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The Integration of HSV and GLCM Features with LDA for Classification of Breadfruit Maturity Levels

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ABSTRACT

Breadfruit is a perennial plant that has historically been distributed throughout Southeast Asia as a food source. Breadfruit that has entered the harvest period or has fallen on its own has several levels of maturity, namely raw, unripe, ripe, and rotten. Breadfruit that has been separated from the tree will have the same characteristics, namely green and slightly yellowish or brownish in colour. The research problem centres on the trouble buyers and sellers have when determining the maturity level of breadfruit. Based on this problem, the purpose of this study is to classify the maturity level of breadfruit using the LDA method. With image classification, it is hoped that the maturity level of breadfruit can be identified more accurately. The research gap in this study lies in the limited number of feature extraction methods used simultaneously, as well as the infrequent use of LDA methods for classification. In this study, Linear Discriminant Analysis is applied together with GLCM and HSV-based feature extraction. The LDA is a statistical method used for classification. LDA focuses on finding lines that separate two or more classes in a dataset by maximizing the distance between class averages and minimizing variance within classes. GLCM feature extraction is an image-processing technique used to evaluate texture. The contribution of this research lies in its improved classification performance and greater accuracy compared to previous studies. It offers a statistical description of how pairs of gray levels are distributed within an image, helping to reveal texture patterns and characteristics. The results of this study show that the classification of maturity levels in breadfruit images is good. This is measured by an accuracy of 89.9333%, precision of 90.1732%, recall of 89.3333%, and an F1-score of 89.7513%.

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1. INTRODUCTION

Breadfruit is an annual plant that has historically been distributed throughout the Pacific, Polynesia, and Southeast Asia, including Indonesia, as a food source. Breadfruit consists of several types, namely seedless breadfruit (Astocarpus astilis) and seeded breadfruit (Artocarpus mariannensis) [1] [2]. Breadfruit that has entered the harvest period or has fallen on its own has several levels of maturity, namely raw, unripe, ripe, and rotten [3]. Breadfruit that has separated from the tree will have the same characteristics, namely a green colour and a slight yellowish or brownish tint [4]. The maturity level of breadfruit is quite difficult to see visually, which can be detrimental to sellers and buyers of breadfruit. Based on this, the problem of this study lies in the difficulty of distinguishing the level of maturity of breadfruit experienced by sellers and buyers.

By utilising technology, this problem can be overcome with image classification. Image classification is a method of grouping pixels in an image into similar categories. Image classification of breadfruit will facilitate the process of identifying the fruit[5], where it will be possible to see which fruits belong to the raw, unripe, ripe, and rotten categories

[6]. Image classification algorithms vary greatly, such as SVM [7], KNN, ANN, CNN, and so on [8] [9] [10]. In this study, the researcher used one of the image classification methods, namely the LDA [11].

The Linear Discriminant Analysis method functions to divide data into different classes. Grouping is determined based on straight lines or straight lines obtained from linear equations [12].

The purpose of this study is to develop a system capable of classifying the maturity level of breadfruit images and calculating the accuracy, precision, recall, and F1-score values [13]. The contribution and novelty of this research lie in the use of the LDA method to classify breadfruit, accompanied by the use of HSV for colour feature extraction and GLCM for texture feature extraction.

Previous studies related to this research are as follows: Laksono et al researched mulberry fruit. The findings indicated that 24 images were accurately recognized, achieving an 80% accuracy rate. In the subsequent test, 11 images were correctly classified with an accuracy of 91.6%.[14].

Borman et al. are researching oil palm using the LDA method. Image processing of oil palm samples involved applying thresholding for segmentation and extracting features using the HSV method. The research results achieved an accuracy of 85% [15].

Agus Ramadhan et al researched the segmentation and classification of vitamin C content in chilli plants using the LDA method. Chilli images were processed by extracting colour and texture features (RGB, HSV, GLCM). The study obtained an accuracy of 99% on the laboratory data and 97% on the test data [16].

Destriana et al researched pineapples. The output features of LDA are determined by the number of classes and poses analyzed. Here, the classification consists of three categories: young, ripe, and very ripe. The accuracy test results were 83%, which is a good level of accuracy [17].

