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Enhancement of Murky Underwater Images for Optimum Object Detection

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ABSTRACT

Underwater object detection has been a continuous challenge due to its unpredictable murkiness. Murkiness of water are caused by the scattering of lights, weather condition as well as the growth of algae. Loss in visibility due to murkiness made it harder to do object detection underwater. This research project aims to enhance object detection in murky underwater images through image enhancement techniques. The project consists of three main stages: collecting and categorizing a dataset of murky underwater images, applying image enhancement methods, and implementing the You Only Look Once version 5s (YOLOv5s) object detection algorithm for accuracy comparison. The dataset includes separate sets of clear and murky images for training, validation, and testing. Image enhancement techniques, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), grayscale, and colour correction, were utilized to improve the clarity of the murky images. Evaluation was conducted using the Peak Signal-to-Noise Ratio (PSNR) metric. The results show that the CLAHE and grayscale technique improved object detection accuracy by 10% compared to the original images. These findings have significant implications for search and rescue operations and marine conservation efforts.

1. Introduction
1.1 Research Background

Underwater object detection (UOD) is a rapidly evolving field with significant importance in various domains. However, underwater visibility is greatly affected by light penetration from the sun, growth of algae and phytoplankton as well as movement of particulates underwater according to Zhang *et al.,* [1]. Thus, also means underwater visibility varies differently according to different weather conditions which leads to image hazing. According to Akila and Varatharajan [2], image

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hazing are images underwater that got distorted due to scattering of lights that results in low contrast.

The challenges posed by limited visibility and colour distortion in underwater environments have attracted extensive research efforts to overcome these limitations. Improved UOD has implications in oceanic engineering, navy engineering, search and rescue operations, and marine conservation, aligning with Sustainable Development Goals related to marine life protection and climate action. By addressing the challenges of underwater visibility and image hazing, advancements in UOD contribute to the development of sustainable technologies and infrastructure.

The exploration of the ocean depths remains challenging for humans, making it an area of great interest for scientists and Artificial Intelligence (AI) experts. UOD can be approached using both machine learning (ML) and deep learning (DL) methods. DL models outperform traditional ML algorithms in terms of inferencing speed while requiring a longer training period. However, large datasets are required for DL to have optimal accuracy during training [3]. UOD overcomes limitation on underwater search and rescue that uses traditional methods which leads to having tangled lines with its surrounding and the possibility of overlapping in search when swapping divers according to Doornekekamp [4]. Other than that, according to Long [5] turtle conservations effort that was being done in Perhentian Island, Malaysia uses traditional monitoring through patrols near nesting areas by volunteers via land or on boat. Improved accessibility to underwater environments enables more effective marine life conservation efforts.

Currently, work has been done on UOD development but with not much implementation of image enhancement and object detection together. This work aims to collect and categorize murky underwater images, apply statistical image enhancement methods, and compare the accuracy of object detection algorithms on treated and untreated images. By addressing these objectives, the study seeks to demonstrate the effectiveness of combining image enhancement and object detection and provide real-time solutions for practical underwater challenges.

1.2 Literature Review
1.2.1 Object detection under hazy condition

Hazy environment has similar characteristics with those of murky condition underwater. Images outdoor with bad weather usually has lower contrast and visibility due to dispersion of light. Thus, different studies and methods were tested to dehaze the images. Efforts in UOD are corelated and dependent with object detection under hazy environment. Dissecting different studies for object detection under hazy environment will assist and clarify more understanding for UOD and vice versa.

Some of the popular object detection algorithm is the use of deep layers of Convolutional Neural Network (CNN) with transfer learning to handle insufficient datasets using ImageNet by Arif *et al.,* [6]. Another example of image dehazing by Guo *et al.,* [7] that used transfer learning is AlexNet. With the objective to tackle the lack of datasets and low efficiency, AlexNet normalized the image and pre-processed them before transferring it to haze image binary classification and retaining it to become AlexNet.

