CROP DISEASE AND PESTS DETECTION USING CONVOLUTIONAL NEURAL NETWORK TO INCREASE AGRICULTURAL PRODUCTIVITY

By

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ABSTRACT

The Indian economy is extremely reliant on the agricultural productivity. Crop diseases and pests play a major role in the reduction of crop production and quality. Therefore, the detection of diseases and pests is fundamental in precision agriculture task. Manual detection of diseases takes additional time and efforts on the larger area of the farm. The Deep Learning approach is used to detect the diseases and pests more accurately. The Convolutional Neural Network models with object detection model are used to detect the diseases and pest along with infection status by extracting features from the images of leaf, fruit, stem and other parts of the crop. The dataset used for this research work is customized according to the need to resolve limitations of previous approaches. The dataset is main part of this work as it is customized and the results highly depends on what we give as an input. Main objective of this work is to find out best suitable model for our custom dataset. This research work carries out implementation of these models and gives comparison between these results. Accuracy is measured in terms of Mean Average Precision (mAP) and Intersection-over-Union (IoU). Implementation results shows that the best suitable model is Faster RCNN with ResNet101 CNN. The research work aids the farmers to take necessary actions against the diseases and/or pests, by reducing the loss of crop yield and ultimately providing the means to increase the agricultural production.

Keywords: Agricultural Productivity, Deep Learning, Crop Diseases, Convolutional Neural Network, Object Detection

CHAPTER 1

Introduction

1.1 Introduction

Agriculture is the chief sector in the Indian economy and gives contribution in the form of agricultural productivity, it is primary source of livelihood for about 58% of India’s population [1]. And also, it has major contribution of about 18% to the GDP of India [6]. Crop Production is important factor that is directly related to economy and people. To increase the agriculture productivity, precise and on-time detection of crop diseases and pest is needed. Nowadays, crop diseases and pest have become risk to food security because it causes reduction in crop yield. As the population is increasing, to fulfill the requirement of food, crop production should also be increased. In contrast, the improper use of pesticides is causing an adverse effect on the soil and food quality. Proper and accurate diagnosis of plant diseases is one of the important features to take into account [7]. If proper care is not taken of the diseases and pests, then it may result in the reduction of quality and quantity of the crop.

The existing method is the manual detection of the disease by observing the fields continuously by the group of experts, it is a very laborious task and less accurate when monitoring the larger area of the farm. Some farmers are not well known to all the diseases, do not have proper facilities and many times also not aware of how to contact an expert, also sometimes experienced agronomists often fail to successfully diagnose the crop disease. Therefore, the automatic detection of the disease from the images is valuable to aid the expert as it is more accurate and takes less time and efforts.

Diseases and pest cause some characteristic damage on the different crop parts, characteristic symptoms can be visible part of an infected crops [8]. Furthermore, the challenging part of this research work is not only detecting which disease is present but also in approximating how accurate it is and the infection status of the disease.

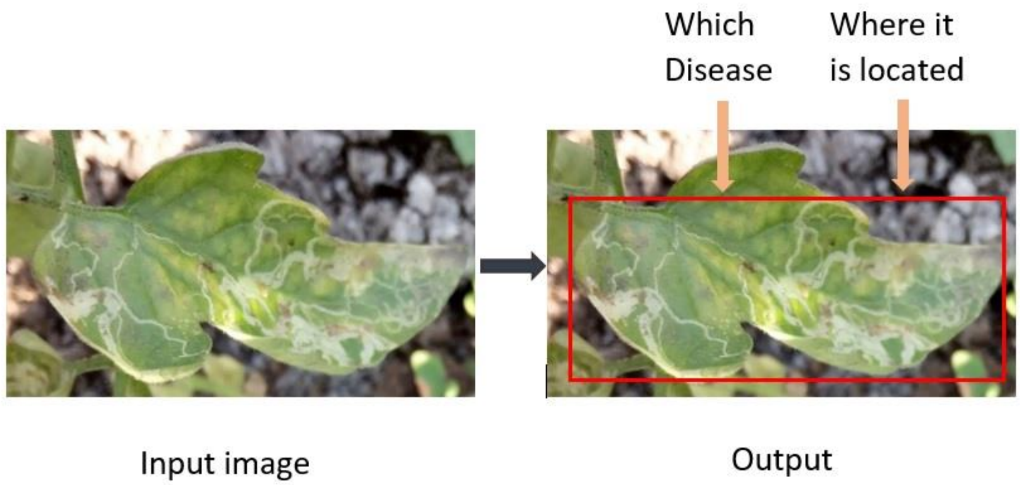


Fig. 1.1 Disease Detection

Deep learning [9] can be used for classification of crop diseases and/or pests which includes detecting diseases in their early stages and also it helps to react in time with crop protection measures. We are comparing different models that are useful in recognizing different diseases and pests in images which are collected in laboratory conditions as well as real field conditions. Additionally, our model is able to deal with complex images and helps in finding infection status or stage of disease such as earlier or last, location in the crop like leaf, fruit or stem, and also able to deal with image's heterogeneous background conditions.

1.2 Motivation

Crop diseases and pests are the main reasons for the loss of agricultural production. Crop diseases reduces quality and quantity of the production. Reasons that affects crops are environmental conditions, pests that spreads diseases, diseases due to bacterial, virus or fungus. It is vital to detect and control diseases and pests for improving the production. Development of new algorithms and models have given the new direction towards the automatic disease detection. Deep learning models provides very efficient results in very much lesser time once trained. Object detection models' developments help in detecting location of the diseases and/or pest. Motivation behind this research work are:

- Improvement in agricultural production
- Minimizing crop production loss by early detecting diseases
- Ensuring food security for the increasing population.

1.3 Objectives

Convolutional Neural Network [9] is very efficient in terms of processing a large amount of data in very less time. We are using the CNN model along with object detection techniques for the processing of the image data of leaf, stem, root, fruits etc. parts of the crop which are infected from diseases and pest. Using deep learning approach, object detection techniques with convolutional neural networks, the objectives can be summarized as:

- To detect the crop disease from the images of all parts of the infected crop.
    - The images in the dataset will be laboratory condition as well as field condition.
    - The images with heterogeneous background will also be considered.
- Detecting location of disease or pest.
- Detection of the various kinds of pests.
- To detect the severity of disease.
- To provide performance comparison of various pre-trained CNN models along with object detection models to detect crop disease based on training-testing ratio, batch size and epochs.

1.4 Problem Statement

Crop diseases and pest detection along with the disease severity estimation using deep learning approaches. Transfer learning technique is used with pre-trained Convolutional Neural Network (CNN) along with object detection models for this research work.

1.5 Scope of the Work

This research work basically uses the transfer learning approach for the detection of disease and pests of the crop. For this work various pre-trained networks are used. So, the scope of the work includes,

- Detecting different diseases and/or pest in initially on one crop and can be extended to various types of crops.
- Comparing various performances of pre-trained networks like Inception [10], ResNet [11], MobileNet [12] etc.
- Comparing different object detection methods such as Faster RCNN [13], SSD [14] and RFCN [15].
- Comparison of results by taking different parameters of fine tuning the models like epochs, learning rate, batch size.

1.6 Thesis Organization

The remainder section of this thesis is organized according to the following chapters:

Chapter 2: Background Theory of Deep Learning, Object Detection and Convolutional Neural Network

Chapter 3: Literature survey and comparison table for the survey.

Chapter 4: Proposed Methodology.

Chapter 5: Experiments and Results.

Chapter 6: Conclusion and Future work.

CHAPTER 2

Background Theory

2.1 Deep Learning

Deep learning is representation learning method which contains multiple levels of representations. In representation learning, a machine is allowed to automatically discover the representations from the raw data, which can be useful in classification or detection task [9]. By composing various smaller and simple non-linear modules at each level higher level and complex features can be learned.

For example, in image classification task, the input image will be given to the model. Image is the array of pixel values, so the first layer can tell the presence or absence of some edges at some angles. The second layer detects objects or shapes consisting the edges. The third layer assembles the shapes and detects more complex shapes or combination of the objects. Thus, the main aspect of deep learning is it automates feature learning process, there is no need to manually specify the features of the image. Some of the applications includes image recognition, speech recognition, natural language processing, reconstructing brain circuits, predicting activity of potential drug molecules.

