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Deep Image Representations for Coral Image Classification

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Abstract

Healthy coral reefs play a vital role in maintaining biodiversity in tropical marine ecosystems. Remote imaging techniques have facilitated the scientific investigations of these intricate ecosystems, particularly at depths beyond 10 meters where SCUBA diving techniques are not time or cost efficient. With millions of digital images of the sea floor collected using Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs), manual annotation of this data by marine experts is a tedious, repetitive and time consuming task. It takes 10-30 minutes for a marine expert to meticulously annotate a single image. Automated technology to monitor the health of the oceans would allow for transformational ecological outcomes by standardizing methods to detect and identify species. This paper aims to automate the analysis of large available AUV imagery by developing advanced deep learning tools for rapid and large-scale automatic annotation of marine coral species. Such an automated technology would greatly benefit marine ecological studies in terms of cost, speed and accuracy. To this end, we propose a deep learning based classification method for coral reefs and report the application of the proposed technique to the automatic annotation of unlabelled mosaics of the coral reef in the Abrolhos Islands, Western Australia. Our proposed method automatically quantified the coral coverage in this region and detected a decreasing trend in coral population, which is in line with conclusions drawn by marine ecologists.

Index Terms

corals, coral population, deep learning, marine images, classification, marine ecosystems.

I. Introduction

Rapidly increasing carbon dioxide levels in the atmosphere due to ever expanding human activities are posing severe threats to marine ecosystems in general [1] and coral reefs in particular [2], [3] and [4]. Increased water temperatures are thought to be responsible for bleaching and death of corals [2]. Some coral species are in danger of extinction due to these adverse effects of climate change, as well as other human induced stressors such as pollution, coastal development and exploitation of marine resources. This has resulted in a dramatic decline in our planet's marine biodiversity [5]. In order to minimize these negative impacts, marine ecosystems need to be surveyed and monitored regularly using robust, cost effective techniques. Today's underwater video cameras mounted on AUVs are an excellent alternative to trawl nets, grabs and towed video surveys for remote monitoring of marine ecosystems as they sample along a pre-programmed survey path, producing geo-referenced imagery of the sea-floor [6]. However, the analyses of raw imagery to extract useful information is not only labour intensive, but it also requires an expert to manually process each image. Typically less than 2% of the acquired imagery ends up being manually annotated by a marine expert, resulting in a significant under-utilization of information [7]. An accurate automatic annotation of marine imagery would enable automatic counting, sizing and movement tracking of specific marine organisms. Computer vision and machine learning based techniques [8] have the potential to automate the annotation of marine images and also reduce the time consumed in manual processing. The accuracy of these techniques depends on the availability of high quality expertly annotated training and testing data.

Convolutional Neural Networks (CNNs) [9] are an important class of machine learning algorithms applicable, among others, to numerous computer vision problems. Deep CNNs, in particular, are composed of multiple layers of processing involving linear as well as non-linear operators. To solve a particular task, the parameters of networks are learned in an end-to-end manner. Image representations extracted from deep CNNs trained on a large dataset such as ImageNet [10] have shown to produce a promising performance for diverse classification and recognition tasks [11], [12], [13], [14] and [15]. Spatial Pyramid Pooling (SPP) [16] and Multi-scale Orderless Pooling (MOP) [17] schemes have made CNNs independent of the input image size and robust for diverse classification and recognition applications.

Image representations extracted from pre-trained deep networks have surpassed hand-crafted features in most image classification and recognition tasks. These learned representations are generic and transferable to other domains such as underwater image classification [18]. This technique is an excellent alternative to end to end network training, the latter being time consuming and computationally expensive. To further optimize the training time and accuracy, the pre-trained CNN can be replaced by a faster and more efficient deep network: a pre-trained deep residual network (ResNet) [19]. Image representations extracted from ResNets (termed as ResFeats) outperformed CNN based features for image classification in general and coral image classification in particular. State of the art classification results on MLC dataset [7] were reported in [20].

This paper proposes a computer vision and deep learning based framework to automatically annotate corals and analyse the trends in their population using CNN based features and ResFeats. This framework is based on a novel coral classification algorithm, which employs the powerful image representations of CNNs and ResNets. Since we do not have ground truth labels for millions of coral reef images, a human expert is included in the loop to corroborate the accuracy of the proposed classification method. With the trained coral classifiers, we analyse the coral reefs of the Abrolhos Islands which form one of Western Australia's unique marine areas. We analyse unlabelled coral mosaics of three sites of this coral reef from two years.

The main contributions of this paper are:

1) A supervised coral image classification method to learn image representations using a deep neural network and show that our technique outperforms the existing methods for classification of coral reef images from Western Australia.
2) Automatic annotation of the unlabelled coral images and mosaics from the Abrolhos Islands in Western Australia using our proposed method.
3) Coral population analysis by generating coral maps for the aforementioned mosaics. Our results are validated by a marine expert and the results are in line with the outcomes of previous researches conducted in this region [3].

The rest of the paper is organized as follows: we briefly discuss the related work in the next section. In Sec. III, we present our proposed approach and explain the features extracted from deep networks. Sec. IV reports the experimental results and coral population analysis. Sec. V concludes this paper.

II. Related Work

In 2010, the Collaborative and Automated Tools for the Analysis of Marine Imagery and Video (CATAMI) [21] project was initiated in Australia to introduce a new classification system that ensures consistent names are given to the marine species seen in underwater images. However, this system does not actually automate the data analysis. It just streamlines the process by facilitating manual data entry and provides a standard protocol for assigning ground truth labels. Previous research ([7], [22], [23], [24] and [25]) have highlighted the potential of using computer vision based techniques for the automatic annotation of benthic data. However, this is an uphill task given the factors such as changing water turbidity, ambiguous class boundaries and underwater color degradation.

