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Object Recognition System with Image Enhancement for Lake Underwater Images

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Abstract: The project aims to develop a system for recognizing objects in underwater images from lakes using a combination of image enhancement techniques and object recognition methods. A system is needed for underwater robots to distinguish objects in a lake while searching for them. Due to limited visibility in underwater photos, it is difficult to accurately capture the shape or color of objects. The objects in the database are chosen based on the assumption that they may fall into the lake and need to be found. Recognition methods for these objects are important for the underwater searching process. The techniques used are the CLAHE for contrast improvement and the YOLOv3 for object detection to improve visual appearance and accurately identify objects. The proposed object recognition system uses Google Colaboratory as the development environment and the Python programming language to implement the system. The labelling process is done by using the LabelImg software. This project proposed the CLAHE_YOLOv3 method to overcome the problems. In this research, an image database for underwater images of lakes in various situations has been created. The developed database can be accessed at the following link: https://bit.ly/3klN9ex. The study compares the performance of the CLAHE_YOLOv3 method to the YOLOv3 technique for object recognition in underwater images. In the experiment, the setting is constant for depth from surface which is 10 cm from the surface and the distance of the object from the camera is 25 cm. The CLAHE technique has improved and enhanced the local contrast in the image, making it appeared sharper and the details are clearer. In the experiment, the accuracy increases from 93.52% for YOLOv3 to 100% for CLAHE_YOLOv3.

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

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1. Introduction

Underwater image enhancement has got a huge amount of attention in both image processing and underwater vision throughout the previous several years. Enhancing underwater photos is a difficult errand due to the confusing underwater surroundings and lighting circumstances [1]. Lakes, seas, and ponds are the three kinds of underwater images. Since light is increasingly diminished as it passes through water, underwater pictures are affected by low visibility. As a result, sceneries are poorly contrasted and fuzzy [2]. The practice of magnifying the comprehensibility or perception of information in images for human viewers while simultaneously supplying improved input for other automated image processing systems is known as image enhancement. The goal of underwater image enhancement is to improve the visual quality of an image by adjusting the color, brightness, contrast, sharpness, and other image properties for certain activity or observer. One or more picture characteristics are changed throughout this operation [3].

Deep neural networks have lately risen to prominence as the most effective way for high-quality computer vision, such as object identification and recognition [4]. Object identification is a subfield of computer vision and image processing that searches visual images for instances of semantic elements of a certain classification (such as humans, homes, or automobiles) [5]. The object detection and recognition algorithms are basically used in order to find the presence of an object, its movement and orientation within an image or real time instance. The algorithm should be able to identify whether an object (or a group of objects) exists when an object is identified and recognized [6]. An underwater robot is one of the technologies that require an object detection system to assess the picture more extensively before recognizing the object. [7].

The project aims to develop a system for recognizing objects in underwater images from lakes using a combination of image enhancement techniques and object recognition methods. A system is needed for underwater robots to distinguish objects in a lake while searching for them. Due to limited visibility in underwater photos, it is difficult to accurately capture the shape or color of objects. The objects in the database are chosen based on the assumption that they may fall into the lake and need to be found. Recognition methods for these objects are important for the underwater searching process. The techniques used are the CLAHE for contrast improvement and the YOLOv3 for object detection to improve visual appearance and accurately identify objects. This project proposed the CLAHE_YOLOv3 method to overcome the problems. In this research, an image database for underwater images of lakes in various situations has been created.

2. Methodology

2.1 Database Development

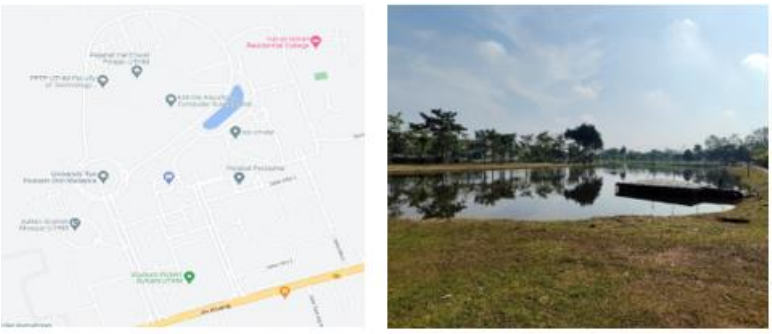
The database consists of 5 different types of classes which represent the real objects which are the Car, Male, Female, Helicopter, and Ring. The experiment has been conducted at a lake located in Universiti Tun Hussein Onn Malaysia (UTHM) main campus in Parit Raja, Batu Pahat Johor, Malaysia. The images have been captured under different conditions and positions to ensure that 64 images of each class target (a total of 638 images) are achieved. The objects and the camera are attached to an acrylic rod and tied with a string. Both the objects and camera are then submerged horizontally into the lake as required by the experiments. The images are captured with a waterproof camera, Dragon Touch Vision 4 Lite. The camera is set to 16 Megapixels to ensure the images captured has the best resolution. The developed database can be accessed at the following link: https://bit.ly/3klN9ex. For labelling of the images, the LabelImg software has been used to draw bounding boxes around objects in an image and assign labels to them. The image for each category is taken in daylight time (10 am-12 noon). The images are captured based on 3 different depths from surface setting (0 cm, 10 cm, and 25 cm), and 3 different distances of objects to camera distance setting (10 cm, 25 cm, and 50 cm) and 7 different angles of object direction (45°, 90°, 135°, 180°, 225°, 270°, 315°), which total in 64 images for 1 category. The surface direction is acquired by dividing the 360° angle into 8 directions, resulting in an angle of 45° for each direction. The conditions considered are summarized as follows:

