CORAL GUARDIAN+: AI-DRIVEN MULTI-MODAL REEF HEALTH MONITORING

INTEGRATING ENVIRONMENTAL & TEMPORAL DATA FOR SMARTER CONSERVATION

1st Noura Al Ali
Higher Colleges of Technology (HCT)
Business Department – Business Analytics Program
Sharjah, United Arab Emirates
H00498786@hct.ac.ae

3rd Shaimaa Alhefeiti
Higher Colleges of Technology (HCT)
CIS Department - Information technology - Networking Concentration
Al Fujairah, United Arab Emirates
H00511474@hct.ac.ae

2nd Alreem Abdulla Almheiri
Higher Colleges of Technology (HCT)
CIS Department – Information Technology - Security and Forensics concentration
Ras Al-Khaimah, United Arab Emirates
H00534158@hct.ac.ae

4th Fatma Saeed Alsuwaidi
Higher Colleges of Technology (HCT)
CIS Department - Information Systems - Business Solutions
Dubai, United Arab Emirates
H00414752@hct.ac.ae

1. ABSTRACT

Coral reefs are vital ecosystems that support marine biodiversity but are increasingly threatened by climate-induced bleaching. Coral Guardian+ is an AI-based system designed for classification, detection, and temporal prediction analysis of coral reef health. We trained a YOLOv8 model on the Coral pathology dataset, which contains 16 classes representing healthy, bleached (in different forms), and dead coral reefs. The model detects and classifies coral health conditions from underwater images. To assess environmental

risk, we performed a hypothetical fusion by combining these image-based results with temperature anomaly data from the NOAA CoRTAD – Coral Reef Temperature Anomaly Database. This enabled us to use trends in sea surface temperature to determine whether coral reefs are likely to be in danger or to be safe. The method aids conservation efforts in sensitive areas, such as the Red Sea, and shows the importance of combining environmental and imaging data for improved coral reef monitoring.

2. INTRODUCTION

These ecosystems are often referred to as "rainforests of the sea" since they are among the most biodiverse ecosystems on Earth. They give essential ecological services and economic advantages and coastal-calming opportunity, sheltering roughly 25% of the marine species. However, among the major threats climate change presents to coral reefs is the variation of sea temperature that causes coral bleaching on a massive scale and their eventual death (Hoegh-Guldberg et al., 2017). The Red Sea is a crucial area for comprehending how reefs may adjust to rising waters because of their renownedly hardy corals (Voolstra & Aranda, 2020).

Despite their significance, coral reef monitoring is still quite difficult. Conventional techniques, including surveys relying on divers, are expensive, time-consuming, and have a narrow scope. Automated, scalable, and precise methods that can identify and forecast coral health issues in real time are becoming increasingly necessary.

Our Coral Guardian+ project seeks to close this gap by creating a system driven by deep learning that can:
1. Detection and classification of coral health using underwater images,
2. Temporal prediction of coral reef risk based on sea surface temperature anomalies.

We used the Coral-pathology dataset, which includes 16 classes covering healthy, bleached (in various forms), and dead coral types. A YOLOv8 model was trained to detect and classify these coral health conditions accurately. Since no available dataset links coral images with environmental data, we performed a hypothetical combination with the NOAA CoRTAD – Coral Reef Temperature

Anomaly Database to estimate the risk level of corals under future temperature trends.

Coral Guardian+ offers a basis for more efficient, scalable coral reef monitoring systems by fusing environmental analysis with visual data. It encourages proactive conservation measures, especially in vital habitats like the Red Sea, where large-scale coral loss can be avoided with early stressor detection.

3. LITERATURE REVIEW

Coral reefs are vital ecosystems that support marine biodiversity, but they are becoming increasingly threatened by bleaching, ocean acidification, and climate change. Coral reef research has changed because of recent advancements in environmental observation and artificial intelligence (AI), which offer scalable and efficient instruments for assessing and maintaining coral reef health... This evaluation consolidates seven significant studies, categorized into three themes: (1) ecological effects on coral ecosystems, (2) AI-based coral identification and segmentation, and (3) datasets on coral bleaching and monitoring standardization. These studies indicate that coral monitoring has improved, but they also reveal ongoing issues with integrating multimodal AI with environmental and temporal data. Our initiative, Coral Guardian+, seeks to address this issue

3.1 ENVIRONMENTAL IMPACTS ON CORAL ECOSYSTEMS

Important information about the environmental stressors impacting coral reefs is provided by two research. In Coral Reef Ecosystems under Climate Change and Ocean Acidification, Donner et al. (2018) investigate how coral physiology is disrupted by rising sea temperatures and ocean acidification, resulting in bleaching and coral death. Temperature-driven bleaching thresholds are quantified by their worldwide study, which uses environmental datasets such as NOAA CoRTAD. However, they do not have region-specific models, especially for the Red Sea. Similar to this, Hughes et al. (2023) examine past bleaching data in Six Decades of Global Coral Bleaching Monitoring, highlighting the necessity of uniform monitoring procedures. Predictive modeling is limited by the temporal data provided by their high-resolution global mass coral bleaching database (GCBD), which also reveals disparate data gathering techniques across different locations. Both studies underscore the urgency of understanding environmental drivers but do not integrate AI for real-time monitoring, a gap our project addresses by combining environmental data with AI-driven analysis.

