Can convolutional neural network machine learning algorithms accurately classify species of coral off the coast of Hawaii?

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Abstract

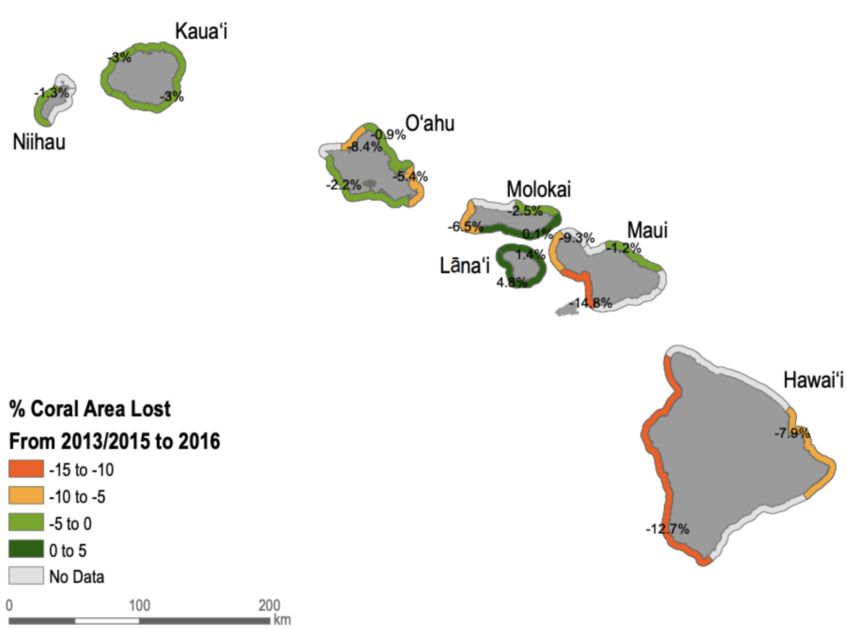
This study investigates the effectiveness of employing machine learning to annotate images of coral reefs located in Hawaii, with a focus on the two coral species, Pocillopora and Porites. Coral reefs play a crucial role in supporting marine ecosystems by providing a habitat. Coral reefs also provide protection for marine and land organisms during adverse weather conditions and sustaining a quarter of all marine species. To develop an algorithm capable of annotating images of coral reefs in the State of Hawaii, images were captured and analyzed using limited preprocessing techniques to reduce possible bias. La'aloa Beach Park was used to gather all images for this study. Each image was cropped to a square shape, and those that lacked coral or were blurred were excluded from the dataset. The resulting images were sorted and labeled according to their corresponding species. To train the algorithm, 80% of the images were used, while the remaining 20% were allocated for testing purposes. Using Matlab, the algorithm was developed and refined to achieve high accuracy levels for both species. Specifically, the algorithm for Pocillopora yielded an average accuracy of 82.59%, while that of Porites was 86.59%. These results provide evidence that machine learning can be used effectively to annotate images of coral reefs in Hawaii. Further experiments are necessary to assess the scalability of this approach in annotating a larger dataset of coral reef images.

Keywords: Machine Learning, Supervised Machine Learning, Coral Species

INTRODUCTION

Coral reefs offer economic and environmental benefits to residents in the State of Hawaii. Coral reefs are one of the main supporters of the health of coastal marine ecosystems, supporting a quarter of all marine species(Burke et al., 2008). Coral reefs not only support other marine species but they support habitat protection for both marine and land organisms during rough swells or large storms(Maran, 2019). In addition to ecosystem benefits, coral reefs also remain a huge economic factor for communities in coastal areas. In the State of Hawaii alone the evaluation of the total asset reefs provided was estimated to be nearly $10 billion, with an annual net benefits for residents of $360 million(Herman and Beukering, 2010). Despite all the benefits, coral reefs have been in a major crisis. Over the last 30 years coral reefs have declined dramatically, decreasing on average by 80%(Gardener et al., 2003). The State of Hawaii has not been spared from this dramatic decrease. Shown below, a map created by NOAA-PIFSC depicts the area of coral lost along the coast of Hawaii(Rosinski and Birkeland, 2016).

