Research Article

Plant Leaf Image Recognition Based on Convolutional Neural Network

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ABSTRACT

The objective of this research is to develop a computer system which can recognize Thai leaf images by using convolutional neural network. The developed system is called "plant leaf image recognition system (PLIRS)". The system consists of four modules, namely: 1) image acquisition, 2) training dataset, 3) image recognition and 4) result presentation module. The system dataset consists of 10,800 leaf-images of 54 Thai plant-leaf species. The average time to train the dataset is 1.4357×10^4 seconds. The precision rate of the system is 96.99 percent with the average access time of 1.3649 second/image.

Keywords: confusion matrix, convolution neural network, leaf image, plant leaf image recognition, ResNet50

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Introduction

Approximately 450,000 plant species around the world are named, and almost two thirds live in tropics, and a third are at risk of extinction [1]. Thailand is a tropical country which is located in Southeast Asia. Therefore, there is a variety of plant species in every part of Thailand. Smitinan, (2021) created dataset of Thai plants which consists of 11,500 species with Thai names [2]. Therefore, it is impossible for a person, even a Thai person to know every Thai plant name. Therefore, the main objective of this research is to develop a computer system which can help people identify plant names by using only a plant leaf image. People can take a leaf image with a simple mobile phone camera and send the leaf image to identify a plant name from the PLIRS.

Many researchers and scientists employ three basic leaf features to recognize leaf images, namely: color, shape and texture features. Moreover, they also apply many computer techniques to build a computer system to recognize a leaf image, namely: support vector machine (SVM), k-nearest neighbor (KNN), artificial neural networks (ANN) and deep learning method [3]. Each technique has the following brief details.

Support Vector Machine (SVM)

The advantage of the SVM method is that it is the best to deal with small samples, nonlinear and high dimensional pattern recognition [4]. The comparison between different researchers (year), their extraction features, number of plant-leaf species, number of training, dataset size and precision rates using the SVM classification technique is shown in Table 1.

Table 1 The comparison between researchers who used SVM technique to recognize leaf images.

Researcher(s) (year)	Features	Plant leaf species	Dataset size (images)	Precision rates	Ref.
Prasad, (2011)	color, histogram, shape	23	624	95.02%	5
Ren, (2012)	histogram, shape	65	2,625	97.73%	6
Dimitris, (2014)	shape, histogram, edge	47	2,350	98.13%	7
Imah, (2017)	color, shape, margin, texture	15	720	92.98%	8
Kan, (2017)	shape, texture	12	240	93.33%	4

K nearest-neighbor (KNN)

A KNN is a nearest-neighbor classification model which can alter both the distance between the same feature and the number of nearest neighbors of a set of features [9]. The comparison between different researchers (year), their extraction features, number of plant leaf species, number of training, dataset size and precision rates of the KNN classification technique is shown in Table 2.

Table 2 The comparison between researchers who used KNN technique to recognize leaf images.

Researcher(s) (Year)	Features	Plant Leaf Species	Dataset Size (Images)	Precision Rates	Ref.
Wang, (2010)	shape	30	900	80.12%	9
Pornpanomchai, (2011)	color, shape	32	328	93.29%	10
Wang, (2011)	shape	220	6,600	91.30%	11
Yang, (2014)	contours	50	1,500	91.60%	12
Tsolakidis, (2014)	color, shape	47	2,350	97.18%	13
Wu, (2015)	color, shape	23,025	1,500,000	91.51%	14
Sahay, (2016)	shape	21	420	85.20%	15

Artificial Neural Network (ANN)

An artificial neural network is an interconnected group of nodes with their arcs simulating a human brain. Normally, a human brain consists of nerve cells, axon and dendrites. The ANN nodes classify in three layers, namely: input-nodes, hidden-nodes and output-nodes. Pattern recognition trains ANN to assign the correct target set of input patterns. Once trained, ANN can be used to recognize a pattern which has never been seen before [15]. The comparison between some researchers who employed ANN to recognize leaf images is shown in Table 3.

Table 3 The comparison between researchers who used the ANN technique to recognize leaf images.

