Harnessing Computer Vision and Deep Learning to Monitor Coral Reef Health

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ABSTRACT

Coral reefs have emerged as the most biodiverse and important entities in the marine ecosystem, as they house 25% of all marine organisms. As water temperatures rise in some sea areas, coral reef colors gradually turn white. This phenomenon, known as coral bleaching, signifies the deterioration of coral reef health and poses a significant threat to their survival. There is an urgent need for rapid and effective solutions to mitigate these threats, limit the spread of bleaching, and protect coral reefs. This study proposes a novel system that utilizes deep learning and computer vision to assess coral reef health and detect early signs of bleaching. Focusing on coral reefs in the Red Sea, the YOLOv8 and YOLOv9 object detection models were used on an augmented dataset of 10,285 labeled images representing healthy, bleached, and dead corals. The system includes a user-friendly interface for image classification and automatic notification of relevant authorities upon detection of bleaching or death. The evaluation results showed that YOLOv9 achieved a slightly higher mean Average Precision (mAP) of 89% compared to YOLOv8 (88%), demonstrating the effectiveness and potential of the system for real-time coral reef monitoring. This research offers a practical, automated solution for early detection, reducing human effort and achieving faster results, ultimately saving coral reefs from irreversible damage.

Keywords-computer vision; deep learning; object detection; YOLO; coral reefs

I. INTRODUCTION

Coral reefs are the most biodiverse structures in the marine ecosystem. Although they make up less than 1% of the oceans, they are home to 25% of all marine organisms. Their importance lies in providing a wide range of essential ecosystem services to people worldwide, including cultural and educational value, tourism, fishing, coastal protection, and medical advances. Globally, coral reef activities generate US $2.7 trillion each year and almost a billion people directly depend on them for their livelihood [1]. Many factors pose threats to coral health, the main drivers being global climate change, rising ocean temperatures [2, 3], and ocean acidification [4], which act as significant triggers for coral bleaching. Coral bleaching is the phenomenon where coral reefs turn white as they expel symbiotic algae, known as Zooxanthellae, in response to stress as a survival mechanism [5]. Although a bleached coral may endure for a period, its survival ultimately depends on the return of other algae to coexist with it; otherwise, it will die. Additional factors, such as oil and sewage pollution, contribute to the vulnerability of coral reefs, promoting the emergence of diseases [6].

Widespread global bleaching events [7, 8] and bleaching events in the Saudi Red Sea [9] have witnessed a significant decline in coral reefs. Since 1980, the rate of decline in coral reef populations has increased to 30-50% [10]. Mitigating these threats and reducing the spread of diseases to preserve coral reefs requires a proactive approach, including early diagnosis and identification of diseases. This goal can be implemented by processing and classifying underwater bleaching coral images. Given the prolonged nature of manual treatment and diagnosis, there is an urgent need for rapid and effective automated techniques. Early detection of diseases is crucial for prompt intervention, enabling relevant authorities to protect coral reefs and support marine conservation.

This research sought to create a system to detect coral reef health, integrating the power of computer vision and deep learning techniques and operating with high efficiency and accuracy. By processing images taken of Red Sea coral reefs, the model determines their health, whether they are bleached, dead, or healthy. The system then informs the relevant authorities, such as the KAUST Reef Ecology Lab or the National Center for Wildlife, allowing rapid intervention measures to be taken to protect coral reefs and ensure the sustainability of the marine environment. This innovative approach not only enhances detection efficiency but also facilitates timely action to mitigate impacts on coral reefs.

II. LITERATURE REVIEW

Many studies have taken advantage of modern technologies, such as deep learning and computer vision, to meet the challenges related to underwater object detection. This section provides a comprehensive literature review on the discovery of underwater targets, divided into four subsections: the first includes an overview of coral classification based on species, the second focuses on the detection of bleached corals, the third presents studies on coral disease detection, and the final subsection provides an overview of the different versions of the YOLO model used to detect marine objects.

