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# Faster-RCNN Based Deep Learning Model for Pomegranate Diseases Detection and Classification

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***Abstract***

*India is the largest producer of pomegranates in the world which earns a high profit. However, due to atmospheric conditions such as temperature variations, climate, and heavy rains, pomegranate fruits become infected with various diseases, resulting in agricultural losses. The two most common diseases seen in the Karnataka region are bacterial blight and anthracnose, both of which cause a significant production loss. This paper has detected and classified these two diseases by extracting knowledge from custom trained models using Deep Learning. To overcome the traditional methods, Faster-RCNN helps us to do better object detection.*

***Keywords***

*Anthracnose, Deep Learning, Faster-RCNN, Object detection, Tensorflow Bacterial blight.*

## INTRODUCTION

Asian countries have been manufacturing pomegranates to a larger extent. The exports of pomegranates are growing year by year. Over the past few years, agriculture has swung and is turning into a supply of financial benefit generation. In India, 11.0 lakh tones of pomegranate are produced on 1.5 lakh hectares of land. Maharashtra is India's leading pomegranate producer, India grant 2/3 rd. of the total.

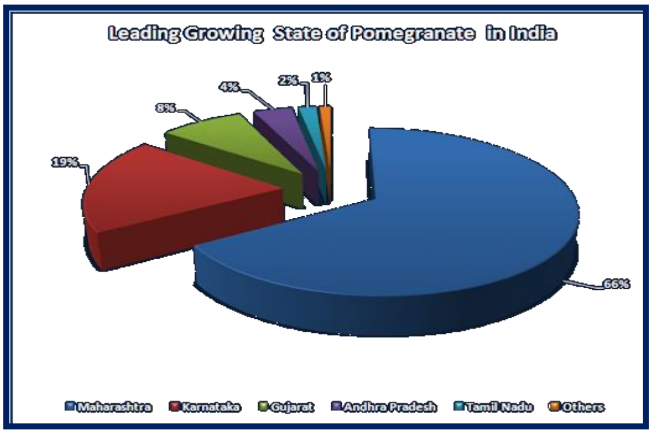


**Fig -1:** Productivity of Leading Pomegranate Growing States in India.

### Importance of Disease Detection in Fruits:

India is an agricultural dependent country as it stands second largest producer of fruits and there is a high demand for quality of fruits in market. The cultivation of fruits faces threat of several diseases caused by pest, micro-organs, weather conditions, soil profile and deficiency of nutrition etc. Which leads to significant reduction in crops when it comes to fruits preservation from diseases diagnosis is very essential to enhance crop production and thus, improve the economic growth [12].

### Two Most Common Diseases in Pomegranate Are:

***1)Bacterial blight*:** Dark color irregular spots appear on fruits, and the leaves start dropping, and fruit crack appears in V and L shape and spreads rapidly throughout the farm and cause severe destruction. ***2)Anthracnose:*** it's a kind of fungi that causes irregular brown spots and this disease also leads to severe fruit loss. In the present situation, Farmers in India lack knowledge about how to use pesticides properly; as a result, a proper agriculture system would assist farmers in crop management and decision-making using advanced technology. The intelligent system will detect and diagnose diseases in the fruits for their purpose, and it will restrict the growth of the diseases. Researchers have developed machine learning technology to solve the problems of the farmers [1]. Deep learning is one of the most commonly used subfields of machine learning. It helps in the prediction of various problems and provides solutions [2][3].

