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Green Chilli Leaf Disease Detection Using Convolution Neural Networks

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Abstract

Currently in Malaysia, the price of imported red chilli is cheaper compared to local red chilli. Local farmer needs to be more efficient in the production and one of the ways is to detect the plant diseases. The most significant indicator of a sick plant is by observing the leaf. The leaf will wilt, curled up, spotted yellowish or easily fall to the ground. Different sickness leads to different symptoms on the leaf and occasionally there can be more than one disease affecting the plant. Farmers need to exactly identify the type of disease in order to treat the disease either to use fertilizer, pesticides or simply kill the plant. With so many diseases that can infect a plant, disease detection became harder. One way to overcome this problem is to semi-automate the process using modern technique such as deep learning. Deep learning is a method to extract useful pattern from data with as little human effort involved as possible. In this work, Convolutional Neural Network (CNN) is deployed for image-based red chilli disease detection. The result have shown that 97% accuracy has been achieved in the detection of healthy, crumpled, and yellow leaf.

Keywords: Disease detection, Chilli plant, Convolution Neural Networks,Green Leaf, pesticides.

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1 Introduction

1.1 Background Study

Chilli is one of the important plantation in the tropical and subtropical regions used in various dishes. The larger the demand, the price will sky-rocket if the supply is scares, but if there are more supply than demand, the price will be cheaper [1]. Among the production problems faced by farmers are rotten chilli. Chilli can be infected with a variety of diseases. There are more than 21 type of known incest and non-incest that cause leaf curl disease and chilli venial mottle virus (CVMV), aphids and thrips mites [2]. According to their finding, curl leaf caused by viral infection found as a major disease that affected the plant. Conventional method of detecting plant disease is to inspect manually each plant's leaves [3].

Different sickness leads to different symptoms on the leaf and occasionally there can be more than one disease affecting the plant. This traditional method is time consuming and requires several workers if the farm is medium to large-scale.

By adopting modern technique such as the deep learning, the problem arises from conventional farming for plant disease detection can be solved effectively. This research work focuses on plant disease detection from chilli leaves using the Convolutional Neural Network (CNN) method. There are some studies that are relatively close to what this paper presents. According to [4], the lowest accuracy for a CNN is 95%. Comparing to other classification method that were used, CNN remained unchallenged. The studies show an accuracy from 91% to 98% for separated datasets using a total of 30,000 images to detect a variety of plant, leaves and diseases.

1.2 Supervised Learning

There are few definition of machine education and one of these definitions is "a study field that enables computers to learn and not to be specifically programmed," as defined in 'Machine Learning' [5][19][20]. In [6], Yann LeCunn mentions, “machine learning is the science of sloppiness." In a nutshell, we fed a bunch of data and we gave only the data and answers to what the computer was, the rest, we set the rules in relation to the expert system. Any of them are supervised learning, semi-controlled learning, unattended learning and strengthening learning.

Trained with labelled images, like a known input for the planned output. For instance, cat or dog input data points may be tagged. The learning algorithm collects a set of inputs along with the relevant outputs. By comparing the real output of the algorithm, the errors are discovered.

Then the model is changed accordingly to previous error. Supervised learning uses label values to approximate by methods like classification, regression and increase in gradient for more unmarked data. In a nutshell like giving a cheat sheet to the AI where it already knows the answer, learn from the answer, and test it on unseen data. Supervised learning used to predict the likeliness on what is going to happens, in this case the likeliness of the plant gotten a disease or not. Figure 1 shows Differences between Conventional Programming and Machine Learning

