Statistical Features Extraction of Discrete Curvelet Transform for Surface Quality Evaluation of Mangosteen

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***Abstract*—Fast discrete curvelet transform can be used in differentiating between good and defect of mangosteen surfaces. However, the transformed surface image need to be extracted by features extraction methods to be used by Linear Discriminant Analysis (LDA) for detecting whether the surface condition is a defect or not. In this paper, we test commonly used extraction methods consist of mean, energy, entropy, standard deviation, variance, sum, correlation, contrast, and homogeneity to see which are suitable to be used in detecting mangosteen surface defects. Furthermore, we use K-Fold Cross Validation method to check the accuracy and 120 images as test materials. Finally, the highest accuracy is shown standard deviation by 91,7% and followed by the variance by 88,4%.**

***Index Terms*—Features Extraction, Linear Discriminant Analysis, Fast Discrete Curvelet Transform**

I. Introduction

Mangosteen became the largest contributor of foreign exchange in Indonesia. Central Bureau of Statistics (BPS) in Fruit and Vegetable Plant Statistics recorded mangosteen exports in 2015 reached US $ 17.2 million. The main export destination countries are Thailand, Malaysia, and Hong Kong [1]. As an export commodity, its quality must be maintained so that the fruit can be accepted by consumers in both domestic and international markets. To maintain the production quality, the mangosteen production company must choose non-defect mangosteen after harvesting. Then, the company will pack and sell the good quality ones, while the defective mangosteens will be processed further into other useful products. [2]

Defect in fruit surface commonly caused by bruises, scratches or other mechanical damage. Fast discrete curvelet transform(FDCT) that can change an image into a multi-scale object and combined by machine learning for example Linear Discriminant Analysis (LDA) are proven classifying fruits. [3], [4] In fact, FDCT results need to be extracted into features so that LDA can consume it and do the detecting job. There are many statistical features extractions method in image processing that can be used include energy, variance, standard deviation, contrast, entropy, homogeneity, mean, sum, and correlation [5].

In [6], [7], or [8], statistical features extractions are used to extract every features then analyze it in their next research step. In this paper, we want to use these methods to classify mangosteen based on the existence of a defect in the surface focused that approach. The problem is which features extraction methods should we use in order to keep the effectivity of FDCT and LDA. So, we test every extraction methods that mentioned before and find the best methods among others. The next sections are organized as follows: Section 2 explains our related work. Section 3 discusses the experimental study. Section 4 concludes this written paper and explain our future work.

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II. Related Work

Detection of this mangosteen surface defect involves a procedure that can be summarized in Figure 1.

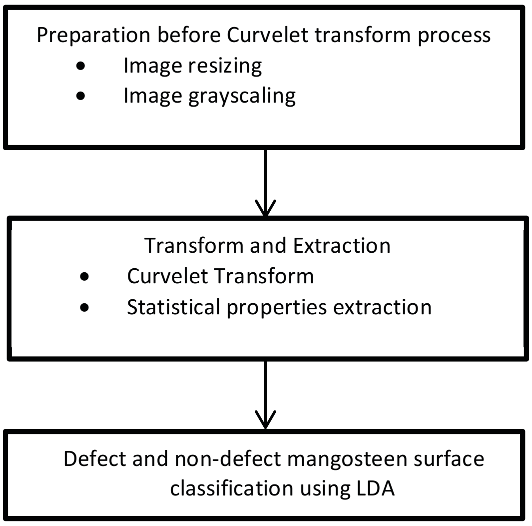


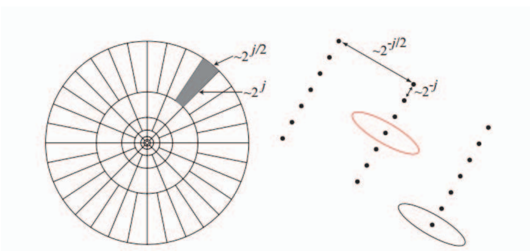
Fig. 1. The classification process

A. Image Pre-processing

In this step, we prepare the image to be ready before being processed using curvelet transformation method. Before anything else, the color images are resized to 512x512 dimensions. Then, the images are converted to grayscale level. The purpose of resizing and grayscaling the input images are to simplify and reduce processing time.

