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Mackerel Tuna Freshness Identification Based on Eye Color Using K-Nearest Neighbor Enhanced by Contrast Stretching and Histogram Equalization

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Abstract.
Purpose: The present study focuses on the development of a robust fish freshness classification system based on the application of different digital image processing techniques from mackerel tuna eye images toward better classification.
Methods: Contrast stretching and histogram equalization were done to improve image quality before the classification. The system contained 250 training images in a dataset, for five freshness classes which are 3, 6, 9, 12, and 15 hours post-catch, with 50 test images. For classification, the K-Nearest Neighbor (KNN) algorithm was employed with a parameter setting of K = 5, ensuring effective differentiation between the various freshness levels based on the enhanced image features.
Result: The results depicted very low MSE values after enhancement at 6 hours, as low as MSE = 0.0012606 and PSNR = 28.9944 dB for contrast stretching, and for 12 hours, histogram equalization gave the best results, MSE = 0.0030712 and PSNR = 25.127 dB. Further, classification done through the KNN classifier with K=5 gave results with accuracy as high as 100% was achieved on the testing data, proving that the model was successfully able to identify the classes of freshness.
Novelty: The novelty in the present research work is the integration of advanced image-processing techniques, which allow the achievement of an improved level of detection of fish freshness and a very useful solution to the seafood industry in view of product quality and safety assurance. Generally, the paper epitomizes an important milestone in the application of machine learning and image processing for the assessment of the quality of foods.

Keywords: Contrast stretching, Histogram equalization, Image classification, Image enhancement, K-nearest neighbor
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INTRODUCTION

Global fresh fish production is marred by problems in catch handling and quality maintenance [1], [2]. Due to the rise in population and awareness of healthy eating that involves good intake of proteinous food like fish, fresh fish is in increasing demand [3]. Since many value chains in the chain from catch to consumer are often long, fish quality is usually degraded during its passage down the value chain, especially for freshness [4], [5]. Other factors include bad temperature during storage, delayed distribution, and lack of good freshness monitoring technologies. A lack of cold chain infrastructure in most of the developing countries further exacerbates this situation. Therefore, there is a worldwide growth in the need to find ways that are more accurate and time-saving for the freshness check of fishes using image-processing technology, which can check some of the physical attributes of fishes-like eye color-which could indicate freshness [6]. This new approach would then be able to make quick, precise decisions with respect to maintaining the quality of fish within its value chain in a number of various parts of the world.

All these problems with fresh-keeping measures urgently need some innovative alternatives like real-time estimation of freshness in fish using image-processing technology [7], [8]. Non-invasive quality monitoring is carried out because physical indicators-for example, eye color-change due to deterioration. To get the

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correct freshness level from captured images, image enhancement such as contrast stretching and histogram equalization is performed [9].

This, integrated with machine learning algorithms like K-Nearest Neighbor, can support fast classification of fish freshness upon preset parameters [10]. Besides, the adoption of this system along the entire value chain-from catch to consumer-will reduce the deterioration of fish due to poor temperature management, delays in distribution, or simply lack of monitoring in an area without the cold chain system. A solution that speeds up decision-making processes, not only in speed but with quality control at each batch, conserving more produce to meet the demands of the world to have fresh seafood.

Saputra et al. [11] proposed using K-Nearest Neighbor as a classification algorithm in fish freshness classification, adopting the RGB value of color from the fish eye image. They gathered 150 fish eye image datasets one, five, and ten hours after catching. Preprocessing steps involved in such images included cropping and segmentation, hence extraction of features in RGB value form for classification into predefined categories of freshness. This dataset consisted of 120 training images and 30 test images. The best result among them is 93.33% for K=1. This would therefore mean that, besides the usual classification methods, such as chemical and biochemical analysis or sensory analysis, which is time-wasting and more prone to human fatigue, KNN will be a strong model in fish freshness classification using digital images.

