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FISH IDENTIFICATION AND FRESHNESS CLASSIFICATION THROUGH IMAGE PROCESSING USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

The demand for fish is continuously rising due to its high nutritional value. Inexpert manual determination of fish freshness can cause false assessment and result to the possibility of food poisoning. This study developed an android application that automatically identifies the three most consumed fish in the Philippines, namely milkfish, round scad, and tilapia. Through image processing, the application classifies the freshness of the fish from level 1 (stale) to level 5 (fresh) by using the RGB values of the eyes and gills as well as determining its remaining shelf life. The software was developed by iterative learning of a feed forward neural network with 30 fish samples per species that were used to obtain a total of 800 images each for the eyes and gills. The results of the study showed that the device yields acceptable results in identifying the fish and in determining its freshness.

Keywords: artificial neural network, feed-forward neural network, digital image processing, matrix laboratory, edge detection.

INTRODUCTION

Fish demand has been increasing worldwide due to its high nutritional value fit for consumption. Being one of the best sources of omega-3 fatty acids which are essential for brain growth and development, many consumers substitute fish with pork, beef, and chicken meat to meet their daily protein needs.

As much as the consumers wanted to buy and eat freshly caught fish, it is common to local markets to display and sell two-week old fish prior to the day they were collected from the seas. To guarantee the safety of fish consumers, one must practically check for quality indicators to determine whether the fish they are going to eat is fresh or not [1]. The conventional method of determining fish freshness is through sensory evaluation of the gills and eyes of the fish. Although these factors are observable by the naked eye, a regular consumer cannot accurately identify the freshness of the fish just as some highly skilled personnel.

In this regard, this paper aims to develop a method that could conveniently identify, classify the freshness and predict the remaining shelf life of the raw fish.

CONCEPTUAL LITERATURE

The most consumed fish products in the Philippines is milkfish (Chanoschanos) which is consumed 13.0 g/day or 4.7 g/year, followed by round scad (Decapterus punctatus) which is consumed 12.8 g/day or 4.7 g/year, and tilapia (Oreochromis niloticus) which is consumed 12.5 g/day or 4.6 g/year[2].

Milkfish, known in the Philippines as bangus (*Chanoschanos*), is an essential food that is widely cultured in the Philippines and remains in high demand for distribution in the Indo-Pacific region and is an important commodity in Southeast Asia. It is considered the Philippines' national fish because it has the largest production and consumption among the other fish species. Philippines is among the top three milkfish producers in the world with its smooth, sweet flesh and melt-in-the-mouth belly fat. And according to Dr. Rafael D. Guerrero III, an academician and a former executive director of the Philippine Council for Aquatic and Marine Research and Development (PCAMRD), bangus contributed to Philippines' economic state with 55 percent of its production in the world comes from the country [3].

Round scad, known in the Philippines as galunggong (*Decapterusmacrosoma),* has been one of the most acquired small aquatic species of fish that can be harvested in huge quantities in the Philippines [4]. The fish is a staple for most Filipinos living in coastal areas. The pricing of round scad is considered a barometer of the economy of the nation with more than 7,100 islands and is commonly known as the poor man's fish for its very affordable market price.

Saint Peter's Fish, also known as tilapia (*Oreochromis niloticus*), is recognized in aquaculture as the third most important fish worldwide because of its high protein content and large size which grows rapidly to harvest size in six to seven months [5]. Tilapia is quite popular in the Philippines and has been introduced into local waterways and is farmed for food. It is common in almost all the major rivers and lakes in the country, including Laguna de Bay, Taal Lake, and Lake Buhi.

Related studies on fish freshness evaluation

There are many studies conducted that used different methods in relation with evaluating the freshness of the fish. One study in [6] used an electronic nose that will determine fresh fish and preserved fish. The fish samples' odor profile was gathered and were normalized. Their features were extracted using Case-Based Reasoning method.

A study in [7] proposed a system that can classify the freshness of fish that focused on the three most consumed aquatic species in the Philippines, namely bangus, galunggong, and hasa-hasa, through the use of image processing on the color of fish's eyes and gills. The basis of the quality evaluation of the fish freshness used in the said study is in [8]. It also determines the shelf life of a raw fish after it has been stored in slurry ice for preservation. It used MATLAB as the programming language to easily determine the freshness of fish and Support Vector Machine (SVM) as an algorithm that classifies clusters of data coming from the captured images. The methods used for image processing section comprise of image enhancement, image segmentation, edge detection, RGB detection, feature extraction and feature comparison. By doing so, the captured image is compared to the images stored in the database.

