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Research Article

Identification of the Freshness Level of Tuna based on Discrete Cosine Transform on Feature Extraction of Gray Level Co-Occurrence Matrix using K-Nearest Neighbor

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Abstract

Gorontalo Province is one of the provinces that have fishery potential and has a large sea area that can be managed to support the economy and development of the province. Gorontalo is also one of the tuna-producing provinces in Indonesia, where tuna is also one of the mainstay fisheries commodities. This study aimed to combine transformation and texture feature extraction methods to improve the identification of the freshness level of tuna. This research used Discrete Cosine Transform as transformation detection and Gray Level Co-Occurrence Matrix as texture feature extraction. To find out the value of the proximity of the training data and image testing of tuna fish, the K-Nearest Neighbor classification method was employed. Then, the Confusion Matrix was used to calculate the accuracy level of the K-Nearest Neighbor classification. This research was carried out with 4 stages of testing, namely at angles of 0°, 45°, 90°, and 135°, and using the values of k=1, 3, 5, and 7. The test results of using training data of 428 images and testing data of 161 images in four classes used with angles of 0°, 45°, 90°, 135°, and the value of k=1, 3, 5, 7. The highest accuracy results was obtained at an angle of 0° with a value of k = 1 of 94.40%, while the lowest accuracy value was at an angle of 90° and 135° with a value of k=7 of 59%. This showed that the Discrete Cosine Transform transformation method was very effective to improve the performance of texture feature extraction of Gray Level Co-Occurrence Matrix in extracting tuna image features. It was proven from the results of the accuracy of the K-Nearest Neighbor classification obtained.

Keywords: Identification; Classification; DCT; GLCM; KNN; Confusion Matrix.

Introduction

Gorontalo Province has high fishery potential and has a large sea area. If the area can be managed to support the economy and development of the province. Gorontalo province has a coastline of 903.7 km with a length of the northern coast (Sulawesi Sea) 331.2 km and the southern coast (Tomini Bay) 572.5 km. Meanwhile, Gorontalo Province has a water area of 963,843.63 Ha or (9,638.44 Km2) consisting of 6,678.80 Km2 of Tomini Bay, Sulawesi Sea 2,959.64 Km2 and the Exclusive Economic Zone (EEZ) of Sulawesi Sea is 40,000 Km2. There are 131 coastal villages in Gorontalo province and 123 small islands [1]. Gorontalo Province is one of the tuna-producing provinces in Indonesia, Tuna catches in Gorontalo have been exported to several countries. Tuna is one of the mainstay fisheries commodities in Gorontalo which also involves many small fishermen, most fishermen in Gorontalo still use the principles of traditional catch handling and have not followed the principles of good and correct handling so that the freshness and quality of tuna decreases which causes a decrease in raw materials for the production of fresh tuna meat [2] .

In this study, feature extraction was used as a description to distinguish the freshness level of tuna. The Gray Level Co-Occurrence Matrix (GLCM) feature extraction method works based on the Discrete Cosine Transform (DCT) transformation approach. In general, DCT is a one-to-one mapping transformation of an array consisting of pixel values into components that are divided based on their frequency [3]. Meanwhile, Gray Level Co-Occurrence Matrices (GLCM) is a feature extraction method using statistical calculations based on the original image pixel value and the neighboring relationship between two pixels at a certain distance and orientation, and for the result of this study used the K-Nearest Neighbor (K-NN) classification method to identify tuna images. The K-NN method in

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classifying data or objects was very effective and efficient. This K-NN technique was very simple and easy to implement and can produce more precise accuracy level, and can perform training of larger amounts of data [4] [5]. Miftahus Sholihin has conducted research "Identification of Freshness of fish based on Gill Image using Convolution Neural Network Method" from the results of research conducted to obtain an accuracy rate of 97.7% [6]. Meanwhile, the research conducted by Fitri Astutik on the "Quality Recognition System of Gourami Fish With Wavelet, PCA, Histogram HSV and Classification (K-NN)" obtained an accuracy rate of 89.5%[7].

Method

In this study, the Discrete Cosine Transform (DCT) method was used for tuna image transformation to improve the Gray Level Co-Occurrence Matrix (GLCM) performance when extracting tuna texture features, while the K-Nearest neighbor (KNN) was used as a classification of the freshness level of tuna based on the results of the extraction of texture features of the Gray Level Co-Occurrence Matrix on the image of tuna fish. To measure the level of accuracy of the classification results of K-Nearest neighbors used the Confusion Matrix. The tuna image data in this study was resized to a size of 400 x 400 and then rotated with angles of 0°, 45°, 90°, and 135°. **Figure 1** below is the stage of processing tuna image data in this study.