Simanullang et al. [12] conducted Identification of Fish Freshness Targeting Mujair Fish using the K-Nearest Neighbor Classification Method. The researcher uses an eye image of the fish. RGB color features are transformed into grayscale in order to enhance the contrast and equalization by histogram for improving the image quality. The obtained images were then further classified into predefined freshness categories using KNN classification. Results obtained from them show the KNN classifier give 98% accuracy of classification to show the efficiency of the method in distinguishing between freshness and non-freshness of fish. This high accuracy reveals the potential of KNN as a promising model for detecting fish freshness with digital eye images. Thus, offering an efficient solution with a high degree of accuracy to reduce fraudulent practices in the sales of fish.

Widadi et al. [13] conducted a freshness classification using fisheye images of tilapia fish, combined with image processing and machine learning techniques. In their paper, it reports on the collection of 640 fisheye images taken from 10 tilapia fish within an interval of 0-16 hours after being removed from water, with some variation by camera distance to simulate a number of scenarios. Generally speaking, there are two major processes involved in feature extraction and classification. Four features were extracted from the pixel values, namely, the mean, standard deviation, skewness, and kurtosis. K-Nearest Neighbor algorithms were used for classification. For the checking performance of the classification, it was tested by k-fold cross-validation and a confusion matrix. This gave an astonishing result-an accuracy rate of 100% for two classes of freshness: 0-2 hours and 2-4 hours. With four classes of 0-2 hours, 2-4 hours, 10-12 hours, and 14-16 hours, the average accuracy degraded to 75%. Also, in consideration of all the classes, the accuracy went down to 45%. Therefore, from the fact that the accuracy in classification degrades for larger time intervals, although the results in this paper essentially demonstrate the feasibility of image processing techniques combined with KNN for early freshness detection, it can be concluded.

According to the third study related above, this research proposes an alternative novel for determining the freshness of mackerel tuna using AQU images of the fish eye and the K-NN method. Improvement of the method would be done by Contrast Stretching and Histogram Equalization techniques. This study adopted a more in-depth process compared with the former two studies mentioned, which either used RGB color feature value only or grayscale conversion. Contrast stretching tries to make the dispersion of the contrast in the image more apparent, while histogram equalization makes the brightness uniform in the image. Both are supposed to further improve the accuracy of the results of the extracted fish-eye features for a better freshness classification result with KNN. It will be effective in determining the freshness of fish, something that is considered very important in maintaining its quality along the value chain.

METHODS

First would be data collection for training and testing in the flow of the proposed system. In the training phase, preprocessing of the collected dataset is done, feeding the value of K, training of K-Nearest Neighbor model gives the accuracy of model. Improvements in image enhancement techniques would be done first, such that image quality improvement may be done effectively for classification using contrast stretching and histogram equalization in the test phase. The performance of the model in both phases was tested with MSE and PSNR after getting the accuracy. To complete, the single prediction test through the trained KNN model in the classification phase was done by showing the feature-based classification results of a given input image, ensuring a high level of accuracy in the testing of the model and quality in the image classification via MSE and PSNR. The proposed workflow can be seen in Figure 1.

