A Novel Automatic Method for Cassava Disease Classification Using Deep Learning

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Abstract—**Cassava is an important Thai industrial crop. Thailand is a leader in cassava production; therefore, the large volume of cassava has been produced and exported from Thailand. However, cassava disease is the main factor to reduce cassava production and directly affects farmers' income. In this study, we aimed to introduce a novel method to automatic cassava disease classification by using deep learning algorithms. An input data was a collection of cassava leaves images containing five different classes, i.e., healthy, Cassava brown streak virus disease (cbsd), Cassava Bacterial Blight (cbb), Cassava green mite (cgm) and Cassava mosaic disease (cmd). Notwithstanding, we focused on the cbsd only in this study forasmuch as this disease has a high impact on the production. We conducted an experiment to evaluate method performance. Our system provided reasonable performance. The accuracy and F-measure of the system were 0.96. This is evidence that our system is applicable to efficiently classify the cassava diseases automatically. In future works, we will investigate an appropriate solution to classify other diseases of cassava.**

Index Terms—**Cassava disease, cbsd, Deep learning, Convolution Neural Networks, Classification**

I. Introduction

Cassava or Tapioca (Manihot esculenta Crantz) is the tuber crop that contains the major source of carbohydrate. Cassava can be grown well in all environments, even in poor conditions such as drought and infertile soil. In Thailand, cassava is considered as the economic crop as well as the key agro-industrial crop since it is primarily transformed into starch and dried cassava and further processed to the high-value products such as modified starch, ethanol, monosodium glutamate, sweeteners, etc. [1]. Furthermore, Thailand is known as the world leader in cassava production. According to the statistical data in 2017 reported by Food and Agriculture Organization of the United Nations (FAO), Thailand ranked third in term of production volume (30.97 million tonnes), but production volume per harvested area or yield is quite low (23.07 tonnes/ hectare) when comparing with other producers [2].

Since cassava is easy to grow and requires less nurturing, this tuber crop is extensively cultivated by farmers in almost every part of Thailand, except only the southern region. In 2018, the Office of Agricultural Economics reported that the cassava plant areas in Thailand were estimated as 1.38 million hectares approximately, cultivated by 523,589 households scattering over 50 provinces. Considering the cassava industry in the context of the supply chain, it related to many stakeholders consist of farmers, manufacturers, exporters, and customers [1], [3]. However, the farm phase is determined as the critical part since it related to a large number of farmers who lack the ability to access the right information and appropriate knowledge for farm management. Likewise, Thai cassava farmers remain to confront the low yield and perform cassava cultivate base on their experience which could not guarantee the right practice [4]. Other than cultivation methods, an epidemic of cassava disease is the significant factor affects to cassava yield as well as plant security. Due to cassava is propagated from stems, it is vulnerable to be infected by many kinds of viruses. The epidemic diseases normally found in cassava including Cassava brown streak virus disease (cbsd), Cassava bacterial blight (cbb), Cassava green mite (cgm), and Cassava mosaic disease (cmd). The researchers from FAO stated that, it is unclear to examine the disease outbreak due to lack of suitable detecting systems [5]. A large number of farmers cannot detect whether cassava contains the disease until the fresh roots are harvested because the symptom only appears on the roots. However, there are still approaches to reduce the effects of the disease by controlling the movement of infected cassava to prevent the virus from spreading to other areas. Consequently, there is the necessary to provide the tools for coping with these problems.

Previously, there were the existing studies which employed deep learning technique to classify cassava disease from the leaves image [6], [7]. It revealed that there were many classes of cassava disease, but the observed disease rarely found in Thailand. Another existing research work applied the deep learning technique i.e. Convolutional Neural Network (CNN) to classify cassava diseases from leaves image. Ramcharan *et al.* [8] proposed a new deep learning model to classify the three cassava diseases and two types of pest damage. They used transfer learning to train a deep convolutional neural network. Their study could provide a reliable model with expected performance. They also further developed the system to a mobile application [9].

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However, they did not discuss the image contained multiple leaves. Our system used the object detection to locate the cassava leave positions and then crop the detected leave. Therefore, this is our strength to be able to detect multiple leaves. In this study, multiple models were constructed to obtain high accuracy results. The first model aimed at identifying healthy leaves and diseased leaves. The results generated by the first model were latterly sent to the second model to detect only the cassava leaves. The selected cassava leave image in the second model then sent to the third model to classify merely the leaves that defected by cbsd.

