A Survey on ML-Based Techniques to Estimate Coral Reef Cover: State of the Art and Challenges

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Abstract. Even the slightest change in the environment can impact a sensitive ecosystem on earth, and the Coral ecosystem can be stated as one of them. The diver-based approach for monitoring coral reefs is very rigorous and has limitations in covering the area. The surge in the development of small and low power intelligent hydrobots (AUVs and ROVs) has given rise to automating the visual monitoring of reefs. These vehicles are smart enough to convert the raw data into information such as bleaching, biodiversity, and coral cover related to the health of the reef. The paper surveys recent advances in techniques to estimate coral reef Cover and identifies future research challenges. The swift developments in the deep learning arena of computer vision have led to rigorous research to associate it with various problem statements that would require high accuracy and speed. As such, an application like coral detection, classification, segmentation, and consequently measuring parameters, namely surface area, rugosity value, and biomass, are widely being explored using Machine learning and Deep learning approaches of Artificial Intelligence.

Keywords: Coral Segmentation, Random Forest, LGBM,

1 Introduction

Coral reefs are biologically diverse and highly productive ecosystems that support more species per unit area than any other marine environment, including about 4,000 species of fish, 800 species of hard corals, and hundreds of other species. Coral reefs act as a source of new drugs in the health sector that could be used to treat cancer, arthritis, human bacterial infections, viruses, and other diseases. Despite their services, coral reefs are degraded at an unprecedented rate that eventually leads one-third of the reef-building corals to an elevated risk of extinction from climate change, and local stressors [1]. Climate change and its associated processes, including warming seas, acidifying oceans, altered currents, and frequent storms, cause myriad effects on coral reefs affecting their structure and function [2].

Thus, monitoring the coral reef; and analyzing their health and other parameters, including their occupied area, becomes critically important. The estimation of the Coral Cover to understand the coverage of a particular type of species over time is essential to scrutinize either the decline or growth in a particular coral. There exist various methods that are implemented to estimate the Coral cover in a specific area like Projected area, Aluminum foil calculation, Latex, Scanning, Dye uptake, Waxing, Geometric shape fitting, Photogrammetry,3-D reconstruction using video, Laser scanning, X-Ray, CT. as studied by [3]. The effectiveness of these methods widely depends on the structure of the corals. The corals are often categorized into massive (M), simple branching (SB), and complex branching structures (CB), and the estimation accuracy varies [4]. Photogrammetry is another method that has been explored to obtain an estimation of coral cover [5]. However, the accuracy of the estimation is mainly dependent on the quantum and quality of the photos collected.

In this paper, we analyze various Artificial Intelligence (AI) integrated methods used in coral classification, segmentation and estimation of coral cover. The recent advances in the Convolutional Neural Networks (CNN) like Inception v3, ResNet, and DenseNet have been used successfully. Highly efficient results are obtained in terms of speed and accuracy on datasets like EILAT and RSMAS. CNN has also been used to engineer feature extraction and semantic segmentation, to classify pixels in a given image into classes of interest in a supervised method. These segmented classes are then used for the estimation of coral cover. However, the main challenge lies in obtaining the training dataset and manually annotating the training data set for these algorithms. We used the segmentation aspect in the traditional machine learning (ML) technique using the random forest to mitigate this challenge and compared it to deep learning methods.

Though segmentation methods using CNN like Unet [6] are very efficient, methods involving traditional machine learning have also fetched impressive results on smaller datasets and in comparatively lesser computational time. It shows that the traditional ML methods can also have good potential with fewer resources and time. The study is extended towards understanding how traditional ML techniques like Random Forest (RF) [7], and Light Gradient Boosting Machine (LGBM) [8] perform in a challenging domain of coral image segmentation with low dimensional training data, low computational power and time.

2 Related Study:

Most of the literature published deals with detecting corals and their classification and implements deep learning, and traditional ML approaches fetch accuracy over 70%. Monitoring coral reefs to record changes is an expertized domain. A domain-specific approach in this scenario is fundamental. In [9] authors concluded that intelligent domain adaption is required to obtain a better performance. They present an analogy of a trained CNN that may perform well on low light images in the air but may not detect objects underwater using the same network. The type of dataset used to train an AI network plays a vital role in its performance. As mentioned in the previous section, the approach that works well on a massive category of corals will not yield the same result for a different dataset. The training data must be diverse and include a balanced number of images.

