Advanced and Sustainable Technologies
ASET
E-ISSN 2976-2294

Volume 5, No 2, September 2026 [1-9]

Automatic Classification of Coral Reef Model based on Deep Learning Method for Underwater Images

Piyapat Promnukul[1], V. Vijayasarveswari[1,2]*, Yasmin Mohd Yacob[3] and Zainudin Bachok[4]

[1]Faculty of Electronic Engineering & Technology, Pauh Putra Campus, Universiti Malaysia Perlis (UniMAP), 02600 Arau, Perlis, Malaysia.
[2]Advanced Communication Engineering (ACE) Centre of Excellence, Universiti Malaysia Perlis, Kangar, Perlis, Malaysia.
[3]Centre of Excellence for Advanced Computing, Pauh Putra Campus, Universiti Malaysia Perlis (UniMAP), 02600 Arau, Perlis, Malaysia.
[4]Institute of Oceanography and Environment (INOS), Universiti Malaysia Terengganu, 21030 Kuala Nerus, Terengganu, Malaysia.

Received 3 January 2026, Revised 10 March 2026, Accepted 8 May 2026

ABSTRACT

Coral reefs play a vital role in maintaining the balance of marine life. However, coral reefs are facing threats due to human activities and environmental issues. Coral reefs' population is slowly decreasing day by day. It is crucial to monitor the health of coral reefs. Traditionally, researchers use manual monitoring to assess the health of coral reefs. This way is too time-consuming and not accurate. Therefore, an automatic coral reef monitoring model is proposed by using image classification and deep learning. Underwater images of coral reefs are collected from various locations. The datasets consist of 20830 images from seven different locations. The images are classified by using a deep learning method called YOLOv11. YOLOv11 consists of three main components, backbone, neck and head. Backbone extracts the features from the image using the C3k2 block. Neck combines all the extracted features. The head provides the final coral classification output and the model or class scores. Using YOLOv11, coral reef classification achieves an F1-score of up to 70%. YOLOv11 helps to detect and classify the coral reef automatically and faster compared to the manual method.

Keywords: Classification of coral reef, YOLOv11, Deep learning.

1. INTRODUCTION

Coral reef ecosystems are distributed across Peninsular Malaysia, Sabah and Sarawak. Coral reefs are among the most important underwater ecosystems because of their importance to tourists and the marine ecosystem. Despite their importance, coral reefs are threatened by climate change, coral bleaching, development, human activities, and pollution. Therefore, regular check-ups to maintain coral reef health are crucial. Coral reef classification is traditionally done manually. The researchers record videos underwater at the beach in Terengganu. The experts examine each image in the videos and manually identify the coral reef based on the structure, shape and texture [1]. Repeated observations of the images are needed to verify the presence of a coral reef. However, the time consumed by this manual method is very high. The possibility of experts identifying wrongly is very high. The coral reef may be underestimated or misinterpreted. This leads to inaccurate data, and the protection plan is targeted to the wrong coral species. Therefore, the automatic classification of coral reefs is crucial for more accurate detection in less

*Corresponding author: vijaya@unimap.edu.my

time. Recent advances show that machine learning and deep learning methods are promising tools for the automatic classification of coral reefs.

Multiple researchers have researched the automatic classification of coral reefs. Machine learning methods such as Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART) have been used for coral reef image classification [2-4]. RF is used for image classification for bleach detection and achieves up to 97% accuracy [2]. Similarly, RF outperforms SVM and CART to examine spatial and temporal changes in coral reefs [3]. On the other hand, a multilayer perceptron is used for coral reef image classification, achieving 73% accuracy [4]. Besides machine learning, deep learning is widely used for characterizing coral reefs. MobileNetV2, VGG16, and Residual Neural Network (ResNet) are used to identify healthy coral reefs. Here, ResNet obtains the highest accuracy [5]. Likewise, ResNet50 achieves high accuracy up to 90% [6]. However, CNN achieves the highest accuracy of 89% among other deep learning methods, ResNet, and Vision Transformer (ViT) in [7]. Similarly, a Convolutional Neural Network (CNN) was used to classify healthy and bleached coral, achieving an accuracy of 87.6% [8]. ResNet-152, EfficientNet-B0, and DenseNet-121 are used for image classification to classify healthy and bleached coral reefs. Here, EfficientNet achieves the highest accuracy of more than 80% [9]. Again, DenseNet-169 and VGG19 are used for coral reef classification, and both achieve approximately 80% accuracy [10]. The YOLO-based approach is one of the deep learning methods widely used for coral reef classification. YOLOv5, YOLOv8, YOLOv9, YOLOv10, and YOLOv11 have achieved high accuracy and a high mean average precision (mAP) for coral reef classification compared to other deep learning models. Most models achieve an accuracy of more than 80% [11-17]. These models are very effective to accurately detecting underwater images.

