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Effect of Applying the YOLO Object Recognition System for Developed Lake Underwater Images Database

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ABSTRACT

There are differences between underwater physical particles at the seas and lakes, where lake underwater conditions tend to be more brownish or greenish because lakes are inland bodies of water which do not have direct contact with the seas. Lake underwater image databases with higher turbidity images are difficult to find. Thus, there is a need to create a dataset for these kinds of images to be used for real lake underwater research. For applications such as underwater robot, a system that can distinguish objects in the lake is needed when looking for them. As for object selection for this database, the objects are selected based on the assumption that these kinds of objects may fall into the lake and there is a need to search and find them back. Therefore, a method that could recognize these kinds of objects is important in the underwater searching process. The study's goal is to develop an image database for lake underwater images and investigate the accuracy of object recognition system in different lake underwater conditions. The YOLOv3 has been used in this study as a method of identifying the object in the image. A total of 315 images are used, where the ratio is 80% for training and 20% for testing. The tools utilized in this study are the LabelImg and Google Colaboratory software. According to the result and analysis, when tested with all of the experiments under various lake underwater settings, YOLOv3 has achieved an overall accuracy of 92.32% for given underwater conditions.

Keywords:
Object recognition; underwater image; YOLO

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 goal of underwater image enhancement is to improve the

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visual quality of an image by adjusting the colour, brightness, contrast, sharpness, and other image properties for certain activity or observer. One or more picture characteristics are changed throughout this operation [3]. Artificial Intelligence has significantly impacted many fields, for example education [4], healthcare [5], and others. Deep neural networks [6] have lately risen to prominence as the most effective way for high-quality computer vision, such as object identification and recognition [7]. 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, or automobiles) [8]. The object recognition algorithms are basically used 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 [9]. An underwater robot is one of the technologies that require an object detection system to assess the picture more extensively before recognizing the object [10].

Image enhancement and restoration technology have grown and improved substantially in our high-tech era during the previous few decades [11]. However, many of those approaches are focused on reducing the damage caused by air pollution. Underwater images are not degraded by air pollution, but they are affected by physical particles in underwater conditions that cause images to become hazy [7]. There are differences between underwater physical particles at the seas and lakes, where lakes underwater tend to be more brownish or greenish because lakes are inland bodies of water which do not have direct contact with the seas [12]. Because of the limited visibility of underwater photos, especially in deeper water, it is difficult for photographers to capture the real shape or colour of the objects. To improve object recognition accuracy, a large enough dataset is required to train the object recognition algorithm.

Furthermore, lake underwater image databases with higher turbidity images are difficult to find. Thus, there is a need to create a dataset for this kind of images to be used for real lake underwater research. For application such as underwater robot, it a system is needed that can distinguish objects in the lake when looking for them [10]. In previous research [13], the database needed to be trained with higher performance GPU as lower specs of GPU has an effect and decrease training time. Due to Google Colaboratory's training period constraint, optimization of algorithm and training process for database training is needed to encounter this problem. As for object selection for this database, the objects are selected based on the assumption that these kinds of objects may fall into the lake and there is a need to search and find them back. Therefore, a method that could recognize these kinds of objects are important in underwater searching process.

The study's goal is to develop an image database for lake underwater images and investigate the accuracy of object recognition system in acquired different lake underwater conditions. The objectives of this study are: (i) to create an image database for underwater images of lakes in various situations, which has been utilized for image recognition, (ii) to apply an object recognition system for lake underwater images training and testing, and (iii) to evaluate the developed system's performance. In this study, an image database for lake underwater images in different conditions has been developed. For this research, the setting of the experiment has been conducted in a real lake surrounding while previous research [13] was conducted in controlled conditions. As for object selection for this database, the objects are selected based on the assumption that these kinds of objects may fall into the lake and there is a need to search and find them back. The images are taken from different object depths from surface, object distances to camera, and object surface directions, respectively. Therefore, a method that could recognize these kinds of objects are important in underwater searching process. This study provides the investigation result on the accuracy of object recognition system in acquired different lake underwater conditions.

