The Challenge of Aqua Creatures Specie Classification in the Aquarium Innovation Theme

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Abstract

The aqua creatures are lively, diverse, and abundant; nowadays, their survival depends on the proactive endeavor of human society on the environment cares; recognizing them conveniently and effectively is the first step to care. Recently, the fast-growing applications of the computer vision techniques along with the Internet-of-Things attract both the researchers' and the practitioners' attention. Such applications give the alternative to the traditional approaches to observe the moving objects more efficiently with higher precision through image capturing. In the common aquarium themes, the compartment may contain the same aqua-creature specie or non-mutual offensive species. The objective of the mono-specie scenario identification is to tell the difference between the compartments' species, while the other scenario can identify the specie of the individual aqua-creature within the multi-specie compartment. This paper is the few studies that aim to facilitate the aquarium operations, especially in the animal state observation. It discusses the technical challenges in dealing with the aqua-creatures images collected from the aquarium scene. For this purpose, the paper presents two comprehensive aqua-creature identification approaches were applied the neural networks for different operational scenarios. The contribution of this paper is to explore the potential in caregiving operations and the aquatic education based on the computer vision techniques of species identification. Further derived applications, such as illness detection and adult-creature counting, can be widely applied in the real aquaculture farm.

Keywords: Computer vision, Neural networks, Analytic framework, Service engineering

1 Introduction

Our oceans have been polluted by various sources for years, including from the chemical waste, microplastics, oil-spills, and household trashes. This getting-worse ocean pollution has significantly jeopardized the survival of aquatic-creatures. Not only had put the aqua creatures in danger, but also impacted to those topper predators throughout the food-chain [1]. Although we have put the measurements and regulations in place to counter this ocean pollution, but the outcomes are yet convinced. Therefore, to cherish our oceans more proactively, how to intensify the public awareness and make change the attitude through education will be the key to success [2]. The aquarium, delivering the aqua creatures related knowledge, making the public awareness on ocean caring, is posited to be an effective and convenient place where presents lively and amazing species to the audiences. The *Monterey Bay Aquarium* is one of the perfect examples who has dedicated themselves to ocean preservation education for years [3].

On the other hand, despite of the world slacking economic growth, the aquarium business has been relatively less-impacted and still maintaining high annual growth [4]; this implies that people are constantly interested in the aqua-creature presentations, especially the parents with their children and it is worth to invest in the innovation attracting more audiences. Many aquariums have launched their mobile applications to interact with the audiences is a proof of such an innovative investment.

Recently, the applications of the artificial intelligence (AI) are emerging fast in many fields and widely applied in facial recognition in security and automatic optical inspection in quality control. Applying these technologies on the aqua-creature specie-identification seems booming in exploring the potential valuable applications to this aquarium industry, such as using both texture and shape features as inputs and applying the statistical procedures [5] or applying the Convolutional Neural Networks (CNN) on the images [6] to classify the aqua species are widely used. However, each aqua theme has its own obstacles and needs to apply these techniques, several common questions were often raised: (1) how the computer

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vision can help in improving the aquarium operations; (2) what is the best practice framework to initiate the project; (3) what will be the costs in terms of the hardware investment and the software development; and (4) can these techniques be manageable by the aquarium staffs. Form these various concerns of aquariums, it clearly implies that the solutions are unlikely to simply replicate the practice from others.

In the actual aquarium theme, offering mobile app has become a common approach to interact with the potential audiences and the visitors in the scene. Getting the impression from the emerging facial recognition applications, the mobile users are more interested in image-driven information retrieval. A following question is the aquariums already applying the classification to offer a better experience in interacting with the audience into their apps' feature? This paper revisited the apps published in the *Google Play* that offer the fish-identification features; some of these apps limit the identification of certain water area and species; for instance, the *FishID* claims it can quickly identify the fishes found in the Indo-Pacific area limit to the selected species of fish and coral [7]; the *Marine Aquarium Fish Guide* provides an encyclopedia with lots of interesting facts about aquarium plants and marine fish with colorful photo fish [8] the user has to look up the database visually from image to image to merit with the fish found. Apparently, such apps cannot satisfy the audiences' need when they wish to learn more on about the target aqua creature in the aquarium. This is the current app's gap where the specie classification can fit in the aqua knowledge and interests to provide a more convenient way during the interaction with the aquarium.

