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RESEARCH ARTICLE

Fish spoilage classification based on color distribution analysis of eye images

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ABSTRACT

Fish contains many nutrients beneficial to human health, which makes fish an essential component of a healthy diet. Omega-3 fatty acids, primarily found in fresh fish, can play a critical role in protecting heart and brain health. Freshness is one of the most important quality criteria of the fish to be selected for consumption. It is known that there may be pathogenic bacteria and toxins to human health in fish that are not stored in the right conditions and transferred by wrong logistics methods. One of the widely used approaches for evaluating the freshness of fish is sensory, which would be highly subjective and error-prone. Moreover, sensory analysis is widespread and one of the fastest approaches for evaluating large quantities of fish. At that point, a computer-aided diagnostic system can accelerate the evaluation of the degree of spoilage, reduce the human resources required for this task, and minimize the possibility of spoiled fish consumption. In this study, a fully automated freshness assessment mechanism based on the analysis of digital eye images of fish is proposed. Accordingly, the unsupervised clustering approach was used for feature extraction, and each image was divided into three regions according to their color distribution. The freshness was evaluated according to the intensity difference between these clusters. The results show that the proposed feature extraction approach is highly distinctive for the discrimination of spoilage and can be used to distinguish fresh fish from spoiled fish using machine learning methods without supervision.

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Introduction

Fish is a source of fat, protein, and vitamins such as D and B2, which can be important for human health. Therefore, regular consumption of fresh fish will be an essential component of a balanced diet. One factor that makes the consumption of fresh fish important is the presence of omega-3 fatty acids, which the human body cannot produce but can be taken into the body through fish consumption (Weichselbaum et al., 2013). It is suggested that these fatty acids may reduce the risk of heart disease and stroke (Zhang et al., 1999), and may also be influential in brain development and the protection of health (Uauy & Dangour, 2006). In addition, fish, which is recommended by doctors to be consumed at least twice a week, is also a healthy protein source with low unsaturated fat and cholesterol (Osman et al., 2001).

Although fish is one of the healthiest options in the market, which is recommended for frequent consumption, spoiled fish can be critically dangerous for individuals (Rawat, 2015). Some of the most common bacteria found in spoiled fish are *Vibrio parahaemolyticus* and *Vibrio cholerae*. These bacteria can cause severe food poisoning, nausea, vomiting, diarrhea, dehydration, and death in severe cases (Novotny et al., 2004). In addition, Salmonella bacteria, found in spoiled fish (Sheng & Wang, 2021), can be life-threatening, especially in individuals with weakened immune systems. Moreover, consumption of spoiled fish can lead to histamine fish poisoning, which causes urticaria, hypotension, flushing, and headache (Lehane & Olley, 2000). For this reason, fish that have started to contain harmful bacteria and toxins that may cause food poisoning due to improper storage or waiting should be classified as spoiled, and their consumption should be prevented.

Visual inspection is one of the standard methods of distinguishing spoiled fish from fresh fish (Pons-Sánchez-Cascado et al., 2006). The eyes of a fresh fish should be bright, its general appearance should be shiny and moist, and it should have a non-irritating mild fish odor (Shewan et al., 1953). The fish's texture, appearance, color, and smell provide the necessary information about its freshness. However, the manual inspection would be time-consuming and error-prone due to the subjectivity of different inspectors (Venugopal, 2002; Azeriee et al., 2009). At that point, automation of fish freshness detection may be critical for human health in cases where large amounts of fish are stored or transferred (Vuori, 1992).

