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Fish Freshness Identification Using Machine Learning: Performance Comparison of k-NN and Naïve Bayes Classifier

Anton Yudhana*
Department of Electrical Engineering, Universitas Ahmad Dahlan, Yogyakarta, Indonesia
eyudhana@ee.uad.ac.id

Rusydi Umar and Sabarudin Saputra
Master Program of Informatics, Universitas Ahmad Dahlan, Yogyakarta, Indonesia
rusydi@mti.uad.ac.id, sicoccinela@gmail.com

Abstract
Fish is one of the food sources that should be examined for freshness before being consumed. The consumption of rotten fish can cause various diseases. The rotten fish have changed color on the gills, skin, flesh, and eyes and have a pungent odour. Fish freshness can be assessed using a variety of conventional methods, but these methods have limitations, such as requiring relatively expensive equipment, trained personnel and being destructive. The machine learning method is used because it is non-destructive, reduces costs, and is easy to use. This study aims to identify the freshness of fish using k-nearest neighbor (k-NN) and Naïve Bayes (NB) classification methods based on the fish-eye image. The features used in the classification process are RGB and GLCM. The research stages consist of the fish collection process, image acquisition and class division, preprocessing and ROI detection, feature extraction and dataset split, and the classification process. Based on these results, it can be stated that the k-NN method has better performance than NB with average accuracy, precision, recall, specificity, and AUC of 0.97, 0.97, 0.97, 0.97, and 0.97.

Category: Artificial Intelligence

Keywords: Fish freshness identification; Machine learning; Fisheye images; Computer science; k-NN; Naïve Bayes

I. INTRODUCTION

Fish is one of the marine potentials that are important in fulfilling the nutritional needs of the human body [1-3]. Fish contains essential nutrients that the body requires, such as vitamins, minerals, and proteins, to reduce the risk of cancer, coronary heart disease, and stroke, as well as to treat high blood pressure and raise IQ (intelligence quotient) [4-7]. The sources of marine fish supply increased from 9.0 kg/capita in 1961 to 20.5 kg/capita in 2018 [8, 9]. In 2018, 46% of aquatic food production came from the sea, of which 52% was fish for public consumption [9]. Global human growth, estimated at 9.7 billion people in 2050, will increase food demand by 20%–70% [10]. The total consumption of fish and processed fish products in the world reaches 128 million tons and the average individual consumption is 18.4 kg/year [4]. Indonesia is the country with the fourth largest population which is

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*Corresponding Author

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predicted to increase to 318.9 million people by 2045 [11]. Indonesia is the second largest fish-producing country after China, which plays an important role in the economy by increasing income, diversifying livelihoods, supplying animal protein, and earning foreign exchange [3, 12]. Fulfilment of animal protein demand in everyday life reaches 26.61% of total protein and fish contributes about 47.23% or 12.57 g/day of the total animal protein requirement [13].

The nutrient content of fish is the main factor in increasing fish consumption as it is beneficial to the health of the human body [7, 14]. Based on this, the catching and distribution of fish on the market requires attention to its quality and freshness [7, 15, 16]. Freshness is an important factor for fish quality, and its assessment is an important issue for fish management companies [17]. Fish management by companies and fish markets plays an important role in determining the quality of the fish that will be distributed to consumers because once caught, the fish begin to experience a process of decay caused by biochemical reactions, bacterial growth, physical and chemical changes in the fish body, thereby reducing the quality of fish [4, 15, 18-22]. For consumers, the fish quality is not only about safety and taste but also about freshness which is influenced by the management process and storage procedures after catching [16, 21, 23]. The quality of the fish can be seen from several aspects, namely changes in the body and eye color, texture, taste, and smell [14, 16]. Fresh fish have the same characteristics and appearance as live fish, while rotten fish experience discoloration of the gills, skin, meat and eyes, and have a pungent odour due to biochemical reactions in the fish body [4, 24]. Eating rotten fish can have adverse effects on consumer health such as vomiting, respiratory problems, diarrhea and stomach cramps [7, 25].

