THE UNIVERSITY of EDINBURGH

Edinburgh Research Explorer

Automatic annotation of coral reefs using deep learning

Citation for published version:
Mahmood, A, Bennamoun, M, An, S, Sohel, F, Boussaid, F, Hovey, R, Kendrick, G & Fisher, RB 2016, Automatic annotation of coral reefs using deep learning. in *OCEANS 2016 MTS/IEEE Monterey.* Institute of Electrical and Electronics Engineers, pp. 1-5, OCEANS 2016 MTS/IEEE Monterey, Monterey, California, United States, 19/09/17. https://doi.org/10.1109/OCEANS.2016.7761105

Digital Object Identifier (DOI):
10.1109/OCEANS.2016.7761105

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Peer reviewed version

Published In:
OCEANS 2016 MTS/IEEE Monterey

General rights
Copyright for the publications made accessible via the Edinburgh Research Explorer is retained by the author(s) and / or other copyright owners and it is a condition of accessing these publications that users recognise and abide by the legal requirements associated with these rights.

Take down policy
The University of Edinburgh has made every reasonable effort to ensure that Edinburgh Research Explorer content complies with UK legislation. If you believe that the public display of this file breaches copyright please contact openaccess@ed.ac.uk providing details, and we will remove access to the work immediately and investigate your claim.

OPEN ACCESS

Download date: 12. Oct. 2024

Automatic Annotation of Coral Reefs using Deep Learning

A. Mahmood*, M. Bennamoun*, S. An*, F. Sohel†, F. Boussaid*, R. Hovey*, G. Kendrick* and R.B. Fisher‡
*The University of Western Australia, Australia; email: ammar.mahmood@research.uwa.edu.au
†Murdoch University, Australia
‡University of Edinburgh, Scotland

***Abstract*—Healthy coral reefs play a vital role in maintaining biodiversity in tropical marine ecosystems. Deep sea exploration and imaging have provided us with a great opportunity to look into the vast and complex marine ecosystems. Data acquisition from the coral reefs has facilitated the scientific investigation of these intricate ecosystems. Millions of digital images of the sea floor have been collected with the help of Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs). Automated technology to monitor the health of the oceans allows for transformational ecological outcomes by standardizing methods for detecting and identifying species. Manual annotation is a tediously repetitive and a time consuming task for marine experts. It takes 10-30 minutes for a marine expert to meticulously annotate a single image. 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, accuracy and thus in better quantifying the level of environmental change marine ecosystems can tolerate. We propose a deep learning based classification method for coral reefs. We also report the application of the proposed technique towards the automatic annotation of unlabelled mosaics of the coral reef in the Abrolhos Islands, Western Australia. Our proposed method automatically quantifies the coral coverage in this region and detects a decreasing trend in coral population which is in line with conclusions by marine ecologists.**

***Index Terms*—corals, deep learning, marine images, classification, marine ecosystems.**

I. Introduction

The automatic annotation of marine images allows for transformational ecological outcomes by standardizing methods to detect and identify species. It frees up experts from the tediously repetitive task of manual annotation. It also enables rapid and accurate processing of massive datasets. An ever expanding human activity coupled with climate change have severely damaged marine ecosystems, which play a key role in our planet's ability to sustain life. Yet accurate automated technology to monitor the health of our oceans exist only on a limited scale. Marine scientists still have to manually annotate a massive amount of raw underwater imagery. This research aims to address this bottleneck by developing advanced deep learning and computer vision based models for automatic annotation of imagery from coral reefs.

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 pollution, industrial fishing and exploitation of marine resources. This has resulted in a dramatic decline in our planet's marine biodiversity [5]. 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 flight path, producing geo-referenced imagery of the sea-floor [6]. However, analysing 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 loss 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], also known as deep networks, 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.