Researcher(s) (Year)	Features	Plant Leaf Species	Dataset Size (Images)	Precision Rates	Ref.
Kulkarni, (2013)	color, shape, texture	32	1,600	93.82%	16
Hati, (2013)	color, shape	20	534	92.00%	17
Chaki, (2015)	color	31	930	67.70%	18
Wang, (2016)	shape, texture	405	28,577	96.67%	19
George, (2017)	color, shape, leaf vein	10	150	95.30%	20
Chaki, (2019)	color, shape, texture	55	1,100	n/a	21
Tang, (2016)	shape	100	1,600	93.50%	22

Deep learning method

A convolutional neural network (CNN) is a kind of deep learning method. The CNN is a feed-forward artificial neural network which reduces the complexity of the network by using local connections, weight sharing and pooling operations together. It uses multiple convolutions in parallel to extract various leaf image features and applies a full connection neural network to classify a recognition result [23-24].

The comparison between some researchers who employed CNN to recognize leaf images is shown in Table 4.

Table 4 the comparison between researchers who used the CNN technique to recognize leaf images.

Researcher(s) (Year)	Features	Plant Leaf Species	Dataset Size (Images)	Precision Rates	Ref.
Jeon, (2017)	-	8	3,767	94.00%	24
Kang, (2018)	-	63	2,739	96.08%	25
Zhang, (2019)	-	15	375	94.80%	26

Based on the previous research, there is no consensus as to which method is the best one. A deep learning method is a good method to recognize a leaf image because it is easy to train the neural network and generate very high precision rates. The PLIRS adopted a deep learning method to develop the system. The details of the PLIRS is described in the next section.

Materials and Methods

The system was developed on the following computer hardware and software. The Intel® Core i5^{TM} 11400 CPU @ 2.6 GHz (Intel's headquarters is in Santa Clara, CA, USA) was used as the central processing unit, RAM 8 GB, and Windows 10 was the software system (Microsoft Corp.; Redmond, WA, USA). MATLAB R2020b (The Math Works Inc.; Natick, Massachusetts, USA) with license number 40598465 was the developing software. The digital camera used in this research was the Huawei Y9 (Huawei Technologies Co., Ltd., Shenzhen, China).

Conceptual diagram

The PLIRS conceptual diagram starts when a user takes a plant leaf image by using a mobile-phone-camera. After that, the leaf image is submitted to the computer system for identifying the plant species. Finally, the developed system displays the recognition results, as shown in Figure 1.

System structure chart

The PLIRS system structure chart is composed of four main modules, namely: 1) image acquisition, 2) CNN training, 3) leaf image recognition and 4) result presentation (as shown in Figure 2). Each module has the following details.

Image acquisition

This module captures plant leaf images which are laid on a piece of white A4-paper. A photo of each leaf is taken by a Huawei Y9 mobile phone camera in both a front and rear image, as shown in Figure 3 (a) and (b), respectively. The width and height of the input image are 4,160x3,120 pixels with 96 dpi (dot per inch). All leaf species in this research are normal plants which can be found in Bangkok, Thailand. 54 plant species were used, and 200 images per species were taken. 10,800 leaf images were taken during 13 May–9 June 2021, and used for this research leaf dataset.

