Techinical Report
Plant Disease Classification : Tomato
8 August 2019

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Abstract

The focus of the report is to investigate the use of machine learning, more specifically, deep convolutional network in plant disease classification. The target host for this report focuses on tomato with 10 common diseases. There are six networks trained for this project, with the networks being trained with and without L2 regularisation loss respecively for every dataset used. All the networks trained are able to achieve a Top 1 accuracy of more than 90 % on the validation dataset, hence proving the feasibility of using deep learning for plant disease detection. However, the network performs poorly on detecting tomato plant diseases with tomato plant images other than lay-flat leaf scans when only trained with Plant Village dataset. This can be inferred from a low Top-1 accuracy achieved on an additional test dataset from IPM. The networks are trained again by adding in the IPM images as training images and the performances are re-evaluated. Serving as a proof of concept, there is a complementary computer programme with Graphical User Interface which allows the user to select a plant image and detect the possible plant disease solely through the image.

1 Introduction

Plant diseases have been threatening the global food security apart from affecting the livelihood of the small-holder farmers. To cater to this problem, various measures have been taken to mitigate the occurrence of crop loss due to plant diseases. Above all, correct identification of plant diseases will need to be carried out first so that plant disease control measures can be conducted. Understanding the need of plant disease identification, PlantVillage dataset, being a non-profit initiative, has gathered plant images from 38 categories of crop diseases. The aim of the initiative is to encourage the use of machine learning algorithms among the researchers to predict a plant disease based on the image. As a result, instant plant disease identification can be made possible by analysing visual imagery either on a computer or on a smartphone [1]. This dataset will be utilised in training our tomato plant disease detection model and the performance will be evaluated. Besides, additional images of tomato plant getting infected are sourced from IPM Images [2] to verify the network performance and to train the network further.

2 Methodology

2.1 Overall framework

The framework proposed for identify plant diseases in this article is a type of supervised learning method, namely deep learning or convolutional neural network (CNN). To achieve this, every input

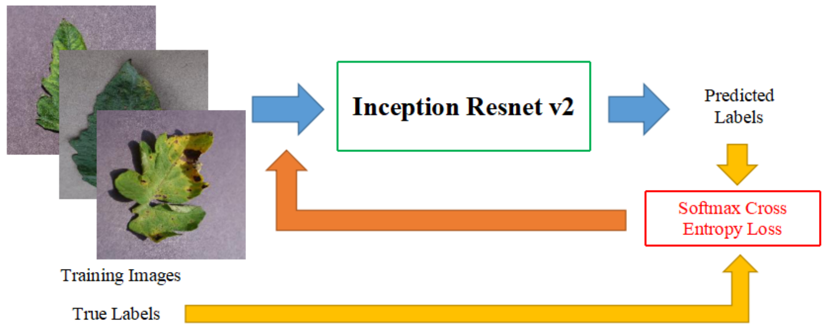


Figure 1: Illustration of the framework used in the tomato disease detection model.

or training image has to be annotated with its ground truth label so that the network can learn the appropriate weights to map the output label to the input image correctly. To enable weight updating, the softmax cross-entropy loss between the true label and the predicted label will be computed. The optimiser will update the network weights following the gradient descent algorithm in minimising the sofmax cross-entropy loss.

Figure 1 illustrates the overall framework used in the plant disease detection model.

2.2 Network Architecture

The convolutional neural network used for the tomato plant disease detection model is the Inception Resnet-v2 model [3]. Inception Resnet-v2 is the current state-of-the-art architecture in image classification - it comes with the lowest Top-1 Error and Top-5 Error for single-crop - single-model experimental results, when being proposed in the original paper. The weights of the network was pre-trained on the Plant Clef 2017 dataset. This will lead to a faster convergence of the learning curve as the feature maps have already learned the plant features. Besides, it also leads the network to better generalisation and prevents network overfitting.

3 Experiments and Results

3.1 Dataset

3.1.1 Plant Village Dataset

The Plant Village dataset contains 54,305 colour images of diseased and healthy plant leaves from 38 classes. Since the plant of our interest is the tomato plant, tomato images are filtered out for training the network. This reduces the dataset to 18,160 images with 10 categories, with 9 categories being diseases and 1 category being the healthy plant. 80 % (14,522) of the images are divided into the training dataset, while the remaining 3,637 images are used as the validation dataset. Note that the training and validation images from Plant Village dataset are the same for all the six networks trained.

Table 1 lists out the diseases of interest together with their labels.

3.1.2 IPM Dataset

Another 436 images are sourced from IPM Images [2] to diversify the types of tomato plant images used in training network. However, the images does not contain the images of the plants infected with target spot. The images are assigned with the same labels as the Plant Village dataset. This dataset will serve as:

1. the entire test dataset for the networks trained in Run 1 and 2, and;
2. the additional training dataset for the networks in Run 3 to 6. For Run 3 and Run 4, the networks are trained without healthy plant images from IPM Dataset - the healthy plant images will only be included in the training of Run 5 and 6 networks. This is to examine the effect of adding healthy, non-leaf-scan tomato plant images on the network performance

Table 1: Tomato plant diseases along with their labels and number of images.

