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A deep learning-based system for coral reef image segmentation using YOLOv8 with EfficientNet-B0 in Indonesian waters

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ABSTRACT

Manual coral point count with excel extension (CPCe) analysis requires approximately 4–6 hours to process one 50-image station, limiting the scale of coral reef monitoring. This study presents an artificial intelligence-based workflow using YOLOv8 with an EfficientNet-B0 backbone to automate benthic cover estimation. A total of 8,147 underwater images from 151 transects across 39 Indonesian coral reef stations were annotated into eleven benthic categories for model training, while evaluation was conducted using the 2021 Derawan Islands dataset. During validation, YOLOv8 achieved an average mAP@0.5 of 0.58, recall of 0.79, and an average absolute percentage cover error of 9.8% compared with CPCe. The model processed each image in 3.13 seconds, equivalent to 156.47 seconds per 50-image station, representing a 92–138× speedup over manual CPCe analysis. These results show that the proposed workflow can support scalable and near-real-time coral reef monitoring across Indonesia.

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1. INTRODUCTION

Indonesia, the world's largest archipelagic nation, comprises over 17,000 islands and hosts approximately 51,000 km² of coral reefs [1]. These ecosystems support biodiversity, fisheries, tourism, and coastal protection [2], but are increasingly threatened by climate change and local anthropogenic pressures [3]-[5]. Effective reef conservation therefore requires accurate and scalable monitoring. Historically, coral reef monitoring in Indonesia relied on conventional transect methods, such as point and line intercept transects, which were often limited to accessible reefs due to logistical constraints and reliance on SCUBA diving [6], [7]. Coral reef monitoring has increasingly adopted image-based methods and standardized data workflows to improve documentation and comparability across monitoring programs [8].

Despite the broader use of image-based reef surveys, benthic classification still relies heavily on trained experts and manual annotation tools such as CPCe, which are time-consuming and subject to observer variability [9], [10]. These limitations have encouraged the use of artificial intelligence (AI) to automate coral reef image analysis, as AI-based recognition systems have shown strong performance in various image classification tasks [11]. Recent application of YOLOv8 for coral instance segmentation in Indonesian waters achieved a mAP50 of 98.2%, precision of 96.7%, and recall of 95.9%, indicating its potential for large-scale reef monitoring [12]. Image segmentation is particularly relevant because it identifies not only object classes but also their spatial extent. Although semantic segmentation has been applied to benthic habitat mapping with more than 85% overall accuracy using unsupervised algorithms, it does not provide the object-level discrimination offered by instance segmentation [13].

YOLOv8 was selected because it supports both object detection and instance segmentation, enabling the identification of individual benthic objects with pixel-level masks. The default backbone was replaced with EfficientNet-B0 to improve computational efficiency, as EfficientNet uses compound scaling to balance network depth, width, and input resolution [14]. Training images were annotated using Roboflow to ensure labeling consistency, and the resulting YOLOv8-EfficientNet-B0 model was evaluated for multiclass benthic segmentation. This study compared the model-generated benthic cover estimates with manual coral point count with excel extension (CPCe) analysis using the 2021 Derawan Islands dataset as a case study. The proposed workflow aims to support scalable coral reef image analysis for monitoring applications in Indonesia. This study aimed to estimate benthic cover using YOLOv8-EfficientNet-B0, compare the results with manual CPCe analysis, and evaluate inference speed for scalable coral reef monitoring.

2. METHOD

Photographic data were collected by the Coral Reef Monitoring Research Team at 39 survey sites under the COREMAP-CTI program and archived in the National Scientific Repository (RIN) of BRIN. The dataset covers 2013–2021 and includes 8,147 underwater images from 151 transects, consisting of 7,550 images with quadrat frames and 597 images without frames. For model evaluation, a subset from the Derawan Islands in 2021 was used because it contained clear benthic categories and high-quality annotated images. This subset was chosen due to its clear representation of various benthic categories and its ecological importance within the Indonesian coral reef network. The use of Derawan as a case study provides a practical demonstration of the model's performance in a real-world setting.

The underwater photo transect (UPT) technique was used to collect coral reef bottom imagery. This method involves establishing a 50-meter transect line along the reef slope at a depth of approximately 4–7 meters, with photographs taken at 1-meter intervals using 44 × 58 cm frames. Each transect produced approximately 50 photo frames, taken from a distance of approximately 150 cm to ensure optimal image resolution and clarity. This approach has been validated as an effective method for coral reef assessment in recent studies as shown in Figure 1 [15].