In this study, the novel classification method is presented to cope with the difficulty in the detection of cassava leaves defected by cbsd. The proposed novel classification method should be beneficial to relevant parties, especially the farmers who are the most vulnerable sector in the whole supply chain. Moreover, the novel classification method helps to prevent the drastic damage caused by the disease's outbreaks which influences the plant security. The strength of this proposed method is to be able to handle the real-world data with acceptable accuracy. In fact, the dataset here was downloaded from the internet; but they were collected in real scenarios. Indeed, the images included different shade, light, texture, and perspective that caused the difficulty in our training process. This problem may solve by using techniques of image processing. They can normalize and standard the data images beforehand and then process them to the system. However, most image processing techniques were time-consuming and may reduce image quality. Thus, another strong point of this method is that we developed the system not involving the image processing but still be able to manipulate the data contained different characteristics. The novelty of this system is a new method of defected cassava leaf detection and classification. This is the first-trial method to integrate both object detection and classification on the cassava leaf contained various characteristics.

II. Related Works

Cassava is one of the Thai industrial crops with very high annual production costs [10]. It mainly produces in northeastern Thailand due to a suitable climate and land. Therefore, presently, there are many studies in different study domains that emphasize to increase cassava's quality and quantity for exportation and local consumption.

In the logistics area, several studies attempted to discover efficient solutions to improve the performance of crop distribution. Witchayut and Nanthi [11] proposed the design of the distribution rail network for cassava transportation. Within the next few years, the dual-track railway should be constructed to cover important areas of the country, i.e., central, north-eastern, and eastern Thailand. Therefore, railways are always an optimal solution to distribute crops to other areas of Thailand. They considered several factors influencing a transportation mode selection such as customer satisfaction, characteristics of products, and cost. As a result, they compared the traditional and new distribution networks proposed in their study and found that the new network could reduce distribution costs by over 50%. Rattanasit *et al.* [12] presented a decision support system using Geographic Information System (GIS) to analyze the Cassava Service Centres (CSC) location where collects cassavas. K-means algorithm was chosen to address a problem to optimize the number and location suitability of CSC with GIS and network data. Their goal was to minimize cost for investment and transportation distance to transfer cassava to CSC. Their proposed system provided the better result when analyzing with 20-node of CSC location assigned by the system. The cost and distance reduced to 49.5 and 13.3% respectively. This study area mostly focused on finding an optimal solution to distribute the cassava in effective ways. However, those are external factors that can be improved by good management. Another serious factor is plant disease because it is an uncontrollable factor. Some diseases affect cassava productions directly.

Fig. 1-Fig. 4 present characteristics of cassava diseases appearing through the cassava leaves.

Cassava brown streak virus disease (cbsd) [13] is a pernicious disease of cassavas that had scourged in East Africa [14] since 1936. This disease is characterized by necrosis and violent chlorosis. Cassava leaves inflected the disease exhibit a yellowish and mottled appearance.

Cassava Bacterial Blight (cbb) [15] is a disease caused by bacteria. The symptom is clearly visible on cassava leaves included blight, wither, necrosis and dieback. Angular necrotic brown spots spread restricted to the bottom of the leaves. After they enlarge and unionize, the leaves died.

Cassava green mite (cgm) [16] is a plant disease caused by mite attacking cassava young leaves. The mite inserts its piercing mouthparts into leaves' cell and breaks the cell contents. It sucks chlorophyll from the cells that lead the leaves mottled and die [17].

Cassava mosaic disease (cmd) [18], [19] is a disease caused by viruses. Its symptoms are apparently visible on the cassava leaves. The leaves' chlorophyll is mosaic scatter including the appearance of the cassava leaves distorted and the cassava itself stunted growth.

Figure 1. Cassava brown streak virus disease [20]

Figure 2. Cassava Bacterial Blight [20]

Figure 3. Cassava green mite [20]

Figure 4. Cassava mosaic disease [20]

To detect these plant diseases, farmers require the particular skills to analyze the symptom and accurately classify the disease in order to provide suitable treatment. However, they need specific training to acquire skills. Nevertheless, if the farmer cannot identify the disease and provide the treatment in time, this situation may lead to pestilence and destroy agriculture industries. That straightforwardly impacts industrial productivity and causes to lose farmers' income. Therefore, many artificial intelligent studies have been proposed.

