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Implementing K-Nearest Neighbor to Classify Wild Plant Leaf as a Medicinal Plants

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ABSTRACT

The public has difficulty distinguishing medicinal leaves from wild plant leaves due to the similarity in leaf shape. Therefore, this study aimed to create a system to help increase public knowledge about wild plant leaves that also function as medicinal plants by the KNN method. Leaves of wild plants, namely Rumput Minjangan, Sambung Rambat, Rambusa, Brotowali, and Zehneria japonica, are also medicinal plants in comparison. Image processing techniques used were preprocessing, image segmentation, and morphological feature extraction. Preprocessing consists of scaling and splitting the RGB components and using an RGB component decomposition process to find the color component that best describes the leaf shape and generate the blue component image. The segmentation process used a thresholding technique with a gray threshold value (T) of less than 150, which best separates objects and backgrounds. Some morphological feature extraction used are area, perimeter, metric, eccentricity, and aspect ratio. Based on the results of this research, the KNN method with variations in K values, namely 13, 15, and 17, obtained a system accuracy of 94.44% with a total of 90% training data and 10% test data. This comparison also affected the increase in system accuracy.

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1. INTRODUCTION

One of the plants known worldwide as medicine is Gotu Kola or Centella asiatica L. (Urban). Gotu Kola has many other names, such as Indian Pennywort, Centella asiatica, Hydrocotyl chinensis, Barmi, Bokkudu, Brahma, Herb, Horsefoot, Herbaceous Pepagan, and Mandooka (WHO monograph) [1]. Gotu kola is found in warmer regions (tropical climate) such as India, Sri Lanka, parts of China, Mexico, South America, Venezuela, and Madagascar [2]. Gotu kola is a herbaceous plant that grows throughout the year without a stem and has a kind of rhizome with creeping stolons. The leaves are single, round, kidney-shaped (like the kidneys), 1-7 cm in diameter, and the surface is uneven with serrated leaf edges. The benefits of Gotu kola leaves are to increase the body's resistance (longevity), cleanse the blood, and improve digestive disorders and fertility in women. In Australia, Gotu kola is used as a remedy for dementia and stress and to rejuvenate the body and brain [3]. In Indonesia, Gotu kola is a horticultural product in the medicinal plant sector [4]. The increasing public interest in traditional medicine is marked by the number of traditional medicines circulating in the community. Traditional medicine is one of the nation's cultural heritages that needs to be preserved, researched, and developed again. The number of studies on traditional medicines is expected to advance traditional medicine [3]. Gotu kola is commonly found in open, moist, fertile soils such as paddy fields, meadows, beside ditches, and along roads [5]. A common problem is that the similar shape of the leaves makes it difficult for the average person to distinguish between Gotu kola and wild leaves. Researchers have developed a system to help the public classify Gotu kola and other wild plants.

Some of the studies referenced in this study were the introduction of medical sheets in 2012 using image processing techniques and neural network algorithms. The image processing techniques used in this study were grayscale color conversion, segmentation, and edge detection. Next, the research uses 2D Gabor filter feature extraction to detect Diseases in tomato leaves. In addition, the feature extraction method was also used to identify Indonesian medicinal plants [6]. In another study, K Nearest Neighbor was used with a K = 5 value and 92% accuracy to identify plant species based on extracting morphological features from the leaves [7]. In addition to morphological features, GLCM texture features can be used in classifying leaf images by using the adjacency value of K = 1 to get an accuracy rate of 98% [8]. The K-Nearest Neighbor method was also used to identify Siamese citrus leaf disease with an accuracy of 70% [9], identify cucumber leaf disease with an accuracy of 90% [10], classify leaf images of sweet potato varieties with an accuracy of 95% [11] and classifying tomato quality damage with an accuracy of 86.6% [12].

