Hierarchical Clustering of Corals using Image Clustering

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ABSTRACT

Several approaches have been taken by different scientists over the years to create taxonomy of coral species by looking at their morphology. On molecular examination, the taxonomies created have revealed to have incorrect classifications. In this project we aim to find a relationship between different types of corals and classify them by using image classification and clustering techniques on a coral dataset provided by Queensland Museum (QM), Australia. We use the VGG16 [9], InceptionV3 [10] and DenseNet [5] models which are pretrained on the ImageNet dataset, to train and extract feature embeddings from the coral images in the QM dataset. These embeddings are then clustered using the Agglomerative Hierarchical Clustering to obtain a general hierarchy of corals. We show that DenseNet performs the best among the three models on the image classification task and can be used to extract the feature embeddings. Using Agglomerative Hierarchical Clustering with average link criterion on these embeddings, we can generate a general hierarchy of corals.

CCS CONCEPTS

• **Information systems** → *Digital libraries and archives*; • **Computing methodologies** → **Neural networks**.

KEYWORDS

Convolutional Neural Networks, Image Clustering, Feature Extraction, Hierarchical Clustering

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1 INTRODUCTION

Since the 1980s, the analysis of the skeletal structure and morphology of the corals has been used by different scientists for the construction of coral taxonomies. Most of these methods use skilled human observers to manually establish the relationships between different types of corals. Although these methods have successful classified many corals, they often have inaccuracies and limitations when compared with the molecular study of the corals [11]. The researchers find it difficult to re-classify and resolve the inconsistencies across the different coral collections and taxonomies. There are digital collections of images of different types of corals collected from all over the world, maintained by institutes like the Queensland Museum, Australia. Image classifications algorithms have shown to be better at pattern recognition tasks than humans for some tasks and hence may be used to accurately re-classify the different types of corals [8] from different digital collections of coral images based on their morphology and texture. Some convolutional neural network (CNN) based approaches have been implemented to classify coral images and have achieved good accuracy [3, 7].

In this study we propose the use of state-of-the-art image classification models like VGG16 [9], DenseNet [5] and InceptionV3 [10], to learn and extract important feature embeddings from a dataset of coral images provided by the Queensland Museum (QM coral dataset). For this purpose, we use transfer learning by using pretrained parameters of these models trained on the ImageNet dataset [1]. The extracted embeddings, when clustered using hierarchical clustering, represent the relationship between different coral types. The resulting clustering can therefore be used to get a general hierarchy between the different types of corals. The QM coral dataset contains 8745 images of corals belonging to 1006 different coral categories.

2 LITERATURE REVIEW

Many approaches have been proposed and implemented on the task of classifying corals. Modasshir et al. [7] proposed a new type of CNN called MDNet, which used multi-scaled patches on point annotated data and dense connections between its layers to classify coral images, instead of relying on pixel data. Another approach was proposed by Gomez et al. [3], which implemented a two-level classifier using ResNet models. A ResNet model in the first layer identifies whether the image is a texture or structure image and based on that, the coral species is identified using either a ResNet model trained on the RSMAS texture dataset or a ResNet model trained on the StructureRSMAS dataset. Though this approach assumed the independence of the texture and structural features in classification of corals, it had a good accuracy on the classification task. Although the above-mentioned approaches were effective, they required considerable amounts of data to train the models to obtain good accuracy. Like most real-world datasets, the dataset we use in this work is limited in size and hence the above approaches might not give a good classification performance.

Zhu et al. [12] show that 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. Mahmood et al. [6] proposed a hybrid approach to transfer learning, where handcrafted features

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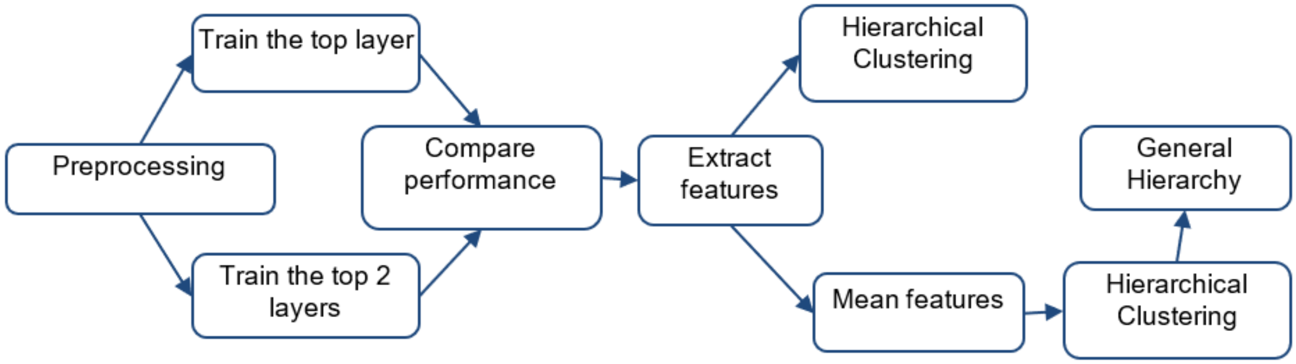