In the present day, deep learning becomes an important role to address the agricultural problem to identify the plant disease. Deep learning is a part of machine learning that trains training data by using network layers with multiple neurons. Due to its deep layers, deep learning possibly extracts higher levels of data features. With this concept of deep learning, there are several algorithms presented and applicable to various kinds of data inputs such as deep neural networks [21], deep belief networks [22], recurrent neural networks [23] and convolutional neural networks [24].

Convolutional Neural Networks (CNN) is a deep learning algorithm that is effectively applicable to visual data. It contains two parts: a convolution layer and a classification layer by multiple layers of neural networks. Zhang *et al.* [25] designed a new framework of CNN containing 13 layers. They classified fruit categories based on fruit image features. The image data were performed by three different data augmentation: image rotation, Gamma correction, and noise injection. As a result, the method provided a high accuracy, i.e., 95%, that was higher than state-of-the-art studies. Lee *et al.* [26] presented a method using CNN that included Deconvolutional Networks (DN) to classify 44 different plant species by analyzing color representation and shape of plant leaves. DN is a procedure to realize a transformation of input data features by projecting the data feature maps back to the image pixel space. The method provided high accuracy, up to 99% that was outperformed to other state-of-art methods. In addition, pre-trained algorithms for object detections have been developed, e.g., Faster Region Convolutional Neural Networks (Faster R-CNN). The Faster R-CNN [27] was evolved from CNN, Region CNN (R-CNN), and Fast R-CNN respectively. It usually provides better performance in both terms of speed and accuracy compared to those previous algorithms. It consists of four steps as following:

1) Extracting image features in the convolution layer
2) Bounding interest regions by using Region Proposal Network (RPN)
3) Training and learning the bounded regions
4) Classifying each bounded region of input images

Jiang *et al.* [28] proposed a face detection method using the Faster R-CNN applied to a large scale data and compare performance between their proposed method and other 11 other top detectors on Face Detection Dataset and Benchmark (FDDB). An experiment showed that the Faster R-CNN was fastest and also provided high accuracy. This algorithm might obtain better performance if the algorithm was retrained an appropriate facial image training set.

III. Methodology

This study addressed the difficulty of cassava disease classification by proposing the novel method of classification using deep learning. The main objective was to propose the novel method to classify the healthy and unhealthy cassava leaves which were infected with the disease of cbsd.

The classification technique used in the study was Faster R-CNN, which is a pre-trained algorithm for object detection. Note that the pre-trained algorithm is a model already trained and learned by existing sources. That means the algorithm had been realized the previous data. However, to increase the model's performance, we also apply a transfer learning to this pre-trained algorithm; thus, it could learn and train our data further.

To implement the model, we utilized Keras (https://keras.io/) environment with TensorFlow [29]. A programming language was Python3 included Numpy. We implemented the model via Google Colaboratory (https://colab.research.google.com/) which included computer specifications as follows:

- GPU: 1xTesla K80, having 2496 CUDA cores, compute 3.7, 12GB (11.439GB Usable) GDDR5 VRAM
- CPU: 1xsingle core hyperthreaded, i.e., (1 core, 2 threads) Xeon Processors @2.3Ghz (No Turbo Boost), 45MB Cache
- RAM: 12.6 GB Available
- Disk: 320 GB Available

A. Dataset

Our dataset is a collection of cassava leaves images that represent five classes of leaves status, i.e., cbsd, cbb, cgm, cmd, and healthy.

Here, we used two datasets to train two different models. For the first model (Model1), the size of the dataset (Dataset1) was 1000 images that were separated into 500 healthy leaves images and 500 unhealthy leaves images. For the second model (Model2), the size of the dataset (Dataset2) was 1013 images that were separated to 530 images representing the cassava leaves contracted the cbsd and 483 images representing the cassava leaves not contracted the cbsd but was also unhealthy.

B. Method for Cassava Disease Classification

We designed a method of cassava leaves classification based on the appearance of a disease's symptoms. The cassava leaves inflected the symptom, e.g., cbsd, cbb, cgm, and cmd, often present the brown spots scattering over the leaves (Fig. 1-Fig. 4). With the characteristics of the color feature, this is possible to extract the particular feature from the cassava leaves images and classify them by using CNN. For this method, we aimed to classify the healthy or unhealthy cassava leaves and emphasized to the unhealthy leaves to further distinguish between leaves inflected cbsd or not inflected cbsd. We selected the cbsd as our target of classification because this disease considerably influents agriculture productivity that also causes the amount of country exportation.

