Hierarchical Clustering of Corals using Transfer Learning

Rudra S.
School of Information Technology and Electrical Engineering
The University of Queensland, Qld., 4072, Australia

Abstract

In this project we aim to find a hierarchical relationship between different types of corals by using transfer learning techniques and clustering on the coral dataset. We use the pretrained models VGG16, InceptionV3 and DenseNet to train and extract feature vectors from coral dataset. These vectors are then clustered using the Agglomerative Heirarchical Clustering to obtain a Hierarchy of corals.

1 Introduction

Since the 1980s, analysis of the skeletal structure and morphology of the corals has been used for the construction of coral taxonomy. Most of these methods used skilled human observers. Although these methods have successful classified many corals, they often have inaccuracies and limitations when compared with the molecular study of the corals [1]. Image classifications algorithms today have proved to be better at pattern recognition tasks than humans and hence can be used to accurately classify the different types of corals [2] based on their morphology and texture. We try to achieve this goal in this project by using the state-of-the-art image classification models using transfer learning. The dataset we used was provided by the Queensland Museum, Australia and contains coral images belonging to 1006 different categories. We propose the use of pretrained transfer learning models to learn and extract important features from the given coral images. These features when clustered using hierarchical clustering could represent the relationship between different coral types. For this we will be using pretrained models to extract important features from the dataset and then group the corals based on their similarity.

2 Literature Review

Many approaches [3,4] using CNNs have been proposed and implemented on the task of classification of corals. Although most of them were effective, they required considerable amounts of data to train the model to obtain good accuracy. But our dataset is limited and has less than 10 labels per class, hence might not give a good performance.

The paper [5], shows that different transfer learning approaches based on ResNet, with few-shots learning and data augmentation can achieve good accuracy with a dataset having less than 100 labels per class. This shows that transfer learning can work well on image classification with very limited data. The paper [6] implements two different models, one that applied transfer learning from ImageNet dataset to coral texture images dataset and second which applied transfer learning from MLC-2008 coral dataset to coral texture images dataset. These approaches could achieve high accuracy making them candidates to be used in this project.

3 Methodology

Preprocessing: The dataset consisted of 8745 images of corals belonging to 1006 different categories. The images were taken from different sources. To ensure quality and uniformity across images, only the images of corals taken in laboratory environment were used. Categories containing too few images (less than 3) were removed. Hence a final dataset of 3998 coral images belonging to 502 categories was obtained and used for project. Since the number of images per category was still low, different methods of data augmentation like rotation, horizontal and vertical flipping, zooming in, sheering, and changing the brightness were used to increase the dataset.

Transfer Learning: Three different pretrained image classification models were trained on the coral dataset. These were VGG16, InceptionV3 and DenseNet. Each of these models have been pretrained on the ImageNet dataset and the resultant weights were imported and used as initial weights for training. At first the models were trained by replacing their top layer and training only the last layer on the coral dataset. In a second approach, the last two layers of the models were trained on the coral dataset to check if it improved the performance. The model with the best performance was selected for further processing.

Extracting features: Once trained the top layer of the model was removed and feature vectors of the images were extracted by passing each of them as input to the model. These vectors represented the images in such a way that could capture the similarities (or dissimilarities) between them. The method of Principal Conponent Analysis (PCA) was used to reduce the dimensions of the vectors.

Heirarchical Clustering: The Agglomerative Heirarchical Clustering algorithm was used to cluster the feature vectors. The clustering was implemented using the Single-link, Complete-link, Average-link and Ward's criteria. The performance across these different clusterings was tested using the Silhouette score. This process was repeated by calculating the mean vectors for each category to obtain the general hierarchy.

