

HYBRID NEURAL NETWORK BASED ON SFAM AND CNN FOR GRAPE LEAF DISEASE DIAGNOSIS

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Abstract

Agricultural industry plays an important role in Thailand as its production has an impact on the domestic economy and exportation. Well-timed control and management of various factors causing plant diseases are essential to help the quality control of products and reduce damage such as the outbreak of plant diseases. However, the stage identification of occurring diseases is complicated for selecting the appropriate chemicals for treatment or controlling their amount possibly affects soil and water quality in the surrounding environment. To reduce the mentioned problem, this paper presents the AI system which can accurately diagnose as well as consider the disease characteristics. Besides, this system can also be used to identify the disease type and the time that firstly found disease. The architecture model of Simplify Fuzzy Adaptive Resonance Theory Map (SFAM) is developed to learn and remember the 2-levels of the information in the process of recognizing occurring diseases and their stage on grape leaves. In this paper, the hybrid algorithm is used for diagnosing grape leaf diseases from real-life images in the actual surroundings by using the combination between the SFAM and the Convolutional Neural Network (CNN). This algorithm can be called 2-Levels Convolutional Simplify Fuzzy Adaptive Resonance Theory Map (2LCSFAM). The Grape leaf is tested for the diagnosis of 3 grape leaf diseases including Downey, Rust, and Scap. The test results showed the accuracy value equals 87.14 percent in average. Thus, the proposed system can efficiently identify the types of the diseases and stages of infection by using only the image from the Grape leaf.

Keywords: Plant disease diagnosis, simplify fuzzy adaptive resonance theory map, convolutional neural network, 2 level convolutional simplify fuzzy adaptive resonance theory map

Introduction

Nowadays, the world population has increasingly concerned about health. This results in the increasing demand for vegetables and fruits. Therefore, timely care and control of plant diseases are important in determining the product quality. Controlling the outbreak of diseases causing the least impact

potentially creates the trade credibility for manufacturers and farmers. The plants show the symptoms caused by living organism or surroundings factors resulting in plant abnormalities through many aspects such as stems, fruits or leaves by which the plants can clearly show their symptom.

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such as the disease color and nature, as well as its severity level. In general, to control the expansion or outbreak of diseases, the farmers prefer to use drug spray in the whole plot, or groups of plants showing the disease symptoms. Such prevention possibly causes the excessive use of chemicals resulting in chemical residues. Thus, considering the disease symptoms of the Low-Level stage, or the first phase can control the immediate disease expansion, and reduce the cost of using excessive chemicals which possibly affect the environmental resources both soil and water quality in cultivated and nearby areas. However, the current agricultural industry uses modern technology to help solve problems of plant diseases such as smart farm systems (Amandeep *et al.*, 2017), indoor cropping systems which use the model of collecting surroundings in the plots (Dwarkani *et al.*, 2015), or the use of detection sensors to collect information in the plots (Ramya *et al.*, 2017) with the application of artificial intelligence theory to help in learning and remembering the diseases occurring on the leaves of plants by using digital image processing for data preparation and limiting the affected area for learning of the system (Song *et al.*, 2012).

In the past, there were research related to the plant disease diagnosis by segregating data group, and remembering the patterns by using images to detect and identify disease characteristics, such as (Burks *et al.*, 2000) presenting the weeds segregation using color features together with statistical analysis to distribute the two groups of data or more by statistically using image analysis at the gray level to extract distinct features of the image (Aitkenhead *et al.*, 2003), extracting cultivated plants from weeds by measuring and calculating the proportion of plants and weeds together with the use of self-management theory in data segmentation (Dong *et al.*, 2005) which has been continuously developed and the principles of color analysis are applied with hybrid neural networks for image segmentation using the principle of separating different color groups, and grouping similar colors on the images with self-management theory (Huang *et al.*, 2007). Then, the detection of plant diseases in seedlings is presented by using artificial intelligence processes together with color analysis, and the extraction of detailed image using statistical analysis methods (Meunkaewjinda *et al.*, 2008). The presentation of grape leaf diseases diagnosis from color images using Hybrid Artificial Intelligence theory with the presentation of self-management networks, and Back-Propagation Neural Network (BPNN) to extract the area of plant leaves from unrelated image components. Then, the self-management network is used together with the genetic theory and supporting vector to separate the color groups of the diseases

from the plant leaves. Additionally, Gabor Wavelet is used to extract the distinct features of the diseases. Accordingly, the supporting vector is used to diagnose the occurring diseases. The system operation is complicated due to the use of two sets of hybrid neural networks in the same system. In addition, the pattern of extraction of the distinct feature of disease is complicated. This makes it difficult to find the suitable value used for learning of the system.