In the training of the model, input image is given and the output is generated in the form of scores, one score for each class and the vector is formed of scores, the desired class should have highest score of all the class. But as the model is not trained, it is unlikely to happen. Next, we compute the objective function to measure error, which is distance between desired score and output score. According to the error model modifies its adjustable parameters to reduce the distance, these adjustable parameters are known as the weights. Weights are the real numbers that are used to define input-output function of the model. To adjust the weights of the model, computation of gradient vector is needed by the learning algorithm.

Gradient vector indicates by which amount the error would be increase or decrease if the weights are increases very little and weights are adjusted. The objective function, is averaged over all training examples, most of the practitioners uses stochastic gradient descent (SGD) [9]. After training, the performance of the system is measured on a different set of examples called a test set. The key advantage of deep learning is that the features of the input can be learned automatically, not manual feature extraction is required. A deep learning architecture is multilayer architecture, where each layer consists of the simple modules which are used for learning purposes. Each module transforms its input to increase selectivity and invariance of the representation. As the non-linear layers increases in the model a system is able to identify more complex features of the input.

In the backpropagation process, computation of gradient of an objective function with respect to weights of modules of the model is done. Here, gradients can be compared to the derivatives of the chain rule. Feed forward neural network which learn to map a fixed-size input to a fixed-size output. To transit from one layer to the next, a weighted sum is computed which consists of inputs from the previous layer, it uses non-linear function such as rectified linear unit (ReLU), which is $f(z) = \max(z, 0)$ and also ReLU typically learns much faster in networks with many layers. Units that are not in the input or output layer are conventionally called hidden units. The hidden layers can be seen as distorting the input in a non-linear way and makes them linear by the last layer fully-connected layer [9].

2.2 Object Detection

Faster Region-based Convolutional Neural Network (Faster R-CNN)

Faster R-CNN model carry out detection in two phases. First stage consists of Region Proposal Network (RPN) in which an image is given as input and it goes to a feature extractor which processes the given image [13]. Features at transitional level are used to predict the proposals of objects, each are assigned with a score. RPNs are trained using anchors, system decides whether an anchor contains object or not. Anchors are decided based on the IoU between the ground-truth and predicted values of the detection. In the second phase, previously generated box proposals are used to extract features from the same feature map. Those features are given as input into the last layers of the feature extractor, and predicts the class probability and bounding box for each region. The complete process occurs on a single integrated network, it also allows the model to share full-image convolutional features with the detection network, therefore it provides cost-free proposals of regions. Faster R-CNN has influenced numerous applications because of its outstanding results in terms of precise and accurate output on complex object recognition and classification.

Single Shot Detector (SSD)

The SSD [14] uses a feed-forward CNN for handling the problem of object recognition. The network generates a collection of bounding boxes in some numbers and also scores which are used to show object's presence in each box. The SSD is able to deal with objects of several sizes by uniting predictions from multiple feature maps with different resolutions. Additionally, SSD compresses the process into a single network, proposal generation is not computed separately hence, it saves computational time.

Region-based Fully Convolutional Network (R-FCN)

The R-FCN [15] method is similar to Faster R-CNN, but instead of getting features from the layer where proposals are predicted, features are collected from the last layer. So, using this method the amount of memory utilized in region computation is minimized.

In the paper [15], they are showing that ResNet-101 as feature extractor can perform as good as Faster R-CNN.

2.3 Convolutional Neural Network

The Convolutional Neural Network is composed of various convolution and pooling layers, lastly ends with the fully connected layers. The advantage of CNN is that, it automatically extracts the features of the input images. CNN has three main components, which are convolution layer, pooling or subsampling layer, and fully connected layer as shown in the Fig. 2.1.

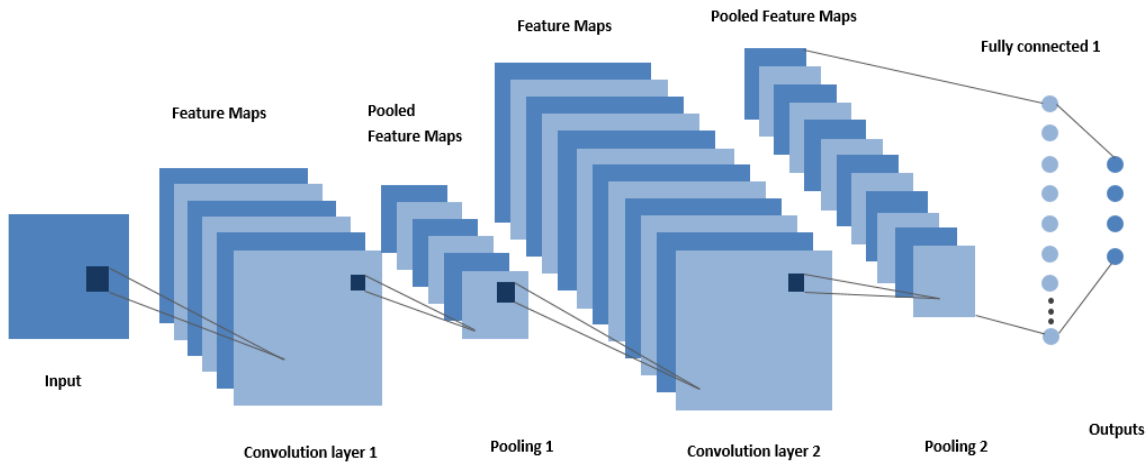


Fig. 2.1 Convolutional Neural Network [13]

The input is three-dimension image to the convolutional layer. Here, three dimension represents the height and width of the image and the number of channels. For example, the value of last dimension is 3 when the image is RGB image. The convolution layer extracts the features of the image using different kinds filters and generates the feature maps. A filter consists of values which are known as weights and is trained to detect specific features of the input image.

Convolution layer also uses ReLU activation function for non-linearity, which is Rectified Linear Units that computes ReLU(z) = max (0, z). It is used to speed up the overall training process. The output of the convolution layer which is feature maps, act as an input in the pooling layer. The dimensionality of the features extracted at convolution layer is then reduced by the pooling layer. More convolution and pooling layers are included in the model to extract more features of the image. At last, the fully connected layer uses the learned high-level features by the model for classifying the input images into predefined classes with the help of a softmax activation function [8]. The model adjusts its filter values or weights through the backpropagation. The loss function is used to calculate the updated weights one method is to calculate the MSE (Mean Squared Error).

CHAPTER 3

Literature Review

3.1 Literature Review Papers

1. **Paper Title:** Tomato Crop disease classification using pre-trained deep learning algorithm

   Authors: Aravind Krishnaswamy Rangarajan, Raja Purushothaman, Aniirudh Ramesh

   Publication / Journal Name: Procedia Computer Science 133 (2018) by Elsevier

   Summary:

   - In this study, images of tomato leaves are taken from PlantVillage dataset is provided as input to two deep learning-based architectures namely AlexNet and VGG16 net.
   - Comparison between those two models is given in this paper.

   Observations:

   - The parameters that affects performance of models such as number of images and batch size, weight and bias learning rate have been analyzed.
   - Using 13,262 images, the classification accuracy is 97.29% for VGG16 and 97.49% for AlexNet.

   Limitations:

   - They have used only Leaf images in the database
   - They do not use field conditioned images
   - They only have taken tomato images

2. **Paper Title:** Pest identification via deep residual learning in complex background

   Authors: Xi Cheng, Youhua Zhang, Yiqiong Chen, Yunzhi Wu, Yi Yue

   Publication / Journal Name: Computers and Electronics in Agriculture 141 (2017) by Elsevier

   Summary:

   - For identification of pest with the heterogeneous background, a method is proposed in this paper which uses the concept of deep residual learning.
   - Comparison is given between support vector machine and traditional BP neural networks, the accuracy of detecting pests in this method is improved while having images with heterogeneous background.

   Observations:

   - A classification accuracy of 98.67% for 10 classes of crop pest images with complex farmland background was achieved using deep residual network.

   Limitations:

   - They have taken very less training data.
   - They don't have taken and crop specific pests.

3. **Paper Title:** Automatic image-based plant disease severity estimation using deep learning

   Authors: Guan Wang, Yu Sun, and Jianxin Wang

   Publication / Journal Name: Hindawi, Computational Intelligence and Neuroscience, Volume 2017

   Summary:

   - They have used the apple black rot images from the PlantVillage dataset.
   - Those images are annotated by experts by assigning them to four stages. After that various deep convolutional neural networks are trained to detect the severity of the disease.
   - The performances are compared in this paper, which are trained from scratch and fine-tuned by transfer learning.

Observations:

- The performance of deep VGG16 model trained with transfer learning is 90.4% on the test set.

