



Comparative Study of Herbal Leaves Classification using Hybrid of GLCM-SVM and GLCM-CNN

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Article history: Received June 17, 2023; Revised July 04, 2023; Accepted July 19, 2023; Available online August 16, 2023

Abstract

Indonesia is a tropical country with a diverse range of plants that ancient people used for traditional medicines. However, the similarity in shape of the leaves became an obstacle to distinguishing them. Therefore, technological advancements are expected to help identify the herbal leaves to use them right on target according to their efficacy. In this research, image classification of *katuk* (*Sauropus Androgynus*) and *kelor* (*Moringa Oleifera*) leaves is applied using 3 different algorithms i.e hybrid of GLCM feature extraction and SVM implementing 4 kernels namely linear, RBF, polynomial, and sigmoid; hybrid of GLCM and CNN and pure CNN. A dataset of 480 images has been collected with 2 different scenarios, including bright and dark intensities. Based on the result, a hybrid of GLCM and SVM showed the highest accuracy of 96% in the dark intensity test using a linear kernel, while sigmoid obtained the lowest accuracy of 35%. On the other hand, it has been discovered that CNN obtained the highest performance in the bright intensity test with an accuracy of 98%. While in the dark intensity test, a hybrid of GLCM and CNN is superior, obtaining 96% accuracy. In conclusion, CNN is more powerful for image classification with bright intensity. For dark intensity images, both the hybrid of GLCM+SVM (linear) and the hybrid of GLCM+CNN are fairly recommended.

Keywords: Convolutional Neural Network; GLCM-CNN; GLCM-SVM; Herbal Leaves Classification; SVM Kernels.

Introduction

Indonesia is one of the tropical countries that sustain various endemic plant species growing, which can be used as medicinal materials [1]. With the diversity of these plants, ancient people used them as a medium of traditional medicine or processed into herbal drinks which contained no chemicals. One part of herbal plants often used in traditional medicine is the leaves [2]. However, the similarity between different types of leaves and the lack of public knowledge makes this an obstacle in distinguishing them [3].

In the existing field of research, the application of biological science is considered not too efficient to be used by the community in identifying leaf species because special skills are needed in their use [4], and the complexity of leaf characteristics requires long-term learning, which will certainly take a lot of time [5]. In this modern era, technological progress develops rapidly in a very short time to develop and perfect existing technology [6] to get more accurate results with minimal effort [7]. The application of technology to overcome problems in distinguishing types of objects can be made by utilizing one of the fields of computer vision, namely, pattern recognition which implements classification algorithms and produces numerical information from the object analysis process [8].

Leaf image classification has been carried out by several previous studies, such as research [9] related to diseases in chili peppers which can be seen from the symptoms on the leaves using the GLCM method as feature extraction. The study involved 400 leaf image data, where each class consisted of 100 data. The image is then converted from RGB to grayscale. After going through the feature extraction and preprocessing stages, the data is tested using the Support Vector Machine (SVM) method to obtain accurate results. From this study, the highest accuracy value was obtained, which was 95%.

Leaf classification research has also been conducted to determine diseases in corn leaves using GLCM feature extraction and SVM methods. There were 2 classes of leaves analyzed, totaling 3600 images. At the pre-processing stage, the contrast stretching method is carried out so that when conversion is carried out during the extraction of GLCM features, the results is more optimal. The SVM algorithm is then used to classify the data. The last stage is data evaluation so that an accuracy value of 99.7%, recall of 99.7%, precision of 99.6%, and f-measure of 99.6% is obtained [10].

Furthermore, research using another method, namely Convolutional Neural Network (CNN), has been carried out by [11] classifying and identifying objects taken from Kaggle with a total data of 1152 images with CNN architecture using data rate division per batch consisting of 20 batch sizes to facilitate in the epoch process. The highest accuracy value obtained is 95%, and the validation accuracy value is 94%.