Percentage of Coral Area Lost in the State of Hawaii



All of this incredibly alarming decrease in coral reefs is due to the rise of unsuitable conditions. With recent estimates anticipating that 99% of coral reefs will be in unsuitable conditions by 2055(PLOS, 2022). Unsuitable conditions are conditions where salinity and ocean temperatures are above a threshold causing fecundity of coral reefs not to be met. This alarming crisis has garnered global attention. According to the United Nation more than $1.9 billion was pledged to coral reefs between 2010 and 2016(UN Environment Programme, 2018). With all this money and attention, one factor remains to be solved, the surveying of coral reefs. Each year an estimated 1,000,000 photos are taken of coral, and only 1% are used due to the annotation of humans requiring an extensive amount of time and resources(Beijbom et al,. 2012). If more images were able to be annotated, there would be a greater amount of data to be analyzed. This annotation gap is trying to be closed with machine learning approaches(Chirayath and Instrell, 2019).

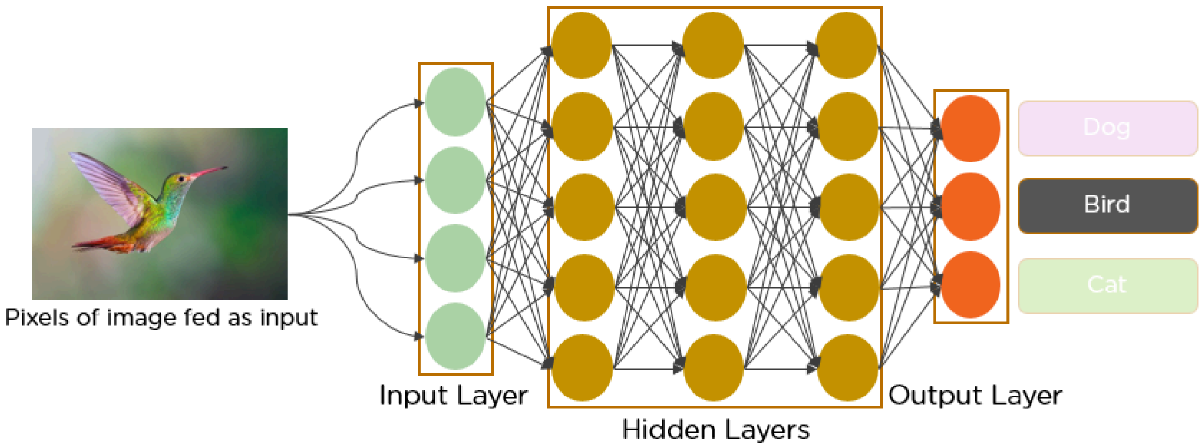
Machine Learning

Machine learning(ML) is a very broad field used in many circumstances of automation. For the purposes of this study, ML shall be defined from Tom Mitchell's engineering definition, "A computer program is said to learn from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E"(Mitchellet al., 1986). Using this definition and applying it to ML algorithms used to categorize images we can set the framework for how a ML algorithm can be implemented to categorize images of coral. In this definition; E becomes imputed images, P becomes model accuracy, and T is the systematic categorization of coral images by species. Today in the image recognition field, two main ML approaches are used, unsupervised learning and supervised learning.

Unsupervised learning algorithms are used when ML needs to identify and learn patterns from unlabeled input data(Ghahramani, 2004). Supervised learning however, is used when ML needs to identify and learn patterns from labeled input data(Cunningham et al., 2005). For this study the inputted data will be labeled with the species of coral gathered. The machine learning algorithm will then need to find a pattern to help with the identification of individual species of corals. For this reason supervised learning algorithms will be focused on throughout the Literature Review. The supervised learning algorithm that is used for image classifications has been the Convolutional Neural Network(CNN).

The creation of the CNN was in 1959 by David Hubel and Torsten Wiesel. Hubel discovered how to use a unique pattern recognition system between images to correctly classify two types of cells(Hubel and Wiesel, 1959). CNN models have since been used in many recognition applications. From recognizing letters and numbers in 1998, to automatically identifying wild animals through a camera-trap(Lecun, Bottou, Bengio and Haffner, 1998)(Cunningham, et al. 2022). Today with advancement in computational technology, CNN can be used with minimal resources and are now able to be created using online-based workstations.

The best way to think of CNN is visualizing it like a network of artificial neurons. This network consists of multiple connections that interact with each other by numeric weight, which has three main layers. The first layer is the input layer. This is where the data from the input is broken up into multiple values, sometimes consisting of 1,000s of individual values. The second layer will find multiple patterns from the first layer, typically consisting of 5 to 25 distinct patterns of recognition. The final layer makes a pattern on the patterns found in the third layer and outputs the usable information to allow an algorithm to predict what the input was(Hijazi and Kumar 2017). This whole process can be seen by the diagram below, showing the three layers and the imputed image plus the output classification of the image (Mingyu and Huang, 2019).



