Application of gaussian filter and extraction features for quality control of fruit raw materials in the puree industry

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Abstract. The purpose of research in using Android-based raw material quality control applications in fruit puree factories is to enhance the industry's precision, uniformity, and efficiency. This application is developed to implement digital image processing utilizing two distinct methods: Gaussian filters and feature extraction. The implemented application captures guava data using the camera of an Android phone and subsequently resizes the image to dimensions of 600x600 pixels. Subsequently, the image colors are recovered by employing a Gaussian filter that operates on normalized Red-Green-Blue values. A minimum of 120 photos of red guava fruit from the raw material of one of the puree companies were subjected to image processing procedures. The application solely focuses on the color and texture of the fruit's skin, ensuring that the sample remains undamaged while adhering to hygienic guidelines. The ripeness degree of guava fruit is determined by employing an image classification algorithm with the K-nearest neighbor method. The application validation using K-fold cross-validation achieved an accuracy of 90.0% and a precision of 90.27% when applied to color imagery. When feature extraction was used, the accuracy was 83.3%, with a precision of 83.4%. Color extraction provides a more precise method for identifying ripe guava. The utilization of guava fruit ripeness detection in the quality control of raw materials for the puree sector has been simplified and made more user-friendly through the development of an Android-based application. Officers are not obligated to possess specialized expertise regarding the quality of raw materials.

Keywords: red guava, fruit puree industry, image processing, gaussian filter, feature extraction.

1. Introduction

Indonesia is a nation renowned for its diverse range of tropical fruits, which provide the potential for exportation and the creation of numerous processed goods. According to data provided by the Central Statistics Agency, Indonesia experienced a 23.21% increase in fruit exports in June 2020. The value amounted to USD 430.4 million, corresponding to IDR 6.25 trillion (BPS, 2020). The Ministry of Industry's 2015-2025 long-term strategy focuses on the establishment of fruit processing industries that are closely linked to the production of raw materials.

One of the fruit processing industries that continues to grow in Indonesia is the fruit juice and puree beverage industry. Puree products are derived directly from whole fruit and processed into primary ingredients for the manufacturing of syrup and fruit juice beverages. Indonesia is a major importer of fruit puree due to its very low local production (Hermawan et al., 2019). Fruit puree is a highly durable product with a prolonged shelf life, capable of lasting for several months. Nevertheless, fruit puree may undergo a decline in vitamin C concentration, as well as alterations in flavor and color, while being stored (Bal et al., 2014).

One of the fruit varieties that are a source of vitamin C is red guava (Padang and Maliku, 2017). Red guava has a high vitamin C content, even higher than the vitamin C content of oranges and mangoes, known as the icon of vitamin C. The highest vitamin C content is obtained from well-ripened fruit (153.0196 and 149.4421 mg/100 g for outer meat and inner flesh) and the lowest (98.4370 and 86.3855 mg/100 g for outer flesh and inner flesh), respectively, raw.

Indonesia's guava production in 2020 was 396,268 tons, with the largest production in Central Java. Ekawati *et al.* (2019) noted a number of products that can be developed from guava, but red guava (*Psidium guajava* L.) is a perishable climacteric fruit. Parimin (2007) reported that post-harvest damage of red guava reached 30-40%.

In the era of Industry 4.0, the quality assessment of industrial raw materials has advanced to a new stage by using instrumentation, sensor recognition, and artificial intelligence. Raditya et al. (2012) utilized a TCS3200 color sensor as a detector to assess the maturity of the fruit by analyzing its color.

The program has the capability to automate the process of categorizing the level of fruit ripeness following the harvest of fruits.

Perdana et al. (2019) conducted research to identify the sort of food that underwent preprocessing, followed by a conversion of the color model from RGB to HSI. The next procedure is the extraction of color features with Color Moment, which will generate the mean, standard deviation, and skewness features of each image color channel. In addition, the features are derived using Morphological Shape Descriptors (MSD), resulting in the generation of features such as length, width, diameter, and aspect ratio. Once the characteristics of the food image are acquired, classification is performed using the Naive Bayes technique aided by the Log Sum Exp function for probability computation.

