Identification of Lime Leaf Diseases with Deep Learning Technique on Android Smartphone

N Thammachat¹, P Bootkote¹, S Thanimkarn¹ and C Preecha²
¹Curriculum of Agricultural Machinery Technology, Faculty of Agriculture, Rajamangala University of technology Srivijaya, Nakhon Si Thammarat, 80110, Thailand
²Curriculum of Plant Science, Faculty of Agriculture, Rajamangala University of technology Srivijaya, Nakhon Si Thammarat, 80110, Thailand

Email address: nasaporn.t@rmutsv.ac.th

Abstract. Leaf plant diseases are difficult to recognize because the symptoms of the disease appear very similar causing farmers to solve problems that don't match the symptoms of the disease. This research presents the creation of a smartphone application for the identification of lime leaf diseases with deep learning technique. This uses 2 sets image data classified by plant disease specialist, 400 images for algorithm training and 100 images for algorithm testing for each disease. Algorithm development using Convolutional Neural Network that imitates the working of human brain neurons. This uses the supervised learning network type. The algorithm was developed based on the TensorFlow Framework, Google's open source library, and was used by Android Studio software to build smartphone applications in the Android operating system. For use, the algorithm that has been learned through the process of learning is embedded into the developed smartphone application. Then it was tested the application accuracy. The results of a smartphone application in the identification of lime leaf diseases found more than 90% accurate.

1. Introduction
Lime was an economic crop growing almost all over the country. In 2018, 108,779 rai of perennial area, 107,634 rai of a yield area, 152,335 tons of a yield and 1,415 kilograms of a yield per rai. The information of each region was as shown in table 1 [1]. Lime fell into citrus genus that was very useful and valuable because it could be used to cook, to make a beverage and had medicinal properties. Also, limes were high in vitamin C, so limes were popular as a cosmetic ingredient, making it important and needy throughout the year. Not just only the summer every year that affected the production of lime yields, diseases and pests of limes also greatly did. When considering some diseases of limes that appeared on leaves, stems, branches and fruits were very similar, the agriculturists then used the wrong method of treatment. Therefore, the diseases still remained, then causing the epidemic.
Table 1. Lemon planting data and yield for 2018 [1]

| Region           | Perennial Area (rai) | Yield area (rai) | Yield (trees) | Yield per rai (kg) |
|------------------|----------------------|------------------|--------------|-------------------|
| Northern Region  | 28,124               | 27,878           | 38,438       | 1,379             |
| Northeastern Region | 1,872              | 1,764            | 459          | 260               |
| Central Region   | 71,996               | 71,342           | 109,980      | 1,542             |
| Southern Region  | 6,787                | 6,650            | 3,458        | 520               |
| Total            | 108,779              | 107,634          | 152,335      | 1,415             |

Today, Artificial Neural Network, which imitated the function of the human brain, was widely used specifically for identification, such as for plants [2], fruits [3-4] and plant diseases [5-7]. The results were that in the identification of plant diseases, most of them used effective neural networks and longer learning, so-called deep learning. Deep learning is utilizing neural networks with multiple layers and a large amount of data than traditional ML algorithms. Deep learning can be used to every type of data such as image, text, etc. The popular deep neural network is the Convolutional Neural Network (CNN) [7]. And by comparing CNN’s different architectures, such as LeNet, AlexNet, GoogLeNet, and VGG to identify plant diseases, finding that it was more than 90% accurate [6]. CNN was also developed as an application on smartphones to identify plant diseases, such as grape disease [8-9], wheat diseases [5] and citrus disease [10]. However, no development of smartphone applications for lime foliar and citrus disease identification using the CNN was found. Therefore, the researchers appreciated the effectiveness of the algorithm which was developed by using CNN towards lime foliar disease. If the algorithm was used to create an application on a smartphone, it would be a great benefit to lime and citrus agriculturists.

2. Convolutional Neural Network

The strengths of CNN network are the capability of both feature extraction and classification of images, which is unlike the conventional machine learning methods that can only classify and group data. The CNN network consists of convolution layers, max pooling layers, a fully connected layer or a hidden layer, and a classification layer shown in Figure 1. The details are as follows.

![Figure 1. Convolutional Neural Network](image-url)
Convolutional layer is the result finding of the neuron connected from the local region of the image by reducing the size of the image to a square with the value of the dimension of the image equal to 3 in case of RGB image. The calculation of the convolution layer would make through the sub-region, which is calculated as dot product and kernel. Kernel must be smaller than the image size. The result obtained from the convolution is called Feature Map as shown in Figure 2.

