Plant Species Classification Using Leaf Edge Feature Combination with Morphological Transformations and SIFT Key Point

Jiraporn Thomkaew* and Sarun Intakosum

Department of Computer Science, Faculty of Science, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand; Email: sarun.in@kmitl.ac.th (S.I.)
*Correspondence: jiraporn.th@rmutsv.ac.th (J.T.)

***Abstract*—This paper presents a new approach to plant classification by using leaf edge feature combination with Morphological Transformations and defining key points on leaf edge with SIFT. There are three steps in the process. Image preprocessing, feature extraction, and image classification. In the image preprocessing step, image noise is removed with Morphological Transformations and leaf edge detect with Canny Edge Detection. The leaf edge is identified with SIFT, and the plant leaf feature was extracted by CNN according to the proposed method. The plant leaves are then classified by random forest. Experiments were performed on the PlantVillage dataset of 10 classes, 5 classes of healthy leaves, and 5 classes of diseased leaves. The results showed that the proposed method was able to classify plant species more accurately than using features based on leaf shape and texture. The proposed method has an accuracy of 95.62%.**

***Keywords*—plant species classification, leaf edge, SIFT, random forest, morphological transformations**

I. Introduction

Computer vision is one of the research topics on the use of digital images to enable computers to analyze and extract images like humans that are currently popular. Today, many researchers have come up with the idea of computer vision to increase efficiency and be more accurate such as image preprocessing, image segmentation, feature extraction, and image classification concepts. This corresponds to the current technology developed to support the use of digital images more and apply to a wider range of professions, such as a medical computer-aided vision for ultrasound image analysis [1–4], image retrieval [5], face detection [6], as well as agricultural fields such as leaf identification [7] and leaf detection. with disease [8] etc.

The most common way to classify plant species is by their leaf shape. Because each plant species has different leaf characteristics and has specific characteristics of that species such as leaf size, leaf margins, leaf color, leaf veining, etc. which can help to correctly identify plant species. At the same time, there are many other plants that differ in cultivars but have similar leaf shapes however the misclassification of these plants by humans, can cause errors. Therefore, a method of classification of plant species using machine learning has been proposed to solve the problem. The classification of plant species using machine learning has continued to evolve and the trend is increasing. Computer vision is used to help recognize and train the feature of plant leaf images. In addition, image enhancement [9] has been improved prior to importing images to make machine learning more accurate including the development of machine learning models that can classify complex species more accurately and can operate in real-time [10].

Image preprocessing is an important step to improve image quality before the images are imported into the learning model. If the image is of good quality, it will be able to extract the feature of the image more fully and accurately because machine learning models learn images from their features. Therefore, if the image is sharp and without noise, the distinctive features of the image can be extracted more precisely because the classification of the plant species using the leaf image extracts the feature of the plant leaf such as the color, shape, and texture of the plant [11], plant leaf veins [12], teeth indicator [13] etc.

This paper presents a plant classification focusing on leaf edge features using the healthy plant leaves and diseased plant leaves from the PlantVillage dataset using these steps as follows: remove the background of the plant leaf images, converting the color model from RGB to a grayscale and binary image, remove image noise with Morphological Transformations and the edge of plant leaves are detected with Canny Edge Detection. Scale-Invariant Feature Transform (SIFT) is used to define key points along the edge of plant leaf shapes. Plant leaf features were extracted by using Convolutional Neural Network (CNN) and plant species were classified by Random Forest. The second part of this paper presents the related work, the third part presents proposed methods, and the results are shown in the fourth and final parts with the conclusion and future work.

Manuscript received September 5, 2022; revised October 5, 2022; accepted November 15, 2022.

doi: 10.18178/joig.11.1.91-97

II. Related Work

In this section, we present articles related to the classification of plant species using features such as color, shape, texture, and leaf veining, among others, and data classification models as presented by many researchers as follows:

Bisen [7] Propose an automatic classification of plants by Deep Convolutional Neural Network using plant leaf feature. Image is processed to remove image noise, rotation, centering, resizing, normalization, rescaling, and data augmentation are performed before images are used for train models. Proposed a CNN used for plant classification with a hidden layer for learning and extracting image features to be used for plant identification. It has input size 300 × 300 × 3 followed by 8 layers 7 × 7 and output 98 × 98 followed by 16 filters 7 × 7 and output 92 × 92 max-pooling layer reduction. 92 is 42 convolutional and max-pooling layers. The next layers are 32 and 64 filters 5 × 5 layers, and the output layer has 128 vector units. The experiments were performed with the Flavia dataset and the Swedish leaf dataset. The results showed that the models proposed were able to automatically recognize plant species with 97% accuracy.

