Accredited Ranking SINTA 2
Decree of the Director General of Higher Education, Research, and Technology, No. 158/E/KPT/2021
Validity period from Volume 5 Number 2 of 2021 to Volume 10 Number 1 of 2026

Published online on: **http://jurnal.iaii.or.id**

JURNAL RESTI
(Rekayasa Sistem dan Teknologi Informasi)
Vol. 6 No. 5 (2022) 768 - 775 ISSN Media Electronic: 2580-0760

Texture Feature Extraction in Grape Image Classification Using K-Nearest Neighbor

Pulung Nurtantio Andono[1], Siti Hadiati Nugraini[2]
[1,2]Program Studi Magister Teknik Informatika, Fakultas Ilmu Komputer, Universitas Dian Nuswantoro Semarang
[1]pulung@dsn.dinus.ac.id, [2]shnugraini@dsn.dinus.ac.id

Abstract

Indonesian Grapes are a vine. This fruit is often found in markets, shops, roadside. Along with the development of computer technology today, computers can solve problems by classifying objects and objects. How to apply GLCM and K-NN methods for classification of grapes. The purpose of this study is to apply the GLCM and K-NN methods in the classification of grapes. The dataset used from kaggle.com sources, the data tested are 3 types of grapes, the number of images is 2624. The fruit that will be used for data collection and classification process is limited to three types of grapes, namely grape blue, grape pink and grape white. How to apply GLCM and K-NN methods for classification of grapes. The feature extraction of GLCM used in this study is the feature contrast, energy, correlation, and homogeneity. From testing the test data, the highest accuracy value is 99.5441% with k = 2 at level 8, while the lowest accuracy value is 24.924% at each k level 2. The GLCM level value is very influential on the accuracy results, namely the higher the GLCM level value, the higher the GLCM value. accuracy is getting better.

Keywords: *KNN, GLCM, grape, classification*

1. Introduction

Vineyards is one of high bervitamin fruit that was one of export commodity in indonesia , especially in the pandemic. This is in line with the increase in income in agriculture where the government has urged the domestic become a key player the fruit market within the country and overseas [1]. In the process of export, fruit at the beginning of the established sorting manually. Sorting out in the field before harvest produce in and then transported to collector. clocked in to a factory. The process of sortir early in the field, sometimes take a long time so that it needs a solution [2]–[5]. One of the solutions is the processing technique by using visual imagery of the captured using a camera [3], [4], [6]–[8].

The problem in the process of sorting the grapes and the usefulness aspect of image processing techniques that feel suitable to be applied, it is necessary to choose an algorithm. Some algorithm classifications, image especially classifications not disallow module loading has been done by some researchers, machine learning algorithm for example K-Nearest Neighbor (KNN), decision, tree random, forest support vector (machine svm), clustering and k-means. linear regression. The process of proximity between is the easiest way pixel image which may be done by implement statistical methods in algorithms machine learning [9]–[11], Especially in K-Nearest Neighbor (KNN) [12]–[14]. Image classification is the stage where the process of grouping image types based on their class from training data image samples that have known texture extraction results as in KNN. Algorithms used for classifying K-NN / image data based on data ready the image of an algorithm and form a reference for trainer K-NN class of image data to determine the value K. K itself is based the number of neighbors class closest in determination of the types of classes in test data image. Data image training and data in the form of test results of GLCM. After determining the value of k, then perform a distance calculation to determine the proximity of the distance from the training data image sample and the test data image. Calculation of proximity can use Euclidean Distance as the default calculation on the K-NN algorithm. The results of these calculations are then used to group the test data images against the specified k value with the number of closest class neighbors based on the training data images. To improve accuracy in K-NN, use feature extraction such as feature extraction and feature extraction. In this research, feature extraction is Gray Level Co-Occurrence Matrix

Accepted: 13-06-2022 | Received in revised: 26-09-2022 | Published: 31-10-2022

(GLCM). is a technique used to obtain a 2nd-order statistical value by calculating the probability of a close relationship between two pixels at a certain distance (d) and angle (θ). The one conducted on a calculation GLCM use ko-okurensi matrix. GLCM have process who almost similar to knn so as to fit it when combined [10], [15].