Generally, the image processing used is color conversion to other color spaces such as HSV, HSI, and CIELab. However, in this study, researchers focused on the process of splitting RGB components by looking for RGB images that best represent objects. The process of RGB components splitting to find the color component that best describes the leaf shape and generate the blue component image. The segmentation process uses a thresholding technique with a gray threshold (T) value range of 150 to 250 to find the best threshold value for combining objects and backgrounds. The difference in this study compared to previous research is that the data of the research object is not completely the same, there is one type of leaf that is the same being studied, namely Centella asiatica, in Husin's research, so we only adopt some of its image processing techniques such as segmentation, morphological feature extraction (eccentricity [7], and metric [11]). In addition, in previous studies, the features used were area, perimeter, and form factor. However, in this study, five shape features are used: area, perimeter, metric, eccentricity, and aspect ratio. Based on the explanation of the research references above, this study aims to create a system to help increase public knowledge about wild plant leaves that also function as medicinal plants by the KNN method. This study used variations in K values, namely K = 1 to K = 17, to distinguish Centella asiatica leaves from other wild leaves and classify the types of wild plant leaves, which are also medicinal plants.

2. RESEARCH METHOD

This research consists of several stages, such as leaf data collection, preprocessing, segmentation, feature extraction, and classification, as shown in Figure 1.

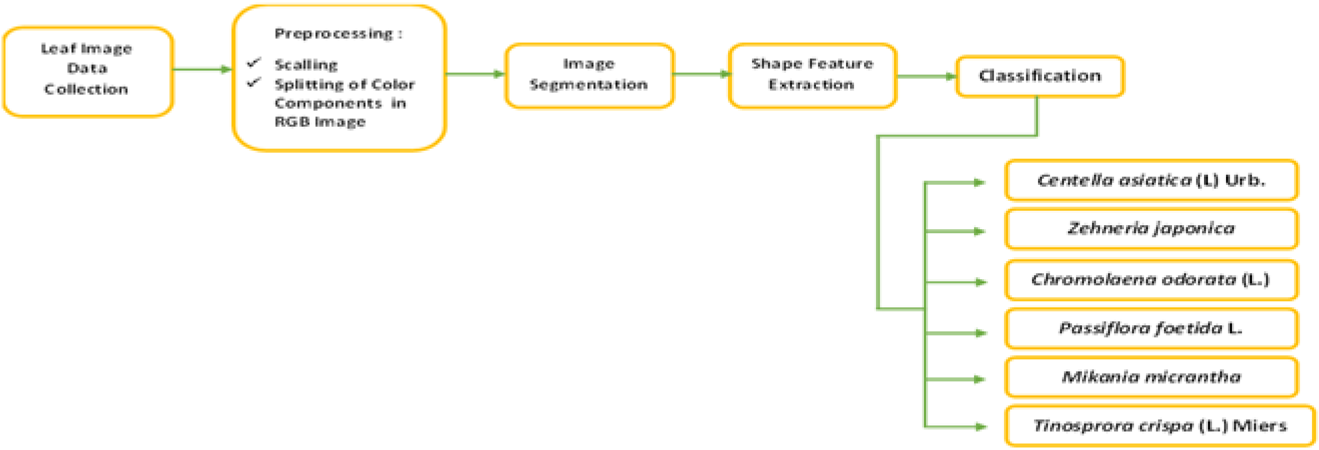

Figure 1. The Research Block Diagram

2.1. Leaf Data Collection

The data used is the primary data collected by the researchers themselves. The leaves of other wild plants were also used to compare in this study, as this plant usually grows alongside wild plants. The wild plants used are plant leaves that grow like the leaves of the gotu kola plant, as shown in 2. The total data used is 180, consisting of 30 data on each (Table 1).

Table 1. Kinds of Wild Leaf Data

Leaf	Description	Leaf	Description
	Local Name: Pegagan (Gotu Kola) Family: Apiaceae (Umbelliferace) Species: *Centella asiatica* (L) Urb. Benefit: 1. Antipyretic (Fever Reducing) 2. Antitoxic (Anti Poison) 3. Diuretic (Urine Laxative) 4. Cell Revitalization 5. Antibiotics		Local Name: - Family: Cucurbitaceae Species: *Zehneria japonica* Benefit: 1. Fever 2. Stomach Ache (Diarrhea) 3. Skin Disease 4. Jaundice 5. Kidney Dysfunction [13]
	Local Name: Rumput Minjangan Family: Compositae Species: *Chromolaena odorata* (L.) or *Eupatorium odorotum* L. Benefit: 1. Burns and Internal Wounds 2. Stomach Ach 3. Indigestion		Local Name: Sambung Rampat Family: Asteraceae Species: *Mikania micrantha* Benefit: 1. Antibacterial dan Antimicrobial 2. Parainfluenza type 3 inhibitor and Respiratory Syncytial Virus [14]