Figure 2. The illustration of the convolutional Layer. The dot production calculation between sub-region of the image and convolution kernel. [2]

Max pooling layer is the intermediate layer between the convolution layers to downsample the feature map. It is divided into local regions, then local regions are divided into p x p / p which are set to be between 2 and 5. Therefore, the largest value in each pool will be chosen as a representative. Then, the system will stride to the local region continuously, for example, stride forwards with the rate of 2 pixels of each move, until meeting the last point of feature map. The calculation of max pooling is shown in Figure 3.

Figure 3. The illustration of max pooling with 2x2 kernel and stride 2. [2]

Fully connected layer is used to classify objects. Every neuron in this layer is completely connected with convolution and pooling layers, also known as the structure of the neural network, in which the result number is the number of groups to be classified.
Inception-v3 was developed from GoogLeNet, the first version of inception deep convolutional architecture, after which it was developed to be Inception-v2, which was about the batch normalization, while Inception-v3 was about factorization ideas which were aimed at reducing the number of connections or parameters without degrading network performance. The details are as follows.

(1) Factorization into smaller convolutions is a replacement of $5 \times 5$ convolution with $3 \times 3$ convolutions of 2 layers, resulting in a decrease number of parameters from $25 \times (5 \times 5)$ to $18 \times (3 \times 3)$ parameters. The parameter is reduced by $28\%$ as shown in Figure 4 and the inception module is as shown in Figure 5.

![Figure 4](image1.png)

**Figure 4.** Mini-network replacing the $5 \times 5$ convolutions [12]

(2) Factorization into asymmetric convolutions is the replacement of $3 \times 3$ convolution with $3 \times 1$ convolution followed by $1 \times 3$ convolution, resulting in a $33\%$ decrease in the number of parameters shown in Figure 6. According to the theory, the argument towards the replacement with any $n \times n$ convolution by a $1 \times n$ convolution would happen and to be followed by a $n \times 1$ convolution and the computational cost saving increases dramatically as $n$ grows. Inception module was shown in Figure 7.

![Figure 5](image2.png)

**Figure 5.** Inception modules where each $5 \times 5$ convolution is replaced by two $3 \times 3$ convolution [12]
Figure 6. Mini-network replacing the $3 \times 3$ convolutions. The lower layer of this network consists of a $3 \times 1$ convolution with 3 output units. [12]

Figure 7. Inception modules after the factorization of the $n \times n$ convolutions. [12]

3. Materials and Methods

3.1. Study the data of lime foliar disease, algorithms development, and applications
Explore the lime foliar disease in Nakhon Si Thammarat area to be collected as visual data to develop algorithms for plant disease identification. The images obtained first went through disease classification by plant disease experts. The expertly classified images were divided into 2 data sets: 400 images for algorithm training and 100 images for algorithm testing for each disease.

3.2. Algorithm development
The algorithm was developed based on the TensorFlow Framework, Google's open source library. The development of the algorithm includes the following process: 1) preprocessing by resizing RBG image to 224x224 and converting the visual data into numerical data in the range of 1 to 225 to 3 layers of data including R, G, and B; 2) model creation by Convolutional Neural Network (CNN) by using Inception-v3 architecture because it gave the least error value when comparing with other architectures [12] and
the 120 training epochs, the classification output of 6 classes by the number of diseases were all assigned; 3) model evaluation to obtain the training accuracy and the validation accuracy of the test.

3.3. Creation of smartphone application

Creation of smartphone application in the Android operating system using Android Studio software for the application, embedding learning algorithms into smartphone applications. Test applications on smartphones to determine the accuracy and error of identification with 50 images for each disease.

4. Results and Discussion

4.1. The results of the study of the lime disease

From the study, the lime foliar diseases, where were caused by bacteria, such as canker and greening; by fungi, such as greasy spot, sooty mold, root and foot rot; by algae, such as algal spot or red rust; by virus, such as tristeza; and by nutrient deficiency, such as zinc deficiency. The details of the disease are as follows.

4.1.1 Canker disease was caused by Xanthomonas axonopodis pv. citri bacteria. It could occur on the leaves, branches, stems, and fruits of lime. The first staged symptoms were a juicy clear pin-sized circular spot. Then, it got larger and was swollen like sponges with light yellow color. Later, it turned to be a convex with dark brown color, then it was scabbed and crusty like ringworms. The center of lesion was dented and had a pale-yellow halo surrounding the lesion on the leaves. The scabs on the fruits might be larger than on the leaves and might have a rubber flowing out of the scabs, and might cause the fruits to break transversely, starting from the edge of scabs when being exposed to water or heavy rain, and the fruits tent to fall off as it got aged [13-16].

4.1.2 Zinc deficiency disease was caused by zinc deficiency. The first staged symptoms happened with the young leaves. The veins and midribs of the leaves turned yellow and then the symptoms were more obvious as if the veins and the midribs of the leaves were green on the laminas or the yellowish leaves. Severe deficiency would make the young leaves smaller, and the tip of the leaves would be slender and pointed up [14, 17, 18].