1.2 Overview of Underwater Image Database

Because of the limited visibility of underwater photos, especially in deeper water, it is difficult for photographers to capture the real shape or colour of the objects. To improve object recognition accuracy, a large enough dataset is required to train the object recognition algorithm. Furthermore, lake underwater image databases with higher turbidity images are difficult to find. Thus, there is a need to create a dataset for this kind of images to be used for real lake underwater research. Table 1 shows summary of databases overview.

Table 1
Summary of databases overview

Ref	Methods	Description	Advantages	Disadvantages
[1]	Underwater seas Databases (UIEB Dataset)	A large-scale real world underwater image enhancement benchmark (i.e., UIEB) which contains 950 real sea underwater images.	The images in the dataset have high resolution, which allows for detailed analysis of the images.	The dataset may contain images that are low-resolution or have poor lighting conditions.
[11]	Underwater Data set (TURBID Dataset)	Different levels of image degradation on a planned seabed scenario with 3D objects, contain all different aspects found in a real sea floor (controlled condition setting)	Can evaluate image restoration method and can be tested to any vision algorithm that is sensitive to turbidity	It necessitates manual turbidity condition construction, implying that the turbidity value cannot be measured.
[12]	Underwater lake dataset (Blue Bot Dataset)	Image data of target fish species, as well as images of fish in various natural orientations, lighting, and water conditions. Data gathered in Barbados, Carlisle Bay.	The image can be capture easily with underwater robot that can help in taking high resolution image at a deeper depth of water.	The cost of using the equipment is too high.
[13]	Underwater controlled condition lake dataset	Large dataset consists of 1152 images	The images can be captured easily according to requirement of underwater conditions	Interference of unwanted objects in images

1.3 Overview of Object Recognition Algorithms

Object detection is critical while analysing important regions of underwater surveillance as well as resource exploration or examination. The capacity to analyse objects while also extracting the underlying information highlights the significant research worth of object recognition in the underwater.

To construct an object recognition system for this project, a suitable technique is required. To enhance object detection in underwater images, the You Only Look Once version 3 (YOLOv3) is suggested. The rationale for employing this approach is to improve the accuracy of underwater picture object detection. By enabling the real-time inference with GPU, the YOLOv3 can perform faster object detection.

2. Methodology
2.1 Introduction

The study's process and approach are covered in this chapter. The overall workflow of the study's production is detailed here, as well as the planned database development and approach for this study, which focuses on object recognition. The project was created utilizing the Python language and the Google Collaboratory. The first step is to create a database with different types of items that represent real objects in underwater photographs. The second step aims to build the You Only Look Once version 3 (YOLOv3) object recognition system. Finally, the performance of the suggested technique is evaluated in terms of object recognition accuracy. Table 2 shows the summary of overview for object recognition techniques.

Table 2
Summary of overview for object recognition techniques

References	Methods	Advantages	Limitations
[14-19]	YOLO	YOLO can be applied for multiple object tracking. YOLO also perform faster when enabling real-time inference.	YOLO facing difficulty in recognising an open image dataset.
[20]	Single Shot Multi-Box Detection (SSD)	SSD is designed for real-time object detection, and it is able to detect objects in an image quickly with high accuracy.	SSD may not perform as well on small or low-resolution objects.
[21]	Faster R-CNN	Faster R-CNN reduces the number of frames to generate proposed box so lower the detection speed.	The mean average precision result is not high

2.2 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 images have been captured under different conditions and positions to ensure that around 63 images of each class target (a total of 315 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 into the lake as required by the experiments. The developed database can be accessed at the following link: bit.ly/3ABP5V7. 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 around 63 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 in Table 3.

Table 3
Object settings for lake underwater image database

Criteria	Setting
Object depths from surface	0 cm, 10 cm, 25 cm
Object distance to camera	10 cm, 25 cm, 50cm
Object surface direction	45°, 90°, 135°, 180°, 225°, 270°, 315°

2.3 Object Recognition Technique: You Only Look Once Version 3 (YOLOv3)

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. After completing labelling all the images, the bounding box is saved in a txt file in the same image path. The Google Colaboratory is used to perform object recognition using the YOLOv3. The prepared data images folder is moved to the Google drive directory. Then the training process is performed. After the training is finished, testing is executed.

