



Application of YOLOv8 Algorithm for Coral Reef Disease Detection as an Effort to Prevent Marine Habitat Damage in Batam

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Abstract

Research in 2019 in Batam City showed that out of 19 coral reef fisheries support facilities, 16 were declared not good. Coral reef damage increased from 36.28% to 39.44%. This is due to the threat of coral reef damage due to international shipping lane areas, human activities such as destructive fishing, pollution, sedimentation, and global warming. These threats can cause coral diseases such as black band disease (BBD), brown band disease (BrB), Bleaching Coral, and yellow band disease (YBD). The Underwater Photo Transect (UPT) method collects data in the field in the form of underwater photos and analyzes them to obtain quantitative data. This method has a weakness, namely the low level of accuracy in detecting coral reef diseases. This study proposes coral reef disease detection using the YOLO model YOLO8l, YOLO8x, and YOLO8m. The results of the model evaluation test with a threshold value of 0.5 to 0.95 against the test data show that the three models can detect coral reef diseases with an accuracy of 99%. These results prove that the YOLOv8 model in this study is suitable for the real-time detection of coral reef diseases to replace the Underwater Photo Transect (UPT) method, which has low accuracy. Applying the YOLOv8 method will help Prevent Marine Habitat Damage in Batam City.

Keywords: coral; detection; disease; YOLOv8

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1. Introduction

Geographically, the Batam City Regional Marine Conservation Area (KKPD Batam City) is located at 104019'40"-104018'02" North Latitude and 0037'43"-0041'54" East Longitude. The KKPD Batam City covers an area of approximately 66,867 hectares, within which coral reefs constitute one of the key ecosystems [1]. Dugas Waters is a coastal area in the northern part of Batam City, precisely in Sekupang District, Batam City. Dugas Waters has the potential for coral reef resources and is a beach tourism destination [2]. The results of the 2019 study, Batam City has 19 coral reef fisheries supporters. From the study, 16 were declared to be in poor condition [3]. Damage to coral cover in Batam City increased from 36.28% to 39.44%. This occurs because of the threat of coral reef damage due to national and international shipping lanes [4], human activities such as destructive fishing, pollution, sedimentation, and global warming [5]. These threats

cause coral diseases such as Black Band Disease (BBD) [6], Brown Band Disease (BrB), Dark Spots Disease (DSD), Yellow Band Disease (YBD) [7], and White Syndromes (WS) [8]. Coral reef assessments can be performed using a range of methodologies, including the Line Intercept Transect (LIT) method [9], which is widely utilized in coral reef surveys [10], the Point Intercept Transect (PIT) method, which evaluates reef conditions based on the proportion of live coral cover [11], and the Underwater Photo Transect (UPT) method [12]. The UPT method is collecting data in the form of underwater photos and analyzing them to obtain quantitative data [13]. This method is less effective and efficient and can only provide estimates of coral reef observations [14]. From the background of the problem, technology is needed to detect coral reef diseases in the Batam Sea in real time with higher accuracy. In this study, the proposed deep learning method is YOLOv8. The YOLOv8 (You Only Look Once) algorithm is a

target detection method based on a Convolutional Neural Network (CNN) [15]. This algorithm offers several advantages, including high processing speed, strong detection accuracy, and real-time object monitoring capabilities [16]. In testing the YOLO method for fish farming using aquaculture techniques, detection performance largely depends on recognizing fish behavior underwater. However, water conditions—affected by lighting and water quality—pose significant challenges for fish detection. Consequently, poor water quality can make observing fish behavior difficult. This study proposes the YOLO algorithm for detecting fish behavior underwater. The results showed that the detection of the YOLOv7 algorithm was 92.86% [17]. Object detection in foggy environments is challenging. This study employs a combination of the IDOD (Image Defogging) module and the YOLOv7 algorithm. The experimental results demonstrate improvements in both image quality and object detection performance, as well as enhanced perception for autonomous driving in foggy conditions [18]. Corn is one of the leading food commodities in Southeast Asian countries, including Indonesia. Corn production is highly dependent on the health of corn plants. Conventional methods are usually used to control corn plant diseases. However, this method is not effective and efficient. This study uses YOLOv8 to detect corn plant diseases. The study's results showed high accuracy with an mAP 50 value of 0.965 [19].

