An Image Processing Study: Image Enhancement, Image Segmentation, and Image Classification using Milkfish Freshness Images

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ABSTRACT

This Research uses sophisticated image processing techniques to handle the important problem of assessing the freshness of milkfish. Researcher presenting a CNN classification method that is trained by ResNet-101, is put through a rigorous evaluation process that includes GLCM feature extraction, parameter setup, and thorough confusion matrix assessments. The effects of both Image Enhancement and Image Segmentation techniques on texture characteristics during GLCM extraction are carefully analyzed at various freshness levels, measuring Contrast, Homogeneity, Correlation, and Energy values. With training using Adam optimization, a batch size of 16, a learning rate of 0.0001, and 30 epochs, the suggested CNN is configured to produce a balanced convergence period of 23 minutes and 36 seconds. The suggested approach performs exceptionally well in evaluation, reaching a remarkable accuracy of 99.72% throughout training. Additional testing during the testing phase confirms its effectiveness, since all metrics (recall, precision, and F1-score) remain at 100%. These outcomes highlight the resilience of the ResNet-101-based CNN in this particular image processing job and demonstrate its effectiveness in correctly categorizing milkfish freshness levels.

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1. INTRODUCTION

Milkfish has become one of the ocean fisheries that become one of the Indonesia’s main food products, this is shown based on the data provided by “Badan Pusat Statistik” where in 2020 Indonesia has produced more than 14 million tons of cultured fishes [1], at the same year, milkfish occupied the fifth position in the largest production of cultured fish with a production amount of more than 800 thousand tones, followed by carp fish, catfish, grouper, snapper, and gourami [2]. This shows that milkfish has an important role in Indonesia’s food product commodity, therefore it needs to be utilized as best as possible. Fish freshness has become the main consideration of someone to buy fishes, and a benchmark in determining the quality of a fish [3] [4]. Overtime, fish will start to decay because of the changing chemical composition in its body, the decomposition process will be shown on the physical appearance of the fish mainly on its eyes, skin, and gills [5]. Mainly, traditional methods with the help of human labor are used to determine the fish freshness level by observing physical characteristics of the fish. Those physical characteristics are the colors, texture, and odor. However, this method could result in different results that vary from each people, therefore this method is considered as less efficient [6]. The development of computer technology in the field of computer vision has been applied in the fish freshness level classification [3].

Currently, computer vision technology is utilizing deep learning method, mainly CNN (Convolution Neural Network), this is because CNN is considered to have a good performance in recognizing and processing the information obtained from the image data, on the visual cortex as the humans do [4], [7], [8], [9], [10]. In this research, segmentation and classification is performed in order to classify freshness level of the milkfish that divided into four classification classes, namely fresh, less fresh, starting to rot, and rotten class. This research is based on previous existing research [11], with applying some updates to the methodology by applying segmentation to the milkfish image data, and then performing classification from resnet-50 to resnet-101.

Based on literature review of this related researches have been done regarding the use of deep learning mainly CNN (Convolution Neural Network) in the classification of fish freshness level, some of it are presented as follows. Research [3] is performing classification of gourami fish freshness level with using YOLOv4-Tiny to detect an area or ROI (Region of Interest) that is specific to the area of fish's eyes and gills, then training and testing process for the classification model is using EfficientNetV2-S architecture, the obtained result shows that YOLOv4-Tiny is able to get mean average precision of 93,5% in ROI detection, while EfficientNetV2-S is able to get classification accuracy of 93%. Research [4] is performing classification of lemuru fish freshness level with using VGG-16 architecture and performs testing using K-Fold Cross Validation, the obtained result shows that VGG-16 with fold value of 4 are able to get accuracy of 98,4%; specificity of 98,5%; and sensitivity of 98,5%. Research [11] is performing milkfish freshness level that divided into four level of freshness with using ResNet-50 architecture and Adam optimizer for both for training and testing process, the obtained result shows that ResNe-50 architecture with Adam optimizer is able to get training accuracy of 99,35% and testing accuracy of 100%. Research [12] is performing classification of various kind of fishes with using MobileNetV3-Large and MobileNetV3-Small architecture both for training and testing, the obtained result shows that MobileNetV3-Small is able to get testing accuracy of 68%, precision of 69%, and recall of 67%, while for MobileNetV3-Large is able to get testing accuracy of 68%. Research [13] is performing classification of milkfish with using transfer learning approach and using MobileNet, ResNet, DenseNet, and NasNet architecture both for training and testing, the obtained result is MobileNet is able to get testing accuracy of 74%, ResNet of 53%, DenseNet of 74%, and NasNet of 72%. As additional information, CNN can be utilized to perform other than fish freshness classification, following researches are the example of it. Research [14] is performing classification of cars in the Indonesian domestic car market with using AlexNet architecture, its purpose is to find out and analyze car usage trends, the obtained result shows that AlexNet is able to get training accuracy of 99,74% and testing accuracy of 100%. On the other hand, research [15] is performing Javanese script identification using DCNN (Deep Convolution Neural Network), its purpose is to be able not only recognize the basic characters, but also the compound vowels script with a total of 120 classes, the obtained result shows that the proposed DCNN model is able to get accuracy of 99,65%.

