Classification of Nile Tilapia's Freshness Based on Eyes and Gills Using Support Vector Machine

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Abstract. Fish is one of the foodstuffs that contain high protein and essential amino acids the body needs. Nile Tilapia is a fish that the people of Indonesia widely consume. The high nutritional content of tilapia and affordable prices make this fish popular with the public. The difference between fresh and unfresh tilapia can be assessed from organoleptic tests, including gill color, texture, and smell. Consumers can check by looking at the condition of tilapia based on its distinguishing physical characteristics such as eyes, gills, flesh texture, skin, and fish mucus. However, not everyone knows and understands these typical characteristics. Therefore, we need a system that can classify the freshness level of tilapia. In this study, the freshness level of tilapia will be classified based on the color and texture features of the eyes and gills using the Support Vector Machine. The GLCM approach is used to extract texture features, whereas the HSV method is utilized to extract color features. The total number of photos used in this investigation was 840, which were separated into training and testing data. With an image size of 256 × 256 pixels, the combined feature of HSV + GLCM achieves the highest accuracy of 94.28%.

Keywords: Nile Tilapia · Classification · Feature · Image Processing · Fish

1 Introduction

Fish is one of the foodstuffs that contain high protein and essential amino acids the body needs. Statistics from the Ministry of Maritime Affairs and Fisheries show that the national fish consumption rate (MMR) continues to increase yearly. The national MMR in 2021 is 55.37 kg/capita [1]. This figure increased compared to the previous year which was 54.56 kg/capita. With the increase in fish consumption, the demand for fish will also increase. One of the fish that has increased demand is Nile tilapia. Nile tilapia is a fish that the people of Indonesia widely consume. The high nutritional content of Nile tilapia and affordable prices make this fish popular with the public.

Everyone who likes to consume tilapia certainly wants fresh tilapia with high quality both in terms of taste and nutritional content. The difference between fresh and non-fresh Nile tilapia can be assessed from organoleptic tests, including gill color, texture

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and smell [2]. Visually, consumers can check the freshness of tilapia by looking at the condition of tilapia based on its distinguishing physical characteristics such as eyes, gills, meat texture, skin and fish mucus. However, not everyone can distinguish fresh and non-fresh tilapia based on these characteristics. In addition, this method based on visualization also gives different results for each person or is very subjective. Due to the differences and errors that often occur when checking the freshness of Nile tilapia with the visual method, it is necessary to develop an automatic tilapia freshness detection system. The system is built using a computer by implementing various algorithms and methods of image processing and machine learning (classification) [3]. Various methods can be used to classify the freshness of Nile tilapia, one of which is the Support Vector Machine (SVM) method.

Support Vector Machine (SVM) is a classification method based on the largest margin. The SVM method finds the best dividing boundary by finding the maximum distance from all data points. In a previous study, the SVM method successfully identified beef's freshness and yielded an accuracy of 97% [4]. The following research is the detection of fish freshness based on the eyes and gills [5]. SVM also has advantages in determining the distance using a support vector so that the computational process becomes fast [6]. Therefore, the SVM method can be used for the freshness classification of Nile tilapia. As for the features that will be used, namely the color and texture features. The color and texture features will be extracted from the gills and eyes of the Nile tilapia. The color feature will use the Hue Saturation Value (HSV) color space model. HSV is a color with a segmentation that almost detects colors that can be captured by the eye's retina [7]. As for the texture features, we will use Gray Level Co-occurrence Matrix (GLCM). GLCM was the most potent texture descriptor used in image analysis [8]. One of the studies that used a combination of HSV and GLCM methods, namely the identification of woven fabric motifs resulted in the highest accuracy of 91.67% [9].

2 Literature View

Previous studies related to the classification of fish freshness based on the eyes and gills have been carried out previously by several researchers. Identification of the freshness of Nile tilapia using the convolutional neural network algorithm [10] with an accuracy of 98.88%, However, this study only focuses on the classification of sick and healthy Nile tilapia. The following research is the classification of Katsuwonus Pelamis (Skipjack tuna or Skipjack), Euthynnus Affinis (Tongkol) and Coryphaena Hippurus (Mahi-mahi) using transfer learning and Matlab applications, obtaining an accuracy of 99.63% [11]. The next research will classify fish species using a combination of contrast limited adaptive histogram equalization (CLAHE) with adaptive features threshold by fuzzy c-means [12]. In addition, research related to fish detection and species classification uses deep learning and obtains an accuracy of 91.2% [13].