Since color and texture are the discriminating factors in coral images, color and texture based image descriptors are more suitable for coral classification. Corals have arbitrary shapes and the class boundaries between coral and non-coral regions are not well defined in terms of shape as well. Hence, shape based image descriptors have not been used extensively for this task. Color and texture based features are preferred in tandem to maximize classification accuracy for coral images. Moreover, no generic combination of these features has been found to achieve best results for a variety of coral datasets. Different groups of researchers have relied on multiple combinations of color and texture based features for a given dataset. Essentially, color, texture and shape are the main discriminating factors, and thus associated hand-crafted features were designed. A number of prominent studies conducted for coral classification using hand-crafted features are summarized in the following.

Normalized Chromaticity Coordinate (NCC) for color and Local Binary Pattern (LBP) for texture followed by a 3-layer back propagation neural network were used to classify five classes: living corals, dead corals, corals with algae, abiotics and algae in [26]. Theoretically, NCC features are invariant to illumination conditions and LBP is robust to brightness changes. However, the NCC and LBP features were not discriminative enough for complex underwater images. This method was further used to classify three coral classes in 300 images. A combination of LBP and hue based features improved the performance further [26].

A color based descriptor consisting of normalized color histogram, Bag of Words (BoW) for Scale-Invariant Feature Transform (SIFT) with 24-bin Hue-histograms was used to classify 453 marine images in [23]. A voting scheme was used to classify the test images into 8 classes. The main focus of this approach was to use the color information effectively. Image normalization was employed to overcome illumination variations and underwater color attenuation. However, this method is not suitable for random point annotations and is prone to missing key details in complex images containing multiple species. Also, BoW on SIFT features cannot represent texture accurately in complex underwater scenes. A combination of normalized color histogram and a discrete cosine transform (DCT) descriptors [22] was tested with 3000 images containing 18 distinct classes. For classification, a novel approach was proposed based on probability density weighted mean distances. Although this method is fast, the weights of the descriptors still need to be manually set, rendering it less robust in underwater imagery.

A Maximum Response (MR) filter bank followed by texton maps for feature extraction at multiple scales was proposed in [7] to classify the Moorea Labelled Coral (MLC) dataset (with four non-coral and five coral classes). A dictionary was generated for texton maps using a subset of training images and k-means clustering. Transforming the images into the L*a*b color space boosted the overall performance. A Support Vector Machine (SVM) classifier with a Radial Basis Function (RBF) kernel was employed for classification. MLC dataset contained images from three years: 2008, 2009 and 2010. A temporal survey of the coral reef was presented in this paper as well.

Multiple combinations of hand-crafted features for color and texture (such as Completed Local Binary Patterns (CLBP), grey level co-occurrence matrix (GLCM), Gabor feature, and opponent angle and hue channel color histograms) were accessed for multiple benthic datasets in [25]. For classification, different combinations of basic classifiers (such as SVM, k-nearest neighbours (KNN), neural networks and probability density weighted mean distance (PDWMD)) were proposed. Different combinations of features and classifiers were tested to achieve the best performance for the six test datasets. The descriptors used in this work were modified to deal with scale invariance and variable illumination conditions.

A hybrid approach based on hand-crafted and CNN features for coral classification was proposed in [18]. Domain independent off-the-shelf CNN features were concatenated with the texture and color based features of [7] to complement each other. These hybrid features when tested on MLC dataset, outperformed the previous methods by a significant margin to achieve the state-of-the-art. To the best of our knowledge, this was the first application of off-the-shelf CNN features for coral image classification.

The work in [27] reported the first application of an end-to-end CNN for coral classification.

In their work, reflectance and fluorescent images were combined with the RGB images to obtain a 5-channel hyper-channel images. The fluorescent images encoded the contrast information for the corals and the reflectance images provided context for the non-fluorescent substrates. Since a traditional CNN have only three channels for input (*i.e.*, R, G and B), a novel 5-channel CNN architecture was proposed for the registered images. The performance of this 5-channel CNN was compared with a traditional CNN and also with the baseline performance of [7]. The resulting architecture achieved a 22% reduction in the error rate obtained by the baseline method.

In the following, we describe our proposed method to automate the annotation of coral images and to assess the population of corals in Western Australia. Moreover, three image mosaics of the coral reef of this region are analysed to detect and quantify the trends associated with the coral population.

III. Proposed Method

The proposed method is outlined in Fig. 1. The training image set consists of images from multiple locations in Western Australia, a subset of the Benthoz15 dataset [28]. These images are used to train a deep network which then classifies unlabelled images and mosaics. Marine experts are included in this pipeline to give feedback on the classification accuracy. The best performing classifier is then used to generate coral maps from the mosaics of the Abrolhos Islands. Next, we explain the key components of the proposed method in the following subsections.

A. CNN Features for Coral Classification

Image representations extracted from deep neural networks, trained on large datasets such as ImageNet [9] and fine tuned on domain specific datasets, have shown state-of-art performance in numerous image classification problems [14]. The activation vectors of the first fully connected layer of a pre-trained VGGnet [29] are employed as feature representations in our work. The weights of this deep network are fine tuned using the Benthoz15 dataset [28] which consists of expert-annotated and geo-referenced marine images from Australian seas.

Coral images consist of irregularly shaped assemblages of species, which hinders the segmentation ground truth assignments. Also, a single image may contain multiple species which rules out the possibility of assigning one specie-level label to each image. Subsequently, it is a common practice in marine imagery to annotate the images with randomly selected pixel labels.