In the system developed in [9], fish freshness was determined by taking images of the fish using mobile phone without some added extra sensors used. The said study based the standard ofquality assessment of fish using sensory evaluationin [10]. Extracted information from the image was analyzed and trained with ANN, and with these, four different features were to determine the fish freshness. The first three were all related to the shape of the fish and the other one was related to its color. In this study, 90% of freshness detection of fishes was correctly recognized from the obtained features of the shape. The results were proven success to detect the freshness of the fish with the used of these techniques.

Automated determination of kinds of fish

Edge detection for image analysis was used in [11]. Different fish species have unique edges that defined the boundaries and regions of the image and differentiate fishes like poisonous with dangerous, and from salt and fresh water. The said study used canny method which gave accurate and successful results for identifying fish with MATLAB as the software analyzer.

Moreover, in [12], a system was presented that used object's shape and color for identifying an object with constant illumination of 674 lumens and constant distance of 40cm, and used ANN to train the captured image's values for evaluation resulting to 99.9996072% accuracy.

SYSTEM DESIGN AND IMPLEMENTATION

The software design is made using MATLAB, C++, OpenCV and Android Studio. MATLAB (Matrix Laboratory) is a programming language developed by Math Works and is used for numerical analysis, computations and creating neural networks. After training the data sets in MATLAB, the generated C codes will be used for transferring MATLAB codes to Java codes. OpenCV is a library that is widely used for image processing and can be easily imported in Android Studio. Android Studio is an integrated development environment that is widely used in creating user interfaces for smart phones and offers great functionality in creating high quality applications and designs.

The user has two options upon opening the application: "Choose image from gallery" or "Capture image using camera". From the image, there are three different parts of the image that will be analyzed; eyes, gills and skin. These parts are extracted by using codes from OpenCV then its RGB values will be saved. The RGB values will be the input of the neural network and it will give an output that corresponds to its freshness level (1 - stale, 5 - fresh).

RESEARCH DESIGN

Figure-1 shows the block diagram of the study for training phase. The figure includes image acquisition of the fish eyes and gills through the phone camera and will be taken under a constant illumination. The image will then undergo edge detection for automatic identification of the variety of fish. The image will then be segmented into three parts: the eyes, the gills, and the body. The RGB data gathered from the fish eyes, gills, and body will be processed and fed to the artificial neural network. Feed-forward Neural Network will be the Artificial Neural Network architecture used in this study for freshness classification and fish variety identification of the images. Back propagation algorithm will be used for training the ANN to achieve the desired output. The trained output will then be generated into C codes by MATLAB Coder implemented for android use.

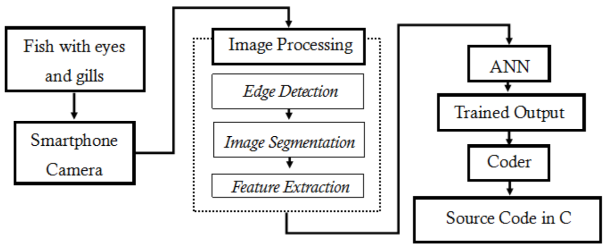

Figure-1. Block diagram (training).

On the other hand, Figure-2 shows the block diagram of the study for testing phase. When a user captures an image of the fish, the application analyzes the image and then the data will be fed to the feed-forward neural network.

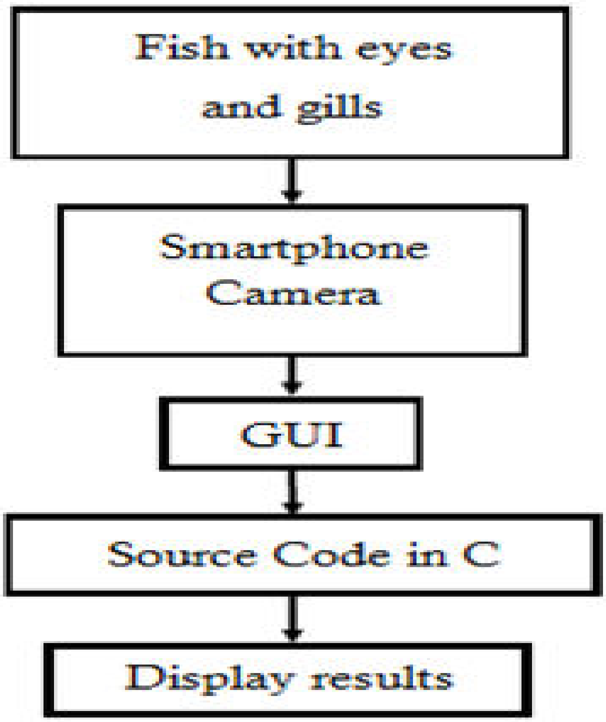

Figure-2. Block diagram (Testing).