B. Discrete Curvelet Transform

Curvelet transformation is a transformation of multiscale geometric with a given frame element based on scale, orientation parameters and location. It is also observed that the curvelet transformation encompasses the entire spectrum of frequencies so that there is no loss of information. Curvelet Transforms can provide rare signal representations that have edges along the ordinary curve. The early curvelet construction was then redesigned and reintroduced as Fast Digital Curvelet Transform (FDCT). [9]



(a) (b)

Fig. 2. Curvelet transform in frequency domain (a) and Curvelet transform in the spatial domain (b) [9]

To do the curvelet transform, it takes first 2D Fast Fourier Transform (FFT). Then it devides the field of Fourier 2D frequencies into pieces (like the gray region in figure 2). [3]

In this step, grayscale images transformed using FDCT to be Curvelet object that can be seen in Figure 3. Maximum level of a curvelet object obtained by [9],

$$Num\ of\ scales = \log_2(n) - 3 \tag{1}$$

where n is dimension value of the array. We used 512x512 image dimensions so the maximum scale of curvelet would be around 6. All scales will not be used in this research. We tested all features extraction in each scale and had concluded that for this case, the best scale to be used is scale 2.

(a) (b) (c)

Fig. 3. Colorful mangosteen (a), Grayscale level mangosteen (b), and Curvelet transform result of mangosteen

C. Statistical Properties Extraction

In this process, the chosen features are extracted by following methods:

1) Mean

Mean is the average or average value of an array. Mean from a feature is obtained by summarize every value in it and divide the sum value by feature's dimension value, the mean for *M x N* dimensien is defined in the following equation:

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} A_{ij} \tag{2}$$

Figure 4 shows that the distribution of 60 defects marked by "o" and 60 non-defects marked by "x" data coincide. Furthermore, non-defect images tend to have higher values compared to the defect ones. The condition happens because defect spot on surface have lower value than non-defected one.

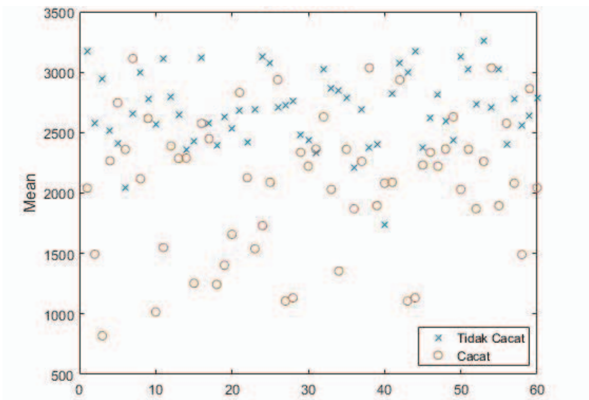


Fig. 4. Mean features extraction

2) Energy

Energy is the level of pixels uniformity of an image. The higher the energy value, the more uniform texture. The equation for calculating energy can be seen in the following equation:

$$Energy = \sum_{i,j} P(i,j)^2 \tag{3}$$

Figure 5 shows that Energy plot has similarity with Mean. The defects and non-defects features coincide and the non-defect ones tend to have higher values.

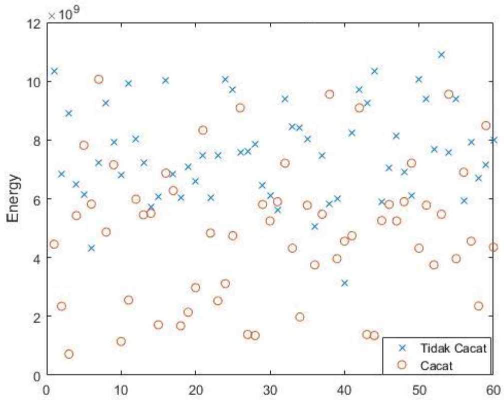


Fig. 5. Energy features extraction

3) Entropy

Entropy of a grayscale image is a statistical measurement of the image pixels randomness that can be exploited to characterize the input texture image [10]. Entropy is defined as follows:

$$E = -\sum(p * \log_2 p) \tag{4}$$

where p contains the normalized histogram counts. Figure 6 shows that Entropy plot contrary to Mean or Energy plot. The defects and non-defects features are coincided and the non-defect ones tend to have l

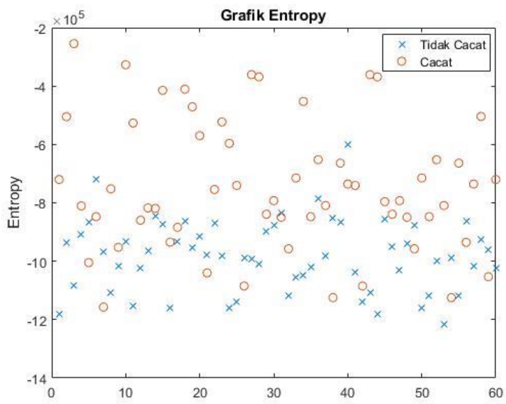


Fig. 6. Entropy features extraction

4) Standard Deviation

For a random variable vector A consisting of scalar observations N, the standard deviation is defined as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}|A_{i,j}-u_{ij}|^2}{M*N}} \tag{5}$$

Figure 7 shows a clear difference between the defects and non-defects features. The defect features average to have higher values.