Copy-move attacks are the most common attacks on videos/images, where an object is copied and moved into the frame of the video so that it can create an illusion to falsify content. This study uses YOLOv8 to localize falsified objects. The results show that YOLOv8 can detect manipulated objects with an mAP value of 0.99, recall of 0.99, and precision of 0.99 [20]. This study is used to detect or track people with disabilities such as paralysis, lack of limbs (Amelia), or amputation. This study uses the YOLOv8, YOLOv7, and YOLOv5 methods to detect people with disabilities. The experimental results demonstrate that the YOLOv8 model exhibits strong performance, achieving a precision of 0.906, a recall of 0.943, and a mean Average Precision (mAP) of 0.951.

The contributions in this study are as follows: conducting real-time detection, which can be integrated into coral reef conservation strategies, by facilitating monitoring and assessment of ecosystem health; exploring transfer learning techniques, which allow model adjustments to specific coral reef datasets, thereby increasing the relevance and precision of the results; YOLOv8's ability to provide increased accuracy and speed compared to using the Line Intercept Transect (LIT), Point Intercept Transect (PIT), and Underwater Photo Transect (UPT) methods which allow more effective coral reef detection, even in poor lighting conditions or complex environments.

2. Methods

2.1 Main Stage Research

This study uses the You Only Look Once version 8 (YOLOv8) architecture through six main stages, the first stage is dataset selection to ensure the quality and representativeness of image data, The second stage is data preprocessing such as normalization, augmentation, and cropping to improve input quality, The third stage is data labeling to provide annotations on image areas that represent disease symptoms, The fourth implementation of the YOLOv8 model with architectural configuration and hyperparameter tuning, The fifth stage involves evaluating the model's performance using standard metrics such as precision, recall, and mean Average Precision (mAP). The final stage focuses on analyzing the disease detection accuracy to determine the model's effectiveness in identifying coral reef diseases within the test dataset.

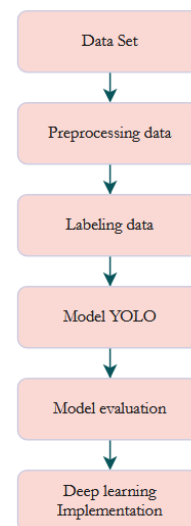


Figure 1. Research Method

2.2 Dataset

The dataset utilized in this study comprises a collection of digital imagery that serve as the primary data for training and evaluating coral reef disease detection models in Batam waters. Data sources were obtained from various institutions with authority and credibility in the marine sector, including the official websites of maritime research institutions, the Batam Coral Reef Conservation program, documentation of research projects and academic collaborations, and international databases provided by the Coral Triangle Initiative and the National Oceanic and Atmospheric Administration (NOAA).

This diversity of sources not only ensures the availability of images with varying marine environmental conditions but also enriches the visual representation of coral reef diseases, thus ensuring the dataset has sufficient validity and reliability to support the development and testing of YOLOv8-based models.

2.3. Data Preprocessing

In the data pre-processing stage, coral reef disease images will first be processed through a cropping technique to extract areas deemed relevant, especially parts of the coral reef that show disease symptoms such as discoloration, spots, or tissue damage.

This cropping process aims to remove elements that do not have a significant contribution to the analysis, such as seawater backgrounds, shadows, and foreign objects around the image, which have the potential to become noise and reduce the quality of model learning. Thus, the cropping results allow the YOLOv8 model to focus more on key features related to coral reef disease, thereby increasing the efficiency of the training process, accelerating model convergence, and improving detection accuracy during the evaluation stage.

2.4 Data Labeling

Labeling refers to the image annotation process in which each relevant object is assigned a specific label or tag, enabling the model to accurately identify and learn these objects during the training phase. This process involves determining the object name, category or class of the object, as well as marking the object's location in the form of bounding box or polygon coordinates, according to the needs of the detection architecture used.

The information generated from the labeling serves as ground truth which is the main reference for the object detection algorithm in distinguishing between target and background classes, so the quality and consistency of the labeling greatly influence the model's performance in the training and evaluation processes. The data labeling process can be seen in Figure 2.