Image processing

Figure-3 shows the image processing flowchart. The image of the fish is captured using the phone camera. Before image segmentation, the algorithm will check the orientation of the image and rotate it since image processing technique is made to analyze the image in landscape or it will cause some errors. The image is then segmented into three parts: the eyes, the gills, and the skin. The white background of the image is removed first before segmenting the gills and the skin. The output values gathered from segmenting the image will be fed to the feed-forward neural network. Fish identification and freshness classification will then be displayed via phone screen.

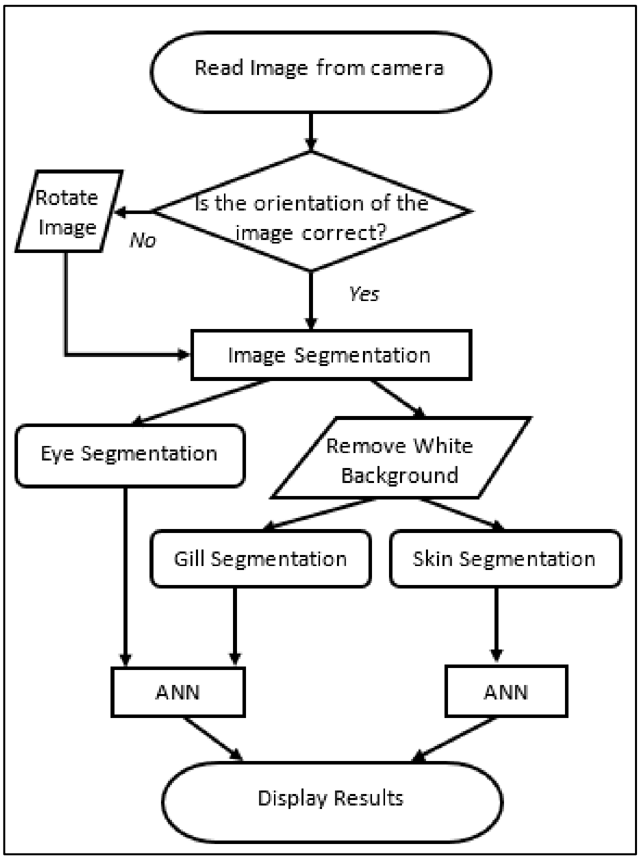

Figure-3. Image processing flowchart.

Figure-3 shows the process in removing white background. From left to right then top to bottom: the original image, the grayscale image, the binarized image, complement image, the circular mask and the masked image.

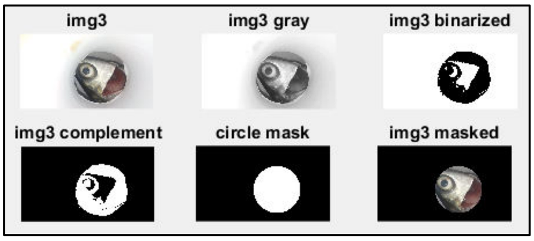

Figure-4. Removal of the white background.

Meanwhile, a set of images segmented from a sample image, as shown in Figure-4, are used for the identification, classification and computation of shelf life of a fish.

Figure-5. Segmented images.

Figure-6 shows the eye segmentation flowchart. During image acquisition, the center of the eye is placed under the cross marking in the camera view. The marking serves as the reference point for image segmentation. A circular mask is then applied to the cropped image. The mean of the red value in the image is then fed to the feed-forward neural network.