Tomato Plant Disease	Label	Plant Village	IPM Images
Tomato: Bacterial Spot	0	2127	48
Tomato: Early Blight	1	1000	70
Tomato: Healthy	2	1591	105
Tomato: Late Blight	3	1909	94
Tomato: Leaf Mold	4	952	53
Tomato: Septoria Leaf Spot	5	1771	28
Tomato: Two Spotted Spider Mite	6	1676	1
Tomato: Target Spot	7	1404	0
Tomato: Tomato Mosaic Virus	8	373	10
Tomato: Tomato Yellow Leaf Curl Virus	9	5357	31

Table 2: Different runs and the dataset used

Run	Training and Validation Dataset	Test Dataset
1 & 2	Plant Village	IPM Images
3 & 4	Plant Village and IPM Images (excluding "Healthy" class)	None
5 & 6	Plant Village and IPM Images	None

for predicting healthy plant images. 20 % of the IPM dataset are randomly set aside for validation.

3.2 Experiment Setup

3.2.1 Image Preprocessing

Firstly, all the training images are resized to 299×299. Random cropping, horizontal flipping and colour distortion are applied to the training images before feeding the images into the network. This allows the network to learn features that are invariant to their locations in the images and various transforms.

During network inference, the centre crop of the testing images will be used.

3.2.2 Network Hyperparameters

There are six networks trained in the project. The first two networks are trained only with the Plant Village dataset; while the remaining four networks are trained with both the Plant Village and IPM Images dataset, as summarised in Table 2. The addition of IPM Images dataset into the training dataset is to allow the network to learn more disease-relevant features other than the features contained in leaf scans. Althought the number of IPM Images dataset is insignificant as compared to the number of images in the Plant Village dataset, we are still interested to how the network performs due to this change.

The networks are trained with Adam optimizer with an initial learning rate of 0.00001. A drop out rate of 0.2 is used to prevent network overfitting (keeping 80 % of the neurons before the fully-connected layer). The gradient is clipped as 1.25 to prevent the occurrence of exploding gradients.

While softmax cross entropy loss is used as the primary loss function for the neural network, the networks are trained with and without L2 regularisation loss respectively for the same training dataset. This is to examine the effect of using L2 regularisation loss on the learning of tomato plant disease model because Loshchilov and Hutter [4] has shown that coupling the Adam optimiser with L2 regularisation loss leads to poor generalisation of the network. The authors also showed that L2 regularisation and weight decay regularisation when rescaled by the learning rate are not equivalent for the Adam optimizer, as opposite to the standard stochastic gradient descent. Therefore, it would be interesting to see if the same trend occurs for the tomato plant disease detection model.

Table 3 summarises the hyperparameters used for training the six networks in the experiment.

Table 3: Network hyperparameters used for training networks.

Parameter	Run 1, 3 and 5	Run 2, 4 and 6
Batch Size	64	64
Optimizer	Adam Optimizer	Adam Optimizer
Initial Learning Rate	0.00001	0.00001
Gradient Clipping	1.25	1.25
Loss Function	Softmax Cross Entropy	Softmax Cross Entropy
L2 Regularisation Loss	Yes	No

Table 4: Network performance for different runs

Accuracy	Run 1	Run 2	Run 3	Run 4	Run 5	Run 6
Training (Top 1)	99.94 %	92.19 %	98.44 %	98.44 %	98.44 %	96.88 %
Validation (Top 1) - Plant Village	99.73 %	98.93 %	99.70 %	99.67 %	99.75 %	99.75 %
Validation (Top 3) - Plant Village	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %	100.00 %
Validation (Top 1) - IPM Images	NA	NA	48.89 %	53.33 %	78.89 %	78.89 %
Validation (Top 3) - IPM Images	NA	NA	68.89 %	70.00 %	92.22 %	91.11 %
Test (Top 1)	21.28 %	21.74 %	NA	NA	NA	NA
Test (Top 3)	44.62 %	48.28 %	NA	NA	NA	NA

3.3 Results and Discussions

This section summarises the performances of the two networks trained in experiment by tabulating the accuracy, plotting the confusion matrix and analysing the failure cases.

3.3.1 Network Accuracy

In Run 1 and 2, the networks are only trained with the images from Plant Village Dataset. The networks are tested with additional images from IPM Images. It is observed that adding L2 regularisation loss into the network trained using this dataset will weaken its learning on leaf-scans, as the Top 1 validation accuracy drops from 99.73 % to 98.93 %. Since the additional images contain many other images which are not leaf scans (fruit, stem, bud, entire view, microscopic view and far view), the test accuracy for Run 1 and 2 are low (see Table 4). However, the Top 1 and Top 3 accuracy on the same IPM validation images increases when the network is trained with L2 regularisation loss as in Run 2.

At the same time, Table 4 also shows that the Top 1 accuracy of Run 1 and Run 2 networks are 99.73 % and 98.93 % respectively with the validation dataset, while the Top 3 accuracy are both 100 %. In other words, the ground truth disease of the validation images will always be among the top 3 predictions for these two tomato plant disease detection models.

For Run 3 and 4, the networks are further trained with images from IPM Images (without healthy tomato plant images) in addition to the training images used in Run 1 and 2. This opens up the possibility of using non-leaf-scan images for predicting tomato plant diseases, provided if there are sufficient training images from such categories. No extra test set is used for testing the network trained in Run 3 and 4. It is observed that adding only infected tomato plant images from IPM dataset into the training can deteriorate the network predictions on Plant Village validation images, although to a small extent. Meanwhile, adding L2 regularisation loss into the network using these training images will actually improve the network predictions on IPM validation images (with Top 1 and Top 3 validation accuracy increasing from 48.89 % to 53.33 % and from 68.89 % to 70.00 % respectively); while the effect is insignificant on the Plant Village validation images.