Based on the previous researcher, YOLO is a promising candidate for better accuracy and speed. Therefore, the YOLOv11 model will be used for automatic coral reef classification. In this research, underwater videos were obtained from the Institute of Oceanography and Environment (INOS) at Universiti Malaysia Terengganu (UMT). These images are used to train the YOLOv11 for detection. Roboflow is a platform used for data preprocessing and model training.

2. MATERIAL AND METHODS

In this section, the classification of coral reefs using a deep learning method by using the obtained coral images is explained. Figure 1 shows the flowchart of the overall experimental process for this research. The process starts with the data collection of coral reef videos from the beach. Coral reef images are extracted from videos, and a data preprocessing method is used to clean the images prior to image processing. The images are fed into a deep learning model for classifying coral reefs based on the percentages of coral reef presence and absence in the images.

2.1 Data Collection

The coral reef videos were recorded around Terengganu, covering seven different locations. The videos are provided by INOS and UMT. 20830 images are extracted from the recorded videos. Based on the images, the experts manually identify their content in eight categories: coral, algae, other invests, dead coral, water, sand, salt and rock, unknown, and tape, wand shadow. There are 19 types of coral. These different types of coral images are fed into the model for detection. Table 1 shows the details of the images collected from the recorded videos.

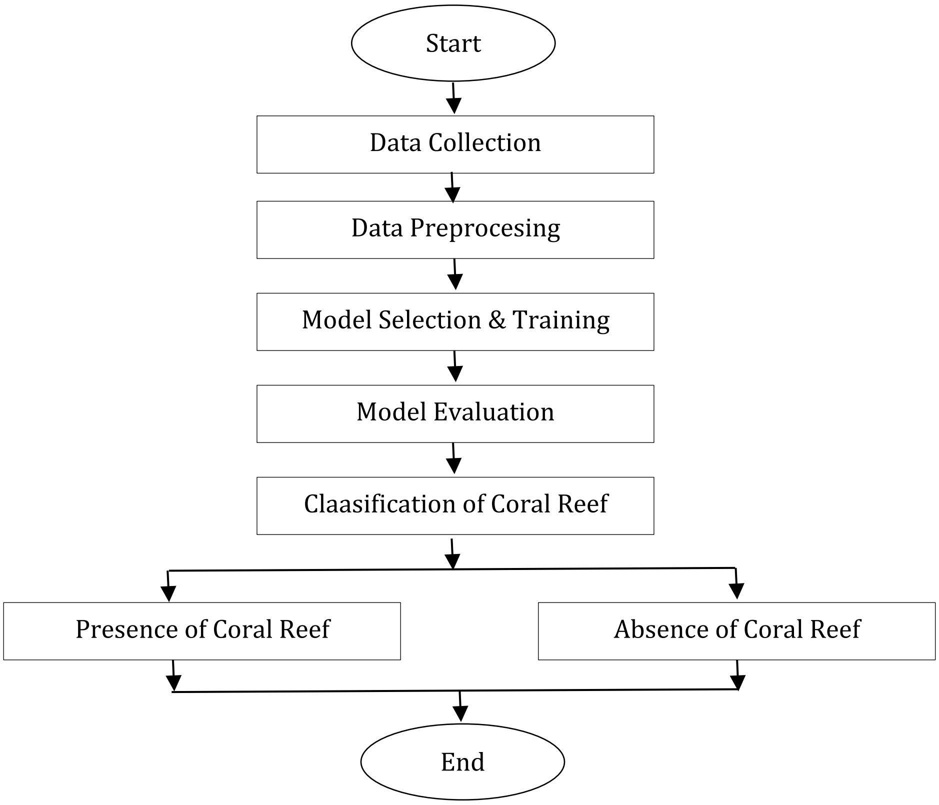


Figure 1: The overall work process.