In Indriani's research, et. al [9], have done the process at maturity of a fruit tomatoes use knn classifications. In this research KNN implemented within the value of K=1,3,5,7,9 and 11. High accuracy 100 % on a coin. = 3, While accuracy the lowest in K = 3 and K = 9 namely 88 %. Accuracy best resulting from the addition of features the extraction of glcm and hue saturation value (HSV).

Another study conducted by Partiningsih et al. [16] used KNN with Linear Binary Pattern (LBP) extraction features and image contrast enhancement. The dataset used is 360 images, with a distribution of 300 training images and 60 testing images. The best accuracy produced is 96.67%. In the research were also carried out the comparison between processing LBP alone and the improvement LBP contrast turned up. Proved that the increase in contrast to improve accuracy.On cellsize 128, the highest 96,67. percent accuracyOn celsize 32 and 64 tertingi accuracy in the to percent and percent 91,67 95 lbp implementation is the cellsize 32,64 128 and yields only accuracy highest 95 % although accuracy is lowest in be 75 percent. Research conducted by Irawan et. al. [17], In the process of content-based image retrieval of (CBIR) using KNN, features the extraction of GLCM and a color histogram in the classification of kind of medicine. Herbs a drug used is the part the bulbs of the image of ginger, galingale, saffron, and black meeting curcuma. The data used as training data are 250 images and 25 images are used as testing data and divided into 3 tests. The result of this research system can recognize the image of the drug herbs appropriate to its kind with accuracy highest obtained 72 %.

I In this paper, experiments have been carried out in classifying grapes using the GLCM and K-NN methods which are divided into several stages, namely preprocessing which converts the RGB image into a gray image, then feature extraction with the GLCM method is carried out to obtain the input value to be classified. using the KNN algorithm. In classifying the types of grapes using 2624 datasets consisting of 1966 training data images and 658 test data images consisting of 3 types of grapes where the pixel resolution has been equated.

Research Methods

2.1. Grape

The fruit of a grape is a plant whose fruit are climbing [1].

(a) Blue Grape

(b) Pink Grape

(c) White Grape

Figure 1. Types of Grapes used in the study

The fruit is often be found in the market, the store, the roadside.Some kind of wine used in research this is a kind of wine, blue red wine and white wine as at table 1.Wine blue has a dark blue leather and has an oval shape, while pink wine colored pink to reddish and have a spherical form somewhat oblong, and white wine having a rind and whitish green have a spherical form.

2.2. Digital image

In general, digital images are the result of processing from a computer in the form of picture or images that have values or pixels obtained mathematically [1], [13], [18], [19] so as to produce a two-dimensional image or image f(x,y).), where the image f(x,y) is the light intensity with the value of x and the value of y which is a point of brilliance level. The digital image produces a matrix whose column and row indexes at each point represent the gray level.

2.3. Pre-processing

Previously, a picture or image had to go through a cropping process first, then the image was divided into two, namely training data and test data. The next step converts all images to grayscale. The training data in this study were 1966 images and testing data were 658 images.

2.4. Gray Level Co-occurrence Matrix (GLCM)

Gray Level Co-occurrence Matrix (GLCM) is one of the methods of feature extraction on textures [10], [20]–[25] and is included in second-order statistics as a technique for obtaining values by calculating the probability of the neighboring relationship or proximity of two pieces. pixels at a predetermined distance (d) and angle (θ). Angle Direction in GLCM The results that can be obtained from the calculation of the GLCM method are, among others [24], [26]:

Contrast:

Is a calculation that deals of the amount of diversity in intensity grayscale image [9].

DOI: https://doi.org/10.29207/resti.v6i5.4137

$$\text{Con} = \sum_x \sum_y (x-y)^2 \ p(x,y) \qquad (1)$$

Correlation:

Provides clues to the presence of a linear structure in the image by showing a measure of the linear dependence of the degree of gray in the image image.

$$\text{Cor} = \sum_x \sum_y \frac{(x-\mu x)(y-\mu y)\ p(x,y)}{\sigma x\ \sigma y} \qquad (2)$$

Energy:

Determine the intensity of keabuan with the size of the concentration of certain couples at matrix.

$$\text{Eng} = \sum_x \sum_y p(x,y)^2 \qquad (3)$$

Homogeneity:

The number of gray levels of image pixels will be higher if they have the same value. This also applies to the inverse value of GLCM.

