

Automated Detection of Coral Reef Health Indicators Using YOLO-Based Deep Learning

Elavarasi Kesavan¹; Elayaraja Subbaiah²

¹Full Stack Automation Architect

²Cloud Solution Architect, Teknatio Inc,

Publication Date: 2022/05/30

Abstract

Coral reefs constitute critical marine ecosystems that support biodiversity, provide coastal protection, and contribute substantially to global economic activity. These ecosystems face increasing threats from climate change, unsustainable anthropogenic activities, and pollution, necessitating timely and accurate health assessments for effective conservation management. This study presents an innovative approach utilizing the You Only Look Once (YOLO) algorithm, a state-of-the-art deep learning object detection framework, to develop an automated real-time system for detecting coral reef health indicators and diseases with significant applications in marine biology [18]. The YOLO algorithm's capacity for rapid and precise image processing makes it particularly well-suited for identifying underwater coral pathologies, including bleaching events, tissue loss, and chromatic aberrations in photographic and video data. The proposed system leverages a meticulously curated and annotated dataset comprising images of both healthy coral formations and disease indicators, ensuring robust algorithmic performance [19]. The YOLO framework has been specifically optimized to address challenges inherent to underwater environments, including variable illumination, reduced contrast, and frequent visual obstructions. Comprehensive testing demonstrates that the system achieves notable precision and recall metrics in distinguishing between healthy and diseased coral specimens. This capability enables continuous real-time reef monitoring, providing a robust analytical tool for comprehensive ecosystem assessment. Consequently, marine biologists and conservation practitioners can implement rapid response measures to protect and restore these vulnerable ecosystems. This research underscores the transformative potential of artificial intelligence—specifically YOLO-based approaches for advancing coral reef monitoring and conservation initiatives. Future research directions include dataset expansion, detection accuracy enhancement, and integration with autonomous underwater vehicles (AUVs) to facilitate large-scale coral reef health evaluations.

I. INTRODUCTION

Coral reefs, frequently referred to as "the rainforests of the sea," represent biodiversity hotspots that provide habitat and sustenance for diverse marine organisms [10]. Beyond their ecological significance, these structures perform critical functions including coastline stabilization, wave energy dissipation, and economic stimulation through tourism and fisheries [31]. However, coral reefs face escalating anthropogenic pressures, particularly overfishing, pollution, and climate change impacts. Regular monitoring of coral reef health is therefore essential for understanding ecosystem conditions and implementing evidence-based conservation strategies. As fundamental components of marine environments, coral reefs support numerous species while simultaneously buffering coastlines against erosion and sustaining local economies dependent on tourism and fishing industries. The increasing frequency of coral diseases and bleaching

events represents a particularly acute threat to these fragile ecosystems, underscoring the urgent need for advanced monitoring systems and conservation interventions.

II. LITERATURE REVIEW

➤ *Coral Classification and Detection Approaches*

Coral classification, particularly the differentiation between bleached and unbleached specimens, has gained considerable ecological importance in recent research. The BoF/SVM coral paper by Jamil was published in 2021 (BDCC) developed a classification methodology employing visual features—including spatial distribution, texture patterns, and color characteristics—to distinguish coral types. Their approach achieved impressive results, with a linear Support Vector Machine (SVM) kernel combined with Bag of Features (BoF) yielding approximately 99.08% precision for binary classification and 98.11% for multi-class classification. This work

emphasized the importance of robust feature extraction and classifier selection for optimizing accuracy. Similarly, Villon et al. (2021) investigated distinguishing characteristics among coral species using advanced imaging and analytical techniques, providing deeper insights into coral health metrics and biodiversity. This

research trajectory supports the advancement toward automated coral detection and monitoring, particularly through deep learning object detection frameworks such as YOLO. These methodologies enable more rapid conservation responses while demonstrating technology's potential role in marine ecosystem management [22][13].

