13. Coral Classification

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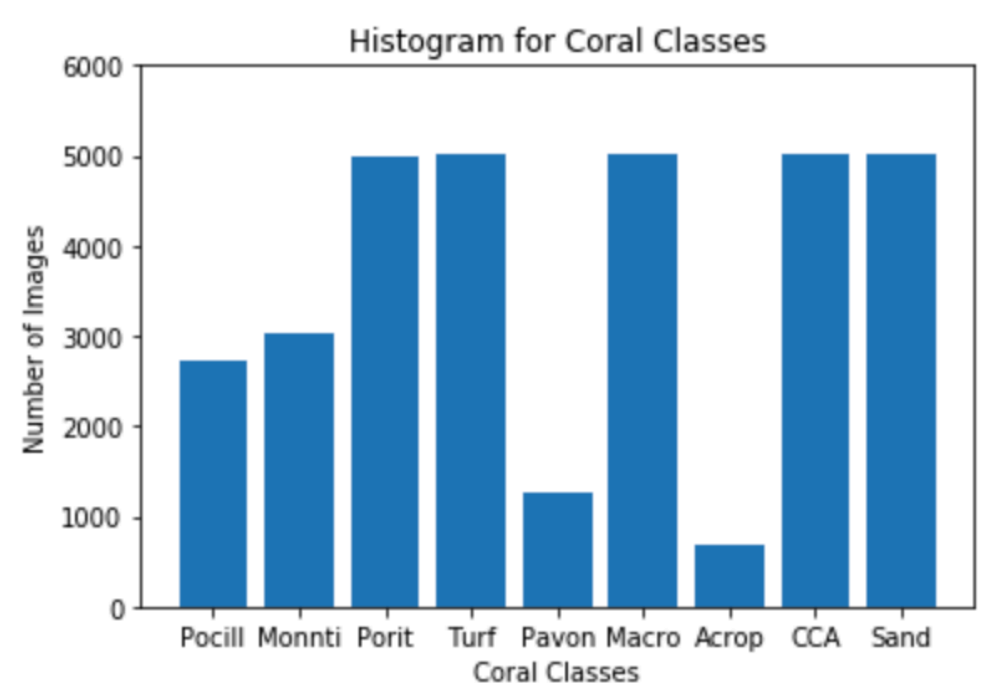
Abstract

The coral reef ecosystems are diverse, fragile, and extremely important to the biosphere. Recently, they have been greatly impacted by the global climate change and have gained significant attention from research and government organizations. Our project intends to help the study on climate impact on different types coral reef colonies by providing a coral image classification methodology with machine learning models such as K-Nearest Neighbors, Random Forest, and Convolutional Neural Networks. These models we have chosen achieved test accuracies of 76.9%, 77.4%, and 65.8%, respectively.

Data

We choose the Moorea Coral Reef LTER dataset, which contains over 2,000 coral reef images from the island of Moorea in French Polynesia from 2008 to 2010. Each coral image has 200 random points annotated with one of the 9 classes for which 5 of them are coral genera (Acropora, Pavona, Montipora, Pocillopora, and Porites) and 4 are non-coral classes (Crustose Coralline Algae, Turf algae, Macroalgae and Sand). In the original dataset, each picture contains multiple corals of different classes. For simplicity, we will use a processed dataset from the UCSD Computer Vision group, which contains 32,686 cropped images such that each image contains only one class of coral/algae. The number images of each class of coral/non-coral is shown in the figure below.

