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Fine-Grained Analysis of Coral Instance Segmentation using YOLOv8 Models

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Abstract: Within the geographical boundaries of Indonesia, coral reefs flourish as intricate ecosystems bustling with a variety of marine creatures that play a crucial role, in preserving biodiversity. However this delicate harmony faces threats from climate change and human activities, leading to the risk of species loss. Despite growing awareness surrounding these challenges effectively and swiftly monitoring conditions remains a task. Existing methods for assessing corals often fall short due to requiring extensive specialist knowledge, lacking large-scale coverage, and being costly to implement. To tackle these obstacles this research suggests an approach for automated reef monitoring using instance segmentation with a YOLOv8 model. Leveraging YOLOv8 segmentation capabilities enables efficient analysis of corals. A systematic process is employed involving data collection, preparation (including techniques like Histogram Equalization), training the model on a reef dataset, model evaluation and enhancing the segmentation mask. The outcomes reveal the YOLOv8m Pp model with 96.7% precision 95.9% recall rate and a mean Average Precision (mAP50) score of 98.2%. This study demonstrates the potential of YOLOv8 to accurately segment instances for monitoring reefs in Indonesia, hence facilitating improved conservation strategies.

Keywords: Automated Monitoring; Coral Reefs; Instance Segmentation; Marine Ecosystems; YOLOv8

INTRODUCTION

Indonesia, situated within the Coral Triangle, is a global hotspot for coral reef biodiversity. Coral reefs, commonly known as "marine rainforests", are diverse ecosystems that support marine life and maintain the overall health of our planet (Li, 2019). Despite covering only a small portion of the seafloor, coral reefs are home to a diversity of marine life on par with terrestrial ecosystems. They provide a habitat for fish invertebrates and other marine creatures (Denley et al., 2020). These habitats are critical to fisheries as they serve as breeding and nursery grounds for the supporting communities of species that depend on marine resources (Burns et al., 2022). Additionally, coral reefs fuel coastal economies through tourism and sustainable fishing. People from throughout the globe are lured to enjoy the hypnotic beauty of reefs via activities, such snorkeling and scuba diving contributing to local economies (Lara-Pulido et al., 2021). Coral reefs also serve as defenses protecting coastlines, from erosion and the impact of storm surges (M. Zhao et al., 2019).

However, Indonesia's coral reefs suffer major dangers. Climate change, particularly increasing ocean temperatures and acidity, impairs coral development and threatens their health (Zhong et al., 2023). Ocean acidification due to seawater soaking up CO2 slows the development of coral skeletons, worsening the stress on their ecosystems (Hoadley et al., 2019). In addition, overfishing and damaging fishing practices considerably contribute to the issues confronting coral reef ecosystems (Eddy et al., 2021). Given the vital role coral reefs play in Indonesia's environment and economy, effective monitoring and conservation efforts are crucial. Advanced technologies such as remote sensing and photogrammetry allow us to study coral reefs at multiple scales. Although remote sensing offers broad-scale monitoring, it cannot distinguish individual coral colonies (Candela et al., 2021). In addition, expensive operational costs limit its widespread use (Hendee et al., 2020).

The field of coral reef research has been significantly transformed by recent advancements in Convolutional Neural Networks (CNN) techniques (Picek et al., 2020). Models such, as YOLO (You Only Look Once) provide an effective approach that incorporates instance segmentation allowing researchers to precisely locate and outline colonies in the reef. he necessity of having an accurate technique of separating objects into segments is underscored by the quick improvements, in real-time detectors (Bolya et al., 2019). This degree of precision plays a role in capturing not only the arrangement of coral species and assessing their health but also correct species. Recently, instance segmentation can help researchers in monitoring and classify coral species (Zhong et al., 2023). Instance

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segmentation has become particularly important because of its properties that allow solutions to identify and segment object instances at the individual level (Dumitriu et al., 2023). Understanding coral reefs involves a deep comprehension of the diverse species composition and intricate patterns of growth (Montano, 2020). However, properly extracting information might be challenging through to the complexity of underwater ecosystems (Steffens et al., 2019).