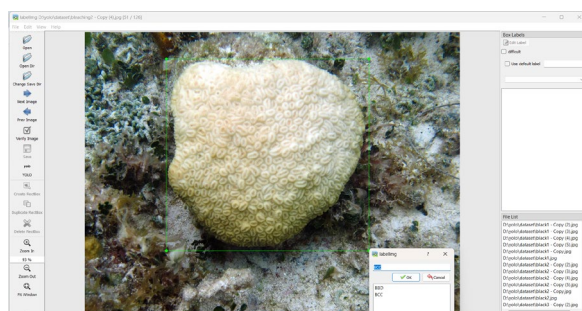


Figure 2. Data Labeling Process

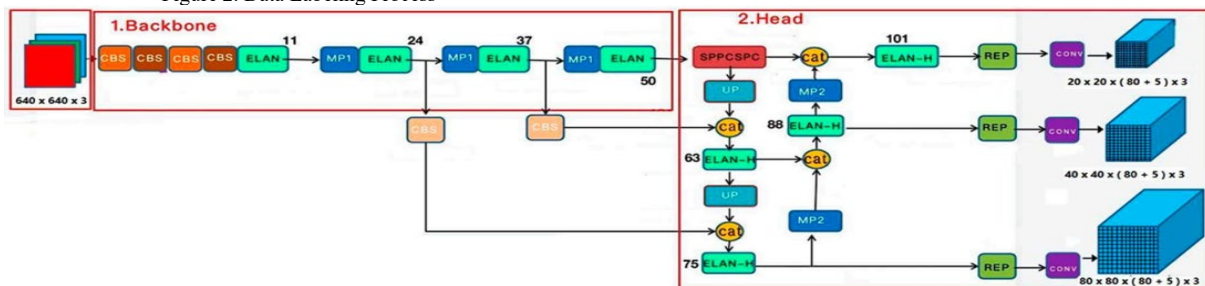


Figure 5. YOLO Flow

Figure 5 illustrates the overall workflow of YOLOv7. Before entering the backbone, the input image is resized to 640×640 pixels. In the head network layer, the REP

2.5 YOLOv8 Model

YOLOv8 is the most recent evolution of the YOLO series of real-time object detection models, providing cutting-edge performance in both accuracy and processing speed. It surpasses previous object detectors, achieving a superior mean Average Precision (mAP) of 54%, positioning it among the most advanced models available as shown in Figure 3, and for latency can be seen in the Figure 4 [21].

The performance metrics of the YOLOx, YOLOm, and YOLOl models can be seen in the Table 1.

Table 1 Performance Metrics

Model YOLO	size (pixels)	mAP 50-95	Speed CPU (ms)	Speed A100 TensorRT (ms)	params (M)
v8m	640	50.2	234.7	1.83	25.9
v8l	640	52.9	375.2	2.39	43.7
v8x	640	53.9	479.1	3.53	68.2

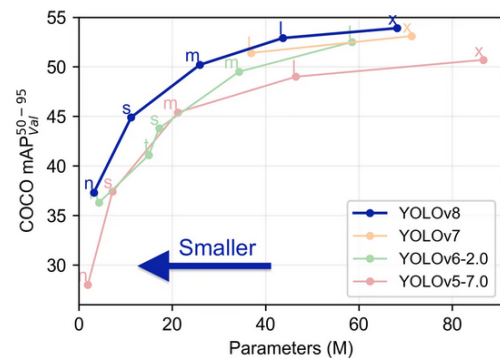


Figure 3. Parameters YOLOv8

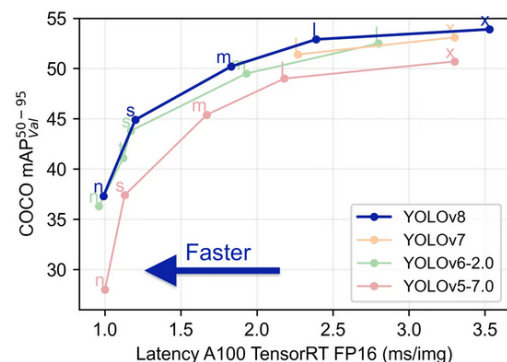


Figure 4. Latency YOLOv8

and convolution (Conv) modules are used to generate the predicted results for object detection[22].

The system works by detecting coral reef diseases in the waters of Batam using a camera connected to a PC server. The camera will take pictures or videos, then the system will detect using the YOLOv8 algorithm. If coral reef disease is detected, the accuracy level of the YOLOv8 algorithm will be calculated.

2.6 Model Evaluation

Model evaluation is an analytical step aimed at assessing the performance of the YOLOv8 algorithm in detecting and classifying coral reef diseases based on the available input data. The evaluation process employs a set of quantitative performance metrics, including precision, recall, F1-score, and mean Average Precision (mAP), to assess the model's accuracy, sensitivity, and overall predictive balance.

Furthermore, a confusion matrix is used to illustrate the distribution of model predictions relative to actual data, facilitating the analysis of classification errors in the form of false positives and false negatives. The evaluation also compares model performance on training data, validation data, and test data to identify potential overfitting or underfitting. In this study, this evaluation procedure is a crucial step in ensuring the reliability, validity, and generalizability of the model before its implementation in real-world conditions.