Based on the presented literature review, Convolution Neural Network or CNN can be used to perform not only fish freshness level classification, but also several classification approach such as car type and Javanese script classification, this conclude that the use of CNN is still relevant to date. This research is based on the existing research [11] where classification is to be performed to milkfish, that is divided into four different classification classes. Dataset used in this research is a dataset containing 1803 of milkfish image data that is divided into fresh class, less fresh, starting to rot, and rotten class. The update of method applied to this research is done by applying segmentation to the milkfish image data and using a complex layers CNN architecture, namely ResNet-101.

The following is the outline of the research: The researcher provides a thorough understanding of the background and context for the work on image processing approaches for evaluating milkfish freshness in **Section 1**, where the introduction and literature review are also explored. In **Section 2**, the researcher describes the technique and proposed scheme in depth, explaining the processes taken for picture enhancement, segmentation, and classification within the specific context of the Milkfish Freshness Dataset. The findings of the processing techniques are analyzed, and their implications for the assessment of milkfish freshness are covered in **Section 3**, along with their presentation and discussion. **Section 4**, which concludes the study, summarizes the main findings, discusses the goals of the research, and suggests future directions for this field of study.

2. METHOD

Image enhancement, image segmentation, and image classification are the three main areas of image processing that are the focus of this study. To guarantee that there is a sufficient amount of data available, the research starts with the initial dataset gathering step. The Image Enhancement step is the first preprocessing step that improves the quality of dataset photos for the best results in later steps. After the Image Enhancement stage, the Image Segmentation stage comes into focus. By breaking the image down into more specific parts, this process aims to make analysis easier later on. The feature extraction approach is used to evaluate the efficacy of the Image Enhancement and Segmentation stages, guaranteeing that modifications and segmentations provide a representation that complies with study specifications.

The Image Classification stage represents the end of this inquiry. The processed and divided images are now classified according to predetermined standards. The confusion matrix is an assessment parameter used to gauge Image Classification performance. Based on flow of proposed method, the process can be seen in **Figure 1**.

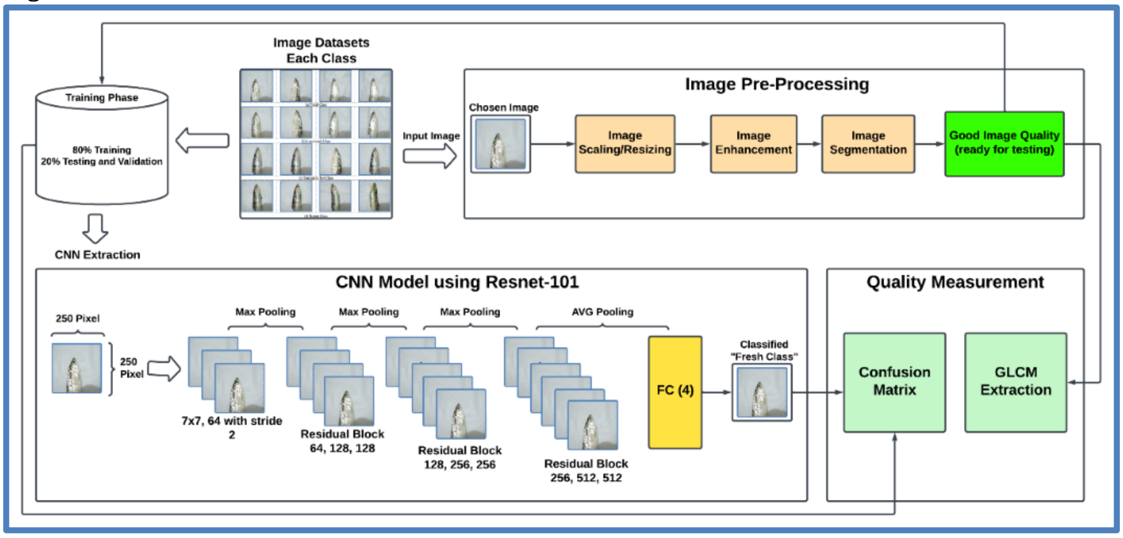
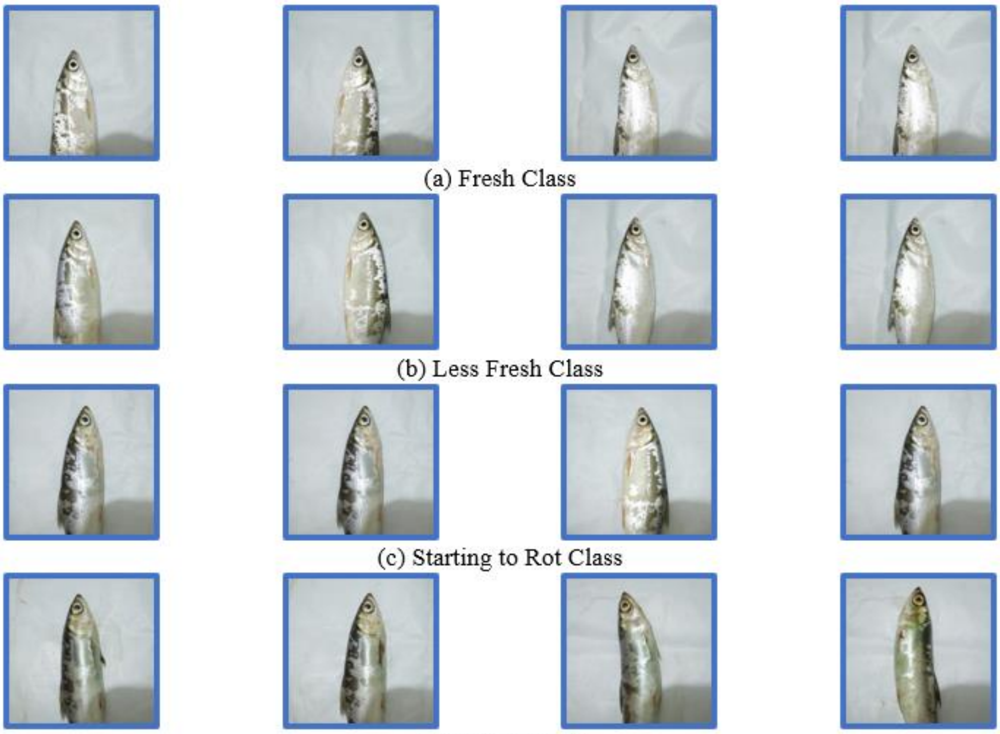