Limitations:

- They have taken only one crop images.
- The dataset has not more images.
- They have identified the disease severity only for one specific disease.

4. **Paper Title:** Deep learning models for plant disease detection and diagnosis

   Authors: Konstantinos P. Ferentinos

   Publication / Journal Name: Computers and Electronics in Agriculture- 145 (2018) by Elsevier

   Summary:

   - In this paper, to perform disease detection, convolutional neural network models are developed and trained on healthy and diseased crop leaves through deep learning techniques.
   - Training of the models was performed on database, which has 87,848 images of 25 different plants divided into 58 classes.

   Observations:

   - Various deep learning models are trained, with the best performance of 99.53%.

   Limitations:

   - They have used only Leaf images in the database
   - They do not use field condition images.

5. **Paper Title:** Using deep learning for image-based plant disease detection

   Authors: Sharada P. Mohanty, David P. Hughes and Marcel Salathe

   Publication / Journal Name: Frontiers in Plant Science, September 2016, Volume7

   Summary:

- An open dataset of 54,306 images of crop leaves having diseases which are collected in laboratory conditions.
- Those images are used to train a deep convolutional neural network to identify 14 crop types and 26 types of diseases.

Observations:

- The model achieves an accuracy of 99.35% on a test set, which shows great performance of the model.

Limitations:

- They have used only leaf images in the database
- They do not use field conditioned images.

6. **Paper Title:** Deep neural networks based recognition of plant diseases by leaf image classification.

   Authors: Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk, and Darko Stefanovic

   Publication / Journal Name: Hindawi Publishing Corporation, Computational Intelligence and Neuroscience, Volume 2016

   Summary:

   - The model developed in this paper is able to identify different types of plant diseases which are 13 types, and has the ability to differentiate background from the main part of crop.

   Observations:

   - The experimental results on the model which is trained in this paper has achieved results between 91% and 98%
   - For stand-alone class tests on average 96.3% on CaffeNet model is achieved.

   Limitations:

   - They have used only leaf images in the database
   - They do not use field conditioned images

3.2 Comparison Table of Literature Review

Literature review shows some limitations of previous works which are needs to be resolved in our work. Following table shows the comparison of research papers.

Table 3.1 Literature Review Comparison Table

Sr no.	Paper Title	Database used	CNN used	Remarks
1	Tomato Crop disease classification using pre-trained deep learning algorithm (2018) [17]	Tomato crop; 7 Classes 13,262 images from PlantVillage dataset.	Comparison: AlexNet and VGG16	• Tomato disease are detected • Upper side of leaf images only • No field condition images • Images of one crop only
2	Pest identification via deep residual learning in complex background (2017) [18]	10 classes; 550 images	Comparison: AlexNet, ResNet-50, ResNet-101	• Pests are detected • Very less training data
3	Automatic image-based plant disease severity estimation using deep learning. (2017) [19]	Apple Black rot disease from plant village dataset; 2086 images	Comparison: VGG16, VGG19, Inception-V3, ResNet50	• Four stages of disease will be detected • Only Leaf images • No field condition images • Only one plant images

4	Deep learning models for plant disease detection and diagnosis (2018) [20]	25 types of plants; 58 classes; 87,848 images	Comparison: AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat, VGG	• Only Leaf images • Actual field condition images in training are less
5	Using deep learning for image-based plant disease detection. (2016) [21]	14 types of plants; 38 classes; 50,306 images	Comparison: AlexNet and GoogLeNet	• PlantVillage Dataset is given • Only Leaf images • No field condition images
6	Deep neural networks based recognition of plant diseases by leaf image classification (2018) [22]	5 plants; 15 classes; 30,880 images	CaffeNet	• Laboratory and leaf images only

CHAPTER 4

Proposed Methodology

4.1 Projected Methodology

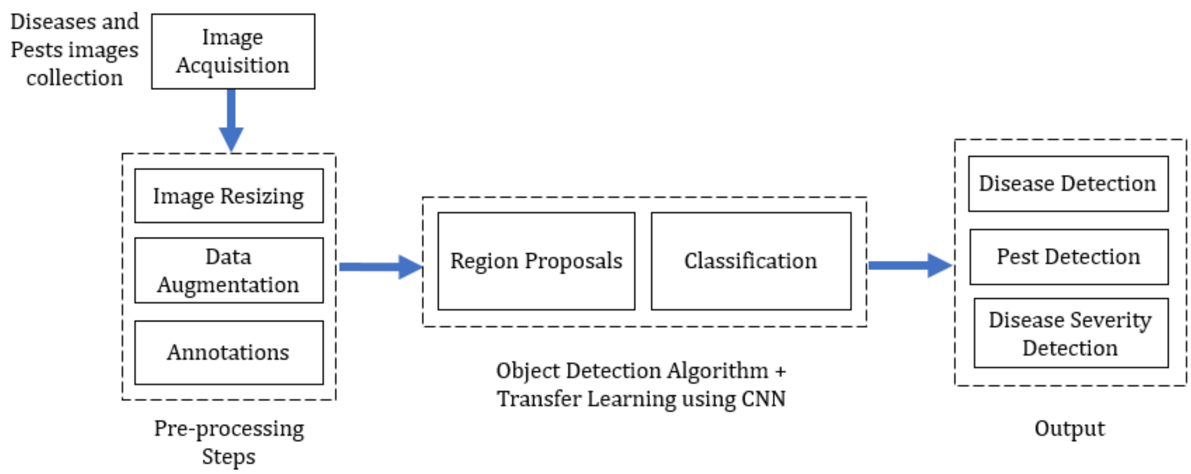


Fig. 4.1 Proposed Workflow

4.2 Description of Methodology

The proposed workflow consists of the main three stages: Collecting images, pre-process them and finally train the model for the acquired dataset. All of these phases are described in detail as following.

1. Image Acquisition

Tomato crops can be infected by various diseases and pests. There are various reasons that can cause effects on the crops; such as environmental conditions, pests that spreads diseases and various bacteria and virus. Those infection is visible on respective parts of the crop such as fruit, root, stem and leaf. So, we need images of all parts of the crop. Images collected from three different sources to form dataset for training our models, those are taken from following:

1. Real field condition images:
   - Images are captured from the farm near Shampara Taluka, District-Bhavnagar, State - Gujarat.
   - Using Mobile Phone Camera with 20MP resolution.
2. PlantVillage dataset [21]:
   - Diseases not spread in the above area are taken from this open dataset to generalize the database
3. Images downloaded from the various Internet resources:
   - Images of different parts like fruit and stem images are downloaded from the agriculture institute websites and forums.

Table 4.1: Dataset Classes: Each class having images from different sources

Sr. No.	Disease Name	Class Name	Part infected	PlantVillage	Real Field images	Internet resources	Total Images
1	Tomato Bacterial Spots	tbs1	Leaf	270	-	-	270
2	Tomato Bacterial Spots	tbs2	Leaf	285	-	-	285
3	Healthy Fruit	thf	Fruit	-	-	279	279
4	Healthy Leaf	thl	Leaf	210	-	-	210
5	Tomato Late Blight	tlb1	Leaf	163	122	-	285
6	Tomato Late Blight	tlb2	Leaf	247	43	-	290
7	Tomato Leaf Miner	tlmn	Leaf	-	301	-	301
8	Tomato Pith Necrosis	tpn	Stem	-	-	192	192
9	Tomato Spotted Wilt Virus	tsw	Fruit	-	-	196	196
10	Tomato White Fly- Pest	twf	Pest	-	-	221	221
Total images							**2529**

Sample images of Tomato Diseases affected on different parts of the crop:

Disease: Tomato Late Blight
Part: Lower side of the leaf
Image source: Captured image

Disease: Tomato Pith Necrosis
Part: Stem
Image source: Internet

Disease: Tomato Spotted Wilt Virus
Part: Fruit
Image source: Captured image

Heterogeneous background
Image source: Captured image

White Fly Pest images
Image source: Internet

More than one disease present
Diseases: Tomato Late Blight and
Tomato Leaf Miner
Image source: Captured image

Fig. 4.2 Dataset sample images

Disease severity stages:

Dataset is divided into three stages as healthy stage, early stage and last stage for crop diseases. Sample images of the dataset for tomato late blight diseases according to the stages are shown in the following figure:

Stage 1: Healthy
Image source: PlantVillage

Stage 2: Early stage (Late Blight)
Image source: Captured images

Stage 3: Last stage (Late Blight)
Image source: Captured images

Fig. 4.3 Disease severity stages

2. Pre-processing

Image Resizing:

All images are taken from different sources as described in above section. Therefore, all images are in different sizes and it is important to resize images in same size while giving database as input while training the model. Image resizing process in which all images in the dataset are resized to 640 x 480 (depends on model).