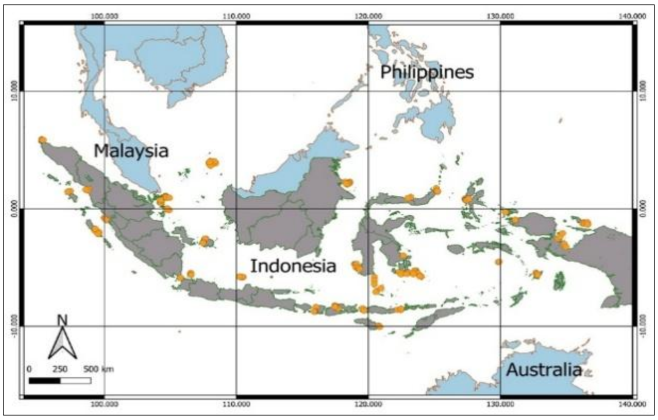


Figure 1. Survey map across the Indonesian archipelago showing data collection points (in yellow) used as training data for the deep learning model (YOLOv8) in benthic habitat identification

3. MATERIAL

Benthic and substrate categories were identified based on established tropical marine resource survey guidelines [16] and simplified into 11 classes: hard coral, dead coral, dead coral with algae, soft coral, sponges, macroalgae, other biota, rubble, sand, silt, and rock. The dataset included information on location, reef condition, habitat, depth, and lighting. All framed images used a 58 × 44 cm steel quadrat as the area of interest (AOI). Overall, 8,147 images with a median size of 4000 × 3000 pixels produced 231,906 annotations, as shown in Figure 2.

Figure 2. Distribution of image sizes and aspect ratios in the dataset

Dataset preparation, including annotation, augmentation, and data splitting, was performed using the cloud-based Roboflow platform. Images were labeled into predefined benthic categories, while augmentation steps such as flipping, cropping, affine transformation, blurring, and noise addition were applied to improve training variability [17]. Similar coral segmentation studies have also used Roboflow for image annotation and applied augmentation techniques such as flipping, cropping, brightness adjustment, and noise addition to improve dataset robustness [18]. This workflow produced a reproducible dataset for YOLOv8 instance segmentation training as shown in Figure 3.

Data separation into training, validation, and test sets was performed directly within the Roboflow platform. As shown in Figure 4, an example of coral object segmentation annotation in a 44 × 58 cm² frame is displayed in the Roboflow interface, illustrating how benthic features are appropriately labeled. These steps ensure a complete structured dataset that is immediately ready to train the YOLOv8 instance segmentation model.

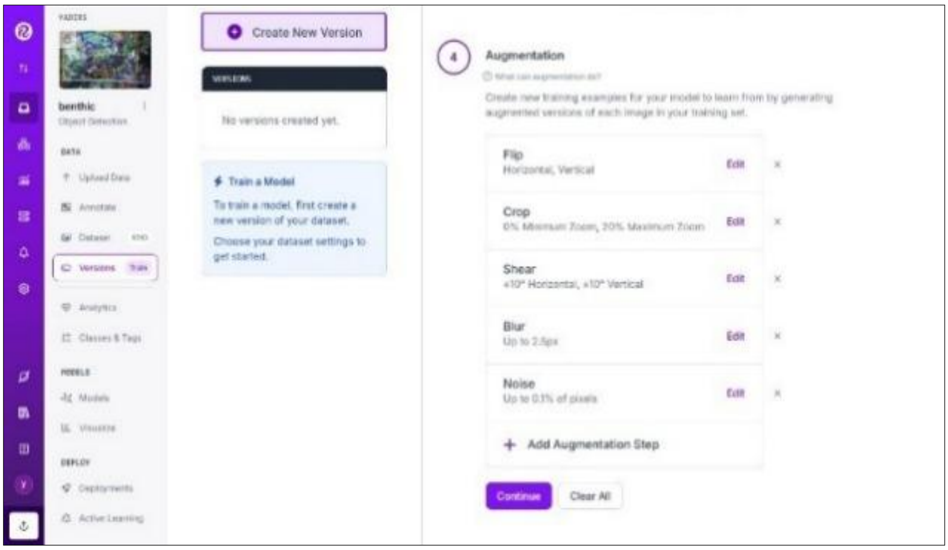


Figure 3. Shows the interface of the cloud-based application Roboflow augmentation process