The statistical texture extraction method is a viable approach for determining the Ripeness categorization of red guava fruit. In his 2018 study, Adhim utilizes statistical techniques, specifically Mean, Variance, Skewness, Kurtosis, and Entropy, to identify the maturity of red guava based on fruit skin texture. The study also aims to assess the accuracy of the system after conducting tests. The study utilized photos of red guava fruit captured with a camera, which were subsequently resized to dimensions of 255 by 235 pixels and converted to the *.bmp file type. (Adhim, 2018).

The thermal imaging technique is a non-destructive technology employed to measure the temperature emitted by an object without physical touch. This type of research can be utilized to ascertain the level of ripeness in crystal guava fruit. The research examination utilized three distinct stages of fruit ripeness: green, yellowish-green, and greenish-yellow. The findings indicated a positive correlation between the level of ripeness of the crystal guava fruit and the corresponding increase in its temperature. The increase in temperature showed a substantial correlation with the decrease in fruit hardness (R2 = 0.997), free acid (R2 = 0.936), and starch (R2 = 0.903). Additionally, it showed a strong correlation with the increase in Brix (R2 = 0.866) and sucrose (R2 = 0.968). (Widodo et al., 2021).

In a study by Prahudaya et al. (2017), they investigated the texture and color of guava to classify its quality using the K-nearest neighbors (KNN) algorithm based on color and texture features. After conducting multiple tests with different values of K, the highest accuracy rates were observed at K=3, K =5, and K=7, with an accuracy rate of 91.25%.

This work utilized Gaussian filters and feature extraction, together with the KNN approach, to accurately determine the ripeness of red guava by analyzing the color and texture of the fruit's skin. This research application aims to facilitate the Puree business inefficiently and precisely evaluating the freshness of guava fruit without the need for prior peeling.

2. Methods

Color Feature Extraction Stage

During the color feature extraction stage, three components, specifically red, green, and blue, are utilized to represent each color. The color features are extracted with the assistance of a Gaussian filter to capture the most favorable color values. Figure 1 illustrates the process of extracting color features.

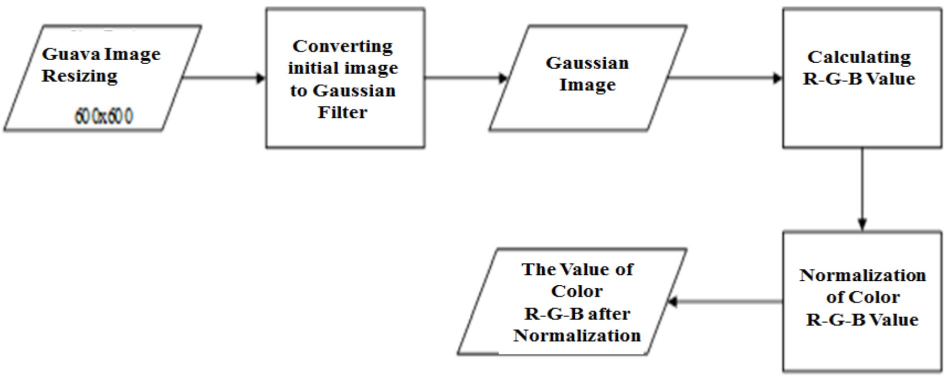

Figure 1 Color feature extraction.

Visible color refers to the range of light wavelengths that are reflected by objects and detected by the visual sense, which is subsequently interpreted by the brain as a certain color. Image processing involves various color models, including NTSC, YIQ, RGB, YCbCr, HSV, CMY, CMYK, and HSI. The RGB color model, comprising the primary colors red, green, and blue, is employed for display on monitors. The term "primary colors" is used to describe these three colors. The intensity of each tree color is measured on a scale of 0 to 255, with 255 being the maximum value (8-bit). Yellow is formed via the blending of red and green hues, resulting in an RGB value of 255 255 0 (Muntasa and Purnomo, 2010).