A. Classification of Coral Reefs Based on Species

Advances in monitoring and classifying coral reefs based on species have shown promising results, mainly through applying deep learning techniques. In [11], a deep Convolutional Neural Network (CNN) was proposed to monitor coralligenous reefs for biodiversity assessment, automating species identification and monitoring their ecological status. A custom CNN achieved 72.59% accuracy in recognizing 61 coralligenous species, outperforming human accuracy, and a semi-automated tool was developed to reject uncertain results. In [12], the ResNet-50 network architecture with a 5500-image dataset was used to identify 11 types of coral reefs (500 images for each type) and study their coverage rate at four locations in the Gulf of Aqaba (Eilat). The accuracy results yielded 82.01%. Although the system faced challenges in distinguishing between distinct coral species, it demonstrated high accuracy in identifying prominent features. In [13], the VGG16, YOLOv5, and YOLOv8 models were used to classify images of coral reefs. YOLOv8, which had never been utilized for this purpose before, outperformed YOLOv5 with an accuracy of 97.8%. The VGG16 model also made a substantial contribution, achieving an accuracy of 97%. To improve robustness, 1,188 photos of five different coral species were included in the dataset.

B. Detection of Coral Reef Health

Other studies have used different CNN architectures for the crucial task of detecting and assessing coral reef health. In [14], a U-Net model (CNN) with a ResNet-18 backbone was used for the semantic segmentation of coral images by assigning labels to individual pixels in coral images, classified based on 10 semantic categories, including bleached corals. The model was trained on a dataset generated using seven sources from the CoralNet website and tested using coral images from the Red Sea (Eilat). The U-Net model was trained using different experiments, including different training data sizes, densities of labeled pixels in the ground truth, imbalances of the semantics, and fine-tunings. The results showed the superiority of the U-Net model trained on a medium-sized dataset (4,658 images), and an outperformance when trained on larger datasets (8,537 images). Fine-tuning the model with a weighted loss and domain shift also led to an improvement and a slight increase in the accuracy rate. However, this approach did not improve predictions for the less-represented classes.

In [15], a coral reef classification model was developed that classified coral into two groups: stressed and healthy. The model achieved up to 90% accuracy using a CNN architecture similar to ResNet-50 and Inception V3. Keras was utilized to create a sequential model, incorporating two 2D convolutional layers with essential parameters and applying the ReLU activation function across all trained neural networks, using a dataset of 120 images. In [16], a study on automating coral reef assessment was presented using drones and RGB images combined with deep learning. The neural network was based on a multiresolution U-Net architecture for automated coral image segmentation. The deep learning model achieved high precision (0.96) and recall (0.92) for unbleached corals, while for bleached corals, precision was 0.28, and recall was 0.58. To address pixel errors, bleached coral objects were created from neural network classifications. The method demonstrated a precision of 0.76 in regions with more than 2000 bleached corals, highlighting the effectiveness of drone-based RGB imagery and AI in coral reef monitoring. The study suggested future work involving additional training data to enhance the model's accuracy in various shallow-water coastal ecosystems.

In [17], a unique model was proposed that combined ColorTexture and handcrafted AlexNet DNN on raw features, to generate a bag of hybrid visual features (RL-BoHVF) for noise-tolerant bleached corals. Using the Bag-of-Features (BoF) method, lower overall dimensions were observed with a classification accuracy of 96.20% achieved on a balanced dataset collected from the Great Barrier Reef in Australia consisting of only 342 images. In [3], a BoF-based approach was employed to detect and localize bleached corals using a Deep CNN (D-CNN) called CoralNet. The dataset contained 15,000 images of the Great Barrier Coral Reef of Australia. The BoF approach was employed, combining handcrafted descriptors and the D-CNN model. The SVM classifier was used to classify the extracted features, achieving an accuracy of 99.08% on the Eilat dataset.

C. Detection of Coral Reef Diseases

Recent studies have focused on the various diseases that affect coral reefs, as early detection is essential to mitigate disease spread and protect these ecosystems. The challenge lies in addressing the image of coral reefs infected with various diseases and accurately identifying and classifying them. In [18], corals were classified as healthy, unhealthy, or dead based on color and appearance through image recognition. This study considered HSV and RGB color spaces to extract features in coral reef image classification and dealt with new feature descriptors, MDCP and DDVP, to improve classification accuracy. HSV-MDCP and RGB-MDCP were combined to build the feature vector. DDVP reduced computational complexity and enhanced the proposed framework for classification results with different classifiers, such as Decision Tree (DT), SVM, CNN, etc. The proposed framework included segmentation, feature extraction, and classification steps, effectively outperforming and improving classification accuracy between 80% and 99%.

