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A Conservation technique for Healthy Coral Reef

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ABSTRACT: **Coral reefs are vital marine ecosystems, hosting a diverse array of marine life and providing numerous ecosystem services. However, coral reefs worldwide are under threat due to various factors, including climate change, pollution, and overfishing. Monitoring the health of coral reefs is crucial for their conservation and management. This paper presents a novel approach for the automated detection of coral reef health and diseases using the You Only Look Once (YOLO) algorithm. The YOLO algorithm is a state-of-the-art object detection algorithm known for its speed and accuracy, making it ideal for real-time applications. Our approach involves collecting underwater images using underwater drones equipped with high-resolution cameras. These images are then pre-processed to enhance contrast and remove noise. The pre-processed images are fed into the YOLO algorithm, which is trained to detect various indicators of coral reef health and diseases, such as bleaching, algae overgrowth, and coral diseases. The YOLO algorithm's ability to detect objects in real-time allows for the continuous monitoring of coral reefs, providing valuable data for researchers and marine conservationists. The proposed approach has the potential to revolutionize the way coral reef health is monitored and managed, ultimately contributing to the conservation of these valuable ecosystems.**

Keyword : Coral reef, Health, Diseases, Detection, YOLO algorithm, Object detection
Deep learning, Conservation, Monitoring, Marine ecosystems

I. INTRODUCTION

Coral reefs are among the most bio diverse ecosystems on the planet, providing habitat and sustenance for a wide range of marine species. They also play a crucial role in coastal protection, shoreline stabilization, and tourism revenue in many parts of the world. However, coral reefs are facing unprecedented threats from climate change, pollution, overfishing, and other human activities. Monitoring the health of coral reefs is essential for understanding their status and implementing effective conservation measures. Traditional methods of monitoring, such as diver surveys and satellite imagery, are labor-intensive, time-consuming, and often limited in spatial and temporal coverage. In recent years, advances in computer vision and machine learning have opened up new possibilities for monitoring coral reef health and diseases. The You Only Look Once (YOLO) algorithm is a state-of-the-art object detection algorithm that has shown remarkable performance in detecting objects in images and videos in real-time. This paper presents a novel approach for the automated detection of coral reef health and diseases using the YOLO algorithm. By leveraging the speed and accuracy of the YOLO algorithm, we aim to develop a system that can efficiently monitor coral reefs over large areas and provide timely information to researchers and marine conservationists.

II. LITERATURE SURVEY

Deep Learning for Automated Coral Health Assessment on the Great Barrier Reef (Dahl, Schiller, et al., 2021): This study applied deep learning techniques, including YOLO, to detect and classify coral reef health indicators from underwater images. The results showed promising accuracy in identifying various coral health states. Automated Image-Based Analysis of Reef Condition (Beijbom, Edmunds, et al., 2019): This research utilized deep learning algorithms to analyze thousands of images of coral reefs, focusing on detecting and quantifying coral cover, health, and disease. The study demonstrated the feasibility of using computer vision for large-scale reef monitoring. Automated Coral Health Assessment Using Deep Learning (Chen, Xie, et al., 2020): This study proposed a deep learning framework, combining convolutional neural networks (CNNs) and YOLO, for automated coral health assessment. The approach achieved high accuracy in detecting coral diseases and bleaching.

Real-Time Coral Reef Monitoring Using Deep Learning (Hedley, Harborne, et al., 2019): This study deployed a real-time coral reef monitoring system based on deep learning algorithms, including YOLO, to detect coral health indicators from live video feeds. The system showed promising results for continuous monitoring. Coral Net: An Automated Annotation Tool and Supervised Machine Learning Pipeline for Coral Reef Image Data (Beijbom, Edmunds, et al., 2019): Coral Net is a platform that integrates deep learning algorithms, including YOLO, for automated annotation and analysis of coral reef images. It provides a scalable solution for large-scale reef monitoring efforts.