2.7 Confusion Matrix

A confusion matrix serves as a key evaluation tool for assessing a model's accuracy and error rate in object detection and classification tasks. It compares the model's predicted outcomes with the actual ground truth data, thereby providing a comprehensive depiction of the model's performance in detecting coral reef diseases. As presented in Table 2, True Positives (TP) denote the number of samples correctly identified as positive, whereas False Positives (FP) represent negative samples that were incorrectly classified as positive. Conversely, False Negatives (FN) indicate positive samples that were misclassified as negative, while True Negatives (TN) refer to negative samples that were accurately identified as negative.

Analysis based on this confusion matrix allows researchers to identify misclassification patterns, assess the reliability of the YOLOv8 model, and serve as the basis for calculating other performance metrics, such as precision, recall, F1-score, and accuracy. In the context of this research, the confusion matrix plays a crucial role in providing empirical validation of the effectiveness of the coral reef disease detection model in supporting marine ecosystem conservation.[22].

Table 2 Confusion Matrix

Actual Class	Positif	Negatif
True	TP	FN
False	FP	TN

2.8 Precision

Precision is an evaluation metric used to measure the accuracy of bounding box (bbox) predictions in

detecting the correct object. Formally, precision is calculated by dividing the number of correctly classified positive predictions (True Positives) by the total number of positive predictions generated by the model. Precision is calculated as the ratio of True Positives to the sum of True Positives and False Positives. A high precision value indicates that the majority of positive predictions made by the model accurately correspond to the target objects. This metric is crucial for evaluating the reliability of a detection system, particularly in minimizing prediction errors manifested as false alarms [23], as shown in Formula 1.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (1)$$

2.9 Recall

Recall is an evaluation metric that quantifies a model's capability to detect all actual positive instances within an image. Formally, it is defined as the ratio between the number of correctly identified positive predictions (True Positives) and the total number of actual positive instances in the dataset, represented by the sum of True Positives and False Negatives.

A high recall value indicates that the model has the ability to detect most of the target objects that are actually present, making this metric very important in assessing the sensitivity of a detection system, especially to minimize cases of missed target objects, as shown in Formula 2.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

2.10 Disease Detection Accuracy

Disease detection accuracy is an evaluation metric used to assess the extent to which the predictions of a detection model match the actual health conditions of coral reefs. Within the YOLOv8 framework, accuracy is determined by calculating the proportion of correct predictions comprising True Positives and True Negatives relative to the total number of predictions generated. This metric reflects the model's effectiveness in accurately distinguishing between healthy and disease-affected coral reefs.

A high accuracy value indicates that YOLOv8 is able to consistently represent the real conditions of coral reef ecosystems, so it can be used as an important indicator in assessing the reliability of detection systems to support conservation efforts and prevent damage to marine habitats.

3. Results and Discussions

This study uses the YOLOv8 method by training the YOLOv8m, YOLOv8l, and YOLOv8x models. YOLOv8m is one of the variants of the YOLOv8 model developed for object detection. The "m" in YOLOv8m refers to "medium." In terms of complexity and performance, this model is between smaller and larger sizes. The "l" in YOLOv8l refers to "large," this model is larger and more complex than the smaller variants,

such as YOLOv8m. YOLOv8x indicates a model with a size of "extra large" or "extra big."

This model is designed to provide optimal performance in object detection, focusing on high accuracy and the ability to detect objects in complex conditions. In this study, the dataset to be used is divided into four classes as in Table 3.

Table 3. Dataset Class

No	Class	Desc	Total Image
1	BBD	Black Band Disease	100
2	BCC	Bleaching Coral	100
3	BRD	Brown Band Disease	100
4	YBD	Yellow Band Disease	100

3.1 Results

The data training process uses Google Colab with a 400 and 40 images dataset for image validation. It is carried out for 100 epochs. The models used for the training process are YOLOv8m, YOLOv8l, and YOLOv8x. The results of image validation after training are shown in Figure 6.