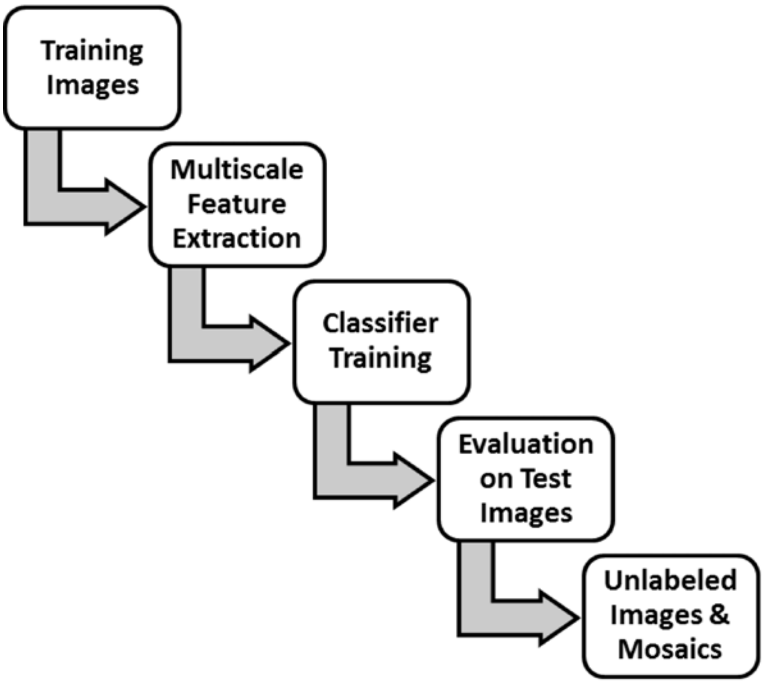

Fig. 1: Block diagram of our proposed framework.

Each training image has up to 200 pixels marked with corresponding ground truth labels. State-of-art deep learning architectures take an input image of a fixed size and hence image or patch ground truth labels are required. To overcome this problem, square patches were extracted with the labelled pixel at their centre. There is no restriction on the size of these patches. Instead of using the whole image for training, we extracted patches at multiple scales centered around the given labelled pixels. We achieved higher classification accuracy when multi-scale patches were used instead of just one fixed size. This technique is termed as spatial pyramid pooling (SPP) [16]. This patch extraction method makes the resulting features scale invariant. A 2-layered neural network was then used to classify corals from non-corals. More details on the classification process are given in our previous work [18].

Selecting patch sizes that give the best classification accuracy is an important step. We trained our classifier using multiple patches at different scales and achieved the best performance when the following four patch sizes were used: 56×56, 112×112, 224×224, and 448×448. Feature extraction at different scales ensures an efficient encoding of coral species independently of

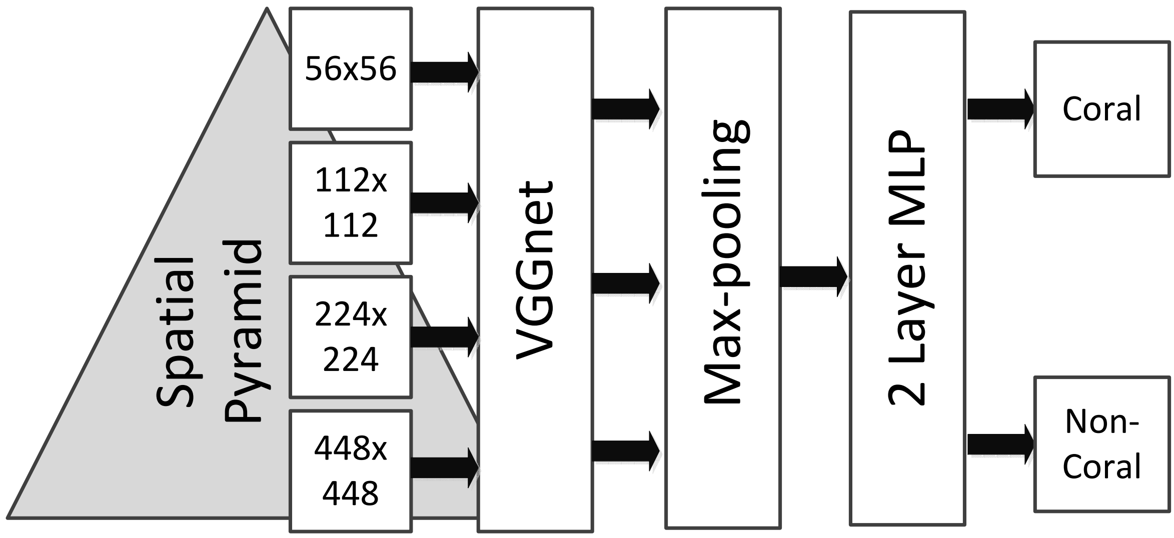

Fig. 2: Block diagram of the proposed classification method for CNN features.

their scale. The image representations extracted at these four scales were then max-pooled to retain the most prominent information, which is present in the neighbourhood of a labelled pixel. These multi-scale deep features were used to train a Multi Layer Perceptron (MLP) network for classification. This network consists of two fully connected hidden layers of neurons followed by an output layer with 2 nodes: corals and non-corals. The number of neurons in the hidden layers was optimized for best performance. Max pooling was used to pool the features extracted at multiple scales to make the feature vector scale invariant. Max pooling followed by an MLP has been shown to outperform an SVM based classification method for coral classification in [18]. Fig. 2 shows the block diagram of our proposed classification method for CNN based features.