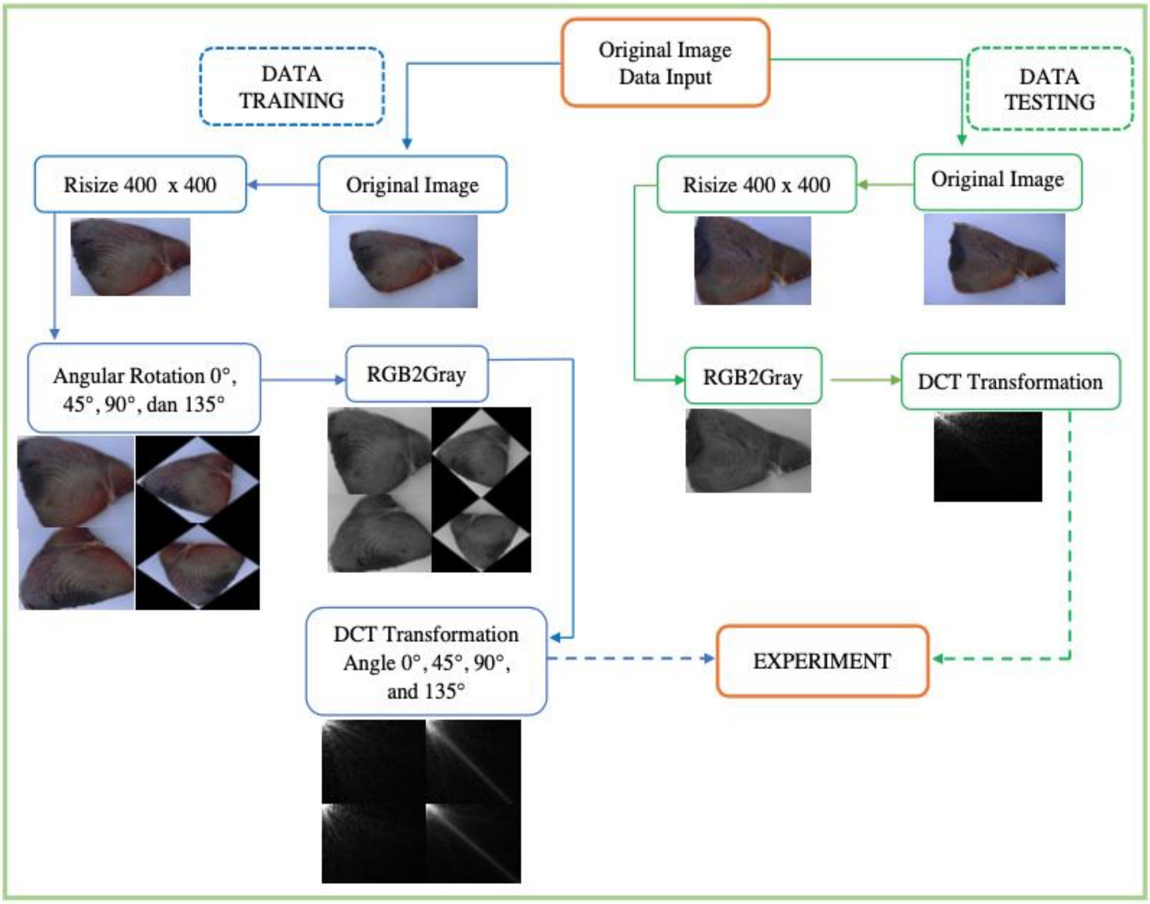

Figure 1. *Tuna Fish Image Data Processing Framework*

A. Discrete Cosine Transform

Discrete Cosine Transform (DCT) is a technique used to convert signals into frequency components [8], its formation by calculating the value of the result of the transformation [3]. In this study, the tuna image could only be transformed into frequency form using DCT which aimed to optimize the Gray Level Co-Occurrence Matrix (GLCM) performance in extracting texture features of tuna images.

DCT transformation in general for (N by M Image) is defined in the following equation [3] :

$$F(u,v) = \left(\frac{2}{N}\right)^{\frac{1}{2}} \left(\frac{2}{M}\right)^{\frac{1}{2}} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \Lambda(i).\Lambda(j).cos\left[\frac{\pi.v}{2.N}(2i+1)\right] cos\left[\frac{\pi.v}{2.M}(2j+1)\right].f(i,j) \qquad (1)$$

$$\Lambda(i) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for} \xi = 0 \\ 1 & \text{otherwise} \end{cases}$$

The following is an explanation of the basic DCT operations:

o Image enter N by M

o F(i, j) is the pixel intensity in row I and column j

o F(u, v) is the DCT coefficient in row k1 and column k2 DCT matrix

o The DCT input is an 8x8 array of integers. This array contains the Grayscale level of each pixel.

o 8-bit pixels have levels from 0 to 255 pixels

B. *Gray Level Co-Occurrence Matrix* (GLCM)

In this study, GLCM was used as a feature extraction of tuna image textures. GLCM itself was a texture feature extraction method that works based on statistical calculations that trace the original pixel value with the neighboring relationship between two pixels at a certain distance [9] [10] [11]. The steps to calculate the features in GLCM were to create a Co-Occurrence matrix first, then proceed to determine the spatial relationship between the reference pixel and neighboring pixels based on the angle and distance *d* [12], the distance *d* used was 1 expressed in degrees with an angle of 0°. GLCM was calculated based on how often a Gray Level *i* pixel appears horizontally, vertically, or diagonally in pairs with a Gray *Level j pixel* [9]. Meanwhile, the features that would be used in this research were the Correlation, Entropy, and Inverse Difference Moment (IDM) features. **Figure 2** below is the angle of the Gray Level Co-Occurrence Matrix used in this study.