4 Results

The processed coral dataset of 3998 images belonging to 502 coral categories was used to train each of the models (VGG16, InceptionV3 and Densenet). Among these, the DenseNet model when trained on its top two layers gave the best performance (see Table 1 and 2), hence it was used to extract feature-vectors from the images. The dimensionality of these features was reduced from 51192 to 428 dimensions using PCA. On performing Agglomerative clustering on these features, it was found that using single-link criterion gives the best silhouette score. The clustering of mean features calculated for each category also had the best silhouette score when single-link Agglomerative clustering was used. The resultant hierarchy of mean vectors was selected as the general coral hierarchy. The silhouette scores have been mentioned in Table 3.

	VGG16	InceptionV3	DenseNet
Train Acc.	46.55%	76.32%	70.07%
Train Loss	3.34	15.60	8.15
Test Acc.	20.44%	24.79%	28.81%

Table 1: Accuracy and loss of models with only top layer trained. (Acc. stands for Accuracy)

	VGG16	InceptionV3	DenseNet
Train Acc.	55.28%	72.77%	88.74%
Train Loss	1.7191	12.72	0.70
Test Acc.	21.11%	25.63%	39.70%

Table 2: Accuracy and loss of models with the top two layers trained. (Acc. stands for Accuracy)

Criterion	Mean vectors	Feature Vectors
Average-link	0.3861	0.0132
Ward's	0.0200	0.0132
Complete-link	0.3845	0.0137
Single-link	0.3843	0.0029

Table 3: Silhouette scores of hierarchical clustering.

5 Conclusion

As seen from the results, using the DenseNet Model on the coral dataset gives us the best performance on the task of classification of coral images into their categories. Although it had a high training accuracy of 88.74%, the test accuracy is low at 39.7. This could be because of the low number of images available per category (~6 image per category) as well as the low diversity in data (most images in a category are of the same coral sample). The best clustering obtained had a silhouette score of 0.3861 suggesting some overlap between clusters. Although these results are average in terms of accuracy, they might still be very useful for finding the possible closely related categories to a given coral. It could also be used to find the how closely two corals are related. The methodology used proves that transfer learning can be very useful on coral classification tasks. In future work we need to collect more images per category to improve the quality features generated and get better clustering.

Acknowledgment

I acknowledge the motivation and guidance of my supervisor Prof. Gianluca Demartini. I also thank the Queensland Museum for providing the dataset and Dr. Tom Bridge for providing the domain knowledge.

References

[1] J. Veron, "Overview of the taxonomy of zooxanthellate Scleractinia," Zool. J. Linn. Soc., vol. 169, no. 3, pp. 485–508, 2013, doi: 10.1111/zoj.12076.
[2] J. Pavlus, "Computers Now Recognize Patterns Better Than Humans Can," Scientific American, 2016.
[3] M. Modasshir, A. Q. Li, and I. Rekleitis, "MDNet: Multi-Patch Dense Network for Coral Classification," Ocean. 2018 MTS/IEEE Charleston, Ocean 2018, pp. 1–6, 2019, doi: 10.1109/OCEANS.2018.8604478.
[4] A. Gómez-Ríos, S. Tabik, J. Luengo, A. S. M. Shihavuddin, and F. Herrera, "Coral species identification with texture or structure images using a two-level classifier based on Convolutional Neural Networks," Knowledge-Based Syst., vol. 184, p. 104891, 2019, doi: 10.1016/j.knosys.2019.104891.
[5] W. Zhu, B. Braun, L. H. Chiang, and J. A. Romagnoli, "Investigation of Transfer Learning for Image Classification and Impact on Training Sample Size," Chemom. Intell. Lab. Syst., vol. 211, no. February, p. 104269, 2021, doi: 10.1016/j.chemolab.2021.104269.
[6] A. Gómez-Ríos, S. Tabik, J. Luengo, A. S. M. Shihavuddin, B. Krawczyk, and F. Herrera, "Towards highly accurate coral texture images classification using deep convolutional neural networks and data augmentation," Expert Syst. Appl., vol. 118, pp. 315–328, 2019, doi: 10.1016/j.eswa.2018.10.010.

Biography

Rudra Arun Sawant: Student at University of Queensland, pursuing the degree Master of Computer Science (Management).