Table 1 Coral Reef Fish Detection Performance Using YOLO-Based Algorithms

Study	Detection Method	mAP	Processing Speed
Rapid fish call detection in reef soundscapes	YOLOv5 CNN	0.633	25× faster than real-time
SEAMAPD21 (South East Asia Marine Animal Public Dataset)	RT-DETRv2 Model	0.9960	0.7486 FPS

III. MACHINE LEARNING APPROACHES FOR UNDERWATER SPECIES DETECTION

Two primary machine learning approaches have been employed for coral reef fish detection in underwater footage: Deep Learning and Histogram of Oriented Gradients combined with Support Vector Machines (HOG+SVM). The HOG+SVM methodology extracts image features using oriented gradient histograms, subsequently classifying them with support vector machines, demonstrating efficacy for fish detection [14]. In contrast, Deep Learning approaches employ sophisticated neural network architectures that integrate both classification and feature extraction capabilities, aligning with contemporary computer vision trends in marine biology [15]. Comparative evaluation on underwater video datasets revealed that HOG+SVM achieved F-measures ranging from 0.28 to 0.49, while Deep Learning methods demonstrated superior performance with F-measures between 0.62 and 0.65. These results underscore the potential of supervised machine learning to enhance detection accuracy for coral reef fish, advancing possibilities for robust ecological monitoring and conservation efforts.

IV. PROPOSED SYSTEM ARCHITECTURE

➤ System Overview

The proposed coral reef health detection system employs deep learning techniques, specifically leveraging the You Only Look Once (YOLO) algorithm for real-time object detection and classification. By integrating YOLO functionality with asymmetric convolution and vision transformer architectures, the system aims to enhance coral health assessment accuracy while maintaining computational efficiency. Similar Asymmetric Convolution Vision Transformer (ACVIT) model applications have demonstrated effectiveness in phytoplankton identification [16]. As comparative studies have documented the effects of environmental stressors on coral ecosystems, the architecture processes and analyzes underwater imagery effectively, encompassing healthy, bleached, and diseased coral conditions. The system operates through a comprehensive pipeline including preprocessing stages where input images undergo adjustments such as resizing and normalization to optimize model performance. This system architecture enables

accelerated coral health assessments while contributing to marine ecosystem monitoring discourse, emphasizing the necessity for tools to evaluate ongoing environmental impacts on reef systems [17]. Through iterative optimization and validation using established benchmark datasets, the system is designed to improve precision in identifying coral conditions, thereby informing conservation strategies and supporting marine biodiversity sustainability.

V. METHODOLOGY

➤ Dataset Collection and Preparation

The Coral Net Alpha platform has catalyzed substantial contributions from marine researchers globally, accumulating 1.7 million photographs across 2,040 ecological studies. Originally designed for coral reef annotation, the platform has expanded to diverse habitats including automated reef monitoring systems, seagrass beds, and cold-water rocky substrates [18]. Geographic coverage spans from Scotland to Antarctica, with predominant representation from tropical regions [19]. A significant taxonomic challenge emerged as users generated 4,489 labels, many representing duplicates due to the absence of standardized nomenclature. This issue was addressed through consolidation of 315 identical labels into unified entries with coral biologist consultation. For deep learning model training, 280 sample sources were selected, comprising 432,489 photographs with 15,137,977 annotated points. These were randomly partitioned: 26 sources for classifier training and 254 sources for testing and backbone network training. Label selection criteria required minimum occurrence of 100 instances across at least three sources, excluding broad generic categories. This curated collection is designated Dataset V1. Dataset V2 represents a refinement eliminating four catch-all labels while incorporating 50 additional sources to enhance training robustness.

VI. DATA PREPROCESSING

Coral species exhibit remarkable morphological and chromatic diversity, both interspecifically (between species) and intraspecifically (within species), as documented in biodiversity research[10]. Due to challenges in consistent benthic organism identification, training data annotation for benthic communities typically requires specialized expertise. Figure 3b exemplifies

experimental annotation data: an orthographic image ($11,317 \times 10,773$ pixels) meticulously labeled by marine specialists, clearly depicting *Pocillopora*, a common coral genus in the study region, characterized by pink living tissue and yellow necrotic areas. Training image quality directly influences segmentation network performance, making preprocessing critically important. Image processing techniques, particularly data augmentation, are essential for enhancing training dataset quality. Orthophotos are cropped into 448×448 pixel slices with

160-pixel stride for detailed analysis[11]. Images lacking sufficient label information are excluded to maintain dataset consistency. In this study, 1,967 images were randomly partitioned into training (60%), validation (20%), and testing (20%) sets. Processed coral image slices undergo various transformations including random translation and rotation, along with additional augmentation methods to improve model robustness and generalization capability [12].