## LITERATURE SURVEY

One of the important research areas is the automated method for detecting disease-affected fruits, as it offers numerous benefits in terms of fruit preservation. Although a lot of research is done in this area, Artificial Intelligence is rarely used for this purpose. To detect multi-fruit classification, the authors proposed a Deep learning approach that uses a faster R-CNN. Fruits such as mango and pitaya are used as ingredients. The dataset was actual data obtained from a farmer during harvest time, and it was divided into two classes for object detection training: mango and pitaya. On the TensorFlow platform, authors used the MobileNet model. In this study, they achieved 99 % accuracy rate [4]. In this paper, using plant leaf photos, the authors propose a deep-learning-based approach for detecting leaf diseases in a variety of plants. They identified and developed deep learning methodologies for good results, and they considered three major detector families: The Faster Region-based Convolutional Neural Network (Faster R-CNN), the Region-based Fully Convolutional Network (R-FCN), and the Single Shot Multibox Detector (SSD). The proposed system capable of identifying various types of diseases and dealing with complex scenarios from within a plant's area [5 ]. In a deeper analysis using deep learning techniques, Rismayati and Rahari SN [6] investigated CNN's sorting of salak fruits. authors used neural networks to analyze the salak image and classification scheme in a region of interest (RoI). With 3x5x5, they make six filter layers in the first layer. The second layer generates 18 filters size of 6x3x3. The accuracy rate was 81.45%. To solve image classification problems faster, the R-CNN and Quick R CNN methods are used. This method was chosen because it has the highest level of precision in a variety of tests at 1 frame per second (Frame Per Second).

**Table -1:** Comparison table of various versions of RCNN.

| | R-CNN | Fast R-CNN | Faster R-CNN |
|---|---|---|---|
| Time taken for per image | 50 seconds | 2 seconds | 0.2 seconds |
| Speed up | 1x | 2x | 250x |

## PROPOSED METHOD

In this article, we propose a system for detecting pomegranate diseases like anthracnose andbacterialblight via TensorFlow for object detection on a Faster R-CNN. Based on the literature survey, we create our own dataset. For each classifier, i.e., each object label, we collected almost 200-300 images. We used online tool for Image Annotation process where we have uploaded all our dataset, and set the object names (Classifiers) as anthracnose and bacterialblight and used rectangle for creating xml files as annotation directories. After labeling images or Annotations we converted them into CSV (train.csv, test.csv) format because of tensorflow [7] specifications. CSV files are converted into TFrecord format to enhace the training. Once the training has been completed successfully, the protocol buffer(.pb) file is generated with the python inference graph. This graph file can create a user interface on Android or a web application in which a camera is used to detect an object using the trained TensorFlow model.

### Convolutional neural network

In [15] CNN's architecture as consisting of an input layer followed by a Conv layer. The dimensions of the conv layer vary depending on the data and problem, so they must be adjusted accordingly. There is an activation layer after the Conv Layer, which is normally ReLU because it produces better performance. A pooling layer is used to minimise the scale after certain Conv and Relu combinations. The flattening layer is used to flatten the input for the completely connected layer after some variation of previously established architecture. The third layer, after the first two, is the output layer.

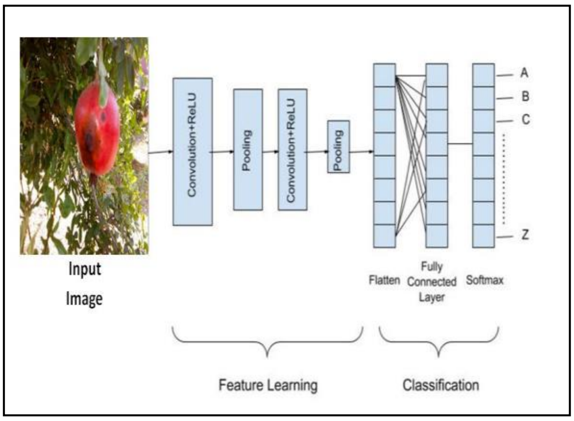


**Fig -2:** CNN's architecture

### Faster Region-Based Convolutional Neural Network (Faster R-CNN)

Faster R-CNN is a Convolutional Neural Network-based object recognition architecture that uses a Region Proposal Network (RPN). It is commonly used in Deep Learning and Computer Vision and is considered one of the most effective object detection architectures.

