Real-time reef fishes identification using deep learning

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Abstract. Reef fishes is an important part in maintaining the balance of various components in the coral reef ecosystem. The existence of reef fish on coral reef ecosystems is a marker of the ecosystem in good condition. Furthermore, it is important to observe the condition of reef fish in a coral reef ecosystem to determine the population and diversity of reef fish in the ecosystem. Observation of reef fish generally by performing a manual visual census by scuba diver. In entering the industrial revolution 4.0 era there is a need to develop technology that is used to monitor the condition of reef fish in a coral reef ecosystem. The development of technology will certainly help researchers, and later on ecosystem manager, in observing the condition of reef fish with automatic identification. The technological development that can be done to observe reef fish is by applying deep learning. In this research we used YOLO deep learning algorithm for automatic identification. YOLO has the advantage of faster object detection. Application of deep learning to identify fish automatically is illustrated using underwater video recording of reef fish.

1. Introduction
Reef fishes is an important part in maintaining the balance of various components in the coral reef ecosystem. Reef fish play a role in the food chain in coral reef ecosystems and even reef fish can also be used as an indicator of the healthiness of coral reef ecosystems [1]. Closely related to the existence of reef fishes inhabiting a coral reef ecosystem may express the healthiness of the inhabited Coral Reef and vice versa [2]. Normally, the diversity and number of fish inhabiting a reef fishes make the coral reef ecosystem as a feeding ground, a spawning ground and a nursery ground. The existence of reef fish in a coral reef ecosystem indicates that the ecosystem is in a good condition [3].

It is important to monitor the population of reef fish in a coral reef ecosystem to determine the condition of a coral reef ecosystem. Observation of reef fish generally by performing a manual visual census by scuba diver. There is a need to develop technology that is used to monitor the condition of reef fish in a coral reef ecosystem. The technology that has been developed to monitor reef fish is the Underwater Camera System [4]. The use of this system can make it easier for researchers to monitor the condition of a coral reef ecosystem without the need to do a visual census manually by diving. Monitoring is done simply by looking at the monitor results of the recording conducted by underwater camera, but this system has a weakness where the identification of fish is still done manually.

It is necessary to develop technology that can identify fish automatically. Development can be done by utilizing computers to be able to identify automatically, but conventional computer vision techniques cannot perform well in water to be able to identify automatically [5]. The technology that can be used to identify automatically is use deep learning model. Deep learning is a part of artificial intelligence so that the computer can recognize the objects it sees [6]. Deep learning models after conducting training on models is able to identify fishes automatically.
2. Methods

2.1. Tools and materials
The tools used in this study are Labeling software, Microsoft Office 365, and Anaconda Navigator software with Python 3.7 programming language and the modules used are TensorFLow, Numpy, and OpenCV. The materials used in this study are pictures of reef fish and reef fish videos.

2.2. Research procedure
The study was conducted in some stages. These stages include building YOLO algorithm, collecting datasets and labeling datasets, training datasets, and testing models of training results.

2.2.1. Algorithm building. The algorithm used in this study is called as YOLO. This algorithm has the advantage in identifying objects quickly and it is also good for real-time identification. It is also good because the model good to identify the active fish swimming fishes. It is also good because the model good to identify the active fish swimming fishes. The model may have a better result due to the Artificial Neural Network (ANN) is applied in the model. More over the active adjustment of the cluster dimensions may result to best prediction of the object positions. The output from the identification of this algorithm is in the form of bounding boxes and the names of the objects that have been identified [7]. This algorithm divides the image that will be identified into an S x S grid, then in each grid there is an anchor box that evaluates each grid to predict objects in the image [8]. Identifying many objects with this algorithm is done simultaneously, so this identification is faster than other algorithms [9]. The result is shown in the following pictures (fig. 1).

![YOLO detection model](image)

**Figure 1.** YOLO detection model [8].

Based on Figure 1 can be seen the process of identifying objects on the YOLO algorithm. The process of producing bounding boxes is obtained from a small anchor box, then the small anchor box will automatically evaluate each pixel in the image to predict the position of the object in the image. Anchored boxes that have detected an object will have an Eigen value. The anchored boxes which have an intersection and the same eigen value will form one bounding box that adjusts to the size of the object that has been identified.

2.2.2. Data set collection and data labelling. The dataset is used to train the model to recognize the object to be identified. The dataset is actually some pictures of a reef fishes to be identified. It takes lots of pictures used for training to train the model so that until the model can identify and recognize the object to be identified. The collected dataset collected must also be high in varied variation so that the model can recognize objects in various circumstances. The dataset that has been collected dataset is then labelled to mark the object to be identified in the picture. Labelling is done absolute using Labeling
software. The output generated in this process is a file with an *.xml extension containing the values of each pixel in the labelled object. Labels in each species must have a number that is not much different. The difference in the number of labels in each species produces a model that is not good, the model will better recognize the fish that has the most labels while the fish species with the least number of labels will be difficult to be recognized by the model.