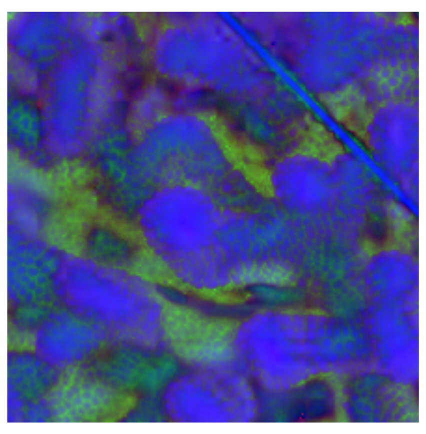


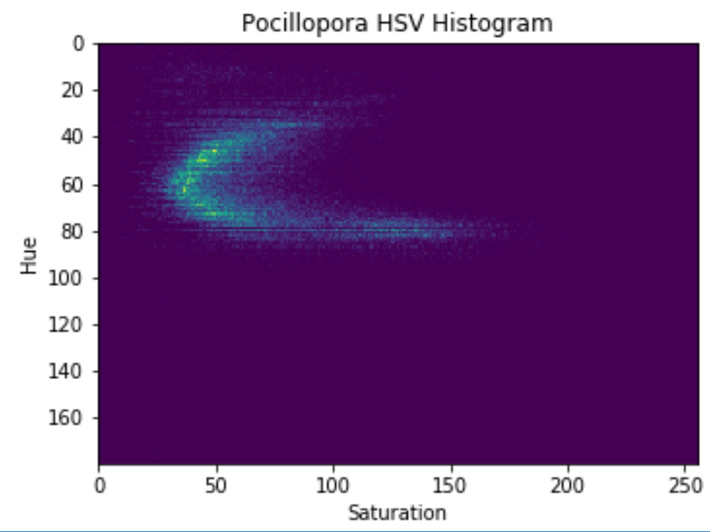
Features

We extract features in the following 3 ways for training different models:

1. Raw images (RGB value matrices)
2. Gray scale images
3. KAZE descriptor with mode RGB
4. HSV (Hue, Saturation, Value) histogram

KAZE is basically a fusion of FAST keypoint detector and BRIEF descriptor with many modifications to enhance the performance. We chose RGB and HSV histograms as derived features because images of different types of corals may have different common colors, hue, and/or saturation values. Such possible distinct properties will show as peaks in the histograms. The example below shows a coral of the Pocillopora Class, its converted HSV image, and its HSV histogram. In the histogram, there are peaks at (Hue, Saturation) values of around (60, 50).





Models

- **K Nearest Neighbor (KNN)**

KNN classifies objects with the label of highest frequency from its K neighbors. We pick K = 2 which achieves the best results on our dataset.

