TOMATO LEAF DISEASE DETECTION USING DEEP LEARNING

A PROJECT REPORT

Submitted by

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to

The APJ Abdul Kalam Technological University

In partial fulfillment of the requirments for the award of the degree of

MASTER OF COMPUTER APPLICATIONS

Thangal Kunju Musaliar College of Engineering
Kerala

DEPARTMENT OF COMPUTER APPLICATIONS

MAY 2022

DECLARATION

I undersigned hereby declare that the project report on ''TOMATO LEAF DISEASE DETECTION USING DEEP LEARNING " , submitted for partial fulfillment of the requirements for the award of degree of Master of Computer Applications of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of Prof.Vaheetha Salam. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that we have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in our submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University.

Kollam

20/05/2022

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TKM COLLEGE OF ENGINEERING

C E R T I F I C A T E

This is to certify that, the project report entitled **"TOMATO LEAF DISEASE DETECTION USING DEEP LEARNING"** submitted by **CHAITHRA K V (TKM19MCA009)** to the APJ Abdul Kalam Technological University in partial fulfillment of the requirements for the award of the degree of Master of Computer Applications, is a bonafide record of the project work carried out by her under our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

Internal Supervisor | Head of the Department | External Examiner

ACKNOWLEDGEMENT

First and foremost I thank GOD almighty and my parents for the success of this project. I owe sincere gratitude and heart full thanks to everyone who shared their precious time and knowledge for the successful completion of my project.

I am extremely grateful to **Dr. Fousia.M.Shamsudeen**, Head of the Department, for providing me with best facilities.

I would like to thank my project guide **Prof. Vaheetha Salam**, Department of Computer Applications, who motivated me throughout the work of my project.

I profusely thank all other faculty members in the department and all other members of TKM College of Engineering, for their guidance and inspirations throughout my course of study.

I owe my thanks to my friends and all others who have directly or indirectly helped me in the successful completion of this project.

Chaithra K V

ABSTRACT

Automatic classification process in images has been used in many fields, especially agriculture and medical fields in recent years. Especially in our country, image processing studies are needed to improve agriculture and increase productivity in agriculture. Diseases in plants are a problem that often occurs in agriculture. The disease can be caused by pests or maintenance errors. This resulted in a decrease in agricultural production. The decline in production has resulted in a decline in economic yields produced by farmers. Diseases of tomato plants often appear on the leaves.

In this study 10 types of leaf disease were used. In this study, the major tomato leaf diseases that significantly affect tomato efficiency were examined and the convolutional neural networks deep learning methods was applied for the automatic classification of these diseases. It is thought that the model applied in this study can also be applied on other agricultural crops, so that the contribution of image processing to agriculture will increase gradually. The model developed in this work uses deep learning techniques: ResNet152V2 and MobileNetV2. ResNet152V2 achieved an accuracy of 98.21% for ten class classification using images and MobileNetV2 achieved an accuracy of 91.69%. However, the best results were obtained by applying ResNet152V2 method. It can be concluded that all the architectures performed better in classifying the diseases when trained with deeper networks on images. The performance of each of the experimental studies reported in this work outperforms the existing literature.

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Chapter 1

Introduction

Crop disease detection is the basis of crop disease prevention to guarantee crop quality. Traditional detection methods for crop disease mainly depend on manual observation and consequently lead to low detection efficiency and poor reliability. Farmers lack professional knowledge, and agricultural experts cannot serve the field at all times so that they miss the best time for prevention. In recent years, image processing, pattern recognition, computer vision and other technologies have developed rapidly. Computer automatic detection of diseases provides method for effectively solving agricultural problems. Traditional machine vision methods require complex preprocessing and design of image features, which is time consuming and labour intensive. In particular, the effectiveness of this method depends largely on the accuracy of the artificial design features and the learning algorithm. Neural networks contribute to image recognition. They have excellent nonlinear fitting capabilities so that they can achieve higher accuracy in some image recognition tasks. With the rapid development of deep learning, the accuracy of image classification and object detection has greatly improved, and it can accurately classify large datasets, even better than humans in many aspects. Deep learning has the advantage of directly extracting classification features. Additionally, the deep learning feature extraction method is suitable for classification on various occasions and has a strong generalization ability. There is a difference between traditional machine learning techniques and deep learning in that the latter can automatically learn representations from data, such as videos, images, or text, without entering manually coded rules or direct human intervention. Their architectures are highly flexible, and thus can learn immediately from the data and raise their predictive accuracy by providing it with more data. The main objective of this work was to develop a deep learning framework to automatically detect tomato leaf disease using images and to classify the result, which will help in quickly and easily diagnosing the disease.

1.1 Problem Statement

To present a hybrid model that employs technique to extract relevant features related to image of tomato leaf using ResNet152V2 and MobileNetV2 in order to detect and identify type of disease that infect tomato plant. However, crop diseases are a difficult problem for many farmers so it is important to master the severity of crop diseases timely and accurately to help staff take further intervention measures to minimize plants being further infected. To improve grain production has become one of the most important issues facing all countries.

1.2 Objectives

The main objectives of the project are as follows:

- Developing deep learning model for the identification of tomato leaf disease.
- Training the deep learning model with data set using pre-trained ResNet152V2 and MobileNetV2 architectures.
- Testing both the models and find its accuracy.

Chapter 2

Literature Survey

Literature review is the comprehensive study and interpretation of literature that relates to a particular topic. When one uses literature review research questions are identified, then one seek to answer this research questions by searching for and analyzing relevant literature. Some importance of literature reviews is that new insights can be developed by the re-analyzing the results of the study. A literature review is both a summary and explanation of the complete and current state of knowledge on a topic as found in academic books and journal articles. There are two kinds of literature reviews you might write at university: one that students are asked to write as a stand-alone assignment in a course, and the other that is written as part of an introduction to, or preparation for, a longer work, usually a thesis or research report. The focus and perspective of your review and the kind of hypothesis or thesis argument you make will be determined by what kind of review you are writing. One way to understand the differences between these two types is to read published literature reviews or the first chapters of theses and dissertations in your own subject area. Analyses the structure of their arguments and note the way they address the issues.

2.1 Purpose of the Literature Review

1. It gives readers easy access to research on a particular topic by selecting high quality articles or studies that are relevant, meaningful, important and valid and summarizing them into one complete report.

2. It provides an excellent starting point for researchers beginning to do research in a new area by forcing them to summarize, evaluate, and compare original research in that specific area.

3. It ensures that researchers do not duplicate work that has already been done.

4. It can provide clues as to where future research is heading or recommend areas on which to focus.

5. It highlights the key findings.

6. It identifies inconsistencies, gaps and contradictions in the literature.

7. It provides a constructive analysis of the methodologies and approaches of other researchers.

2.2 Related works

2.2.1 Non linear classification

Support vector machines are a set of supervised learning methods used for classification, regression and outliers detection. The advantages of support vector machines are: Effective in high dimensional spaces. Still effective in cases where number of dimensions is greater than the number of samples. In this method system uses resizing, thresholding and Gaussian filtering for image preprocessing. To design an automated system with the help of embedded system so that this fungicide mixture will be automatically sprayed using spraying mechanism [3].

This system selects appropriate features such as color and texture of images and then uses an SVM classifier for cotton leaf disease classification. Experimental results show that good performance was achieved.Support vector machines are a set of supervised learning methods used for classification, regression and outliers detection. The advantages of support vector machines are: Effective in high dimensional spaces. Still effective in cases where number of dimensions is greater than the number of samples [5].

It extracts color and texture features and feeding them to a multiclass SVM classifier. The classification accuracy on average for SVM was found to be greater than 95 percentage . Support vector machines are a set of supervised learning methods used for classification, regression and outliers detection. The advantages of support vector machines are: Effective in high dimensional spaces. Still effective in cases where number of dimensions is greater than the number of samples [10].

2.2.2 Brinjal leaf disease classification

It extracts useful features automatically but it uses a minimal dataset. This method uses K different randomly-initiated points in the data, and assigns every data point to the nearest centroid. After every point has been assigned, the centroid is moved to the average of all of the points assigned to it [4].

It segmented brinjal leaf disease by a K-means clustering algorithm and was very effective in recognizing leaf diseases. This method uses K different randomly-initiated points in the data, and assigns every data point to the nearest centroid. After every point has been assigned, the centroid is moved to the average of all of the points assigned to it [8].

It was divided into four stages: image acquisition, image segmentation, feature extraction and classification. K-means was used to compute disease features. The accuracy of bacterial leaf spot and target spot of cotton leaf disease was as high as 90 percentage and 80 percentage respectively. This method uses K different randomly-initiated points in the data, and assigns every data point to the nearest centroid. After every point has been assigned, the centroid is moved to the average of all of the points assigned to it [9].

2.2.3 Grape leaf disease classification

They first located the diseased region for segmentation by KNN, and then extracted grape leaves color and texture features. Finally, they detected the type of leaf disease by classification techniques. This system achieved an accuracy of 88.89 percentage on the test set. Support vector machines are a set of supervised learning methods used for classification, regression and outliers detection. The advantages of support vector machines are: Effective in high dimensional spaces. Still effective in cases where number of dimensions is greater than the number of samples [6].

This method achieved a wonderful performance in plant diseased leaf image segmentation and recognition. KNN is based on the local minimum of the target function which is used to learn an unknown function of desired precision and accuracy. It can achieve high accuracy in a wide variety of prediction-type problems [7].

2.2.4 Deep learning techniques

Random data augmentation was carried out to prevent over-fitting in the experiment.Data augmentation is the process of modifying, or augmenting a dataset with additional data. This additional data can be anything from images to text, and its use in machine learning algorithms helps improve their performance. Due to the lack of a relatively complete and high quality crop disease database, the classification of some rare diseases or species is still not ideal [1].

The restructured residual dense network model can obtain significant improvements over most of the state-of-the-art models in crop leaf identification, as well as requiring less computation to achieve high performance. Multi-hop connection can make errors spread to each layer of the network more quickly, which can alleviate the problem of difficult training. This hybrid deep learning model combines the advantages of deep residual networks and dense networks, which can reduce the number of training process parameters to improve calculation accuracy as well as enhance the flow of information and gradients [2].

It proposes a template model for discovering common geometric patterns and co-occurrence statistics of patterns in object's local area, and extracting features from aligned common patterns for fine-grained image categorization. The method of strong supervision requires not only category label, but also component label and key position box. This method has achieved good results, but the disadvantage is that it requires expensive manual labeling, and the location of manual labeling may not be the best discriminating area, which completely depends on the cognitive level of the annotator [11].