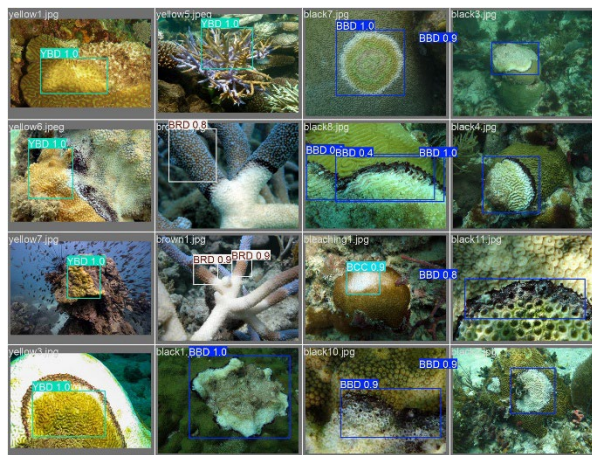


Figure 6. Image Validation Result

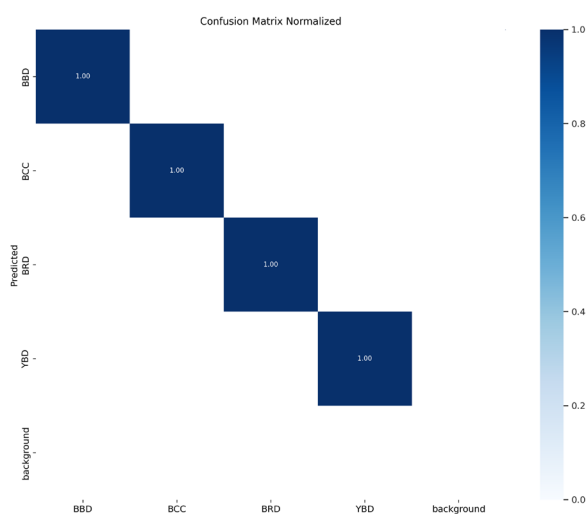


Figure 7. Confusion Matrix Model YOLO8l

In Figures 7, 8 and 9, the confusion matrix is used to evaluate the truth value and error rate of YOLOv8 detected results. A value of 1.00 in the confusion matrix

indicates that the YOLO8l, YOLO8x, and YOLO8m models have a very high level of truth in detecting coral reef disease.

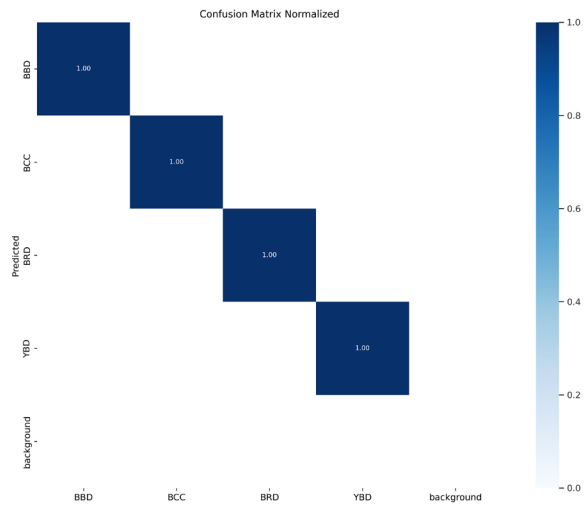


Figure 8. Confusion Matrix model YOLO8x

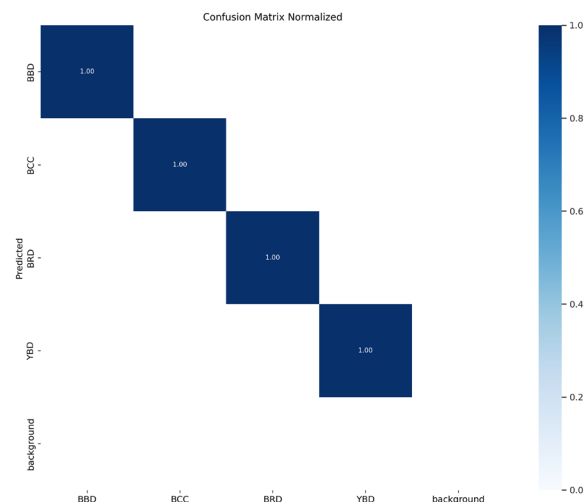


Figure 9. Confusion Matrix model YOLO8m

Table 4 explains the precision performance of the YOLO8l, YOLO8x, and YOLO8m models in detecting coral reef diseases, including Black Band Disease (BBD), Bleaching Coral (BCC), Brown Band Disease (BRD), and Yellow Band Disease (YBD), with very high precision results.

Table 4. Precision Confidence

No	Class	YOLO8l	YOLO8x	YOLO8m
1	BBD	0.996	0.995	0.996
2	BCC	0.995	0.995	0.993
3	BRD	0.989	0.987	0.986
4	YBD	0.981	0.976	0.979

As seen in Figures 10, 11 and 12, the difference in precision results for all classes in the YOLO8l model is 0.916, YOLO8x is 0.980, and YOLO8m is 0.942.

The ability of the YOLOv8, YOLOv8, and YOLOV8m models to identify all coral reef disease image objects

after validation showed a high value, namely 1.00, as in Table 5.

