A Proposed Rapid Image Processing-Based Method for Fish Freshness Determination on Mobile Application

Thu Thi Anh Nguyen, Minh Le, Hai Ngoc Vo,
Duc Tran Hong Nguyen, Tuan Tran Anh Phuoc and
Tuan Van Pham

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Proposed Novel Fish Freshness Classification using Effective Low-Cost Threshold-based and Neural Network Models on Extracted Image Features

Anh Thu T. Nguyen, Minh Le, Hai Ngoc Vo, Duc Nguyen Tran Hong and Tuan Tran Anh Phuoc, Tuan V. Pham

The University of Danang - University of Science and Technology, Danang, Vietnam
ntathu@dut.udn.vn, minhle.lm28@gmail.com, vongochai.vnh@gmail.com, nguyentranhongduc.dmx@gmail.com, thagsau@gmail.com, pvtuan@dut.udn.vn

Abstract. The quality of food has been becoming a great concern not only in Vietnam but also all over the globe. Quality of fish in terms of fish freshness is therefore highly attracted by the research and industry community. This paper proposes novel fish freshness classification models based on threshold-based and neural network-based approaches on extracted image features. These features are identified based on physiological characteristics of fish eyes at the fresh and stale statuses, including 12 intensity slices, minimum intensity, haziness, histogram, and standard deviation. The nine proposed models (4 threshold-based and 5 neural network-based) were trained on the training set composing of 49 fisheye images of the 4 Crucian carp fishes at two main groups of time points (0-5hour and 21-22hour after death) and tested on the testing set including 18 images from the fifth fish sample. The results of 8/9 models at their 100% of accuracy on the training set and 7/9 at their 100% of accuracy on the testing set. These results confirm our four proposed feature assumptions and reveal the feasibility of the proposed models based on extracted features which are non-invasive, rapid, low cost, effective and environmental-effect minimized and consequently, highly potential for further studies and mobile application for freshness classification.

Keywords: Fish Freshness, Image Processing, Feature Extraction, Classification, Threshold, Neural Network.

1 Introduction

In the food industry, fish freshness is the key factor to determine the quality of fishery products. A food with stale or spoiled fishes not only lessens its nutrient, taste but can lead to food poisoning for its customer. One of the main agents of spoilage is bacteria which grows quickly in number when the fish dies, especially in warm and humid weather [1] such as in tropical countries such as Vietnam.

Since the importance and popularity of fishery foods, through years there have been many studies on different approaches for fish quality and freshness measurement or prediction. In order to detect fish freshness, there have been two main methods - sensory and instrumental evaluations, according to Ni et al. in 2017 [4]. The sensory evaluation can be conducted through the senses of smell, taste, touch and hearing by humans.

Meanwhile, the instrumental assessment has been studied and developed based on chemical, biological, physical, electrical approaches, etc. such as Torrymeter [5], biosensor, nanotechnology [6] and more.

However, the sensory method is normally limited due to personal experiences or is sometimes discernible and misinterpreted. Most of the instrumental methods also show the disadvantage of equipment utilization, experience of fresh fish sorting, time-consumption, expensiveness, invasion, etc. Therefore, these equipment are not always available for customer usage. Nevertheless, among a diversity of instrumental methods, the image processing based techniques for fish quality and freshness determination are noticeable since its non-invasive, safe and mostly low-cost tools which bases on calculation and analysis of variation of intensity, spectrum, etc. of the digital images captured from the object.

To name a few, a study in 2012 [6] observed the change and quantification of RGB color indices of the fish eye and gill images at different periods of time of death in comparison with a meter Torrymeter on three types of fishes. This showed that the meters provided precise and fast measurements while the RGB indices could only show the deterioration from day 3 of spoilage and a variety of species have different levels of deterioration. In 2014, Jun Gu and Nan He [7] introduced a rapid and non-devastive method by calculating statistics features of gray values of eye iris and the surface texture features to accomplish freshness detection. The results reached the detection accuracy rate of 86.3%. Also in 2016, Isaac et al. [8] introduced an automatic and efficient method for gill segmentation for fish freshness validation and determination of any pesticide with the results of maximum correlation of 92.4% with the ground truth results. In 2018, Navotas et al. showed a built android application that automatically classifies the freshness of three types of fish at 5 levels by using RGB values of eyes and gills with acceptable results, but needs independent light source and aided devices [2].

