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Performance analysis of local binary pattern and k-nearest neighbor on image classification of fingers leaves

A. D. Ningtyas[a], E. B. Nababan[a,*], S. Efendi[a]

[a] *Program Study of Computer Sciences, Faculty Computer Sciences and Information Technology, Universitas Sumatera Utara, Medan, Indonesia*

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Abstract

The K-Nearest Neighbor (KNN) method is often used by researchers for the classification process because it has a relatively great level of accuracy, however it also has a weakness which is sensitive of the noises. This research is aims to introduce an object recognition (identification) system of fingers leaves by classified using the KNN method. To resolves the weaknesses of the KNN method, the researcher has used the Local Binary Pattern (LBP) method to extract features of the leaves. For the comparison in feature extraction, the researcher has used the Gray Level Co-Occurrence Matrix (GLCM) method. The data that were used on this research are papaya leaves and chaya leaves (with the labels such as good and damage forms). In this research, an experimental design has been carried out that was differentiated by according to the comparison (of ratio) between training data and testing data (NI/Np), there were 90 training data and 45 testing data, where the feature extraction method used the 10 of features. Experimentally, it was shown that by using the ratio NI/Np = 67%:33%, the performance or system performance for classifying the images of fingers leaves by using the LBP extraction method showed that training data was obtained the results close to 95% and testing data was obtained the results close to 76%, while by using the GLCM extraction showed that training data was obtained the results close to 83% and testing data was obtained the results close to 58%.

Keywords: K-Nearest Neighbor Method, Local Binary Pattern Method, Gray Level, Co-Occurrence Matrix Method, Image Classification.

*Corresponding author
Email address: ernabrn@usu.ac.id (E. B. Nababan)

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1. Introduction

Technology will continue to be developed with the aim of helping facilitate the work done by humans. Currently, humans are very dependent on technology, because the human brain has limitations in processing or remembering certain information. Human thinking ability is not always able to accommodate a lot of information for a long time, therefore it requires the transition of manual knowledge to a digital system. The development of technology in the digital world has the potential to affect the efficiency of human activities. One of the technologies that currently developing is a system that involves computerized recognition using methods and concepts to identify an object.
Plant classification is a technique where leaves are selected as one of the objects to be classified based on different morphological features [12]. A recognition system based on the classification of leaves can be useful in providing a collection of information about a plant encountered and a source of information for the common person.
The classification method that is well-known and commonly used for pattern recognition is the K-Nearest Neighbor (KNN) method, because this method is a simple algorithm by calculating the distance between training data and test data, so it has a fast computational process [14]. The KNN method can also be able to recognize objects based on the texture characteristics of the object's image [1].
Based on the various studies described in the previous paragraph, the authors are interested in conducting research using the Local Binary Pattern (LBP) feature extraction method, and as a comparison the Gray Level Co-Occurrence Matrix (GLCM) method with the KNN classification method is used.The images that will be classified are finger leaves, namely papaya leaves and Chaya leaves, because these leaves are the most commonly found and there are still many common people who have not been able to distinguish the two types of finger leaves, and have a relatively high similarity.

2. Methods

2.1. Feature Extraction Method

Feature extraction is a very important step in image processing to detect and classify objects [5]. This extraction step extracts significant information from the image content, which maximizes intra-class similarity and minimizes inter-class similarity. The vectors obtained by feature extraction are used to train and test the data at the classification stage [8].

2.1.1. Local Binary Pattern Method

The Local Binary Pattern (LBP) is used to describe texture features. LBP has many advantages, namely simple, and has less computational complexity than other algorithms, and is not sensitive (intensive) to different lighting intensities, so that LBP is able to describe local texture features of the image [13]. LBP is an effective method because it can adapt between different traditional statistical and structural models of texture analysis. LBP has gained popularity due to its robustness to gray-scale changes caused by noises, such as lighting variance, and computational simplicity [2].
The LBP function is formulated as follows:

$$LBP_{P,\ R}(x,\ y) = \sum_{i=0}^{p-1} s(p_i - p_c)2^i \tag{2.1}$$

Where the function $s(x)$ is defined as follows:

$$s\left(p_i - p_c\right) = \begin{cases} 1, & p_i - p_c \geq 0 \\ 0, & p_i - p_c < 0 \end{cases} \tag{2.2}$$