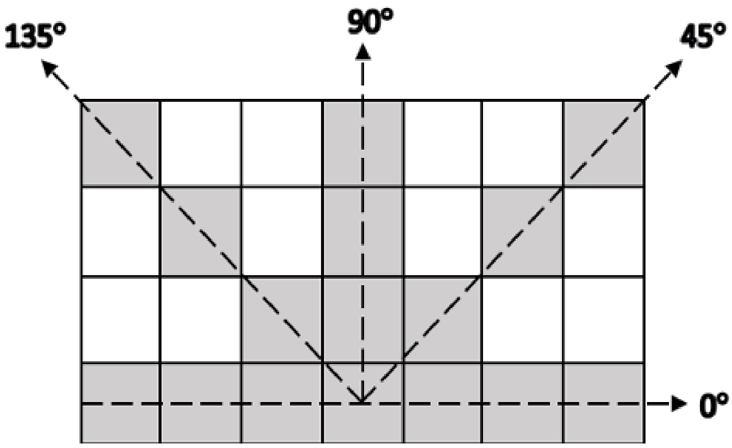

Figure 2. Angle Direction GLCM

As shown in **Figure 2**, the selection of neighboring pixels starts from the right. Relationship 1, 0 is a relationship of 2 pixels with a value of 1 followed by a pixel with a value of 0.

The sample pair of the 2-pixel GLCM matrix is shown in **Figure 3** below :

0	4	6	6	6	4
3	4	5	5	4	3
5	4	4	4	3	1
5	3	4	4	2	0
3	3	2	2	1	1
3	1	1	0	1	2

(a) DCT Image

0,0	0,1	0,2	0,3	0,4	0,5	0,6
1,0	1,1	1,2	1,3	1,4	1,5	1,6
2,0	2,1	2,2	2,3	2,4	2,5	2,6
3,0	3,1	3,2	3,3	3,4	3,5	3,6
4,0	4,1	4,2	4,3	4,4	4,5	4,6
5,0	5,1	5,2	5,3	5,4	5,5	5,6
6,0	6,1	6,2	6,3	6,4	6,5	6,6

(b) Pixel composition

0	1	0	0	1	0	0
1	2	1	0	0	0	0
1	1	1	0	0	0	0
0	2	1	1	2	0	0
0	0	1	2	3	1	1
0	0	0	1	2	1	0
0	0	0	0	1	0	2

(c) Number of pixel pairs

Figure 3. Pair 2 Pixel Matrix GLCM

The matrix in **Figure 3** (c) is a framework matrix. The matrix should be reprocessed into a symmetrical matrix by adding the value of the transposed result. **Table 1** below is the process of adding transpose values for the formation of a symmetric matrix.

Table 1. Symmetrical Matrix Formation

Symmetrical Matrix Formation																						
0	1	0	0	1	0	0		0	1	1	0	0	0	0		0	2	1	0	1	0	0
1	2	1	0	0	0	0		1	2	1	2	0	0	0		2	4	2	2	0	0	0
1	1	1	0	0	0	0		0	1	1	1	1	0	0		1	2	2	1	1	0	0
0	2	1	1	2	0	0	+	0	0	0	1	2	1	0	=	0	2	1	2	4	1	0
0	0	1	2	3	1	1		1	0	0	2	3	2	1		1	0	1	4	6	3	2
0	0	0	1	2	1	0		0	0	0	0	1	1	0		0	0	0	1	3	2	0
0	0	0	0	1	0	2		0	0	0	0	1	0	2		0	0	0	0	2	0	4

After the symmetric matrix was formed, the matrix normalization stage of the image would be carried out which aimed to eliminate the dependence on the image size. The following **Table 2** shows the matrix normalization process.