Data Augmentation:

Data augmentation is used to reduce overfitting problem in deep learning models. Images in test dataset may be in a different type of condition, for example orientation, location, scale and brightness. This technique is used to increase overall performance by generalizing the model. The main goal of this process is to train the model to learn those features, which are unique to each class and helps to discriminate one class. Various types of techniques can be applied to the dataset of training images like rotation, flipping, zooming, and shearing. The augmentation methods make the good generalization of model.

Data Annotation:

In object detection models, it is important to give label to each object of image to process those images accurately. Therefore, we should manually annotate the areas of each image which consists of the disease or pest with a box and accordingly class. Some diseases are having very similar features and symptoms, also as we are dividing them according to disease stages so in all stages some features will be very similar. So, it is important to get expert advice to identify disease or pest and stages of diseases. This advice can be helpful to distinguish the objects in the images and assigning label to each of them.

The annotation process is used to give label to each class and area of the diseases and/or pests in the image. The outputs of this step are the x and y coordinate values of the bounding boxes which can be of different sizes and class of disease and pest. The Intersection-over-Union (IoU) is used to evaluate that ground truth bounding boxes with the predicted values of the network while testing. Since some of the images are collected in the real field conditions, some areas corresponding to the background could be included in the image, making the problem more challenging. Those images with heterogeneous background are also need to be accurately annotated, as model depends on what we give as input for the learning process. If annotations are wrong in some images, model will learn wrong features and it results in wrong detection ultimately reduces precision and accuracy of our model. Therefore, it is vital to give accurate knowledge to model and annotation process is very important in whole implementation phase.

3. Transfer Learning

Transfer learning is a very useful to develop classification network using little amount data, by fine-tuning the parameters of a network pretrained on a large dataset, such as ImageNet [20]. In this phase, the database is given as an input in the model and we are using transfer learning technique for the process of feature extraction and classification. By definition we can say that transfer learning is one type of machine learning technique, which uses the knowledge from the trained model of one problem for training of other but related tasks.

Generally, people prefer Transfer learning approach, as learning from scratch requires more time. In deep learning, first few layers are used to extract the features, so we can use that features in our model by removing some of the last layer and adding our layers. We are fine tuning CNN models by adding dense layers at the end of the model with SoftMax activation function. The model is loaded with pre-trained weights from the ImageNet. The ImageNet dataset consists of the 1.2 million images of 1000 classes of different categories.

The CNN model is able to classify the disease as per the classes mentioned in the training. Object detection models such as Faster RCNN, RFCN and SSD needs CNN for classifying the objects they have detected depending on models' individual processes. After implementing the work for one crop, the process can be implemented for more crops, so we will include more crops from the PlantVillage dataset, more field condition images and the images downloaded from the Internet. So, we are using transfer learning with object detection models and CNNs as it provides more accurate results and saves time than doing training from scratch and using custom CNNs.

CHAPTER 5

Experiments and Results

5.1 Experimental setup

Implementation done for this research work needed high-end Graphical Processing Unit (GPU), which we have taken from the open source environment of Google. Also training or processing time is very much and RAM capacity needs to be more. Tools and technologies that we have used to carry out this research are briefly explained in following text.

LabelImg-v1.8.1:

LabelImg is a graphical image annotation tool. This tool is used for annotating images with labels around each object areas. It provides GUI in which images can be loaded and drawing squares around the area we need to label the object of its corresponding class. It provides two different kind of outputs in PASCAL VOC format and YOLO format. Here, we are using TensorFlow API so annotations are saved as XML files in PASCAL VOC format [2].

Google Colaboratory:

Colaboratory is open source environment like jupyter notebook, it does not require setup and runs in the cloud. In Colaboratory, code can be written, executed and saved in google drive also. Analysis and results can be shared to others and resources can be accessed for free from your browser. Google Colab provides a single 12GB NVIDIA Tesla K80

GPU that can be used up to 12 hours continuously and notebooks supports Python 2.7 and 3 versions [3].

We have used google colab throughout the training of our all models. We have set colab runtime environment to GPU and Python 2.7. Dataset is loaded to notebook at runtime from the google drive. After the execution all data will be reset so it is important to save data and results at safe place like google drive or local computer.

TensorFlow:

TensorFlow is an open source software library which can be used for numerical computation with data flow graphs. The TensorFlow provides flexible platform that allows to deploy computation to one or more CPUs or GPUs in a server, desktop or mobile device with a solitary API [22]. We have used TensorFlow Object Detection API and its model zoo for the training.

Python 2.7:

Google Colab provides an environment that uses Python language in notebook for development purpose. It provides Python 2.7 and Python 3 for usage in code development, but we are using Python 2.7 for writing our model in Colab notebook.

5.2 Initial Results of Experiments

We have implemented the proposed methodology using object detection and convolutional neural network approach. For these experiments, we have used three types of object detection models Faster RCNN, RFCN and SSD. These models use CNNs for the classification of objects. CNNs that we have used with object detection models are ResNet101, ResNet50, Inception and MobileNet. All these CNNs are supported in Tensorflow object detection API.

General flow of the code:

- Load dataset on google colab notebook with Python 2 and GPU backend.
- Install all dependencies used in TensorFlow framework.
- Clone all the models from TensorFlow Model Zoo.

- Compile all protobuf files.
- Create label map - which includes id and name of the class.
- Convert all images and its annotations into TFRecord (TensorFlow Record) format.
- Specify all the paths in the configuration file of the used object detection model.
- Train the model; assign training directory, dataset, label map file.
- Export the frozen model which stores all detections and weights.
- Perform testing on frozen model.

The different types of files and setup we have used is specified in the following images:

1. Directory Structure of Google Colab Notebook

   In google colab, the file structure is similar to Linux operation system. Here, we have created a folder named datalab, in which we store all our data. In this particular folder, we have stored images and annotations for training and test folder stores images that we are going to test our model with. The pretrained model is also stored which is checkpoints of trained model.

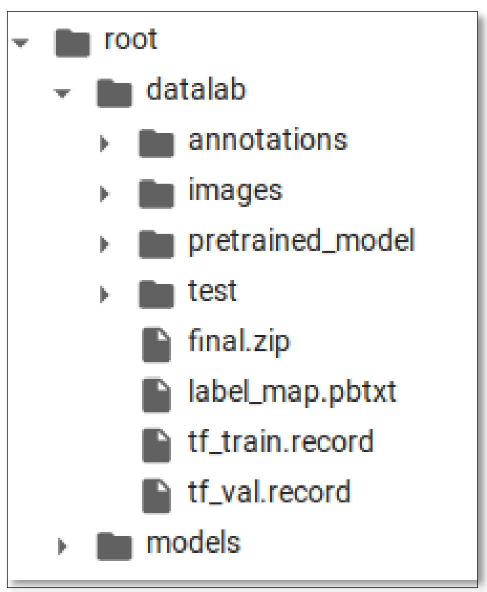


Fig. 5.1 Directory Structure

2. Example of annotation of data

   Annotation is very important for performing object detection on images. We have to specify the coordinates of objects as ground truth. The example file is shown in below figure, which has image with bounding box on right and its background code on left side.

```xml
<annotation>
    <folder>images</folder>
    <filename>tlmn_046.jpg</filename>
    <path>D:/Dissertation/Dataset/Final/Final/train/images/tlmn_046.jpg</path>
    <source>
        <database>Unknown</database>
    </source>
    <size>
        <width>640</width>
        <height>480</height>
        <depth>3</depth>
    </size>
    <segmented>0</segmented>
    <object>
        <name>tlmn</name>
        <pose>Unspecified</pose>
        <truncated>0</truncated>
        <difficult>0</difficult>
        <bndbox>
            <xmin>171</xmin>
            <ymin>168</ymin>
            <xmax>374</xmax>
            <ymax>347</ymax>
        </bndbox>
    </object>
</annotation>
```

Fig. 5.2 Annotation File

3. Label map file

   For providing class names to each image while training the model, we have to give names to each and every class with its id. This information is stored in label map file, which is supported by TensorFlow Object Detection API.

```
item
{
    id: 1
    name: 'tbs1'
}
item
{
    id: 2
    name: 'tbs2'
}
item
{
    id: 3
    name: 'thf'
}
item
{
    id: 4
    name: 'thl'
}
item
{
    id: 5
    name: 'tlb1'
}
item
{
    id: 6
    name: 'tlb2'
}
item
{
    id: 7
    name: 'tlmn'
}
item
{
    id: 8
    name: 'tpn'
}
item
{
    id: 9
    name: 'tsw'
}
item
{
    id: 10
    name: 'twf'
}
```

Fig. 5.3 Label map file

4. Evaluation Metrices

   In object detection models, two most important metrics are mean average precision (mAP) and Intersection-over-Union (IoU). mAP is used to measure the accuracy of the trained model and for the precision of bounding boxes IoU is used.