In this study, according to our assumptions, we firstly identified meaningful fisheye features on the fisheye images which could help differentiating fresh status from stale status of the fishes. The features were then extracted through image processing steps to input into nine low-cost corresponding classification models based on threshold and neural networks for training and then for testing. Optimal threshold values and parameters were selected for the models based on the self-built training dataset to reach possible highest accuracy at the balance of true positive and true negative rates. Subsequently, the models were tested on the self-built testing dataset for their performance evaluation.

2 Hypothesis Analysis and Proposed Assumptions

According to published studies on physiological characteristics of fish eyes when a fish turns from fresh to stale status [10] and from our observations on self-built dataset as demonstrated in Fig. 1a, our assumptions on noticable fisheye image features are given and by that, the image processing methods are then implemented to extract these noticeable features of the iris and the pupil of the eye for later process. A fish anatomy is demonstrated in Fig. 1b.

(a) (b)

Fig. 1. Our self-built data at different time points after death (0, 1, 2, 3, 4, 5 and 21, 22 hours) (a) and a fish anatomy [11] (b).

Particularly, when a fish is fresh, its eyes turn out bright, clear, transparent, full. These characteristics may probably relate to the transparency, fullness and smoothness of the cornea and anterior chamber layers of the eye. Consequently, the pupil area looks really dark. However, when a fish is spoiled, its eyes become opaque, cloudy, wrinkled, sunken, and pupils are grey as if there was a haze layer covering the whole eye. Therefore, the pupil area becomes grayer. This means the frequency distribution of pixels in the pupil area lying in a very low value zone (around black color) will be shifted to a higher value zone (around gray color) in the intensity histogram. This leads to our assumptions 1, 2, 3 on the color intensity of pixels in pupil area for feature extraction supporting classification purpose. On the other hand, the iris of the fresh fish's eye seems to be more colorful than the stale fish's one whose iris generally demonstrates opaque white color. Besides, the fresh fish eye with a full, smooth and bright surface makes it easy to display spectacular reflection spots when being imaged, and then the intensity at these pixels will reach saturation. This means the color intensity variation in the fish eye image, especially in the iris area, is higher. This leads to our next assumption 4 on color intensity variation.

Assumption 1: The background intensity of the pupil area (without spectacular reflection effect) increases as the fish gets stale. Corresponding extracted feature: Minimum Intensity Feature - F1.

Assumption 2: The haziness level on the whole eye area increases as the fish gets stale. Corresponding extracted feature: Haziness Feature - F2.

Assumption 3: The group of low-intensity pixels (within the pupil area) in the intensity histogram will shift far away from value "0" as the fish gets stale. Corresponding extracted feature: Histogram Feature - F3.

Assumption 4: Level of variation in intensity at the iris area will decrease as the fish gets stale. Corresponding extracted feature: Standard Deviation Feature - F4.

Based on these assumptions, our attempt is to classify fresh and stale fishes based on these extracted features using threshold-based and neural network-based and evaluate on the performance of these methods.

3 Methodology

The overall diagram of our proposed fish freshness classification models including training and testing phases as described in Fig. 2. In that, the collected images in both training and testing phases are pre-processed and then processed for feature extraction.

These features enter the corresponding training processes to find the best threshold values for threshold-based models or optimal parameters for neural network models on the training dataset. The trained models will be used to classify the input image from the testing dataset into Class1 (fresh status) or Class 2 (stale status).

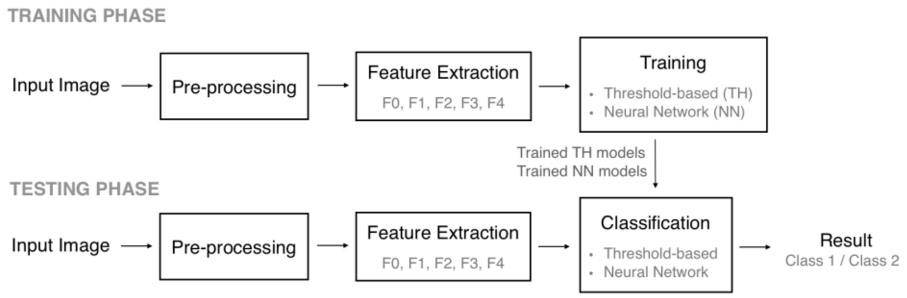


Fig. 2. The overall diagram of the proposed fish freshness classification models.

