Jurnal Teknik Informatika (JUTIF) Vol. 6, No. 4, Agustus 2025, Page. 2107-2122
P-ISSN: 2723-3863 https://jutif.if.unsoed.ac.id
E-ISSN: 2723-3871 DOI: https://doi.org/10.52436/1.jutif.2025.6.4.5146

Automated Classification of Mungkus Fish Freshness Based on Eye and Gill Images Using the Naive Bayes Algorithm

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Received : Jul 19, 2025; Revised : Jul 20, 2025; Accepted : Jul 20, 2025; Published : Aug 19, 2025

Abstract

The problem of assessing the freshness of fish, especially Mungkus fish, is usually directed at several physical indicators, such as eye appearance, gill condition, meat quality, and odor. This traditional method is often considered inaccurate and requires certain expertise, therefore a more effective and objective method is needed to assess the freshness level of Mungkus fish, which in turn can provide benefits for both fishermen and the public in general. The solution to this problem by using the Naïve Bayes method in classifying the freshness level of Mungkus fish based on eye and gill images has proven to be a fairly efficient approach. The Naïve Bayes method itself is a simple but very effective algorithm in the field of machine learning, and operates based on Bayes' Theorem with the assumption that features are independent of each other. This method can be applied in the initial stage of classification by utilizing basic features taken from images of fish eyes and gills. Based on testing 30 new data sets, the clustering system demonstrated an accuracy rate of 66.67%, indicating that 20 data sets were correctly classified according to their actual conditions. On the other hand, 10 data sets, or 33.33%, could not be categorized correctly. Of the 30 old data sets tested, the system was able to correctly classify 19 (63.33%), while 11 (36.67%) still had errors in their classification predictions. Overall, the system successfully performed data clustering with 65% accuracy, with the remaining 35% still showing errors in the classification process.

Keywords : *Classification, Fish Freshness, Mungkus Fish, Naïve Bayes.*

1. INTRODUCTION

The Mungkus fish, better known by its scientific name Sicyopterus stimpsoni, is a type of freshwater fish typically found in sandy and rocky habitats. Furthermore, the Mungkus fish can also live in fast-flowing or moderately clear waters. One of the unique characteristics of this fish is its habit of attaching itself to rocks. On the top of its belly is a special structure called a cupak. This structure allows the Mungkus fish to firmly adhere to rock surfaces, and its primary food is the moss that grows on rocks. This fish is one of the freshwater fish species rich in nutrients and provides good benefits for human health. This fish is known to contain various essential nutrients, including high-quality protein, omega-3 fatty acids, vitamin D, and various minerals needed by the body [1]-[2]-[3]-[4]-[5].

These fishermen typically immediately enter the river to catch the fish with the goal of selling and distributing them. Fishing methods for mungkus fish still rely on basic or conventional equipment. Their numbers are currently dwindling, resulting in fewer fish in the wild, which has led to a rise in market prices. This fish is increasingly rare in its natural habitat, with its habitat confined to South Bengkulu Regency, Bengkulu Province [6]-[7]-[8]-[9]-[10].

The relatively high price of fish often leaves people facing the reality of receiving fish that is not fresh and not worth the cost they have spent on consuming mungkus fish. This is due to a lack of understanding of the freshness level of fish, which can negatively impact health if consumed by consuming mungkus fish that is not fresh. In general, people tend to choose fish that looks fresh and is

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of good quality. The process of evaluating fish freshness is usually still done manually, namely by observing changes in the color of the eyes and gills, the level of elasticity of the flesh, and the aroma produced. However, this traditional method often leads to confusion in assessing whether the fish is truly fresh [11]-[12]-[13]-[14].

Problems in assessing fish freshness typically focus on several physical indicators, such as eye appearance, gill condition, flesh quality, and odor. These traditional methods are often considered imprecise and require specialized expertise. Therefore, a more effective and objective method for assessing the freshness of mungkus fish is needed, which could benefit both fishermen and the public at large.

The solution to this problem using the Naïve Bayes method to classify the freshness level of mungkus fish based on eye and gill images has proven to be quite efficient. The Naïve Bayes method itself is a simple yet highly effective machine learning algorithm, and operates based on Bayes' Theorem, assuming that features are independent of each other. This method can be applied in the initial stages of classification by utilizing fundamental features taken from eye and gill images. Color changes in these two elements are significant indicators that can be used to determine the freshness level of fish. Thus, the Naïve Bayes algorithm has the ability to recognize certain patterns that describe the condition of fish, both fresh and not fresh.