Table 1: Data sample.

Covered Areas in Terengganu	Depth of Sea	Number of Extracted Images	Categories	Coral Types
Christmas Garden	Deep Shallow	20830	Coral Algae Other invests Dead coral Water Sand, salt and rock Unknown Tape, wand shadow	Acropora Astrea Astreopora Disploastrea Echinapora Favia Favites Fungia Galaxea Goniastrea Isopora Lobophyilia Montipora Pavona Platygyra Poclilopora Porites Stylophora Turbinaria
Dinding Laut,	Deep Mid			
Batu Menangis	Deep Mid Shallow			
Pantai Pasir Cina	Mid Shallow			
Pantai Pasir Tenggara	Shallow			
Pantai Vietnam	Shallow			
Teluk Air	Deep Mid Shallow			

2.2 Data Preprocessing

Before the images are classified, preprocessing methods are applied to the images to clean and display them correctly. In this research. Roboflow is used to prepare the data. The images are uploaded, and Roboflow labels the data using the bounding boxes. Roboflow cleans images by resizing, auto-orienting, adjusting brightness and contrast, cropping or tiling, and removing all empty and blurred images. The following shows the steps taken for data preprocessing.

1. Upload the images inside the RoboFlow.
2. Label the images and fix the bounding box.
3. Data Cleaning – All empty or blurred images are removed from the training set.
4. Resizing the Image - To standardize image size. The size is the default YOLO size, 640 x 640.
5. Auto-Orient Images - Rotate or flip the images to appear in an upright orientation.
6. Adjust brightness - Increase or decrease the light to make the picture clearer.
7. Contrast of Images - Adjust the images to the object appears clearer than the background.
8. Crop or Tile Images - Cropping the large or crowded picture to remove the irrelevant background. Split the large images into smaller tiles to detect the small objects.
9. The dataset is prepared for the model training.

2.3 Model Selection & Training

You Only Look Once (YOLO) is a deep learning algorithm commonly used for classification and detection across various applications. YOLO is better compared to CNN. YOLO predicts the class in a single pass, whereas CNNs usually look at the image multiple times to predict the class. The evolution of YOLO, as shown in Figure 2, from YOLOv1 to YOLOv11.

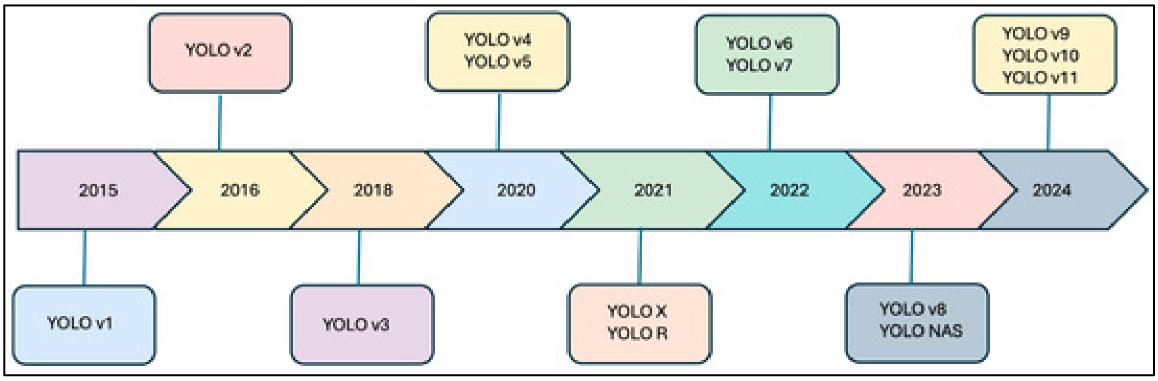


Figure 2: YOLO model evolution [18].

YOLOv11 is the enhanced version of YOLOv8 for better speed and accuracy. YOLOv11 has three main components: backbone, neck, and head, as shown in Figure 3.