It automatically locate infected regions and extract relevant features for disease classification. RNN-based approach is more robust and has a greater ability to generalize to unseen infected crop species as well as to different plant disease domain images compared to classical CNN approaches. A recurrent neural network (RNN) is a special type of an artificial neural network adapted to work for time series data or data that involves sequences. Ordinary feed forward neural networks are only meant for data points, which are independent of each other [12].

It consists of a set of parallel deep convolutional neural networks, each of which is optimized for classification in accordance with a given granularity. In other words, the multiple granularity CNN consists of a set of single-granularity descriptors. Saliency guidance in the hidden layer selects regions of interest (ROI) from a common pool of candidate image blocks generated from the bottom up. Learning discriminant feature representation from discriminant region plays a key role in fine-grained image categorization [13].

It uses transfer learning technique fine tuning is used, but the time complexity of the paper is very high. Fine-tuning, in general, means making small adjustments to a process to achieve the desired output or performance. Fine-tuning deep learning involves using weights of a previous deep learning algorithm for programming another similar deep learning process. Although fine-tuning proves beneficial in training new deep learning algorithms, it can be used only when the dataset of an existing model and the new deep learning model are similar to each other [14].

Chapter 3

Methodology

Plant disease detection can be performed using different classifiers and a multitude of techniques have been used in the past for this purpose. In this thesis, the classifiers that were used for performing the detection were the ResNet152V2 and MobileNetV2. The results of both the classifiers were used to find the best performing model on the disease detection of tomato leaves from the dataset.There is 10 types of various classes and they are:

1. Septoria leaf spot
2. Tomato Healthy
3. Bacterial spot
4. Spider mites Two spotted spider mite
5. Tomato Yellow Leaf Curl Virus
6. Early blight
7. Target Spot
8. Leaf Mold
9. Tomato mosaic virus
10. Late blight

3.1 Proposed System

To overcome the limitations of traditional Tomato leaf disease detection, the method of automatically detecting Tomato leaf disease is developed with better accuracy. Deep learning-based image processing has been shown to be effective in automated detection of tomato leaf disease. However, deep learning typically requires a large number of labelled samples for training, which is time consuming and it requires the input of human experts. Transfer learning, where a model is pre-trained for a task on an existing labelled database is adapted to be reused for a different but related task, is a common workaround to this issue. In the paper, two models are presented based on the applications of deep learning and convolutional neural networks based on transfer learning that are capable of classifying automatically the tomato leaf disease. The proposed methodology uses ResNet152V2 and MobileNetV2 deep transfer learning algorithms that extracts the features from the tomato leaf image that describes the presence of disease automatically.

3.2 System Architecture

The system architectural design is used to abstract the overall outline of the software system and the relationships, constraints, and boundaries between components. It is an important tool as it provides an overall view of the physical deployment of the software system. This study uses two well-known convolutional neural network models ResNet152V2 and MobileNetV2 for detection of disease. This demonstrates that using pre trained models for image classification is an effective way to detect disease. The figure 3.1 below shows system architecture. The proposed system consist of four major phases:

• Data preprocessing

• Training the data set

• Evaluation of the model

• Deploying the model using Gradio

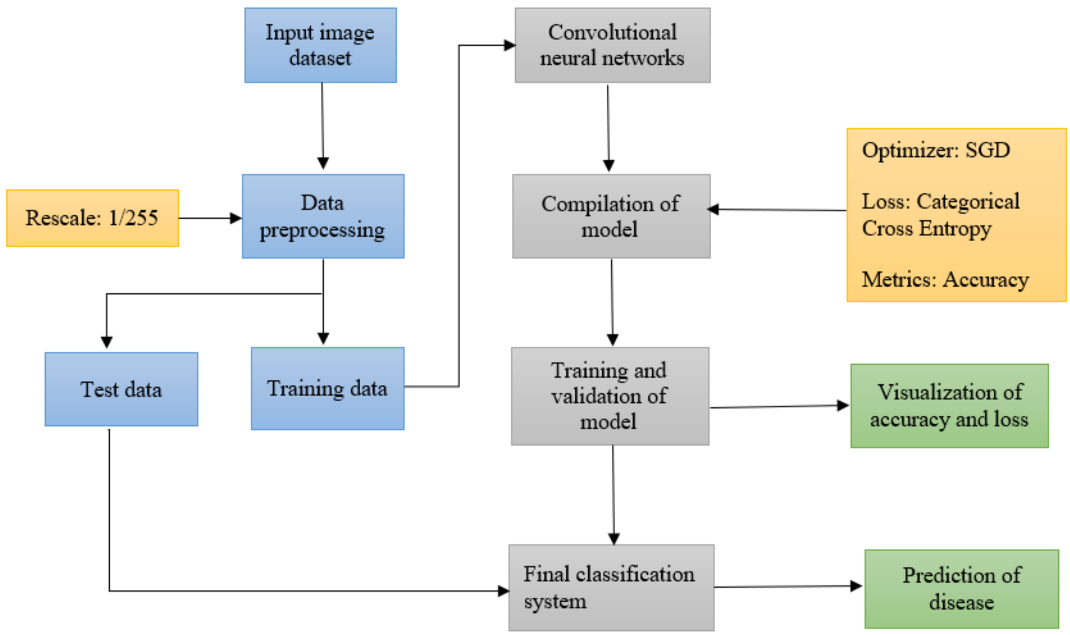

Figure 3.1: System Architecture

3.2.1 Data set

The dataset used for tomato leaf disease detection is based on a Tomato leaf dataset which is released on the Kaggle website. All the images are tomato leafs consisting of the RGB format. The Keras open-source deep learning framework along with the TensorFlow backend is employed to build and train the Convolutional Neural Network. The dataset obtained consisted of the training, testing images, each divided by the ten classes. A total of approximately 22,930 images of tomato leaves are present. The data is modified into the training and validation set to enhance the system and increase efficiency. A total of around 12845 images are included in the training set and similarly, a total of 5500 images are allocated to the validation set in order to improve the overall accuracy.A total of around 4585 images are included in the testing set.

3.2.2 Data Preprocessing

Data preprocessing is an integral step in Machine Learning as the quality of data and the useful information that can be derived from it directly affects the ability of our model to learn; therefore, it is extremely important that we preprocess our data before feeding it into our model. Data preprocessing is a process of preparing the raw data and making it suitable for a deep learning model. It is the first and crucial step while creating a deep learning model. For achieving better results from the applied model in Deep Learning projects the format of the data has to be in a proper manner.

The dataset has been pre-processed to handle various situations like attributes with missing data, attributes having no values or attributes having the value of and NA's. Misleading data like having different datatype or the format of the feature is different from what is other than required has also been taken into consideration. Here after loading the images, resize the images because the imges are of different length and widths. Also normalize the image pixels by dividing by 255.

3.2.3 Training the model

Another performance enhancing method in deep models especially in CNNs which is named as transfer learning. Transfer learning is the idea of overcoming the isolated learning paradigm and utilizing knowledge acquired for one task to solve related ones. There are three different transfer learning approaches in CNNs. These are feature extractor, fine-tuning and pre-trained models. The study, used fine tuning approach which is motivated by observing in early layers of CNNs have more generic features such as edges, colors. The models used in the propoed system are Resnet152V2 and MobileNetV2. Both Resnet152V2 and MobileNetV2 models are trained separately and these models are saved as H5 files.

3.2.4 Testing the model

The proposed Resnet152V2 and MobileNetV2 models are tested with testing data images for classifying the tomato leaf disease from tomato leaf images. Testing accuracy is most important performance matrix of classification algorithm.The accuracy of proposed ResNet152V2 is much higher than MobileNetV2 in testing.

3.2.5 Implementing the model in Gradio

Here, we developed a basic API using Gradio where user can upload tomato leaf image which is to be detected and the system predicts the name of tomato leaf disease.

3.3 ResNet152V2 Architecture

ResNet152v2 Architecture Residual Network (ResNet) is a CNN architecture with hundreds or thousands of convolutional layers. Previous CNN structures decreased the efficacy of additional layers. ResNet contains a huge number of layers, with strong performance. The primary difference between ResNetV2 and the original (V1) is that V2 uses batch normalization before each weight layer. In the field of image recognition and localization tasks, ResNet has strong performance that demonstrates the importance of many visual recognition tasks.

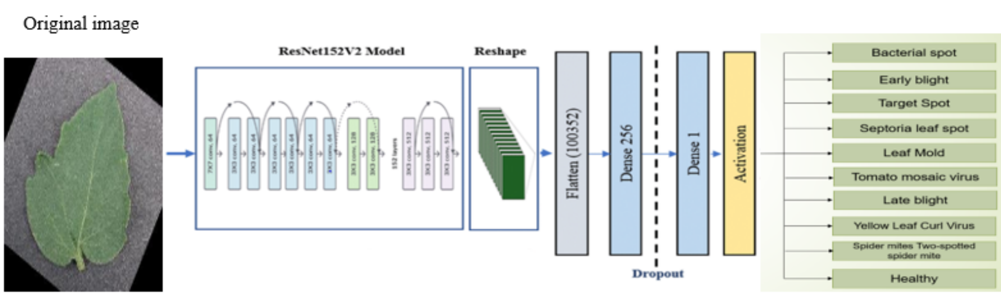

Figure 3.2: ResNet152V2 Architecture

3.4 MobileNetV2 Architecture

The architecture of MobileNetV2 is based on an inverted residual structure where the shortcut connections of the residual block are between the thin bottleneck layers. The intermediate expansion layer of the MobileNetV2 uses lightweight depth-wise convolutions in order to filter the features. In traditional residual models, expanded representations in the input are used. MobileNetV2 consists of the primary full convolution layer through 32 filters, followed by 19 residual bottleneck layers.

