Classification of Coral Reef Species using Computer Vision and Deep Learning Techniques

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ABSTRACT

Coral reefs are among the most diverse and productive ecosystems, teeming with life and providing many benefits to marine life and human communities. Coral reef classification is popular for many important reasons, such as assessing biodiversity, prioritizing conservation actions to protect vulnerable species and their habitats, and many other objectives related to scientific research and interdisciplinary studies on marine ecosystems. Classifying images of coral reefs is challenging due to their great diversity and subtle differences in morphology. Manually classifying them is a time-consuming process, especially when dealing with large datasets. This can limit the scalability and efficiency of scientific research and conservation efforts. This study proposes an automated classification approach using computer vision and deep learning techniques to address these challenges, employing models such as YOLOv5l, YOLOv8l, and VGG16 to classify images of coral reefs. The dataset, comprising 1,187 images of five coral species, was augmented for robustness. YOLOv8l demonstrated superior performance with an accuracy of 97.8%, significantly outperforming the other models in terms of speed and accuracy. These results demonstrate the potential of advanced deep-learning models to improve coral reef monitoring and conservation efforts. This approach aims to streamline classification processes, improving the efficiency and scalability of coral reef research and conservation initiatives worldwide.

Keywords-biodiversity; marine ecosystem; coral reefs; computer vision; deep learning; classification; YOLO; VGG16

I. INTRODUCTION

Coral reefs, often called the rainforests of the sea, are crucial marine ecosystems that support a wide range of marine biodiversity. These complex structures, formed by coral polyps, provide essential habitats for millions of aquatic species and offer significant benefits to human populations worldwide, as they play a crucial role in supporting fishing and tourism, protecting coastlines from storm surges, and participating in vital biogeochemical cycles. However, coral reefs are under severe threat from climate change, pollution, overfishing, and harmful fishing techniques. These challenges emphasize the urgent need for effective conservation strategies. A key aspect of such a strategy is the ability to accurately and efficiently monitor and understand the biodiversity and health of coral reefs. Traditional methods that rely on manual observation and cataloging by marine scientists are meticulous and time-intensive, limiting their application on a large scale. This study investigates the existing gaps in coral reef monitoring and conservation and proposes an innovative solution that adopts automated classification systems using advanced computer vision and deep learning techniques. By streamlining the identification process, this approach aims to enhance the ability to quickly monitor and respond to changes that affect coral reef ecosystems. Ultimately, the goal is to improve the effectiveness and scalability of coral reef research and conservation efforts, making a significant contribution to global initiatives that aim to preserve these vital marine resources.

II. LITERATURE REVIEW

In [1], Region-Based Convolutional Neural Networks (RCNN) and TensorFlow models were used to improve the accuracy of coral reef detection and classification. Although RCNN models are computationally intensive and require extensive manual annotation, this study achieved classification accuracies of up to 90% for various coral substrates. This was achieved by correcting the format of trained annotations to match the required format and through meticulous manual annotations and testing. This approach demonstrated the potential of RCNN models not only in coral reef monitoring but also in other image analysis applications. In [2], CNNs and Deep Belief Networks (DBNs) were used to automate the classification of coral reefs from image data. These deep learning models offer several advantages, including accurate recognition of coral structures, automation of data analysis, and reducing human errors. However, they require high computational resources and extensive labeled datasets. Despite these challenges, CNNs and DBNs proved to be efficient and reliable for coral reef monitoring, showing their potential to improve conservation efforts by providing accurate assessments of reef health and biodiversity.