However, each aquarium has its unique features to exhibit and the content of storytelling. Usually, these features and contents are aquarium location dependent and its neighbor nature environment oriented. These business constraints discourage the aquariums to use third-party apps to distinguish the uniqueness from the competitors. After all, making the differentiation is still the fundamental survival rule of running the business. Therefore, the further questions are, can the aquarium develop the specie classification models by themselves? If the answer is positive, then the methods used must be easy use and understandable. What are the side-effects and factors that they should avoid when training these models? To save the repeated time in making try-and-error, the framework must be comprehensive and flexible to cope with the aquarium specific needs.

The objectives of this work are: (1) to tell the specie difference to prevent the aqua-creature was miss displaced; (2) to tell the specie difference between compartments to facilitate the visitor learning; (3) to tell the water contaminated condition in the compartments to replace water in time; and (4) to identify the species of the identified individuals in the multi-specie compartments with high background noises. The paper presents the challenge of handling with the collected low-contrast images and applying the divide-and-conquer tactics to serve various aquarium operation needs.

2 Data Collection

The data were collected from the "Aquatic Animal Center [1]" by webcams. The compartments cultivate single or few specific species of aqua creatures, respectively. The aquarium compartments are often near-closed systems, it means that every time the caregiver feeds the aqua-creatures, the residual nutrients remain in the compartment and the aqua creatures also excrete waste into the water. These leftovers are toxic to the aqua creatures within. This *Nitrogen Cycle* is a biological process that involves the continual circulation of nitrogenous compounds such as ammonia, nitrite, and nitrate to process wastes in the natural water [9]; it is the main reason that causes the water blurred and poor visibility from outside the compartment. This will increase the difficulty in applying the computer vision techniques through time times.

2.1 Tilted Images

There were six aquarium videos taken with different time lengths recorded in the *MPEG4* format—each frame dimension is *1920x1080* pixel which is quite big and will consume more computing resources in processing it. There were 114,419 images extracted from these videos. The videos were not taken at a precise and unified manner, the distances and the angles between the camera and the aquarium compartment exterior varied. The Table 1 illustrates few sample images by compartments; apparently, the angle of *V1* was higher than *V2*, both *V5* and *V6* were taken upside down, and each compartment has its own noise situation requires various image adjustment. Undoubtedly, the poor quality of image will significantly impact the accuracy and the complexity during the specie classification process. The top-left image with a yellow box shows the area where the process should concern; the rest of the area is irrelevant to the classification. Therefore, the images must be extracted only the concerning area in the compartment, respectively. To avoid the distortion, the proper coordinate transformations also need to apply to the extracted images to adjust the viewports perpendicular to the compartment centers accordingly. The transformation calculation requires the coordinates of the four corner points about the concerning area and the desired dimensions to project the adjusted image [10].

[1] http://aac.ntou.edu.tw/

Table 1. Sample tilted images by compartments

Compartment	Compartment	Compartment
V1	V2	V3
		
V4	V5	V6
		

The Table 2 illustrates the sample transformed images. However, once the transformed images are set, the following image preprocessing tasks can be commenced, including: (1) reducing the background noises—such as from the light source side effect and the compartment fixtures; (2) smoothing and sharping the aqua-object' edges—the common treatments to enhance the image quality; (3) tagging the aqua-objects within—positioning the box coordinates surrounding the aqua-object; and (4) augmenting the aqua-objects—generating more samples to cover the uncaught angles and coordinate shifts.

Table 2. Perspective transformed sample images

Compartment	Compartment
V2	V3
	

2.2 High Noise Images

There were six additional aquarium videos taken with different time lengths recorded in the MOV format—QuickTime File Format (QTFF), few sample images by specie are illustrated in Table 3. Each compartment contained multiple species of aqua creatures. Unlike the previous videos, these were taken with care, especially the distances and the angles of camera lens. Obviously, the background of these images contains the reflection noises caused by the light. There were 211,039 images processed in total; each compartment still has its own noise situation requires various image adjustment. Again, the light and the background will interfere the computer vision model training.