i. Object depths from surface (0 cm, 10 cm, 25 cm)

ii. Object distance to camera (10 cm, 25 cm, 50cm)

iii. Object surface direction (45°, 90°, 135°, 180°, 225°, 270°, 315°)

Figure 1 shows the location of experiment; (a) UTHM Google Map, (b) G3 lake and Figure 2 shows the examples of underwater image acquisition.



(a) (b)

Figure 1: Location of experiment; (a) UTHM Google Map, (b) G3 lake

Car	Male	Female	Helicopter	Ring

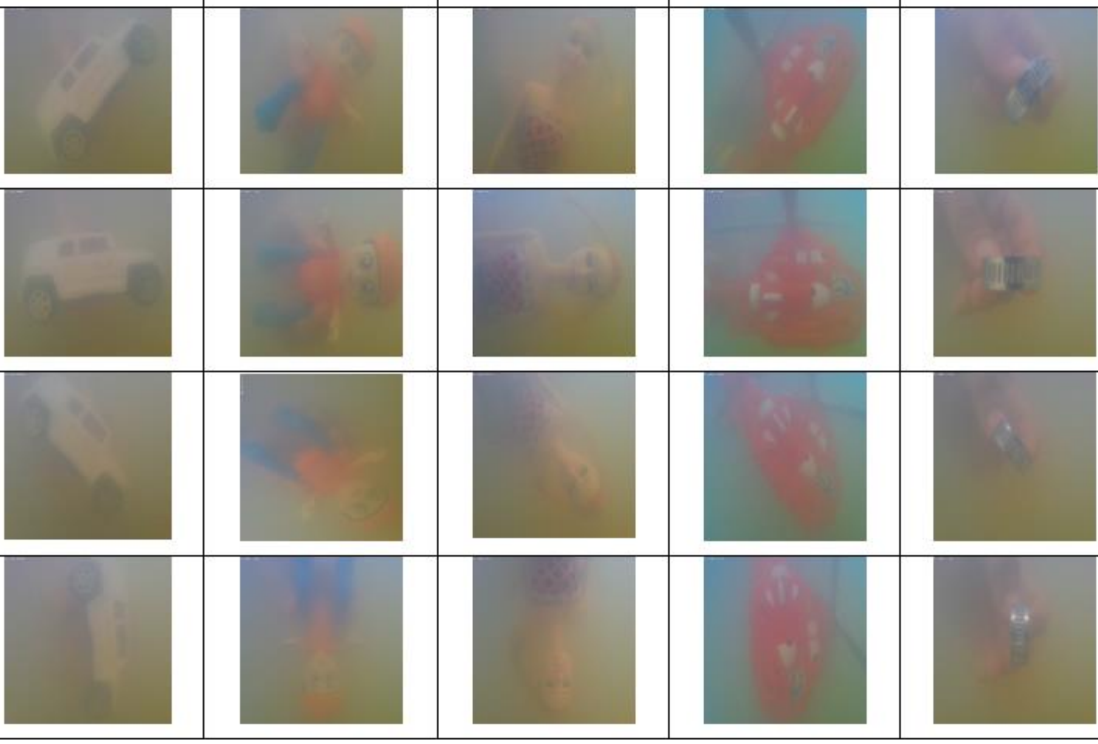


Figure 2: Example of underwater image acquisition

The proposed object recognition system uses Google Colaboratory as the development environment and the Python programming language to implement the system. The labelling process is done by using the LabelImg software. The system's accuracy is tested by feeding images into it, and the results are illustrated as shown in Figure 3.