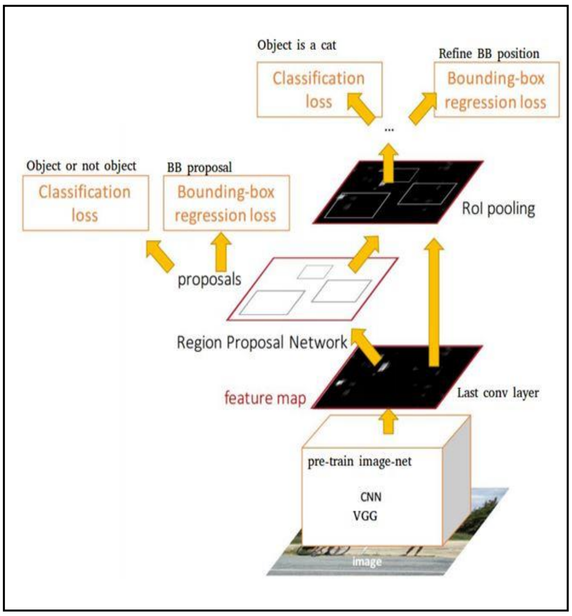


**Fig -3:** Faster RCNN

It takes an image and sends it to the ConvNet, which creates feature maps for it. Use the Region Proposal Network (RPN) to generate object proposals from these feature maps, and then use the ROI pooling layer to make all of the proposals the same size. Finally, submit these suggestions to a fully linked layer in order to define and predict the bounding boxes of the image.

### *(Visual Geomerty Group) VGG 16*

In [14] It's a 16-layer deep network that's used for feature extraction. We can load a pre-trained version of the network that can be trained on millions of images from the ImageNet database. The network has been pre-trained to classify images into 1000 different object categories.

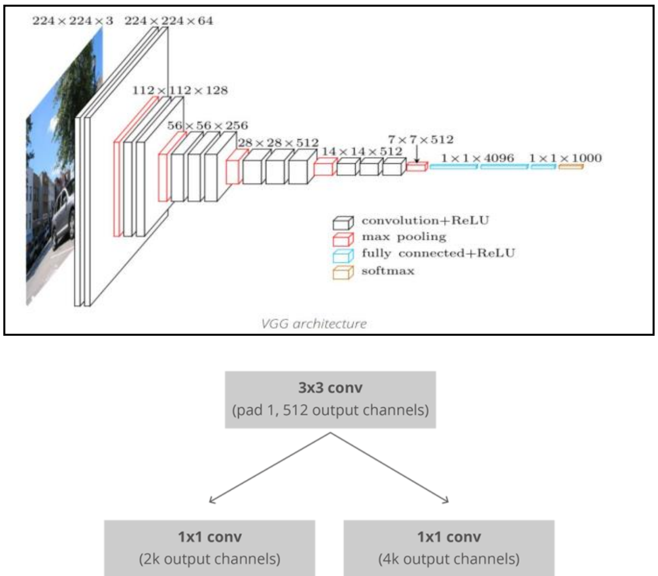


**Fig -4:** VGG 16 Architecture

VGG16 will eliminate the pre-trained network's bottleneck (classifier) layer. Then, with the exception of the last few convolutional layers, all weights are frozen, and we attach our own classifier with a very low learning rate.