Astrianda et al researched tomatoes. From 54 test datasets, an accuracy of 95% was obtained in determining tomato maturity using LDA with the CIElab colour model [18].

After reviewing several previous studies, the difference between previous studies and the study to be conducted in this research is the integration of HSV and GLCM features with the LDA method, and the classification of fruit ripeness is carried out on breadfruit, whereas in previous studies, the classification of breadfruit was rarely conducted.

2. RESEARCH METHOD

2.1 Research Stages

The stages of research for identifying the maturity level of breadfruit images are depicted in the following figure :

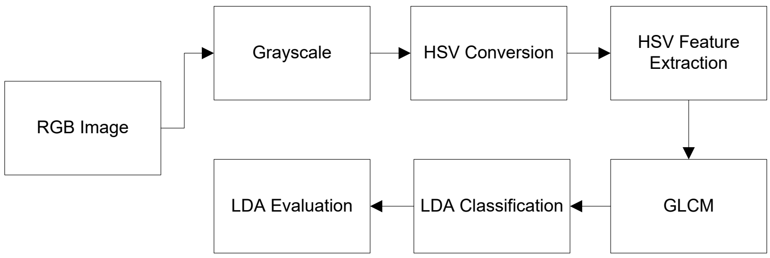

Figure 1. Research Framework

Figure 1 shows that the initial stage of the research begins with inputting RGB images, which are then converted to grayscale and HSV. At the HSV feature extraction stage, each Hue value, Saturation value, and Value value will be taken from the image. This is followed by the GLCM stage [19][20], which is a method for calculating image feature values such as Contrast value, Energy value, Homogeneity value, and Correlation value. After obtaining all the feature values processed in the HSV feature extraction stage and the GCLM stage[21] [22], the next stage is LDA classification [23]. Classification is the stage of placing object classes based on the feature values obtained by calculating these values using the LDA method. The final stage is LDA evaluation, where the classification results will be analyzed and evaluated using the Confusion Matrix method.

2.2. Linear Discriminant Analysis

LDA is a technique used for extracting features that uses a combination of mathematical and statistical operations using different statistical properties for each object [24]. The purpose of the LDA method is to find a linear projection (often referred to as a "Fisher image") to maximize the covariance matrix between classes so that class members are more dispersed and ultimately improve object recognition success.

The following is the formula for LDA (Linear Discriminant Analysis) [25]:

$$f_1 = \mu_i\, C^{-1} X_k^T - \frac{1}{2}\mu_i\, C^{-1}\, \mu_i^T + \ln(p_i) \tag{1}$$

Where:
f1 = discriminant function
µi = total mean of all features i
C = covariance
ln = natural logarithm
pi = prior probability of class i

$$\mu = \frac{xi_1 + xi_2 + xi_3 + \cdots xi_n}{xi_n} \tag{2}$$

Where:
µ = average of class features
xi = features in class-i

$$\mu\text{global} = \frac{x_1 + x_2 + x_3 \ldots\ldots x_n}{x_n} \tag{3}$$

$$x_i^0 = x_i - \mu\text{global} \tag{4}$$

$$C_i = \frac{(x_i^0)^T x_i^0}{n_i} \tag{5}$$

$$C(r,s) = \frac{1}{n}\sum_{i=1}^{g} n_1 c_1(r,s) \tag{6}$$

$$C(r,s)^{A-1} = \frac{1}{|A|}\begin{pmatrix} d & -b \\ -c & a \end{pmatrix} = \frac{1}{ad-bc}\begin{pmatrix} d & -b \\ -c & a \end{pmatrix} \tag{7}$$

$$\mathrm{P} = \frac{\sum xi}{\sum x_n} \tag{8}$$

Where:
µglobal = average of all features of a class
x_i^0 = mean corrected
C_i = class-i covariance
$C(r,s)$ = global covariance matrix
$C(r,s)^{A-1}$ = inverse of the global covariance matrix
P = prior probability of each class