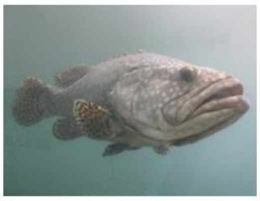
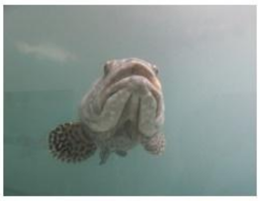
2.3 Solo-Living Specie Images

For large size aqua creatures, putting a few of them into a single compartment will give the creatures more living space. Some species require more spaces, and some species are hostile or special habitat that cannot coexist with others into the same compartment. Since the compartment only contains few creatures within, the classifying these images with less samples can be conducted otherwise. The Table 4 illustrates the solo living specie images, labeled with the class *FD*, and crowd living ones labeled with the class *FC*. Apparently, these classes of the aqua creatures are quite different in size; the solo-living ones usually are much bigger (dimensions) than the crowd ones. This implies choosing the sample images for model training will mater the result.

Table 3. High noise images by compartments

Compartment	Compartment	Compartment
V7	V8	V9
		
V10	V11	V12
		

Table 4. Solo and crowd living species sample images

Classes	Sample Images			
FC				
FD				

For example, the solo-living images, if the samples mixed with the front faces and the body shapes may not converge the classification model. Simply because the features are quite different between faces and the bodies. For those crowd species, because they usually swim side by side, it is a challenge in sampling. The sample image cannot contain more than one fish, otherwise, the classification model may “think” the specie has two tails. On the other hand, the caregiver gives more attention, eliminating the waste in water frequently to reduce the *Nitrogen Cycle* side-effect, of these large size aqua creatures than the smaller ones. The water quality will affect the outcomes in model training and the classifying the species.

3 Classification

The aquarium often requires checking the aqua object’s living behavior to see if there is any abnormality, for example, the illness will make the creature move sluggishly; the lacking off oxygen or too much toxic sediment at the bottom will force the creatures move up toward the water surface; or comparing the appearance change at different times. To meet the requirement under various scenarios, the specie classification approaches must also be developed accordingly.

3.1 Tilted and High Noise Images

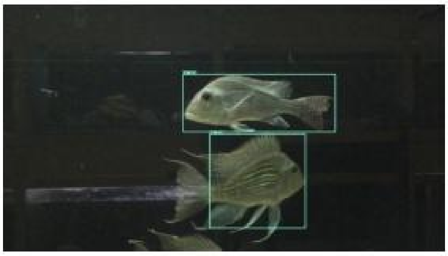
This paper has put tremendous efforts to label the objects from the images, the aqua creatures’ bodies, to collect the object coordinates into a data structure; a sample record illustrated in Table 5. There are six fields in the structure: (1) **Class**—the specie identification; (2) **Top-Left Point**—the top-left point of the object rectangle; (3) **Bottom-Right Point**—the bottom-left point of the object rectangle; (4) **Image-File**—the file name of the image; (5) **Image Width**—the width of the source image; and (6) **Image-Height**—the height of the source image.

Table 5. Sample aqua object label data structure

Class	V2		Image File	F000073.jpg
Top-Left Point	1388	3	Image Width	1920
Bottom-Right Point	1918	227	Image Height	1080

This paper applied the transfer learning based on the pre-trained **ResNet50** model—very suitable for computer vision such as object detection and image classification tasks [11] and applied the **Single Shot Multibox Detector** (SSD)—a special single neural network for object detection to deal with various object sizes and resolutions [12] approach to detect the objects in the image. The sample validated results from the trained model, illustrated in Table 6, shows the model has successfully identified the objects.

Table 6. Aqua object specie identification sample results

Frame ID	2848	17860
Class V2		

Nevertheless, the reason why some objects were not identified was because those objects with high noises were deliberately ignored during the labeling. The objects over the noises were not labeled, including the criteria of: (1) the overlapped objects; (2) the partial shape objects; (3) unclear shape objects; and (4) the objects along with the background reflection in the frame. The classification results were very satisfying by the aquarium caregivers: (1) **mAP** (Mean Average Precision)—measures how accurate the predictions were—0.847; (2) **mAR** (Mean Average Recall)—measures how good the trained model found all the positives were—0.776; and (3) **IoU** (Intersection over Union)—measures the overlap between two boundaries—0.95.