The RGB color model is based on a cube-shaped cartesian coordinate system. The range of values R, G, and B represent all color vectors in three-dimensional space R-G-B, as shown in Figure 2. The RGB color model is a combination of three color layers to produce one composite color. Retrieval of the information value of each color element is carried out by normalizing each color element determined by the following equation.

$$r = \frac{R}{255} \tag{1}$$

$$g = \frac{G}{255} \tag{2}$$

$$b = \frac{B}{255} \tag{3}$$

Description:

R = Unnormalized red values
G = Unnormalized green values
B = Unnormalized blue value
r = Normalized red value
g = Normalized green value
b = Normalized blue value

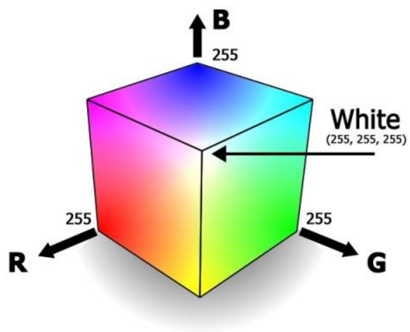

Figure 2 RGB color space model.

Gray Level Co-occurrence Matrix (GLCM) Texture Extraction Stage

The extraction process is one of the important characteristics used in identifying objects or image patterns, because the right image extraction method will be able to provide detailed information about the class of an image. The method that can be used for image texture extraction is the GLCM method. Co-occurrence matrix using the gray level matrix is to take an example of how a certain gray level occurs in relation to other gray levels. The gray level matrix is a matrix whose elements are the relative frequency of joint occurrences of the combination of gray levels between pairs of pixels with a certain spatial relationship. At the texture extraction stage, GLCM is used to produce texture values in the image. The GLCM texture extraction is shown in Figure 3.

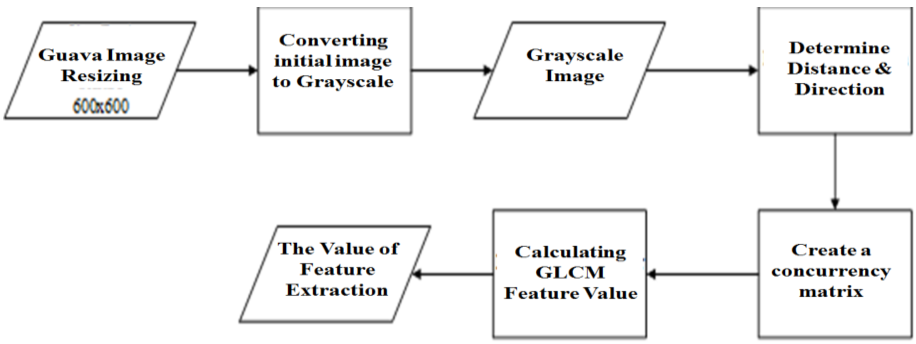

Figure 3 GLCM *texture extraction.*

For example, it is known that an image Q(i,j), and P is a matrix. The element P(i,j) states the number of times the point occurs in the image based on a certain position. Matrix P is a co-occurrence matrix defined by angle and distance d. Based on the P matrix, it can be calculated the values of texture characteristics such as contrast, correlation, entropy, energy, and homogeneity (Osadebey, 2006).

Here are some of the formulas used to extract texture features.