Reddy and Varma *et al.* [9] Propose on identifying plant species by color image analysis with Convolutional Neural Network. Image quality is improved with image enhancement, image denoising, image segmentation, and binarization. Feature extraction from morphological shape features and texture features. The proposed neural network consists of four convolutional layers, followed by two fully-Connected layers, four max-pooling layers, and a final soft-max layer to store image features. Experiments were performed on 5 datasets: Leaf snap, UCI leaf, PlantVillage, Flavia, and Swedish datasets. The results showed that the CNN model proposed was able to extract features better than manual feature extraction. The accuracy of classification was better than conventional methods from experiments with the Flavia, Swedish, UCI leaf, PlantVillage and Leaf snap datasets with 100%, 100%, 100%, 89.99%, and 97.99% accuracy, respectively.

Zhang and Zheng *et al.* [11] Propose on Plant Leaf Identification using Principal Component and Linear Discriminant Analysis. It processes images by converting RGB images to grayscale and converting grayscale images to binary using OTSU's thresholding method and morphology methods (opening operation and closing operation). The color image is then transformed into a texture image without background by converting it to an HSI color model using saturation values to obtain a texture image by combining images from the saturation image matrix and binary image matrix and extracting the image feature from the texture image. Feature extraction from Shape features (geometric feature, Hu moment invariants features, and structural characteristics), Texture features (GLCM, fractal dimension, LBP, Gabor features). The image feature vectors were reduced by CPA and LDA, and the leaves were classified using the Back Propagation Neural Network. The experiments were performed with Flavia leaf image datasets and ICL leaf image datasets. The results showed that the proposed method used a multiple feature extraction method from the image (GC + Hu + SC + GLCM + FD + LBP + Gabor) in combination with the feature vector reduction with CPA and LDA, and then classification with BPNN. The highest accuracy can be achieved at 94.22% for the Flavia dataset and 87.82% for the ICL dataset.

Gayathri Devi and Neelamegam [14] presents a method for detection of rice leaf disease, 5 classes of rice leave diseased and 1 class of rice leaves healthy using image processing. Diseased rice leaves were segmented with K-means clustering, and then image features were extracted using integrated features from SIFT, DWT and GLCM. KNN, ANN, Bayesian and multiclass SVM were used as image classifiers. The results showed that using image features from SIFT, DWT, and GLCM, combined with multiclass SVM classification, the accuracy was 98.63% which was higher than that of the other methods.

III. Proposed Methods

This section presents the step proposed in this article. There are three steps as follows: 1) image preprocessing converts RGB color images to grayscale images and converts them to binary images. Image noise is also removed with Morphological Transformations and detection image edge with Canny Edge Detection 2) Identify key points on leaf edge using SIFT, and feature extraction with CNN, and 3) Plant leaves were classified by Random Forest. The framework of the proposed method is shown in Fig. 1.

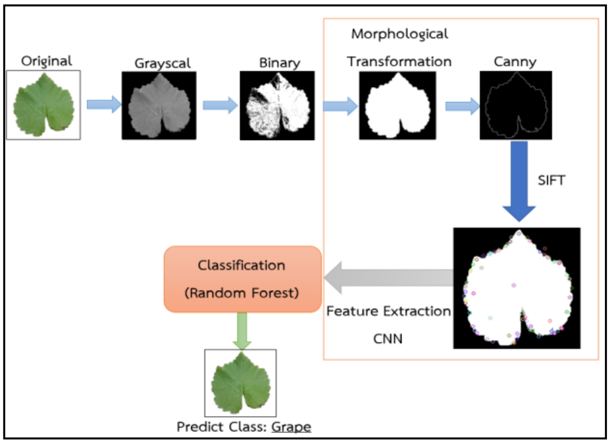


Figure 1. Framework of proposed methods.