With the recent advancement of the YOLO model, YOLOv8 to be precise offers a promising solution for automated coral segmentation. YOLOv8 can achieve efficient segmentation, due to its ideal encoder-decoder architecture to capture global context information in images (Yang et al., 2023). This capability overcomes the limitations of existing methods, which often have difficulty accurately identifying individual corals on densely populated or geometrically complex reefs (Bello et al., 2023).

Previous research have proved the potential of YOLO in identifying marine creatures. The research by (Lv et al., 2022) attained a 77.2% F1 score in recognizing tiny and camouflaged marine creatures. Research by (Quoc Toan, 2022) used YOLO for early identification of crown-of-thorns starfish with a precision of 0.93, recall of 0.77, and F1 score of 0.84, benefiting coral reef conservation efforts. These papers illustrate the potential of deep learning in marine biology research and conservation.

The sheer amount of data collected from coral reefs overwhelms traditional analysis methods. However YOLOv8 thats specifically tailored for habitat analysis, offers a promising solution. By utilizing YOLOv8 for instance segmentation, researchers can gain a reliable and faster way to monitor reef health. This involves keeping tabs on the trends in development the mix of species and the overall state of well being. Ultimately YOLOv8 aims to delve into understanding coral reef ecosystems through faster information extraction from image and video data, empowering more effective conservation efforts.

LITERATURE REVIEW

Underwater environments present many challenges for automated analysis due to factors such as light scattering and the presence of complex backgrounds. Recent advances in deep learning and image segmentation techniques have the potential to overcome these challenges and enable deeper understanding and analysis of underwater ecosystems. This review provides an overview of recent research that uses such techniques to address various challenges in bottom detection and analysis, with a particular focus on applications related to coral reef species monitoring and underwater environmental monitoring.

Several studies have focused on developing automated systems for detecting and tracking animals in underwater environments. In particular, the study by (Chen et al., 2024) which proposed a deep learning method for instance segmentation on underwater images overcame data limitations and image quality issues and achieved a significant improvement in segmentation accuracy compared to no preprocessing. Another study by (Corrigan et al., 2023) compared the YOLACT and Mask R-CNN methods for detecting plastic debris in underwater images. Both models produced good performance, with YOLACT being faster but slightly less accurate. Research by (Dumitriu et al., 2023) focused on the detection of rip currents, a safety issue on beaches. They developed a new dataset and YOLOv8 baseline for instance segmentation and achieved promising results, emphasizing the potential of deep learning in improving beach safety. Similarly, research (Salau & Krieter, 2020) explored the use of camera-based object detection with deep learning methods to analyze the behavior of a dairy herd in an open pen system, demonstrating the potential of this technique in the field of animal husbandry.

Challenges arising from the complex and often color-distorted nature of underwater imagery have also been addressed such as the work of (Bello et al., 2023) who proposed a novel approach combining Generalized Color Fourier Descriptor (GCFD), Convolutional Neural Networks (CNN), and Mask R-CNN to improve segmentation accuracy in underwater environments. In addition to coral reefs, (Lv et al., 2022) also applied neural networks to improve the detection of small and camouflaged marine organisms, demonstrating the versatility of this technique for various underwater animal analysis tasks. Similarly, (Quoc Toan, 2022) investigated the use of deep learning methods to efficiently detect crown-of-thorns starfish, aiming to support coral reef conservation efforts through early detection and intervention. Finally, research by (S. Zhao et al., 2022) developed a new algorithm for real-time object detection with YOLOv4-tiny on underwater robots by introducing structural enhancements and new attention modules, achieving high accuracy and fast detection speed on embedded systems.

This review has underscored the very promising progress for improving the understanding and management of the underwater environment through potential applications in areas such as marine safety, animal tracking, conservation efforts, and environmental monitoring. While underwater object detection shows promise, for marine uses it falls short in analyzing intricacies. Current methods focus on detection limiting the study of individual coral colonies. This review suggests a strategy using YOLOv8 for coral segmentation allowing for in depth analysis. Expanding on studies that looked into preprocessing techniques for object detection our goal is to enhance these methods further to tackle issues like light dispersion and color distortion. By combining instance segmentation and exploring preprocessing techniques, there is potential to enhance the accuracy of reef monitoring and support more effective conservation efforts.

