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Classification of Skipjack Freshness Quality Based on Local Binary Pattern and Gray Level Co-Occurrence Matrix Using K-Nearest Neighbor

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Abstract

Katsuwonus pelamis or skipjack tuna is one of the results of fishing commodities from Gorontalo Province. The quality of fresh fish can be degraded easily if not handled and stored properly. Thus, in this study an automatic system for classifying the freshness level of skipjack tuna based on digital image processing techniques was introduced. It uses Local Binary Pattern (LBP) to extract local texture features and Gray Level Co-occurrence Matrix (GLCM) for statistical texture analysis with classification done by K-Nearest Neighbor (K-NN) algorithm using Euclidean distance as a measurement between features. There were 819 training images and 140 test images used in four categories: Fresh, Not Fresh, Worth Consuming, and Rotten. Tests on several values of k showed that the highest accuracy was at k = 1 with an accuracy rate of 86.42% while the lowest was at k = 9 with a rate of 49.28%. This indicates that the combination LBP-GLCM applied in K-NN has potentiality to capture texture difference effect from various levels fish freshness. This method is non-destructive and could be onboard application for fish quality monitoring as well as automatic system for freshness evaluation.

Keywords: Skipjack Tuna; Image Processing; Local Binary Pattern; Gray Level Co-occurrence Matrix; K-Nearest Neighbor.

Introduction

The fishery sector has a strategic position within the economy of Gorontalo Province wherein skipjack tuna (Katsuwonus pelamis) is one among its marine commodities that have high commercial value due to being rich in protein content and nutritional values useful for human health (Pemerintah Provinsi Gorontalo, 2017; Gobel *et al.*, 2019). This potential can be realized since deterioration from catching to marketing happens very fast through bacterial and enzymatic activities spoiling fish once cold-chain management is not properly applied (Rindengan & Mananohas, 2017). The local fishery authority UPTD-BPPMDPP of Gorontalo Province declares all fresh fish products must comply with quality and food safety standards. Unfortunately, traditional fishing and post-harvest practices are still common which results in poor product quality as well as a huge loss of marketable raw material for processing industries. Assessment of fish freshness through digital image analysis provides an efficient alternative method objectively compared to conventional sensory evaluation Some visual indicators such as surface texture, color variation, and clarity of the eye could be quantified computationally for more consistent assessments (Fitriyah *et al.*, 2020; Sarimin *et al.*, 2019). Among several image-processing approaches, Local Binary Pattern (LBP) technique has been found effective in extracting texture information by comparing intensities between each pixel with its neighbors within a local matrix (Lamasigi *et al.*, 2020; Novitasari *et al.*, 2018). On another side, Gray Level Co-occurrence Matrix (GLCM) method statistically characterizes spatial relationships among pixel intensities which enhances pattern recognition in texture-based analyses (Lamasigi & Bode, 2021; Lamasigi, 2021). The classification stage of this study implements the K-Nearest Neighbor algorithm as a non-parametric method known for its simplicity yet performing robustly over diverse feature-based classification problems (Sultoni *et al.*, 2019; Roberto, 2019). Previous research proved reliable results by combining LBP and GLCM toward image-based freshness detection for fish species like tuna and pomfret (Novianto & Erawan, 2020; Lamasigi, 2022). This study will follow up on those results by classifying skipjack tuna freshness using a hybrid feature extraction framework based on LBP and GLCM with K-NN as the classification model to test texture-based differentiation at various levels of fish image freshness.

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Background Theory

Local Binary Pattern (LBP)

The Local Binary Pattern (LBP) method, first introduced by Ojala *et al*., is a widely used feature extraction technique for capturing texture information in digital images (Lamasigi *et al*., 2020; Novitasari *et al*., 2018). This method operates by comparing the intensity of a central pixel with those of its surrounding neighbors within a predefined local window—commonly a 3×3 matrix. The central pixel serves as a threshold; each neighboring pixel is assigned a binary value of 1 if its intensity is greater than or equal to that of the center pixel, or 0 otherwise. The resulting binary sequence of eight bits represents the local texture pattern, which is then converted into a decimal number to replace the original central pixel value. Mathematically, the position of a neighboring pixel $P(x_p, y_p)$located on the circumference of a circle with radius Rcentered at (x_c, y_c)can be expressed as follows (Sultoni *et al*., 2019):

$$x_P = x_c + R\cos\left(\frac{2\pi p}{p}\right) \tag{1}$$

The general formulation of the LBP operator can be written as (Lamasigi, 2021):

$$y_P = y_c + R\,sin\left(\frac{2\pi p}{p}\right) \tag{2}$$

Where:

$$LBP_{P,R}\,(x_c\,, y_c\; = \sum_{P=0}^{P=1} s\left(g_p - g_c\right)2^p \tag{3}$$
$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

Information:
P: The number of neighboring pixels
R: Value of distance/radius
g_c: The value of center pixel
g_p: Neighbor pixel value
x_c, y_c: Center coordinates

Through this binary comparison process, each pixel's local texture can be represented by one of $2^8 = 256$unique labels, corresponding to all possible binary combinations within an eight-neighbor system. This process captures fine-grained variations in texture, which are highly relevant for identifying freshness levels in skipjack tuna, as texture irregularities often indicate degradation of tissue structure due to microbial and enzymatic activity (Fitriyah *et al*., 2020; Rindengan & Mananohas, 2017). The step-by-step LBP computation begins with a convolution of the grayscale image using the $s(g_p - g_c)$function. The outcome of this operation forms an 8-bit binary value for each 3×3 pixel region (Figure 1).