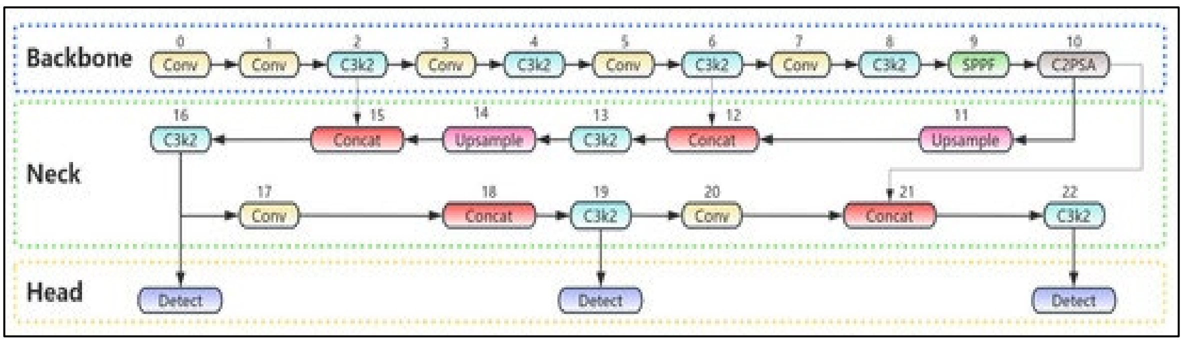


Figure 3: YOLOv11 Model Architecture [19].

Figure 4 shows how the YOLOv11 detection model is used in this research. Backbone is a primary feature extractor that transforms raw data samples into multi-scale feature maps. Neck is a feature fusion module. The neck has specialized layers to improve the feature representations. Head is a prediction mechanism to generate the output from the given data [19-20].

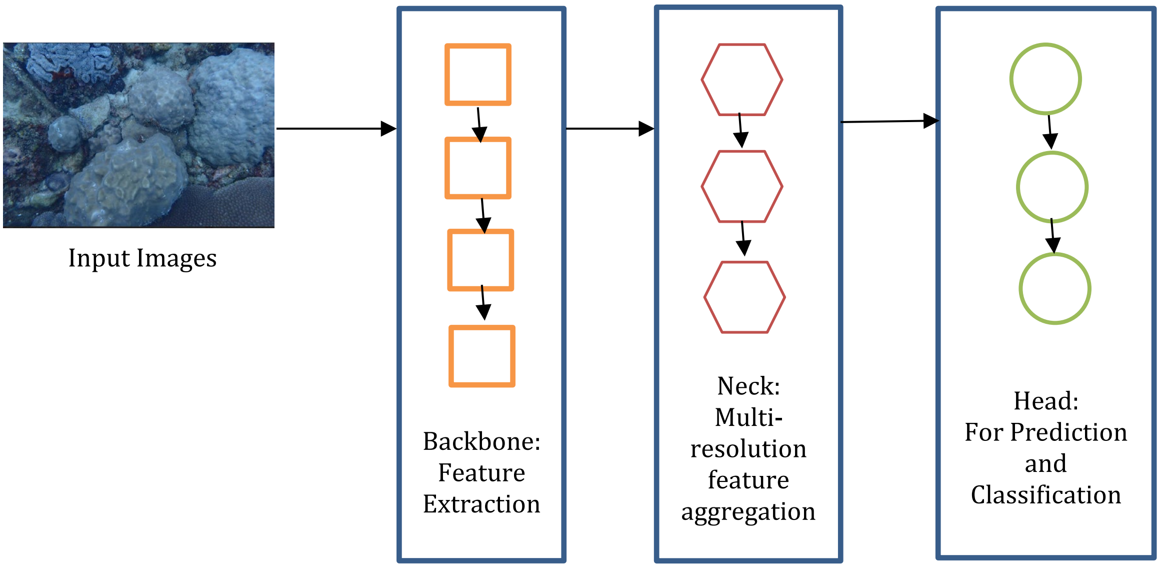


Figure 4: YOLOv11 Detection Model.