2.2. Preprocessing

Preprocessing is the initial stage of digital image processing techniques that aim to improve the quality of an image. The preprocessing methods used in this study are scaling and RGB component splitting. Scaling is the process of changing the pixel size of an image to be larger or smaller, which aims to normalize the data. The original image size of 6944 x 9248 pixels was changed to a size of 300 x 300 pixels. The second process is splitting the RGB color space, namely the image of the red component, the image of the green component, and the image of the blue component [9]. From this process, the next process used is image segmentation.

2.3. Image Segmentation

Image segmentation is then performed to split the subject from the background using the following Equation (1) [15]:

$$Leaf\ (x,y) = \begin{cases} if\ L_i(x,y)\ <\ T\ then\ 1 \\ if\ L_1(x,y)\ \geq\ T\ then\ 0 \end{cases} \tag{1}$$

T is the threshold process for splitting the object (leaf) from the background. If the gray value is less than the threshold, the object will be white (1), and if the gray value is greater than the threshold, the object will be black (0). The thresholding technique is also usually called the Otsu method, but in this method, the threshold value (T) is obtained automatically [16], different from the formula equation used. The success of this method also varies for each image based on the threshold value.

2.4. Extraction of Form Features

Morphological features (shapes) are features that represent the shape of the object to be analyzed. Some of the methods used are chain code, attribute topology, and attribute geometry. Chain Code is commonly used to encode an object's shape (contour). The chain code starts by specifying the first pixel of the object. Based on these pixels, the chain code is formed by following the chain code direction rules. The chain code is used to calculate the area (A) and perimeter (P) [12]. Other features used are metrics, eccentricity, and aspect ratio. The metric is the comparison value between the area (A) and the perimeter (P) of the object. Metrics range in value from 0 to 1. To get a metric, use the following Equation (2).

$$leaf\ metric = \frac{4\pi \times A}{p^2} \tag{2}$$

The eccentricity of an object is the ratio of the distance between the foci of the ellipse to the length of the major axis. Where the value of a is the major axis and b is the minor axis. Eccentricity is worth between 0 - 1. Equation (3) is used to get the eccentricity value. Aspect Ratio (AR) is the object's width-to-height ratio. The following Equation (4) is used to calculate the aspect ratio.

$$Leaf\ eccentricity = \sqrt{1 - \frac{b^2}{a^2}} \tag{3}$$

$$Leaf\ AR = \frac{Width}{Height} \tag{4}$$

2.5. K-Nearest Neighbor (KNN) Classification

K-Nearest Neighbor (KNN) algorithm is a method for classifying objects based on the training data closest to the object [10]. KNN algorithm is a method that uses a supervised learning algorithm [12]. The purpose of the KNN algorithm is to classify new objects based on attributes and training samples. The results of the new test sample are classified based on the majority of the categories in the KNN. The KNN algorithm classification process uses image feature extraction data. Previously, the data from the image feature extraction was divided into training data and testing data. The training and testing data are used to find the closest distance using Euclidean Distance [9] in Equation (5). Where x_i is training data, y_i is test data, and i is data variable.

$$ED = \sqrt[2]{\Sigma_i^n (x_i - y_i)^2} \tag{5}$$

3. RESULT AND ANALYSIS

The stages of digital image processing that need to be considered are the process of splitting RGB components, which produces a red component image, a green component image, and a blue component image, as shown in Figure 2. Based on Figure 2, the blue component image represents the most significant color difference between the object and the background where the leaf object has a darker color than the background, while in the green component image, the leaf object has a color similar to the background. For the red component image, the leaf object is slightly darker than the background. After splitting the RGB color space components, the image segmentation process is carried out using a thresholding technique using Equation (1). A histogram image is used to determine the T value or threshold, as shown in Figure 3.