Lastly, additional healthy tomato plant images from IPM Images are added into the training of networks in Run 5 and 6, in addition to infected tomato plant images. This time, adding healthy

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Two Spotted Spider Mite	Target Spot	Tomato Mosaic Virus	Tomato Yellow Leaf Curl Virus
Bacterial Spot	421	1	0	7	1	2	0	3	0	1
Early Blight	1	199	0	9	1	3	0	0	0	1
Healthy	0	0	336	2	1	0	0	0	0	1
Late Blight	1	3	2	389	4	0	0	2	0	0
Leaf Mold	0	3	0	0	198	0	0	1	0	0
Septoria Leaf Spot	0	11	0	2	3	338	0	5	2	0
Two Spotted Spider Mite	0	1	0	0	0	0	330	5	0	0
Target Spot	0	1	2	0	0	0	2	276	0	0
Tomato Mosaic Virus	0	0	0	1	1	0	0	0	75	0
Tomato Yellow Leaf Curl Virus	12	0	0	5	1	0	3	0	0	1058

Figure 2: Confusion matrix for Mobile Net V2

tomato plant images helps restore the network predictions on the Plant Village validation images. Meanwhile, adding L2 regularisation loss does not impact on the learning much - the Top 1 and Top 3 accuracy for Plant Village validation images as well as the Top 1 accuracy for IPM validation images remain the same throughout; while the Top 3 accuracy for IPM validation images decreases slightly from 92.22 % to 91.11 %.

From the results discussed previously, it can be inferred that the effect of adding L2 regularisation loss is marginal in the experiment, and is subject to the training dataset used for the tomato plant disease detection model. While the addition of L2 regularisation loss allows the network to predict better on the tomato images with more diverse image types from IPM dataset; it can negatively impact the network predictions on the Plant Village validation dataset. At the same time, adding all the training images from IPM dataset can actually improve the network predictions on both Plant Village and IPM images. This shows that the networks are able to learn useful features from non-leaf-scan images in identifying tomato plant diseases although the size of IPM dataset is small as compared to the Plant Village dataset.

3.3.2 Confusion Matrix

Confusion matrix is used to tabulate the classification results for the six networks trained in the experiment. For Run 1 and 2, two confusion matrix are plotted for validation and test dataset respectively; while there is only one confusion matrix for the networks trained in Run 3 to 6.

From Figure 3 and 5, it can be clearly seen that the network trained in Run 1 and Run 2 does not yield accurate prediction results with the test dataset from IPM Images. This further testifies that a convolutional neural network trained with leaf scans only is not able to learn features related to disease or infections that exist on other plant organs.

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Two Spotted Spider Mite	Target Spot	Tomato Mosaic Virus	Tomato Yellow Leaf Curl Virus
Bacterial Spot	426	0	0	0	0	0	0	0	0	0
Early Blight	0	197	0	3	0	0	0	0	0	0
Healthy	0	0	319	0	0	0	0	0	0	0
Late Blight	0	0	1	381	0	0	0	0	0	0
Leaf Mold	0	0	0	0	191	0	0	0	0	0
Septoria Leaf Spot	0	0	0	1	0	354	0	0	0	0
Two Spotted Spider Mite	0	0	0	0	0	0	336	0	0	0
Target Spot	1	1	0	0	0	0	0	279	0	0
Tomato Mosaic Virus	0	0	0	0	0	0	0	0	75	0
Tomato Yellow Leaf Curl Virus	2	0	0	1	0	0	0	0	0	1069

Figure 3: Confusion matrix for Run 1 validation (Plant Village) images

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Two Spotted Spider Mite	Target Spot	Tomato Mosaic Virus	Tomato Yellow Leaf Curl Virus
Bacterial Spot	0	25	1	12	0	10	0	0	0	0
Early Blight	2	33	0	30	0	2	2	0	0	1
Healthy	3	37	9	32	5	8	7	1	0	3
Late Blight	3	40	1	41	0	7	1	0	0	1
Leaf Mold	5	14	0	26	0	7	1	0	0	0
Septoria Leaf Spot	4	5	0	8	0	7	0	0	0	0
Two Spotted Spider Mite	1	0	0	0	0	0	0	0	0	0
Target Spot	0	0	0	0	0	0	0	0	0	0
Tomato Mosaic Virus	0	4	0	5	1	0	0	0	0	0
Tomato Yellow Leaf Curl Virus	0	10	0	4	6	7	0	1	0	3

Figure 4: Confusion matrix for Run 1 test (IPM) images

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Two Spotted Spider Mite	Target Spot	Tomato Mosaic Virus	Tomato Yellow Leaf Curl Virus
Bacterial Spot	425	0	0	0	0	0	0	0	0	1
Early Blight	0	184	0	7	1	3	1	4	0	0
Healthy	0	0	319	0	0	0	0	0	0	0
Late Blight	0	0	1	381	0	0	0	0	0	0
Leaf Mold	0	0	0	1	190	0	0	0	0	0
Septoria Leaf Spot	0	1	0	1	0	351	0	0	2	0
Two Spotted Spider Mite	0	0	0	0	0	0	335	0	0	1
Target Spot	0	1	1	1	0	2	1	275	0	0
Tomato Mosaic Virus	0	0	0	0	0	0	0	0	75	0
Tomato Yellow Leaf Curl Virus	5	0	0	2	0	0	2	0	0	1063

