A Smart Agriculture Framework to Automatically Track the Spread of Plant Diseases using Mask Region-based Convolutional Neural Network

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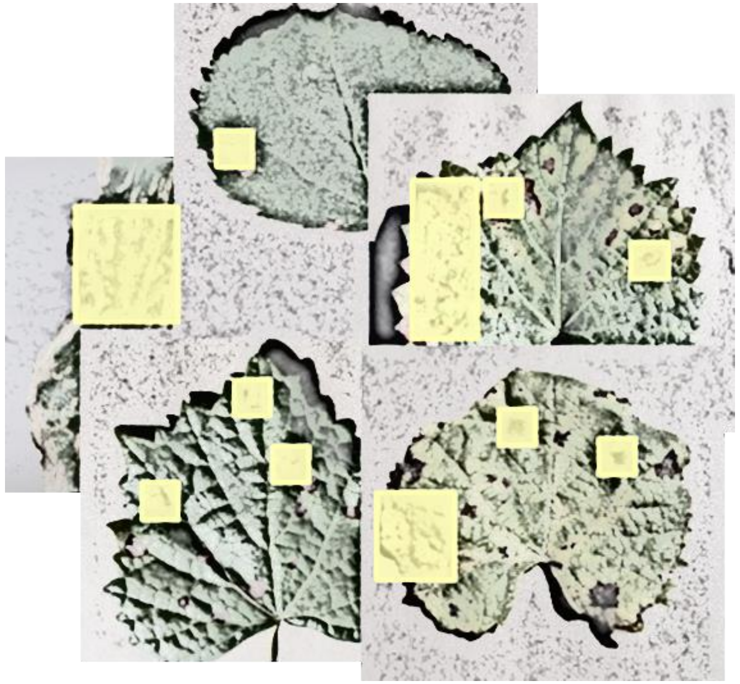
Presenter : V. K. V. V. Bathalapalli

Outline of the Talk

- Introduction
- Problem Addressed
- Related Prior Works
- Proposed Solution of the Current Paper
- Disease Detection & Localization System Development
- Performance Evaluation & Results
- Conclusions & Future Work

Introduction

- Agriculture is one of the major industries of today's society.
- Plants, like all living things, are prone to diseases.
- Diseases vary with seasons and plant types.
- If plant diseases are not identified and addressed in a timely manner, it results in increased food insecurity.
- Early detection and disease severity estimation are key to disease management, containment, and prevention.



Plant Disease

- Trees are prone to various fungal pathogens that cause diseases.
- These diseases can affect plants at any stage of growth and manifest in a variety of plant components, from stems to fruits.
- Symptoms may include discoloration, form change, wilting, galls, and cankers.
- Disease symptoms are predominantly manifested on leaves.
- Most of the research on identifying plant diseases is focused on leaves or fruits.

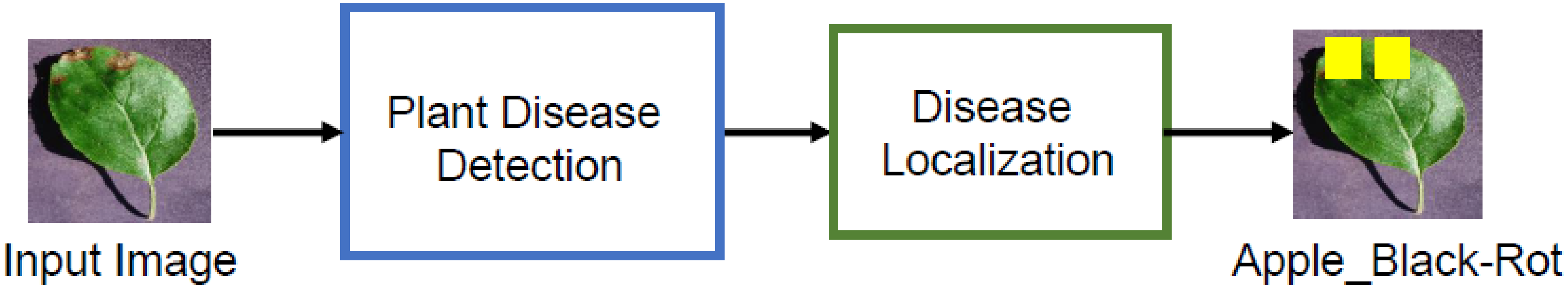
Problem Addressed

- Manual observation is still the most common method of detecting plant diseases.
  - Labor intensive.
  - Ineffective.
  - Requires expert services.
    - Expensive.
- Wrong identification causes wrong use of pesticides.
  - Causes secondary damage.
- Automatic and accurate monitoring of plant diseases is necessary along with disease identification.