4.1.3 Algal spot or red rust disease was caused by Cephaleuros virescens algae. The first staged symptoms were grayish-green spots, with velvet-like fine lines of 0.3-0.5 centimeters, and then the spots turned orange or rusty iron colors. At the stage where the algae produced fully ripe spores, the scabs looked like orange velvet. The symptoms of the branches were similar to those of the leaves, but if there were severe symptoms, the bark would crack. Dry scabs were similar to Canker disease caused by bacteria[16].

4.1.4 Tristeza disease was caused by the Citrus Tristes Virus (CTV). Young leaves turned pale green or alkaline, resembling a mild lack of nutrients. The leaves show a short, transparent condition, the leaves are small, the leaves are usually yellow, pale, or unevenly green. New splinters or dwindling branches often dry to death from the tip of the branch. It's very fruitful, but it's often easy to fall off. The effect is small. The area of the trunk or large branches is not smooth, similar to the trunk or branches, twisting into waves or grooves, many of which are long parallel along the trunk or branches. Diseased trees often grow slower than normal trees, often shabby and eventually die [14].

4.1.5 Greasy spot disease was caused by the Phomopsis citri fungus, which started destroying the leaves from the young age. The characteristics of the disease were small clear spots under the laminas and then
the spots became yellow and green or brown convex and then became bigger brown or black convex spreading all over the leaves. Oily and non-irritation to the hands, feeling like stain of the saliva mixed with betel, spat by betel chewers, were the present characteristics of the convex. The diseased leaves turned yellow and fell off before they should [14, 16]

4.1.6 Sooty mold was caused by the Capnodium citricola and Meliola spp. fungus. It could occur on leaves, branches and fruits. It was found to be a stain or black flaky of black fungus. When rubbing or scraping, it came off as dirty flakes, causing the green part of the plant was not able to get sunlight for normal photosynthesis. For large branches, it was often found the cracks and rubber flowing [16-18]

4.1.7 Greening disease was caused by fastidious bacteria. The symptoms were that the young leaves turned yellow with green vein, which was like the leaves having zinc deficiency. The leaves were smaller, narrower, pointed up, and yellow or green with rash all over the leaves. New ruptures were reduced and dry ingress from the tip of the branches were found. The size of the fruits was smaller and the fruits were easy to fall off. The shell color was uneven when the fruits were ripe. The root system was not strong. An unusual incident of less branching of the capillary root was detected. Diseased trees often grew slowly and were susceptible to other diseases, shabby and eventually dying [14, 16].

4.1.8 Root and foot rot were caused by Phytophthora parasitica fungi and might be caused by water trapping. The foliar symptoms were the burning leaves, both in young to fully grown leaves, and dark brown spots were found around the centers and the edges of the leaves. The tips of the leaves were brown and juicy. The scabs were quickly enlarged. The young leaves got burnt and fell off [16, 18].

4.2 Image of the lime foliar disease

From the field trip to Nakhon Si Thammarat Province in order to collect the images of lime disease, with adequate images for the algorithm development it was found the following six most common foliar diseases; (a) canker, (b) zinc deficiency, (c) tristeza, (d) algal spot or red rust, (e) greasy spot, and (f) sooty mold. The disease symptoms were as shown in figure 8.

Figure 8. Examples of symptoms of the lime foliar disease.
4.3 Results of algorithmic development

According to Figure 9, the training of the algorithm since epoch fourth provided an accuracy value of 91.89-100% and the validation accuracy value was 75.66-90.42%. For the number of algorithm training, it should not be less than 20 epochs (Figure 10).

![Training and validation accuracy](image1)

**Figure 9.** Training and validation accuracy.

![Training and validation loss](image2)

**Figure 10.** Training and validation loss.

4.4 Results of smartphone application creation in Android operating system.

Developed applications could be installed on Android smartphones. To start, activate the application on the smartphone, then the screen will be displayed as shown in figure 11, where the application would run in real time. Activate your smartphone's camera when the application was opened, and then used the smartphone's camera to the lime leaves to acknowledge the detectable disease. The screen displayed the disease by the percentage that the camera could capture in descending order.

4.5 Results of accuracy in the trial of the developed lime disease identification application.

From the trials using 6 lime disease classification applications with 50 images of each disease, it was found that the accuracy of classification was in the range of 94.98 percent and the mean was 96 percent. Table 2 presents the details.
Figure 11. The main screen of the plant disease application.