B. ResFeats for Coral Classification

Residual networks as deep as 152 layers are still easier to optimize as compared to 19-layer deep CNNs (such as VGGnet [29]). They owe this attribute to residual learning [19] and identity short-cut mappings [30]. We adopted the ResFeat extraction method of [20] and used a 152-layer deep ResNet. In this method, ResFeats are extracted from the deeper convolutional layers of the source network, ResNet-152 [19] in this case. The extracted features are 3-dimensional arrays: the first and the second dimensions being the size of the feature vector and the third dimension represents the number of channels in that layer. These features are used to train a shallow CNN (sCNN) classifier for coral classification with random initializations and the trained network is finally used to annotate the test images. ResFeats extracted from the last convolutional layer are 3-dimensional arrays (i.e., $7 \times 7 \times 2048$). In order to use SVMs for such large feature vectors, a dimensionality reduction step must be included. The first convolutional layer of the 4-layer sCNN classifier reduces the dimension of ResFeats. Experimental results given in the next section demonstrated the superior discriminating power of ResFeats compared to CNN features. Therefore, we opted to use ResFeats for further experiments. Fig. 3 shows the block diagram of our proposed classification method for ResFeats.

Multi-scale Data Augmentation: To address the inherent class imbalance problem, we propose to sub-sample the majority class *i.e.*, non-corals and augment the minority class *i.e.*, corals with patches extracted at multiple scales. Scale selection is more important for corals than non-corals because of the varying size of coral species. Note that the max-pooling module of Fig. 2 has been replaced by a data augmentation module in Fig. 3. In order to increase the number of coral samples in our training data, we extract the coral patches at four different scales (56, 112, 224 and 448 pixel square patches) and augment them instead of taking a max-pool. This technique effectively increases the number of coral samples by a factor of four. It also removes any scale invariance in corals. Non-coral patches are only extracted at one suitable scale, square patches of 112 pixels, and used for training the classifier. This data augmentation technique proved effective in decreasing the number of misclassification instances of corals at test time. Further discussion on ResFeats for coral classification and experiments with data augmentation are provided in the next section.

C. *Unlabelled Mosaics and Coral Maps*

In order to validate the automatic annotations, unlabelled images and mosaics from the Abrolhos Islands were annotated with the best performing trained coral classifier. We analysed mosaics of three different sites of the Abrolhos Islands spanning an area of 625 sq. meters each for years 2010 and 2013. Fig. 4 shows the path followed by the Sirius AUV [28] to capture the coral reef and some sample images. A marine expert was added in the loop to validate the labels assigned by this classifier and to assert that the trained model is reasonably good. After validation, the coral mosaics of each site were analysed to investigate the changes in the coral population. We focused on generating coral maps for these sites to investigate the health of coral population for each site over a period of three years. These coral maps were automatically

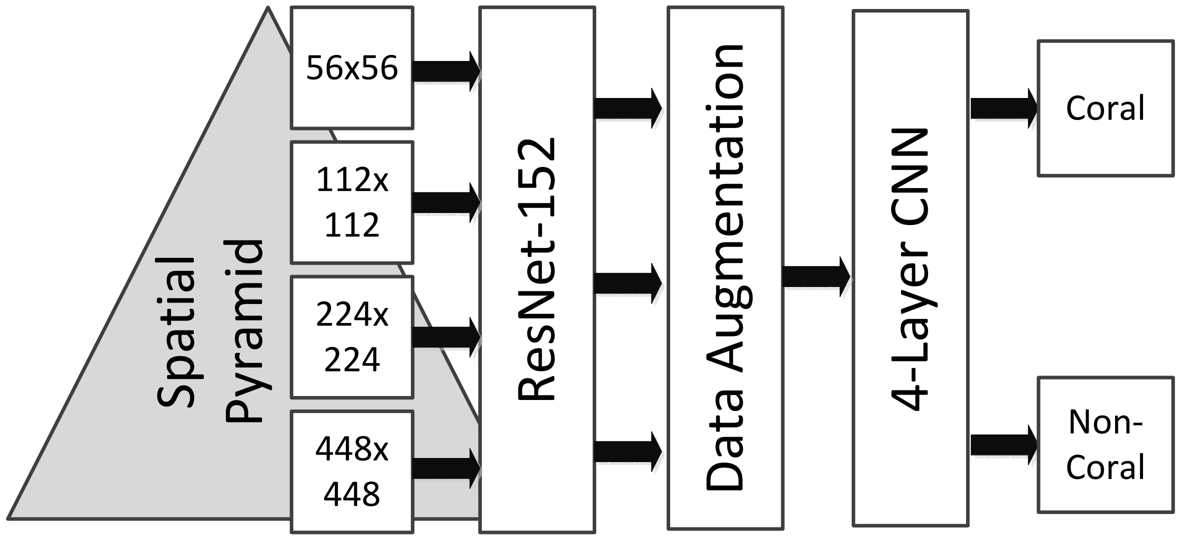

Fig. 3: Block diagram of the proposed classification method for ResFeats.

generated by our classifier and provide useful insight for quantifying the population changes of the reef. Marine experts included in the loop to corroborate the accuracy of these maps validated the results of our proposed method.

IV. Experiments and Results

A. *Benthoz15 Dataset*

This Australian benthic data set (Benthoz15) [28] consists of an expert-annotated set of georeferenced benthic images and associated sensor data, captured by an autonomous underwater vehicle (AUV) around Australia. Many marine experts spent several minutes to manually annotate each of these images according to the CATAMI protocols. For each image, up to 50 randomly selected pixels were hand labelled using the Coral Point Count with Excel Extensions (CPCe) software package [31]. The whole dataset contains 407,968 expert labelled points, on 9,874 distinct images collected at different depths from nine sites around Australia over the past few years. We have used only a subset of this dataset containing images from Western Australia (WA) to train our classifier. This subset consists of 3,749 images with 237,923 expert-annotated points collected over a span of 3 years (2011 to 2013). There are 35 distinct class labels in this subset, with pixel labels ranging from 7 to 56,000 per class. This makes the classification quite challenging. Nine out of these 35 classes belong to coral species. Table I details some statistics