In [3], a real-time marine life detection system was proposed, which utilized YOLOv3, YOLOv5, YOLOR-P6, and YOLOR-W6. The evaluation was based on Average Precision (AP), averaged over 10 thresholds from 50% to 95% (AP50:95). The results showed that YOLOv3 achieved an accuracy of 0.542 for fish and 0.902 for turtles, while YOLOv5 scored 0.464 and 0.771, respectively. YOLOR-P6 achieved 0.487 for fish and an impressive 0.995 for turtles, while YOLOR-W6 achieved 0.512 for fish and 0.902 for turtles. Surprisingly, deeper networks did not consistently outperform simpler ones, possibly due to the small dataset size. YOLOR-P6 and YOLOR-W6 excelled in large datasets but may have struggled with smaller ones. On the contrary, YOLOv3, being simpler, fit better and attained higher precision. In [4], deep learning methods, including YOLOv3 and RetinaNet, were used to locate and classify coral reefs, overcoming challenges such as data imbalance and image size limitations. Classical feature-based methods, such as PCA and Naive Bayes, were also explored to improve performance. The evaluation revealed significant improvements, especially with image enhancement techniques such as the RD algorithm. However, the transferability of the results varied, with a performance improvement on geographically similar data, suggesting avenues for further research and improvement.

In [5], deep learning and CNN techniques were used to develop a more efficient and faster classification method. Specifically targeting Scleractinian (Stony) corals, this study investigated structural-level techniques, particularly for branching corals, which present significant classification challenges due to their structural diversity. The training dataset, comprising approximately 2200 manually annotated images across 10 different coral types, was balanced to ensure equal representation. Two training approaches, namely the Grayscale and RGB approaches, were employed, with the RGB achieving superior results. The overall accuracy was 94.5%, indicating correct predictions for most cases. However, challenges arise with complex coral structures and similar-looking species, leading to prediction inaccuracies. In [6], an automated coral lifeform classification model was developed using the YOLOv5 deep learning framework. The YOLOv5 algorithm was employed for model training, with performance evaluation based on metrics such as recall, precision, Fl score, and accuracy. This study utilized a dataset from Sogod Bay in the Philippines, comprising 549 manually classified images across seven coral lifeforms. The model achieved an overall accuracy of 89.29%, demonstrating its potential utility in reef conservation and monitoring efforts. Future research directions included expanding the dataset to encompass more diverse coral lifeforms and exploring alternative deep-learning approaches to further improve model accuracy and efficiency. In [7], a CNN-based model was developed to classify 14 different coral reef species using a multinomial classification approach. The model used a CNN with three layers and the Rectified Linear activation Function (ReLU). Maximum pooling was applied after each convolution, and Adam was used to optimize the model. The model was trained in an augmented dataset using different approaches in batches of 32 images in nine epochs. For most coral species, it performed perfectly in terms of precision, recall, and F1 score. However, it had difficulty detecting Palythoas, resulting in a small number of misclassifications. Palythoas had the highest number of misclassified corals (6 out of 522), followed by Acropora Cervicornis (4 out of 2053). Despite these limitations, the model achieved an accuracy of 99.49%.

In [8], coral reef images were classified using deep features and a novel descriptor, called the Local Inter Cross Weber Magnitude (LICWM) pattern. This study used VGG-16 and the

Local Inter Cross Weber Magnitude Pattern (LIWMP) to classify and extract features from coral reef images. LIWMP was based on Improved Weber's Local Descriptor (IWLD) and worked with VGG-16 to extract deep features for classification. KNN and Random Forest were used to classify the RSMAS and EILAT datasets. The results showed that LIWMP outperformed current approaches, such as LAP, LBP, IWBC, CLBP, and ILDP, and KNN outperformed Random Forest. Integrating VGG-16 increased performance, reaching 98.8%. LIWMP can be further investigated by combining it with other machine learning techniques. In [9], 3D reconstructions were generated from images obtained during underwater surveys, and then CNNs were used to classify the reconstructed elements. Different approaches were tested to merge information from multiple views, achieving high overall classification accuracies of approximately 96%. This study demonstrated the potential of this method for ecological applications, such as evaluating the distribution and abundance of coral reef species. In addition, the researchers made their classifier and data publicly available. In [10], CNN-RNNs were used to extract high-level image features and employ a frequency-based multiscale classification algorithm using an overcomplete wavelet. Through multiple trials, the system was trained with various substrate configurations and subsequently tested on the ImageCLEFcoral 2021 challenge dataset. The results revealed an average accuracy of 70% for each substrate characterization. This method achieved improved classification results in identifying substrates of different classes, demonstrating the sensitivity, specificity, and adaptability of the system to medium-resolution datasets.