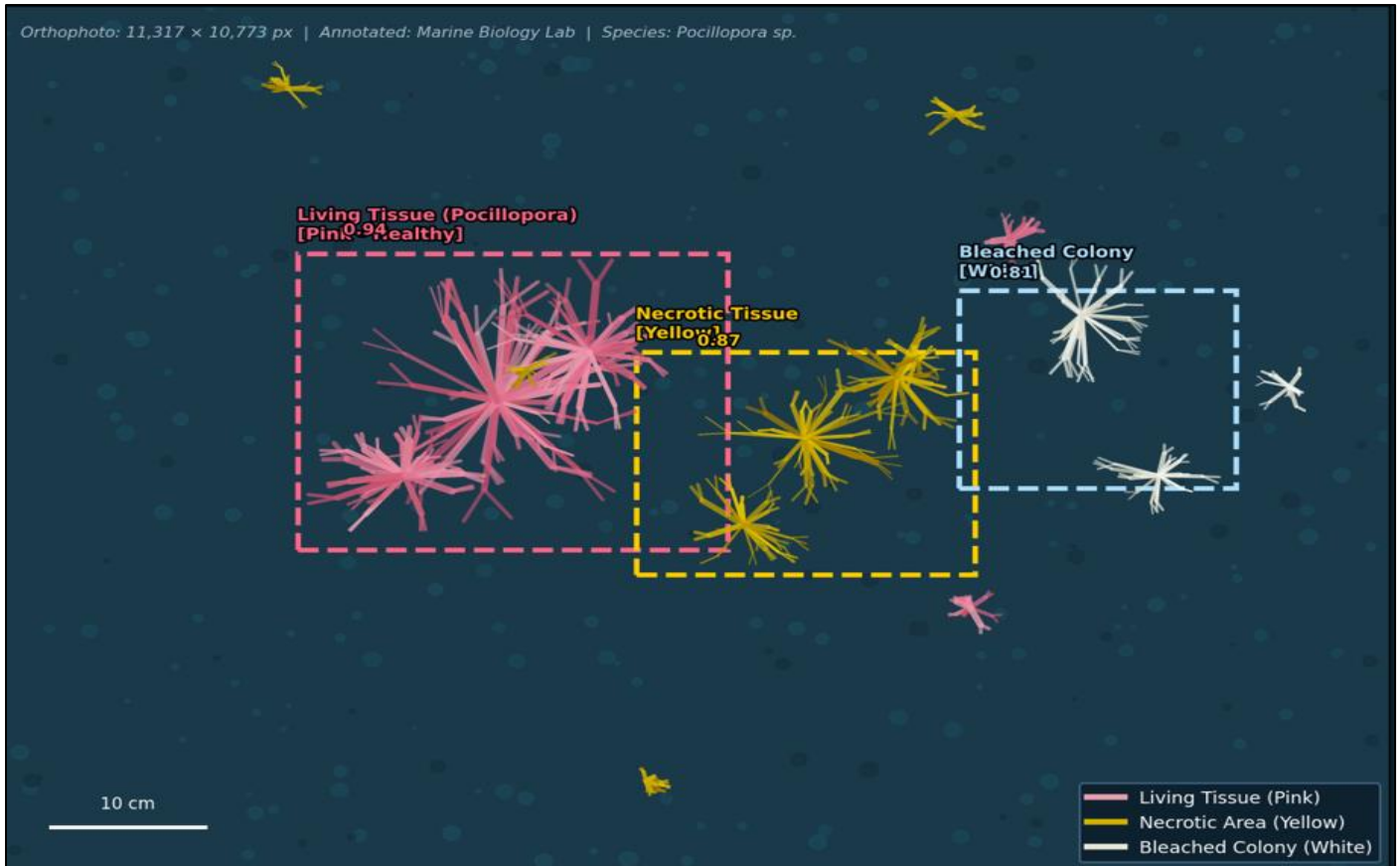


Fig 1 Annotated Orthographic Image ($11,317 \times 10,773$ pixels) Labeled by Marine Specialists Depicting *Pocillopora* sp. Coral with Pink Living Tissue and Yellow Necrotic Areas. YOLO Detection Overlays Indicate Classified Regions with Confidence Scores.