In this paper, we propose a computer vision and deep learning based framework for the automatic annotation of unlabelled coral images. This framework is based on a novel coral classification algorithm, which employs the powerful image representations of CNNs. Since we do not have ground truth labels for millions of coral reef images, a human expert

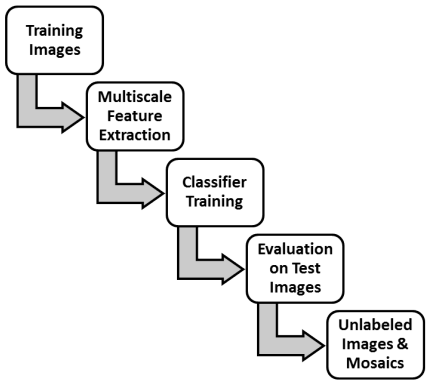


Fig. 1: Block diagram of our proposed framework.

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 include: **(1)** a method to learn features using a CNN for coral reef classification; **(2)** automatic annotation of unlabelled coral images and mosaics from the Abrolhos Islands in Western Australia; **(3)** coral population analysis for these mosaics.

II. Related Work

In 2010, Collaborative and Automated Tools for the Analysis of Marine Imagery and Video (CATAMI)[18] was initiated in Australia. It introduced a new classification system to ensure that 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 project by facilitating manual data entry and provides a standard protocol for assigning ground truth labels. Previous research ([7], [19], [20], [21] and [22]) 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.

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 Benthoz15 dataset [23]. 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. Classification Process

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 [24] are employed as feature representations in our work. The weights of this deep network are fine tuned using the Benthoz15 dataset [23] which consists of expert-annotated and geo-referenced marine images from Australian seas.

It is a common practice in marine imagery to annotate the images with pixel labels. Each training image has 50 pixels marked with corresponding ground truth labels. State-of-art deep learning architectures take an input image of fixed size and hence image or patch ground truth labels are required. To overcome this bottleneck, 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 centred 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 [25].

B. Unlabelled Mosaics and Coral Maps

The 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. 2 shows the path followed by the Sirius AUV [23] 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. 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 generated by our classifier and provide useful insight for quantifying the population changes of the reef. Marine experts were included in the pipeline to corroborate and comment on the authenticity of these maps.

IV. Experiments and Results

A. Benthoz15 Dataset

This Australian benthic data set (Benthoz15) [23] consists of an expert-annotated set of georeferenced benthic images and associated sensor data, captured by an autonomous underwater vehicle (AUV) around Australia. 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. There are almost 40 distinct class

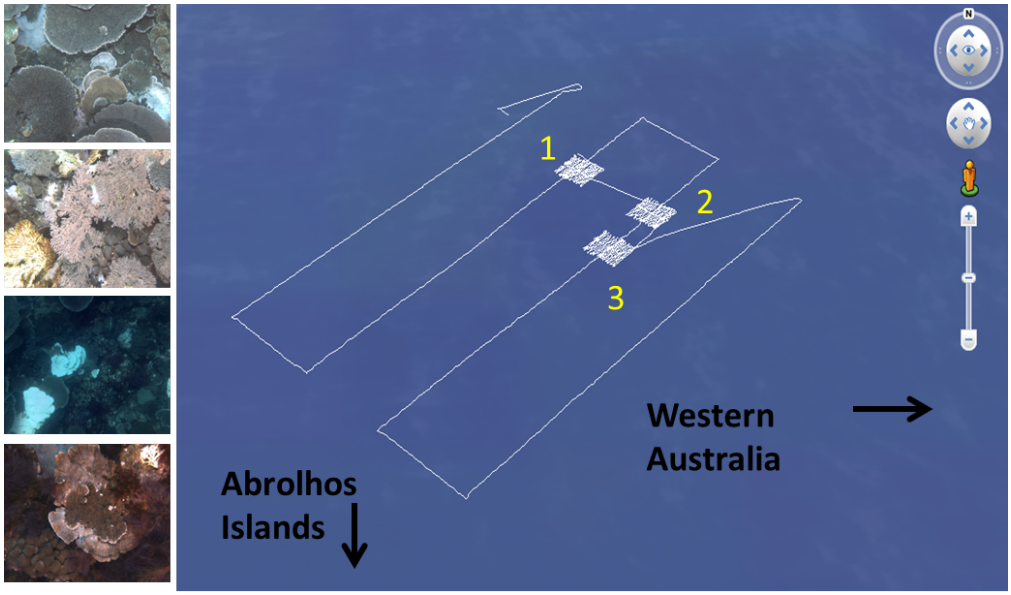


Fig. 2: The path traversed by the Sirius AUV over the 3 years near the Abrolhos Islands in WA and sample images. Latitude=28 degrees 48 minutes South. Longitude = 113 degrees and 57 minutes East.