Literature Review

To narrow down the scope of research and ensure a targeted approach, only studies that explored the use of Convolutional Neural Networks (CNNs) for the classification of coral species were considered. A comprehensive review of existing literature revealed that several past research studies have attempted to classify and identify coral species using various types of CNNs. These studies have employed different models, algorithms, and datasets to achieve their research objectives.

One of the most recent coral classification studies that used a supervised CNN, was conducted in the Gulf of Eilat in 2020(Raphael, et al. 2020). During this study the researchers took over 5,000 underwater images of a shallow reef in the Gulf of Eilat. They used these images and labeled them according to their coral type–Stylophora, Lobophyllia, Montipora, Platygyra, Acropora, Cyphastrea, Porites, Echinopora, Pavona, Goniastrea, and Favia–the 11 common corals found in the Gulf of Eilat. The research team captured images utilizing a GoPro device from a singular location. Doing minimal preprocessing, cropping and resizing the images, the researchers used two CNN architectures to create their algorithm(VGG-16 and ResNet-50). Testing their algorithms, they found that an average accuracy between the 11 coral types was roughly 82.3%. The algorithm with the highest accuracy was 93.5% accurate and the algorithm with the lowest accuracy was 67% accurate. This study had a minimum data set of 5,000 images for all the 11 coral types. This study shows that using supervised CNN architectures with a minimum data set can be used to accurately categorize coral species.

Another research study conducted in 2014 used two already labeled and gathered datasets to create an image recognition software(Robertson and Lane,2014). These datasets were from the Moorea Labeled Corals and Atlantic Deep Sea. Their research study looked at how different preprocessing measures could change the accuracy of CNN algorithms. To measure the accuracy of their algorithms they used an F-score. F-score is a common measure of a machine learning algorithm's accuracy, the formula is 2x[(Precision x Recall) / (Precision + Recall)]. This score indicates if a system is balanced and simultaneously has good precision. They had two variables with their preprocessing, which were color enhancement and image normalization. During color enhancement the researchers had four groups, Original, ZCZ Whitening, Weber Descripto, and Phase Congruency. Each group was subject to their corresponding whitening equations. There were two methods for image normalization, linear contrast and z-score normalization. With all these different color enhancement variables, the study found that there were insignificant performance differences on the accuracy of algorithms. On the other hand, z-score normalization had a positive difference on accuracy of algorithms. This study found that the preprocessing of images only has a significant effect if the preprocessing uses normalization throughout the image pixels.

The final study examined was a comprehensive research effort conducted on Caribbean coral reefs(Pollock, Morris, Willis, and Bourne, 2011). This study focused on disease diagnosis and classification, specifically honing in on four distinct coral species. The algorithm that the researchers created was used to determine whether or not the coral species was bleached. In total, 23,540 images were gathered from five different locations off the coast of Haiti, with each species being represented in the dataset. After image collection, limited preprocessing was required, and a simple crop of all images to squares was performed. Using a CNN model developed by OpenML, the researchers achieved an average accuracy of 89.2% in recognizing coral bleaching across the four species. The study provides important insights into the use of machine learning algorithms for coral reef classification and disease diagnosis. It showcases the efficacy of deep learning techniques for processing large volumes of image data and extracting relevant features to make accurate predictions.

Gap

Shown by the literature review, there have been multiple research studies in the past that looked directly at using CNN machine learning to create an algorithm that classifies or diagnoses different coral species. This indicates that it could be done with a dataset of coral species from the coast of Hawaii. There is however, a fundamental lack of understanding of if coral reefs in Hawaii could be used in a CNN model. This is due to little to no research having been done using CNN machine learning to classify species of coral off the coast of Hawaii. Furthermore, researchers who have developed CNN models based on coral identifications have yet to use images gathered from only the coast of Hawaii to create a model, furthering the gap of understanding.

My research will deliberately gather images off the coast of Hawaii and use them to create a CNN to classify species of coral. This will increase the fundamental understanding of if machine learning algorithms can be used off the coast of Hawaii.

This leads to the question of this study, “Can convolutional neural network machine learning algorithms accurately classify species of coral off the coast of Hawaii?” To address the research question, a criterion for accuracy has been established with a threshold of over 80%, which is commonly used as a benchmark in evaluating machine learning algorithms(Mahmood et al., 2014). This criterion is based on previous studies on coral recognition algorithms and aims to ensure that the algorithm created in this research is sufficiently reliable for practical applications. By gathering images specifically off the coast of Hawaii, this research will provide insights into the coral species diversity in the region and how well it can be recognized by a CNN model. The results of this research could have significant implications for coral reef conservation efforts in Hawaii and beyond, as well as for the development of more effective machine learning algorithms for coral recognition.