1. *Contrast*
   Contrast expresses the content of local variations in the image. The *higher the contrast value*, the higher the level of contrast.
   $$Contrast = \sum_{i,j} |i - j|^2 P(i,j) \quad (4)$$
2. *Correlation*
   Correlation expresses the size of the linear relationship of the *graylevel value of* the neighboring pixel.
   $$Correlation = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)P(i,j)}{\sigma_i \sigma_j} \quad (5)$$
3. *Entropy*
   Entropy expresses the degree of randomness of the pixels of an image. The higher the *entropy value*, the more random the texture is.
   $$Entropy = \sum_{i,j} P(i,j) \log P(i,j) \quad (6)$$
4. *Energy*
   Energy expresses the degree of uniformity of the pixels of an image. The higher the energy value, the more uniform the texture.
   $$Energy = \sum_{i,j} P(i,j)^2 \quad (7)$$
5. *Homogeneity*
   Homogeneity expresses the measure of proximity of each element of the *co-occurrence matrix.*
   $$Homogenity = \sum_{i,j} \frac{P(i,j)}{1+|i-j|} \quad (8)$$

Description:
P = GLCM matrix normalization
i = row index of matrix P
j = column index of matrix P

K-Nearest Neighbors

The *K-Nearest Neighbor* (KNN) algorithm is a classification method that groups new data based on the distance of the new data to several nearby data / neighbors (Santoso, 2007). Test samples are projected on multi-dimensional space, each dimension representing a feature of the data. The working principle of KNN is the process of finding the closest neighbor to the tested data sample. If the nearest neighbor falls into category A, then the sample can be called class A. The distance of the neighbors is usually calculated based on the Euclidean distance with the following formula:

$$d_i = \sqrt{\sum_{i=1}^{p} (x_{2i} - x_{1i})^2} \quad (9)$$

where:
at = Euclidean distance
x1 = Sample data
x2 = Test sample
i = Variable data
dist = distance
p = Data dimensions

At the study stage, this algorithm stores feature vectors in learning data. On the same feature classification is calculated for the data set. The distance of all vectors of the new learning data is calculated, and the closest number of k pieces is taken. A good k value for K-NN depends on the data, with a high k value reducing the effect of noise on classification.

The accuracy of the KNN algorithm is strongly influenced by the presence or absence of irrelevant features or the weight of these features is not equivalent to their relevance to the classification. Steps to calculate the K-Nearest Neighbors method:

1. Specifies the parameter k (number of closest neighbors).
2. Calculate the square of *the Euclidean distance of* the object against the given training data.
3. Then sort the objects into groups that have the *smallest* Euclidean distance
4. Collect category Y (Classification of nearest neighbors based on k value)

5. By using the nearest neighbor category, that is, the majority, the category of objects can be predicted.

Identification Phase
The identification stage involves classifying guava fruit images using the K-Nearest Neighbors approach. This approach involves utilizing KNN computations to determine the closeness value between the color and texture extraction data of the test image and the training data. Figure 4 illustrates the information in a diagrammatic form.

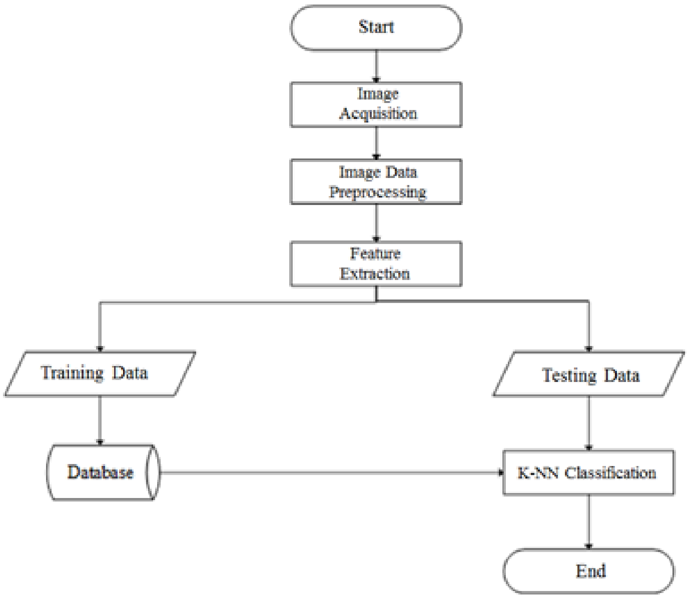

Figure 4 Stages of determining the ripeness level of guava fruit using KNN.