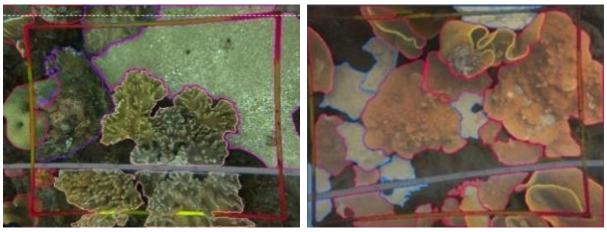


Figure 4. Instant segmentation of benthic objects using the roboflow platform

4. YOLOv8 BASED SEGMENTATION METHOD

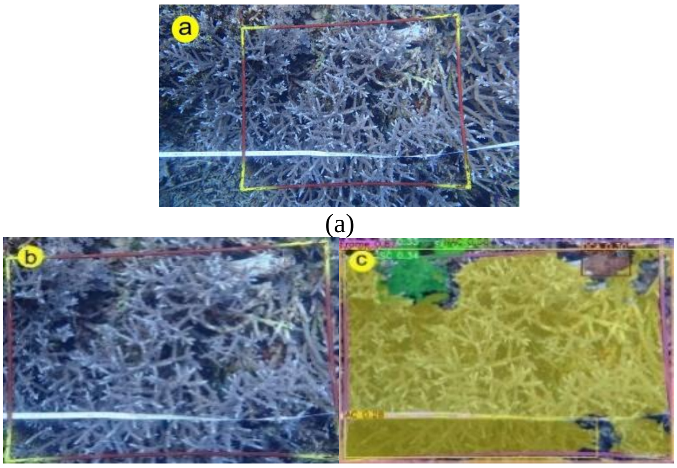
In line with the evolution of the YOLO series starting from YOLOv1 [19], YOLOv2 [20], YOLOv4 [21], YOLOv5 [22], and YOLOv8 [23], this study selected the YOLOv8m variant because it offers an optimal balance between accuracy and computational efficiency as well as built-in support for instance segmentation which is critical in seabed cover analysis. Meanwhile, EfficientNet [14] introduced a compound-scaling approach that balances network depth, width, and input resolution to maximize accuracy per FLOPS. EfficientNet-B0 was integrated as the YOLOv8m backbone to improve segmentation efficiency while maintaining computational performance. The resulting model comprises:

- Backbone: EfficientNet-B0 (5.3 million parameters; 0.39 billion FLOPS) for lightweight feature extraction.
- Neck: path aggregation network (PANet) for multiscale feature fusion.
- Head: A decoupled detection head that handles classification, bounding box regression, and mask prediction.

The model was implemented in Python using the Ultralytics YOLOv8 framework and trained on an NVIDIA A100 GPU for 100 epochs with 640 × 640 px input images as shown in Figure 5. Training parameters and data augmentation were applied to improve stability, reduce overfitting, and increase model robustness [24]. The system also automatically detected the 58 × 44 cm² frame as the AOI and cropped this region using a custom Python script before segmentation. Figures 5(a)-5(c) summarizes the image-processing workflow, including original image input, AOI cropping, and final YOLOv8-based benthic segmentation.

The YOLOv8 architecture is modified by replacing the default backbone with EfficientNet-B0, a lightweight convolutional network known for its performance in balancing efficiency and accuracy. Related work on coral instance segmentation has shown that custom down- and up-sampling modules (e.g. ADown_HWD) and fusion attention mechanisms can improve mAP50 by up to 10.5% over the baseline YOLOv8n [18]. This modification is implemented by defining a custom class named YOLOv8EfficientNet, where the output of EfficientNet is passed through a custom neck layer (1280→512 convolutions), and further to the head layer for bounding box, class, and mask prediction. The model configuration is managed through a YAML file, which details important components such as the backbone, neck, head, input image size, and number of classes. For training, the standard YOLOv8 pipeline is used, with only a few adjustments to suit the specific architecture. These settings are specifically aimed at improving the model’s ability to extract features, making it more effective at analyzing high-resolution underwater images and accurately detecting small or overlapping seabed objects. Figure 6 illustrates the modified YOLOv8-EfficientNet-B0 architecture, highlighting the backbone replacement used for lightweight feature extraction.

The evaluation results showed that the modified model achieved stable training, strong generalization capability, and competitive segmentation performance compared to the baseline YOLOv8 model. To analyze the percent cover of benthic and substrate categories, the open-source software CPCe version 4.1 was used, applying 30 random points to each image [25]. Each point was linked to a benthic component or substrate within the image frame and manually identified by an observer based on predefined categories. The percent cover for each category was then calculated using the following formula. Figure 7 shows the CPCe interface used to assign 30 random points for manual benthic cover estimation.