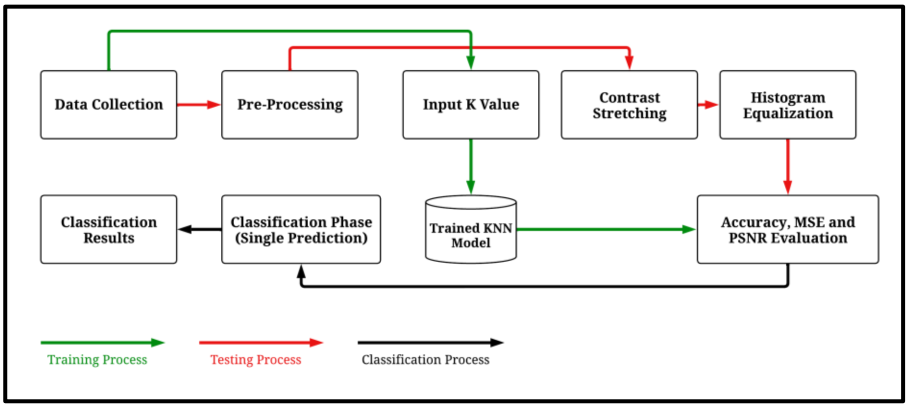
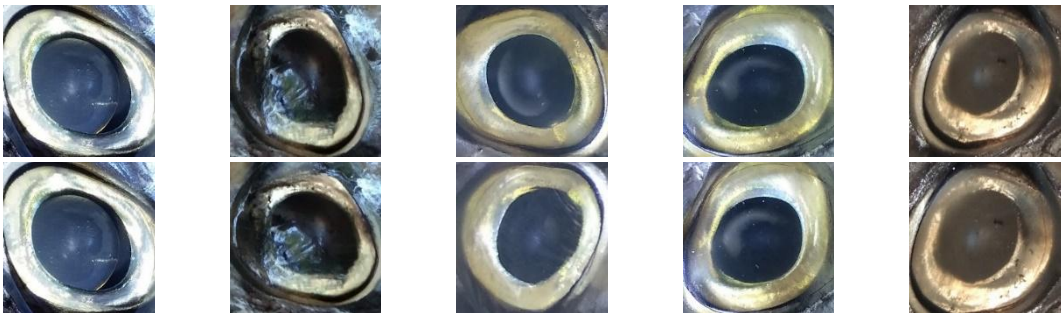


Figure 1. Proposed workflow

Data collection

The data used in this work consist of 300 images of cut fish eyes and were taken from five classes according to the degree of freshness in hours from catching. Those belong to classes representing different times of 1, 2, 3, 4, 5, respectively. Class 1 consists of fishes that are 3 hours post-catch, Class 2 fishes 6 hours post-catch, Class 3 fishes 9 hours post-catch, Class 4 fishes 12 hours post-catch, and Class 5 fishes 15 hours post-catch. The image files are in RGB format and resolution of 256x256 pixels. Where the dataset consists of images per class contains 50 images for training and 10 images for testing, meaning that the total number of training images is 250 and images for testing are 50. A balanced dataset like this therefore can help to take great variations in the representative stages of the fish freshness for proper training and testing of the K-nearest neighbor model in the classification of the fish freshness. The sample of dataset each class can be seen in Figure 2 (a) – (e).



(a) 3 hours (b) 6 hours (c) 9 hours (d) 12 hours (e) 15 hours

Figure 2. Sample unprocessed datasets each class

Contrast stretching

Contrast stretching is an enhancement, which enhances the apparent contrast of features in an image by stretching the range of the intensity levels [14]. In this process, the contrast of the image is spread such that the dark regions become darker, and the bright region becomes brighter; hence, the stretching of pixel intensity values in the complete range [15], [16]. This will, in turn, be very helpful for contrasting minute changes in color in the eye, which indicates the freshness of the fish. Thus, providing a good scope for the algorithm such as K-Nearest Neighbor, marking the right classification among different classes of freshness by redistributing the pixel values and hence improving the visual contrast between the regions which may differ in the picture. This would definitely avoid the loss of important features in the low-contrast view images, thereby improving successive image processing stages such as histogram equalization and feature extraction. The contrast stretching used in this study was carried out using algorithm 1.

Histogram equalization

Histogram Equalization is one of the methodologies for contrast stretching in bringing out the visual quality of a picture by giving it proper redistribution of its pixel intensity value [17]. It transforms the histogram of the image-that is, the distribution of pixel intensities-into a near-flat distribution. Primarily, it maps source pixel intensities according to their CDFs into new values. The result is thus an image where the contrast is stretched, more so in the low range of variation in intensity areas, such that details are brought out better [18]. Such a technique works on images with both light and dark backgrounds and foregrounds, and forms the idea for many enhancements or structure enhancement techniques in applications as varied as medical imaging to computer vision. The histogram equalization used in this study was carried out using algorithm 2.

