

UNIVERSITI TEKNOLOGI MARA

**AUTOMATED UNDERWATER
VISION SYSTEM FOR DETECTION
AND CLASSIFICATION OF MARINE
LIFE USING CNN YOLO-BASED
MODEL**

MOHAMED SYAZWAN ASYRAF BIN ROSLI

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ABSTRACT

The exploration of underwater ecosystems requires thorough observation and investigation for different marine habitats leads to the usage of an underwater vision system. This method is superior as a non-destructive approach for video monitoring technique that takes advantage from the advancement of camera vision technology. However, manual processing of real-time or recorded video is a time-consuming, laborious, and highly possible for fatigue errors during analysis. This is due to the water murkiness and low-light projection that yield low visibility, hence limits the ability to precisely explore the underwater environments. Driven by these challenges, there is a need for an automated real-time method that can replace the manual analyzing process and be able to work under constraints environments. Recently, the integration of computer vision and machine learning has given solutions to improve the underwater detection system by using intelligent classifier algorithm in real-time computer vision to detect underwater animals with challenging environments. Therefore, this study is proposed to develop an automated underwater object detection model based on Deep Convolutional Neural Network (DCNN) by using You Only Look Once (YOLO). In this research, several single-stage detectors of YOLO models namely as YOLOv3, YOLOv4, YOLOv5 including their subset models were evaluated for benchmarking and comparison purpose. All models were trained and tested using three open-source datasets for assessing the models' performances based on quantitative metrics and image processing speed. Hence, the proposed YOLO model is further improved based on the model optimization using a challenging The Brackish Dataset. The Adaptive Moment Estimation (Adam) optimizer and Learning Rate on Plateau are employed to optimize the model's training regime. Significantly, the comparison results show that YOLOv5s outperformed others in terms of mean average precision (mAP) up to 97.7% and inference speed of up to 125 Frame Per Second (FPS). Meanwhile, the Adam optimizer with a detailed learning rate and momentum fine-tuning provides sufficient convergence rate and assisting YOLOv5s achieve better performance of mAP which is 0.6% higher than SGD implementation and 13.72% better than original author for The Brackish Dataset implementation. As a conclusion, the proposed YOLO model is successfully improved with high precision performance for detecting underwater object in a challenging underwater environment. Thus, the model also provides sufficient image processing and speed capability at real-time which will help marine biologists in elevating underwater research for analyzing underwater video with minimal human intervention.

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