Chemical analysis is another preferred method for diagnosing spoiled fish. Accordingly, the number of chemicals such as trimethylamine (TMA) and volatile basic nitrogen (VBN) produced during the putrefaction process is measured (Vuori, 1992). In addition, the pH value of the fish is one of the parameters that can be used as a criterion for spoilage (Vajdi et al., 2019). Although these tests can be a more objective criterion for freshness, they should be performed by experts in a laboratory environment, increasing the cost and the time required for the diagnosis process. Accordingly, an effective computer-aided mechanism would decrease the time and effort required to eliminate spoiled fish, especially in massive transportation and storage cases. Several methods were previously presented for the automation of freshness estimation. For example, in one study, an electrode is used (applied to the fish muscle and skin) for detecting spoilage objectively (Azeriee et al., 2009). Raman spectroscopy is also one of the methods utilized for the assessment of fish quality (Herrero, 2008). Besides the invasive or instrumentation-based methods, digital images of the fish are also analyzed for rapid evaluation of spoilage. For example, in one study, fish gills are automatically segmented for evaluating statistical image features for an efficient fish quality assessment (Issac et al., 2017). Additionally, an investigation of the relationship between RGB (Red, Green, Blue) values of pixels and Quality Index Method scores has revealed that it would be possible to assess spoilage with respect to RGB values. Similarly, Lalabadi et al. (2020) proposed a supervised machine-learning method to classify several color space-based features, including RGB. In addition to RGB-based studies, Jarmin et al. (2012) have compared a fish freshness meter and quantification of RGB color indices. They have revealed that RGB color space-based features effectively detect spoilage after three days. A fuzzy logic-based classification mechanism is implemented by Muhamad et al. (2009) for detecting spoilage of fish. Also, their mechanism performs on RGB color indices.

Digital images of the fish eye are similarly analyzed in this study. An innovative combination of image processing and an unsupervised clustering approach is combined to extract a distinctive visual feature that characterizes spoilage. Accordingly, each eye image is clustered into three regions after preprocessing then the average intensity difference is measured between the most and least dark clusters. The final classification is performed with unsupervised clustering again to assign each image to a class.

Material and Methods

The spoilage process causes a dramatic change in the appearance of the fish eye. Eyes that once appear bright and clear can become dull, cloudy, and discolored. It was observed that color changes around the pupil increase the gray-level intensity contrast on images of the spoiled fish eye. A few eye images of spoiled and fresh fish are shown in Figure 1.

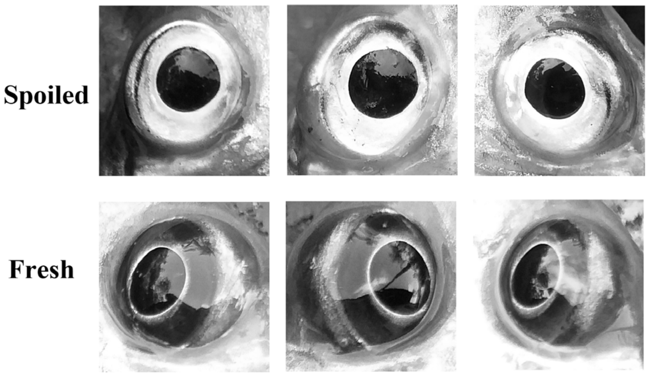

Figure 1. Color change around the pupil caused by spoilage is shown

Gray-level intensity refers to the brightness level of a specific pixel in a gray-level image, which may vary from black (0 intensity, valued with 0) to white (maximum intensity, valued with 255). This study was based on the correlation between gray-level intensity contrast change in the eye region and spoilage. Accordingly, a combination of algorithms, including blurring, was implemented in the MATLAB environment. Each eye image sample was initially preprocessed and then clustered to be divided into three regions with respect to RGB values. Next, each region's average intensity value was calculated to determine the darkest and brightest regions. Accordingly, maximum intensity difference was accepted as a critical feature extracted for final classification. Finally, the data set was clustered again to assign each sample to a class. A block diagram of the implemented mechanism is given in Figure 2.