The majority of the research reports are based on coral texture classification using CNN involving Inception v3, ResNet, and DenseNet, as implemented by [10]; wherein corals that were manually annotated and classified were used to train a model, and four classes produce accuracy at a rate of 85% to 95%. With further use of Mobilenet, due to its depth separable convolution layers, achieved an average accuracy of 93%, and this CNN was used to detect coral from the sand. Further, size estimation was done using a distance-based algorithm [11].

Transfer learning is yet another feat that has assisted in enabling to teach a CNN from models pre-learned on a particular task rather than learning from scratch. Some of the most widely used pre-train models include Oxford VGG Model, Google Inception Model, Microsoft ResNet Model. VGG-16 being the most prominently used, as seen in [10] and [12]. ResNet-50 CNN [13], was used on 5500 images to classify corals into eleven categories of coral species. Image enhancement and Feature extraction of corals also significantly collaborate towards accuracy. Thus, again reiterating that deep learning techniques largely depend on the types of datasets provided to train them.

DL has an advantage with its ability to automatically extract features in contrast to traditional machine learning, where feature extraction is manually performed. Feature extracted using methods like Local Binary Pattern (LBP) and Local Arc Pattern (LAP) for the Coral and subsequently using VGG -16 Architecture, is observed to provide better features extracting in coral reef images [14]. Classifiers like K Nearest Neighbor (KNN) and the Random Forest, when integrated with these feature extraction techniques using methods like SHIFT, SURF, etc., provided accuracy around 97%, which is as good as integrating a deep learning method [14]. Photogrammetry and three-dimensional reconstructions of coral reefs using CNN have also been used to more accurately classify the coral and after that used to estimate their cover after scaling them back appropriately; software like Metashape software (Agisoft photo scan) and blender have contributed efficiently to producing the 3D mesh required [15], [16]. 3D reconstruction has also been attempted by using 3D point clouds using the 'Structure From Motion (SFM) ' approach. Thereafter, implementing 3D surface cover over the 3D point clouds, the accuracy for classification obtained using an SVM classifier was 76.6% [17].

It is now evident from the studies carried out that any classification, object detection, or segmentation methods can be carried out by initially, 1) processing the data and annotation on data, 2) conceiving a model that is apt for the problem statement at hand and 3) lastly, grading the model on the results produced based on specific parameters or metrics. Additionally, the dataset's quantity and quality play a critical role in the process. Thus, there is a need to mention the various Image enhancement techniques the researchers have implemented to process the underwater dataset used for classification. Integrated Colour Model (ICM) is a technique that equalizes the color contrast using RGB method and also increases the true color and HSI intensity by stretching the saturation [18]. There are Color Correction approaches such as Unsupervised Color Correction (UCM) is based on color balancing, contrast correction of RGB color model and HSI color model [18]. Histogram Equalization, Contrast Limited Adaptive Histogram Equalization (CLAHE) and their modified algorithms [19], are some of the widely used methods. Studies have also been done for underwater image restoration using the CNN deep learning approach. An end-to-end underwater image restoration algorithm was implemented in [20] to improve the contrast and color cast of the recovered images.

Semantic Segmentation

In this article, we study how the segmentation aspect from the Computer Vision domain can assist in monitoring Coral reefs and estimate their surface coverage. Image segmentation is a computer vision task wherein a particular region of an image is labeled based on the information it provides about the image. An image is a collection of pixels; thus, dividing pixels with similar attributes is precisely the segmentation process. Here a pixel belonging to a category is labeled or masked. Image segmentation is used widely in the biomedical field to detect abnormal human cells like cancerous cells. Through semantic segmentation, one can annotate the images for different object classes present either sparsely or densely using various available tools like CPCe [21], Apeer, labelme etc.. Further, these annotated images could be used as training data set.

As described in [21], deep learning can vastly contribute in domains with large and high dimensional data in images, video, and audio [22] and reference therein). However, in case of limited data available for training, traditional ML methods can produce good quality results [23], which is more understandable than deep learning results [24]. To realize the performance of methodologies adopted; two basic traditional machine learning approaches and a particular deep learning approach were studied and elaborated in the next section.

Machine Learning approaches

One of the initial papers published by Ray Solomanoff as ``an Inductive Inference Machine'' [25] highlighted the importance of training patterns in systems describes how the previous result in an iteration can be used to shape new trial solutions. Random Forest (RF) [7] does just that in the form of decision trees. RF can be considered a collection of decision trees that will result depending on the maximum number of decision tree predictions. RF will predict a class in the case of a random forest regressor or classify it into a class using the RF classifier model. It uses the bagging process, where each decision tree randomly samples the data and produces an uncorrelated forest of the decision trees whose prediction by committee is more accurate than that of any individual tree. Though here, the time consumed to classify or predict is high. Light Gradient Boosting Machine (LGBM) [8] also uses a decision tree-based ML approach, which was designed to be very fast. The split here happens leaf-wise, based on the best fit. LGBM works on a histogram-based algorithm, wherein feature values are put into discrete bins, increasing the training procedure. Due to this, discrete bin usage for replacing feature values continues, thereby utilizing lesser memory.