Table 2. The accurate results in the trial of the developed lime disease classification application.

| Disease               | Number of images (>80 %) | Number of images (<80 %) | %Accuracy | %Loss |
|-----------------------|--------------------------|---------------------------|-----------|-------|
| 1) Canker             | 49                       | 1                         | 98.00     | 2.00  |
| 2) Zinc deficiency    | 47                       | 3                         | 94.00     | 6.00  |
| 3) Tristeza           | 47                       | 3                         | 94.00     | 6.00  |
| 4) Algal spot or Red rust | 49                 | 1                         | 98.00     | 2.00  |
| 5) Greasy spot        | 48                       | 2                         | 96.00     | 4.00  |
| 6) Sooty mold         | 48                       | 2                         | 96.00     | 4.00  |
| Average               | 48                       | 2                         | 96.00     | 4.00  |

5. Conclusions
The algorithm of lime disease identification was developed with the CNN, the Inception-v3 architecture from TensorFlow Framework command set provided a 91.89-100% train accuracy and a validation accuracy of 75.66-90.42%. The accuracy of validation depends on the number of training epochs. When the developed algorithm was used to create a smartphone application in an Android
operating system by Android Studio software. The using results of the developed application was more than 90% accurate for all diseases. It can be seen that the developed algorithm is feasible for its improvement by increasing the number of the images or newly detected diseases. This application is very useful for agriculturists to prevent disease from being symptomatic.

References

[1] Office of Agricultural Economics 2018 Information of agricultural products "Lime" Retrieved from http://www.oae.go.th/

[2] Sanuksan J and Surinta O 2018 Deep Convolutional Neural Networks for Plant Recognition in the Natural Environment J Sci Technol MSU 38(2) pp 113-124

[3] Wang C, Tang Y, Zou X, SiTu W and Feng W 2017 A robust fruit image segmentation algorithm against varying illumination for vision system of fruit harvesting robot Optik 131 pp 626-631

[4] Dorj U O, Lee M and Yun S 2017 An yield estimation in citrus orchards via fruit detection and counting using image processing. Computers and Electronics in Agriculture 140 pp103–112

[5] Johannes A, Picon A, Alvarez-Gila A, Echazarra J, Rodriguez-Vaamonde S, Navajas A and Ortiz-Barredo A 2017 Automatic plant disease diagnosis using mobile capture devices, applied on a wheat use case. Computers and Electronics in Agriculture 138 pp 200-209

[6] Iqbal Z, Attique K M, Sharif M, Hussain S J, Habib ur Rehman M, and Javed K 2018 An automated detection and classification of citrus plant diseases using image processing techniques: A review. Computers and Electronics in Agriculture 153 pp 12-32

[7] Barbedo J G A 2019 Plant disease identification from individual lesions and spots using deep learning. Biosystems Engineering 180 pp 96107

[8] N. Petrellis 2017 Mobile Application for Plant Disease Classification Based on Symptom Signatures. Proceedings of the 21st Pan-Hellenic Conference on Informatics pp 1-6

[9] Suppatoomsin C and Srikaew A 2018 Imagery Grape Leaf Disease Diagnosis Based on a GA-SASOM Algorithm The Journal of Industrial Technology 14(3) pp 44-61

[10] Petrellis N 2019 Plant Disease Diagnosis for Smart Phone Applications with Extensible Set of Diseases Appl. Sci 9 (9) p 1952

[11] Md. Z. Alom et al. 2019 A State-of-the-Art Survey on Deep Learning Theory and Architectures Electronics 8 p. 292

[12] Szegedy C, Vanhoucke V, Ioffe S, Shlens J, and Wojna Z 2015 Rethinking the Inception Architecture for Computer Vision

[13] Kositcharoenkul N 2008 Canker disease of citrus plants. Academic documents. Plant Protection Research and Development Office, Department of Agriculture Bangkok 82pages

[14] Bhirnuwat A, Thaweechai N, Meerink P, Ratriyat W and Jamsawang J 1999 Regulation of Orange Mite Insect Disease and Management 2nd edition Department of Plant Pathology Kasetsart University

[15] Siwakorn N, Puangphaet B, and Songsang P n.d. Using medicinal plants to control grapefruit canker Plant Pathology Research Group Plant Protection Research and Development Office

[16] Na Nakorn S, Chaisiptprecha N, Thonglua T, and Intamanee W 2014 Production of Pomegranate Siam Pomelo in Pak Phanang River Basin Nakhon Si Thammarat Province Tropical Fruits and Perennials Research Unit Faculty of Agriculture Rajamangala University of Technology Srivijaya Nakhon Si Thammarat Campus Sai Yai. Somthawee Printing House Nakhon Si Thammarat Province 62pages

[17] Maneenetr N n.d. Fruit disease and prevention and eradication. Community Agricultural Book Project Ruengsang printing Bangkok 72 pages

[18] Chaiprasart P n.d. Lemon Planting "Restoring and Healing Victims by Researching NRCT” National Research Council of Thailand (NRCT)
Acknowledgments
This research was supported by a research scholarship of revenue budget in 2020 of Rajamangala University of Technology Srivijaya.