F(x,y)=

x,y	1	2	3	4	5	6	7	8	9	10
1	253	253	254	254	106	178	253	251	251	250
2	253	253	253	246	100	121	135	248	250	250
3	251	253	253	98	79	93	88	94	250	248
4	250	251	253	93	100	75	77	78	250	248
5	250	251	253	108	93	83	75	75	250	247
6	250	251	253	98	81	83	80	72	250	248
7	250	251	253	102	99	86	81	249	250	250
8	250	251	253	254	104	79	88	253	251	250
9	250	253	253	253	126	114	253	253	253	251
10	251	253	254	254	254	254	254	254	253	253

Nilai pixel *Grayscale*

253	253	254
253	253	253
251	253	253

S(gp-gc)

1	1	1
1		1
0	1	1

Figure 1. First Correlation Matrix 3×3

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These binary values are then transformed into their respective decimal equivalents to generate the final LBP-coded image (Figure 2).

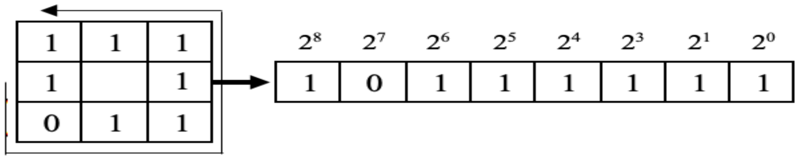

Figure 2. Calculation of Decimal Values From a 3×3 Matrix

A single pixel comparison producing the binary sequence 10111111 corresponds to a decimal value of 191, which replaces the original central pixel value. This process continues iteratively across the entire image, producing a pixel-wise feature map that encodes the textural distribution of the fish's surface (Figures 3–4).

x,y	1	2	3	4	5	6	7	8	9	10
1	253	253	254	254	106	178	253	251	251	250
2	253	191	253	246	100	121	135	248	250	250
3	251	253	253	98	79	93	88	94	250	248
4	250	251	253	93	100	75	77	78	250	248
5	250	251	253	108	93	83	75	75	250	247
6	250	251	253	98	81	83	80	72	250	248
7	250	251	253	102	99	86	81	249	250	250
8	250	251	253	254	104	79	88	253	251	250
x,y	1	2	3	4	5	6	7	8	9	10
9	250	253	253	253	126	114	253	253	253	251
10	251	253	254	254	254	254	254	254	253	253

Figure 3. Value of Decimal Placed at 10×10 Pixels

x,y	1	2	3	4	5	6	7	8	9	10
1	253	253	254	254	106	178	253	251	251	250
2	253	191	239	0	143	14	15	31	47	250
3	251	31	163	215	239	71	143	31	38	248
4	250	63	35	251	64	255	79	31	34	248
5	250	62	34	193	195	161	239	223	34	247
6	250	62	34	243	255	99	241	255	50	248
7	250	62	50	241	224	208	185	60	122	250
8	250	62	126	0	224	255	124	112	240	250
9	250	60	254	243	241	248	124	250	241	251
10	251	253	254	254	254	254	254	254	253	253

Figure 4. Sample Calculation Results for All Pixel Values

Gray Level Co-occurrence Matrix (GLCM)

The Gray Level Co-occurrence Matrix (GLCM) is a second-order statistical approach that analyzes the spatial relationship between pairs of pixels in an image. It quantifies how frequently a pixel with a specific gray level $i$occurs adjacent to a pixel with another gray level j, based on a defined spatial orientation and distance (Lamasigi & Bode, 2021; Sarimin *et al.*, 2019). GLCM computation is carried out by first constructing a co-occurrence matrix that records the frequency of gray-level pair occurrences. The relationship between the reference pixel and its neighbor is defined using a distance parameter $d = 1$and evaluated at four angular directions—0°, 45°, 90°, and 135°—as shown in Figure 6 (Lamasigi, 2021; Lamasigi, 2022).

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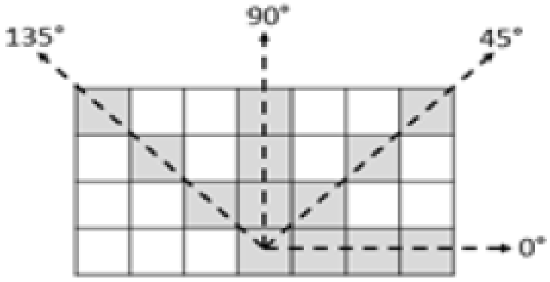

Figure 5. Angle Direction of GLCM

These orientations capture textural information in both horizontal and diagonal directions, which enhances the robustness of the extracted features. Once the co-occurrence matrices for all directions are computed, the rightward pixel adjacency (horizontal direction) is typically selected for illustration, as depicted in Figure 6.