A. Leaf Data Set

Experimenting with plant leaf images from the PlantVillage dataset [15] from www.kaggle.com. This includes all 38 classes of healthy and diseased plant leaves. However, this study selected five classes of healthy plant leaves and five classes of diseased plant leaves: Cherry Disease, Cherry healthy, Grape Disease, Grape healthy, Potato Disease, Potato healthy, Strawberry Disease, Strawberry healthy, Tomato Disease, and Tomato healthy. The image has an RGB color model with an image size of 256 × 256 pixels, and 4015 plant leaves images. An example of plant leaves is shown in Fig. 2.

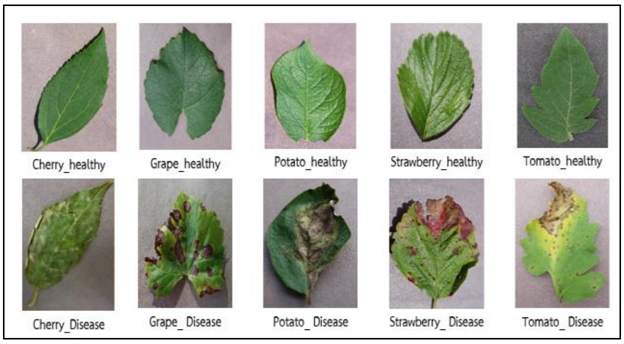


Figure 2. An example of plant leaves from PlantVillage dataset.

B. Leaf Preprocessing

1) Color transform: the image preprocessing step is the image preparation process. PlantVillage images are RGB color model images, so image preprocessing is performed to improve image quality. The first step is to remove the background of the image. The RGB image was converted to a grayscale image and the grayscale image was converted to a binary image using the OpenCV library. The minimum and maximum threshold values are optimized for the image and Otsu's threshold is used for automatic thresholding of thresholds to make the image binary.

2) Morphological transformations: from the image Color Transform step, the result is a binary image with image noise. Therefore, Morphological Transformations are used to remove image noise. Morphological Transformations is an image preprocessing process using image morphology that works well with binary images. This requires a structuring element or kernel value that is a parameter for the function of Morphological Transformations. Morphological Transformations are available with several functions such as Erosion, Dilation, Opening, Closing, Morphological Gradient, Top Hat, and Black Hat. In this paper, the Opening and Closing operators based on Erosion and Dilation are used to remove noise in binary images.

Opening operation is similar to Erosion, but with less erosion, it removes some unwanted bright foreground pixels from the boundaries of the foreground image. But you still have to keep the foreground area similar to the image input. The result depends on the configuration of the structuring element. In this study, the opening operation was used to extend the edge of the plant leaves to be connected completely and remove some leaf edge pixels that are affected by the light and shadow of plant leaves.

The closing operation works similarly to Dilation. In other words, Closing will enlarge the image area in the foreground image to reduce the area background. In order to cover the leaks on the image to look like a complete foreground area. The closing operation was used to remove image noise on plant leaf images obtained after grayscale conversion to binary images.

After using the Opening operation and Closing operation, a binary image with only the leaf edge of the leaves is obtained, which can be used to detect the edge of the leaves with Canny Edge Detection. It is a popular algorithm for detecting the contours of objects in images, developed by Canny [16] in 1986.

C. Feature Extraction

Classification of plant species and plant leaf diseases is mainly featured by the color, shape, texture, and vein of the plant leaves. In this study, the focus was on the use of shape characteristics of plant leaves by using only the plant leaf edge with the defining of leaf edge key point.

1) Scale-Invariant Feature Transform (SIFT) developed by Lowe [17]. It is an algorithm for finding key points on an image to compare the similarity of two images. Key points are used for calculating the features of each image and the feature is independent of the image size, position, and orientation. This allows the important feature to be extracted from the image [18]. There are four steps as follows:

a) Scale-space extrema detection is the process of finding important key points on an image. Input images are blurred with Gaussian Blur. The image will have a different blur with the σ value of each octave, resulting in the difference of Gaussian (DoG) and stored with the Gaussian Pyramid, which is the expected key point of focus. It can be calculated from Eq. (1).

$$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y) \tag{1}$$

where $G(x, y, \sigma)$ is Gaussian Kernel;

$I(x, y)$ is the pixel value at the position of the image;

σ is Gaussian Kernel width value;

b) Keypoint localization is the process of defining key points. If a Difference of Gaussians (DoG) value is found, it compares to 8 neighboring pixels in the same octaves and 9 pixels in the previous and next octaves, for a total of 26 pixels. Pixels that are local extremum are also designated as candidates for key points. Then, any key points are compared with low contrast, and key points at the edge are removed to reduce the number of key points.