1st Algorithm: Contrast Stretching Enhancement

```
function ContrastStretching (image, N_min, N_max):
    I_min = min (image)
    I_max = max (image)

    for each pixel (x, y) in image:
        I_new (x, y) = ((I (x, y) − I_min) / (I_max - I_min)) * (N_max - N_min) + N_min
        Image (x, y) = I_new (x, y)

    return image
end
```

2nd Algorithm: Histogram Equalization Enhancement

```
function HistogramEqualization (image):
    histogram = computeHistogram (image)

    cdf = [0] * L
    Cdf [0] = histogram[0]
    for i from 1 to L − 1:
        cdf[i] = cdf[i − 1] + histogram[i]

    Total_pixel = width(image) * height(image)
    normalized = [0] * L
    for i from 0 to L − 1:
        normalized[i] = cdf[i] / Total_pixel

    for each pixel (x, y) in image:
        image (x, y) = floor((L − 1) * normalized[image(x, y)])

    return image
end
```

The 1st algorithm, enhances the image contrast by rescaling the pixel values to a new intensity range defined by N_{min} and N_{max}, using the minimum and maximum pixel values in the original image for normalization. Each pixel's new value is computed by a linear transformation that stretches the intensity values to the desired range. The 2nd algorithm, improves contrast by redistributing pixel intensities across the full range. It calculates the cumulative distribution function (CDF) from the image's histogram, normalizes it, and then maps the original pixel intensities to new values based on the CDF, ensuring a more even distribution of intensity levels throughout the image. Both algorithms aim to enhance contrast, but Contrast Stretching directly adjusts intensity ranges, while Histogram Equalization modifies the distribution of pixel values for a more uniform contrast.

K-nearest neighbor (KNN)

KNN is one of the popular supervised algorithms in machine learning for classification [19]. In this case, such a technique can be used for the determination of how close a given sample is to its nearest neighbors within the feature space for freshness classification in fish. It takes, in general, for features to be extracted from pictures of the fish's eyes, such as RGB values or other derived attributes from the images, in order to classify the fishes into different freshness classes. Normally, KNN works its way by calculating the distance-Euclidean-between the new input data and all other data points in the training set [20], [21]. The word "K" means the number of neighbors taking part in the classification. Once the neighbors are found, the majority class among those nearest neighbors assigns the class of the classification result. With respect to fish freshness, the classes can be terms in time since the fish was captured, such as 3 hours, 6 hours, or 9 hours since capture. KNN works pretty well because it is simple and assumes nothing regarding the distribution of the points. Therefore, it can be used in problems, such as freshness detection from images, in which data may not follow traditional distributions.

Performance evaluation

The accuracy, MSE, and PSNR will be the metrics for performance evaluation for the fish freshness classification model [22], [23]. Accuracy is an inlet number of fish sample cases rightly classified of the total inlet number of samples and essentially reflects the model's ability to correctly identify different freshness levels. High accuracy means that a strong robustness exists within the model of classification. Since the MSE is the average of the squared differences of the predicted versus original image pixel values, it allows the error rate for the model to be gauged. The lesser the value of MSE, the closer the predictions to the actual values, which essentially means better performance. PSNR gives the quality of image reconstruction if there is some sort of processing on the images. A higher PSNR reflects that after different steps of image processing, such as contrast stretching or histogram equalization, the model maintains the quality of the image better, which is very important for correct classification of freshness from fish eye images. It will, therefore, correctly test the performance of the model in carrying out its classification task without compromising the quality of the images.

$$Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ Data\ Training} \times 100 \tag{1}$$

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j) - K(i,j))^{2} \tag{2}$$

$$PSNR = 10\log 10\left(\frac{\max\ \_pixel\_value^{2}}{MSE}\right) \tag{3}$$

where, the original value of a pixel at position (i,j) of an image be depicted as $I(i,j)$, and the value of the predicted or pre-processed pixel at the position (i,j) be depicted as $K(i,j)$. The dimension of the considered image is $m \times n$, where m depicts the height and n depicts the width. The Mean Square Error predicts the average of the square of the differences between the real pixel values and those predicted, enabling one to obtain a figure approximating the prediction error in this image processing model.