Previous research on Determining Fish Freshness Using Gill Images with a Convolutional Neural Network Approach relied on 150 fish gill image data grouped into three categories: fresh fish, stale fish, and rotten fish [15]-[16]. Classification of Freshness Quality of Tuna Fish Based on Eye Color Using Backpropagation Method is used to train the network in fish image classification, so that it can identify the level of freshness of fish by classifying the freshness of tuna fish based on eye color [17]. Implementation of the Naïve Bayes Classification Method in Predicting the Amount of Household Electricity Usage 60 household electricity usage data tested using the naïve Bayes method, obtained a percentage result of 78.3333% for prediction accuracy, where of the 60 household electricity usage data tested, there were 47 household electricity usage data that were successfully classified correctly [18]-[19]. A device for identifying the quality of fish freshness using the K-Nearest Neighbor approach based on eye color based on Atmega 328 as a way to recognize the freshness level of the fish being tested [20]-[21]-[22]-[23]. Analysis of Feature Extraction and ROI (Region of Interest) in Assessing the Freshness of Milkfish by Utilizing Gray Level Co-occurrence Matrix to analyze digital images based on Gray Level Co-occurrence Matrix (GLCM (GLCM [24]. Classification of Mushrooms Based on Genus Using the CNN Method: Similar morphological characteristics. Therefore, a model is needed that can classify mushrooms based on edible and poisonous genera [25]-[26]-[27].

The purpose of this stage is to make it easier for users to obtain information quickly and accurately by looking at the Accuracy level based on the Precision and Recall values and the results of this classification, users can immediately determine whether the fish is in the fresh category or not without requiring manual analysis.

2. METHOD

This study uses a quantitative method in classifying the freshness of Mungkus Fish using digital images using the Naïve Bayes method. This approach involves processing image datasets, applying pre-processing, and training and testing system models with the following stages: starting from system preparation, image input, feature extraction, processing, validation and results.

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2.1. Flowchart

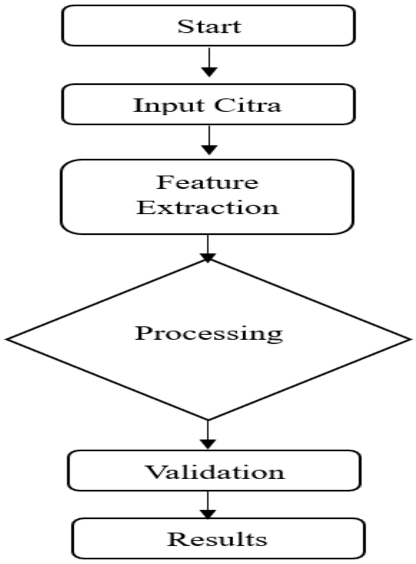

Figure 1. System Flowchart

The stages are as follows:

2.1.1. Start (System Preparation)

The initial phase begins with system preparation or familiarization. In this phase, the system undergoes a series of checks to ensure all components, both software and hardware, are ready. This ensures the system can operate properly and that all technical requirements, such as algorithms, tools, and supporting libraries, are optimally available.

The primary goal of this phase is to ensure the system can begin the classification process without interruption. With proper preparation at the outset, the likelihood of technical errors in subsequent phases can be minimized. This is crucial for ensuring the data input process runs as planned.

2.1.2. Image Input (Input Data In The Form Of An Image)

The next step is to upload images that will be used as test data. In this step, users provide images of fish, specifically the eyes or gills, which will be further processed by the system. This data will then serve as the primary basis for determining the freshness category of the fish.

Uploaded images must meet certain criteria, such as sharp resolution and optimal lighting, to ensure accurate results. This upload process is crucial because image quality directly impacts the accuracy of the feature extraction and classification stages.

2.1.3. Feature Extraction (Ekstraksi Fitur)

Once the image is received by the system, the next step is feature extraction, which aims to identify important characteristics within the image. The system will analyze the image to identify visual attributes relevant to fish freshness, such as color, brightness, or texture.

The output of this process is numeric data or specific attributes that will be utilized by the Naive Bayes algorithm. With the extracted features, the image data will be easier to process because it has been converted into information that the computer can understand.

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2.1.4. Processing (Classification Process With Naive Bayes)

In the processing phase, the system begins applying the Naive Bayes algorithm to the previously obtained feature data. This algorithm calculates probabilities based on the available training data, then classifies whether the image is fresh or not.

Naive Bayes operates based on calculating probabilities between features for a given class. After all probabilities are calculated, the system assigns the category with the highest probability value as the final classification result.

2.1.5. Validation (System Accuracy Testing)

The next step is the validation process, which aims to assess the system's ability to categorize fish images. The validation process is carried out by comparing the system's classification results with data that has been labeled with truth, thus determining the system's accuracy level.

The goal of this step is to assess how well the system predicts new data and to determine whether the algorithm needs improvement. Validation results are typically presented in the form of accuracy, error percentage, or other evaluation metrics such as precision and recall.