$$\text{Hom} = \sum_x \sum_y \frac{p(x,y)}{1+|x-y|} \qquad (4)$$

Explanation: x= Value line in a matrix kookurensi, y=Value columns in a matrix kookurensi

p (x,y)= The value of lines (x) and columns (y) on kookurensi matrix

μx = average of line value (x) = $\sum_x \sum_y xp(x,y)$

μy = average of column value (y) = $\sum_y \sum_y yp(x,y)$

σx = Variance matrik (x) = $\sqrt{\sum_x \sum_y (x-\mu x)^2\ p(x,y)}$

σy = Variance matrik (y) = $\sqrt{\sum_x \sum_y (y-\mu y)^2\ p(x,y)}$

The results of the data will be used as data from algorithms classifications for finding class of an object on image.

2.5. K-Nearest Neighbor (KNN)

K-Nearest Neighbor (KNN) algorithms or methods is often used in data having a label in classifications and hold a identification based on the nearest distance [27], [28]. Algorithm k-nearest neighbor in processing digital image can be used as reckoning the distances towards an object or image to perform the process of identification or classifications. The purpose of the KNN method for image processing is to be able to identify new objects based on training data and test data with the working principle of determining the closest distance from data that has been evaluated with training data [11], [29]–[31]. In determining the shortest distance based on an object conducted research process to determine knn can be calculated based on using Euclidean Distance. The following is conducted at calculation KNN stages:

1. Determine the value of K to n based on the number of neighbors.
2. Counting the square of distance euceldian on an object that is on the training.
3. Rank calculations of the outcome of the number 2 respectively starts from the highest value to the lowest value.
4. Collecting based on the class tested in the nearest neighbor classification process at the nth K value.
5. After doing the classification with K-nearest which is declared as a class on the object is the one that often appears or the majority.

By using the K-Nearest Neighbor method in calculating distances and classifying it can be implemented easily, so you only need to identify a function for calculating the distance between one object and all other objects as the closest distance calculation. [20], [32], [33]. However, the K-Nearest Neighbor algorithm has a drawback, namely it is necessary to determine the k parameter (number of nearest neighbors) and if there is one variable or several variables missing between instances, the calculated distance from one object to another is undefined.

2.6. Data collection

When conducting this research, the method used by researchers in collecting primary and secondary data is to simplify and expedite the research process. The following are the methods used in data collection.

1. Primary Data

Primary data is a result of research so that it obtains data directly which can be done using certain techniques in data collection. The primary data source used in this research was obtained from the results of taking pictures using a smartphone device against objects in the form of images of grapes.

2. Secondary Data

Secondary data is data obtained based on documented research results and also data from other parties or sources. Secondary data sources used to conduct this research are used as a source of support and reference from primary data in the research process. The secondary data contained in this study was obtained by means of documentary research, namely by writing and searching for data related to problems when conducting research through articles, internet, books, journals, literature studies, discussion forum notes related to research.

2.7. Proposed Method

This study uses a data set of 2624 image samples, consisting of 1966 training data samples and 658 test data samples using images of grapes of Semarang and Malang types. The steps used for grape classification include preprocessing, GLCM feature extraction, and

DOI: https://doi.org/10.29207/resti.v6i5.4137

K-NN classification. Figure 2 is the stage of the classification process that has been carried out.

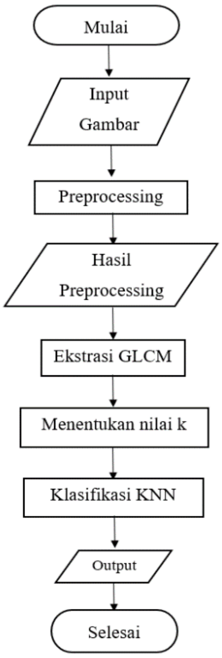


Figure 2. Image Classification Stages

2.8. Result test method

Accuracy is the final stage in a study that determines how much percent the accuracy of the research program is. The calculation of accuracy in this study uses a confusion matrix as a determinant of the final result.

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \times 100\% \qquad (6)$$

Explanation: TP=Amount *True Positives*, TN= Amount *True Negatives*, FN=Amount *False Positives*, FP= Amount *False Negatives*

3. Results and Discussion

The dataset image has been cropped first as needed before entering the classification process. The training and test images are as illustrated in Table 1.