Besides those methods, another well received method used are pre-processing hazy images by dehazing. A novel dark channel prior (DCP) was used as a dehazing method. This help increase the visibility of the image and the colour contrast of the image with haze. Not only that by removing the haze, more information can be extracted from the scene that is beneficial for feature extraction. However, according to Kaiming He *et al.,* [8] one downside for this method is that it cannot recognize when the surrounding has similar atmospheric light with no shadow cast.

1.2.2 Underwater object detection under murky condition

It was known that underwater images tend to have haze-like effects that causes the image to appear murky. In addition to that, underwater also tend to have colour casts that causes the image to appear to be more yellow or blue. From these, Fu [9] collected new datasets called RUOD which were separated into 4 categories according to different conditions and challenges faced under water. Those categories include haze-like underwater images, colour casts, light interference, and complex marine objects. Fu proposed that RUOD were to be tested on 19 different algorithms which consists of anchor-based that has one stage methods and anchor-free methods.

Another UOD method that was developed to detect and recognize different species underwater by Knausgard *et al.,* [10] utilized YOLOv3 which is a CNN-based method that is accurate, efficient, and suitable for real-time application. To overcome the restricted amount of data, transfer learning is also applied to the dataset called ImageNet. Images used are of varieties of visibility condition to correspond better with real-life surroundings. To get large training data without doing it from scratch while also preventing overfitting, transfer learning can be utilized on ImageNet by Sun *et al.,* [11]. This solution can also be applied for small data samples related to work by Jin and Liang [12].

Other prominent research was done involving the state-of-the art method You Only Look Once (YOLO). Among them, is the work concluded by Pedersen *et al.,* [13] which uses and compares object detection algorithms of fine-tuned YOLOv2 and YOLOv3 used for marine monitoring via the integration with automated underwater vehicles. The latest YOLO series that was integrated with UOD is the YOLOv5. It is a one stage object detection combining adaptive box optimization and mosaic data augmentation using Underwater Robot Professional Contest (URPC) dataset by Wang *et al.,* [14].

Besides those, Convolutional Neural Network (CNN) is regarded as a cutting-edge approach to object detection despite it being known to be computationally intensive. Gomes and Saifuddin Saif's [15] work an enhanced CNN by Oxford's Visual Geometry Group (VGG) called VGGNet. This approach has hybrid feature where feature extractions based on Spatial Pyramid Pooling which uses less resources but is reliable and precise. On the other hand, Zhang [16] proposed image enhancement methods to be integrated together with Single Select Detection Model. However, there is no clear statistical relationship between object detection accuracy and different image quality.

1.2.3 Image enhancement methods

Image enhancements are proven to have assisted in extensive UOD. The distortion in colour of underwater images made it a necessary step before an object detection algorithm is applied. One example is Contrast Limited Adaptive Histogram Equalization (CLAHE). According to Prakash *et al.,* [17] the image is divided into numerous discrete, non-overlapping portions via the CLAHE algorithm. The next step is to compute a histogram for each region, which is then clipped to a limit required for contrast expansion and, for higher quality, converted into Rayleigh's pixel distribution.

Another example is colour balancing. A work by Ancuti *et al.,* [18] utilizes the use of white balancing to improve the image's aspect by removing any undesirable colour castings caused by different illumination or medium attenuation properties. Underwater white balance aims at improving image aspects by removing the colour casting due to illumination and attenuation.

Hybrid image enhancement method Lim and Lau [19] used image dehazing, colour balance and histogram equalization. It utilized DCP as part of their 3 processes in image enhancement by estimating the transition map (depth map) using the dark channel, i.e., to get the minimum value for each R, G and B from the image. It gave better clarity and quality for the images underwater.

1.3 Research Gap

There are many research and advancement that is being done in UOD. However, one notable challenge is the limited dataset in certain environment. This project will further dissect and emphasize on datasets with murky water characteristics. It could come from the haze-like feature of the water, the colour casts that made the water to appear blueish, greenish, and yellowish as well as images affected by light illumination.