2.1.6. Hasil (Output Klasifikasi Akhir)

The final step is communicating the classification results to the user. After all steps are completed, the system will output data on the freshness status of the fish. This data can be presented in written or graphical form on the system interface.

2.2. Data Collection

The data used consisted of 30 images of Mungkus fish, categorized by freshness level, namely fresh and not fresh. All images were in JPG format with a resolution of 150x150 pixels. The image capture process was carried out manually using a mobile phone camera to ensure data authenticity and consistency. Each image was labeled with a corresponding freshness type to facilitate the training and testing of the classification model. This dataset served as the basis for using the Naïve Bayes method to determine freshness levels based on visual attributes.. Links dataset https://drive.google.com/drive/folders/1qQii3c0Zu6Izhu3G8Gj4dv6a95kge022?usp=drive_link.

Table 1. Dataset

File Name	Number of DataSet	Size	Format
Fresh Mungkus Fish	15	150 x 150 px	JPG
Mungkus Fish is Non-Fresh	15	150 x 150 px	JPG
Total	50	150 x 150 px	JPG

2.3. Data Preprocessing

This process includes image adjustment and data enrichment so that the model can learn more effectively from the various variations available. The data is processed through a normalization process using a scale of 1./255 to convert pixel values into the range [0,1]. In the training dataset, additional variations such as rotation, shift, zoom, shear, and flipping are applied to improve the model's generalization ability, while in the validation dataset only normalization is performed. Next, the data is processed in batches using flow_from_directory(), which ensures a uniform format for training and evaluation of the model in identifying the freshness of Mungkus Fish..

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2.4. Model Training

The third stage involves model training, which is done by utilizing the Naïve Bayes Method to extract patterns from images and classify the freshness of Mungkus Fish.

Precision is the ratio between the number of correct positive predictions (True Positive) and the total number of positive predictions (i.e. True Positive + False Positive).

$$Precesion\ = \frac{TP}{TP+FP} \tag{1}$$

$$= \frac{20}{20+10} = \ 0.6667$$

Recall is the ratio between the number of correct positive predictions (True Positive) to the total actual positive data (i.e. True Positive + False Negative).

$$Recall\ = \frac{TP}{TP+PN} \tag{2}$$

$$= \frac{20}{20+10} = \ 0.6667$$

Accuracy is the ratio between the number of correct predictions (True Positive + True Negative) to the total amount of data.

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

$$= \frac{20+20}{20+20+10+10} = \frac{40}{60}$$

- TP (*True Positive*) = Correct prediction for positive class
- TN (*True Negative*) = Correct prediction for negative class
- FP (*False Positive)* = Wrong prediction, model thinks positive when it is actually negative
- FN (*False Negative*) = Wrong prediction, model thinks negative when it is positive

3. RESULT

Through the steps of design, coding, testing, and finally implementation, the application of the Naïve Bayes method for the freshness classification of mungkus fish based on eye and gill images has succeeded in creating an efficient system in carrying out classification. This system was created using the MATLAB programming language, which allows the freshness classification of mungkus fish to be carried out into two categories, namely fresh or not fresh, based on the analysis of eye and gill images of the fish. The input data used are images taken by the camera, which are then processed and analyzed by the system to provide an estimate of the freshness level of the fish.

The interface display of the system that applies the Naïve Bayes method in the freshness classification process of mungkus fish based on eye and gill images will be presented in the following image:

3.1. Gui View Of Naïve Bayes Classification

The Naïve Bayes Main Menu view displays all application components, including buttons, axes, and text, designed to meet the application's needs in classifying the freshness of mungkus fish. In this view, each element is designed to provide easy access and interaction for users. The available buttons allow users to start the classification process, display feature extraction results, reset, and more. Axes are used to display relevant images, such as the original image, feature extraction results, and classification. Text serves to provide additional information or output results from the application.

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Overall, this view unifies all menus and application components according to needs to ensure the classification process can be carried out effectively.