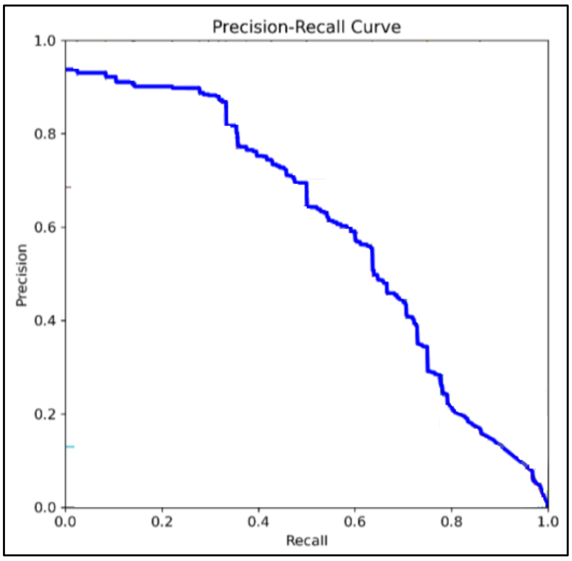
2.4 Model Evaluation

The performance of YOLOv11 for coral reef classification is evaluated. The dataset is equally divided using Roboflow into three sets for training, validation and testing of the model. The evaluation of the model is measured by using validation/testing sets. The evaluation metrics considered are recall, F1-score, and mean average precision (mAP). The model's output is a detection of the average of different coral types, indicating whether coral is present or absent in the image.

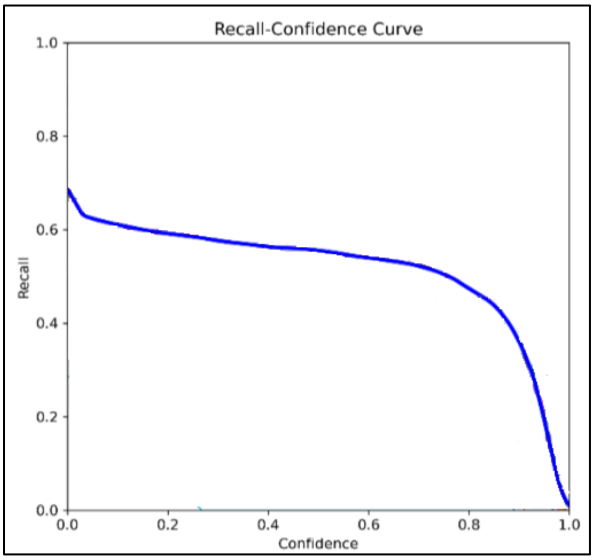
3. RESULTS AND DISCUSSION

In this section, the results that are obtained are discussed. Figure 5 shows the performance of the model to classify the coral reef. This result is the average classification across all coral types, as shown in Table 1. For the YOLOv11 model, the mean average precision (mAP) achieves approximately 0.60 at mAP@0.5. F1 scores up to 0.70 for this model, whereas recall scores up to 0.70. Based on these results, the overall detection performance is moderate. Almost 30% of objects are misclassified. The F1 score shows the model is precise but not sensitive enough to images.

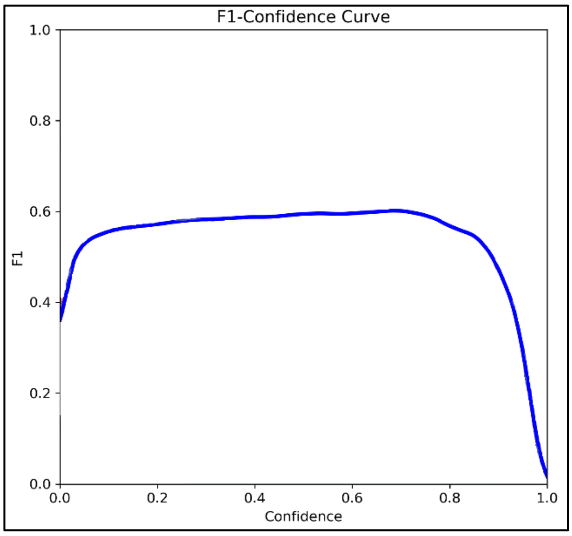
Based on the output images, the precision of the detection of each coral is indicated in the image. Figure 6 (a) shows examples of correctly detected coral in the YOLOv11 model. Here, Galaxea is detected with an accuracy of up to 85%, and Astrepora is detected with 89% accuracy. Figure 6(b) shows that the model detects Acropora at 59% (moderate detection). Figure 6(c) shows the low detection rate for this model, Isopora, at only 29%. Low detection is due to confusion with other coral reef species ot misclassified as background.