Related Prior Works

Work	Year	Details	Damage Localization/ Remarks
Wang et al.	2021	Attention network with EfficientNet-B4 + Image Augmentation.	No
Chao et al.	2020	DenseNet + XceptionNet + SVM	No
Bansal et al.	2021	DenseNet121 + EfficientNetB7 + NoisyStudent networks	No
Di et al.	2022	DF-Tiny-YOLO	No
Wang et al.	2019	Faster R-CNN + Mask R-CNN	Yes
Afzaal et al.	2021	Mask R-CNN + Systematic approach to Image Augmentation	Yes
Current Paper	2022	Mask R-CNN + Basic Image Augmentation	Yes Higher mAP

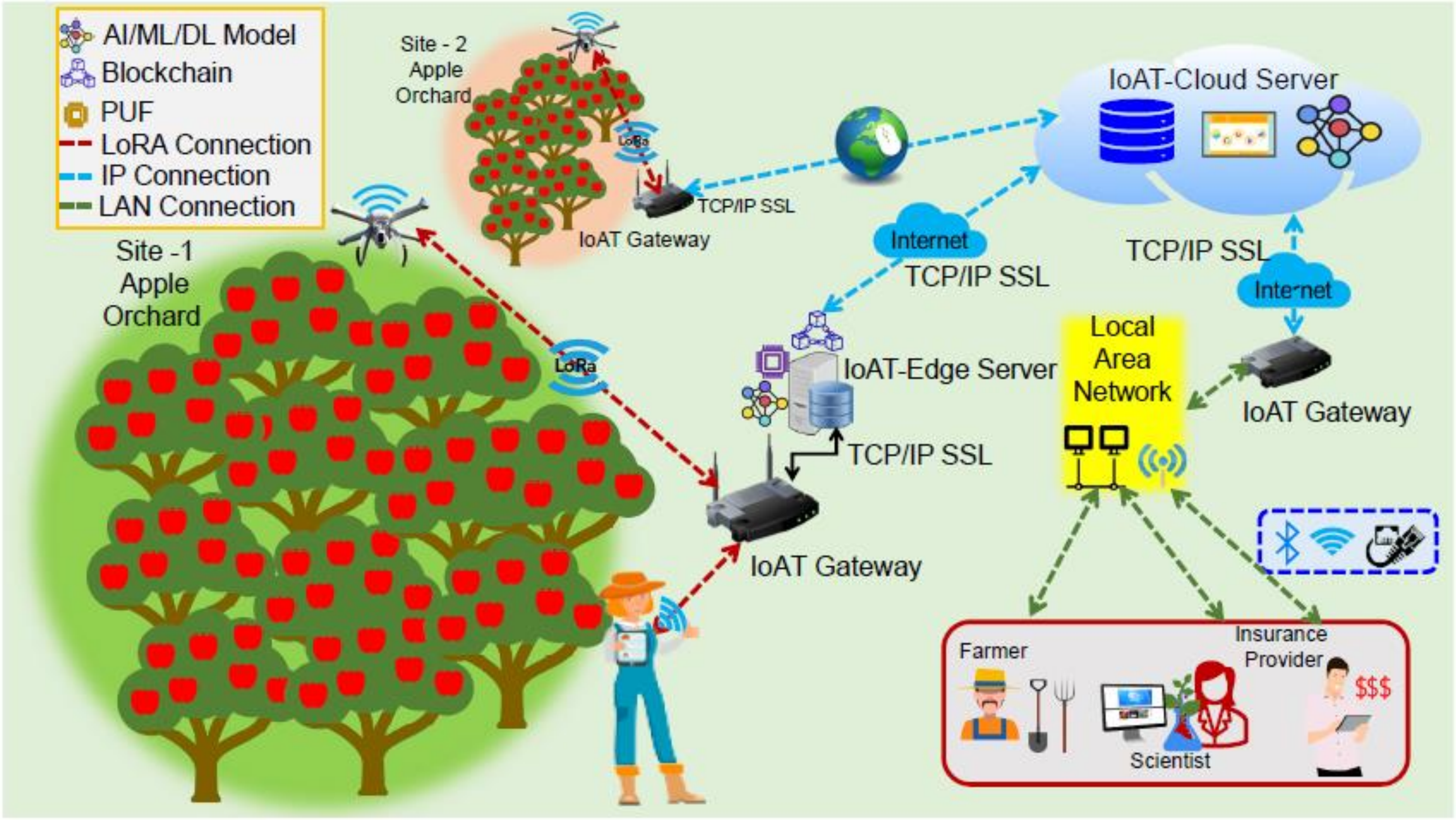
Proposed Solution of the Current Paper



- Early detection of the plant diseases.
- Fully automatic method.
- No expert service is needed for disease detection.
- Very little effort is needed from the users' side. Users only need to take pictures of the damaged leaves.
- This process is the first step of disease severity estimation.
- Estimation of disease severity plays a pivotal role in calculating the optimal quantity of pesticides.