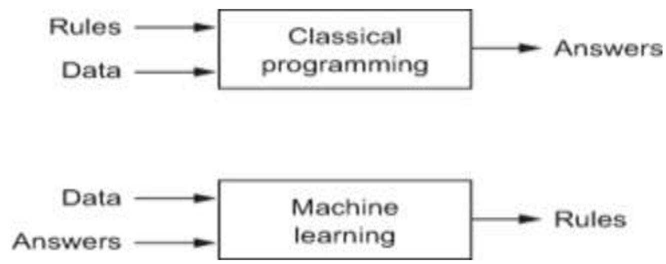

Figure 1 Differences between Conventional Programming and Machine Learning

1.3 Convolutional Neural Networks

CNN is a type of neural network, stack against multiple times and often compromised one or more convolutional layer and sometimes with pooling layer and dropout layer. A convolutional layer act as a feature extractor that extract feature of the input such as edge, corner, and endpoints. Pooling layer is where the resolution of the images is scaled down. Dropout layer is where the neuron is killed at random to make the model architecture to better at generalize rather than memorizing all the training data.

According to [7], CNN yield the highest success in image recognizing such as face detection and handwriting recognition hence the origin of MNIST datasets were used as a handwritten images. CNN uses succession layer of trainable convolutional layer and sub-sampling to perform detection of a specific object.

1.4 Current Method to Detect the Disease

As discussed before the method used to detect disease in plant are such as Support Vector Machine (SVM), Artificial Neural Networks (ANN) and Convolution Neural Networks (CNN). However, not all the studies conducted above used the same variables. It can be confirmed that a method to do feature extraction for each picture has been used. A study conducted by [8], they use chilli and as stated in their paper there are threshold for their colour feature extraction and texture feature extraction.

Also stated by [3] a traditional method for analysing & grading of diseased chilli is naked eye observation. This method requires a lot of time and can be tedious. In some country, they require expert in knowing what the exact disease is that happening to the plant such as cassava plant. Some disease is either seed borne, or air borne and stems from bacterial infection, fungi, and virus. The use of chemical fungicides would result in the development of fungal resistance and the risk of environmental pollution. An alternative way of controlling plant diseases was suggested the use of biological control agents [9].

1.5 Comparison of The Existing Methods

Table 1 provides Experiment done by Previous Researcher.

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Method	Plant type	No. of disease	Accuracy
CNN [10]	Peach, cherry, Pear, Apple, and Grapevine	13	96.3%
SVM [11]	Chilli	4	80%
SVM [12]	Palm Oil	4	80%
ANN [13]	Pomograte fruit	4	90%
Back-propagation NN [7]	Cotton plant	3	85.25%

1.6 Type of Chilli Plant Diseases in Malaysia (general)

There are more than 21 type of known incest and non-incest that cause leaf curl disease and chilli venial mottle virus (CVMV), aphids and thrips mites in Malaysia [14][15][16]. According to their finding, curl leaf caused by viral infection found as a major disease that affected the plant. There is also other known disease such as grey mould, white fly, and yellowish.

Grey mould [17] is a common fungal infection that occur to the plant. It is a type of air borne disease, usually attack plant when it undergoes stress or wound within the stem. We cannot visibly see with naked eye when the spore enters the plant but can be seen when plant has fruit. Once the fruit start ripens it will turn into a brown mush. Once that happens, grey mould can be seen on part of the plant. Either underside of the leaf, stems, flower, or fruits.

Yellowish occurs when the plant is deprived from water and nutrients. As the results, the plant growth will be staggered. Chilli plant leaves are yellow due to water and nutrient scarcity. One of most common causes of yellow leaves on a chilli plant is either caused by bad irrigation or nutrient shortages. Chilli plants are also stunted in both cases, and usually chilli flowers or fruits are rotten. Increasing the amount of water and fertilizer may solve this issue [11].

The next insect is white fly [17]. Whiteflies are much closer to sap-sucking aphids and resemble very tiny moths. If you get an outsized infestation and the whiteflies are interrupted, they may fly away and generate a white flecks miniature snowstorm. In hotter areas, including greenhouses, you are apparently looking for whiteflies. Then again, survivors of a whiteflies area unit region will not turn away from cooler temperatures.