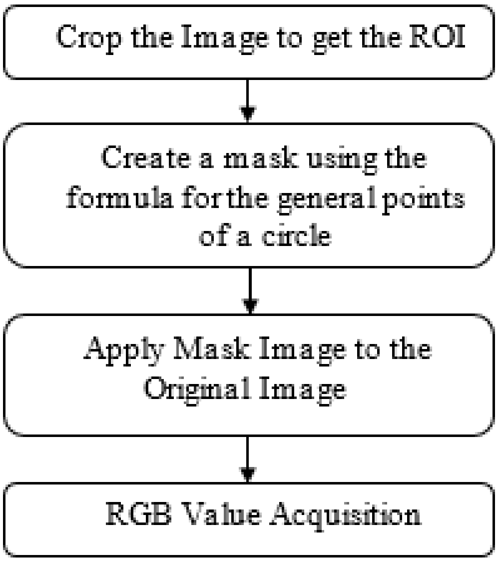

Figure-6. Eye segmentation flowchart.

Figure-5 shows the images for masking the eyes. From left to right: the cropped eye, the mask image, and the cropped eye with the applied mask. The following equation is used to create a circular mask to be applied on the cropped eye image:

$$(x-h)^2+(y-k)^2=r^2 \qquad (1)$$

where:

x = the abscissa of any point of the circle
y = the ordinate of any point of the circle
h = the abscissa of the center point of the circle
k = the ordinate of the center point of the circle
r = the radius of the circle

The points (x,y) represent the pixels of the image lying on the circle while the points (h,k) represent the centroid of the pupil of the sample fish. The matrix of the created mask is then multiplied to the matrix of the cropped image to generate the masked cropped eye image.

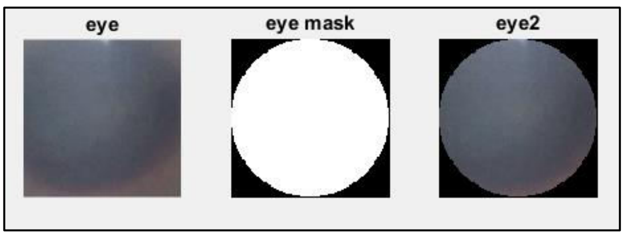

Figure-7. Eye masking.

Figure-8 shows the process for segmenting the gills. After removing the white background, the image is cropped to get the region of interest (ROI). The CIELAB color space or CIE L*a*b* color space is an attempt at providing a perceptually uniform color space which is necessary for segmenting the gills.

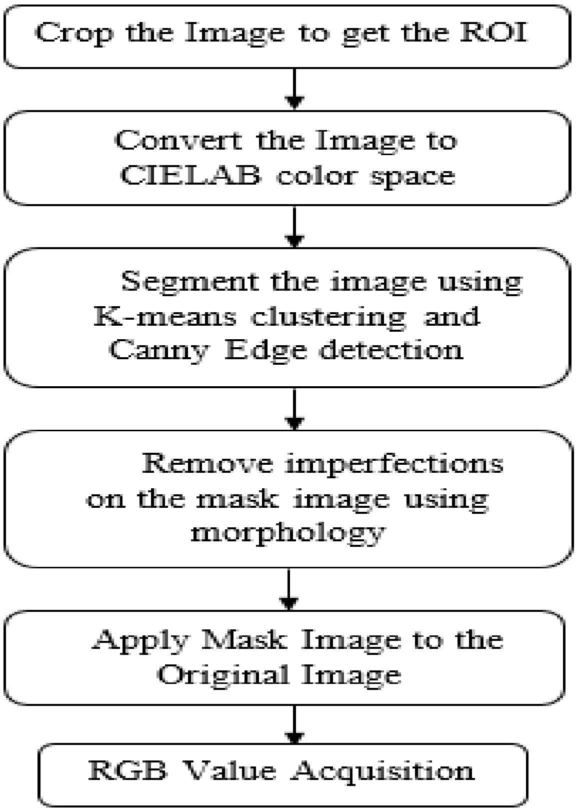

Figure-8. Gill segmentation using K-means clustering.

Figure-6 shows the process for segmenting the gills; from left to right: the cropped image, image in CIELAB color space and the clustered image of the gill using k-means algorithm.

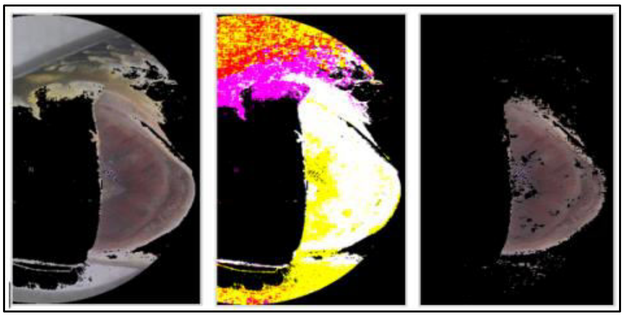

Figure-9. Gill segmentation using K-means clustering.