2.2.3. Data set training. Training data is important to introduce to the model so that it can recognize the object to identify. This data training process uses the collected dataset images and files with the *.xml format generated from the data labelling process. The ANN model in deep learning consists of three main layers, namely the input layer, the hidden layer, and the output layer. The ANN in deep learning is shown in Figure 2. In this dataset training process, the input layer is propagated at the hidden layer and will produce a weight value at the output layer. The weight value is then used to identify fish automatically. The training set stage consists of two stages, namely forward propagation and back propagation. Forward propagation propagates the input layer at the hidden layer and produces an output in the form of a weight value, then back propagation propagates backward to correct the weight value obtained. Both processes are repeated until the best weight value is obtained to identify the object [10].

The hidden layer architecture in YOLO consists of several main layers, namely the convolutional layer, the pooling layer, and the connected layer. The hidden layer architecture used in this algorithm can be seen in Figure 3. The architecture consists of 24 convolutional layers, 4 pooling layers, and 2 connected layers. The architecture is arranged in such a way as to be able to identify objects quickly.
2.2.4. Test the model. The last process carried out in this study is to test the results of the training that has been done. The process of testing the training results is carried out using the weight value obtained from the training results. The difference between the training results testing process and the dataset training process is that the training results testing process only does forward propagation. This process only tests the weight obtained from the training results can be used to detect the desired object, so that this process does not perform the backward propagation process that is used to improve the weight obtained. The test was carried out on one hundred pictures containing 24 species to be identified. The next step is analyzing the results obtained in the process of identifying automatically using deep learning.

3. Results

3.1. Dataset

The dataset used in this research uses 24 species of reef fish. The number of labels for each fish species used in the training process can be seen in Table 1. The number of labels in each species influences the accuracy of the model for identifying fish species. The more labels on each fish, the better the model for identifying fish to be identified [11].

| Species                       | Number of labels |
|-------------------------------|------------------|
| Chaetodon tifasciatus         | 405              |
| Heniochus acuminatus          | 422              |
| Forcipiger flavissimus        | 357              |
| Chaetodon auriga              | 440              |
| Chaetodon semilarvatus        | 387              |
| Chelmon rostratus             | 411              |
| Pygoplites diacanthus         | 409              |
| Pomacanthus imperator (juvenile) | 408              |
| Paracanthurus hepatus         | 386              |
| Acanthurus leucosternon       | 447              |
| Acanthurus Achilles           | 439              |
| Balistoides conspicillum      | 410              |
| Pomacanthus imperator         | 442              |
| Amphiprion ocellaris          | 435              |
| Pterois volitans              | 400              |
| Zebrasoma flavescens          | 383              |
| Channomuraena vittata         | 275              |
| Centropyge loriculus          | 407              |
| Zebrasoma xanthurum           | 400              |
| Holacanthus tricolor          | 451              |
| Pomachanths annularis         | 398              |
| Rhinecanthus aculeatus        | 410              |
| Pomacanthus paru (juvenile)   | 389              |
| Holacanthus passer (juvenile) | 423              |

Based on Table 1, it can be seen that the highest number of fish species in Holacanthus tricolor while the smallest number of labels in the Channomuraena vittata species. The difference in the number of labels in each species should not be significant. Significant differences allow the identification results
obtained tend to produce species with more labels. The number of labels used for the training dataset based on Table 1 above does not differ greatly between species.

3.2. Training loss
The process of evaluating the model at the training stage of the data can be seen in Figure 4. Based on Figure 4 it can be seen that the value of training loss is getting smaller which indicates the process of evaluating the model in order to recognize the object to be identified. A small loss value indicates the model has been able to recognize the object to be identified. The data training process carried out in this study was carried out up to step 8793 to get a weight that could recognize objects.

Weight results obtained from the training process are then used to identify fish in images, videos or real-time recording. This research obtained weight used in pictures and videos. Weight testing in the image is done to test the model to identify fish in the image and to find out the accuracy value of the model that has been made. Tests are also carried out on the video to test the model to identify moving objects.

3.3. Model accuracy
Model testing is done to see the accuracy of the models that have been made. Tests carried out by identifying 24 species of fish found in one hundred images. The calculation is done by looking at the percentage accuracy of the model in identifying each fish species. Accuracy results from fish identification can be seen in Table 2.