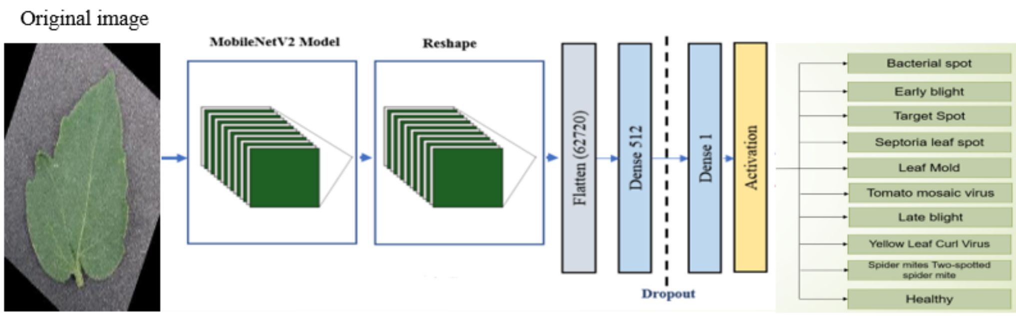

Figure 3.3: MobileNetV2 Architecture

ResNet152V2 and MobileNetV2 are also used as feature extraction models, as shown in Figures 3.2 and 3.3, respectively. These models can train the input based on their pre-trained initial weights. This approach accelerates the training and coverage to high accuracy. Each model architecture contains the original model followed by a reshape step, flatten step, first dense layer, a dropout layer, second dense layer, and finally an activation function that classify the images. Their architectures are illustrated in Tables 3.1 and 3.2, respectively. The total parameters of the ResNet152V2 amount to 84,022,273: the trainable parameters amount to 83,878,529, and the non-trainable parameters amount to 143,744. For the MobileNetV2, they amount to 34,371,649: 34,337,537 and 34,112 trainable and non-trainable parameters, respectively.

Layer (Type)	Output Shape	Parameters
resnet152v2 (Model)	(None, 4, 4, 2048)	58,331,648
reshape_2 (Reshape)	(None, 4, 4, 2048)	0
flatten_2 (Flatten)	(None, 100352)	0
dense_3 (Dense)	(None, 256)	25,690,368
dropout_2 (Dropout)	(None, 256)	0
dense_4 (Dense)	(None, 1)	257

Table 3.1: The pre-trained ResNet152V2 model architecture

Layer (Type)	Output Shape	Parameters
mobilenetv2_1.00_224 (Model)	(None, 7, 7, 1280)	2,257,984
reshape_2 (Reshape)	(None, 7, 7, 1280)	0
flatten_2 (Flatten)	(None, 62720)	0
dense_3 (Dense)	(None, 512)	32,113,152
dropout_2 (Dropout)	(None, 512)	0
dense_4 (Dense)	(None, 1)	513

Table 3.2: The pre-trained MobileNetV2 model architecture

3.5 Gradio

Gradio is an open-source python library which allows you to quickly create easy to use, customizable UI components for ML model, any API, or any arbitrary function in just a few lines of code. We can integrate the GUI directly into our Python notebook, or we can share the link to anyone. Then use the Gradio functions to build an image classification model. Finally, deploy the web application so that it can be accessed using a browser.

Benefits of using Gradio:-

- Enables you to create demos of your machine learning model. These demos can be used to present ideas to clients, users, and team members before the actual application is implemented.
- Gradio allows the collection of feedback from the user. A developer can, therefore, make the necessary improvements.
- When using Gradio, you can easily identify bugs and errors in the model. This enables you to remove the bugs before production.
- Gradio has an easy setup which makes it easier to build models of machine learning apps.
- Gradio enables you to permanently deploy an application on online servers.
- Gradio generates a public link that enables other users to interact with the application remotely.

3.6 Software requirements and specification

The software used for the project:

• Python

• Google Colaboratory

1. PYTHON

Python is an object-oriented programming language created by Guido Rossum in 1989. It's ideally designed for fast prototyping of complicated applications. It has interfaces to several OS system calls and libraries and is protractile to C or C++. several massive corporations use the Python programming language embody NASA, Google, YouTube, BitTorrent, etc. Python programming is widely utilized in AI, natural language Generation, Neural Networks and other advanced fields of computer science. Python is programming language open supply, high-level artificial language developed by Guido van Rossum within the late Eighties and presently administered by Python Software Foundation. It came from the ABC language that he helped produce early on in his career. Python is a powerful language that you can use develop games, write GUIs, and develop web applications. It's a high-level language. Reading and writing codes in Python is far like reading and writing regular English statements. As a result, they're not written in the machine-readable language, Python programs got to be processed before machines can run them. Python is an understood language. This implies that each time a program is run, its interpreter runs through the code and interprets it into machine-readable byte code. Python is an object-oriented language control users to manage and management data structures or objects to make and run programs. Everything in Python is, in fact, top-notch. All objects, data types, functions, methods, and classes take an equal position in Python. Programming languages are created to satisfy the requirements of programmers and users for an efficient tool to develop applications that impact lives, lifestyles, economy, and society. they assist build lives better by increasing productivity, enhancing communication, and rising potency. Languages die and become obsolete once they fail to live up to expectations and are replaced and superseded by languages that are more powerful. Python programming language artificial language that has stood the test of time and has remained relevant across industries and businesses and among programmers, and individual users. It's a living, thriving, and extremely helpful language that's extremely recommended as a primary programming language for those that want to dive into and experience programming.

- Python is Interpreted : Python is processed at runtime by the interpreter. You do not need to compile your program before executing it. This is similar to PERL and PHP.
- Python is Interactive : You can actually sit at a Python prompt and interact with the interpreter directly to write your programs.
- Python is Object-Oriented : Python supports Object-Oriented style or technique of programming that encapsulates code within objects.
- Python is a Beginners Language : Python is a great language for the beginnerlevel programmers and supports the development of a wide range of applications from simple text processing to WWW browsers to games.
- An easy and intuitive language just as powerful as those of the major competitor
- Open source, so anyone can contribute to its development
- Code that is as understandable as plain English

2. Google Colaboratory

Google Colab was developed by Google to provide free access to GPU's and TPU's to anyone who needs them to build a machine learning or deep learning model. Google Colab can be defined as an improved version of Jupyter Notebook.Jupyter Notebook is an application that allows editing and running Notebook documents through a web browser or an Integrated Development Environment (IDE). Instead of files, it will work with Notebooks.Notebook documents can include executable lines of code along with text, images, figures, tables, graphs, equations, and much more graphical data. In simple words, Notebook documents are a way of creating human-readable executable documents. In a Notebook, cells are the building blocks. Everything in a Notebook is composed of cells. There are two types of :

- Text cell :- A text cell can contain text, images, links and much more. You can double-click a text cell to edit its contents. The text cell supports Markdown markup language.
- Code cell:- A code cell contains the executable code. A code cell has a run button to its left that lets you execute the contents of the cell. When you run a cell the output is displayed under the cell.

Google Colab provides tons of exciting features that any modern IDE offers, and much more. Some of the most exciting features are listed below.

- Interactive tutorials to learn machine learning and neural networks.
- Write and execute Python 3 code without having a local setup.
- Execute terminal commands from the Notebook.
- Import datasets from external sources such as Kaggle.
- Save Notebooks to Google Drive.
- Import Notebooks from Google Drive.
- Free cloud service, GPUs and TPUs.
- Integrate with PyTorch, Tensor Flow, Open CV.
- Import or publish directly from/to GitHub.

Chapter 4

Result And Discussion

Convolutional Neural Network (CNN) have been quite successful in disease identification. Also by using pre trained CNN models on large scale datasets, important features can be learned which can be used in image classification. The efficiency of the model is rated high. After the model is constructed, compile the neural net using a categorical cross entropy selected as loss function, SGD used as the optimizer and batch size is given 32. Different approaches are used for avoiding over fitting. Firstly, the dropout method was used after fully connected layers. Secondly, Early stopping is used for avoiding overfitting.

4.1 Training and Validation results

Training gives optimized results, with high accuracy of 99.78 percentage for ResNet152V2 and 97.80 percentage for MobileNetV2 and corresponding loss of 0.008 and 0.081 respectively for training. For ResNet152V2 and MobileNetV2 its, 97.45 percentage and 89.51 percentage accuracy respectively for validation. The given table 4.1 shows both models training and testing accuracy.

Model	Training Accuracy	Testing Accuracy
ResNet152V2	99.78	98.21
MobileNetV2	97.80	91.69

Table 4.1: Accuracy of ResNet152V2 and MobileNetV2

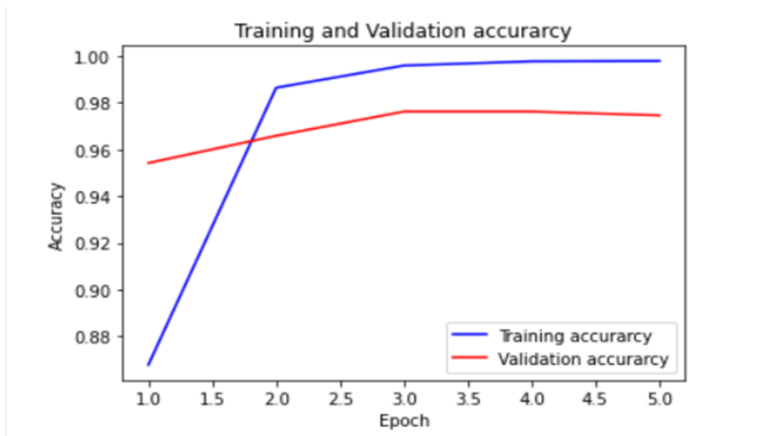

Figure 4.1: Training and validation accuracy of ResNet152V2

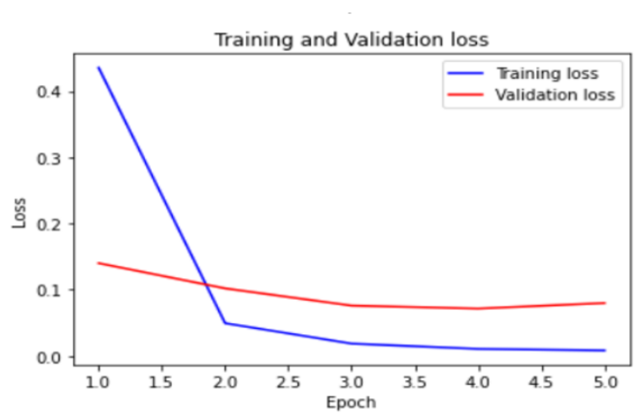

Figure 4.2: Training and validation loss of ResNet152V2

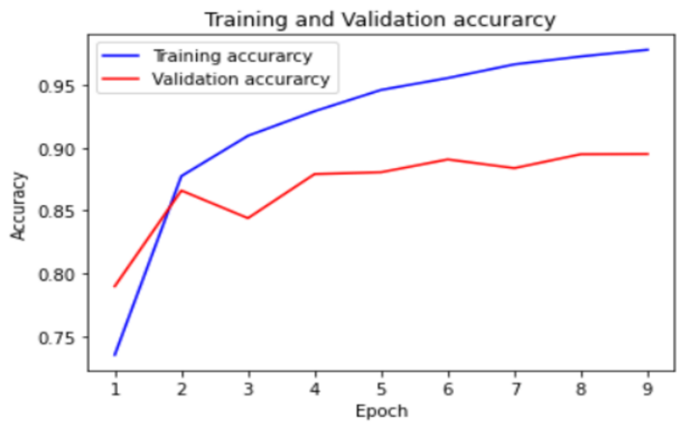

Figure 4.3: Training and validation accuracy of MobileNetV2

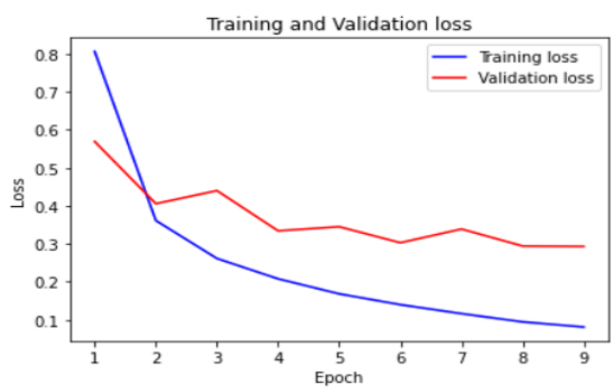

Figure 4.4: Training and validation loss of MobileNetV2

4.2 Confusion matrix

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm. It allows easy identification of confusion between classes e.g. one class is commonly mislabeled as the other. Most performance measures are computed from the confusion matrix.
The important terms included in confusion matrix are as following:

- True Positive (TP) :Observation is positive, and is predicted to be positive.
- False Negative (FN) : Observation is positive, but is predicted negative.
- True Negative (TN) : Observation is negative, and is predicted to be negative.
- False Positive (FP) : Observation is negative, but is predicted positive.