A worth noted lessen learn to obtain better detection results was the image preprocessing does matter. The training will save lots of time if the image with less noises, to resolve this problem, this paper conducted an additional image preprocessing: (1) find the image with the least number of objects, no target object at all is the best; (2) use this image as the base frame; (3) extract the target objects from other image according to the labeled box coordinates; (4) apply image processes, sharpen, canny—edge outlining, and morphological—shape feature detection, illustrated in Table 7, if the target object's shape was not clear; (5) the shape compute XOR-NOT logic operation against the image and the base frame to get the common background frame; (6) paste back the target sharpened objects according to the labeled box coordinates to the common background frame; and (7) generate a new image to train. This additional preprocessing will eliminate the noises a lot and let the training focus on the target objects and ignore the others with small contour areas.

Table 7. Image sharpen process

Original	Canny	Morphological
		

3.2 Solo-Living Specie Images

Each image was classified with the tags denoting which class the image should belong to. This paper applied a deep learning model to calculate the feature vectors for each image. The deep learning model extracts each image characteristics into a feature vector by applying the transfer learning of **Inception V3** model [13]. After calculating all Cosine distances between images, the model applied the **Multidimensional Scaling** (MDS) [14] to project images onto a plane fitted to the given distances, illustrated in Figure 1, and conducted the **Hierarchical Clustering** (HC) [15] to partition the images into groups, illustrated in Figure 2, to tell which image's features are closer to the others based on their distances in between.

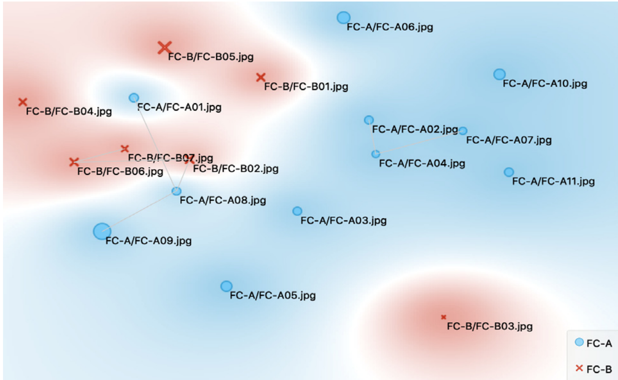


Figure 1. MDS classification diagram

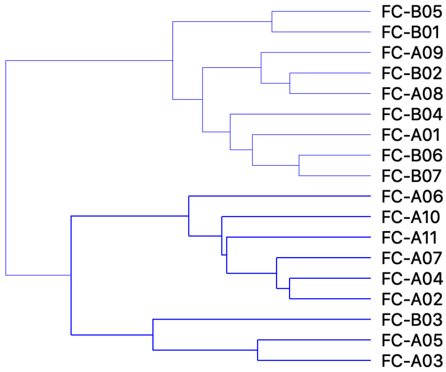


Figure 2. Hierarchical clustering diagram

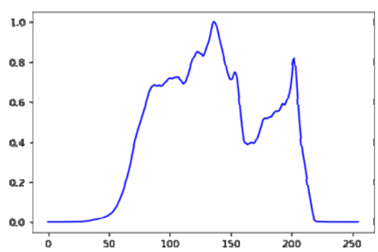
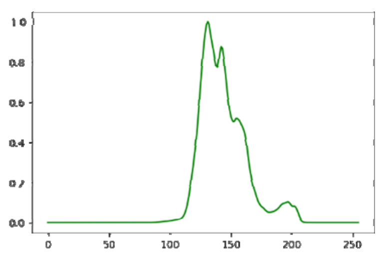
To validate the trained model, this paper picked few samples from the same species, but mixed with the images with multiple fish to see if the model is robust. In the MDS classification diagram, it shows that there were two images miss-classified, namely the *FC-A01* and the *FC-B03*; while in the HC diagram, two main clusters *FC-A* and *FC-B*, there were three images miss-classified in *FC-B* and one image miss-classified in the *FC-A* cluster.