(a) Precision-Recall Curve



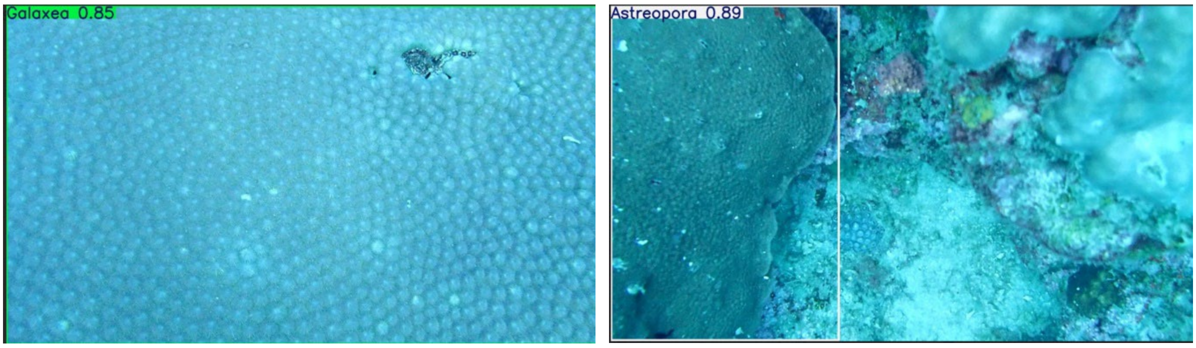
(b) Recall-Confidence Curve



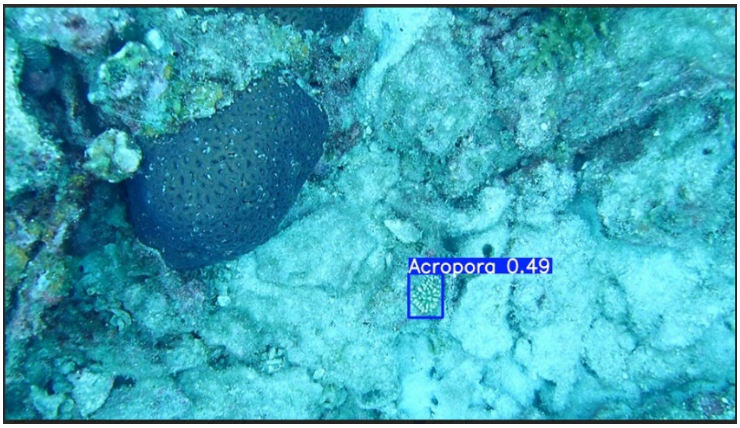
(c): F1 Confidence Curve

Figure 5: YOLOv11 Model Performance.

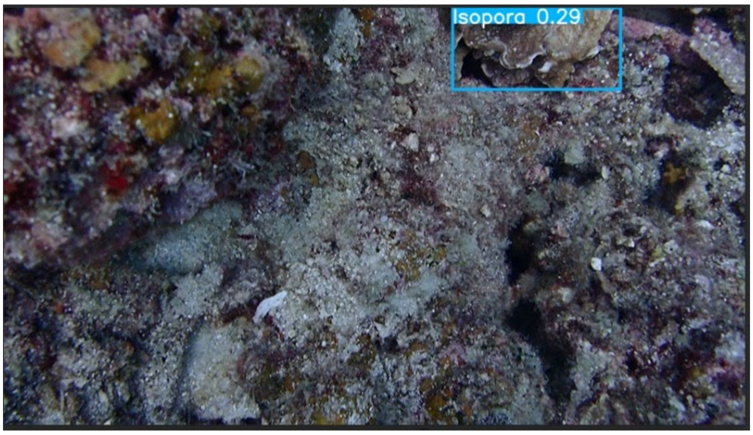
The performance obtained is moderate recall and mAP values. This suggests some coral reefs are misidentified. This result is due to an imbalanced dataset or a low number of data points for a certain coral category. Some coral reef datasets are small, and the model does not have enough training data for that particular coral reef category. Therefore, this led to low recall and MAP values. At the same time, there is some confusion about whether the coral reefs look similar. Despite this result, Fi reflects that the model detection is good and reasonable. Therefore, this model maintains a strong ability to detect coral reefs. As mentioned in [1], coral reef detection has previously been done manually. An expert will examine and observe the structure, texture and shape to identify the coral reef type. This is time-consuming and requires an expert to observe manually. YOLOv11 can classify the coral reefs automatically faster compared to the traditional way. The results indicate reliable prediction, but still need some improvement to improve recall and mAP.