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.

labels in this dataset which make it quite challenging. Table. I details some statistics of the Western Australia (WA) subset of this dataset. We have used a subset of this dataset containing images from Western Australia (WA) to train our classifier. This subset consists of 4,750 images with 237,500 expert-annotated points collected over a span of 3 years (2011 to 2013).

B. Pre-processing

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 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.

C. Classification Experiments and Results

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 these three patch sizes were used: 28×28, 224×224, and 448×448. These correspond to small, medium and large scales. Feature extraction at different sizes insures an efficient encoding of coral species independently of their size.

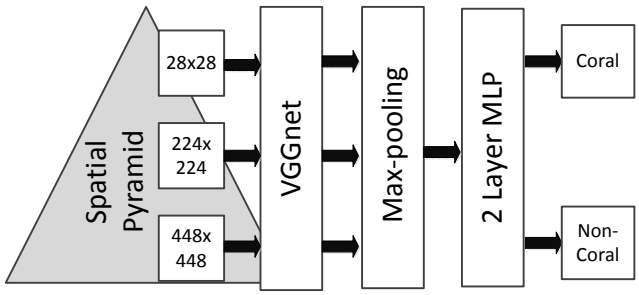


Fig. 3: Block diagram of the proposed classification method.

The image representations extracted at these three 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 were optimized for maximum performance. Fig. 3 shows the block diagram of our proposed classification method.

We conducted three 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 and the images from 2012 and 2013 constitute 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 consists of all the remaining images from the same years. Table. II shows the details and reports the preliminary results

Experiment	# of Training Samples	# of Test Samples	Accuracy
Exp 1: Train and test on 2011	108,000	53,000	97.00%
Exp 2: Train on 2011 and test on 2012 and 2013	108,000	130,000	92.45%
Exp 3: Train and test on 2011,2012 and 2013	157,173	80,750	95.33%

TABLE II: Overall classification accuracies for different experiments

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

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

of coral classification on Benthoz15 dataset. We achieved a classification accuracy greater than 90% in all of our experiments.

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. The main reason being the changes occurring in the coral reefs with 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 abundance of non-coral labels in the dataset.

D. Coral Population Analysis

For the coral population analysis of the Abrolhos Islands, we automatically annotated the unlabelled mosaics using our best classifier. Outputs were validated by a marine expert as ground-truth labels were not available. 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. Results of this analysis reveal a decline in coral cover at all three from 2010 to 2013. This loss of corals was expected as an acute warming event occurred in 2011 which resulted in significant coral bleaching. 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]. 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 our efficiency of transferring information to managers and policy makers.

V. Conclusion

In this work, we applied pre-trained CNN image representations extracted from VGGnet to a coral reef classification problem. We investigated the effectiveness of our trained classifier on unlabelled coral mosaics of the Abrolhos Islands. We analysed the coral reef of the Abrolhos Islands to investigate the trends in coral population. We generated coral maps for this region and quantified the coral population automatically. Our framework detected the decreasing trend in the coral population of this region as well. The proposed framework is an important step towards investigating the long-term effects of environmental change on the effective sustenance of marine ecosystems automatically.

Acknowledgment

This research was partially supported by Australian Research Council Grants (DP150104251 and DE120102960) and the Integrated Marine Observing System (IMOS) through the Department of Innovation, Industry, Science and Research (DIISR), National Collaborative Research Infrastructure Scheme. The authors also acknowledge NVIDIA for providing a Titan-X GPU for the experiments involved in this research.