Figure 1. Proposed Scheme

2.1. Milkfish Freshness Datasets

The starting dimensions of the Milkfish Freshness dataset, which was obtained from a previous study, were 1980 x 1980 x 3. The dataset is converted to 250 x 250 x 3 dimensions in order to maximize computing performance for the next picture classification training phase. In order to avoid overburden during model training, this scaling was done. There are a total of 1804 examples in the privately curated dataset, which are split into four different classes: Fresh, Less Fresh, Starting to Rot, and Rotten. A fair amount of the dataset is included in each class, which helps to provide a thorough and balanced representation for further analysis [11]. Based on sample image datasets can be seen in **Figure 2**.


(a) Fresh Class
(b) Less Fresh Class
(c) Starting to Rot Class
(d) Rotten Class
Figure 2. Sample Image Datasets Each Class

The dataset shown in **Figure 2** is the starting point, from which the other pre-processing procedures described in the suggested methodology which is shown in **Figure 1** are derived. The suggested technique outlines an organized workflow that will be followed for a series of pre-processing processes, such as Scaling/resizing, Enhancement, and Segmentation, on this raw dataset. **Figure 1** illustrates the technique, which provides a methodical road map for converting the raw dataset into a well-processed and optimized set of pictures, guaranteeing the robustness and precision of the subsequent classification tests.

2.2. Image Enhancement

Image Enhancement involves various techniques to address issues such as low contrast, noise, and other imperfections, ultimately enhancing the overall appearance of the image [16], [17]. To raise the chosen sample image's image quality, image enhancement is required. Using the parameter [0.5 0.9], which specifies the range of pixel intensities that are increased to boost the image contrast, the $imadjust$ function is used in the first stage to adjust the original image's intensity. The function fspecial $('motion', 2, 299)$ is then used to construct a point spread function (PSF) that mimics the impact of motion blur on the image in the second step. Afterwards, the picture deconvolution procedure will make use of this PSF. The last step is to apply Wiener deconvolution to the image that has been PSF motion blur corrected for intensity using the $deconvwnr$ function [16], [18]. Based on image enhancement processing can be seen in **1st algorithm**.

1st algorithm: Image Enhancement Processing

```
function enhancedImage = enhanceImage (originalImage)
    % Step 1: Adjust image intensity using imadjust
    adjustedImage = imadjust (originalImage, [0.5 0.9], []);
    % Step 2: Create a motion blur point spread function (PSF)
    PSF = fspecial ('motion', 2, 299);
    % Step 3: Perform image deconvolution using Wiener deconvolution
    deconvolvedImage = deconvwnr (adjustedImage, PSF);
    % Return the enhanced image
    enhancedImage = deconvolvedImage;
end
```

2.3. Image Segmentation

In computer vision, segmenting an image into discrete and significant sections is a basic operation known as image segmentation [19], [20]. This algorithm helps in the process of segmenting images by using a predetermined threshold value to identify objects from the background in the picture when used in conjunction with the $performImageSegmentation$ function. Two parameters are sent to the function: thresholdValue, which lets users customize the segmentation process according to their own needs, and $imagePath$, which indicates the path to the image file. In order to produce a binary picture, the program first reads the image, transforms it to grayscale, and then $thresholds$. Objects are successfully separated from the backdrop in the resultant segmented image, laying the groundwork for additional analysis and interpretation in a variety of computing [21]. Based on image segmentation processing can be seen in **2nd algorithm**.