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2 Methodology

Figure 2 CNN flow

The presented work is based on four main processes as depicted in Fig.2. Starting off from data acquisition, the images of healthy leaves and sick leaves from chilli plants are fed to the neural network. The data can be raw images, CSV file or any other form of input. For data acquisition, this experiment will take some picture as done by previous researcher [16] as they put the sample at a piece of A4 paper.

The next step is data pre-processing is where the raw data undergoes transformation of image augmentation, as for this experiment, is using horizontal and vertical augmentation [6]. It also functions as a proper way to achieve lower loss when training as there are more training data.

After pre-processing, classification is applied to the data images [5]. At this point, is can be clear to know whether the NN is overfit or underfit. The classifier is this paper is trained using 6 hidden layers to classify either the leaf healthy or sick

The output layer is where our classification makes based on dataset that it never seen before, in this experiment's images. The classifier can be tested by using this method to further know either the model is doing good or bad based on unseen images.

Dropout layer by [18] is a common way to reduce any overfitting when training a neural network. Dropout arbitrarily kill the neuron during training session to prevent overfitting. There are 3 type of fitting in neural network which is underfitting, normal fitting or appropriate fitting and overfitting. For the model that will be constructed, the model firstly needs to be monitored either it needs dropout layer or not. Not every model needs to have this special layer. The more hyperparameter tuning does not generally translate to a better model.

The equation below is used to calculate the output kernel for convolution filter on each layer

$$((W-K+2P)/S)+1 \tag{1}$$

W = Input shape, K = Kernel/Filter size, P = Padding, S = Stride

3 Results and Discussions

3.1 Trained Sequential Model

Figure 3 Model 7 accuracy and loss

For both Fig. model 7 and 3, the only differences between those 2 models is the batch size. Batch sizes play a crucial role as it is one of training parameter that we need to set before training. Batch sizes define how many images that pass through the network during training. The advantage of using batch size is it use less memory as a small amount of data were feed to the network.

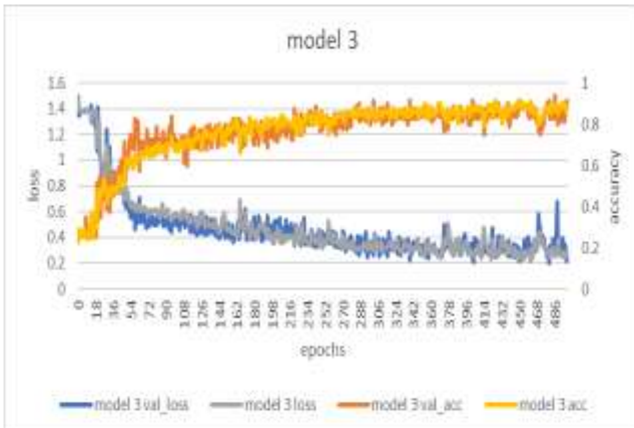

Figure 4 Model 3 accuracy and loss

Too large of batch size lead to poor generalization and vice versa. For Fig. 4 model 3, it was trained using batch size of 32 and model 7 is 10.