In addition to that, not much combination of image enhancement and object detection deep learning algorithms has been done. Most of the object detection methods are known to either be computationally expensive or took longer time to produce satisfactory results. This research will further elaborate on choosing better combinations of image enhancement and object detection methods that can cater to real-time application that can be integrated together with Autonomous Underwater Vehicle.

2. Methodology

2.1 Image Enhancement

This project focuses on enhancing the quality of original murky images through image processing techniques. The original images from Underwater Image Enhancement Benchmark (UEIB) dataset by Li *et al.,* [20] are used as Set A and then are divided into two sets: Set B and Set C. Set B undergoes Contrast Limited Adaptive Histogram Equalization (CLAHE) and is converted to grayscale. Set C, on the other hand, undergoes CLAHE and colour correction to enhance the green colour. These preprocessing steps aim to improve the clarity of objects in the images, particularly for object detection purposes. CLAHE involves adjusting parameters such as Tile Grid Size and Clip Limit to address noise amplification and enhance contrast. Common Tile Grid Sizes are (8,8) and (16,16), while Clip Limit values range from 0.01 to 4.0. This project used Tile Grid Size of (8,8) and Clip Limit of 2,2.5 and 3. The different sets are illustrated in Figure 1.

Fig. 1. Set A (Top), Set B (Middle) and Set C (Bottom) Images

2.2 Object Detection

After image enhancement, the different sets were labelled and annotated using Roboflow before proceeding to object detection. YOLOv5s is selected due to its suitability for smaller datasets and quick processing for object detection. The paper outlines the versatility of YOLOv5 in terms of exporting formats and highlights the use of TensorBoard for logging and visual model inspection. TensorBoard aids in monitoring training progress by displaying statistical results, training loss graphs, precision, recall, and mean Average Precision (mAP) for each image. The experimental environment of choice is Google Colab, a cloud based Jupyter notebook, with essential libraries such as matplotlib, CV2, numpy, requests, and random.

2.3 Evaluation

The evaluation is performed using mean average precision (mAP) as a metric. The intersection over union (IoU) is employed to calculate the overlap between the ground truth bounding box and the proposed method. True Positive (TP) and False Positive (FP) instances are identified based on the IoU threshold, allowing for the calculation of precision and recall. A precision-recall graph is generated, and the area under the curve is computed using 11-point interpolation to determine the average precision (AP). The mean average precision is obtained by summing the AP values for each class and dividing by the total number of classes.

Additionally, PSNR is used as a measure of image enhancement effectiveness according to Islam *et al.,* [21]. PSNR compares pixel values and quantifies the difference between the original and enhanced images, where a higher PSNR value indicates reduced distortion and noise. The calculation involves converting images to a floating-point representation, computing the mean squared error (MSE), and then applying the PSNR formula using the maximum possible pixel value (MAX) and the MSE. Equation used to find PSNR is shown in Eq. (1). Overall, the methodology can be illustrated as Figure 2.

$$\mathrm{PSNR} = 20\log_{10}(\mathrm{MAX}) - 10\log_{10}(\mathrm{MSE}) \tag{1}$$