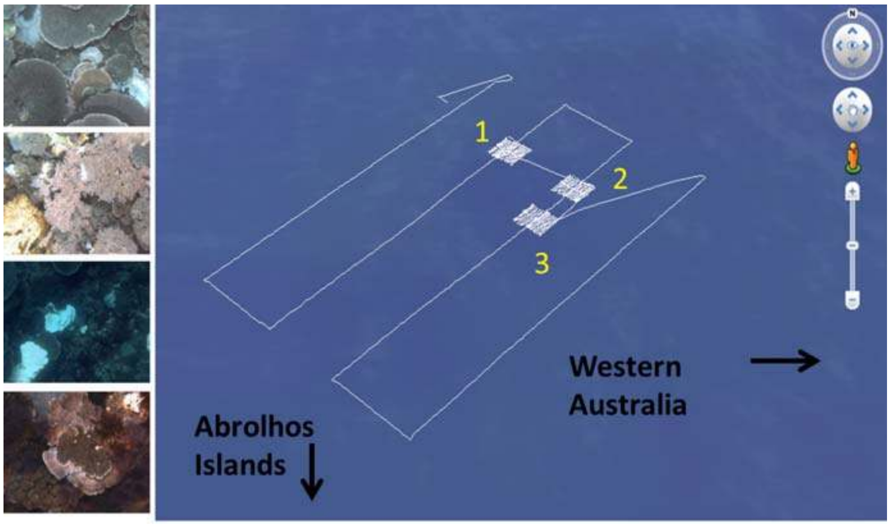

Fig. 4: The path traversed and the three 25×25 m grids surveyed by the Sirius AUV over the 3 years near the Abrolhos Islands in WA and sample images. Location is 28° 48’ S and 113° 57’ E. The depth of these sites is 15 meters. Four sample images from this region are shown as well.

Site	Survey Year	# of Labels	# of Images
Abrolhos Islands	2011, 2012, 2013	119,273	1,377
Rottnest Island	2011	63,600	1,272
Jurien Bay	2011	55,050	1,101

TABLE I: WA subset of Benthoz15 in numbers.

of the Western Australia (WA) subset of this dataset. For binary classification experiments, all the coral species are merged together in one class and the remaining classes are bundled together in a non-coral class. For multi-class classification experiments, nine coral classes are retained and the non-coral classes are merged in one class, resulting in 10 distinct classes. Table. VII in the appendix details the class labels and number of training and test samples for each class.

B. Pre-processing and Implementation Details

We applied color channel stretch on each image in the dataset. We calculated the 1% and 99% intensity percentiles for each color channel. The lower intensity was subtracted from all the

Experiment	# of Training Samples	Coral Samples	# of Test Samples	Coral Samples
Exp 1: Train and test on 2011	108,000	9,636	53,000	4,624
Exp 2: Train on 2011 and test on 2012 and 2013	108,000	9,636	129,923	23,884
Exp 3: Train and test on 2011,2012 and 2013	157,173	22,678	80,750	10,824
Exp 4: Exp 3 with multi-scale data augmentation	88,665	51,150	43,440	24,442

TABLE II: Training and test set distribution of different experiments with the number of coral samples in each set.

intensities in each respective channel and the negative values were set to zero. These intensities were then divided by the upper percentile. The resulting intensities achieved a better performance compared to the original ones.

We used two deep network architectures in our experiments namely VGG-16 (configuration D) [29] and ResNet-152 [19]. We used the publicly available models of these two networks, which were pre-trained on the ImageNet dataset [9]. We implemented our proposed method and the sCNN classifier network using MatConvNet [32].

C. Binary Classification with CNN Features

We conducted three sets of experiments to evaluate our classifier: **(i)** the classifier was trained on two-thirds of the images from the year 2011 and tested on the remaining images from the same year, **(ii)** the images from year 2011 were used for training while the images from 2012 and 2013 formed the test set, **(iii)** the training set consisted of two-thirds of the images from the years 2011, 2012 and 2013, whereas the test set consisted of all the remaining images from the same years. Table III shows the details of our experiments and reports the results of coral classification on the Benthoz15 dataset. We used a 3-fold cross validation scheme in our experiments and the mean classification accuracies are reported in Table III along with the standard deviations. We achieved a classification accuracy greater than 90% in all of our experiments. Table III also shows that our MLP classifier consistently outperforms the linear SVM classifier. The best performance is achieved when the training and testing sets contain images from the same year. The performance dropped when the experiments were done across multiple years. This illustrates the difficulty encountered when the training and test set have images from different years. This may be due to the changes occurring in the coral reefs with

Method	Experiment	Accuracy (%)	Precision (%)	Recall (%)
CNN Features + SVM	Exp 1: Train and test on 2011	96.1±0.6	98±1.0	82±1.5
	Exp 2: Train on 2011 and test on 2012 and 2013	91.4±0.4	90±1.0	79±1.0
	Exp 3: Train and test on 2011,2012 and 2013	95.1±0.5	97±1.0	84±1.5
	Exp 4: Exp 3 with multi-scale data augmentation	89.0±0.5	88±1.5	89±1.0
CNN Features + MLP	Exp 1: Train and test on 2011	96.5±0.5	99±0.5	80±1.0
	Exp 2: Train on 2011 and test on 2012 and 2013	92.3±0.3	96±1.0	70±1.5
	Exp 3: Train and test on 2011,2012 and 2013	95.3±0.4	91±1.0	82±1.0
	Exp 4: Exp 3 with multi-scale data augmentation	89.6±0.6	89±1.0	90±1.0
ResFeats + SVM	Exp 1: Train and test on 2011	97.0±0.3	99±0.5	80±1.5
	Exp 2: Train on 2011 and test on 2012 and 2013	92.4±0.4	95±1.0	70±1.0
	Exp 3: Train and test on 2011,2012 and 2013	95.1±0.6	93±1.5	85±1.5
	Exp 4: Exp 3 with multi-scale data augmentation	91.1±0.4	91±1.0	90±1.0
ResFeats + sCNN	Exp 1: Train and test on 2011	**97.3**±0.3	99±0.0	81±1.0
	Exp 2: Train on 2011 and test on 2012 and 2013	**94.0**±0.3	97±1.0	71±1.5
	Exp 3: Train and test on 2011,2012 and 2013	**96.6**±0.4	95±1.0	84±1.0
	Exp 4: Exp 3 with multi-scale data augmentation	**91.8**±0.5	93±0.0	93±1.0