In [19], machine learning was combined with open-source data to build a model capable of identifying and diagnosing coral states as healthy, bleached, or diseased. The dataset comprised 335 images of healthy and unhealthy coral reefs collected from government archives, atmospheric records, and large surveys. The Labelbox platform was utilized for image annotation, with labels on various coral conditions such as healthy, bleached, black band disease, dark spot disease, white syndrome, or yellow band disease. Using the Mask R-CNN architecture for training and validation, this study achieved more than 85% accuracy in distinguishing healthy from unhealthy corals, with a particular emphasis on accurately identifying bleached corals. However, this study highlighted the need for more comprehensive data on different disease categories to improve model performance. In [6], a coral reef classification model used a CNN for early detection of diseased and dying corals. The diseases included white band disease, black band disease, and yellow band disease. A dataset comprising 200 images of Persian Gulf corals was collected to evaluate the proposed model, which achieved 95% accuracy.

D. Marine Object Detection using YOLO

Recent studies have employed advanced techniques, particularly various YOLO models, for the detection of marine organisms. In [20], a Multi-Scale Feature Fusion Network (MAFFN) was introduced as part of the YOLOv5 architecture, referred to as MAFFN YOLOv5. A dataset of 1,000 coral images was manually annotated and classified into five categories: healthy coral, bleached coral, white pox, stripe, and dead coral. The MAFFN YOLOv5 model achieved an accuracy of 90.1%, outperforming previous advanced detectors. In [21], underwater targets were detected using an improved YOLOv7 model. This study addressed challenges such as inaccurate feature extraction and slow detection speeds in complex underwater environments. The YOLOv7-AC model was introduced, which incorporates advanced modules such as ResNet-ACmix and the AC-E-ELAN structure, enhancing feature extraction and model efficiency. Evaluations on the URPC and Brackish datasets showed mean Average Precision (mAP) of 89.6% and 97.4%, respectively, confirming the model's superiority in underwater detection.

In [22, 23], the YOLOv8 model was utilized to detect fish species, although with different objectives. In [22], the focus was on enhancing fish detection under occlusion by integrating Real-Time Detection Transformer (RT-DETR) features into a modified YOLOv8 model, achieving significant improvements in detection accuracy with a dataset of 1,850 images featuring occluded fish. In [23], the objective was to evaluate the effectiveness of YOLOv8 in detecting native fish species in Indonesia. The dataset was split into subsets for training, validation, and testing, allowing a comprehensive evaluation of the model under various environmental conditions. YOLOv8 demonstrated enhanced performance in object detection accuracy and speed, achieving overall detection accuracies of 92.3% for head detection and 86.9% for tail detection. This pre-trained model can effectively monitor marine environments by detecting various objects, including coral reefs, efficiently.

In conclusion, despite the abundance of research based on coral reef classification, whether aimed at identifying species or diseases in most areas where coral reefs are common, no research in this regard has shed light on the eastern part of the Red Sea. Although different techniques and different versions of YOLO have been used in the classification of organisms, YOLOv8 and YOLOv9 have not been used to detect the health status of coral reefs. These latest versions have proven their high ability and exceptional capabilities to identify organisms with high accuracy and speed. This study used them to achieve the highest possible accuracy in detecting the health state of coral reefs in the Red Sea and compare their performance.

III. METHODOLOGY

A. Study Design and Procedure

Figures 1 and 2 provide an overview of the method and system design. Figure 1 outlines the main workflow stages, including data collection, preprocessing, model training, and evaluation, while Figure 2 illustrates the system architecture, detailing how the detection model is integrated into a real-time monitoring system that can alert users to instances of bleached or dead coral. The method begins with data collection, where images of coral reefs were gathered from publicly available datasets and manually annotated into three classes: healthy, bleached, and dead coral. This was followed by data preprocessing, which included annotation, augmentation, and resizing all images to 640×640 pixels. The dataset was then split into training, validation, and testing sets in a 92:4:4 ratio, resulting in 9,498 training images, 388 validation images, and

399 testing images. In the model training phase, YOLOv8l and YOLOv9l were fine-tuned on the preprocessed dataset. These models were selected for their balance of accuracy and speed, making them suitable for real-time applications. The trained models were evaluated using several metrics, including mAP, accuracy, precision, recall, and F1 score, to assess their performance in distinguishing between the three coral health conditions.