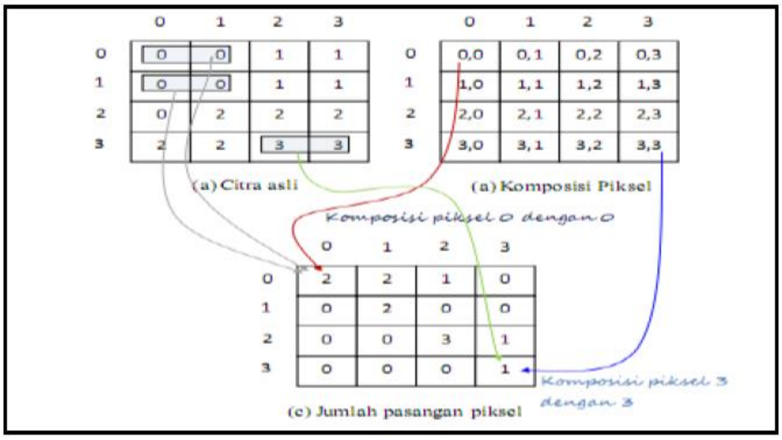

Figure 6. Pair 2 GLCM Matrix Pixels

To ensure symmetry, the GLCM is then combined with its transpose to produce a symmetric matrix, as illustrated in Figure 8 (Novianto & Erawan, 2020; Fitriyah *et al*., 2020).

$$\begin{bmatrix} 2 & 2 & 1 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 3 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} + \begin{bmatrix} 2 & 0 & 0 & 0 \\ 2 & 2 & 0 & 0 \\ 1 & 0 & 3 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 4 & 2 & 1 & 0 \\ 2 & 4 & 0 & 0 \\ 1 & 0 & 6 & 1 \\ 0 & 0 & 1 & 2 \end{bmatrix}$$

Transpos

GLCM sebelum dinormalisasi

Figure 7. Formation of a Symmetrical Matrix

This symmetrization ensures that co-occurrence counts are bidirectional, reducing directional bias in texture characterization. To prevent the extracted features from being influenced by image size, normalization is performed on the matrix elements so that the sum of all entries equals one. This normalization step, shown in Figure 9, allows the GLCM values to represent relative probabilities rather than raw counts (Rindengan & Mananohas, 2017; Gobel *et al*., 2019).

$$\begin{bmatrix} \frac{4}{24} & \frac{2}{24} & \frac{1}{24} & \frac{0}{24} \\ \frac{2}{24} & \frac{4}{24} & \frac{0}{24} & \frac{0}{24} \\ \frac{1}{24} & \frac{0}{24} & \frac{6}{24} & \frac{1}{24} \\ \frac{0}{24} & \frac{0}{24} & \frac{1}{24} & \frac{2}{24} \end{bmatrix}$$

Figure 8. Matrix Normalization

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From each normalized GLCM, four key texture features are calculated—contrast, correlation, angular second moment (ASM), and entropy—following the standard formulations in texture analysis (Lamasigi *et al*., 2020; Novitasari *et al*., 2018; Sultoni *et al*., 2019):

Contrast: $Contrast = \sum_{i}^{L} \sum_{j}^{L} |i - j|^2 \cdot GLCM(i,j)$ (4)

Correlation: $Correlation = \frac{\sum_{i=1}^{L} \sum_{j=1}^{L} (i-\mu_i)(j-\mu_j) \cdot GLCM(i,j)}{\sigma_i \sigma_j}$ (5)

Angular Second Moment (ASM): $ASM = \sum_{i=1}^{L} \sum_{j=1}^{L} [GLCM(i,j)]^2$ (6)

Entropy: $Entropy = -\sum_{i=1}^{L} \sum_{j=1}^{L} GLCM(i,j) \cdot \log[GLCM(i,j)]$ (7)

These features quantify textural distinctions corresponding to different freshness categories in biological images, making them particularly suitable for fish freshness detection tasks.

K-Nearest Neighbor (K-NN)

The K-Nearest Neighbor (K-NN) algorithm is a supervised learning technique used to classify objects based on their proximity to other labeled data within a multidimensional feature space. In this approach, a new instance is assigned to the class most common among its $k$nearest neighbors from the training dataset. The distance between data points is typically measured using the Euclidean distance, which quantifies similarity between feature vectors (Lamasigi, 2022; Lamasigi & Bode, 2021; Roberto, 2019; Sultoni *et al*., 2019). The Euclidean distance is mathematically represented as follows:

$$d(x,y) = \sqrt{\sum_{j=1}^{n} (x_j - y_j)^2} \quad (8)$$

Information:
d: Distance of test data to training data
x_j: Test data feature j with $j = 1,2,\dots,n$
y_j: Training data feature j with $j = 1,2,\dots,n$

A smaller value of $d(x,y)$indicates a higher similarity between two feature vectors, meaning the test image is more likely to belong to the same class as its nearest neighbors. K-NN is chosen for texture-based classification due to its simplicity, strong performance, and minimal need for parameter tuning compared to other machine learning models (Fitriyah *et al*., 2020; Sarimin *et al*., 2019).

Confusion Matrix

Model performance is evaluated using a Confusion Matrix, which compares predicted classifications with actual labels to assess the accuracy of the model. Each cell in the matrix represents the number of samples classified correctly or incorrectly for each class (Lamasigi, 2021; Novitasari *et al*., 2018). The confusion matrix provides a comprehensive view of classification performance across all categories, enabling calculation of metrics such as accuracy, precision, recall, and F1-score.

Methodology

Research Framework

Several sequential stages were undertaken in the research process, forming an integrated classification procedure for skipjack tuna freshness assessment based on digital image analysis. The workflow comprised image preprocessing, feature extraction, classification, and performance evaluation. A comprehensive overview of the processing pipeline is illustrated in Figure 9.