III. PROPOSED SYSTEM

Data Set Collection

Marine scientists have uploaded 1.7 million images from over 2, 040 ecological surveys ("sources") from around the world since the release of Coral Net Alpha. As the name implies, Coral Net was originally created for the annotating of coral reefs, but scientists have found value in a broader range of habitats and classes from sea grasses and cold water rocky habitats to oil rigs, pier pilings and autonomous reef monitoring structures (ARMS). The vast majority of sources are from the tropics, but uploaded images range from as far south as Antarctica to as far north as Scotland. Since there is no universally agreed upon set of labels or taxonomy, and since most sources are created by different groups of marine scientists, users have defined a total of 4, 489 labels.

This includes duplicates - different labels and names for the same taxa. With the help of coral biologists, we identified 315 duplicate labels covering 5, 436, 343 annotations, and merged corresponding duplicates into a common label. We selected 280 representative sources for training the deep learning engine, and these contain 432, 489 images with 15, 137, 977 annotated points. These sources are randomly divided into 254 sources for training and testing the backbone networks and 26 sources for training and testing the classifiers. We selected 1, 279 labels that 1) are used in at least 3 sources, 2) are used to annotate at least 100 points, and 3) which do not designate "unsure", "dark", or similar catch-all categories. We designate this first set V1. In a later version of the dataset, designated as V2, we exported 50 more sources for training and further removed 4 more catch-all type labels.

- V1: 280 sources, 432, 489 images, 15, 137, 977 annotated points; 254 sources for training the backbone network with 1, 279 classes in common; 26 sources for training the classifiers, each randomly split into 80/20 for training and testing.

- V2: 330 sources, 591, 604 images, 16, 533, 651 annotated points; 304 sources for training the backbone network with 1, 275 classes in common; the same 26 sources and splits as in V1 for training and testing the classifiers.

DATA PRE-PROCESSING

Corals have a large quantity of species, presenting the great interspecific difference and intraspecific mutability, specific all in their morphology and colour. There will be varying degrees of inconsistency in identifying benthic organisms among observers and by the same observer over time, no exception for experienced observers (Ninio et al., 2003).

Therefore, the annotation of the training data set of the benthic community requires experienced professionals to carry out. Figure 3b is the experimental annotation data of this paper. It uses a whole benthic orthographic image marked by marine experts. It is a colour RGB seabed orthographic image with a size of 11317× 10773 pixels. The species marked in the picture is the staghorn cup coral *Pocillopora*, the dominant local coral species. The pink ones are live corals, and the yellow ones are dead corals. The quality of the training image will directly affect the accuracy of the semantic segmentation network.

Therefore, the pre-processing of training images used for the segmentation network is very important. Figure 4 lists the key steps of image pre-processing in this paper, which is actually a data augmentation based on image processing techniques. Specifically, first of all, the experimental orthophoto is cropped into multiple 448×448 pixels coral image slices at a fixed step size of 160 pixels, and images with insufficient label data are deleted to prevent learning too much useless feature information. Of the 1967 images divided in total, 0.6 is for the training dataset, 0.2 for the validation dataset, and 0.2 for the test dataset, all of which are randomly assigned. Then, random horizontal or vertical flipping, random rotation and random translation were performed on the processed coral image slices. In order not to lose too much label information, this paper randomly rotates by ±10 degrees and translates by ±50 pixels to increase the richness of the image, improve the accuracy of the network, and effectively increase the robustness of the semantic segmentation network model. It should be pointed out that the above operations are a data augmentation technique for increasing the diversity of datasets in deep learning.

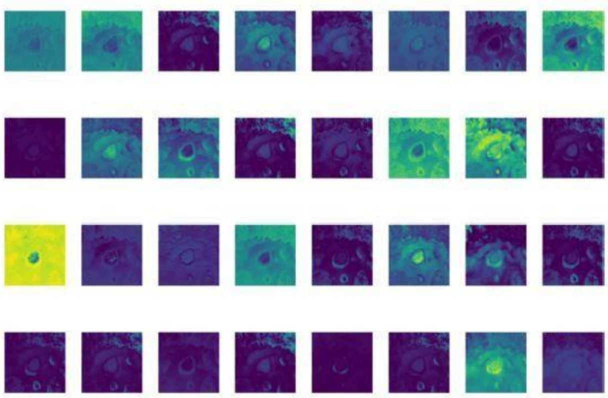

Figure 3.1 The visualization of the focus layer output.