RESULTS AND DISCUSSIONS

In the Results and Discussion section through an enhancement process using contrast stretching and equalizing the histogram shown in Figure 3. These two enhancing techniques have been applied in order to improve visual quality in the captured fish eye images before classification. These enhancement techniques are quantitatively analyzed according to the MSE and PSNR metrics, which are important in the context of image processing considering their fidelity. A more complete result with respect to MSE and PSNR will be given in Table 1, emphasizing the improvements through the enhancement processes and further its impact on the overall classification performance.

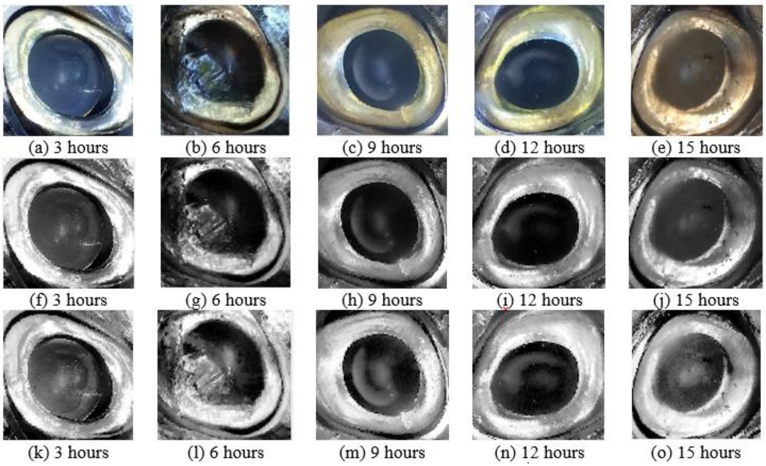


Figure 3. Results of enhanced dataset each class (a) – (e) Represents originali image, (f) – (j) Represents results of contrast stretching, (k) – (o) Represents results of histogram equalization

These improvements resulting from the separate use of contrast stretching and histogram equalization techniques provide a good picture of the quality of fisheye images in different freshness class. In Table 1, the MSE generated by contrast stretching was peculiarly low, with the best performance at 6 hours with MSE = 0.0012606, PSNR = 28.9944 dB, and 3 hours at MSE = 0.0014009, PSNR = 28.536 dB. These relatively lower MSEs with high PSNRs mean that this enhancement technique retained good qualities of images in these classes. Conversely, the highest MSEs obtained from the histogram equalization, most especially at 6 hours, gave MSE = 0.02906 and PSNR = 15.367 dB, meaning the degradation in the quality of this particular class. However, by applying the histogram equalization technique, better performance was found at 12 hours, such that MSE = 0.0030712, PSNR = 25.127 dB. Probably, this one worked well. In general, the obtained results so far indicate the proper choice of the enhancement method with regard to the characteristics of the fish freshness images. Since the chosen enhancement technique influences both quality metrics and further classification performance.