Where:

P : the number of neighboring pixels involved

R : the distance/radius value of the 3x3 pixel block

(x, y) : pixel location in the image or the center coordinator of a 3x3 pixel block

$s(\ )$: threshold function

p_i : the gray level value of each neighboring pixel.

p_i :coordinates can be obtained from $(-R\sin(2\pi i/P),\ \ R\cos(2\pi i/P))$ if the coordinates of p_c are $(0, 0)$ through radius R

p_c : the gray level value of the center pixel (pixel x and y)

2.1.2. Gray Level Co-Occurrence Matrix (GLCM) Method

GLCM was originally developed by a computer scientist named Robert Haralick in 1973 with 28 features to describe spatial patterns [7]. GLCM extracts textures effectively and has better accuracy and computation time than other extraction methods. Gray level produces distance (representing pixels) and angle (representing degrees) of the image [15].

Each index can highlight certain texture properties, such as smoothness, stiffness, and irregularity. Texture is a term used to characterize tonal variations or levels of gray in an image [9]. The directions used to perform the GLCM analysis are horizontal (0 degrees), vertical (90 degrees) and diagonal (45 and 135 degrees) [11]. However, in this study, the angles used were all angles 0, 45, 90 and 135 which were then averaged. Meanwhile, the distance value (d) taken is 1. The calculation of the value of GLCM begins by determining the direction and distance that will be used to calculate the image value, then calculates the number of paired pixels that are formed and then forms a GLCM matrix, then normalized using equation (2.3) as follows:

$$MatrixGLCMNorm = \frac{1}{\sum MatrixGLCM} MatrixGLCM \tag{2.3}$$

2.2. K-Nearest Neighbor (KNN) Classification Method

KNN is the simplest method of all machine learning schemes and algorithms or classification algorithms, and stores all available cases and classifies new cases that are viewed based on the same size [4].

Distance function in KNN method to perform classification. One example of the distance method, namely the Euclidean Distance method, is useful for making comparisons between data samples that are closer to other data samples in certain classes [3]. KNN is used to classify objects based on the calculation of the Euclidean distance between two vectors [6]. Euclidean distance is the distance in numeric data. Euclidean distance is defined in the formula [10]

$$d\left(y_i, y_j\right) = \sqrt{\sum_{r-1}^{n} \left(\left(a_r(y_i) - a_r\left(y_j\right)\right)^2\right.} \tag{2.4}$$

Where :

$d\left(y_i, y_j\right)$= *Euclidean distance*

$y_i = i^{th}$ *record data*

$y_j = \ j^{th}\ record\ data$
$a_r = \ t^{th}\ data$
$i, j = 1, 2, 3, \ldots..n$

2.3. Fishbone's Diagram

Fishbone diagram is a diagram to analyze the cause of a problem or condition which is often referred to as a cause effect diagram.
The following is a fishbone diagram based on research using the LBP extraction method and the KNN classification method which can be seen in Figure 1.