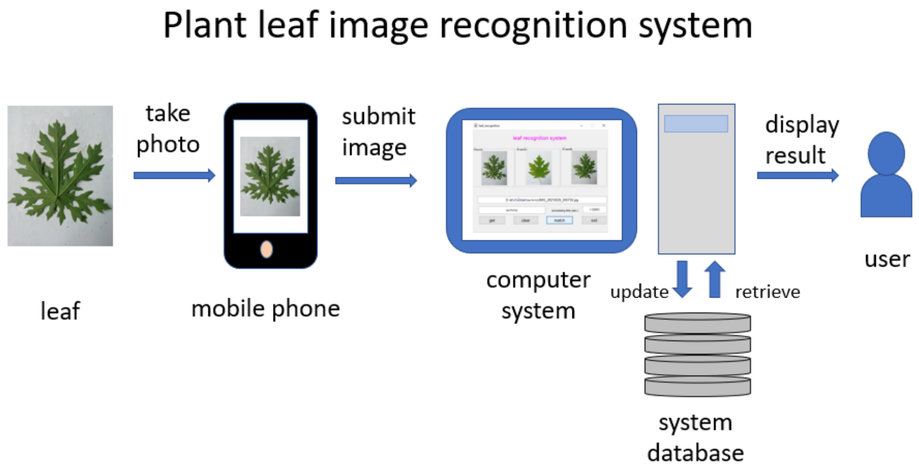

Figure 1 The PLIRS conceptual diagram

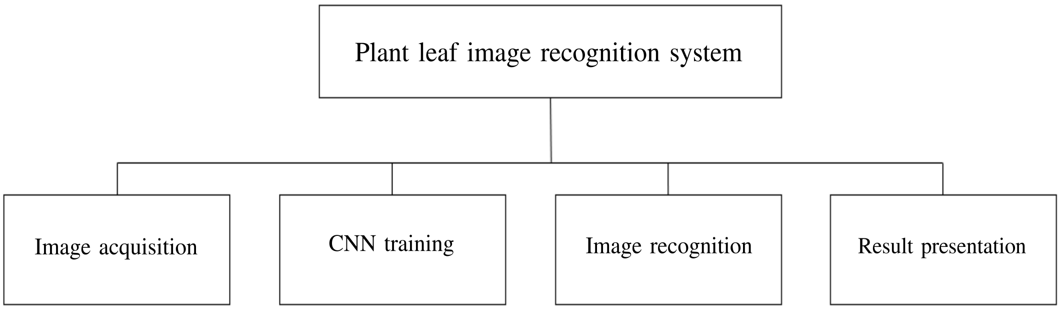

Figure 2 The system structure chart

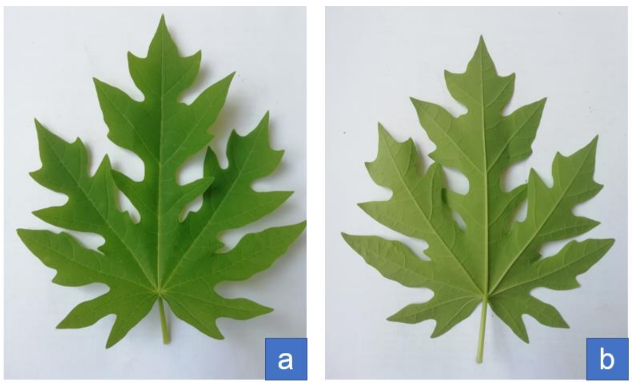

Figure 3 The sample of leaf images of both sides (a) front image (b) rear image

CNN training

This research employed a convolutional neural network called "ResNet50" in the MATLAB toolbox for training and testing the PLIRS. The ResNet50 contains fifty layers, which can train and match more than a million images. Erdem, (2020) illustrated the ResNet50 architecture as shown in Figure 4 [27-28]. The structure of the CNN contains five layers, namely: input layer, convolutional layer, rectified linear unit layer, pooling layer and fully connected layer. Each layer has the following details.

1. The input layer is an input image layer which resizes the original image to a suitable size for the CNN (224x224 pixels with 3 channels).
2. The convolution layer filters images to find their features and matching feature points during testing. The ResNet50 employs a scatter plot filter to compare the reduced feature vector of an image.
3. The rectified linear unit (ReLU) layer swaps every negative number of the pooling layer with 0. This layer helps the CNN to keep learning important information of an image.
4. The pooling layer shrinks down unnecessary information and preserves the most important information and keeps it for maximum value.
5. The fully connected layer takes the high-level filtered images and translates them into categories with labels. The output of the CNN consists of 54 nodes, which is equal to a number of plant-leaf species in this research.

The output result of ResNet50 is selected from the highest percentage of features matching. The PLIRS trained the system with 80 percent of the dataset (8,640 images) and tested the system with 20 percent of the dataset (2,160 images). The average training dataset took 1.4357×10^4 seconds to train. The PLIRS cannot update an unknown leaf image into the dataset because the CNN needs to compare all the images in a dataset and generate the matching output results.