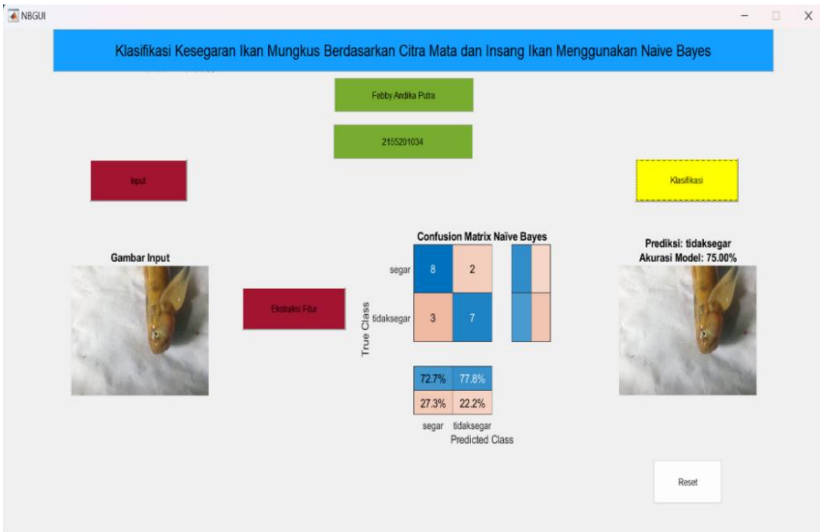

Figure 2. Naïve Bayes classification display

3.2. Image Input View

Image input is the first step in the application, allowing users to open or load images from a predefined folder. Once an image is selected, it will be displayed in the Image Input menu as initial data ready for processing by the system. This feature makes it easy for users to select and display images directly from the provided directory, without requiring additional steps. This allows users to quickly begin the classification process based on uploaded images, ensuring an efficient workflow.

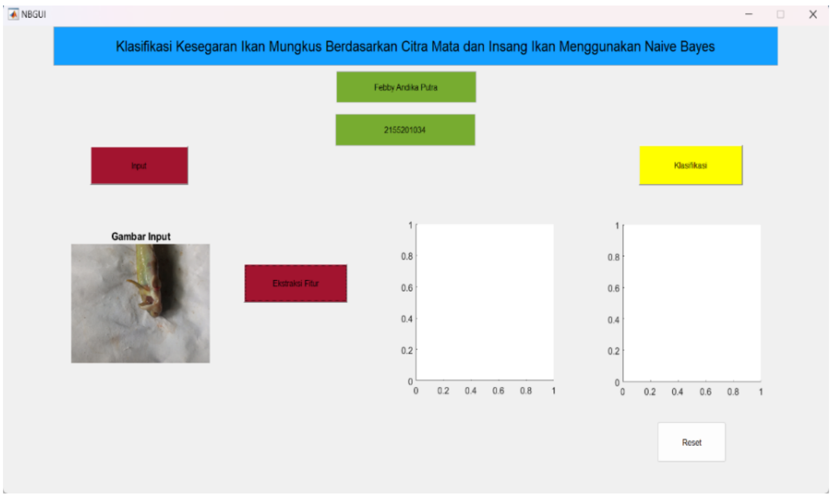

Figure 3. Image Input View

3.3. Feature Extraction View

The Feature Extraction view is a crucial part of the system, displaying the results of the feature extraction process for the input image. At this stage, the system extracts important characteristics from the image, such as relevant patterns or features, which will be used in the subsequent classification process. The extraction results are numerical values that describe the features identified in the image. Furthermore, a confusion matrix is displayed in the Feature Extraction menu to provide an overview of the model's accuracy and performance in classifying images. This view allows users to easily monitor

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and analyze the feature extraction results, facilitating a better understanding of how data is processed within the system.

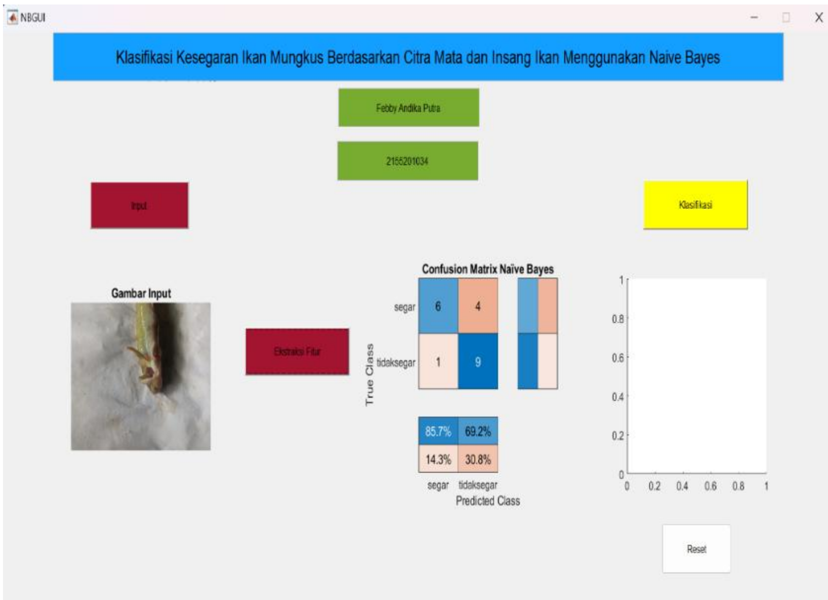

Figure 4. Feature Extraction View

3.4. Classification Results Display

The application is managed through a graphical interface developed in Tkinter. Users upload images of Mungkus fish, select the classification method they wish to use, namely Naïve Bayes, and can view the classification results directly.