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METHOD

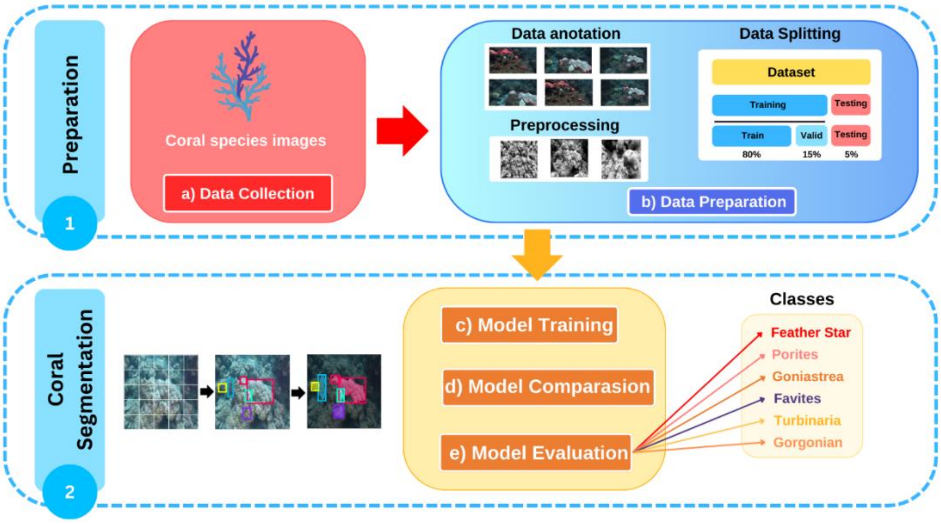

Fig. 1 Research Methodology

This research applies the system development method (Talaat & ZainEldin, 2023) with stages that can be seen in Fig. 1. The authors adapted this methodology to perform the task of segmentation as well as differentiation of individual coral colonies. This, involved data collection, data preparation, training the YOLOv8 model on a coral dataset, model evaluation, and interpretation.

Dataset

This study investigates the effectiveness of exposure and luminance adjustments in enhancing YOLOv8's coral reef detection performance. We leverage a two-part dataset including:

Core set, this dataset consists of 755 coral reef images captured using a Remotely Operated Vehicle (ROV). The dataset is publicly available on Roboflow (Varma, 2024) and can be downloaded from the link to the dataset on Roboflow: https://universe.roboflow.com/nuthan-varma-b5j2d/segmentation_corals.

Secondary set, this set comprises 1359 images generated through data augmentation of the core set. Each image in the core set is annotated with labels for six coral species: Favites, Feather-star, Goniastrea, Gorgonian, Porites, and Turbinaria. Minor inconsistencies and missing annotations were addressed through manual correction.

Both datasets undergo standard preprocessing, including automatic orientation and resizing to 640x640 pixels to meet YOLOv8's input requirements. To ensure model robustness, the data is further split into training (80%), validation (15%), and testing (5%) sets. The secondary dataset receives additional exposure and luminance adjustments (Adaptive Equalization, Histogram Equalization, Contrast Stretching) to simulate real-world lighting variations and enhance feature visibility. These techniques have been proven to improve the quality of underwater images by manipulating pixel intensities and addressing uneven illumination (Lei et al., 2021).

Adaptive Equalization and Histogram Equalization techniques work by redistributing the pixel intensity distribution across the entire grayscale range. This process enhances low-contrast regions in the image, potentially revealing subtle coral reef features that might be obscured by uneven lighting (Peng et al., 2022; Qin et al., 2019).

Contrast Stretching, on the other hand, expands the contrast between light and dark areas within the image. This can be particularly beneficial for highlighting coral structures that might otherwise blend into the background under certain lighting conditions (Lai et al., 2022).