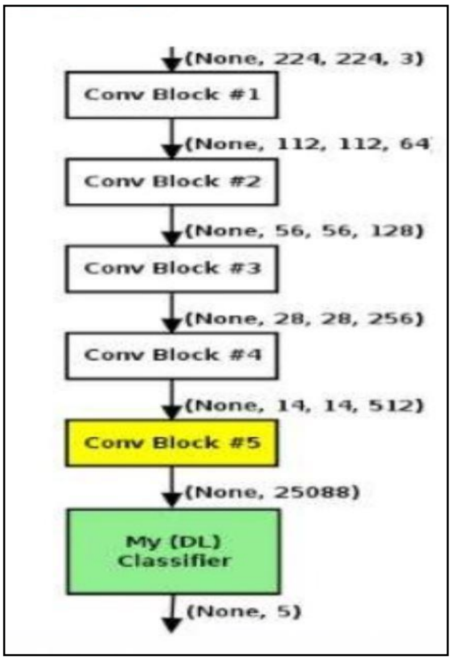


**Fig-5:** VGG16 Model

**Region Proposal Network (RPN)**

The area proposal network will take all the anchors (reference boxes) and produce two different outputs for each of the anchors, resulting in a list of good object proposals. The first is a "objectness" score, which indicates how likely the anchor is to be an entity; RPN is unconcerned about the type of object. We'll use this objectness score to weed out the bad predictions in the second step. The bounding box regression is the second production, which is used to modify anchors to match the items that are being predicted. The function map, which is convoluted returned by the network as an imput, is used by RPN to implement in a completely convolutional way. With 512 channels and a 3x3 kernel dimension, the convolutional layer is used. Then, using a 1x1 kernel, we'll have two parallel layers of convolution, with the number of channels determined by the number of anchors per point.

We get two performance predictions per anchor for classification. Its score isn't an object (background), but it is an object (foreground).Adjustment layer for regression or bounding box. We generate four predictions: Δxcenter, Δycenter, Δwidth, and Δheight, which we combine with the anchors to form final proposals We have a strong set of object proposals using the final proposal co-ordinates and their "objectness rating."

***Anchors***

The network generates the maximum number of k- anchor boxes for each sliding window. For each of the different sliding positions in the image, the default value of k=9 (3 scales of (128*128, 256*256, and 512*512) and 3 aspect ratios of (1:1, 1:2, and 2:1) is used. As a result, we get N = W* H* k anchor boxes for a convolution feature map of W * H. These region suggestions were then passed through an intermediate layer with 3*3 convolution and 1 padding, as well as 256 (for ZF) or 512 (for VGG-16) output channels. This layer's output is passed through two 1*1 convolution layers, the classification layer, and the regression layer.

The classification layer has 2*N (W * H * (2*k) output parameters, while the regression layer has 4*N (W * H * (4*k) output parameters (denoting the coordinates of bounding boxes) (denoting the probability of object or not object).

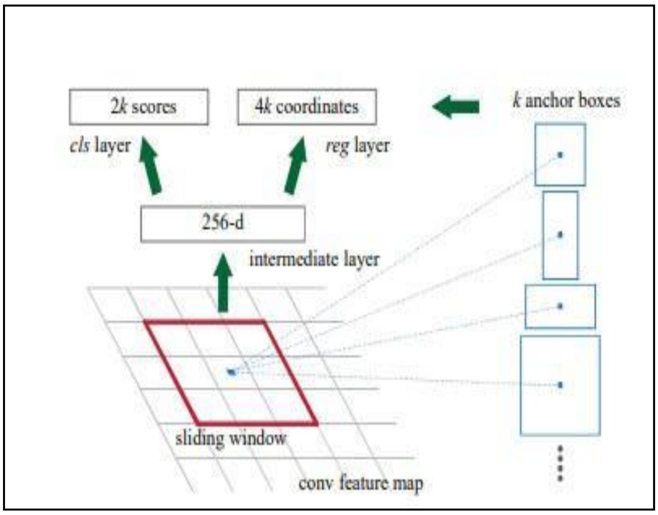


**Fig -6** Anchors**.**

***ROI Pooling***

Region of interest pooling (also known as RoI pooling) is a popular operation in convolutional neural network object detection tasks. The problem of a fixed image size requirement for an object detection network is solved by ROI pooling. By doing max-pooling on the inputs, ROI pooling creates fixed-size function maps from non-uniform inputs. The number of output channels is equal to the number of input channels for this layer.