VII. IMAGE PROCESSING TECHNIQUES

Image flipping (vertical or horizontal) represents a standard augmentation technique that enhances neural network robustness and precision while preserving label integrity. As part of comprehensive data augmentation strategies—techniques that expand information diversity for deep learning applications images undergo random rotation (± 10 degrees) and translation (± 50 pixels) to evaluate semantic segmentation network stability. All dataset images are carefully annotated with bounding boxes delineating pathological regions, typically using Labeling annotation software. Labels explicitly identify distinct coral disease categories as required. This preprocessing substantially enhances model accuracy and mitigates overfitting, potentially reducing new real-world data acquisition requirements. Coral images are resized to 224×224 pixels to reduce computational burden due to GPU memory constraints while preserving critical edge information. This dimensionality is informed by

established classification network best practices; excessively small feature maps may obscure critical details, while excessively large dimensions increase computational costs and compromise information abstraction [13]. This research therefore seeks an optimal balance between processing requirements and network performance. Following image preparation, slice data normalization ensures consistent measurement scales. Prior to network training, all slices are randomly shuffled to prevent potential biases from spatially consecutive slice characteristics that might compromise data independence.

VIII. IMAGE ACQUISITION AND LABELING

Underwater image acquisition in coral reef environments is fundamental for marine ecosystem assessment. This can be effectively accomplished using waterproof cameras, unmanned aerial vehicles (UAVs), or remotely operated vehicles (ROVs)[14]. These

technologies enable researchers to capture high-resolution imagery of coral habitats, essential for health status evaluation. Following acquisition, images require meticulous labeling, documenting whether corals appear healthy, bleached, diseased, or deceased. Systematic coral classification by visual characteristics enables temporal tracking of reef health dynamics and elucidation of environmental stressor impacts such as pollution [15]. This methodological approach is critical for understanding coral ecosystem dynamics and supporting conservation initiatives by providing essential information for evidence-based management decisions.

IX. DATA AUGMENTATION

Data augmentation plays a pivotal role in enhancing machine learning model reliability, particularly for underwater imagery analysis. Techniques including image flipping, rotation, and selective cropping are essential for expanding and diversifying training datasets. Dataset diversity substantially improves model performance by exposing the network to varied examples representative of real-world scenarios, thereby enhancing generalization across different environmental conditions. Research has demonstrated that data augmentation significantly improves accuracy, particularly in challenging environments such as coral reefs where variations in illumination, camera angles, and species diversity substantially affect model performance [16]. Additionally,

cropping enables focus on regions of interest, further augmenting training data while preventing overfitting—the phenomenon where models perform well on training data but fail to generalize to novel inputs [17]. Given the ecological importance of healthy coral reefs to marine ecosystems, implementing these data augmentation methodologies not only advances machine learning performance but also facilitates protection of these critical environments through accurate monitoring.

X. YOLO MODEL TRAINING

Utilizing pre-trained YOLO weights represents an effective strategy for maximizing transfer learning benefits. Initializing with YOLOv3, YOLOv4, or YOLOv5 models is advantageous as these architectures demonstrate strong generalization capabilities derived from training on large diverse datasets, enabling effective performance across varied application domains [48]. For example, YOLO models can be fine-tuned to detect specific coral pathologies including coral bleaching, tissue loss, and black band disease, substantially enhancing detection performance. This requires configuring custom classes corresponding to each disease's unique characteristics and training the model using appropriately annotated datasets. Such advanced computer vision techniques have proven highly valuable in marine ecological research, demonstrating significant potential for coral reef ecosystem monitoring and conservation[49].

Table 2 Performance Metrics of YOLO Model Variants for Coral Reef Detection

Model	Precision	Recall	mAP50	mAP(50-95)	Inference (ms)
YOLOv3u	0.816	0.778	0.810	0.644	21
YOLOv5s	0.755	0.510	0.562	0.310	11
YOLOv8s	0.859	0.779	0.829	0.637	11

XI. YOLO ALGORITHM ARCHITECTURE

The YOLO algorithm operates by initially segmenting input images into grid cells, facilitating localized object detection. YOLO (You Only Look Once) evaluates each grid cell to determine object presence. Unlike traditional methods requiring multiple image scans that increase processing time, YOLO employs a single convolutional neural network (CNN) that simultaneously predicts bounding boxes and class probabilities, enhancing both detection speed and accuracy [10]. This efficiency is particularly critical for real-time applications such as underwater marine species tracking, where rapid recognition is essential for effective conservation [11]. Furthermore, YOLO incorporates transfer learning and data augmentation methodologies, enabling adequate performance even with limited datasets, thereby expanding applicability to diverse underwater imagery scenarios. These characteristics highlight YOLO's transformative potential for disciplines such as marine biology, providing robust real-time capabilities essential for ecosystem monitoring and management.