3.2 AI-DRIVEN CORAL DETECTION AND SEGMENTATION

Three papers focus on AI applications for coral reef monitoring, particularly in detection and segmentation. In Scalable Semantic 3D Mapping of Coral Reefs with Deep Learning, King et al. (2022) use convolutional neural networks (CNNs) to create a deep learning framework for 3D coral mapping. Although their methodology is computationally demanding and achieves excellent accuracy in semantic segmentation, its scalability for real-time monitoring is limited. In CoralVOS: Dataset and Benchmark for Coral Video Segmentation, Li et al. (2023) present a video segmentation dataset and benchmark that employs models such as Mask R-CNN to dynamically monitor coral health. While effective for temporal analysis, CoralVOS focuses on video data, overlooking static imagery or environmental correlations. However, Raphael et al. (2023) employ YOLOv8 in Automatic Coral Detection employing YOLO to precisely and efficiently (mAP > 0.85) identify coral in underwater pictures. However, environmental factors like pH and temperature—which are crucial for thorough monitoring—are not included in their approach. These studies demonstrate AI's potential but fall short in combining detection with environmental and temporal data, a core innovation of Coral Guardian+.

3.3 CORAL DATASETS AND COST-EFFECTIVE MONITORING

Two studies address datasets and cost-effective AI solutions for coral monitoring. Modasshir et al. (2023) in The Coralscapes Dataset present a comprehensive dataset for semantic scene understanding, including annotated coral images for classification and segmentation tasks. Coralscapes supports models like ResNet-18, which we adopt in our project, but its static imagery lacks temporal environmental context. Pavoni et al. (2022) in Coral Reef Monitoring Using machine learning to assess coral cover and health, artificial intelligence is promoted as a more affordable option to manual surveys. Although their method is 30% less expensive than traditional approaches, it is limited in its ability to provide insights relevant to a certain place due to its reliance on generalized models (e.g., Red Sea corals). Both studies enhance data availability and affordability but do not address multimodal integration, a focus of our project.

SYNTHESIS AND RESEARCH GAP

The works under consideration demonstrate important developments in the study of coral reefs. The effects of climate change and acidification are quantified in environmental research (Donner et al., 2018; Hughes et al., 2023), but AI integration for predictive monitoring is absent. Strong identification and segmentation capabilities are shown in AI-focused articles (King et al., 2022; Li et al., 2023; Raphael et al., 2023), with models such as YOLOv8 and ResNet attaining high accuracy. These methods, however, frequently work independently, concentrating on either video (CoralVOS) or pictures (Coralscapes) without taking environmental factors like those in NOAA

CoRTAD or GCBD into account. Though they increase accessibility, datasets and cost-effective techniques (Modasshir et al., 2023; Pavoni et al., 2022) do not provide temporal and region-specific analysis, especially for understudied regions like the Red Sea.

4. METHODOLOGY

This study employed a deep learning-based approach to detect and classify coral reef pathologies using the YOLOv8 (You Only Look Once version 8) object detection framework. The methodology consisted of several key stages: dataset acquisition, model training, evaluation, and inference.

4.1 DATASET COLLECTION

This study utilized two main data sources: - A labeled image dataset for coral pathology obtained from Roboflow. The dataset was split into training, validation, and test sets, formatted for YOLOv8 object detection. A coral reef temperature dataset in `.hdf` format containing sea surface temperature records across various reef locations and years. This dataset was used to examine environmental trends affecting coral health. In addition to the final dataset used, several publicly available coral datasets were initially reviewed. However, many of these proved unsuitable due to issues such as unclear labels, poor segmentation quality, or mismatched annotation formats. For example, one dataset contained segmented coral images but lacked consistent labeling standards, which prevented effective model training. These limitations reinforced the importance of selecting a well-annotated dataset to ensure reliable object detection and accurate ecological monitoring.

4.2 DEEP LEARNING MODEL TRAINING

The YOLOv8 object detection model was trained using the annotated coral pathology dataset. The model was initialized with the `yolov8m.yaml` configuration and trained from scratch over 150 epochs with an image resolution of 640×640 pixels. Training was performed using Ultralytics' YOLO library, and the model weights were saved for further use.

4.3 MODEL EVALUATION AND INFERENCE

Following training, the test set was used to validate the model, and measures like precision, recall, and mean Average Precision (mAP) were assessed. Next, unknown coral images were inferred using the top-performing model (`best.pt`). The predictions were saved and visualized to assess the model's accuracy in detecting coral pathologies.

4.4 CORAL TEMPERATURE ANALYSIS

The Python packages xarray, pandas, and matplotlib were used to process the coral reef temperature data, which was taken from NOAA's sea surface temperature (SST) archives in NetCDF (.nc) format. The Red Sea and Arabian Gulf were included in the region of interest, which was located between latitudes 5° and 35°N and longitudes 30° and 65°E. The daily SST files for January 1–7, 2024 were downloaded. To separate this area, the dataset was spatially sliced for each day, and the average SST was computed for every pixel.

The differences in water temperatures throughout the course of the seven days were then investigated through a temporal analysis. Plotting the average daily SST readings as a time series was how this was accomplished. High-risk days were identified as those with mean SSTs over a predetermined threshold of 29.5°C, suggesting possible thermal stress conditions for coral ecosystems. To investigate connections between heat stress and coral disease outbreaks, the final figure emphasized temperature trends and anomalies.

4.5 INTEGRATION OF AI PREDICTION AND ENVIRONMENTAL DATA

As shown in **Table 1**, the workflow of *Coral Guardian+* demonstrates how deep learning and environmental data are combined to monitor coral reef health. The process begins with collecting underwater coral images along with environmental data such as sea surface temperature. These inputs

are fed into a YOLOv8 model, where training, detection, testing, and validation are performed to classify coral conditions. In the **temporal risk analysis** stage, the classified images are compared with temperature trends to identify possible links between heat stress and coral degradation. The results are then visualized in a dashboard that predicts bleaching risk. This integrated system allows for better understanding of the relationship between climate impact and coral health.