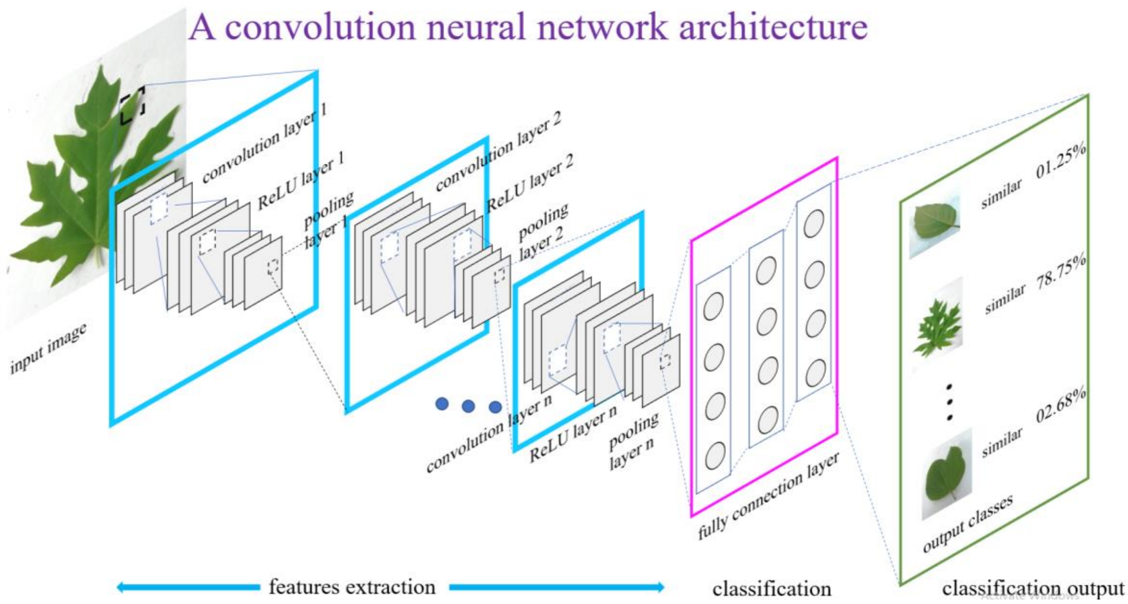

Figure 4 A convolutional neural networks structure in this research

Image recognition

This module starts when users take an unknown leaf image with a simple mobile-phone-camera in a .JPG file-format. Then, they submit the leaf image to the PLIRS for recognizing. After that, the PLIRS recognizes the unknown leaf-image by using the ResNet50 in MATLAB. Finally, the PLIRS displays the recognition results via the PLIRS graphic user interface (GUI). The average access time to recognize a leaf image is 1.3649 seconds.

Result Presentation

This section shows the plant leaf recognition results. The GUI of PLIRS consists of three display graphic windows, three display text boxes and four push buttons as shown in Figure 5. The PLIRS graphic user interface has the following details.

The three display graphic windows show a close-up of the plant leaf images and have the following details:

1. The window of the input leaf image as shown in Figure 5, label 1
2. The window of the front leaf recognition result as shown in Figure 5, label 2
3. The window of the rear leaf recognition result as shown in Figure 5, label 3

The three display text boxes have the following details:

1. The display of the file name of the plant leaf image shown in Figure 5, label 4
2. The display of the recognition result box as shown in Figure 5, label 5
3. The display of the processing time value as shown in Figure 5, label 6

The four push buttons have the following details:

1. The get image button for getting a plant leaf image as shown in Figure 5, label 7
2. The clear button for clearing all PLIRS values as shown in Figure 5, label 8
3. The match button for recognizing a plant leaf image as shown in Figure 5, label 9
4. The exit button for exiting the system as shown in Figure 5, label 10.