Table 1. Research dataset

No	Jenis	Visual Citra	Data latih	Data Uji
1.	Blue Grape		984	328
2.	Pink Grape		492	164
3.	White Grape		490	166
Total			1966	658

3.1. Converting RGB to Grayscale

The most famous color model is Red Green Blue (RGB). As the name suggests, this model represents color using individual values for red, green, and blue. The RGB model is used in almost all digital displays around the world. The process of converting a truecolor RGB image to a grayscale image uses the rgb2gray function to convert the pixels of an RGB image to grayscale (0 to 7 scale).

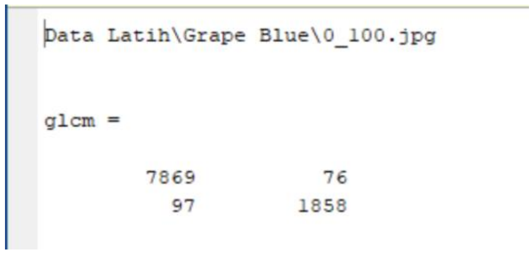
```
Convert RGB to grayscale
  citra=rgb2gray(imread(filename));
```

3.2. Recognition Analysis of GLCM Feature

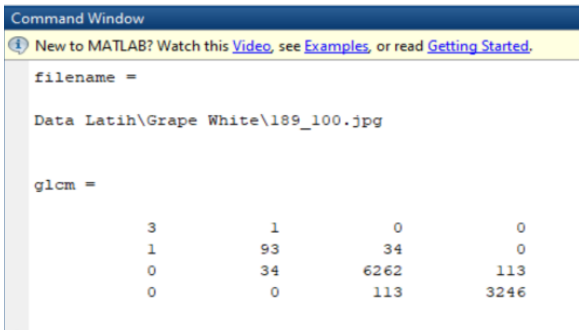
GLCM computes the statistics specified in the properties of the glcm gray level co-occurrence matrix. graycoprops normalizes the GLCM matrix so that the number of elements is equal to 1. Each element (r, c) in normalized GLCM is the joint probability of the occurrence of a pixel pair with a specified spatial relationship having a gray level value of r and c in the image. graycoprops uses normalized GLCM to compute properties.

```
Calculation of GLCM
glcm=graycomatrix(imgw,'NumLevels',2,'offset',[0 1])
glcm=graycomatrix(imgw,'NumLevels',4,'offset',[0 1])
glcm=graycomatrix(imgw,'NumLevels',6,'offset',[0 1])
glcm=graycomatrix(imgw,'NumLevels',8,'offset',[0 1])
```

The GLCM matrix with the number of levels equal to 2 and given the parameters d=1 and θ=0°, is shown in Figure 3. Figure 3 is the value of the GLCM feature matrix using training data at levels 2, 4, 6, and 8.

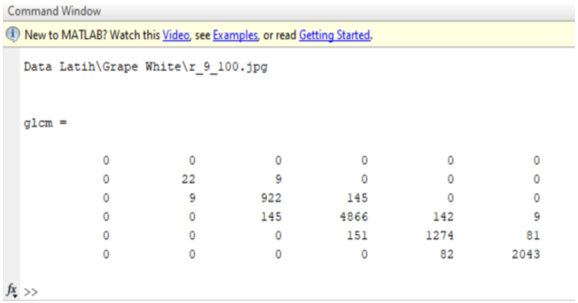


a. level 2

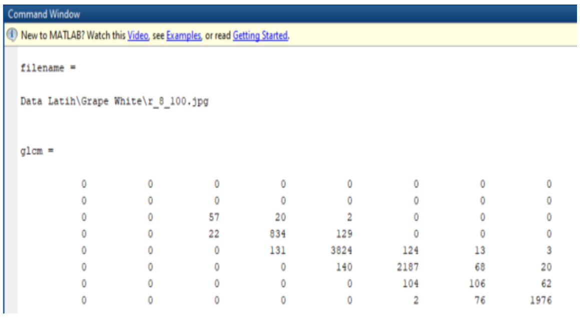


b. level 4

DOI: https://doi.org/10.29207/resti.v6i5.4137



c . level 6



d. level 8

Figure 3. GLCM Matrix Values in the folder of training data

The total value of the GLCM matrix pixels above is 9900 in Figure 3, the resulting values are as follows:

P1,1 = 7869/ 9900 = 0.7948
P1,2 = 76/ 9900 = 0.0077
P2,1 = 97/ 9900 = 0.0098
P2,2 = 1858/9900= 0.1877

If the normalization value has been obtained, then it is calculated using GLCM elements such as contrast, correlation, homogeneity and energy.