TABLE III: Overall classification accuracies for different experiments using the methods of the first column along with the precision and the recall values for coral class.

time. The major causes of misclassification were: the ambiguous boundaries between corals and non-corals, dead corals (non-coral species start covering corals) and the imbalance between the coral and non-coral labels in the dataset.

However, the recall values of corals are less than precision for each of these three experiments. Improving the recall for corals is as important as improving the precision or overall accuracy of the classifier. For a single image with 50 labelled coral points, a recall of value of 80% implies that 10 coral labels will be misclassified as non-corals. One might add that with an accuracy of 98%, 49 out of 50 points are correctly identified in every image. It is worth noting here that the training data is imbalanced towards non-corals and a higher overall classification accuracy alone cannot justify the classification performance. In the next sub-section, we use ResFeats along with multi-scale data augmentation to improve the recall for corals at the expense of a slight decrease in precision.

D. Binary Classification with ResFeats

Table III shows the overall classification accuracies of ResFeats for the three baseline experiments and a fourth experiment with data augmentation at multiple scales. ResFeats achieves higher classification accuracy than the CNN based features. For experiment 4, the coral samples from the year 2011 are extracted at four scales to decrease the majority of non-corals in the training and test sets. Images from the years 2012 and 2013 are used without any augmentation. The non-corals from 2011 are sub-sampled as well. Table II shows that the coral samples form less than 15% of the training set for the first three experiments. After data augmentation, the percentage of the coral samples in the training set has increased to 57%. Therefore, the resulting training set for experiment 4 is less imbalanced. ResFeats achieve a classification accuracy of 91.90% in this experiment which is lower than the first three experiments. However, the precision and recall values for coral class are 93% each. For every given image with 50 randomly selected points, our classifier will correctly annotate 46 points. Moreover, for every 50 points which are corals, 46 points will be correctly annotated as corals. The resulting classifier can annotate 3 images per minute with 50 sample points per image, implying an annotation rate of 180 images per hour (9000 points per hour or 2.5 points per second) for coral images. The average time for the manual annotation with 50 sample points per image is 8 minutes, or equivalently, a trained marine scientist can annotate up to 8 images per hour (400 points per hour).This fact emphasizes on the efficiency of our proposed method.

E. Multi-class Classification

Up until now, we have discussed the classification experiments between two classes: corals and non-corals. There are nine coral classes in the Benthoz15 dataset with the number of annotated points per class ranging from 7 to 10,000. All the non-coral species in this dataset are bundled into one non-coral class for this experiment resulting in a total of 10 classes. Table IV compares the overall classification accuracies achieved by CNN based features with ResFeats in this experiment. ResFeats outperformed the traditional CNN features by a margin of 4.46%. The main reason of classification errors in the multi-class experiment is the under representation of some coral classes in the training data of Benthoz15. Table V outlines the class distribution of the Benthoz15 dataset used in multi-class classification experiment and also shows precision and recall values for each class for the best performing CNN features and ResFeats methods respectively.

Method	# of Classes	Accuracy (%)
CNN Features + SVM	10(9 coral, 1 non-coral)	76.3±0.6
CNN Features + MLP	10(9 coral, 1 non-coral)	76.6±0.5
ResFeats + SVM	10 (9 coral, 1 non-coral)	80.4±0.4
ResFeats + sCNN	10 (9 coral, 1 non-coral)	**81.1**±0.5

TABLE IV: Overall classification accuracies for multi-class coral classifaction on Benthoz15 dataset.

F. Coral Population Analysis

For the coral population analysis of the Abrolhos Islands, we automatically annotated the unlabelled mosaics using our best binary classifier: ResFeats + sCNN from experiment 4. We opted for this classifier due to its high recall rate for coral class. Outputs were validated by a marine expert as ground-truth labels were not available. A human expert requires on average 256 minutes to manually label a mosaic of this size (1600 pixel labels). However, our algorithm automatically annotated these 1600 pixel points in under 11 minutes. Coral cover maps were then generated using the best performance classifier for years 2010 and 2013, and percentage coral cover was calculated for each site and year. Fig. 5 shows a geographical map of these three sites. The results of this analysis reveal a decline in coral coverage at all three sites between years 2010 and 2013 as reported in Table VI. Fig. 6 presents the coral maps of the three sites generated using our method for year 2010 and 2013. A decrease in coral population is evident from these coral maps for all the sites under study. This loss of corals was expected as an acute warming event occurred in 2011, which resulted in significant coral bleaching [3]. Importantly, the magnitude of decline reported here is comparable to those previously reported across a similar time period for the Abrolhos Islands from imagery annotated by marine experts, with an average decline in coral cover from 73% to 59% across multiple sites [3]. Moreover, the mosaics which were provided by marine experts had small registration errors and missing data. This accounts for the minor changes from “non-corals” to “corals” in the coral maps which are generated by our algorithm (*e.g.*, the bottom left corner of Fig. 6 b and e).