Table 1 Methods and Tools Used

Method	Tool/Library Used
Image Dataset Collection	Roboflow API
Temperature Data Extraction	h5py (for .hdf files)
Object Detection Training	YOLOv8 (Ultralytics)
Evaluation & Prediction	Ultralytics metrics
Data Integration & Analysis	Python analysis

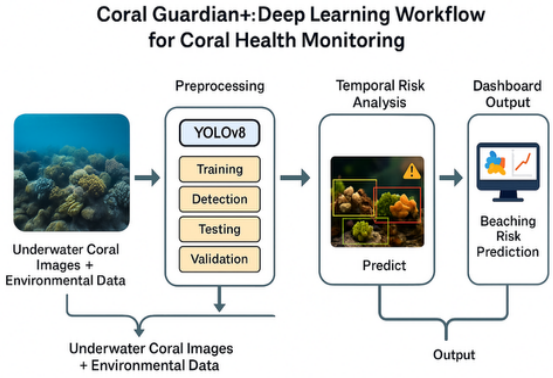
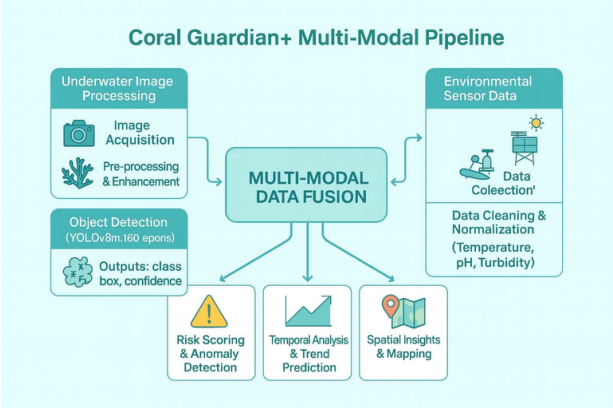


Figure 1 The process of Coral Guardian+: Deep Learning for Coral Reef Health Monitoring with Environmental and Temporal Analysis

4.6 MULTI-MODAL FRAMEWORK

To enhance the robustness of the system, a multi-modal analysis framework was implemented that combines coral detections from YOLOv8m with environmental metrics, specifically sea surface temperature (SST) anomalies. This integration allows for a more holistic understanding of reef health by capturing not only the visible condition of the coral but also the environmental stressors driving change. The framework strengthens the system's capacity to track thermal stress trends, detect early signs of bleaching by correlating subtle visual cues with rising temperatures, and generate risk maps that highlight vulnerable areas. By moving beyond visual-only assessments, the framework provides conservationists with deeper insights into both the state and causes of coral stress.



4.7 ADVANCED ANALYSIS

The combination of visual and environmental data also enables advanced analytical capabilities that extend beyond conventional object detection. For instance, the system is able to detect bleaching at an early stage, before severe whitening is visible, by identifying correlations between subtle image features and temperature anomalies. Similarly, it can link sudden increases in SST to localized bleaching events, helping identify potential environmental trigger points. By integrating these insights, the framework produces coral risk maps that forecast areas and time periods with elevated bleaching probability. This transforms the system from a monitoring tool into a predictive early-warning mechanism for reef conservation.

5. RESULTS

5.1 YOLOV8S (70 EPOCHS) MODEL PERFORMANCE

5.1.1 TRAINING CONVERGENCE AND BASELINE ACCURACY

The YOLOv8s model trained for 70 epochs demonstrated a promising baseline for coral pathology detection. As shown in the loss curves (Figure 2), the training and validation losses—box loss, classification loss, and distribution focal loss—declined steadily, indicating good convergence. The validation mAP50 reached approximately 0.36, with mAP50-95 around 0.24, highlighting modest object detection accuracy for a lightweight model.

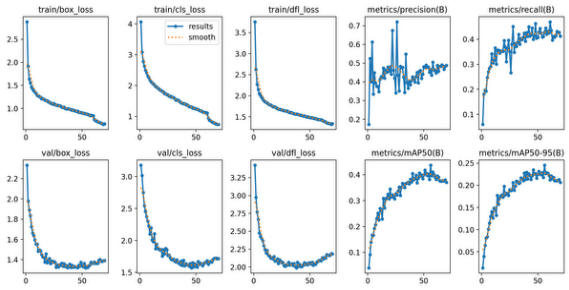


Figure 2 YOLOv8s Training and validation loss curves

5.1.2 CONFUSION MATRIX AND CLASS-LEVEL PRECISION

The confusion matrix (Figure 3) revealed strong performance for the dominant class "bleached_corals" with 209 correct predictions, but also exposed frequent misclassifications between similar categories such as "healthy coral" and "bleached disease." The F1-confidence curve peaked at 0.45 (Figure 4), while the precision-confidence and recall-

confidence curves showed stable precision (0.99) and recall (0.77) across most classes (Figures 5 and 6, respectively).