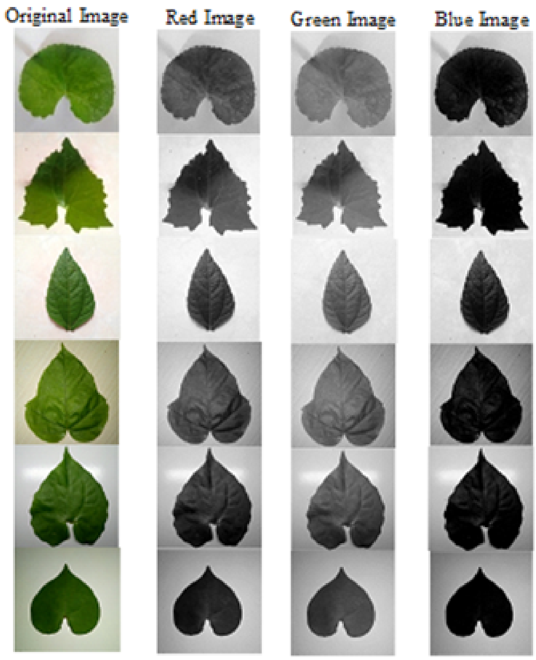

Figure 2. RGB Color Space Component Splitting Process

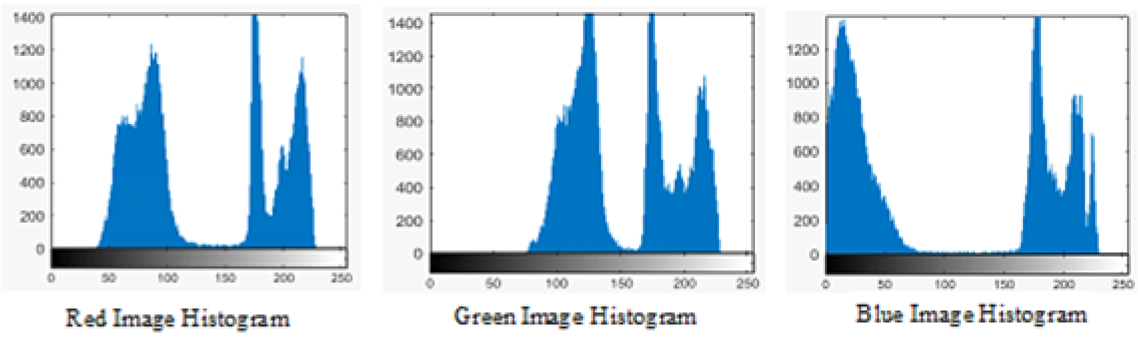

Figure 3. RGB Component Image Histogram

Based on Figure 3, the image histograms for the red and green components have a similar graph. The graph shows the distribution of the gray degree values. In contrast, the histogram of the blue component image has a graph that shifts to a gray value (0). In the Blue Image Histogram, there is a graph with gray values in the range of 150 250; based on Figure 2, the graph does not represent an object (leaves) but represents a background. Therefore, the threshold values used are 50, 100, 150, and 200, as shown in Figure 4.

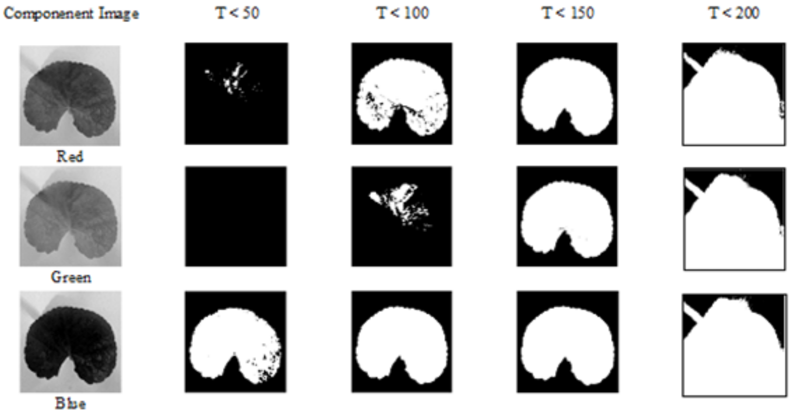

Figure 4. Image Segmentation Results with Variation of Threshold Value (T)

