Coral Species Identification

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Business Problem

Coral reefs are an integral ecosystem in the near-surface zone of the ocean, the euphotic zone. These areas are an explosion of diversity, similar to rain forests on land. Evaluating the health of coral reefs is a fundamental part of numerous business ventures such as fishing, in addition to understanding the overall health of the ocean. Classifying coral with underwater images manually takes up a large amount of time since corals grow close together and make up very large structures. This project aims to automate this process, creating a more efficient step in additional projects that could explore coral bleaching.

Background

Coral reefs are a necessary and important structure located typically within the first 200 ft of ocean water. They are an expanse of hard calcium carbonate structure with small living plankton in them called zooxanthellae. The coral polyps living within them gather food from the water column and the zooxanthellae use the biproducts from the polyps to help photosynthesize.

Like many other types of animals, these also have numerous species that can look strikingly different from each other. There are six main types of coral species that can be found globally. Small polyp stony corals (SPS) feature that typical hard skeleton with small nodules all over them. The most popular species of this type is the Acropora. Large polyp stony corals (LPS) which have large and flowy polyps that overtake the stony skeleton. Gorgonians are the third type which is considered a soft coral, however, they have a leathery skeleton that is a mix between a true soft coral and a true hard coral. Their polyps extend far out of their skeletons and look like large fans. Soft corals are not typically the structure of coral reefs, but can be found within other hard corals, they cannot bear weight on top of them like hard corals can. Zoanthids are more of a designer species of coral, with very colorful polyps, but can still be found on coral reefs globally. Lastly, mushroom corals which is a type of soft coral that can look like the underside of a mushroom.

Understanding which coral species makes up a majority of the reef structure can help with evaluating the overall health of the reef and at what stage of maturity the reef is at. Younger reefs will have less diversity and smaller size corals, while large mature reefs will have little to no rock or other bottom structure visible, the coral will have overtaken all structures.

Data

Two datasets including photo images of corals in .jpg, .jpeg, and .png were used. The initial dataset was collected by the Rosenstiel School of Marine and Atmospheric Sciences (RSMAS) which features textural images of 14 different coral species. Because they are texture images, the structure of the coral is not shown in the image. A second dataset, named StructureRSMAS was created by Gómez-Ríos et al. (2019) that includes the same 14 coral species but with images that includes the entire structure of the coral. This is an important dataset since these 14 species have a significantly different structural appearance. There are a total of 766 images in the RSMAS dataset and 409 images in the StructureRSMAS dataset.

Assumptions

The assumptions for the neural networks in classifying images is that there are an equal number of photos for each class. If this isn't the case, weights must be applied to each class to even the evaluation of the network. In addition, the photos in the dataset must be the same size.

Methods

Images from both datasets were grouped into one for the initial classifier with classes of "RSMAS" and "StructureRSMAS". After, data was split into a training and validation set with

940, and 235 files respectively. Then, using Tensorflow and Keras, a model with 5 layers of a convolutional 2D component with a ReLU activation and a max pooling component. Then, the model is flattened and to classify as a binary model a sigmoid layer to finish. Accuracy was added with an Adam optimizer with a learning rate of 0.001 into the compile command. The model was then trained for 10 epochs. Once completed, the model was evaluated and accuracy and loss was graphed to visualize results.

For modeling the StructureRSMAS data, a test/train split of 80/20 was used across a total of 240 images in 12 classes. While a keras tuner was used and numerous iterations of a convolutional neural network, a low accuracy was found. Because of the problems with the h5py package, additional filtering methods or pre-trained models were unable to be used. In the instance they could be, a convolutional neural network using the Bayesian optimization method would have been attempted. If that produced low accuracy results, a pre-trained method such as ResNet50 would have been attempted.

When splitting the RSMAS data, to maintain uniform weights across classes, each class had 22 images each. With 12 classes, the total amount of data for the texture model was 263. This was split using an 80/20 ratio for training and testing sets. A convolutional neural network was set with 3 convolutional and pooling layers, starting with 32 filters and increasing to 96. A dropout layer of 0.8 was added, and a dense layer of 512. The activation of the output layer was softmax since it was evaluating over 12 classes. When compiling, the Adam optimizer was used with sparse categorical cross entropy for loss over 10 epochs. The same visualization featuring accuracy and loss was created for the texture model.

Analysis

When evaluating the sequential binary classification neural network for classifying an image as a texture image or a structure image, there was a training accuracy of 85% and a validation accuracy of 86% (Figure 1). Losses for each were 0.62 and 0.38 respectively (Figure 1).

Figure 1: Training and validation accuracy and loss for binary convolutional neural network for determining structure and texture images featured on a line graph by epoch.