In the above mentioned research, it is a research group related to plant disease diagnosis, detection and data segmentation by using digital image processing together with hybrid neural network. In general, to find out the distinct features or parameters to transfer to learning part of the system commonly requires the algorithm the operator himself has to detect the suitable distinct features for training. This process is time-consuming due to the all randomized selection which takes a long time to complete. In addition, there is a chance of errors caused by the duplicate parameters, resulting in the decreasing learning efficiency, or low reliability of the hybrid neural network. Convolutional Neural Network (CNN), which is proposed to help reduce the mentioned problems. It can automatically detect the distinct features and efficiently reduce the amount of parameters of too many Convolutional Neural Networks used for training. CNN's research have been extensively used, for example, (Cires *et al.*, 2011) using a computer image processing unit associated with the theory of Convolutional Neural network, and efficiently reduce the amount of parameters to classify the group of objects, and identify letters characters (Krizhevsky *et al.*, 2013), learn a large dataset of 1.2 million high resolution images using the convolutional neural network theory, with 1,000 groups of samples, and increase the calculation speed by using a computer image processing unit (Orillo *et al.*, 2014), identify the diseases occurring on rice plots by using Back-propagation neural network (BPNN), and use the trichology of color value principle for extracting leafy areas from the background, (Long *et al.*, 2015) take Convolutional neural network to divide the parts of images by training pixel by-pixel, and use semi-instructional learning based on the Alex's Net model in testing (Gong *et al.*, 2014). Convolutional neural network has been extensively used, and continuously developed. The convolutional neural network has been developed by adjusting the distinct feature of multi-level model to function with images comprising many components with higher efficiency. The advantage of this model is that it can be divided into multiple groups in a single image. (He *et al.*, 2014) The improved Convolutional Neural Network can work with more calculation layers, and

efficiently help process the various sets of different image sizes (Simonyan *et al.*, 2015). The properties of Convolutional neural network depends on its feature and number of filters. The test results showed that the efficiency of the Convolutional neural network increases when increasing the extraction layers of the image characteristics. The number of additional layers must correspond to the image size to avoid creating meaningless and overlapped information. In this research, the system has been presented to diagnose a grape leaf disease and its stage using a new algorithm, based on the Simplify Fuzzy Adaptive Resonance Theory Map: SFAM, and Convolutional Neural Network: CNN), which is called the 2-level Convolutional Simplify Fuzzy Adaptive Resonance Theory Map: 2LCSFAM. This proposed Convolutional neural network has been developed to potentially learn and remember information at two levels using the principle of creating sub-neural network weight together with vigilance parameter values for only neural network weight groups, and the improvement of the automatic vigilance parameter values, making each vigilance parameter value suitable for the neural network weight of each data type for training, and increasing the ability to extract distinct features using the CNN model, in which the user does not have to choose the parameters for testing by himself. From the advantages of the developed Convolutional neural network, the system can continuously learn information without restarting when a new dataset which has never been trained is fed. The details of system operation are presented in the next section.

Materials and Methods

Architecture of 2LCSFAM

The architecture of the 2-level Convolutional Simplify Fuzzy Adaptive Resonance Theory Map: 2LCSFAM is an architecture of hybrid neural network designed to automatically extract distinct features. It can learn and remember information at two levels, and can continuously learn in case that new dataset, which has not been taught, is submitted as shown in Figure 1. It is the development of the structure of the SFAM in the traditional pattern to potentially build a sub-neural network weight group, or the neural network weight at the second level by controlling the condition of neural network weight value improvement, and the creation of neural weight network from the use of multiple vigilance parameters, as well as the increasing ability to extract the distinct features by CNN. The working model of 2LCSFAM is to send the images to be learned and simultaneously specify the type of the image indicating the disease type as well as its