Table 5. Recall Confidence

No	Class	YOLO8l	YOLO8x	YOLO8m
1	BBD	1	1	1
2	BCC	1	1	1
3	BRD	1	1	1
4	YBD	1	1	1

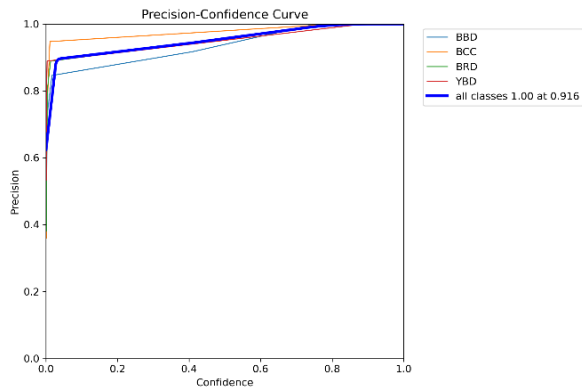


Figure 10. Precision Confidence YOLO8l

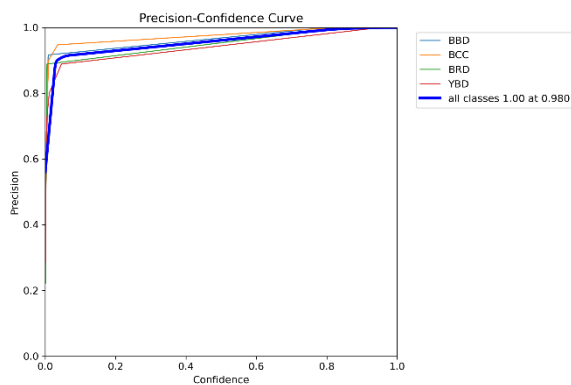


Figure 11. Precision Confidence YOLO8x

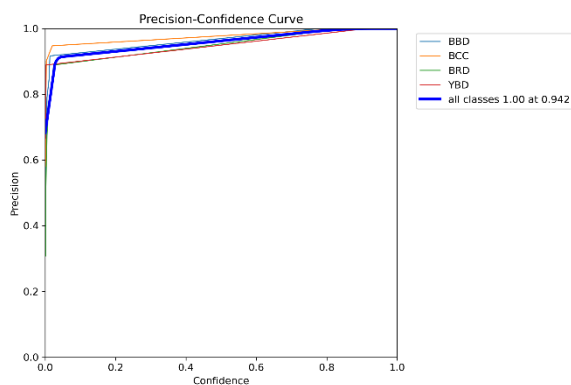


Figure 12. Precision Confidence YOLO8m

The difference in the identification results of all objects for all classes in the YOLO8l, YOLO8x, and YOLO8m models has a value of 1.00 which can be seen in Figures 13, 14, and 15.