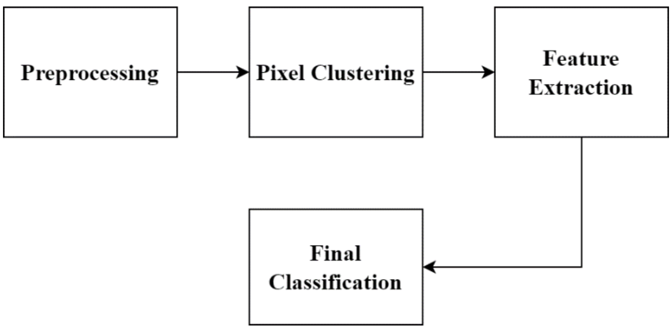

Figure 2. A block diagram showing the stages of the proposed methodology is given

Data-set

All images are taken from the original dataset formed by A. Agustyawan. The dataset includes 40 fish eye images, half of which belong to spoiled fish (Agustyawan, 2021). Sample images are taken from a 10 cm distance with a Samsung A6+ cellphone camera with a 4608 × 3456 pixels resolution (f/1.7, 26mm wide). It should be noted that the camera is focused on the eye pupil, and all eye images are cropped from original data with a 500 × 500 pixels fixed size.

Preprocessing

The main goal of the preprocessing stage was to decrease the complexity of the following clustering task. To achieve that goal, a blurring operation is implemented, reducing the image's sharpness or clarity. It was aimed to suppress high-frequency distortion. Accordingly, a circularly symmetric gaussian lowpass filter averages the colors of neighboring pixels. The result is a smoothed version of the original image, with less high-frequency information and more low-frequency information. The effect of the applied filter is shown in Figure 3.

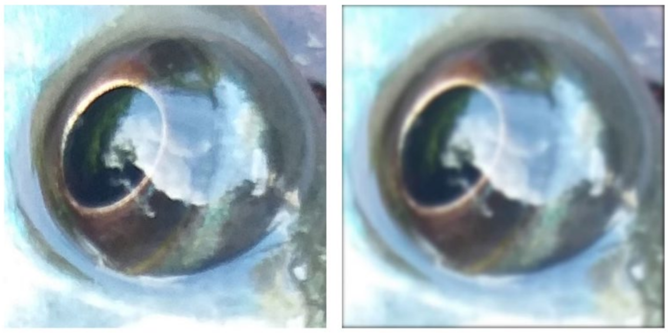

Figure 3. A sample image from the dataset (right) and the output of the blurring process (left) is shown

Clustering Process

Data clustering is grouping similar observations together in a search space. Unsupervised clustering was implemented for two purposes in this study. The first objective was dividing each image into three regions of pixels with respect to RGB values, and the second objective was the classification of extracted features. The K-means approach was preferred for automated clustering. It is a widely used unsupervised machine learning technique based on cluster centroids. It works by dividing observations into k clusters where k is the number of classes determined by the user. The algorithm iterates to minimize the sum of the squared distances between each data point and the centroid of its assigned cluster (MacQueen, 1967). Accordingly, the objective function desired to be minimized defined as:

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} \| x_i - v_j \|^2 \quad (1)$$

Where c_i is the number of observations in ith cluster. c is the number of cluster centroids, and $||x_i - v_j||$ is the Euclidean distance between an observation and cluster centroid.

Implemented algorithm first selects random k initial cluster centroids. Then calculates, the distance of each observation to cluster centroids, and each observation assigns to the closest cluster centroid, followed by a recalculation of centroids and distances. The algorithm iterates until no change in centroids are observed. The k-means clustering approach is cost-effective and easy to implement while it can handle large datasets.

In this study, red, green, and blue channel values of each pixel were accepted as an observation than the k-means algorithm was performed to divide each sample image into three regions (Figure 4).

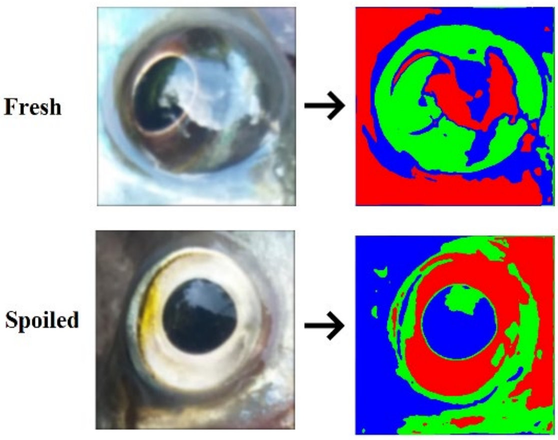

Figure 4. Different regions formed by clustering process is shown in different colors for a fresh and a spoiled sample