c) Orientation assignment is the procedure for calculating the magnitude and direction of Gradient by assigning each key point a fixed value for rotation. Key points are calculated with neighboring areas based on the scale and magnitude and gradient direction of each area, stored in a 36 bin histogram covering 360 degrees and weighted according to gradient magnitude and gaussian-weighted. The histogram vertex that is greater than 80% of the vertex is considered a new orientation. Creating key points with the same location and size but in different directions will make the image matching more efficient. It can be calculated from Eqs. (2), and (3).

$$m(x, y) = \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2} \tag{2}$$

$$\theta(x, y) = \tan^{-1}\left(\frac{L(x, y+1) - L(x, y-1)}{L(x+1, y) - L(x-1, y)}\right) \tag{3}$$

d) Keypoint descriptor is a process of creating a key point descriptor by using the neighborhood of the key point size 16 × 16 windows as a direction. It is divided into 4 × 4 sub-blocks, and an 8-bin histogram is created to store the size and direction of the 8-gradient direction. So, get a 4 × 4 × 8 or 128 bin vectors for each feature.

In this article, SIFT is used to define key point plant leaf edge after binary image conversion and leaf edge detection with Canny Edge Detection. Because of focuses on the classification of plant leaves by using the leaf edge of plants.

2) Convolutional Neural Network (CNN)

After defining the key points on the plant leaves to achieve the key point features of the image. The next step is to extract the feature from the image. We used CNN for image feature extraction. The input image is an image that has been pre-processed and the plant leaf is already defined key point. The sequential model of the CNN is used to extract features from the image into a set of features for plant classification. Feature extraction using CNN is implemented through the Keras library's sequential model function, which consists of an input layer, a hidden layer, and an output layer. The proposed CNN has added the eight filter layers, as shown in Fig. 3. Each layer consists of BatchNormalization and MaxPooling to allow models to extract image features more fully and accurately. The multiple filters in the hidden layer improved models to extract image features more fully and accurately. In addition, adding BatchNormalization makes it possible to increase the speed of the data training and increase the accuracy of feature extraction.

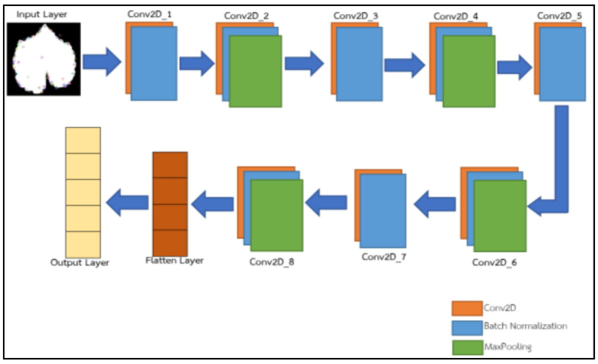


Figure 3. proposed the CNN model for the feature extraction.

D. *Leaf Classification*

Image feature extraction with the CNN model obtained a vector of plant leaf edge feature. The last step was the classification of plant species by using the leaf edge feature combined with the key point using SIFT and extracted feature by the CNN model using Random Forest as a classifier. Random Forest combines the several Decision trees, and individual trees in the same Random Forest are not related Wang [19]. Each decision tree is given a different data set of image features and a different data set for training and testing. Then, the decision tree predicts the image from that feature. If the decision tree predicts which class the image is most probable, Random Forest classifies that plant leaf based on the decision tree's vote.

IV. RESULTS AND DISCUSSION

This paper presents a new method for classifying plant species by using leaf edge feature combination with SIFT key point. To be used for detecting the leaf edge of plant leaves. 4015 leaves images from PlantVillage Dataset for learning and testing. The images were divided into five classes of healthy leaves and five classes of diseased leaves. There are three steps: Image preprocessing, feature extraction, and classification. The results of the experiment are as follows:

A. Leaf Preprocessing

Before the image feature extraction step, the image is preprocessed in the first step. The image of plant leaves from the PlantVillage Dataset has RGB colors and different backgrounds, lights, and shadows. Therefore, the preprocessing step is to remove the background image of the plant leaf image. The RGB image is converted to a grayscale image and the grayscale image is converted to a binary image. To be used for detecting the leaf edge of plant leaves. Configures the threshold and combination with Otsu's threshold. Because the image has different light and shadow. After converting the image to binary, it was found that the image was noise and the leaf edge was detected and the key point on the leaf edge was identified. As a result, the SIFT algorithm detects the noise area of the image as well. Therefore, image noise was removed by using an Opening operation and Closing operation as shown in Fig. 4. After removing noise on the image with Opening operation and Closing operation, then using leaf edge detection with Canny Edge Detection, the leaf edge of plant leaves was obtained.