The importance of fish freshness as an indicator of fish quality should be of concern to fish management companies, market managers and the government in controlling the process of catching and distributing fish to consumers [17, 26]. Efforts to control the distribution of fish are closely related to the process of monitoring and evaluating the quality of the freshness of fish [27]. The process of monitoring and assessing the freshness of fish can be carried out by various methods based on physical, chemical, microbiological and sensory parameters [17, 28]. Various methods can carry out the process of monitoring and evaluating fish freshness, namely using sensors [1, 2, 19, 25, 29, 30], a spectrometer [31], chemical detection techniques based on liquid and gas chromatography, as well as physical detection techniques [2, 28]. The use of sensors, spectrometers, physical recognition, and detection of chemical substances are popular methods that are accurate in determining the freshness of fish, but have limitations such as requiring relatively expensive equipment, requiring trained personnel and destructive testing [7, 14, 17]. The government provides a fish quality testing laboratory at a lower cost using biosensors and nanotechnology, but the equipment is not easily accessible to fishermen and the general public [21]. This is a challenge in the process of identifying the freshness of fish so that the fish management process can be carried out quickly, reliably and simply without compromising the quality of the fish [17].

Innovation in the process of identifying the freshness of fish can be done using machine learning (ML)-based computer vision technology [7, 14]. ML is a machine algorithm-based learning technique using certain parameters [32-34]. ML consists of supervised learning, unsupervised learning and reinforcement learning [35]. Supervised learning is a classification method for certain classes. Supervised learning consists of a decision tree (DT) algorithm, k-nearest neighbor (k-NN), neural network (NN), random forest (RF), support vector machine (SVM), Naïve Bayes (NB), radial basis function (RBF) and self-organizing map (SOM) [27, 36-38]. The classification of fish freshness based on machine learning was carried out using the SOM method for the process of generating key features in the form of signal data obtained from ultrasonic scanning [36]. The results of feature extraction were analyzed by the RBF method to estimate the freshness of the fish meat. The research [39] uses the SVM method based on the red colour parameter in the eyes and gills of the fish. Wavelet transform and wavelet coefficients were used to assess the freshness of fish on the basis of gills [21]. Identification of fish freshness based on gill tissue as a result of exposure to heavy metals using the p-value determination method [40]. Identification of the hazardous metal content in the eye tissue based on the translation of features using the C and S values from CMYK and HSV color channels after conversion from red, green, and blue (RGB) colors [41]. Analysis of pesticide content based on eye tissue segmentation in the spatial domain using the artificial neural network (ANN), SVM, NB and RF methods [22]. Identification of the freshness of fish based on the backpropagation method [42].

Previous research has shown that the use of ML as an innovative method of assessing the freshness of fish has been widely practiced. In general, the object used is an image containing the attributes of eyes, gills and fish skin. However, there is still potential for research development by utilizing different attributes, feature extraction methods and classification techniques to determine the reliability of these components in identifying the freshness of fish. Based on consideration of ML method development and previous research, this study aims to identify fish freshness based on RGB color features and the grey level co-occurrence matrix (GLCM) of fisheye images. The RGB fisheye color feature is used as a parameter because changes in the freshness level of the fish also affect the fisheye color. The proposed classification techniques are the k-NN and NB methods taking into account the level of accuracy of both methods.

Fig. 1. Steps of the fish freshness identification process.

II. MATERIALS AND METHODS

A. Fish Sample Collection

The fish sample in this study was *Selarides leptolepis*. Fish samples were obtained from fishermen on Depok Beach, Kretek District, Bantul Regency, Yogyakarta Special Region, Indonesia. The number of fish used as a sample is five fish. The fish that have just been caught are then separated between the body and the head as only the fish's eye is the subject of this research. After separating the fish heads, they are immediately placed on the image-captured media as fresh fish. The fishes were then stored for 12 hours at room temperature. The fishes were left to rot and showed discoloration of the eyes. The steps of the fish freshness identification process are shown in Fig. 1.

B. Image Acquisition and Class Division of a Fish Sample

The image acquisition process uses a box-shaped set. The image capture box is equipped with a lamp as a light. The lamp is placed on top of the box at an angle of 32 degrees to the object. The inner background of the box is the same color on each side. The image acquisition box is shown in Fig. 2. The image acquisition tool used is a 16MP mobile phone camera. The cell phone is placed on top of the box with a hole to direct the camera into the box. The fish acquisition box is useful for ensuring the consistency of the shooting process in terms of distance, lighting and background. The image acquisition stage is to place the fish head in certain coordinates on the bottom of the box just below the cell phone camera hole and take the fish head image eight times according to the cardinal directions for each side of the fish head. The image acquisition results are divided into two classes of freshness, namely the fresh fish class (image taken when the fish has just been taken from the fishermen) and the rotten fish class (image taken after 12 hours of storage).