Feature Extraction and Final Classification

The calculated feature led us to classify spoiled samples. It was based on significant intensity contrast change. Accordingly, RGB samples were converted to single-channel grayscale. The conversion was based on calculating a weighted average of the three channels to obtain a single intensity value for each pixel. The formula for the conversion process is given below:

$$I = 0.2989 * R + 0.5870 * G + 0.1140 * B \qquad (2)$$

Where R, G, and B are the red, green, and blue color channels of a pixel, and the coefficients 0.2989, 0.5870, and 0.1140 represent the luminance sensitivity of the human eye to each color channel.

Three regions were formed previously by assigning each pixel to one of the clusters. After gray-level conversion, the average region intensity was calculated for each cluster. The region with the lowest average intensity was called the darkest region, while the highest average intensity was called the brightest region. Numerical average intensity differences between these clusters were accepted as a key feature for classification. The distinctiveness of the calculated feature was objectively evaluated in the final classification stage.

The final decision stage involves another clustering process. In that stage, each image was accepted as an observation of the search space and represented by a previously calculated feature. Accordingly, each image is assigned to one of the classes as spoiled or fresh with respect to intensity contrast.

Results and Discussion

Fresh fish should have black pupils and clear corneas (Dowlati et al., 2013). It would be possible to observe a discoloration in spoiled fish eyes which most likely causes an increase in the average intensity difference. Three major color regions would be observed in a fish eye image. In most images, the darkest region is the iris area, and the lighter-colored areas include white contours around the iris. Accordingly, the whole image was divided into three clusters. It is also possible to analyze the images with more than three clusters; however, since the average of maximum and minimum areas were considered splitting the image into smaller regions will likely have a limited impact on the final result.

While the region with the highest average intensity value was accepted as the brightest region, the region with the lowest average intensity value was accepted as the darkest region, and the difference between these two regions was taken. The histogram in Figure 5 shows the variance of the intensity contrast in case of spoilage.

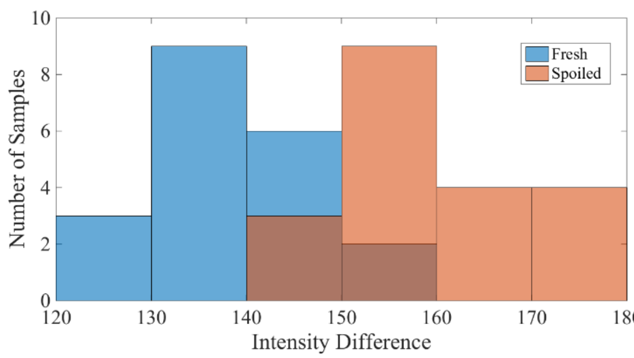

Figure 5. Variance of intensity difference is indicated in histogram form

Table 1. Average results of ten runs are given with standard deviations. Test set1, set2, set3 have 50%, 70% and 80% spoiled images, respectively

Test Sets	Value	F-Score	Accuracy	Sensitivity	Specificity	Precision	Recall
Test Set 1	Mean	0.947	0.950	0.900	1.000	1.000	0.900
	Std	0.000	0.000	0.000	0.000	0.000	0.000
Test Set 2	Mean	0.925	0.940	1.000	0.914	0.880	1.000
	Std	0.121	0.097	0.000	0.138	0.193	0.000
Test Set 3	Mean	0.900	0.940	1.000	0.925	0.850	1.000
	Std	0.161	0.097	0.000	0.121	0.242	0.000

The images used in the data set were not taken at a fixed angle. The presented figure shows that the proposed intensity-based feature changes significantly in the case of spoilage. Based on this, it can be said that the effect of light reflection and angle is relatively small. Moreover, the applied blurring suppresses the effect of reflection and high-frequency local noise.

