A Review of Agriculture Crop Diseases Detection Using Deep Learning

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Abstract

Crop diseases has been causing a lot of loss in agriculture sector. The fast and accurate diagnosis of crop diseases is crucial in preventing and limiting loss from the crop diseases. To achieve this goal, method such as deep learning can be used to detect crop diseases. In this study, we review and study the performance of three convolutional neural network model, which is VGG16, VGG19 and Resnet50 model to classify crop diseases. Transfer learning with full connected layer are used, to shorten and decrease the training time and images needed. The dataset used for the experiments is from online plant disease database which is Plant Village Dataset. 210 images of tomato leaves are used in this research. The precision, recall, accuracy and F1-score are calculated for performance evaluation. The result show that Resnet50 perform the best compared to the other deep learning models with accuracy of 92%.

Keywords: *Crop diseases, deep learning, convolutional neural network, transfer learning*

1. Introduction

In the current modern era, advancement of computing technology has changed our daily live rapidly. Computers nowadays become more mobile and powerful than ever before. The potentials of advancement of computer that benefit the society in engineering, medicine, commerce, law, agriculture is massive. Agriculture also benefits from the advancement of the technology greatly. They are many researchers conducted by leveraging artificial intelligence and computer vision to detect crop disease in agriculture goods. Without artificial intelligence, crop disease detection is usually done using naked eye or lab equipment, which slow and time consuming. By using artificial intelligence, we can get faster, precise, and efficient result compare to the human beings that prone to the human error.

In Malaysia, agriculture sector is a significant part of Malaysia economy. It estimated that in 2019, the agriculture sector contributed about 7.1 percent of Malaysia's GDP, equivalent of RM101.95 billion [1]. However, this sector has face same problem every year, which is crop diseases. According to a research, in the palm tree sector, its projected that in the year 2020, 65.6 million of palm tree or 443 430 ha of palm field area are infected by agriculture crop disease known as Ganoderma [2]. Crop disease is not just a major problem in Malaysia alone, but also its affect globally. 35 percent of maize production lost are due diseases and pests

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[3]. Based on this reason, its strongly indicate that an early and effective crop diseases detection method needs to be developed to combat this problem.

2. Machine learning application

Nowadays, the advancement of machine learning algorithm like k-Nearest Neighbor (kNN) and Support Vector Machine (SVM) has enabled them to be used in crop diseases detection. One of advancement is by researcher in [4] by improving data collection for machine learning. They tackle this plan by integrating image processing and segmentation in their methodology. They also use SVM in their classification process. It can note that their room of improvement by integrating their algorithm with technique like feature extraction.

One of the researchers [5], has use soft computing technique to classify crop diseases in pepper plant. Soft computing technique that are used are green pixel masking and threshold-based segmentation. For the feature extraction, Grey Level Co-occurrence Matrix (GLCM) were calculated from the image. Then the feature extracted will be feed to a Propagation Neural Network for crop disease classification.

Other research [6], has use global-local singular value decomposition to tackle similar problem. Their goal to use this algorithm to identify cucumber diseases, coupled with another machine learning algorithm. Based on their research, SVD proven to be effective for feature extraction. Then by using SVM as classifier, combine with a recognition method based on watershed algorithm, they manage to achieve satisfactory and accurate result. But this experiment is run on small dataset, due to the algorithm's expensive computation requirement.

Up Robust Feature (SURF) for feature extraction, in order to classify crop disease of maize has been use in [7]. Like other studies before, they also extract GLCM feature with the histogram from the image. As the classifier, SVM were use with three different kernel function which is linear, polynomial and radial basis function (RBF). There also similar research [8], that used Histogram of an Oriented Gradient (HOG) as feature extractor. Texture, color and Hu moment were taken to be analyzed. Even though the data use for the analysis is small, both of the study achieves great result.

3. Convolution Neural Network

One of the machine learning algorithms, convolutional neural network also known as CNN is a deep feedforward neural networks, which is constructed by imitating the connective pattern of neurons in the human visual cortex. CNN play a major part in many deep neural models that used in image classification. Usually, a CNN architecture consists of multiple layer which is convolutional, pooling, fully connected and activation layer. The convolution layers are made up from a series of convolution kernel, which is used to obtain features from small squares of input data such as curves, edges and shapes. The convolution kernel parameters should optimize depending on the size of the input image and the architecture of the network. Next, the pooling layer is used to reduce the dimensionality of images and then resulting in less computational power needed to process the successive layer. The pooling layer will reduce the spatial dimension of the extracted feature maps and network parameters by non-linear operation like average-pooling, sum-pooling and max-pooling. The fully connected layer or dense layer is a part of final layer in convolutional neural network that are used to recognized features with the output classes. The output of dense is a one-dimensional vector which is obtained from flattening the output of previous pooling layer. Lastly, the fully-connected layer can be used to classify the output.