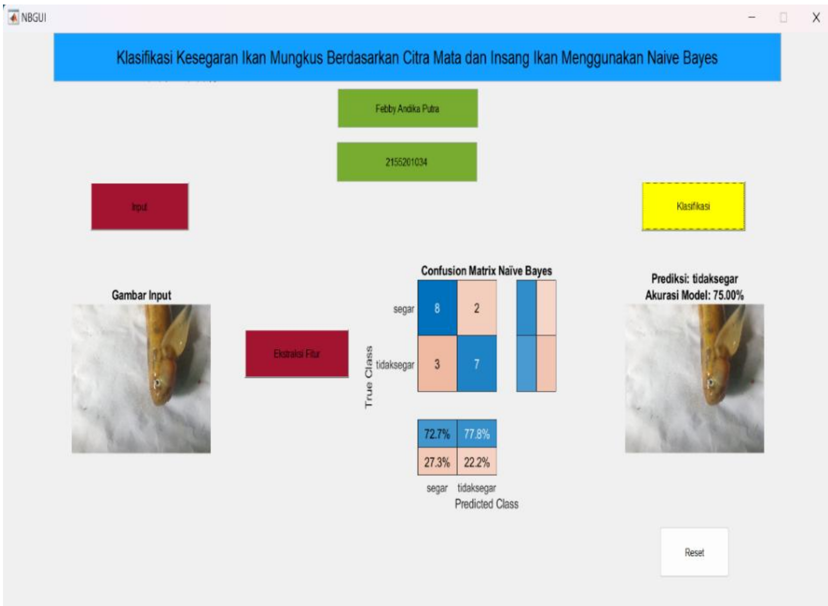

Figure 5. Classification Results Display

The classification process is carried out with the following steps: :

1. Users upload images of Mungkus Fish that they wish to classify
2. The system performs data processing
3. The Naive Bayes model is run to predict the freshness of Mungkus Fish based on the uploaded image.

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4. The classification results are displayed in the GUI, along with the predicted probabilities for each class.

The Classification Results view displays the final results of the image classification process that has been processed by the system. In this menu, users can see the category or class of the analyzed image, whether the image is included in the "fresh" or "not fresh" category based on the image of the fish's eyes and gills. Furthermore, this view also shows the accuracy of the predictions generated by the system, which can help users understand the extent to which the model has succeeded in correctly classifying images. With the classification results view, users can easily evaluate the system's performance and obtain useful information regarding fish freshness.

4. DISCUSSIONS

4.1. System Trial

4.1.1. Training Data

System testing was conducted to evaluate the performance of the algorithm in classifying the freshness of Mungkus Fish using the Naïve Bayes method based on digital images. The training data used consisted of two classes, namely training data for Fresh Mungkus Fish and training data for Unfresh Mungkus Fish. The testing process involved using training data to train the Naïve Bayes model.