Based on Table 2 it can be seen that the highest percentage of accuracy in *Pomacanthis imperator* fish with an identified percentage value of 90.70%, while the accuracy value is correctly identified the lowest in *Forcipiger flavissimus* at 68.18%. The highest percentage of fish identified wrongly was in the Chaetodon semilarvatus fish at 14.00% and the lowest identified one in 0.0% was found in several fish, *Pomacanthis paru* (Juvenile), *Centropyge loriculus*, *Amphiprion ocellaris*, *Pterois volitans*, *Acanthurus achilles*, *Acanthurus leucosternon*, and *Heniochus acuminatus*. The fish with the largest unidentified percentage in the *Forcipiger flavissimus* species was 22.73, and the smallest in the *Pomacanthis imperator* was 6.98%. The overall result of the model used for identification is 82.82%.

The percentage of fish identified correctly shows the model can identify fish in the picture according to the fish species. Percentage of fish identified incorrectly can be seen in the results obtained by the model that can identify fish by providing a bounding box but the results given are not in accordance with the actual fish species. The percentage of fish not identified can be seen from the results obtained there is no bounding box in the image of the fish to be identified. The results of the three parameters can be seen in Figure 5.
Table 2. Model accuracy.

| Species                      | Correctly identified (%) | Incorrectly identified (%) | Not identified (%) |
|------------------------------|--------------------------|----------------------------|-------------------|
| Chaetodon tifasciatus        | 82.61                    | 8.70                       | 8.70              |
| Heniochus acuminatus         | 82.93                    | 0.00                       | 17.07             |
| Forcipiger flavissimus       | 68.18                    | 9.09                       | 22.73             |
| Chaetodon auriga             | 88.24                    | 3.92                       | 7.84              |
| Chaetodon semilatratus       | 76.00                    | 14.00                      | 10.00             |
| Chelmon rostratus            | 90.57                    | 1.89                       | 7.55              |
| Pygoploites diacanthus       | 87.23                    | 4.26                       | 8.51              |
| Pomacanthus imperator (juvenile) | 88.24                  | 1.96                       | 9.80              |
| Paracanthurus hepatus        | 83.64                    | 1.82                       | 14.55             |
| Acanthurus leucosternon      | 88.00                    | 0.00                       | 12.00             |
| Acanthurus achilles          | 84.78                    | 0.00                       | 15.22             |
| Balistoides conspicillum     | 82.26                    | 3.23                       | 14.52             |
| Pomacanthus imperator       | 90.70                    | 2.33                       | 6.98              |
| Amphiprion ocellaris         | 81.48                    | 0.00                       | 18.52             |
| Pterois volitans             | 83.72                    | 0.00                       | 16.28             |
| Zebrasoma flavescens         | 68.97                    | 13.79                      | 17.24             |
| Channomuraena vittata        | 86.11                    | 2.78                       | 11.11             |
| Centropyge loriculus         | 89.58                    | 0.00                       | 10.42             |
| Zebrasoma xanthurum          | 84.48                    | 5.17                       | 10.34             |
| Holacanthus tricolor         | 79.37                    | 4.76                       | 15.87             |
| Pomachanthus annularis       | 78.43                    | 1.96                       | 19.61             |
| Rhinecanthus aculeatus       | 76.00                    | 2.00                       | 22.00             |
| Pomacanthus paru (juvenile)  | 84.91                    | 0.00                       | 15.09             |
| Holacanthus passer (juvenile) | 84.62                   | 3.85                       | 11.54             |

Figure 5(a) shows the results of incorrect identification of *Zebrasoma flavescens*. *Zebrasoma flavescens* in the model were identified as *Chaetodon semilatratus*. Figure 5(b) shows the correct identification results, in this picture *Holacanthus tricolor* can be identified as *Holacanthus tricolor*. Figure 5(c) shows the results where the model cannot identify the fish in the picture. The two fish were not identified by the absence of bounding boxes and fish species names on the two fish.

There are two problems in the model testing conducted. The first problem is the model can identify fish but the results of identification do not match the actual fish species and the second problem is the model cannot identify the fish in the picture. The results of incorrect identification can be caused by the model being fooled by the shape and color of the fish that tend to be similar. Based on the results of Figure 5 (a) *Zebrasoma flavescens* identified as *Chaetodon semilatratus* can be caused by the two dominant colors, yellow. These problems can be overcome by adding a dataset that can show the differences of the two fish so that the model can correctly identify fish. The second mistake is that the model cannot identify the fish in the picture, this can be due to the fish being confused with the color of the fish with the background color. This can cause the model cannot see fish in that position. Another thing that can also be caused by the position of the fish when identified makes it difficult for the model to recognize fish. These two things can be overcome by collecting more varied data collection so that in any position the model can correctly identify fish.
Figure 5. Identification result (a) incorrectly identification (b) correctly identification (c) not identified.

4. Conclusion
Fish characterization using Deep Learning to identify reef fish has been done successfully. Identification of 24 species of reef fish can be accomplished with the highest percentage of detection accuracy in *Holacanthis tricolor* fish with a percentage of 90.70% and the smallest percentage of accuracy found in *Forcipiger flavissimus* fish with a percentage of 68.28% with an overall accuracy of the model of 82.82%.

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