3.3. Calculating GLCM Features

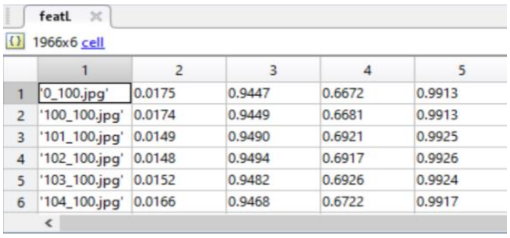
Table 2. Extraction Results of GLCM Manual Feature.

Contrast	**Correlation**	**Energy**	**Homogeneity**
0.0175	0.9447	0.6672	0.9913

From the calculations in Table 2, it is known that the GLCM value is the same as the result of the following Matlab function:

```
GLCM image normalization
glcm=cell2mat(struct2cell(graycoprops(glcm)))
;
```

Based on the function above, we get the results as shown in Figure 4.



	1	2	3	4	5
1	'0_100.jpg'	0.0175	0.9447	0.6672	0.9913
2	'100_100.jpg'	0.0174	0.9449	0.6681	0.9913
3	'101_100.jpg'	0.0149	0.9490	0.6921	0.9925
4	'102_100.jpg'	0.0148	0.9494	0.6917	0.9926
5	'103_100.jpg'	0.0152	0.9482	0.6926	0.9924
6	'104_100.jpg'	0.0166	0.9468	0.6722	0.9917

Figure 4. Value Display of Feature Extraction.

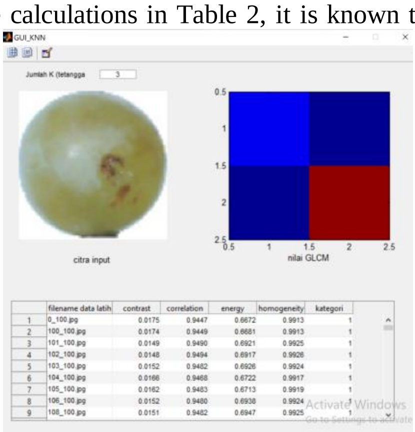
The picture above shows the value of the GLCM feature extraction results in the matlab workspace, starting from column number 2 which is contrast, then 3 is correlation, number 4 is energy and column 5 is homogeneity.

3.4. The Extraction Results of GLCM Feature.

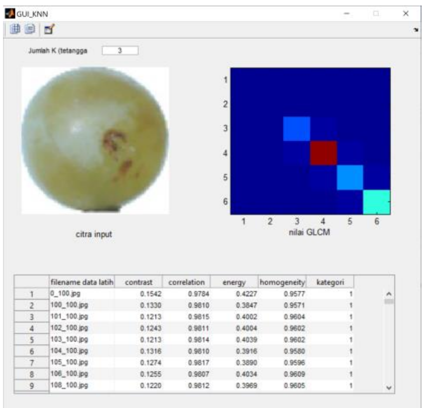
The level of similarity between the images is calculated using the Euclidean distance measurement method. The value of the train image that has the smallest distance from the test image means that the image is the most similar to the test image. To perform feature extraction with GLCM, the RGB image is converted into a grayscale image. Below are the results of an experiment with the calculation of 4 features of energy, contrast, homogeneity, and correlation.

```
GLCM features
graycoprops(GLCM,{'contrast','homogeneity','c
orrelation','energy'})
```

Based on Figure 5, the value of the GLCM feature extraction in the matlab program which consists of contrast, correlation, energy and homogeneity at level 2 to level 8.