Table 2. Matrix Normalization

Matrix Normalization						
0/24	2/24	1/24	0/24	1/24	0/24	0/24
2/24	4/24	2/24	2/24	0/24	0/24	0/24
1/24	2/24	2/24	1/24	1/24	0/24	0/24
0/24	2/24	1/24	2/24	4/24	1/24	0/24
1/24	0/24	1/24	4/24	6/24	3/24	2/24
0/24	0/24	0/24	1/24	3/24	2/24	0/24
0/24	0/24	0/24	0/24	2/24	0/24	4/24

Table 3. Matrix Normalization Results

Matrix Normalization Result Value						
0.00	0.08	0.04	0.00	0.04	0.00	0.00
0.08	0.17	0.08	0.08	0.00	0.00	0.00
0.04	0.08	0.08	0.04	0.04	0.00	0.00
0.00	0.08	0.04	0.08	0.17	0.04	0.00
0.04	0.00	0.04	0.17	0.25	0.13	0.08
0.00	0.00	0.00	0.04	0.13	0.08	0.00
0.00	0.00	0.00	0.00	0.08	0.00	0.17

After getting the results of the normalization division of the image matrix see **Table 3**, the calculation of correlation features, entropy, and IDM would be carried out [4] [9] [10] [11]. The following is an equation that was used to calculate the Correlation, Entropy, and IDM features :

$$Korelasi = \frac{\sum_{i=1}^{L}\sum_{j=1}^{L}(ij)(GLCM(i,j) - \mu_i{}'\mu_j{}'}{\sigma_i{}'\sigma_j{}'} \quad (2)$$

Where *i* is the row value and *z* is the column value, is the sum of the values of *i* or *j*.

$$Entropi = -\sum_{i=1}^{L}\sum_{j=1}^{L}(GLCM(i,j)\log(GLCM(i,j) \quad (3)$$

Where (*i,j*) is the value in a row and column *j*, divided by the number 1 and then added by the squared value of *i*-j.

$$IDM = \sum_{i=1}^{L} \sum_{j=1}^{L} \frac{(GLCM(i,j)^2}{1+(i-j)^2} \quad (4)$$

Where (i,j) is the value in row 1 of column j, divided by the number 1 and then added by the squared value of i-j.

The above equation was obtained from the mean which was the intensity of the gray image and the standard deviation first. The standard deviation was obtained from the square of the variance which showed the distribution of pixel values in the image with the following formula [13]:

$$mean\ i = \mu_i{}' = \sum_{i=1}^{L} \sum_{j=1}^{L} i * GLCM(i,j) \quad (5)$$

$$mean\ i = \mu_j{}' = \sum_{i=1}^{L} \sum_{j=1}^{L} j * GLCM(i,j) \quad (6)$$

$$varian\ i = \sigma_i^2 = \sum_{i=1}^{L} \sum_{j=1}^{L} GLCM(i,j)(i - \mu_i')^2 \quad (7)$$

$$varian\ j = \sigma_j^2 = \sum_{i=1}^{L} \sum_{j=1}^{L} GLCM(i,j)(i - \mu_j')^2 \quad (8)$$

$$standart\ deviasi\ i = \sigma_i = \sqrt{\sigma_i^2} \quad (9)$$

$$standart\ deviasi\ j = \sigma_j = \sqrt{\sigma_j^2} \quad (10)$$

C. *K-Nearest Neighbour* (K-NN)

K-Nearest Neighbor is a method that works using a supervised algorithm where the results of query instances are classified based on the majority and categories in K-NN. The purpose of the K-NN algorithm is to classify new objects based on attributes and training samples. K-NN uses the neighboring classification as the predictive value of the new test sample, near or far neighbors are usually calculated based on the Euclidean distance. Euclidean distance serves to test a measure that can be used as an interpretation of the proximity of the distance between two objects [9][14][15][16]. Which is represented by the following equation [12]:

$$d_i = \sqrt{\sum_{i=1}^{n} (x_{2i} - x_{1i})^2} \quad (11)$$

Information:

di = Euclidean distance to-i

x2i = training data to-i

x1i = data testing to-i

D. *Confusion Matris*

The confusion matrix performs tests to estimate true and false objects. The test sequence is tabled in a confusion matrix where the predicted class is shown at the top of the matrix and the observed class is at the left. Each cell contains a number that represents the number of true cases of the observed class to predict, **Table 4** is a table of the confusion matrix model used [9][14] [16]:

Table 4. Confusion Matrix Model

Pred / True	Fresh	Not Fresh	Worthy	Not Feasible
Fresh	***True Fresh***	False Not Fresh	False Worthy	False Not Feasible
Not Fresh	False Fresh	***True Not Fresh***	False Worthy	False Not Feasible
Worthy	False Fresh	False Not Fresh	**False Worthy**	False Not Feasible
Not Feasible	False Fresh	False Not Fresh	False Worthy	**False Not Feasible**

Information :

TP = positive tuple which is classified as positive

TN= negative tuple which is classified as negative

FP= negative tuple which is classified as negative

FN = negative tuples classified as positive

Dataset

In this study, the data used was tuna image data which consisted of training data and testing data. **Table 5** shows the total amount of data used in each class that has been determined.

Table 5. Total Training and Testing Data

CLASS	Training Data	Testing Data
	Amount	***Amount***
Fresh	108	42
Not Fresh	104	36
Worthy	72	30
Not Feasible	144	53
Total	428	161

Figures 4 and 5 below are samples of the training and testing data used.