In addition to these preprocessing steps, data augmentation techniques will be employed on the secondary dataset. Data augmentation involves artificially expanding the dataset by generating variations of existing images, such as rotations, flips, and brightness adjustments.

Ultimately, the goal is to improve the YOLOv8 model's ability to detect coral reefs accurately. By comparing the model's performance under different preprocessing methods, this study aims to identify the most effective approach for robust coral reef detection in diverse lighting conditions.

YOLOv8

The You Only Look Once (YOLO) algorithm first appeared in 2016, YOLO is a single-shot type detector that uses the Fully Convolutional Neural Network (CNN) method to process images. Unlike traditional methods that analyze images separately, YOLO treats the entire image as a single unit, predicting bounding box and class probabilities in one step. This results in significant speed improvements, making YOLO ideal for real-time applications (Zhong et al., 2022).

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Over the years, YOLO has evolved into many iterations, each building upon the success of the previous. YOLOv5, released in 2020, the algorithm was established as a state-of-the-art method in object detection for its impressive speed and accuracy improvements (Jiang et al., 2021). Now, YOLOv8 or You Only Look Once version 8, is the latest iteration of the famous YOLO algorithm in the field of object detection. Developed by Ultralytics, this latest iteration introduces key architectural innovations such as CSPNet and PANet, resulting in significant improvements in speed and accuracy (Inui et al., 2023).

One of the key differences of YOLOv8 lies in its anchorless detection mechanism. Unlike traditional anchor-based methods, YOLOv8 explicitly estimates the center of an object instead of predicting its distance from a predefined anchor box. This approach significantly reduces the number of box predictions, streamlining the Non-Maximum Suppression (NMS) process. YOLOv8 offers five models YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x) designed for identification, segmentation, and classification tasks, with variations in precision and speed (Talaat & ZainEldin, 2023).

Although an official paper detailing the development of YOLOv8 has not been published, some insight can be gained from publicly available resources. Ultralytics' GitHub repository provides a visual summary of the YOLOv8 model structure, and the Ultralytics founders have discussed the YOLOv8 segmentation model (YOLOv8-Seg) architecture in a GitHub issue (https://github.com/ultralytics/ultralytics).

YOLOv8-Seg builds upon the YOLOv8 object detection framework by enabling pixel-wise segmentation. This means it not only identifies objects (coral reefs) in an image but also generates detailed masks that precisely separate them from the background. The model accomplishes this through a three-part architecture: Backbone, Neck, and Head.

Backbone, this initial layer, utilizes the CSPDarknet53 feature extractor to extract key features from the input image. This process progressively reduces the image size while increasing the number of feature channels, enabling the capture of complex details crucial for coral reef identification.

Neck, the neck refines the extracted features. It may include additional layers or mechanisms like Feature Pyramid Networks (FPN) or Path Aggregation Networks (PAN) to combine features from different image scales. This step ensures the model captures both large and small coral structures within the image.

Finally, the **Head** makes the final predictions. Unlike the standard YOLOv8 model, YOLOv8-Seg has two heads: **Detection Head**, similar to YOLOv8, this head predicts bounding boxes and class probabilities for detected objects (coral reefs) and **Segmentation Head**, drawing upon principles established in the YOLACT architecture (Bolya et al., 2019), predicts a detailed segmentation mask for each detected coral reef. This head upscales features and performs pixel-by-pixel classification to identify whether each pixel belongs to a coral reef or the background (X. Zhao et al., 2023).

Evaluation Metrics

This research focuses on the accuracy of instance segmentation, so the evaluation uses segmentation-specific metrics such as precision (P), recall (R), mean Average Precision (mAP), and F1-score. It should be noted that bounding box metrics such as Intersection over Union (IoU) are not used in this study as they are not relevant to instance segmentation.