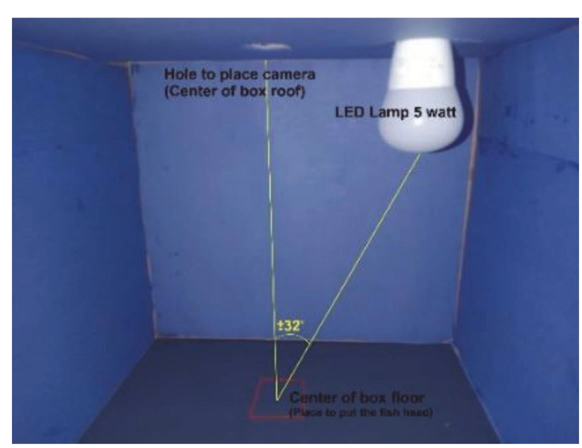


Fig. 2. Box for the image acquisition process.

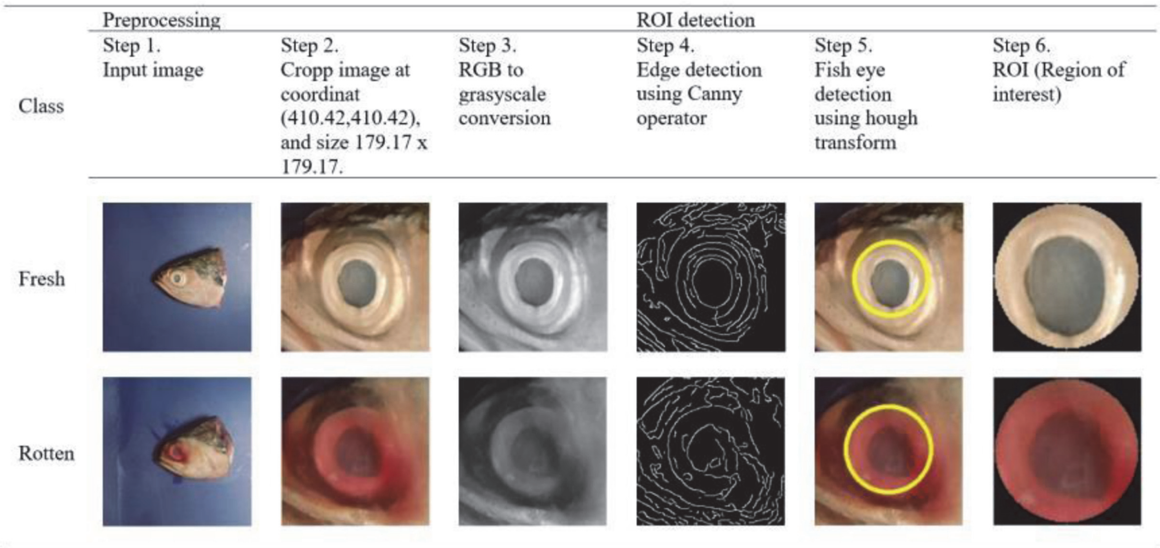


Fig. 3. Preprocessing and ROI detection results.

C. Preprocessing and ROI Detection

The preprocessing stage includes cropping the image at certain coordinates and scales. Crop and detection was carried out using MATLAB R2015a. The crop method is used to reduce the edge detection area that will be carried out at the region-of-interest (ROI) detection stage. The ROI used in the fish freshness classification process is the fish eye. The ROI detection process includes image input, image cropping, RGB image conversion to grayscale, edge detection using the Canny operator, fish-eye detection with the Hough transform method, cropping ROI detection results, displaying ROI cropping results in RGB color channels and converting RGB ROI images into a grayscale image. The RGB ROI image is used in the RGB value feature extraction process and the grayscale converted RGB ROI image is used in the GLCM feature extraction process. The preprocessing and ROI detection stages are shown in Fig. 3.

D. Feature Extraction of ROI and Dataset Split

To better differentiate class groupings during classification, feature extraction aims to identify differences in patterns. Examples of characteristics or features include color, shape, geometry, size and texture [43]. The feature extraction in this study is based on the RGB color and GLCM characteristics. MATLAB is used to perform the RGB and GLCM values extraction process. RGB colors are the three primary colors that make up a pixel image. By using an 8-bit system for each component, an RGB image utilizes a 24-bit image in terms of system capacity. The color intensity of each pixel in the RGB image ranges from 0 to 255 [44].