K-means clustering is a data-partitioning algorithm that splits a given n data set (data with no defined categories or groups) into a fixed number of k clusters. The image was divided into three clusters by using k-means clustering based on the two-color channels, the red-green chromaticity (a*) and the blue-yellow

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chromaticity (b*), from CIELAB color space. Initially, cluster centers are assigned at random and continuously change as each data is assigned to its respective cluster which results to new cluster centers until these no longer change after several itineration.

For the k-means clustering, the following equation is used to measure the distance between each data and the initial cluster center:

$$dist(x, y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{2}$$

where:

dist = distance between the data x to the mean y of the cluster
x = data
y = mean of the cluster
n = number of features

The resulting distance is used to determine which cluster a specific data is closer. This is repeated to each data depending on the desired number of cluster to which an image will be divided. The two-color channels of the CIELAB color space represent the number of features while the initial mean of the cluster is determined by the randomly assigned cluster centroid.

The equation presented is used in acquiring the mean of the newly grouped data or cluster:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3}$$

where:

$\bar{x}$ = sample mean
n = number of data values
x = data value

Therefore, there was no definite cluster where the gills would be assigned to. As observed, the generated a* and b* cluster centers of the gills are positive and has the biggest sum among the cluster centroids. The proponents have used that information to automatically select the respective cluster with the gills.

Figure-7 shows the continuation of the process for segmenting the gills. From left to right: segmented gills, grayscale image, and image using Canny Edge Detection. Edge detection is an important tool for image processing used for finding the boundaries of objects within an image. In this study, Canny Edge Detection was used to detect edges and suppress noise at the same time. It then finds the intensity gradient of the image and applies maximum suppression to remove any unwanted pixels which may not constitute the edge.

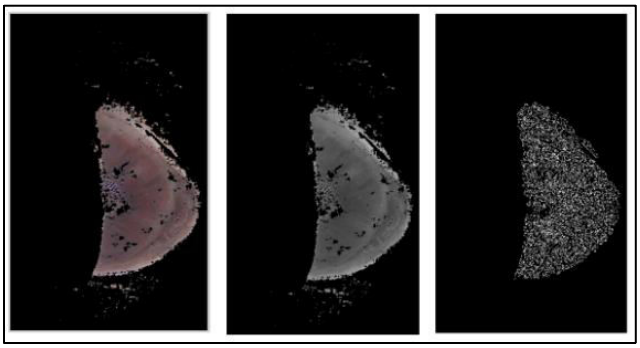

Figure-10. Gill segmentation using canny edge detection.

Figure-8 shows the continuation of the process for segmenting the gills. From left to right: dilated image, filled image and morphological closing image.

Morphological image processing checks an image with a small shape or template called a structuring element. A disk-shaped 2-D morphological structuring element was used on the image to preserve the circular nature of the gills when applying dilation. It is used to fill the gaps and smoothening the edges in the image.

A masked image made by using the algorithms above is then applied to the cropped image. The centroid of the object is then measured and is used as the reference for cropping the image. The mean of the red value in the image is then fed to the feed-forward neural network.

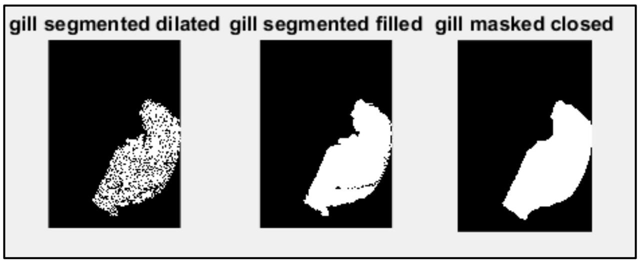

Figure-11. Gill segmentation using morphology.

Hardware development

An android smartphone was used for the study. It has an android operating system version 5.1 Lollipop, 2 GB RAM, and a 13-megapixel camera with autofocus and LED flash.

A 3D printed smartphone case and tube, ashown in Figure-9, was used in this study for easy image capturing of the fish's eye and gill. The case was designed specifically with exact dimensions for the phone. The tube was designed to have a constant illumination and a certain height of the fish when acquiring the image necessary for the study. The model is made of PLA or Polyactic Acid Plastic. It is made up from plants like corn, potatoes and sugarcane; hence it is biodegradable. The proponents chose the material due to its flexibility and can be used to print smaller details and sharper corners.

