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CAMARINE: A FISH SPECIES RECOGNITION SYSTEM THROUGH YOU ONLY LOOK ONCE

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Abstract: Data collection for marine sciences has always been arduous, mainly because of cost. The higher the cost is, the slower the growth of knowledge. To ease that cost, Camarine was built. An application for fish species recognition, Camarine used the algorithm You Only Look Once (YOLO) to seep through convolutional layers to detect and identify fish species. Twelve species of fish were categorized according to likeness and lack thereof. Over 4800 images were augmented to sport better results for the trained model. For testing, around 600 images were collected in various locations, including experiments done in a controlled environment. Results in detection showed an average of 88.63%, while the results in identification showed an average of 88.10%. For fishes of different appearances but the same species, the recorded accuracy was 92.66%. And for fishes of similar appearance but different species, the recorded accuracy was 86.60%. And finally, for general identification, 90.83% was the recorded accuracy. This all cumulates to the said 88.10% identification accuracy. Indeed, YOLO works well with identification, but this remains untested against turbid underwater images.

Keywords: *object detection, fish detection, You Only Look Once*

1. INTRODUCTION

If the seas and other bodies of water were to be compared to food, it would be a soup that contained a vast stock of knowledge. However, over 90% of that soup is still left unexplored. These diverse ecosystems wait to be explored and fully understood, but early scientists were constrained by the technology of their time. As such, the field of aquatic sciences is young compared to terrestrial sciences (Garrison, 2015). They could not observe nor sample aquatic species properly and data gathering was difficult to achieve (Garrison, 2015). But now that technology has caught up to cater to specific needs to study the blues, opportunities have opened for computer scientists to explore breakthroughs that could help marine scientists. Nevertheless, there have been marine biodiscovery bottlenecks due to chronic underfunding that ultimately resulted in the slow growth of knowledge, as argued by Sigwart *et al.* (2021). Though researchers got paid, it was hardly enough to publish discoveries. Diving gears and the cost of diving itself were expensive, making sampling more difficult for marine scientists.

One proposed solution was automated fish identification to ease costs. To properly detect and identify fishes, the You Only Look Once (YOLO) architecture was employed as Camarine's main framework. One problem considered in fish recognition was the fish themselves. They are diverse organisms that comprise over 33,000 different species (Oosting *et al*., 2019). With this number, species are bound to evolve convergently to have almost identical morphology, which could be difficult to identify correctly (Torres & Santos, 2018). Although visual traits such as size, shape, and color usually distinguished fish species (dos Santos & Gonçalves, 2019), accurate fish species recognition was challenging due to the similarities in the shapes and patterns or the subtle variations between the species (Jalal *et al*., 2020).

Accurate identification of species is important in assessing biodiversity, conservation efforts, and population management strategies. Misidentification of species might pose a threat not only to the species itself but also to the ecosystem through inaccurate monitoring processes and inappropriate usage of resources. In furthering conservation efforts, this might result in an unobserved decline in fish stock (Torres & Santos, 2018). With these dilemmas mentioned, we focused on determining the performance of Camarine in distinguishing similar-looking fishes and fishes that are the same species but looked differently. YOLO could just be the perfect algorithm for that.

YOLO is a powerful real-time object detector algorithm (Bouchard, 2021). As Camarine's primary framework, it made the detector efficient even in compact devices. The YOLOv4 had increased performance compared to its predecessor, the YOLOv3 (Bochkovskiy *et al.*, 2020). Speed and accuracy were both improved in YOLOv4. Using YOLOv4 would yield great fish recognition results, both for smartphones and desktop/laptop computers. Moreover, to strengthen the accuracy of detection, augmentations were added to data training. It focused on crops and cut-outs of fish gills, fins, mouth, scales, and the overall morphology of the fishes. Through this, Camarine could learn even the subtle variations of the physical appearances between species that seemed identical. Therefore, it regulated vagueness in training, particularly for fish species that looked rather similar to other fish species.