3.1 Pre-processing

The eye region composing of the iris and pupil area in the captured image was segmented for analysis. This region of interest is resized to an uniform size of 250x 250 pixels, and then converted to grayscale image instead of RGB image. No normalization or white balance is applied on the segmented region. The purpose of this pre-processing step is to reduce computational complexity of the developed algorithms as will be presented in next sections.

3.2 Feature Extraction

In order to eliminate unexpected factors such as unexpectedly specular reflection received when capturing fisheye images, and also to reduce the workload of image processing, we firstly extracted a primary feature - noted as F0 - including a set of 12 central cutting slides along the eye image. In addition, four more secondary features - noted as F1, F2, F3, F4 - were then derived from F0 for further analysis relating to our assumptions and support distinguishing two classes of fresh and stale fish.

12 Intensity Slices Feature (F0). Twelve intensity slides are extracted on every 250x250 pixel fisheye image. In that, one intensity slice (a vector of 1x250 pixels) is created by cutting a central horizontal line from left to right of the image. The image is then rotated every angle of 15 degree from 0 to 180 degree to form 12 different slices. The aim of utilizing intensity vectors from the sampling step instead of whole image intensity values is to simplify the large data of the whole image by representative acquisition of intensity value along the images.

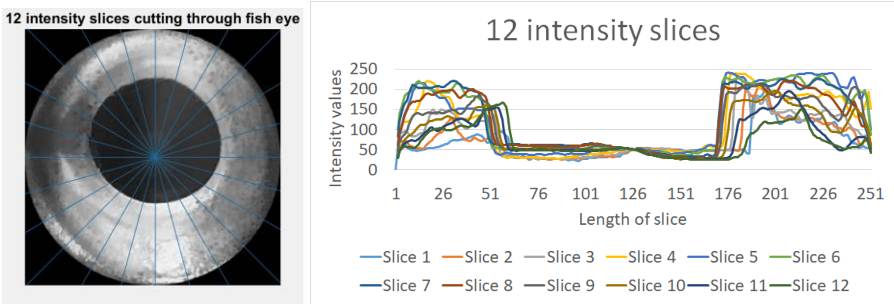


Fig. 3. 12 Intensity Slices collected on a fisheye image.

Minimum Intensity Feature (F1). In order to determine background intensity of the pupil area without specular reflection effect, the minimum value of each of 12 intensity slides was calculated. This minimum value comes from the pixel belonging to the iris area since the intensity of this area is extremely lower than other areas. Subsequently, an average value of the 12 minimum values from 12 slides was calculated. Except the high value due to specular reflection, this calculation took into account the haziness (applying on the whole eye) of a fish eye when getting stale.

Haziness Feature (F2). Another secondary feature is the haze thickness of the fish eye which increases over time after death. Two different algorithms used for haziness estimation were proposed by Kaiming et al. [3] with approximate dark channel prior and Dubok et al. [9] with simple dark channel prior. Both authors represent the general model for describing a hazy image I with scene radiance J, transmission map t (haze thickness) and atmospheric light A. Given **x** is a 2D vector representing the pixel's coordinates located in the image; t(x) is a scalar in [0, 1], then:

$$\mathbf{I}(\mathbf{x}) = \mathrm{J}(\mathbf{x})\mathrm{t}(\mathbf{x}) + \mathbf{A}(1-\mathrm{t}(\mathbf{x})) \quad (1)$$

Considering **J**(**x**) as a dark pixel, Kaiming et al. defined that all other pixels following the same condition with **J**(**x**) are considered also as dark pixels [3]. This leads to recovering the scene radiance (dehazed image) J from an estimation of the transmission map t (F2) and atmospheric light according to:

$$\mathbf{J}(\mathbf{x}) = (\mathbf{I}(\mathbf{x})-\mathbf{A})/\mathrm{t}(\mathbf{x}) + \mathbf{A} \quad (2)$$

An example of haze thickness of a fish eye at different time points is demonstrated in Fig. 4. This shows a trend of increasing haziness on the whole eye when the fish becomes stale.