2nd algorithm: Image Segmentation Processing

```
function segmentedImage = performImageSegmentation (imagePath, thresholdValue)
    % Step 1: Read the image
    originalImage = imread (imagePath);
    % Step 2: Convert the image to grayscale
    grayImage = rgb2gray (originalImage);
    % Step 3: Define the threshold value (adjust as needed)
    % Input parameter thresholdValue can be used or a default value set
    thresholdValue = 0.7;
    % Step 4: Perform thresholding to obtain a binary image
    binaryImage = imbinarize (grayImage, thresholdValue);
    % Output the segmented image
    segmentedImage = binaryImage;
end
```

2.4. Image Classification

Image classification [22], [23], [24], [25] becomes a vital technique for differentiating and classifying photographs of milkfish according to their freshness levels in the particular context of evaluating milkfish freshness. This categorization process is greatly enhanced by the use of convolutional neural network (CNN), as the network learns and pulls relevant information from the pictures on its own [21], [26]. This characteristic allows for the accurate distinction of several freshness states, including less fresh, fresh, beginning to rot, and rotten. Using CNNs in this way simplifies the classification process and results in a strong model that can efficiently recognize and classify photos of milkfish with remarkable accuracy [27].

Based on the ResNet-101 architecture, a CNN is used in this study to perform the image classification problem. A deep neural network best renowned for its performance in picture classification tasks, ResNet-101 is an expanded version of ResNet-50. By using ResNet-101, the results of a prior research that used ResNet-50—which produced an astounding 99.35% accuracy—are improved upon [11]. ResNet-101 is anticipated to improve the model's capacity to identify minute details in milkfish images, this might lead to an increase in classification accuracy and robustness for freshness levels due to its deeper and more complex architecture. Refinement and advancement of image classification models for more accurate and dependable outcomes in the context of milkfish freshness evaluation are demonstrated by the use of ResNet-101. Based on CNN layer using resnet-101 can be seen in **3rd algorithm**.

3rd algorithm: CNN Layers Based on Resnet-101
function ResNet-101_CNN ($image$): % Step 1: Input layer input_layer = Input ($shape = (image\_height, image\_width, num\_channels)$) % Step 2: Initial Convolutional and Pooling Layers Conv2D $(64, (7,7), strides = (2,2), padding = 'same')(input\_layer)$ BatchNormalization Activation($'relu'$) MaxPooling2D($(3,3), strides = (2,2)$) % Step 3: First Residual Blocks - ResNet-101 resnet_block ($x, filters = [64, 126, 128], stage = 2, block = 'a', strides = (1,1)$) identity_block ($x, filters = [64, 128, 128], stage = 2, block = 'b'$) identity_block ($x, filters = [64, 128,128], stage = 2, block = 'c'$) % Step 4: Second Residual Blocks - ResNet-101 resnet_block ($x, filters = [128, 256, 256], stage = 2, block = 'a', strides = (1,1)$) identity_block ($x, filters = [128, 256, 256], stage = 2, block = 'b'$) identity_block ($x, filters = [128, 256, 256], stage = 2, block = 'c'$) % Step 4: Third Residual Blocks - ResNet-101 resnet_block ($x, filters = [256, 512, 512], stage = 2, block = 'a', strides = (1,1)$) identity_block ($x, filters = [256, 512, 512], stage = 2, block = 'b'$) identity_block ($x, filters = [256, 512, 512], stage = 2, block = 'c'$) % Step 6: Average Pooling Layer GlobalAveragePooling2D () % Step 7: Fully Connected Layer Dense ($num\_classes = '4', activation = 'softmax'$) **end**

Based on **3rd algorithm**, input layer accepts dimensions of image_height, image_width, and $num\_channels$ for an image. Beginning with a convolutional layer featuring 64 $filters$ of size $(7,7)$, a stride of $(2,2)$, and "$same$" padding, the subsequent layers include batch normalization, ReLU activation, and max-pooling with a window size of $(3,3)$ and a stride of $(2,2)$. Following this are additional residual blocks, comprising two identity blocks ('b' and 'c') and a projection shortcut block ('a'), each composed of convolutional layers with unique filter sizes. These blocks adhere to the ResNet-101 structure. Consistent with the ResNet-101 concept, the architecture incorporates more residual blocks. Spatial dimensions are then reduced through the application of the Global Average Pooling Layer. The final layer of the architecture is a fully connected layer with the number of classes ($'num_{classes} = 4\ class'$) for the softmax activation function.