2. METHODOLOGY

2.1 Outcome generation process

The development of the system first required the identification of possible sources of data, both primary and secondary. The data were divided between training and testing sets. The training set was annotated and then augmented before being fed to the system to generate the weights file. Meanwhile, the testing set was reserved for later experiments. Upon several rounds of training and further development, the system was deemed potent enough to move forward with testing.

Experiments were performed manually by pitting the predicted and actual values. Results were recorded in a confusion matrix and mapped accordingly, whether it was true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The resulting counts were separated categorically and statistically treated using the Paired Sample Sign Test.

2.2 Sources of data

The primary source of data was the live fish that were kept in habitable tanks. Additional data were also collected from pet shops. All these data are for freshwater fish species. In terms of saltwater specimens, an expedition was set to the Manila Ocean Park. Photos were captured using GoPro 9 camera, producing high-quality media for training and testing. The secondary source of data came from photos and videos on the internet. These data were used both for training and testing.

Tables 1, 2, and 3 showed the test of identification of the 12 species under study.

Table 1. Test of different appearance but same species (A).

Common Name	Scientific Name	Count
Fighting Fish	*Betta splendens*	25 males & 25 females
Emperor Angelfish	*Pomacanthus imperator*	25 juveniles & 25 adults

Table 2. Test of similar appearance but different species (B).

Common Name	Scientific Name	Count
Guppy	*Poecilia reticulata*	50
Platy	*Xiphophorus maculatus*	50
Koi	*Cyprinus rubrofuscus*	50
Goldfish	*Carassius auratus*	50
Humphead Parrotfish	*Bolbometopon muricatum*	50
Mameng	*Cheilinus undulatus*	50
Moorish Idol	*Zanclus cornutus*	50
Silver Angelfish	*Pterophyllum spp.*	50

Table 3. Test of general identification (C).

Common Name	Scientific Name	Count
Plec	*Hypostomus plecostomus*	50
Mola	*Mola mola*	50

2.3 System architecture

Figure 1 shows the detection and identification process of Camarine. Visual media such as photos and videos would be fed to Camarine. Through YOLO, the trained weight from data training would be utilized. YOLO uses CSPDarknet53 as its backbone. Feature extraction would be done to get the important features of the fish relative to its weight. The backbone is divided into two parts, the first part circumvents the base layer, which becomes an input for the next layer, and the latter part undergoes DenseBlock. Before moving to the neck, the algorithm adds a Spatial Pyramid Pooling (SPP) block to increase the receptive field and separate the most important features. Moving up to the neck, feature aggregation would collect the data from extraction to combine. At last, final touches would be done in the head through anchor box prediction and non-max suppression. Through the k-means procedure, anchor boxes are determined that represent the dataset, and then the anchor box with the highest confidence will be chosen through non-max suppression (Solawetz, 2021).