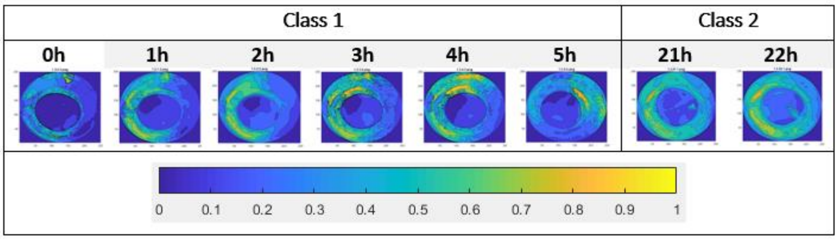


Fig. 4. 2D Contour plot of haze thickness of a fisheye image over times.

Histogram Feature (F3). Histogram has been used in this study as a graphical illustration for intensity distribution in a grayscale image whose intensity is in the range of [0, 255], at a selected step size. The Histogram algorithms in MATLAB have been applied for each grayscale image to provide a histogram graph. Pixels with the same value are distributed into a group. By that, the darker intensities are distributed close to the left of the graph than the brighter and inversely, as demonstrated in Fig. 5.

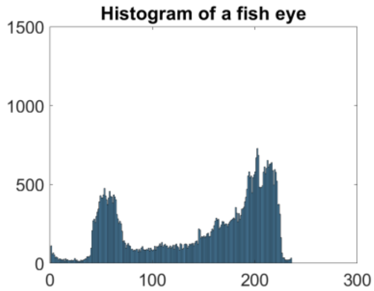


Fig. 5. Histogram of a grayscale image of fish eye.

Standard Deviation Feature (F4). Standard deviation (STD), in mathematical terms, is a descriptive statistical quantity used to measure the dispersion of a data set. STD is simply defined as the square root of variance. Variance is the squared difference from the mean and then taking the average of the result. For a random variable vector A made up of N scalar number of observations (A_1,A_2,A_3,…) with μ is the mean of A, the general equation for standard deviation is:

$$\delta = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} |A_i - \mu|^2} \tag{3}$$

Taking into account the standard deviation of intensity of the iris area as in Assump 4, the standard deviation in this paper is calculated by taking an average of 12 intensity slices of every image and estimating variation of 12 slices compared with the average line. MATLAB has been used for all the calculations.

4 Experiments and Results

4.1 Database Setup

In this research, there are more than 100 images taken from various angels on the five samples of live Crucian carp fish. All fisheye images of each fish sample were captured several times after each hour, from the most freshness to the most staleness status of the sample. All fish samples were placed in the same room and stored without freezing or providing water around in a normal condition. The room temperature was about 27°C. The eye region of interest is cut by using automatic tools and editing manually after that for some eye images which were not cut completely. Table 1 performs a training and testing database for this study. The fresh fish group, named as Class 1, consists of images taken from 0h - 5h, while the spoiled fish group, named as Class 2, includes images shot from 21h - 22h, respectively.

Table 1. Distribution of fisheye images on training and test dataset.

Images		Database			
		Training	Testing	Sum	SUM
Class 1 (4 fish samples)	0h	8	2	10	38
	1h	6	2	8	
	2h	3	2	5	
	3h	3	2	5	
	4h	3	2	5	
	5h	3	2	5	
Class 2 (1 fish sample)	21h	11	3	14	29
	22h	12	3	15	
SUM		**49**	**18**	67	**67**

4.2 Performance Evaluation Criteria

In this research, three measures are introduced to evaluate classification performance of the proposed algorithms: True Positives Rate (TPR), True Negative Rate (TNR) and Accuracy (Acc). These statistic measures are calculated from the number of observations in confusion matrix as follows:

$$\text{TPR} = \frac{TP}{TP+FN},\ \text{TNR}= \frac{TN}{TN+FP},\ \text{Acc}= \frac{TP+TN}{TP+FN+TN+FP} \tag{4}$$

Where TP: "true positives" (freshness detection with fresh fishes); FN: "false negatives" (no freshness detection with fresh fishes); TN: "true negative" (no fresh detection with spoiled fishes), and FP: "false positives" (freshness detection with spoiled fishes).

4.3 Training

The threshold-based classifiers have been trained on the Secondary Features F1, F2, F3, F4 to form the four corresponding models: TH_F1, TH_F2, TH_F3, TH_F4. On the other hand, the neural network classifiers have been developed for the Primary Feature and the four Secondary Features which leads to the formation of five corresponding models: NN_F0, NN_F1, NN_F2, NN_F3, NN_F4.