The below figures indicates the confusion matrix based on the classification results. Fig 4.5 indicates the confusion matrix of ResNet152V2 model and Fig 4.6 indicates the confusion matrix of MobileNetV2 model.

The confusion matrix represent like this:

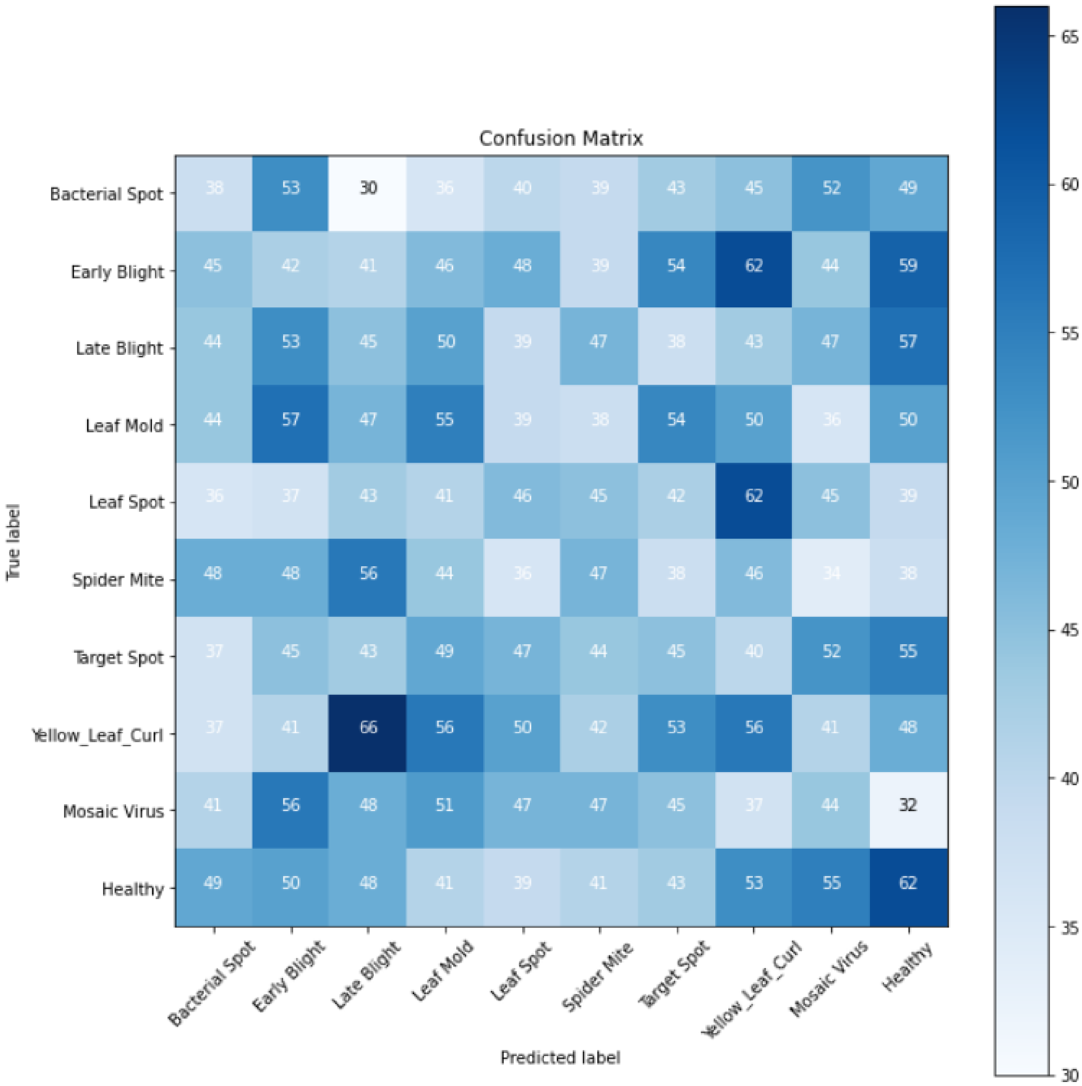

Figure 4.5: Confusion matrix of ResNet152V2

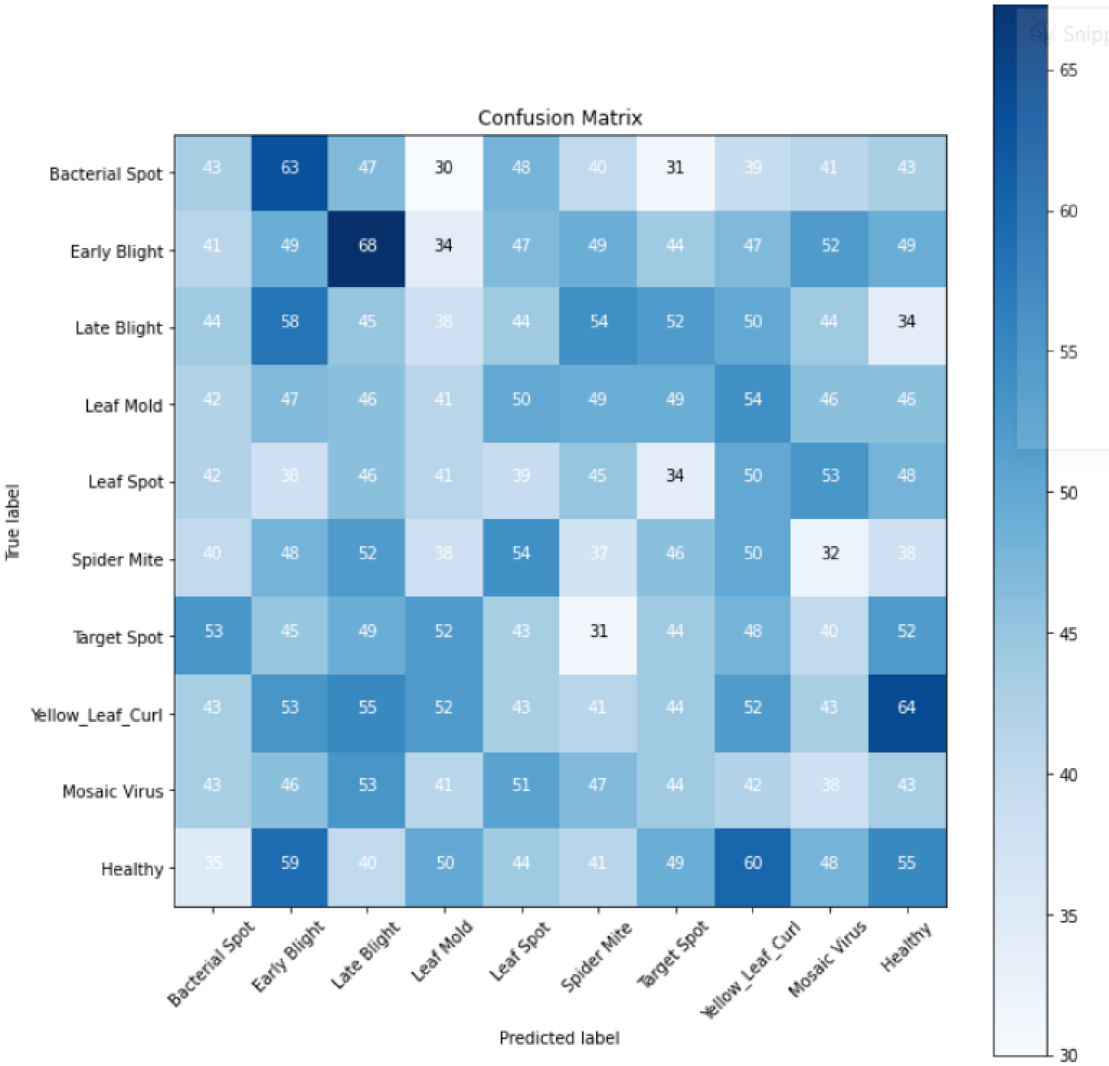

Figure 4.6: Confusion matrix of MobileNetV2

4.3 Performance metrics

The below table indicates the performance metrics to calculate accuracy based on the classification results. The most important performance matrix is precision. Precision is the fraction of relevant instances among the retrieved instances of classification techniques. The precision value of the proposed ResNet152V2 is superior to the MobileNetV2 model.

Precision = T P/(T P+FP)

Recall is also one of the most common performance metrics to estimate the performance of the classification model. The recall is the fraction of the total amount of relevant instances that were actually the retrieved instance of the classification algorithm.

Recall = T P/(T P+TN)

In statistical analysis of binary classification the f1 score is a measure for testing accuracy. It considers both the precision and the recall of the classification algorithm to compute the f1 score.

F1score = precision Recall/(precision+Recall)

Support is the number of actual occurrences of the class in the specified dataset. Imbalanced sup- port in the training data may indicate structural weaknesses in the reported scores of the classifier and could indicate the need for stratified sampling or re-balancing. Support doesn't change be- tween models but instead diagnoses the evaluation process.