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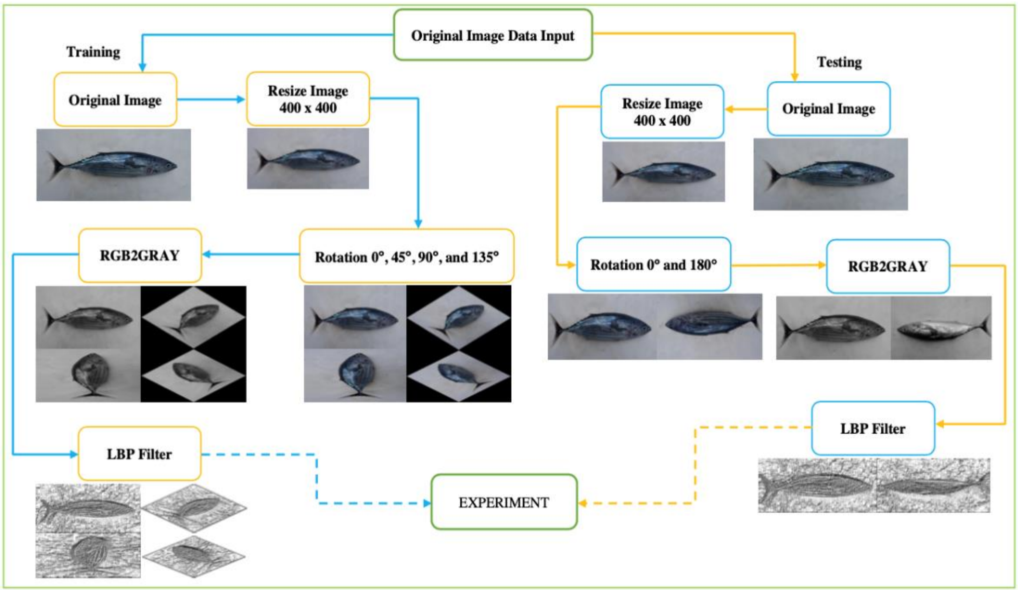

Figure 9. Image Data Processing Framework

Dataset Description

The dataset used in this study consisted of skipjack tuna images categorized into four freshness classes: Fresh, Not Fresh, Worth Consuming, and Rotten. The data were divided into training and testing sets, as summarized in Table 1 (Rindengan & Mananohas, 2017; Gobel *et al*., 2019).

Table 1. Amount of Training and Testing Data

CLASS	Training Data	Testing Data
Fresh	100	43
Not Fresh	76	36
Worth Consuming	76	33
Rotten	40	28
Total	292	140

The training data were further augmented through rotation at angles of 0°, 45°, 90°, and 135°, resulting in a total of 819 training images—comprising 252 fresh, 350 not fresh, 147 worth consuming, and 70 rotten samples. Testing images were rotated at 0° and 180°, producing 140 samples distributed across the same four categories (Lamasigi *et al*., 2020; Novianto & Erawan, 2020). Representative examples of training and testing images are shown in Figures 10 and 11, respectively.

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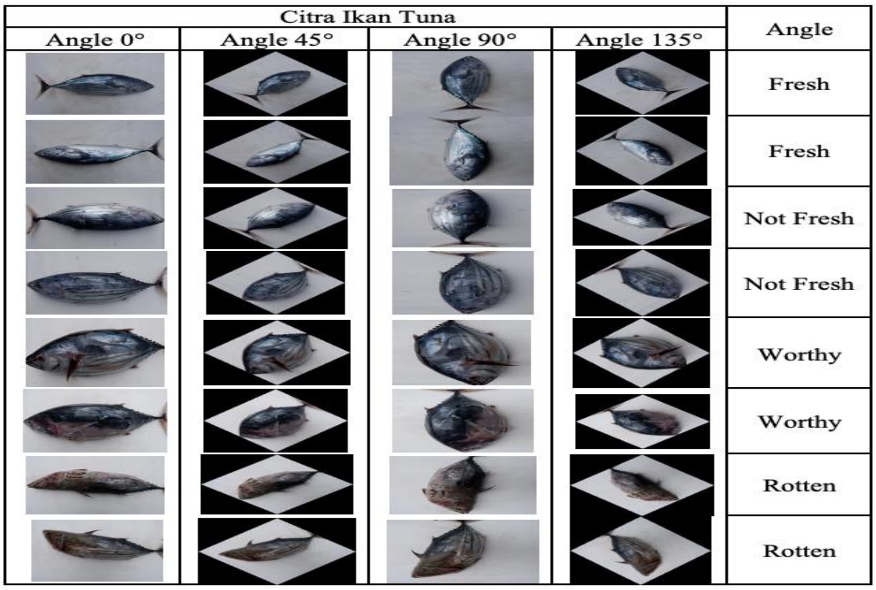