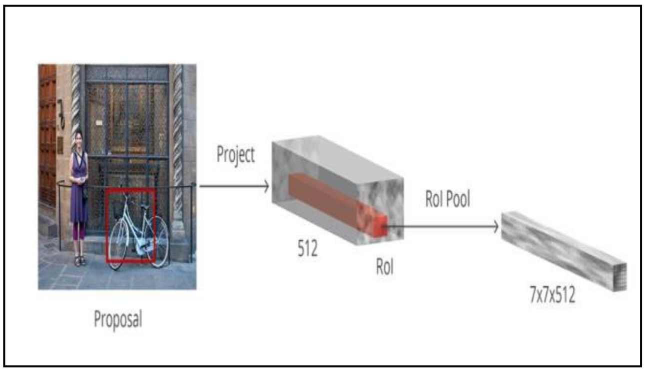


**Fig -7** Region of interest pooling

### APPROACH

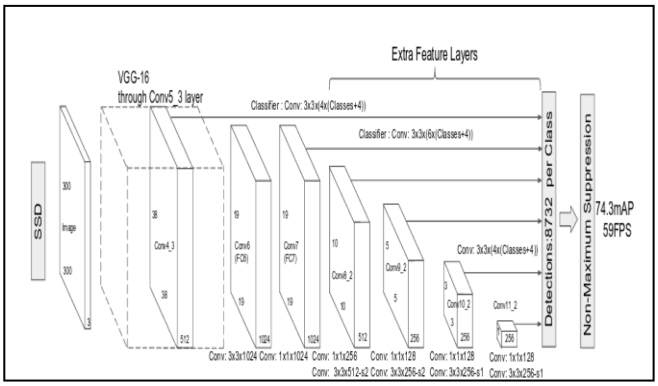


**Fig-8:** SSD Architecture

This project's network is focused on single-shot detection (SSD). Normally, the SSD begins with a VGG [8] model that has been transformed to a completely convolutional network. Then we add some additional convolutional layers to better manage larger subjects. A 38x38 feature map (conv4 3) is generated by the VGG network. The additional layers result in function maps that are 19x19, 10x10, 5x5, 3x3, and 1x1. As seen in the following diagram, both of these feature maps are used to predict bounding boxes at different scales (later layers are responsible for larger objects).

### IMAGE ANNOTATION

PASCAL VOC [9] offers structured image datasets for object type recognition as well as a common collection of resources for accessing the datasets and annotations. Our PASCAL VOC dataset has two classes and a task that is based on it. The PASCAL VOC dataset is well-marked and of good quality, allowing for evaluation and comparison of various approaches. The PASCAL VOC dataset has a smaller amount of data than the ImageNet dataset, making it ideal for researchers evaluating network programmes. As shown in the following figure, our dataset is also based on the PASCAL VOC dataset norm.

```
<?xml version="1.0"?>
- <annotation>
    <folder>images</folder>
    <filename>3p.jpg</filename>
    <path>images/3p.jpg</path>
  - <source>
      <database>Unknown</database>
    </source>
  - <size>
      <width>300</width>
      <height>168</height>
      <depth>3</depth>
    </size>
    <segmented>0</segmented>
  - <object>
      <name>Bacterialblight</name>
      <pose>Unspecified</pose>
      <truncated>0</truncated>
      <difficult>0</difficult>
    - <bndbox>
        <xmin>55.000003814697266</xmin>
        <ymin>0</ymin>
        <xmax>257.0000305175781</xmax>
        <ymax>167</ymax>
      </bndbox>
    </object>
</annotation>
```