Here is a more detailed explanation of how the LDA method works [26] :
1. Labelling features
2. Separating features according to their classes
3. Calculating the average features of each class (Equation 2).
4. Calculating the global average of each feature group (Equation 3).
5. Calculating the corrected mean of each class (Equation 4)
6. Calculate the covariance matrix for each class (Equation 5)
7. Calculate the global covariance matrix (Equation 6)
8. Calculate the inverse of the global covariance matrix (Equation 7)
9. Calculate the prior probability for each class (Equation 8)
10. Calculate the discriminant function for each class (Equation 1)

2.3 Gray Level Co-occurrence Matrix

The Gray Level Co-occurrence Matrix is a texture feature extraction method used in images that describes the spatial relationship (proximity) between pixel gray levels [27]. GLCM is a method that calculates how often certain gray level pairs appear side by side at a certain distance and direction within an image [28] [29]. Various texture statistical features are then calculated from this matrix. GLCM has several features such as contrast, correlation, energy, homogeneity, and entropy .

Here is how the GLCM method works[30]S:

1. Determine the parameters:
   - Distance (d) → for example, 1 pixel
   - Direction (θ) → 0°, 45°, 90°, 135°
2. Calculate the occurrence of pixel pairs (i, j) according to distance & direction
3. Arrange the results into a GLCM matrix
4. Extract texture features

2.4 Hue, Saturation, Value

HSV (Hue, Saturation, Value) is a color model that represents colors based on how humans perceive them, unlike RGB, which is based on device components [31]. HSV is widely used in image processing and computer vision because it is more intuitive for color analysis [32][33]. The components of HSV are H (color type: red, green, blue, and others), S (color saturation level), and V (brightness level) [34]. Here's how the HSV method works [35]:

1. Input RGB image
2. Convert RGB → HSV
3. Separate H, S, and V channels
4. Feature extraction (average, histogram, etc.)
5. Used for segmentation or classification

2.5 Research Dataset

In this study, breadfruit images were trained first before proceeding to the classification stage. In this study, there were four classes of breadfruit maturity levels, namely unripe, raw, ripe, and rotten according to Figure 1 [36]. According to Figure 2, the study employed 2000 images gathered from primary and secondary data. Some of the breadfruit images were taken directly using a cell phone camera, while others were obtained through image augmentation. The following are samples of breadfruit images:

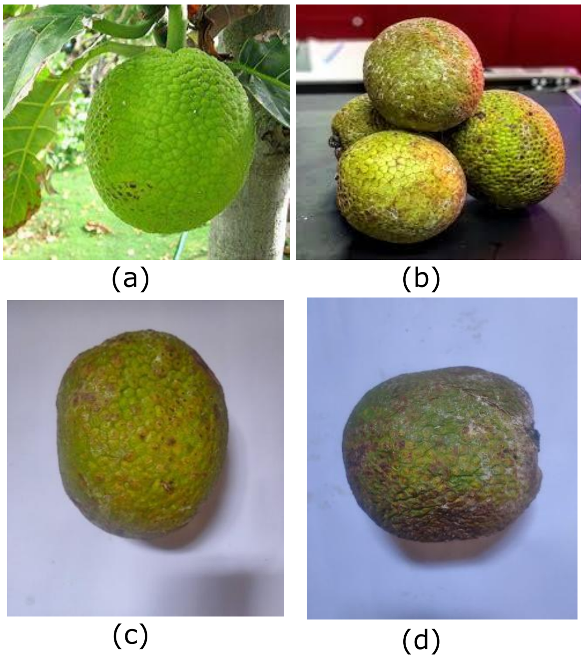

Figure 1. Breadfruit : (a) Raw Breadfruit, (b) Unripe Breadfruit, (c) Ripe Breadfruit, (d) Rotten Breadfruit

The following is the distribution of research data for each level of breadfruit maturity:

Table 1. Breadfruit Image Data

Maturity Level of Breadfruit	Total
Raw Breadfruit	500 Image
Unripe Breadfruit	500 Image
Ripe Breadfruit	500 Image
Rotten Breadfruit	500 Image

3. RESULTS AND DISCUSSION

3.1 Testing of Training Data

The training data needs to be tested to evaluate how the model learns from the given training data. The process of testing the training data is considered necessary to monitor the training process and detect whether overfitting/underfitting will occur. The following is the distribution of training data for each level of breadfruit maturity.

