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# Contrast Enhanced Object Recognition (CLAHE_YOLOv3) Technique for Clear and Medium Level Turbidity Lake Underwater Images

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**Abstract**: This study discusses object recognition based on the underwater image that has to cope with physical particles, especially in lake underwater environments, making it difficult to achieve high-quality underwater images. In this study, we have developed a controlled condition image database specifically for lake underwater images in different turbidity levels. The developed database can be accessed at the following link: https://bit.ly/3thcM2w. It is based on 5 different object classes, which are Fish, Aeroplane, Helicopter, Luggage and Submarine. Each set of objects contains 1152 images. The test images are selected from 2 categories of water conditions, which are the clear water and medium turbidity water classes. The object recognition technique of the YOLO version 3, YOLOv3, is used as an algorithm to recognize the object. The proposed method introduced in this study is the combination of the image enhancement technique, the CLAHE and object recognition of YOLOv3, CLAHE_YOLOv3. The proposed method has improved the average accuracy of object detection by using the YOLOv3 alone by 11.83% for both clear and medium turbidity conditions of lake underwater images.

**Keywords**: Image Processing, CLAHE, Contrast Enhancement, Database, Lake, Object Recognition, Turbidity, Underwater, YOLO

## 1. Introduction

Underwater image has received a lot of interest in both image processing and underwater vision over the last few years [1]. These images can be divided into three categories: lakes, seas, and ponds. Underwater images taken at a lake are the most difficult of the three groups because physical particles

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in underwater environments make it difficult to achieve high-quality underwater images. Deep neural networks have recently emerged as the leading method for high-quality computer vision, including object recognition and object detection [2]. Specifically, object recognition is a part of computational technology in computer vision and image processing that detects instances of semantic objects of a certain class (such as people, houses, or cars) in visual images [3]. An underwater robot is one of the applications that need an object detection system to analyze the image more clearly before classifying the object [4]. Object recognition gets considerably more difficult if the particles in the water are cloudy and it will dim the environment's illumination. [5]. Therefore, an object recognition technology that can recognize objects in turbidity existence is needed.

The Faster R-CNN algorithm [6]-[7] is proposed for underwater object recognition. The regional proposal region is the fundamental building component for the Faster R-CNN, which may reduce detection test time and increase detection accuracy when the dataset is trained. The experimental data is made up using the control condition idea, which is to fill up the tank with water and capture a picture from the tank with varied parameter conditions. According to the results of this research, the Faster R-CNN has the lowest test time and the highest ideal accuracy compared to the other methods, CNN, R-CNN, and Fast R-CNN. However, the accuracy is difficult to increase due to the deficiency of a trained dataset for the model.

On the other hand, the YOLO version 3 (YOLOv3) [2] is a technique for object recognition that does not need the RPN to generate anchor boxes and can directly anticipate the target location and category. As a result, the speed of the detecting algorithm can be increased. Through multi-scale detection, the YOLOv3 algorithm increases the recognition accuracy of small target objects. However, during the real test procedure, it showed that the detection impact for several small targets is insufficient, and there are still a significant number of false detections and missed detections. The darknet53 [8] method is used to achieve fine-grained image detection by combining up sampling and down sampling image tensors and proposes a network structure based on double image segmentation and up sampling to recover the size of image detection.

There are many underwater image databases available. However, the databases specifically for lake underwater images are limited to find, for example, the databases for underwater image detection and recognition [1]. Moreover, raw data alone is usually insufficient to support object recognition applications' needs. Often, there are feature monotonous content and a limited number of scenes, as well as few degradation characteristics and inadequate data.

Thus, this study proposes a technique for object recognition based on the CLAHE [9] image enhancement and YOLO version 3, named the CLAHE_YOLOv3. Furthermore, a controlled condition image database specifically for lake underwater images in different turbidity levels has been developed to be used for the performance evaluation of the proposed object recognition technique.

## 2. Methodology

The database consists of 5 different object classes which represent the real-world application and the system can be utilized by underwater robots to handle underwater search and rescue operations, which are Fish, Aeroplane, Luggage, Helicopter and Submarine. The images have been captured with different water conditions and object positions to ensure that 1152 images of each class target are achieved. The condition of the water is based on turbidity which is measured by using a turbidity sensor. For the labelling of the images, the LabelImg software [10] has been used to develop a region of interest for each image captured. The developed database can be accessed at the following link: https://bit.ly/3thcM2w.

The images for each object category are taken in daylight time (10am-12am) and (5pm to7pm), which total 1152 images for each category. There is a difference between the conditions of light (10am–12am) and (5pm–7pm), where (10am–12am) is in white light and (5pm–7pm) is in orange or red light.