Table 1. Results of MSE and PSNR each enhancement processing

Enhanced Method	Sample Enhanced Datasets	MSE	PSNR
Contrast Stretching	3 Hours	0.0014009	28.536 dB
	6 Hours	0.0012606	28.9944 dB
	9 Hours	0.013776	18.6089 dB
	12 Hours	0.0083638	20.776 dB
	15 Hours	0.0040726	23.9012 dB
Histogram Equalization	3 Hours	0.0041753	23.7931 dB
	6 Hours	0.02906	15.367 dB
	9 Hours	0.0093141	20.3086 dB
	12 Hours	0.0030712	25.127 dB
	15 Hours	0.016384	17.8559 dB

Having obtained all MSE and PSNR results for every processing method, the next step was the training of the KNN model, keeping the value of the parameter K = 5. Previous research and empirical evaluation have shown that K=5 often provides a reasonable trade-off in terms of accuracy and computational efficiency, especially in scenarios with moderately sized datasets such as the one used in this study. From this phase of training, an accuracy of 100% was achieved on the testing data. This high value of accuracy justifies that all test samples were correctly classified into TP through the set of conducted experiments. That is to say, the two preprocessing techniques-contrast stretching and histogram equalization-make the features of the different freshness classes fairly distinctive while being handled by the KNN model. The outstanding performance underlined the robustness and reliability of the model in its practical application concerning the classification into freshness classes and proved the suitability of the preprocessing methods adopted for this research. Results of classification can be seen in Table 2.

The result of the classification phase is given in Table 2, showing the performance of the KNN model on the best parameter setting, corresponding to K=5. The classifier was trained on 250 images from five different freshness classes, specifically 3, 6, 9, 12, and 15 hours from the catch. Hence, the KNN algorithm has classified the images within the test set with highly accurate results for all categories of freshness. Results have presented the fact that this model leverages the enriched features resulting from the pre-processing to classify fish freshness reliably and correctly.

Table 2. Results of classification each enhancement processing

Enhanced Method	Actual Class	Predicted Class	Conclusion
Contrast Stretching	3 Hours	3 Hours	True Positive
	6 Hours	6 Hours	True Positive
	9 Hours	9 Hours	True Positive
	12 Hours	12 Hours	True Positive
	15 Hours	15 Hours	True Positive
Histogram Equalization	3 Hours	3 Hours	True Positive
	6 Hours	6 Hours	True Positive
	9 Hours	9 Hours	True Positive
	12 Hours	12 Hours	True Positive
	15 Hours	15 Hours	True Positive

From Table 2, the performance of the K-Nearest Neighbor model is excellent in both the enhancing techniques, which are contrast stretching and histogram equalization. Indeed, all the test images belonging to five categories of freshness classes, namely, 3, 6, 9, 12, and 15 hours post-catch, had a true positive result, establishing the efficiency of the model in classifying between different classes of freshness in fish. This holds coherence for all classes and goes further to testify to the robustness of the applied preprocessing techniques that greatly improved the feature for classification. This further supports KNN's effectiveness within practical scenarios in the classification of fish freshness and, therefore, promises to be a robust tool within quality control at the heart of the seafood industry.

CONCLUSION

It concludes that a contrast stretching and histogram equalization method in enhancing images for fish freshness classification was done through research into captured eye images. It was perceived that a contrast stretched always resulted in low values of MSE with high PSNRs, particularly in the classes at 3- and 6-hour post-catch, which is indicative of better retention of image quality in these classes. Compared with histogram equalization, it had a higher MSE at the very beginning and improved at 12 hours, its effectiveness probably depends on time. Then, further training is done by KNN, with the best K-parameter value equated to 5; a great result of 100% accuracy is achieved, proving that our model is able to distinguish between each level of fresh. These results underline the importance of image preprocessing for the improvement of classification performance and thereby make methods applied within this research workable in real-world applications of fish freshness identification. It generally supports the fact that such techniques have promising prospects with a view to integrating them into quality and safety assurance systems for fish products on the market. In the future, the varieties of fish species and freshness classes are expected to increase, hence making the model more robust and generalized. For example, advanced deep learning methods such as convolutional neural networks can realize better feature extraction compared to other traditional methods like the K-Nearest Neighbor. Real-time image analysis goes hand in glove with integrating mobile applications intended for on-site freshness assessment that could be of help to customers and retailers since it may offer an efficient method of quality assurance.

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