Table 2. Breadfruit Training Data

Maturity Level of Breadfruit	Total
Raw Breadfruit	350 Image
Unripe Breadfruit	350 Image
Ripe Breadfruit	350 Image
Rotten Breadfruit	350 Image

Table 2 above shows the amount of data used for the training process, where 70% of the 2000 breadfruit images were used, namely 1400 image data, each of which used 350 image data. Figure 2 shows the training data processing results:

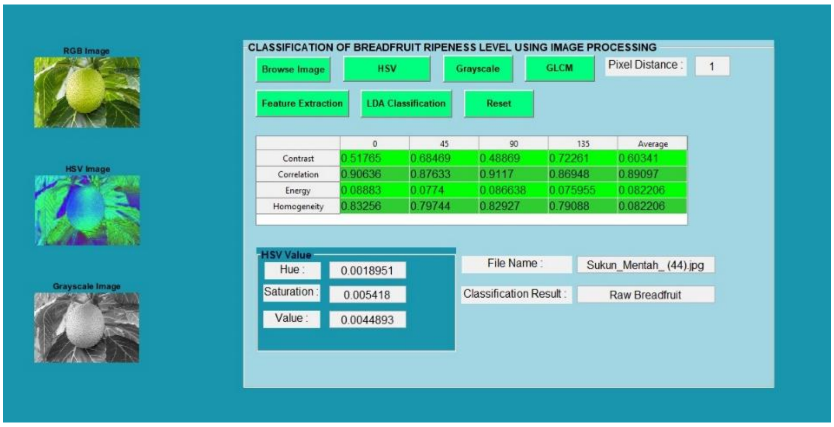

Figure 2. Processing of Training Data

The detailed outcomes of the training data testing are shown in Table 3 below:

Table 3. Results of Training Data Testing

Class	Correctly Classified by The System	Misclassified by The System	Number of Images
Rotten Breadfruit	345	5	350
Ripe Breadfruit	316	34	350
Unripe Breadfruit	326	24	350
Raw Breadfruit	269	81	350
	Total Image		1400
Correct Image		1.256	
Incorrect Image		144	

Table 3 shows several images of fruit that were classified correctly and incorrectly by the system. There were 345 images of rotten breadfruit that were classified correctly by the system, and 5 images that were classified incorrectly. There are 316 images of ripe breadfruit that are correctly classified by the system, and 34 images that are incorrectly classified by the system. There are 326 images of unripe breadfruit that are correctly classified by the system, and 24 images that are incorrectly classified by the system. The system correctly classified 269 images of raw breadfruit and incorrectly classified 81 images. Of the total training images, there were 1,400 images, of which the system correctly classified 1,256 images and incorrectly classified 144 images.

3.2 Testing of Test Data

Test data is data used to measure model performance or show how well the model can perform classification. The following is the division of test data for each level of breadfruit maturity.

Table 4. Breadfruit Test Data

Maturity Level of Breadfruit	Total
Raw Breadfruit	150 Image
Unripe Breadfruit	150 Image
Ripe Breadfruit	150 Image
Rotten Breadfruit	150 Image

In Table 4 above, the amount of data used for the testing process was 30% of 2000 breadfruit images, or 600 image data, each of which used 150 images.The detailed outcomes of the test data evaluation are shown in Table 5 below:

Table 5. Testing Results on Test Data

Class	Correctly Classified by The System	Misclassified by The System	Number of Images
Rotten Breadfruit	149	1	150
Ripe Breadfruit	104	46	150
Unripe Breadfruit	135	15	150
Raw Breadfruit	148	2	150
	Total Image		600
Correct Image		536	
Incorrect Image		64	

Table 5 shows details of the test data, indicating which data were classified correctly and incorrectly by the system. There were 149 images of rotten breadfruit that were classified correctly by the system, and 1 image that was classified incorrectly. There are 104 images of ripe breadfruit that are correctly classified by the system and 46 images that are incorrectly classified by the system. There are 135 images of unripe breadfruit that are correctly classified by the system, and 15 images that are incorrectly classified by the system. The system correctly classified 148 images of raw breadfruit and incorrectly classified 2 images of the total 600 test images; the system correctly classified 536 images and incorrectly classified 64 images.