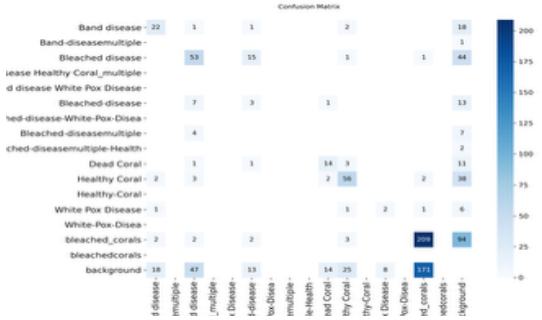


Figure 3 YOLOv8s confusion

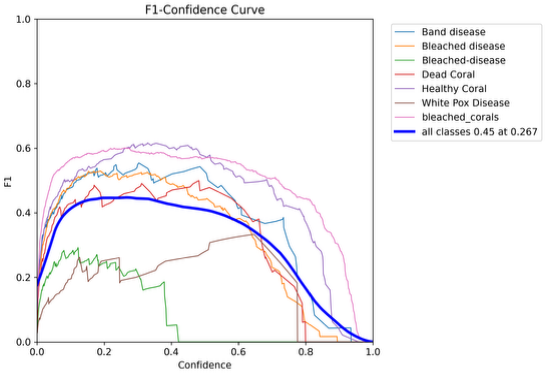


Figure 4 YOLOv8s F1-Confidence Curve

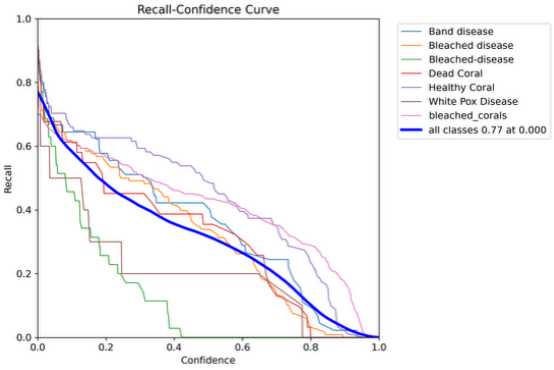


Figure 5 YOLOv8s Recall-Confidence Curve

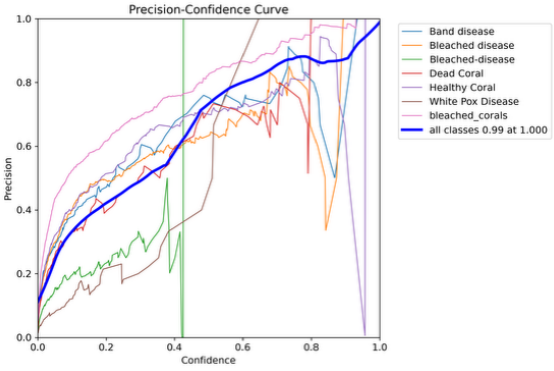


Figure 6 YOLOv8s Precision-Confidence Curve

5.1.3 VISUAL DETECTION RESULTS AND MODEL LIMITATIONS

Detection samples (Figure 7) showed consistent bounding box predictions with confidence scores above 0.7 in many test images, particularly for bleached coral clusters. However, there was little detection of physically identical or minority classifications, such as "dead coral" and "White Pox Disease." These findings imply that although YOLOv8s is computationally efficient, unusual class detection and fine-grained classification would necessitate further training or a larger model.

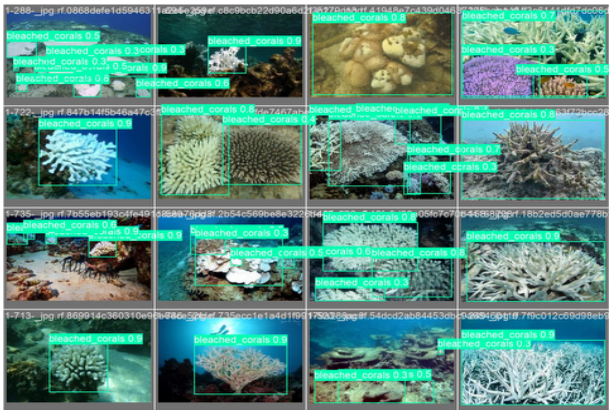


Figure 7 YOLOv8s Detection Results on Test Images

5.2 YOLOV8M (150 EPOCHS) MODEL PERFORMANCE

5.2.1 IMPROVED OPTIMIZATION AND DETECTION ACCURACY

The YOLOv8m model, which was trained across 150 epochs, fared better than the YOLOv8s model in almost all evaluation metrics. As shown in (Figure 8), training and validation losses declined smoothly, reflecting better optimization over time. The mAP50 reached 0.407, with mAP50-95 holding steady around 0.23—similar to YOLOv8s but with consistently higher class-wise precision and reduced noise in the validation curve.

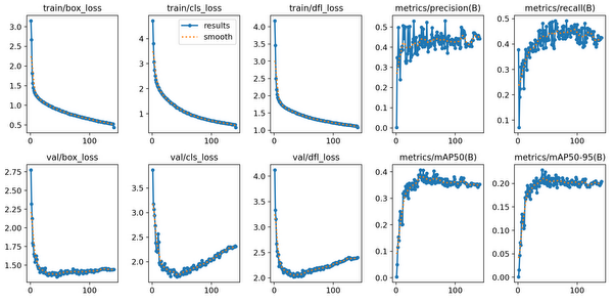


Figure 8 YOLOv8m Training and Validation Loss Curves

5.2.2 CONFUSION MATRIX AND EVALUATION METRICS

According to the confusion matrix (Figure 9), the model correctly identified 197 instances of “bleached_corals” and achieved stronger separation for challenging classes such as “dead coral” and “band disease.” While the peak F1-score (0.43) remained close to YOLOv8s (Figure 10), precision peaked at 1.00 at a confidence threshold of 0.959 (Figure 11), showing more confident predictions. The recall-confidence curve (Figure 12) and precision-recall curve (Figure 13) further confirmed the model’s higher recall and average class performance, especially for “healthy coral” (0.528) and “bleached_corals” (0.552).