Performance metrics of both ResNet152V2 and MobileNetV2 models are shown in table 4.2 and table 4.3 respectively. The outcomes of the most common performance matrix such as classification accuracy,precision,recall and f1 score shows that proposed ResNet152V2 gives a better performance than MobileNetV2. Also figure 4.7 shows sample images from dataset.

	precision	recall	f1-score	support
Bacterial Spot	0.09	0.09	0.09	425
Early Blight	0.09	0.09	0.09	480
Late Blight	0.10	0.10	0.10	463
Leaf Mold	0.12	0.12	0.12	470
Leaf Spot	0.11	0.11	0.11	436
Spider Mite	0.11	0.11	0.11	435
Target Spot	0.10	0.10	0.10	457
Yellow_Leaf_Curl	0.11	0.11	0.11	490
Mosaic Virus	0.10	0.10	0.10	448
Healthy	0.13	0.13	0.13	481
accuracy			0.10	4585
macro avg	0.10	0.10	0.10	4585
weighted avg	0.10	0.10	0.10	4585

Table 4.2: Performance metrics of ResNet152V2

	precision	recall	f1-score	support
Bacterial Spot	0.10	0.10	0.10	425
Early Blight	0.10	0.10	0.10	480
Late Blight	0.09	0.10	0.09	463
Leaf Mold	0.10	0.09	0.09	470
Leaf Spot	0.08	0.09	0.09	436
Spider Mite	0.09	0.09	0.09	435
Target Spot	0.10	0.10	0.10	457
Yellow_Leaf_Curl	0.11	0.11	0.11	490
Mosaic Virus	0.09	0.08	0.09	448
Healthy	0.12	0.11	0.12	481
accuracy			0.10	4585
macro avg	0.10	0.10	0.10	4585
weighted avg	0.10	0.10	0.10	4585

Table 4.3: Performance metrics of MobileNetV2

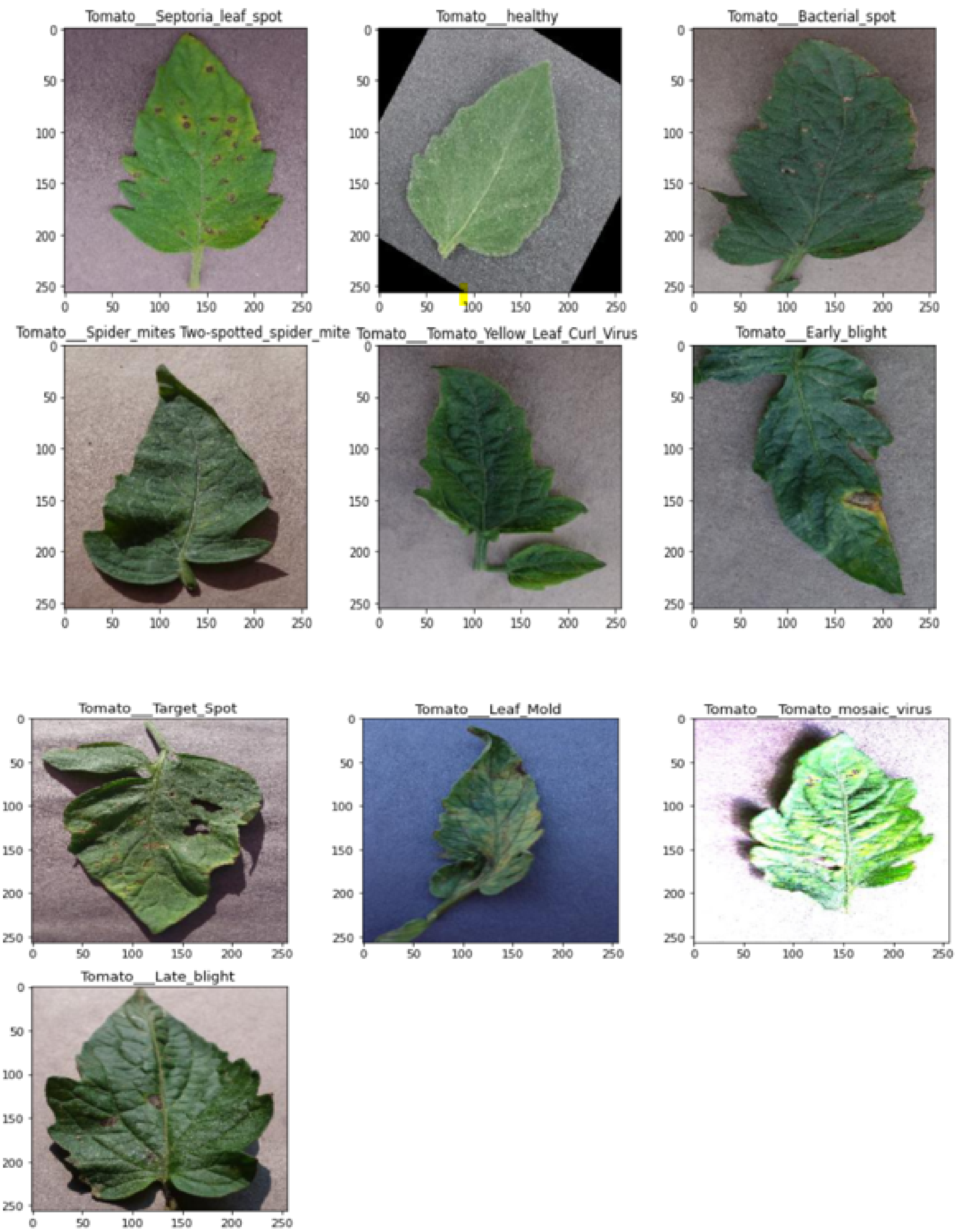

Figure 4.7: Data samples

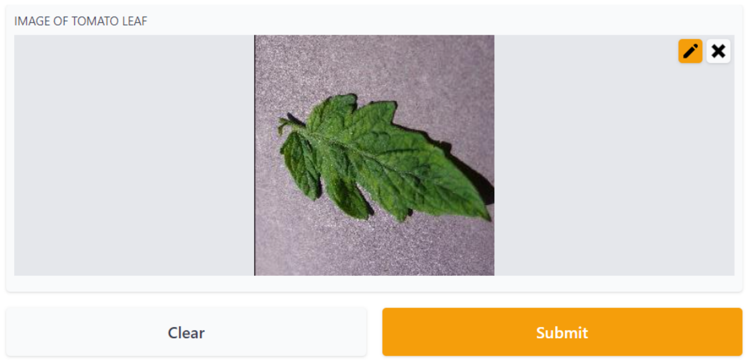

Figure 4.8: Input image

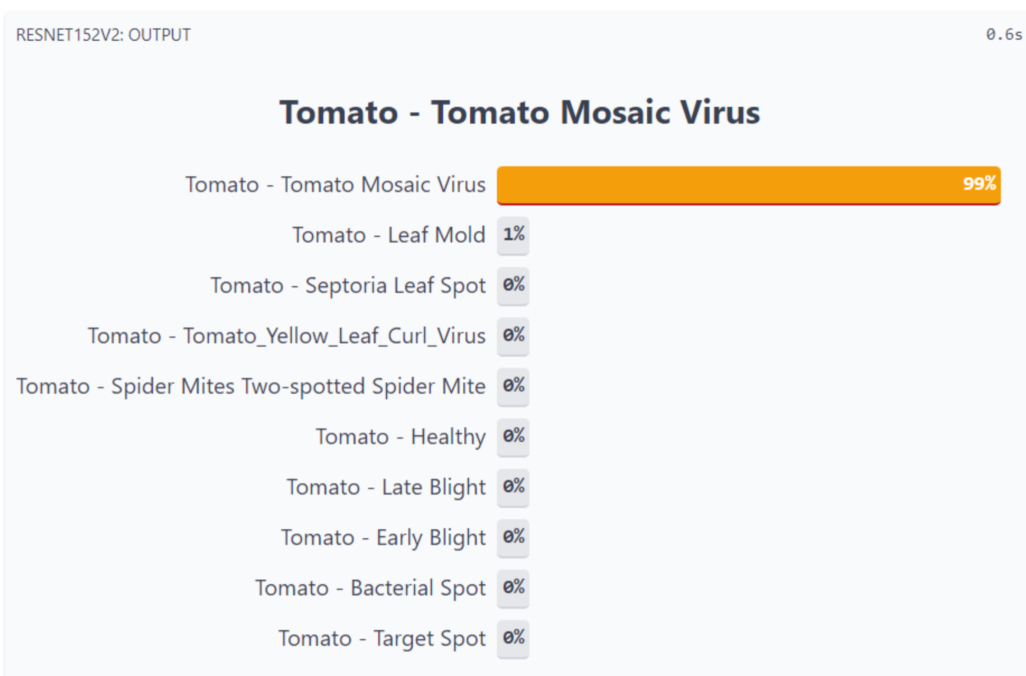

Figure 4.9: Output of ResNet152V2 model

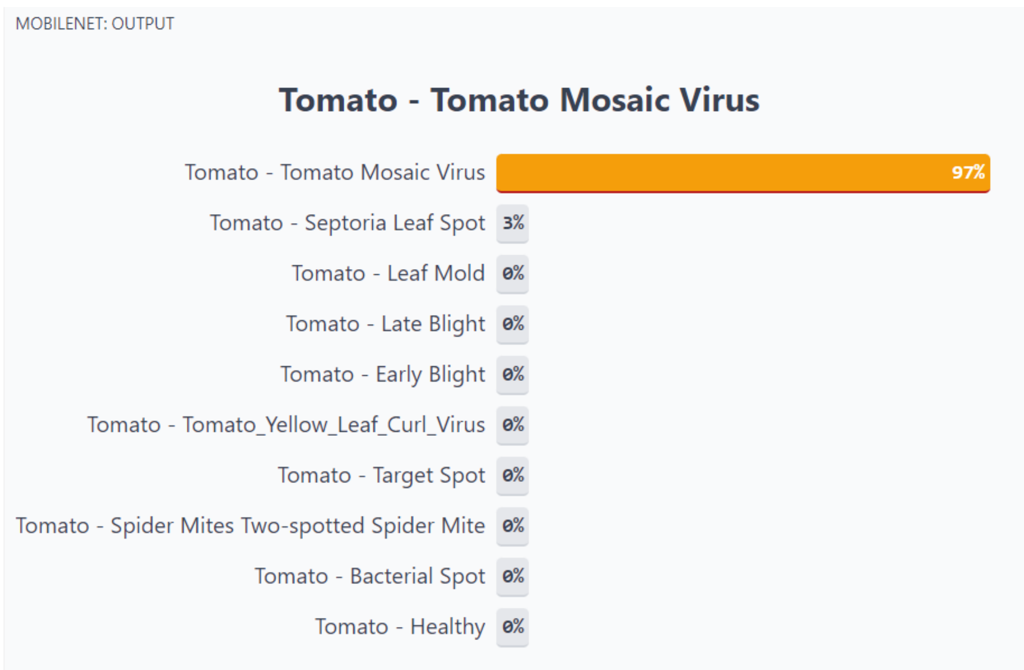

Figure 4.10: Output of MobileNetV2 model

Chapter 5

Conclusion

Therefore, it is concluded that the deep learning model proposed classifies the tomato leaves for disease detection in a very accurate manner. The loss of the model is minimized while training and the accuracy simultaneously increases through each epoch stages in order to yield distinct results for classifying the diseases. The pre-processing stages help to ensure that the performance of convolutional neural networks and deep neural networks is not subjected towards over fitting, thus the results obtained will always remain coherent. With a smaller number of convolutional layers, the proposed model predicts adroitly whether a given sample of tomato leaves has disease, or is normal. This is immensely helpful for early and accurate detection of tomato leaf disease.