Precision (P) is a measure of the algorithm's ability to correctly predict areas, expressed as the ratio of correctly predicted areas to total detected areas (1). Recall (R) is the percentage of successfully predicted categories out of the total number of required categories (2). Mean Average Precision (mAP) evaluates the prediction accuracy of segmentation instances by considering the degree of overlap between the predicted mask and the ground truth mask (3) (4). The F1 score considers precision and recall equally, thus providing a balanced measure of model performance (5). On the other hand, the confusion matrix is a table used to evaluate the performance of the classification model. It provides a detailed breakdown of the model's predictions, which makes it possible to identify classes that need improvement. Larger values of mAP and F1-score imply higher prediction accuracy and overall model robustness.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$AP_i = \frac{Precision}{N} \tag{3}$$

$$mAP = \frac{\sum_{i=1}^{K} AP_i}{K} \tag{4}$$

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$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

Where TP (true positive), TN (true negative), FP (false positive), FN (false negative), N (total samples, AP_i (average precision for class i), and K (detected coral reef categories).

RESULT

To ensure a fair comparison of models, the authors employed Google Colab, a cloud-based platform offering access to powerful computational resources. This eliminates bias introduced by varying hardware configurations, as all models leverage Google Colab's predefined specifications, which include an NVIDIA Tesla T4 GPU with 2560 CUDA cores, 16 GB of GDDR6 memory, 320 GB/s memory bandwidth, and a compute capability of 7.5. This standardized environment ensures a level playing field for model evaluation.

The authors also used pre-tuned hyperparameters that were predefined and consistent for all models. This approach eliminates the influence of different hyperparameter combinations, thus allowing a focused evaluation based solely on the model architecture and preprocessing techniques applied as shown in Table 1.

Table 1. Pre-tuned hyperparameter

Hyperparameter	***Setup***
Epoch	25
Batch Size	16
Optimizer	SGD
Learning rate	0.01
Image Size	640x640
Confidence Score	0.25

The training process leverages Stochastic Gradient Descent (SGD) as the optimization algorithm. SGD iteratively updates the model's weights based on the learning rate, which is set to 0.01 in this case. The model is trained for 25 epochs, meaning the entire dataset is passed through the network 25 times. To balance training efficiency and GPU memory usage, a batch size of 16 images is used. The input images are pre-processed to a uniform size of 640x640 pixels before being fed into the model. Additionally, a confidence score threshold is set to 0.25 as an initial threshold.

This first experiment investigates the impact of different preprocessing techniques (Adaptive Equalization - AE, Contrast Stretching - CS, Histogram Equalization - HE) on instance segmentation performance. We selected the YOLOv8-m (medium-size) models as a foundational component of our experiment. We evaluate two key factors: mAP@50 for detection accuracy and training time for efficiency. The following visualizations in Fig 2, will compare these metrics for each technique, allowing us to identify the preprocessing method that offers the best balance between accuracy and computational cost for this specific task.

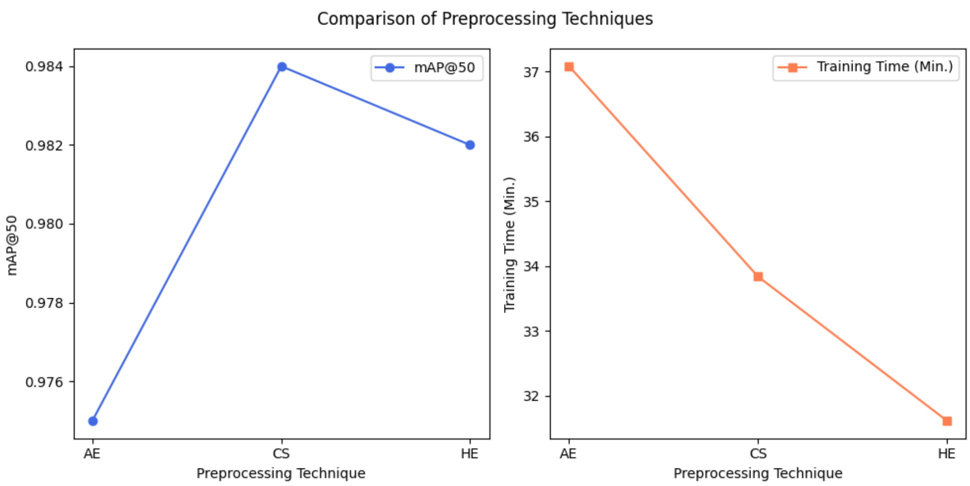

Fig. 2 Preprocessing Techniques Comparison

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As shown in Fig. 2, Histogram Equalization (HE) achieved a precision of 0.967, recall of 0.954, and mAP@50 score of 0.982. Additionally, HE exhibited the lowest training time (31.62 minutes) compared to Adaptive Equalization (37.08 minutes) and Contrast Stretching (33.84 minutes).