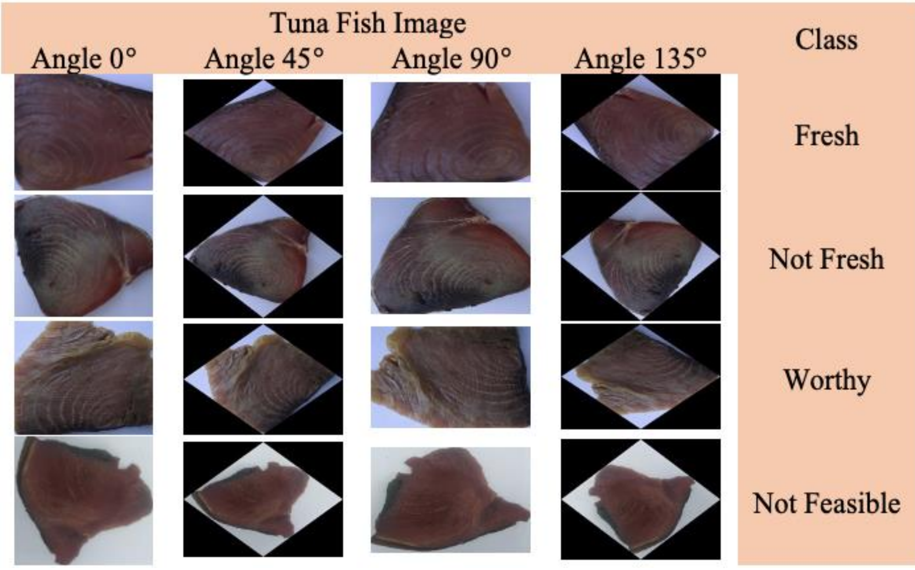

Figure 4. Sample Data Training

The training data was resized to 400 x 400 pixels and then rotated at 0°, 45°, 90°, and 135° angles. And for data testing, only image resizing would be carried out with a size of 400 x 400 pixels as shown in Figure 5 below.

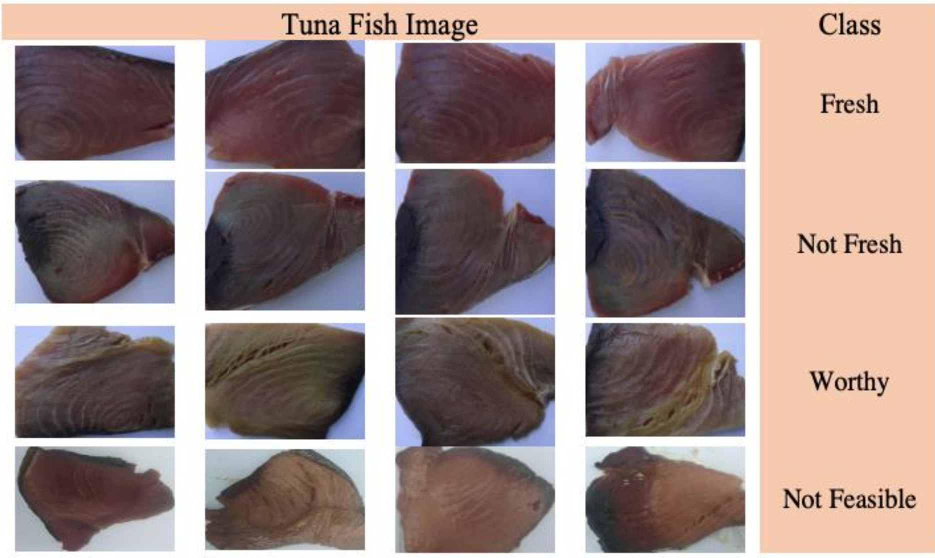

Figure 5. Sample Data Testing

Results and Discussion

The purpose of this study is to measure the accuracy of the K-Nearest Country classification in identifying the freshness level of tuna based on the Discrete Cosine Transform in the feature extraction of the Gray Level Co-Occurrence Matrix. The test will be carried out based on the 4 angles used, namely 0°, 45°, 90°, dan 135° using the values of k=1, 3, 5, and 7. From the results of tests carried out at the angle and the value of k used, the highest accuracy results are at an angle of 0° with a value of k = 1 which is 94.40, and the lowest accuracy results are at angles 45°, 90°, and 135° with a value of k = 7 that is equal to 59%.

Table 6 below shows the highest accuracy results for each angle and the value of *k* used.

Table 6. Highest Accuracy Results at Every Angle θ and k

Highest Accuracy		
Angle θ	***Value k***	***Accuracy %***
0°	1	94.4099
45°	1	90.6832
90°	1	89.441
135°	1	89.441

Figure 6, below is a graph of the highest accuracy results at each angle and k value.