Proposed Solution

Proposed A-CPS



Proposed A-CPS for automatic tracking of plant diseases.

Things

UAVs and Smart Phone Cameras

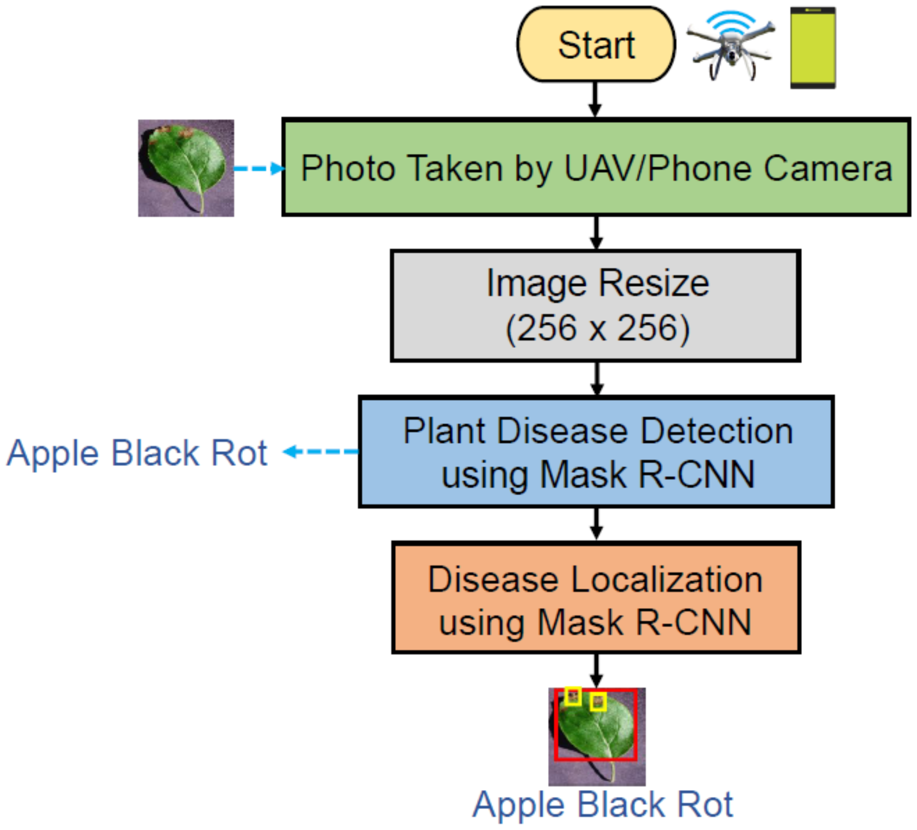
Stakeholders

Farmers, Insurance Providers, and Scientists

Networking

LoRA, TCP/IP

Process Workflow for Disease Detection and Localization System



- Photo of the leaves are taken.
- They are resized to 256x256 to be detected using the trained model.
- A Mask Region-based Convolutional Neural Network (R-CNN) is used to detect the disease along with the disease localization.
- Here, the problem is considered as an object detection problem.
- Object detection is a task in computer vision that involves identifying the presence of one or more items in each image as well as their location and the category of object that they belong to.

Evolution of Mask R-CNN

R-CNN

1. Extract Region Proposals using Selective Search Algorithm.
2. Compute Features using CNN from Proposals (basically ROI).
3. Classify the Proposals from the features using SVM.

Fast R-CNN

1. Extract Features.
2. Obtain Region of Interest (ROI) using ROI Pooling from the Feature Maps.
3. 2 Sets of FC Layers: one for Class Label Other for Box Location.