5.1 Advantages

The main merits of proposed model are:

- No need of an expert knowledge to identify the disease.
- The system provide more accuracy and efficiency for tomato leaf disease prediction.
- Early diagnosis of disease.

5.2 Future Enhancement

This paper presents a hybrid model that employs technique to detect and identify type of disease that infect tomato plant using ResNet152V2 and MobileNetV2. ResNet152V2 gives more accuracy as compared to MobileNetV2. This project has an immense scope in the field of agriculture and can be continued for other such insightful innovations. Future work will be concentrated on improving the architectures used and other deep learning models other than this. For future research, variety of challenges and research directions could be considered. Some general research directions are to consider more plant diseases with different conditions.

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APPENDICES

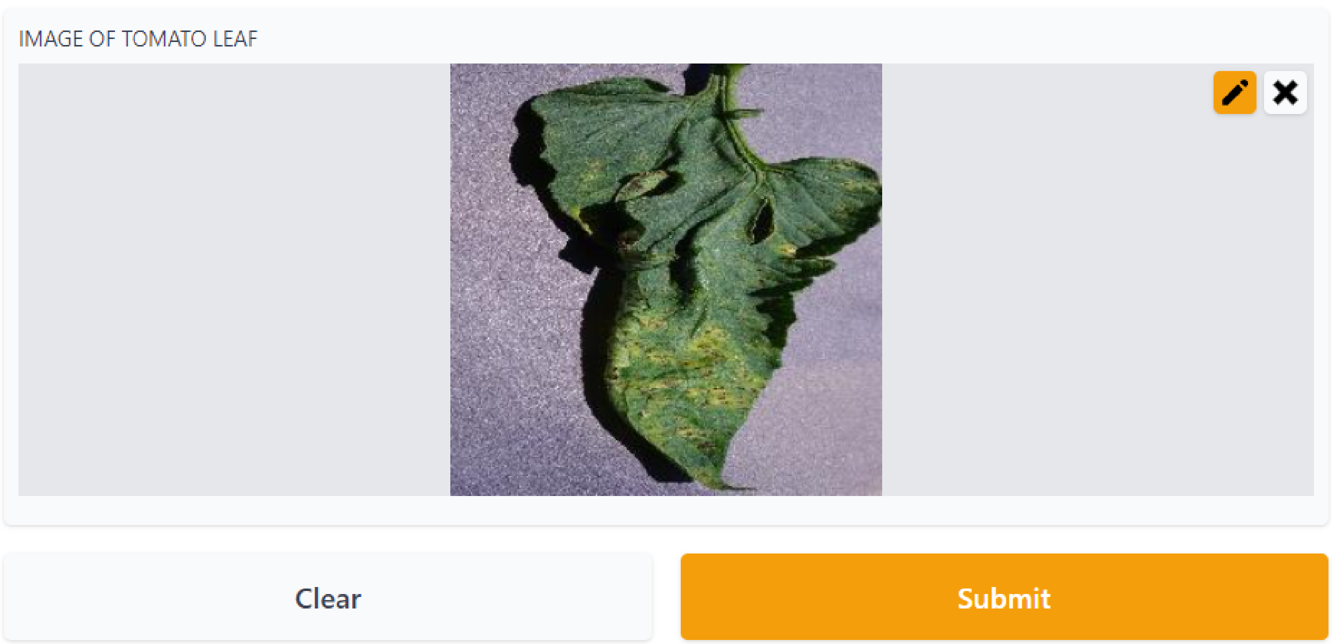

Figure A.1: Input image

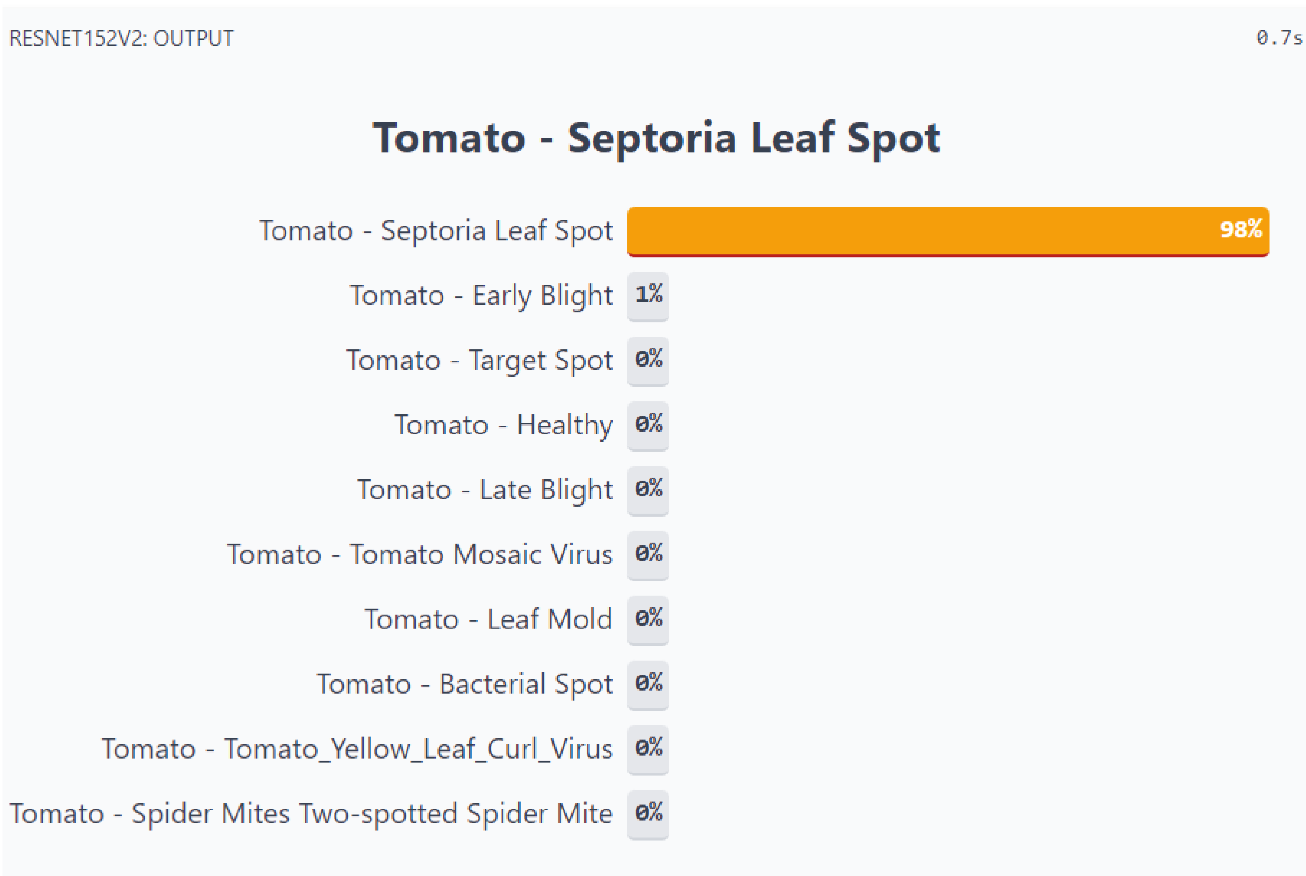

Figure A.2: Output of ResNet152V2 model