(a) Excellent Model Prediction.



(b) Moderate Model Prediction.



(c) Low Model Prediction.

Figure 6: Detection of Coral by YOLOv11.

4. CONCLUSION

This research proposes an automatic coral reef classification based on a deep learning method. The YOLOv11 model is used to classify the coral reefs. The performance of this model is moderate, and it is a balanced detection model, with F1 scores up to 70%. The result indicates this model is capable of detecting the coral reefs in real time faster compared to the manual way. The mAP and recall achieve moderate values, indicating that some coral reefs are misinterpreted, particularly in low-quality images. Therefore, in the future, some image enhancements should be applied before feeding the images into YOLOv11 for better detection. Overall, the model's performance is suitable for automatic coral reef classification.

ACKNOWLEDGEMENTS

This work is supported and funded by the Ministry of Higher Education, Malaysia, FRGS-EC/1/2024/WAS05/UNIMAP/02/2. The dataset is provided by the Institute of Oceanography and Environment (INOS), Universiti Malaysia Terengganu 21030 Kuala Nerus, Terengganu, Malaysia.

REFERENCES

[1] Razak, F., Lua, W. Y., Abd Rasid, N. H., Aziz, N., Repin, I. M., Xue, X. Z., Safuan, C. D. M. Adopting Marine Spatial Planning (MSP) using coral health assessment as indicator: A case study in Pulau Redang Marine Park, Malaysia. Ocean & Coastal Management, vol 248 (2024) pp.106943. https://doi.org/10.1016/j.ocecoaman.2023.106943

[2] Narciso, G. A. M., Tamondong, A. M., Blanco, A. C., Nakamura, T., Nadaoka, K. Supervised image classification model for coral bleaching detection using a bi-temporal Sentinel-2 image stack. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, vol 48 (2024) pp.395-401. https://doi.org/10.5194/isprs-archives-XLVIII-4-W8-2023-395-2024

[3] Manessa, M. D. M., Ummam, M. A. F., Efriana, A. F., Semedi, J. M., Ayu, F. Assessing Derawan Island's coral reefs over two decades: A machine learning classification perspective. Sensors, vol 24, issue 2 (2024) pp.466. https://doi.org/10.3390/s24020466

[4] Fauzan, A. C., Sari, H. E. Coral reef image classification using Multilayer Perceptron. MATICS: Jurnal Ilmu Komputer dan Teknologi Informasi (Journal of Computer Science and Information Technology), vol 17, issue 2 (2025) pp.76-81. https://doi.org/10.18860/mat.v17i2.32134

[5] Menaga, D., Deborah, S. L., Makizhna, M. Deep learning models for coral reef health classification: MobileNetV2, VGG16 and ResNet. International Conference on Sustainability Innovation in Computing and Engineering (ICSICE 2024) (2025) pp.1241-1251. https://doi.org/10.2991/978-94-6463-718-2_103

[6] Anwarul, S., Tanwar, R. CoralClassify: Advancing coral health monitoring using deep learning. Procedia Computer Science, vol 259 (2025) pp.88-97. https://doi.org/10.1016/j.procs.2025.03.310

[7] Macrohon, J. J. E., Hung, G. Deep learning models for coral bleaching classification in multi-condition underwater image datasets. arXiv preprint (2025).