There are 15 separate test images for each category prepared for the experiments performed. The condition considered are summarized as follows:

- Turbidity (600NTU, 1000NTU, 1300NTU and 1600NTU)
- Object heights from surface (1cm, 25cm, 40cm)
- Object to camera distance (15cm, 20cm, 25cm, 30cm, 35cm and 40cm)
- Object surface direction (front, 45° ,90° ,135° ,180° ,225° ,270° ,315°)

Figure 1 shows the example of images captured for the developed database.

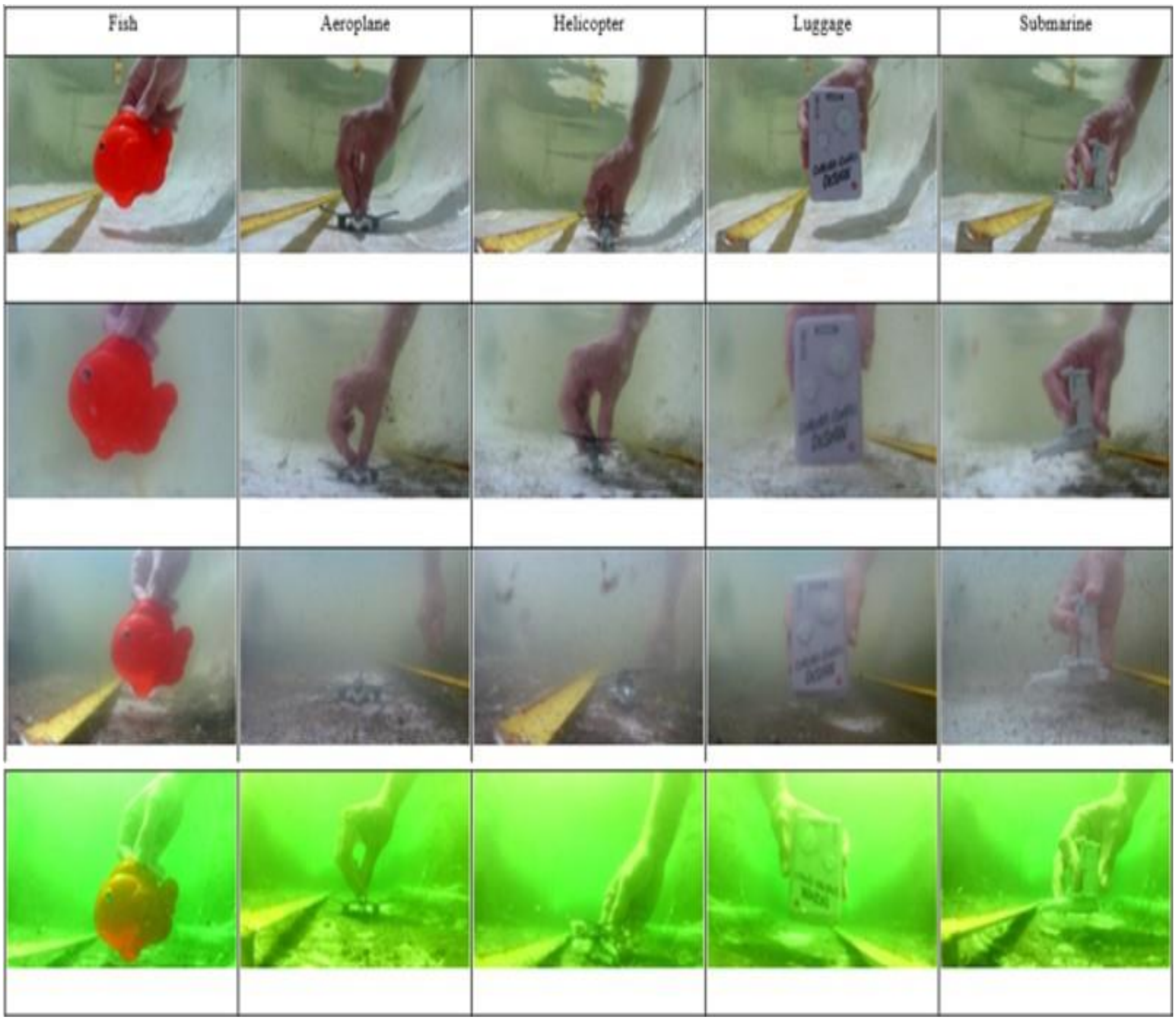



**Figure 1: Example of images captured for developed database**

Figure 2 shows how the CLAHE_YOLOv3 technique works for object recognition. Based on the flowchart shown in Figure 2, the process involves 2 phases, which are the image enhancement process and the recognition process. In the first step, we capture an image in a lake underwater environment for a recognition test. After the image is captured, the CLAHE is applied to the image using Google