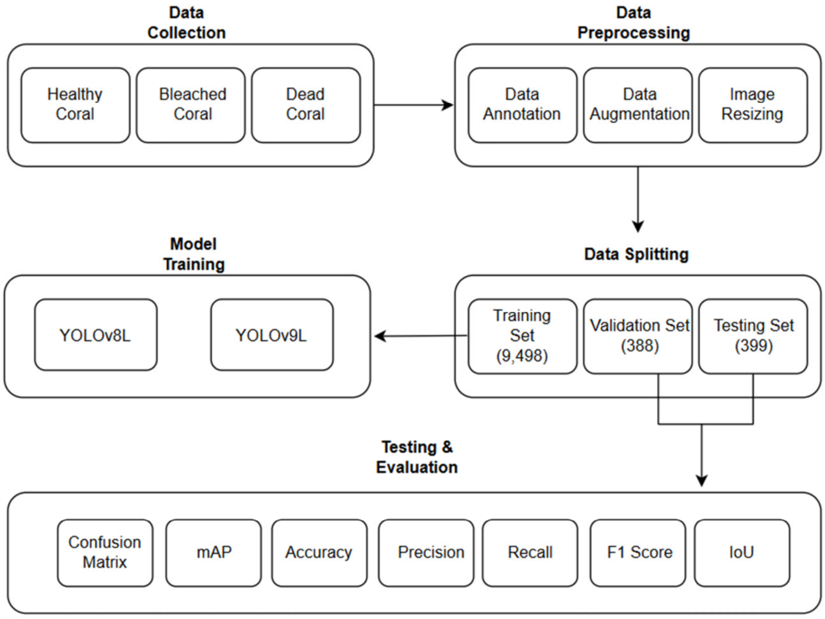

Fig. 1. Workflow of the Coral Reef Health Detection System.

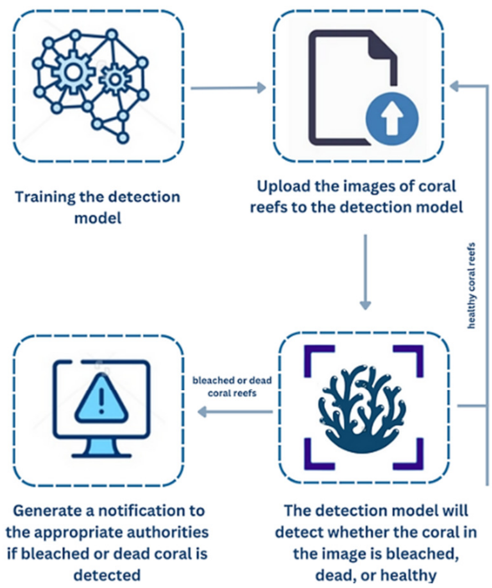

Fig. 2. System architecture and program flow.

B. Dataset Details

A dataset [24] was compiled from publicly accessible coral reef datasets at KAUST and Red Sea International, available on the CoralNet [25] and the Ocean Agency [26] websites. This dataset comprises around 3,000 images, with 1000 healthy, 1000 bleached, and 1000 dead corals. First, 300 images of each coral status were manually collected and annotated, which were then augmented using Roboflow until they reached 1000 images for each type. In detail, for bleached coral reef images, 600 images were collected manually from Coral Net [25] and annotated. As a shortage of bleached images was encountered, 168 bleached coral reef images were collected and annotated from Kaggle [27], which were augmented to 582 images. For healthy coral reef images, 281 images were manually collected and annotated, reaching 843 images after augmentation, and 127 healthy coral reef pre-annotated images were collected from Roboflow [28, 29]. For dead coral reefs, 1000 images were collected and annotated from Coral Net [25].

Finally, the dataset was augmented to a total of 10,285 images. The annotation process involved drawing a bounding box around the object of interest to be detected, and a class name was assigned to this object. This dataset encompasses three classes: dead, bleached, and healthy. Next, a new dataset was created specifically for instance segmentation, which consisted of 2264 images, stemming from the original Marjan object detection dataset. The bounding boxes in each image were manually converted into polygonal shapes. Segmentation involves splitting an image into many relevant and uniform parts or objects based on their intrinsic qualities, such as color, texture, shape, or brightness. Image segmentation aims at simplifying and/or transforming an image's representation into something more relevant and easier to examine. Each pixel in this image is labeled, and all pixels in the same category have a similar label applied to them.