Figure 4 shows that the red, green, and blue component images have different threshold values. In the red and green component images, the best segmentation image depicts the shape of the leaf when T $<$ 150. Whereas in the blue component image, when T $<$ 150 and T $<$ 100, it produces an equally good segmented image. However, when the three images use T $<$ 100, only the blue component image represents the best leaf image compared to other color components. The result of the segmentation image from the red and green component images looks incomplete, so the image that best describes the original shape of the leaf is the blue component image. However, before the segmentation process, this threshold value was tested on five other leaf classes (especially on the blue component image), as shown in Figure 5. Based on Figure 5, when the threshold value (T) is less than 150, the images of leaves 1, 2, and 3 produce a segmented image with an intact leaf object, while the images of leaves 4, 5, and 6 result in an incomplete segmentation image. The threshold value that best represents the results of the segmentation image with the most intact object is T $<$ 100. However, when using this value, the segmentation image results in the images of leaves 2 and 3 are slightly incomplete at the base and tips of the leaves. A dilation process is carried out to improve the results of the segmentation image. The dilation process is a morphological operation technique that will add pixels to the boundaries between objects in a digital image, as shown in Figure 6.

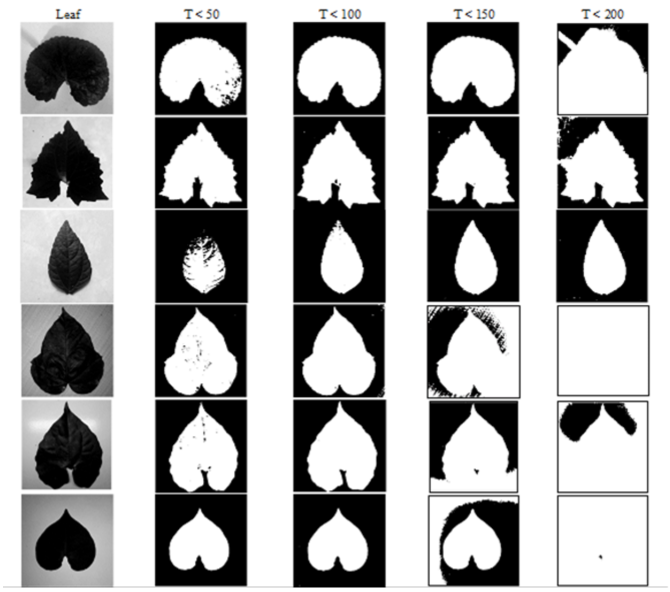

Figure 5. Results of Segmentation Image of Each Leaf Based on Variation of Threshold Value

Figure 6. Effects of selecting different switching under dynamic condition

After the segmentation process, the next step is feature extraction. Feature extraction aims to extract an object's unique and most descriptive value. These unique features can be in the form of color, shape, and texture. However, in this study, what distinguishes Gotu Kola from other leaves is its shape, so the feature extraction used is morphological. TThe morphological features used in this study consist of area, perimeter, metric, eccentricity, and aspect ratio, the average value of which from 180 data (divided into six leaf classes) is described in Table 2.

Table 2. Morphological Feature Values in Each Leaf Class

Class		Area	Perimeter	Metric	Eccentricity	Aspect Ratio
	Min	30871,250	2311	0,056	0,280	1,042
Centella asiatica (L) Urb	Max	52758,125	3341	0,083	0,780	1,599
	Mean	41878,383	2780,267	0,068	0,586	1,263
	Min	23733,125	2028	0,041	0,321	1,056
Zehneria japonica	Max	50028,875	3585	0,078	0,771	1,569
	Mean	35193,529	2949,767	0,051	0,586	1,267
	Min	13698,25	1470	0,059	0,458	1,125
Chromolaena odorata (L.)	Max	31904,875	2316	0,094	0,889	2,186
	Mean	21734,683	1936,000	0,073	0,787	1,712
	Min	28816,125	2220	0,062	0,157	1,013
Passiflora foetida L.	Max	54956,625	3105	0,090	0,637	1,297
	Mean	41891,183	2701,667	0,072	0,438	1,133
	Min	25789,5	2248	0,047	0,299	1,048
Mikania micrantha	Max	49377,875	3112	0,073	0,725	1,451
	Mean	38542,375	2801,433	0,062	0,544	1,216
	Min	13828,25	1628	0,061	0,234	1,029
Tinosprora crispa (L.) Miers	Max	32134,875	2488	0,084	0,614	1,267
	Mean	23886,225	2078,833	0,069	0,439	1,124