**Fig -9** Image Annotation


**Fig -10** Labeling Tool

**Fig -4:** Table example of the labeled dataset.

| filename | width | height | class | xmin | ymin | xmax | ymax |
|---|---|---|---|---|---|---|---|
| 1 (1).jpg | 1024 | 974 | anthracno | 65 | 55 | 961 | 973 |
| 1 (10).jpg | 300 | 400 | anthracno | 72 | 163 | 244 | 357 |
| 1 (11).jpg | 896 | 504 | anthracno | 102 | 55 | 725 | 462 |
| 1 (12).jpg | 1024 | 576 | anthracno | 129 | 44 | 855 | 576 |
| 1 (13).jpg | 450 | 300 | anthracno | 20 | 52 | 214 | 265 |
| 1 (13).jpg | 450 | 300 | anthracno | 214 | 51 | 424 | 240 |
| 1 (14).jpg | 450 | 300 | anthracno | 115 | 12 | 420 | 300 |
| 1 (15).jpg | 480 | 360 | anthracno | 130 | 43 | 387 | 279 |
| 1 (16).jpg | 800 | 600 | anthracno | 194 | 156 | 618 | 547 |
| 1 (17).jpg | 1300 | 956 | anthracno | 4 | 132 | 217 | 424 |
| 1 (17).jpg | 1300 | 956 | anthracno | 221 | 379 | 539 | 757 |
| 1 (17).jpg | 1300 | 956 | anthracno | 509 | 197 | 992 | 749 |
| 1 (18).jpg | 1280 | 720 | anthracno | 45 | 27 | 644 | 683 |
| 1 (18).jpg | 1280 | 720 | anthracno | 553 | 176 | 1246 | 720 |
| 1 (18).jpg | 1280 | 720 | anthracno | 779 | 9 | 1280 | 428 |
| 1 (19).jpg | 3184 | 3184 | anthracno | 347 | 297 | 2776 | 2922 |