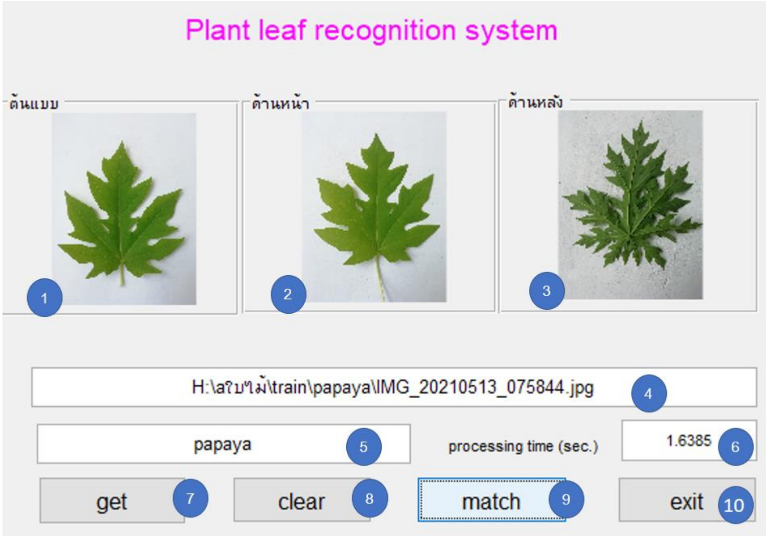

Figure 5 the graphic user interface of PLIRS

Results and Discussion

Experimental results

The PLIRS conducted the experiment with a simple mobile phone camera, which users can easily access. There are 10,800 plant leaf images of 54 species in the system dataset, in which there are 200 images per species. The PLIRS employed a MATLAB function called “confusion.getMatrix” to calculate statistical values for measuring the system performance. There are three steps to calculate the system performance, namely: 1) convert multi-class confusion matrix, 2) calculate the statistical values and 3) find average statistical values. Each step has the following details.

1. Convert multi-class confusion matrix to a true positive (tp), false positive (fp), false negative (fn) and true negative (tn), as shown in Table 5.

2. Calculate the statistical values, namely: accuracy, error, sensitivity, specification, precision, of the PLIRS. Each statistical value has the following details.

2.1 Accuracy is one of the most common measurements of the recognition performance and it is defined as a ratio between the correct object recognition to the total number of objects, as shown in Equation 1.

$$\text{Accuracy} = (tp + tn) / (tp + fp + fn + tn) \quad (1)$$

2.2 Error is the opposite of accuracy, which is defined as a ratio between the incorrect object recognition to the total number of objects, as shown in Equation 2.

$$\text{Error} = (fp + fn) / (tp + fp + fn + tn) \quad (2)$$

2.3 Sensitivity (true positive rate, hit rate or recall) represents the positive correct object recognition to the total number of positive objects, and it is estimated according to Equation 3.

$$\text{Sensitivity} = tp / (tp + fn) \quad (3)$$

2.4 Specificity (true negative rate or inverse recall) is expressed as the ratio of the correctly recognized negative objects to the total number of negative objects, as shown in Equation 4.

$$\text{Specification} = tn / (fn + tn) \quad (4)$$

2.5 Precision is a measure of how well a recognition performs with a specific object, as shown in Equation 5.

$$\text{Precision} = tp / (tp + fn) \quad (5)$$

The statistical values, namely: accuracy, sensitivity, specification, precision, of 54 plant species are shown in Table 6.

3. Find average statistical values, which are accuracy, error, sensitivity, specificity and precision. The average statistical values are:

Accuracy:	0.9659
Error:	0.0341
Sensitivity:	0.9659
Specificity:	0.9994
Precision:	0.9699

Table 5 The multi-class confusion matrix of the PLIRS
(tp = true positive, fp = false positive, fn = false negative, tn = true negative)

No.	Common name	Scientific name	tp	fp	fn	tn
1	Thai basil	*Ocimum tenuiflorum* L.	192	2	8	10598
2	Ribbon plant	*Dracaena sanderiana*	199	1	1	10599
3	Kalanchoe	*Kalanchoe blossfeldiana* Poelln.	197	3	3	10597
4	Jack fruit tree	*Artocarpus heterophyllus* Lam.	193	1	7	10599
5	Galanga	*Alpinia siamensis* K.Schum.	198	1	2	10599
6	Camellia	*Camellia japonica* L.	200	17	0	10583
7	Chong kho	*Bauhinia purpurea* L.	198	0	2	10600
8	Shoe flower	*Hibiscus rosa-sinensis* L.	199	2	1	10598
9	Java apple	*Eugenia javanica Lam.*	197	24	3	10576
10	Desert rose	*Adenium obesum (Fosk.)* Roem. & Schult.	200	6	0	10594
11	Wildbetal leafbush	*Piper sarmentosum* Roxb.	198	1	2	10599
12	Javanese cassia	*Cassia javanica* L.	191	5	9	10595
13	Eukien tea	*Carmona retusa (Vahl.) Masam.*	189	4	11	10596
14	Bungor	*Lagerstroemia floribunda* Jack	198	45	2	10555
15	Ivy gourd	*Coccinia grandis* (L.) Voigt.	196	2	4	10598
16	Pong pong	*Cerbera odollam* Gaertn.	193	3	7	10597
17	Waterkanon	*Ruellia tuberosa* Linn.	195	0	5	10600
18	Yellow bell	*Tecoma stans* (L.) Kunth	196	5	4	10595
19	Pomegranate	*Punica granatum* L.	167	0	33	10600
20	Lotus	*Nelumbo nucifera* Gaertn.	199	2	1	10598
21	Zinnia	*Zinnia violacea* Cav.	200	0	0	10600
22	Sage rose	*Turnera ulmifolia* L.	198	2	2	10598
23	Andaman Redwood	*Pterocarpus indicus* Willd.	172	0	28	10600
24	Devil tree	*Alstonia scholaris* L. R. Br.	196	1	4	10599
25	Cayenne pepper	*Capsicum frutescens* L.	199	3	1	10597
26	Gardenia jasmine	*Gardenia augusta* L. Merr.	174	9	26	10591
27	Kaffir lime,	*Citrus hystrix* DC.	197	1	3	10599
28	Common lime	*Citrus aurantifolia* (Christm.) Swingle	173	0	27	10600
29	Mango	*Mangifera indica* L.	192	4	8	10596
30	Carandas-plum, Karanda	*Carissa carandas* L.	189	1	11	10599
31	Star gooseberry	*Phyllanthus acidus* L. Skeels	199	0	1	10600