severity level. The extraction process of distinct features uses the Alex's network model and his filter sets. 2LCSFAM is designed to reduce feature complexity of parameter, time consuming problem, as well as the ability to learn and remember information at 2 levels by using the same dataset. In case that the new disease type is added to the system, 2LCSFAM can learn continuously without restarting. The system can take used-to- trained neural network to process by adjusting the neural network weight and creating a new set of neural network weight by the system itself. To explain, as the system is designed to have many vigilance parameters values, each value will be used to determine the adjustment of neural network weight in each group. When the neural network weight value in any group has changed, the vigilance parameters will adjust themselves to suit the amount of neural network weight in that group. This makes the data segregation and diagnosis to be more flexible and accurate.

Figure 1 is the architecture of 2LCSFAM, which is divided into two parts to clearly illustrate the work process. The top part of the figure is the extraction of the distinct features of the image through the convolutional process with various filters in order to find the suitable distinct feature parameters in the system training process. Below is

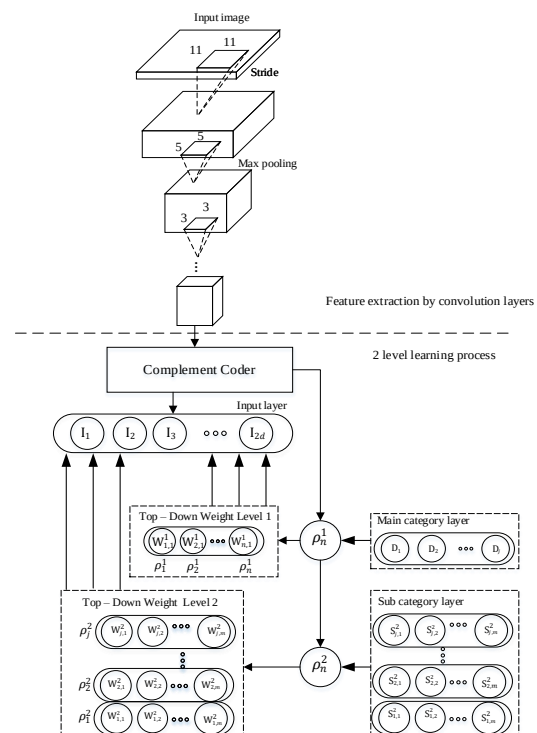


Figure 1. The architecture of 2 level convolutional simplify fuzzy adaptive resonance theory MAP

the learning model of the hybrid neural network system of which structure consists of the input layer, the neural network weight layer, the class for remembering the neuronal cell type that the system has already trained. In this research, according to the architecture, Convolutional neural network is designed to have two layers of neural network weights to store neural weights so that it can recognize grape leaf diseases and their stages. Each neural network weight group will have a vigilance parameter value p for only its own group. This vigilance parameter has the condition to improve itself when the neural network weight in any group is improved or changed. The vigilance parameter values will be reduced in order to decrease the condition for data diagnosis. In addition, the vigilance parameters will be increased when new neural weights are created to increase the details of the diagnosis in case of the availability of many neural weight values or many groups of datasets trained into the system.

The Learning Algorithm of 2LCSFAM

When the input image is sent to the system through the distinct feature extraction process by the convolutional layer of the hybrid neural network. The parameters obtained from this process will be forwarded to the input layer for use in training. The operation in this part is presented in the Feature extraction. The function of 2LCSFAM is performed as Hierarchy starting from the level 1, or the main neural network weight group. When the working process in the main group is finished, level 2, or the subgroup neural network weight is activated by starting from standardizing the input using Equation 1, then calculate the activation function of the neural network weight in the main group by using Equation (2):

$$I_i = (\bar{a}, \bar{a}^c) = (a_1, a_2, a_3, \dots, a_d, 1 - a_1, 1 - a_2, 1 - a_3, \dots, 1 - a_d) \quad (1)$$

$$T_n(I_i) = \frac{|I \wedge W_n^1|}{\alpha + |W_n^1|} \quad (2)$$

where W_n^1 is neural network weight function
 n is the number of main layer (Layer 1)
 I is input
 α is a constant value close to 0
 $T_n(I_i)$ is the activation function of the main layer