(a) (b) (c)

Figure 5. Sequential YOLOv8 image-processing workflow: (a) original image with quadrat frame, (b) cropped AOI, and (c) segmentation result with benthic masks and confidence scores

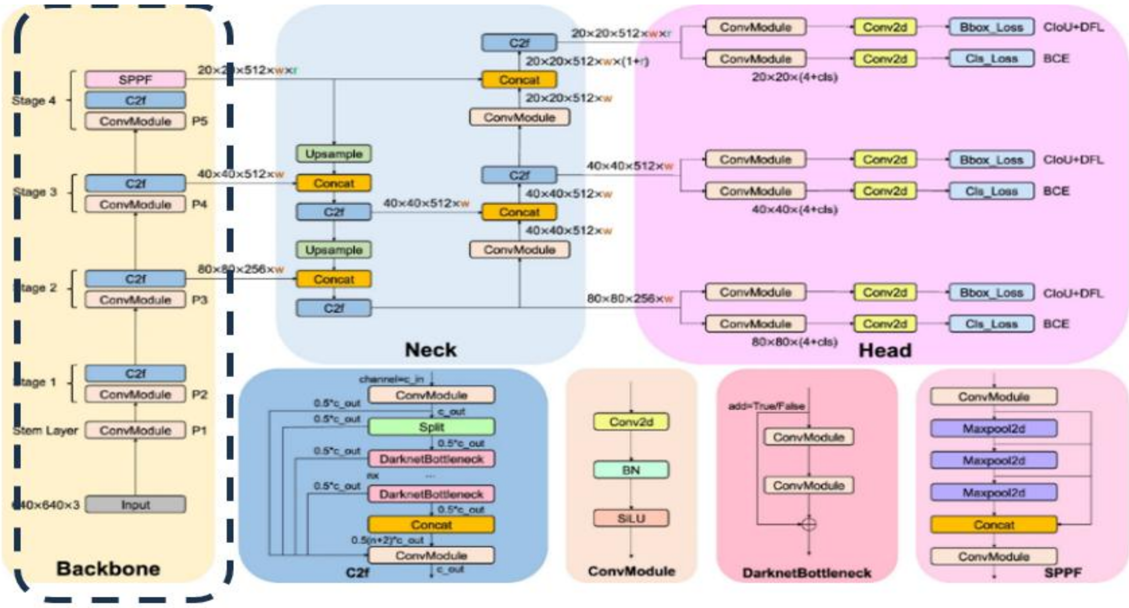


Figure 6. Modified YOLOv8 architecture showing the EfficientNet-B0 backbone replacement for feature extraction

$$Percent\ cover(\%) = \frac{Total\ point\ of\ category}{Total\ number\ of\ points} \times 100$$