Table 2 shows the value of morphological features in each leaf class. The value of these features is used as input from the K-Nearest Neighbor intelligent system. The K-Nearest Neighbor (KNN) algorithm is a method for classifying objects based on the training data that is closest to the object. The KNN method is also a supervised learning method with training data (X) and testing data (Y), as shown in the comparison in Table 3. The total number of data is 180, divided into six leaf classes or 30 data in each class.

Table 3. System Accuracy Results Based on K Value Variations and Comparison of Training - Testing

X : Y	System Accuracy Percentage (%)								
	K = 1	K = 3	K = 5	K = 7	K = 9	K = 11	K = 13	K = 15	K = 17
50 : 50	58,89	58,89	60	62,22	67,78	66,67	62,22	66,67	63,33
60 : 40	55,56	59,72	61,11	62,5	66,67	70,83	70,83	68,06	69,44
70 : 30	55,56	59	62,96	64,81	64,81	68,52	72,22	72,22	70,37
80 : 20	52,78	50	58,33	61,11	58,33	72,22	69,44	72,22	69,44
90 : 10	61,11	61,11	83,33	88,89	88,89	88,89	94,44	94,44	94,44

Based on Table 3, the results of the highest accuracy of the system are 94.44% with a comparison of training data and testing data that is 90:10, with K values of 13, 15, and 17. While in a comparison of 80 : 20, the accuracy obtained is 69.44% for K = 13 and K = 17 and 72.22% for K = 15. In a comparison of 70:30, the system accuracy obtained is 72.22% for K = 13 and K = 15 and 70.37% for K = 17. In a ratio of 60:40, the system's accuracy obtained is 70.83% for K = 13, 68.06% for K = 15, and 69.44% for K = 17. Finally, in a comparison of 50 : 50, the system's accuracy obtained is 62, 22% for K = 13, 66.67% for K = 15, and 63.33% for K = 17. These results indicate that the comparison between the amount of training data and the amount of testing data is the main factor that increases the system's accuracy. The greater the amount of training data used, the better the system's accuracy. The system uses the training data to learn to recognize patterns in each leaf class so that when testing data is used, the system can classify the data into predetermined classes based on the Euclidean Distance. Based on the results of the research we have done on the digital encyclopedia of sweet potato varieties using KNN with shape features with a value of K = 17, an accuracy of 87.5% was obtained. However, when this method was applied to another case study, namely classifying Centella asiatica as a medicinal plant, the system obtained an accuracy level of 94.44%.

This shows that the previous method can be used in other case studies and produces higher accuracy. Of course, this is based on the leaf shape used as data and feature extraction, which has changed, such as changing length and diameter features to become eccentricity and aspect ratio. If we compare it with several reference methods, several different aspects are described in Table 4. The table shows that the leaf objects studied are different. The edge detection method is not used because the image does not find it difficult to find the boundary between the object and the background. The features used in this study were carried over from previous studies, i.e., morphological features such as area, perimeter, eccentricity, and addition, and the aspect ratio calculated is the height divided by the width of the leaf. The classification method used is KNN because, in the research of K. Saputra and B. Adi Prasetya, this method can classify leaf types with an accuracy rate of more than 92%. However, if we follow K. Saputra's research where the number of research objects is five types of herbal leaves, we add two parameters, namely metric and aspect ratio, and use a value of K = 5, our system accuracy is 83.33%, so we use the value K = 13, 15 and 17, there is an increase in system accuracy to 94.44%. From the results of these comparisons, the addition or replacement of morphological features can improve the system's accuracy.