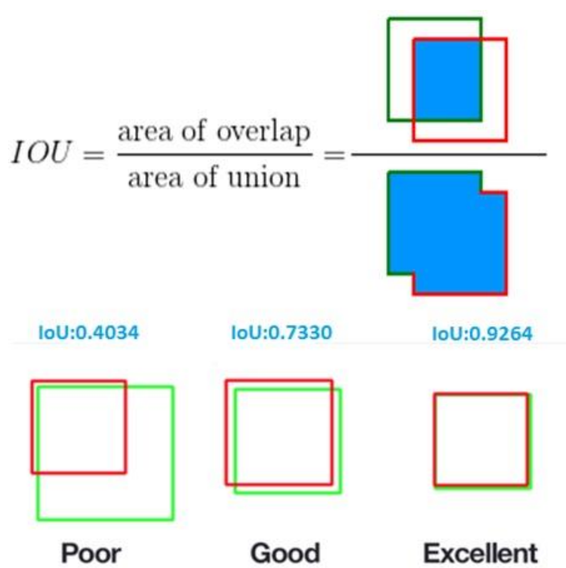


Fig. 5.4. Evaluation Metrics

The following table shows different performances of the deep learning models used for object detection in TensorFlow Object Detection API. These values can be considered as standard values and used for the comparison.

Table 5.1 TensorFlow Detection Model Zoo [16]

Sr. No.	Model Name	Execution Time (in ms)	coco mAP	output
1	ssd_mobilenet_v1_coco	30	21	Boxes
2	ssd_inception_v2_coco	42	24	Boxes
3	faster_rcnn_inception_v2_coco	58	28	Boxes
4	faster_rcnn_resnet101_coco	106	32	Boxes
5	faster_rcnn_resnet50_coco	89	30	Boxes
6	rfcn_resnet101_coco	92	30	Boxes

First, we have performed our experiments on all models using various hyper parameters according to the model. Hyperparameters plays very important role for getting better results in deep learning models. In this research work we have taken Epochs, Learning Rate and Batch Size as hyperparameters of our model. We have taken different values of the hyperparameters according to the model's standard values of each of the parameters. The results we have retrieved are shown in detail in following tables; here, time is measured in seconds.

Table 5.2. Results of Faster RCNN

	Steps	Learning Rate	Batch Size	mAP	Loss	Time
Inception	3000	0.0002	1	52.33	0.2498	1349
	3500	0.0002	1	53.67	0.204	1571
	4000	0.0002	1	51.76	0.1862	1670
	4000	0.0003	1	52.55	0.1743	1671
	3000	0.002	1	55.99	0.2319	1363
	4000	0.002	1	53.21	0.2451	1674

	3000	0.00002	1	21.71	0.3159	1356

	Steps	Learning Rate	Batch Size	mAP	Loss	Time
ResNet50	3000	0.0003	1	49.41	0.2272	2051
	3500	0.0003	1	53.3	0.1829	2609
	4000	0.0003	1	54.25	0.2328	2829
	4000	0.003	1	49.67	0.3245	3169
	3000	0.003	1	50.8	0.2571	2101
	3000	0.00003	1	29.12	0.27	2084

	Steps	Learning Rate	Batch Size	mAP	Loss	Time
ResNet101	3000	0.0003	1	59.84	0.2289	3398
	3500	0.0003	1	60.8	0.2739	5686
	4000	0.0003	1	68.34	0.1983	5314
	4000	0.003	1	67.51	0.2384	5066
	3000	0.003	1	54.98	0.3218	4145
	3000	0.00003	1	30.27	0.3528	3089

Table 5.3 Results of SSD

	Steps	Learning Rate	Batch Size	mAP	Loss	Time
Inception	3000	0.004	24	49.82	1.1568	5416
	3500	0.004	24	61.64	1.4226	6282
	4000	0.004	24	88.51	1.0901	5302
	4000	0.004	12	87.41	0.7921	3766
	3000	0.04	24	32.08	1.75	5277

	4000	0.0004	24	74.18	1.1489	5481

	Steps	**Learning Rate**	**Batch Size**	**mAP**	**Loss**	**Time**
MobileNet	3000	0.004	24	28.45	1.213	4202
	3500	0.004	24	40.93	1.6006	4668
	4000	0.004	24	38.31	1.1515	5658
	4000	0.004	12	50.68	0.8092	2985
	3000	0.04	24	14.22	1.9643	4175
	4000	0.0004	24	75.74	0.7703	4284

Table 5.4. Results of RFCN

	Steps	**Learning Rate**	**Batch Size**	**mAP**	**Loss**	**Time**
ResNet101	3000	0.0003	1	65.72	0.2128	2689
	3500	0.0003	1	65.96	0.1948	3230
	4000	0.0003	1	64.65	0.2295	3576
	4000	0.003	1	58.63	0.2376	5468
	3000	0.003	1	52.98	0.2444	2671
	3000	0.00003	1	43.97	0.2514	3219

5.3 Initial Result Analysis

Our initial experiments show good performance in all of the models, but highest accuracy is achieved in Faster RCNN object detection model with ResNet101 as classification network. So, we evaluated that model with some complex images to check the results. Most of the images shows good accuracy but some are showing problems like no detection, more than desired detection and wrong detection. These conditions are making model less accurate than it should be. Therefore, problems like these should be solved and taken into serious issues to make the model more precise and object detection more specific. These problems are addressed as following.