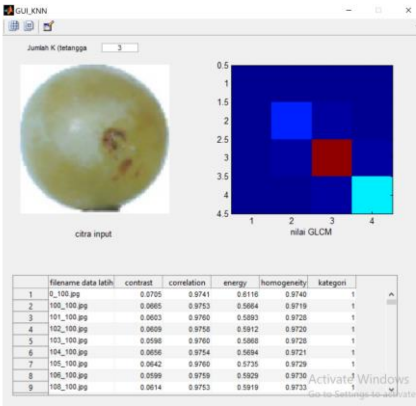


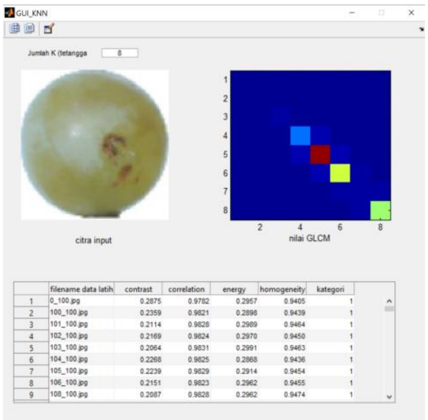
Level 2



Level 6

DOI: https://doi.org/10.29207/resti.v6i5.4137





Level 4 Level 8

Figure 5. App view by GLCM level

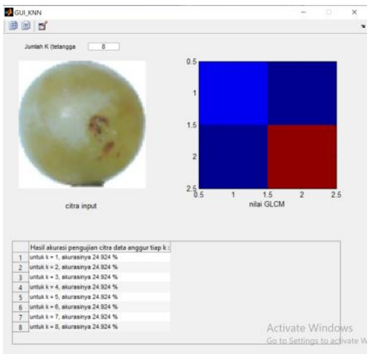
3.5. Classification Using K-Nearest Network (KNN).

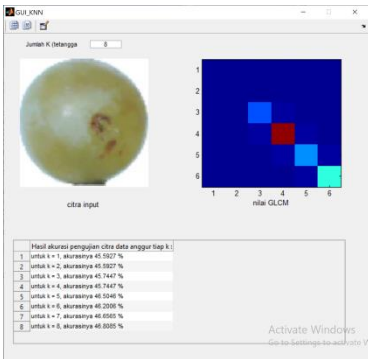
Table 3. Labeling on Training Data

No	File Name	Contrast	Correlation	Energy	Homogeneity	Category
1	0_100.jpg	0.0705	0.9741	0.6116	0.9740	1
2	100_100.jpg	0.0665	0.9753	0.5664	0.9719	1
3	101_100.jpg	0.0603	0.9760	0.5893	0.9728	1
4	102_100.jpg	0.0609	0.9758	0.5912	0.9720	1
5	103_100.jpg	0.0598	0.9760	0.5868	0.9728	1
…	….	…	…	…	…	…
985	0_100.jpg	0.4042	0.9745	0.2428	0.9294	2
986	100_100.jpg	0.3731	0.9730	0.1838	0.9336	2
987	101_100.jpg	0.3667	0.9733	0.1830	0.9335	2
988	102_100.jpg	0.3721	0.9730	0.1854	0.9356	2
…	…	…	…	…	…	…
1964	r_7_100.jpg	0.1039	0.9691	0.2479	0.9530	3
1965	r_8_100.jpg	0.1062	0.9689	0.2461	0.9530	3
1966	r_9_100.jpg	0.1083	0.9686	0.2445	0.9520	3

Table 4. Labeling on Test Data

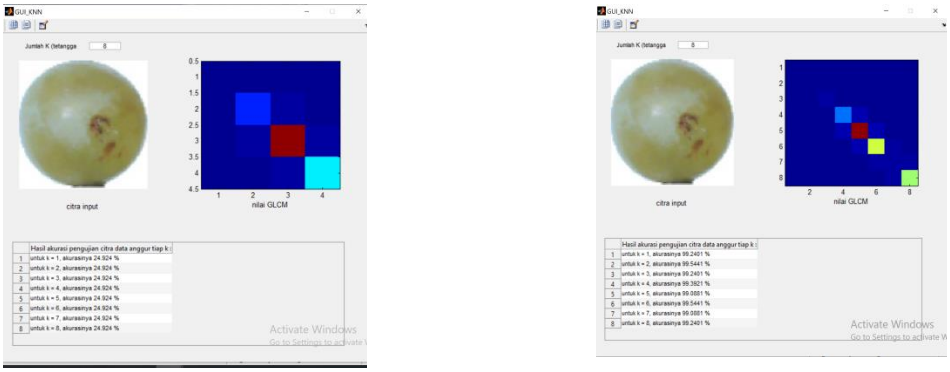
No	Nama File	Contrast	Correlation	Energy	Homogeneity	Category
1	107_100.jpg	0.2144	0.9823	0.2951	0.9452	1
2	111_100.jpg	0.2149	0.9833	0.2851	0.9438	1
3	146_100.jpg	0.2342	0.9810	0.2879	0.9393	1
4	148_100.jpg	0.2339	0.9812	0.2874	0.9404	1
…	…	…	…	…	…	…
329	321_100.jpg	0.4028	0.9738	0.2286	0.9289	2
330	322_100.jpg	0.3958	0.9740	0.2270	0.9280	2
331	323_100.jpg	0.3947	0.9742	0.2298	0.9286	2
…	…	…	…	…	…	…
656	r_97_100.jpg	0.0857	0.9783	0.3565	0.9666	3
657	r_98_100.jpg	0.1011	0.9746	0.3510	0.9657	3
658	r_99_100.jpg	0.0846	0.9785	0.3550	0.9672	3