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Figure-12. Case and tube model for the smartphone for easy capturing of the fish's eye and gill.

EXPERIMENTS AND RESULTS

The field testing is verified through sensory evaluation by fisheries experts from the Philippines' Bureau of fisheries and aquatic resources.

Tables 1, 2, and 3, as shown in the appendix, the lists of freshness level and identification of the fish freshness analyzer and the sensory evaluation from BFAR on 30 samples of milk fish, round scad, and tilapia, respectively.

Tables 4, 5, and 6, presents the comparison of the results of the freshness level classification of the proposed system compared with the sensory evaluation of certified aqua culturists.

The confusion matrix shows the summary of results from the test conducted with the representatives from BFAR. The columns show the output class generated by the freshness analyzer while the rows show the target class obtained through sensory evaluation of the checkers from BFAR. The green diagonal cells show the number and the percentage of correctly classified samples of the fishes while the orange cells show the incorrectly classified number of samples.

In this confusion matrix as shown in Figures 10, 11, and 12, 27 out of 30 Milkfish, 28 out of 30 Round scad, and 30 out of 30 Tilapia samples, respectively, were correctly classified with an acceptable tolerance within one level of degree. This results to 90%, 93.33%, and 100% accuracies for the classification of Milkfish, Round scad, and Tilapia, respectively, during this test.

Freshness Analyzer
(Output Class)

Sensory Evaluation (Target Class)	CLASS	1	2	3	4	5	
	1	**3** 10%	**1** 3.33%	**0** 0%	**0** 0%	**0** 0%	100% 0%
	2	**0** 0%	**3** 10%	7 23.33%	**0** 0%	**0** 0%	100% 0%
	3	**2** 6.67%	**1** 3.33%	**6** 20%	**1** 3.33%	**0** 0%	80% 20%
	4	**1** 3.33%	**0** 0%	**2** 6.67%	**2** 6.67%	**1** 3.33%	83.33% 16.67%
	5	**0** 0%	**0** 0%	**0** 0%	**0** 0%	**0** 0%	- -
		50% 50%	100% 0%	100% 0%	100% 0%	100% 0%	**90%** **10%**

Figure-13. Confusion matrix of the test results of milk fish freshness classification.

Freshness Analyzer
(Output Class)

Sensory Evaluation (Target Class)	CLASS	1	2	3	4	5	
	1	**2** 6.67%	**0** 0%	**0** 0%	**0** 0%	**0** 0%	100% 0%
	2	**0** 0%	**0** 0%	**3** 10%	**0** 0%	**0** 0%	100% 0%
	3	**0** 0%	**1** 3.33%	**5** 16.67%	**0** 0%	**1** 3.33	85.71% 14.29%
	4	**0** 0%	**1** 3.33%	**8** 26.67%	**5** 16.67%	**3** 10%	94.12% 5.88%
	5	**0** 0%	**0** 0%	**0** 0%	**0** 0%	**1** 3.33%	100% 0%
		100% 0%	50% 50%	100 0%	100% 0%	80% 20%	**93.33%** **6.67%**

Figure-14. Confusion matrix of the test results of round scad freshness classification.

Freshness Analyzer
(Output Class)

Sensory Evaluation (Target Class)	CLASS	1	2	3	4	5	
	1	**0** 0%	**0** 0%	**0** 0%	**0** 0%	**0** 0%	- -
	2	**0** 0%	**0** 0%	**1** 3.33%	**0** 0%	**0** 0%	100% 0%
	3	**0** 0%	**2** 6.67	**4** 13.33%	**2** 6.67%	**0** 0%	100% 0%
	4	**0** 0%	**0** 0%	4 13.33%	**11** 36.67%	**2** 6.67%	100% 0%
	5	**0** 0%	**0** 0%	**0** 0%	**1** 3.33%	**3** 10%	100% 0%
		- -	100% 0%	100% 0%	100% 0%	100 0%	**100%** 0%

Figure-15. Confusion matrix of the test results of tilapia freshness classification.

CONCLUSIONS

After a series of tests and evaluations with the representatives from the Bureau of Fisheries and Aquatic Resources, the analysis of the results shows that the device can identify fish and classify its freshness. As observed, each type of fish differs in its corresponding RGB values of its classes therefore three feed-forward neural networks were used for freshness classification. Since constant illumination is one of the most crucial factors in image processing, independent light source must be contained from the external source whenever pictures are taken through the aid of the customized tube and case. The feed-forward neural networks were generated in MATLAB

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while the whole algorithm and graphical user interface was created in Android studio. Using OpenCV Library functions, image processing of the application was made achievable in Android Studio.