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3.2 Pre-trained Model

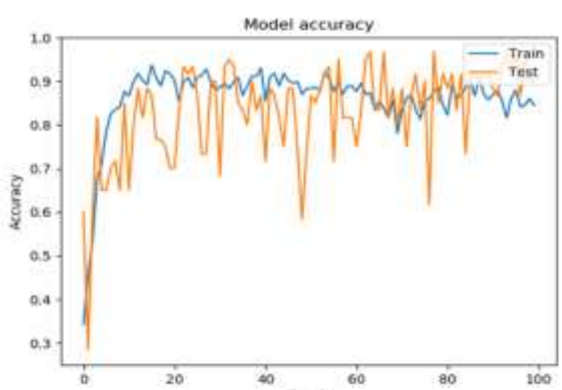

Figure 5 VGG 16 accuracy

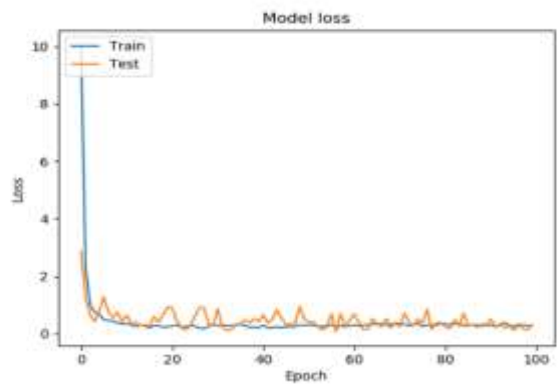

Figure 6 VGG 16 loss

Fig. 6. VGG 16 is one of the pre-trained model that this experiment will be using. The model is very interesting as this model has the lowest training time across every other models. With just 100 epoch, this model already completed training this is because the total number of parameter that this model has, it has 138 million parameter. Out of the many, we can use this pre-trained model for our classification. For this experiment, we need to do some modification to this network as we want the neural network make classification against created dataset. By doing that, the model was shrunk to only 58 million parameter with the intention to get faster training time and better accuracy.

Comparing this model with a new model trained from scratch, now it is clear that more parameter is better, do keep in mind that more parameter also making any model prone to overfitting. As the results stated, VGG16 has more parameter compared to new model. This is because VGG16 are trained to classify across 1000 different classes while the new model only trained to classify 3 class. Another reason is from the 1000 different classes, VGG16 models have learn a lot of different shape, edges, color, and many other different features from the 1000 classes compared to only 3 classes. That is why VGG16 perform much better compared to this new model.

3.3 Machine Learning Model

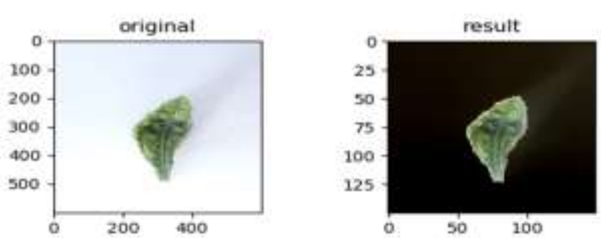

Figure 7 Morphological transformation 1

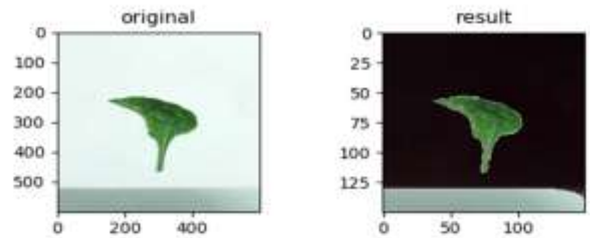

Figure 8 Morphological transformation 2

With that said this experiments also conducted with some machine learning model such as Fig.9. SVM and Fig.10. Neural Network. Below are the results. Before it is done, the images need to be pre-processed for it to be feed into any machine learning models. With that, the experiment uses morphological transformation where the background of the image is subtracted and replace with black pixel as shown above. After that, the sum of pixel for each images are extracted and placed into an excel file. There is many other form of image pre-processing that can be use such as gaussian blur, edges, and contour. Figure 7 and 8 shows Morphological transformation .