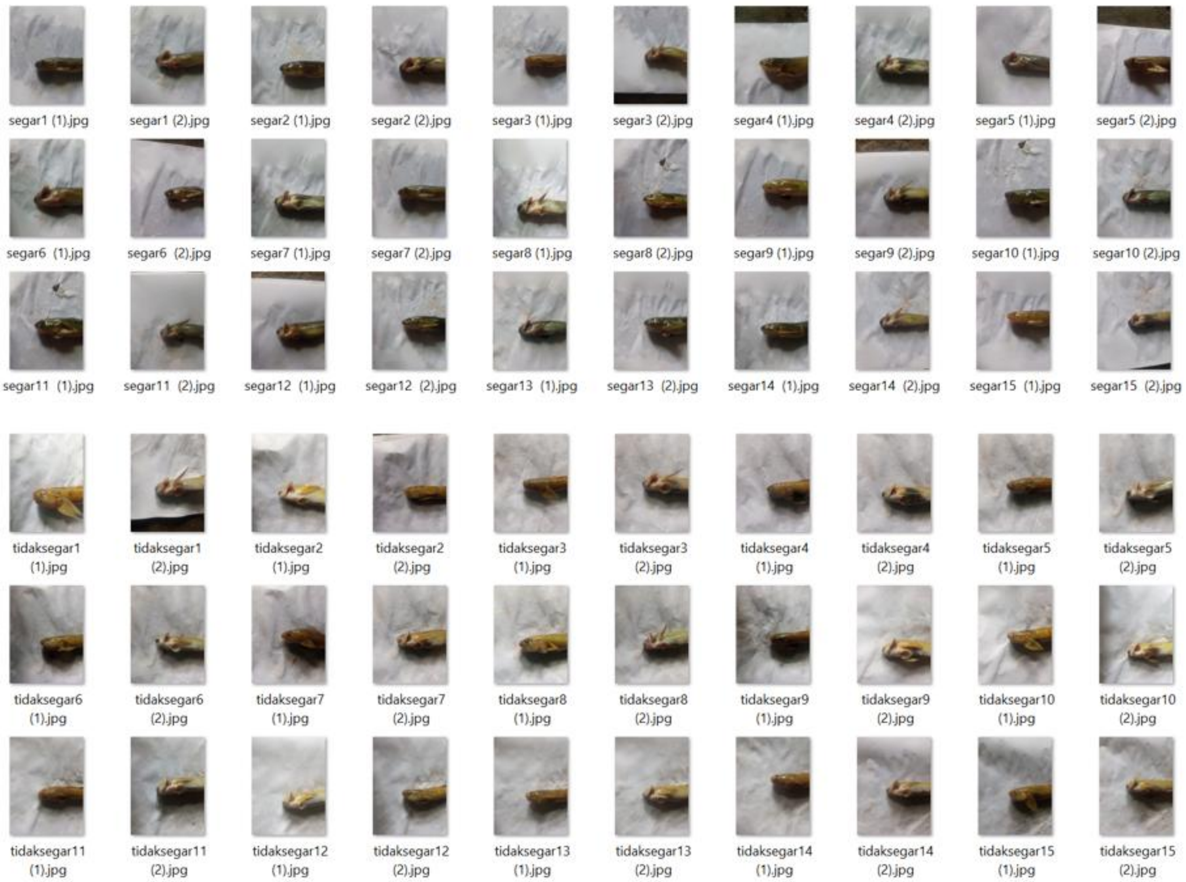

Figure 6. Training Data

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4.1.2. Test Data

In this study, the test data consisted of two classes: fresh and non-fresh. Each image in the test data was processed using the Naive Bayes method to determine its freshness level. The classification results from each method were then evaluated using accuracy, precision, recall, and F1-score metrics to determine the model's ability to distinguish between fresh and non-fresh images.

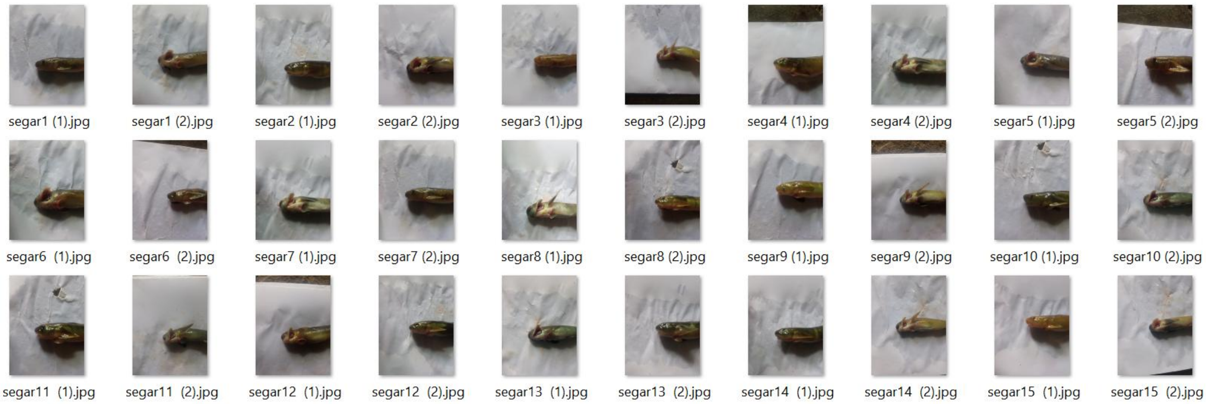
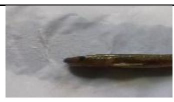


Figure 7. Fresh Mungkus Fish Test Data

Figure 8. Test Data for Non-fresh Mungkus Fish

4.1.3. Freshness Classification Process Of Mungkus Fish

Table 2. Classification Results of The Naïve Bayes Model

No	Data Name	Type	Picture	Precession	Recal	Accuracy	Kategori
1.	Fresh 1(1)	Eye		0.6667	0.6667	66.67%	Fresh
	Fresh 2 (2)	Gill		0.7500	0.5000	66.67%	Non-Fresh
2.	Fresh 2 (1)	Eye		0.7143	0.8333	75.00%	Fresh
	Fresh 2 (2)	Gill		0.6667	0.3333	58.33%	Fresh