C. Data Acquisition and Preparation

A custom dataset for coral reef health was created, consisting of 1,545 images [24]. Of these, 1,000 images were manually labeled and 545 were prelabeled. The dataset includes three categories that correspond to the health conditions of coral reefs: healthy, bleached, and dead. Most of the images were collected from publicly accessible coral reef datasets provided by KAUST and Red Sea International, available on the CoralNet website [25]. Additional images were obtained from the Ocean Agency website [26], Kaggle [27], and Roboflow [28, 29], ensuring the inclusion of high-quality images, which is crucial for improving model learning and achieving high-accuracy results. Data annotation was performed manually using the Roboflow platform [30]. During the annotation process, bounding boxes were drawn around the objects of interest in each image that were intended to be detected. Additionally, class names were assigned to these objects for classification purposes based on the three categories mentioned above. The annotated images were then scaled to 640×640 pixels to satisfy the input size requirements of the models. Furthermore, to expand the dataset and reduce overfitting, its size was augmented to 10,285 images. This technique involved creating different versions of the original images using four techniques: rotation, flipping, shifting, and scaling. These techniques were carefully chosen to improve model generalization while keeping essential visual elements, as coral images are naturally complex and sensitive. Given the complex structure of coral structures, it is critical to use transformations that do not change the original images but instead produce new variations from different perspectives. This ensures that the model correctly recognizes the conditions of the coral reef while maintaining data integrity. By including controlled perspective modifications, these augmentations provide more diverse images for each coral reef state, thus improving model robustness and minimizing overfitting. Table I outlines the data augmentation techniques used with the dataset.

TABLE I. AUGMENTATION TECHNIQUES UTILIZED

Technique	Description
Flip	Horizontally or vertically.
Rotation	Within a range of -15° to +15°.
Shear	+10° horizontally and +10° vertically.
Saturation	-25% and +25%, altering the image's vibrancy (e.g., grayscale to vivid).

Finally, the dataset was divided into three subsets for training, validation, and testing. The training set contained 9,498 images, the validation set contained 388 images, and the test set included 399 images. This distribution follows a split ratio of 92% for training, 4% for validation, and 4% for testing.

D. Testing and Evaluation Methods

The proposed system was evaluated using several metrics to determine its effectiveness. These metrics are important quantitative tools for evaluating different aspects of the detection model performance and can be used to compare different models. This study used confusion matrices, accuracy, precision, recall, IoU, mAP, and F1 score, which are the building blocks of computer vision model assessment [31]. The confusion matrix is a foundational tool for evaluating binary and multiclass classification models, represented as a table that compares predicted and actual values, organizing the results into four distinct categories: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). TP refers to instances where the model correctly identifies the positive class, TN refers to instances where the model correctly identifies the negative class, FP refers to cases where the model incorrectly predicts the positive class, and FN refers to cases where the model fails to identify the positive class and instead predicts it as negative.

Accuracy measures the model's ability to correctly predict the class labels of the instances in the dataset. Accuracy provides a general overview of model performance across all classes. Precision measures the model's ability to distinguish between TP and FP, offering insight into how effectively it avoids FP. Recall, also referred to as sensitivity or true positive rate, measures the model's ability to capture all relevant objects in an image, thereby evaluating its ability to identify objects of interest. F1-score is the harmonic mean of precision and recall, providing a balanced measure to compare performance. IoU is used to measure the intersection area between two bounding boxes. It assesses the quality of a predicted bounding box against the ground truth. MAP averages precision across multiple recall levels and IoU thresholds, providing a comprehensive evaluation of the model's precision-recall trade-off. Common thresholds include mAP@50 and mAP@[50:95], reflecting different levels of localization stringency.