The HSV color space has been used in studying fresh marine fish identification based on HSV color and morphology [14] using fish gills and eyes. This study provides the highest accuracy of 90% with the HSV method and 85% with the texture method. The GLCM method has also been used in previous studies to identify the freshness level of tuna. The results of this study obtained an accuracy of 81.6%. And the accuracy results obtained indicate that GLCM works nicely to improve accuracy [15]. The GLCM feature is also used for X-Ray image classification using machine learning [16].

As for the Support Vector Machine (SVM) method, it has been used in various studies. Research on the classification of beef freshness level using the SVM method was successfully carried out with an accuracy of 97% [4]. The SVM method is also used in research on fish freshness detection based on eyes and gills [5].

From this explanation, in this study, a system of "Classification of Nile Tilapia Freshness Levels Based on Eyes and Gills Using a Support Vector Machine will be built". The eyes and gills of Nile tilapia will be used as parameters to determine the freshness level of tilapia. The eyes and gills of Nile tilapia will be extracted to obtain color and texture features which will then be classified using the Support Vector Machine (SVM). The SVM method is used as a classification method because, in previous studies, SVM has succeeded in detecting the freshness of milkfish, obtaining an accuracy rate of 98.2%. For color feature extraction, the HSV color space was used, and in previous studies, the HSV color space had a success rate of up to 90%. As for the texture features, the GLCM method is used. In previous studies, the GLCM method gave the highest accuracy of 98.5%. In previous studies, combining the HSV and GLCM color space can give up to 100% accuracy.

3 Methods

3.1 Tools and Materials

The camera takes fish pictures using the Xiaomi Note 9 Pro smartphone, 64 MP. While the materials used in this study are:

1. Nile tilapia with the amount of 30 fish. The parts of the Nile tilapia that will be used are the eyes and gills.
2. The eyes and gills of Nile tilapia are 840 images in JPG format with a maximum size of 512 × 512 pixels. The eye and gill images will be divided into two classes: fresh and not fresh. Image acquisition using a 64 MP HP camera with a distance of 15 cm and an angle of 90° will be taken every 30 min for 8 h starting at 0 h and stored at room temperature. Eye and gill images taken at 0–3 h will enter the fresh class, while eye and gill images taken at 4–7 h will enter the unfresh class. This fresh and unfresh class division is based on the organoleptic value of tilapia [2].

3.2 Research Flow

1. Nile Tilapia Image Data Collection
   The first step of this research design is data collection of tilapia. For image capture of Nile tilapia, the eyes and gills were taken, the camera used was a 64 MP HP camera. Image capture distance is 15 cm with an angle of 90° The data used in this study were 840 images. The data for the fresh class is 420 images with a division of 210 for the eye image and 210 for the gill image. Meanwhile, data for the non-fresh class is 420 images with a division of 210 for the eye image and 210 for the gill image.

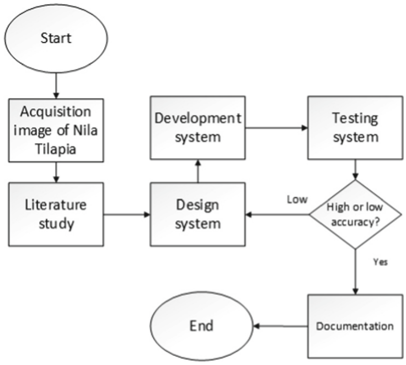

Fig. 1. Research Flow

2. Literature Study
   The second step is conducting literature to study the development method and the working principle of the method used, namely the SVM method for classification and HSV and GLCM for image feature extraction.
3. System Design
   The third step is to design the system. At this stage, the system is designed to classify the freshness of Nile tilapia with the methods used, namely HSV and GLCM for image feature extraction and the SVM method is used as a classification method.
4. System Development
   The fourth step is to start the system development with the method used. In this study, the methods used are HSV and GLCM for image feature extraction and SVM as a classification method.
5. System Testing
   After the system development is complete, the fifth stage is to test the system. The success of the system is measured by the accuracy obtained. If the accuracy is good enough, the next step is documentation.
6. Documentation
   The last step is making a documentation. From the beginning of data collection to the end of system. Figure 1 shows the research flow.