Figure 10. Sample Training Data

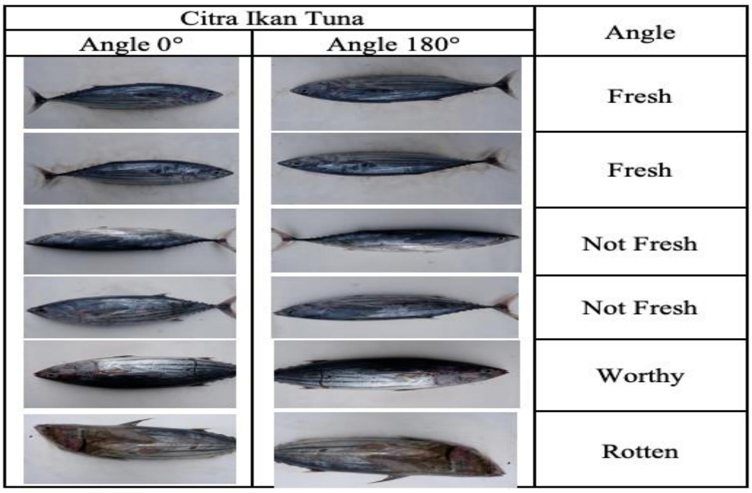

Figure 11. Testing Data Samples

Image Preprocessing

All images were standardized by resizing them to 400 × 400 pixels so that input dimensions would be uniform across all datasets. In the next step, predetermined angles (0°, 45°, 90°, and 135°) rotated the images to increase data variability and improve feature robustness during classification, as recommended by Lamasigi (2022). The resized and rotated images were then converted from RGB to grayscale format. This conversion was necessary to reduce computational complexity and allow focus on texture-based characteristics rather than color information (Novianto & Erawan, 2020).

Feature Extraction

Local Binary Pattern (LBP) Implementation

Feature extraction for grayscale images employed the Local Binary Pattern method. LBP compares each pixel intensity value with its neighbors within a 3×3 window; if a neighboring pixel has a higher value than the center pixel, it gets an assigned value of 1 and otherwise gets assigned 0. The resulting binary sequence is then converted into decimal representation which replaces the original center pixel value, forming a texture descriptor of the image (Lamasigi *et al*., 2020; Novitasari *et al*., 2018). This transformation captures local texture variations corresponding to visual changes in fish freshness as validated previously by similar studies based on image recognition (Sultoni *et al*., 2019). A summary of sample outputs from the LBP filtering process applied to skipjack tuna grayscale images at rotation angles of 0°, 45°, 90°, and 135° is presented in Table 2.

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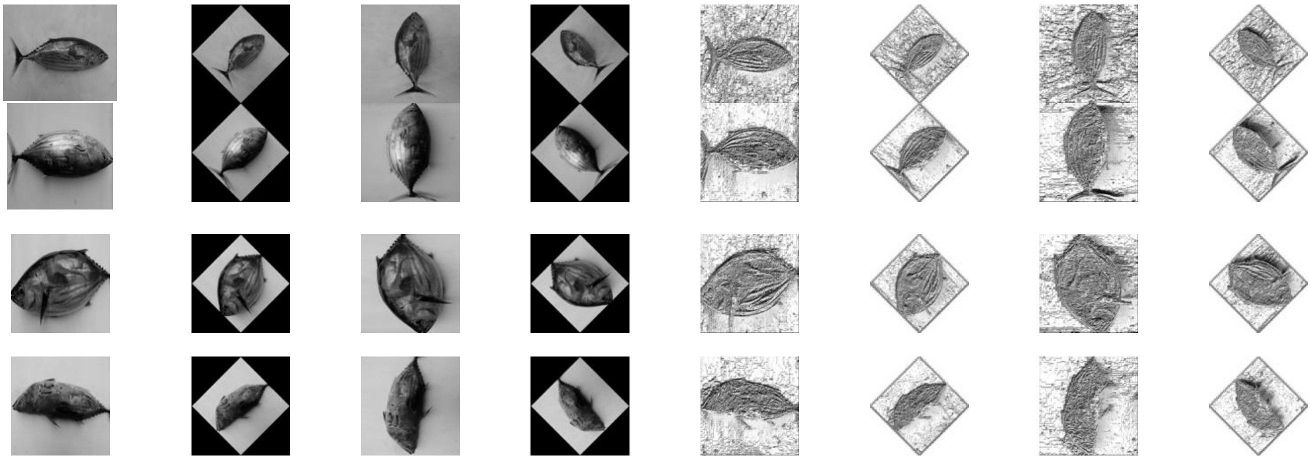
Table 2. Sample LBP Filtering Results for Skipjack Tuna Grayscale Images

Citra Grayscale				Pixel-Wise LBP			
0°	45°	90°	135°	0°	45°	90°	135°



Gray Level Co-occurrence Matrix (GLCM) Implementation
After LBP processing, extracted images underwent Gray Level Co-occurrence Matrix analysis for statistical texture features such as contrast, correlation, angular second moment, and entropy. GLCM quantifies spatial relationships between pixel pairs by how often combinations of pixel intensities occur in specified directions at a distance of one pixel (Lamasigi, 2021; Lamasigi & Bode, 2021). In this study, GLCM was computed at four angular directions (0°, 45°, 90°, and 135°) with distance parameter $d = 1$. These features were selected because they have been proven effective in characterizing structural and surface patterns found in biological imagery—the most relevant application being tasks related to detecting fish freshness (Sarimin *et al.*, 2019). These feature maps form the foundation for subsequent statistical analysis using GLCM in the next stage of the methodology (Sarimin *et al.*, 2019; Gobel *et al.*, 2019).

Classification Implementation
Feature extraction then proceeded to classification using the K-Nearest Neighbor algorithm, which is an instance-based supervised learning method that assigns new data instances into classes based on majority voting among $k$nearest neighbors within feature space (Roberto, 2019). Its similarity measure is computed using Euclidean distance metric between test sample and training samples for proximity determination. In texture-based image analysis, K-NN has gained much attention due to its simplicity, flexibility toward different datasets, and high classification accuracy (Fitriyah *et al.*, 2020; Lamasigi, 2022). Testing was conducted using various values of $k = 1,3,5,7$, and 9 to determine the optimal number of neighbors that yields the highest accuracy.