3. Results and Discussion

Puree *Production Process*
The utilized raw material consists of ripe red guava sourced from several places in Indonesia. The level of ripeness of the Red Guava fruit is crucial in determining the amount of Vitamin C present in the final puree. In the process of small and medium-scale fruit puree production, the officer determines the maturity level of the fruit raw materials using organoleptic evaluation. However, this method is subjective and can be influenced by weariness, potentially affecting the accuracy of the assessment results.

After being chosen, the raw materials undergo a washing and selection process. Some are promptly cut into pieces and pressed, while others are stored in a Cold Storage facility for future use. The outcome is compressed, strained, sweetened with sugar, and subsequently heated to the boiling point. The administration of sodium benzoate and citrate salts for wheezing is performed. Figure 5 displays the production flow chart for Puree.

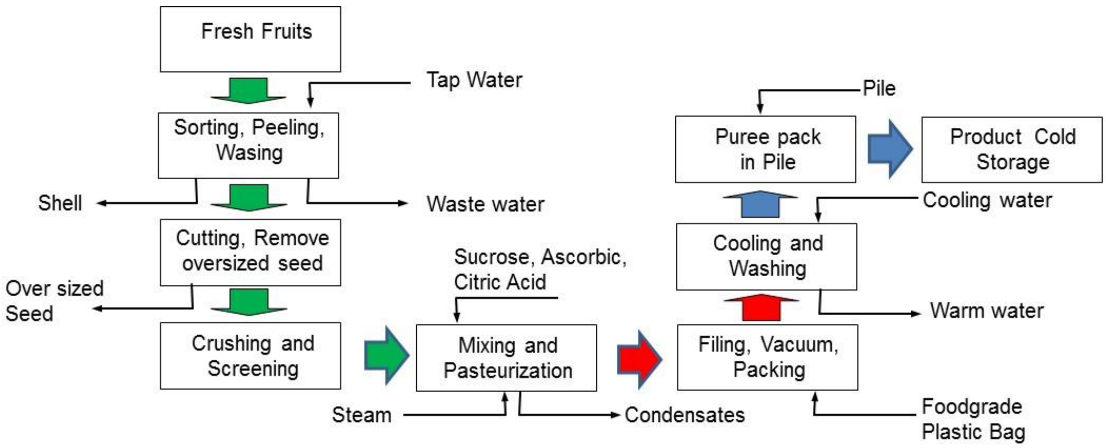

Figure 5 The process of making fruit juice at SME's *puree* fruit.

The presence of the red hue in red guava serves as a sign of its level of ripeness. According to Fitriana and Royani (2019), red guava has significant bioactive components, including ascorbic acid and other phenolic compounds such as apigenin, myricetin, and anthocyanins. Furthermore, carotenoids such as β-carotene and lycopene are present, exhibiting promising antioxidant properties. A study conducted by Sinaga et al. (2015) discovered a correlation between the presence of natural antioxidants in red guava and an increase in both blood hemoglobin levels and VO_2 max. In their study, Wahyuntari and Wahtini (2019) found that the ascorbic acid included in red guava fruit significantly enhances the absorption of iron, hence aiding in the restoration of hemoglobin.

Handling of the Maturity Quality of Maturity of Guava

In the activity of collecting guava image training data, the acquisition process is carried out using a mobile camera that has a pixel quality of 13MP. The samples collected were 120 guava fruit images consisting of 2 classes of guava maturity levels. There are 60 mature guava images and 60 immature guava images. Figure 6 Here are some examples of image samples obtained from the results of the image acquisition process carried out.

Image samples from the "Ripe" class

(a) *Ripe Image Sample*

Image samples from the "Unripe" class

(b) *Unripe Image Samples*

Figure 6 Guava sample image.

Preprocessing

The pre-processing stage is to perform feature extraction on the guava fruit image. The original image is inputted and *resized* to 600x600 pixels so that it is uniform. Furthermore, the image is extracted using color segmentation with the help of *gaussian filters*, and texture extraction with GLCM to obtain characteristic values from each extraction, the result is as Figure 7.