2.5. GLCM Extraction

Gray Level Co-occurrence Matrix (GLCM) extraction is a method in image processing used to characterize the spatial relationships of pixel intensities within an image [28], [29], [30]. When processing photos of fresh milkfish, the results of image enhancement and image segmentation are quantitatively assessed using GLCM extraction. With this method, texture-related characteristics from the co-occurrence matrix, such as contrast, energy, and homogeneity, may be measured. The metrics that are based on GLCM are useful tools for evaluating the effectiveness of picture enhancement and segmentation procedures. Based on GLCM equation can be seen in **eq (1) – (4)**.

$$Contrast = \sum_i \sum_j (i-j)^2 p_{(i,j)} \tag{1}$$

$$Correlation = \sum_i \sum_j \frac{(i-\mu i)(j-\mu j)p_{(i,j)}}{1+|i-j|} \tag{2}$$

$$Homogeneity = \sum_i \sum_j \frac{p(i,j)}{1+|i-j|} \tag{3}$$

$$Energy = \sum_i \sum_j p(i,j)^2 \tag{4}$$

Where, the first equation represents Contrast, which is calculated as the summation over all pixel pairs (i,j) of the squared difference between their intensity values, weighted by the probability of their occurrence $P(i,j)$. It quantifies the local variations in pixel intensities. The second equation denotes Correlation, where the correlation between pixel values is computed by considering their differences from the mean values (μi and μj), normalized by the product of their standard deviations (σi and σj). Correlation provides insights into the linear dependencies between pixel intensities. The third equation represents Homogeneity, calculated as the sum of the probabilities $P(i,j)$ divided by the absolute difference between pixel values. This metric quantifies the closeness of pixel intensities in the GLCM. Energy, as shown in the fourth equation, measures the sum of squared probabilities $P(i,j)2$. While not explicitly utilized in the current context, Energy signifies the orderliness or uniformity in the distribution of pixel intensities.

2.6. Confusion Matrix Measurement

Confusion matrix is a type of table that is frequently used in classification progress to evaluate how well a prediction model is performing [26], [31]. With the ability to discern between true positives, true negatives, false positives, and false negatives, this matrix offers an in-depth synopsis of the model's predictions. Regarding the field of milkfish freshness prediction, the confusion matrix serves as a useful instrument for assessing how well the model performs when it comes to correctly categorizing samples into groups like fresh, less fresh, starting to rot, and rotten. The confusion matrix facilitates a detailed examination of the model's advantages and disadvantages by classifying the model's predictions into various groups. This allows predictive algorithms to be improved in terms of accuracy while evaluating the freshness of data. Based on matrix equation can be seen in **eq (5) – (8).**

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{7}$$

$$F1-score = \frac{2*(Precision*Recall)}{(Precision+Recall)} \tag{8}$$

Where, accuracy provides an overall measure of model correctness and is defined as the ratio of properly predicted instances (true positives and true negatives) to the total number of occurrences. By computing the ratio of true positives to the total of true positives and false positives, precision evaluates the accuracy of positive predictions. A low percentage of false positives is indicated by high accuracy. By taking into account the ratio of true positives to the total of true positives and false negatives, recall, sometimes referred to as sensitivity, assesses the model's capacity to accurately identify all pertinent occurrences. The F1-score provides a fair assessment of a model's performance by taking into account both false positives and false negatives. It is a harmonic mean of accuracy and recall.

3. RESULTS AND DISCUSSION

In this research, A system with compatible hardware, including a 256 GB SSD, an Intel Core I3 10th generation processor, 16 GB of RAM, and a GTX 1030 graphics card, was used to conduct the experimental evaluation for this study. The system configuration that was selected is specifically designed to satisfy the processing requirements of the image processing activities that are being conducted in this study. To take advantage of the hardware ensemble's computational power, MATLAB 2020a was used to carry out the experiments. Equipped with a specialized graphics processing unit, a solid-state drive, a sufficient amount of RAM, and the designated CPU, the picture enhancement, segmentation, and classification procedures are executed smoothly and efficiently.