The GLCM extraction method is a feature extraction method based on texture values. The GLCM method is used to determine the relationship of texture values between pixels based on operations on the second-order statistics of the image [45, 46]. The GLCM feature extraction process uses two neighbouring pixels. The GLCM determines the brightness level frequency value of two paired pixels. The matrix with the same number of rows and columns as the grey image size is used to represent the image's GLCM attribute. The frequency values of the two provided pixels are used to calculate the matrix's elements. The two pixels used can vary depending on the area. The second-order statistical probability value in this GLCM matrix element can be determined based on the grey value of each image row and column pixel. As the intensity value of the image is distributed, the value of the pixel matrix becomes larger. The following GLCM features were used in this study, namely contrast, correlation, energy, and homogeneity. The flow of the extraction and classification process is shown in Fig. 4.

Contrast is a parameter that measures the intensity of the contrast between a pixel and its neighbor over the entire image [46]. Eq. (1) is used to calculate the contrast value.

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \tag{1}$$

Correlation is used to calculate the linear dependencies of grey tones in an image. It describes how a pixel is related to its neighbor [46]. Eq. (2) is used to calculate the correlation.

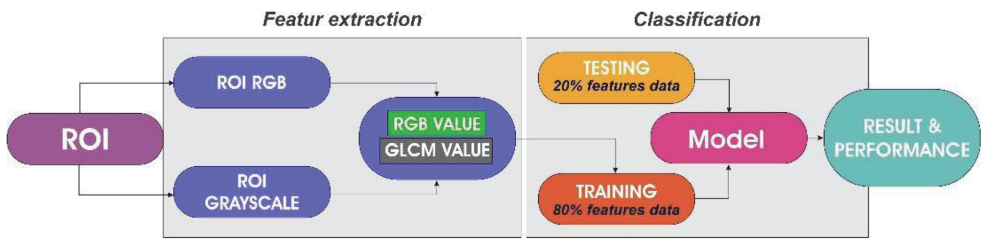


Fig. 4. Process of features extraction and classification.

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (2)$$

Energy is also known as uniformity, which gives the number of square elements in the GLCM matrix through the homogeneous region to the inhomogeneous region [46]. The energy has a high value if the repeatability of the image pixel value is high. Eq. (3) is used to calculate the energy value.

$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2 \quad (3)$$

The term homogeneity refers to the similarity of pixels. The value of the GLCM matrix of a homogeneous image is 1. It is very low if the image texture requires only minor changes [46]. Eq. (4) is used to calculate the homogeneity value.

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (4)$$

$$\mu = \sum_{i,j=0}^{N-1} iP_{ij} \quad (5)$$

$$\sigma^2 = \sum_{i,j=0}^{N-1} P_{ij}(i-\mu)^2 \quad (6)$$

where P_{ij} is the normalized GLCM matrix element, μ is the mean of the GLCM matrix which can be calculated by Eq. (5), σ is the intensity variance value of all pixels that can be calculated using Eq. (6) and N is the total of grey level pixels of the image.

These properties are used to construct the GLCM feature matrix that can correctly represent an image using fewer parameters. MATLAB supports all extraction methods for RGB and GLCM values. The outcomes of the extraction procedure are saved in a features database table. The extracted data features are divided into 80% as training data and 20% as test data such as the research conducted by [47]. The training and test data have been saved in a different file in .csv format.

E. Classification with k-NN and NB

The ML classification method used in this study is k-NN and NB. k-NN is one of the machine learning techniques used to predict a phenomenon and categorize data that has not yet been assigned to a category into category with the most similar properties [48]. Finding the shortest distance between the evaluation data and its nearest neighbor in the training data is the basis of the k-NN algorithm. The k-NN algorithm can solve classification problems in various fields by showing accurate and meaningful results [49, 50]. The classification process uses the value of k to see the closest amount of data related to the class identification [14]. The *k* value in k-NN is the number of nearest neighbors of a data that will be classified. This study uses several values of *k*, namely *k*=1, *k*=3, *k*=5, *k*=7, and *k*=9. Several values are used to obtain the classification model with the best performance. The calculation of the neighborhood distance using the Euclidean distance is shown in Eq. (7).

$$d(x,y) = \sum_{k=1}^{N-1} \sqrt{(x_k - y_k)^2} \quad (7)$$

where $d(x,y)$ is the distance between x and y, x is data whose class is unknown, y is data from each specified class and N represents the total of data x and y.