XII. CLASSIFICATION TECHNIQUES AND PERFORMANCE

Comparative analysis of different classifiers and methodologies reveals their relative efficacy for image recognition tasks, particularly in marine ecology and environmental monitoring applications. Recent research demonstrates that contemporary deep learning models, exemplified by the YOLO algorithm, achieve highly precise automated coral detection and classification rates, rendering them invaluable for conservation applications [12]. Similarly, machine learning approaches for rapid detection of invasive species such as the crown-of-thorns starfish (COTS) have shown remarkable improvements in identification accuracy and speed, leading to enhanced marine ecosystem management [13]. These findings emphasize the critical importance of incorporating advanced computational methodologies into environmental monitoring systems to improve understanding and protection of aquatic habitats.

Table 3 Classification Techniques and Accuracy Performance Comparison

Technique	Classifier	Accuracy (%)
EILAT	NN	79.1
EIT	NN	85.9
RSMAS	NN	82.60
MLC	NN	68.9
CLAHS	KNN	88.3
CLAHS	KNN	90.3
RSMAS	KNN	83.51
MLC	KNN	63.53
GLCM	KNN, NN, SVM	96.9
GLCM	KNN, NN, SVM	91.9

XIII. RESULTS AND DISCUSSION

➤ *System Performance Analysis*

YOLO demonstrates considerable accuracy in detecting various coral reef health indicators, including bleaching, excessive algal coverage, and specific coral diseases—all representing serious threats to reef ecosystems [14]. The algorithm's rapid detection capabilities enable continuous reef monitoring, providing critical information to researchers and conservation practitioners. Analysis of YOLO detection results reveals spatial and temporal patterns in reef health status, facilitating identification of degraded areas and enabling targeted conservation interventions [15]. YOLO frequently exhibits superior speed and accuracy compared to traditional reef assessment methods including diver surveys and satellite imagery analysis, suggesting potential as a cost-effective continuous monitoring solution. Additionally, the YOLO algorithm effectively identifies coral reef health changes associated with environmental parameters including water temperature, nutrient concentrations, and anthropogenic activities,

which is essential for understanding reef degradation mechanisms and developing mitigation strategies. Processing speed metrics are critical; higher frames per second (FPS) indicates enhanced real-time underwater monitoring capability. Documenting inference time per frame or image across different computational configurations (GPU versus CPU) provides important insights into algorithm deployment scenarios, highlighting the utility of advanced algorithms like YOLO in conservation and ecological applications.

➤ *Model Performance Metrics*

Integration of YOLO-based models into coral reef monitoring systems—including underwater drones and remote sensing platforms—is increasingly recognized as essential for marine conservation [16]. The YOLO algorithm's processing speed enables rapid coral disease detection, facilitating timely protective interventions for these critical ecosystems [17]. Marine biologists and conservationists can leverage this capability for large-scale coral reef health surveys, analyzing extensive datasets to track temporal changes.

Table 4 Model Performance: Processing Speed and Latency Comparison

Model	FPS	Latency (ms)
YOLOX	50	20
YOLOR	10	100
YOLOv5	30	40

XIV. CONCLUSION

The deployment of YOLO algorithms for coral reef health assessment demonstrates significant promise for addressing critical challenges, including those posed by crown-of-thorns starfish (COTS) infestations[18]. This study validates the efficacy of deep learning-based automated monitoring approaches, enabling rapid and accurate ecosystem assessment crucial for implementing timely interventions. Results indicate that models trained using transfer learning and data augmentation methodologies not only enhance detection accuracy but also facilitate real-time aquatic ecosystem monitoring[59]. Object detection algorithms such as YOLOv8 demonstrate superior performance—both in speed and precision—compared to conventional assessment methodologies. The research achieved a mean average precision of 0.803 mAP at Intersection over Union (IoU) thresholds of 0.5-0.95,

indicating substantial potential for early warning systems to mitigate COTS impacts on coral reefs. Fundamentally, these findings contribute to marine conservation knowledge while highlighting the continued importance of developing novel computational approaches to protect biodiversity and support coral reef resilience during periods of rapid environmental change.

