Multi Label Plant Disease Classification using Deep Learning

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Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

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Abstract

In smart agriculture, disease detection and classification for diverse plants in farm fields is very important and critical in agriculture quality production.Traditional methods for identifying plant disease employed agriculture professionals or plant pathologists performing empty eye inspection to detect leaf disease. This approach of detecting plant leaf disease traditionally can be subjective, time-consuming, as well as expensive, and requires a lot of people and a lot of information about plant diseases. Deep learning and Machine learning model based applications have been in circulation for this task since the past few years. These applications have been quite successful in classifying the plant disease based on the leaf image. However due to the nature of the models they can only classify the infected leaf into only one class. So In the off chance that a plant might have two or more diseases they will remain only partially detected. We propose a multi label classification model to counter this problem. We have utilized a custom tomato leaf data set consisting of images belonging to six classes and it includes images of plants having single disease and multiple diseases. We have applied transfer learning approach using two existing architectures (Inception.V3 and Xception) to get more optimized results by training them under multiple scenarios. We were able to achieve a test accuracy of 93% for Xception based model and 89% for Inception.V3 based model. Experimental results have shown that our models achieved a good accuracy rate for plant leaf disease detection and classification using the multi label approach.

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Chapter 1

Introduction

1.1 Concept behind plant disease classification

Healthy plants are essential to ensure proper food production as a large portion of our dietary requirement are fulfilled by agricultural produce. And like all living organisms, Plants also suffer from multiple diseases. These disease can originate because the plant is infected with some pathogen like virus, fungi, bacteria etc or if the plant is suffer from some form of nutritional deficiency. Statistically there are more number of diseases caused by pathogens than diseases caused due to nutritional deficiency. Some of the diseases are also specific to certain plants and do not affect the rest.

When a plant is afflicted with a disease the symptoms can be gathered from the leaf of the infected plant. These symptoms tend to be the most prominent ones despite there might be other symptoms showing in other parts of the plant. Different diseases tend to produce different effects on the leaf of the plant. Some diseases cause large spots while some might cause rotting of the leaf while some might cause shrivelling of the leaf and so on. Many of the times nutritional deficiency causes a change in the pigmentation of the plant's leaf. Sometimes the same disease might cause different effects in different plants thus the plant type also plays a major role in figuring out what disease it is suffering from.

The traditional method for plant disease classification involves agricultural professionals inspecting the leaves of the infected plant to study the affect the disease had on the leaf and there by using these effects to classify the disease. In essence the effect that diseases has on the leaf becomes the features on which the agricultural professional bases his classification of the disease. And at times a plant can present with features from multiple diseases and in these cases the agricultural professional has to make the right classification as underlying conditions might completely change the course of treatment for the plant. This puts plants suffering from multiple diseases or conditions at a heightened risk of being miss diagnosed.

This method of physical inspection of the plant can be quite tedious and subjective with respect to the classification methodology as different people might perceive the same features as different diseases based on their experience with plants as some of these features are quite similar to view and can be miss leading.