1. **No detection at all: Faster RCNN with ResNet101**

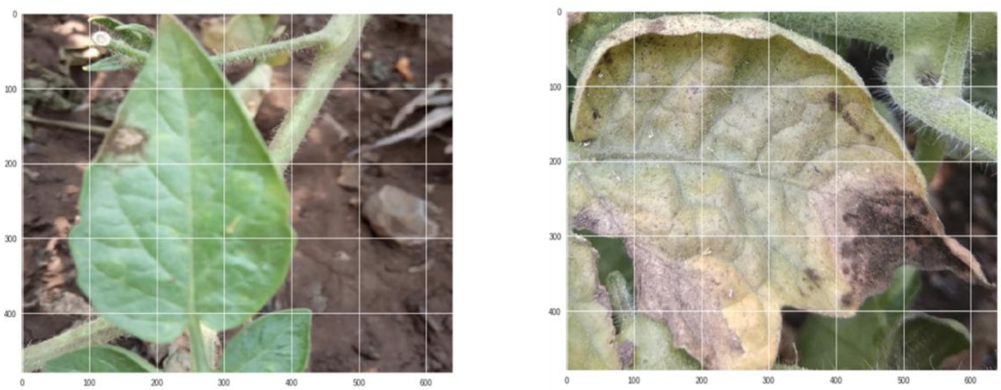


Fig. 5.6 some of the test images shows no detection

2. **Wrong Detection: Faster RCNN with ResNet101**

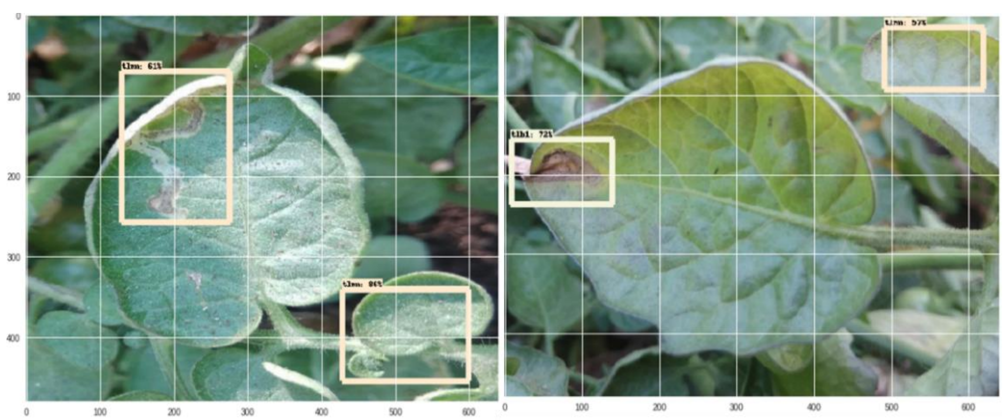


Fig. 5.7 Some test images get detection of diseases even if it is not present

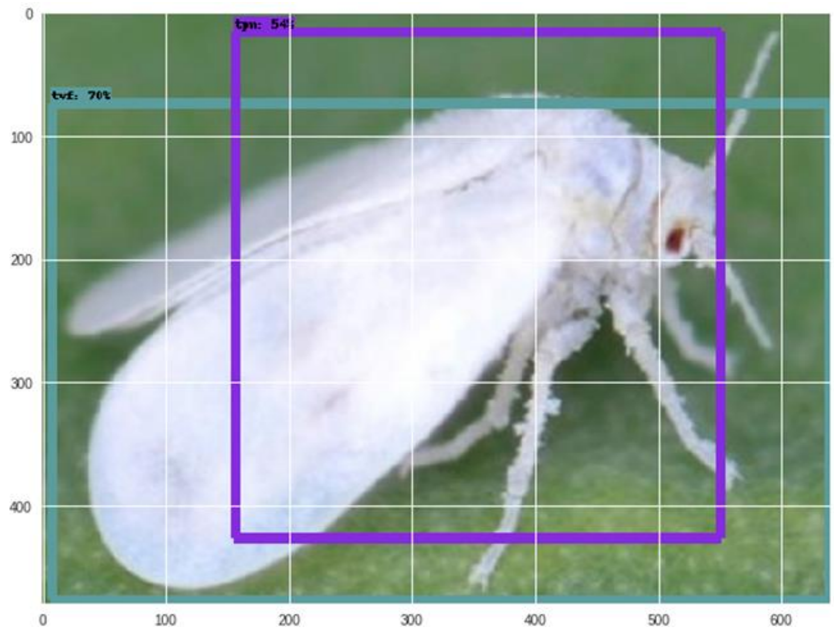


Fig. 5.8 Along with right pest detection wrong disease is also detected

3. Too much detection when not required: Faster RCNN with ResNet101

Fig. 5.9 More than necessary bounding boxes are generated

5.4 Tuning of Models

As the initial results of our experiments shows some limitations and problematic situations in detecting diseases and/or pests. We tried to solve those problems by tuning the models. Tuning of the deep learning models can be performed by changing and setting parameters of models like learning rate, batch size, steps used to train the models. After performing the fine-tuning of models, results are derived as below. Following images shows detection of test images according to the model.

Tomato Spotted Wilt Virus | Pest: White Fly | Tomato Leaf Miner

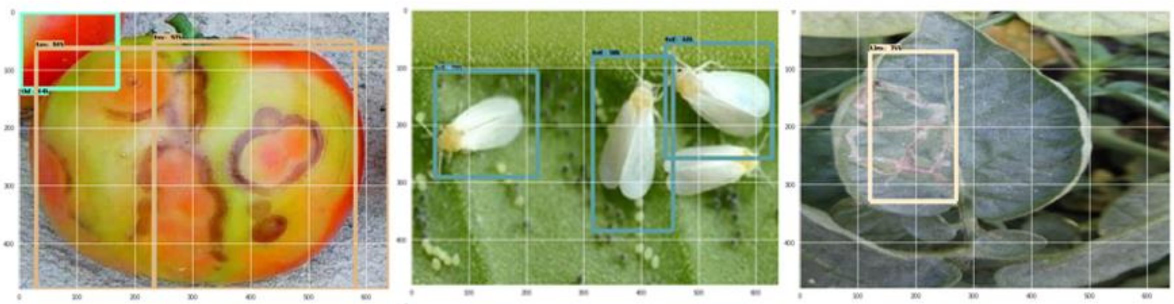
Fig. 5.10 Result Images of SSD with MobileNet

Tomato Spotted Wilt Virus | Pest: White Fly | Tomato Leaf Miner

Fig. 5.11 Result Images of Faster R-CNN with Inception

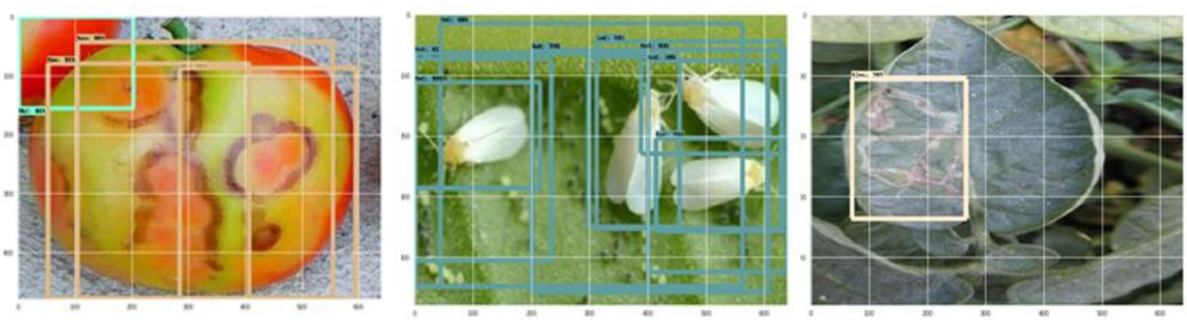
Tomato Spotted Wilt Virus | Pest: White Fly | Tomato Leaf Miner

Fig. 5.12 Result Images of SSD with Inception



Tomato Spotted Wilt Virus | Pest: White Fly | Tomato Leaf Miner

Fig. 5.13 Result Images of R-FCN with ResNet101



Tomato Spotted Wilt Virus | Pest: White Fly | Tomato Leaf Miner

Fig. 5.14 Result Images of Faster R-CNN with ResNet50

Tomato Spotted Wilt Virus | Pest: White Fly | Tomato Leaf Miner

Fig 5.15 Result Images of Faster R-CNN with ResNet101

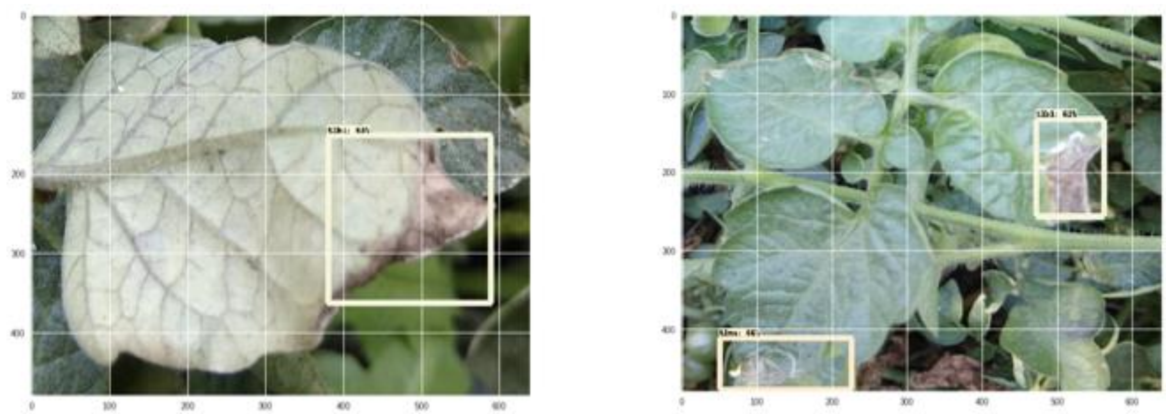


Fig. 5.16 Outputs of test images which resolves the research gap of previous works

Following table shows the comparison of results we achieved after training all the models. Execution time is the time that model takes to finish the training process and mAP is Precision of trained model averaged while evaluating the model for test images. For showing standard output values of model we have taken results for IoU = 0.50 in each model.