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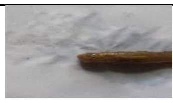
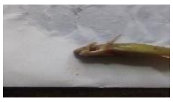
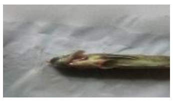
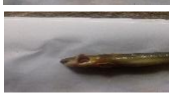
3.	Fresh 3 (1)	Eye		0.3333	0.3333	33.33%	Fresh
	Fresh 3 (2)	Gill		1.0000	0.3333	66.67%	Fresh
4.	Fresh 4 (1)	Eye		0.8000	0.6667	75.00%	Non-Fresh
	Fresh 4 (2)	Gill		0.5000	0.6667	50.00%	Fresh
5.	Fresh 5 (1)	Gill		1.0000	0.6667	83.33%	Fresh
	Fresh 5 (2)	Eye		0.6667	0.6667	66.67%	Non-Fresh
6.	Fresh 6 (1)	Gill		0.6667	0.6667	66.67%	Fresh
	Fresh 6 (2)	Eye		0.6000	0.5000	58.33%	Fresh
7.	Fresh 7 (1)	Gill		0.5714	0.6667	58.33%	Fresh
	Fresh 7 (2)	Eye		0.4000	0.3333	41.67%	Non-Fresh
8.	Fresh 8 (1)	Gill		0.4286	0.5000	41.67%	Non-Fresh
	Fresh 8 (2)	Eye		0.6667	0.6667	66.67%	Fresh
9.	Fresh 9 (1)	Eye		0.5000	0.6667	50.00%	Fresh
	Fresh 9 (2)	Gill		0.6250	0.8333	66.67%	Fresh
10.	Fresh 10 (1)	Eye		0.5000	0.6667	50.00%	Non-Fresh
	Fresh 10 (2)	Gill		0.7143	0.8333	75.00%	Fresh
11.	Fresh 11 (1)	Eye		0.8333	0.8333	83.33%	Fresh
	Fresh 11 (2)	Gill		0.7500	0.5000	66.67%	Non-Fresh
12.	Fresh r12 (1)	Gill		0.7500	0.5000	66.67%	Non-Fresh

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	Fresh 12 (2)	Eye		0.8333	0.8333	83.33%	Fresh
13.	Fresh 13 (1)	Gill		0.6250	0.8333	66.67%	Non-Fresh
	Fresh 13 (2)	Eye		0.5714	0.6667	58.33%	Segar
14.	Fresh 14 (1)	Eye		0.6000	0.5000	58.33%	Non-Fresh
	Fresh 14 (2)	Gill		0.6667	0.6667	66.67%	Fresh
15.	Fresh 15 (1)	Eye		0.5000	0.5000	50.00%	Fresh
	Fresh 15 (2)	Gill		0.6667	0.6667	66.67%	Fresh
16.	Non-Fresh 1 (1)	Eye		0.6667	0.6667	66.67%	Fresh
	Non-Fresh 1 (2)	Gill		0.6000	0.5000	58.33%	Non-Fresh
17.	Non-Fresh 1(1)	Gill		0.5714	0.6667	58.33%	Fresh
	Non-Fresh 2(2)	Eye		0.4000	0.3333	41.67%	Fresh
18.	Non-Fresh 3 (1)	Eye		0.4286	0.5000	41.67%	Fresh
	Non-Fresh 3 (2)	Gill		0.6667	0.6667	66.67%	Fresh
19.	Non-Fresh 4 (1)	Eye		0.5000	0.6667	50.00%	Non-Fresh
	Non-Fresh 4 (2)	Gill		0.6250	0.8333	66.67%	Fresh
20.	Non-Fresh 5 (1)	Eye		0.5000	0.6667	50.00%	Non-Fresh

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	Non-Fresh 5 (2)	Gill		0.7143	0.8333	75.00%	Non-Fresh
21.	Non-Fresh 6 (1)	Eye		0.6667	0.6667	66.67%	Non-Fresh
	Non-Fresh 6 (2)	Gill		0.6000	0.5000	58.33%	Non-Fresh
22.	Non-Fresh 7 (1)	Eye		0.5714	0.6667	58.33%	Non-Fresh
	Non-Fresh 7 (2)	Gill		0.4000	0.3333	41.67%	Non-Fresh
23.	Non-Fresh 8 (1)	Eye		0.4286	0.5000	41.67%	Non-Fresh
	Non-Fresh 8 (2)	Gill		0.6667	0.6667	66.67%	Non-Fresh
24.	Non-Fresh 9 (1)	Eye		0.5000	0.6667	50.00%	Non-Fresh
	Non-Fresh 9(2)	Gill		0.6250	0.8333	66.67%	Fresh
25.	Non-Fresh 10(1)	Eye		0.5000	0.6667	50.00%	Fresh
	Non-Fresh 10(2)	Gill		0.7143	0.8333	75.00%	Fresh
26.	Non-Fresh 11 (1)	Eye		0.8333	0.8333	83.33%	Non-Fresh
	Non-Fresh 11(2)	Gill		0.7500	0.5000	66.67%	Fresh
27.	Non-Fresh 12(1)	Gill		0.7500	0.5000	66.67%	Fresh
	Non-Fresh 12(2)	Eye		0.8333	0.8333	83.33%	Non-Fresh