Then, find the winner-take-all neural network using Equation (3):

$$T_{k1}(I_i) = \max_n T_n(I_i) \quad (3)$$

Calculate for match function using Equation (4):

$$MF_1(I_i) = \frac{|I_i \wedge W_n^1|}{|I_i|} \quad (4)$$

Check Resonance conditions by using Equation (5):

$$MF_1(I_i) > \rho_n^1 \quad (5)$$

In the case that the Resonance fails, the network will reset to find a new winner take-all neural network. The conditions will be rechecked before updating the neural weight values in the main layer by using Equation (6):

$$W_n^{1*new} = \beta(I \wedge W_n^{1*old}) + (1 - \beta)W_n^{1*old} \quad (6)$$

where W_n^{1*new} is updated neural network weight value
 W_n^{1*old} is original neural network weight value
 β is a constant value

After updating neural network weight values, vigilance parameter value will adjust itself under the condition of Equation (7):

$$\rho^{new} = (1 - \Delta)\rho^{old} \quad (7)$$

where Δ is a constant value

In the case that the neural weight is not updated, the vigilance parameter value will remain the same. In the case that the system creates a new set of neural network weights, the vigilance parameter value of that neural group will be higher adjusted according to Equation (8):

$$\rho^{new} = (1 + \Delta)\rho^{old} \quad (8)$$

The vigilance parameter value of the new neural network weight set will be primary value. Then, the input is sent to the group of sub-neural weight function by selecting it from the corresponding main group. Each main neural network weight group has its own subgroups. When passing the resemblance conditions in the main group, the neural network weight values in the subgroups will be calculated by using the same principle. Calculate for the neural network weight function in the subgroup by using Equation (9):

$$T_{n,m}(I_i) = \frac{|I \wedge W_{n,m}^2|}{\alpha + |W_{n,m}^2|} \quad (9)$$

where $W_{n,m}^2$ is the number (n) of neural network weight value function of sublayer
 $T_{n,m}(I_i)$ is activation function of sublayer

Then, find winner take-all of sublayer by using Equation (10):

$$T_{k2}(I_i) = \max_n T_{n,m}(I_i) \quad (10)$$

where m is the number of neural network weight groups in sublayer

Calculate for match function by using Equation (11):

$$MF_2(I_i) = \frac{|I_i \wedge W_{n,m}^2|}{|I_i|} \quad (11)$$

Check the Resonance conditions by using Equation (12):

$$MF_2(I_i) > \rho_j^2 \quad (12)$$

In case of not passing the resonance condition, the network will reset the system to find the new winner take-all neural network, and recheck the conditions before updating the neural network weights in the sub-neural network weight using the same equation as the main neural network weight does in Equation (6).

2LCSFAM Diagnostic Algorithm

For data diagnosis or classification process, the system performs operations from the main layer to the sublayer. When winner take-all neural network in the main layer is identified, the system will continue processing to subsequently find the winner take-all neural network of the sub-layer. To find the winner take-all neural network in the main layer can be proceeded as follows.

1) Calculate for the activation function of the neural network group in the main layer by using Equation (13):

$$T_n(I_i) = \frac{|I \wedge W_n^1|}{\alpha + |W_n^1|} \quad (13)$$

2) Calculate for the winner take-all neural network of the main layer by using Equation (14):

$$T_{k1}(I_i) = \max_n T_n(I_i) \quad (14)$$

3) Calculate for match function by using Equation (15):

$$MF_1(I_i) = \frac{|I_i \wedge W_n^1|}{|I_i|} \quad (15)$$

4) Check resonance conditions by using Equation (16):

$$MF_1(I_i) > \rho_n^1 \quad (16)$$

In the case of passing the resonance conditions, the winner-take-all neural network will be the answer in the process identifying main groups in which the group type is shown in the winner take-all neural network group. In the case that the winner - take-all neural network does not pass a resonance condition, the system will reset the value to find a new winner take-all neural network. If there is no neural network passing the resonance conditions, the system will diagnose that the input sent into the system is not matched, or the system cannot specify this data group. When a winner take-all neural network is achieved in the main group, the system will send its position to the linked subgroups. Then calculate for that of the sublayer by calculating from process 1) to 4) with the same method of calculating and checking the conditions as that for finding it in the main group. However, the vigilance parameter which is used to detect resonance conditions is specific to that group. The winner take-all of the main groups and the sub-groups will become the answer to the system, referring to the occurring disease type and its severity.