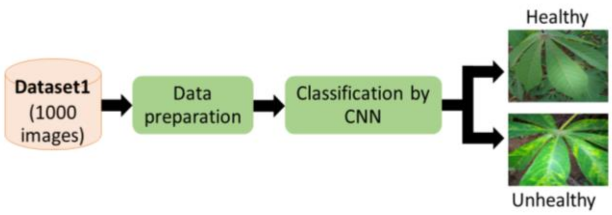

Figure 5. Illustration of a process to create the Model1

Our method is presented in Fig. 5 and Fig. 6 that consists of two models and three different training datasets. For Model1 (Fig. 5), we used the 1000-image Dataset1 which contained cassava leaves images both inflected the disease and healthy. Within this dataset, we gathered 500 healthy leaves images and 125 images from each disease in a total of 500 images. After collecting the data, the data preparation should be processed. We cleaned the data by selecting only quality images for classification. For example, after we observed the dataset, we found that some images unfocused on the cassava leaves themselves but the environment. These images were not suitable to be used for training in the classification system; since they should omit from the dataset. Then, we trained the CNN model with the architecture shown in Fig. 6 by splitting the dataset to the 800-image training set and the 200-image test set for model evaluation. Note that the data in the training set were selected randomly; furthermore, data gathered from all classes had been balanced. The detail of each CNN layer is described as follows:

- 1 layer of input layer 32×32
- 3 layers of hidden layer Conv2D
- 1 layer of hidden layer maxPolling 16×16
- 2 layers of hidden layer Conv2D
- 1 layer of hidden layer maxPolling 8×8
- 4 layer of hidden layer Conv2D
- 1 layer of hidden layer dense
- 1 layer of hidden layer Flatten
- 1 layer of output layer dense

The neural networks parameters were set as follows:

- Learning rate = 0.00001
- Optimizer = adam

Outputs of the Model1 was the classification results between the class of Healthy and the class of Unhealthy.

The process of Model2 is shown in Fig. 7. For the system process, an input of the Model2 was the output from Model1 labeled as the Unhealthy class. The purpose of this model is to identify the unhealthy leaves whether inflect the cbsd disease. In the preparation process, to fulfill the training stage of the model, we collected all unhealthy leaves data in a total of 1,013 images, to train the Faster R-CNN and CNN model with the same parameters as shown in Fig. 6. The Faster R-CNN had been trained to detect the cassava leaves existed in the input images. After the detection, our system cropped the result images only the cassava leaves and discarded the rest such as the background. The cropped results were assembled to Dataset3 and were performed to the CNN for the cbds disease classification.

Here, we concluded the process of the system. The data in Dataset1 were applied to CNN and classified as Healthy or Unhealthy. Regards to data classified as Unhealthy, they were processed continuously to the Model2 as Dataset2. It inputted to the Faster R-CNN for the object detection and then cropped the images detected bounding boxes to remove the image background. This step is necessary to improve the performance of classification. The CNN algorithm needs to extract the image features in its convolution process; since omitting uninterest regions from the images should keep the algorithm to emphasize only the particular regions (cassava leaves). These cropped data were formed to Dataset3 which was classified by CNN to two classes: cbsd and not cbsd.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 32, 32, 32)	896
conv2d_2 (Conv2D)	(None, 32, 32, 64)	18496
conv2d_3 (Conv2D)	(None, 32, 32, 64)	36928
max_pooling2d_1 (MaxPooling2	(None, 16, 16, 64)	0
conv2d_4 (Conv2D)	(None, 16, 16, 64)	36928
conv2d_5 (Conv2D)	(None, 16, 16, 64)	36928
max_pooling2d_2 (MaxPooling2	(None, 8, 8, 64)	0
conv2d_6 (Conv2D)	(None, 8, 8, 32)	18464
conv2d_7 (Conv2D)	(None, 8, 8, 32)	9248
conv2d_8 (Conv2D)	(None, 8, 8, 32)	9248
conv2d_9 (Conv2D)	(None, 6, 6, 32)	9248
dense_1 (Dense)	(None, 6, 6, 256)	8448
flatten_1 (Flatten)	(None, 9216)	0
dense_2 (Dense)	(None, 2)	18434

Figure 6. CNN architecture

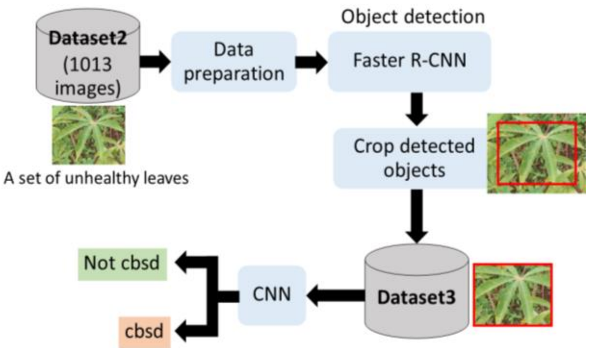

Figure 7. Illustration of a process to create the Model2

IV. Evaluation and Discussion

For the experiment, we used the test dataset to validate the model performance. Here, we evaluated the models separately and also presented the overall performance of the system.