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28.	Non-Fresh 13(1)	Eye		0.6250	0.8333	66.67%	Non-Fresh
	Non-Fresh 13(2)	Gill		0.5714	0.6667	58.33%	Non-Fresh
29.	Non-Fresh 14(1)	Eye		0.6000	0.5000	58.33%	Non-Fresh
	Non-Fresh 14(2)	Gill		0.6667	0.6667	66.67%	Non-Fresh
30.	Non-Fresh 15(1)	Eye		0.5000	0.5000	50.00%	Non-Fresh
	Non-Fresh 15(2)	Gill		0.6667	0.6667	66.67%	Non-Fresh

4.2. Calculation

4.2.1. Fresh Calculations

Fresh1 (1) (Eye)

$$Precesion = \frac{TP}{TP+FP} = \frac{2}{2+1} = \frac{2}{3} = 0.6667$$

$$Recall = \frac{TP}{TP+PN} = \frac{2}{2+1} = \frac{2}{3} = 0.6667$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{2+2}{2+2+1+1} = \frac{4}{6} = 0.6667 = 66.67\%$$

Fresh2 (2) (Gill)

$$Precesion = \frac{TP}{TP+FP} = \frac{3}{3+1} = 0.7500$$

$$Recall = \frac{TP}{TP+PN} = \frac{1}{1+1} = \frac{1}{2} = 0.5000$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{1+1}{1+1+0+1} = \frac{2}{3} = 0.6667 = 66.67\%$$

4.2.2. Non-Fresh

Fresh1 (1) (Eye)

$$Precesion = \frac{2}{2+1} = 0.6667$$

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$$Recall = \frac{2}{2+1} = 0.6667$$

$$Accuracy = \frac{2+2}{6} = \frac{4}{6} = 0.6667 = 66.67\%$$

Fresh2 (2) (Gill)

$$Precesion = \frac{2}{2+1} = 0.6000$$

$$Recall = \frac{2}{2+2} = \frac{1}{2} = 0.5000$$

$$Accuracy = \frac{2+1}{6} = \frac{3}{6} = 0.5833 = 58.33\%$$

Complete calculation of the freshness classification of Mungkus Fish data in the links https://drive.google.com/drive/folders/1qQii3c0Zu6Izhu3G8Gj4dv6a95kge022?usp=sharing.

Based on the test results on 30 fresh data sets, the classification system was able to provide correct results of 66.67%, or equivalent to 20 data sets that were successfully classified according to their original conditions. Meanwhile, there were 10 data sets or 33.33% that were not successfully classified correctly. Of the total 30 fresh data sets tested, the system successfully classified 19 data sets (63.33%) correctly, while 11 data sets (36.67%) were still incorrect in the classification prediction process. Overall, the system successfully classified data with an accuracy level of 65%, while the other 35% of the data sets still experienced errors in the classification process.

Naïve Bayes can still be used as an alternative method because the process is simpler and faster, although its accuracy is not as high as CNN and the CNN method provides more accurate results compared to Naïve Bayes because it is able to learn image characteristics in more depth but can be used simultaneously even though the Naïve Bayes method accuracy is not as high as CNN this method is an alternative because the process is simpler and faster.

The evaluation revealed that the system successfully identified most images with satisfactory accuracy. Fresh and non-fresh fish were identified through visual attribute analysis, such as eye clarity and gill color. However, there were some cases where classification errors occurred, where fresh fish were detected as non-fresh, or vice versa. These inaccuracies were generally caused by similarities in visual characteristics between the categories, such as similar eye and gill color, lighting conditions during image capture, and the angle of the image, which affect the appearance of these visual features. Overall, the classification system demonstrated consistent performance with good accuracy. Identification was performed automatically based on the provided images, and the prediction results were displayed as Fresh or Non-Fresh.

5. CONCLUSION

Based on the analysis of 30 new data sets, the classification system demonstrated an accuracy of 66.67%, meaning 20 data sets were correctly categorized according to their original state. Meanwhile, 10 data sets, or 33.33%, were not categorized accurately. Of the 30 old data sets tested, the system was able to correctly categorize 19 (63.33%), while 11 (36.67%) were still incorrect in their classification

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predictions. Overall, the system successfully grouped data with an accuracy rate of 65%, with the remaining 35% of data still experiencing errors in the classification process.

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