diseased corals formed a training set to improve diagnostic accuracy. Images were obtained from reliable sources and then annotated to distinguish between healthy coral and disease lesions. Eighty percent of these images were used to train the models, images encompassing the six different classes, and the remaining data was used for testing the functionality of the trained model. The ML algorithm is currently able to identify the various classes at a 99.7% accuracy and can pinpoint the location of (segment) the coral and any visible disease with a 98.7% accuracy.

This algorithm is going to be made available to NOAA and private companies such as National Geographic so that it can be used freely. It will also encourage more tourists to obtain photographs of corals, run them through the algorithm, and upload the results to coral health databases like NOAA's Deep Sea Coral Data Portal.

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