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Detection of disease in tomato plant using Deep Learning Techniques

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Abstract

With continual advances in technology, there is an increased demand to provide enough food for more than seven billion people. This work is limited to automated detection of disease in cultivated land as it is a serious threat to food production and affects the livelihood of the small-scale farmers. In conventional farming practices, skilled people are employed to scout the land manually and detect the presence of disease in the land by visual inspection. The row by row manual detection of diseases in cultivated land is laborious and time-consuming. At times, the laborious work is prone to error. With the help of advanced image processing techniques and algorithms, this work aims at developing an automated mechanism for detecting the diseases in cultivated land. Deep learning techniques, specifically with deep detector: Faster R-CNN with deep feature extractor: ResNet50, is used to detect and classify tomato disease in plants. Trained and tested the proposed system with our tomato dataset, which has 1090 comprehensive images of early, medium, and final stages of tomato disease. Our proposed system successfully detects early blight, leaf curl, septoria leafspot, and bacterial spot of tomato disease even in complex plant surrounding areas.

Keywords: tomato disease; detection; real-time images; deep-convolutional neural network.

1. Introduction

The major factors that lessen food production include weeds, climatic changes, plant diseases, and so on. Extensive data shows that 80% of the food production is produced by the small-scale farmers in developing countries like India [1] and similarly [2] expressed that 50% of the yield reduction occurred by the severity of pests and diseases. A plethora of methods have been developed to prevent yield loss caused by diseases. A preventive method at the seedling stage is not sufficient to avoid epidemics, whereas rigorous monitoring needs to be considered for early detection of disease in the crop. In conventional farming, expertise people are employed to visually inspect row by row to detect plant diseases, and it is time-consuming, labor-intensive work, and sometimes error prone as it is done by humans. Moreover, the availability of phytopathology experts is not constantly available, particularly in poor and segregated zones [3]. Regardless of the approach, the first crucial step is to identify the plant disease correctly for effective disease management.

Precision farming is the new Agricultural Evolution which can harness the power of science and technology to improve crop productivity. Precision farming aims at minimizing pesticides and fertilizers used to reduce the overall farm expenses. It involves methods that can effectively detect and cure diseases or pests through precisely targeting the amount of fertilizers or pesticides respectively as required. As precision farming is shifting to the new techniques from the traditional methods, it has shown improvements in various sectors of agriculture. The sole purpose of Precision farming is to get real-time data to increase crop productivity and maintain the quality of crops. The technologies which are used in precision agriculture are sensors and remote sensing, Mapping and surveying, high precision positioning system, variable rate, Global navigation satellite system, Automated steering systems mapping, Computer-based applications, and so on. The introduction of drones into precision farming practices has entirely changed the market scenario. The Drone can be used to achieve multiple objectives during farming including sowing of seeds, spraying of fertilizers and pesticides, and monitoring of crop growth. To perform these activities a drone must be equipped with a camera, sprayer with containers for pesticide/fertilizer. The drone can be employed to analyze the crop health frequently and can detect the abnormalities in the early stage. The Drone captured information (image/ video) can be analyzed in real-time using a video/image analytics system based on machine learning or deep learning technologies to understand the crop growth pattern and predict the yield. The modern drones are equipped with a multispectral camera which uses in the estimation of the vegetation indices.

Image processing is adopted for more than two decades in the automation of certain agricultural practices. The images captured by remote sensing devices are used for the detection and classification of plant diseases. In recent years, deep learning techniques are used in combination with plant disease detection from leaves, fruits, stem of the plants. Deep learning uses several layers to extract high-level features from real-time input images without using hand-crafted features and then extracted features are passed to different classifiers such as k-nearest neighbors, support vector machines and fully connected neural network for disease classification. The present work is to develop an automated mechanism for analyzing the images captured from simple camera devices in real-time using a combination of image processing and deep learning techniques and detect the four categories of tomato plant diseases namely early blight, bacterial spot, septoria leafspot, and leaf curl.

1.1 Tomato disorders

According to Food and Agriculture Organization of the United Nations census shows, nearly 170 kilotons of tomatoes were produced in 2014 worldwide [21]. Approximately 170.8 million tons of tomatoes were produced worldwide in 2017. Whereas China alone, produced 31% of world's total tomato production. 18.7% of the total production was accounted from India as shown in figure 1. Diseases and pests that appear in fields can easily infect tomatoes. In addition to the fruit, pests and diseases affect other plant parts, which are the roots, stems and plant's leaves. Generally, there were two plant substances shown in figure 2, which affect plant tomatoes i.e living or biotic substances include fungi, virus, bacteria and insects causes bacterial spot, septoria leafspot, leaf curl, early blight, fusarium wilt, leaf mold, mosaic virus, powdery mildew diseases. Non-living or abiotic substances encompass several environmental changes like high humidity, temperature change, poor soil pH, insufficient nutrients, and excess moisture. This work is carried out on septoria leafspot, early blight, bacterial spot and leaf curl.

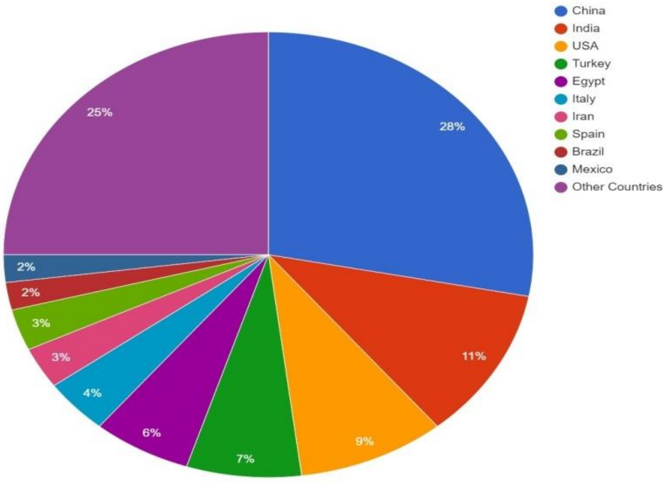


Figure 1. Worldwide production of tomato plant (source: Jacobs and C.P. Bean, G.T. Rado and H. Suhl, 1963): shows top 10 countries tomato production in 2017.

1.2 Problem statement

In this research work, the problem addressed is to detect anomalies in the cultivated land, especially in disease detection from the tomato crop. Generally, plants are articulated bodies; however, a single model that detects and discriminates different diseases from plants can be very hard to define. The growth of the crop is not uniform and the variability in the intra-class between crops is increased because of their non-rigid structure. The research focuses on building an automated deep learning based detection and classification of plant disease models that capture salient features of the diseases and distinguishes them from other objects of interest i.e crop.