3.3 Pre-processing

In this study, preprocessing consists of cropping, resizing, and image color conversion. Cropping is done to take the required image and remove the unnecessary part. An example of cropping can be seen in Fig. 2.

Resizing changes the image resolution to 256 × 256 pixels and 512 × 512 pixels. Figure 3 is an example of resizing an image. The cropping process is carried out outside the system, while the resizing process is carried out inside the system.

After the image resolution is changed, the image color space is converted from RGB to grayscale color space. Grayscale images will be used in the GLCM method. Figure 4 is an example of the conversion result from RGB color space to grayscale.

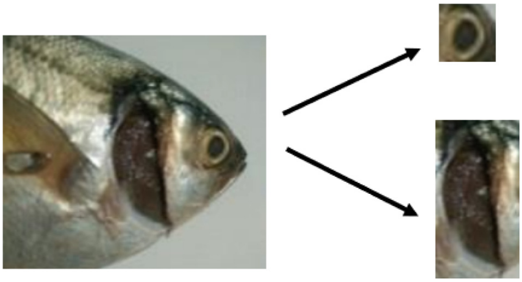

Fig. 2. Cropping process

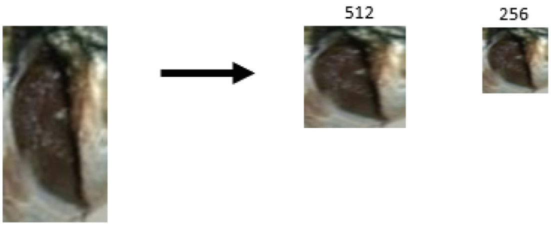

Fig. 3. Resizing process

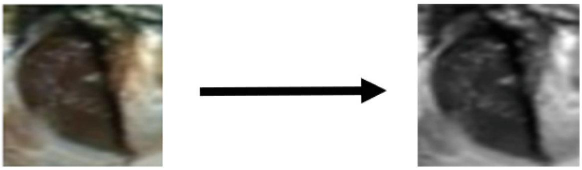

Fig. 4. Result of conversion from RGB to grayscale

The process of cropping, resizing, and converting the color space to the image is done to simplify the feature extraction process to be performed on the image. This preprocessing stage was carried out on the existing fish eye and gill images.

3.4 Classification

The following is the flow diagram of the classification process, which can be seen in Fig. 5. Figure 5 illustrates the process of classifying the freshness level of Nile tilapia based on eyes and gills using SVM. There are 2 main process in classifying the freshness level of Nile tilapia, namely training and classification. The data used in this study were 840 images. The data for the fresh class is 420 images with a division of 210 for the eye image and 210 for the gill image. Meanwhile, data for the non-fresh class is 420 images with a division of 210 for the eye image and 210 for the gill image.

3.5 Training Phase

The stages of the training process can be explained as follows:

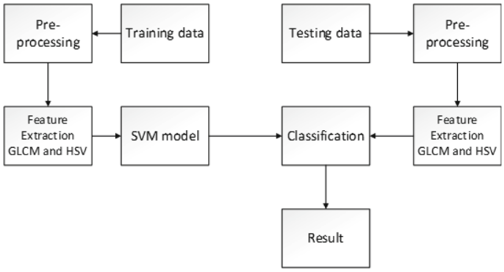

Fig. 5. Classification process

1. Input image of gills and eye of Nile tilapia as training dataset. The image that is entered into the system is an image that has been cropped. Next, the resizing process will be divided into two different sizes 256 × 256 pixels and 512 × 512 pixels. The resizing process is carried out to reduce computation time. In addition, two different image sizes will be added as the parameters in the training scenario. The cropping process is carried out outside the system to save computing time in the system. While the resizing process is carried out in the system. The total image used in the training process is 588, consisting of 294 images for each class.
2. The preprocessing step is the initial step of processing the original image before extracting it in the training and testing processes. Cropping process is carried out outside the system, therefore the preprocessing carried out inside the system is the resizing and gray scale process.
3. Feature extraction carried out in this study is divided into two, namely the extraction of texture features and color features. Texture feature extraction was carried out using the GLCM method, while color feature extraction was done using the HSV method.
4. The training model with SVM is carried out to get the model of the training phase that can be used to classify the freshness of Nile tilapia.