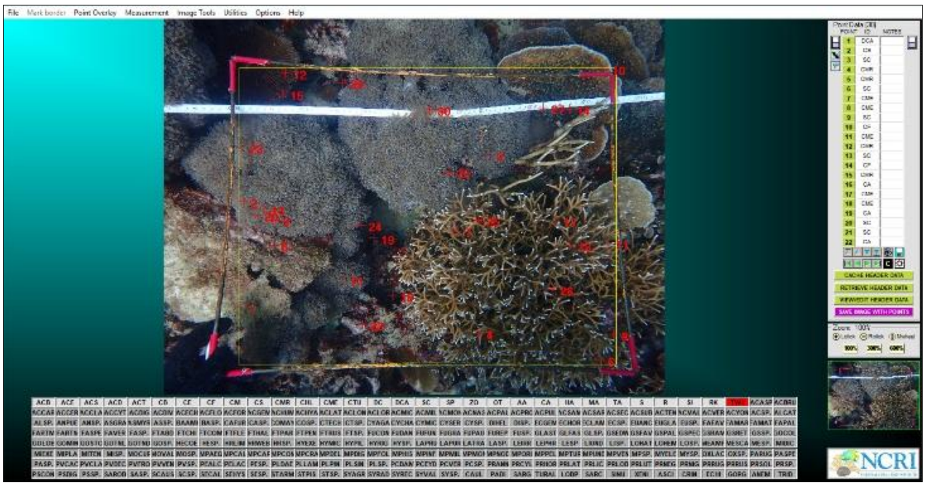


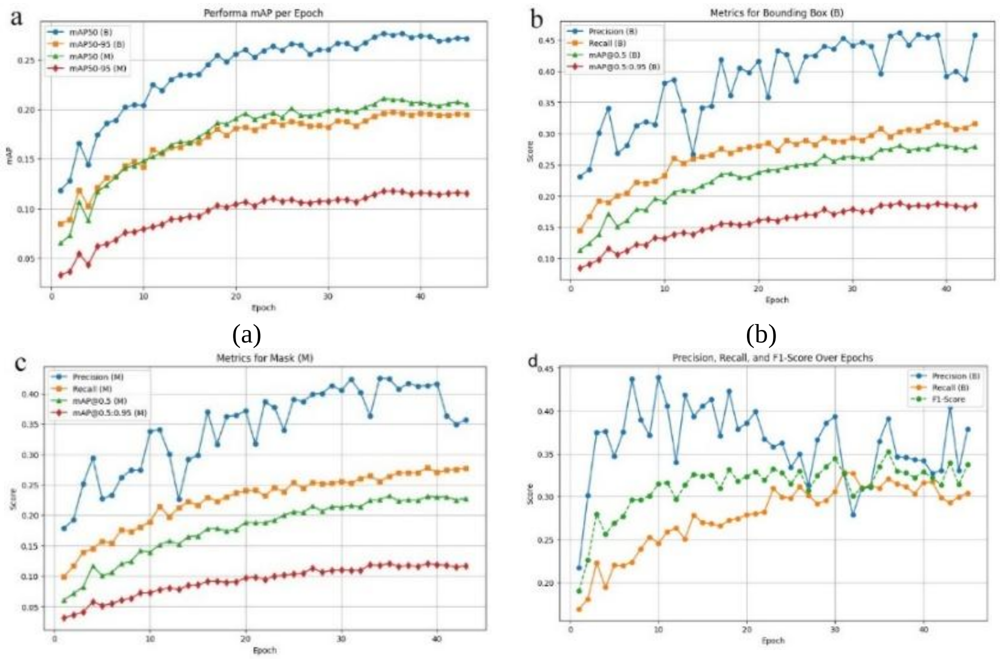
Figure 7. CPCe interface showing 30 random points used for manual benthic cover and substrate classification within the quadrat frame

5. RESULTS AND DISCUSSION

To evaluate bounding box detection and instance segmentation performance, the model was assessed using precision, recall, F1-score, and mean average precision (mAP) at IoU thresholds of 0.5 and 0.5:0.95 for both bounding boxes and segmentation masks [12], [23]. Precision improved from 0.25 to 0.45, while recall increased from 0.15 to 0.30. The mAP50 for bounding boxes exceeded 0.5, while the segmentation mask score was slightly lower. In Figure 8 qualitative analysis demonstrated that the model consistently identified small benthic objects, aligning with earlier research that leveraged improved YOLOv8 architectures under similarly demanding underwater conditions [18]. Figures 8(a)-(d) presents the training performance curves for bounding box detection and segmentation masks, including mAP, precision, recall, and F1-score.

YOLOv8 showed strong segmentation performance across multiple benthic categories, echoing trends seen in earlier coral reef imaging studies [12], [13], [18], which reported mAP50 scores above 0.98 for YOLOv8 in coral reef segmentation tasks. As shown in Figure 9, the model accurately detected the steel frame area as the AOI before automatic cropping. The segmented output identified NAC as the dominant class, with confidence scores ranging from 0.39 to 0.89. The model also accurately detected SP (Sponge) 0.48 in magenta, other biota (OT) 0.44 in purple, and dead coral with algae (DCA) in brown, with confidence scores of 0.30. The steel frame itself was detected in pink, which served as the primary segmentation boundary as shown in Figures 9(a) and (b).

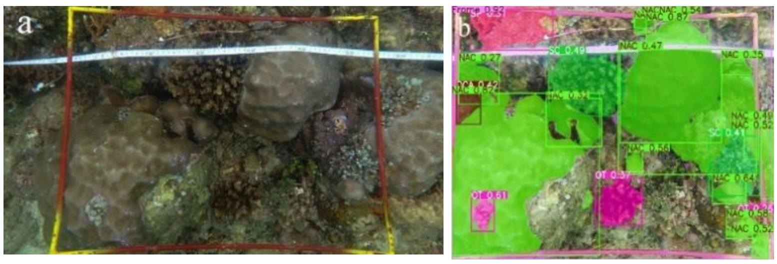
A mAP@0.5 of 0.745 was recorded, consistent with benchmark results reported in similar coral segmentation studies within comparable underwater environments [26]. Additionally, the IoU values for most classes exceed 0.7. The precision (0.824) and recall (0.893) metrics further indicate consistent performance, particularly for dominant categories such as hard corals (HC) and soft corals (SC).



(a) (b)

(c) (d)

Figure 8. YOLOv8 training performance: (a) mAP curves, (b) bounding box precision and recall, (c) mask precision and recall, and (d) precision, recall, and F1-score over epochs



(a) (b)

Figure 9. YOLOv8 segmentation results: (a) original input image and (b) image after model detection showing multi-category segmentation in underwater imagery, including steel frame, NAC, SP, DCA, and OT, prior to cropping

Qualitative evaluation revealed that the segmentation results could be categorized into three performance levels, as illustrated in Figure 10. In the best-case results, the model produced accurate and well-defined segmentations for multiple benthic classes, including AC (yellow), SC (green), NAC (light green), and DCA (brown) as shown in Figures 10(a)-10(i). Medium-quality outputs showed reasonably accurate predictions, although some misclassifications occurred-often due to visual similarities between categories. In the lowest-quality cases, detection errors such as overlapping masks and incorrect class predictions were evident, typically caused by poor lighting conditions, low contrast, or ambiguous benthic textures.