3.3 Discussion

This section outlines the evaluation of the breadfruit classification model based on a confusion matrix. This section explains the evaluation of the breadfruit classification model based on the confusion matrix. The accuracy, precision, recall, and F1-score values are described in Table 6 below.

Table 6. Confusion Matrix Evaluation of Breadfruit Classification using the LDA Method

Data	Accuracy	Precision	Recall	F1-Score
Training Data	89,7143%	90,3147%	89,7143%	90,0264%
Testing Data	89,9333%	90,1732%	89,3333%	89,7513%

Table 6 above illustrates the evaluation comparison of the training and testing datasets. The training data has a higher precision value than the test data, which is 90.3147%, while the test data has a precision value of only 90.1732%. The F1-score for the training set is higher than the F1-score for the test set. In the training data, the F1-score is 90.0264%, while in the test data, it is only 89.7513%. The accuracy in the test data is also higher than in the training data, which is 89.9333%, while in the training data it is only 89.7143%. The recall on the training data is also higher than on the test data, at 89.7143%, while on the test data it is only 89.3333%. The confusion matrix results for the training data are shown in the image below :

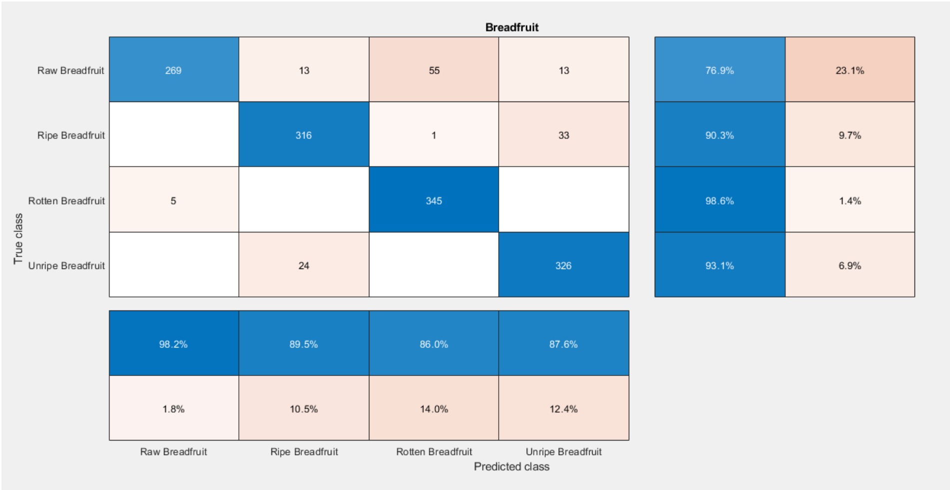

Figure 3. Confusion Matrix of the Training Dataset

Figure 3 presents the confusion matrix of the training data, which indicates the data correctly classified by the system with blue blocks compared to the true class or actual data and the predicted class or data classified by the system. There were 345 images of rotten breadfruit that were correctly classified by the system, and 5 images that were incorrectly classified by the system, in which the 5 images of rotten breadfruit were classified by the system as the raw class. There were 316 images of ripe breadfruit that were correctly classified by the system and 34 images that were incorrectly classified by the system, of which 1 image was classified as rotten breadfruit and 33 images were classified as unripe breadfruit. There were 326 images of unripe breadfruit that were correctly classified by the system and 24 images that were incorrectly classified by the system, of which 24 images of unripe breadfruit were classified by the system as ripe. There were 269 images of unripe breadfruit that were correctly classified by the system and 81 images that were incorrectly classified by the system, of which 55 were classified as rotten breadfruit, 13 images were classified as ripe breadfruit, and 13 images were classified as unripe breadfruit. The confusion matrix results for the testing data are shown in the image below :