Other studies have also been conducted by [12] to identify diseases in tomato leaves by combining GLCM feature extraction approaches, CNN methods and SVM methods in their classification. In the segmentation stage, the main focus is to get the Region of Interest (ROI) by converting RGB to HSV (Hue, Saturation, Value). For feature extraction, it uses GLCM by converting images into grayscale and then conducting a training process on images with the CNN method. From these two methods, the accuracy value for GLCM was 82.63%, and the accuracy value for CNN was 96.63%. The last process is to determine whether the leaves are classified as healthy or not by classifying them using the SVM method.

From the study, comparing CNN and SVM methods has never been done so the author will combine GLCM feature extraction with 2 different methods and testing using CNN to compare which method will produce the highest accuracy value for the leaf image classification process.

In this study, the classification of objects is focused on the leaves because the leaves are relatively easy to identify compared to other plant parts and are almost available at any time [13]. The types of leaves to be used are katuk leaves (*Sauropus Androgynus*) and Moringa leaves (*Moringa Oleifera*) using the extraction feature of the GLCM because it is considered very good as a texture descriptor for the image analysis process [14]. GLCM extraction will calculate the frequency of pixel occurrence from the provided image and then determine the best quality in the extraction process from the dataset [15]. The SVM method is applied in this study because it can classify the margins of each class optimally and very quickly in a complex computational calculation process [16]. In addition, this research will also utilize CNN method because this method can identify objects independently and has a high level of accuracy in the image recognition process [17]. The purpose of this study is to assist in classifying the image of herbal leaves against the two types of leaves and then comparing which method is better used in image recognition by analyzing the comparison of the accuracy values generated from those three methods.

Method

This study tested the image dataset using 3 different algorithms, namely by using classification between GLCM and CNN and classification with CNN directly. The stages of this research is described in [Figure 1](#).

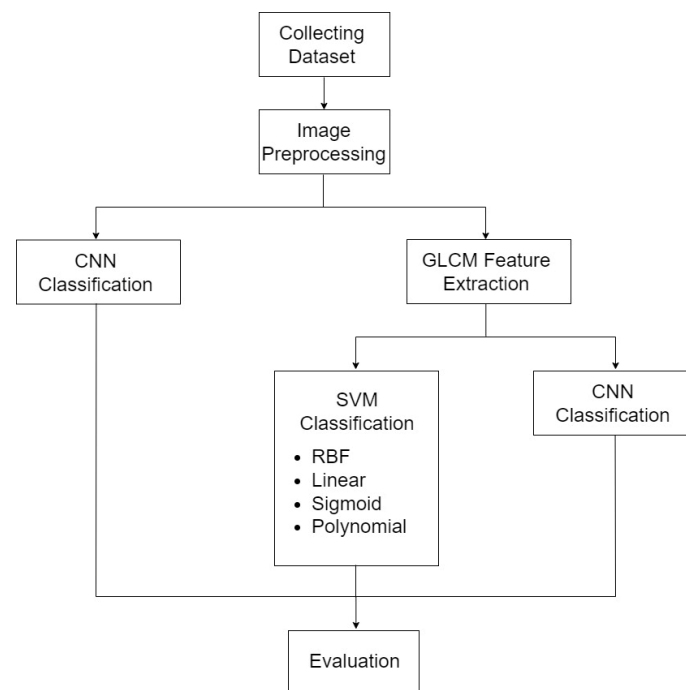






Figure 1. Step of Research

A. Dataset

The dataset was collected by photographing directly at objects using mobile phones with 64 mp camera specifications in dark and bright lighting. These objects were located in one of the forest areas in Gowa Regency, South Sulawesi. The data collected amounted to 480 images, where the data for each class was 120 images with an object size of 600×600 pixels. **Table 1** shows images of each scenario from 2 different classes.

Table 1. Example of Leaf Imagery for Each Lighting Scenarios

Object Classes	Lighting Scenarios	
	Bright	Dark
<i>Katuk</i>		
<i>Kelor</i>		

B. Image Preprocessing

Image Preprocessing is a step to improve image quality and eliminate noise to simplify the next step of the process and improve accuracy [17]. There are 3 steps used, namely labelling, cropping, and resizing. At the labelling step, each class is grouped and named according to the leaf type, so it helps to identify. After labelling, the image is cropped to remove the background and only take the required parts. The last step is resizing to equal all the image sizes, thereby improving the computational processing.