Mathematical statement is as follows,

$$\boldsymbol{Y}\text{out} = \text{for}\left\{ \text{X}[\mathbf{I}] \quad \begin{array}{l} \mathbf{0} \text{ if disease} \\ \mathbf{1} \text{ if normal} \end{array} \right.$$

$\text{X}[\mathbf{I}]$: Tomato leaf images as input $\quad \boldsymbol{Y}\text{out} = 1$ if leaf has a disease

$\boldsymbol{Y}\text{out} = 0$ if leaf is healthy

1.3 Objectives

- To propose a more suitable deep learning architecture to detect and classify tomato diseases specifically early blight, septoria leaf spot, bacterial spot and leaf curl by using deep detector: Faster R-CNN with "deep feature extractors" such as ResNet50.
- Train and test the proposed system end-to-end on tomato disease dataset specified in this work, which contains comprehensive images of different tomato diseases, taken at early, medium and final stages of infection status.

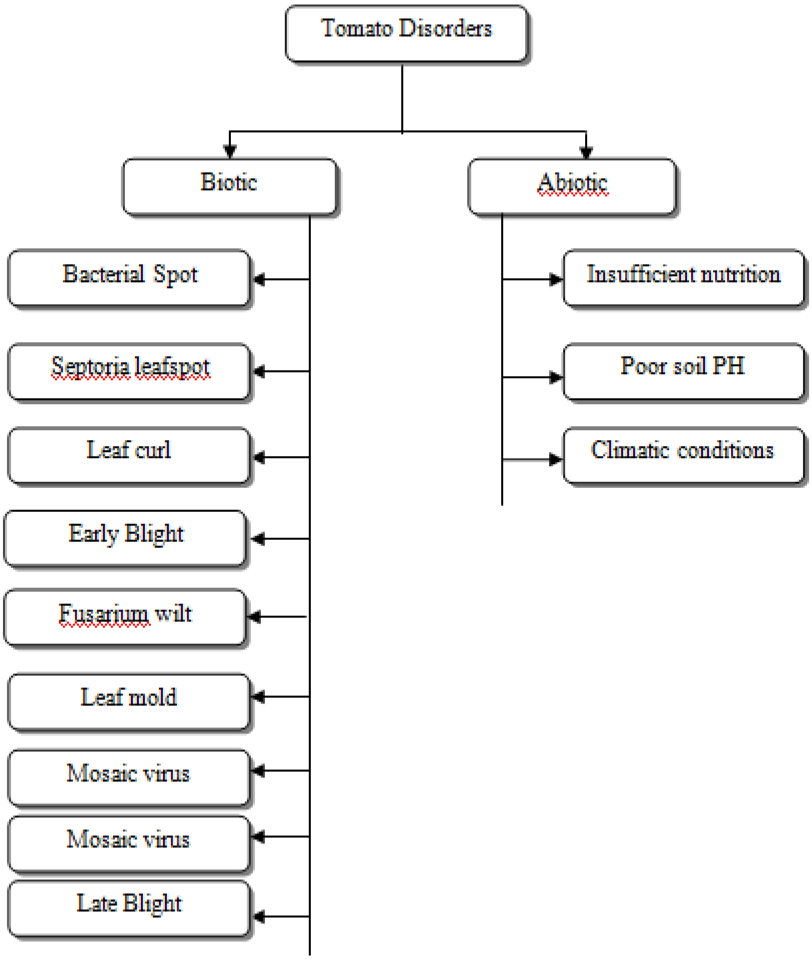


Figure 2. Various diseases of tomato plant: Tomato diseases are caused by fungi, virus, bacteria and insects.

2. Literature survey

This section analyzes numerous research work carried out in pest and plant disease detection.

2.1 Related work

Several research works have shown, image-based evaluation methods are more reliable and replicable than visual human evaluation. In [3] the authors developed a method with image segmentation to measure disease severity in black and white background, which reduces time for the measurement of disease severity and also eliminates human error. Many of these approaches to identify plant diseases based on images use the same basic technique. Firstly, pre-processing procedures used for background elimination and infected plant regions are segmented. This then extracts discriminative features for further study. Eventually features are classified for a particular task with supervised or unsupervised classification methods.

Assess [4] is an interative tool for estimating disease severity. The LeafDoctor app [5] is a smartphone app used to compute disease severity and also distinguish infected areas and healthy region in color images. However, Assess and LeafDoctor applications are semi-automated since they rely heavily on hand-crafted feature extraction and threshold-based segmentation. It will be hard to determine correct threshold without human help to segment similar color lesions of different diseases.

The automatic plant disease identification and disease severity is very promising in deep learning. The Table 1 shows recent deep learning based research work carried out on tomato pest and disease classification with positive results. In [6] author extracted images of tomato leaves from the PlantVillage dataset, which has 14828 images distributed in nine classes of diseases (early blight, late blight, leaf mold, bacterial spot, leaf curl, septoria spot, spider mites, target spot and mosaic virus). To eliminate hand crafted features, author introduced convolutional neural network (CNN) and trained classifier with raw input images. Analyzed the deep models (AlexaNet and GoogleNet) by visualization approaches, which recognize symptoms and classify disease lesions on leaves. Images in PlantVillage dataset were taken at controlled conditions in the laboratory which holds a drawback of this model.

Author [7] has developed a CNN model with transfer learning and VGG16 for the identification of pest and disease in tomato plants. In original work, VGG16 was trained to identify thousand categories with 1.26 million images. Author collected 7040 images from china which contains (leaf curl, leaf mold, late blight, bacterial spot, septoia leafspot, target spot, spider mites, gray spot and mosaic virus and healthy) categories with 640 images each, in order to identify different tomato diseases and pests VGG16 extracts features from raw images and combined with SVM for the classification of diseases. The overall system performance relies, however, on fairly high quality images but not low quality images.

In [8] the author collected 5000 images from different farms in Korean Penisula. Author wanted to detect and identify tomato disease and pest classes with location in image by seeking a better deep learning architecture. The author considered faster R-CNN [13], SSD [14] and R-FCN [15] with various feature extractors (VGGnet, ResNet). Moreover, author suggested data augmentation to decrease false positive in training and to improve accuracy. The system was able to identify gray mold, pest, leaf mold, leaf miner, canker, powdery mildew, low temperature, nutritional deficiency and whitefly. Because of a smaller number of annotated samples, certain classes with large difference in patterns appear to be confused with similar diseases and cause false positives.