Level 2 Level 6

DOI: https://doi.org/10.29207/resti.v6i5.4137



Level 4 Level 8

Figure 6. Display of clarification results using K-NN based on GLCM level

The test display is shown in Figure 7. In Figure 5 at point a, it is shown that the accuracy value of k=1 to k=8 is 24.924%. The lowest accuracy value is because the GLCM value is too small so it cannot represent the texture characteristics of grapes. In Figure 7 at point b, it is known that the accuracy value of k=1 to k=8 is 24.924%. The lowest accuracy value is because the GLCM value is too small so it cannot represent the texture characteristics of grapes. In Figure 5 at point c, the highest level 6 accuracy of KNN is obtained with a value of 46.8085% for k=8, while the lowest accuracy is indicated by a value of 45.5927% for k=1. From Figure 5 at point d, the highest accuracy of KNN level 8 is obtained with a value of 99.5441% for k=2, while the lowest accuracy is indicated by a value of 99.2401% for k=1. Based on Figure 4, it is known that GLCM with level 2 produces the lowest accuracy while GLCM with level 8 shows the highest accuracy. The results of the highest accuracy analysis for each level are shown in Figure 7.

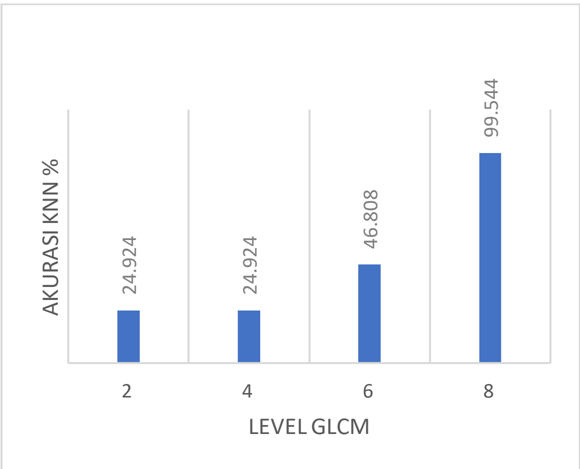


Figure 7. Accuracy gain percentage.

Level is a multiplication matrix consisting of a 2x2 matrix and so on until level 8 is an 8x8 matrix. In Figure 4, the accuracy values of the matrix 2,4,6 and 8, so that the diagram is taken the highest accuracy value for each level (matrix). Starting from level 2 the highest accuracy value is 24.924%, then level 4 gets the highest accuracy value, which is 24.924%, then for level 4 the highest accuracy value is 46.808% and for level 8 the highest accuracy value is 99.544%.

4. Conclusion

Based on the research that has been done above, the results and conclusions from the application of the K-Nearest Neighbor algorithm with preprocessing mean RGB in classifying wine images are as follows: (1)In this study, it can be shown that it can be distinguished by using the GLCM feature extraction method to be classified in the K-Nearest Neighbor algorithm based on the calculation of the Eucledian distance. (2). The results of the classification of grapes obtained the highest accuracy value of 99.5441% with k = 2 at level 8, while the lowest accuracy value obtained a value of 24.924% at each k level 2.

This research cannot be separated from its shortcomings, to improve the results of further research can be done as follows:

1. This study can use various data image objects to enrich the training data so that it can improve research results with accurate values.
2. Change the background color to white or black.
3. Research can be done by adding more data to the test data and training data to obtain more accurate results.
4. Based on the research above, it is necessary to develop a system, especially in the addition of other preprocessing algorithms to allow for an increase in the results of better accuracy values in further research.

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DOI: https://doi.org/10.29207/resti.v6i5.4137