Future studies include fish identification and classification of fish freshness using a smartphone subjected to varying illumination sources and a more detailed classification of fish freshness i.e. introduction of divisions between the different classes e.g. the division between class 1 and 2; 1.2, 1.4, 1.6, 1.8.

APPENDIX

Table-1. Field testing of milkfish.

Fish sample	**Sensory evaluation**	**Fish freshness analyzer**	
	Freshness level	**Identification**	**Freshness level** (Eyes & Gills)
B1	4	Milkfish	4
B2	3	Milkfish	3
B3	4	Milkfish	5
B4	3	Milkfish	4
B5	4	Milkfish	4
B6	3	Milkfish	3
B7	4	Milkfish	3
B8	3	Milkfish	1
B9	4	Milkfish	3
B10	3	Milkfish	3
B11	3	Milkfish	3
B12	3	Milkfish	1
B13	4	Milkfish	1
B14	3	Milkfish	3
B15	3	Milkfish	3
B16	2	Milkfish	3
B17	2	Milkfish	3
B18	2	Milkfish	3
B19	2	Milkfish	2
B20	2	Milkfish	3
B21	2	Milkfish	3
B22	3	Milkfish	2
B23	2	Milkfish	3
B24	2	Milkfish	2
B25	1	Milkfish	1
B26	2	Milkfish	3
B27	2	Milkfish	2
B28	1	Milkfish	1
B29	1	Milkfish	2
B30	1	Milkfish	1

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Table-2. Field testing of round scad.

Fish sample	Sensory evaluation	Fish freshness analyzer	
	Freshness level	Identification	Freshness level (Eyes & gills)
G1	4	Round scad	3
G2	4	Round scad	3
G3	4	Milkfish	3
G4	4	Milkfish	3
G5	4	Round scad	4
G6	4	Round scad	4
G7	4	Milkfish	3
G8	4	Round scad	3
G9	4	Milkfish	2
G10	3	Round scad	3
G11	3	Round scad	3
G12	2	Round scad	3
G13	3	Round scad	2
G14	3	Round scad	3
G15	3	Milkfish	3
G16	4	Milkfish	5
G17	4	Round scad	4
G18	3	Milkfish	3
G19	4	Round scad	4
G20	4	Round scad	4
G21	2	Round scad	3
G22	1	Milkfish	1
G23	2	Round scad	3
G24	1	Milkfish	1
G25	5	Round scad	5
G26	4	Round scad	5
G27	4	Milkfish	5
G28	3	Round scad	5
G29	4	Round scad	3
G30	4	Milkfish	3

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Table-3. Field testing of Tilapia.

Fish sample	Sensory evaluation	Fish freshness analyzer	
	Freshness level	Identification	Freshness level (Eyes & gills)
T1	3	Tilapia	2
T2	4	Tilapia	4
T3	4	Milkfish	3
T4	3	Tilapia	3
T5	4	Tilapia	5
T6	4	Tilapia	5
T7	4	Tilapia	5
T8	3	Tilapia	2
T9	4	Milkfish	4
T10	4	Milkfish	4
T11	3	Milkfish	4
T12	2	Tilapia	3
T13	4	Round scad	3
T14	4	Tilapia	3
T15	4	Tilapia	4
T16	4	Tilapia	4
T17	5	Round scad	5
T18	5	Tilapia	4
T19	4	Tilapia	4
T20	3	Round scad	3
T21	3	Tilapia	3
T22	4	Round scad	3
T23	4	Tilapia	4
T24	4	Tilapia	4
T25	3	Milkfish	3
T26	4	Tilapia	4
T27	5	Tilapia	5
T28	4	Tilapia	4
T29	4	Tilapia	4
T30	3	Tilapia	4

Table-4. Freshness level classification results of milk fish using the proposed system and the sensory evaluation made.

No.	Proposed System	Sensory Evaluation	No.	Proposed System	Sensory Evaluation
1	4	4	16	4	4
2	3	3	17	3	3
3	5	4	18	4	5
4	4	3	19	3	4
5	4	4	20	4	4
6	3	3	21	3	3
7	3	4	22	4	3
8	1	3	23	3	1
9	3	4	24	4	3
10	3	3	25	3	3
11	3	3	26	3	3
12	1	3	27	3	1
13	1	4	28	4	1
14	3	3	29	3	3
15	3	3	30	3	3

Table-5. Freshness level classification results of round scad using the proposed system and the sensory evaluation made.