Performance Evaluation
The Confusion Matrix was used to assess model performance by comparing predicted and actual classifications to compute accuracy, precision, error rates, etc. The experimental setup followed standardized evaluation practices found in previous digital image classification research in fisheries and agricultural applications (Rindengan & Mananohas, 2017; Gobel *et al.*, 2019). The general structure of the confusion matrix used in this study is shown in Table 3.

Table 3. Confusion Matrix Model Structure

Confusion Matrix Evaluation k=1				
Class	Fresh	Not Fresh	Worth Consuming	Rotten
Fresh	True Fresh	False Not Fresh	False Worth Consuming	False Rotten
Not Fresh	False Fresh	True Not Fresh	False Worth Consuming	False Rotten
Worth Consuming	False Fresh	False Not Fresh	True Worth Consuming	False Rotten
Rotten	False Fresh	False Not Fresh	False Worth Consuming	True Rotten

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Results

GLCM Feature Extraction Outputs

From the GLCM calculations, the four feature values—contrast, correlation, ASM, and entropy—were obtained for both training and testing datasets. These values quantify textural distinctions corresponding to different freshness categories in skipjack tuna images, which serve as the input features for subsequent classification using the K-Nearest Neighbor (K-NN) algorithm (Roberto, 2019). The computed sample values for each feature are summarized in Table 2, showing clear variations between fresh and deteriorated fish images, consistent with prior findings on texture-based freshness detection (Sarimin *et al.*, 2019; Lamasigi, 2021).

Table 4. Sample GLCM Feature Values

Training Feature Values				Testing Feature Values			
Contrast	Correlation	ASM	Entropy	Contrast	Correlation	ASM	Entropy
5604.596	0.611449	0.089653	0.458154	5074.986	0.636806	0.122253	0.505213
5109.592	0.614705	0.378530	0.688893	5970.578	0.654358	0.122111	0.504030
4597.114	0.591798	0.375905	0.686645	5376.624	0.646852	0.136444	0.526415
5496.940	0.658508	0.103552	0.495150	5106.546	0.637255	0.138627	0.512797
5786.023	0.611195	0.094109	0.460582	5950.932	0.654830	0.138048	0.510515
4933.952	0.619810	0.385418	0.693416	5401.970	0.656390	0.154375	0.539631
4671.155	0.590568	0.383647	0.692443	4988.245	0.645192	0.143202	0.521807
5547.824	0.661034	0.109914	0.505949	5829.536	0.662338	0.143358	0.521046

Classification Performance Across Different k Values

The classification process aimed to measure the performance of the Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM) feature extraction methods when integrated with the K-NN classifier. The results demonstrated that the best classification accuracy was achieved at $k = 1$with an accuracy rate of 86.42%, while the lowest was observed at $k = 9$, achieving 49.28%. The detailed confusion matrices for each $k$value are presented in Tables 5–9, illustrating the model's classification performance across all categories.

Table 5. Confusion Matrix Calculation Results at k = 1

Class	Fresh	Not Fresh	Worth Consuming	Rotten
Fresh	33	0	0	2
Not Fresh	2	26	1	1
Worth Consuming	1	2	40	3
Rotten	0	5	2	22

Table 6. Confusion Matrix Results (k = 3)

Class	Fresh	Not Fresh	Worth Consuming	Rotten
Fresh	23	7	5	1
Not Fresh	2	17	12	2
Worth Consuming	0	5	38	0
Rotten	1	3	8	16

Table 7. Confusion Matrix Results (k = 5)

Class	Fresh	Not Fresh	Worth Consuming	Rotten
Fresh	21	8	6	1
Not Fresh	2	16	13	2
Worth Consuming	0	6	37	0
Rotten	2	4	13	9

Table 8. Confusion Matrix Results (k = 7)

Class	Fresh	Not Fresh	Worth Consuming	Rotten
Fresh	18	11	6	1
Not Fresh	4	13	15	1
Worth Consuming	0	4	39	0
Rotten	8	2	13	5

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Table 9. Confusion Matrix Calculation Results at k = 9

Class	Fresh	Not Fresh	Worth Consuming	Rotten
Fresh	18	11	6	1
Not Fresh	4	13	15	1
Worth Consuming	0	4	39	0
Rotten	8	2	13	5

Performance Visualization

The relationship between the number of neighbors (k) and classification accuracy is illustrated in Figure 12, which clearly shows a decreasing accuracy trend as $k$increases.