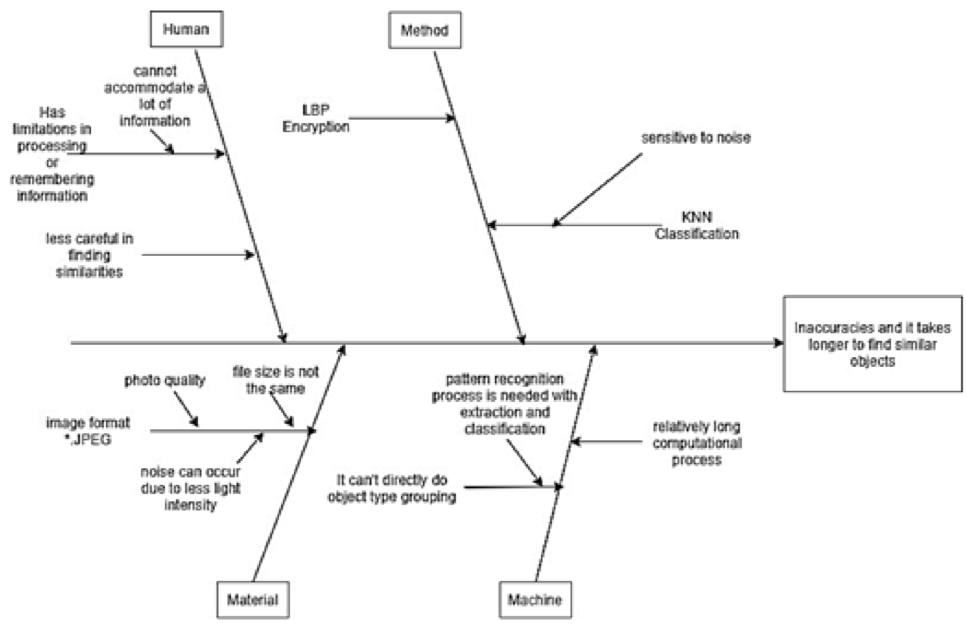

Figure 1: Fishbone Diagram

The conclusion shown in Figure 1 of the fishbone diagram is the need to build an automatic system that can accommodate a lot of information in terms of finding similar objects, especially leaves by using a preprocessing process where the stages of changing the image size, and converting the image to gray (grayscale), the extraction process using LBP method, and the classification process using the KNN method. Based on the problem, the image has different sizes and different photo quality so that it can allow noise in the image, so it takes resizing the image to be the same and the pattern recognition process. However, the KNN method has a weakness that is sensitive to noise, so it takes a method that has resistance to noise, namely the LBP extraction method.

3. Result and Discussion

The test is divided into 2 parts, namely testing the training data and test data. In this study, testing on training data is as much as 67% of the total, which is about 90 data from 135 data. While the test on the test data that is as much as 33% of the total, which is about 45 data from 135 data. The method used is the LBP extraction method with the KNN classification method, but this study also uses the GLCM extraction method with the KNN classification method which is used as a comparison of the best extraction method. The test results on the LBP-KNN training data can be seen in Figure 2.

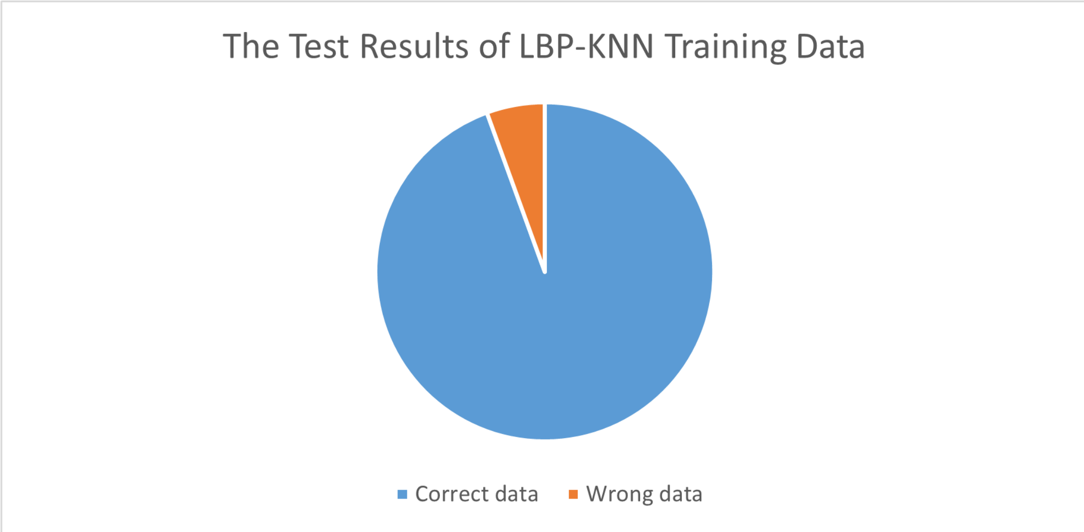

Figure 2: Diagram of LBP-KNN Training Data Test Results

The test results on the LBP-KNN test data can be seen in Figure 3.