Table 4. The Comparison of Research Results

	Research Object	Results and Evaluation
Wiharto et al. [15]	Ten species of tomato leaves	The results of research using the 2D Gabor filter and SVM obtained an accuracy of 90.37%.
Borman, et. al [6]	Indonesian medicinal plants	PCA is used for feature extraction based on the characteristics formed. The classification method uses KNN, and the accuracy is 88.67%.
K. Saputra and S. Wahyuni [7]	Five species of herb leaves	Extraction of leaf morphological features such as area, perimeter, s, and eccentricity. The best model for the resulting k-NN classifier is when the value of k = 5 with an accuracy of 92%.
B. Adi Prasetya et al. [11]	Four species of sweet potato	Extraction of leaf morphological features such as area, perimeter, metric, length, diameter, ASM, IDM, entropy, contrast, and correlation at angles of 0, 45, 90 and 135. The K-Nearest Neighbor method can classify sweet potato leaf images with an accuracy of 95% with variations in K = 23 and K = 25 values.
Proposed method	Six species of wild leaves	Extraction of leaf morphological features such as area, perimeter, metric, eccentricity, and aspect ratio. The best model for the resulting k-NN classifier is when the value of k = 13, 15, and 17 with an accuracy of 94.44%.

4. CONCLUSION

Based on the discussion and analysis above, this study aims to classify the image of gotu kola leaves, which is compared with five classes of liar leaves that define the shape of gotu kola leaves. The difference with previous research lies in the type of leaf and the image processing technique used. Previous research used conversion to grayscale color space before the segmentation process. We replace the process by splitting the components of the RGB color space to find the component that best represents the object's shape or clearly shows the difference between the object and the background. If we use grayscale color conversion, the difference between the object and the background is not clearly visible. At the RGB component splitting stage, the blue component is a color space that can represent the best leaf shape with a threshold value of $T < 100$ for the image segmentation process. After the segmentation process, there are still several types of leaf images that are not perfect, so morphological processes such as dilation are used to improve the results of the segmentation image. The feature extraction process takes parameters from the segmentation image results. In this research, morphological features such as area, perimeter, metric, eccentricity, and aspect ratio are used. These features are inputs from the K-Nearest Neighbor method with the provisions of comparing training data and testing data that is 90:10 with the highest accuracy of 94.44% (K = 13, K = 15, and K = 17). Based on the research results above, comparing the amount of training and testing data also affects the increase in system accuracy. If a large amount of data is used for training, the system will be more trained in studying the pattern of each class so that it can distinguish the class of each leaf better and minimize classification errors. The level of accuracy of the system using KNN is very good. However, it needs further development by comparing the leaf classification using other classification methods such as Nave Bayes or Artificial Neural Network (ANN) because KNN is a simple, intelligent system method.

5. DECLARATIONS

AUTHOR CONTIBUTION

The first author is a correspondent author and digital image processing expert, the second author is a translator, the third author is a research student, the fourth author is an agricultural expert, and the fifth author is an artificial intelligence expert.

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COMPETING INTEREST

There is no conflict of interest in this article.

REFERENCES

[1] K. Jhansi, D & Manjula, “The Antioxidant Potential of Centella asiatica: A Review,” *Journal of Medicinal Plants Studies*, vol. 7, no. 2, pp. 18–20, 2019.

[2] B. Sun, L. Wu, Y. Wu, C. Zhang, L. Qin, M. Hayashi, M. Kudo, M. Gao, and T. Liu, “Therapeutic Potential of Centella asiatica and Its Triterpenes: A Review,” *Frontiers in Pharmacology*, vol. 11, no. September, pp. 1–24, 2020.

[3] I. M. S. Harsa, “Efek Pemberian Ekstrak Daun Pegagan (Centella Asiatica) Terhadap Penyembuhan Luka Sayat Pada Tikus Putih Jantan (Rattus Norvegicus) Galur Wistar,” *Jurnal Ilmiah Kedokteran Wijaya Kusuma*, vol. 9, no. 1, pp. 21–27, 2020.

[4] C. A. Mareta, “Efektifitas Pegagan (Centella Asiatica) Sebagai Antioksidan,” *Jurnal Medika Hutama*, vol. 02, no. 01, pp. 402–406, 2020.