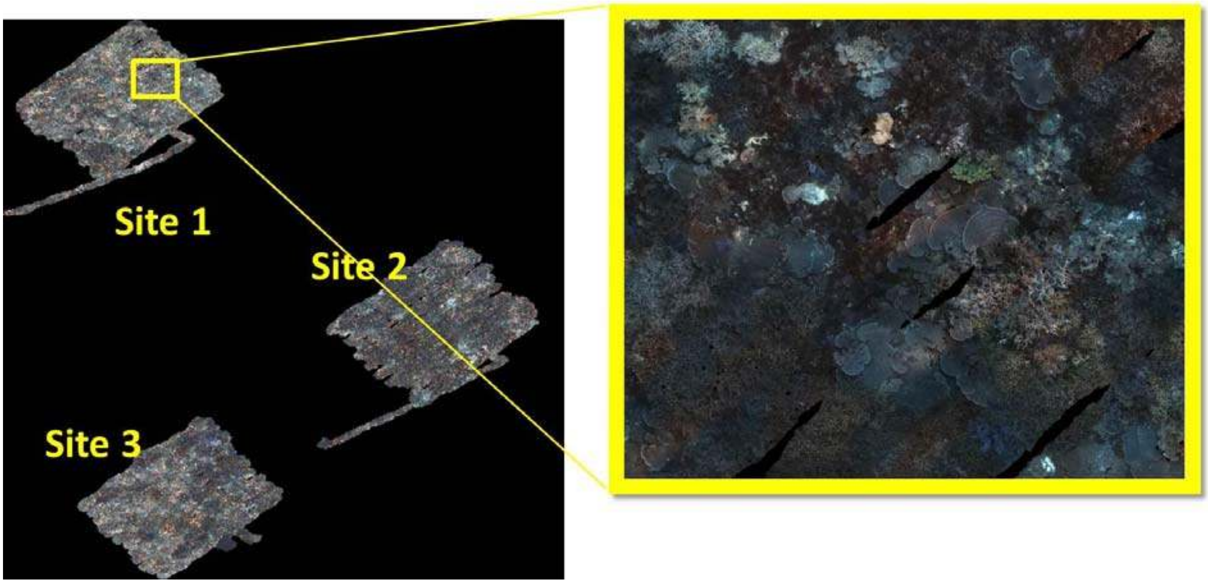

Fig. 5: Left: Map for the three sites of the Abrolhos Island. Right: A zoom-in to a small area of site 1 mosaic.

Class	Training	Test	CNN: Pr (%)	CNN: Re (%)	ResFeats: Pr (%)	ResFeats: Re (%)
Non-corals	142876	61527	86±1.5	95±1.0	91±1.0	95±1.0
Cnidaria	24	4	0±0.0	-	0±0.0	-
Cnidaria: Corals	9277	3871	54±1.0	44±1.0	60±1.0	49±1.0
Cnidaria: Corals: Stony corals	12713	5195	56±1.0	42±1.0	60±1.0	50±1.0
Cnidaria: Corals: Stony corals: Sub-massive	84	27	0±0.0	0±0.0	0±0.0	-
Cnidaria: Corals: Stony corals: Massive	35	17	0±0.0	0±0.0	0±0.0	-
Cnidaria: Corals: Stony corals: Encrusting	1237	616	8±1.0	7±1.0	11±1.0	11±1.0
Cnidaria: Corals: Black & Octocorals	9	0	-	-	-	-
Cnidaria: Corals: Black & Octocorals: Whip	10	1	0±0.0	-	0±0.0	-
Bryozoa	307	93	0±0.0	0±0.0	0±0.0	0±0.0

TABLE V: Class distribution of WA subset of Benthoz15 dataset for multi-class classification alongwith precision (Pr) and recall (Re) values for the two multi-class classification experiments: CNN Features + MLP and ResFeats + sCNN