Faster R-CNN

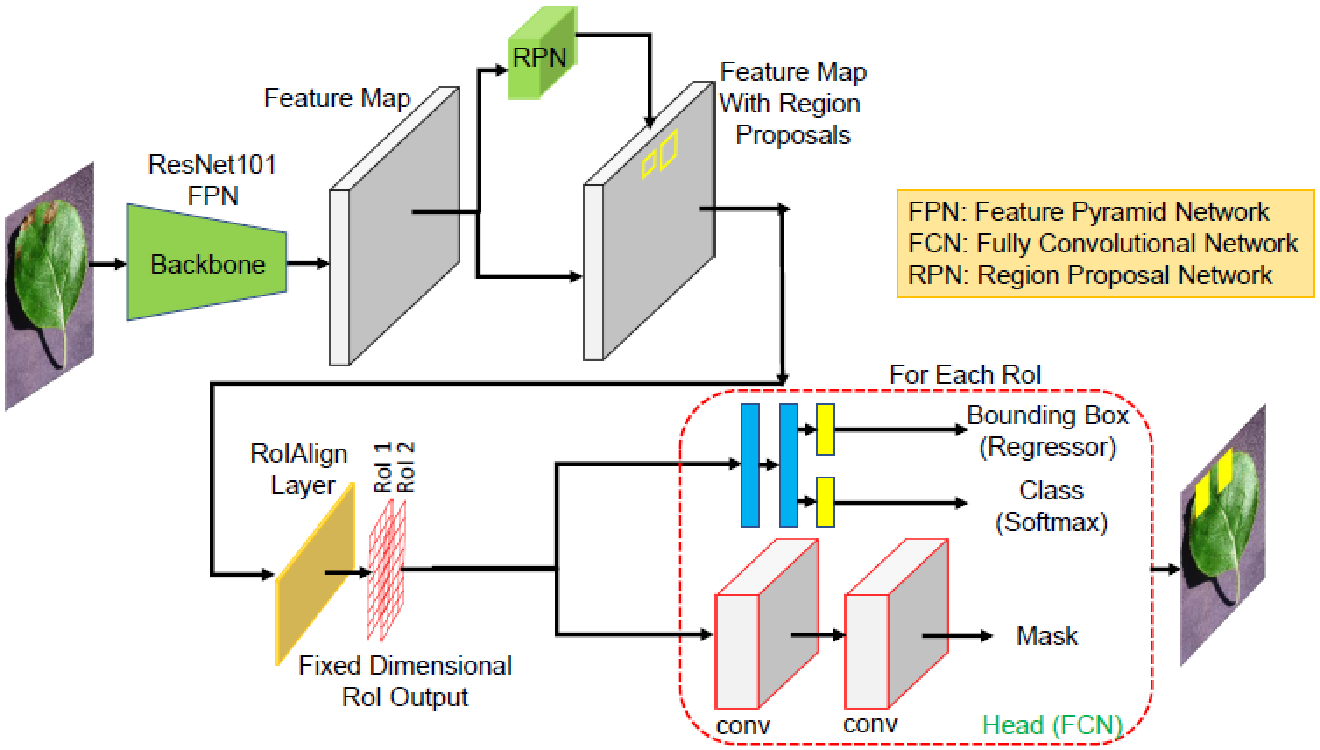
1. Extract Features.
2. Obtain Region Proposal using Region Proposal Network (RPN) from the Feature Maps.
3. Obtain Region of Interest (ROI) using ROI Pooling from the Proposals.
4. 2 Sets of FC Layers: one for Class Label Other for Box Location.

Mask R-CNN

1. Extract Features.
2. Obtain Region Proposal using Region Proposal Network (RPN) from the Feature Maps.
3. Obtain Region of Interest (ROI) using ROI Align Module from the Proposals.
4. 2 Sets of FC Layers: one for Class Label Other for Box Location.
5. Additional Branch from ROI Align Module.

- Mask R-CNN has been used to localize the damage of the leaves caused by apple plant diseases.
- It is built over Faster R-CNN.
- Here, along with the class label and bounding box as in Faster R-CNN, a mask is generated for the detected object to localize the damage area.
- However, for our work, accurate masks for the damage have not been generated.
- It's the initial work for a future detailed project.