E. Training YOLOv8 and YOLOv9 Models

The selection of YOLOv8 and YOLOv9 was driven by their optimized object detection capabilities and the potential to improve accuracy in recognizing the health status of coral reefs. While several versions of YOLO have been used to identify organisms, YOLOv8 and YOLOv9, have not yet been applied specifically to this task. YOLOv9 brings significant innovations, including Programmable Gradient Information (PGI) and the Generalized Efficient Layer Aggregation Network (GELAN), which solve issues of information loss and computational efficiency. These advances improve real-time detection performance, establishing new standards for accuracy and speed. YOLOv8 has already shown remarkable performance in recognizing organisms due to its high accuracy and quickness. This study aimed to evaluate the performance of YOLOv8 and YOLOv9 and select the most appropriate model for detecting the health of coral reefs with the maximum possible accuracy. Table II shows the hyperparameters of the YOLOv8 and YOLOv9 models to maintain consistency during training and evaluation.

TABLE II. UNIFIED HYPERPARAMETERS BETWEEN YOLOV8 AND YOLOV9 MODELS

Hyperparameters	Values
Epochs	300
Optimizer	SGD
Learning rate	0.001
Image size	640
Batch size	16

Epochs refer to the number of training epochs, with each epoch representing a complete pass through the training dataset. The optimizer is responsible for updating the model parameters to minimize the loss function, contributing to faster convergence. The learning rate is the step size used by the optimizer to approach the minimum of the loss function, crucial for balancing training speed and stability.

F. System Architecture and Operational Flow

As shown in Figure 2, the system architecture begins with training the YOLOv8 detection model using a dataset of annotated images that represent healthy, bleached, and dead corals. Once trained, the model was deployed via a user-friendly interface built upon the Streamlit framework that allows authorities or marine researchers to upload either a single image or a zip file containing multiple coral reef images. If a single image is submitted, the model classifies its condition and returns an immediate status message. In the case of a zip file, the system analyzes all included images and generates a downloadable csv file that lists the detected status of each. If the system detects bleached or dead corals, it automatically triggers a notification alert to the relevant environmental authorities. This real-time alert system allows for timely interventions, helping prevent the spread of coral disease and supporting conservation efforts.

IV. RESULTS AND DISCUSSION

A. YOLOv8 Results

In this study, after experimenting with various parameters to optimize performance, the YOLOv8 achieved its highest accuracy of 88% when trained for 300 epochs. Table III presents the model performance evaluation metrics.

TABLE III. YOLOV8 PERFORMANCE EVALUATIONS FOR EACH CLASS

Classes	Precision	Recall	mAP50
All	90%	83%	88%
Bleached Coral	91%	81%	87%
Dead Coral	92%	88%	92%
Healthy Coral	87%	80%	85%

Figure 3 presents the training and validation loss curves for the YOLOv8 model. The training loss curve shows how effectively the model learneσ from the training data, while the validation loss curve indicates how well the model generalizes to new data. All training loss curves (box, classification, DFL) decreased steadily, indicating effective learning. The validation losses show a decreasing trend, indicating that the model effectively generalizes its learning to the validation set. Finally, precision, recall, mAP50, and mAP50-95 all show an upward trend, reflecting improvements in the model's detection and classification capabilities over time.