References

[1] S. C. Doney, M. Ruckelshaus, J. E. Duffy, J. P. Barry, F. Chan, C. A. English, H. M. Galindo, J. M. Grebmeier, A. B. Hollowed, N. Knowlton, *et al.*, "Climate change impacts on marine ecosystems," *Marine Science*, vol. 4, 2012.

[2] O. Hoegh-Guldberg, P. J. Mumby, A. J. Hooten, R. S. Steneck, P. Greenfield, E. Gomez, C. D. Harvell, P. F. Sale, A. J. Edwards, K. Caldeira, *et al.*, "Coral reefs under rapid climate change and ocean acidification," *science*, vol. 318, no. 5857, pp. 1737–1742, 2007.

[3] T. C. Bridge, R. Ferrari, M. Bryson, R. Hovey, W. F. Figueira, S. B. Williams, O. Pizarro, A. R. Harborne, and M. Byrne, "Variable responses of benthic communities to anomalously warm sea temperatures on a high-latitude coral reef," *PloS one*, vol. 9, no. 11, p. e113079, 2014.

[4] T. P. Hughes, A. H. Baird, D. R. Bellwood, M. Card, S. R. Connolly, C. Folke, R. Grosberg, O. Hoegh-Guldberg, J. Jackson, J. Kleypas, *et al.*, "Climate change, human impacts, and the resilience of coral reefs," *science*, vol. 301, no. 5635, pp. 929–933, 2003.

[5] B. Worm, E. B. Barbier, N. Beaumont, J. E. Duffy, C. Folke, B. S. Halpern, J. B. Jackson, H. K. Lotze, F. Micheli, S. R. Palumbi, *et al.*, "Impacts of biodiversity loss on ocean ecosystem services," *science*, vol. 314, no. 5800, pp. 787–790, 2006.

[6] S. B. Williams, O. R. Pizarro, M. V. Jakuba, C. R. Johnson, N. S. Barrett, R. C. Babcock, G. A. Kendrick, P. D. Steinberg, A. J. Heyward, P. J. Doherty, *et al.*, "Monitoring of benthic reference sites: using an autonomous underwater vehicle," *IEEE Robotics & Automation Magazine*, vol. 19, no. 1, pp. 73–84, 2012.

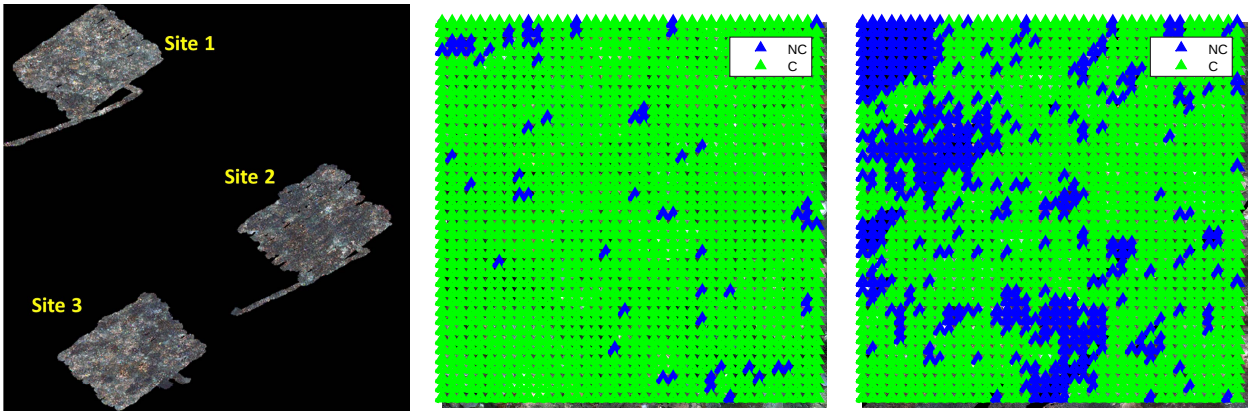
[7] O. Beijbom, P. J. Edmunds, D. Kline, B. G. Mitchell, D. Kriegman, *et al.*, "Automated annotation of coral reef survey images," in *2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1170–1177, IEEE, 2012.