This approach applying the unsupervised methods is simple and easy-to-operate for aquarium. Since the compartment only contain a few objects within, the area besides the objects is the water. This paper applied **Histogram** calculation [16] against the water regions and recorded the water condition changes daily into a data structure: (1) compartment identification—a unique number of the aquarium; (2) observed date—the timestamp of the image taken; (3) the water regions—multiple records, the coordinates of water; (4) images—multiple records, the image taken against the water regions; and (5) the color histograms—multiple records, the histogram of each GRB color plane. This histogram history data is especially useful to the caregivers; they can see the water deteriorating trend and double check the recent water conditions to see if the compartment cleansing work is needed.

3.3 Approaching Detection

The histogram can also tell the lively condition about the aqua creatures. To simplify the calculation, this paper transformed the color images into grayscale ones to reduce the histogram dimensions to one, illustrated in Table 8. Sample histograms. If the histogram value changes through a period are "small" by comparing a preset reasonable standard deviation valve—applying the **Time Series** analysis to tell the idleness of a series of signals; it means the creatures were moving slowly from place to place [17]. A reminder is sent to the caregivers that the creatures might have health problems or more aeration is needed. Using the data structure of histogram history, the difference is the color planes transformation, and the target region is the whole image.

Table 8. Sample histograms

Original	Gray Scaled	Histogram
		
		

As far as the object detection concerns, some of the images were "blank", the aqua creatures stayed in far places or hidden in the bottom of the compartment. There is no need to process these no-object images. The grayscale histogram can help exclude those images were under the accepted valve.

4 Implementation Framework

The purpose of the proposed framework aims to build up an aqua-creature characteristic database; it helps the average observer to identify the specie or even more about the health conditions of the creature easily through image observations. The framework illustrated in Figure 3. Aqua-Creature identification framework, has six major tasks: (1) **Setup Observation Environment**—including the "*Prepare the Aquarium Container*", "*Setup Edge Device*", "*Setup Distance Measuring Sensors*", and "*Setup Cameras*" subtasks. The edge device serves as a low power-consumption computing unit which has hardware interfaces to connect to an ultra-sonic distant sensor and a camera. This edge device is deployed on each wall of the container. (2) **Setup Information Systems**—including the "*Setup Network*", "*Setup Database*", and "Devices Connectivity Tests" subtasks. The reliability of the sensor device network is crucial to the quality of the identification; a series of rigorous connectivity test are needed. (3) **Develop IoT Programs**—including the "*Distance Measuring Sensing*", "*Picturing Trigger*", and "*Write Characteristic Database*" subtasks. Predefining a distant range according to the sensitivity of the distance measuring. (4) **Collect Creature Images**—the edge device continuously takes the pictures when the creature approaching into the distance range. (5) **Tagging Creature Characteristics**—including the "*Develop AI Algorithms*", "*Derive Creature Identification Model*", and "Write Creature Characteristics Descriptor" subtasks. The descriptor—labeling the target object coordinates—will be stored into the database as the AI algorithm training dataset. (6) **Creature Identification Verification**—if the correctness is satisfied the need, then the observed specie identification process is done, otherwise go back to the "*Develop AI Algorithms*" subtasks.