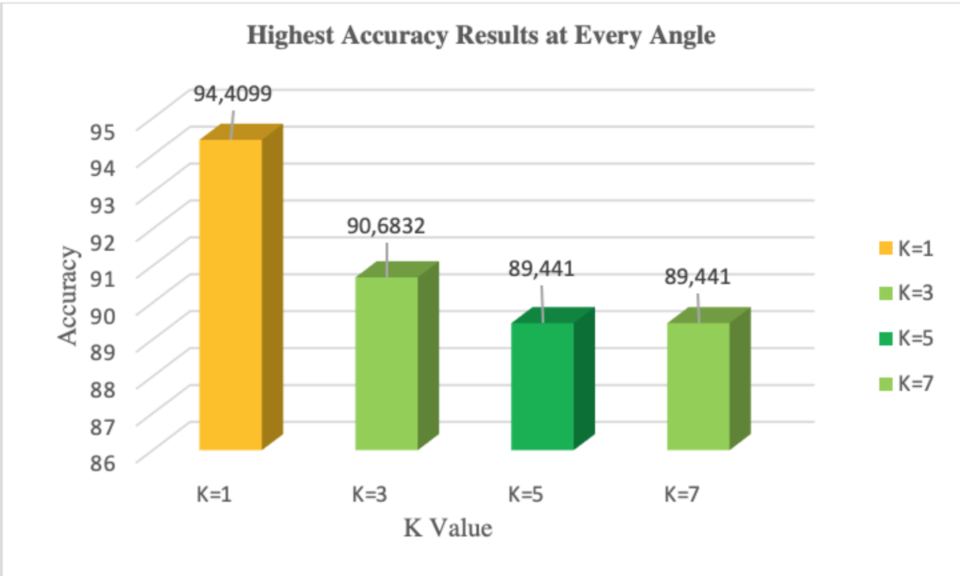

Figure 6. Highest Accuracy Result Chart

The graphic above shows that the results of the experiments carried out in this study. The highest accuracy value was obtained at an angle of 0° with a value of *k* = 1 of 94.40%. Meanwhile, at 90° and 135° angles, the highest accuracy value was the same with the value of k=1 which was 89.44%. Below was a graphic image of the experiment conducted at angles 0°, 45°, 90°, 135°, and for all k values used, namely k=1, 3, 5, and 7.

A. Angle Test Results 0° and the value of k=1, 3, 5, and 7

The results of the tests carried out at an angle of 0° indicated different accuracy results for each k value, the test was carried out 4 times based on the k values of 1, 3, 5, and 7. The highest accuracy result was at a value of k = 1, which was 94.40%, and the lowest was at a value of k = 7, which was 62.73%.

In Table 7 the following is a calculation of the confusion matrix from the highest accuracy results at an angle of 0° with a value of k = 1.

Table 7. Confusion Matrix Calculation Results at the value of k=1 angle 0°

Class	**Confusion Matrix Evaluation *k*=1 Angle 0°**			
	Fresh	***Not Fresh***	***Worthy***	***Not Feasible***
Fresh	33	1	0	2
Not Fresh	1	27	0	0
Worthy	2	1	42	1

Class	Confusion Matrix Evaluation *k*=1 Angle 0°			
	Fresh	*Not Fresh*	*Worthy*	*Not Feasible*
Not Feasible	0	1	0	50

$$Accuracy = \frac{33+27+42+50}{161} = 94.40\%$$

Color Explanation :
Test Data Correct
Incorrect Test Data

Figure 7 below shows a graph of the accuracy results on the 0° angle test using the values of k=1, 3, 5, and 7.

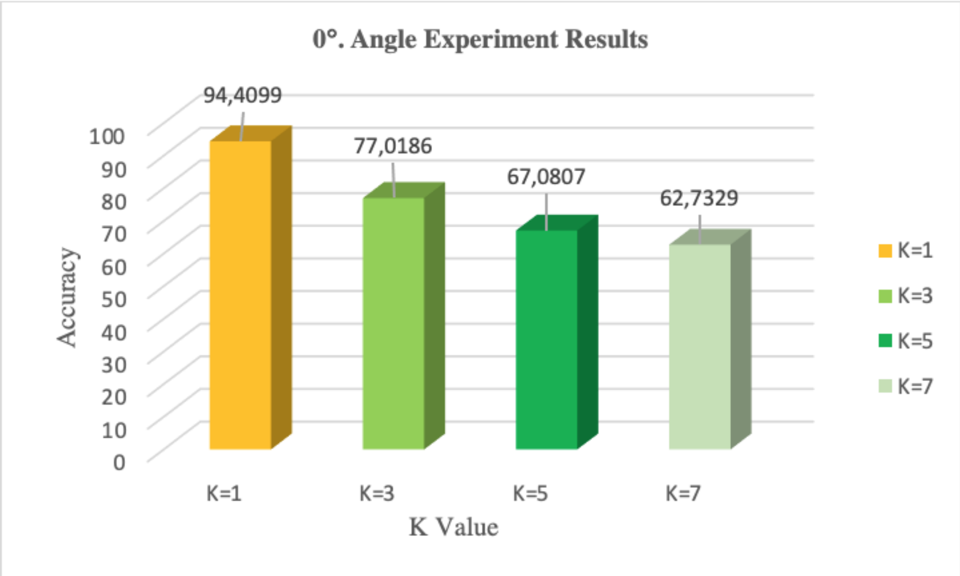

Figure 7. Angle 0° Accuracy Result

B. Angle Test Results 45° and the value of k=1, 3, 5, and 7

From the tests carried out at an angle of 45° using the values of k=1, 3, 5, and 7, the highest accuracy result was at the value of k=1 which was 90.68%, and the lowest was at the value of k=7 which was 62.73 %.