The author in [9] used 9000 images of infected and healthy tomato leaves that had been taken in laboratory to classify five diseases from PlantVillage dataset (leaf curl, bacterial spot, septoria leafspot, early blight and leaf mold). For data visualization full color model was able to classify disease spots, on other hand gray scale model learnt leaf shape's, visual patterns of the diseases. Whereas full color model achieved more accuracy compared with gray scale model. Images were taken under controlled conditions for the PlantVillage dataset which holds a drawback of the model.

A diverse dataset was used by the author in [10] that includes images from nursery, farm and PlantVillage dataset. In order to identify early blight, powdery mildew and downy mildew author trained CNN. Using the Softmax activation function, a classification model is used to calculate disease class's confidence score. All feature maps in previous layers are completely connected to fully connected layer. The learned high-level features of a fully connected layer with Softmax function classify input images into powdery mildew, early blight and downy mildew. Images were taken under controlled conditions for the PlantVillage dataset which holds a drawback of the model.

A selection of 500 images from local fields and 2,100 images of tomato leaves on the internet was taken into consideration in [11]. The author uses transfer learning in order to train CNN, in which leaves were graded as being good, bad and average in three categories for pest intensity in the Google inception model. By using transfer learning the system execution speed is fast.

The author in [17] Collected 2,779 images from google images of hornworms, powdery mildew, cut worms, early blight and whiteflies. Each disease category has 550 images is not substantial for training, which also holds an overfitting problem. Data augmentation techniques like vertical flips and random scale is used to overcome the overfitting problem. Convolutional neural network (CNN) is effective for understanding image content whereas training CNN from scratch requires extensive computing power and large amounts of data. To overcome the author did transfer learning on Google's Inception model.

Author from[18] constructed a deep learning architecture with feature extractor: CNN model (ALexNet, SqueezeNet) for the detection of leaf curl, bacterial spot, mosaic virus, target spot, late blight, early blight, spider mites, septoria leafspot and leaf mold. SqueezeNet model is 80 times less than the AlexNet. Thanks to its light weight with less computing requirements. Author describes the advantage of upgrading the model with a smaller network. PlantVillgae dataset, which holds a drawback as it has cropped tomato leaf images, which were taken under controlled conditions (laboratory).

Table 1. Summary of research work for tomato disease detection using deep learning techniques

Sl. No	Method	Dataset	Remarks	Ref. No.
1	CNN	From PlantVillage Dataset 14828 tomato's leaves images distributed in nine classes of diseases.	PlantVillage dataset images were taken at controlled conditions in laboratory.	[6]
2	CNN	Dataset comprises 11 different categories, 7040 images, 640 images in each category.	Overall system performance relies, on fairly high quality images but not low quality images	[7]
3	Faster R-CNN, SSD, R-FCn	Dataset contains five thousand images collected from different farms in Korean Peninsula	Because of less number of annotated samples, certain classes with large difference in patterns appear to be confused with similar diseases and cause false positives.	[8]
4	deep-CNN	Exacted 9,000 tomato disease and healthy images from a public dataset PlantVillage	The images are taken under controlled conditions.	[9]
5	CNN	Dataset contains images from nursery, PlantVillage dataset and farms	Images in PlantVillage dataset are taken at controlled conditions in laboratory.	[10]
6	CNN, Transfer Learning	Dataset contains 2100 images from inte rnet and 500 images from local farms.	Execution speed of system is fast due to usage of transfer learning on inception model.	[11]
7	Tensorflow's Inception V3	Dataset contains 2779 images from google.	Training CNN from scratch require extensive computing power and large amounts of data. To overcome transfer learning was done on Google's Inception model.	[17]
8	ALEXNET, SqueezeNet	Plant Village dataset	SqueezeNet takes lesser data and updation speed is higher.	[18]
9	AlexNet, VGG16 net	Plant Village dataset	AlexNet gave reasonable accuracy in terms of computational load compared with VGGnet	[19]

In [19] author has built a tomato leaf classification model with healthy, mosaic virus, leaf curl, target spot, late blight, spider mites and leaf mold tomato disease and pest of 13262 images, which is the input to pre-trained AlexNet and VGGnet. The performance of VGGnet and AlexNet was calculated by deciding different mini-batch sizes, increasing image numbers and adjusting weight and bias of learning rate. When the number of images were 373, maximum accuracy was achieved. As the weight and bias learning rates were increased VGGnet accuracy was decreased. On other hand AlexNet gave reasonable accuracy in terms of computational load.

2.2 Challenges

It is difficult to build a comprehensive dataset of images for training a machine learning model, as disease progresses the visual features of diseases get changed. So, images has to be collected regularly. The images in dataset has to be labelled by correct disease category, is pruned to error sometimes as it is done by humans and labor-intensive work, which can be avoided in deep learning based techniques.

3. Methodology

The following section presents more suitable deep learning architecture to detect diseases specifically early blight, septoria leaf spot, bacterial spot and leaf curl in tomato plants.

3.1 System Overview

The aim of this work is to automate deep learning based tomato disease detection system to identify four different disease categories which affects tomato crop. The figure 3 specifies brief summary of our proposed system. And also a detailed description of individual parts in tomato disease detection system is specified below.

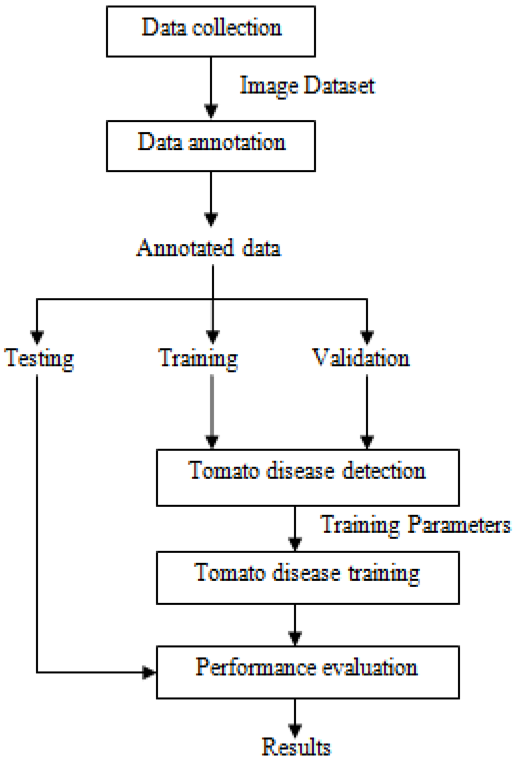


Figure 3. Brief summary of automated deep-learning based disease detection system for tomato. Our model takes raw image and predicts disease category.