[5] D. Eka, K. Sari, T. Widowati, and N. Atika, “Kelayakan Daun Pegagan (Centella Asiatica (L .) Urban) Sebagai Bahan Dasar Sabun Untuk Kulit Kering,” *Beauty and Beauty Health Education Journal*, vol. 12, no. 2, pp. 78–85, 2023.

[6] R. I. Borman, R. Napianto, N. Nugroho, D. Pasha, Y. Rahmanto, and Y. E. Pratama Yudoutomo, “Implementation of PCA and KNN Algorithms in the Classification of Indonesian Medicinal Plants,” in *2021 International Conference on Computer Science, Information Technology, and Electrical Engineering (ICOMITEE)*, oct 2021, pp. 46–50.

[7] K. Saputra and S. Wahyuni, “Identifikasi Jenis Tanaman Berdasarkan Ekstraksi Fitur Morfologi Daun Menggunakan K-Nearest Neighbor,” *Jurnal Teknik dan Informatika*, vol. 5, no. 1, pp. 24–29, 2018.

[8] S. A. Rosiva Srg, M. Zarlis, and W. Wanayumini, “Identifikasi Citra Daun dengan GLCM (Gray Level Co-Occurence) dan K-NN (K-Nearest Neighbor),” *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 21, no. 2, pp. 477–488, 2022.

[9] R. H. Ariesdianto, Z. E. Fitri, A. Madjid, and A. M. Imron, Nanda, “Identifikasi Penyakit Daun Jeruk Siam Menggunakan K-Nearest Neighbor,” *Jurnal Ilmu Komputer dan Informatika (JIKI)*, vol. 1, no. 2, pp. 133–140, 2021.

[10] L. N. Sahenda, A. A. Ubaidillah, Z. E. Fitri, A. Madjid, and A. M. N. Imron, “Application of Feature Selection for Identification of Cucumber Leaf Diseases (Cucumis sativa L.),” *JISA (Jurnal Informatika dan Sains)*, vol. 04, no. 02, pp. 173–178, 2021.

[11] B. A. Prasetya, Z. E. Fitri, A. Madjid, and A. M. N. Imron, “Ensiklopedia Digital Varietas Ubi Jalar Berdasarkan Klasifikasi Citra Daun Menggunakan KNearest Neighbor,” *Elektrika*, vol. 14, no. 1, pp. 1–6, 2022.

[12] N. E. Paulina, Z. E. Fitri, A. Madjid, and A. M. N. Imron, “Klasifikasi Kerusakan Mutu Tomat Berdasarkan Seleksi Fitur Menggunakan K-Nearest Neighbor,” *MIND (Multimedia Artificial Intelligent Networking Database) Journa*, vol. 6, no. 2, pp. 144–154, 2021.

[13] M. J. Roldan, T. Chin, Y. Tsai, A. L. Castillo, and O. B. Villaflores, "Cytotoxic and Angiosuppressive Potentials of Zehneria japonica (Thunb. ex Murray) S.K. Chen (Cucurbitaceae) Crude Leaf Extracts," *Philippine Journal of Health Research and Development*, vol. 22, no. 01, pp. 43–52, 2018.

[14] M. M. Sheam, Z. Haque, and Z. Nain, "Towards the antimicrobial, therapeutic and invasive properties of mikania micrantha knuth: A brief overview," *Journal of Advanced Biotechnology and Experimental Therapeutics*, vol. 3, no. 2, pp. 92–101, 2020.

[15] W. Wiharto, F. H. Nashrullah, E. Suryani, U. Salamah, N. P. T. Prakisya, and S. Setyawan, "Texture-Based Feature Extraction using Gabor Filters to Detect Diseases of Tomato Leaves," *Revue d'Intelligence Artificielle*, vol. 35, no. 4, pp. 331–339, 2021.

[16] P. Rosyani and S. Saprudin, "Deteksi Citra Bunga Menggunakan Analisis Segmentasi Fuzzy C-Means dan Otsu Threshold," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 20, no. 1, pp. 29–36, 2020.