The following **Table 8** below is the calculation of the highest accuracy results at the value of k = 1 using a confusion matrix.

Table 8. Confusion Matrix Calculation Results at the value of k=1 angle 45°

Class	Confusion Matrix Evaluation *k*=1 Angle 45°			
	Fresh	*Not Fresh*	*Worthy*	*Not Feasible*
Fresh	33	2	1	1
Not Fresh	0	26	1	4
Worthy	2	0	39	0
Not Feasible	1	2	1	48

$$Accuracy = \frac{33+26+39+48}{161} = 90.68\%$$

Color Explanation :
Test Data Correct
Incorrect Test Data

Figure 8 below shows a graph of the results of the accuracy of the 45° angle test using the values of k=1, 3, 5, and 7.

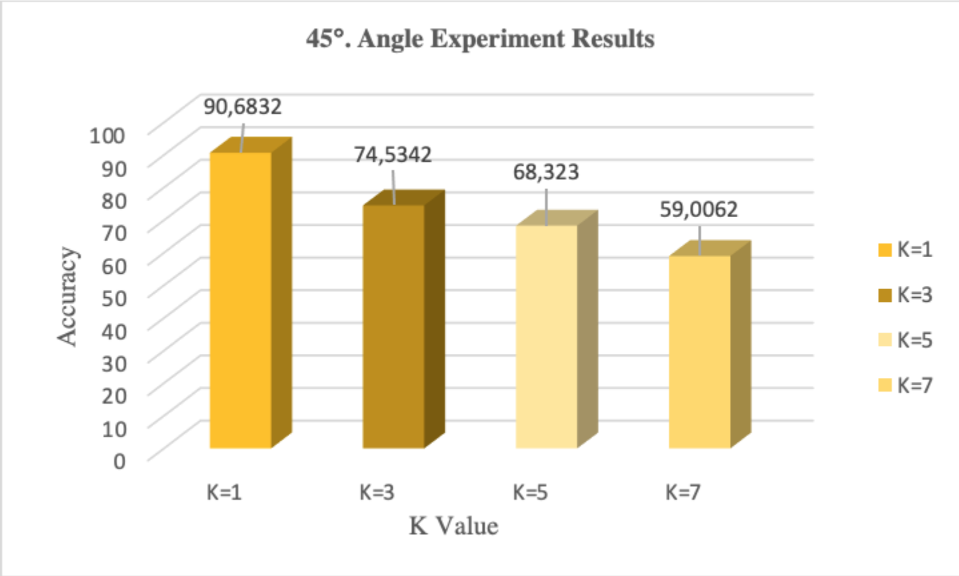

Figure 8. Angle 45° Accuracy Result

C. Angle Test Results 90° and the value of k=1, 3, 5, and 7

Tests carried out at an angle of 90° obtained the highest accuracy results at a value of k = 1, which was 89.44%, and the lowest accuracy was at a value of k = 7, which was 59%.

The following in **Table 9** is the calculation of the highest accuracy results at the value of k = 1 using a confusion matrix.

Table 9. Confusion Matrix Calculation Results at the value of k=1 angle 90°

Class	Confusion Matrix Evaluation *k*=1 Angle 90°			
	Fresh	***Not Fresh***	***Worthy***	***Not Feasible***
Fresh	33	1	3	2
Not Fresh	2	24	0	2
Worthy	1	1	39	1
Not Feasible	0	4	0	48

$$Accuracy = \frac{33+24+39+48}{161} = 89.44\%$$

Color Explanation :
Test Data Correct
Incorrect Test Data

In **Figure 9**, the following graph shows the results of the 90° angle test accuracy using the values of k=1, 3, 5, and 7.