Grape Leaf Disease Diagnosis System

The grape leaf disease diagnosis system presented in this research was divided into 4 parts, namely Input preparing, Feature extraction. Learning process, and Disease Classification. In Figure 2, it is a diagram showing the operation of the grape leaf disease diagnosis system. The input image is fed into the data preparation process by dividing the

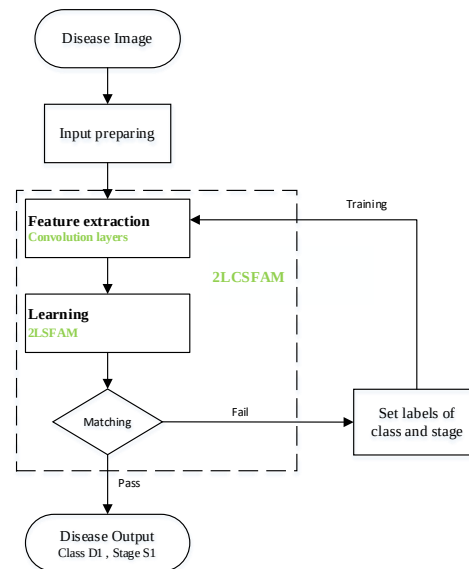


Figure 2. Diagram of the grape leaf disease diagnosis system

image into parts suitable for learning. From then, the distinct features parameter is extracted and forwarded to the layer used for learning of the system. The hybrid neural network is developed to be able to recognize information at two levels: the disease type, and the stage of the disease severity divided according to the appearance on the grape leaves. The resemblance of the datasets are investigated to diagnose what disease the inputs are infected, and in what severity level. In the case that the hybrid neural network fails the resemblance, and cannot identify the type of input, it can be immediately trained without restarting.

Input Preparing Before Processing

In this research, all of grape leaf image are collected from Suranaree University of Technology Farm (SUT farm) by DSLR Camera (Canon 60D) in real- life environment. The grape leaf disease diagnosis has been performed to identify the types of the diseases and stages of infection. The types of the diseases include Downey, Rust, and Scap and the stages of infection are divided into two phases: low level, and high level. The information before being sent to the feature extraction is the selection of grape leaf areas without brightness and contrast modification because all of the image adjustment process will be performed by the filters of 2LCSFAM. The information is divided into four types including Downey, Rust, Scap and no disease. The images used in this research were determined to be 227×227 pixels. Figure 3 shows the diagram of the dataset collection and the display result of the diagnosis program. Figure 4 shows the feature of each disease on grape leaves comparing with the one with no disease.

Feature Extraction

The 2LCSFAM extraction process uses a convolution method between images and various filters, applying a convolutional function with the model of Alex's network, consisting of 5 levels of convolution. The dataset of each filter level has different characteristics. The output obtained from the convolution in each layer is used as input in the next layer. The filter size to be used is reduced in order to decrease the number of parameters and maintain significant implications for the system training process. In Figure 5, the diagram shows the operation of the extraction of distinct features of 2LCSFAM by convoluting between the input image and the filter in each layer through the final filter. After that, the coefficient in the final filter is arranged in a dataset with the d number of coefficients and forwarded to the training process. (Figure 6(a)) is the sample image of the output obtained from the convolution between the input

image and the convolution layer 1, totaling 96 sets of outputs from all 96 filters. (Figure 6(b)) is an example of the output obtained from the 5th layer and passes the process of coefficient reduction. From then, this dataset will be forwarded to the training section of 2LCSFAM to remember and create the neural weight groups of the system.