The YOLOv3 [19] architecture and DarkNet framework are used to construct an optimal underwater object identification model in this study. For underwater image training, the image dataset is pre-processed, labelled, and captioned. The mean average accuracy and training arcs are also used to evaluate performance. The YOLOv3 approach for object identification is shown in Figure 1. To begin, the input picture is segmented into a 13x13 grid of cells using the YOLOv3 convolutional neural network. The cells are all responsible for recognizing the image's boundary boxes. Following that, the Darknet-53 is employed as the YOLOv3's backbone to improve accuracy. To extract the characteristics of the photos and train the images, YOLOv3 and Darknet-53 are utilized. For the test image, the detector function is utilized to create boundary boxes and class predictions. The number of batches for YOLOv3 is 64, the number of subdivisions is 16, maximum batches is 10000, 5 classes and number of filters is 30 for this research.

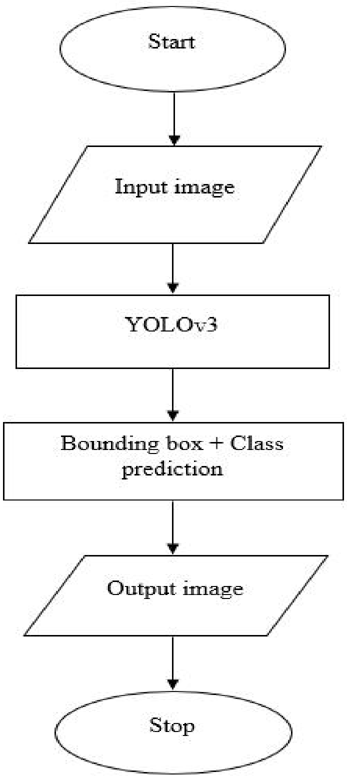

Fig. 1. Flowchart of YOLOv3

2.4 System Setup

Firstly, the research has been conducted at the Tasik Kemajuan UTHM, a lake located in Universiti Tun Hussein Onn Malaysia (UTHM) main campus in Parit Raja, Batu Pahat Johor, Malaysia. The images are captured with a waterproof camera, Dragon Touch Vision 4 Lite. The camera used for the project had a resolution of 16 Megapixels for photos and 1080p 60fps for video. The captured images size is 5120 x 3840 pixels. Then, the database is processed using the LabelImg software to draw bounding box and assign the label around the object in images. After that, the object recognition technique is developed using Google Colaboratory. The Google Colaboratory has been executed by using a personal desktop. The configuration settings for Experiment 1, Experiment 2, and Experiment 3 are different based on the requirement of each experiment. Because of the time limitations by the Google Colaboratory, the number of maximum batches, classes, and filters may be differed. In this study, the training time taken for Experiment 1 is 5 hours, Experiment 2 takes 7 hours meanwhile Experiment 3 is 10 hours, respectively. The configuration setting for training is shown in Table 4.

Table 4
Configuration setting for training

Type of experiments	Number of batches/ number of subdivisions	Maximum batches	Classes	Filter
Experiment 1	64/16	2000	1	18
Experiment 2	64/16	6000	2	21
Experiment 3	64/16	10000	5	30

2.5 Performance Assessment Technique-Average Accuracy

The average accuracy [22] is used to obtain the value of recognition average accuracy based on the 4 underwater conditions. The formula for average accuracy is shown in Eq. (1).

$$\text{Average accuracy} = \frac{\text{Total percentage of Accuracy}}{\text{Number of underwater condition images}} \tag{1}$$

3. Results

3.1 Result and Analysis for Image Database Development

In Table 5, the underwater image acquisition has been arranged based on the Car, Male, Female, Helicopter, and Ring categories. It shows the image of each object according to different underwater conditions. The turbidity is between high to relatively high level during the acquisition of the images due to rain in previous days. Table 5 setting shows different angles of the object varying from 45° to 315°, with a depth of 10 cm inside the lake from the surface and distance of 10 cm from object to the camera. The turbidity in the water causes the images to be blurred and hazy. However, with these setting for object distances from surface and camera, the objects can still be seen in the images.