C. Gray Level Co-Occurrence Matrix

GLCM is one of the feature extractions that is often used in extracting an image. GLCM compares the differences in grayness levels and sees the relationship between each pixel of an image. In this study, there are 6 features that is used, including energy, contrast, correlation, homogeneity, dissimilarity, and angular second moment (ASM).

Energy (E) is a feature that expresses the pixel intensity level of an image [18]. Energy can be calculated by Equation 1.

$$E = \sum_x \sum_y P(x, y)^2 \quad (1)$$

Contrast (I) is a feature used to show the difference between an image and another image, whether it is influenced by the level of brightness or color of each image [18] with Equation 2 [19].

$$I = \sum_x \sum_y (x - y)^2 P(x, y) \quad (2)$$

Correlation (C) is a feature that calculates grayscale relationships for several pixel pairs in an image and shows the correlation between linear and degree grayscale [18] images using Equation 3.

$$C = \frac{\sum_x \sum_y (x - \mu_s)(y - \mu_v) * P(x, y)}{\sigma_s \sigma_v} \quad (3)$$

Homogeneity (H) is a feature that indicates the number of grayscale levels that have something in common. If the resulting pixels are more similar, the homogeneity value is higher [20]. Homogeneity can be calculated using Equation 4.

$$H = \sum_x \sum_y \frac{1}{1 + |x - y|^2} P(x, y) \quad (4)$$

Dissimilarity (D) is a feature that shows the difference in the number of grayscale levels in the image. If the resulting pixel has a high degree of difference, the dissimilarity value is higher [20]. Dissimilarity can be calculated using Equation 5.

$$D = \sum_x \sum_y |x - y| P(x, y) \quad (5)$$

ASM is a feature that represents the degree of homogeneity in an image where an image will have a high ASM value if it has a high homogeneity similarity [20]. ASM can be calculated by Equation 6 [19]:

$$ASM = \sum_x \sum_y [P(x, y)]^2 \quad (6)$$

Information:

Σ	: Variance
μ	: Average
$P(x, y)$: X and Y pixel pair values

D. Support Vector Machine

SVM is one of the classification methods of supervised learning that works by separating two or more classes and then mapping data to feature spaces so that data can be grouped so that the best hyperplane is produced [9], [10]. The main purpose of the SVM classification method is to convert data into vectors to produce values that is used to obtain the highest accuracy [21].

This study compared 4 kernels contained in SVM, namely linear, Radial Basis Function (RBF), polynomial, and sigmoid. Linear is the most commonly used kernel for analyzing data that can be separated linearly and has many features in different data types. RBF or gaussian kernel, is a kernel that has often been used for various types of data because this kernel has a good level of computing so that it can produce the right value. Polynomial is a kernel usually used in non-linear data to solve problems after all training data has been normalized. A Sigmoid is a kernel that will activate artificial neurons from neural network derivatives [22].

E. Convolutional Neural Network

CNN is a subset of Supervised Learning that recognizes an object from previous learning data [11]. The CNN algorithm also includes parts of the Multilayer Perceptron (MLP) and Deep Neural Network that are typically used for classifying images in two-dimensional form. The processes within CNN include image or data input, feature extraction, classification, and output [23].

The convolutional layer is the first component in CNN formed from neurons to produce a length and height filter (pixels). Each part of the object is extracted based on stages by paying attention to several components on the feature map [4]. The next stage is the pooling layer using features from the previous stage and then processing so that the system can still detect objects with various engineering [17]. The pooling process also aims to reduce overfitting to make the calculation process more efficient [4]. Furthermore, the Flatten stage aims to get vectors from the results of changes in the feature map [11]. The last stage is Dense, which combines all neurons to optimize classification results. The CNN architecture used in this study can be seen in Figure 2.