Despite these studies to classify coral reef species in most regions where coral reefs are prevalent, no study in this respect examined the eastern half of the Red Sea. Although several methods and versions of YOLO have been used to identify coral reef types, the most recent version, YOLOv8, has not been used for this purpose. YOLO models have demonstrated a great capacity to recognize organisms with high accuracy and speed, especially YOLOv8, in addition to comparing it with other YOLO versions in detecting various objects [11, 12]. This study uses and compares YOLOv5 and YOLOv8. In addition, the YOLO models are compared with the VGG16 model, which has also proven its ability to achieve high accuracy in object classification tasks [13, 14]. This comparison aims to determine the model that delivers the best performance and achieves the highest level of accuracy in classifying coral reefs in the Red Sea.

III. METHODOLOGY

A. Dataset

The CoralReef_Species dataset was prepared [15], which is available on Roboflow, using publicly available and free datasets from CoralNet websites [16]. Acanthophyllia, Caulastrea, Branch, Bushy, and Cynarina coral reefs are the five types shown in the collection of images. Using the RoboFlow website, each type of coral reef was collected and assigned a bounding box annotation. Data augmentation techniques were used to increase the size of the dataset until it contained 1,188 images. The dataset includes 215 images of Branch coral reefs, 228 images of Bushy coral reefs, 240 images of Cynarina coral reefs, 280 images of Caulastrea coral reefs, and 240 images of Acanthophyllia coral reefs. The objective of the augmentation procedure was to expand the amount of the dataset by performing multiple operations, including scaling images to 416×416 pixels, rotating them 90° clockwise and counterclockwise, and randomly rotating them between -15° and +15°. Finally, the dataset was divided into three parts, a training set, a validation set, and a test set, with the following distribution: 1,095 images for training, 47 images for validation, and 46 images for testing.

B. Models

1) You Only Look Once (YOLO)

YOLO is a state-of-the-art object detection model that revolutionized real-time object detection, instance segmentation, and image classification tasks. It operates by dividing the input image into a grid and predicting bounding boxes and class probabilities directly from the grid cells. This approach allows YOLO to achieve impressive detection speeds while maintaining high accuracy. YOLO is well known for its optimal performance among computer vision models [17].

2) YOLOv5

YOLOv5 is a popular object detection model that has been designed for real-time processing in classification tasks, offering a balance between speed and accuracy. The architecture of YOLOv5 for classification involves several key components: the backbone, typically a CNN like CSPDarknet53 that extracts features from the input images, the neck that further processes these features, enhancing their representation using a Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) to combine features at different scales, and the head, responsible for predicting the class of the input image based on the processed features, typically consisting of fully connected layers that output class probabilities [18].

3) YOLOv8

YOLOv8 is an updated and enhanced version of the popular YOLO model series, incorporating several improvements over YOLOv5, particularly in terms of speed and accuracy. The key architectural elements of YOLOv8 for classification include the backbone, which uses more efficient architectures such as EfficientNet, providing better feature extraction with fewer parameters. The neck in YOLOv8 utilizes advanced methods such as the Bi-directional Feature Pyramid Network (BiFPN), enhancing the feature maps from the backbone for better representation. The classification head in YOLOv8, similar to YOLOv5, consists of fully connected layers that output class probabilities and can also incorporate advanced techniques, such as attention mechanisms, to improve performance [19].