Colaboratory [11]. The last step for the first phase is the generation of a new image from the CLAHE image enhancement technique. The second phase starts with the installation of the darknet YOLOv3 at the Google Colaboratory. After the database is inserted or downloaded, the process to train the database with the YOLOv3 is continued using Google Colaboratory. Next, the accuracy of the model trained using the Google Colaboratory is tested using the output image after applying the CLAHE image enhancement.

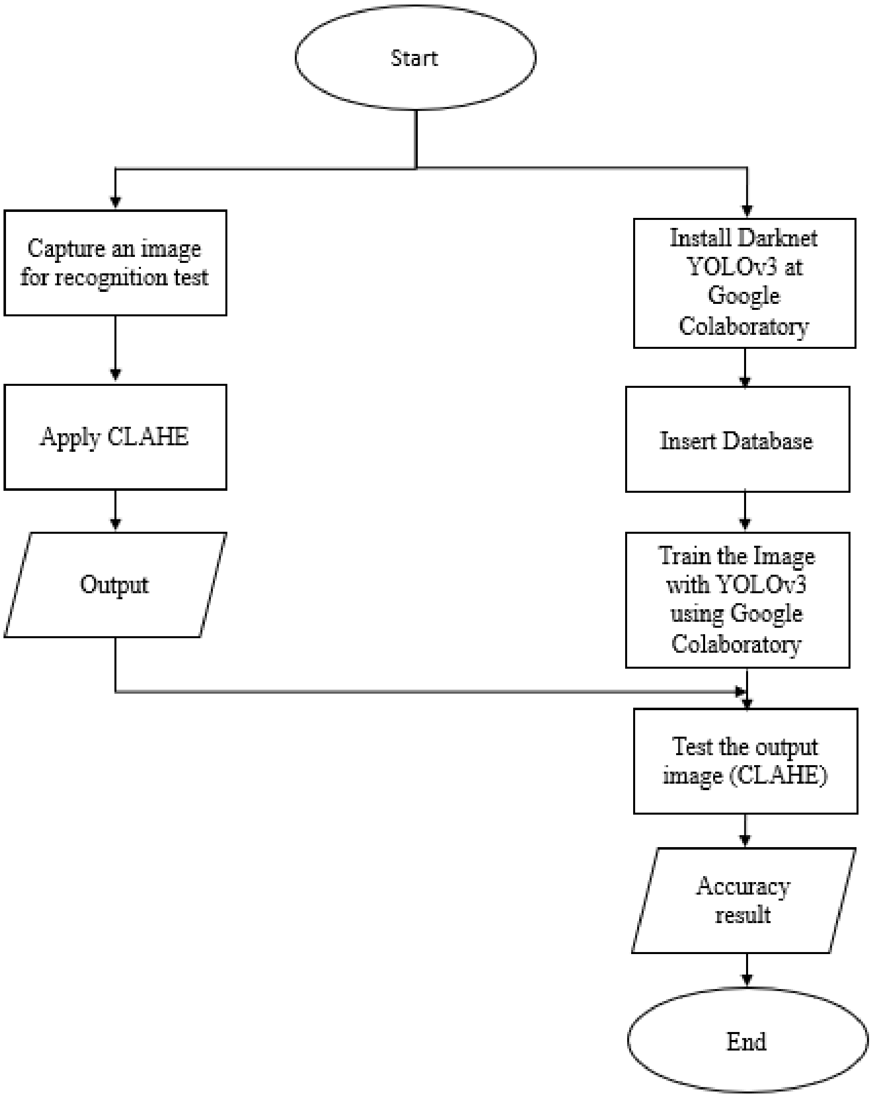



**Figure 2: The CLAHE_YOLOv3 Flowchart**

## 3. Results and Discussion

The YOLOv3 technique is utilized to compare the performance of the proposed technique. The test image underwater conditions for both object recognitions are clear water and medium turbidity water conditions. The experiment is performed by training the system based on single classes, and the system is tested with only 1 class for each object.