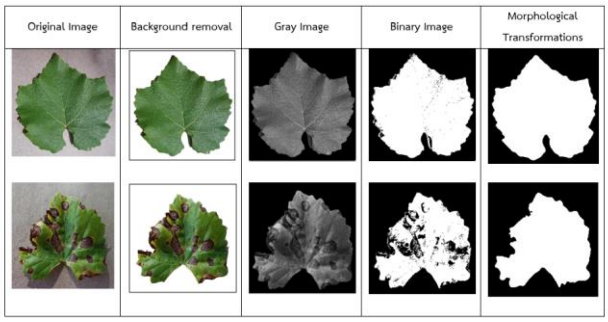


Figure 4. Step for converting RGB images to grayscale and binary images, used opening and closing.

B. Feature Extraction

After the image has been preprocessed and detected edge with Canny Edge Detection, the leaf edge of the plant leaf is obtained. If the leaves are healthy, they will have a leaf edge that resembles the leaf morphology. But if the leaves are diseased, the leaf edge of the plant is unusual. The next step is to determine the key points of the leaf edge with the SIFT algorithm. SIFT defines key points along leaf edge detected from Canny Edge Detection, as shown in Fig. 5. Then extraction feature of the plant leaf edge from an image with the CNN model.

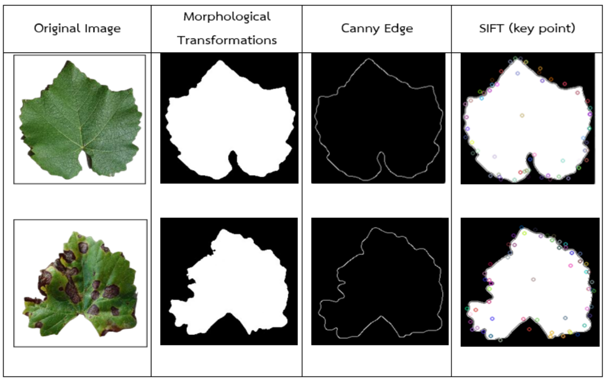


Figure 5. Canny Edge Detection and key points on leaf edge with SIFT.

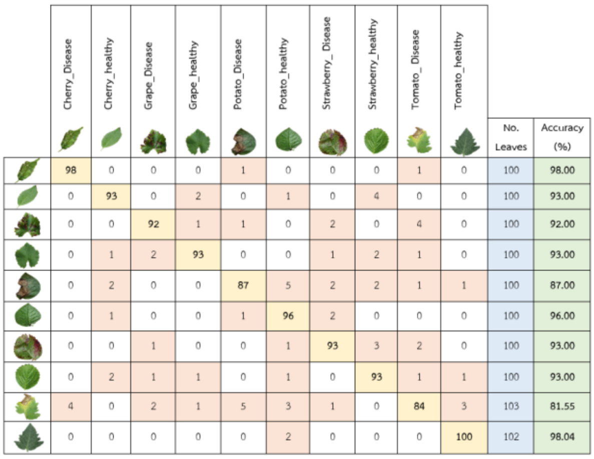
C. *Leaf Classification*

The final step of this research is the classification of the plant species using the plant leaf edge feature extracted from the image feature in previous step using Random Forest as a plant classifier. The image dataset was divided into the training set 70%, validation set 20%, and test set 10%, of 70 epochs. Experiments were performed to compare the results with the leaf datasets that identified key points on the leaf edge but does not remove image noise, contour properties, and texture properties. The results showed that the proposed method has a maximum leaf classification accuracy of 95.62% as shown in Table I. The class that can be predicted most accurately is Tomato healthy, Cherry Disease, and Potato healthy was 98.04%, 98.00%, and 96.00% accurate, respectively. The classes with the least accurate predictions were Tomato Disease, Potato Disease, and Grape Disease with 81.55%, 87.00%, and 92.00% accurate, respectively. The class Tomato_ Disease was shown to be the least accurate as diseased tomato leaves altered leaf shape and leaf edges. Therefore, when the diseased tomato leaves are subjected to image processing, the shape of the tomato leaves is slightly similar to the potato leaves of the Potato_Disease class. Like any other class of diseased plant leaves because these are classes of diseased plant leaves, some diseases cause leaf color to change but the leaf shape changes slightly. As a result, it retains a shape similar to that of the healthy plant leaf class. The confusion matrix is shown in Fig. 6.