For the structure model, a convolutional neural network examined 12 classes of coral species. The keras tuner determined the best hyperparameters for this model to be 32 filters for the first convolution and 64 for the second. The dropout was suggested to be 0.5 but better results were found with a dropout of 0.2. Learning rate was most accurate at 0.001. Overall, results for this model were below average, with the final training accuracy of 0.99 but a validation accuracy of 0.33 (Figure 2). Final loss for this network were 0.08 and 3.52 respectively (Figure 2).

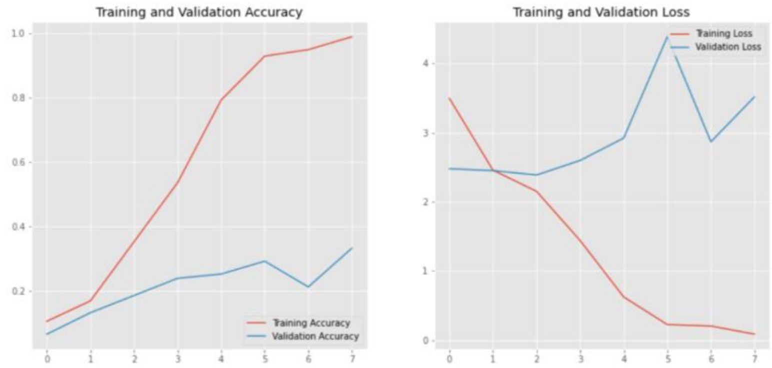

Figure 2: Training and validation accuracy and loss for categorical convolutional neural network for determining structure images featured on a line graph by epoch.

Using a similar approach to the structure vs. texture model, the texture convolutional neural network looked at 12 classes instead of 2. Final training accuracy for this model was 92.3% while the validation accuracy was 75% (Figure 3). Losses for this model were 0.21 and 0.94 respectively (Figure 3). This difference between training and validation sets was a little more broad than structure vs. texture model.

Figure 3: Training and validation accuracy and loss for categorical convolutional neural network for determining texture images featured on a line graph by epoch.

Conclusion

Because of the larger difference in classes from the first model with evaluated whether an image was of the texture of a coral versus the structure of the coral, the creation of this neural network was much quicker and easier. This model alone would be useful for someone who is just researching one of these qualities to find images that suits their needs. The texture model was more difficult and required some trial and error when choosing hyperparameters to run in the model. After some time, a decent model was found. These images can be categorized with 75% accuracy, many species could be looked once over by a researcher to confirm the model's choices. The structure model required more data to be trained and tested properly and would benefit from a transfer learning method. Once run properly, these models run together could help make the process of coral species identification more streamlined.

Limitations

The biggest limitation with this project is the amount of photos gathered for both the RSMAS dataset and the StructureRSMAS dataset. A more comprehensive dataset with thousands of images would allow the model to be fully trained from the beginning versus having to use transfer learning methods. In addition, the issues with the h5py package prevented the use of more advanced neural networks and tuning techniques, something crucial to the structure identifying portion of this project.

Ethical Assessment

These datasets are popular in classification publications, so an air of caution must be made as to not produce the same ideas as other authors. Finding new models or different ways to classify the images brings a new take on the project.

Challenges

Numerous challenges were presented with a project of this type. The quality of photos taken of corals can vary for many reasons. Reefs are an intricate combination of many types of corals, some of which overlap, creating a difficulty in imagine just one species. In addition, lighting and weather can change the appearance of anything underwater, making it brighter, darker or dappled with light. Not only that, the type of camera can influence the photo quality and distance from the target can create varying images and perceptions.

Future Uses

A model such as this will significantly reduce the time needed to classify images for further research. If new reefs are discovered, the types of species residing on that reef could be determined by the model to give researchers a baseline of what species are present and allow them to determine the concentrations of those species.

In instances where coral must be evaluated for health such as coral bleaching, images can be added to determine whether the coral is alive and healthy, determined by color, or dying and turning white. Another health-related use would be training the model to evaluate bare coral and coral overrun by algae, which could kill it.

Implementation Plan

This model would be best used through distribution over a source such as GitHub, where the model can be downloaded to a research computer to be able to run images. In addition, as improvements are made throughout time, new versions of the models can be uploaded to provide more comprehensive species predictions.

Literature Cited

Gómez-Ríos, A., Tabik, S., Luengo, J., Shihavuddin, A. S. M., & Herrera, F. (2019). Coral species identification with texture or structure images using a two-level classifier based on Convolutional Neural Networks. Knowledge-Based Systems, 184, [104891]. https://doi.org/10.1016/j.knosys.2019.104891