The first object recognition is based on the YOLOv3 algorithm, where the result is shown in Table 1. From the result, we can see for each object, the YOLOv3 is able to generate the bounding box and accuracy based on the object in the image. In recognition, the YOLOv3 resulted in object losses. In this experiment, the object losses occurred when the system recognized fish in both clear and medium turbidity water conditions images. The object losses happened when the Intersection Over Union (IOU) cannot give the best prediction of object accuracy in the image [12]. In medium turbidity water conditions, the YOLOv3 is able to achieve 90% above accuracy for Fish, Luggage and Submarine object classes. The object loss accuracy for fish decreased to 33% when we test the image using the proposed technique.

**Table 1: The accuracy result of YOLOv3**

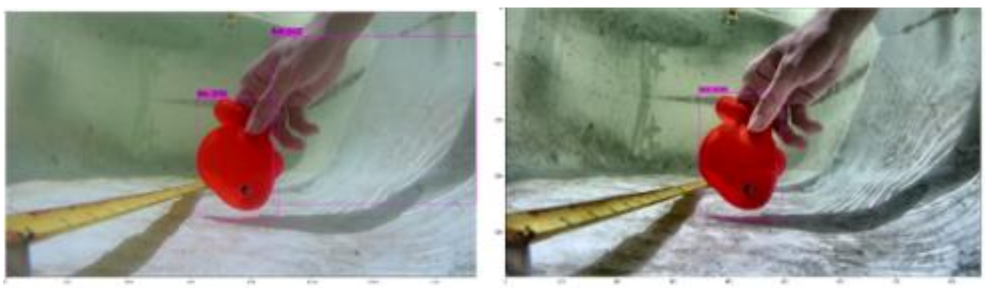
| Underwater condition | Fish (%) | Object losses fish (%) | Aeroplane (%) | Helicopter (%) | Luggage (%) | Submarine (%) |
|---|---|---|---|---|---|---|
| Clear water | 95 | 53 | 79 | 80 | 79 | 36 |
| Medium turbidity | 90 | 33 | 86 | 53 | 100 | 90 |

Table 2 shows the result of object recognition using the proposed technique, CLAHE_YOLOv3. The experiment setting is similar to those in the YOLOv3 experiment. It can be observed that in clear water images, the CLAHE_YOLOv3 is able to recognize 99% of the Fish object class. However, object losses also occurred with this technique. The CLAHE_YOLOv3 is also able to achieve above 80% recognition of each object for Helicopter and Submarine classes in the same water condition. Furthermore, in the medium turbidity water condition, the CLAHE_YOLOv3 achieved above 90% accuracy for Fish, Aeroplane and Luggage classes.

**Table 2: The accuracy result of CLAHE_YOLOv3**

| Underwater condition | Fish (%) | Object losses fish (%) | Aeroplane (%) | Helicopter (%) | Luggage (%) | Object losses for Luggage (%) | Submarine (%) |
|---|---|---|---|---|---|---|---|
| Clear water | 99 | 53 | 78 | 85 | 79 | 28 | 81 |
| Medium turbidity | 97 | 0 | 93 | 53 | 100 | 0 | 85 |

From Figure 3, we can observe that the CLAHE_YOLOv3 algorithm is capable of eliminating the bounding box that is not fit the object in the images for Fish in medium turbidity underwater conditions.



(a) (b)

**Figure 3: Visual comparison of object recognition result (a) The result of YOLOv3 (b) The result of CLAHE_YOLOv3**

The performance comparison of the YOLOv3 and proposed system (CLAHE_YOLOv3) is shown in Table 3 in terms of the accuracy average. In this experiment, we can observe that the overall average accuracy performance of the CLAHE_YOLOv3 improved by 11.83% compared to those of the YOLOv3. The performance of the proposed CLAHE_YOLOv3 improved, especially for medium turbidity condition images.

**Table 3: The accuracy comparison of YOLOv3 and CLAHE_YOLOv3**

| Underwater Condition | YOLOv3 Average (%) | CLAHE_YOLOv3 Average (%) | Accuracy Percentage Increase (%) |
|---|---|---|---|
| Clear water | 70.33 | 71.90 | 2.23 |
| Medium turbidity | 75.00 | 82.20 | 9.60 |
| | | **Total % Increase** | 11.83 |

## 4. Conclusion

Based on the analysis, we can observe that the CLAHE_YOLOV3(proposed) shows improved performance compared to the YOLOV3 technique in underwater object recognition in different water conditions. It shows improved performance in clear and medium turbidity underwater condition images with an average accuracy improvement of 70.33% to 71.90 for clear water and 75.00% to 82.20% for medium turbidity, which totals the average recognition accuracy improvement to 11.83%. It also shows that the CLAHE_YOLOV3 (proposed) is more accurate if trained with similar class images. The proposed method is also able to reduce the object loss issues occurred in medium turbidity image conditions.

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