For Table 6 the setting for image acquisition angle of 315°, with distance of 10 cm for the object from the camera, but different depth from the surface which are 0 cm (near surface), 10 cm, and 25 cm. When the distance of objects is nearer to camera, the objects can still be seen although the distance from surface differ.

In Table 7, the setting for the images captured are 315° angle, a depth of 25 cm from the surface, with distance of 25 cm from the object and camera. When the object distances from the surface and camera are longer, the image turbidity tend to be higher and object visibility become less clear.

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Table 5
Example of underwater image acquisition (different angle comparison)

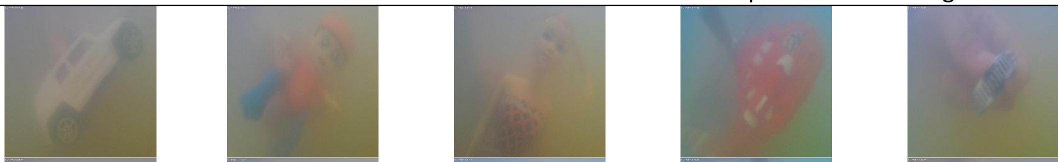
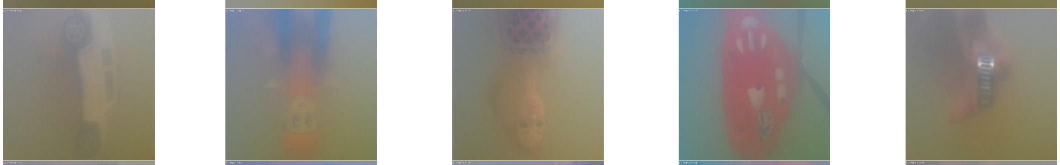
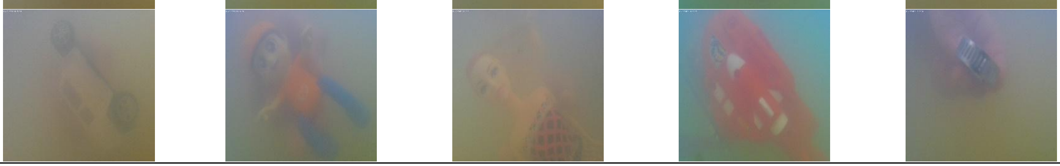
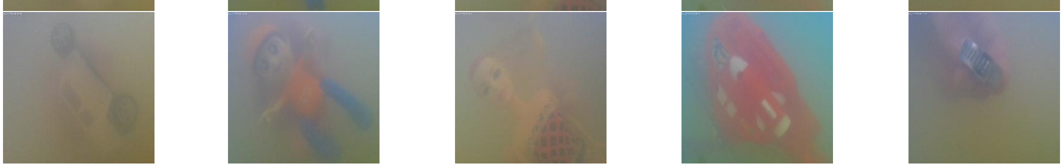
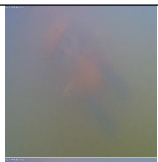
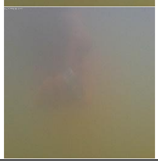
Angle	Car	Male	Female	Helicopter	Ring
45°					
90°					
135°					
180°					
225°					
270°					
315°					

Table 6
Underwater image acquisition (different depth (from surface) comparison)

Depth	Car	Male	Female	Helicopter	Ring
0 cm					
10 cm					

25 cm					

Table 7
Underwater image acquisition (different distance (from camera) comparison)

Distance	Car	Male	Female	Helicopter	Ring
10 cm					
25 cm					
50 cm					

3.2 Result and Analysis for Object Recognition System, Yolov3, for Experiment 1: Training Database For 1 Category with Similar Category Test Image

For Experiment 1, original image of Car from the image database is used for training and testing. For original images, there are a total of 63 images taken under different underwater condition. These images were then fed to the YOLOv3.

3.2.1 Visual effects inspection for Experiment 1

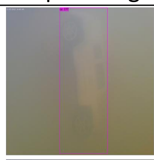
Table 8 shows the original image and test images for Experiment 1. The bounding box and accuracy of images were generated after test images were fed into YOLOv3. The setting for Experiment 1 is constant for depth from the surface which is 10 cm from the surface and the distance of the object from the camera is 25 cm.