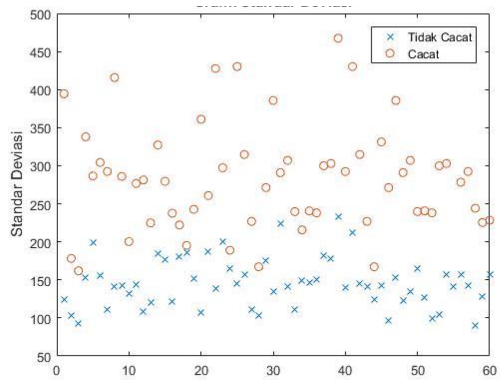


Fig. 7. Standard deviation features extraction

5) Variance

Variance is the square of the standard deviation. Variance gives a measure of signal deviation from its mean value. For real or imaginary inputs, u, by the size of M x N, the variances are given by the following equation:

$$\sigma^2 = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}|A_{i,j}-u_{ij}|^2}{M*N} \tag{6}$$

Figure 8 shows a clear difference between the defects and non-defects features. The defect features average to have higher values.

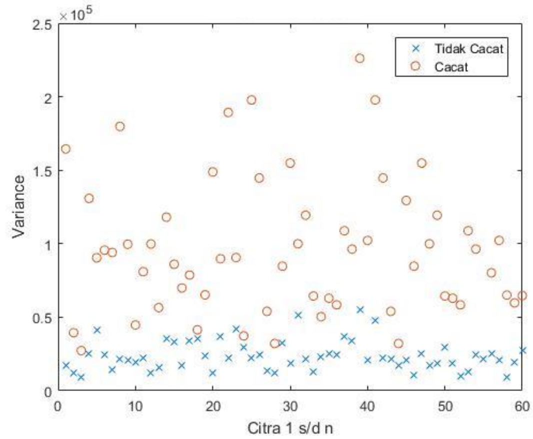


Fig. 8. Variance features extraction

6) Sum

The Sum is the total addition of array elements. The equation for sum count can be seen in the following equation:

$$Sum = \sum_{i=1}^{M}\sum_{j=1}^{N} A_{ij} \tag{7}$$

Figure 9 shows a clear difference between the defects and non-defects features. The non-defect features average to have higher values.

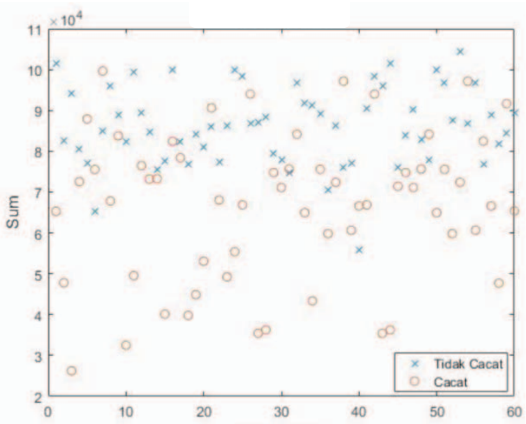


Fig. 9. Sum features extraction

7) Correlation

Correlation represents the size of the linear relationship between the gray level of neighboring pixel level. The equation for calculating energy can be seen in the following equation:

$$Correlation = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)P(i,j)}{\sigma_i \sigma_i} \tag{8}$$

Figure 10 shows that between the defects and non-defect features have differences. If we zoom it, every feature has difference value but still they coincide.

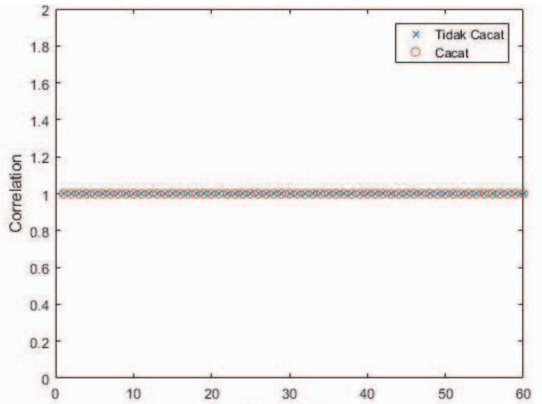


Fig. 10. Correlation features extraction

8) Contrast

Contrast represents the local variation content in the image. The higher the contrast the higher the contrast. The equation for calculating contrast can be seen in the following equation:

$$Contrast = \sum_{i,j} |i-j|^2 P(i,j) \tag{9}$$

Figure 11 shows defects and non-defects features coincide. Furthermore, non-defect ones tend to have higher values.