[8] Shao, X., Chen, H., Magson, K., Wang, J., Song, J., Chen, J., Sasaki, J. Deep learning for multilabel classification of coral reef conditions in the Indo-Pacific using underwater photo transect method. Aquatic Conservation: Marine and Freshwater Ecosystems, vol 34, issue 9 (2024) pp.e4241. https://doi.org/10.1002/aqc.4241

[9] Ogidi, M. S., Sah, M. Binary classification of coral reefs using deep learning for enhanced monitoring. 2025 9th International Symposium on Innovative Approaches in Smart Technologies (ISAS) (2025) pp.1-7. https://doi.org/10.1109/ISAS66241.2025.11101789

[10] Greeshma, P. M., Pallavi, K. G., BanuShree, T., Pranitha, T. M., Vinodh Kumar, S. Exploring machine learning models for coral reef classification from images. Journal of Emerging Technologies and Innovative Research (JETIR), vol 11, issue 5 (2024) pp.1-7.

[11] Alshahrani, A., Ali, H., Saif, E., Alsayed, M., Alshareef, F. Classification of coral reef species using computer vision and deep learning techniques. Engineering, Technology & Applied Science Research, vol 14, issue 5 (2024) pp.16478-16485. https://doi.org/10.48084/etasr.8044

[12] Ouassine, Y., Conruyt, N., Kayal, M., Martin, P. A., Bigot, L., Regine, V. L., Zahir, J. Deep learning for automated coral reef monitoring a novel system based on YOLOv8 detection and DeepSORT tracking. Ecological Informatics, vol 89 (2025) pp.103170. https://doi.org/10.1016/j.ecoinf.2025.103170

[13] Younes, O., Jihad, Z., Noël, C., Mohsen, K., Philippe, A. M., Eric, C., Regine, V. L. Automatic coral detection with YOLO: A deep learning approach for efficient and accurate coral reef monitoring. European Conference on Artificial Intelligence (2023) pp.170-177. https://doi.org/10.1007/978-3-031-50485-3_16

[14] Lu, Z., Liao, L., Xie, X., Yuan, H. SCoralDet: Efficient real-time underwater soft coral detection with YOLO. Ecological Informatics, vol 85 (2025) pp.102937. https://doi.org/10.1016/j.ecoinf.2024.102937

[15] Hung, G., Rodriguez, I. F. A comparative study of YOLOv8 to YOLOv11 performance in underwater vision tasks. arXiv preprint (2025).

[16] Wu, Y., Jiang, T., Xi, Z., Yin, F., Wang, X. YOLO-AR: An improved artificial reef segmentation algorithm based on YOLOv11. Sensors, vol 25, issue 17 (2025) pp.5426. https://doi.org/10.3390/s25175426

[17] Tao, J., Tian, H., Huang, S., Ye, Y., Xiong, Y., Huang, S., Wu, J. Coral-YOLO: An intelligent optical vision sensing framework for high-fidelity marine habitat monitoring and forecasting. Sensors (Basel, Switzerland), vol 25, issue 23 (2025) pp.7284. https://doi.org/10.3390/s25237284

[18] Ali, M. L., Zhang, Z. The YOLO framework: A comprehensive review of evolution, applications, and benchmarks in object detection. Computers, vol 13, issue 12 (2024) pp.336. https://doi.org/10.3390/computers13120336

[19] He, L., Zhou, Y., Liu, L., Ma, J. Research and application of YOLOv11-based object segmentation in intelligent recognition at construction sites. Buildings, vol 14, issue 12 (2024) pp.3777. https://doi.org/10.3390/buildings14123777

[20] Khanam, R., Hussain, M. YOLOv11: An overview of the key architectural enhancements. arXiv preprint (2024).

Conflict of interest statement: The authors declare no conflict of interest. This research is funded by the Ministry of Higher Education, Malaysia, FRGS-EC/1/2024/WAS05/UNIMAP/02/2 and no role in the design of the study; in the collection, analyses or interpretation of data; in the writing of the manuscript; or in the decision to publish the results must be declared in this section.

Author contributions statement: Conceptualization: Piyapat Promnukul, V.Vijayasarveswari, Yasmin Mohd Yacob; Methodology, V.Vijayasarveswari, Yasmin Mohd Yacob; Software, Piyapat Promnukul; Resources, Zainudin Bachok; Investigation, Piyapat Promnukul; Writing & Editing, V.Vijayasarveswari; Supervision, Yasmin Mohd Yacob;

Data Availability Statement: The data that support the findings of this study are available from the corresponding author upon reasonable request.