Figure 5: Confusion matrix for Run 2 validation (Plant Village) images

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Two Spotted Spider Mite	Target Spot	Tomato Mosaic Virus	Tomato Yellow Leaf Curl Virus
Bacterial Spot	2	21	0	13	0	9	1	0	0	2
Early Blight	6	35	0	28	0	0	0	0	0	1
Healthy	7	40	2	25	17	9	1	1	0	4
Late Blight	5	35	1	47	0	3	0	0	1	2
Leaf Mold	7	14	0	21	0	9	1	0	0	1
Septoria Leaf Spot	5	6	0	9	0	4	0	0	0	0
Two Spotted Spider Mite	0	0	0	1	0	0	0	0	0	0
Target Spot	0	0	0	0	0	0	0	0	0	0
Tomato Mosaic Virus	0	3	0	3	1	0	0	0	0	3
Tomato Yellow Leaf Curl Virus	2	5	0	9	3	6	0	1	0	5

Figure 6: Confusion matrix for Run 2 test (IPM) images

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Two Spotted Spider Mite	Target Spot	Tomato Mosaic Virus	Tomato Yellow Leaf Curl Virus
Bacterial Spot	428	1	0	2	1	0	0	0	0	4
Early Blight	0	206	0	6	1	1	0	0	0	0
Healthy	1	3	320	11	1	1	0	0	0	3
Late Blight	0	0	1	395	4	0	0	0	0	1
Leaf Mold	1	2	0	5	198	2	0	0	0	0
Septoria Leaf Spot	1	2	0	4	0	354	0	0	2	0
Two Spotted Spider Mite	0	0	0	0	0	0	336	0	0	0
Target Spot	0	0	1	0	0	0	0	280	0	0
Tomato Mosaic Virus	0	0	1	0	0	0	0	0	76	0
Tomato Yellow Leaf Curl Virus	0	0	0	1	1	0	0	0	0	1077

Figure 7: Confusion matrix for Run 3 validation (Plant Village & IPM) images

Actual \ Predicted	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Two Spotted Spider Mite	Target Spot	Tomato Mosaic Virus	Tomato Yellow Leaf Curl Virus
Bacterial Spot	430	2	0	0	1	1	0	0	0	2
Early Blight	0	208	0	4	1	1	2	4	0	0
Healthy	1	4	319	13	0	1	0	0	0	2
Late Blight	0	0	1	395	3	1	0	0	0	1
Leaf Mold	1	3	0	1	197	0	0	0	0	0
Septoria Leaf Spot	0	3	0	1	0	355	0	0	2	0
Two Spotted Spider Mite	0	0	0	0	0	0	336	0	0	0
Target Spot	0	0	1	0	0	0	0	280	0	0
Tomato Mosaic Virus	0	0	0	0	0	0	0	0	76	1
Tomato Yellow Leaf Curl Virus	0	0	0	2	0	0	0	0	0	1077

Figure 8: Confusion matrix for Run 4 validation (Plant Village & IPM) images

Predicted

Actual	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Two Spotted Spider Mite	Target Spot	Tomato Mosaic Virus	Tomato Yellow Leaf Curl Virus
Bacterial Spot	431	1	0	0	2	2	0	0	0	2
Early Blight	0	209	0	4	1	0	0	0	0	0
Healthy	0	1	338	0	0	0	0	0	0	1
Late Blight	0	1	2	397	1	0	0	0	0	0
Leaf Mold	1	0	0	0	200	1	0	0	0	0
Septoria Leaf Spot	0	3	0	0	0	358	0	0	0	0
Two Spotted Spider Mite	0	0	0	0	0	0	336	0	0	0
Target Spot	0	1	0	0	0	0	0	280	0	0
Tomato Mosaic Virus	0	0	1	0	0	0	0	0	76	0
Tomato Yellow Leaf Curl Virus	1	0	2	1	1	0	0	0	0	1074

Figure 9: Confusion matrix for Run 5 validation (Plant Village & IPM) images

Predicted

Actual	Bacterial Spot	Early Blight	Healthy	Late Blight	Leaf Mold	Septoria Leaf Spot	Two Spotted Spider Mite	Target Spot	Tomato Mosaic Virus	Tomato Yellow Leaf Curl Virus
Bacterial Spot	430	2	0	1	1	4	0	0	0	2
Early Blight	0	209	0	5	0	0	0	0	0	0
Healthy	0	1	338	0	0	0	0	0	0	1
Late Blight	0	0	2	398	1	0	0	0	0	0
Leaf Mold	1	1	0	0	200	0	0	0	0	0
Septoria Leaf Spot	2	2	0	0	0	357	0	0	0	0
Two Spotted Spider Mite	0	0	0	0	0	0	336	0	0	0
Target Spot	0	1	0	0	0	0	1	279	0	0
Tomato Mosaic Virus	0	1	0	0	0	0	0	0	76	0
Tomato Yellow Leaf Curl Virus	1	0	2	0	0	0	0	0	0	1076

Figure 10: Confusion matrix for Run 6 validation (Plant Village & IPM) images

Meanwhile, Figure 8 and 9 show that including healthy tomato plant images from IPM dataset in network training will aid the networks to generalise better. This can be testified through the increasing number of correctly classified healthy tomato plant images in the validation dataset. Besides, the number of images that are incorrectly predicted as "healthy" also decreases.

3.3.3 Qualitative result

In this section, the prediction results of the network will be evaluated qualitatively. In particular, Table 5 to 9 sample the images that are correctly predicted in all the six networks trained in the experiment. On the other hand, Table 10 to 14 summarise the failure cases from the Plant Village dataset for networks trained without L2 regularisation (Run 1, 3 and 5); while Table 15 to 16 summarise the types of failure cases from the IPM dataset.

All the sampled correctly predicted images in Table 5 to 9 consist of leaf images. Therefore, it can be inferred that in order for the networks to predict accurately, the input image has to be a leaf-scan, a near leaf-scan, or at least contain leaves.