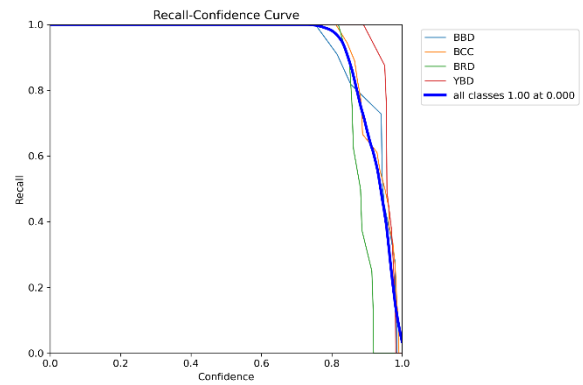


Figure 13. recall confidence curve YOLO8l

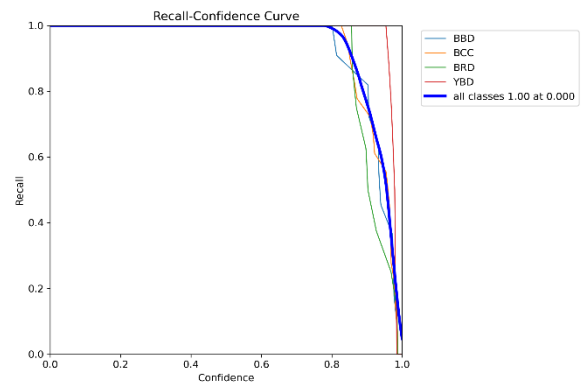


Figure 14. recall confidence curve YOLO8x

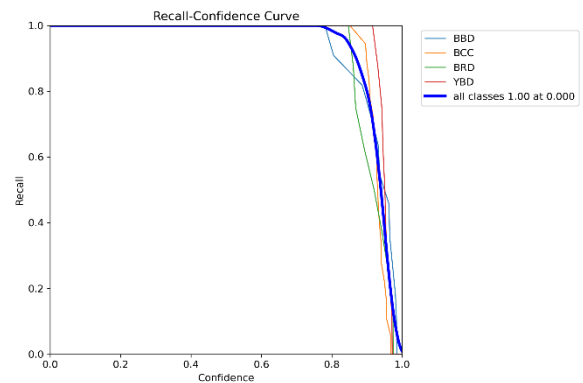


Figure 15. recall confidence curve YOLO8m

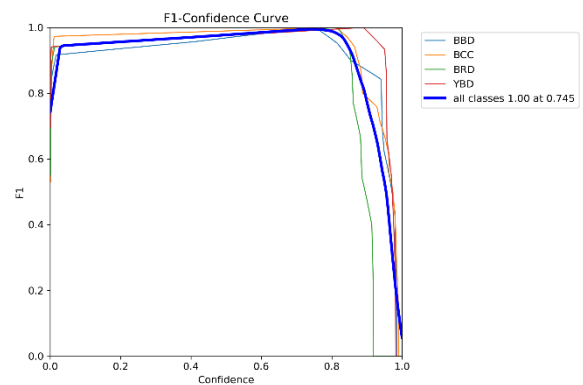


Figure 16. F1 confidence curve YOLO8l

The F1 score on the YOLOv8 model reached its highest point of 1.00 with an optimal confidence value of 0.745 when detecting coral reef diseases as in Figure 16.

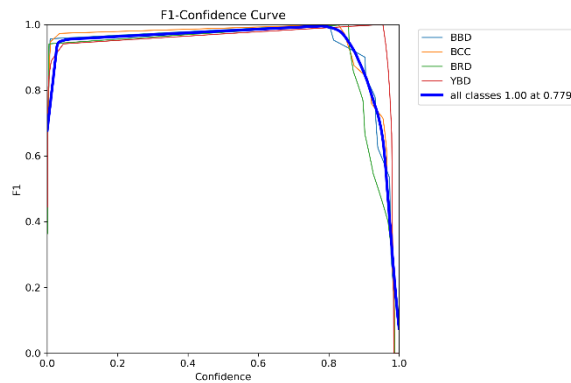


Figure 17. F1 confidence curve YOLO8x

The F1 score on the YOLOv8 model reached its highest point of 1.00 with an optimal confidence value of 0.779 when detecting coral reef diseases as in Figure 17.

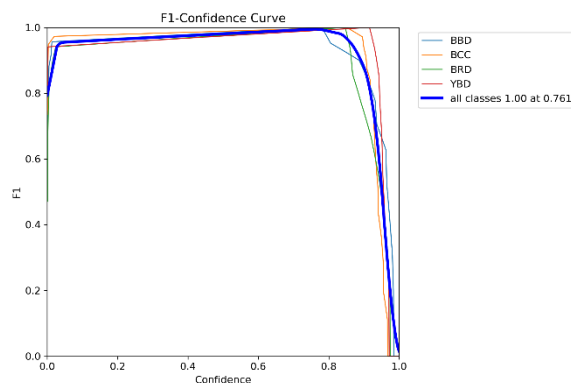


Figure 18. F1 confidence curve YOLO8m

The F1 score on the YOLOv8 model reached its highest point of 1.00 with an optimal confidence value of 0.761 when detecting coral reef diseases as in Figure 18.

In Table 6, the Mean Average Precision (MAP) values in the YOLO8l, YOLO8x, and YOLO8m models are detection evaluation values with a threshold value of 0.5.

Table 6. Precision - recall

No	Class	YOLO8l	YOLO8x	YOLO8m
1	BBD	0.92	0.918	0.933
2	BCC	0.876	0.883	0.863
3	BRD	0.692	0.721	0.699
4	YBD	0.886	0.857	0.869

Evaluation of the YOLO8l model for all classes of coral reef diseases with threshold values of 0.5 to 0.95 showed very good performance results, namely 99%, as in Figure 19.

Evaluation of the YOLO8x model for all classes of coral reef diseases with threshold values of 0.5 to 0.95 showed very good performance results, namely 99%, as in Figure 20.

Evaluation of the YOLO8m model for all classes of coral reef diseases with threshold values of 0.5 to 0.95 showed very good performance results, namely 99%, as

in Figure 21.