In the second experiment, the authors focused on comparing the performance of two YOLOv8-m (medium size) models trained on different datasets: one that underwent a predefined preprocessing pipeline (YOLOv8m-Pp) and another that did not go through any preprocessing (YOLOv8m-Wp) as shown in Fig. 4.

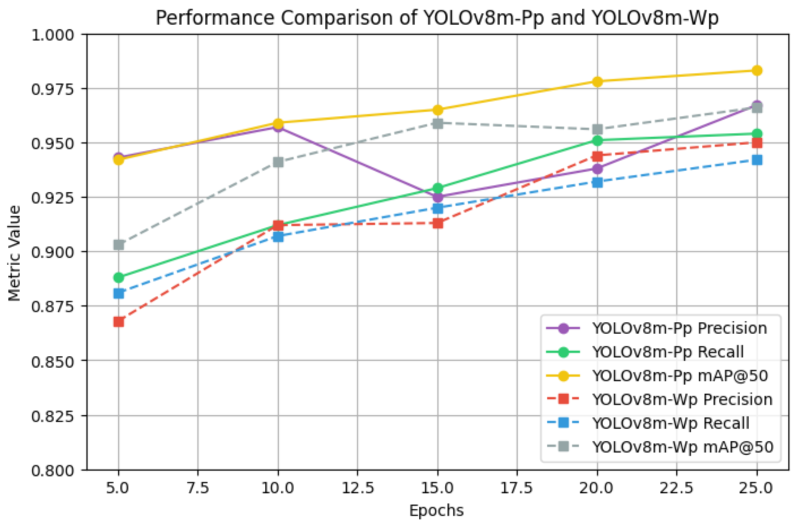

Fig. 3 Performance Comparison between YOLOv8m-Pp (Preprocessing) and YOLOv8m-Wp (Without Preprocessing) models

Fig. 3, presents the training results for both YOLOv8m models: YOLOv8m-Pp (with preprocessing) and YOLOv8m-Wp (without preprocessing). As the number of epochs increases, we observe a steady improvement in all three metrics (precision, recall, and mAP@50) for the YOLOv8m-Pp model, reaching its peak performance at 25 epochs with a precision of 0.967, recall of 0.954, and mAP@50 score of 0.983. Conversely, YOLOv8m-Wp consistently exhibits lower performance across all metrics throughout the training process. While it also reaches its peak at 25 epochs, its highest scores (precision: 0.950, recall: 0.942, mAP@50: 0.966) are all lower than those achieved by YOLOv8m-Pp.