No.	Common name	Scientific name	tp	fp	fn	tn
32	Papaya	*Carica papaya* L.	199	0	1	10600
33	Jusmine	*Jasminum sambac* L. Aiton	198	47	2	10553
34	Indian mulberry	*Morinda citrifolia* L.	163	0	37	10600
35	Pudding pine	*Cassia fistula* L.	191	2	9	10598
36	Picara	*Excoecaria cochinchinensis* Lour.	194	1	6	10599
37	Temple tree	*Plumeria obtusa* L.	200	1	0	10599
38	Nodding clerodendron	*Clerodendrum wallichii* Merr.	197	7	3	10593
39	Kitchen mint	*Metha cordifolia* Opiz.	199	6	1	10594
40	Tangerine	*Citrus Reticulata* Blanco	200	47	0	10553
41	Pomelo	*Citrus maxima* Merr.	178	1	22	10599
42	Babylon willow	*Salix babylonica* L.	200	3	0	10597
43	Queen's flower	*Lagerstroemia speciosa* L. Pers.	196	4	4	10596
44	Cemetery tree	*Polyalthia longifolia* Benth Hook.f. var. Pandurata	192	2	8	10598
45	Zephyranthes	*Ixora chinensis* Lamk., *Ixora spp.*	168	4	32	10596
46	Asclepiadaceae	*Dischidia nummularia* Variegata	200	0	0	10600
47	Sword fern	*Nephrolepsis biserrata* cr.Furcan	200	2	0	10598
48	Paper flower	*Bougainvillea hybrid*	197	20	3	10580
49	Andaman satinwood	*Murraya paniculata* L. Jack	197	1	3	10599
50	Redbird cactus	*Pedilanthus tithymaloides* L. Poit.	197	11	3	10589
51	Water jasmine	*Wrightia religiosa* (Teijsm & Binn.) Benth. ex Kurz	194	62	6	10538
52	Sweet basil	*Ocimum basilicum* L.	192	0	8	10600
53	Kan phai Mahidol	*Afgekia mahidoliae* B.L. Burtt & Chermsir.	198	2	2	10598
54	Bodhi tree	*Ficus religiosa* L.	198	0	2	10600

The PLIRS employed the CNN to recognize plant leaf images, which have the multi-class confusion matrix, as shown in Table 5. The average statistical values, namely: accuracy, error, sensitivity specificity and precision are 0.9659, 0.0341, 0.9659, 0.9994 and 0.9699, respectively. Statistical values of each plant leaf species are shown in Table 6 as follows.