Hypothesis

Based on the literature, and in light of the impressive outcomes of prior studies, such as the Gulf of Eilat study, which yielded an average accuracy of 82.3%, and the Caribbean coral image study, which achieved an average accuracy of 89.2%. It is my belief that training a machine learning model to classify coral species off the coast of Hawaii will result in accurate classification of the species.

METHODS

Location Analysis

To begin with, the initial step in gathering images for the study involved selecting an appropriate location off the coast of Hawaii. In order to ensure the success of the study, the selection of the location was based on three main factors; safety, accessibility, and the presence of coral samples. To determine the most suitable site for gathering images, multiple potential locations were evaluated using a decision matrix. The decision matrix was used to rank each potential site based on the three factors mentioned earlier. The scores were given on a scale of 1-5, with a higher score indicating better suitability.

The first factor considered was safety, and points were awarded based on the presence of a lifeguard and the nature of the shore break. For example, if the beach had a lifeguard present, it was given a score of five. If there was no lifeguard, the score was one. Similarly, if the shore break was mild, it received a higher score than a location with a heavy shore break. The second factor evaluated was accessibility, and points were awarded based on how easy it was to access the beach and the water. For instance, if the beach had a proper entrance and exit to the water, it would receive a higher score than a location with difficult access. The final factor considered was the presence of coral samples. The area of coral present at the beach was measured using data from the Hawaii Statewide Coral GIS Program. This data was used to allocate points, with a higher score awarded to locations with a greater area of coral present. Below are tables representing the criteria for points.

Safety:	Heavy shore break and rapid currents	Heavy Shore break or rapid currents	Medium shore break and no rapid currents	Lifeguard or mild shore break is	Lifeguard and mild/no shore break
Score:	1	2	3	4	5

Accessibility:	Rocky Beach and a long walk to get down/into water	Rocky Beach or a long walk to get down/into water	Slightly rocking beach and medium walk to get into	Slightly sandy beach	Sandy beach and short walk to get int
Score:	1	2	3	4	5

Long walk - 5 or more miles, Medium walk, 5-1 miles, Short Walk 1 mile or less

Samples present:	Less than 500 sq ft of coral	501-1,000 sq ft of coral	1,001-5,000 sq ft of coral	5,001-10,000 sq ft of crap	More than 10,001 sq ft of coral
Score:	1	2	3	4	5

Below is the decision matrix of all beaches considered. Decision matrices have a customary employment in making decisions in a research setting. This was exemplified in the study previously talked about which was conducted in the Caribbean, where a decision matrix was employed to determine the optimal locations for image gathering(Pollock, Morris, Willis, and Bourne, 2011).

Decision Matrix of Possible Locations

Location	Safety	Accessibility	Samples Present	Total Score
Kealakekua Bay Park	3	3	2	8
Kua Bay Beach	4	4	2	10
Makalawena Beach	3	2	3	8
Aiopio Beach	5	4	3	12
Ho'okena Beach Park	3	3	4	10
La'aloa Beach Park	4	4	5	13
Kuki'o Beach	3	3	1	7

Scale: 1-poor, 2-Below Average, 3-Average, 5-Excellent

The location that had the highest score of 13 was La`loa Beach Park. La`aloa Beach Park address is 77-650077 Ali'i Dr, Kailua-Kona, HI 96740, and coordinates 19.592244, -155.971916. Below is a Google Earth image of the location with a red square indicating where the images were gathered(Google, 2022).

Image Gathering and Processing

Images were gathered from the La'aloa Beach Park using a GoPro HERO10. The camera was set to picture mode and a resolution of 3840 x 2160. The images gathered were of two species of coral, Porites and Pocillopora. The selection of Porites and Pocillopora as the target species for this study was driven by two primary factors. First, these two species are the dominant coral species in the State of Hawaii, making them ideal candidates for the study. Second, these species were the only ones present at the chosen location for image collection, providing a consistent and controlled sample set for analysis.

Machine learning models require large amounts of data to effectively learn and interpret datasets. Therefore, it is crucial to collect a sufficient number of images for each dataset of coral species, with at least 5,000 images needed to train the machine learning model properly. Due to the large number of images needed, it is not possible to gather them all in a single day. Thus, three days were selected for image collection, with images being taken between the hours of 10:00 am and 3:00 pm each day. This time was picked to ensure optimal lighting conditions, coinciding with the sun's zenith. This methodology was derived from an established study that employed machine learning techniques to classify freshwater algae(Mosleh et al., 2012).