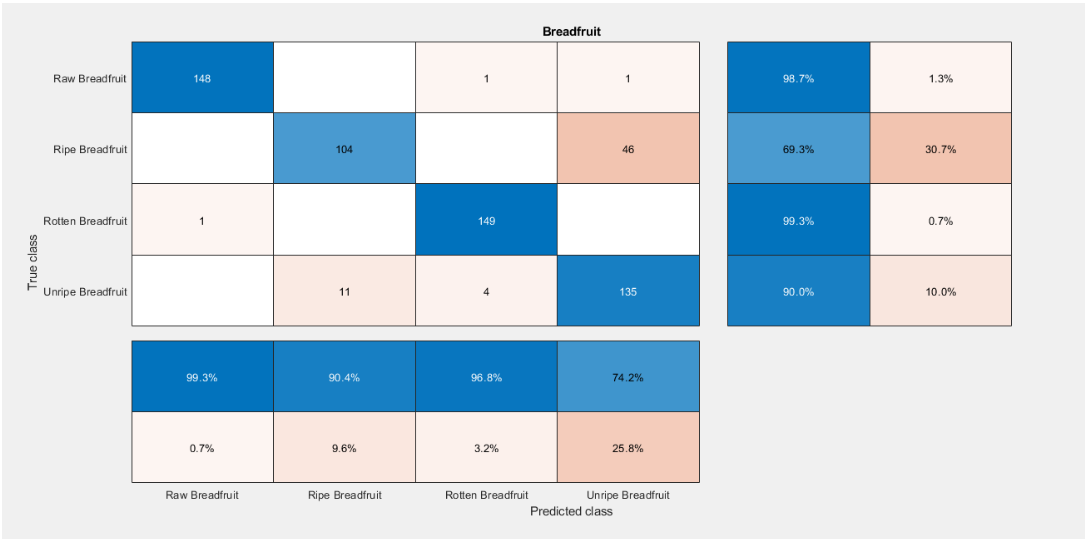

Figure 4. Confusion Matrix of The Testing Dataset

Figure 4 presents the confusion matrix of the testing data, which indicates the data classified correctly and incorrectly by the system. There were 149 images classified correctly by the system as rotten breadfruit and 1 image classified incorrectly by the system as raw breadfruit. There were 104 images of ripe breadfruit that were correctly classified by the system, and 46 images that were incorrectly classified by the system, of which 46 images were classified as unripe breadfruit. The system correctly classified 135 images of semi-ripe breadfruit and incorrectly classified 15 images, of which 4 images of semi-ripe breadfruit were classified by the system as rotten breadfruit and 11 images were classified as ripe breadfruit. There were 148 images of raw breadfruit that were correctly classified by the system and 2 images that were incorrectly classified by the system, of which 1 image was classified as rotten breadfruit, and 1 image was classified as unripe breadfruit.

Table 7 below shows a comparison of the results of several related studies. This table shows that the combination of HSV and GLCM in feature extraction can gradually improve classification accuracy.

Table 7. Comparison of Research Results with Related Research

Author	Algorithm	Research Object	Accuracy
Destriana [17]	LDA + HSV	Pineapple	83%
Laksono [14]	LDA + HSV	Mulberry	85.8%
Ulandari [37]	ANN + HSV + GLCM	Orange	86.88%
Fathoni [38]	KNN + GLCM	Grape Leaf	88.6%
Hamdan Pratama (This Research)	LDA + HSV + GLCM	Breadfruit	89,93%

From Table 7 above, we can see that research combining LDA and HSV can achieve an accuracy of 85.8%, but after adding GLCM, the accuracy can increase to 89.93%. This increase is significant at 3.05%.

4. CONCLUSION

According to the findings of the study that was carried out, the classification of breadfruit maturity levels based on colour and texture features using the LDA method has demonstrated good performance. This can be seen through the results of the Confusion Matrix test for training data, with results of 89.71% accuracy, 90.31% precision, 89.71% recall, and a 90.03% F1-score. For the test data, the accuracy obtained was 89.9333%, the precision of 90.1732%, the recall of 89.3333%, and the F1-Score of 89.7513%. The limitation of this study lies in the classification of the object. In this study, the LDA method can only classify seedless breadfruit. The contribution of this study lies in its classification performance, particularly in its improved accuracy, which is 3.05% higher than that of previous studies. The implication of this study is that it reinforces the theory that fruit ripeness is not only determined by color but also by changes in surface texture, meaning that the HSV and GLCM features were successfully applied in classifying fruit species using the LDA method. In future research, researchers can develop this study by trying to classify breadfruit with seeds and adding more features, both colour feature extraction and texture feature extraction.

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