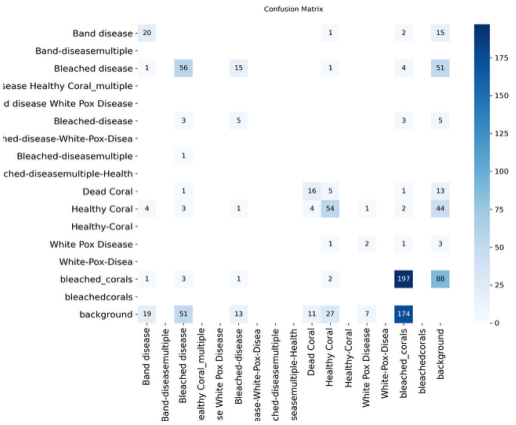


Figure 9 YOLOv8m Confusion Matrix

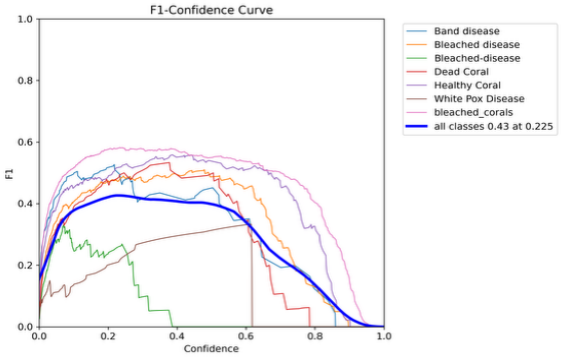


Figure 10 YOLOv8m F1-Confidence Curve

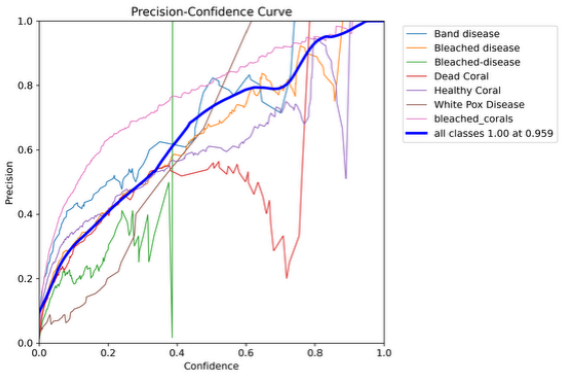


Figure 11 YOLOv8m Precision-Confidence Curve

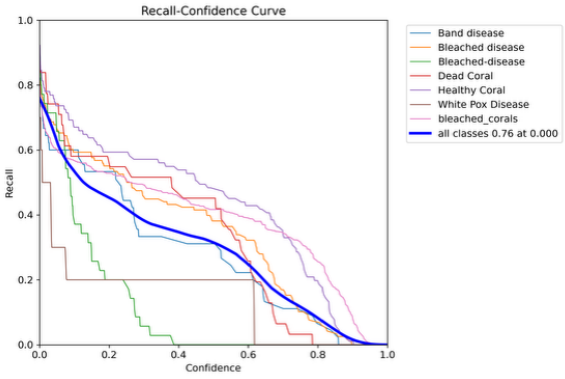


Figure 12 YOLOv8m Recall-Confidence Curve

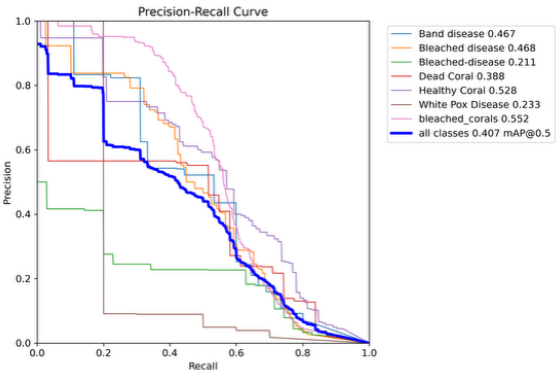


Figure 13 YOLOv8m Precision-Recall Curve

5.2.3 Visual Output Quality and Rare Class Recognition

Visual detection results (Figure 14) displayed higher-quality bounding boxes, even in cluttered underwater environments, with most predictions showing confidence levels above 0.8. Unlike the smaller model, YOLOv8m succeeded in identifying rarer classes, making it more suitable for field-level deployment in coral reef health monitoring.

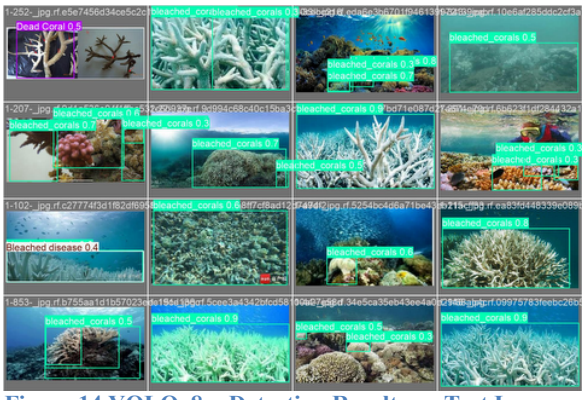


Figure 14 YOLOv8m Detection Results on Test Images

5.3 YOLOv8s vs YOLOv8m Performance Comparison

Table 2 presents a qualitative comparison between the detection results of the YOLOv8s

and YOLOv8m models. It highlights the differences in detection confidence levels, bounding box accuracy, and performance on rare coral classes. YOLOv8m consistently delivered higher confidence and tighter box predictions, making it more suitable for real-world coral monitoring.

Table 2 Visual Comparison of Detection Outputs

Model	Detection Confidence	Bounding Box Quality	Detection on Rare Classes	Example Images
YOLOv8s	Mostly 0.3 – 0.7	Good for dominant classes	Weak	See Figure 7
YOLOv8m	Mostly 0.5 – 0.9	Sharper and tighter boxes	Improved	See Figure 14

Table 3 summarizes the quantitative performance metrics of YOLOv8s and YOLOv8m. The comparison shows that while YOLOv8s offers faster training and lighter architecture, YOLOv8m yields higher accuracy and better detection of minority classes, making it a more robust choice for detailed coral classification tasks.

Table 3 Performance Summary – YOLOv8s vs YOLOv8m

Metric	YOLOv8s (70 Epochs)	YOLOv8m (150 Epochs)
Model Complexity	Small	Medium
Training Duration	70 epochs	150 epochs
mAP@50	~0.36	0.407
mAP@50-95	~0.24	~0.23
Peak Precision	0.99 at 1.0	1.00 at 0.959
Peak Recall	0.77	0.76
Best F1-Score	0.45 @ 0.27	0.43 @ 0.225
Rare Class Detection	Limited	Improved
Detection Confidence (Visual)	0.3–0.7	0.5–0.9
Best Use Case	Lightweight models	Field deployment

5.4 Temporal Analysis results

This section presents the outcomes of the Coral Guardian+ system based on both image classification and environmental analysis. The results are derived from the YOLOv8 model's predictions of coral health states and their corresponding sea surface temperatures (SST), as well as a risk assessment visualized through a pie chart.