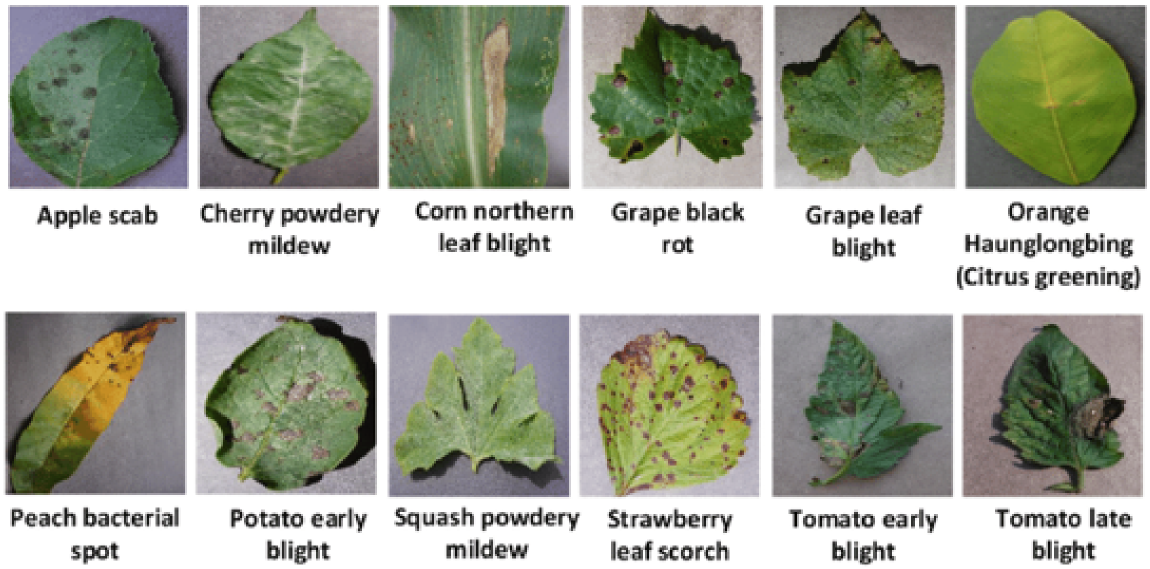


Fig. 1.1 A Few Plant Diseases

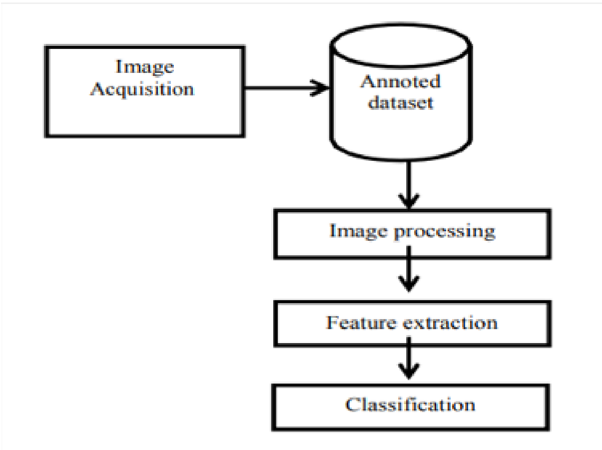
Chapter 2

Background

2.1 The Tech Approach

With the introduction of Machine Learning for classifications purposes researchers have found ways to use this capability for plant disease classification. It was found that once the machine was trained with enough data about each disease it should be capable of making accurate classification of new images. This method would save time while maintaining a consistent classification methodology. Many applications were also developed based on this philosophy and these applications provided a handy and portable method for classification of plant disease there by speeding up the duration in which treatment can be provided.
The traditional approach for machine learning based classification requires the pre-processing of plant leaf images to extract features from them manually. The pre-processing involves utilising multiple image filters. These extracted features would then be used to train a Machine learning model for the classification of plant diseases.
One such work involving the traditional approach was done by a group of researchers [3] who have utilised random forest classifier on plant disease data set. The data set consists of 87000 RGB images of healthy and unhealthy plant leaves having 38 classes out of which they have selected 25 classes for experimentation. The images were first converted to grey scale to reduce the dimension and then smoothened. Various features like shape, texture, edges were extracted from the images.Later features were selected on the basis of correlation of variables with target variable. Features contributing little have been dropped and only those features that contributed enough to bring a change were retained. These features were then utilized to train a Random Forest Classifier.Each tree is trained by using different subsets of the whole data set.They have attained an overall accuracy of 93% with accuracy for classifying the diseases of a particular plant ranging from 87% to 98%. The accuracy they have attained was

greater than similar such models of the time and was much more computationally efficient.



2.2 The Modern Take

With the advent of Deep learning classification of image data became much more simpler and efficient. Deep learning models introduced the concept of end to end learning. Deep Neural networks were capable of extracting the features from the image all by themselves and then they utilised these extracted features to learn how to classify the image. This eliminated the need for hand engineered features. Convolutional Neural Networks were especially powerful when it came to image data. The initial Convolution, pooling layers took care of the feature extraction while the final fully connected layers handled the classification of the image. Deep Learning method was not only convenient to use but also provided better results in comparison to machine learning approach. And as such many of the recent works focus on utilising Deep Neural Networks for Plant Disease Classification.

One paper discusses how Convolutional neural network have been used for classification of diseases in three different plants [4]. A group of researchers have utilized Deep Learning ConvNets on a subset of Plant Village data set. The data set contained images of three types of plants(potato,pepper,tomato) and consisted of a total of 15 classes. They have utilized a custom CNN architecture which contained : 3 Convolutional layers with the ReLu Activation function is applied on them, a max-pooling layer with dimensions 2x2 and a SoftMax layer as the classifier. The Adam optimizer is also used. They were able to achieve accuracy of 98.3%,98.5%,95% for the respective types of plants.