Table 8
YOLOv3 visual effects for Experiment 1

Underwater condition	Test image	Output image	Detected object accuracy result
Angle: 45° Depth: 10 cm Distance from camera: 25 cm			Car 97%
Angle: 90° Depth: 10cm Distance from camera: 25 cm			Car 96%

Angle: 135° Depth: 10 cm Distance from camera: 25 cm			Car 96%

Table 8. Continued
YOLOv3 visual effects for Experiment 1

Underwater condition	Test image	Output image	Detected object accuracy result
Angle: 180° Depth: 10 cm Distance from camera: 25 cm			Car 97%
Angle: 225° Depth: 10 cm Distance from camera: 25 cm			Car 98%
Angle: 270° Depth: 10 cm Distance from camera: 25 cm			Car 94%
Angle: 315° Depth: 10 cm Distance from camera: 25 cm			Car 98%

3.2.2 Accuracy analysis for Experiment 1

Car is the database image that was utilized in Experiment 1. From this experiment the YOLOv3 can recognized object very well in the distances of 10 cm from the surface and 25 cm from the camera although the turbidity level is relatively high if trained and tested with the similar category object. Table 9 shows the accuracy of recognition For Experiment 1.

Table 9
Accuracy for Experiment 1

Underwater condition (object's angles)	Accuracy of test image
45°	97%
90°	96%
135°	96%
180°	97%
225°	98%
270°	94%
315°	98%

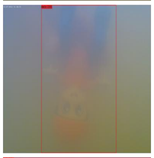
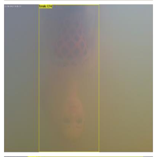
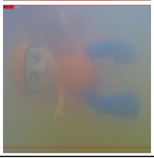
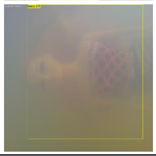
3.3 Result and Analysis for Object Recognition System, Yolov3, for Experiment 2: Training Database From 2 Categories with Relatively Identical Shape Objects

Experiment 2 uses the images database for male and female as their shapes are identically similar. In this experiment, a total of 126 images are taken from the original images database of Male and Female. These images were fed to YOLOv3 for training and testing.

3.3.1 Visual effects inspection for Experiment 2

Table 10 shows the visual analysis of test images for these two categories. After feeding the images into YOLOv3, the bounding box and accuracy are generated in the images. The setting for Experiment 2 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.

Table 10
YOLOv3 visual effects for Experiment 2

Underwater condition (object's angles)	Male		Female	
Upward (0°)		Detected: Male accuracy: 84%		Detected: Female accuracy: 57%
Right side (90°)		Detected: Male accuracy: 99%		Detected: Female accuracy: 92%
Downward (180°)		Detected: Male accuracy: 96%		Detected: Female accuracy: 94%
Left side (270°)		Detected: Male accuracy: 94%		Detected: Female accuracy: 79%

3.3.2 Accuracy analysis for Experiment 2

Table 11 shows the accuracy result of the Male and Female images after being fed into the YOLOv3. In this experiment, a total of 126 images are taken from the original images database of Male and Female. These images were fed to YOLOv3 for training (80%) and testing (20%). From Experiment 2, it was observed that Male images were able to recognize objects very well at a distance of 10 cm and 25 cm from the camera, even though the object angle for the upward condition was only 84% for Male images. For Female category, it is not recommended to use YOLOv3 if the turbidity level is relatively high for angle of 0° and 270° because the accuracy detection is lower. However, the system can still detect the object as Female.

Table 11
Accuracy for Experiment 2

Underwater condition (object's angles)	Accuracy (male image)	Accuracy (female image)
Upward (0°)	84%	57%
Right side (90°)	99%	92%
Downward (180°)	96%	94%
Left side (270°)	94%	79%

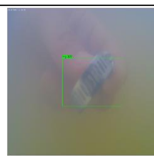
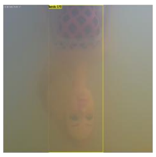
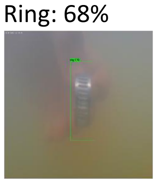
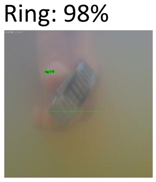
3.4 Result and Analysis for Object Recognition System, Yolov3, for Experiment 3: Training Database From 5 Categories with Relatively Different Shape Objects

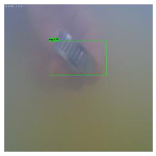
For Experiment 3, a total of 315 images were taken under different underwater conditions for training and testing purposes. The accuracies and bounding boxes were generated in the images after being fed into the YOLOv3. These images were first used for training the YOLOv3. After training, a test was executed to produce the output image. The setting for Experiment 3 was consistent with the depth from the surface, which was 10 cm, and the distance of the object from the camera was 25 cm.