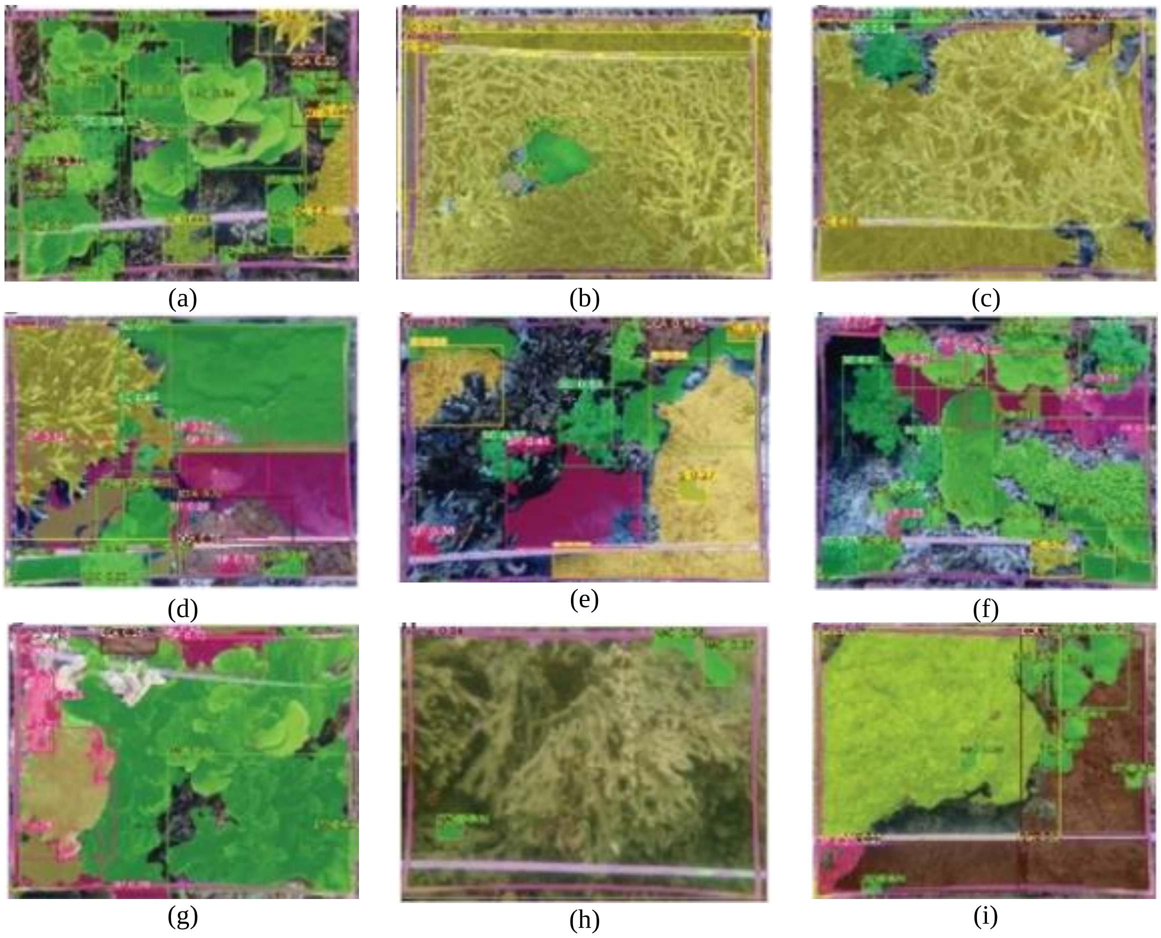


Figure 10. Representative segmentation results of the YOLOv8 model: (a), (b), (c) Best results, (d), (e), (f) medium results, and (g), (h), (i) results with detection errors

Analysis of the DERC01 transect data revealed an average absolute difference of 9.78% between manual CPCe estimates and YOLOv8 predictions. Table 1 details the percentage cover analyzed by CPCe and predicted by YOLOv8 for each benthic category, along with the absolute error and inference time. Figure 11 compares the percentage cover estimates obtained from manual CPCe analysis and YOLOv8 prediction for the DERC01 transect, including the overall category average.