Mask R-CNN Network Structure



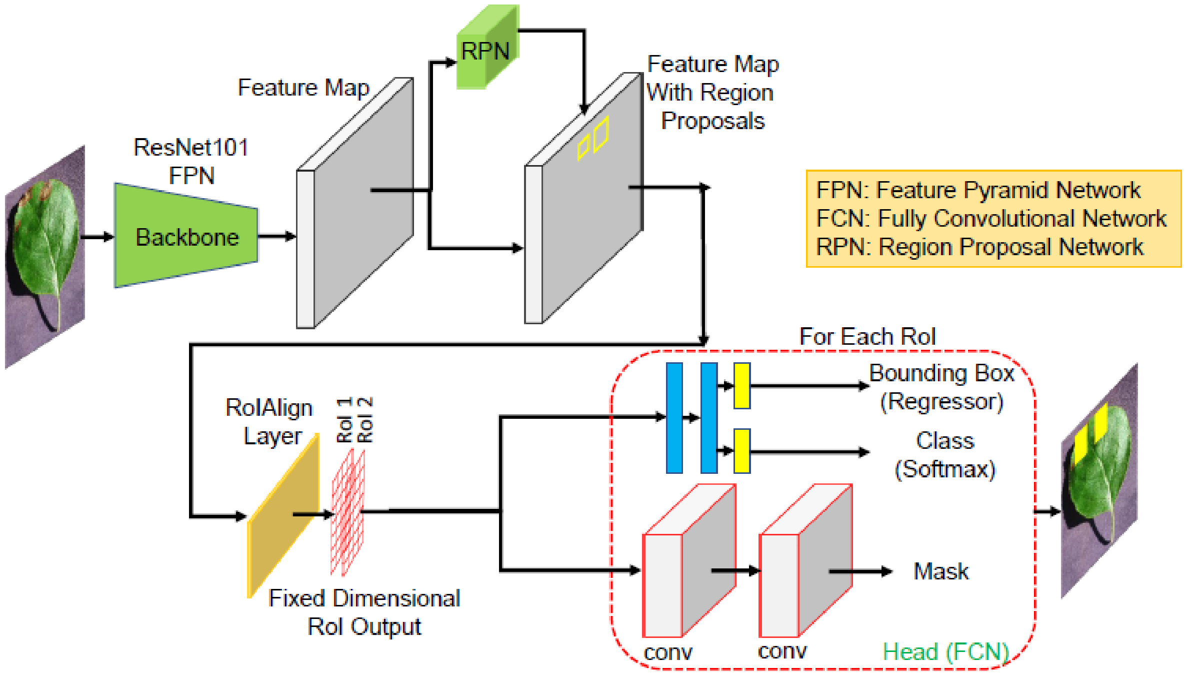
Backbone Network

It is used for feature extraction of the input image. Initially, ResNet101 + Feature Pyramid Network (FPN) and ResNet50 + FPN, have been tested. Finally, ResNet101 + FPN have been selected as the backbone network. ResNet networks, are pre-trained on ImageNet dataset.

Region Proposal Network (RPN)

Multiple regions of interest (RoI) are generated using a lightweight binary classifier in RPN. Detection minimum score is set to 0:9 to include all the damages. RPN simply tells us whether there is something in that area.

Mask R-CNN Network Structure (Contd..)



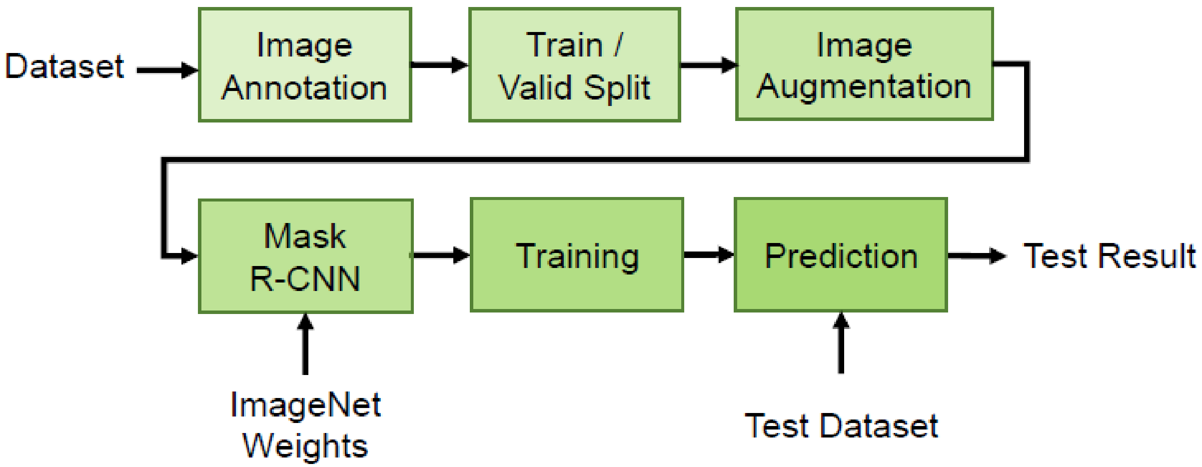
Region of Interest (RoI)

The RoIAlign layer changes the shapes and sizes of different proposals to the same shape and size and aligns the features with the input. Number of RoI is the same as the number of detected objects. RoI is noted when the Intersection over Union (IoU) of ground truth boxes for the predicted regions are greater than or equal to 0.5.

Head

Head takes care of the classification and segmentation. Classification results are predicted by the first branch of fully connected layers and softmax activation function, and the regression output at the second branch of fully connected layer is used to determine the location of the proposed regions in terms of the coordinates of the proposals. A Fully convolutional network (FCN) generates binary masks.

Disease Detection & Localization System Development



- In this work, Matterport's implementation of the Mask R-CNN, based on Keras and TensorFlow, has been followed.
- We have modified the scripts and hyper parameters as per the need of the application.
- First, data has been selected and annotated for object detection purposes.
- Then, the dataset has been split into two parts: train and validation.
- Training of the network has been performed with augmented data.
- Transfer learning has been used.
- Finally, it was evaluated with the test dataset.

Dataset Details

- From PlantVillage Dataset
  - 850 infected apple leaves for training and validation.
  - 70:30 ratio for train : validation.
  - 175 images for testing.

Types	Number of Images		
	Total	Train	Validation
Apple Black Rot	300	210	90
Cedar Apple Rust	250	175	75
Apple Scab	300	210	90
	850	**595**	**255**

Apple Rust

Small, orange-red dots occur on the leaves' fronts in the early stages of Apple Rust. These spots grow to become an orange-yellow patch with red edges. A single leaf can have dozens of disease spots if the infection is severe. 12 weeks after the commencement of sickness, the spot's surface is covered with little bright yellow dots.