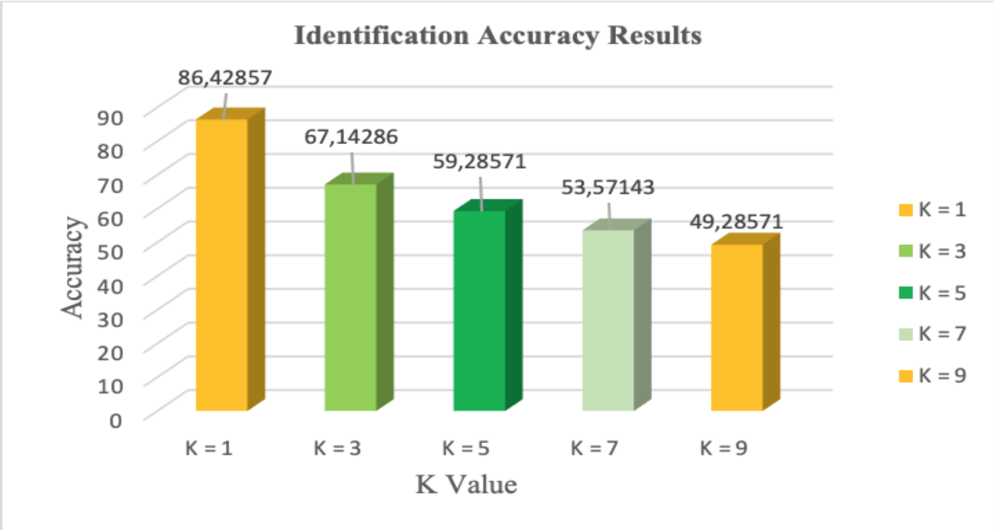

Figure 12. Graph of Accuracy Results at Each k Value

Discussion

The experimental results demonstrate that the integration of Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM) for texture-based feature extraction, combined with K-Nearest Neighbor (K-NN) classification, achieves promising performance in determining skipjack tuna freshness levels. The highest classification accuracy of 86.42% was obtained at $k = 1$, while accuracy progressively declined to 49.28% at $k = 9$. This finding indicates that smaller $k$values allow the model to capture finer distinctions between texture features in skipjack tuna images, which correspond closely with differences in freshness levels (Sarimin *et al.*, 2019; Lamasigi, 2022). The superior performance at $k = 1$suggests that the extracted texture features—contrast, correlation, angular second moment (ASM), and entropy—exhibit sufficient discriminative power to differentiate between the four freshness categories without requiring averaging across multiple neighbors. This observation aligns with previous studies on fish freshness detection, where localized texture variations have been identified as critical indicators of tissue degradation caused by microbial activity and enzymatic breakdown (Fitriyah *et al.*, 2020; Novianto & Erawan, 2020; Rindengan & Mananohas, 2017). The observed decline in accuracy as $k$increases can be attributed to the averaging effect inherent in K-NN when multiple neighbors are considered. At higher $k$values, the decision boundary becomes smoother, leading to misclassification when feature distributions overlap between adjacent freshness classes (Roberto, 2019; Lamasigi *et al.*, 2020). For instance, the "Not Fresh" and "Worth Consuming" categories may share similar textural characteristics during transitional degradation stages, making them difficult to distinguish with larger neighborhoods (Sultoni *et al.*, 2019; Lamasigi & Bode, 2021).

Additionally, the dataset exhibits class imbalance, with fewer samples in the "Rotten" category (70 training images) compared to "Not Fresh" (350 training images). This imbalance may exacerbate performance degradation at higher $k$values, as the majority class dominates the voting process (Novitasari *et al.*, 2018). The achieved accuracy of 86.42% is competitive with existing literature on fish freshness detection. Sarimin *et al.* (2019) reported similar performance (80–85%) using HSV color space and GLCM features with Radial Basis Function networks for pomfret fish. Fitriyah *et al.* (2020) employed Binary Similarity measures on fish eye images with comparable results. The present study extends these findings by specifically targeting skipjack tuna—a species of significant economic importance in Gorontalo Province, where tuna fisheries contribute substantially to regional

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livelihoods and food security (Gobel *et al*., 2019; Pemerintah Provinsi Gorontalo, 2017). Compared to the curve-fitting approach by Rindengan and Mananohas (2017), which focused on fish eye characteristics, the LBP-GLCM combination offers more comprehensive surface texture representation. The use of rotation-based data augmentation (0°, 45°, 90°, 135°) enhances the model's invariance to image orientation, a practical consideration for real-world deployment (Lamasigi, 2022; Novianto & Erawan, 2020). The proposed method holds significant potential for application in the fisheries sector, particularly in Gorontalo Province where skipjack tuna is a key commodity. Automated freshness assessment systems based on digital image analysis can support quality control processes from post-harvest handling at fishing ports to retail distribution (Gobel *et al*., 2019; Pemerintah Provinsi Gorontalo, 2017). By providing objective, rapid, and non-destructive freshness evaluation, such systems can reduce reliance on subjective sensory assessments, minimize post-harvest losses, and enhance consumer confidence in product quality. Integration of this technology into mobile or embedded platforms could facilitate on-site freshness monitoring by fishermen, traders, and quality inspectors, thereby improving traceability and compliance with food safety standards (Pemerintah Provinsi Gorontalo, 2017; Gobel *et al*., 2019).

Analysis of the confusion matrices reveals that the model performs best in distinguishing "Fresh" and "Worth Consuming" categories, with relatively few misclassifications at $k = 1$. The "Fresh" category achieved a true positive rate of 94.3% (33 out of 35 correctly classified). However, confusion persists between "Not Fresh" and "Rotten" classes, particularly at higher $k$values, suggesting that textural differences between moderately and severely degraded fish may be less pronounced (Fitriyah *et al*., 2020; Sarimin *et al*., 2019; Rindengan & Mananohas, 2017). Several limitations warrant consideration. First, the dataset size—particularly for the "Rotten" category—is relatively small, which may limit generalization capability. Second, the current approach relies solely on grayscale texture features, neglecting potentially informative color-based indicators such as gill redness and skin brightness (Sarimin *et al*., 2019; Fitriyah *et al*., 2020). Future studies should explore hybrid feature extraction methods combining LBP-GLCM with color descriptors (e.g., HSV, Lab color spaces) and investigate deep learning approaches for automated feature learning (Lamasigi, 2022; Novitasari *et al*., 2018). Additionally, expanding the dataset and implementing weighted K-NN or adaptive distance metrics could improve classification robustness across all freshness levels (Roberto, 2019; Lamasigi & Bode, 2021).