From the experiment was plant leaf classification using leaf edge feature combination with SIFT leaf edge key point (proposed method), the maximum classification accuracy of 95.62 %. Key points on the leaf edge without removing noise on the image with an accuracy of 92.44%, a shape feature and a texture feature with an accuracy of 81.84%, a shape feature with an accuracy of 75.84%, and a texture feature with an accuracy of 70.89%, respectively.

TABLE I. SHOWS THE RESULTS OF THE COMPARISON OF THE CLASSIFICATION ACCURACY

	Feature	Accuracy (%)
1.	Shape	75.84
2.	GLCM	70.89
3.	Shape + GLCM	81.84
4.	Key point (SIFT) without Morphological Transformations	92.44
5.	**Propose Morphological Transformations + SIFT**	**95.62**



	Cherry_Disease	Cherry_healthy	Grape_Disease	Grape_healthy	Potato_Disease	Potato_healthy	Strawberry_ Disease	Strawberry_healthy	Tomato_ Disease	Tomato_healthy	No. Leaves	Accuracy (%)
	98	0	0	0	1	0	0	0	1	0	100	98.00
	0	93	0	2	0	1	0	4	0	0	100	93.00
	0	0	92	1	1	0	2	0	4	0	100	92.00
	0	1	2	93	0	0	1	2	1	0	100	93.00
	0	2	0	0	87	5	2	2	1	1	100	87.00
	0	1	0	0	1	96	2	0	0	0	100	96.00
	0	0	1	0	0	1	93	3	2	0	100	93.00
	0	2	1	1	0	1	0	93	1	1	100	93.00
	4	0	2	1	5	3	1	0	84	3	103	81.55
	0	0	0	0	0	2	0	0	0	100	102	98.04

Figure 6. Confusion matrix.

Additionally, experiment with two other datasets, the Flavia dataset, and the Swedish dataset, to compare the performance of the proposed methods. Shown as shown in Table II. The results showed that the Flavia dataset had an accuracy of 98.00% and the Swedish dataset with an accuracy of 97.01%, respectively. The results of the three datasets, PlantVillage dataset, Flavia dataset, and Swedish dataset showed that the Flavia dataset and Swedish dataset had higher accuracy than the PlantVillage dataset because both the Flavia dataset and the Swedish dataset are clearly differentiated by plant species. The PlantVillage dataset is a dataset that contains the leaves of the same species but is divided into healthy and diseased leaves. Sometimes the diseased leaves retained the same shape as the healthy ones. Therefore, the accuracy of the leaf classification was reduced but the accuracy was still good.

TABLE II. COMPARES EXPERIMENTAL RESULTS WITH OTHER AUTHORS

	Author	Feature	Dataset	Accuracy (%)
1.	Bisen *et al.* [7]	CNN (an automated plant identification system)	Swedish leaf	97.00
2.	Reddy *et al.* [9]	Texture, Morphological shape features, CNN	PlantVillage, Flavia, Swedish	89.99 100, 100
3.	Malarvizhi *et al.* [12]	shape, color and vein texture, Random Forest	Flavia	90
4.	Goyal *et al.* [20]	Shape + Vein Multi class Twin Support Vector Machine (MTSVM)	Flavia	98.11
5.	Kolivand *et al.* [21]	Leaf Venation	Flavia	98.6

6.	Kumar *et al.* [22]	Texture, Shape, morphological features, MLP and Adaboost	Flavia	95.40
7.	Pankaja *et al.* [23]	Texture, Shape, Color, Random Forest	Swedish, Flavia	97.58
8.	Wang *et al.* [24]	elliptical half-Gabor filters, maximum gap local line direction pattern, SVM	Flavia, Swedish	98.40 97.83
9.	Yang *et al.* [25]	Shape, Texture features, BP-RBF	Swedish	96.2
10.	**Proposed**	**Morphological Transformations + SIFT, Random Forest**	**PlantVillage** **Flavia** **Swedish**	**95.62** **98.00** **97.01**