3.6 Testing Phase

The testing phase has the same sequence of steps as the training phase. The difference is only in the output, where the output in the testing phase is the final classification result.

3.7 Gray Level Co-occurrence Matrix

GLCM is a matrix that describes the frequency of occurrence of pairs of two pixels with a certain intensity in a distance d and a direction orientation with a certain angle in the image. Distance is expressed in pixels, usually 1, 2, 3 and so on. Angle orientation is expressed in degrees, namely 0, 45, 90 and 135°. The direction of the angle in the GLCM matrix can be seen in Fig. 6 [4].

GLCM is a second-order statistical texture feature extraction method. Where pairs of pixels with specific values and defined spatial relationships in an image are entered into a matrix, statistical features are extracted from this matrix. Calculations provide functions that characterize the texture of an image. The number of rows and columns

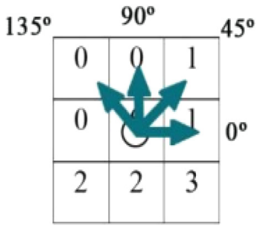

Fig. 6. Direction in GLCM

in the matrix equals the number of gray levels in the image. The P(i,j) matrix elements are entries in the normalized gray-tone spatial dependency matrix. Some of the features of GLCM include contrast, inverse different moment (IDM), correlation, energy, and homogeneity [16].

3.8 Color Space

The RGB color model is a color model based on the concept of adding intense primary light, namely Red, Green, and Blue. If the room is entirely dark, it means the room have no light. No lightwave signal is absorbed by our eyes or RGB (0,0,0). If a red light is added to the room, the room will change color to RGB red (255,0,0). All objects in the room can only be seen in red. Likewise if the light is replaced with green or blue. RGB color space can be seen in Fig. 7.

HSV is an example of a color space representing colors as seen by the human eye. H comes from the word "hue", S comes from "saturation", L comes from the word "luminance", I comes from the word "intensity", and V comes from "value". It can be seen in Fig. 8. The extracted HSV features include mean, deviation standard, and skewness.

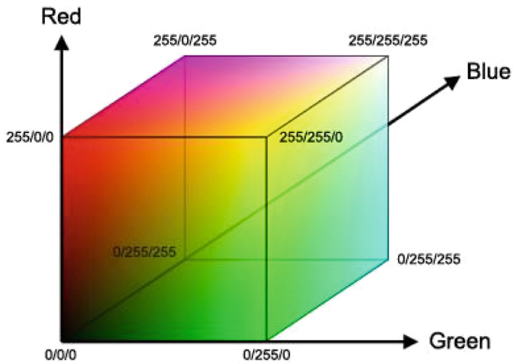

Fig. 7. RGB color space

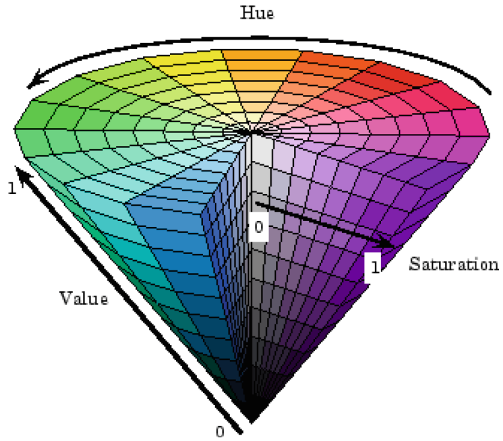

Fig. 8. HSV color space

3.9 Support Vector Machine

SVM is a machine learning method with the working principle of Structural Risk Minimization (SRM). This SVM aims to find the best hyperplane that separates two classes in the input space. SVM is a learning system that uses a hypothetical space in the form of linear functions in a high-dimensional feature space. The SVM technique is related to data mining and machine learning because it can predict the class of new data [6].