Figure 1: System design to generate a coral classification hierarchy.

were used along with the features obtained from the pretrained VGGNet. The hand-crafted features were colour and text based features selected from the same patch as the CNN based features. The model could achieve better performance than other benchmark models on the MLC coral dataset. Dong and Wang [2] suggested an iterative approach using hand crafted features at the start. It used transfer learning and unsupervised learning in each iteration to choose reliable labels and optimize them. The above approaches using hand-crafted features face a limitation in cases where obtaining them is difficult, like in the case of our work. A promising solution to this problem was proposed by Gomez et al. [4] by adding two new layers to the pretrained CNN models and training them. They implemented two different models, one that applied transfer learning from the ImageNet dataset [1] to coral texture images and a second one which applied transfer learning from the MLC-2008 coral dataset to a coral texture image dataset. These approaches could achieve high accuracy making them candidates to be used in our work.

3 METHODOLOGY

Preprocessing: The QM coral dataset consists of 8745 images of corals belonging to 1006 different categories. The images were taken from different contexts, like, for example, in a laboratory environment, in situ under the water environment, and under a microscope. Many of them contain background objects and colors. Some are also of very poor image quality and blur. The high quality images taken under the microscope are very few in number and belong to only a few coral categories. To ensure uniformity and good image quality across all images, only the images of corals taken in the laboratory environment were used, since they did not contain any background and were of good quality. Also, the coral categories containing too few images (less than 3) were removed to ensure that each class was adequately represented. After this pre-processing, a final processed QM coral dataset containing 3998 coral images belonging to 502 categories was obtained and used for this work. Each category on average, has about 6 coral images belonging to it. Since the number of images per category is 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 size. This dataset was then split into training and testing, with 80% of the dataset used for training and 20% used for testing.

Transfer Learning: Three different pretrained image classification models were trained on the QM coral dataset. These were VGG16 [9], InceptionV3 [10] and DenseNet [5]. Each of these models have been pretrained on the ImageNet dataset [1]. The ImageNet weights were imported and used as initial weights for training. The top layer of each of these models was replaced with a dense layer. Two approaches were taken in training the models. In the first approach, only the top layer of the models was trained on the QM coral dataset. Whereas, in a second approach the top two layers of the models were trained on the QM coral dataset. The performance of

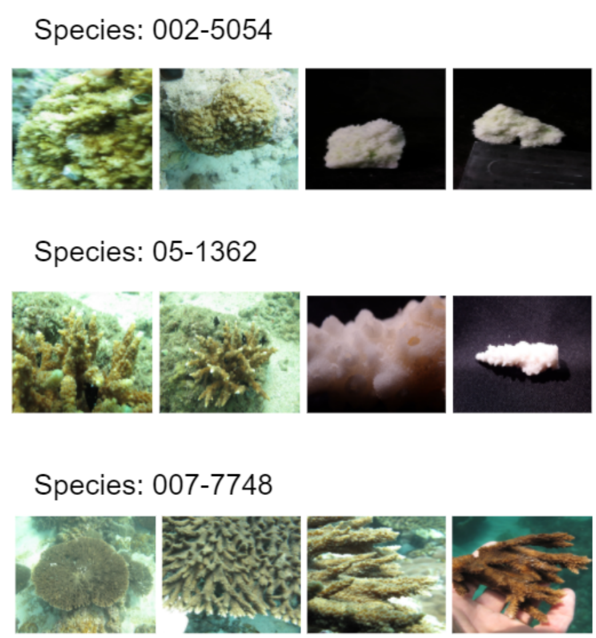

Figure 2: Sample images from the QM coral dataset.