To evaluate the proposed methods' performance, we compared the proposed method's accuracy with the state-of-the-art CNN model as in Table III. Comparative results showed that the proposed method had better leaf classification accuracy than ResNet50, VGG16, and Inception-V3, and was equal to InceptionResNetV2. Thus, it is demonstrated that the proposed method can optimize the classification of Random Forest because the extraction of the leaf image feature with the CNN model results in a more complex and complete leaf image feature. Then categorizing leaf images with Random Forest, each decision tree receives different and independent of the leaf image feature. Therefore, decision trees are not related to each other. However, the proposed method is still less efficient at classifying plant leaf data than Xception and DenseNet121. Because Xception uses depthwise separable convolutions, it has better feature extraction and data classification, and DenseNet121 uses feature input from all previous layers, therefore, achieving a more complete feature.

TABLE III. COMPARES EXPERIMENTAL RESULTS WITH OTHER CNN MODELS

CNN Model		Accuracy (%)
1.	ResNet50	86.07
2.	VGG16	93.73
3.	Inception-V3	95.42
4.	InceptionResNetV2	95.62
5.	Xception	96.52
6.	DenseNet121	96.82
7.	**Proposed Methodology**	**95.62**

V. CONCLUSION

In this paper, we present the classification of plant species by using leaf edge feature combination with SIFT leaf key points. There are three steps: image preprocessing, feature extraction, and image classification. The PlantVillage dataset was used for the experiment. The results showed that the proposed method had a 95.62% classification accuracy, which worked well with different leaf shape plant leaf datasets and the similar shape of the leaves of plants may decrease the accuracy of the classification of the data. In addition, the proposed method was used to experiment with the Flavia dataset and Swedish dataset. The results showed that the Flavia dataset had an accuracy of 98.00% and the Swedish dataset had an accuracy of 97.01%. From the experiments with all three datasets, the proposed method was suitable for the dataset that which the leaves had clearly different leaf characteristics (Flavia dataset). A dataset in which plant leaves are similar (PlantVillage dataset) may require other properties to identify similar plant leaves. For example, leaf width and length feature or color feature can be used in combination with the classification of diseased plant leaves.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

J. T. presented the idea and conducted the experiment. Sarun Intakosum examined and analyzed the results. The research article was written by J. T. and the research article was reviewed by Sarun Intakosum. All authors have put great emphasis on editing and improving the article until it becomes a complete article.

REFERENCES

[1] S. A. Agnes, J. Anitha, S. I. A. Pandian, and J. D. Peter, "Classification of mammogram images using multiscale all Convolutional Neural Network (MA-CNN)," *Journal of Medical Systems*, vol. 44, no. 30, pp. 1–9, 2020.

[2] A. M. Alhassan and W. M. N. W. Zainon, "Brain tumor classification in magnetic resonance image using hard swish-based RELU activation function-convolutional neural network," *Neural Computing and Applications*, vol. 33, pp. 9075–9087, 2021.

[3] J. Li, Y. Pei, F. Akhtar, T. Mahmood, and L. Zhang, "Fundus image-based cataract classification using a hybrid convolutional and recurrent neural network," *The Visual Computer*, vol. 37, pp. 2407–2417, 2021.

[4] Y. Zhang, S. Wang, H. Zhao, Z. Guo, and D. Sun, "CT image classification based on convolutional neural network," *Neural Computing and Applications*, vol. 33, pp. 8191–8200, 2021.

[5] P. Wei and B. Wang, "Food image classification and image retrieval based on visual features and machine learning," *Multimedia Systems, Special Issue Paper*, pp. 1–12, 2020.

[6] S. Gupta, K. Thakur, and M. Kumar, "2D-human face recognition using SIFT and SURF descriptors of face's feature regions," *The Visual Computer*, vol. 37, pp. 447–456, 2021.

[7] D. Bisen, "Deep convolutional neural network-based plant species recognition through features of leaf," *Multimedia Tools and Applications*, vol. 80, pp. 6443–6456, 2021.

[8] J. Basavaiah and A. A. Anthony, "Tomato leaf disease classification using multiple feature extraction techniques," *Wireless Personal Communications*, vol. 115, pp. 633–651, 2020.