The following is a discussion of classification cases that can be linearly separated. In this case, the separator function sought is linear. This function is defined in Eq. (1).

$$f(x) = w.x + b \tag{1}$$

By measuring the hyperplane's margin and determining its greatest point, the optimal separating hyperplane between the two classes can be identified. The margin is the separation between the nearest pattern in each class and the hyperplane. A support vector is the name given to this closest pattern. The circles and squares on the dotted lines *cd* and *ef* are support vectors, and the *ab* line in Fig. 9 depicts the optimum hyperplane, which is situated directly between the two classes.

Each training data is represented by (x_i, y_i), where $i = 1, 2, \ldots, N$, and $x_i = \{x_{i1}, x_{i2}, \ldots, x_i q\}$. T is an attribute (feature) set for the training data i. $y_i \in \{-1, +1\}$ represented class label. Hyperplane linear classification can be seen in Fig. 9, formulated in Eq. (2)

$$w.xi + b = 0 \tag{2}$$

3.10 Evaluation

In this study, the classification results were evaluated by calculating the values of True Positive, True Negative, False Positive, and False Negative. True Positive is the number of correct classification results for a positive class. True Negative is the number of correct

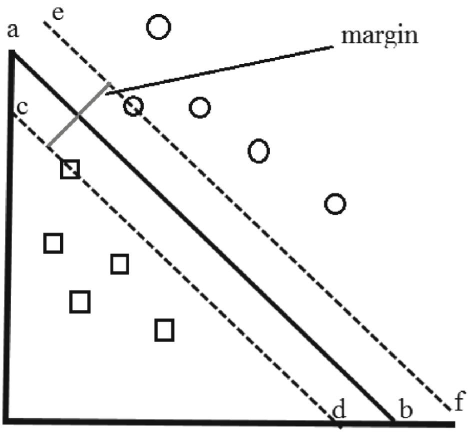

Fig. 9. Hyperplane margin

Table 1. Confusion matrix table.

Classification result **True class**	**Positive**	**Negative**
Positive	TP	FN
Negative	FP	TN

classification results for a class with a negative value. False Positive is the number of incorrect classification results for a positive class. False Negative is the number of incorrect classification results for a class with a negative value. The confusion matrix can calculate the four values. It can be seen in Table 1 [4]. These values are then used to calculate the evaluation parameters of the classification results.

Accuracy can be defined as the proportion of two classes (positive and negative) from the total number of classes tested. The following is Eq. (3) to calculate the accuracy value.

$$accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{3}$$

Recall is the proportion of correctly classified positive classes. The following Eq. (4) will show the calculation for the recall value.

$$recall = \frac{TP}{TP + FN} \tag{4}$$

Precision is the proportion of the positive class classified as true positive compared to the overall result classified as positive. Equation (5) shows the calculation for precision.

$$Presisi = \frac{TP}{TP + FP} \tag{5}$$

4 Result and Discussion

4.1 Effect of Image Resolution on Accuracy

This test was conducted to test the effect of image resolution on accuracy. This test aims to obtain a better image resolution for classifying Nile tilapia's freshness level based on the eyes and gills color and texture features. Images with 256 × 256 pixels and 512 × 512 pixels are used both in the training and testing process, then comparisons are made to the classification results. The accuracy of the classification results based on image resolution can be seen in Tables 2, 3, and 4.

In Tables 2, 3, and 4, it can be concluded that image resolution does not affect the HSV feature's accuracy but the GLCM feature's accuracy. In Table 2 the accuracy of GLCM with a resolution of 512 × 512 is lower than 256 × 256 with a difference of 3.49% and the combined accuracy of HSV + GLCM decreases by 2.06%. Table 3 on gill images with a resolution of 512 × 512 got the higher accuracy than 256 × 256 with a difference of 0.08% and a combined HSV + GLCM of 0.24%. In Table 4, the image has a resolution of 256 × 256 got better accuracy than 512 × 512 with a difference of 2.38% and the combined accuracy of HSV + GLCM is 0.40%. From Tables 2, 3, and 4 it can be seen that by combining the features of HSV + GLCM the classification results obtained have increased.