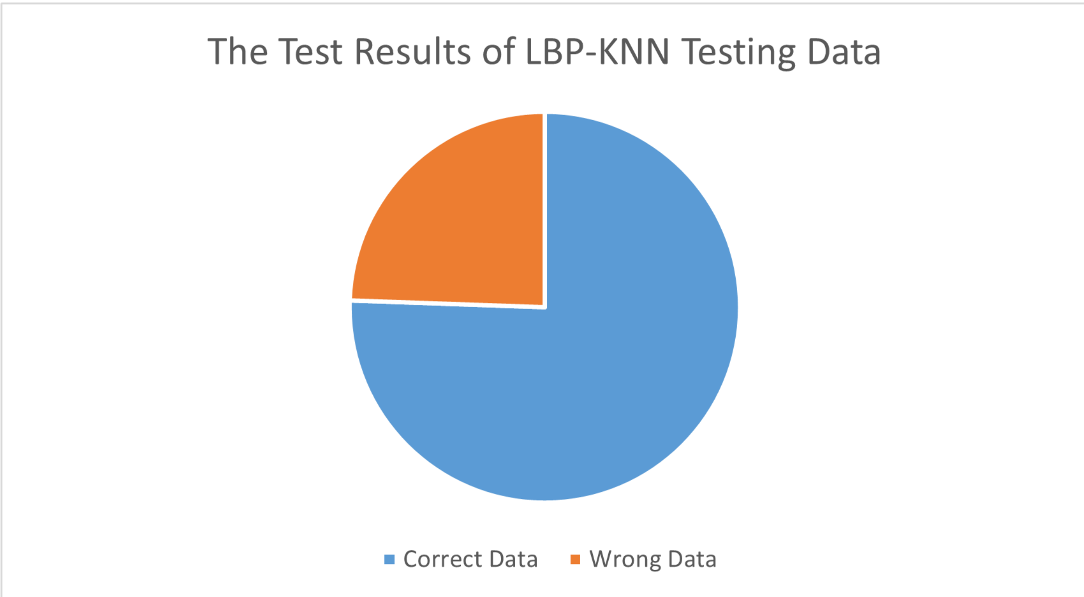

Figure 3: Diagram of LBP-KNN Test Data Test Results

The test results on the GLCM-KNN training data can be seen in Figure 4.

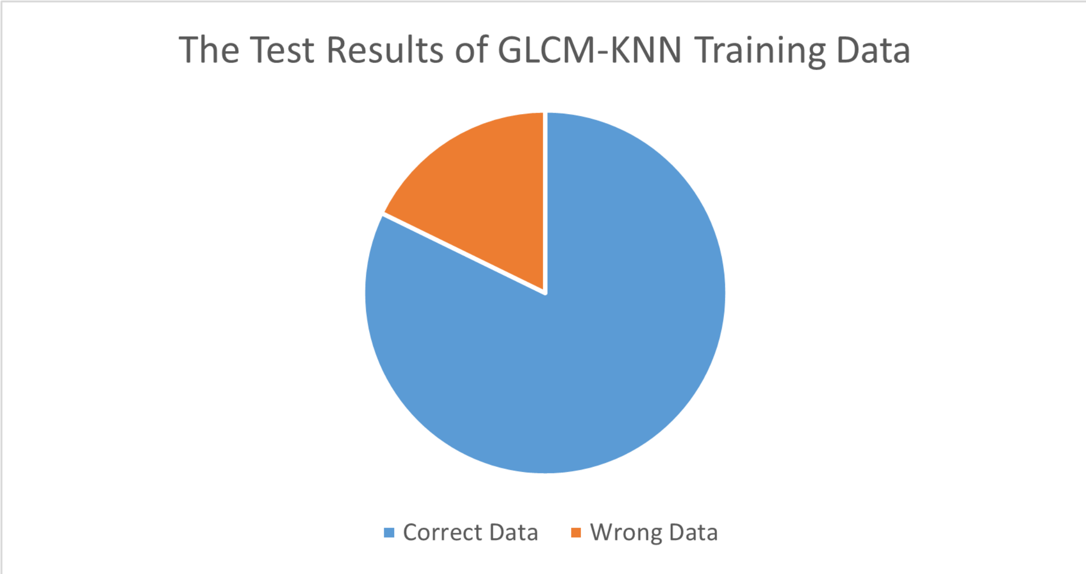

Figure 4: Diagram of GLCM-KNN Training Data Test Results

The test results on the GLCM-KNN test data can be seen in Figure 5.