[9] S. R. G. Reddy, G. P. S. Varma, and R. L. Davuluri, "Optimized convolutional neural network model for plant species identification from leaf images using computer vision," *International Journal of Speech Technology*, pp. 1–28, 2021.

[10] R. Gajjar, N. Gajjar, V. J. Thakor, N. P. Patel, and S. Ruparelia, "Real-time detection and identification of plant leaf diseases using convolutional neural networks on an embedded platform," *The Visual Computer*, pp. 1–16, 2021.

[11] L. Zhang, Y. Zheng, G. Zhong, and Q. Wang, "Research on leaf species identification based on principal component and linear discriminant analysis," *Cluster Computing*, vol. 22, pp. 7795–7804, 2019.

[12] K. Malarvizhi, M. Sowmithra, D. P. Gokula, and B. Kabila, "Machine learning for plant species classification using leaf vein

morphometric," *International Journal of Engineering Research & Technology (IJERT)*, vol. 10, pp. 513–516, 2021.
[13] M. Mohtashamian, M. Karimian, F. Moola, K. Kavousi, and A. Masoudi-Nejad, "Automated plant species identification using leaf shape-based classification techniques: A case study on Iranian maples," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, vol. 45, pp. 1051–1061, 2021.
[14] T. G. Devi and P. Neelamegam, "Image processing based rice plant leaves diseases in Thanjavur, Tamilnadu," *Cluster Computing*, vol. 22, pp. 13415–13428, 2019.
[15] D. P. Hughes and M. Salathe, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," arXiv:1511.08060, 2015.
[16] J. Canny, "A computational approach to edge detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-8, no. 6, pp. 679–698, 1986.
[17] D. G. Lowe, "Distinctive image features from scale-invariant key points," *International Journal of Computer Vision*, vol. 60, pp. 91–110, 2004.
[18] N. Charfi, H. Trichili, A. M. Alimi, and B. Solaiman, "Bimodal biometric system for hand shape and palmprint recognition based on SIFT sparse representation," *Multimedia Tools and Applications*, vol. 76, pp. 20457–20482, 2017.
[19] Z. Wang, H. Li, Y. Zhu, and T. Xu, "Review of plant identification based on image processing," *Archives of Computational Methods in Engineering*, vol 24, pp. 637–654, 2017.
[20] N. Goyal, K. Gupta, and N. Kumar, "Multiclass twin support vector machine for plant species identification," *Multimedia Tools and Applications*, vol 78, pp. 27785–27808, 2019.
[21] H. Kolivand, B. M. Fern, T. Saba, M. S. M. Rahim, and A. Rehman, "A new leaf venation detection technique for plant species classification," *Arabian Journal for Science and Engineering*, vol. 44, pp. 3315–3327, 2019.
[22] M. Kumar, S. Gupta, X. Z. Gao, and A. Singh, "Plant species recognition using morphological features and adaptive boosting methodology," *IEEE Access*, vol. 7, pp. 163912–163918, 2019.
[23] K. Pankaja and V. Suma, "Plant leaf recognition and classification based on the Whale Optimization Algorithm (WOA) and Random Forest (RF)," *Journal of The Institution of Engineers (India): Series B*, vol. 101, pp. 597–607, 2020.
[24] X. Wang, W. Du, F. Guo, and S. Hu, "Leaf recognition based on elliptical half gabor and maximum gap local line direction pattern," *IEEE Access*, vol. 8, pp. 39175–39183, 2020.
[25] X. Yang, H. Ni, J. Li, J. Lv, H. Mu, and D. Qi, "Leaf recognition using BP-RBF hybrid neural network," *Journal of Forestry Research*, vol. 33, pp. 579–589, 2022.

Jiraporn Thomkaew received the M.S. degree from the Department of Computer Science, Faculty of Science, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand in 2011. She is a Ph.D. student in computer science at the Faculty of Science at King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand. Her primary research interests include field is image preprocessing and computer vision.

Sarun Intakosum is a professor with the Computer Science at the Department of Computer Science, Faculty of Science, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand. He received a Ph.D. degree in computer science from the Asian Institute of Technology, Thailand in 2001. He received an M.S. degree in computer science from George Washington University, USA, an M.S. in computer science from Chulalongkorn University, Thailand in 1993, and a B.S. degree in mathematics from Chulalongkorn University, Thailand in 1989. His primary research interests include field is web services and SOA, distributed computing, software engineering, and computer education.