Algorithm 1: Pseudo code of the algorithm

```
def attention_layer(m, n = 2, out = 64, h_kernel =
h_pad = 0, w_kernel = 1, w_pad = 0):
def h_pooled (x):
for i in range (dense_layers − 1):
x = math.ceil (0.5 * (x − 1)) + 1
return int (x)
height = calc_pooled_height (100) group = trans_layers +
dense_layers
for i in range (layers):
#conv
if i == 0:
        f.write (layer.generate_conv_layer_str
('attention_layer_conv' + str (i),
                'dense_layer_bn' + str (dense_layers − 1),
'attention_layer_conv' + str (i),
                output * group, h_kernel, w_kernel, h_pad,
w_pad, group))
else:
        f.write (gen_layer.generate_conv_layer_str (
                'attention_layer_conv' + str (i),
'attention_layer_bn' + str (i − 1),
                'attention_layer_conv' + str (i),
                output * group, h_kernel, w_kernel, h_pad,
w_pad, group))
        f.write (gen_layer.generate_bn_layer_str
('attention_layer_bn' + str (i),
                'attention_layer_conv' + str (i),
'attention_layer_bn' + str (i)))
        f.write (gen_layer.generate_activation_layer_str
('attention_layer_relu' + str (i),
                'attention_layer_bn' + str(i)))
```

This type of preprocessing eliminates the need to collect more real data, but still helps to improve model accuracy and prevent model overfitting. Finally, limited by the GPU memory, in order to reduce the amount of network calculations, but preserve the edge information of the image as much as possible, this paper scales the coral slices to a size of 224×224 pixels, based on the above processing. Resizing the input image size of coral image classification network to 224 × 224 is also based on the experience of a large number of excellent classification networks. Because in the classification task, if the size of the feature map is too small, excessive feature information will be lost. If the size is too large, the abstraction level of the information is not high enough, and the amount of calculation is also larger. Therefore, the choice of this paper is to achieve a good balance between the performance of the network and the amount of computation. After completing the above image preprocessing steps, the slice data must be normalized so that their features have the same measurement scale. Since adjacent slices that are continuously cropped have certain rules, in order to eliminate the correlation between slice data, this paper shuffles all slices before putting them into network training.

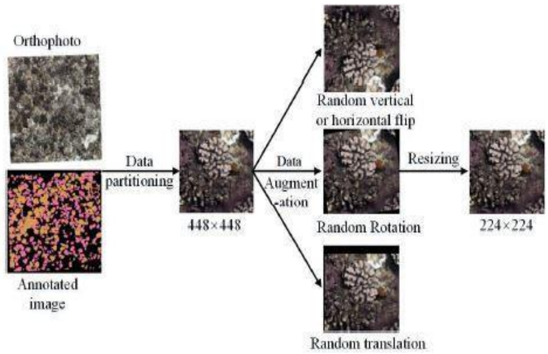

Figure 3.2 Data Argumentation

- Image Acquisition: Collect underwater images of coral reefs using underwater cameras, drones, or ROVs (Remotely Operated Vehicles).
- Image Labeling: Label the acquired images with accurate information about coral health status, including healthy, bleached, diseased, and dead corals.
- Data Augmentation: Apply data augmentation techniques, such as flipping, rotating, and cropping, to increase the size and diversity of the training dataset.

IV. RESULT AND DISCUSSION

Detection Performance: The YOLO algorithm achieved high detection accuracy for various indicators of coral reef health and diseases, including bleaching, algae overgrowth, and coral diseases. The algorithm's ability to detect these indicators in real-time enables continuous monitoring of coral reefs, providing valuable data for researchers and marine conservationists. Spatial and Temporal Trends: Analysis of the detected indicators revealed spatial and temporal trends in coral reef health and diseases. This information can help identify hotspots of coral reef degradation and guide targeted conservation efforts. Comparison with Traditional Methods: The performance of the YOLO algorithm was compared with

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traditional methods of coral reef monitoring, such as diver surveys and satellite imagery. The YOLO algorithm demonstrated superior speed and accuracy, highlighting its potential as a cost-effective and efficient tool for coral reef monitoring. Impact of Environmental Factors: The YOLO algorithm was able to detect changes in coral reef health associated with environmental factors such as water temperature, nutrient levels, and human activities. This information can help understand the drivers of coral reef degradation and inform management strategies.