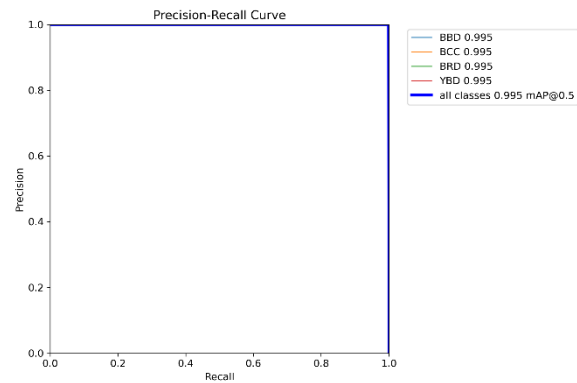


Figure 19. precision-recall curve YOLO8l

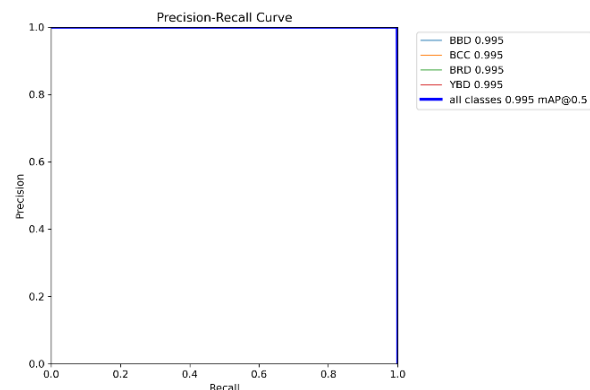


Figure 20. precision-recall curve YOLO8x

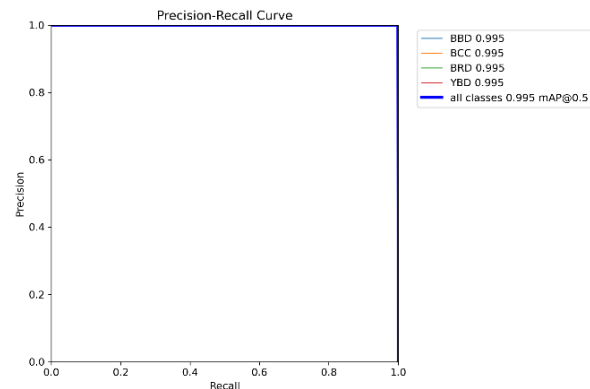


Figure 21. precision-recall curve YOLO8m

3.2 Discussions

The final result of the implementation of YOLOv8 deep learning on the coral reef disease detection experiment of the YOLOv8m, YOLOv8l, and YOLOv8x models obtained detection results with a high level of accuracy of 99% and a Mean average precision value of 0.995. The final results can be seen in Table 7. Based on table, it can be seen that the best YOLO model is YOLO8l.

Table 7. Testing Result

Model	MAP 50	MAP 50-95	Precision	Recall	Accuracy
YOLO8l	0.995	0.843	0.990	1.0	99%
YOLO8x	0.995	0.844	0.988	1.0	99%
YOLO8m	0.995	0.840	0.986	1.0	99%

One of the main obstacles in this study is the limited dataset of coral reef diseased images, especially those relevant to the condition of the waters in Batam. Limited data availability, varying image quality, and difficulty in obtaining accurate annotations from marine biota experts are challenges in building a representative dataset for optimal YOLOv8 model training.

Further research can be directed at developing a real-time monitoring system based on drones or ROV (Remotely Operated Vehicles) integrated with the YOLOv8 model, so that disease detection on coral reefs can be carried out directly in the field with high efficiency and wider area coverage.

4. Conclusions

The results of the study on the detection of coral reef diseases Black Band Disease (BBD), Bleaching Coral (BCC), Brown Band Disease (BRD), and Yellow Band Disease (YBD) using the YOLO8l, YOLO8x, and YOLO8m models, showed very good performance as seen from the precision, recall, F1, and mean Average Precision (MAP) values which were very accurate. The evaluation results of the YOLO8l, YOLO8x, and YOLO8m models with threshold values of 0.5 to 0.95 showed that the three models were able to detect coral reef diseases with an accuracy of 99%. As an original contribution, this study provides a new approach using the YOLOv8 model which is faster and more accurate than the Underwater Photo Transect (UPT) Method, in identifying symptoms of disease in coral reefs. YOLOv8 enables better detection at high speed even in difficult underwater conditions. This study offers an innovative and efficient approach to monitor marine ecosystems in Batam. The original contributions of this study include the development of a disease detection model that can be applied in coastal areas, dataset compilation, and the creation of an automated monitoring system that can help coral reef conservation and protection efforts more effectively and sustainably.

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