From the previous tables, most of the wrongly predicted images do not resemble the predicted class although some misclassified images do resemble the predicted class (e.g. "Late Blight" misclassified as "Healthy" in Table 11. This means that the wrong predictions are mostly the outliers for the probability distributions of trained networks.

Meanwhile, some correct predictions in Run 1 are misclassified in Run 3 and 5; while some wrong predictions in Run 1 are rectified in Run 3 and 5. This shows that the addition of IPM Images has impacted the learning of the convolutional neural network on the original Plant Village training dataset.

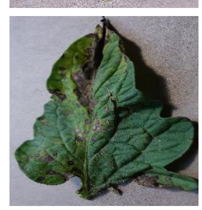
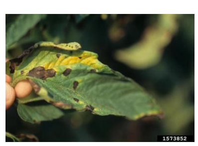
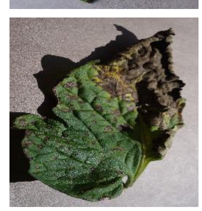
Images (Plant Village)	**Images (IPM Images)**	**Class**	**Training Images**
			
	/	Bacterial Spot	
			
			
		Early Blight	
			

Table 5: Correct predictions from all the six networks trained in the experiment

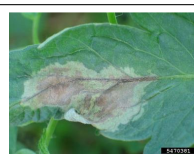
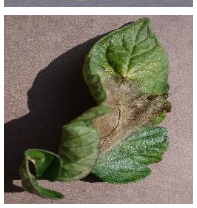
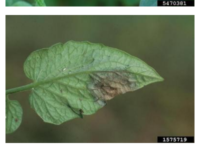
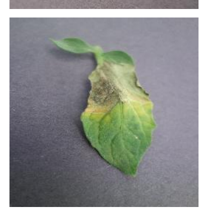
Images (Plant Village)	**Images (IPM Images)**	**Class**	**Training Images**
			
	/	Healthy	
			
			
		Late Blight	
			

Table 6: Correct predictions from all the six networks trained in the experiment (continued)

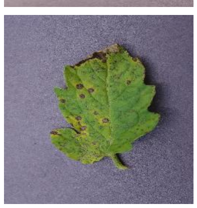
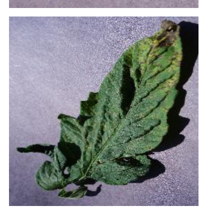
Images (Plant Village)	Images (IPM Images)	Class	Training Images
			
	/	Leaf Mold	
			
			
	/	Septoria Leaf Spot	
			

Table 7: Correct predictions from all the six networks trained in the experiment (continued)

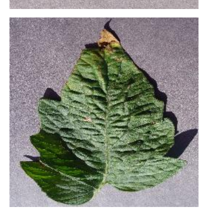
Images (Plant Village)	**Images (IPM Images)**	**Class**	**Training Images**
			
	/	Two Spotted//Spider Mite	
			
			
	/	Target Spot	
			

Table 8: Correct predictions from all the six networks trained in the experiment (continued)

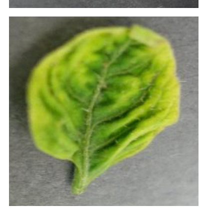
Images (Plant Village)	Images (IPM Images)	Class	Training Images
			
	/	Tomato Mosaic Virus	
			
			
		Tomato Yellow Leaf Curl Virus	
			

Table 9: Correct predictions from all the six networks trained in the experiment (continued)

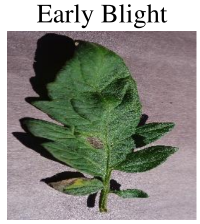
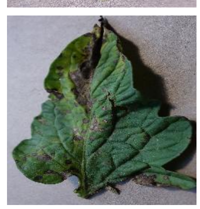
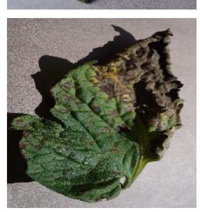
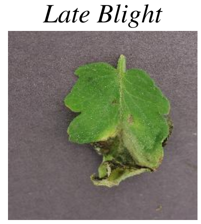
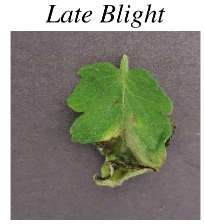
Image	Actual Class	Predicted Class (Run 1)	Predicted Class (Run 2)	Predicted Class (Run 3)
 	Bacterial Spot	Bacterial Spot   	*Yellow Leaf Curl Virus*   	*Yellow Leaf Curl Virus*   
	Early Blight	Early Blight   	*Late Blight*   	*Late Blight*   

Table 10: Failure cases among the Plant Village dataset for networks trained without L2 regularisation loss

Image	Actual Class	Predicted Class (Run 1)	Predicted Class (Run 2)	Predicted Class (Run 3)
 	Early Blight	*Late Blight*   	*Late Blight*   	*Late Blight*   
	Late Blight	*Healthy*   	*Healthy*   	*Healthy*   

Table 11: Failure cases among the Plant Village dataset for networks trained without L2 regularisation loss (continued)