3.4.1 Visual effects inspection for Experiment 3

Table 12 illustrates the visual inspection of test images with different categories.

Table 12
YOLOv3 visual effects for Experiment 3

Angle	Car	Male	Female	Helicopter	Ring
45°	 Car: 86%	 Male: 95%	 Female: 95%	 Helicopter: 98%	 Ring: 100%
90°	 Car: 99%	 Male: 99%	 Female: 95%	 Helicopter: 98%	 Ring: 100%
135°	 Car: 94%	 Male: 90%	 Female: 95%	 Helicopter: 99%	 Ring: 68%
180°	 Car: 89%	 Male: 91%	 Female: 90%	 Helicopter: 77%	 Ring: 98%
225°	 Car: 99%	 Male: 97%	 Female: 95%	 Helicopter: 94%	 Ring: 98%
270°	 Car: 93%	 Male: 95%	 Female: 82%	 Helicopter: 95%	 Ring: 100%

315°	 Car: 88%	 Male: 99%	 Female: 87%	 Helicopter: 99%	 Ring: 96%

3.4.2 Accuracy analysis for Experiment 3

The accuracy under various underwater situations is shown in Figure 2. By feeding the test photos into YOLOv3, the accuracy is attained. From Experiment 3, it was observed that the YOLOv3 method is still considered good, even though the turbidity level was relatively high for training and testing. Most underwater conditions achieved an accuracy percentage higher than 90%.

Accuracy for Experiment 3

	45°	90°	135°	180°	225°	270°	315°
Car	86%	99%	94%	89%	99%	93%	88%
Male	95%	99%	90%	91%	97%	95%	99%
Female	95%	95%	95%	90%	95%	82%	87%
Helicopter	98%	98%	99%	77%	94%	95%	99%
Ring	100%	100%	68%	98%	98%	100%	96%

Fig. 2. YOLOv3 accuracy for Experiment 3

3.5 Total Recognition Average Accuracy of Object Recognition System

According to Table 13, the YOLOv3 performs well, with Experiment 1 obtained accuracy of more than 90% accuracy by using only the Car database for training. For Experiment 2, by using the YOLOv3, the total average accuracy is lower than 90% because upward object's angle for both Male and Female have a low percentage with 84% and 57%, respectively. The side angle's image accuracy for Female is 79%, which cause of lower of total average accuracy for Experiment 2. This technique is still considered as being effective even if it cannot detect with higher accuracy for Experiment 2. YOLOv3 generates an average accuracy of 93.52% for five broadly varied types of objects. This accuracy is thought to be outstanding for Experiment 3 because it identifies more accurately, which is higher than 90% accuracy for all classes.

Table 13
Total average accuracy for YOLOv3

Type of experiment	Total average accuracy
Experiment 1: Training database for 1 category (car only)	96.57%
Experiment 2: 2 relatively identical shape objects (male and female only)	86.88%
Experiment 3: 5 relatively different shape object (all classes)	93.52%
Total average accuracy for all experiments	92.32%

4. Conclusions

The YOLOv3 has been used in this study as a method of identifying the object in the image. The tools utilized in this study are the LabelImg and Google Colaboratory softwares. Developing a database of underwater lake images under various situations is one of the goals of this study. The images are based on many situations, including five distinct objects and camera distances, seven different angles, and three different water depths. The second goal, which is to apply an object detection system for lake underwater images, has been accomplished as well. According to the result and analysis, when testing with all the experiments under various lake underwater settings, YOLOv3 has achieved overall accuracy of 92.32% for given underwater conditions.

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