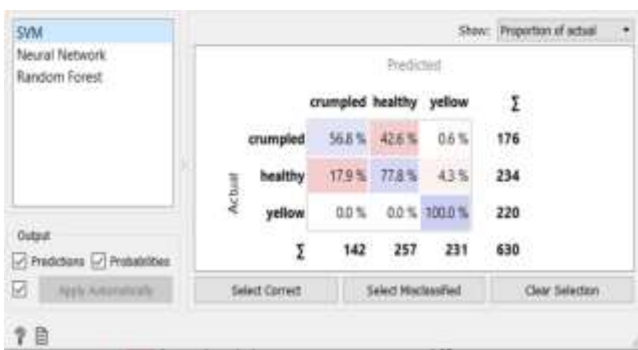

Figure 9 SVM Confusion Matrix

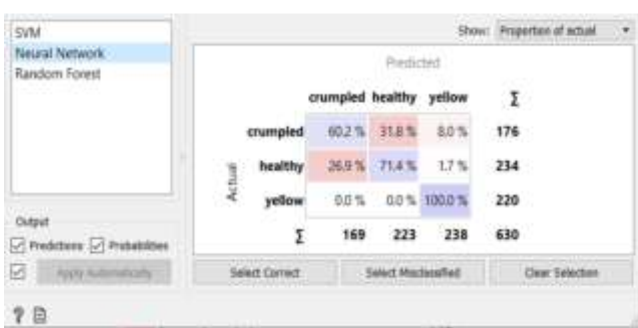

Figure 10 Neural Network Confusion Matrix

From all the confusion matrix above, it is safe to say that Neural Network and SVM is neck and neck in terms of healthy while the Neural Network clearly has better advantage. From both confusion matrix above, both models have problem classifying between the healthy leaf and crumpled leaf. This is because the number of green pixel for both is similar, the yellow class with the highest accuracy is because the presence of red pixel. Overall, this clearly tells us we either need more images or other method.

3.4 Summary

As a summary from model 3 and 7 can be used for making prediction for real world data. Based on training results, both models can achieve 97% accuracy to identify healthy, crumpled, and yellow leaf. The differences are model 3 took a significant longer time compared to model 7. There are other trained model based on similar training parameter. As seen on model 8, messing one parameter can change the model entire behavior. For model 3 and 7, we test the model based on other unseen images and other leaf type that have same disease.

We can use CNN model to recognize other type of leaf that have the same disease. Mosaic virus can be found not only in chilli, but also in tomato, cassava, and many other types of plant. We found a dataset from Kaggle and inside it we found tomato mosaic virus. We use the tomato images against model 3 and model 7. Both classifiers show similar results in terms of prediction. In this case, we can choose model 7 as the model have similar prediction as model 3 but shorter training time. These are the results; the model was tasked to classify 10 different leaf that the model never seen before

The difference between machine learning and deep learning is clear, machine learning model rely on pre-processed and structured data such RGB value for this experiment. While deep learning models rely on structure on Artificial Neural Network (ANN). The goal of deep learning is extract useful information in an automated way with little human intervention. That is why deep learning generally more powerful compared to machine learning. With that said, the results below show some of the advantage of CNN

From Table 2, it is very surprising as the model can classify with perfect accuracy for healthy images, 90% accuracy with yellow images and only 60% accuracy with crumpled accuracy. Turns out it can classify with 90% accuracy for tomato images even though the model were trained to recognize chilli leaf. This is one of the benefits of using deep learning as it can classify something even it has incomplete information about something. If we look closely at yellow (5), the prediction leans towards crumpled instead of yellow but for crumpled, the prediction performs worse from expected for crumpled 3 and 5, the model predicted as yellow.