Figure 3: (a) Example of test image, (b) GUI of proposed object recognition system, (c) Output of test image

2.2 Project Flowchart

Figure 4 depicts CLAHE_YOLOv3 object recognition flowchart.

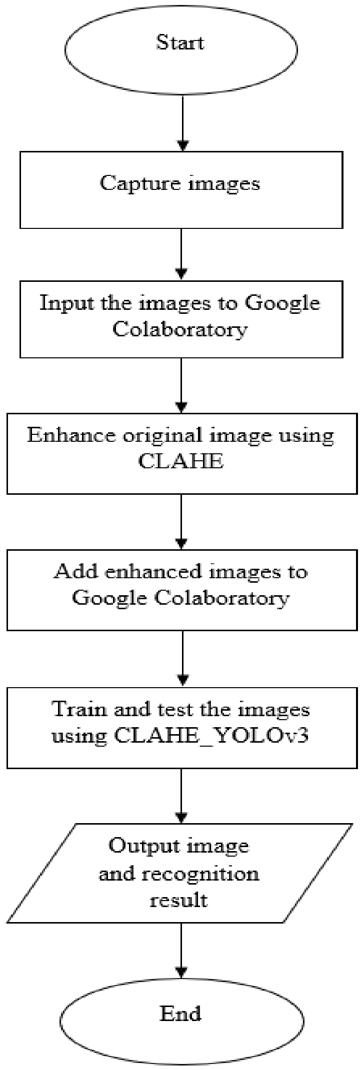


Figure 4: CLAHE_YOLOv3 object recognition flowchart

Based on flowchart in Figure 4, the original images are first enhanced using a technique called the Contrast Limited Adaptive Histogram Equalization (CLAHE) in a tool called the Google Colaboratory. These enhanced images, along with the original images, are then uploaded to the library in the Google Colaboratory. These images are then used to train and test a model called the CLAHE_YOLOv3. The model has various parameters, such as the number of batches set to 64, the number of subdivisions set to 16, a maximum number of batches set to 10000, 5 classes, and a number of filters set to 30. After the training and testing are complete, the output images are observed.

3. Results and Discussion

The results and discussion section presents data and analysis of the study. As shown in the Figure 5, it shows the visual inspection of test images with different underwater conditions for relatively different objects. A total of 638 images is used, which consists of original images and enhanced images. These images were fed to CLAHE to enhance the contrast of each image, then fed to YOLOv3 system for training and testing. After feeding the test images to the CLAHE_YOLOv3, the accuracies and bounding boxes are generated in the images. The setting this experiment is constant for depth from surface which is 10 cm from the surface and the distance of the object from the camera is 25 cm.

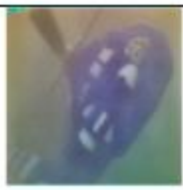
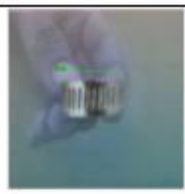
Angle	Car	Male	Female	Helicopter	Ring
45°	 Detected: Car Accuracy: 100%	 Detected: Male Accuracy: 100%	 Detected: Female Accuracy: 100%	 Detected: Helicopter Accuracy: 100%	 Detected: Ring Accuracy: 100%
90°	 Detected: Car Accuracy: 100%	 Detected: Male Accuracy: 100%	 Detected: Female Accuracy: 100%	 Detected: Helicopter Accuracy: 100%	 Detected: Ring Accuracy: 100%
135°	 Detected: Car Accuracy: 100%	 Detected: Male Accuracy: 100%	 Detected: Female Accuracy: 100%	 Detected: Helicopter Accuracy: 100%	 Detected: Ring Accuracy: 100%
180°	 Detected: Car Accuracy: 100%	 Detected: Male Accuracy: 100%	 Detected: Female Accuracy: 100%	 Detected: Helicopter Accuracy: 100%	 Detected: Ring Accuracy: 100%