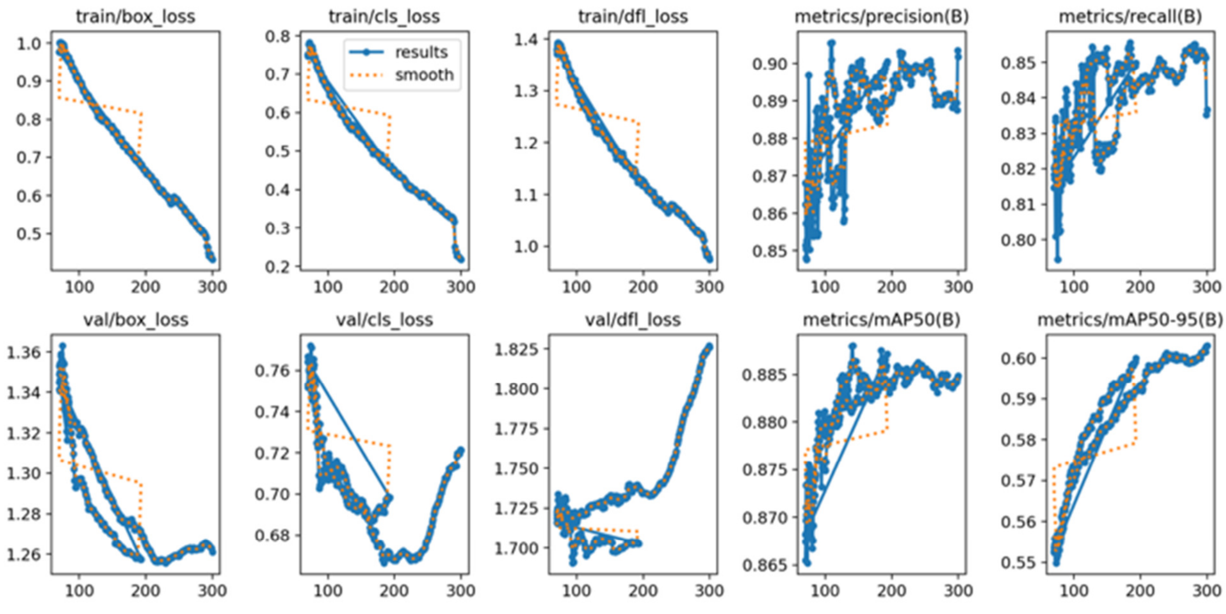

Fig. 3. Evaluation of YOLOv8.

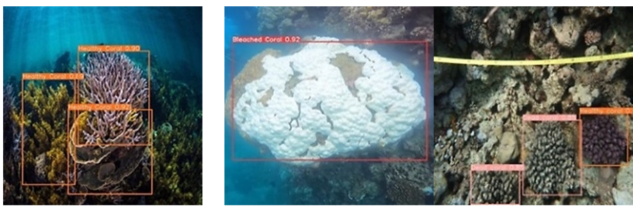

Fig. 4. Yolov8 testing results

Figure 4 demonstrates the model's high accuracy in detecting healthy, bleached, and dead corals, underscoring the effectiveness of YOLOv8 in coral health detection. Overall, these findings underscore YOLOv8's potential as a robust tool for accurately detecting various states of coral health, which is vital for ongoing conservation efforts.

B. YOLOv9 Results

YOLOv9 stands out as a substantial advancement in object detection. This version offers unique technologies such as PGI and GELAN to address concerns of information loss and computational efficiency. These advances help YOLOv9 perform well in real-time object detection, setting a new bar for accuracy and speed in the field. After experimenting with different parameters to achieve the highest accuracy, the model trained for 300 epochs achieved 89% accuracy and the performance metrics in Table IV. Figure 5 shows different aspects of performance over the training iterations. As training progressed, the model improved in terms of bounding box accuracy, classification accuracy, and overall detection precision and recall. Figure 6 demonstrates the efficacy of the YOLOv9l model in identifying and classifying coral reefs according to their health conditions with high confidence scores on images from the test set.

TABLE IV. TRAINING RESULTS

Classes	Precision	Recall	mAP
All	90%	86%	89%
Bleached Coral	92%	86%	90%
Dead Coral	91%	90%	93%
Healthy Coral	87%	81%	85%