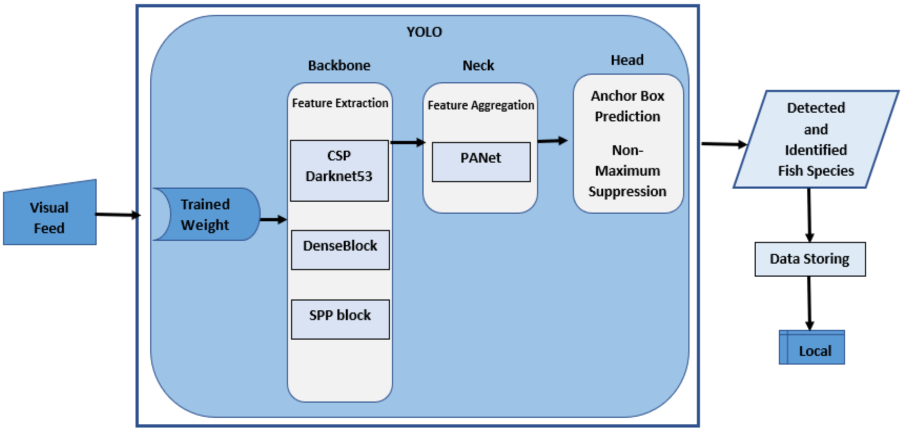
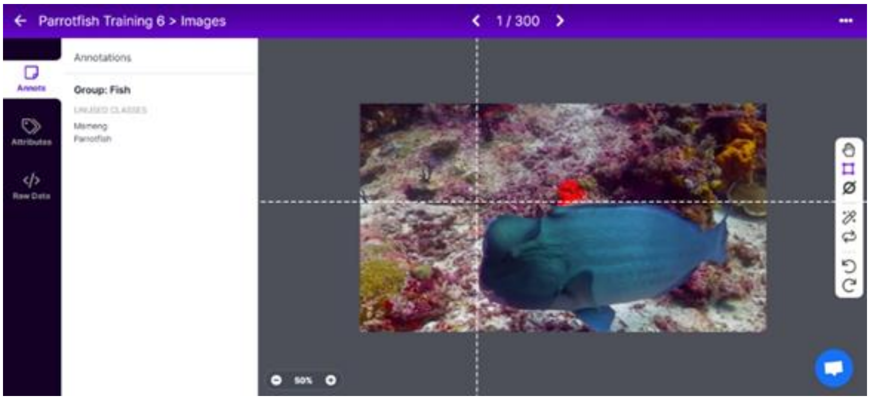


Figure 1. The system architecture of Camarine.

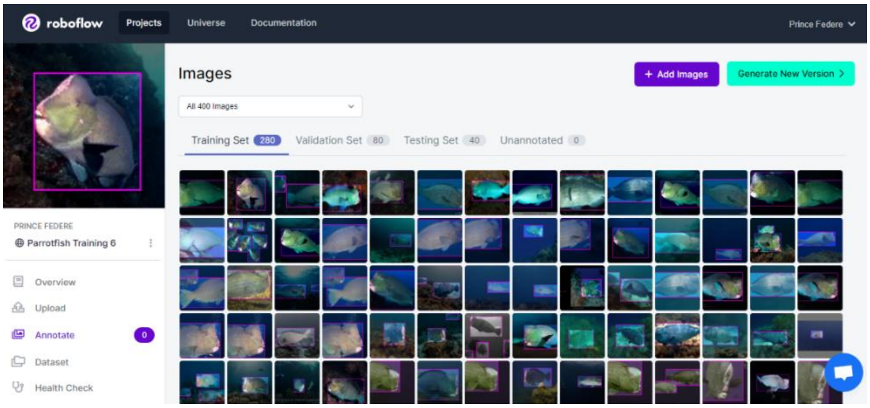
2.4 *Data training*

Using Roboflow (Figure 2a), we started our annotation by removing all null inputs. We then marked several percentages of our total training set of 400 images for each of the 12 classes. We separated them into three sections: Training (70%), Validating (20%), and Testing (10%). This division is the standard among object detection systems (Gholamy *et al.*, 2018) and was applied to all the samples (Figure 2b). We did not use automatic assistive annotations because there were no pre-existing models that catered to the specific species in our classes.

Only 8 augmentation techniques were used out of the 24 techniques available in Roboflow. Upon several pre-testing sessions, we found out that the most optimal augmentations to use are of fewer numbers. Noise distracts reflections, causing more noise. Underwater images behave differently, and the more noise it has, the more distorted their authenticity is. Figure 3 summarizes the construction of training data used by the system, as shown below.



(a)



(b)

Figure 2. The process of annotation through Roboflow.

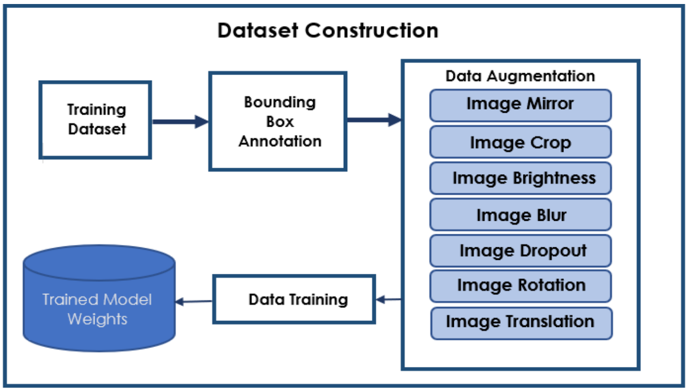


Figure 3. Training dataset construction process.