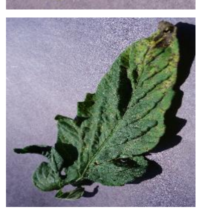
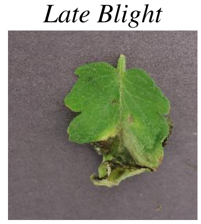
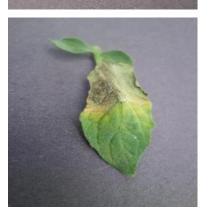
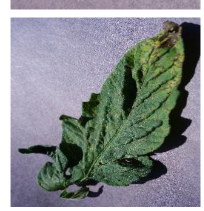
Image	**Actual Class**	**Predicted Class (Run 1)**	**Predicted Class (Run 2)**	**Predicted Class (Run 3)**
	Septoria Leaf Spot	*Late Blight*   	Septoria Leaf Spot   	Septoria Leaf Spot   
	Septoria Leaf Spot	Septoria Leaf Spot   	*Late Blight*   	Septoria Leaf Spot   

Table 12: Failure cases among the Plant Village dataset for networks trained without L2 regularisation loss (continued)

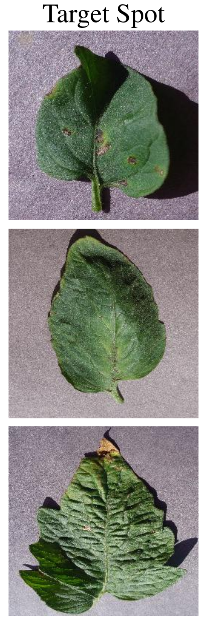
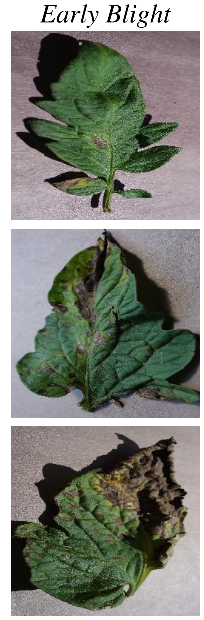
Image	Actual Class	Predicted Class (Run 1)	Predicted Class (Run 2)	Predicted Class (Run 3)
	Target Spot	*Early Blight* 	Target Spot 	Target Spot 
	Target Spot	*Early Blight* 	Target Spot 	*Early Blight* 

Table 13: Failure cases among the Plant Village dataset for networks trained without L2 regularisation loss (continued)

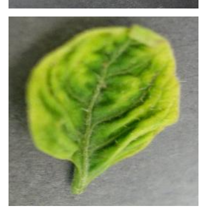
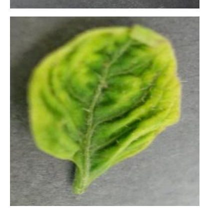
Image	Actual Class	Predicted Class (Run 1)	Predicted Class (Run 2)	Predicted Class (Run 3)
	Yellow Leaf Curl Virus	*Bacterial Spot*   	Yellow Leaf Curl Virus   	*Late Blight*   
	Yellow Leaf Curl Virus	*Late Blight*   	Yellow Leaf Curl Virus   	Yellow Leaf Curl Virus   

Table 14: Failure cases among the Plant Village dataset for networks trained without L2 regularisation loss (continued)

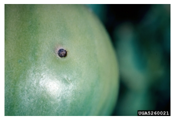
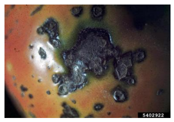
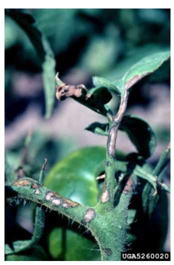
Fruit Organ Type	**Image**	**Actual Class**	**Predicted Class (Run 1)**	**Predicted Class (Run 3)**	**Predicted Class (Run 5)**
Fruit		Bacterial Spot	*Early Blight*	Bacterial Spot	Bacterial Spot
		Bacterial Spot	*Early Blight*	/	/
		Bacterial Spot	*Early Blight*	/	/
		Septoria Leaf Spot	*Bacterial Spot*	/	/
Stem		Bacterial Spot	*Early Blight*	Bacterial Spot	Bacterial Spot
		Early Blight	*Late Blight*	/	/
		Late Blight	*Septoria Leaf Spot*	Late Blight	Late Blight
Far View		Tomato Yellow Leaf Curl Virus	*Early Blight*	Tomato Yellow Leaf Curl Virus	Tomato Yellow Leaf Curl Virus

Table 15: Type of failure cases among the IPM dataset for the networks trained without L2 regularisation loss

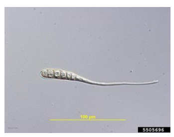
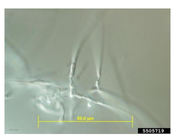
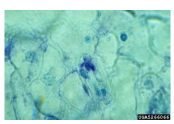
Fruit Organ Type	Image	Actual Class	Predicted Class (Run 1)	Predicted Class (Run 3)	Predicted Class (Run 5)
Bud		Bacterial Spot	*Early Blight*	/	/
Microscopic View		Late Blight	*Early Blight*	*Leaf Mold*	Late Blight
		Early Blight	*Late Blight*	*Septoria Leaf Spot*	Early Blight
		Septoria Leaf Spot	*Late Blight*	*Late Blight*	Septoria Leaf Spot
		Tomato Mosaic Virus	*Early Blight*	Tomato Mosaic Virus	Tomato Mosaic Virus
Entire Plant		Tomato Yellow Leaf Curl Virus	*Late Blight*	Tomato Yellow Leaf Curl Virus	Tomato Yellow Leaf Curl Virus
		Tomato Yellow Leaf Curl Virus	*Early Blight*	*Late Blight*	*Healthy*

Table 16: Type of failure cases among the IPM dataset for the networks trained without L2 regularisation loss (continued)