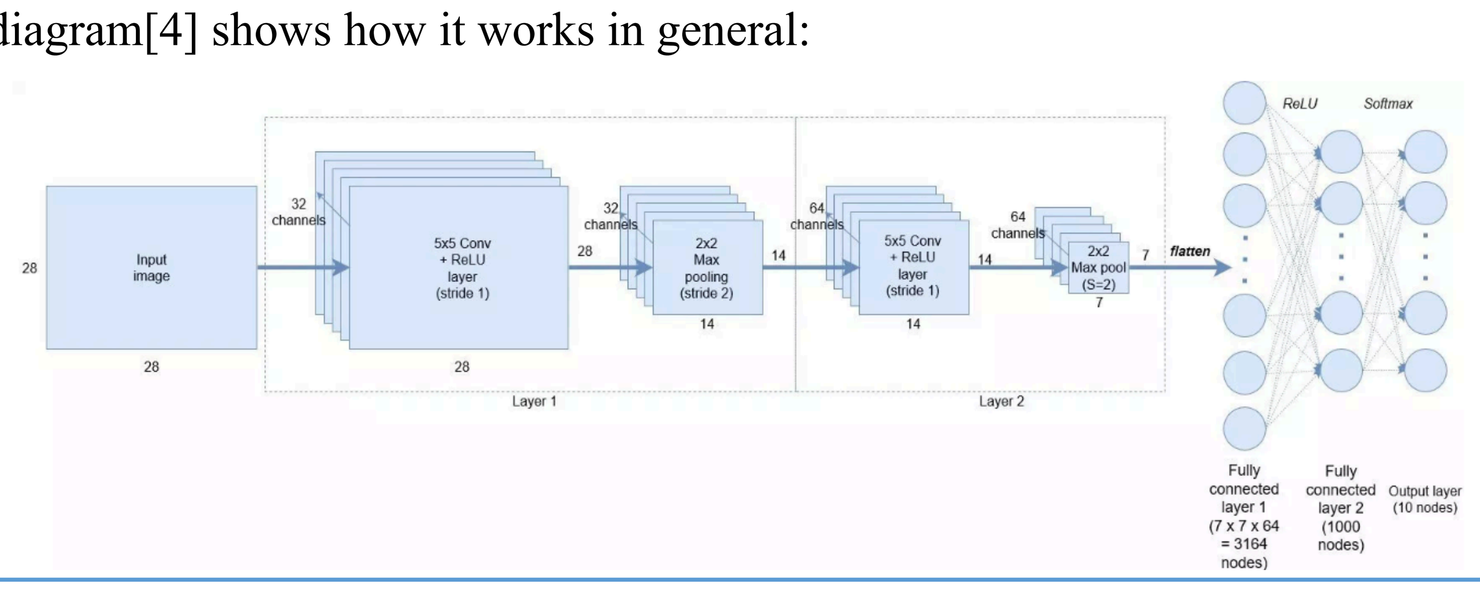
- **Random Forest Classifier (RF)**

RF applies a number of decision tree classifiers by choice on the dataset and uses averaging to improve the predictive accuracy and control over-fitting.[1]

We use 200 trees with maximum depth 30.

- **Convolutional Neural Networks (CNN)**

CNN is one of the deep neural networks used to do image recognition. The below diagram[4] shows how it works in general:

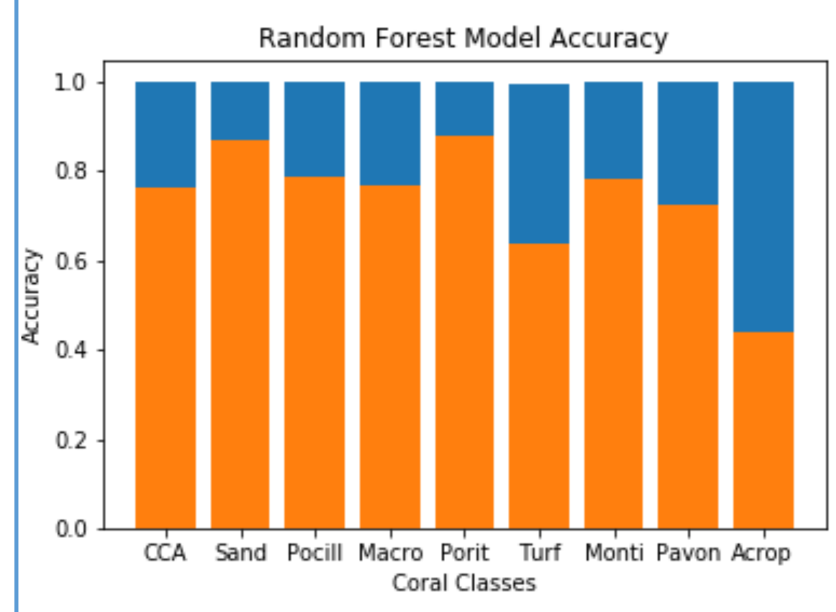


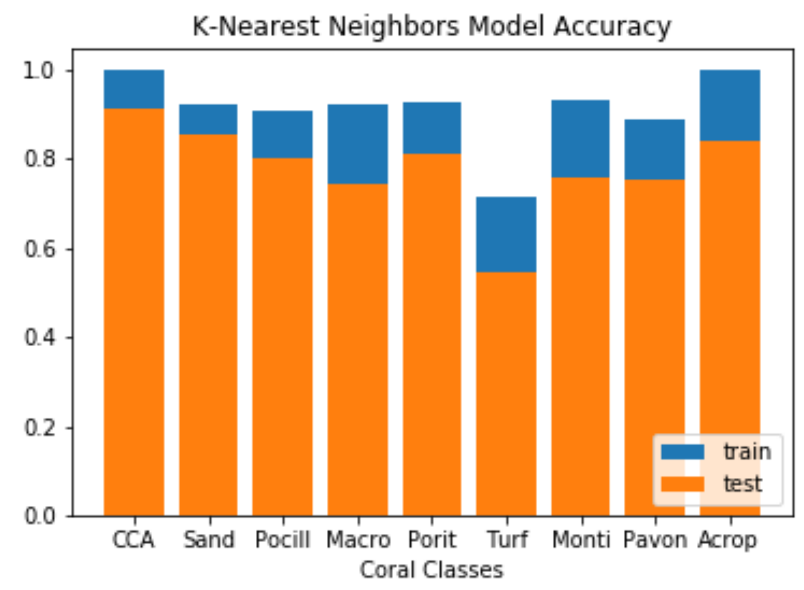
Results

Our dataset contains 32,686 images in total. We split them into training set and testing set by percentage 75% and 25%. CNN are trained using 80% training and 20% testing.

Models	Parameter	Train Error	Test Error
KNN	K = 2 nearest neighbors	9.5%	23.1%
RF	200 trees with max depth 30	0.2%	22.6%
CNN	Large filter size (9,9) 5 Conv-Pool Layers MaxPooling, Dropout ~0.7	10.2%	34.2%

The two figures below shows the class-wise accuracy among corals for KNN and Random Forest Model.





Discussion

For Random Forest Regressor, we first train the regressor with extracted features by using KAZE descriptor, then, we got 47.8% error rate for test data set. The error rate is little bit higher than we expect, similar images are not always similar as we understand it. After we did some research, we found that this algorithms is context-unaware, so they better in finding same images even modified, but not similar. Therefore, we decided to use HSV histogram and RGB value matrices to train this model, you can consider histogram as a graph or plot, which gives you an overall idea about the intensity distribution of an image. It is a plot with pixel values (ranging from 0 to 255, not always) in X-axis and corresponding number of pixels in the image on Y-axis. In this way, we got 22.6% error rate for test data set. Therefore, we can conclude from above that the HSV histogram is a good way to represent these coral images.

We have encountered some difficulties while training our convolutional neural network since we expected to see higher accuracy by using CNNs. Common architectures such as Conv-Pool-Conv-Pool and Conv-Conv-Pool-Conv-Conv-Pool, even after several tries of fine-tuning hyper parameters, did not produce a reasonable testing accuracy, ~10% while achieving very high training accuracy ~90%. After re-examining the dataset, we found that most coral images are dim and blurry (with weird lightings) which made us believe that bigger amount of pixels might be needed for network to recognize the coral (Kernel size increased from (3,3) to (9,9)). Based on this, we manually added more Convolution Layers(with increasing number of filters, larger filter size) and performed normalization. Dropout layers with different values(~0.3-0.7) were also added to avoid overfitting. Eventually we managed to bring testing accuracy to 65.8% with training accuracy to be 89.9%.

Future Work

We could improve the image pre-process by trying different patch sizes first. As the larger the patches size is, the better the results we would get. We also would apply more machine learning models suitable for image classification such as ResNet, NASNet, etc.

REFERENCES

[1]. Sklearn Ensemble Random Forest Classifier. https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

[2] 2019. Moorea Coral Reef LTER.http://mcr.lternet.edu/cgibin/showDataset.cgi?docid=knb-lter-mcr.5006

[3] 2019. UCSD Computer Vision Moorea Labaled Corels. http://vision.ucsd.edu/content/moorea-labeled-corals

[4] CNN Diagram https://adventuresinmachinelearning.com/keras-tutorial-cnn-11-lines/

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