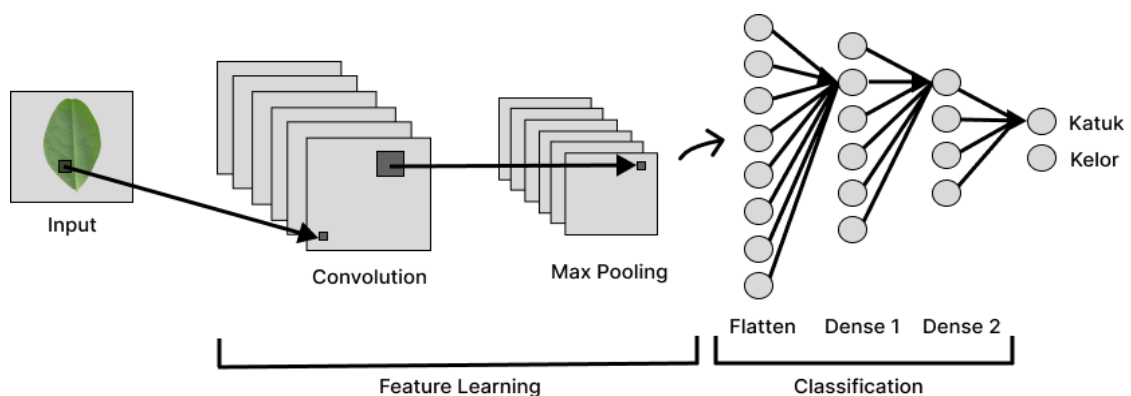


Figure 2. CNN Architecture

Results and Discussion

The collected datasets were then classified into 2 scenarios based on their light intensity to compare performance results using 3 different algorithms. The image then goes through the GLCM feature extraction process by involving 6 parameters, including energy, contrast, correlation, homogeneity, dissimilarity, and ASM. The image is converted into a grayscale and then a matrix. This test was carried out by dividing the data in a ratio of 80% for training data and 20% for testing data, with details of 192 images for training data and 48 images for testing data. Each scenario is tested for

20 epochs and batch sizes 22 in the CNN process. As for the SVM method, testing was carried out on 4 different kernels to compare the more appropriate kernels for this study. The comparison results of testing each algorithm can be seen in [Table 2](#).

Table 2. Classification Performance Results

Lighting Scenarios	Classification Report	Result of each Methods					
		GLCM + SVM				GLCM + CNN	CNN
		Linear	RBF	Polynomial	Sigmoid		
Bright	Accuracy	0.94	0.83	0.81	0.40	0.88	0.98
	Precision	0.94	0.84	0.85	0.39	0.89	0.98
	Recall	0.94	0.84	0.83	0.39	0.88	0.98
	F1-Score	0.94	0.83	0.81	0.39	0.87	0.98
Dark	Accuracy	0.96	0.88	0.92	0.35	0.96	0.96
	Precision	0.96	0.88	0.92	0.35	0.96	0.96
	Recall	0.95	0.87	0.92	0.35	0.95	0.96
	F1-Score	0.96	0.87	0.92	0.35	0.96	0.96

[Table 2](#) indicates that for GLCM and SVM feature extraction, the highest average accuracy, precision, recall, and f1-score values were generated in leaf testing under dark conditions. As for testing for the four SVM kernels, it was found that the linear kernel was the kernel that produced the highest value, with an accuracy value of 0.96 or 96%. Meanwhile, the lowest accuracy produced is 0.35 or 35% of Sigmoid kernel testing. However, the performance results obtained in sigmoid kernels for testing leaves in bright conditions are better than leaves in dark conditions, with an accuracy value of 0.40 or 40%.

Furthermore, the best results for testing the use of GLCM feature extraction against CNN were obtained in leaf testing in dark conditions, with an accuracy of 0.96 or 96%. In terms of leaf testing in bright conditions, an accuracy of 0.88, or 88%, was obtained. The last test, using the CNN method, yielded different results than the prior two previous algorithms. The accuracy of 0.98, or 98%, was obtained when testing leaves under bright conditions. Meanwhile, testing leaves in the dark obtained an accuracy rating of 0.96, or 96%. The performance results from testing the three algorithms above can be seen in the comparison graphs in [Figure 3](#), [Figure 4](#), and [Figure 5](#).