The research procedure begins with the critical processes of image enhancement and segmentation, which lay the groundwork for the later stages of analysis and classification in the context of evaluating the freshness of milkfish. The results can be seen in **Figure 3.**

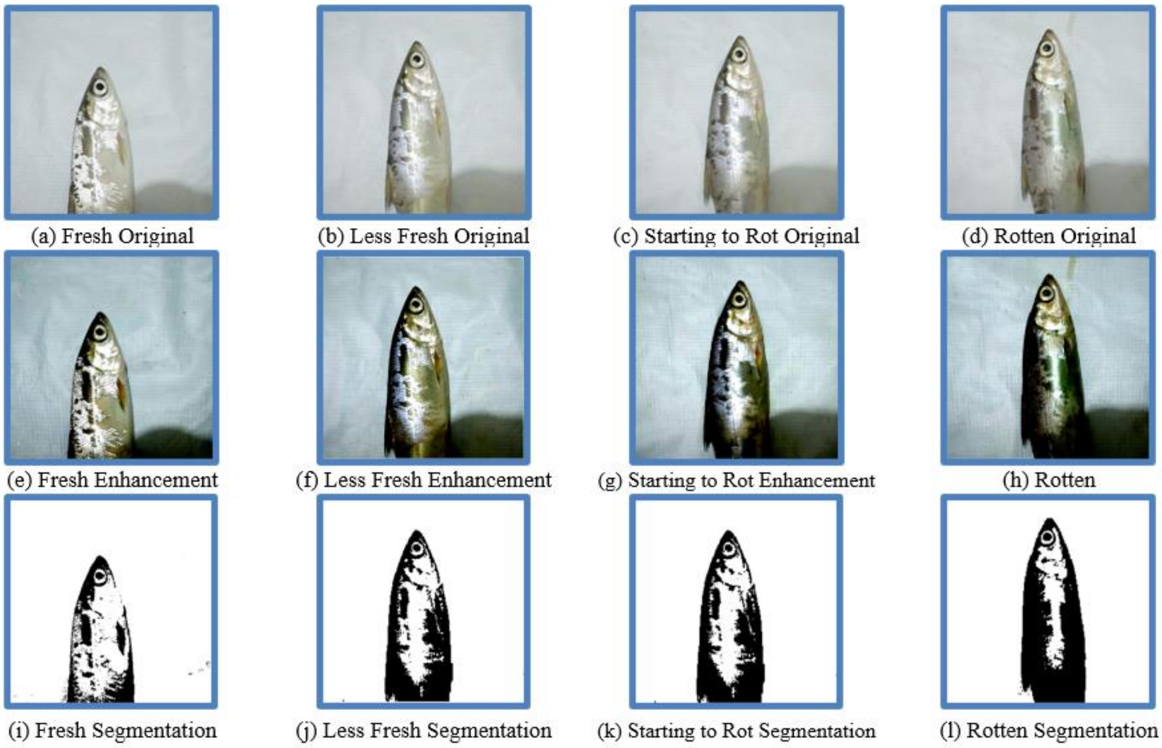


Figure 3. Results of Image Enhancement anf Segmentation each Class

The results of enhancement and segmentation, as shown in **Figure 3**, reveal interesting findings in **Table 1** that present the GLCM features that were retrieved. The table provides a comprehensive understanding of the spatial connections and intensities of pixel values inside the enhanced and segmented pictures, shedding light on how different processing stages affect feature extraction.

Table 1. GLCM Extraction Based on Results of Image Enhancement and Image Segmentation

Testing Method	Sample Testing	Contrast	Homogeneity	Correlation	Energy
Image Enhancement	Fresh.jpg	10730.8319	0.035301	-0.08364	1.7943e-05
	Less Fresh.jpg	11074.8009	0.033846	-0.10846	1.8852e-05
	Start to Rot.jpg	10431.5429	0.037364	0.054793	1.838e-05
	Rotten.jpg	10632.6962	0.037813	0.061254	1.9045e-05
Image Segmentation	Fresh.jpg	9386.1798	0.034285	-0.083606	2.6477e-05
	Less Fresh.jpg	10027.7702	0.031624	-0.079768	2.5371e-05
	Start to Rot.jpg	10273.709	0.036742	0.088752	2.086e-05
	Rotten.jpg	9701.7041	0.03787	0.14293	2.2579e-05

Based on sample testing in **Table 1** using the Image Enhancement method, the Contrast values for Fresh, Less Fresh, Starting to Rot, and Rotten images were 10730.83, 11074.80, 10431.54, and 10632.70, respectively. The corresponding Homogeneity values were 0.035301, 0.033846, 0.037364, and 0.037813. For Correlation, the values were -0.08364, -0.10846, 0.054793, and 0.061254. Lastly, the Energy values were 1.7943e-05, 1.8852e-05, 1.838e-05, and 1.9045e-05 for Fresh, Less Fresh, Starting to Rot, and Rotten images, respectively. These metrics provide a quantitative assessment of the image enhancement technique's impact on texture features across different freshness levels. On the other hand, In the context of Image Segmentation, the sample testing revealed distinct outcomes for various freshness levels. For Fresh.jpg, the Contrast, Homogeneity, Correlation, and Energy values were 9386.18, 0.034285, -0.083606, and 2.6477e-05, respectively. Moving to Less Fresh.jpg, the corresponding values were 10027.77, 0.031624, -0.079768, and 2.5371e-05. Similarly, for Start to Rot.jpg, the metrics were 10273.71, 0.036742, 0.088752, and 2.086e-05, while for Rotten.jpg, they were 9701.70, 0.03787, 0.14293, and 2.2579e-05.