The Bayesian Theorem is referenced by the straight-forward probability classification method known as the NB classifier [32]. According to the theorem, the probability of an event occurring is determined by multiplying the intrinsic probability, which was estimated on the basis of currently available data, by the probability that a similar event will occur again in the future (based on the knowledge of what happened in the past). The Bayes method is a statistical method of inductive inference about classification and regression problems [51]. Bayes' theorem is shown in Eq. (8). The contrast, correlation, energy and RGB homogeneity values are numerical data so that calculations can be performed using Gaussian NB. The Gaussian NB calculation method is shown in Eq. (9).

$$P(h|x) = \frac{P(x|h)P(h)}{P(x)} \quad (8)$$

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (9)$$

where, $P(h|x)$ is the probability of the hypothesis h under the condition of x, $P(x|h)$ is the probability x based on the

Table 1. Classification process using k-NN and NB

	k-NN	NB
Step 1	Input the training data that has been saved in the .csv file to MATLAB.	Input training data that has been saved in the .csv file to MATLAB.
Step 2	Conduct training on the k- NN classifier using the Euclidean distance (as shown in Equation 7) which is implemented in MATLAB. The training is carried out using several k values.	Conduct training on the k- NN classifier using the Euclidean distance (as shown in Equations 8 and 9) which is implemented in MATLAB.
Step 3	Save the training model for each value of k.	Save the training model.
Step 4	Input the testing data that has been saved in the .csv file to MATLAB.	Input the testing data that has been saved in the .csv file to MATLAB.
Step 5	Classify the testing data by calling the training model that was stored for each value of k.	Classify the testing data by calling the training model that was stored.
Step 6	Displays the confusion matrix (as shown in Fig. 5) of the classification results for each k value.	Displays the confusion matrix (as shown in Fig. 5) of the classification results.
Step 7	Calculating the performance of the classification results based on the equations presented in Table 5.	Calculating the performance of the classification results based on the equations presented in Table 5.

condition, $P(h)$ is the probability of the hypothesis h, $P(x)$ is the probability x, h is the hypothetical class of x, and x is the data that has no class. μ and σ were mean and variance data. The classification process is shown in Table 1.

Classification by k-NN and NB was carried out in MATLAB. The performance of the classification method is evaluated based on the value in the confusion matrix. The confusion matrix is a matrix containing the predicted and actual values of classification results that are used to measure the performance of the classification model [14]. This matrix contains information about the actual and predicted classification data obtained by the k-NN and NB classifiers. The confusion matrix format is shown in Fig. 5.

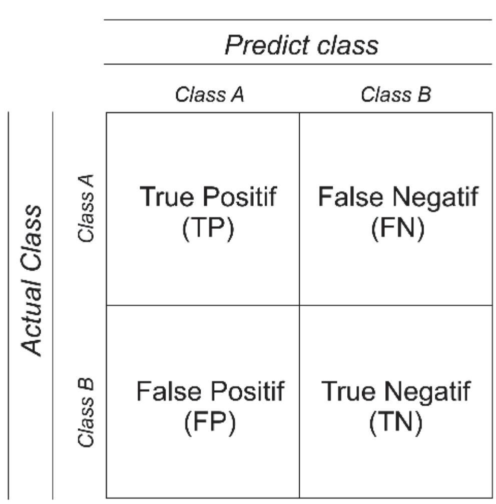


Fig. 5. The format of the confusion matrix in this study.

III. RESULT AND DISCUSSION

A. Acquisition Result and Class Division

The total acquired fish images are 160 images. The total image is divided into 80 images in the fresh class and 80 images in the rotten class. The acquired image is saved in .jpg format with a size of 1000×1000 pixels. Sample image acquisition results for each class are summarized in Table 2. Table 2 shows that the image acquisition of each fish head yields 16 images because it has two sides. The purpose of image acquisition from different directions was to obtain various patterns of changes in the direction of the fish's head. The pattern of variation is useful for obtaining the complexity of the image feature values that will be used as the freshness classification characteristics of the fish.