No.	Proposed System	Sensory Evaluation	No.	Proposed System	Sensory Evaluation
1	3	4	16	4	5
2	3	4	17	4	4
3	3	4	18	3	3
4	3	4	19	4	4
5	4	3	20	4	4
6	4	3	21	2	3
7	3	4	22	1	1
8	3	4	23	2	3
9	2	4	24	1	1
10	3	3	25	5	5
11	3	3	26	4	5
12	3	2	27	4	5
13	2	3	28	3	5
14	3	2	29	2	3
15	3	3	30	4	5

Table-6. Freshness level classification results of tilapia using the proposed system and the sensory evaluation made.

No.	Proposed System	Sensory Evaluation	No.	Proposed System	Sensory Evaluation
1	2	3	16	4	4
2	4	4	17	5	5
3	3	4	18	5	4
4	3	3	19	4	4
5	5	4	20	3	4
6	5	4	21	3	3
7	5	4	22	4	3
8	2	3	23	4	4
9	4	4	24	4	4
10	4	4	25	3	3
11	4	3	26	4	4
12	3	2	27	5	5
13	3	4	28	4	4
14	3	4	29	4	4
15	4	4	30	3	4

REFERENCES

[1] M. Abdulkadir, G. I. Abubakar and A. Mohammed. 2010. Production and characterization of oil from fishes. ARPN Journal of Engineering and Applied Sciences. 5(7): 769-776.

[2] Bureau of Fisheries and Aquatic Resources. 2014. Philippine Fisheries Profile.

[3] E. Davao. 2016. The Backbone of Philippine Aquaculture. Available: http://edgedavao.net/agri-trends/2016/06/01/the-backbone-of-philippine-aquaculture/.

[4] P. C. Pastoral, S. L. Escobar and N. J. Lamarca. 2000. Round Scad Exploration by Purse Seine in the South China Sea, Area III: Western Philippines. In: Proceedings of the Third Technical Seminar on Marine Fishery Resources Survey in the South China Sea, Area III: Western Philippines. SEAFDEC Special Paper No. SEC/SP/41. Southeast Asian Fisheries Development Center, Bangkok, Thailand. pp. 49-64.

[5] Y. Fessehaye. 2006. Natural mating in Nile tilapia (Oreochromis niloticus L.): implications for reproductive success, inbreeding and cannibalism. Wageningen UR. Wageningen, Netherlands. p. 150.

[6] M.S. Najib, N.H. Zamberan, N. Zahed, F.A. Halim, M.F. Zahari, W.M. Mamat and H. Manap. 2016. Fish quality study using odor-profile case-based reasoning (Cbr) classification technique. ARPN Journal of Engineering and Applied Sciences. 11(10): 6691-6696.

[7] L.K.S. Tolentino, J.W.F. Orillo, P.D. Aguacito, E. J. M. Colango, J. R. H. Malit, J. T. G. Marcelino, A. C. Nadora and A. J. D. Odeza. 2017. Fish Freshness Determination through Support Vector Machine. Journal of Telecommunication, Electronic and Computer Engineering (JTEC). 9(2-5): 139-143.

[8] S. E. Johnson, I. J. Clucas. 1996. Maintaining Fish Quality: an Illustrated Guide. Natural Resources Institute (NRI). Chattham, UK.

[9] A. Karagöz. 2013. Fish Freshness Detection by Digital Image Processing. Dokuz Eylül University. İzmir, Turkey.

[10] E. Larsen, J. Heldbo, C. M. Jespersen and J. Nielsen. 1992. Development of a method for quality assessment of fish for human consumption based on sensory evaluation. Developments in food science. 30: 351-358.

[11] S. Malik and T. Kumar. 2016. Various Edge Detection Techniques on Different Categories of Fish. International Journal of Computer Applications. 135(7): 6-11.

[12] J. P. N. Cruz, M. L. Dimaala, L. G. L. Francisco, E. J. S. Franco, A. A. Bandala and E. P. Dadios. 2013. Object recognition and detection by shape and color pattern recognition utilizing Artificial Neural Networks. In: Information and Communication Technology (ICoICT), 2013 International Conference of. pp. 140-144.