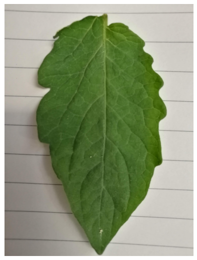
ID	Image	Predicted Class (Run 1)	Predicted Class (Run 3)	Predicted Class (Run 5)
1	1-01 	Late Blight	Late Blight	Late Blight
	1-02 	Bacterial Spot	Bacterial Spot	Bacterial Spot
	1-03 	*Bacterial Spot*	*Bacterial Spot*	*Early Blight*

Table 17: Predictions results on additional tomato leave images using networks trained without L2 regularisation loss

Although the number of IPM training images is insignificant, adding in IPM training images into subsequent trainings has aided in improving the accuracy of IPM validation set. The wrong predictions for IPM images from Run 1 are rectified in the predictions of Run 3 and/or 5, as illustrated in Table 15 to 16. This is an indicator that the networks further trained with IPM dataset is able to learn disease-related features contained in images other than leaf scans. Note that the predictions for some images are excluded in Run 3 and 5 because the images are part of the training dataset for the networks.

3.3.4 Predictions on Real World Images

Apart from the Plant Village and IPM validation dataset, the trained networks are also tested with captured images of plucked tomoto leaves. The results are tabulated in Table 17 to 19. Note that the ground truth for these images are unknown and the images are only tested using the networks trained without L2 regularisation loss.

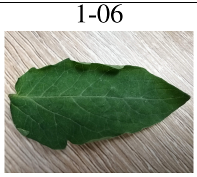
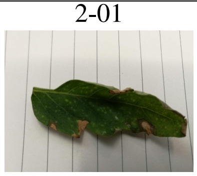
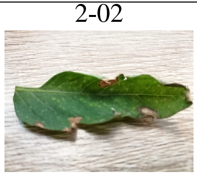
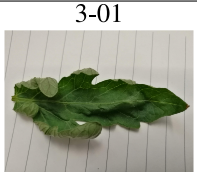
ID	Image	Predicted Class (Run 1)	Predicted Class (Run 3)	Predicted Class (Run 5)
1	1-04 	Late Blight	Late Blight	Late Blight
	1-05 	Late Blight	Late Blight	Late Blight
	1-06 	Late Blight	Late Blight	Late Blight
2	2-01 	*Tomato Yellow Leaf Curl Virus*	*Bacterial Spot*	*Bacterial Spot*
	2-02 	*Late Blight*	*Bacterial Spot*	*Bacterial Spot*
3	3-01 	*Late Blight*	*Late Blight*	*Bacterial Spot*
	3-02 	*Late Blight*	*Early Blight*	*Early Blight*

Table 18: Predictions results on additional tomato leave images using networks trained without L2 regularisation loss (continued)

ID	Image	Predicted Class (Run 1)	Predicted Class (Run 3)	Predicted Class (Run 5)
4	4-01 	Tomato Yellow Leaf Curl Virus	Tomato Yellow Leaf Curl Virus	Tomato Yellow Leaf Curl Virus

Table 19: Predictions results on additional tomato leave images using networks trained without L2 regularisation loss (continued)

According to Table 17 to 19, the networks trained in Run 1, 3 and 5 actually produce the same prediction results for images with ID 1-01, 1-02, 1-04, 1-05, 1-06, and 4-01. Besides, Run 3 and Run 5 produce consistent predictions for images with ID 2-01, 2-02 and 3-02 while giving different prediction from Run 1. This proves that the networks in Run 3 and 5 have learnt features from IPM Images, although the usefulness or accuracy of such features are unknown.

At the same time, the orientation of the leaf captured in the image can actually affect the prediction results. Taking Image 1 as an example, the network in Run 1, 3 and 5 (except for image with ID 1-03) actually predict the image as "Bacterial Spot" when the leaf tip is facing upwards in the image. Otherwise, the images will be predicted as "Late Blight" by these three networks.

Since there is no ground truth for the images, it is unable to identify the prediction accuracy.

4 Graphical User Interface

To enrich the user experience in using the plant disease prediction model, a complementary program with Graphical User Interface is developed. As a result, a user is able to use the model to predict the tomato plant disease using the image of his or her choice, without needing to learn Python scripting skills. Instead, the user can use the model to predict plant disease easily through the simple "Click and Predict" feature. The following explains the procedures involved in predicting the plant disease.

1. The user is to select the image of his or her choice, by clicking the "Select" button.
2. Click on the “Predict” button after choosing the image.
3. The top 3 disease predictions will appear on the screen, along with their probabilities. The database images for the predicted classes will also be shown on the screen for user reference.

5 Conclusion

To conclude, the tomato plant disease prediction model works well when being validated with images from Plant Village dataset. However, the model manifest weaker performances when being tested on non-leaf-scan images from the IPM dataset. At the same time, adding in the training images from IPM dataset in the subsequent trainings allows the network to learn more features from the images. While this addition has insignificant impact on the network predictions for the Plant Village validation images, it improves the prediction accuracy on the IPM validation images especially those from the "Healthy" class.

Besides, the two networks trained on a combination of Plant Village dataset and IPM Images without L2 regularisation loss produce fairly consistent prediction results on the same tomato leaf image. However, it is observed the orientation of the leaf image can affect the prediction result, given that the images are all captured on the same leaf.