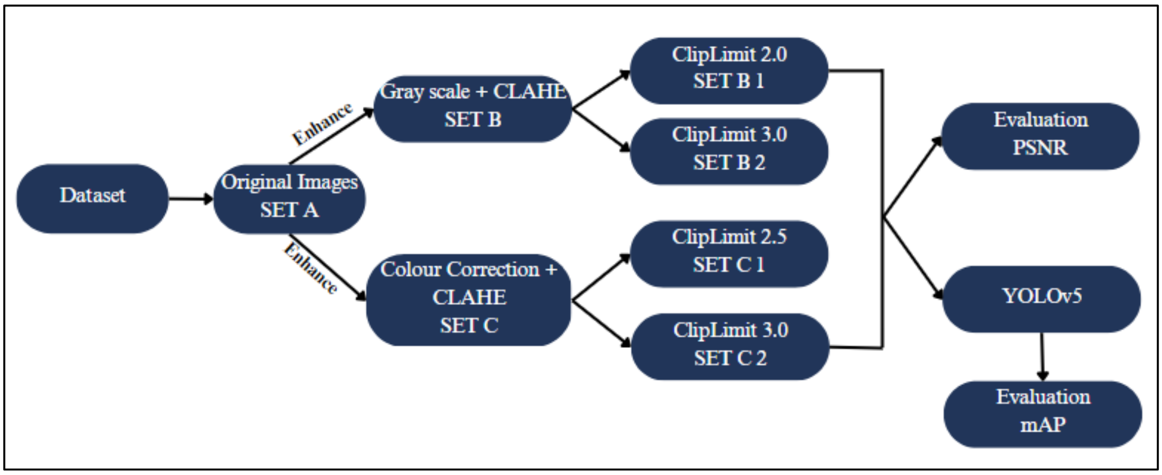

Fig. 2. Flowchart of Methodology

3. Results

3.1 Image Enhancement

PSNR values are calculated for each variation, and it is found that Set B 1, with the lower Clip Limit, achieves higher PSNR, indicating a closer resemblance to the original images. Similarly, for Set C, which has different Clip Limits of 2.5 and 3.0, Set C 1 exhibits higher PSNR compared to Set C 2. The PSNR results is illustrated in **Error! Reference source not found.**. These results suggest that even with higher contrast, images may not necessarily appear closer to their originals.

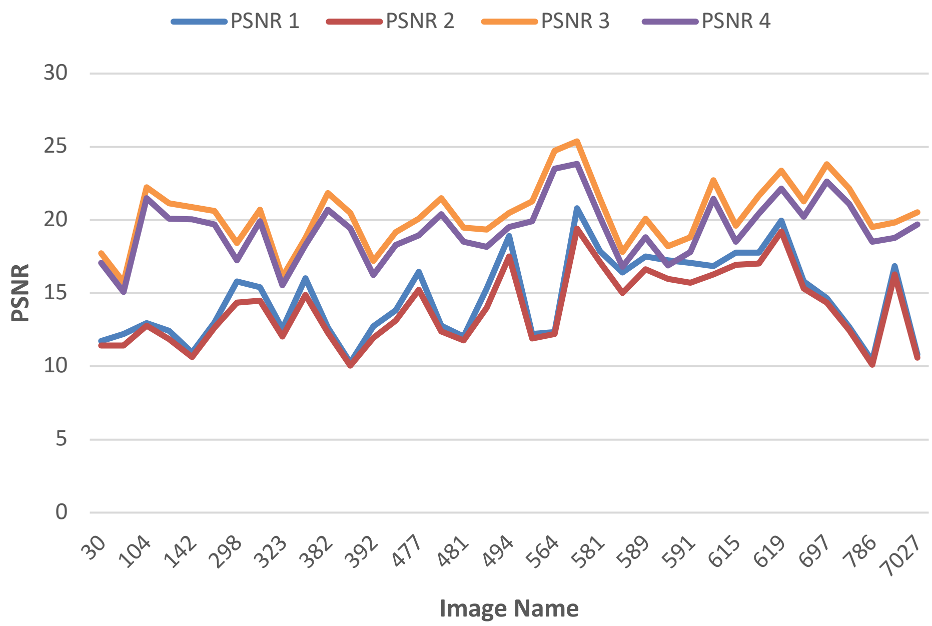

Fig. 3. PSNR for All Sets

3.2 Object Detection

The object detection process involves using the YOLOv5s algorithm on each set, with consistent parameters and 70 epochs for training. Tensorboard is employed to monitor the training progress, showing an increasing trend in precision and recall values, and decreasing object and classification losses for all sets. The effectiveness of the image enhancement methods is evaluated by correlating PSNR values with mean Average Precision (mAP) at an IoU threshold of 0.5. Both Set B and Set C show higher mAP compared to Set A, indicating improved object detection. Set B 1 and Set C 1, with higher PSNR values, achieve better mAP compared to their respective variations (Set B 2 and Set C 2). The mAP of each set can be seen in Table 1.