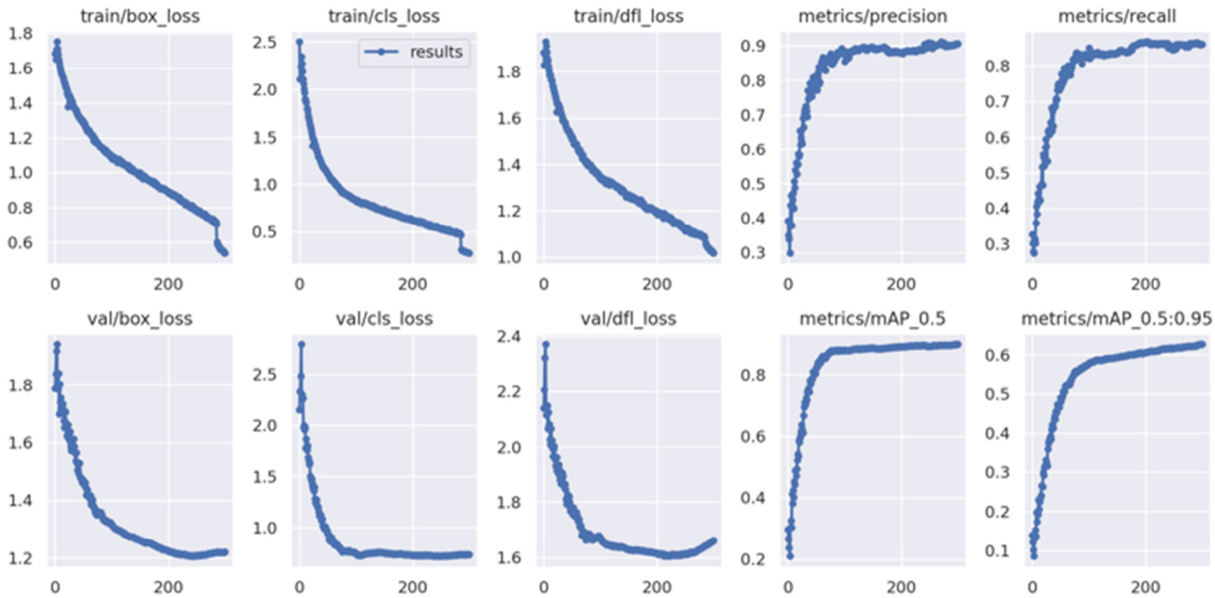

Fig. 5. Evaluation of YOLOv9l.

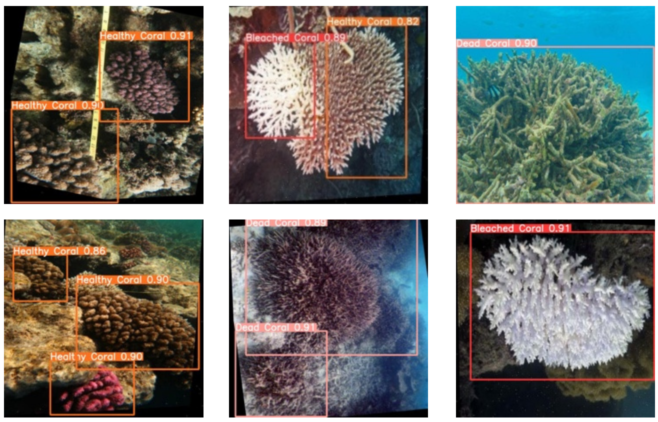

Fig. 6. YOLOv9 test results.

C. YOLOv8 vs YOLOv9 Compare Results

YOLOv9 was superior to YOLOv8, exhibiting high accuracy and a shorter training period. Although YOLOv8 demonstrated the ability to achieve commendable accuracy, its performance was less consistent across various coral reef health states, rendering it less efficient compared to YOLOv9. YOLOv9 was the best option for identifying coral reef health status due to its faster learning and improved overall efficiency.

TABLE V. MODELS' PERFORMANCE COMPARISON

Model	Precision	Recall	mAP
YOLOv8	90%	83%	88%
YOLOv9	90%	86%	89%

V. CONCLUSION

Coral reefs represent a vital economic asset, contributing significantly to marine resources. It is imperative to preserve their ecological integrity, as a thriving coral reef system not only boosts fish populations but also supports diverse marine life, including economically valuable seaweeds. Therefore, safeguarding these ecosystems from bleaching is of paramount importance. The adage "prevention is better than cure" holds particular relevance in the context of coral reef conservation. That is because when coral reefs bleach, they are not dead.

Corals can survive a bleaching episode but are more vulnerable to mortality. For these reasons, this study introduced an advanced computer vision system designed for real-time coral reef health assessment, focusing on early detection of bleaching. Unlike previous approaches, this study employed YOLOv8 and YOLOv9 object detection techniques, trained on an augmented dataset of 10,285 images categorized into healthy, bleached, and dead corals. A key novelty of the proposed system lies in its ability to provide automated alerts to relevant authorities upon detecting signs of coral distress, enabling timely intervention to prevent further damage.

The comparative analysis showed that YOLOv9 slightly outperformed YOLOv8, achieving an mAP of 89% compared to YOLOv8's 88%. Although the performance difference is marginal, this refinement contributes to more accurate and reliable monitoring. Unlike traditional methods that rely on manual assessments or lower-precision models, the proposed system has enhanced detection accuracy and responsiveness, making it a more effective tool for large-scale reef conservation efforts. Future improvement goals focus on two key areas. The first objective is to expand the dataset by incorporating training and testing data specific to coral diseases found in the Red Sea to enhance the accuracy and relevance of the model. The second objective involves improving the response speed by integrating the system with underwater drone cameras, enabling swift recognition and classification of the state of coral reefs.

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