2.5 Data testing

Our sampling procedure was selective. We had a set of parameters that we followed to avoid misleading results. It was hard to rely on randomized sampling as images of fish would have been so varied that it would include problems not computable by YOLO. These self-imposed guidelines were used in training and testing. The parameters we followed were set as follows:

- The image should have at least one fish belonging to Camarine's classes.
- The image should have good pixel quality.
- The image should neither be too bright nor too dark.
- The fish in the image should not be obstructed by its school.
- The fish in the image should not be obstructed by its environment.
- The fish should neither be too near nor too far from the camera.
- The body of the fish should be at least 50% visible.
- The variety of the fish in question should be included in training.

2.6 Data analysis

In quantifying the ratings of Camarine's performance, accuracy records from the experiments were computed.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Values for true positive (TP), true negative (TN), false positive (FP), or false negative (FN) from confusion matrices were used.

3. RESULTS AND DISCUSSION

For this study, two phases of recognition were considered: detection (scanning for object presence) and identification (labeling of the detected object). The identification phase was further divided into three categories: 'different appearance but same species'; 'similar appearance but different species'; and general identification. We shortened them as Category A, B, and C, respectively.

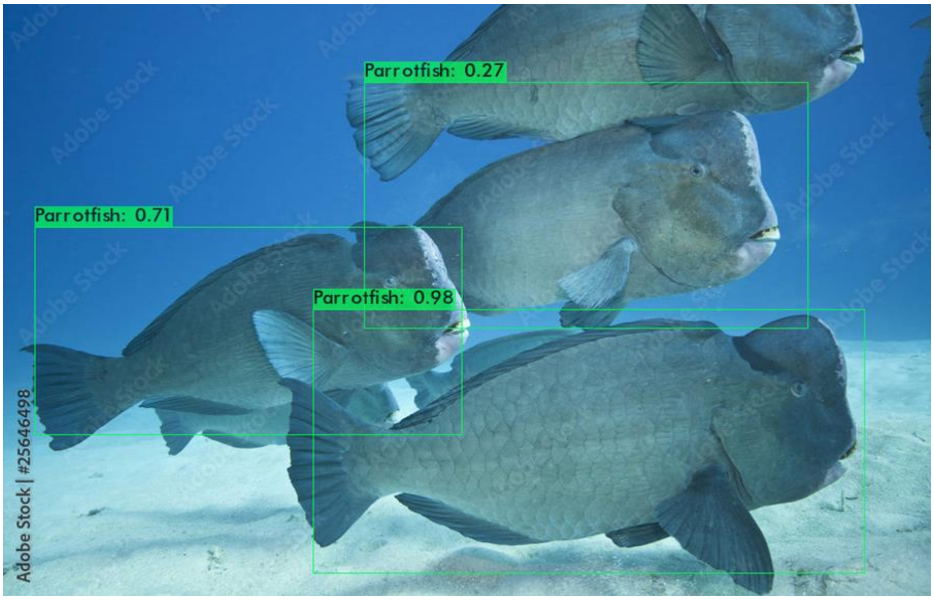


Figure 4. Use of Camarine in detecting Humphead Parrotfish.

Table 4. Detection accuracy using Camarine.

Class	Detection Accuracy
Fighting Fish	92.86%
Emperor Angelfish	92.45%
Koi	90.91%
Goldfish	84.38%
Guppy	86.15%
Platy	82.09%
Humphead Parrotfish	90.00%
Mameng	95.71%
Moorish Idol	82.19%
Silver Angelfish	87.69%
Plec	86.44%
Mola	96.00%
AVERAGE	88.64%

Figure 4 exemplifies how detection and identification works. The bounding boxes encase the individual subjects of each image with a confidence level denoting how much certainty the system has in its prediction.