Threshold-based Approach. A general block diagram of training procedure for threshold-based models is illustrated as in Fig. 6. The threshold values that lead to highest Accuracy at the balance of TPR and TNR achieved on the Training set will be selected. These trained threshold-based models are then applied to the Test dataset for their performance evaluation.

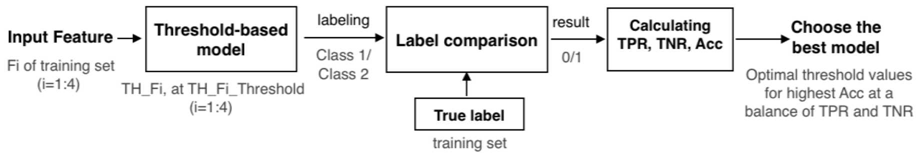
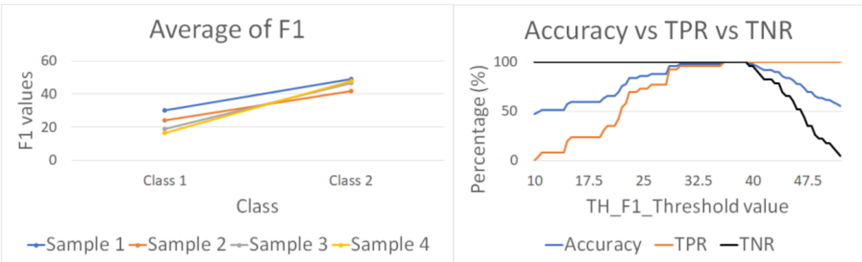


Fig. 6. General block diagram of training procedure for threshold-based models.

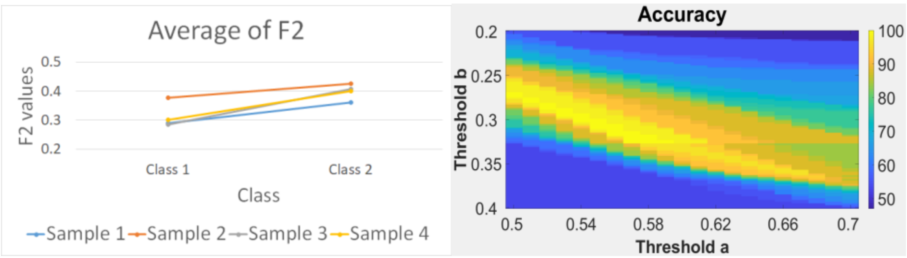
*Minimum Intensity Feature (TH_F1)***.** Fig. 7a demonstrates a clear difference of average minimum intensity values between Class 1 and Class 2, obtained from 4 samples in the training dataset. This confirms the proposed assumption 1. Therefore, the best threshold values will be searched to provide maximum separation between Class 1 and Class 2 which leads to the highest Acc and equal TPR and TNR. Following the threshold-based training procedure, TH_F1_Threshold was varied in a range of [10, 52] (which are the minimum and maximum values of F1 in the training dataset) which results in performance measures as plotted in Fig. 7b. The maximum classification rates consisting of Acc=TPR=TNR=100% are obtained given the TH_F1_Threshold in the range of [36, 39]. The value of 36 is selected to form the best TH_F1 model.



(a) (b)

Fig. 7. Average of F1 values from Class 1 (0-5h) and Class 2 (21-22h) of 4 samples (a) and TH_F1_Threshold evolution (b).

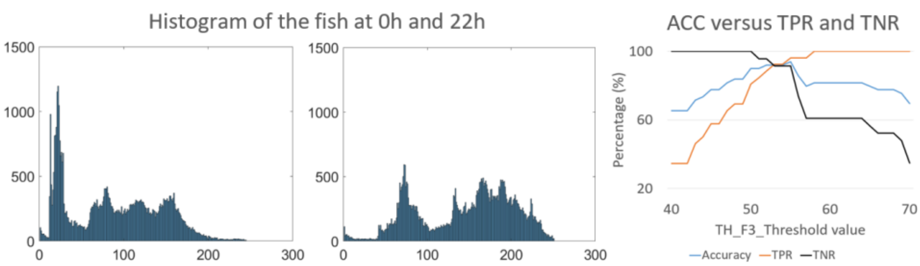
*Haziness Feature (TH_F2)***.** The Simple DCP algorithm has been applied to estimate haze thickness values in the range [0, 1]. The average of the haziness average values of all eye images belonging to Class 1 and Class 2 were calculated, respectively. As described in Fig. 8a, a general increasing trend of haziness can be observed when the fish gets stale. However, due to the impact of glare and lights to the haziness intensity, all haziness values which are larger than a border "a" (noted as TH_F2_Threshold_a) will be eliminated from the average calculation. The value of the border "a" may be varied in a range of [0.5 to 0.7]. The calculated average value of each image is then compared to a threshold TH_F2_Threshold_b which may be varied in a range of [0.2 to 0.4] to justify if the fish belongs to Class1 or Class 2. The colormap of Fig. 8b shows the maximum classification rate of Acc=100% is obtained given the TH_F2_Threshold_(a, b) = (0.54, 0.294).