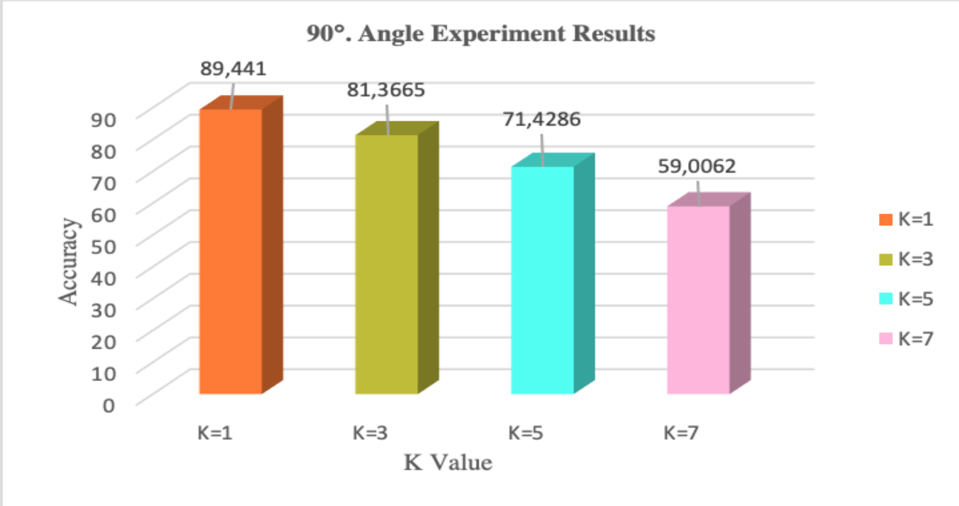

Figure 9. Angle 90° Accuracy Result

D. Angle Test Results 135° and the value of k=1, 3, 5, and 7

From the results of the tests carried out at an angle of 135° using the values of k=1, 3, 5, and 7, the highest accuracy result was found at the value of k=1 which was 89.44%, and the lowest was at the value of k=7 which was 59 %. **Table 10** below is the result of calculating the highest accuracy at a value of k = 1 using a confusion matrix.

Table 10. Confusion Matrix Calculation Results at the value of k=1 angle 135°

Class	**Confusion Matrix Evaluation *k*=1 Angle 90°**			
	Fresh	***Not Fresh***	***Worthy***	***Not Feasible***
Fresh	33	1	3	2
Not Fresh	2	24	0	2
Worthy	1	1	39	1
Not Feasible	0	4	0	48

$$Accuracy = \frac{33+24+39+48}{161} = 89.44\%$$

Color Explanation :

Test Data Correct

Incorrect Test Data

The following **Figure 10** shows a graph of the results of the 135° angle test accuracy using the values of k=1, 3, 5, and 7.

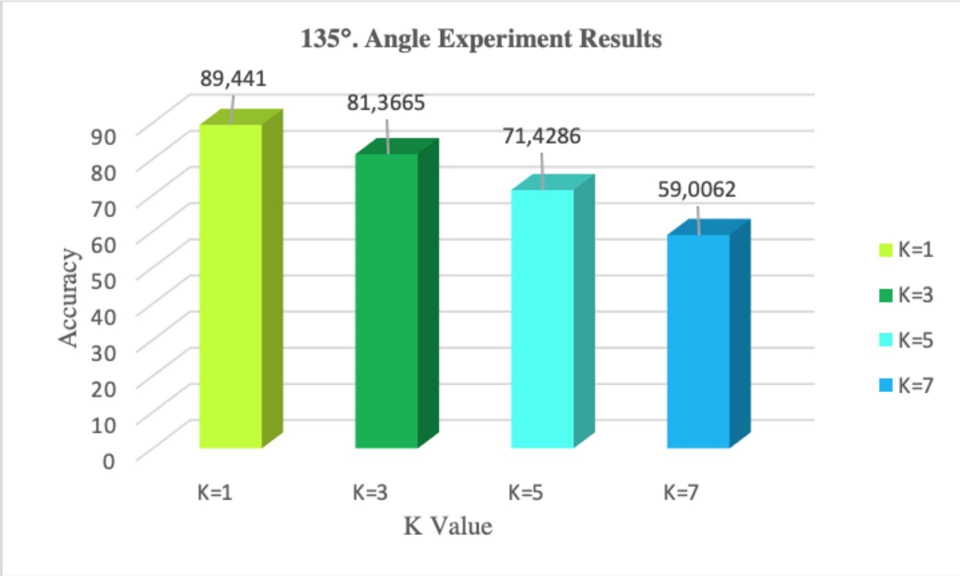

Figure 10. Angle 135° Accuracy Result

Conclusion

From the results of tests carried out on all angles used 0°, 45°, 90°, 135°, and the value of k=1, 3, 5, 7, it showed that the highest accuracy result was at angle 0° with a value of k=1, 94.40% accuracy value. Meanwhile the lowest accuracy was at an angle of 90° and 135° with the same k value of 7, 59% accuracy value. The two angles also had the exact same accuracy value for each value of k. Based on the accurate results obtained in this study, it can be concluded that the Discrete Cosine Transform (DCT) transformation method is very effective in improving the texture feature extraction performance of Gray Level Co-Occurrence Matrix (GLCM) in extracting tuna image features. It can be seen from the results of the obtained accuracy of the K-Nearest Neighbor (K-NN) classification. Hence, the Discrete Cosine Transform method was very successful to improve the performance of the Gray Level Co-Occurrence Matrix method in extracting texture features on tuna images.

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