The detection accuracy was rated at 88.64%. This suggests that YOLO is highly sensitive to objects. To successfully identify the detected objects is an entirely different point of discussion as the metrics used were different; in particular, the presence of true positive values.

Table 5. Identification accuracy of Camarine.

Class	Identification Accuracy
Fighting Fish	92.86%
Emperor Angelfish	92.45%
Koi	86.36%
Goldfish	84.38%
Guppy	86.15%
Platy	82.09%
Humphead Parrotfish	88.33%
Mameng	95.71%
Moorish Idol	82.19%
Silver Angelfish	87.69%
Plec	86.44%
Mola	96.00%
AVERAGE	88.10%

Table 5 presents all the results from the identification aspect of the experiments. While each class might have had its own problems with identification, they all achieved an accuracy of at least 80%. The average accuracy was rated at 88.10%. The highest among these values was from the class of Mola, 96.00%.

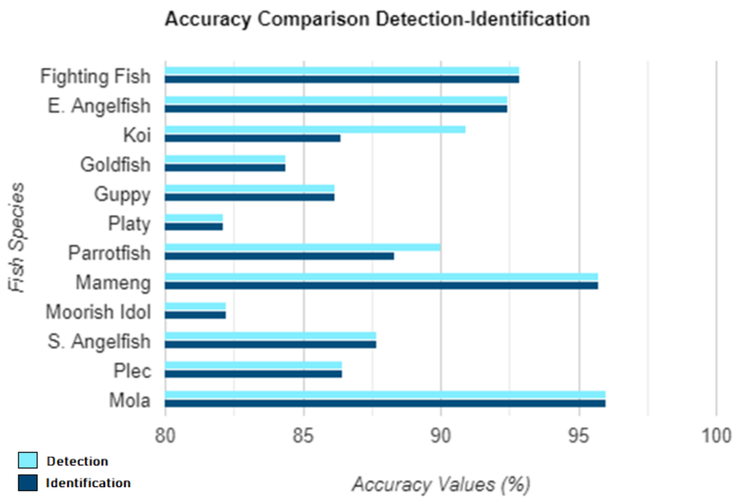


Figure 5. Accuracy comparison between detection and identification metrics of Camarine.

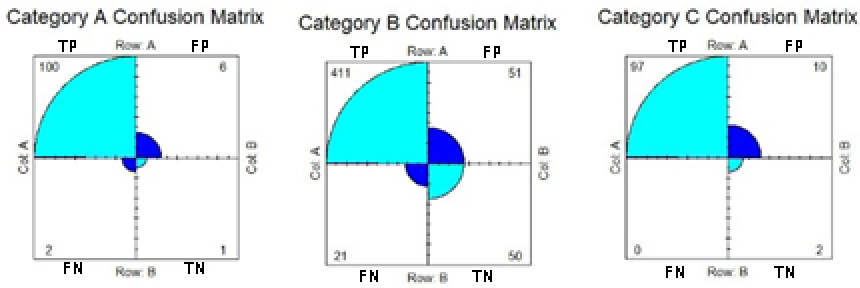


Figure 6. Confusion matrices. Category A, B, and C showing an average of 88.10% TP.

Figure 5 shows the comparison between detection and identification. Not straying far from its identification value, the detection rating of Camarine weighed 88.64%. Only Koi and Humphead Parrotfish detection accuracy had a difference from the rating of their identification accuracy. To deviate from the results of identification, the bounding boxes were reassessed. The criteria for detection did not look critically at whether or not the actual output matched the expected output. As long as it produced a non-null value, it would be weighed as TP. Some FP-valued boxes belonged to this instance. From 90.91% detection accuracy of Koi, it was only valued at 86.36% for identification. And from 90.00% detection accuracy of Parrotfish, it was only valued at 88.33% for identification.