## RESULT AND DISCUSSION

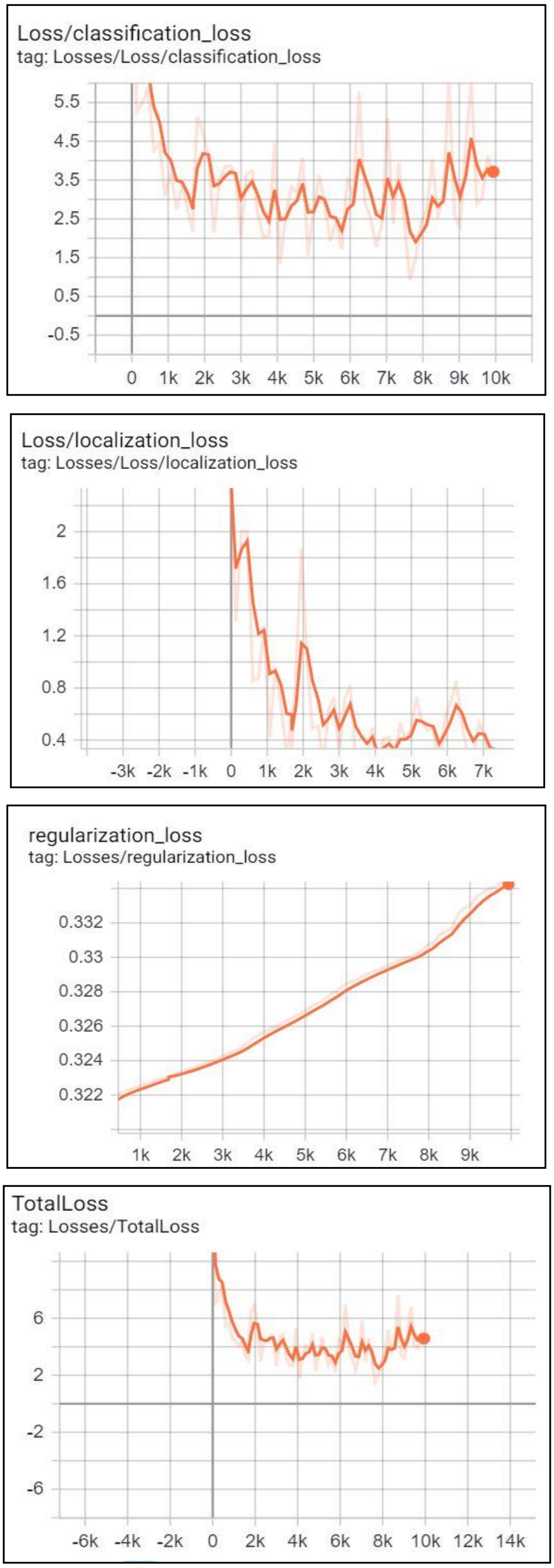


**Fig-11:** Total Losses of Faster-R-CNN

The number and consistency of the dataset will influence the neural network performance accuracy after the images are trained [10]. Deep learning approaches [11] are growing every day in popularity it enables rapid and efficient solutions, especially in the analysis of large amounts of data. This study used a custom dataset to identify pomegranate diseases such as anthracnose and bacterialblight for deep learning applications. Tensorflow played a major role in this.

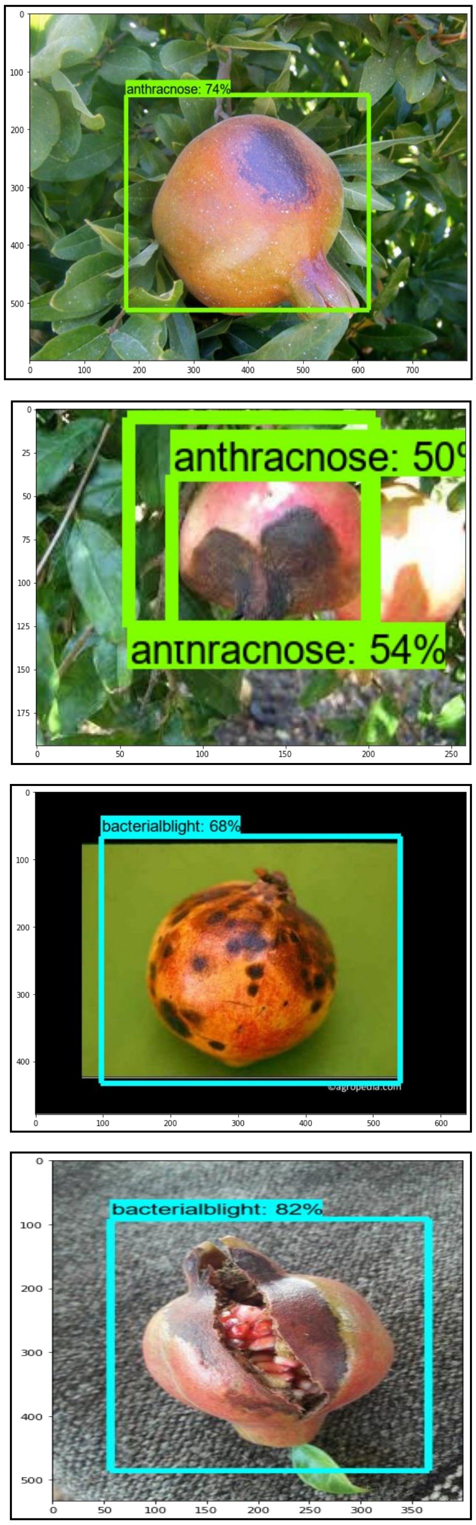


**Fig -12:** Experimental results.

## CONCLUSION

The proposed system is able to detect the diseases in pomegranate and can able to classify them into different categories here we have identified two kinds of diseases anthracnose and bacterialblight . In this study we considered deep learning methodology based on Faster RCNN model which gave an accurate and efficient object detection system.

The goal for the future is to figure out how to overcome the issue of low image resolution causing detection failures. Another choice is to apply this approach to crops other than pomegranates.

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