Conclusion

The results of the experiment show that the combination of Local Binary Pattern and Gray Level Co-occurrence Matrix methods is good for extracting texture features from skipjack tuna images. The extracted features correspond well to different freshness levels so that they can be classified accurately using K-Nearest Neighbor algorithm. Out of all parameter values tested, the best classification performance was achieved at k=1 with an accuracy of 86.42%. The lowest performance was found at k=9 with an accuracy of 49.28%. This indicates that a smaller neighborhood size in K-NN works better for subtle differences in texture corresponding to fish freshness changes. In general, the combination of LBP and GLCM feature extraction techniques with a K-NN classifier is a strong and effective method for determining the freshness of skipjack tuna based on image data. It helps create automated systems that do not destroy fish when checking their freshness and can be used in fisheries and food quality monitoring applications. For future research, it is suggested that segmentation be done on the skipjack tuna image dataset before extracting features. Segmenting the images will make it possible to analyze specific areas like eyes, gills, or skin surface which will result in better accuracy for feature mapping. This preprocessing step can improve LBP and GLCM extraction efficiency thus increasing overall classification accuracy across different k values in the K-NN model.

References

Pemerintah Provinsi Gorontalo. (2017). *Rencana strategis (Renstra) Dinas Kelautan dan Perikanan Provinsi Gorontalo.* https://dinaskp.gorontaloprov.go.id

Gobel, M. R., Baruwadi, M., & Rauf, A. (2019). Analisis daya saing ikan tuna di Provinsi Gorontalo. *Jambura Agribusiness Journal, 1*(1), 36–42. https://doi.org/10.37046/jaj.v1i1.2448

Rindengan, A. J., & Mananohas, M. (2017). Perancangan sistem penentuan tingkat kesegaran ikan cakalang menggunakan metode curve fitting berbasis citra digital mata ikan. *Jurnal Ilmiah Sains, 17*(2), 161. https://doi.org/10.35799/jis.17.2.2017.18128

Lamasigi, Z. Y., Hasan, M., & Lasena, Y. (2020). Local Binary Pattern untuk pengenalan jenis daun tanaman obat menggunakan K-Nearest Neighbor. *ILKOM Jurnal Ilmiah, 12*(3), 208–218. https://doi.org/10.33096/ilkom.v12i3.667.208-218

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Novitasari, A., Purwandari, E. P., & Coastera, F. F. (2018). Identifikasi citra daun tanaman jeruk dengan Local Binary Pattern dan Moment Invariant. *Jurnal Informatika dan Komputer*, *3*(2), 76–83.

Novianto, T. D., & Erawan, I. M. S. (2020). Perbandingan metode klasifikasi pada pengolahan citra mata ikan tuna. *Prosiding Seminar Nasional Fisika dan Aplikasinya (SNFA)*, *5*, 216–223. https://doi.org/10.20961/prosidingsnfa.v5i0.46615

Lamasigi, Z. Y. (2022). Identifikasi tingkat kesegaran ikan tuna menggunakan metode GLCM dan KNN. *Jambura Journal of Electrical and Electronics Engineering*, *4*, 70–76.

Fitriyah, H., Syauqy, D., & Susilo, F. A. (2020). Deteksi kesegaran ikan tongkol (*Euthynnus affinis*) secara otomatis berdasarkan citra mata menggunakan Binary Similarity. *Jurnal Teknologi Informasi dan Ilmu Komputer*, *7*(5), 879. https://doi.org/10.25126/jtiik.2020753839

Sultoni, M. I., Hidayat, B., & Subandrio, A. S. (2019). Klasifikasi jenis batuan beku melalui citra berwarna dengan menggunakan metode Local Binary Pattern dan K-Nearest Neighbor. *Geol. Sains*, *4*(1), 10–15.

Lamasigi, Z. Y. (2021). DCT untuk ekstraksi fitur berbasis GLCM pada identifikasi batik menggunakan K-NN. *Jambura Journal of Electrical and Electronics Engineering*, *3*(1), 1–6. https://doi.org/10.37905/jjeee.v3i1.7113

Sarimin, M., Hayaty, N., Bettiza, M., & Nugraha, S. (2019). Implementasi HSV dan GLCM untuk deteksi kesegaran ikan bawal menggunakan Radial Basis Function berbasis Android. *Sustainable: Jurnal Hasil Penelitian dan Industri Terapan*, *8*(1), 1–7. https://doi.org/10.31629/sustainable.v8i1.1319

Lamasigi, Z. Y., & Bode, A. (2021). Influence of gray level co-occurrence matrix for texture feature extraction on identification of batik motifs using K-Nearest Neighbor. *Jurnal Ilmiah*, *13*(3), 208–218.

Roberto, N. W. (2019). *Penerapan metode K-Nearest Neighbor dalam identifikasi kesegaran ikan.*