A novel feature extraction approach is presented in this study. The approach is based on the measurement of contrast change in the eye region as an effect of spoilage. Several studies have tested the significance of average RGB change for spoilage detection. They have revealed a correlation between average RGB indices variation and the deterioration process (Jarmin et al., 2012; Lalabadi et al., 2020). Moreover, Lalabadi et al. (2020) extracted 54 features from the rainbow trout eye images in one study. They have reported that the R/(R+G+B) kurtosis had the highest impact on class prediction. Although a color-based diagnosis was made in this study, the region was divided into clusters and averaged separately instead of examined as a whole.

The significance of the extracted feature for spoilage detection was evaluated by performing unsupervised clustering to classify spoiled fish. Three experimental test sets were formed with randomly selected samples from the original data set for evaluation. 50%, 70%, and 80% of experimental sets were selected from spoiled samples. Classification is performed ten times for each test set. Results are given in Table 1.

The literature on the subject shows that digital images of the fish eye would be an essential resource for the automated diagnosis of spoilage (Muhamad et al., 2009; Lalabadi et al., 2020). The prime contribution of the study is a low-cost, easy-to-implement, unsupervised clustering-based feature. The histogram presented in Figure 5 indicates that spoilage causes a significant variation, which may lead us to conclude that extracted feature would be effective for classifying spoilage. Lalabadi et al. (2020) have reported that 25 samples were diagnosed with %86 accuracy with the features taken from the eye region. Results given in Table 1 indicate that an unsupervised clustering mechanism classified the spoilage with up to %95 accuracy, and the proposed feature is promising.

Conclusion

The potential of a novel intensity contrast-based feature was evaluated to automate the non-destructive detection of fish freshness. The K-means algorithm was implemented to cluster the region without supervision and was also performed to diagnose spoiled fish. Results show that intensity contrast between the darkest and brightest region varies significantly when the spoilage process starts to affect the appearance of the eye. Moreover, it should be possible to conclude that the presented classification scheme is promising for the automated discrimination of spoiled fish. Implementing a supervised machine learning algorithm with the proposed feature is also possible with a more extensive data-set.

Compliance With Ethical Standards

Conflict of Interest

The author declares that they have no conflict of interest.

Ethical Approval

For this type of study, formal consent is not required.

Data Availability Statements

The datasets analyzed during the current study are available in the "Fresh and not fresh fish dataset" repository, [https://www.kaggle.com/datasets/arifagustyawan/fresh-and-not-fresh-fish-dataset].

References

Agustyawan, A. (2021). Fresh and not fresh fish dataset. Retrieved on January 29, 2023, from https://www.kaggle.com/datasets/arifagustyawan/fresh-and-not-fresh-fish-dataset

Azeriee, A. A., Hashim, H., Jarmin, R., & Ahmad, A. (2009). A study on freshness of fish by using fish freshness meter. In 2009 5th international colloquium on signal processing & its applications (pp. 215–219).

Dowlati, M., Mohtasebi, S. S., Omid, M., Razavi, S. H., Jamzad, M., & De La Guardia, M. (2013). Freshness assessment of gilthead sea bream (*Sparus aurata*) by machine vision based on gill and eye color changes. *Journal of Food Engineering*, *119*(2), 277–287. https://doi.org/10.1016/j.jfoodeng.2013.05.023

Herrero, A. M. (2008). Raman spectroscopy a promising technique for quality assessment of meat and fish: A review. *Food Chemistry*, *107*(4), 1642–1651. https://doi.org/10.1016/j.foodchem.2007.10.014

Issac, A., Dutta, M. K., & Sarkar, B. (2017). Computer vision based method for quality and freshness check for fish from segmented gills. *Computers and Electronics in Agriculture*, *139*, 10–21. https://doi.org/10.1016/j.compag.2017.05.006

Jarmin, R., Khuan, L. Y., Hashim, H., & Rahman, N. H. A. (2012). A comparison on fish freshness determination method. In *Proceedings of the 2012 International Conference on System Engineering and Technology*, Bandung, Indonesia. pp. 1-6.