Once all images were gathered, limited processing was done. All images were cropped down to a square and any unwanted images were deleted. To ensure that a bias would not be introduced into the model, only blurred or images lacking coral were deleted.After the cropping process was completed, all images were then efficiently sorted into two distinct folders, each containing a specific species of coral, ensuring that the images were well-organized and easy to access for further analysis. Manual identification of coral species was carried out to sort the coral. Sorting was done based on their characteristics highlighted from the educational organization Eyes of the Reef Hawaii and the State of Hawaii Division of Aquatic Resources(Eyes of the Reef Hawaii, 2019)(DAR, 2020).

Code

There are many different programs out there to train a CNN model. To decide which one to use, a decision matrix was created. Factors used in the decision matrix were cost, language type, data availability, and computational power required. All factors were weighted the same and scored from 1-5. Cost was awarded based upon how much each software cost either a subscription for the given period of the experiment or the license to use the product. Language type was awarded based on familiarity of the language. Data available was awarded for how easy it would be to access the data required to make a conclusion. Finally computational power was awarded either 1 or 5 depending on if it could run on my computer or not. The computer I used for the CNN model training was a MacBook Pro 2022. Below are the tables of scores and how they are allocated.

Cost:	>$200.01	$200.00-$100.01	$100.00-$50.01	$50.00-$0.01	$0.00
Score:	1	2	3	4	5

Programming Language Type:	Language I do not know	Language I have under a half year experience with.	Language I have one to a half year of experience with	Language I have two to three years of experience with	Language I have three years or more experience with
Score:	1	2	3	4	5

Data Availability					
Score:	1	2	3	4	5

Computational Power Required	Can not run the program on my computer	NA	NA	NA	Able to run the program on my computer.
Score:	1	2	3	4	5

Presented below is a comprehensive decision matrix enumerating all potential software options capable of constructing a Convolutional Neural Network (CNN). Following a rigorous analysis of the matrix, MatLab emerged as the optimal choice for implementing the requisite algorithms.

Decision Matrix of Possible Programs

Name	Cost	Programming Language Type	Data Availability	Computation al Power Required	Total Score
TensorFlow	5	3	3	5	16
Apache Mahout	1	2	3	1	7
MatLab	5	5	4	5	19
Scikit-Learn	4	4	4	5	17
Microsoft Cognitive Toolkit	3	2	3	1	9
RapidMiner	2	1	3	5	11
KNIME	2	1	4	5	12
Anaconda	4	1	3	5	13

The coding language used for the program was MATLAB programming language. The two algorithms were set to have six epochs and hundred-and-forty iterations with a learning rate of 0.0003. The number of epochs represent the amount of times the model will train through the entirety of the data set. The iterations are the amount of times the parameters are updated per epoch. Finally, the learning rate is what governs how much the algorithm will update values based on open outcomes. To determine the accuracy of the model, the images were partitioned into training and testing datasets, with 80% of the images allocated for training and the remaining 20% for testing. Notably these parameters were chosen for this model in accordance with the standard setup for a ML model(Mingyu and Huang, 2019). Below shows all these parameters written out as code ready to run to make a CNN model. Incorporated within the algorithm is a systematic data acquisition process aimed at evaluating its accuracy. As the model progresses through each epoch and analyzes the dataset, it will continue to test its accuracy with images from the testing dataset in order to assess its accuracy. This generates accuracy data points that are used to facilitate the monitoring of the algorithm's performance. In addition to accuracy tracking, the algorithm is also programmed to monitor its loss. Loss in ML application refers to the difference between the target value versus the predicted value by the algorithm.