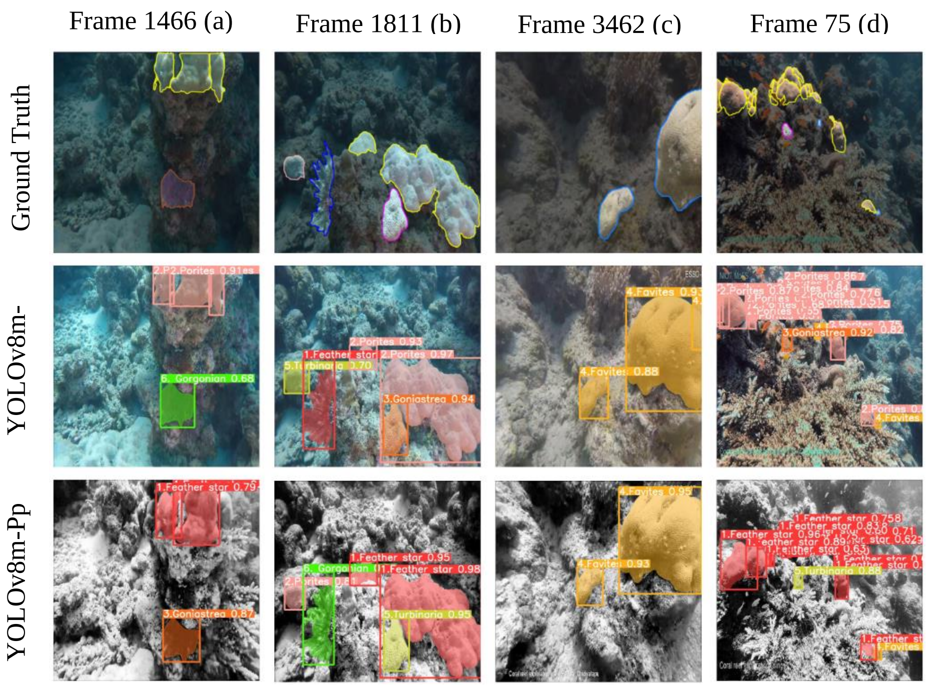

Fig. 4 Segmentation results on the testing dataset. The first two rows show the ground truth labels for coral types. The middle row displays the predictions by YOLOv8m-Wp, and the last row shows the segmentation results by YOLOv8m-Pp.

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This analysis evaluated the performance of YOLOv8m-Wp (without preprocessing) and YOLOv8m-Pp (with preprocessing) in coral reef segmentation. Both models achieved good accuracy in segmenting objects within test images (Fig. 4). Visual inspection revealed that YOLOv8m-Pp displayed slightly better object boundary delineation. However, YOLOv8m-Pp encountered challenges in a specific case as shown in Fig. 4 (d) last row due to potential preprocessing effects on small objects, specifically on the “Favites” class.

The third experiment explores the trade-offs between precision and effectiveness for YOLO models when used for coral reef segmentation. In this study, the authors evaluate the effectiveness of YOLOv8 models in different sizes (nano, small, medium) as well as with and without preprocessing. All models are designed for the same task of instance segmentation. We also compare the performance of YOLOv5-seg and YOLOv7-seg models. All models are designed for the same task of instance segmentation.

The performance of each model in recognizing coral reefs is evaluated using metrics such as Precision, Recall, F1-Score, and mAP@50. These metrics evaluate the model's ability to accurately identify reefs (true positives) with a low rate of false positives (identifying non-reefs as reefs) and false negatives (missing actual reefs). In addition, the chart displays the number of trainable parameters (measured in millions (M)) and training durations (measured in minutes (Min)) to comprehend the intricacy and resource demands of the model.

Table 2 Comparison between experimental results of other YOLO models

Model	**Precision**	***Recall***	***F1-Score***	***mAP@50***	***Params (M)***	***Training Time (Min)***
YOLOv8n	0.942	0.852	0.894	0.886	3.5	19.74
YOLOv8s	0.934	0.854	0.89	0.887	11.7	17.88
YOLOv8m-Wp	0.953	0.84	0.892	0.884	27.2	19.74
YOLOv8m-Pp	0.967	0.954	0.960	0.982	27.2	31.62
YOLOv5-seg	0.937	0.956	0.946	0.961	7.6	14.46
YOLOv7-seg	0.952	0.958	0.955	0.973	37.8	22.2

The results presented in Table 2, among the evaluated models, YOLOv8m-Pp (with preprocessing) reign supreme in accuracy, achieving 0.967 precision, 0.954 recall, 0.960 F1-Score, and 0.982 mAP@50. This underscores the value of preprocessing for this task. For a balance between accuracy and efficiency, YOLOv5-seg emerges as a strong contender. It delivers competitive performance (0.937 precision, 0.956 recall) with a smaller footprint (7.6 Million parameters) and faster training (14.46 minutes) compared to YOLOv8m-Pp (27.2 Million parameters, 31.62 minutes training). While YOLOv7-seg boasts high accuracy (0.952 precision, 0.958 recall), its larger size (37.8 Million parameters) and training time (22.2 minutes) make it less suitable for resource-constrained environments. Finally, YOLOv8n and YOLOv8s prioritize efficiency with minimal parameters (3.5 Million and 11.7 Million respectively) and training times (around 19 minutes for both). However, their accuracy falls short (around 0.94 precision and 0.85 recall) compared to other models.