Figure 6 details the ending of the evaluation of the collated results from the three categories, where the data were divided into separate confusion matrices. From Table 5, there is the final and overall accuracy of 88.10%. Using the data from these confusion matrices, it would put Category A as 92.66%; Category B as 86.60%; and Category C as 90.83%. The ratio between true positive and true negative values to false positive and false negative values was consistent in all the categories, in great favor of the true positive values.

Camarine has the hardest time differentiating between similar-looking species (in particular, between Koi and Goldfish). On one end, Camarine fares well with dissimilar-looking fishes that belong to the same species. It scored higher than subjects from General Identification category.

The classes of Platy and Moorish Idol scored relatively low due primarily to the difficulties in data gathering. It skewed the accuracy ratings through low-quality images (e.g. subjects being too far from the frame, lighting too dim or water too turbid, schooling of fish, etc.). This lack of uniformity is not observed in other samples. This further proves the quality of training files is just as important—if not more—as the robustness of the algorithm itself. This could also speak for the characteristics of the fishes themselves. Their diverse morphology, particularly in their size and coloration, could be too much for computer vision.

4. CONCLUSIONS

After the experiments and recording sessions, the achieved detection accuracy was rated at 88.63%. In testing the viability of bounding boxes, identification accuracy was recorded. It was rated at 88.10%; only marginally a few decimal points lower than its detection counterpart. The identification rating was further divided into three categories of 'different appearance but same species' (92.66%); 'similar appearance but different species' (86.60%); and general identification (90.83%).

Image augmentations did a fine job of helping differentiate among fish species. We limited our augmentations due to how the weights reacted with them; reflections became distorted and false positives became imminent. We also observed a decline in true positives. Specifically, with the augmentation technique of noise increase, Camarine performed relatively poorer. We generally focused on augmentations that only affected the basic features of an image, such as flipping, rotation, and the additional properties within bounding boxes. We omitted augmentations that would cut the features of fish, such as cropping. We also did not include techniques that would change the color of the image to avoid straying the weights from the actual values of its classes. Ultimately, we found out that the best for Camarine is to stay with the basic augmentation techniques, as they perfectly supplement the properties of an underwater image.

YOLO is a reliable algorithm for real-time object detection, as seen from the results generated. It has a long way from becoming perfect, most certainly, but compared to other algorithms existing right now, it stands out. As stated before, YOLO had difficulties in detecting small objects that appeared in groups and detecting objects that had unusual aspect ratios. Camouflage was also a problem, like in most object detection systems. If it is hard for human vision, it would also be hard for computer vision. Schooling was also a problem, as it hid most of the defining features of a fish. The high proximity of a fish to its surroundings made the calculation for bounding boxes confusing. As it goes, results are awful with reflections on glasses. YOLO, same with other algorithms, could not differentiate a real fish from its reflections. It stands to reason that it would go beyond the goals of the algorithm. Most of the problems of YOLO could be reinforced by training, but those would not be perfect solutions.

Just as it was envisioned when the idea for it was initially conceived, Camarine could be used to help marine scientists further their research. Its relatively high accuracy rating is enough for Camarine to be used for its intended purpose of helping in underwater surveys. However, the results for recognition and enhancements could be further improved using the results of the experiments. The prototype was retrained, and a new weights file was created according to the findings of this study, though the results of that new training are yet to be quantified.

5. RECOMMENDATIONS

For a more specialized implementation, a hardware apparatus could be built alongside Camarine and have it deployed on reefs. For problems extending beyond the scope of this study, we hope the proceeding researchers to experiment with more augmentation techniques. We limited our augmentations because of the results of our initial testing, but the necessary augmentations may differ depending on the subjects of the detection. Furthermore, we advise to be cautious with selected augmentations and make sure that it is suitable for the classes of the system. We recommend looking into ways an image can be enhanced to help clear the environment. Most often than not, the environment itself hinders good recognition. Considering that fish live in unpredictable aquatic environments, this tends to happen.

6. ACKNOWLEDGEMENT

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