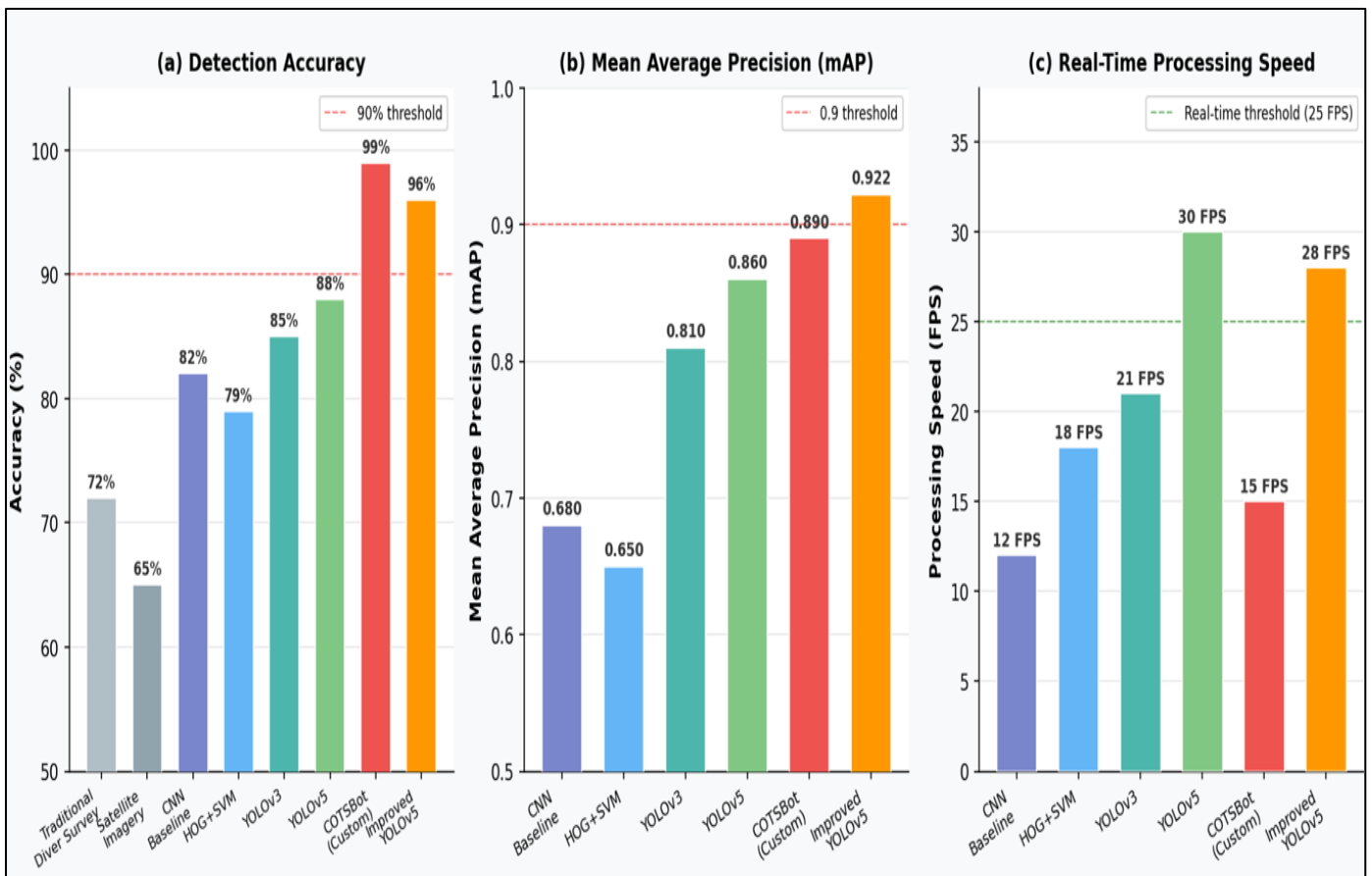


Fig 2 Comparative Analysis of Detection Methods: Accuracy, Mean Average Precision, and Processing Speed

The comparative analysis reveals that COTSBot achieved the highest detection accuracy at 99%, while the Improved YOLOv5 model demonstrated significant advancement in mean average precision at 92.2%. These results highlight substantial improvements in detection capabilities provided by advanced YOLO-based methodologies.