3.2 Data Collection

Collected a comprehensive 1090 real-time tomato leaf images infected by early blight, leaf curl, septoria leafspot, and bacterial spot dataset, images were taken by camera devices at, different illumination (lighting), time, different temperature and humidity levels and the location. Visited different tomato farms in Kallur, Mangapuram, and Piller in Andhra Pradesh, and have been added various types of data to our dataset. Provided following data:

- 12MP, 48MP resolution images.
- Tomato disease images at different infection status (early, medium and final).

- Complex background (e.g. soil, stems).
- Images contain multiple infected tomato disease on single leaf.
- Various sizes of tomato plants (initial, medium, and final growth sizes).
- Images contains partially blurred visual features of disease, or halfway or occlusion (disease is blocked or overlapped with leaves and stems of tomato plant).

The above factors help the proposed system to detect and identify diseases at early, medium and final infection stages and provides confidence score of the disease along with the location in the tomato plant. The table 2 describes the symptoms and where disease begins in a plant and collected samples for early blight, leaf curl, septoria leaf spot, and bacterial spot. The collected 1090 images are resized into uniform size 800 X 600 pixels, 80% images were given for train and validation set and 20% for test set, which contains a variety of images (early blight, leaf curl, septoria leaf spot, healthy and bacterial spot at early, medium and final leaf growth and also infection stages) in both test and test set, which makes our dataset so robust.

Table 2. Shows sample images for early blight, leaf curl, bacterial spot and septoria leafspot diseases symptoms and where these begins on tomato leaf.

Disease	Symptoms	Begins	Sample
Early Blight	On leaves, Concentric diseased spots are formed with half inch diameter.	In general, on older lower leaves, early blight starts and spreads to the plant. Gradually the infected leaves loose strength and die.	
Leaf Curl	No proper growth, upward curling of leaves, lesser leaf size, yellow tint on flowers and leaves.	Initial curling begins on lower leaves and rolls upward followed by an inward curl lengthwise	
Bacterial Spot	Appears on leaves as small (less than 1/8 inch)	First appears on middle of the leaf as yellow-green and darken to brownish-red as they age.	
Septoria Leaf Spot	Several small diseased tan edged spots in diameter 1/8 to ¼ inches and filled with white center.	First appear on bottom of the plant on older leaves underside.	

3.3 Data Annotation

Every image in our dataset is manually labelled for the region contains a disease with bounding box and category which disease belongs to, by using the LabelImg tool, which is a great tool for labelling images. Diseases such as early blight, septoria leafspot and bacterial spot appear to be similar at an early stage, therefore, with the help of experts in the field gained the required information needed to identify the disease category and infected regions visually in the images. The data annotation phase outputs different sized bounding box coordinates along with their respective disease category (ground truth boxes) which are then evaluated as IoU with system predicted bounding box coordinates from testing phase. As the images were taken from the farm, contain complex background like soil, stem and so on. Therefore, while capturing, we need to collect images containing the Region of Interests (ROIs). Compared with others, the proposed model detects and classifies tomato diseases which is in out of focus distance in the images.

3.4 Faster R-CNN Tomato Disease Detection

The aim is to detect and identify four disease categories and location in tomato plant images. The bounding boxes which contain disease should be accurately defined to which the disease belongs, to get precisely results by the system. Faster R-CNN uses Region Proposal Network (RPN) to generated required RoI’s for tomato disease detection. The figure 4 steps were followed by Faster R-CNN tomato disease detection in an image:

- Pass input image to ConvNet and feature maps are returned to RPN.
- RPN uses sliding window on obtained feature maps at each window and produces k fixed size anchor boxes with different sizes and shapes in tomato disease image. For each anchor, RPN predicts probability that an anchor is disease and bounding box regressor to better fit the anchor for disease.
- ROI takes obtained various types, sizes of bounding boxes (object proposals) and crop each proposal in such a way that each proposal contains tomato diseases and collect fixed size feature maps to all the anchors.
- Eventually, feature maps are moved to fully connected layer with a softmax and linear regression layer and classify disease category with bounding boxes in tomato image.