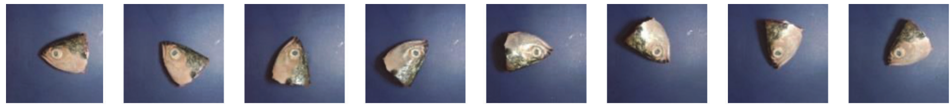
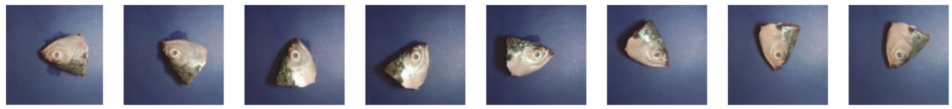
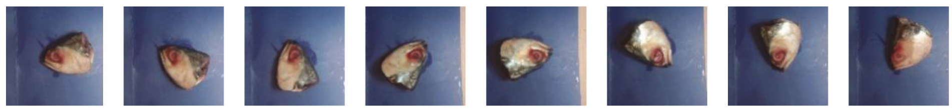
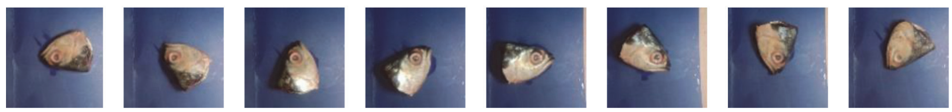
B. Preprocessing and ROI Detection

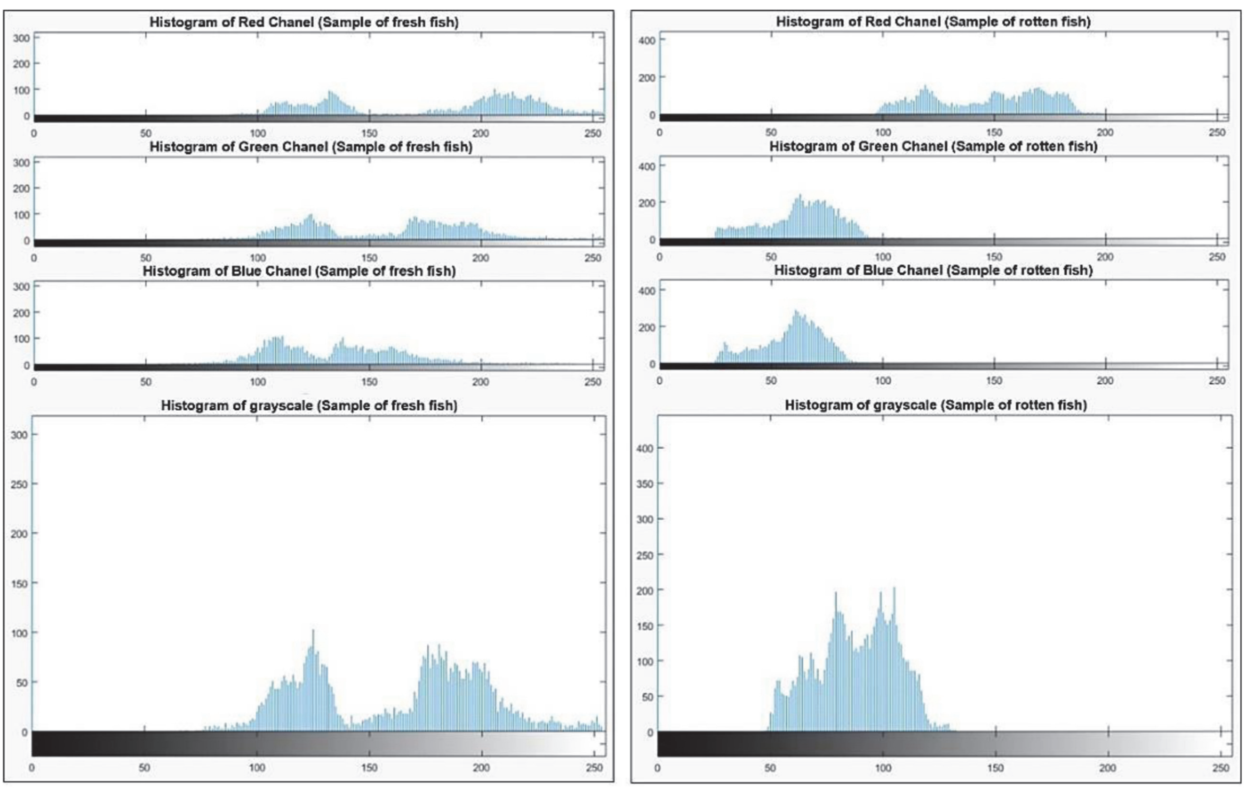
The eye of the fish is circular. Visible fish eyes are bulging, clear and shiny, when fresh. Over time, the shape of the eyes shrinks and their appearance becomes dull, reddish and greyish. As a result, fish-eye tissue can be used as an indicator for assessing the freshness of fish samples. Therefore, the eye tissue has been recognized as ROI for RGB and GLCM feature extraction. The proposed method of obtaining ROI consists of two techniques, namely edge detection and Hough transform. The process of obtaining a fish-eye ROI results is shown in Fig. 3.