Table 5.5 Results Comparison

Sr. No.	Object Detection Model	CNN used	Execution Time (in seconds)	mAP (IoU-0.50)
1	Faster R-CNN	ResNet101	5048	0.9070
		ResNet50	2446	0.8124
		Inception	1320	0.7669
2	SSD	MobileNet	4218	0.4285

		Inception	5231	0.7738
3	R-FCN	ResNet101	3305	0.8411

Comparison graphs generated for all models are as following:

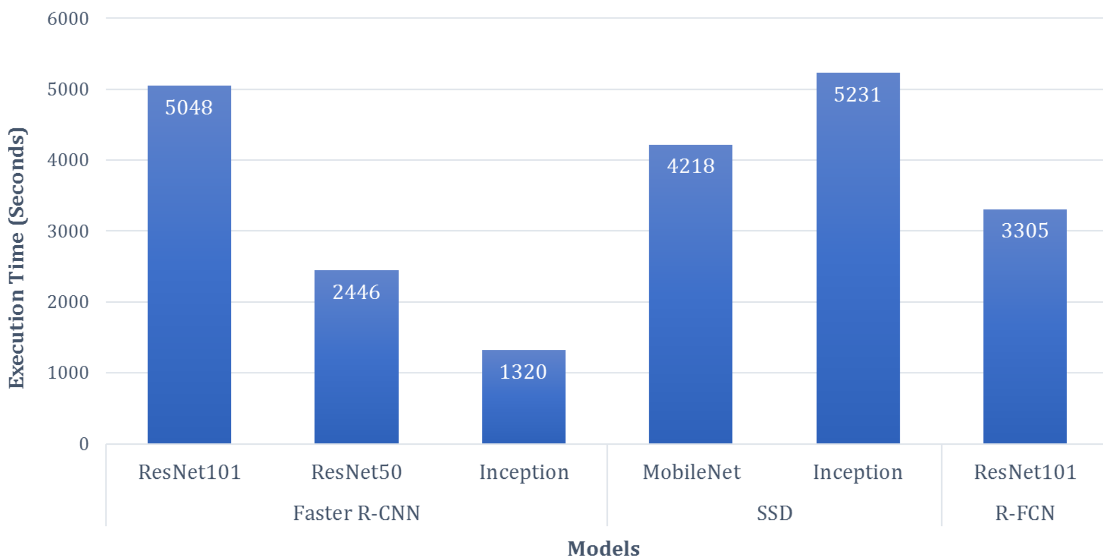


Fig. 5.17 Object Detection Model vs. Execution time

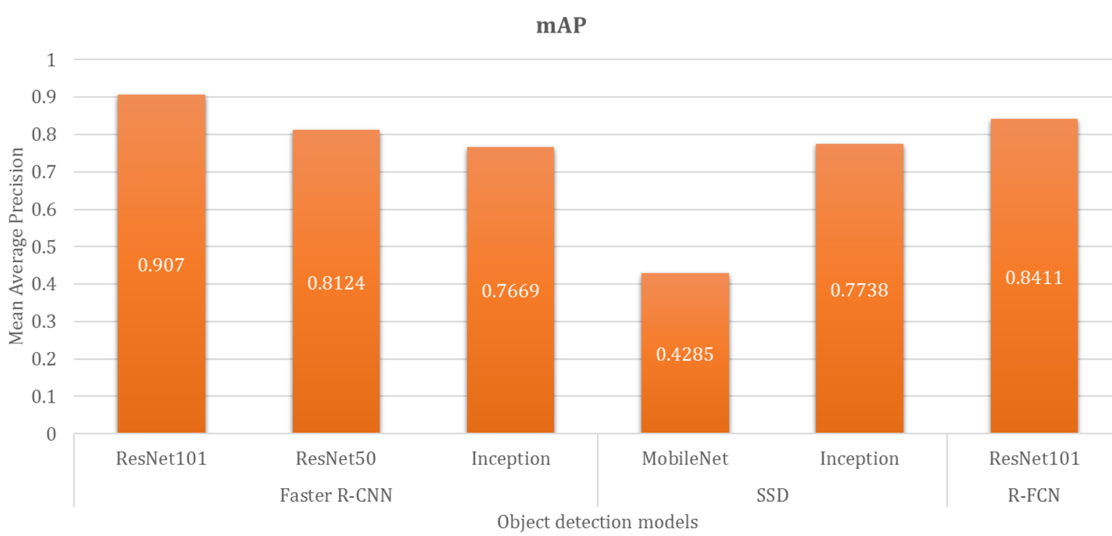


Fig. 5.18 Object Detection Model vs. Mean Average Precision

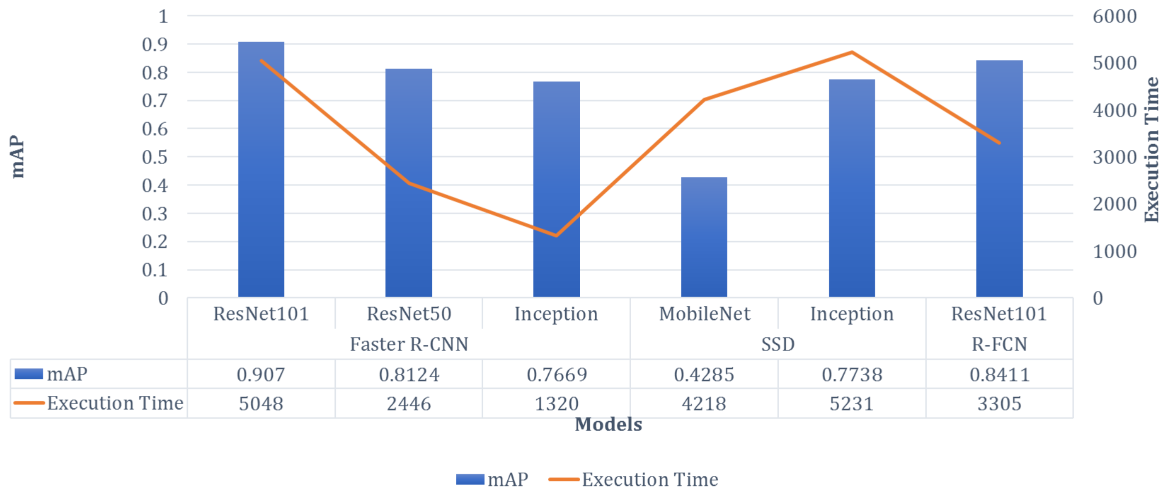


Fig. 5.19 Object Detection Models vs. Execution Time vs. mAP

The confusion matrix generated by our best performing model that is Faster RCNN - with ResNet101 is shown below.

```
Confusion Matrix:
tbs1  tbs2  thf  thl  tlb1 tlb2 tlmn  tpn  tsw twf not-detected
[[166.   8.   0.  25.   9.   0.   0.   0.   0.   0. 161.]
 [  4. 196.   0.   0.   4.   3.   0.   0.   0.   0.  54.]
 [  0.   0. 591.   0.   0.   0.   0.   0.   0.   0.  17.]
 [  0.   0.   0. 139.   0.   0.   0.   0.   0.   0.   0.]
 [  0.   0.   0.   2. 131.  15.  10.   0.   5.   0. 175.]
 [  0.   2.   0.   4.  19. 150.   2.   0.   0.   0.  34.]
 [  0.   0.   0.   1.  11.   3. 300.   0.   0.   1. 133.]
 [  0.   0.   0.   0.   1.   0.   0.  96.   0.   1.  57.]
 [  0.   0.  34.   0.   1.   0.   0.   0. 163.   0.  15.]
 [  0.   0.   0.   0.   0.   0.   2.   0.   0. 303. 184.]
 [252.  44. 217.  96.  57.  31. 116.  25.  32. 148.   0.]]
```

Fig. 5.20 Confusion Matrix of Faster RCNN

CHAPTER 6

Conclusion and Future Work

Crop disease and pest detection is major challenge in the agriculture domain. As all the farmers are not aware about all the diseases and pests that are affecting their crops, how to verify the disease and what measures should be taken, automation helps them to improve the agriculture tasks. The aim of this work is to help farmers in improving the agricultural productivity by detecting the diseases and pest that are infecting the crop. After the survey we have taken in the agriculture field for detection of diseases and pests, we have identified that they have not used the images of every infected part of the crop, most papers have not used the field conditioned images and disease and pest detection has not been combined in any of the research work.

Primary task is to work on the one crop and verify the performance of the proposed work. This work contributes for aiding the farmers and agronomists to detecting the disease and pests and ultimately helps to increase production in the field of agriculture. The proposed methodology is implemented on various types of object detection models using infected different parts of the crop and pests along with the severity. Comparison of object detection algorithms with different types of CNNs is made and as results are shown that currently the best suitable model is **Faster R-CNN with ResNet101** which has highest Average Precision with IoU=0.50 (0.907) and execution time is also not much (5048s). For the future work, various crop types can be added in the dataset to get more generalized dataset and to get more accurate model. Also, more object detection algorithms will be tested on dataset like Mask R-CNN, YOLO.