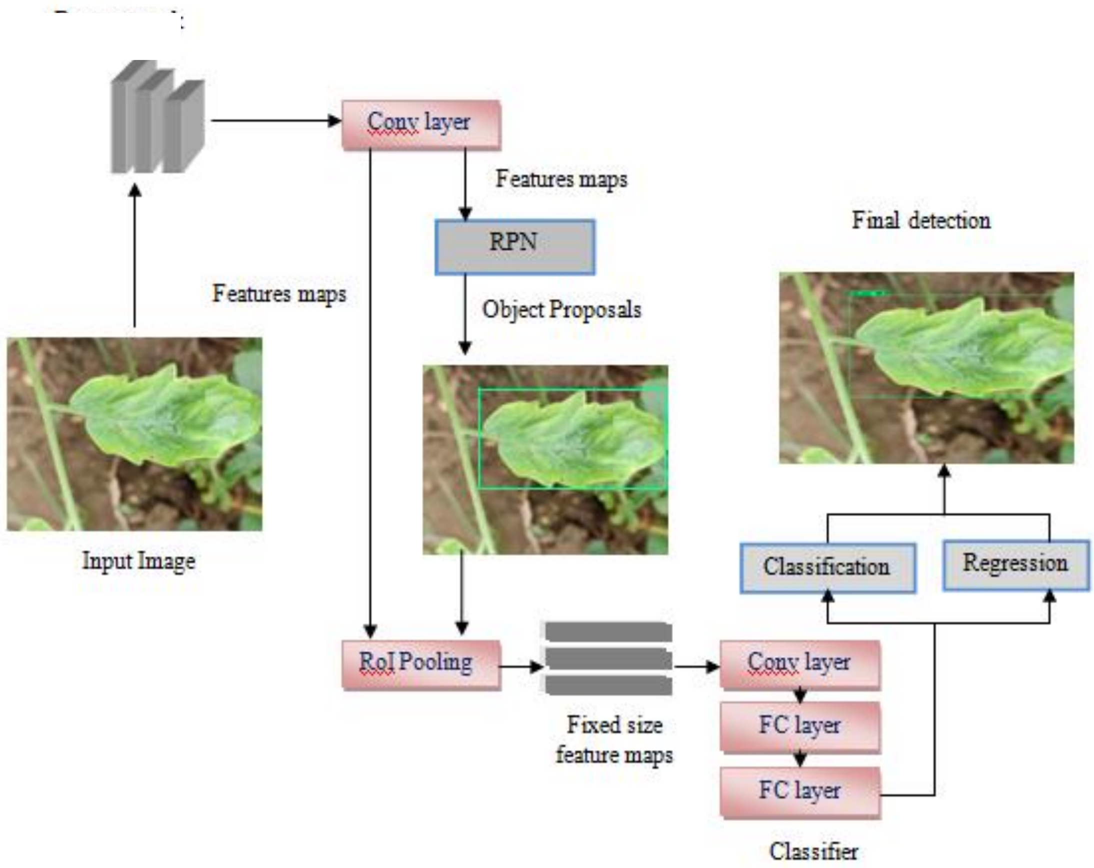


Figure 4. Faster R-CNN with ResNet50 tomato disease detection

3.5 RPN training and loss functions

The anchor box marked to be “positive (disease)” sample, only if the anchor box has IoU greater than or equal to threshold value 0.5 with ground truth box, else considered “negative” sample. Many anchors with same grouth truth box can be labelled as positive sample. For RPN training neither positive nor negative anchors were ignored and gets mini-batch from a single image. When all anchors of image were to be sampled, so that a batch will be made with 100 positive and 100 negative samples, if there were any insufficient positive samples, then padded with negative samples to form a batch. The training loss for the RPN is given by:

$$L(\{ p_i \}, \{ t_i \}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*) \qquad (1)$$

Here,

i – Anchor index in mini-batch

p_i^* - Ground truth box value will be either 0 or 1

p_i - Predicted score for anchor i from classification

$L_{reg}(t_i, t_i^*)$ – Regression loss

$L_{cls}(p_i, p_i^*)$ - Classification loss over two classes (disease v/s healthy)

The $L_{reg}(t_i, t_i^*)$ regression loss is enabled when anchor has disease i.e., groundtruth p_i^* will be equal to 1. The regression layer outputs predicted term t_i with four variables [t_x, t_y, t_w, t_h] whereas regression target t_i^* is computed as

$$t_x^* = \frac{(x^* - x_a)}{w_a}, \quad t_y^* = \frac{(y^* - y_a)}{h_a}, \quad t_w^* = log \frac{(w^*)}{w_a}, \quad t_h^* = log \frac{(h^*)}{h_a} \qquad (2)$$

Here,

h – Bounding box height

(x, y) – Top-left bounding box coordinates

x* - Anchor box coordinates

x_a - Actual bounding box ground truth

w – Bounding box width

4. Experiments and results with discussions

The following section presents result achieved by the proposed system which includes tomato disease dataset, experimental setup, quantitative results, qualitative results, failure analysis and discussion.

4.1 Tomato disease dataset

Tomato disease dataset consists of 1090 real-time images from different farms located in Kallur, Mangapuram, and Piller in Andhra Pradesh, which was collected at different time, season, and various growing stages of disease (early, medium and final). The table 3 represents tomato disease categories and their total number of labelled bounding boxes which are passed to train and test the proposed system. Each image includes one or more tomato disease labelled bounding boxes which depends on the healthy category and infected region in tomato plant.

Table 3: Tomato disease categories and with total number of labelled bounding boxes that tomato disease dataset contains

Category	Total number of labelled Bounding Boxes
Leaf curl	1492
Septoria LeafSpot	397
Bacterial Spot	1219
Early blight	630
Healthy	858
Total	**4596**

4.2 Experimental setup

In order to perform the experiments, the tomato disease dataset which includes four labelled tomato disease categories and healthy class was divided into 60% for the train set contains 738 images, 20% validation set (176 images), and a 20% test set (176 images). To minimize over-fitting problem validation set is used, which is stated in Pascal VOC challenge [16]. Training is performed on train set, and then validation set to evaluate the system. The expected result is achieved with unseen data (which is not seen by the system during training) from test set is passed to our trained system for the final evaluation. Tomato disease dataset data was uploaded to Google Drive, Training and testing process for the system has done in Google collaboration – online platform founded by Google which provides GPU services for free of cost up to 12 hours in a single session.

4.3 Quantitative results

The automated proposed disease detection system detects tomato diseases specifically leaf curl, septoria leafspot, early blight, and bacterial spot in plants using deep detector: Faster R-CNN with "deep feature extractor" such as ResNet-50. In the first instance, performance is assessed with Intersection over Union (IoU) evaluation metric and Average Precision (AP) accuracy metric are used to evaluate the proposed disease detection system.

$$IoU(A, B) = \left|\frac{A \cap B}{A \cup B}\right| \quad (3)$$

Here,

A : labelled bounding boxes ground truth B : Result predicted by network

Result is contemplated as true positive (TP), When predicted IoU exceeds the threshold (≥0.5), if not false positive (FP). Ideally, false positive number has to be small and decides how well a network can be able to detect healthy, leaf curl, septoria leafspot, bacterial spot and early blight categories. To evaluate object detector accuracy IoU is used. AP is the average precision over [0, 0.1, 0.2,..1] Set of recall. The AP calculated to healthy, leaf curl, septoria leafspot, bacterial spot and early blight over all will be the disease detection system mean Average Precision (mAP).

$$AP = \frac{1}{11} \sum_{r \in \{0,\ 0.1, \ldots, 1\}} p_{interp}(r) \quad (4)$$

$$P_{interp}(r) = \max_{\check{r}:\, \check{r} \geq r} p(\check{r}) \quad (5)$$

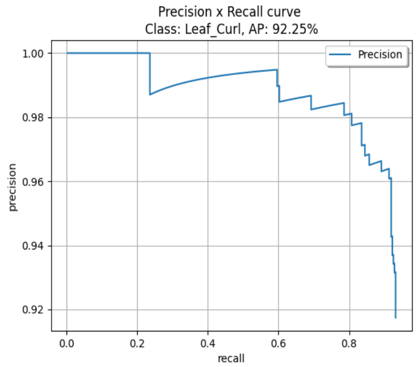
p(ř): precision measure at recall ř,

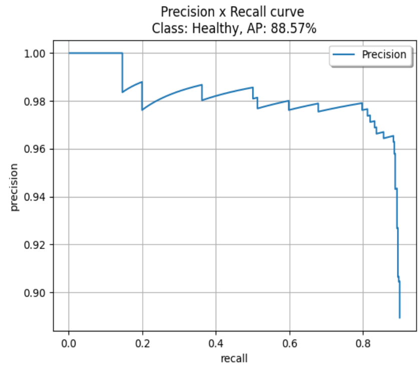
mAP computed for *IoU* = 0.5 and Precision x Recall curve for individual category (Bacterial Spot, Healthy, Leaf Curl, Septoria Leaf Spot) is shown in figure 5. Bacterial Spot, leaf curl and healthy shows AP greater than 81% whereas due to the lacking number of septoria leaf spot and early blight AP is less compared to the other classes as shown in table 4.