Learning and Training Process System

The process of training and learning of the system can be explained in Figure 7. The operation of 2LCFSAM is described in Figure 1 in item 2. From Figure. 7, the training and learning process

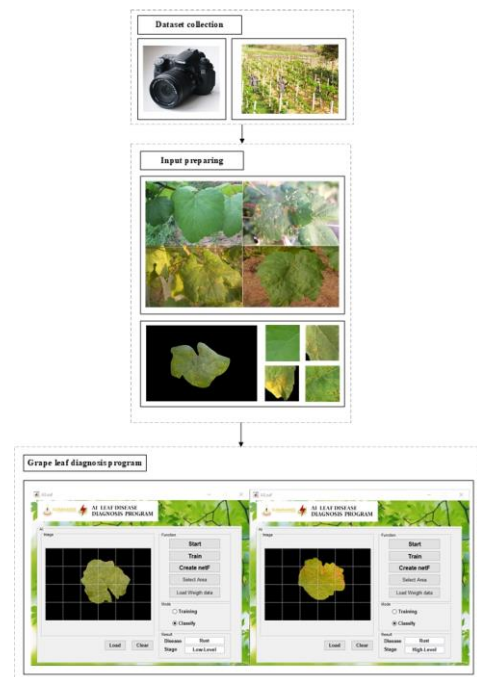


Figure 3. Diagram of the dataset collection and the display result of the diagnosis program

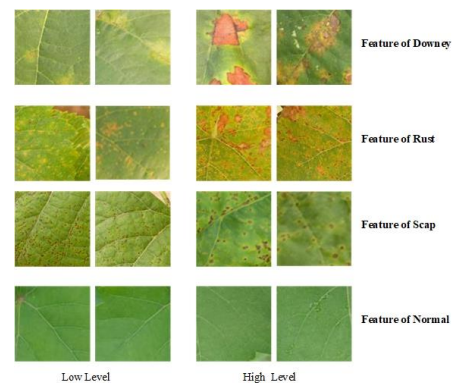


Figure 4. Feature of each diseases on grape leaves comparing with the one with no disease

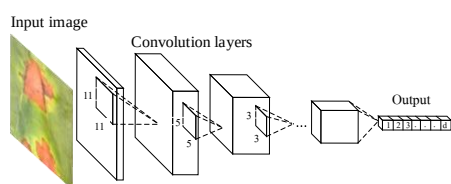


Figure 5. Diagram of the 2LCSFAM feature extraction process

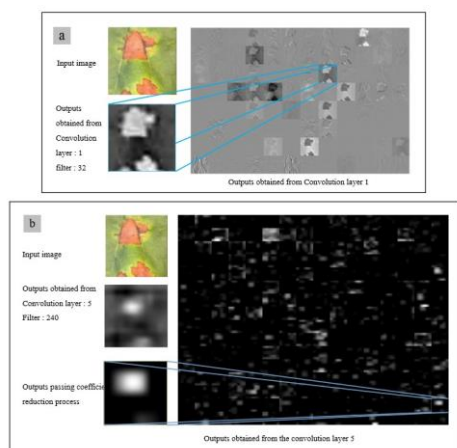


Figure 6. Output from the convolution of: (a) layer 1, (b) layer 5

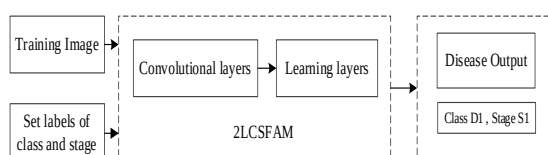


Figure 7. Diagram of operation, training and learning process of the Hybrid neural network

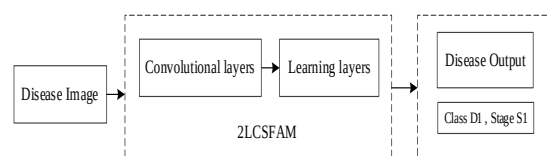


Figure 8. Diagram of 2LCSFAM grape leaf disease diagnostic process function

begins with the input data of the prepared image of grape leaf diseases and subsequently determines the disease type and its severity level. Then, forward to the process of convolution to find the distinct features. The parameter set obtained from this process is forwarded to the learning layer of the hybrid neural network in order to learn the disease type of the grape leaf image, and its severity level.

Diagnosis of grape leaf diseases

The system of diagnostic process begins with putting the images of grape leaf diseases and sending them to the Hybrid neural network that has been trained. Then, the network will seek for the distinct features of the disease and diagnose grape leaf diseases. The network can be set for continuous learning, in the case that the input has high resemblance values enough, the hybrid neural network subsequently updates the neural network weights from the new dataset. This is an advantage of Hybrid convolutional neural network, which will be more intelligent or more effective when a new set of inputs are fed. The function diagram of the grape leaf disease diagnosis process is shown in Figure 8.