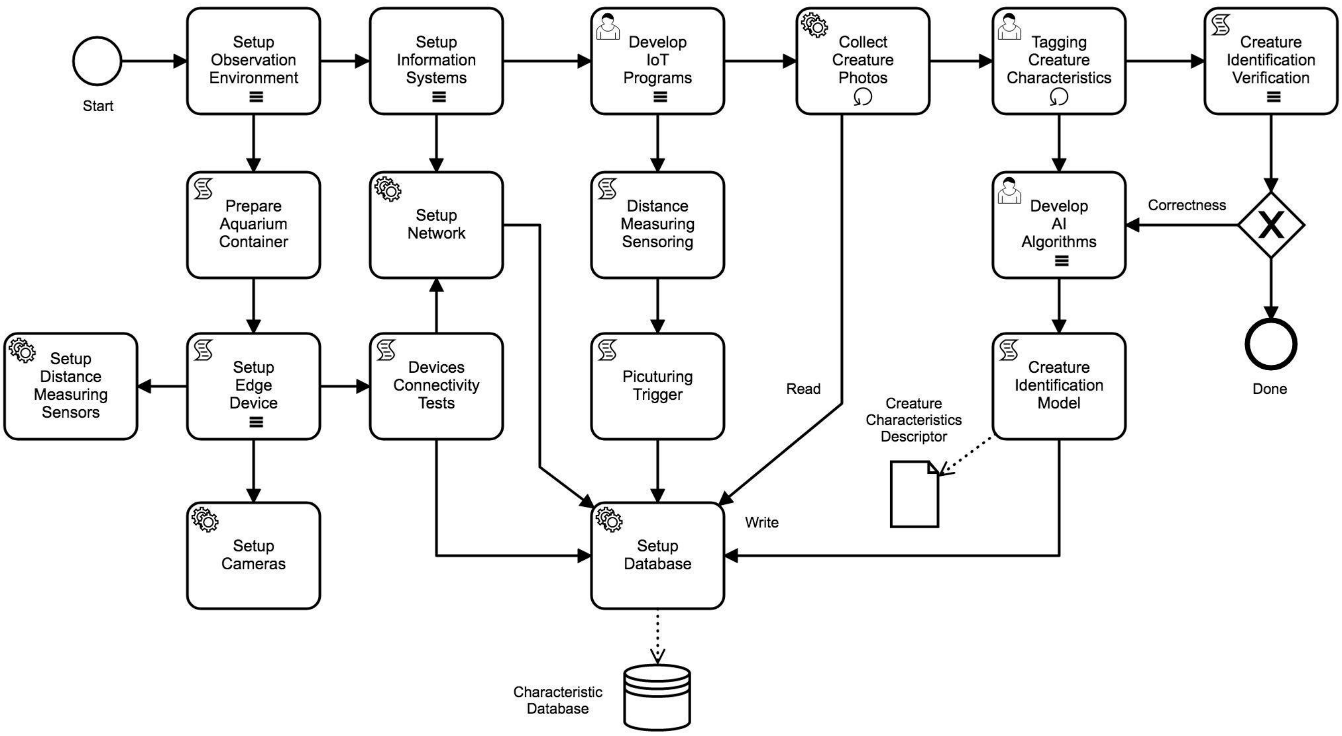


Figure 3. Aqua-Creature identification framework

To keep image history data requires high performance database system. The resolution and the angle of the observing camera is crucial to the accuracy of the training model. Since the compartment conditions may change from time to time, new species will need to be introduced; the preprocessing and training configuration may also need to be tweaked; a flexible analytical framework will make the specie classification tasks conducted in a consistent way.

This paper used **NoSQL** database [18] to store these history images just into a big data table. All multiple records were stored in the vector data fields. The GPUs, Solid-State Disk, and high-capacity RAM are needed to save the computation time during the training process. The whole specie classification application was developed on top of **OpenCV** [19] and **TensorFlow** [20] framework to make the classification more structural, consistent, and easy to collaborate with the others.

5 Conclusion

Aquariums carry social responsibility of aquacultural education to the public. Their business relies on the success of the exhibition of aqua creatures and the branded product sales. How to improve the customer intimacy is the goal of these aquariums' digital transformation [21]. Using mobile devices to retrieve information, interact with apps, and taking photos has become a part of our daily life. Current aqua creature related apps including those offered by the aquariums are still using a text dictionary-like or visual look up the static images to extract information. This gives aquariums a compelling opportunity to embrace the image classification technology to attract and enhance the customer experience. This paper aims to fit the intimacy gap, daily aquarium care, light source, and address the critical success factors—water condition, camera position, model training, and information system—of such an initiative of aqua creature specie classification.

Future research direction will fall into the number counting and behavior tracking against the aqua creatures [22] in the compartment using computer vison. The objective of the future work is to incorporate the process with the aquarium daily operation; it is different than those physical solutions such as using the super-sonic. The challenge will be the size—growing up—and the shape—bit by another aggressive creature—changing. The model must be able to track the individuals in compartment. The future direction is to prepare the grounding for further aquaculture and aquarium industry use.

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Biographies

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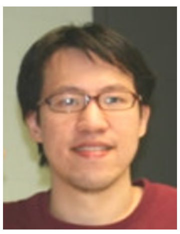

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