Next, after processing in the form of image enhancement and segmentation, the extraction results using the GLCM method are known. The final stage is carried out, namely classification. In this step, training is carried out which divides the entire data into 80% training data and 20% testing data. The training progress uses deep learning and the results can be seen in **Figure 4** and **Figure 5**.

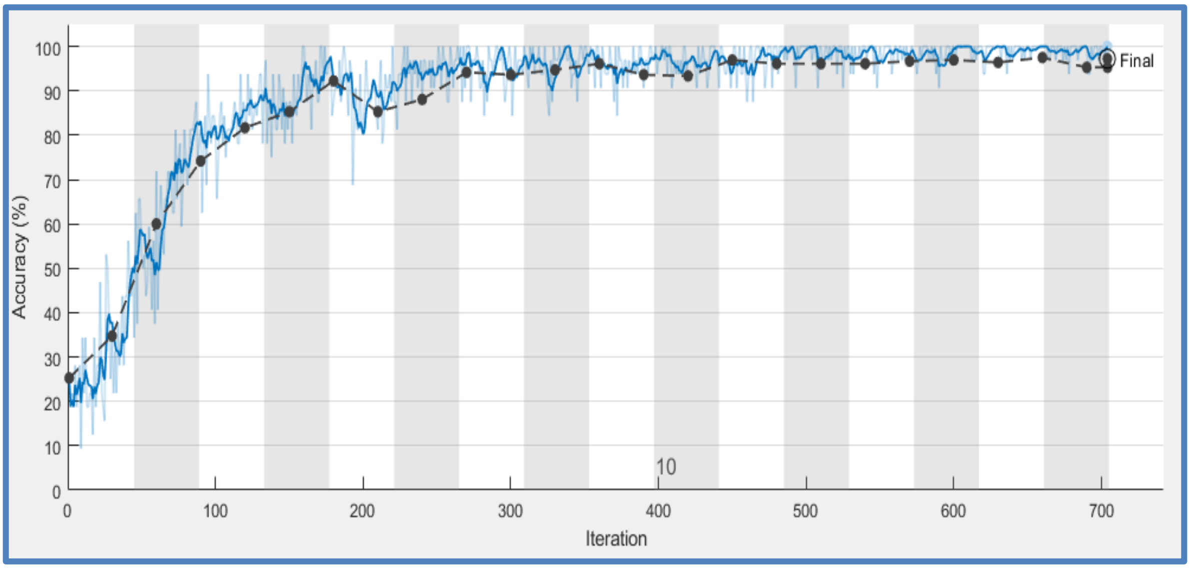


Figure 4. Training Accuracy Based on Deep Learning

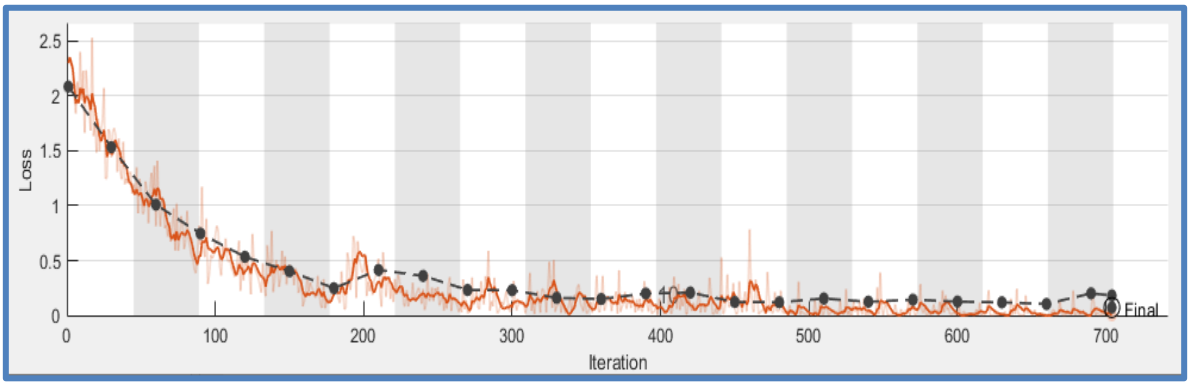


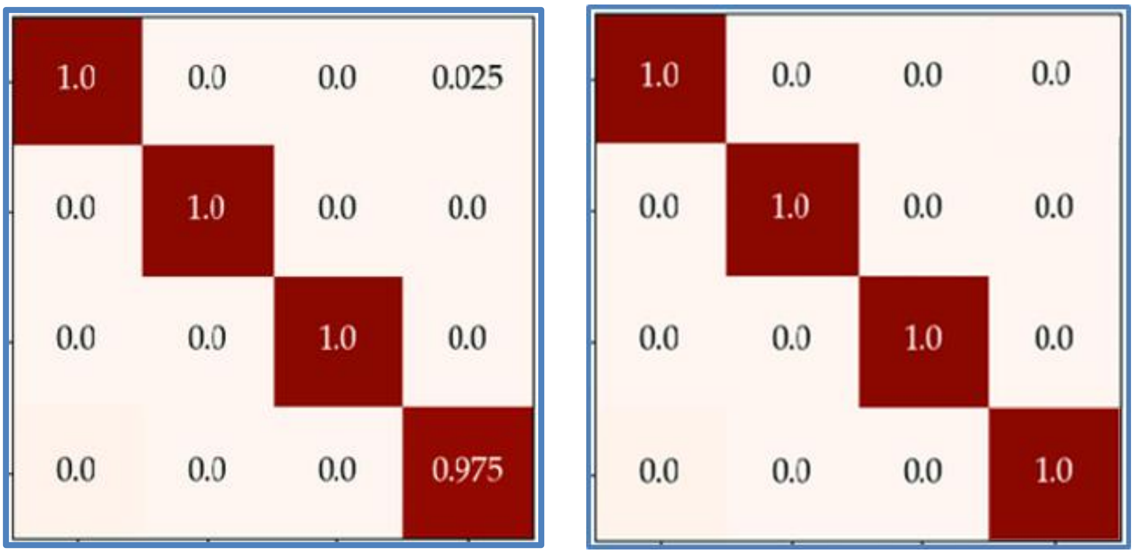
Figure 5. Loss Accuracy Based on Deep Learning

The Training Progression depicted in **Figure 4** and the Accuracy Loss illustrated in **Figure 5** summarize the journey taken through the training phases. This process is carried out using a set of parameters and hyperparameters that are carefully defined and documented in **Table 2**. These parameters serve as guiding principles during training iterations, influencing learning dynamics, accuracy and overall model performance.

Table 2. Parameter and Hiperparameter used for Training

Parameter/Hiperparameter	Previous Study by Al-Ghiffary et al. [11]	Proposed Method
Optimizer	Adam (best optimizer) SGDM RMSProps	Adam
Max Epoch	16	16
Mini Batch Size	32	32
Learning Rate	Unknown	0.0001
Validation Frequency	30	30
Elapsed Time during Training	Unknown	23 Min 36 Sec

The training process was experienced for 23 Min 36 Sec, the process was passed using the parameters and hyperparameters listed in Table 2. Where after the deep learning process was running and the process was complete, the performance was measured using a confusion matrix. The visualization results each class on the confusion matrix can be seen in **Figure 6** and **Table 3**.



(a) Table of Confusion Matrix based on 80% Training (b) Table of Confusion Matrix based on 20% Testing

Figure 6. Results of Table Confusion Matrix

Table 2. Results and Comparison Results with Previous Study

Research	Evaluation	Accuracy	Recall/Sensitivity	Precision	Specificity	F1-Score
Al-Ghiffary et al. [11]	80% Training	99.35% (Average)	100%	100%	100%	-