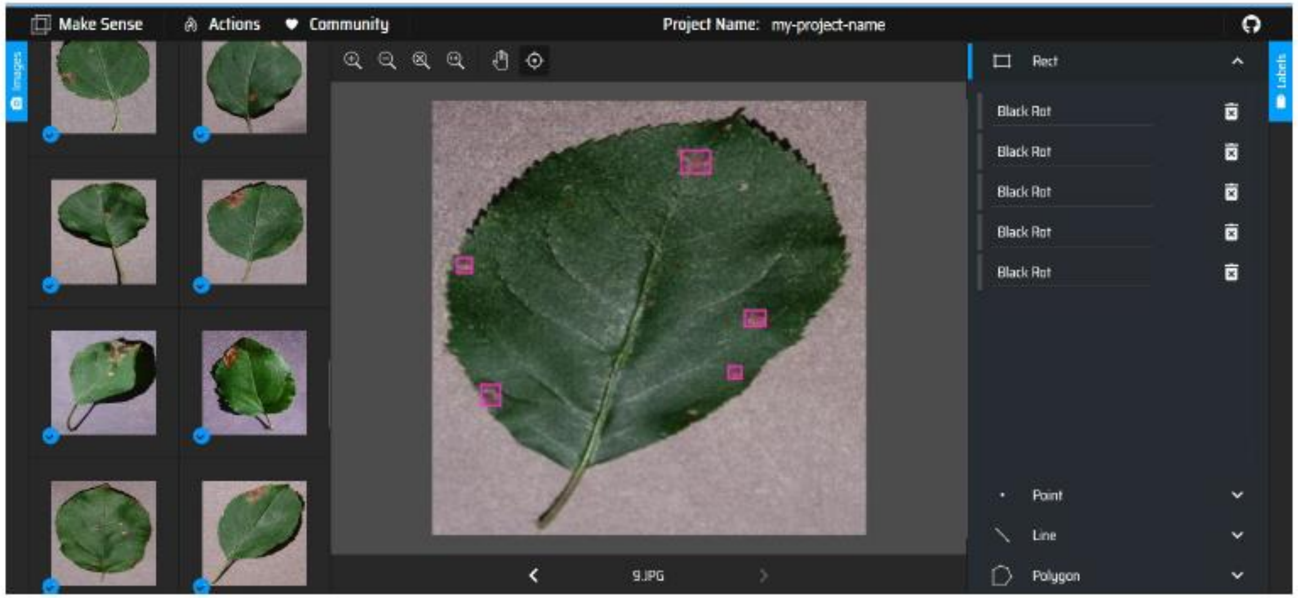
Apple Scab

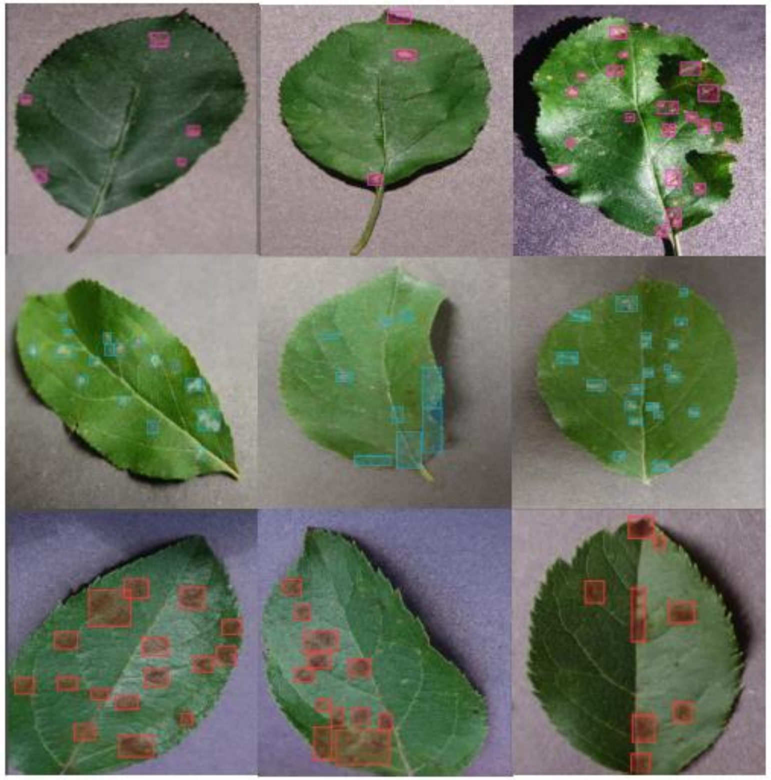
It begins with yellow-green radial or circular patches that become brown to black, with clearly defined edges. Smaller and thicker with curled or twisted leaves are signs of more serious illness. Infected spots will blend into one another, causing large patches to appear on leaves, giving them a burnt look.