Table 1
Compilation of Evaluation Metrics for All Sets

Set	No.	Precision	Recall	mAP@0.5
A		0.919	0.623	0.677
B	1	0.838	0.682	0.774
	2	0.716	0.719	0.691
C	1	0.831	0.626	0.697
	2	0.816	0.6	0.686

However, when comparing Set B and Set C, Set B outperforms Set C in terms of mAP, despite having lower PSNR values. The analysis also reveals that Set B 1 is the most effective in enhancing object detection, with 10% improvement in capacity. Overall, the study concludes that CLAHE with grayscale conversion and a Clip Limit of 2.0 is the superior image enhancement method for object detection in murky underwater images.

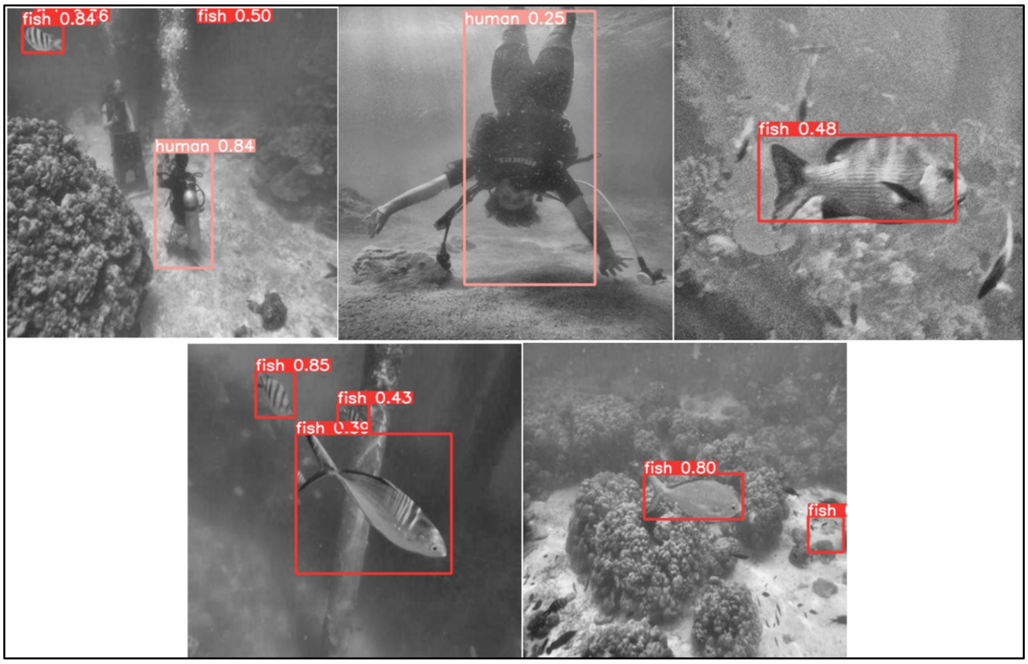

Fig. 4. Tested Images by YOLOv5 for Set B 1

4. Conclusions

This ongoing research project focuses on improving object detection in murky underwater images through image enhancement techniques. Firstly, a dataset of murky underwater images was collected and categorized. Secondly, image enhancement methods such as CLAHE, grayscale, and colour correction were applied to enhance the clarity of the murky images. Lastly, the YOLOv5s object detection algorithm was implemented on both the original and enhanced images to compare their accuracy, and the results were correlated with the PSNR values.

The findings of this research indicate that the CLAHE and grayscale technique improved the accuracy of object detection on murky underwater images by 10% compared to the original images. This contribution is valuable for search and rescue operations and marine conservation efforts. The combination of the YOLOv5s algorithm and image enhancement techniques shows promise for real-life application.

However, the project also has some limitations, such as the limited variety and quantity of the dataset and the relatively low level of murkiness in the images. To further enhance the efficiency of this method, future work could involve expanding the dataset with more diverse classes and variations in murkiness levels. Additionally, employing machine learning techniques for object detection would provide further insight into the effectiveness of image enhancement techniques in underwater object detection.

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