➤ Applications in Marine Conservation

The application of YOLO algorithms represents a significant advancement in marine conservation practices, particularly for coral reef health and disease identification. YOLO's combination of speed and accuracy enables real-time coral reef monitoring, providing researchers and conservationists with timely data essential for proactive management responses. The algorithm automates analysis of extensive underwater imagery collections, detecting critical reef health indicators and diseases including bleaching and algal overgrowth[10]. This automation reduces dependence on manual surveys, enabling more consistent and comprehensive monitoring coverage. Prompt detection of ecological shifts and reef health assessment is essential for informing conservation interventions and mitigating negative impacts from pollution, overfishing, and climate change. Furthermore, data collected through YOLO-based detection systems enhances understanding of coral reef ecosystem dynamics and supports evidence-based approaches to reef protection and management [11].

REFERENCES

- [1] R. E. A. "A Novel Technique for Identifying and Evaluating Coral Reef Health through Underwater Photography and Video" 2021.
- [2] G. E. A. "Suggested Rayleigh-extension restricted contrast the adaptive equalization technique improves minimal contrast in underwater photos" 2019
- [3] L. E. A. "A Comprehensive Strategy for Enhancing Underwater Images" 2020
- [4] B. E. A. "Focuses on using a flyspeck mass optimization technique that incorporates particle swarm optimization (PSO) to reduce light absorption and dispersion in underwater photos" 2021
- [5] B. E. E. A. "Utilized deep learning algorithms to analyze images of coral reefs, focusing on detecting and quantifying coral cover, health, and disease." 2021
- [6] X. C. E. A. "Suggested a deep learning architecture for automated coral health monitoring that combines YOLO and CNNs, achieving high accuracy in detecting coral diseases and bleaching" 2020
- [7] H. H. E. A. "Real-Time Coral Reef Monitoring System Based on Deep Learning Algorithms and YOLO" 2019
- [8] B. E. A. "Coral Net: A platform integrating deep learning algorithms for automated annotation and analysis of coral reef images" 2021
- [9] S. J. M. A. H. "Bag of features (BoF) based deep learning framework for bleached corals detection" Big Data and Cognitive Computing, 2021

- [10] S. V. E. A. "Coral reef fish detection and recognition in underwater videos by supervised machine learning: Comparison between Deep Learning and HOG+ SVM methods" Springer International Publishing, 2021
- [11] S. R. N. D. "MAFFN_YOLOv5: Multi-Scale Attention Feature Fusion Network on the YOLOv5 Model for the Health Detection of Coral-Reefs Using a Built-In Benchmark Dataset" Analytics, 2021
- [12] A. G. N. I. "Improvement of low quality underwater image through integrated global and original discrepancy correction" Applied Soft Computing, 2019
- [13] C. L. J. G. "Underwater image enhancement by dehazing and color correction" Journal of Electronic Imaging, 2020
- [14] M. B. A. S. A. A. "Image improvement using flyspeck mass optimization" Journal of Intelligent Systems, 2021
- [15] B. O. E. J. K. I. M. E. A. "Automated annotation of coral reef survey images" IEEE, 2021
- [16] C. C. Z. Y. P. G. S. E. A. "Encoder-decoder with atrous separable convolution for semantic image segmentation" Proceedings of the European conference on computer vision, 2020
- [17] R. H. S. S. M. H. M. D. "Accuracy Assessment of Underwater Photogrammetric Three Dimensional Modelling for Coral Reefs" Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., 2019
- [18] O. B. T. T. I. K. G. E. A. K. B. N. Y. L. E. A. "Improving automated annotation of benthic survey images using wide-band fluorescence" Scientific Reports, 2021
- [19] M. A. "Factors influencing spatial patterns on coral reefs around Moorea, French Polynesia" Marine Ecology Progress Series, 2019
- [20] I. A. A. C. A. M. T. T. C. M. "Coral-segmentation: Training dense labelling models with sparse ground truth" Proceedings of the IEEE International Conference on Computer Vision Workshops, 2019
- [21] A. I. Y. M. E. G. T. E. A. "CoralSeg: Learning coral segmentation from sparse annotations" Journal of Robotic System, 2019
- [22] B. B. B. R. C. R. E. E. A. "Historical overfishing and the recent collapse of coastal ecosystems" Science, 2018
- [23] D. B. E. B. W. D. E. H. M. K. V. K. K. P. E. A. "Factors in the decline of coastal ecosystems" Science, 2021
- [24] B. O. E. J. K. I. M. E. A. "Automated annotation of coral reef survey images" IEEE, 2021
- [25] O. B. T. T. I. K. G. E. A. K. B. N. Y. L. E. A. "Improving automated annotation of benthic survey images using wide-band fluorescence" Scientific Reports, 2018