4) Visual Geometry Group (VGG)

VGG16, developed by the Visual Geometry Group at the University of Oxford, is renowned for its simplicity and uniformity, featuring 16 convolutional layers. This model was used to classify coral reefs into five classes, leveraging its robust capabilities for image classification.

C. Training Models

YOLOv5l, YOLOv8l, and VGG16 were trained using Google Collab to accelerate training and achieve superior results, as it provides free access to powerful GPUs. All training and testing procedures were carried out on a 15GB NVIDIA Tesla T4 GPU.

1) Training YOLOv5 and YOLOv8

The YOLOv5l-cls and YOLOv8l-cls models, which are versions of the YOLOv5 and YOLOv8 models intended for classification purposes, were trained on the dataset. Models were trained using a set of hyperparameters, including the number of epochs, the optimizer, the learning rate, and others. The experiments were twofold. In the first experiment, the two models were trained for 10 epochs while maintaining the default values for the rest of the parameters. The default parameters for the optimizer and learning rate for YOLOv5 were Adam and 0.001, respectively. For YOLOv8, the default optimizer was AdamW, and the learning rate was 0.000714. In the second experiment, the models were trained while standardizing some parameters as shown in Table I. Adam optimizer was used and the learning rate was set to 0.0001. These standardized parameters were used for both models to determine the extent to which adjusting the parameters affects the results and to ensure a fair comparison.

The following command was used to execute the training process for the YOLOv5l model in the first experiment:

```
!python classify/train.py --model yolov5l-
cls.pt --data
/content/drive/MyDrive/dataset/CoralReef_Specie
s.v21i --epochs 10
```

The parameter `--lr 0.0001` was added to the same command in the second experiment.

The following command was used to execute the training process for the YOLOv8l model in the first experiment:

```
!yolo classify train model=yolov8l-cls.pt
data=/content/drive/MyDrive/dataset/CoralReef_S
pecies.v21i epochs=10
```

The parameter `--lr0 0.0001` was added for the same command in the second experiment.

The reason for specifying the optimizer and learning rate parameters in YOLOv8 is that the default values for these parameters were different. The function of each of the hyperparameters is explained as follows:

- `model`: Selects the classification model from YOLOv5 and YOLOv8.
- `data`: Sets the path to the dataset folder.
- `epochs`: Defines the number of training epochs. An epoch is one complete pass through the entire training dataset.
- `optimizer`: An optimizer updates the model parameters to minimize the loss function.
- `lr`: Defines the learning rate, which is the step size at which the optimizer moves towards the minimum of the loss function.

TABLE I. UNIFIED HYPERPARAMETERS FOR YOLOV5 AND YOLOV8

Hyperparameters	Values
Epochs	10
Optimizer	Adam
Learning Rate	0.0001
Image size	224
batch size	64

2) Training the VGG16 model

The VGG16 model was trained on the same coral image dataset. First, the dataset was preprocessed, which is a requirement for the VGG16 architecture. Resizing ensures uniformity across all input images. Data augmentation techniques were then used to increase the diversity of training data and prevent overfitting. The dataset was then split into training and validation sets to evaluate the model's performance during training. The VGG16 model, pre-trained on the ImageNet dataset, was loaded with its convolutional base frozen to leverage pre-learned features. A custom fully connected layer was appended, comprising a global average pooling layer, a dense layer with 512 units and ReLU activation, and a final dense layer with softmax activation corresponding to the five coral classes. This architecture allowed the model to adapt the learned features from ImageNet to the specific coral reef classification task. The model was compiled using the Adam optimizer with a learning rate of 0.0001, categorical cross-entropy loss for multiclass classification, and accuracy as the evaluation metric. Training was carried out for 30 epochs with a batch size of 32, using early stopping and model checkpoints to save the best-performing model based on validation accuracy. Throughout the training process, the model's performance was monitored using training and validation accuracy and loss curves. Upon completion, the model was evaluated on a separate test set to determine its final accuracy and robustness in classifying the five types of coral reefs.