Table 4. Tomato disease detection results achieved for the proposed system using Faster R-CNN with ResNet50

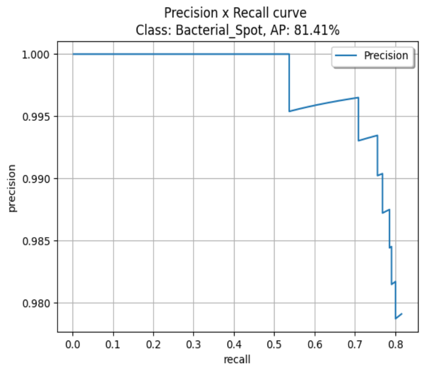
Category	AP
Leaf curl	92.25
Healthy	88.57
Bacterial spot	81.41
Early blight	78.44
Septoria leafspot	64.09
Total mean AP	**80.952**

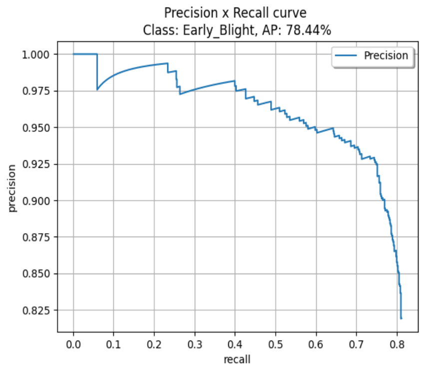
Tensorboard is an tensorflow [21] visualization toolkit provides visualization and tracking of box classification loss, box localization loss, RPN objectness loss, RPN localization loss and total loss, the figure 6 shows that box classification loss is stable, started with high and goes really low and keep around value of 0.75 to 0.02. The figure 7 shows that the box localization loss, how actually the box should be closely located to the image where loss is maintained value between 0.05 to 0.01. The figure 8 shows RPN localization loss, suggestions for the boxes and localization which is related to. RPN localization loss is maintained less than 0.01. The figure 9 shows RPN objectness loss, is the actual what kind of object (disease or not) is found and how far from the result where RPN objectness loss is maintained less than 0.01. The figure 10 shows the resultant loss curve for two lakh epochs' shows how well disease detection system learnt tomato data and achieved less than 0.1 error rate at ninety thousand epochs.



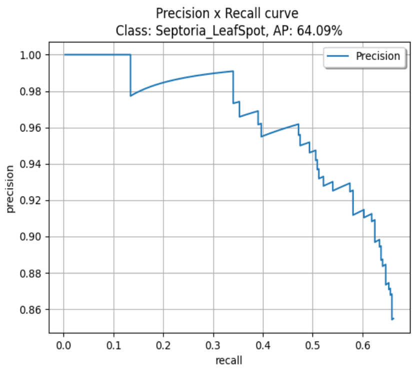


(a) **(b)**





(c) **(d)**



(e)

Figure 5. Precision x Recall curve for (a) leaf curl (b) healthy (c) bacterial spot (d) early blight (e) septoria leafspot