Table 6 The PLIRS statistical values

No.	Common name	Accuracy	Error	Sensitivity	Specificity	Precision
1	Thai basil	0.9600	0.0400	0.9600	0.9998	0.9897

No.	Common name	Accuracy	Error	Sensitivity	Specificity	Precision
2	Ribbon plant	0.9950	0.0050	0.9950	0.9999	0.9950
3	Kalanchoe	0.9850	0.0150	0.9850	0.9997	0.9850
4	Jack fruit tree	0.9650	0.0350	0.9650	0.9999	0.9949
5	Galanga	0.9900	0.0100	0.9900	0.9999	0.9950
6	Camellia	1.0000	0.0000	1.0000	0.9984	0.9217
7	Chong kho	0.9900	0.0100	0.9900	1.0000	1.0000
8	Shoe flower	0.9950	0.0050	0.9950	0.9998	0.9901
9	Java apple	0.9850	0.0150	0.9850	0.9977	0.8914
10	Desert rose	1.0000	0.0000	1.0000	0.9994	0.9709
11	Wildbetal leafbush	0.9900	0.0100	0.9900	0.9999	0.9950
12	Javanese cassia	0.9550	0.0450	0.9550	0.9995	0.9745
13	Eukien tea	0.9450	0.0550	0.9450	0.9996	0.9793
14	Bungor	0.9900	0.0100	0.9900	0.9958	0.8148
15	Ivy gourd	0.9800	0.0200	0.9800	0.9998	0.9899
16	Pong pong	0.9650	0.0350	0.9650	0.9997	0.9847
17	Waterkanon	0.9750	0.0250	0.9750	1.0000	1.0000
18	Yellow bell	0.9800	0.0200	0.9800	0.9995	0.9751
19	Pomegranate	0.8350	0.1650	0.8350	1.0000	1.0000
20	Lotus	0.9950	0.0050	0.9950	0.9998	0.9901
21	Zinnia	1.0000	0.0000	1.0000	1.0000	1.0000
22	Sage rose	0.9900	0.0100	0.9900	0.9998	0.9900
23	Andaman redwood	0.8600	0.1400	0.8600	1.0000	1.0000
24	Devil tree	0.9800	0.0200	0.9800	0.9999	0.9949
25	Cayenne pepper	0.9950	0.0050	0.9950	0.9997	0.9852
26	Gardenia jasmine	0.8700	0.1300	0.8700	0.9992	0.9508
27	Kaffir lime,	0.9850	0.0150	0.9850	0.9999	0.9950
28	Common lime	0.8650	0.1350	0.8650	1.0000	1.0000
29	Mango	0.9600	0.0400	0.9600	0.9996	0.9796
30	Carandas-plum, Karanda	0.9450	0.0550	0.9450	0.9999	0.9947
31	Star gooseberry	0.9950	0.0050	0.9950	1.0000	1.0000
32	Papaya	0.9950	0.0050	0.9950	1.0000	1.0000
33	Jusmine	0.9900	0.0100	0.9900	0.9956	0.8082
34	Indian mulberry	0.8150	0.1850	0.8150	1.0000	1.0000
35	Pudding pine	0.9550	0.0450	0.9550	0.9998	0.9896
36	Picara	0.9700	0.0300	0.9700	0.9999	0.9949
37	Temple tree	1.0000	0.0000	1.0000	0.9999	0.9950

No.	Common name	Accuracy	Error	Sensitivity	Specificity	Precision
38	Nodding clerodendron	0.9850	0.0150	0.9850	0.9993	0.9657
39	Kitchen mint	0.9950	0.0050	0.9950	0.9994	0.9707
40	Tangerine	1.0000	0.0000	1.0000	0.9956	0.8097
41	Pomelo	0.8900	0.1100	0.8900	0.9999	0.9944
42	Babylon willow	1.0000	0.0000	1.0000	0.9997	0.9852
43	Queen’s flower	0.9800	0.0200	0.9800	0.9996	0.9800
44	Cemetery tree	0.9600	0.0400	0.9600	0.9998	0.9897
45	Zephyranthes	0.8400	0.1600	0.8400	0.9996	0.9767
46	Asclepiadaceae	1.0000	0.0000	1.0000	1.0000	1.0000
47	Sword fern	1.0000	0.0000	1.0000	0.9998	0.9901
48	Paper flower	0.9850	0.0150	0.9850	0.9981	0.9078
49	Andaman satinwood	0.9850	0.0150	0.9850	0.9999	0.9950
50	Redbird cactus	0.9850	0.0150	0.9850	0.9990	0.9471
51	Water jasmine	0.9700	0.0300	0.9700	0.9942	0.7578
52	Sweet basil	0.9600	0.0400	0.9600	1.0000	1.0000
53	Kan phai Mahidol	0.9900	0.0100	0.9900	0.9998	0.9900
54	Bodhi tree	0.9900	0.0100	0.9900	1.0000	1.0000

The PLIRS mismatch example is shown in Figure 6. The input image is a pomelo leaf (Figure 6, label 1) and the mismatching output leaf is a sage rose of both sides, the front and rear sides are shown in Figure 6, label 2 and label 3, respectively. The reason of the mismatching is because both the pomelo and sage rose leaf images are very similar.