(a) (b)

Fig. 8. Average of F2 values from Class 1 (0-5h) and Class 2 (21-22h) of 4 samples (a) and Finding the optimal threshold based on graph (b).

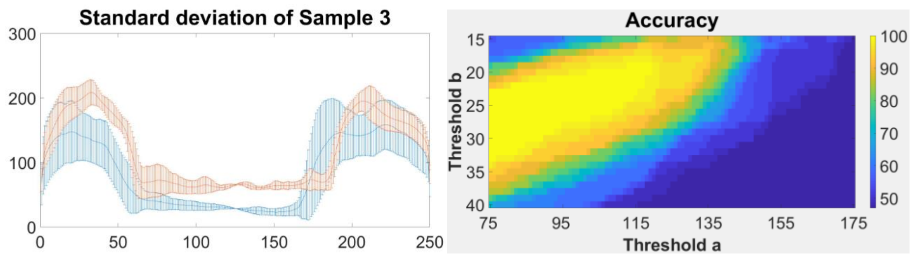
*Histogram (TH_F3)***.** Assumption 3 has been evidenced through histogram of the fresh and stale fish samples, as demonstrated in Fig. 9a. The first main beam which locates closely to the origin for fresh fish has a tendency to shift to the right when the fish becomes stale. Therefore, our aim is to search for a threshold, called TH_F3_Threshold, which can best distinguish between Class 1 and 2 on the first beam location. The TH_F3_Threshold was varied in the range of [0, 90]. The TH_F3_Threshold of 54 was found as the best value to reach 84% of Accuracy, 92.31% of TPR and 91.30% of TNR, as demonstrated in Fig. 9b.



(a) (b)

Fig. 9. Histogram of fresh and stale sample (a) and TH_F3_Threshold Calculation and selection (b).

*Standard Deviation (TH_F4)***.** In order to observe the general trend of intensity variation as stated in Assumption 4, we calculated mean and STD of all coefficients over the 12 slides. The Fig. 10a shows typical curves of mean and STD calculated from images of the Class 1 in the blue graph and that of the image of the Class 2 in the orange graph. It is obvious that STD values of the Class 1 is higher than that of the Class 2 at the two convex regions which correspond to the iris areas of the eyes. The concave regions at the middle graph representing the pupil area, however, do not show a difference between two classes. From that observation, the TH_F4 model has been trained basing on searching two optimal threshold values which could distinguish Class 1 and Class 2 through the value of STD (threshold b) and number of STD having their values larger than b (threshold a), named TH_F4_Threshold (a, b). Based on the minimum and maximum variation of STD values, b was set in the range [15, 40] while a varied between 75 and 175 (corresponding to 30% and 70% of 250 pixels of F4 values). From the colormap result in Fig. 10b, a pair of threshold (a, b) locating at the center of the yellow area has been selected among 360 pairs with 100% Accuracy. The resulting TH_F4_Threshold (a, b) of (100, 25) corresponds to 100% of Accuracy, TPR and TNR on the Training set.



(a) (b)

Fig. 10. Average of average and STD average of sample 3 from 0h-5h (blue) and 21h-22h (orange) (a) and Colormap of Accuracy STD of all (a, b) pairs (b).

Neural Network Approach. In this study, we will build a two-layer feed-forward neural network using the Stochastic Gradient Descent to train the NN models parameters. The input layer has a number of input units which are the same with size of features vectors proposed above. In this research, after considering the size of the self-built database and the task of distinguishing 2 classes, we have selected only 1 hidden unit. The transfer function used the sigmoid function which is a nonlinear function for the output value of about [0, 1]. The network output value of "1" corresponds to the spoiled fish sample, while another output node with value "0" means the fresh fish sample. The maximum number of epochs was set to quasi ∞. The MSE goal of training was set to quasi zero. The learning rate was varied from 0.01 to 0.05 to avoid the case when the input variable value is too large. The input values were normalized for various features, as listed in Table 2.