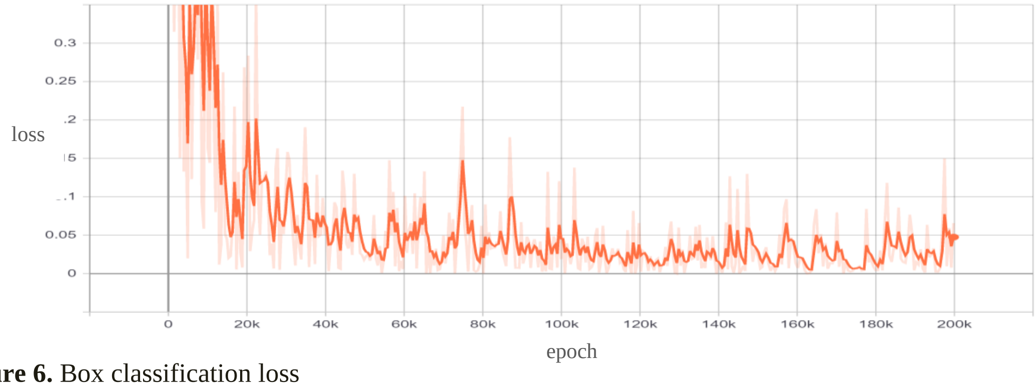


Figure 6. Box classification loss

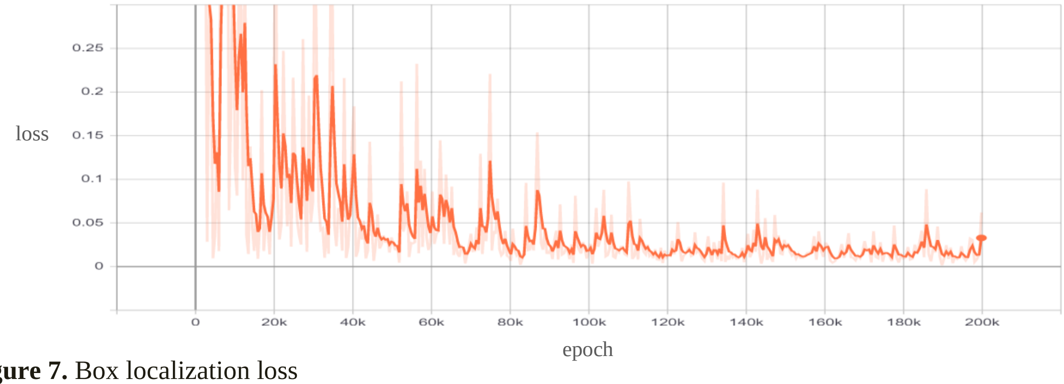


Figure 7. Box localization loss

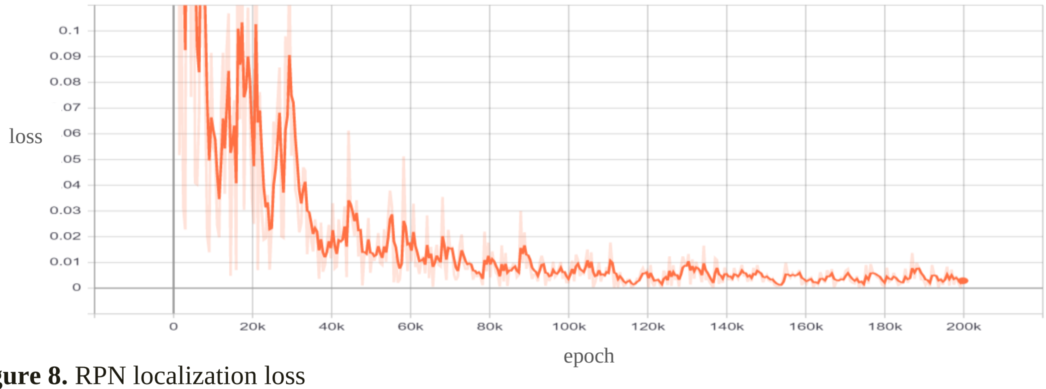


Figure 8. RPN localization loss

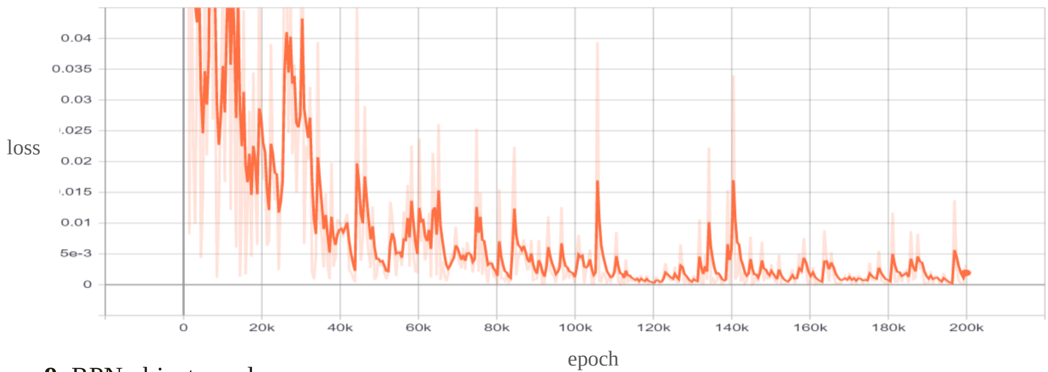


Figure 9. RPN objectness loss

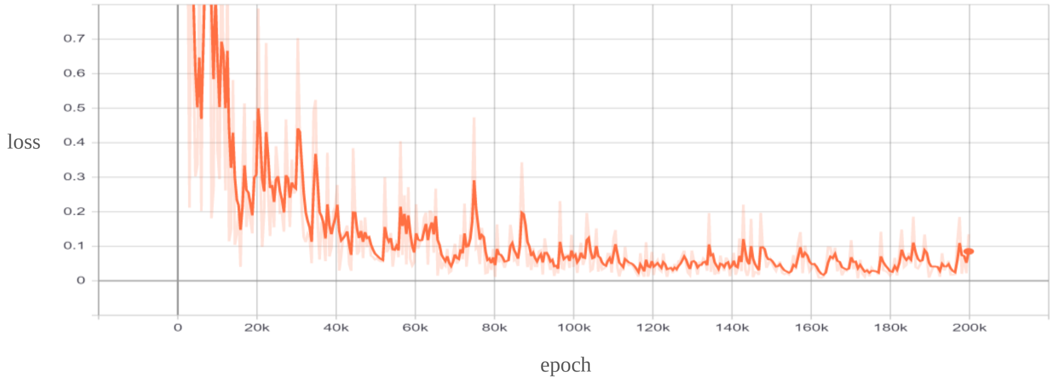


Figure 10. Total loss curve of our proposed system

4.4 Qualitative results

For every image in tomato disease dataset, evaluated performance to all the bounding boxes and confidence score for leaf curl, bacterial spot, septoria leafspot, healthy and early blight. Proposed system detects tomato disease categories with location in the plants at early, medium and final disease stages. As the system detects diseases at early stage in the plant shown from figures a to f, so that farmer can avoid severe loss in the crop in terms of quality and quantity). Trained the proposed system with front side of the tomato leaf images, whereas system able to detect diseases on the back side of the tomato leaves shown in figure h and also detects the diseases which are in out of focus distance refer figure i, j. The proposed system detects disease in complex background (soil, stem, tomato) shown in figure k, l and also detects multiple diseases on a single leaf refer to figure m.