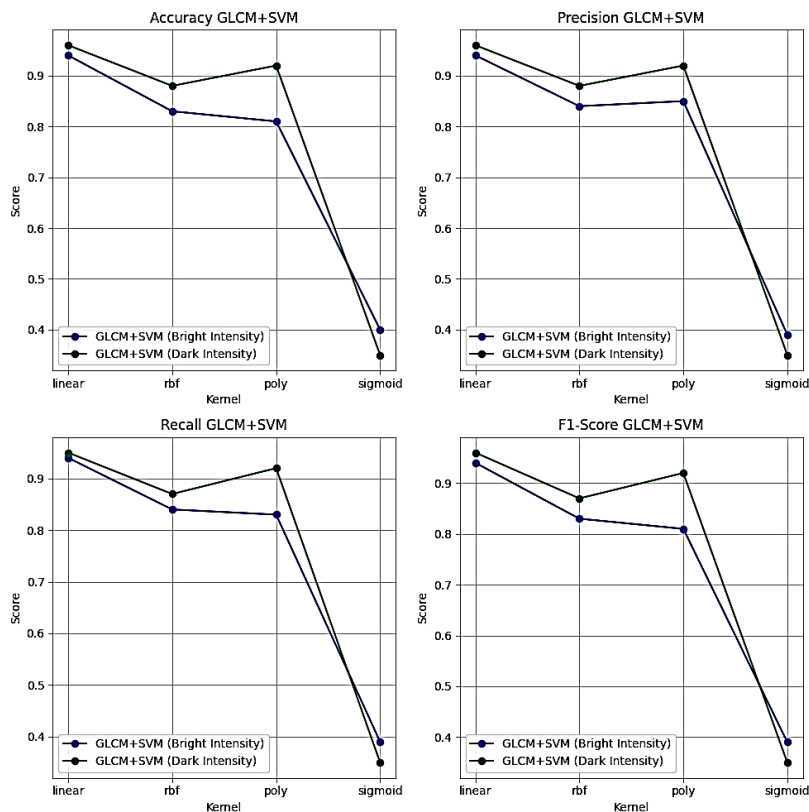


Figure 3. Classification Report for GLCM and SVM

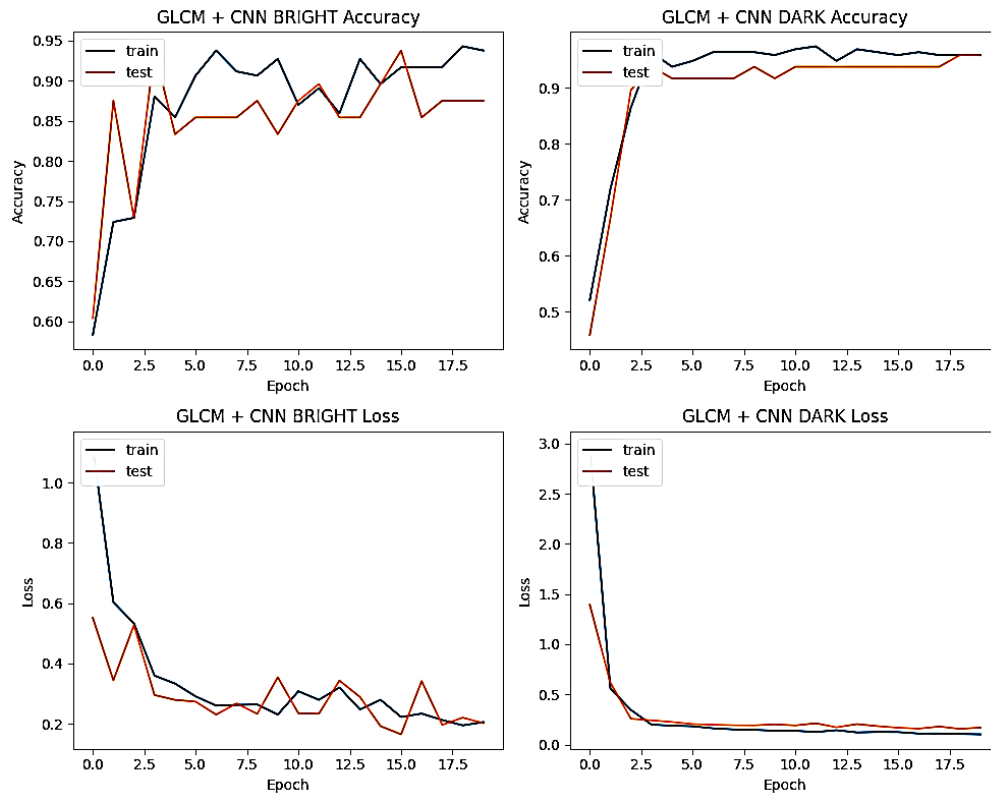


Figure 4. Accuracy and Loss for GLCM and CNN

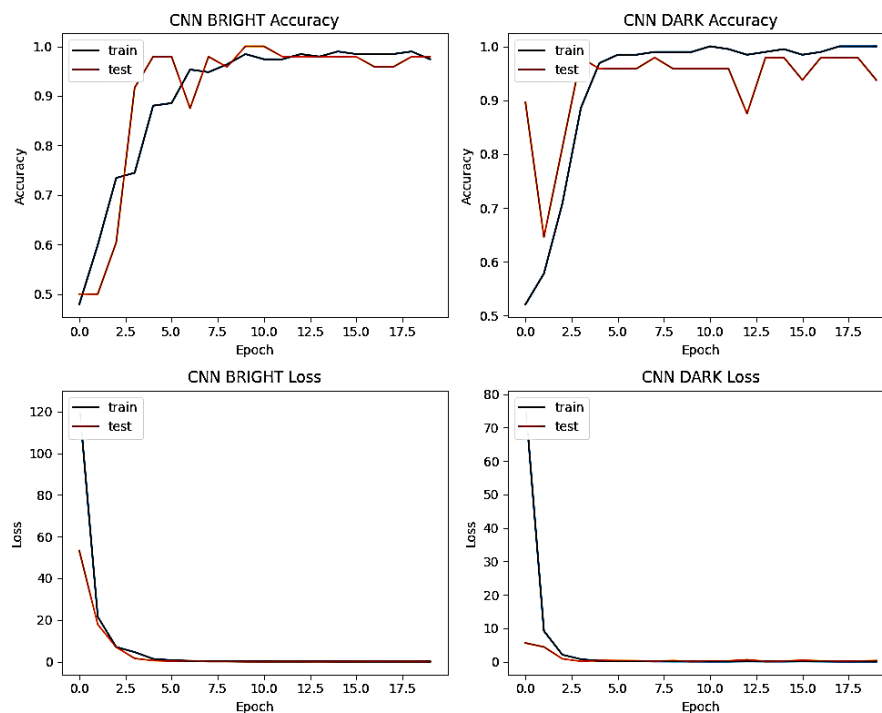


Figure 5. Accuracy and Loss for CNN

Figure 3 illustrates that for GLCM and SVM testing, two kernels have good performance results, namely linear kernels and polynomial kernels in leaf testing in dark conditions. While the sigmoid kernel produces lower performance, results compared to other kernels. In Figure 4, training and testing data's accuracy and loss values are more stable in GLCM and CNN testing on leaves with dark conditions. While the opposite happened in Figure 5, namely testing the CNN method without going through the extraction of previous GLCM features. The accuracy and loss values in training

and testing data are more stable in leaf testing with bright conditions. This is in line with the values obtained in [Table 2](#).

Conclusion

According to the results of this study, leaf testing in the dark produces the highest performance values for SVM and CNN algorithms after the GLCM feature extraction process. When SVM kernel tests were compared, it was discovered that linear kernels, RBF kernels, and polynomial kernels generated good performance outcomes. The most optimal performance results in GLCM and SVM tests are obtained using linear kernels with an accuracy value of 0.96 or 96%. While the sigmoid kernel produces lower performance results with an accuracy value of 0.35 or 35%, this kernel is not recommended for use in this study. Meanwhile, GLCM and CNN tests obtained the highest accuracy of 0.96 or 96%. Furthermore, for testing using the CNN method, the best results were obtained on leaf testing in bright conditions, which was 0.98 or 98%.

Based on these results, it can be concluded that the use of linear kernels contained in the SVM method has more optimal results after passing the GLCM feature extraction process. As for the CNN method, it is superior to use without going through the extraction of GLCM features.

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