[8] C. M. Bishop, "Pattern recognition," *Machine Learning*, vol. 128, 2006.

[9] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, pp. 1097–1105, 2012.

[10] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "Imagenet: A large-scale hierarchical image database," in *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 248–255, IEEE, 2009.

[11] J. Donahue, Y. Jia, O. Vinyals, J. Hoffman, N. Zhang, E. Tzeng, and T. Darrell, "Decaf: A deep convolutional activation feature for generic visual recognition," *International Conference on Machine Learning (ICML)*, pp. 647–655, 2014.



(a) (b) (c)

Fig. 4: Mosaics and Coral Maps: (a) the 3 sites of the Abrolhos Island; (b) Site 3 Coral Map for 2010 and (c) Site 3 Coral Map for 2013. *Legend key: C is coral and NC is non-coral*

[12] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in *2014 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 580–587, IEEE, 2014.

[13] M. Oquab, L. Bottou, I. Laptev, and J. Sivic, "Learning and transferring mid-level image representations using convolutional neural networks," in *2014 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1717–1724, IEEE, 2014.

[14] A. S. Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, "Cnn features off-the-shelf: an astounding baseline for recognition," in *2014 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, pp. 512–519, IEEE, 2014.

[15] S. H. Khan, M. Hayat, M. Bennamoun, R. Togneri, and F. A. Sohel, "A discriminative representation of convolutional features for indoor scene recognition," *IEEE Transactions on Image Processing*, vol. 25, no. 7, pp. 3372–3383, 2016.

[16] Y. Gong, L. Wang, R. Guo, and S. Lazebnik, "Multi-scale orderless pooling of deep convolutional activation features," in *Computer Vision–ECCV 2014*, pp. 392–407, Springer, 2014.

[17] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," in *European Conference on Computer Vision (ECCV)*, pp. 346–361, Springer, 2014.

[18] L. Edwards, "Catami classification scheme for scoring marine biota and substrata in underwater imagery," *CATAMI Classification Scheme for Scoring Marine Biota and Substrata in Underwater Imagery*, pp. 1–17, 2013.

[19] M. D. Stokes and G. B. Deane, "Automated processing of coral reef benthic images," *Limnology and Oceanography: Methods*, vol. 7, no. 2, pp. 157–168, 2009.

[20] O. Pizarro, P. Rigby, M. Johnson-Roberson, S. B. Williams, and J. Colquhoun, "Towards image-based marine habitat classification," in *OCEANS 2008*, pp. 1–7, IEEE, 2008.

[21] B. J. Boom, J. He, S. Palazzo, P. X. Huang, C. Beyan, H.-M. Chou, F.-P. Lin, C. Spampinato, and R. B. Fisher, "A research tool for long-term and continuous analysis of fish assemblage in coral-reefs using underwater camera footage," *Ecological Informatics*, vol. 23, pp. 83–97, 2014.

[22] A. Shihavuddin, N. Gracias, R. Garcia, J. Escartin, and R. B. Pedersen, "Automated classification and thematic mapping of bacterial mats in the north sea," in *OCEANS-Bergen, 2013 MTS/IEEE*, pp. 1–8, IEEE, 2013.

[23] M. Bewley, A. Friedman, R. Ferrari, N. Hill, R. Hovey, N. Barrett, O. Pizarro, W. Figueira, L. Meyer, R. Babcock, *et al.*, "Australian sea-floor survey data, with images and expert annotations," *Scientific data*, vol. 2, 2015.

[24] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[25] A. Mahmood, M. Bennamoun, A. Senjian, F. Sohel, F. Boussaid, R. Hovey, G. Kendrick, and R. B. Fisher, "Coral classification with hybrid feature representations," *IEEE International Conference on Image Processing*, in press.