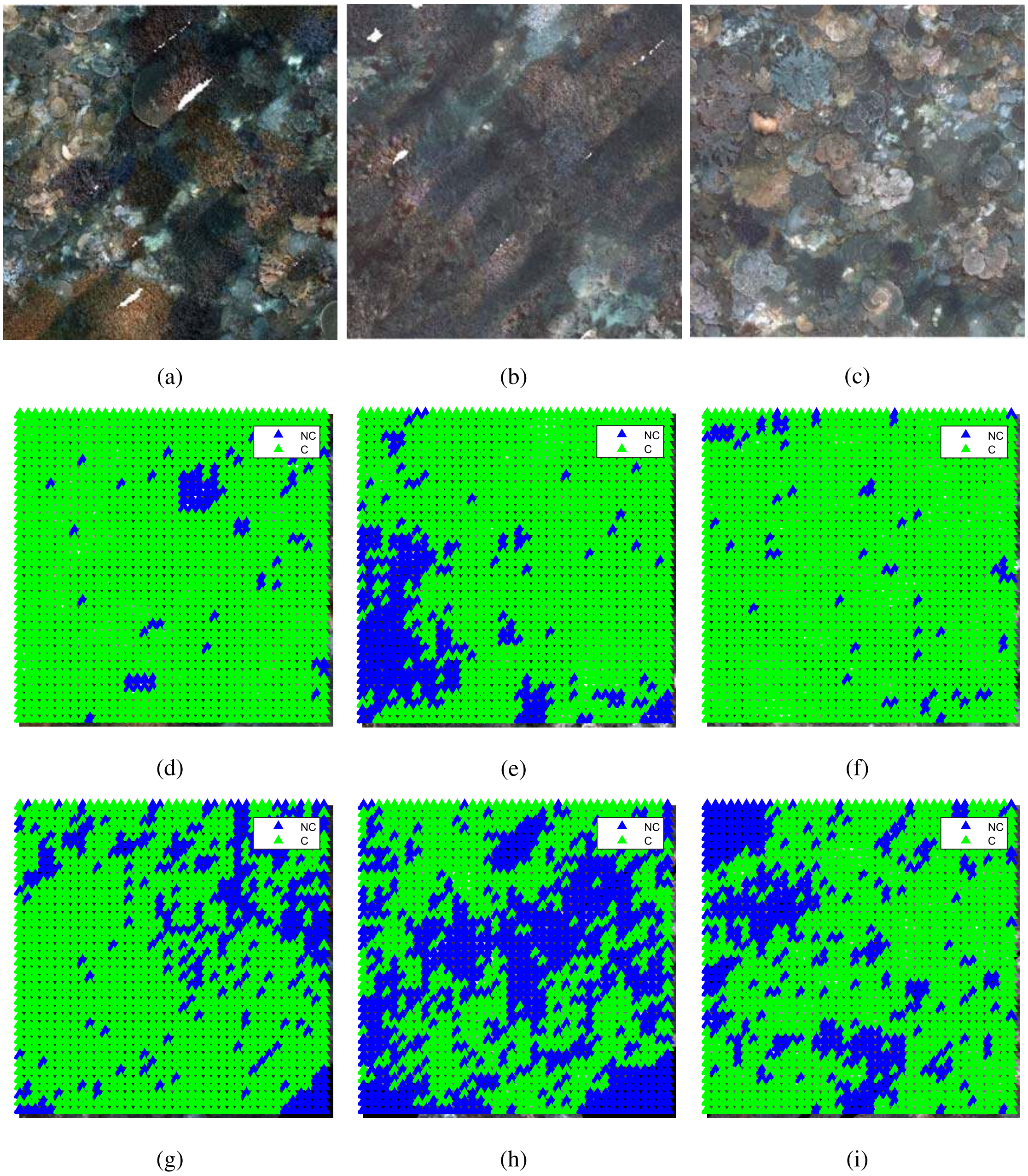

Fig. 6: Coral Maps for the 3 sites of the Abrolhos Island; (a-c) Mosaics for 2010 for the three sites; (d-f) Coral Maps for 2010 for the three sites and (g-i) Coral Maps for 2013 for the respective sites. *Legend key: C is coral and NC is non-coral.*

Site	Coral Coverage in 2010	Coral Coverage in 2013
1	95%	79%
2	82%	53%
3	96%	74%

TABLE VI: Coral coverage of three sites of the Abrolhos Islands for years 2010 and 2013.

V. Conclusion

In this work, we exploited pre-trained image representations extracted from deep neural networks to a coral reef classification problem. We applied generic features extracted from VGGnet and ResNet to classify corals and non-corals. We further investigated the effectiveness of the best trained classifier on unlabelled coral mosaics of the Abrolhos Islands. We analysed the coral reef of this WA region to investigate the trends in coral population. We generated coral maps from the mosaics of this region and quantified the coral population automatically. Our framework automatically detected the decreasing trend in the coral population of this region observed from 2011 to 2013, which is consistent with the previous findings. The proposed framework is an important step towards investigating the long-term effects of environmental change on the effective sustenance of marine ecosystems automatically. The ability to efficiently report coral response to particular impacts (such as intense warming events) or gradual environmental change, is crucial for implementing appropriate management strategies [4]. Our initial results indicate that the combination of AUVs and automated image analysis have the capacity to improve the efficiency of transferring information to managers and policy makers. Our results also aim to offer useful insights for the automatic annotations of benthic images and the limitations of the assessment framework. Future work will extend the proposed automatic population analysis to species of corals in order to generate specie-level spatial and temporal coral distribution maps.

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Appendix

A. Class Distribution of Benthoz15 WA Subset

TABLE VII: Class distribution of WA subset of Benthoz15 dataset

Label	Class ID	Training Samples	Test Samples	Class Name
1	2	39	15	Biota
2	13	2795	1098	Sponges
3	30	26	13	Seagrasses
4	33	8	2	Molluscs: Gastropods
5	38	1	2	Molluscs: Bivalves
6	39	51766	21884	Macroalgae
7	42	32	9	Macroalgae: Sheet-like / membraneous: Green
8	44	30	16	Macroalgae: Large canopy-forming
9	45	41461	17540	Macroalgae: Large canopy-forming: Brown
10	54	149	81	Macroalgae: Filamentous / filiform
11	64	938	471	Macroalgae: Erect coarse branching: Green
12	65	326	144	Macroalgae: Erect coarse branching: Brown
13	66	12688	5515	Macroalgae: Encrusting
14	67	6738	3343	Macroalgae: Encrusting: Red
15	71	1130	333	Macroalgae: Articulated calcareous: Red
16	88	14	3	Echinoderms
17	89	8	2	Echinoderms: Sea urchins
18	118	24	4	Cnidaria
19	126	9277	3871	Cnidaria: Corals
20	127	12713	5195	Cnidaria: Corals: Stony corals
21	129	84	27	Cnidaria: Corals: Stony corals: Sub-massive
22	134	35	17	Cnidaria: Corals: Stony corals: Massive
23	137	1237	616	Cnidaria: Corals: Stony corals: Encrusting
24	143	9	0	Cnidaria: Corals: Black & Octocorals
25	144	10	1	Cnidaria: Corals: Black & Octocorals: Whip
26	165	307	93	Bryozoa
27	231	182	64	Ascidians
28	239	755	296	Substrate
29	241	14535	6268	Substrate: Unconsolidated (soft): Sand / mud (<2mm)
30	245	187	97	Substrate: Unconsolidated (soft): Pebble / gravel
31	249	19	2	Substrate: Unconsolidated (soft): Pebble / gravel: Biologenic: Coral rubble
32	253	6037	2870	Substrate: Consolidated (hard): Rock
33	273	2310	1009	Unscorable.
34	274	103	17	Not of Interest
35	655	599	433	Unknown