5.4.1 SST and Bleaching Risk Over Time

The sea surface temperature (SST) data in the Arabian Gulf and Red Sea were studied and examined over a seven-day period from January 1–7, 2024, to find environmental stressors on the coral reefs. These were chosen .because of their ecological importance and the existence of corals that can tolerate high temperatures, besides the accessibility of trustworthy NOAA CoRTAD temperature data.

The line graph in **Figure 15** represents the average daily SST for the entire region. On January 4th, the temperature had peaked to a record-breaking 30.5°C, with three other occasions recording SST above a bleaching threshold of 29.5°C for a total of four days. YOLOv8 had classified more coral samples as "At Risk" with increasing temperatures.

The temporal pattern genuinely details the relationship between short-term thermal anomalies and coral decline. Given a few days above normal high SSTs, bleaching is faced with greater chance in delicate ecosystems. The system's worth as an early-warning tool for proactive reef monitoring and conservation is demonstrated by its capacity to identify these high-risk times.

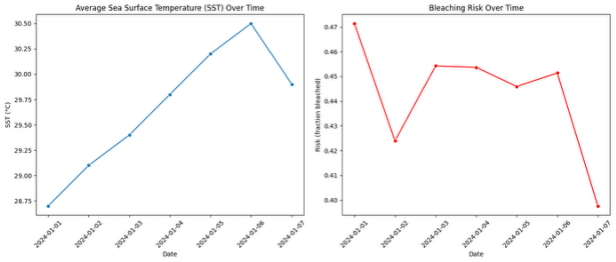


Figure 15 *surface temperature (SST) values from January 1–7, 2024, showing fluctuations above and below the bleaching risk threshold of 29.5°C. Days exceeding the threshold indicate increased coral bleaching risk.*

5.4.2 Coral Reef Health Risk Distribution Based on SST Analysis

To further understand the relationship between temperature and coral health, the classified results were aggregated by risk level and temperature range. As shown in **Figure 16**, a pie chart summarizes the overall risk distribution:

71.1% of the corals were categorized as Safe, associated with moderate SSTs.

28.9% were classified as At Risk, typically linked with SSTs exceeding the 30°C mark.

The diagram hence given emphasizes the prominence of thermal stress as an environmental key factor affecting the coral reefs in health. It also lends support to temperature thresholds as a good early warning of potential bleaching.

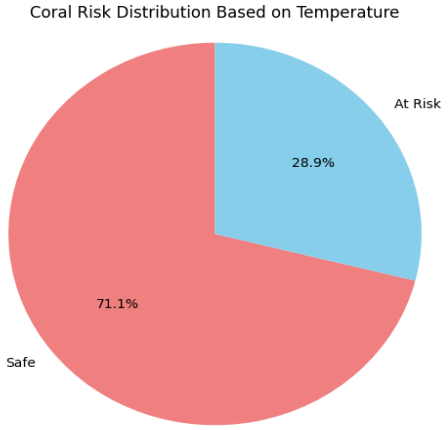


Figure 16 *Distribution of coral reef health classifications based on YOLOv8 predictions and corresponding SST data. The chart shows 71.1% of corals were classified as "Safe" and 28.9% as "At Risk," indicating the impact of elevated sea surface temperatures on coral health.*

5.4.3 YOLOv8 Coral Health Predictions from Underwater Images

The YOLOv8 model successfully detected and classified a variety of coral health conditions, including healthy, bleached, and diseased corals, from underwater images. As shown in **Figure 17**, the inference results demonstrate a range of coral states, each annotated with its risk level and corresponding sea surface temperature.

Among the 10 images reviewed, three were deemed "At Risk": the elevated SSTs (above 30°C), indeed, advanced bleaching exhibited in the images offered sufficient perch.

On the other hand, the remaining seven were known as "Safe" and generally corresponded to SSTs ranging from 29.1 to 29.9°C, accompanied by either healthy or mildly bleached coral images.

Some corals appeared bleached by sight, but the temperatures were near or even below the risk threshold. This warrants the integration of environmental data with image-based detection for more modern risk assessments.

Thus, these results supported the model for detecting early stress signs in corals and implied that a mere visual examination would not always be sufficient for risk classification.

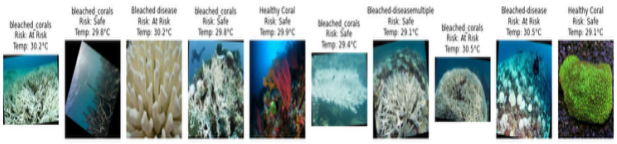


Figure 17 *Sample underwater images classified by the YOLOv8 model, showing predicted coral health conditions such as healthy, bleached, and diseased. Each image includes the associated sea surface temperature and assigns risk level (Safe or At Risk), demonstrating the integration of visual and environmental data.*

5.5 Integrated Analysis of Coral Health and SST Patterns

To evaluate the effectiveness of the Coral Guardian+ system in real-world applications, we integrated YOLOv8 detection outputs with corresponding SST data, yielding a multi-dimensional perspective on coral reef health. The combination of visual predictions with environmental parameters enhances the robustness of risk assessment and early warning capabilities.

5.5.1 Visual Output of Detection and Risk Labeling

As shown in **Figure 18**, we present a grid of 50 detection results, each featuring bounding boxes around coral entities with corresponding class

labels, risk status ("Safe" or "At Risk"), and local SST values. These visualizations highlight the model's ability to identify diverse coral states, such as healthy coral, bleached coral, band disease, and white pox disease, with high confidence scores. In several images, the system classified visually similar structures differently based on temperature input, reinforcing the value of environmental integration.