4. Convolutional neural network-based algorithm in crop disease detection

CNN have different approach to image classification compared to traditional machine learning algorithm like SVM and KNN. Unlike the other algorithm, CNN algorithm didn't need to use feature extraction and image preprocessing for image classification application since, the CNN algorithm consists of layers that capable of similar function. CNN algorithm however usually needs large amount of dataset to perform better in image classification. This problem can be solved by applying transfer learning on the CNN algorithm. Such method is applied by [12], to create a CNN model. The studies purpose is to create a CNN model to detect plant diseases on the rice plant. The CNN architectures were used as feature extractors and output of these were used by SVM for classification. Models produced accuracies of 92 percent. which is quite good.

An additional research was done by [9] , but using more varieties of plant species. They use CNN model like Alexnet, VGG, Googlenet which were trained from scratch and resultant model obtained accuracies of about 99 which is very good. Then a similar research where done by [10],which use transfer learning method and deep learning model of Alexnet and Googlenet. They also achieve great accuracies with the model, however both these models failed miserably when tested on datasets other than the ones under study. From the experiment, the authors suggest that their model is not overfit, and these problems can be mitigated using data augmentation and training some layers of the architectures with problem specific data.

Another application of this algorithm detection and classification of crop diseases. In [11], they have done a research to use modified Faster R-CNN algorithm to detect and classify leaf spot disease in sugar beet. The modified Faster R-CNN manage to score 95.48% accuracy, a bit more than the original Faster R-CNN models, which score 92.89% accuracy. The authors also noted that the lighting affect the accuracy of the classification.

5. Experimental results and discussion

The deep learning model had been run on GPU to decrease their training time. The operating system use is Windows 10 with 64-bit processor with the graphic card Nvidia GeForce GTX1050, and 12GB RAM memory.

The parameters of the experiment and hardware specification for the training system are given in the Table 1.

Table 1 : Experiment and Hardware Specification

Name	**Parameters**
Operating System	Windows 10, 64 bit
Processor	Intel i5-8300H CPU @ 2.30GHz, 2.30GHz
Installed RAM	12 GB
Graphics	GeForce GTX 1050 2GB RAM , NVIDIA
Programming Language	Python
Development Environment	Anaconda, PyCharm, Tensorflow, Keras, OpenCV
Input Dataset	*Plant Village Dataset*
Input dimension	224 X 224 X 3
Batch Size	16
Loss	Categorical Cross Entropy
Activation Function	ReLU (Softmax at Dense Layer)
Learning Rate	0.0001
Epochs	100
Weight	Imagenet

5.1. Dataset

The datasets are taken from online image database, which is Plant Village dataset, which consist of various image of crop diseases. For this experiment, we use tomato leaf images that infected by diseases. We use 5 category of images which is Early Blight, Late Blight, Bacterial Spot, Leaf Mold and also healthy tomato leaves. We use 200 images for training and 10 for validation for each class. The training images are split to 80:20 and 70:30 of train and test ratio.

Table 2.Train Test Validation Dataset

Category	Dataset 1			Dataset 2		
	Training	Testing	Validation	Training	Testing	Validation
Healthy	160	40	10	180	20	10
Early Blight	160	40	10	180	20	10
Late Blight	160	40	10	180	20	10
Bacterial Spot	160	40	10	180	20	10
Leaf Mold	160	40	10	180	20	10

The models were trained for 100 epochs and after the training the models are evaluated against the validation dataset. Experiment is done in two sets, 80:20 and 70:20 train-test rations. The trained models will be use to classify the leaves images from the dataset. After the evaluation, the result will be uses as analyses purposes. In the following equation, data label that predicted correctly will be labeled True Positive. For the data label that will be predicted wrongly are labeled False Positive. Furthermore, negative data label that correctly predicted will be True Negative. Lastly, the positive data label that wrongly predicted will be False Negative. False Negative is positive data label which has been predicted wrong. An analysis is performed on the outcomes resulted from proposed model. Various parameters are used to analyses the performance of crop diseases classification which is- accuracy, sensitivity, specificity, precision and F1 score which were calculated as follows in Equations:

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ number\ of\ images}$$

$$Recall = \frac{True\ Positive}{True\ Negative + False\ Negative}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$F1\ Score = 2 \times \frac{Precision * Recall}{Precision + Recall}$$

5.2. Results

This section provides a detailed analysis of all the results that are obtained with regards to achieving objectives of the project. Three model were chosen for this which is VGG19, VGG16 and Resnet50. These models were chosen for their almost similar execution time. The recall, precision and f1-score obtained for developed models based on data split ratio of 80:20 is as listed in the Table 2 and 70:30 in Table 3. From the table below, we can see that from 80:20 and 70:30 ratio dataset, Resnet50 model have the highest accuracy with 0.92 and 0.91 accuracy respectively. The accuracy with both datasets does not differ much with Resnet50 model. However, for VGG19 and VGG16 models, there quite significant different of accuracy between the datasets. For 80:20 ratio dataset, VGG19 and VGG16 model achieve of average accuracy of 0.86 and 0.85 respectively. On 70:30 ratio dataset, the models get average accuracy of 0.82 and 0.80 respectively. To make sure the models do not overfit, the models then are tested against validation dataset, which is not included in either train or test dataset. This is to ensure the models perform well on the unseen images. The results of models tested against validation dataset where shown on Table 4 and Table 5. From both Table 5 and Table 6, the models have achieved more than 80% accuracy on both datasets. This shows that the models do not overfit and perform well on unseen data.

Table 3. Results for 80:20 ratio dataset

Model	Precision	Recall	Accuracy	F1- Score
VGG19	0.86	0.86	0.86	0.86
VGG16	0.85	0.85	0.85	0.85
Resnet50	0.92	0.92	0.92	0.91

Table 4.Results for 70:30 ratio dataset

Model	Precision	Recall	Accuracy	F1- Score
VGG19	0.83	0.82	0.82	0.82
VGG16	0.80	0.80	0.80	0.79
Resnet50	0.92	0.91	0.91	0.91

The confusion matrix of models that test on validation set are shown below:

Table 5.Models Confusion Matrix for 70:30 test train ratio

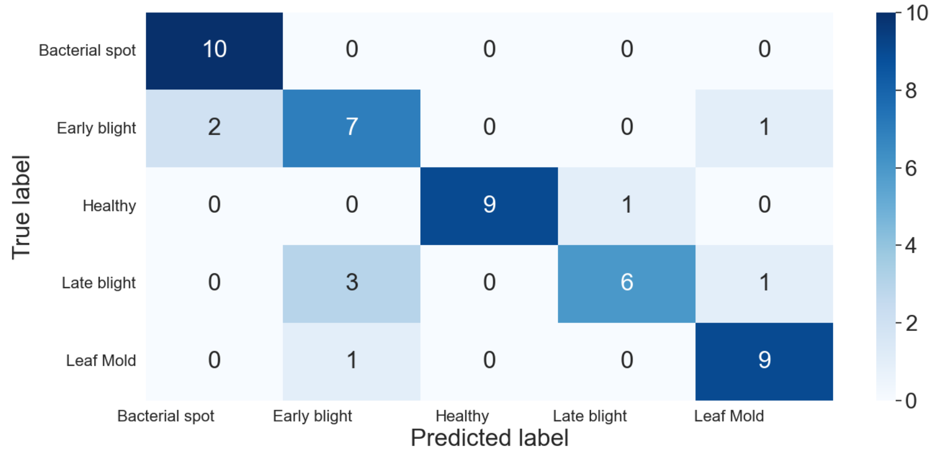
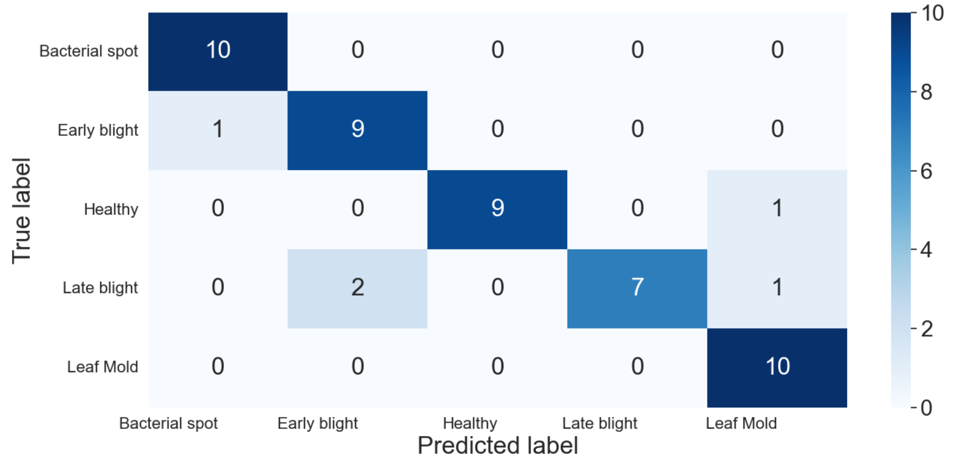
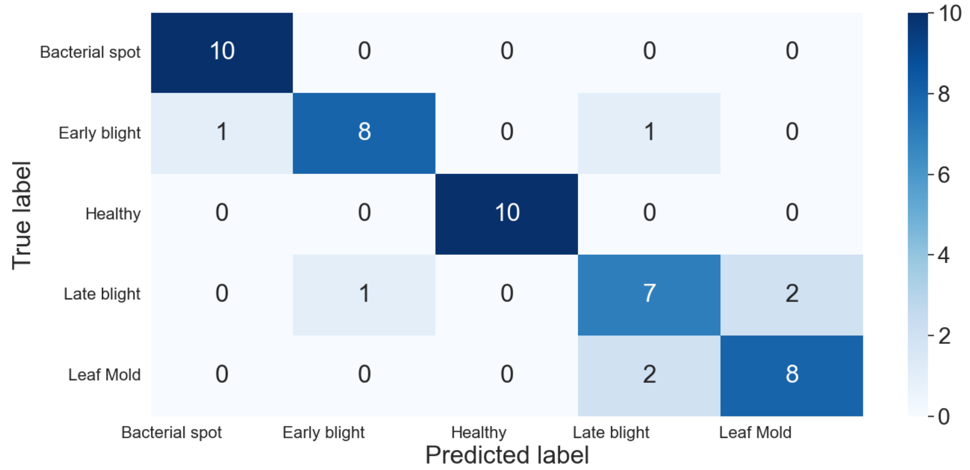
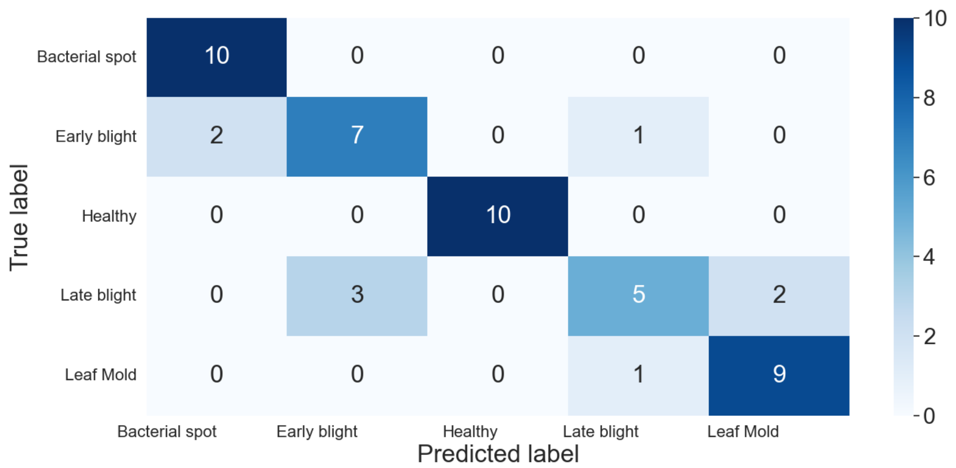
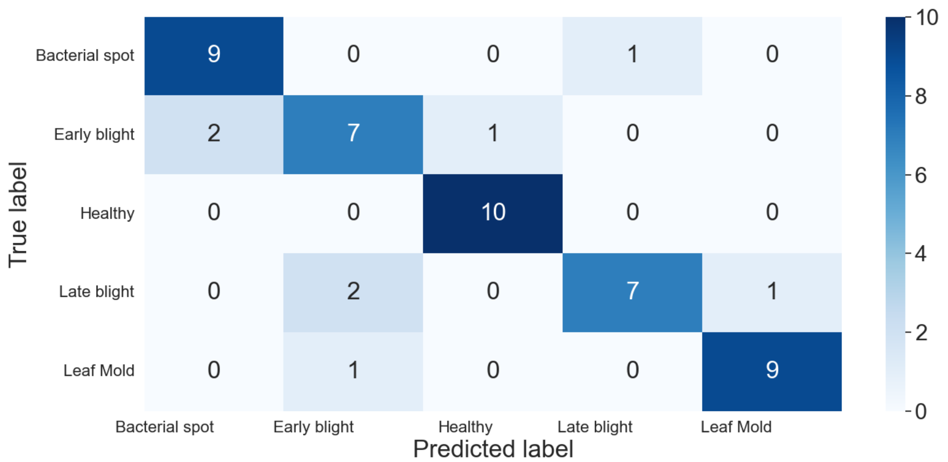
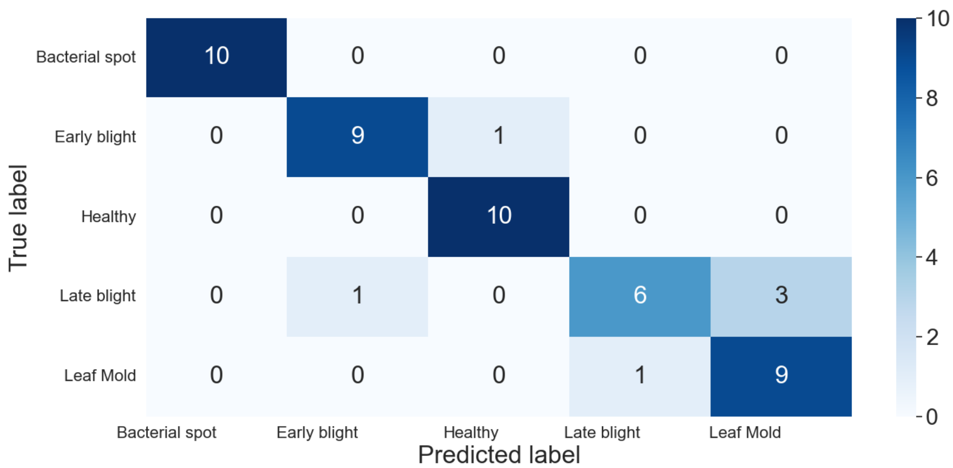