Table 2. The difference in input and normalized values of all neural network-based models.

	NN_F0	NN_F1	NN_F2	NN_F3	NN_F4

Input vector (dimensional)	12x250	12	1	90	250
Normalization	255	100	1	10000	100

4.4 Testing

The trained models in both Threshold-based approach and Neural Network-based approach have been evaluated on the testing set. The obtained confusion matrix and classification measures are shown in Table 3 and Table 4.

Table 3. Confusion matrix of the threshold-based and NN models on the testing dataset.

Confusion matrix		**Predicted label**							
Actual label	**Threshold-based models**	**TH_F1**		**TH_F2**		**TH_F3**		**TH_F4**	
		C1	C2	C1	C2	C1	C2	C1	C2
	C1 (Class 1)	12	2	12	0	11	3	12	0
	C2 (Class 2)	0	4	0	6	1	3	0	6
	Neural Network Models	**NN_F1**		**NN_F2**		**NN_F3**		**NN_F4**	
		C1	C2	C1	C2	C1	C2	C1	C2
	C1 (Class 1)	12	0	12	0	12	0	12	0
	C2 (Class 2)	0	6	0	6	0	6	0	6

Table 4. Performance evaluation of all threshold-based and neural network models.

Performance (%)	**NN_F0**	**TH_F1**	**NN_F1**	**TH_F2**	**NN_F2**	**TH_F3**	**NN_F3**	**TH_F4**	**NN_F4**
TPR	100	100	100	100	100	91.7	100	100	100

TNR	100	66.7	100	100	100	50	100	100	100
ACC	100	88.9	100	100	100	77.8	100	100	100

5 Discussions and Conclusions

This study has proposed novel low-cost methods for fish freshness classification based on simple but reliable extraction of various image features based on observed physiological characteristics of fish eyes, without any setup for imaging. The threshold-based approach and neural network-based approach have been developed for accurate classification. The first new contribution is the proposal of simple and distinctive features: 12 intensity slices F0, minimum intensity F1, haziness F2, histogram F3, and standard deviation F4. The next contribution is the proposed training process to build the threshold-based models and neural network models which lead to nine different freshness classifiers. Specially, these models could not only overcome most of the environmental effects on the captured images but inversely utilize these effects as a useful feature for F4. Furthermore, the study has evaluated and compared classification performance of all these nine proposed models on the self-built dataset which reveals overall and insight of these methods for possible future studies and development in the field.

In details, the nine proposed models (4 threshold-based and 5 neural network-based) were trained on the training set composing of 49 fisheye images of the 4 Crucian carp fishes at two main groups of time points (0-5hour and 21-22hour after death) and tested on the testing set including 18 images from the fifth fish sample. The testing result firstly confirms our four proposed assumptions on the changes of the image features linked to physiological features on fish freshness. Particularly, 8/9 models reach 100% and 1/9 model reaches 84% of accuracy on the training set; and 7/9 models reach 100%, 1/9 models reaches 89% and the rest reaches 78% of accuracy on the testing set. Secondly, the result shows the effectiveness and stability of five neural network-based models for fish freshness classification on five proposed features - F0, F1, F2, F3, F4 - with the classification accuracy of 100% on both training and testing sets. Even without any effort in image processing for a finer secondary feature from the raw primary feature F0, the NN_F0 model still achieves an accuracy of 100% on both training and testing dataset. On the other hand, the classification could be simply implemented with the threshold-based models on four secondary features with the accuracy of 100% for F1, F2, F4, 84% for F3 on training; and 100% for F2, F4, 89% for F1, and 78% for F3 on testing. All these simple and fast fisheye image processing-based models could be potentially applied to build mobile friendly-user apps through imaging for fish freshness determination.

Though all the models reach high classification accuracy in fish freshness classification on the self-built dataset, there are still mis-classification results mainly caused by limited data for training. Therefore, we have been expanding our database taking into account different types of fish, large number of samples, various time points after death for different fresh level detection, etc. This would offer potential applicability in the field of fish freshness determination.

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