Black Rot

For Black Rot, small, purple-black lesions appear on the skin at the beginning of the disease. These develop into spherical spots with a yellow-brown center and brown-purple rims that resemble frog's eyes.

Image Annotation





Black Rot

Cedar Apple Rust

Apple Scab

- MakeSense.AI has been used to annotate the data.
- *Rect* tool has been used for annotating images.
- Annotation files are stored in .xml format with the two diagonally placed corners' coordinates of the bounding box.
- During labeling, different colors are used for different classes.

Training Details

- Transfer learning improved the accuracy of the model and reduced the training time.
- While training, pre-trained ImageNet weights of the ResNet networks are loaded.
- Stochastic Gradient Descent (SGD) has been chosen as the optimizer.
- Initial learning rate was 0.001
- Trained on a system with a NVIDIA Tesla P100 GPU and 25 GB of memory.
- Keras, the deep learning API in Python with TensorFlow at the back-end, scikit-image, pandas, numpy, and imagaug libraries have been used.

Fine Tuned Hyper Parameters

Hyper Parameters	Values
IMAGES_PER_GPU	1
NUM_CLASSES	1+3
STEPS_PER_EPOCH	595
VALIDATION_STEPS	255
LEARNING_RATE	0.001
TRAIN_ROIS_PER_IMAGE	128
RPN_TRAIN_ANCHORS_PER_IMAGE	64
MAX_GT_INSTANCES	200
DETECTION_MAX_INSTANCES	100
IMAGE_MIN_DIM	256
IMAGE_MAX_DIM	256
RPN_ANCHOR_SCALES	[8, 16, 32, 64, 128]

Learning Rate Schedule for Training with ResNet101 + FPN Backbone

Learning Rate (LR)	Trained On	Epochs
0.001	All Layers	1-40
0.0001	All Layers	41-80
0.00003	All Layers	81-120
0.00001	Head	121-160