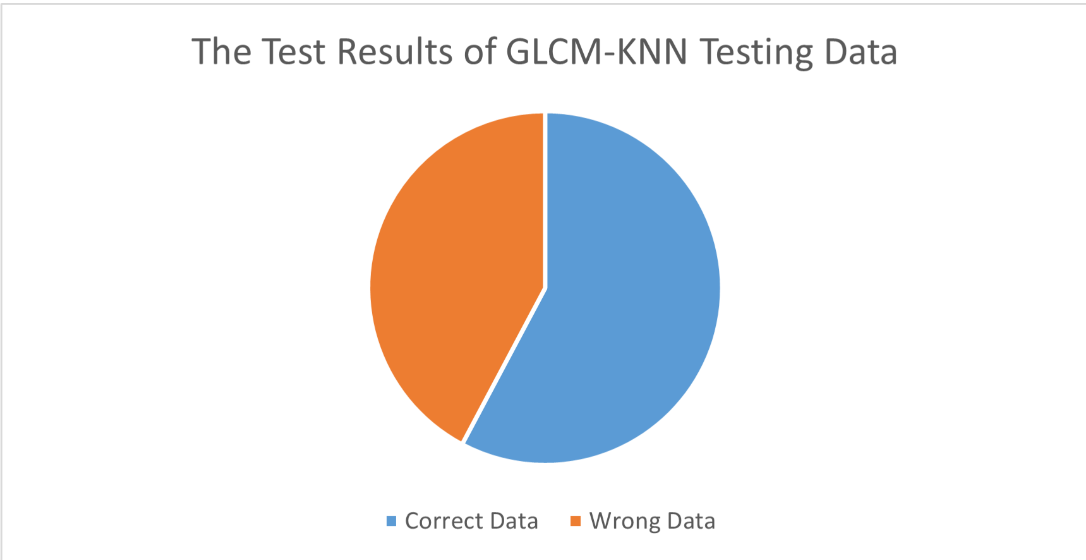

Figure 5: Diagram of GLCM-KNN Test Data Test Result

As previously explained, the classification process was carried out using the LBP method extraction and extraction using the GLCM method, each of which was carried out with 90 training data and 45 test data. Based on the results of the training on 90 training data using the LBP method, 84 recognized images (able to classify correctly) with an accuracy of 94.45%, while the GLCM method obtained 74 recognized images with an accuracy of 82.23%. From 45 test data, it was found that the LBP method can recognize 34 images with an accuracy of 75.56%, while the GLCM method can only recognize 26 images with an accuracy of 57.78%.
From the results of training and testing, it is shown that the accuracy of the classification of leaf types using the LBP-KNN method is relatively better than the GLCM_KNN method. It also shows that the accuracy during training is relatively higher than the accuracy of the test both with the

LBP-KNN and GLCM-KNN methods. This shows that a larger amount of training data has higher accuracy than smaller data. The results also show that the number of features affects the classification accuracy, both the LBP-KNN and GLCM-KNN methods are compared with previous studies, both with different and the same methods.

4. Conclusion

Based on the results of training and testing as well as the analysis carried out in this study, the following conclusions can be drawn: The training conducted on 90 training data with a K = 3 value stated that the LBP method was able to recognize 85 leaf images, and from 45 test data can recognize 34 leaf images, while the GLCM method is able to recognize 74 training images, and 26 leaf images for test data. Based on the test results using the LBP extraction method, the accuracy rate of 94.44% for training data and 75.55% for test data is obtained. While the test results with the GLCM extraction method obtained a level of 82.22% for the test data and 57.78% for the test data. Thus, it can be stated that the performance of the LBP extraction method has advantages compared to the GLCM method in recognizing the type of manjari leaf image.