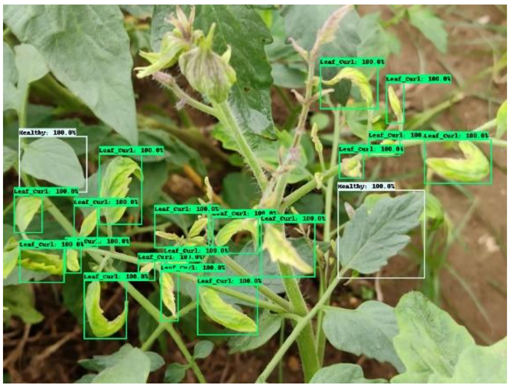


Figure a. Initial stage of leafcurl

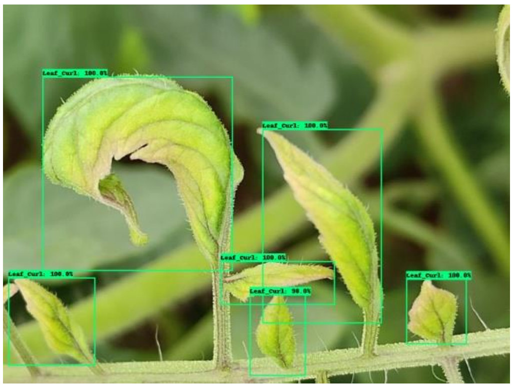


Figure b. Initial and Final stage of leafcurl

Figure c. Final stage of leafcurl

Figure d. Initial stage of Bacterial spot

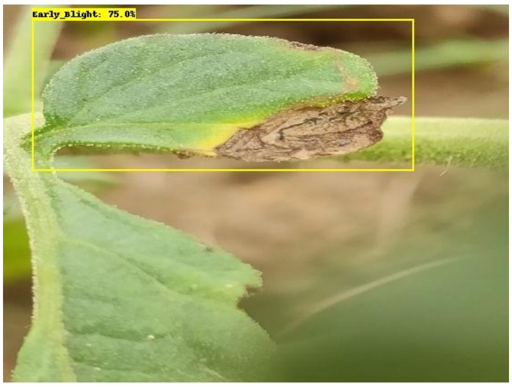


Figure e. Initial stage of Early blight

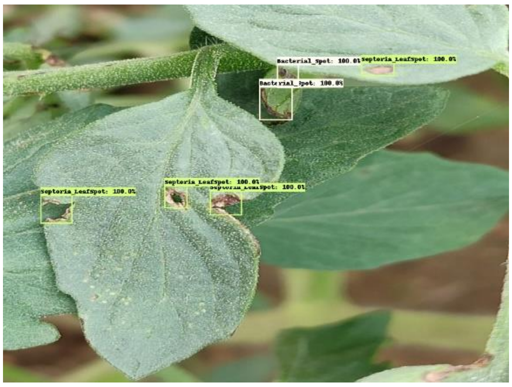


Figure f. Initial stage of Septoria leafspot

Figure g. Final stage of Early blight

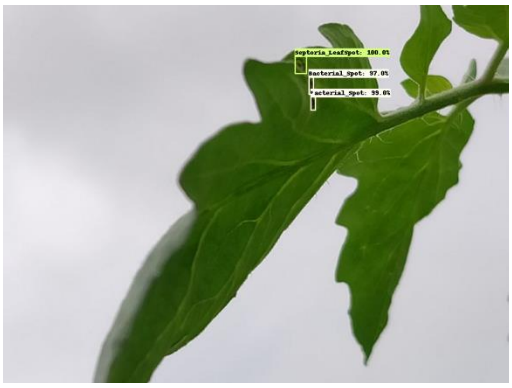


Figure h. Septoria & Bacterial initial stage on lower leaf

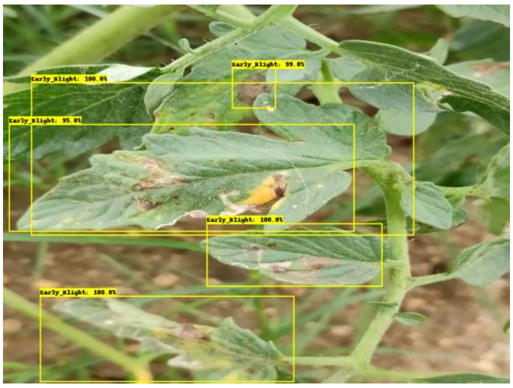


Figure i. Early blight at Out of focus distance

Figure j. Bacterial spot at Out of focus distance

Figure k. Complex background (stem & tomato)

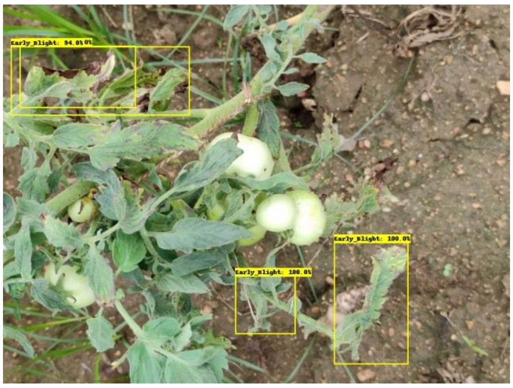


Figure l. Complex background (Soil, Stem, Tomato)

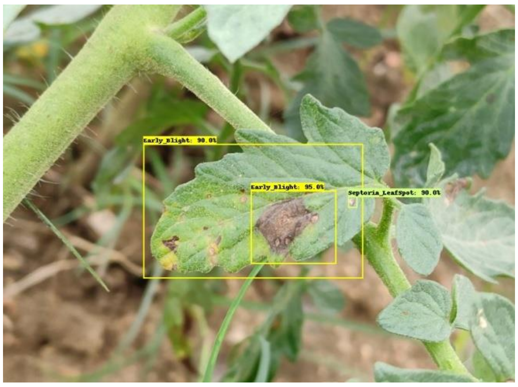


Figure m. Multiple diseases on single leaf

4.5 Failure analysis and discussions

Although the proposed system shows an outstanding performance in detecting leaf curl, early blight, bacterial spot and septoria leaf spot tomato diseases in several conditions like complex background, out of focus distance, the early, medium and final stage of infection status. The proposed system confuses septoria leafspot disease with early blight and bacterial spot disease due to lower number of labelled bounding boxes for septoria leafspot, which results as FP is shown in figure 11, As the disease stages progress on it is difficult to recognize different diseases with their visual features. Further work is to collect more number of samples for septoria leaf spot and improve accuracy.

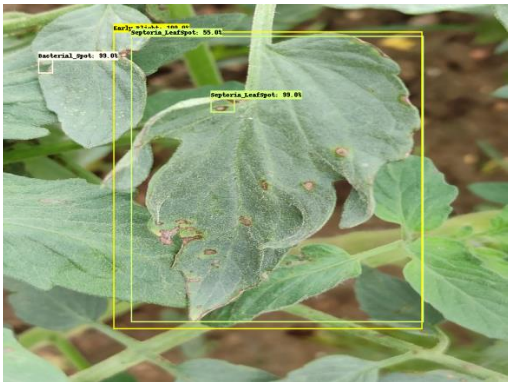


Figure 11. Representation of failure classes

5. Conclusion and future work

This work was focused on reviewing the efficiency of the deep learning architectures for pest and disease detection in cultivated land. Collected a comprehensive 1090 real-time tomato leaf images infected by early blight, leaf curl, septoria leafspot, and bacterial spot dataset, images were taken by camera devices with 12MP, 48MP resolution, different illumination conditions (lighting), all stages of tomato disease (early, medium, final) and given as an input to the proposed system. Different deep learning architectures are used to identify pest and diseases using deep detectors: Faster R-CNN, R-FCN and SSD, combined with VGG Net and ResNet, AlexNet, SqueezeNet. Based on the survey done on pest and disease detection, Faster R-CNN deep learning architecture combined with ResNet provided better performance compared to R-FCN and SSD. Proposed an automated disease detection system using deep detector: Faster R-CNN with ResNet, is a feasible solution for farmers to detect early blight, leaf curl, septoria leafspot and bacterial spot diseases with location in tomato plants. And also trained and tested the proposed system end-to-end with our tomato disease dataset specified in this work, which has 1090 comprehensive images of early, medium, and final stages of tomato disease.

The future scope in disease detection in cultivated land is as follows:

The proposed system detects 4 types of tomato diseases i.e early blight, leaf curl, septoria leafspot and bacterial spot in tomato crop. Furthermore, work can be extended by training the model with other types of tomato diseases i.e late blight, leaf mold, spider mites and so on and also to detect diseases for other crops like potato, peanuts and so on.

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