Table 1. Comparison of benthic cover percentages: manual method (CPCe) vs AI (YOLOv8) on transect 01 derawan 2021 data

Station	Category	% Manual (CPCe)	% AI (YOLOv8)	Absolute Difference (%)
DERC01	HC	47,80	67,13	19,33
DERC01	DCA	27,87	4,49	23,38
DERC01	SC	1,00	4,49	3,49
DERC01	SP	3,13	11,35	8,22
DERC01	OT	0,73	5,01	4,28
DERC01	S	26,56	26,56	0,00
Average		17.85	19.84	9.78

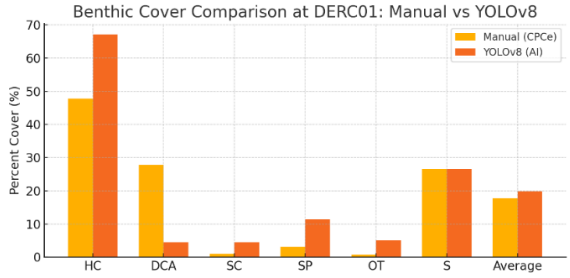


Figure 11. Percent cover comparison between CPCe and YOLOv8 at DERC01

Despite certain mismatches such as the tendency to overestimate live hard coral (67.1% vs. 47.8%) and underestimate covered dead coral with algae (4.5% vs. 27.9%), the model demonstrated a mean absolute deviation of 9.8% when compared with CPCe assessments, indicating its results generally fall within an acceptable margin of manual interpretation [13], [15]. Across the ten Derawan transect stations, the live coral (LC) category exhibited an average absolute difference of 12.88% between manual CPCe estimates and YOLOv8 predictions (Table 2). Figure 12 visualizes the absolute error for each benthic category across Derawan transect stations, showing which classes contributed most to the difference between CPCe and YOLOv8 estimates. Figure 13 compares benthic cover estimates from CPCe and YOLOv8 for selected representative benthic categories.

Table 2. Live Coral (% LC/HC) comparison at Derawan transect stations

Station	% LC (CPCe)	% LC (YOLOv8)	Absolute Difference (%)
DERC01	47.80	67.13	19.33
DERC02	31.53	33.32	1.79
DERC03	21.87	51.09	29.22
DERC05	39.47	44.06	4.59
DERC06	37.69	56.30	18.61
DERC07	24.13	39.74	15.61
DERC08	12.80	20.80	8.00
DERC09	54.00	48.93	5.07
DERC10	32.27	45.60	13.33
DERC11	19.53	32.79	13.26
Average			12.88

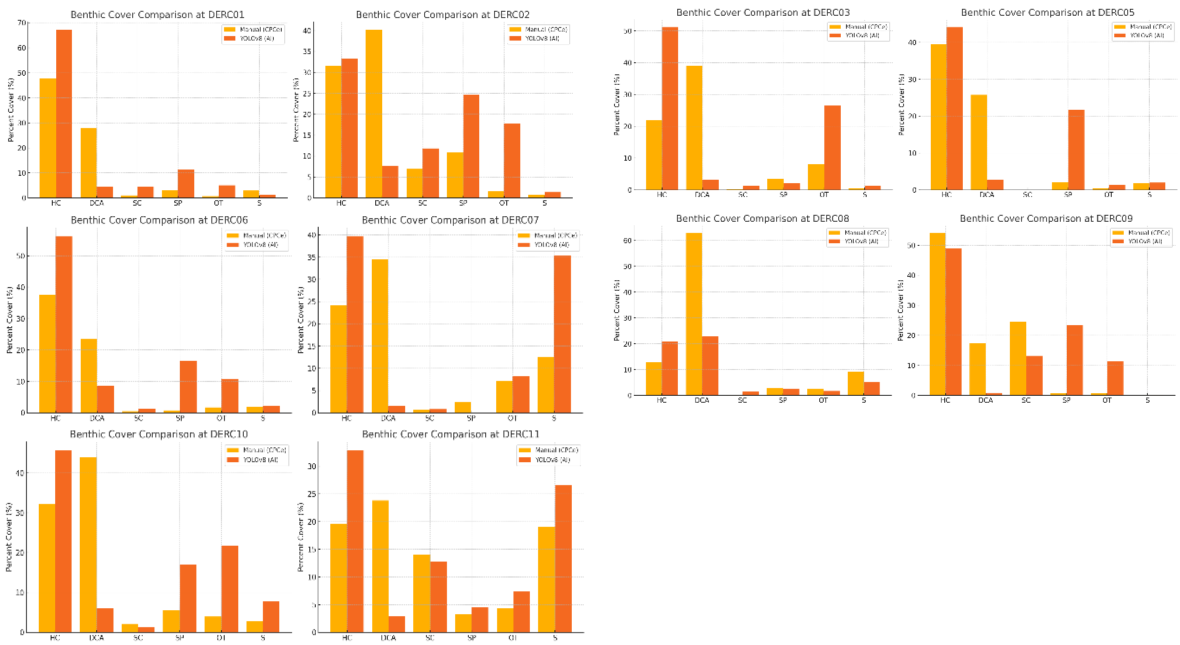


Figure 12. Absolute error per station and benthic category between CPCe and YOLOv8 estimates