C. Feature Extraction and Dataset Division

Feature extraction is carried out to obtain parameter or attribute values that will be used in the classification process. The RGB and GLCM value parameters of each

Table 2. Examples of image acquisition results in each class

Class	Sides of fish head	Acquisition results in eight directions
Fresh	1st side	
	2nd side	
Rotten	1st side	
	2nd side	



(a) (b)

Fig. 6. The distribution of the RGB and grey level intensity values is based on the histogram of the ROI image: (a) fresh fish and (b) rotten fish.

image can be represented by the ROI color intensity value in each freshness class. The distribution of RGB color intensity values and GLCM features can be expressed in red, green, blue, and grey level histograms as shown in Fig. 6.

The ROI of each fish-eye image class reveals variations in RGB color and grey level intensity, as seen in Fig. 6. The grey level intensity is more evenly spread to the right, approaching the value of 255 and the white color intensity is more widely dispersed in fresh fish with the intensity of RGB color. The decay of fish can affect the RGB color value and the intensity of the grey level of the

Table 3. Extraction process of RGB and GLCM values

	Feature Extraction
Step 1	Create a matrix in MATLAB to store the extracted features and a cell array to save the class target.
Step 2	Read the ROI image of the detection results into certain variables.
Step 3	Extraction of red, green, and blue values.
Step 4	Converts the detected ROI image to grey-scale ROI image.
Step 5	Extraction of the contrast, correlation, energy, and homogeneity values using Equations (1–4) based on grey-scale ROI image.
Step 6	Put red, green, blue, contrast, correlation, energy and homogeneity values to the previously created a matrix in step 1.
Step 7	Create a class name for each extracted image and insert it into the cell array that was created in step 1.
Step 8	Combines RGB and GLCM extraction along with their class names.
Step 9	Divide the extraction data into 80% for training data and 20% for testing data, then save it to a .csv file.

fisheye image according to RGB color and grey level intensity distribution for each class. The distribution of these values serves as the basis for the extraction of the GLCM and RGB colors. The extraction process for RGB and GLCM values is shown in Table 3. The feature extraction value is divided into 80% or 128 training data (64 data in fresh class and 64 data in rotten class) and 20% or 32 testing data (16 data in fresh class and 16 data in rotten class) from a total of 160 data with seven features.

D. Classification using k-NN and NB

The final and important step in determining the fish's freshness is the classification process. The performance of the k-NN and NB classifiers was compared for categorizing fish images into the two labelled classes (depending on the circumstances of the fish freshness). The k-NN and NB classification process includes a training and testing process as presented in Table 1. Table 4 shows the outcomes of the freshness classification using the k-NN classifier with varied neighborhood sizes, k, according to the confusion matrix (as presented in Fig. 5). The best classification results among the k-NN classifiers with different neighborhood sizes were attained when k=3, k=7, and k=9, as shown in the table. Accuracy, precision, recall, specificity, and AUC for this model averaged 0.97, 0.97, 0.97, 0.97, and 0.97 for each class, respectively (Table 5). Table 6 displays the classification outcomes using the NB classifier based on the confusion matrix. It shows that the average value of accuracy, precision, recall, specificity, and AUC were 0.94, 0.94, 0.94, 0.94, and 0,94. Based on the performance value of the classification