Table 2. Effect of Eye Image Resolution on Accuracy

Image Resolution	**Accuracy (%)**		
	HSV	***GLCM***	***HSV + GLCM***
256 × 256	71.98	67.77	76.50
512 × 512	71.98	64.28	74.44

Table 3. Effect of Gill Image Resolution on Accuracy.

Image Resolution	**Accuracy (%)**		
	HSV	***GLCM***	***HSV + GLCM***
256 × 256	91.11	78.09	92.93
512 × 512	91.11	78.17	93.17

Table 4. Effect of Eye and Gill Image Resolution on Accuracy.

Image Resolution	**Accuracy (%)**		
	HSV	***GLCM***	***HSV + GLCM***
256 × 256	91.11	78.09	92.93
512 × 512	91.11	78.17	93.17

Table 5. Precision and Recall Value Based on Eye Image Resolution.

Image resolution	Recall (%)			Precision (%)		
	HSV	***GLCM***	***HSV + GLCM***	***HSV***	***GLCM***	***HSV + GLCM***
256 × 256	71.54	59.02	72.35	73.17	72.84	79.60
512 × 512	71.39	58.87	72.06	87.03	63.63	76.52

Table 6. Precision and Recall Value Based on Gills Image Resolution.

Image resolution	Recall (%)			Precision (%)		
	HSV	***GLCM***	***HSV + GLCM***	***HSV***	***GLCM***	***HSV + GLCM***
256 × 256	89.23	79.98	91.94	92.75	77.48	93.94
512 × 512	89.57	78.42	92.55	92.51	78.52	93.81

Table 7. Precision and Recall Value Based on Eye and Gills Image Resolution.

Image resolution	Recall (%)			Precision (%)		
	HSV	***GLCM***	***HSV + GLCM***	***HSV***	***GLCM***	***HSV + GLCM***
256 × 256	90.96	79.29	93.16	94.10	84.12	95.35
512 × 512	91.14	74.99	93.29	93.96	81.44	94.28

The accuracy for each class can be seen from the precision and recall value. Tables 5, 6, and 7 show the precision and recall values of the classification results based on image resolution.

Table 5 shows that HSV features have increased in value in terms of precision and recall, while GLCM and HSV + GLCM show that the larger the eye image, the more difficult it is to recognize because the eye texture will be more similar, and the system will misrecognize the class of the image.

Table 6 shows very slight differences between 256 × 256 pixel and 512 × 512 resolution images. In HSV recall, the larger the image, the value of the recall will increase 0.34%, while in HSV precision, the value will decrease by 0.24%. In GLCM recall, the larger the image, the value of the recall will decrease by 1.56%, while in GLCM precision, the value will increase by 1.04%. In HSV + GLCM recall, the larger the image, the recall value will increase by 0.61%, while in the HSV + GLCM precision, the value will decrease by 0.13%.

Table 7 shows that HSV recall has increased with increasing image resolution, which is 0.18%. Meanwhile, HSV precision decreased by 0.14%. Meanwhile, both GLCM recall and precision decreased with increasing image resolution. For the HSV + GLCM feature, the recall value has increased by 0.13%, and the precision value has decreased by 1.07%.

5 Conclusion

Based on the research that has been done, it can be concluded that:

1. The image resolution of 256 × 256 pixels is the better in terms of accuracy, precision and recall.
2. The highest accuracy is obtained on the HSV + GLCM feature with an image resolution of 256 × 256 pixels using the image of fish eyes and gills, which is 94.28%.
3. The changes in image resolution do not significantly affect the accuracy obtained.
4. The changes in image resolution do not affect the HSV feature.
5. The SVM method was successful in classifying the freshness of tilapia.
6. The color and texture features are suitable for classifying the freshness of Nile tilapia.

For further research can add features while still paying attention to increasing accuracy.

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