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APPENDIX A

Plagiarism Report

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by Shantilal Shah Engineering College Bhavnagar 043

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ESTD - 2007

Master of Engineering

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College Name: Shantilal Shah Engineering College, Bhavnagar

College Code: 0 4 3

Branch Code: 2 3 **Branch Name:** Information Technology

Theme of Title: Artificial Intelligence & Machine Intelligence

Title of Thesis: Crop Disease and Pests Detection using Convolutional Neural Network to Improve Agricultural Productivity

Supervisor's Detail	
Name:	Dr. Dinesh B. Vaghela
Institute:	Shantilal Shah Engineering College, Bhavnagar
Institute Code:	043
Mail Id:	dineshvaghela28@gmail.com.
Mobile No.:	9173772960.

Co-supervisor's Detail	
Name:	
Institute:	
Institute Code:	
Mail Id:	
Mobile No.:	

~ 1 ~

❖ **Comments For Internal Review (2730002)** (Semester 3)

Exam Date : 07/12/2018

Sr. No.	Comments given by Internal review panel (Please write specific comments)	Modification done based on Comments
1)	Clarify that how pests are detected and include its results if possible.	Done
2)	Show the evaluation methodology and evaluation configuration	Done.
3)	Mention Preprocessing technique.	Done.
		(Guide Sign.)

Particulars	Internal Review Panel	
	Expert 1	Expert 2
Name :	B. K. Bonsaniya	C. H. Makwana
Institute :	SSEC, Bhavnagar	SSEC, Bhavnagar
Institute Code :	043	043
Mobile No. :	9824237048	9033166626
Sign :		

Particulars	Internal Guide Details	
	Expert 1	Expert 2
Name :	Dr. Dinesh B. Vaghela	
Institute :	SSEC, Bhavnagar	
Institute Code :	043	
Mobile No. :	9173772960	
Sign :		

~ 2 ~

Enrollment No. of Student : 1 7 0 4 3 0 7 2 3 0 1 4

❖ **Comments of Dissertation Phase-1 (2730003)** **(Semester 3)**

Exam Date : 12 / 12 / 2018

Hall No : 7

Title : Crop Disease and Pests Detection using Convolutional Neural Network to Improve Agricultural Productivity

1. Appropriateness of title with proposal. (Yes/ No) Yes
2. Whether the selected theme is appropriate according to the title ? (Yes / No) Yes
3. Justify rational of proposed research. (Yes/ No) Yes
4. Clarity of objectives. (Yes/ No) Yes

~ 3 ~

Enrollment No. of Student : 1 7 0 4 3 0 7 2 3 0 1 4

Hall No. : 7

Exam Date : 12 / 12 / 18

Sr. No.	Comments given by External Examiners (DP-I) : (Please write specific comments)	Modification done based on Comments
1.	Study deep learning methods clearly	Done
2	Clearly define evaluation matrics.	Done
		(Internal Guide Sign.)

- *Approved* ☑
- *Approved with suggested recommended changes* ☐
- *Not Approved* ☐

Please tick on any on.
If approved/approved with suggession then put marks ≥ 50 %.

➢ ***Details of External Examiners :***

Particulars	*Full Name*	*University / College Name & Code*	*Mobile No.*	*Sign.*
Expert 1	Dr Maulika S Patel	GCET - 011	9428488563	Maulika
Expert 2	Dr Brijesh Bhatt	DDU	9427384523	[illegible]

~ 4 ~

Enrollment No. of Student : 1 7 0 4 3 0 7 2 3 0 1 4

❖ **Comments of Mid Sem Review (2740001)** **(Semester 4)**

Hall No : 03

Exam Date : 11 / 03 / 2019

Sr. No.	**Comments given by External Examiners :** i) The appropriateness of the major highlights of work done; State here itself if work can be approved with some additional changes. ii) Main reasons for approving the work. iii) Main reasons if work is not approved.	**Modification done based on Comments**
–	classification of pest control base crop and non ~~specified~~ pesticides and develop your own classifier.	Done.

Internal Guide Sign.

- *Approved* ☑
- *Approved with suggested recommended changes* ☐
- *Not Approved* ☐

Please tick on any on.

If approved/approved with suggession then put marks ≥ 50 %.

➢ ***Details of External Examiners :***

Particulars	***Full Name***	***University / College Name & Code***	***Mobile No.***	***Sign.***
Expert 1	Prof B V Buddhdev	028, GEC G	9825046179	
Expert 2	Prof J P Patel	017, GEC Patan	9904057079	

APPENDIX C

Compliance Report

Dissertation Phase-1 Comments:

1. **Study deep learning methods clearly.**

   Studied deep learning models such as Convolutional Neural Network and Object Detection models. Different object detection models such as Faster R-CNN, SSD and R-FCN. Pre-trained models of convolutional neural networks like ResNet101, ResNet50, Inception and MobileNet has taken using transfer learning approach.

2. **Clearly define evaluation metrics.**

   Metrics used for object detection models are mean Average Precision (mAP) and Intersection-over-Union (IoU). Mean average precision is used for measuring accuracy of trained model, and IoU is used to detect precision of bounding box of predicting objects.

Mid Semester Review (MSR) Comments:

1. **Classification of pest control base crop and non-pesticides, and develop your own classifier.**

   Dataset is divided based on the usage of pesticides and not pesticide usage. Accordingly, custom classifier is created and tested on that dataset.

APPENDIX D

Paper Publication

The paper related to this research work is presented in IEEE ICECCT 2019 conference held at SVS College of Engineering, Coimbatore from 20 – 22 February, 2019. Following is an acceptance e-mail of paper publication in Proceedings of IEEE ICECCT. The paper will be available online on IEEE Xplore digital library.

Your paper CS 1098 has been accepted for presentation

Inbox × College ×

IEEE ICECCT 2019 <icecct2019@svsce.edu.in> Mon, Dec 17, 2018, 12:06 PM

to me

Dear author,

Greetings!!!!

The review and selection process for your paper ID CS 1098 entitled "**Crop diseases and pest detection using Convolutional Neural Network**" has been complete. **Based on the recommendations from the reviewer(s) assigned for your paper, I am pleased to inform you that your paper has been ACCEPTED by the Technical Program Committee (TPC) for ORAL PRESENTATION** during 2019 Third IEEE International Conference on Electrical, Computer and Communication Technologies (IEEE ICECCT 2019) to be held at SVS College of Engineering, Coimbatore, Tamil Nadu, India during 20 - 22, February 2019. I am also glad to inform you that your paper will be submitted to be indexed in IEEE Xplore. (IEEE holds full rights not to index the paper in IEEE Xplore, if the paper has been found not suitable by IEEE Inc., USA for reasons like possible duplication/plagiarism).

The registration for IEEE ICECCT 2019 is already open, hence you are requested to complete the registration process as soon as possible. Registration will be closed on 15, January 2019. You may send the registration fee as a bank Demand Draft in favor of "**Diligentec Solutions**" payable at **Coimbatore** or you may also send bank cheque to the account details given below together with the filled in registration form. You are also encouraged to directly transfer the registration money to the account given below. Registration form for IEEE ICECCT 2019 shall be found in the conference website under Downloads link.

If you are a member of IEEE and would like to avail the IEEE benefits on the registration fees, please send the scanned copy of your IEEE membership card with the membership number. I would also like to convey you that, you will be given a hard copy of the IEEE ICECCT 2019 proceedings with softcopy.

The following documents shall also be submitted along with the camera ready paper.

1. Camera ready paper in IEEE double column format (in Microsoft office word file)

Paper Presentation Certificate

IEEE

ICECCT
20 - 22, February 2019
Coimbatore | Tamil Nadu | India

2019 Third IEEE International Conference on Electrical, Computer and Communication Technologies
20 - 22, February 2019 | www.icecct.com

CERTIFICATE

This certificate is presented to

Pruthvi P Patel
Student (Masters of Engineering - IT)
Shantilal Shah Engineering College, Bhavnagar
Gujarat Technological University, Ahmedabad, India

for presenting the research paper entitled "Crop Diseases and Pests Detection Using Convolutional Neural Network" in the 2019 Third IEEE International Conference on Electrical, Computer and Communication Technologies (IEEE ICECCT 2019) held at SVS College of Engineering, Coimbatore, Tamil Nadu, India, during 20 - 22, February 2019.

Dr. Thangaprakash Sengodan
Conference Chair

SVS College of Engineering
(Approved by AICTE, Affiliated to Anna University, Chennai, An ISO 9001 : 2008 Certified & Accredited by NAAC)
Arasampalayam, Coimbatore, Tamil Nadu, India - 642 109 | www.svsce.edu.in