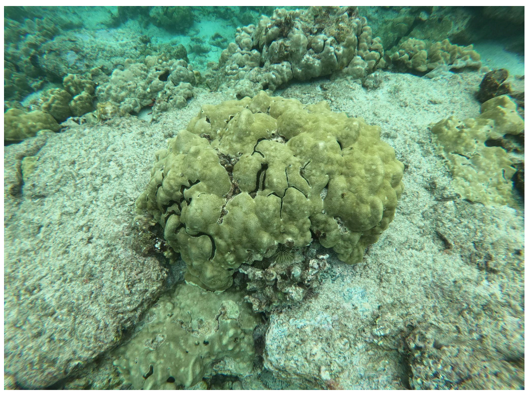
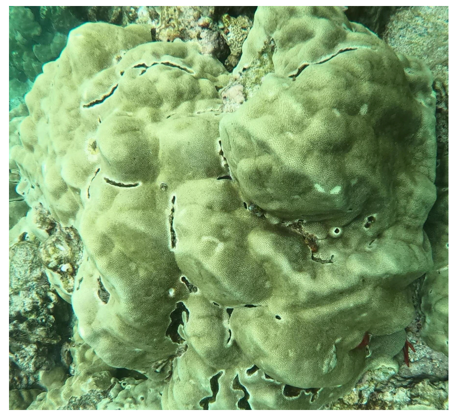
coraldetection.m

```
imds = imageDatastore('MerchData', ...
    'IncludeSubfolders',true, ...
    'LabelSource','foldernames');
[imdsTrain,imdsValidation] = splitEachLabel(imds,0.7);

% visualize a random image
I = readimage(imdsTrain,randi(numel(imdsTrain.Files)));
imshow(I);
net = googlenet;

inputSize = net.Layers(1).InputSize;
augimdsTrain = augmentedImageDatastore(inputSize(1:2),imdsTrain);
augimdsValidation = augmentedImageDatastore(inputSize(1:2),imdsValidation);

% pull a test sample
test_sample_table = augimdsTrain.readByIndex(1);
test_sample = test_sample_table.input{1};

% use GoogLeNet to classify image
label = classify(net,test_sample)
imshow(test_sample);
lgraph = layerGraph(net);

numClasses = numel(categories(imdsTrain.Labels));

newLearnableLayer = fullyConnectedLayer(numClasses, ...
        'Name','new_fc', ...
        'WeightLearnRateFactor',10, ...
        'BiasLearnRateFactor',10);

lgraph = replaceLayer(lgraph,'loss3-classifier',newLearnableLayer);
newClassLayer = classificationLayer('Name','new_classoutput');
lgraph = replaceLayer(lgraph,'output',newClassLayer);

options = trainingOptions('sgdm', ...
    'MiniBatchSize',10, ...
    'MaxEpochs',6, ...
    'InitialLearnRate',3e-4, ...
    'Plots','training-progress');

newNet = trainNetwork(augimdsTrain,lgraph,options);

[YPred,probs] = classify(newNet,augimdsValidation);
accuracy = mean(YPred == imdsValidation.Labels)

% And view individual images

idx = randperm(numel(imdsValidation.Files),4);
figure
for i = 1:4
    subplot(2,2,i)
    I = readimage(imdsValidation,idx(i));
    imshow(I)
    label = YPred(idx(i));
    title(string(label) + ", " + num2str(100*max(probs(idx(i),:)),3) + "%");
end
```

RESULTS

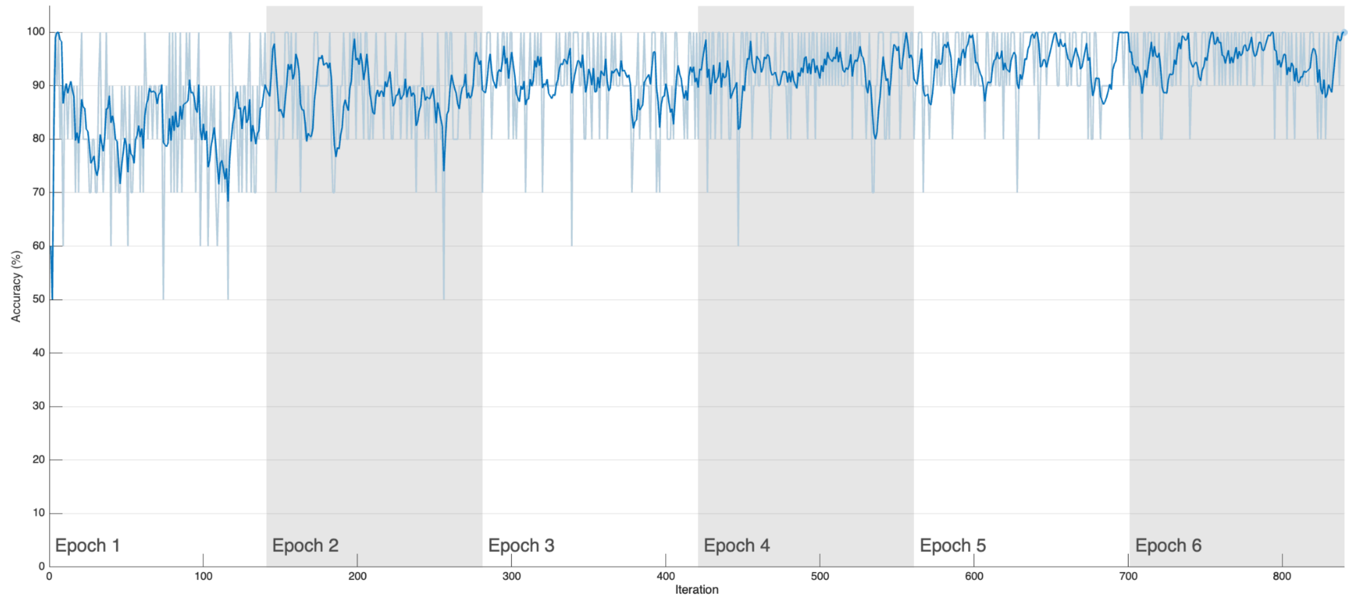
A total of 5,428 images were gathered to train the algorithm for Porites, and a total of 5,112 images were gathered to train the algorithm for Pocillopora. Below is a table showing images with and without processing.