IV. RESULTS

Accuracy is a common evaluation metric to measure the performance of a classification model. It represents the proportion of correctly classified instances out of the total instances evaluated. In other words, accuracy measures the model's ability to correctly classify the class labels of the instances in the dataset. It provides a general overview of how well the model is performing across all classes. It is calculated using the following formula:

$$Accuracy = (TP + TN)/(TP + TN + FP + FN)$$

The confusion matrix is a tool used to evaluate the performance of a model and is visually represented as a table with four different combinations of predicted and actual values. It is suitable for measuring the performance of binary and multiclass machine learning classification problems. The structure of the confusion matrix consists of:

- True Positives (TP), where the model correctly predicted the positive class.

- True Negatives (TN, where the model correctly predicted the negative class.
- False Positives (FP), where the model incorrectly predicted the positive class.
- False Negatives (FN), where the model incorrectly predicted the negative class.

A. YOLOv5

After the end of training in the first experiment, the model achieved an accuracy of 0.913, reflecting the model's general performance in classifying coral types across different classes. This indicates that the model achieved good overall accuracy in classifying the five classes. Regarding the accuracy achieved for each class, Acanthophyllia, Bushy_HC, Branch_HC, Caulastrea, and Cynarina achieved 1, 1, 0.875, 0.909, and 0.889, respectively, as shown in Table II. The accuracy for the Bushy_HC and Branch_HC classes was 100%, suggesting that the model performed exceptionally well in correctly identifying instances of these two classes. Figure 1 demonstrates the accuracy of the YOLOv5l model in 10 epochs with default settings. The model accuracy increases with the epochs. This suggests that the model is learning to correctly classify the images in the training set. The training accuracy reaches a high of approximately 0.91 at epoch 9.

TABLE II. YOLOV5L TRAINING RESULTS AFTER 10 EPOCHS WITH DEFAULT PARAMETERS

Class	Accuracy
All	91%
Acanthophyllia	100%
Bushy_HC	100%
Branch_HC	87.5%
Caulastrea	90.9%
Cynarina	77.8%

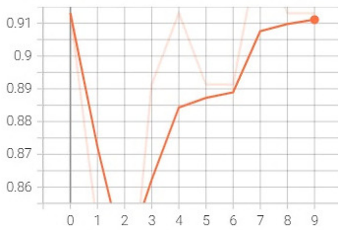

Fig. 1. Accuracy graph for YOLOv5l in 10 epochs and default parameters.

In the second experiment, after adjusting the settings, including changing the learning rate from 0.001 to 0.0001, the classification accuracy for each class improved significantly, as shown in Table III. The YOLOv5l model achieved higher classification accuracy in all classes. Additionally, the overall accuracy of all classes increased to 95.7%. This indicates improved performance and highlights the importance of hyperparameter tuning in improving model accuracy and effectiveness. Figure 3 illustrates that the accuracy of the model increased with the epochs, and the model correctly predicted the top class for most of the test data at the end of the training process.

Fig. 2. Test images for YOLOv5l before adjusting settings.

TABLE III. YOLOV5L TRAINING RESULTS AFTER EPOCH 10 WITH ADJUSTED PARAMETERS

Class	Accuracy
All	95.7%
Acanthophyllia	100%
Bushy_HC	100%
Branch_HC	87.5%
Caulastrea	100%
Cynarina	88.9%

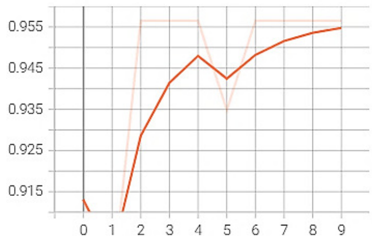

Fig. 3. Accuracy for YOLOv5l in 10 epochs after adjusting parameters.