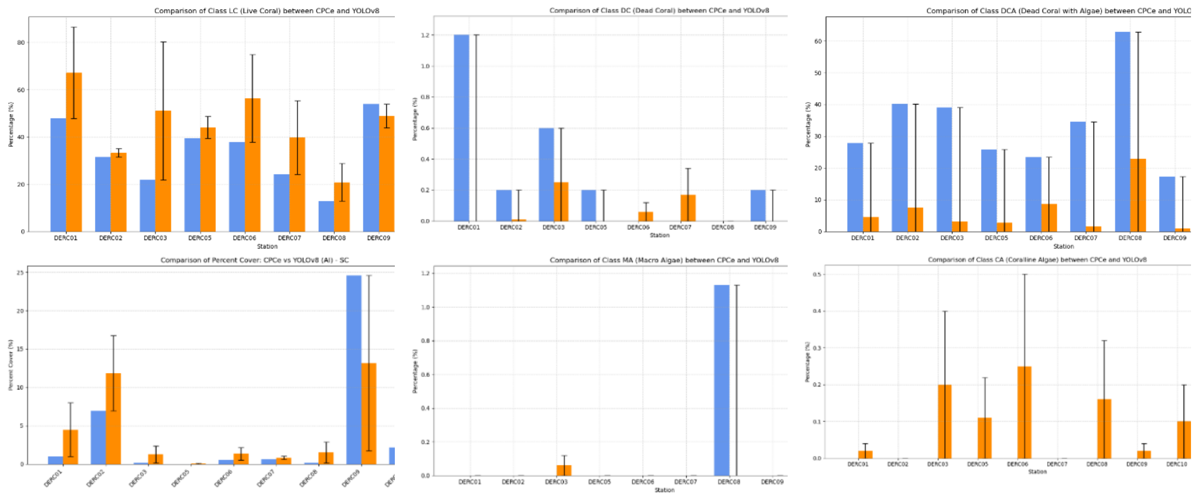


Figure 13. CPCe and YOLOv8 benthic cover comparison for selected representative categories

This study demonstrates that the YOLOv8 instance segmentation model, integrated with the EfficientNet-B0 backbone, effectively identifies eleven benthic classes in underwater coral reef imagery. When tested across ten transect stations in the Derawan Islands, the model achieved an average mAP@0.5 of 0.58 and a recall of 0.79 at the final epoch. Compared to manual estimations using CPCe, the model showed a mean absolute difference in percentage cover of 9.8%. The most significant deviations were observed in hard corals (HC, 19.3%) and dead corals with algae (DCA, 23.4%), while smaller differences were noted in soft corals (SC, 3.5%), sponges (SP, 8.2%), other biota (OT, 4.3%), and sand (S, 0.0%).

These results indicate that the model is generally reliable, although several benthic classes still require further refinement. With an average inference time of 3.13 seconds per image, or approximately 156.5 seconds per 50-image station, the model shows strong potential for near-real-time coral reef monitoring. Consistent with previous YOLO-based coral monitoring studies [26], [27], the results suggest that the proposed YOLOv8-based approach is effective for the Derawan Islands dataset and scalable for broader coral reef monitoring across Indonesia.

6. CONCLUSION

This study presents an efficient and scalable deep learning-based method for estimating benthic cover in coral reef ecosystems. The YOLOv8-EfficientNet-B0 model processed images in 3.13 s per image, achieving a 92–138× speedup compared with manual CPCe analysis. The model showed strong segmentation performance, particularly for dominant classes such as hard corals (HC) and non-Acropora corals (NAC), with IoU values exceeding 0.7 in many cases. However, performance may still be affected by challenging image conditions, including uneven lighting and overlapping small benthic colonies. Future work should expand the training dataset to better represent Indonesia's diverse reef environments, including turbid waters and deeper reef zones, and validate the workflow in real-time monitoring scenarios through edge-based devices or integration with CPCe.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there is no conflict of interest related to this research.

INFORMED CONSENT

Not applicable. This study did not involve human participants, identifiable personal data, or clinical procedures requiring informed consent.

ETHICAL APPROVAL

Not applicable. This study did not involve human participants or animal subjects and therefore did not require ethical approval.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author, R.S., upon request.

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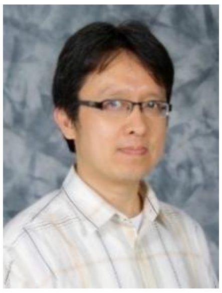

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