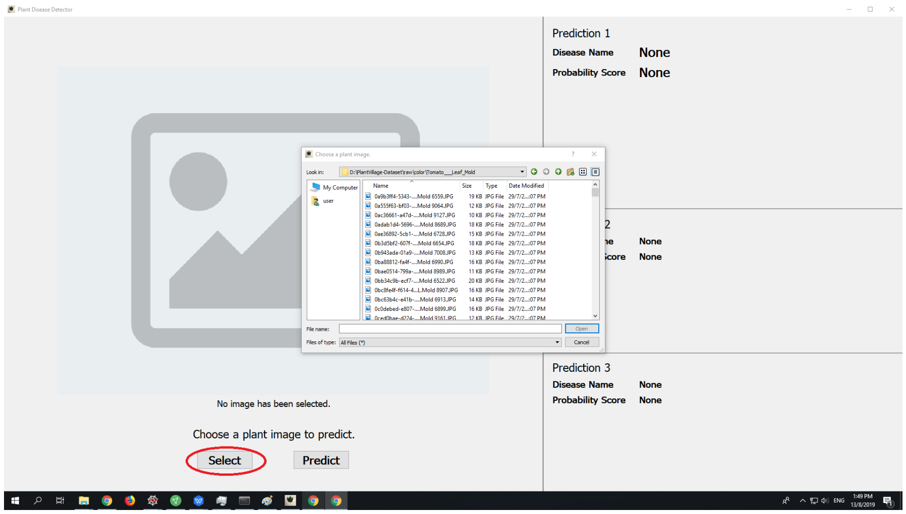


Figure 11: Image selection by user.

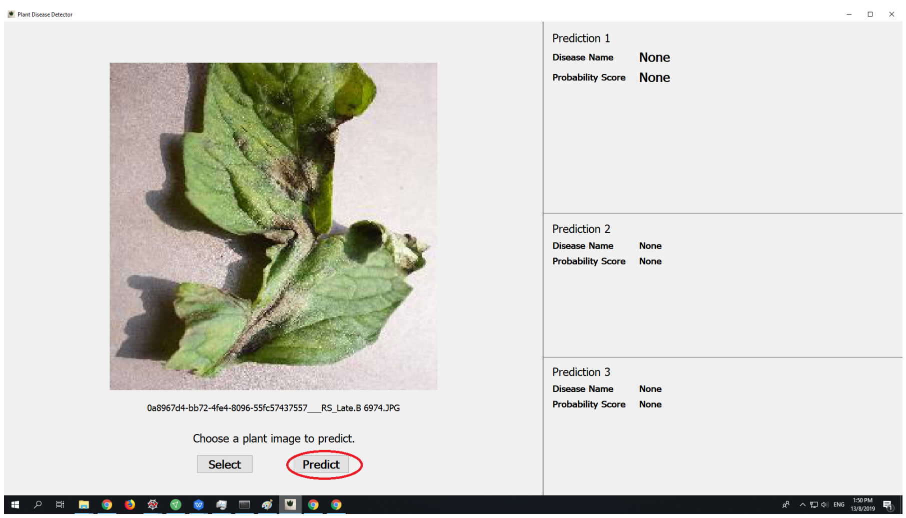


Figure 12: Image prediction.

Lastly, a program with Graphical User Interface is designed for the plant disease prediction model. This is to allow users with no Python scripting skills to use the prediction model at ease, with a simple "Click and Predict" feature.

6 Future Works

For future works, the following can be done:

1. Source more non-leaf-scan tomato plant disease images and include them in the training. This is to allow the network to be more robust in detecting plant disease using non-leaf-scan images, such as fruit or stem images.
2. Adopt and train the Inception-Resnet-v2 model for identifying diseases on other plants such as apple plants, corns and potatoes, provided that there are sufficient and diverse training images.

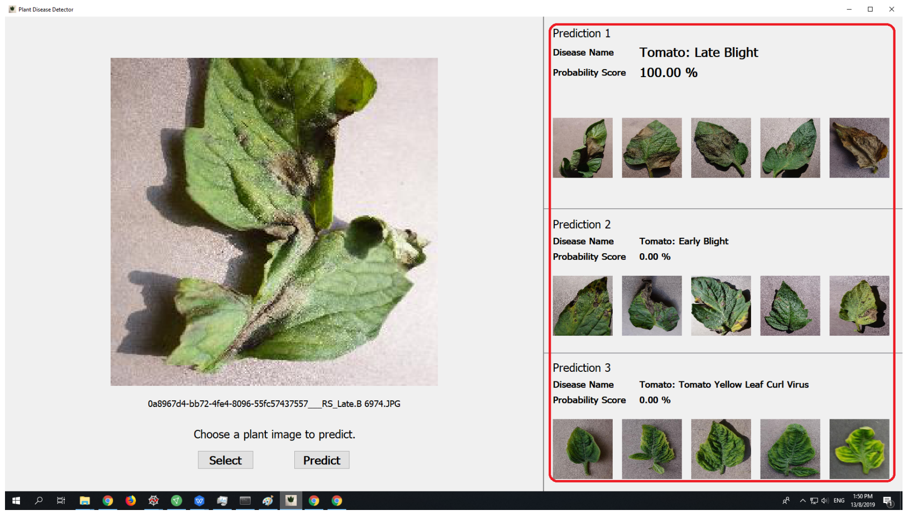


Figure 13: Results shown in the program.

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[3] C. Szegedy, S. Ioffe, V. Vanhoucke, A. A. Alemi, Inception-v4, inception-resnet and the impact of residual connections on learning, in: Thirty-First AAAI Conference on Artificial Intelligence, 2017.

[4] I. Loshchilov, F. Hutter, Fixing weight decay regularization in adam, CoRR abs/1711.05101. `arXiv:1711.05101`.
URL `http://arxiv.org/abs/1711.05101`