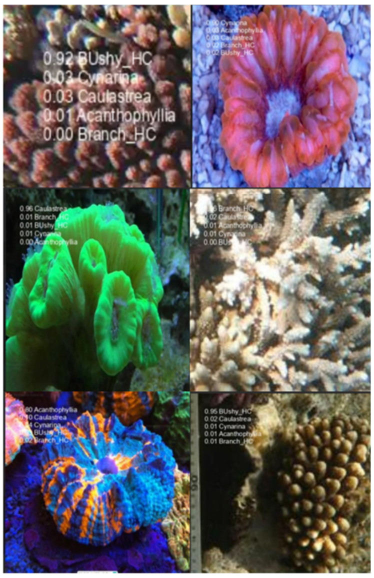

Fig. 4. Test images for YOLOv5l after adjusting parameters.

Figures 2 and 4 illustrate the performance of the YOLOv5 model in the test dataset, showcasing the results before and after adjusting the parameters. As a result, the model successfully identifies and classifies various coral species present, including Bushy, Branch, Caulastrea, Cynarina, and Acanthophyllia, along with their corresponding confidence scores. Figure 5 shows how well the model has learned to classify coral reefs during the training phase. Figure 6 shows an example of the testing batch, highlighting the model performance on unseen data. These figures demonstrate the model's effectiveness in learning from the training data and its ability to generalize to new data, ensuring accurate coral reef classification in practical applications.

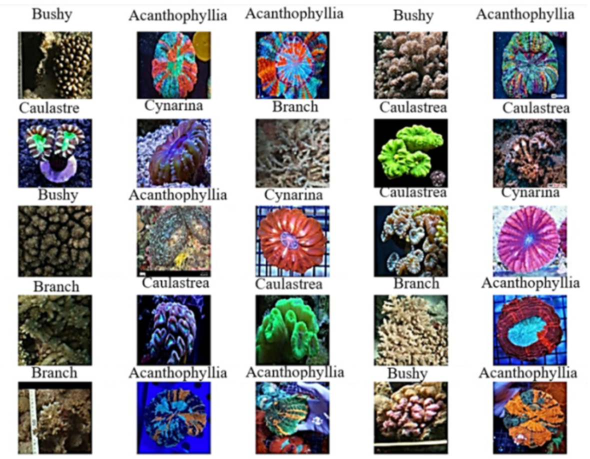

Fig. 5. Training batch for YOLOv5l.

Fig. 6. Testing batch for YOLOv5l.

B. *YOLOv8*

The training results for the YOLOv8l model in the first experiment for 10 epochs, without modifying other settings, show excellent overall performance with 95.7% accuracy, especially for certain coral reef classes, as shown in Table IV. Figure 7 shows the accuracy of the YOLOv8l model in 10 epochs with default parameters. The accuracy starts at approximately 0.82 and increases to approximately 0.95 by epoch 10. This suggests that the model is learning to correctly classify the images in the training set as the number of epochs increases.

TABLE IV. YOLOV8L TRAINING RESULTS AFTER 10 EPOCH WITH DEFAULT PARAMETERS

Class	Accuracy
Overall	95.7%
Acanthophyllia	100%
Bushy_HC	100%
Branch_HC	100%
Caulastrea	91%
Cynarina	89%

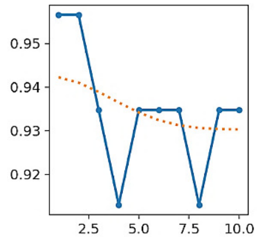

Fig. 7. Accuracy graph for YOLOv8l in 10 epochs and default parameters.

Fig. 8. Test images for YOLOv8l before adjusting parameters.