As for the Model1, we separated the Dataset1 into three sets: the training set, the validate set and the test set. For evaluation, we used only the 160-image validate set and the 241-image test set. The number of training epochs was 500 epochs. Note that the validate set is used to test and find metrics after the model completes the training stage and tune the parameters to improve the model performance. After obtaining the model with the best performance testing with the validate set, the test set is performed in order to evaluate the model with unseen data. During the training stage, we obtained the model accuracy and loss when dealing with the training and validate datasets. As shown in Fig. 8 and Fig. 9, the accuracy and loss provided by the training set and the validate set have been presented. The accuracy is a performance measurement, and its interpretation is how well the model process to these two datasets; whereas the loss means a summation of errors occurring during each epoch in training stages. The model accuracy graph showed that the accuracy had increased in both training and validate sets; although, the accuracy of the training set was higher than the accuracy from the validate set. This is because the model was fine-tuned by the validating set after every training epoch. Also, for the same reason, the loss from the validating set was higher than the loss from the training set in the model loss graph. For evaluating the model by using the test data, we created a confusion matrix (Fig. 10). From this confusion matrix, the accuracy of the model was 0.91. The recall to accurately cover the case of healthy and unhealthy leaves was 0.89 and 0.93 respectively. The precision to correctly predict the healthy leaves was 0.91, and the precision to correctly predict the unhealthy leaves was 0.91. Therefore, the F-measure, which is a measurement to balance the precision and recall, was 0.9 and 0.92 for healthy and unhealthy classes respectively.

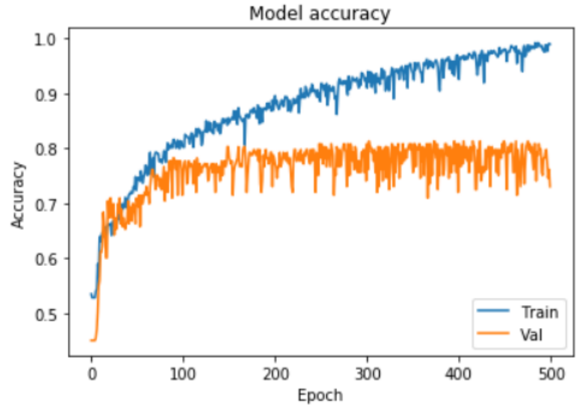

Figure 8. A graph representing a relationship between accuracy and training epochs on the CNN in Model1

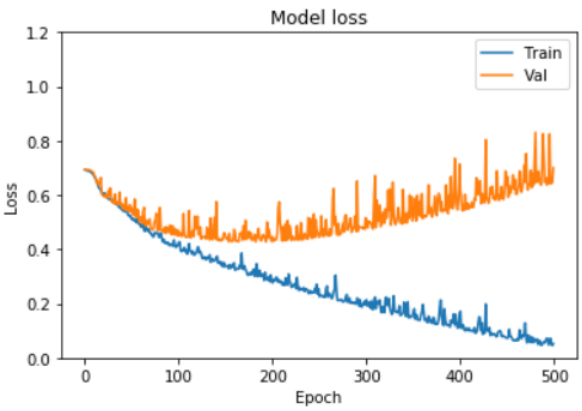

Figure 9. A graph representing a relationship between loss and training epochs on the CNN in Model1