Another such work based on Deep Neural Networks was done by a group of researchers working on Hemp disease classification [7]. They have utilized a custom hemp data set

with 14181 images having been categorized into 5 classes. They have compared multiple architectures in their work and have thus utilized a custom CNN architecture having multiple convolutional layers, an L2 regularization layer, set a padding parameter and modified the dropout parameters. They have also utilized 2 transfer learning models VGG19 and InceptionV3. They have found that transfer learning models have a better accuracy at classifying the data compared to their basic counterpart and also that transfer learning models performed better than the custom CNN model while being more computationally efficient.
Another group of researchers who were also working on Hemp disease prediction utilized a slightly different route [1]. They have tried to compare the accuracy of Deep Neural Networks with a Machine Learning model. They have utilised an SVM based classification model to which the extracted features from the images were fed. Apart from this they have also utilized three DNN models namely VGG16, InceptionV3, AlexNet. The VGG16 model utilised transfer learning while InceptionV3 and AlexNet were used for feature extraction to feed to SVM classifier and Random Forest classifier respectively. It was found that VGG16 had the highest accuracy followed by Modified InceptionV3 followed by Modified AlexNet followed by SVM based model showing that transfer learning techniques are better.
Finally the review paper explaining the various approaches in plant disease classification provided the much needed comparison between the various models of classification [5]. The paper compared 5 methods of classification namely SVM classifier, a regular ANN classifier, KNN classifier, Fuzzy classifier, CNN classifier. They observed that many people utilized SVM classifier when utilising the machine learning approach. They proposed that KNN classifier be used for multi class classification rather than the SVM classifier. They have also observed that CNN performed far better than the other modes there by proving the effectiveness of DNN.

Chapter 3

The Problem

3.1 Problem Statement

As it can be observed from all these works a machine learning or deep learning based approach can be successfully used to classify plant diseases based on images of the leaf. All these models are based on the fundamental principle that a plant can have only one disease at a time which is not true. There are cases where a plant might be suffering from one or more diseases at the same or a plant might have contracted a second condition due to an underlying condition. These cases would be ignored by the models as they are trained to classify the disease into only one class. And there is a chance the plant might need a completely different treatment from the normal because it has multiple conditions. Thus there is a need to classify the plant diseases in a multi label fashion which would ensure that the model would classify the plant as have one or more diseases at the same time. By training the models in this multi label fashion we would be able to ensure that all those case will also be successfully diagnosed there by increasing the scope of the Plant disease classification model.

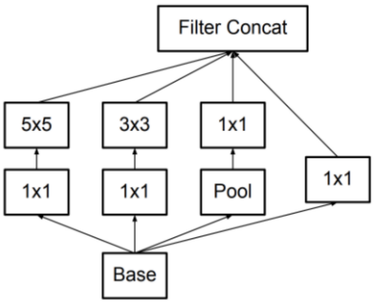
3.2 Approach

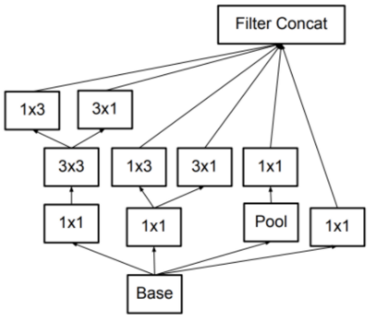
Based on the works previously mentioned it clear that Deep Learning based approach is more favourable in comparison to the Machine Learning based approach for image classification both in terms of ease of implementation and performance. Even among the Deep learning models Transfer Learning based models seem to have an edge in terms of performance while utilising lower computational resources.
Transfer learning is a Machine learning methodology where a model developed for a certain task is re-purposed on a second related task. Transfer learning provides an optimization