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References

[1] T. M. Adepoju, M. O. Oladele, A. Adekiigbe and O. A. Ayofe, *Gender classification based on local binary pattern and K-nearest neighbour*, In: Proc. Int. Conf. Global Emerging Trends (ICGET) , 2018 , pp. 74-78.

[2] M. A. R. Ahad, M. N. Islam and I. Jahan *Action recognition based on binary patterns of action-history and histogram of oriented gradient*, J. Multimodal User Interfaces , 10 (2016) 335-344.

[3] N. Amynarto, Y. A. Sari and C Wihandika, *Pengenalan emosi berdasarkan ekspresi mikro menggunakan metode local binary pattern*, Jurnal Pengembangan Teknologi Informasidan Ilmu Komputer, 2(10)(2018) 3230-3238.

[4] I. L. K. Beli and C. Guo, *Enhancing Face Identification Using Local Binary Patterns and K-Nearest Neighbors*, J. Imaging, (2017) 1-12.

[5] V. Chan, A. Govil and G. Reitmayr, *Systems and methods for incremental object detection using dual-threshold local binary pattern operators*, U.S. Patent No. 9,858,498. Washington, DC: U.S. Patent and Trademark Office,(2018) `https://patents.google.com/patent/US9858498B2/en`.

[6] K. Dutta, D. Bhattacharjee and M. Nasipuri, *TR-LBP: A modified local binary pattern-based technique for 3D face recognition*, In: Proc. 5 th Int. Conf. Emerging Appl. Inf. Technol. (EAIT), 2018, pp. 1-4, `https://doi.org/10.1109/EAIT.2018.8470411`.

[7] R. M. Haralick, K. Shanmugam and I. Dinstein, *Textural features for image classification*, IEEE Trans. Syst. Man Cybern. , SMC-3 (6)(1973) 610-621, `https://doi.org/10.1109/TSMC.1973.4309314`.

[8] A. A. Haghnegahdar, S. Kolahi, L. Khojastepour and F. Tajeripour, *Diagnosis of Tempromandibular Disorders Using Local Binary Patterns*, J. Biomed. Phys. Eng. , 8(1)(2018) 87-96.

[9] M. Hall-Beyer, *Practical guidelines for choosing GLCM textures to use in landscape classification tasks over a range of moderate spatial scales*, Int. J. Remote Sens. , 38(5)(2017) 1312-1338.

[10] O. R. Indriani, E. J. Kusuma , C. A. Sari ,E. H. Rachmawanto and D. R. I. M. Setiadi,*Tomatoes classification using K-NN based on GLCM and HSV color space*, In: Int. Conf. Innovative Creative Inf. Technol. (*ICITech*), 2017, pp. 1-6, `https://doi.org/10.1109/INNOCIT.2017.8319133`.

[11] K. Kevin, J. Hendryli and Herwindiati, *Klasifikasi kain tenun berdasarkan tekstur & warna dengan metode KNN*, Computatio: J. Comput. Sci. Inf. Syst., 3(2)(2019) 85-95.

[12] V. Metre, and J. Ghorpade, *An overview of the research on texture based plant leaf classification*, IJCSN Int. J. Comput. Sci. Network , 2 (3) (2013).

[13] T. Ojala, M. Pietikainen and D. Harwood, *A comparative study of texture measures with classification based on feature distributions*, Pattern Recognit., 29(1) (1996) 51-59.

[14] N. D. A. Partiningsih, R. R. Fratama and C.A. Sari, *Handwriting ownership recognition using contrast enhancement and LBP feature extraction based on KNN*, In: Proc. 2018 5 th Int. Conf. Inf. Technol. Comput. Electr. Eng. (ICITACEE), 2018, pp. 342-346, https://doi.org/10.1109/ICITACEE.2018.8576945.

[15] A. S. Sinaga, *Ekstraksikomunikasi nonverbal menggunakan gray level co-occurrence*, Jurnal Ilmiah Informatika Komputer, 25(3)(2021), 187-196, http://dx.doi.org/10.35760/ik.2020.v25i3.3080