Table of Images With and Without Processing

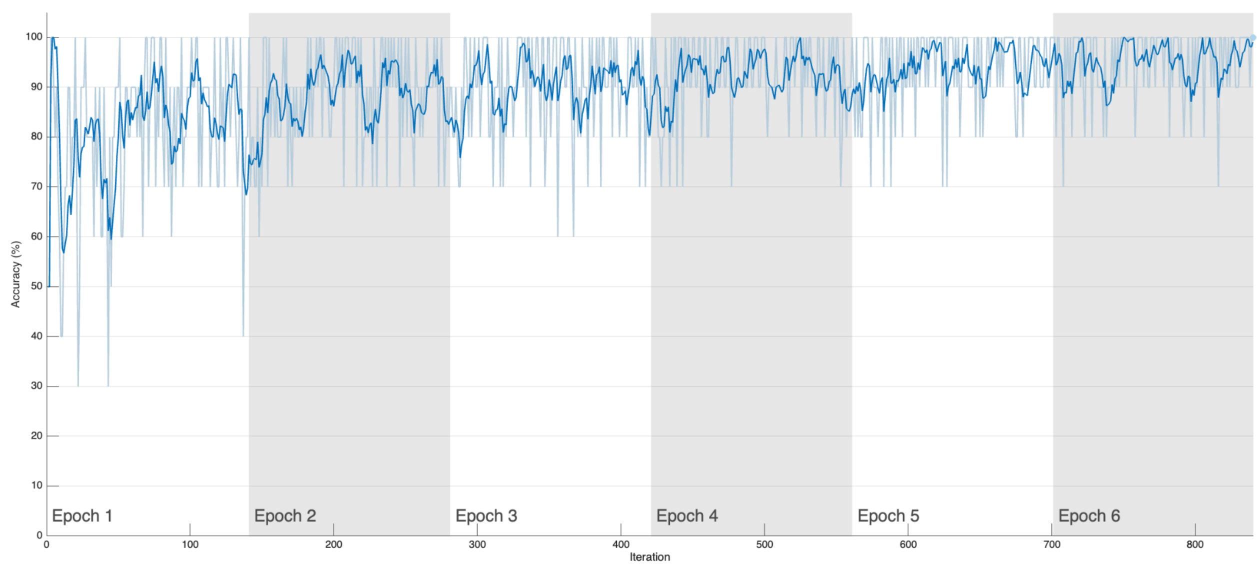
Coral Species	Without Processing	With Processing
Porites		
Pocillopora		

After training both models, the following graphs show the accuracy(y-axis) throughout the epochs(x-axis). Following the two accuracy graphs are the two graphs that show the loss(y-axis) of the models throughout the epochs(x-axis).

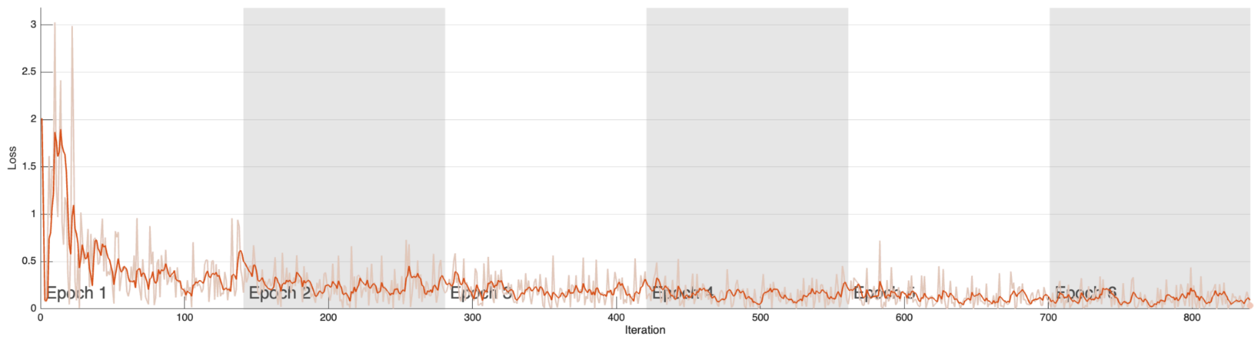
Accuracy of Model One (Porites)