technique that allows rapid progress or improved performance when modeling the second task.Transfer learning is popular in deep learning given the enormous resources required to train deep learning models or the large and challenging data sets on which deep learning models are trained. In Deep Learning transfer learning is utilised by using a pre-trained model as the starting point and then improving the model by building over the existing architecture and training it to be more suitable to the problem at hand. Transfer learning only works in deep learning if the model features learned from the first task are general.
Transfer learning has seen great use in the field of Computer Vision which utilises Image data sets for various computational tasks. The amount of time and computational power required to train custom deep learning models on large image data sets is really high and utilising transfer learning cuts it down by a large margin. By developing a model based on a pre trained general image classification model we can just improve the model to suit our needs while it retains the capability to already classify some of these images. For these types of problems, it is common to use a deep learning model pre-trained for a large and challenging image classification task such as the ImageNet 1000-class photograph classification competition.
The ImageNet project is a large visual database designed for use in visual object recognition software research. It contains nearly 14 million annotated images belonging to nearly 20000 classes.Since 2010 the data set is used in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), a benchmark in image classification and object detection. Every year several large players take part in this contest to pit their new architectures against each other and show their new achievements in the field of object classification and object detection. The research organizations that develop models for this competition and do well often release their final model under a permissive license for reuse. These models can be downloaded and incorporated directly into new models that expect image data as input.
Some of the most famous models for Image classification have been results of this competition. AlexNet, VGG series, DenseNet series, ResNet series, Inception Series, AmoebaNet, MobileNet, Xception, EfficientNet are some of the well know Image classification Architectures that have been introduced in the ILSVRC which have went on to revolutionize the field of Computer Vision. After carefully considering these architectures we have decided to utilize InceptionV3 and Xception for our work on Multi Label Plant disease prediction. Our decision to utilize them is based on the computational efficiency of both these models. Both the models while being light weight and requiring less no of parameters there by reducing the total computation power required produced greater accuracy than models requiring similar parameters and computation.

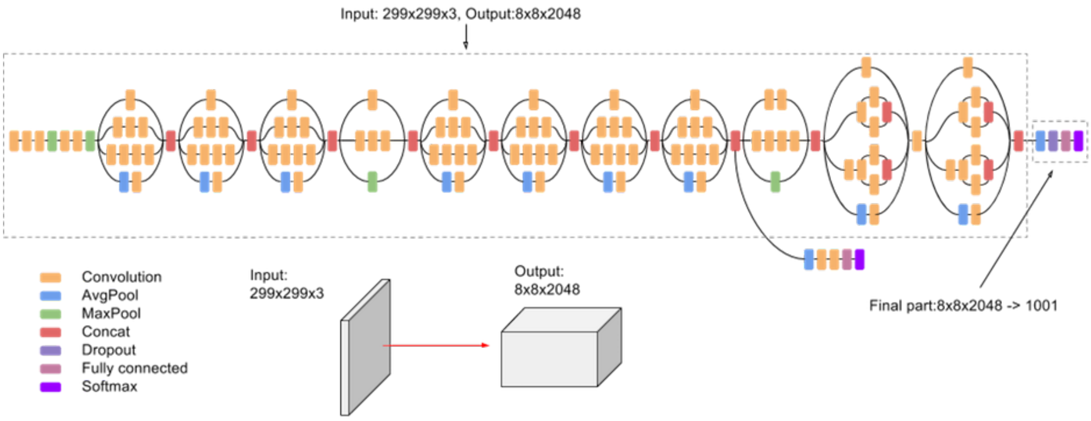
Inception V3

Inception V3[6] is a modified version of the original Inception V1 architecture which was initially introduced as GoogLeNet.When multiple deep layers of convolutions were used in a model it resulted in the over fitting of the data. To avoid this from happening the inception V1 model uses the idea of using multiple filters of different sizes on the same level. Thus in the inception models instead of having deep layers, we have parallel layers thus making our model wider rather than making it deeper. The Inception V1 model had convolutional layers of size 1x1,3x3,5x5,3x3 running in parallel but the 5x5 convolution layer was computationally pretty expensive.