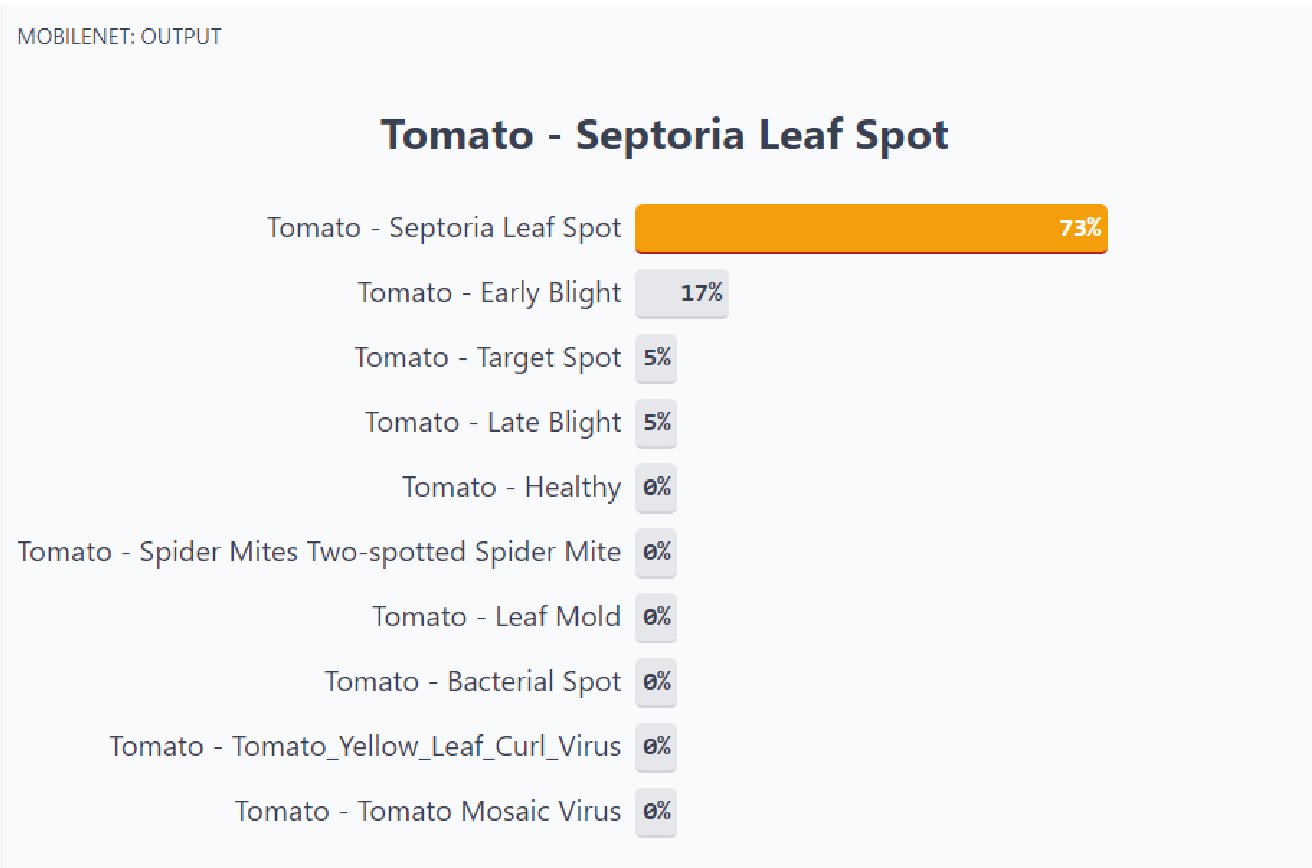

Figure A.3: Output of MobileNetV2 model

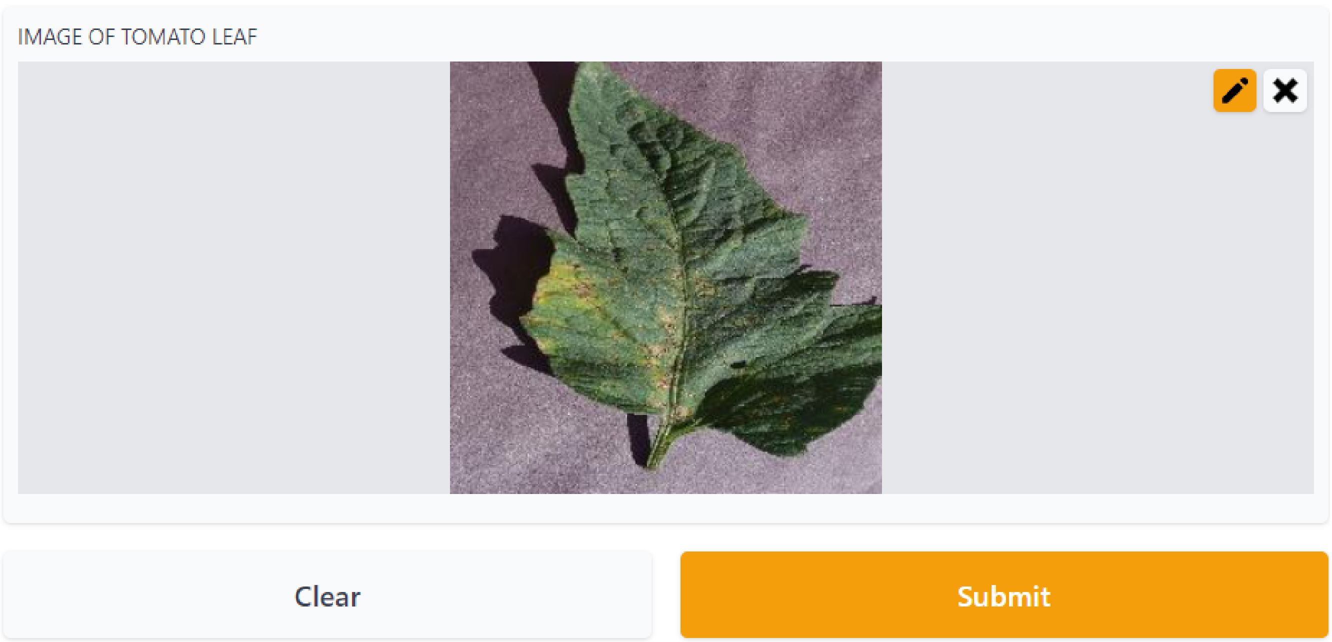

Figure A.4: Input image

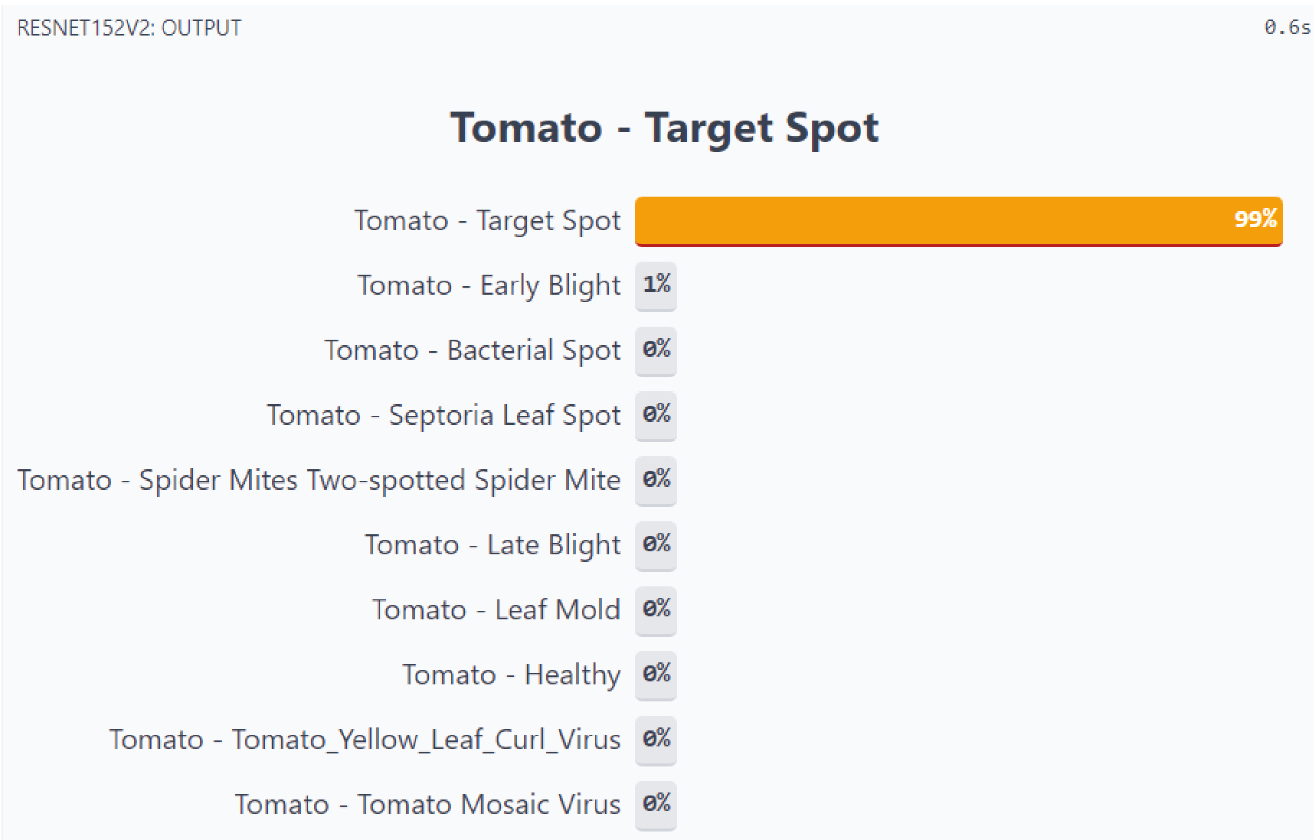

Figure A.5: Output of ResNet152V2 model

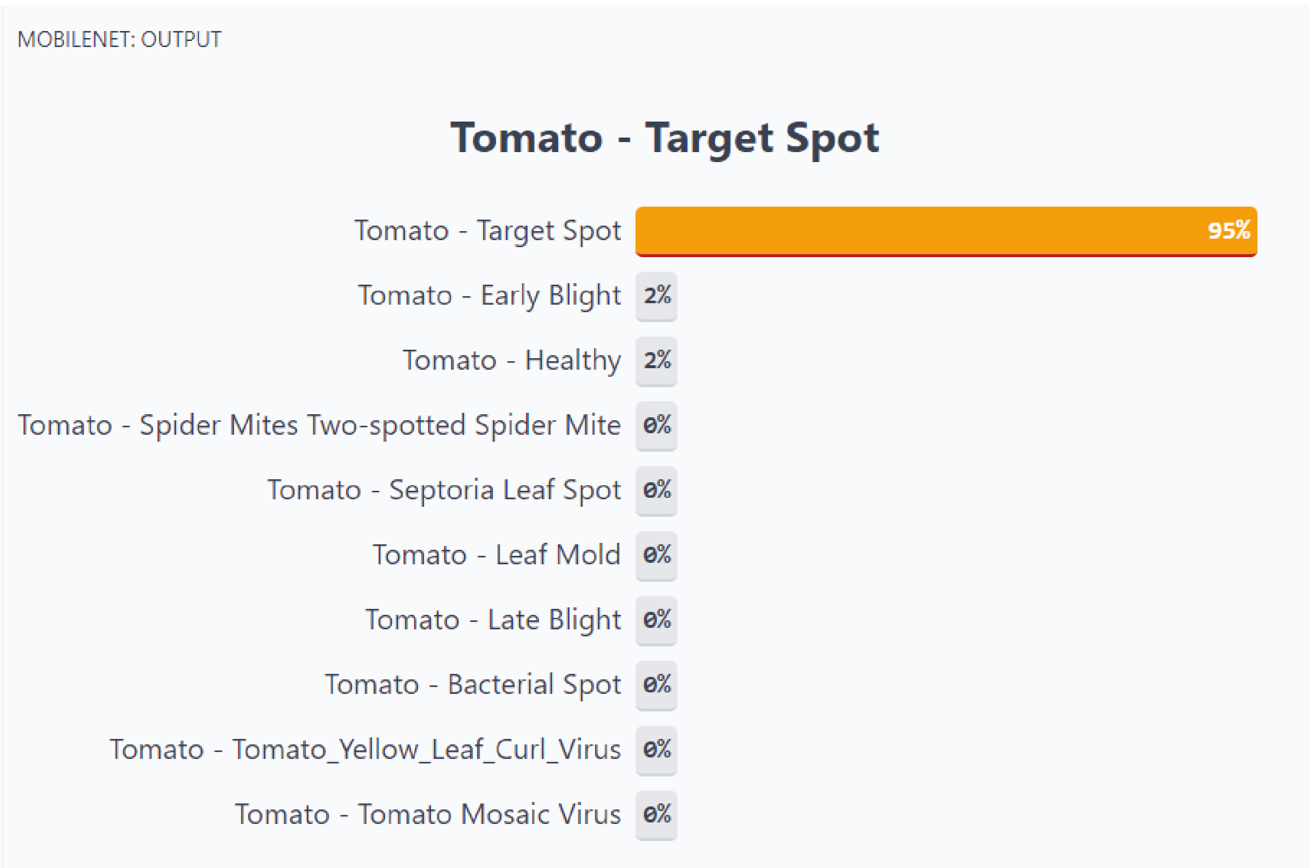

Figure A.6: Output of MobileNetV2 model

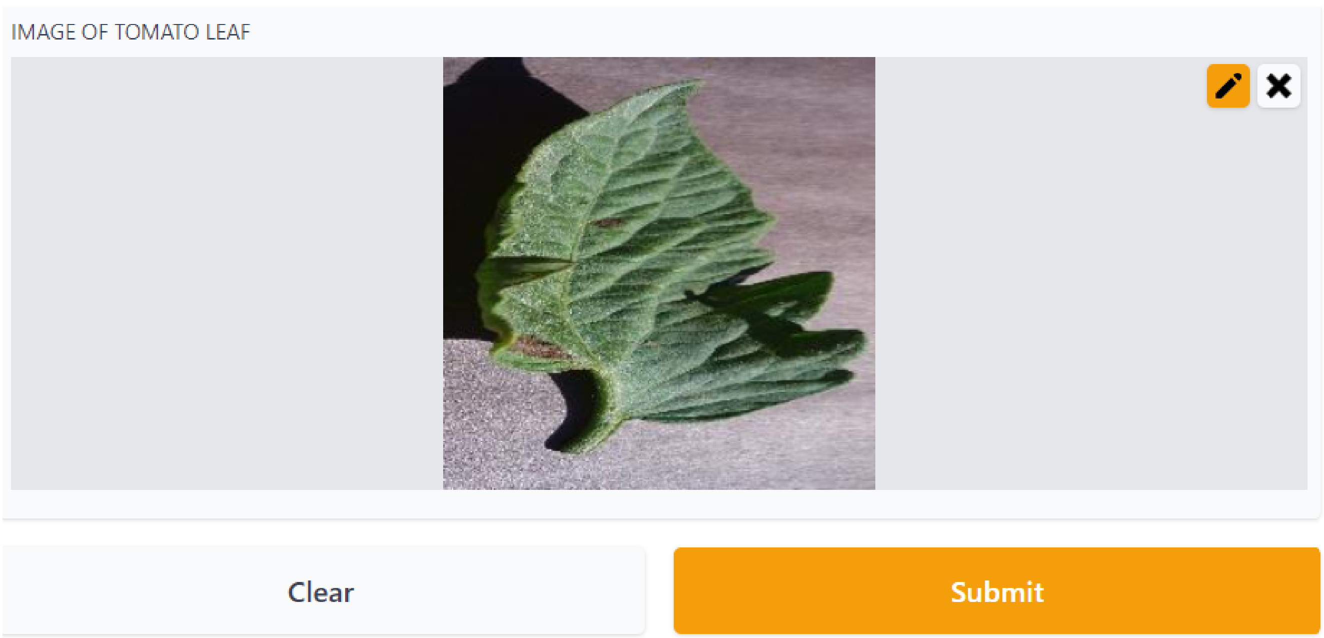

Figure A.7: Input image

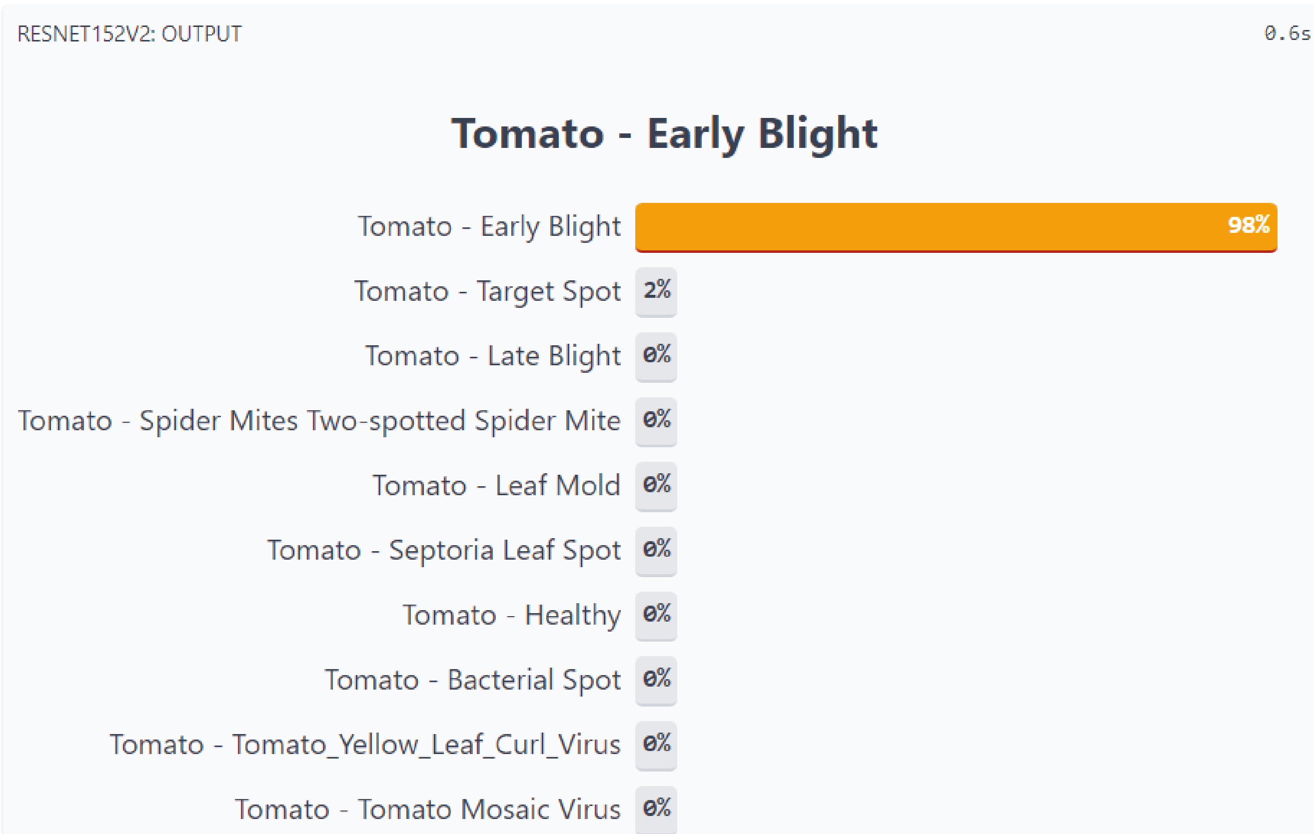

Figure A.8: Output of ResNet152V2 model

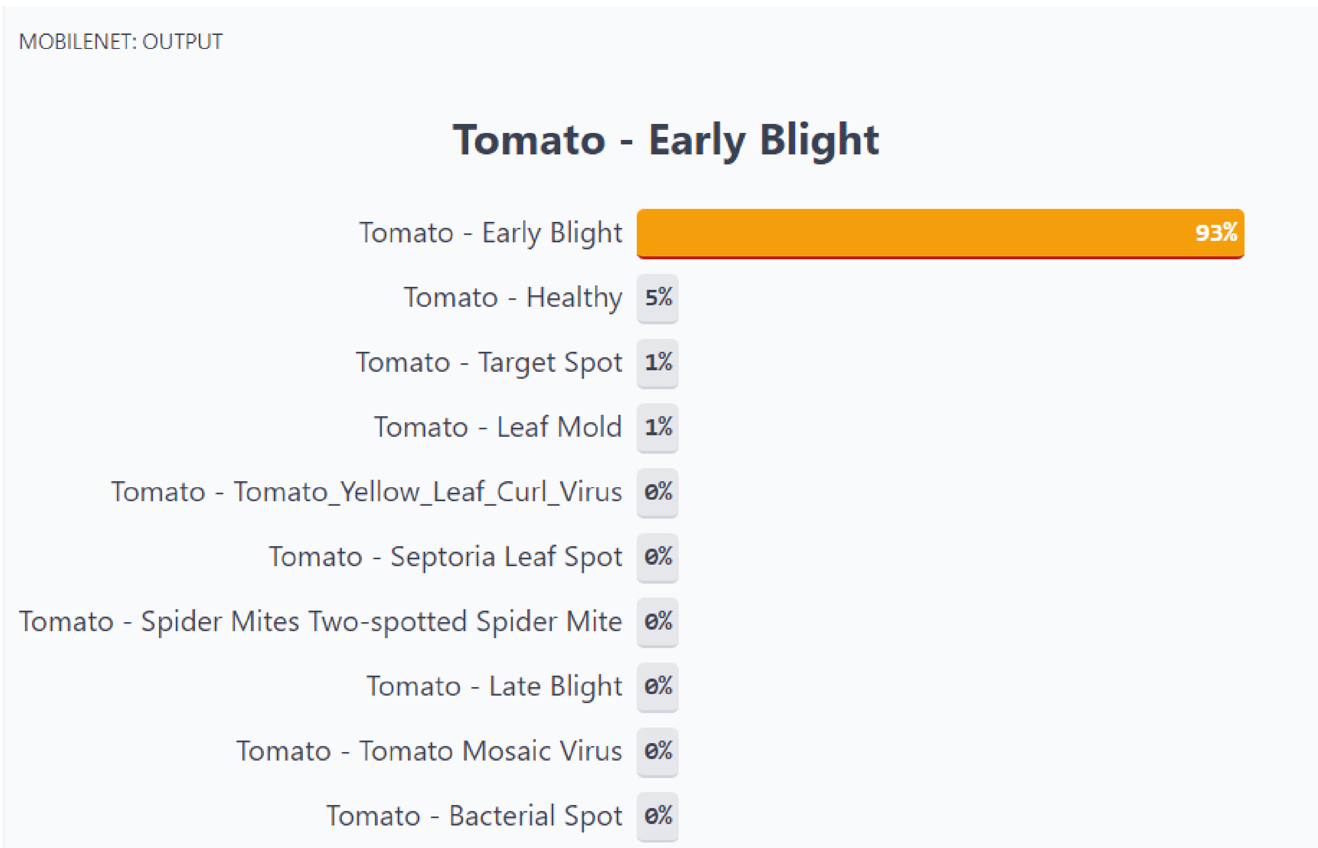

Figure A.9: Output of MobileNetV2 model