Proposed Method	80% Training	99.72%	100%	100%	-	100%
	20% Testing	100%	100%	100%	-	100%

In the previous study by Al-Ghiffary et al. [11], the research achieved commendable results with 80% training data, demonstrating an average accuracy of 99.35%. Notably, their model exhibited impeccable performance in terms of recall, precision, and specificity, each reaching 100%. In comparison, the proposed method, leveraging 80% training and 20% testing data, surpassed these benchmarks. The accuracy of the proposed method soared to 99.72%, showcasing the effectiveness of the employed techniques. Moreover, in the testing phase, the proposed model achieved perfection in terms of accuracy, recall, precision, and F1-score, all attaining a flawless 100%. This comparative summary highlights the enhanced performance of the proposed method in the context of milkfish freshness evaluation.

4. CONCLUSION

The suggested technique was evaluated using a CNN based on ResNet-101. It was evaluated in three stages: GLCM feature extraction, parameter setting, and final assessment using confusion matrices. Throughout the GLCM extraction stage, the Image Enhancement and Image Segmentation techniques show different effects on texture characteristics at different levels of freshness. The values of Contrast, Homogeneity, Correlation, and Energy were measured for every sample testing situation, offering insightful information on the subtleties of the text brought about by the various techniques. Moving on to the setup of the parameter and hyperparameter, the CNN was trained with 30 epochs, a batch size of 16, and Adam optimization. The learning rate was set at 0.0001. With a training time of 23 minutes and 36 seconds, a balanced convergence was guaranteed. After testing, the suggested approach performed remarkably well in predicting the freshness of milkfish. During training, a remarkable accuracy of 99.72% was attained along with perfect metrics of 100% for F1-score, recall, and precision. During the testing phase, all metrics maintained a flawless score of 100%, further validating this high degree of accuracy and precision.

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