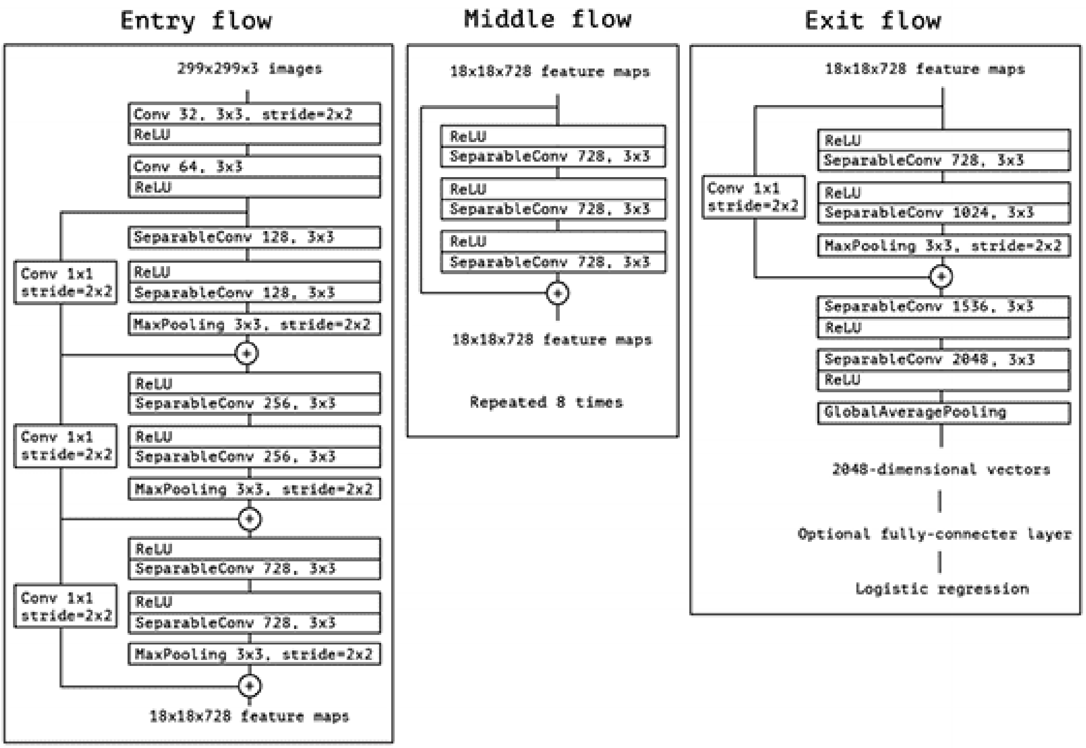


The Inception V3 model used several techniques for optimizing the network for better model adaptation. In Inception V3 larger Convolutions in the model were factorized into smaller Convolutions.To further improve the model spatial factorization into asymmetrical convolution was also followed.To reduce the computational cost the 5×5 convolutional layer was replaced by two 3×3 convolutional layers and 3x3 convolution layers were replaced by 1x3 layer followed by 3x1 layer. These changes along with Auxiliary classifier to improve the convergence of very deep neural networks and efficient grid sizing for dimensionality reduction further improved the model.



Xception

Xception[2] stands for "extreme inception", it takes the principles of Inception to an extreme. The Xception model also has multiple convolution layers running in parallel just like in the case of Inception. In Inception, 1x1 convolutions were used to compress the original input, and from each of those input spaces we used different type of filters on each of the depth space. Xception just reverses this step. Instead, it first applies the filters on each of the depth map and then finally compresses the input space using 1X1 convolution by applying it across the depth.There is one more difference between Inception and Xception. The presence or absence of a non-linearity after the first operation. In Inception model, both operations are followed by a ReLU non-linearity, however Xception doesn't introduce any non-linearity.The data first goes through the entry flow, then after than it. goes through the middle flow (repeating itself 8 times in this middle flow), and finally through the exit flow.



It was also observed both Inception and Xception performed better than the models of their time like VGGNet and ResNet while Xception also had greater accuracy than Inception V3. Xception tells us that with both Depth wise Separable Convolution and Residual Connections, it really helps to improve the accuracy.Xception is claimed to have similar model size with Inception V3 and requires slightly more computation than Inception V3.

Chapter 4

Our Work

4.1 Data set

We have utilized a custom tomato plant data set for our work. The data set contained a total of 3274 leaf images of tomato plant. These images have been obtained mainly from other databases and google images. The initial images were segregated into 6 classes namely Bacterial Spot, Blight, Septoria Leaf Spot, Mosaic Virus, Nutritional Deficiency, Healthy. Additionally images belonging to multiple classes have also been added to the data set to facilitate Multi label learning by the model. It was ensured that only a portion of the images were multi labeled so that the model does not become biased to make multi label predictions all the time. All the images were also reshaped to be of the same size as CNN only accepts images of one size. One hot encoding of the labels was done to facilitate Multi Label Classification and for ease of learning.The entire data set was then split into training set (70%), validation set (15%) and testing set (15%). The Final images were of the shape (256,256,3) given they were RGB.