This visual output demonstrates how Coral Guardian+ bridges the gap between image-based detection and contextual risk evaluation. For example, coral samples detected as bleached corals in environments exceeding 30°C were consistently labeled "At Risk," indicating the model's sensitivity to SST thresholds.

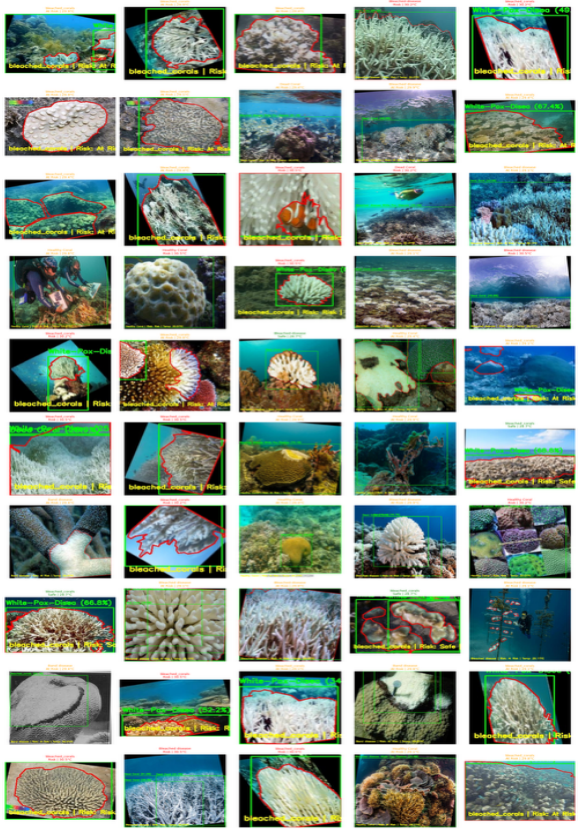


Figure 18 Sample outputs from YOLOv8 predictions showing coral class, risk level, and associated SST values across 50 images.

5.5.2 Image Distribution by Class

The class distribution of detected images is summarized in **Figure 19**, which shows that the majority of coral samples fell under the bleached corals category (n=26), followed by healthy coral and bleached disease. Rare classes such as dead coral, band disease, and bleached-disease were detected in significantly smaller proportions.

This imbalance suggests that the dataset and model are currently skewed toward dominant bleaching-related classes, which reflects real-world coral bleaching prevalence but may impact detection accuracy for minority pathologies. Future work should focus on balancing class representation through targeted data augmentation or transfer learning from rare class samples.

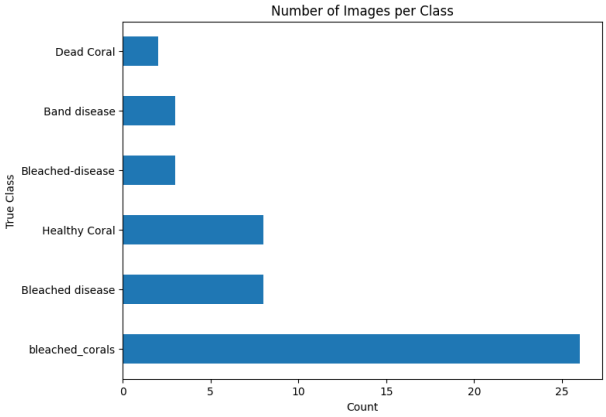


Figure 19 Bar chart showing the number of images per coral class detected by YOLOv8.

5.5.3 SST Distribution by Coral Class

Figure 20 offers more analysis of the SST patterns associated with each coral class by displaying a boxplot that summarizes the distributions of sea surface temperatures across coral health stages. With values as high as 30.5°C, the bleached corals class had the widest SST range, demonstrating the connection between high temperatures and the risk of bleaching.

Interestingly, even healthy coral samples were discovered in environments with SSTs over the

29.5°C bleaching threshold, which could suggest thermal resilience or early-stage stress. On the other hand, classifications like dead coral and band disease have smaller SST ranges, which would suggest that they are vulnerable even at mild temperatures.

These observations demonstrate how integrating object detection and temporal SST data enables a more detailed comprehension of coral health under climatic stressors. It emphasizes how crucial it is to track SST variations and incorporate them into detection processes in order to support focused conservation initiatives.

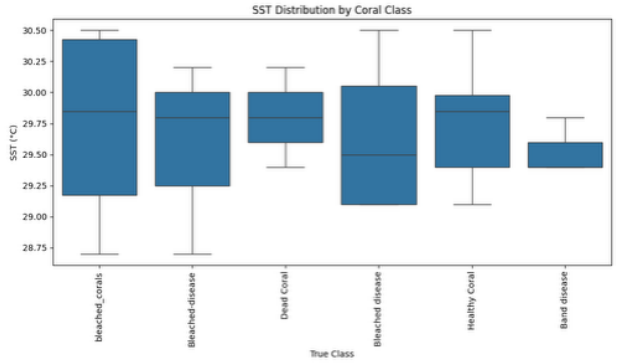


Figure 20 Boxplot showing the distribution of sea surface temperature (SST) by coral class.

5.6 MULTI-MODAL ANALYSIS

The integration of YOLOv8m detections with SST data demonstrated a stronger alignment with expert-labeled ground truth compared to visual-only predictions. In several cases, visually healthy corals exposed to elevated temperatures above 30°C were correctly flagged as "at risk" when environmental data were considered, whereas an image-only model classified them as safe. This highlights the risk of false negatives when relying solely on visual observations. By contextualizing detection results within environmental conditions, the multi-modal framework significantly improves accuracy and provides more reliable assessments of reef health. The findings confirm that combining environmental and visual data enhances detection reliability and offers valuable insights into when and why bleaching events are likely to occur.