Deep Learning Techniques

DL is a subset of ML, where a computer is programmed to learn to classify through images, text, audio, etc. A prevalent Deep Neural network is the Convolutional Neural Network (CNN) which uses the mathematical operation of the convolution of matrices as its fundamental process. Authors in [26] provide a detailed explanation on CNN with the convolutional layers, non-linearity layers, pooling layers, and fully-connected layers. In the case of segmentation, the CNN alone may not be efficient as each pixel of the image needs to be predicted to obtain the original image size back to obtain the reference of multiple objects, thus making it computationally expensive. As such, [27] a Fully Convolutional Network (FCN) was introduced to preserve dimension. In FCN, the concept of up sampling and down sampling is introduced. This model has two parts; in the first part, distinguishing features of the images are obtained, and with every convolution, finer features are fetched. However, the location information of these features is lost during the process. Therefore, the second part of the model uses an up sampling method, which takes in many low-resolution images and produces a high-resolution segmented mapped image.

UNet

The up and down sampling process is also known as encoder and decoder parts. One such deep learning network that extends up sampling and down sampling approach by adding spatial information from the encoder part and concatenating it to the decoder part is how UNET was designed. UNET is widely used in biomedical applications [6]. The main advantage of UNET, as detailed in [6] is that it does not use a fully connected layer at the end. The number of the parameters is reduced and thus can be used to train a small labeled dataset. Since the UNET is very efficient with biomedical images, implementing it to segment coral images is an exciting arena to venture into. In [28], the authors have segmented the coral image using large-scale 2D images. The efficacy of UNET can be explored for segmentation, and further use the segmented pixels for coral to obtain the estimates of the cover.

3 Data set and Experiments

To compare the approaches to perform segmentation through machine learning approach, we implemented segmentation of coral images using Random Forest and LGBM. An ML approach is well-advised when the data set is small. A small subset of 12 training images of corals repeating in most of the images were taken from Eilat Dataset, and the Experiment was performed on GPU system with 8GM RAM. The feature of the image was extracted using Gabor, canny edge, sobel, scharr, prewitt, median and gaussian. Random Forest and LGBM models were trained on the features extracted. The Masked images of the data set were used as ground truth and Segmentation performed.

Refer in figure 1. the chart shows the various accuracy of the various classes existing in the image provided in the test data set for RF & LGBM

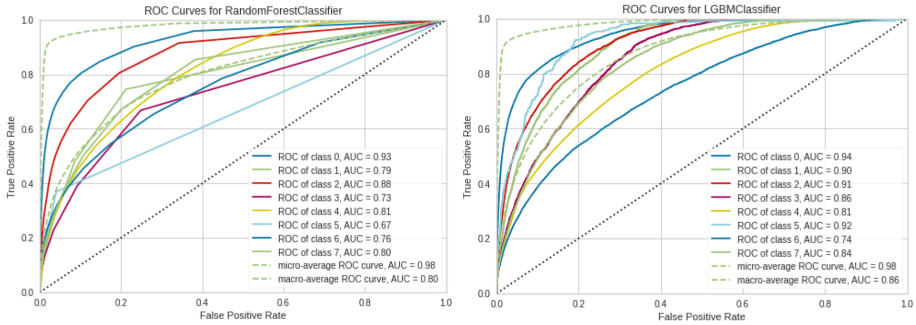

Fig. 1. Graph depicts the ROC curve for Random Forest and LGBM

4 Results and Conclusions:

The Results recorded in table **1.** shows that LightGBM did have comparatively lesser computational time; however, accuracy was tad bit lesser than Random Forest. The benefit of LGBM includes Faster training speed and higher efficiency while maintaining Lower memory usage. The speed of LGBM would be an attribute to be considered, if accuracy can be comprised slightly. Thus, depending on the size and complexity of the number of classes present in the data set, either of the two ML techniques is reasonable and should be considered if the data set is small before venturing into deep Learning techniques.

Research in due course would be considered to be taken up on implementing UNet Network on data set and finding an automatic annotation method to create masks for the images.

Table 1. Table captions should be placed above the tables.

Sr. No	Parameter	Random Forest	Light GBM
1	Execution time	06:31	04:15
2	Accuracy	89.47%	89.1%

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