Adjusting the optimizer and the learning rate for YOLOv8l resulted in outstanding classification accuracy for most classes, with perfect accuracy achieved for four out of five classes, as shown in Table V. The adjustments enhanced the model's ability to classify the Caulastrea correctly, achieving 100% accuracy for this class. However, the classification accuracy for Cynarina remained unchanged at 89%. Figure 9 shows that the accuracy of the model starts at approximately 0.88 and increases to approximately 0.97 in epoch 10. This suggests that the model is learning to correctly classify the images in the training set as the number of epochs increases. There is a significant improvement in accuracy between epochs 9 and 10. Figures 8 and 10 illustrate the performance of the YOLOv8 model on the test dataset, comparing the results before and after adjusting the hyperparameters. Figures 11 and 12 present examples from the training and validation batches for the YOLOv8l model, respectively.

TABLE V. YOLOV8L TRAINING RESULTS ON EPOCH 10 AFTER ADJUSTING PARAMETERS

Class	Accuracy
Overall	97.8%
Acanthophyllia	100%
Bushy_HC	100%
Branch_HC	100%
Caulastrea	100%
Cynarina	89%

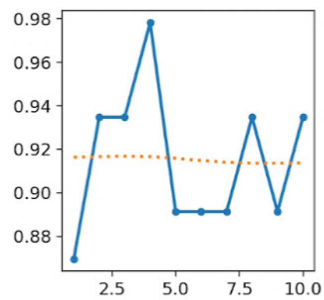

Fig. 9. Accuracy of YOLOv8l in 10 epochs after adjusting parameters.

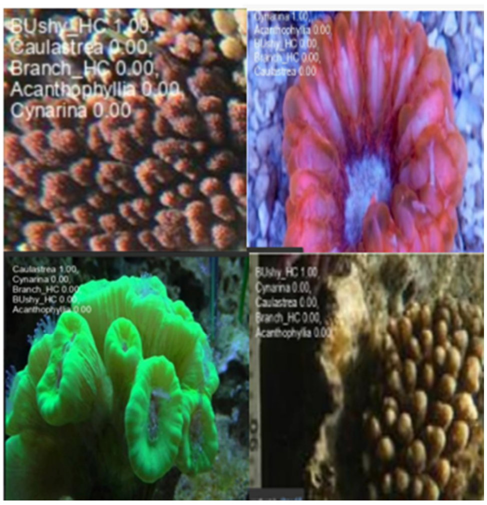

Fig. 10. Test images for YOLOv8l after adjusting parameters.

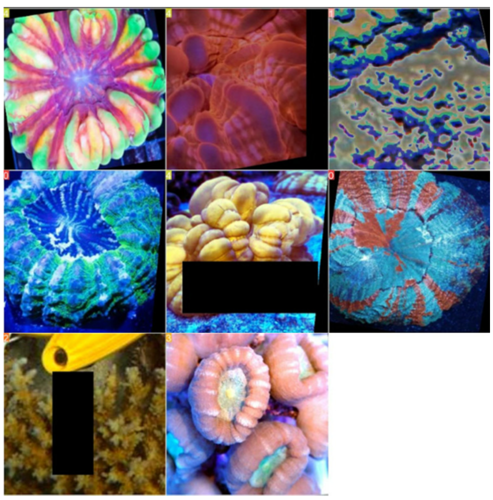

Fig. 11. Train batch for YOLOv8l.

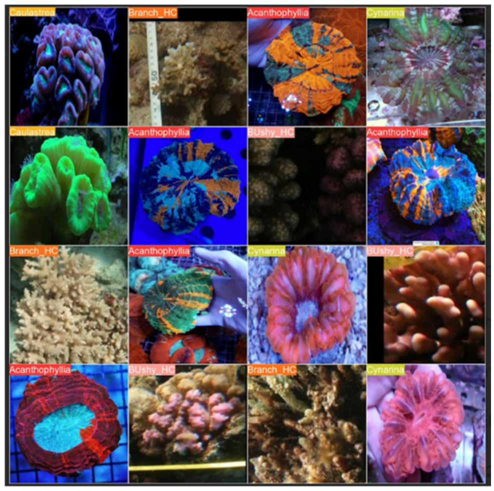

Fig. 12. Validation batch for YOLOv8l.