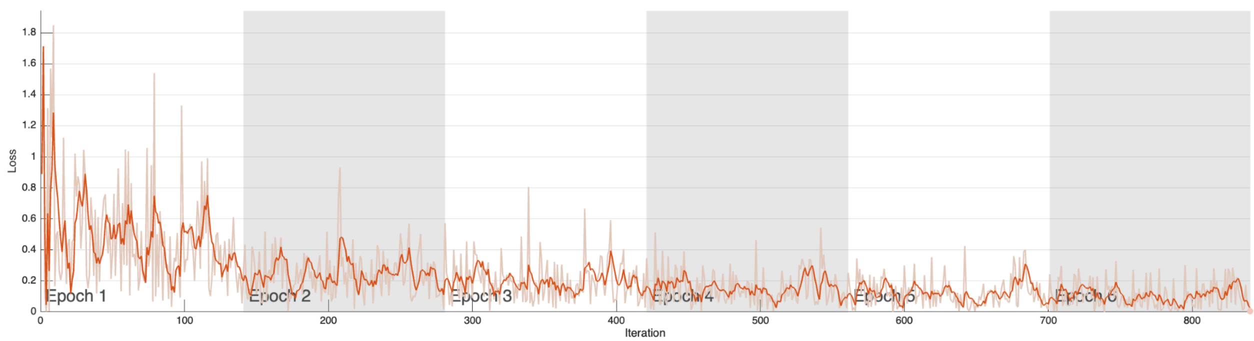
Accuracy of Model Two (Pocillopora)



Loss of Model One (Porites)



Loss of Model Two (Pocillopora)



Conclusion

The hypothesis that a machine learning model trained on images of coral species found off the coast of Hawaii would lead to precise classification of these species has been substantiated. Model One demonstrated an average accuracy of 86.59%, while Model Two demonstrated an average accuracy of 82.59%, with both surpassing the established accuracy threshold of 80%. In addition, the loss metrics for both models were impressive, with Model One achieving an average loss of 0.9578, and Model Two registering an average loss of 1.028.

DISCUSSION

Implications

The findings of this study furnish compelling evidence that machine learning algorithms can be effectively employed to annotate images of coral reefs in Hawaii. Given the stark difference between the number of images collected and those actually utilized in the annotation process, this model has the potential to be deployed for the automatic sorting and categorization of coral reef images without the need for human intervention(Beijbom et al,. 2012). This model could be used to streamline the process of identifying and monitoring coral reefs. This would in turn be crucial for evaluating their health and survival in the face of environmental stressors.

Through the automatic identification of various coral species allows researchers to gather a better understanding of the distribution of coral species. This, in turn, can inform targeted conservation measures and facilitate the protection of these vital ecosystems(Chapman, Ramondt, and Smiley, 2005). My studies and its successful application of using ML algorithms to annotate coral reef images will represent a significant step forward in the field of coral reef research and conservation.

Limitations

While the current study has demonstrated the potential for machine learning algorithms to accurately annotate coral reef images. There were several limitations that should be addressed through further experimentation. A significant limitation to my study was the scalability of the model that was created. My study utilized a dataset of approximately 10,000 images, having 5,000 images for each of the two species. While this may appear to be a substantial number, larger machine learning models often require training on datasets with 100,000s of images(Fung and Mcduff 2019). The small size of the dataset used in this study could affect the scalability of the study and limit its effectiveness for a larger sample portion.

Another major limitation of this study is that it was conducted on a specific beach in Hawaii without any cross validation. It is unclear if the model created in this study would be able to identify coral species from different locations. Given that coral reef ecosystems can differ significantly across locations, the model's effectiveness may be limited in areas where the coral species have different characteristics.

Moving Forward

Moving forward, a way to decrease the limitations highlighted in the previous section, additional experiments could be conducted to see the effectiveness of the ML model. Previous studies have shown that the performance of ML models can improve as the size of the dataset increases (Krizhevsky, Sutskever, and Hinton, 2012). Creating a ML model with larger datasets would allow for a more comprehensive assessment of the model's scalability and performance.

In addition, further research could explore the effectiveness of the approach across different coral reef ecosystems. Coral reefs can vary significantly in terms of their species composition and environmental factors. These variations could affect the performance of the machine learning model. Therefore, when assessing the effectiveness of the approach across different coral reef ecosystems could provide insight into the potential for wider application of the ML model.

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