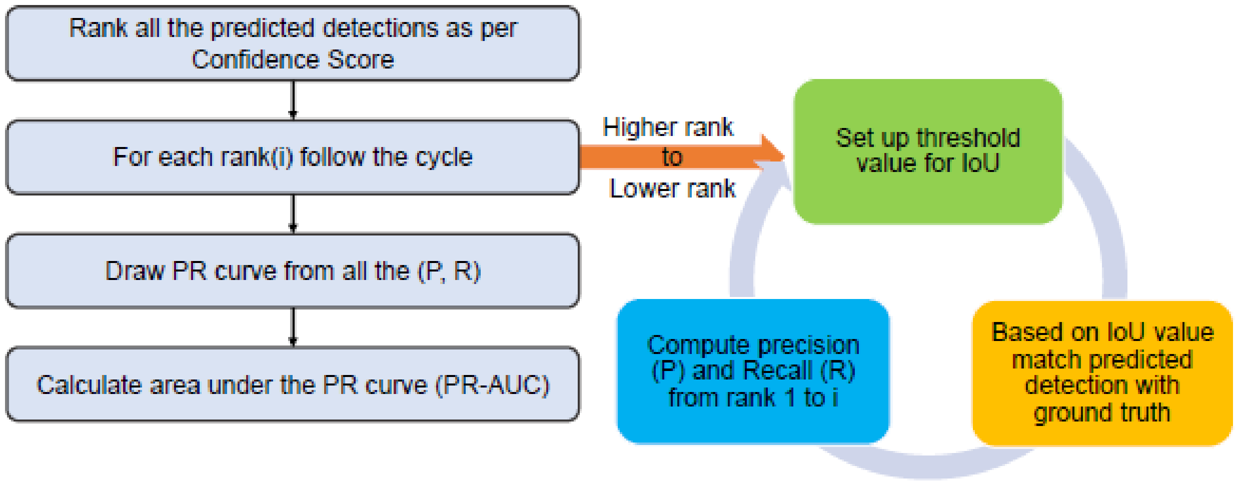
Performance Evaluation

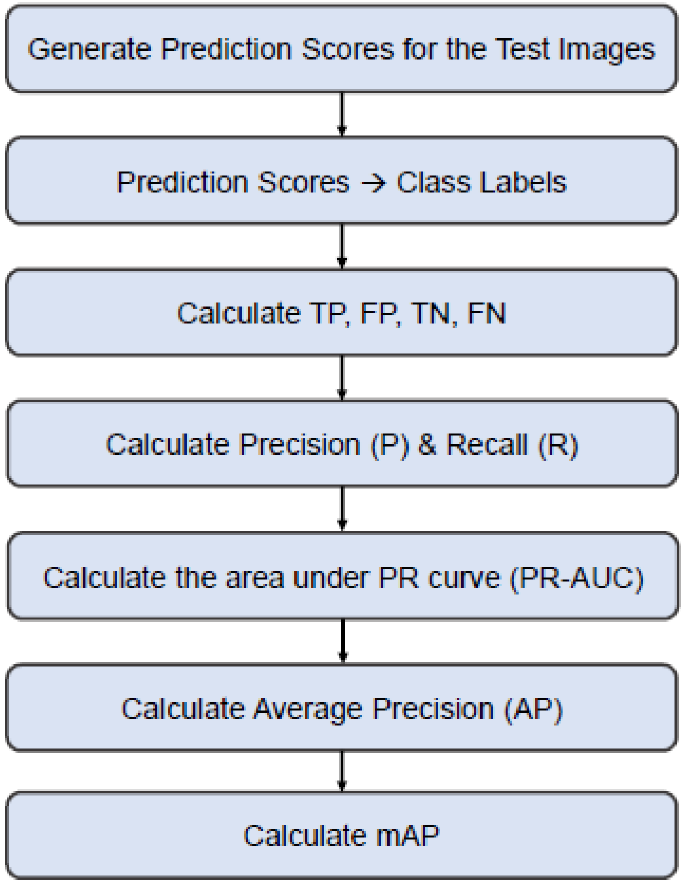
$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$IoU = \frac{TP}{TP + FP + FN}$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i$$

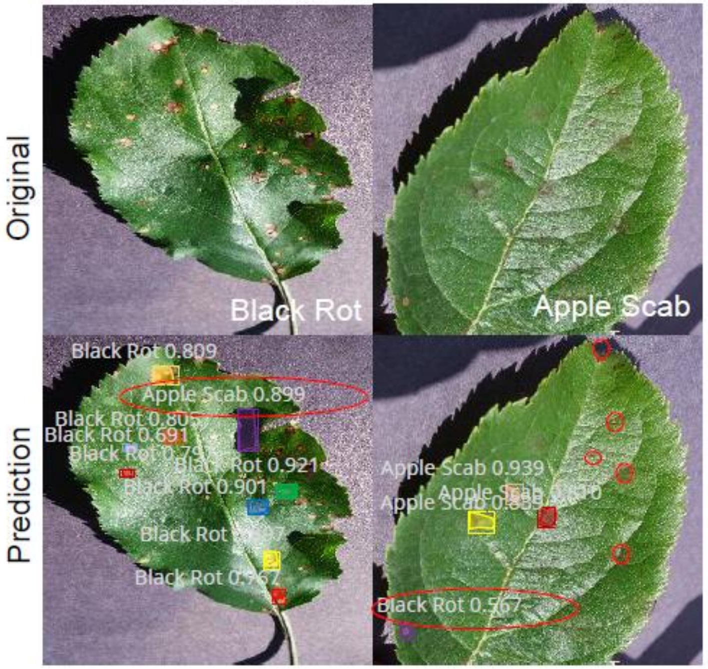




Predicted Result

Mean Average Precision (mAP) for Disease Detection Network

Backbone Network	Image Augmentation	Mean Average Precision [mAP(%)] IoU=0.5
ResNet50 + FPN	Yes	81.9
ResNet101 + FPN	Yes	83.8



Comparative Analysis with the Existing Works

Work	Pre-Training Dataset	Method	Metric	Remarks
Afzaal et al.	MS-COCO	Mask R-CNN + Systematic approach to Image Augmentation	$mAP=$ 82.43%	For Strawberry diseases.
Rehman et al.	ImageNet	Image Enhancement + Mask R-CNN + Ensemble Subspace Discriminant	$mAP=$81.8%, 86.1%	For Apple leaf diseases. More complex method
Current Paper	ImageNet	Mask R-CNN + Image Augmentation	$\mathbf{mAP=83.8\%}$	Automatic tracking of the spread of disease. Case study apple leaf disease.

Conclusions

- Plant diseases are one of the most significant factors that contribute to crop loss.
- Plant disease diagnosis and damage localization are critical to preventing crop loss.
- Damage localization is the initial step of finding Disease Severity.
- Disease severity decides the amount of pesticide needed.
- This Mask R-CNN-based method aims to save time, money, resources, organisms vital for soil and biodiversity, and to store carbon in the soil to combat climate change.
- This preliminary research shows promise towards damage severity estimation.
- More annotated data will increase the mAP of the method.

Future Work

- Damage localization can be extended to disease severity estimation.
- For any plant/crop whenever the annotated dataset is available, the process can be used.
- Inclusion of field data into the training images is needed for a real-world scenario.
- Presence of insects on the leaves affect the results. As future work, it can be addressed.
- When taking pictures with UAV or phone cameras, multiple leaves will be present in the frame. Hence, SOTA object detection can be added before applying the proposed method.
- Work might be extended to calculate the optimum pesticide amount.

Thank You!!