Results and Discussion

System Efficiency Test Results

For system efficiency testing in this research, we apply 4 groups of image datasets to train the Neural Network. The first group contains 50 images of grape leaves with no disease and the other 3 groups contain the images of grape leaves with Downey, Rust, and Scap diseases. In each group of the images with diseases, there are 50 images which the stage of infection is low level and 50 images which the stage of infection is high level. Thus, there are total of 350 images which are used in the training process of the hybrid Neural Network. Examples of datasets are shown in Figure 4.

This research uses parameters for calculating values that indicate the level of the system accuracy, and efficiency as follows: (1) precision, PRE, which is a value representing the efficiency in classifying groups or diagnosing diseases which match the real diseases. It can be calculated from the ratio of TP (true positive), or the diagnosis values matching the real diseases and the images of diseases which the system identifies as plant diseases, but do not match the disease type in the real images, which is called FP. (false positive) with the best value equal to 1. In other words, the system can get 100% accuracy on data diagnosis. (2) the true rate of system diagnostics (true positive rate, recall, sensitivity, hit rate), or REC) is the value used to show the effectiveness of accurate disease diagnosis which can be calculated from the ratio between the accurately diagnosed images of the real disease type and all images. (3) the F-score value is the mean value between system precision and the accurate diagnosis rate.

Table 1 shows the test results of the system efficiency in terms of the number of images by testing all 700 images consisting of 350 used-to-be-trained images: 50 no-disease images, 100 Downey

diseased images, 100 Rust diseased images, and 100 Scap diseased images. The group of diseased images are divided into 50 images at Low Level, and 50 images at High Level. For the new images which have never been trained to the system, there are 350 images: 50 no- diseased images, 100 Downey diseased images, 100 Rust diseased images, and 100 Scap diseased images.

Table 2 shows the precision values of the disease diagnosis which is divided into diseased groups including Low Level (LL) and High Level (HL). The accuracy rate of disease diagnosis and the F- score value, which is the mean between the system precision and the accurate diagnosis rate.

Table 3 shows the mean of the test results of each disease as follows; the diagnosis of either diseased or no diseased grape leaves with the precision rate equal to 95.83%, the accurate diagnosis rate of disease type equal to 93.88%, and F-score value equal to 94.85%. For diagnosing the dataset of diseased grape leaves, the test results are as follows: Downey disease with precision values equal to 84.12%, the accurate disease diagnosis rate equal to 89.42%, and F-score equal to 86.58%. Rust disease with the precision rate of 83.59%, and the accurate

disease diagnosis rate equal to 86.50% with the F-score equal to 85.01%, and the Scap disease with the precision value equal to 88.44%. The accurate rate of disease diagnosis is 84.00% with the F-score equal to 86.16%. This can show the overall system efficiency by using the relation between the accurate rate of disease diagnosis and the inaccurate rate of disease diagnosis (Receiver Operating Characteristics or ROC curve).

In (Figure 9(a)), it shows the system efficiency diagnosis in the form of ROC curve of each grape leaf disease. The characteristic of ROC curve shows the system efficiency of good grape leaf disease diagnosis in all patterns, and when taking ROC curve of each graph to calculate for the area under curve (AUC), the results are as follows; in the case of testing with no diseased grape leaves, AUC equals 0.96, AUC of Downey is 0.9425, AUC of Rust equals 0.9315, and Scap with AUC equals 0.919. From the results of AUC calculation, the calculated values in Downey group is the highest value showing that Downey has the highest diagnostic accuracy of 95.83 percent. The comparison of AUC values for each severity level is presented in Figure 9(b-d).