Table 4. Classification results using the k-NN classifier

Number of neighbors (k)	Class	Confusion matrix		Accuracy	Precision	Recall	Specificity	AUC
1	Fresh	14	2	0.94	1.00	0.88	1.00	0.94
	Rotten	0	16	0.94	0.89	1.00	0.88	0.94
	Avg.			**0.94**	**0.94**	**0.94**	**0.94**	**0.94**
3	Fresh	15	1	0.97	1.00	0.94	1.00	0.97
	Rotten	0	16	0.97	0.94	1.00	0.94	0.97
	Avg.			**0.97**	**0.97**	**0.97**	**0.97**	**0.97**
5	Fresh	14	2	0.94	1.00	0.88	1.00	0.94
	Rotten	0	16	0.94	0.89	1.00	0.88	0.94
	Avg.			**0.94**	**0.94**	**0.94**	**0.94**	**0.94**
7	Fresh	15	1	0.97	1.00	0.94	1.00	0.97
	Rotten	0	16	0.97	0.94	1.00	0.94	0.97
	Avg.			**0.97**	**0.97**	**0.97**	**0.97**	**0.97**
9	Fresh	15	1	0.97	1.00	0.94	1.00	0.97
	Rotten	0	16	0.97	0.94	1.00	0.94	0.97
	Avg.			**0.97**	**0.97**	**0.97**	**0.97**	**0.97**

Table 5. Performance evaluation value of the classification results based on the confusion matrix

Equation	Focus
$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	Effectiveness of the classifier as a whole
$Precision = \frac{TP}{TP + FP}$	The data labels that match the positive labels of the classifier
$Recall = \frac{TP}{TP + FN}$	The ability of a classifier to find positive labels
$Specificity = \frac{TN}{TN + FP}$	How well the classifier can identify the negative labels.
$AUC = \frac{1}{2}(\frac{TP}{TP + FN} + \frac{TN}{TN + FP})$	The capacity of the classifier to prevent misclassification

Table 6. Classification results using the k-NN classifier

Class	Confusion matrix		Accuracy	Precision	Recall	Specificity	AUC
Fresh	14	2	0.94	1.00	0.88	1.00	0.94
Rotten	0	16	0.94	0.89	1.00	0.88	0.94
Avg.			**0.94**	**0.94**	**0.94**	**0.94**	**0.94**

process on data testing, it can be stated that the k-NN method has better performance than the NB classifier method in identifying two classes of fish freshness using RGB and GLCM features.

IV. CONCLUSION

Monitoring the freshness of fish can be carried out using sensors, spectrometers, chemical detection techniques based on liquid and gas chromatography, as well as with the use of physical detection techniques. These methods have a high level of accuracy but have limitations such as requiring relatively expensive equipment, requiring trained personnel and being destructive. To overcome these obstacles, a method has been developed that can reduce costs and is easy to apply using machine learning based on image classification.

The machine learning classification method used is k-NN and NB by utilizing RGB and GLCM color features extraction from fisheye ROI. The process of identifying the freshness of fish includes fish collection, image acquisition and class division, preprocessing and ROI detection, feature extraction and dataset sharing followed by a classification process. Research shows that the k-NN and NB methods can be used to determine the freshness of fish. Based on the results and discussion, it can be stated that the k-NN method has better results than the NB method in identifying two classes of fish freshness.

Future research may use more images and apply image capture techniques in a more diverse environment so that comparisons can be made with this research. In addition, it is highly recommended to develop a system for identifying the freshness of fish using a smartphone for further research.

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Rusydi Umar

Rusydi Umar received B.Eng. and M.Eng. in electrical engineering from Instititut Teknologi Sepuluh Nopember and Universitas Gadjah Mada, Indonesia, in 2001 and 2005, respectively, and the Ph.D. degree from Universiti Teknologi Malaysia in 2011. He is an Associate Professor with the Electrical Engineering Department, Universitas Ahmad Dahlan, Indonesia, and the leader of Center for Electrical and Electronic Research and Development (CEERD). His current research interests include Signal Processing, Wireless Communication, Communication-Multimedia, and Numerical Method.

Rusydi Umar

Rusydi Umar received B.Eng. in electrical engineering from Universitas Gadjah Mada and M.Eng. in informatics engineering from Institut Teknologi Bandung, Indonesia, in 1998 and 2003, respectively, and the Ph.D. degree from University of Hyderabad India in 2014. He is a Lecturer in the Masters Program of Informatics, Universitas Ahmad Dahlan, Indonesia, His current research interests include informatics engineering and cloud & grid computing.

Sabarudin Saputra

Sabarudin Saputra is a student in Master Program of Informatics at Universitas Ahmad Dahlan, Indonesia. His research is focused on image processing, pattern recognition, and artificial intelligence.