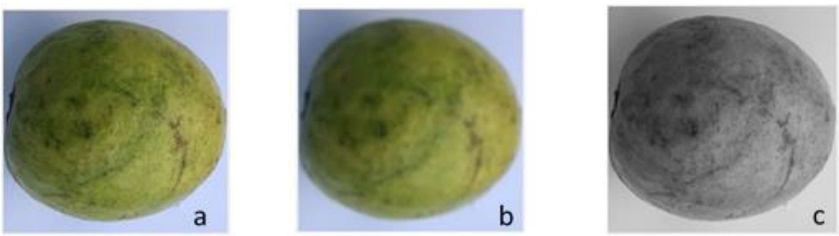

Figure 7 Preprocessing Guava fruit image (a= original image; b=Gaussian image; c= GLCM image).

Implementation Phase Using Android

The Identification page is the most important page of the application, because it serves to identify guava fruit images based on references from training data. The identification page is divided into two, namely identification based on color and identification based on texture. On this page, guava fruit images taken from both cameras and galleries will be extracted features to get the characteristics of each image in the form of color or texture values.

At the stage of the identification process based on the extraction of color features will go through the stage of resizing the image to 600x600 pixels and the Gaussian filtering process which will then be extracted color values through RGB normalization.

While at the stage of the identification process based on the extraction of texture features will go through the image resize stage to 600x600 pixels and then the texture will be extracted through the GLCM method. The appearance of the identification page can be seen in Figure 8.

Figure 8 The Guava identification page on the Android app.

The extraction results will indicate the level of ripeness using the K-nearest neighbors (KNN) approach. This will be done by calculating the K value that represents the nearest Euclidean distance. Based on the classification findings, inferences may be made regarding whether the fruit is ripe or not.

During the production process, this application undergoes ongoing changes based on the ideal findings obtained from each experiment conducted to test system performance. Accuracy refers to the system's ability to identify and evaluate the procedures and data being examined appropriately. The speed of identification is directly correlated with the duration required to determine the ripeness degree of guava fruit from the given image. The requirement for storage media is directly linked to the system's capacity to hold reference data.

Identifying the ripeness of guava fruit for quality control of industrial puree raw materials using an Android-based application is quite straightforward. Officers are not obligated to possess specialized expertise regarding the quality of raw materials. Their primary task is to capture photographs of fruit samples in order to obtain accurate findings for ripeness identification. The application has been effectively deployed and can enhance the efficiency of officers, thereby diminishing reliance on individual skills, minimizing bias, and boosting production.

Application System Validation

The accuracy elements are the sole determinants considered when measuring system performance. The precision of the system is affected by variables such as the brightness level during capturing, the influence of the backdrop, and the existence of blemishes on the guava fruit's skin. Validation trials are conducted to verify the effectiveness of the output generated by the program. This experiment seeks to assess the precision of the application by employing the Confusion Matrix for the calculation process. An investigation will be conducted to ascertain the accuracy of the red guava Ripeness identification software through the analysis of guava photos. The experiment employed the k-fold validation technique to determine the test data with the greatest validation value. This data was subsequently utilized as the test data in the guava Ripeness detection application. The results of the K Fold Validation technique are presented in Table 1.

Table 1 K fold experiment match validation of guava fruit ripeness test results

K-Fold	Amount of Data		Method Accuracy	
	Train Data	Test Data	Color	Texture
K = 1	120	30	73,3%	70,0%
K = 2	120	30	83,3%	76,6%
K = 3	120	30	86,6%	83,3%
K = 4	120	30	80,0%	76,6%
K = 5	120	30	83,3%	76,6%
Average			80,8%	77,9%

The guava ripeness identification program will use the test data from the 3rd iteration of the K-Fold experiment, as it exhibits superior accuracy in comparison to the previous iterations. During this validation experiment, two particular tests will be performed to evaluate the precision. These tests consist of data validation experiments that depend on fruit skin color features, as well as data validation experiments that depend on fruit skin texture parameters. This study aims to identify the parameters that are more precise in determining the ripeness of red guavas. The validation study results are presented in Table 2.