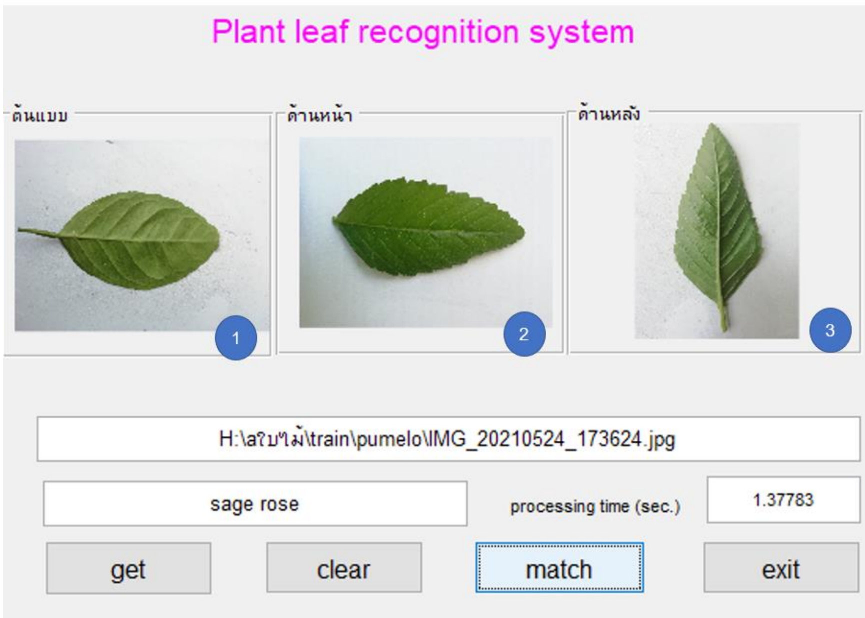

Figure 6 The PLIRS mismatching example

Discussion

There are more than 450,000 plant species around the world having been named and many more are still unknown [1]. For example, Kun phai Mahidol (number 53, Table 5) is a plant species which was only discovered and named by the year 1967. It is impossible for humans to recognize all the plant species around the world. Therefore, many botanists and computer scientists try to develop computer systems to recognize plant species. The computer researchers employ many techniques to recognize plant species with very high precision rates, as shown in Tables 1 to 4. Nevertheless, there are three main problems for researchers to build leaf recognition systems, namely:

1. Some leaf sizes are very big, which makes it very difficult to take a photo of the leaf in one image. For example, a banana (*Musa Acuminata Triploid AAA, Cavendish*) leaf size is around 70-100 cm. wide and 150–400 cm. long, and a teak tree (*Tectona grandis L.f.*) leaf size is around 12–35 cm. wide and 12-75 cm. long, etc. Researchers cannot extract texture features of a leaf image if they take a giant leaf in an image.

2. The leaf datasets are too small compared with the real number of plant species around the world. Wu, (2015) conducted experiments with a huge dataset, containing 23,025 leaf species, but it is very small compared with 450,000 plant species around the world [14].

3. All researchers employed leaf recognition systems only for local leaf images. They do not have global leaf image datasets. Many scientists and researchers hope to have a global leaf image dataset to conduct experiments.

A leaf image recognition system is a challenging task, but very useful for people, especially botanists, to identify the plant species. Researchers need not only to collect all plant leaves around the world to build a plant leaf dataset but also to develop efficient techniques to recognize leaf species.

Conclusion

The PLIRS fulfills the objective of this research, which is to develop a computer system to recognize plant leaf images. The PLIRS employed ResNet50 in MATLAB to build a deep learning technique for recognizing Thai leaf images. The system dataset trained 54 Thai plant species, with each species having 200 images, for a total of 10,800 images. The average training dataset took 1.4357×10^4 seconds to train. The statistical values to measure system performance are accuracy, error, sensitivity specificity and precision, which are 0.9659, 0.0341, 0.9659, 0.9994 and 0.9699, respectively. The system average access time is 1.3649 seconds per image.

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