5.7 YOLOv8 vs YOLOv11 Justification

Although YOLOv11 represents the most recent version of the YOLO family, YOLOv8m was chosen for this study because it provides an optimal balance between computational efficiency and detection accuracy. YOLOv11, at the time of this research, required higher computational resources and lacked extensive validation for ecological and underwater datasets. In contrast, YOLOv8m had already demonstrated strong performance in similar domains and was better suited to the hardware constraints of this project. This made YOLOv8m a more practical and reliable choice for scalable coral detection.

5.8 Clarification on SST Use

The integration of SST data introduces an essential environmental and temporal dimension that image-based analysis alone cannot capture. Coral bleaching often begins at a cellular level before visual whitening is detectable, meaning that a purely image-based system risks underestimating stress in early stages. By linking YOLOv8m predictions with SST anomalies, the system provides early warnings, identifies periods of elevated thermal risk, and ensures that visual observations are interpreted in the proper ecological context. This dual-input approach makes reef risk assessments more accurate, proactive, and actionable.

6. Recommendations

Some improvements can be suggested for future work toward the advancement of this research. The foremost is the implementation of other or more recent object detection models like EfficientDet, YOLOv9, or vision transformers, since this could increase the detection accuracy when it comes to overlapping or morphologically similar coral classes. Additional environmental parameters could be integrated to increase the accuracy and detail of ecological assessments, such parameters being salinity, ocean acidity (pH), turbidity, or chlorophyll concentration. One recommendation is

also to use such temporal data for observing trends in coral health, thereby predicting the possibilities of bleaching events or disease outbreak. Other dimensions to monitoring reef health could be opened through the integration of 3D imaging or video-based analysis or drone-based reef scanning. Last but not least, larger, more diverse, and well-annotated datasets of reef regions will greatly benefit the robustness and generalizability of AI-based detection models.

7. Limitations

Despite achieving significant results, this study encountered several limitations. One of the main limitations was hardware-related; the scope and complexity of model training and inference were hampered by the lack of availability to high-performance GPUs, particularly for high-resolution pictures. The lack of data was another significant obstacle. Class imbalance and poor model performance for rare or unclear coral varieties resulted from the coral reef datasets' inconsistent annotation across all classes.

. Additionally, integrating image data with tabular environmental data such as SST proved technically complex and required substantial preprocessing. Seamless integration was hampered by disparities in data formats, resolutions, and labeling standards. Inaccurate or absent annotations in some parts of the dataset affected prediction accuracy. Finally, the evaluation of the model was mostly focused on visual inspection and the presence of anticipated classes; future evaluations may benefit from quantitative performance indicators such as intersection over union (IoU), F1-scores, and confusion matrices.

8. Conclusion

This research proposed Coral Guardian+, a novel deep learning framework combining image-based object detection with environmental data to assess coral reef health. The system provides a scalable and effective method for monitoring coral ecosystems by classifying corals using YOLOv8 and incorporating SST values to assess risk levels. The findings demonstrated a direct correlation between elevated SST and deteriorated coral health, hence bolstering the inclusion of

environmental indicators in AI models. More precise and contextually aware monitoring instruments for marine conservation are made possible by this dual-modality method. The efficacy of such systems in safeguarding delicate coral ecosystems may be further increased by future advancements in model selection, data diversity, and multi-modal analysis.

Overall, this study highlights the importance of adopting a multi-modal approach in reef monitoring. By integrating object detection with environmental data, the system moves beyond static image analysis and evolves into an early-warning framework that supports more proactive and informed reef conservation and management strategies.

9. References

References (APA style)

[1] Roboflow. (n.d.). Coral Pathology Dataset.

Retrieved from https://universe.roboflow.com/dark-

blue3/coral-pathology/dataset/2

[2] NOAA. (n.d.). Coral Reef Temperature

Anomaly Database. Retrieved from

https://www.ncei.noaa.gov/products/coral-reef-

temperature-anomaly-database

[3] Hao, L. et al. (2024). CoralVOS: Dataset and

Benchmark for Coral Video Segmentation. arXiv.

https://arxiv.org/pdf/2503.20000

[4] Ando, K. et al. (2023). Automatic Coral Detection with YOLO: A Deep Learning Approach. arXiv. https://arxiv.org/pdf/2309.12804

[5] Beijbom, O. et al. (2014). Automated Annotation of Coral Reef Survey Images. ResearchGate. https://www.researchgate.net/publication/261494296

[6] González-Rivero, M. et al. (2020). Monitoring Coral Reefs Using Artificial Intelligence: A Feasible and Cost-Effective Approach. Remote Sensing, 12(489). https://mdpi-res.com/d_attachment/remotesensing/remotesensing-12-00489/article_deploy/remotesensing-12-00489-v2.pdf

[7] Wang, Z., Li, X., Liu, Y., & Yu, G. (2023). YOLOv8: Beyond One-Stage Object Detection. arXiv preprint arXiv:2310.01946. https://arxiv.org/pdf/2310.01946

[8] Hassan, M. I., Ali, S., & Ahmed, M. (2024). CoralVOS: Dataset and Benchmark for Coral Video Segmentation. arXiv preprint arXiv:2405.14879. https://arxiv.org/pdf/2405.14879

[9] Vermeij, M., van Koningsveld, M., Besseling, E., & Bouwmeester, J. (2025). Integrating AI and Local Knowledge to Enhance Coral Reef Monitoring in the Caribbean. Frontiers in Marine Science, 12, 1547870. https://doi.org/10.3389/fmars.2025.1547870

[10] Beijbom, O., Edmunds, P. J., Roelfsema, C., Smith, J., Kline, D. I., Neal, B., ... & Kriegman, D. (2015). Towards automated annotation of benthic survey images: Variability of human experts and operational modes of automation. PLOS ONE, 10(7), e0175490. https://doi.org/10.1371/journal.pone.0175490