Table 1. The test results of the system efficiency shown in the number of images

Diagnosis		Disease type							
		No disease		Downey		Rust		Scap	
		-	-	LL	HL	LL	HL	LL	HL
No disease	-	92	-	3	-	-	-	1	-
	-	-	-	-	-	-	-	-	-
Downey	LL	3	-	87	2	4	3	-	-
	HL	-	-	5	90	2	6	-	6
Rust	LL	-	-	1	-	86	2	12	-
	HL	-	-	4	4	5	87	1	4
Scap	LL	5	-	-	-	3	-	83	5
	HL	-	-	-	4	-	2	3	85
Correction (%)		92	-	87	90	86	87	83	85
Average (%)		87.14							

Table 2. The overall system efficiency test results

Diseases	Level of Disease	Performance		
		PRE	REC	F-Score
No disease	-	95.83	93.88	94.85
	LL	87.88	87.00	87.44
Downey	HL	80.36	91.84	85.71
	LL	84.31	86.00	85.15
Rust	HL	82.86	87.00	84.88
	LL	86.46	83.00	84.69
Scap	HL	90.43	85.00	87.63

Table 3. Mean of the test results of the overall system efficiency

Diseases	No. of Disease Image	Performance		
		PRE	REC	F-Score
No disease	100	95.83	93.88	94.85
Downey	200	84.12	89.42	86.58
Rust	200	83.59	86.50	85.01
Scap	200	88.44	84.00	86.16

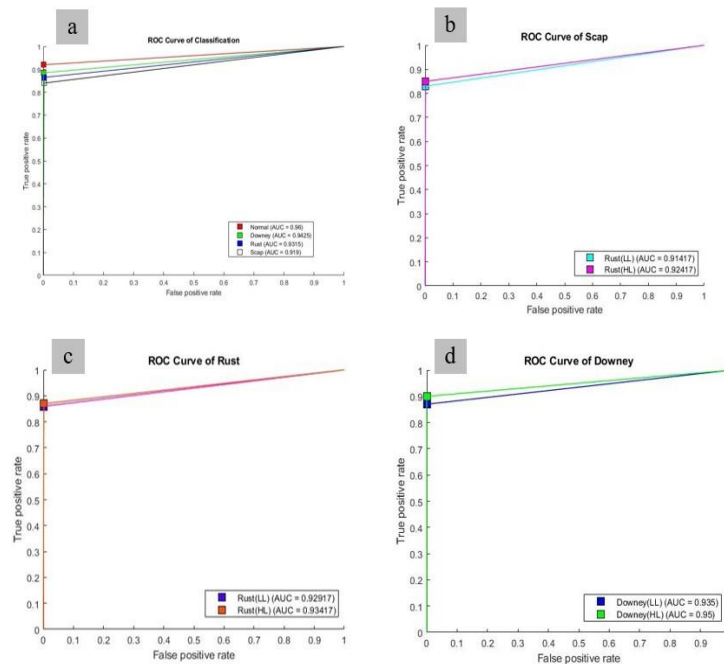


Figure 9. The graph showing the ROC curve of: (a) the system efficiency diagnosis. (b) ROC curve of Scap, (c) ROC curve of Rust, and (d) ROC curve of Downey

Conclusions

This research presents the Hybrid neural network development to potentially learn and remember information at two levels by using the principle of multi-parameter monitor. Each vigilance parameter can be adjusted itself to suit the group of qualified neural network weight values which passed the condition and being trained by testing with the grape leaf disease diagnosis system. Hybrid neural network potentially recognize grape leaf occurring diseases and their severity levels appearing on grape leaves using the same dataset. In addition, this type of hybrid neural network, which can learn continuously, makes the system gain more efficiency whenever a new dataset is fed. The introduction of the distinct feature extraction model using deep learning with a convolution neural network can reduce the processes possibly causing operational errors in the machine learning such as parameter selection for hybrid neural network training, randomization of various parameters, which are time-consuming for testing to find the dataset suitable for training. The recommendations for future research are as follows; the dataset used for training of Hybrid neural networks should be diverse and sufficient to obtain the reliability and efficiency system. The advantages of the developed neural network can increase the efficiencies of the network from continuous training

without repeated training from the beginning of process so that the neural network weights that have already been trained can be applied to other systems or to continue immediate training. In addition, it possibly adds new disease type groups to the Hybrid neural network. The grape leaf disease diagnosis system can be applied to image classification in other groups without parameter adjustment in terms of distinct feature extraction. Besides, the vigilance parameters can be adjusted to suit the dataset required to be tested for the system efficiency.

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