Table 2 Color and feature-based validation trial results

Experiment with K Values	Actual Conditions		System Prediction *Based on Color*		System Predictions *Based on Textures*	
	Number of Images	Condition of Ripeness	Ripe	Unripe	Ripe	Unripe
3	15	Ripe	13	2	12	3
	15	Unripe	2	13	2	13
5	15	Ripe	13	2	14	1
	15	Unripe	1	14	2	13
7	15	Ripe	13	2	12	3
	15	Unripe	0	15	3	12
9	15	Ripe	13	2	12	3
	15	Unripe	1	14	3	12

The following is a calculation of accuracy, precision, and recall in color-based identification for experiments with k = 3 values.

Accuracy $= \frac{\text{TP+TN}}{\text{TP+FP+TN+FN}}$ * 100% = $\frac{13+13}{13+2+13+2}$ * 100% = 86,7%

Precision:

1. Ripe = $\frac{\text{TP}}{\text{TP+FP}}$ * 100% = $\frac{13}{13+2}$ * 100% = 86,7%
2. Unripe = $\frac{\text{TP}}{\text{TP+FP}}$ * 100% = $\frac{13}{13+2}$ * 100% = 86,7%

Recall:

1. Ripe = $\frac{\text{TP}}{\text{TP+FN}}$ * 100% = $\frac{13}{13+2}$ * 100% = 86,7%
2. Unripe= $\frac{\text{TP}}{\text{TP+FN}}$ * 100% = $\frac{13}{13+2}$ * 100% = 86,7%

The following is a calculation of accuracy, precision, and recall in texture-based identification for experiments with k = 3 values.

Accuracy = $\frac{\text{TP+TN}}{\text{TP+FP+TN+FN}}$ * 100% = $\frac{12+13}{12+3+13+2}$ * 100% = 83,3%

Precision:

1. Ripe = $\frac{\text{TP}}{\text{TP+FP}}$ * 100% = $\frac{12}{12+2}$ * 100% = 85,7%
2. Unripe = $\frac{\text{TP}}{\text{TP+FP}}$ * 100% = $\frac{13}{13+3}$ * 100% = 81,3%

Recall:

1. Ripe = $\frac{\text{TP}}{\text{TP+FN}}$ * 100% = $\frac{12}{12+3}$ * 100% = 80%
2. Unripe = $\frac{\text{TP}}{\text{TP+FN}}$ * 100% = $\frac{13}{13+2}$ * 100% = 86,7%

From the results of the KNN calculation experiment using k = 3, it can be seen that the results of accuracy, recall, and precision can be concluded that identification based on color is slightly superior to identification based on texture.

4. Conclusion and Recommendations

The Ripeness of red guava fruit can be determined by utilizing image processing techniques such as applying Gaussian filters and performing feature extraction. This involves analyzing the color and texture of the fruit skin using the K-Nearest Neighbors approach. This program, developed for mobile or Android devices, efficiently assists in determining the ripeness of red guava. It substantially simplifies the process of inspecting the quality of raw materials in the puree sector. The application can accurately determine the ripeness of the red guava fruit solely by analyzing the color or texture of its skin. Evaluating the level of ripeness of red guava fruit using a specific method can minimize prejudice, enhance precision, and improve efficiency in the puree manufacturing sector. According to the validation findings obtained using the confusion matrix validation approach with different K values, the color-based identification method achieves an overall accuracy of 90%, whilst the texture-based identification method achieves an overall accuracy of 83.3%. Therefore, it can be inferred that utilizing fruit skin color for identification is more appropriate for determining the ripeness of red guava fruit. The Ripeness assessment of red guava utilizing image processing in quality control applications can be affected by various aspects, such as the intensity of light during image capture, the impact of the background, and the presence of flaws on the guava fruit's surface. Imperfectly captured images can lead to biased decision making. Additional research is required to examine the components involved in the capture of picture data.

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