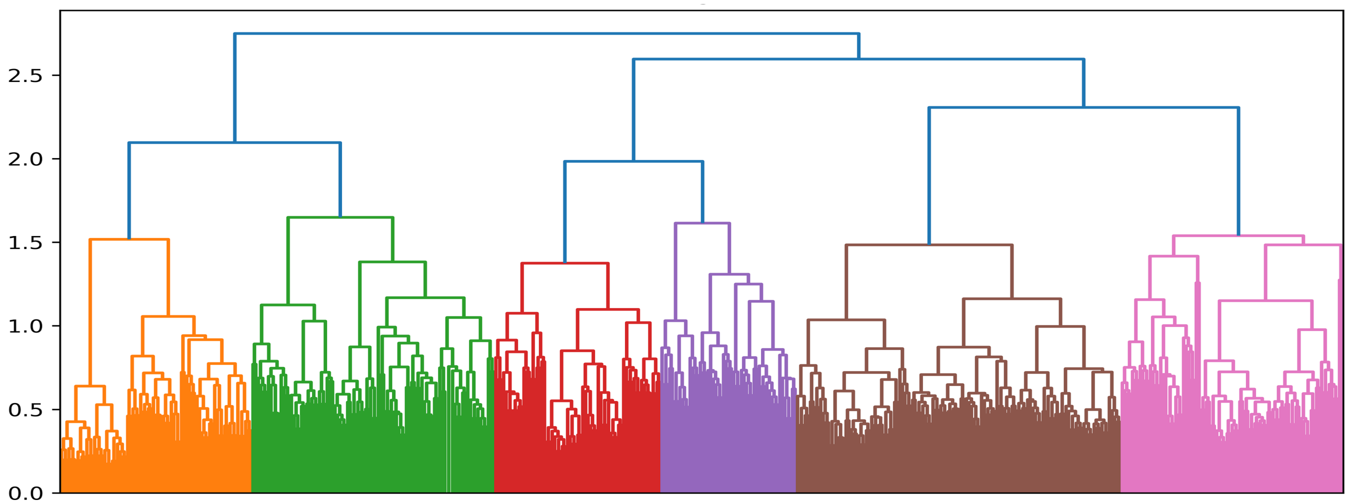

Figure 3: Dendogram showing hierarchical relationships between coral categories (on the horizontal axis are different coral categories)

all models using both the approaches was compared and the model with the best performance was selected for further processing. A baseline model consisting of a simple convolutional neural network with 3 convolutional layers was also implemented and trained to compare against and to analyze the classification performances of the other models.

Extracting feature embeddings: Once trained, the top layer of the model was removed and feature embeddings of the images were extracted by passing each image as input to the edited model. These embeddings represented the images in such a way, that could capture the similarities (or differences) between them. Principal Component Analysis (PCA) was used to reduce the dimensions of these feature embeddings while preserving 99 percent variance among them.

Hierarchical Clustering: The Agglomerative Hierarchical Clustering algorithm was used to cluster the feature embeddings. The clustering was implemented using the Single-link, Complete-link, Average-link and Ward's criterion. The performance across these different clustering results was tested using the Silhouette score. The same process was repeated by calculating the mean feature embedding for each category and then clustering them. The higher the Silhouette score, the better the clustering, hence the clustering of the mean embeddings with the best Silhouette score was chosen as the final representation of the general hierarchy between the coral categories.

4 RESULTS

The VGG16, InceptionV3 and DenseNet models were initialized with the weights imported when they were trained on the ImageNet dataset. The processed QM coral dataset of 3998 images belonging to 502 coral categories was then used to train each of the models. The performance of these models along with that of the baseline model in shown in Table 1 and 2. Among these, the DenseNet model gave the best performance (39.7% Test accuracy) when its top two layers were trained, hence it was selected and used to extract feature embeddings from the images. The dimensionality of these features was reduced from 51192 to 428 dimensions using Principal Component Analysis, while preserving 99 percent of the variance in data. On performing Agglomerative Hierarchical clustering on these features, it was found that, using the Average-link criterion achieved the best Silhouette score (see Table 3). The mean features for each coral category were calculated and were clustered using the Agglomerative Hierarchical Clustering. It also had the best Silhouette score when average-link clustering was used. This clustering would best represent the relationship between coral categories and hence was selected. The resulting general coral hierarchy is shown in Fig 1.

5 CONCLUSION

As seen from the results, using the DenseNet Model on the QM 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 was low at 39.7%. This could be because of the low number of images available per category (around 6 images 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 average clustering with some overlap between clusters. Although the results obtained are relatively average in terms of accuracy and overlap, they might still be very useful for

Table 1: Accuracy and loss of models with only top layer trained.

	Baseline	VGG16	InceptionV3	DenseNet
Train Acc.	34.25%	46.55%	76.32%	70.07%
Train Loss	2.51	3.34	15.60	8.15
Test Acc.	16.58%	20.44%	24.79%	28.81%

Table 2: Accuracy and loss of models with top two layers trained.

	Baseline	VGG16	InceptionV3	DenseNet
Train Acc.	34.25%	55.28%	72.77%	88.74%
Train Loss	2.51	1.7191	12.72	0.70
Test Acc.	16.58%	21.11%	25.63%	**39.70%**

Table 3: Silhouette scores of hierarchical clustering using different criterions.

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

finding the possible relations between the categories. It could also be used to find how closely two corals are related. The methodology used shows that transfer learning can be very useful on coral image classification tasks. Thanks to results we obtained, a simple application was implemented to find closely related corals to a given coral. It takes a coral image (of known or unknown type) as input. It can then output a number of coral categories which are very closely related to the image. These are displayed in decreasing order of closeness. Additional information about the categories like species, genus, clade, subclade, etc. along with their images is also displayed. Coral researchers can use this application as an aid to classify unknown corals or to find closely related coral categories. In future, to improve performance, we will need to collect more images per category and have a more diverse (images of more than one coral specimen) coral image dataset. Pre-training the models on a coral dataset like the MLC-2008 dataset instead of ImageNet could also help improve classification performance of the models. This might help to improve the quality of the features generated which in turn ensures better clustering with less overlap between the coral categories.

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