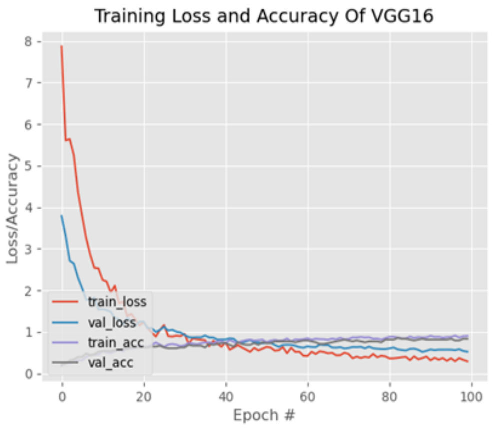
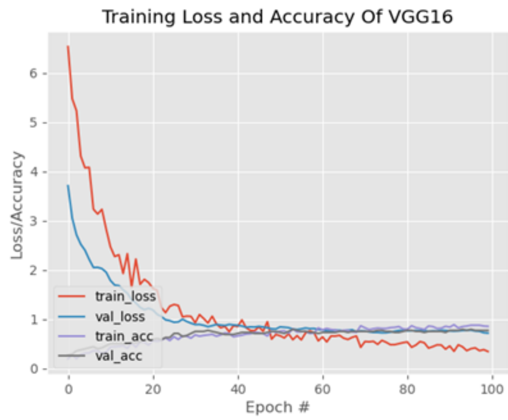
<table>
<tr><th>Models</th><th>Confusion Matrix for 70:30 test train ratio</th></tr>
<tr><td>VGG16</td><td>
</td></tr>
<tr><td>VGG19</td><td>
</td></tr>
<tr><td>Resnet 50</td><td>
</td></tr>
</table>