Figure 5: CLAHE_YOLOv3 visual inspection for the experiment

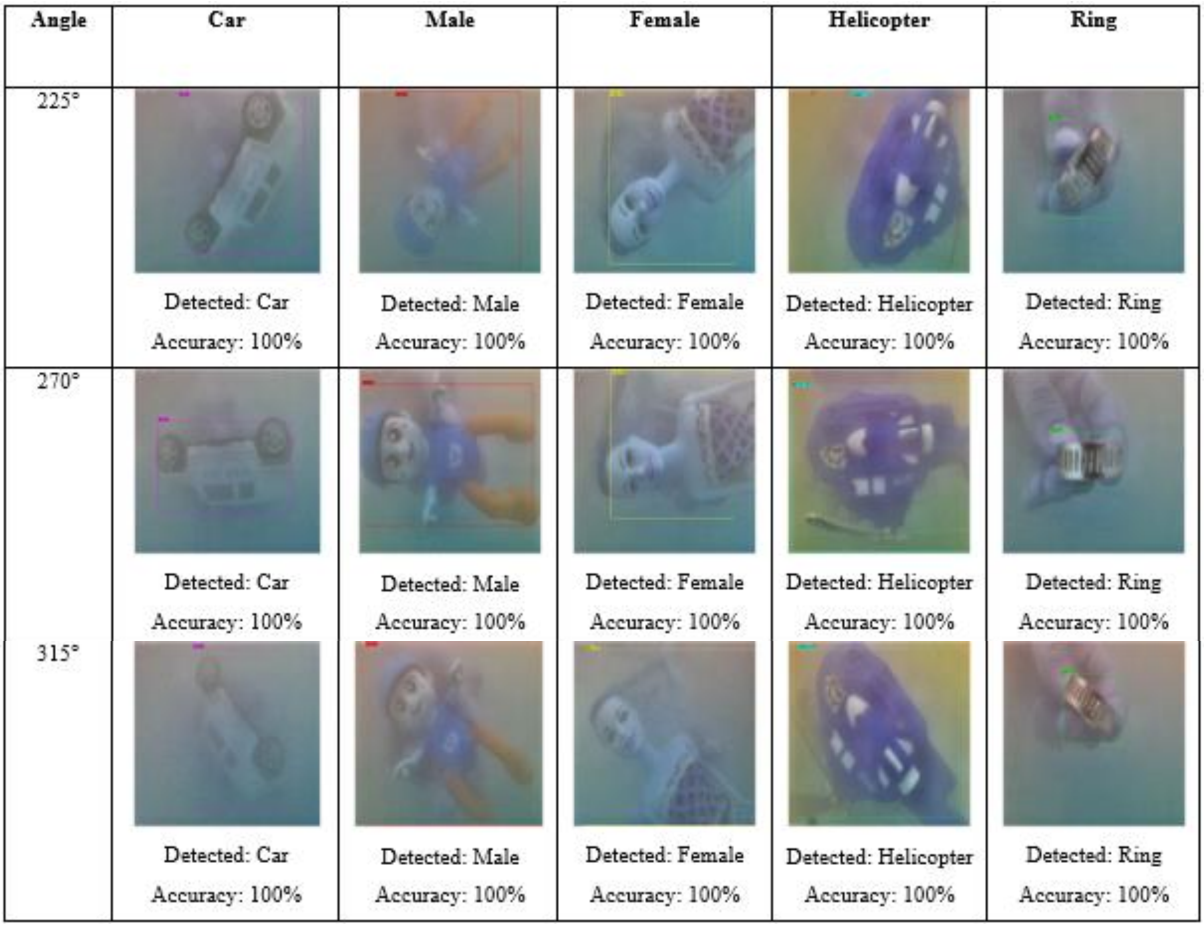


Figure 5: CLAHE_YOLOv3 visual inspection for the experiment (continued)

In Table 1, the average recognition accuracy for the YOLOv3 and CLAHE_YOLOv3 for the experiment is presented. The YOLOv3 average percentage is good since every item achieves greater than 90% accuracy. Using YOLOv3, test images for Car averaged 92.57%. The accuracy for Male is 85.14%, while it is 91.29% for Female. Only utilizing YOLOv3, Helicopter and Ring both reach 94.29%. After using the suggested system (CLAHE_YOLOv3), every object accuracy improves to 100%. The YOLOv3 can provide high recognition accuracy (>90%) if trained with different characteristic object's classes. The utilization of the image enhancement by using the CLAHE has surpassed the performance of the YOLOv3 alone in given experiment condition.

Table 1: The accuracy results for the experiment using YOLOv3 and CLAHE_YOLOv3

Underwater condition (different angle, depth 10 cm, distance from camera 25 cm)	YOLOv3 average (for all classes) (%)	CLAHE_YOLOv3 average (for all classes) (%)
Car	92.57	100
Male	95.14	100
Female	91.29	100
Helicopter	94.29	100
Ring	94.29	100
Total Average Accuracy	**93.52**	**100**

4. Conclusion

In summary, the results of the three experiments show that the CLAHE_YOLOv3 system significantly improves the accuracy of object detection compared to the YOLOv3 alone. In the experiment, the average accuracy of the YOLOv3 is 93.52%, while the average accuracy of the CLAHE_YOLOv3 is 100%. The results of the experiments indicate that the CLAHE preprocessing method is an effective way to improve the accuracy of object detection in underwater images.

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