Table 2 Model performance

Leaf	yellow	Crumpled	Healthy
healthy (1)	0	0	1
healthy (2)	0.00006023	0.00001585	0.99992394
healthy (3)	0.00000043	0	0.9999995
healthy (4)	0	0	1
healthy (5)	0.00000022	0	0.99999976
healthy (6)	0	0	1
healthy (7)	0.00000001	0.00000003	1
healthy (8)	0	0	1
healthy (9)	0.00010477	0.00000024	0.999895
healthy (10)	0	0	1
yellow (1)	0.9990833	0.00072872	0.00018792
yellow (2)	0.9999988	0.00000018	0.0000009
yellow (3)	0.99964774	0.00001022	0.00034201
yellow (4)	0.9999951	0.00000002	0.00000493
yellow (5)	0.06363874	0.93633413	0.00002711
yellow (6)	0.99999034	0.00000765	0.00000203
yellow (7)	0.9972133	0.00277572	0.00001094
yellow (8)	0.9999981	0.00000054	0.00000142
yellow (9)	0.9999857	0.0000019	0.00001245
yellow (10)	0.9999974	0.00000055	0.00000208
crumpled (1)	0.08585122	0.91212577	0.002023
crumpled (2)	0.0002623	0.9996172	0.00012046
crumpled (3)	0.9823245	0.01594855	0.00172707
crumpled (4)	0.17955097	0.8112174	0.0092317
crumpled (5)	0.9719043	0.00050462	0.02759118
crumpled (6)	0.00639397	0.98405182	0.00955422
crumpled (7)	0.2687351	0.71360873	0.01765612
crumpled (8)	0.00860357	0.96179691	0.02959953
crumpled (9)	0.13370998	0.53903705	0.32725295
crumpled (10)	0.00099993	0.00004953	0.9989505
tomato (1)	0.00018306	0.9993587	0.00045823
tomato (2)	0.00000893	0.57600147	0.4239896
tomato (3)	0.00028054	0.9982829	0.00143663
tomato (4)	0.00000017	0.9972613	0.00273853
tomato (5)	0.00000008	0.9999701	0.00002977
tomato (6)	0.00018342	0.997322	0.00249453
tomato (7)	0.00012551	0.9997589	0.00011556
tomato (8)	0.00000145	0.9999931	0.00000549
tomato (9)	0.00000002	0.996759	0.00324105
tomato (10)	0.00005653	0.5906752	0.40926835

As for crumpled 9, the model has confusion between crumpled and healthy while crumpled 10, the model fully predicted healthy. From the prediction, this experiment conclude that the model needs more training data as there are only 315 training data and 60 validation data as well as 40 test data. The model also has imbalance dataset as the highest validation set is yellow with 27 images, followed by healthy with 20 images and 13 images on crumpled. The imbalance of dataset may cause the model prediction behaving as such.

As a conclusion for this experiment there many parameters and hyperparameter that can change the entire model behavior along with distribution datasets. Below are the final model parameter and hyperparameter.

Final model parameters

- 12 covolutional layers with 6 MaxPool layers
- Image augmentation on all training sets

- 3 class as output layers (healthy, crumpled and yellow)
- 10 batch size
- 500 epochs with early stopping at 97% accuracy
- Training size is 315
- Test size at 60
- Multiple dropout layers
- Optimizer is Adam
- Loss is Categorical Crossentropy
- Softmax as output activation function

4 Conclusion and Future Work

This experiments validates the CNN model implementation in a Chilli leaf to detect the sickness that the plant has based on the leaf itself.

It is concluded that this experiment has reached its stated objectives along with other method that implemented using the same datasets. The CNN model is managed to identify and classify the leaf either healthy, crumpled, or yellow. However, the CNN model does have limitation as stated in 4.6, the model has difficulty in distinguishing between a healthy and yellow leaf with crumpled leaf.

This is due to the relatively small datasets that were obtained, adding salt to the wound is there are no clear indication on how many datasets that the new model need to correctly classify and identify; with the total datasets, the new model behave as expected. The model also learns few feature based on the 3 classes it was trained on. Comparing it to other pre-trained models, the pre-trained model blew the new model out of the water with better accuracy and loss with less training time. After the model has completed the training, the performance of the model is evaluated. It can be concluded that this model helps in classifying and identifying based on the leaf. The most interesting part is where the model was tasked to classify the same type of disease on tomato leaf and the model correctly identify it as crumpled. The model does learn the crumpled shape of leaf as intended but may need more datasets

For future work, this model can be improved to increase its proficiency to classify and identify diseases on leaf as we currently know the model know the crumply shape of a leaf when the plant is sick more correctly. The model can be tuned by increasing number of trainable parameter as currently it only have 1.5 million trainable parameter, experimenting with 5x5 or 7x7 convolutional filter with padding, tuning the dropout value or introduce batch normalization layer, increase the number of datasets or use more pre-trained model and compare among it and use better hardware for faster training. There so much can be done to a deep learning model with time being the enemy. Also if implemented to be work with physical hardware, this experiment can be automated for the whole process and provide real time monitoring and disease detection.

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