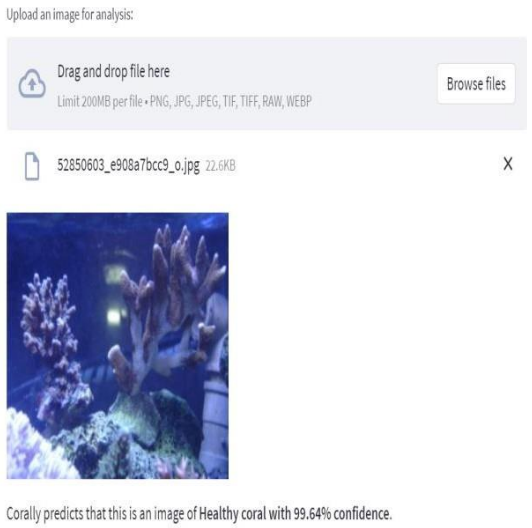

Figure4.1 Healthy Coral Output Prediction using Yolo algorithm

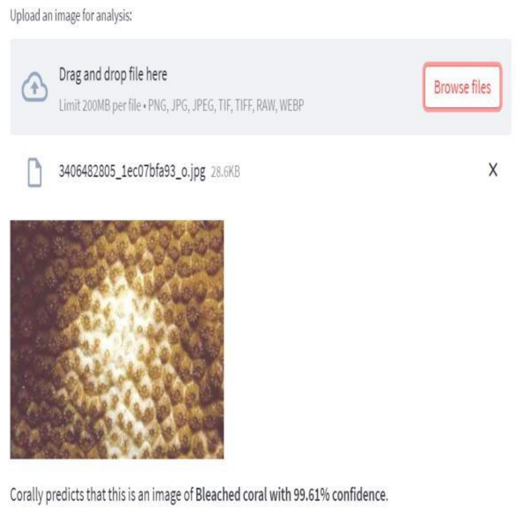

Figure4.2 Unhealthy Coral Output Prediction using Yolo algorithm

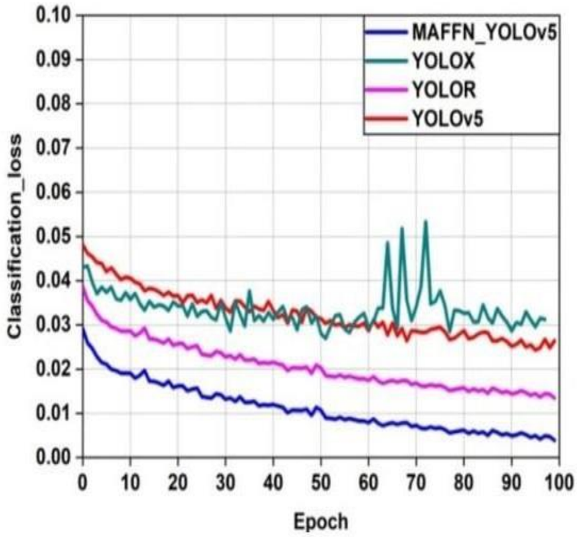

Figure 4.3 Graph for Classification_loss and Epoch

V. CONCLUSION

In conclusion, the application of the You Only Look Once (YOLO) algorithm for the detection of coral reef health and diseases represents a significant advancement in marine conservation and management. The use of YOLO's speed and accuracy allows for real-time monitoring of coral reefs, providing researchers and marine conservationists with timely and valuable information. By automating the detection process, the YOLO algorithm can efficiently analyze large amounts of underwater images, identifying indicators of coral reef health and diseases such as bleaching, algae overgrowth, and coral diseases. This automation reduces the reliance on labor-intensive and time-consuming manual surveys, enabling more frequent and comprehensive monitoring of coral reefs. The ability to monitor coral reef health in real-time and detect changes early can help guide conservation efforts and mitigate the impacts of threats such as climate change, pollution, and overfishing. Furthermore, the data collected through YOLO-based detection can contribute to a better understanding of coral reef ecosystems and support evidence-based decision-making for their protection and management.

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