Table 4.1 Data Set Overview

Image Class	Total No of Images
Bacterial Spot	844
Blight	819
Septoria Leaf Spot	710
Mosaic Virus	294
Nutritional Deficiency	312
Healthy	644

4.2 Training & Results

We have first started our work with a transfer learning model based on Inception V3, We have retained the entire architecture except the last layer as it specific to ImageNet data. We have added a flaten layer to smoothen the output a FC layer with 1024 nodes with ReLu activation followed by a drop out layer with a drop out factor of 0.3 and finally another FC layer with 6 nodes corresponding to the total no of classes with sigmoid activation for the classification. We have also experimented with other drop out factors and found 0.3 to be a better fit for our case. We have utilized binary cross entropy loss with Adam optimizer as the labels were one hot encoded. The model was trained for 10 epochs with a batch size of 32 to optimize both accuracy and computation.After 10 epochs The Inception V3 model had a training accuracy 95% of with a validation accuracy of 89%. The model was finally evaluated on testing set yielding an accuracy of with a loss of 88.6%. The model being quite small and computationally efficient completed training rather quickly.

Table 4.2 InceptionV3 Architecture

Layer	Output Shape	Param #
inceptionv3	(None, 6, 6, 2048)	21802784
Flatten	(None, 73728)	0
Dense	(None, 1024)	75498496
Dropout	(None, 1024)	0
Dense	(None, 6)	6150

We have then built a model based on Xception in a similar approach. We have retained the entire architecture except the last layer . We have then added a flaten layer to smoothen the output a FC layer with 1024 nodes with ReLu activation followed by a drop out layer with a drop out factor of 0.3 and finally another FC layer with 6 nodes corresponding to the total no of classes with sigmoid activation for the classification.We have utilized binary cross entropy loss with Adam optimizer for this model as well. After 10 epochs of training with a batch size of 32 we have obtained a training accuracy of 97.3% and a validation accuracy of 93.5%. On evaluating the model on the testing data set we have obtained an accuracy of 93.1% with a loss of 0.1515. This model took more time to train in comparison to the InceptionV3 model because of the higher computational requirements.

Table 4.3 Xception Architecture

Layer	Output Shape	Param #
xception	(None, 8, 8, 2048)	20861480
Flatten	(None, 131072)	0
Dense	(None, 1024)	134218752
Dropout	(None, 1024)	0
Dense	(None, 6)	6150

In this study to compare the performance of both the models we have generated multiple performance metrics for classification namely Accuracy, Precision, Recall, F1 Score, Loss. We have also compared the computational requirements of both the models by comparing the number of parameters in then model and time taken per each step and epoch. These values can be accessed from the tables below.

Table 4.4 Performance comparison for testing set

Evaluation Metric	Xception	InceptionV3
Accuracy	93.1	88.6
Precision	91.5	87.5
Recall	85.8	80
F1 score	88.5	83.5
Loss	0.1515	0.2066

Table 4.5 Comparison of Computational Factors

Computational Metric	Inception V3	Xception
Total Param	97,307,430	155,086,382
Trainable Param	75,504,646	134,224,902
Non Trainable Param	21,802,784	20,861,480
Time taken / step	6s	11s
Time taken / epoch	460s	775s

4.3 Conclusion

It is clear from these results that both InceptionV3 and Xception based models yield sufficiently good results for Plant disease classification. The Xception model performed better in terms of accuracy when compared to the InceptionV3 model though it took more time for training. The results of the InceptionV3 were not that far behind either and is still acceptable given it requires comparatively lower computation. The Xception model requires more computation but is still quite efficient, It also produces better results and is hence the preferred choice. Models requiring significantly higher computation are also available and utilising these models can further improve the accuracy but the improvement in accuracy with respect to the increase in computation would be quite less.

We believe the accuracy obtained for the Multi Label Disease Classification model for tomato data set is satisfactory and thus it would safe to say that this approach can also be utilised for other plant diseases as well. Just like how we have implemented this method for the tomato plant it can also be implemented for other plants to obtain a Multi Label Plant disease classification system for a large group of plants. This would ensure that more and more plants could be diagnosed correctly there by increasing the scope of Plant disease classification systems.

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