Lalabadi, H. M., Sadeghi, M., & Mireei, S. A. (2020). Fish freshness categorization from eyes and gills color features using multi-class artificial neural network and support vector machines. *Aquacultural Engineering*, *90*, 102076. https://doi.org/10.1016/j.aquaeng.2020.102076

Lehane, L., & Olley, J. (2000). Histamine fish poisoning revisited. *International journal of food microbiology*, *58*(1-2), 1-37.

MacQueen, J. (1967). Some methods for classification and analysis of multivariate observations., *Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability Volume 1: Statistics*, University of California Press. pp. 281-297.

Muhamad, F., Hashim, H., Jarmin, R., & Ahmad, A. (2009). Fish freshness classification based on image processing and fuzzy logic. *Recent Advances in Circuits, Systems, Electronics, Control and Signal Processing: Proceedings of the 8th WSEAS International Conference on Circuits, Systems, Electronics, Control & Signal Processing (CSECS '09)*, Puerto de la Cruz, Tenerife, Canary Islands, Spain. pp. 109–115.

Novotny, L., Dvorska, L., Lorencova, A., Beran, V., & Pavlik, I. (2004). Fish: A potential source of bacterial pathogens for human beings. *Veterinarni Medicina*, *49*(9), 343.

Osman, H., Suriah, A., & Law, E. (2001). Fatty acid composition and cholesterol content of selected marine fish in Malaysian waters. *Food Chemistry*, *73*(1), 55–60. https://doi.org/10.1016/S0308-8146(00)00277-6

Pons-Sánchez-Cascado, S., Vidal-Carou, M., Nunes, M., & Veciana-Nogues, M. (2006). Sensory analysis to assess the freshness of Mediterranean anchovies (*Engraulis encrasicholus*) stored in ice. *Food Control*, *17*(7), 564–569. https://doi.org/10.1016/j.foodcont.2005.02.016

Rawat, S. (2015). Food spoilage: Microorganisms and their prevention. *Asian Journal of Plant Science and Research*, *5*(4), 47–56.

Sheng, L., & Wang, L. (2021). The microbial safety of fish and fish products: Recent advances in understanding its significance, contamination sources, and control strategies. *Comprehensive Reviews in Food Science and Food Safety*, *20*(1), 738–786. https://doi.org/10.1111/1541-4337.12671

Shewan, J., MacIntosh, R. G., Tucker, C., & Ehrenberg, A. (1953). The development of a numerical scoring system for the sensory assessment of the spoilage of wet white fish stored in ice. *Journal of the Science of Food and Agriculture*, *4*(6), 283–298. https://doi.org/10.1002/jsfa.2740040607

Uauy, R., & Dangour, A. D. (2006). Nutrition in brain development and aging: role of essential fatty acids. *Nutrition Reviews*, *64*(suppl 2), S24–S33. https://doi.org/10.1301/nr.2006.may.s24-s33

Vajdi, M., Varidi, M. J., Varidi, M., & Mohebbi, M. (2019). Using electronic nose to recognize fish spoilage with an optimum classifier. *Journal of Food Measurement and Characterization*, *13*, 1205–1217. https://doi.org/10.1007/s11694-019-00036-4

Venugopal, V. (2002). Biosensors in fish production and quality control. *Biosensors and Bioelectronics*, *17*(3), 147–157. https://doi.org/10.1016/S0956-5663(01)00180-4

Vuori, H. (1992). Quality assurance in Finland. *British Medical Journal*, *304*(6820), 162-164.

Weichselbaum, E., Coe, S., Buttriss, J., & Stanner, S. (2013). Fish in the diet: A review. *Nutrition Bulletin*, *38*(2), 128–177. https://doi.org/10.1111/nbu.12021

Zhang, J., Sasaki, S., Amano, K., & Kesteloot, H. (1999). Fish consumption and mortality from all causes, ischemic heart disease, and stroke: an ecological study. *Preventive Medicine*, *28*(5), 520–529. https://doi.org/10.1006/pmed.1998.0472