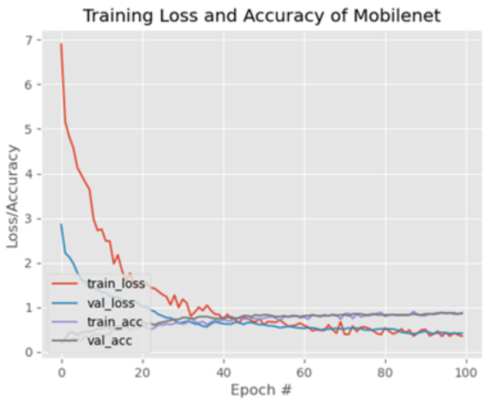
Table 6.Models Confusion Matrix for 80:20 test train ratio

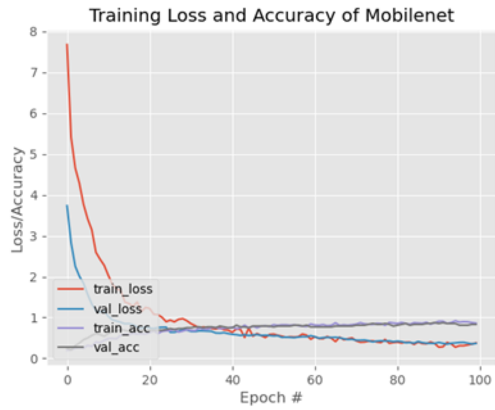
<table>
<tr><th>Models</th><th>Confusion Matrix for 80:20 test train ratio</th></tr>
<tr><td>VGG16</td><td>
</td></tr>
<tr><td>VGG19</td><td>
</td></tr>
<tr><td>Resnet 50</td><td>
</td></tr>
</table>

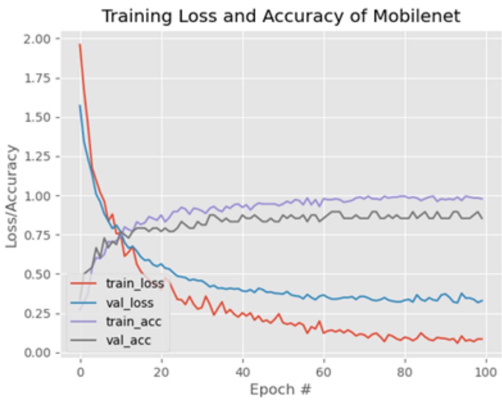
100 epochs are taken in proposed methodology. The training accuracy, validation accuracy, training loss and validation loss for all three models are calculated and plotted, as shown in Figure 1 below. Both training loss and validation loss falling off with an increase in the number of epochs. The training and validation accuracy have significantly surged with the advancement in training iterations.

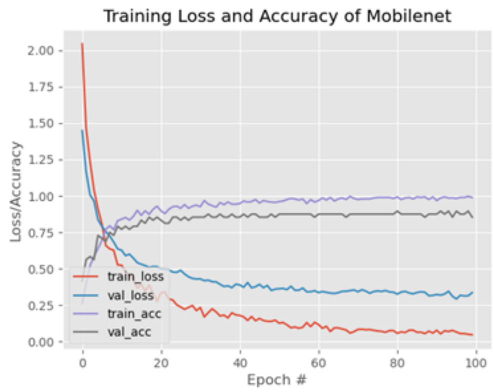
<table>
<tr><th>Models</th><th>80:20</th><th>70:30</th></tr>
<tr><td>VGG16</td><td>


</td><td>


</td></tr>
<tr><td>VGG19</td><td>


</td><td>


</td></tr>
<tr><td>Resnet 50</td><td>


</td><td>


</td></tr>
</table>

Figure 1.Training Accuracy/Loss over Epochs

6. Conclusion

Even though VGG models have estimate size of 500mb, relatively larger than Resnet50 which only around 100mb size. Moreover, small dataset was used in this experiment because, we are using transfer learning. The models were loaded with weight from ImageNet. All these models have inference time around 4ms – 5ms. From the result, we can see that Resnet has the highest accuracy of 91%, both in 80:20 and 70:30 ratio, followed by VGG19 and VGG16. Resnet50 perform better because of the deep residual learning framework even though small [6]. However, both VGG model perform better in 70:30 ratio. This show that VGG models need more test dataset to perform better. Validation set were made to determine no overfitting occur on the model. The confusion matrix show that those models are not overfit since it still performs well on the validation dataset. From the result, we also can see that Early blight have the lowest accuracy across all model, shows that this disease is the hardest to detect.

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