DISCUSSIONS

In the first experiment, our evaluation reveals Histogram Equalization (HE) as the most effective preprocessing technique for this instance segmentation task. HE strikes a remarkable balance between accuracy (high mAP@50) and efficiency (lowest training time). While Contrast Stretching achieved a slightly higher mAP@50, the difference is negligible. HE's significantly faster training makes it the more practical choice, particularly for resource-constrained real-world applications. These findings align with previous studies that have highlighted the importance of image preprocessing in underwater tasks. For instance, (Mohan & Simon, 2020) also reported that Histogram Equalization can improve the performance of object detection models.

In the second experiment, the results demonstrate the effectiveness of Histogram Equalization (HE) preprocessing for the YOLOv8m model. The model trained with preprocessing (YOLOv8m-Pp) consistently outperforms the model trained without preprocessing (YOLOv8m-Wp) in terms of precision, recall, and mAP@50. This improvement in performance highlights how HE can enhance the ability of the YOLOv8m model to accurately detect and classify objects in the instance segmentation task.

In the third experiment, we can say that for tasks demanding the highest accuracy (e.g., critical ecological surveys), YOLOv8m-Pp with preprocessing is the best option despite its higher computational demands (27.2 Million parameters, 31.62 minutes of training). For scenarios where efficiency is a concern (e.g., real-time monitoring with limited resources), YOLOv5-seg emerges as a compelling choice. It offers a good balance between accuracy (0.937 precision, 0.956 recall) and efficiency (7.6 Million parameters, 14.46 minutes training), making it suitable for resource-constrained environments.YOLOv7-seg might be suitable for specific cases where achieving the highest possible accuracy (0.952 precision, 0.958 recall) outweighs the need for efficiency (37.8 Million parameters, 22.2 minutes training). YOLOv8n and YOLOv8s might be useful for preliminary exploration

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or quick deployments due to their speed and lightweight nature (around 3.5 Million and 11.7 Million parameters, around 19 minutes of training for both). However, their lower accuracy (around 0.94 precision and 0.85 recall) might not be sufficient for critical tasks requiring high precision. YOLOv8m-Pp, representing the YOLOv8 medium model with preprocessing applied, achieves the highest accuracy among the evaluated models. This suggests that the preprocessing techniques, which likely include Histogram Equalization along with other adjustments, can significantly improve object detection performance for YOLOv8m in this coral reef segmentation task.

CONCLUSION

This research demonstrates the effectiveness of the YOLOv8 model for real-time coral reef segmentation. The results demonstrate that YOLOv8 successfully detects and segments various coral species with high accuracy (96.7% precision, 95.9% recall, 98.2% mAP@50) using the YOLOv8m-Pp model with Histogram Equalization preprocessing. YOLOv8 effectively segmented various coral species, as shown in Figure 4. This visual confirmation of accurate segmentation across diverse reef structures strengthens the potential for real-time monitoring applications. This approach offers advantages over existing methods by enabling real-time analysis and potentially improving efficiency in monitoring efforts. While training time is longer compared to alternative models like YOLOv5-seg, YOLOv8m-Pp prioritizes accuracy, making it suitable for scenarios requiring detailed species identification.

The research identified limitations in recognizing specific coral species (Feather-star and Turbinaria) due to data constraints. Future efforts will focus on enriching the data for these and other crucial species. Additionally, implementing data augmentation techniques and exploring transfer learning with pre-trained underwater models hold promise for improving the model's generalizability and handling variations in lighting conditions. These advancements can significantly enhance the effectiveness of YOLOv8-based instance segmentation for automated coral reef monitoring and conservation efforts in Indonesia.

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