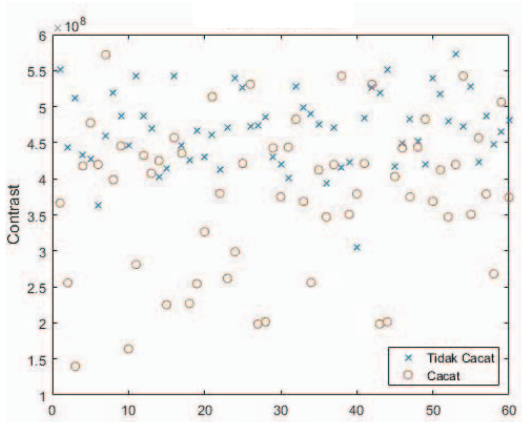


Fig. 11. Contrast features extraction

9) Homogeneity

Homogeneity expresses the size of the proximity of each element of the co-occurrence matrix. It returns a value that measures the proximity distribution of elements in GLCM (Gray-level Co-occurrence Matrix) to the GLCM diagonal. The equation for calculating homogeneity can be seen in the following equation:

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{10}$$

Figure 12 shows defects and non-defects features are coincided. Furthermore, non-defect ones tend to have higher values.

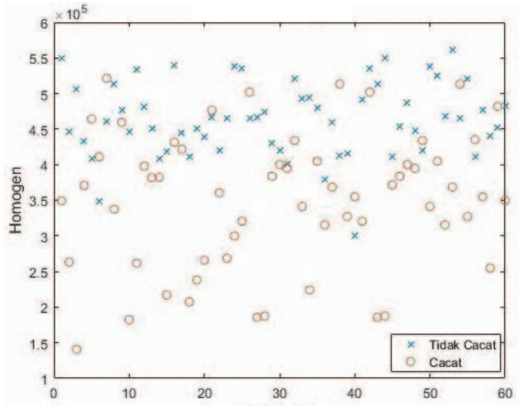


Fig. 12. Contrast features extraction

D. Linear Discriminant Analysis

Linear discriminant analysis (LDA) is a famous scheme for feature extraction and dimensional reduction. Discriminant analysis is a technique of statistical dependency analysis which is useful to classify several groups of objects. [11] Classification is divided the data into two groups, namely defect and non-defect. This LDA classification method takes nine inputs, which is the value of feature extraction in the previous step. This classification process uses nine inputs that are the result of characteristic extraction values, where the input values used are mean, energy, entropy, standard deviation, variance, sum, correlation, contrast, and homogeneity.

During the training phase, the feature extraction values are processed to produce training data that produces the supporting vector on each image, the stored vector collection is stored and the LDA classification model is obtained which can classify the damaged or undamaged images. At the testing stage, the image is processed the same as the training phase. What differentiates from the training phase is in the access test section of the LDA classification model derived from the training results compared to the vector supporting the tested images.

In this classification is used K-Fold Cross Validation to strengthen the research results accuracy, shown in Figure 13. [12]

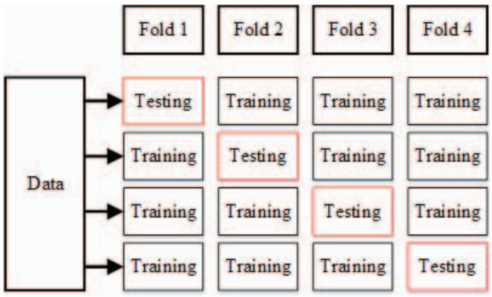


Fig. 13. K-Fold Cross Validation

A total of 120 test images were divided into four validation groups, each group containing 30 test images.

III. Result And Discussions

In this study, as many as 120 images consisting of damaged and undamaged are used for training and each group contains 30 images used for testing process. All images in the database are retrieved using the similar data set of acquisitions. Table I is the results of detection of the classification of mangosteen damage by using feature extraction.

TABLE I. RESULT OF MANGOSTEEN DEFECT DETECTION

Feature Extraction	**Group of classification**				**Average**
	Fold 1	*Fold 2*	*Fold 3*	*Fold 4*	
Mean	80	80	76.7	83.3	80%
Energy	73.3	76.7	70	90	77.5%
Entropy	76.7	76.7	73.3	83.3	77.5%
Standard Dev.	90	90	90	96.7	91.7%
Variance	86.7	86.7	90	90	88.4%
Sum	80	80	76.7	83.3	80%
Correlation	50	50	50	50	50%
Contrast	73.3	73.3	63.3	76.7	71%
Homogeneity	76.7	80	80	86.7	80.8%

IV. Conclusion

Based on this research, it can be concluded that curvelet transformation, its feature extractions and LDA can be used to detect defects in mangosteen fruit surface. From nine feature extraction methods, which have the highest accuracy value are standard deviation with an accuracy of 91.7% and variance with an accuracy value of 88.4%. In Future, we will try other feature extractions that may show better accuracy such as skewness or kurtosis. And also, To improve accuracy on detecting defect, we will combine those three or four feature extraction methods as input in LDA process.

V. Acknowledgment

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