C. *YOLOv5 vs YOLOv8*

As shown in Table VI, YOLOv8l outperformed YOLOv5l in terms of classification accuracy in coral reefs at different learning rates, highlighting its superior architecture and training dynamics. The highest accuracy achieved by YOLOv8l-cls (97.8%) with a learning rate of 0.0001 indicates that it can better generalize and classify data compared to YOLOv5l-cls. Possible reasons for this superiority are that YOLOv8l has a more sophisticated architecture compared to YOLOv5l, allowing it to capture more complex patterns and features in the data, resulting in higher accuracy.

TABLE VI. YOLOV5 VS YOLOV8 RESULTS

Model	No. of epochs	Optimizer	Learning rate	Accuracy
YOLOv5l-cls.pt	10	Adam	0.001	91.3%
			0.0001	95.7%
YOLOv8l-cls.pt			0.0007	95.7%
			0.0001	97.8%

D. *VGG16*

VGG16 trained for 10 epochs without modifying other settings resulted in 70% accuracy, and after changing the number of epochs to 30, the model achieved 97% accuracy, as shown in Table VII, showcasing its effectiveness. Figure 13 shows the loss of VGG16.

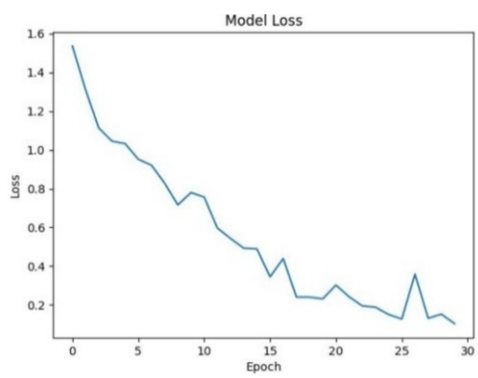

Fig. 13. Loss of the VGG16 model.

TABLE VII. VGG16 RESULTS

Model	No. of epochs	Optimizer	Learning rate	Accuracy
VGG16	10	Adam	0.0001	70%
	30			97%

E. YOLO vs VGG16

As shown in Table VIII, YOLOv8l stands out for its high accuracy and shorter training period. VGG16, although capable of achieving high accuracy, requires longer training, making it less efficient compared to the YOLO models. Differences in performance underscore the importance of adjusting hyperparameters, such as optimizer, number of epochs, and learning rates. YOLO models demonstrate faster learning and better overall efficiency, making them preferable for classifying coral reefs.

TABLE VIII. YOLOV5 AND YOLOV8 VS VGG16 RESULTS

Model	No. of epochs	Optimizer	Learning rate	Accuracy
YOLOv5l-cls.pt	10	Adam	0.001	91.3%
			0.0001	95.7%
YOLOv8l-cls.pt			0.0007	95.7%
			0.0001	97.8%
VGG16	10		0.0001	70%
	30			97%

V. CHALLENGES

A. Complexity of Coral Structures

Coral reefs exhibit a wide variety of shapes, sizes, and colors, making it challenging for computer vision models to differentiate between distinct species accurately based on subtle morphological differences.

B. Limited Dataset Size:

Capturing fine details of coral structures at different scales and resolutions in underwater images is challenging due to factors such as water turbidity, lighting conditions, and image quality, resulting in a scarcity of high-resolution image datasets.

VI. CONCLUSION

YOLOv8 had not been used in the classification of coral reef images. This study used YOLOv8 for this purpose, achieving a remarkable accuracy of 97.8%, surpassing the accuracy attained by YOLOv5, which was 95%. Furthermore, the VGG16 model makes a major contribution, delivering results with 97% accuracy. In the future, classification should be expanded to include more than the five categories of coral reef species used in this study. Furthermore, developing a website that uses YOLOv8 for coral reef classification can help best practices in coral reef conservation.

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