		Prediction	
Actual		healthy	unhealthy
	healthy	93	12
	unhealthy	9	127

Figure 10. A confusion matrix provided by the CNN in Model1

For the Model2, we evaluated two different models, i.e., Faster R-CNN and CNN. The Faster R-CNN was used to detect the interest objects in the images. In this case, we utilized the model to detect unhealthy cassava leaves. The dataset set for training the Faster R-CNN was 114 images labeled as cbsd and not cbsd. The number of test data was 51 images. After the model training, we received 140 results bounded with the detection boxes. Then they were cropped following the bounding boxes. As a result, we discovered that our Faster R-CNN could detect the cassava leaves accurately 123 images from 140 images or 0.87. Fig. 11 denotes an example of results detected from the Faster R-CNN and cropped separately. Another model was the CNN that was used to classify between cbsd and not cbsd. The training dataset for this model was 1013 images included the cropped images from the previous steps about 530 images (cbsd) and the images from other diseases 483 images (not cbsd). It separated to the validate set 161 images and the test set 203 images. We trained this model with 200 epochs. The results were similar to the Model1, i.e., the accuracy of the training set increased after improving the model in every epoch (Fig. 12). For the confusion matrix, the accuracy was 0.96. The precision and recall for the cbsd class were 0.96 and 0.97 respectively. The precision and recall for the not cbsd class were 0.97 and 0.96 respectively. The F-measure of the cbsd and not cbsd classes was the same, 0.96.

Figure 11. An example of results from the faster R-CNN

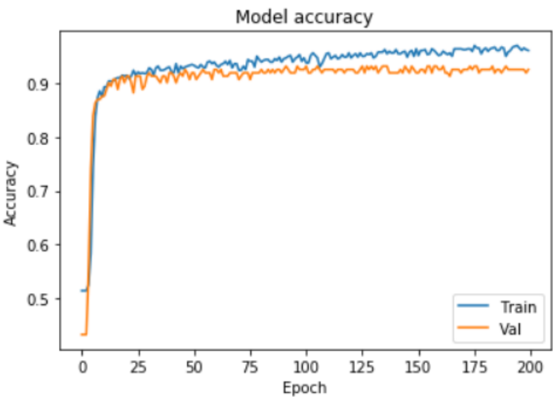

Figure 12. A graph representing a relationship between accuracy and training epochs on the CNN in Model2

		Prediction	
		cbsd	not_cbsd
Actual	cbsd	94	3
	not_cbsd	4	102

Figure 13. A confusion matrix provided by the CNN in Model2

		Prediction	
		cbsd	not_cbsd
Actual	cbsd	70	2
	not_cbsd	1	68

Figure 14. A confusion matrix provided by our system

Therefore, after the system was constructed and trained completely, we attempted to evaluate the overall system by assigning a new unseen dataset to the system which contained 141 images. As shown in Fig. 13, the accuracy of the overall system reached to 0.96. Thus, this is evidence that our proposed system is efficiency and high performance (Fig. 14). It should be recommended to support the farmer's job routines and reduce their burdens potentially.

During the experiment, we encountered some problems and discovered possible solutions. As observed in the data, we found that the data were photo images taking from the farmer fields; therefore, light and shading also affected to the classification model. To mitigate this problem, we attempted to omit the dominant background to reduce the influence of unnecessary features. This is a reason why we decided to use the Faster R-CNN before the classification in the Model2. Furthermore, our data were collected from different diseases that have similar symptoms. In the first place, we planned to classify the cassava leaves by four different diseases. However, the accuracy was low because the symptoms presenting on the images provided similar colors or features. Thus, we decided to reduce the number of candidates of classification for decreasing the losses and errors by separating the classification into two stages representing as Model1 and Model2. The Model1 classified healthy and unhealthy leaves. Then, the unhealthy leaves were continuously distinguished whether they were cbsd or not.

V. CONCLUSION

This study addressed the difficulty of plant disease classification by analyzing the cassava leaves. The main objective was to propose a method to automatically classify between the unhealthy cassava inflected cbsd and healthy cassava. We proposed the novel method to improve the performance of classification by integrating multiple models to classify the disease step by step. There were two main models: Model1 and Model2. The Model1 used to classify the cassava leaves as healthy and unhealthy. The Model2 could identify the unhealthy leaves to the disease, cbsd. As the experimental results, we found that our method provided acceptable performance. The accuracy of the overall system reached to 0.96. In future works, we will improve our model to classify other cassava diseases such as cbb, cgm, and cmd. Moreover, we may compare the performance of this study to other related studies for further discussion and analysis.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Isaman Sangbamrung and Sarunya Kanjanawattana conducted the research and experiments, analyzed the data as well as proposed the method of the study; Sarunya Kanjanawattana and Panchalee Praneetpholkrang wrote the paper; Sarunya Kanjanawattana proved the correctness of the results and had approved the final version of this manuscript.

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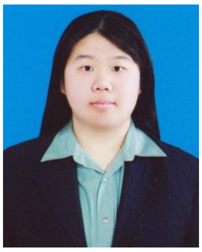

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