aGROdet: A Novel Framework for Plant Disease Detection and Leaf Damage Estimation

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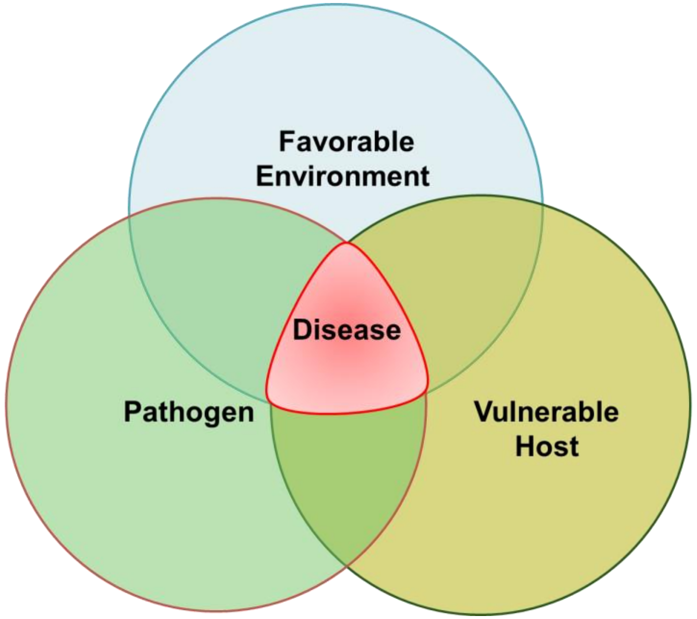
Presenter : V. K. V. V. Bathalapalli

Outline of the Talk

- Introduction
- Problem Addressed
- Related Prior Works
- Proposed Solution of the Current Paper
- Plant Disease Detection – Method and Results
- Estimation of Leaf Damage Severity – Method and Results
- Conclusions & Future Work

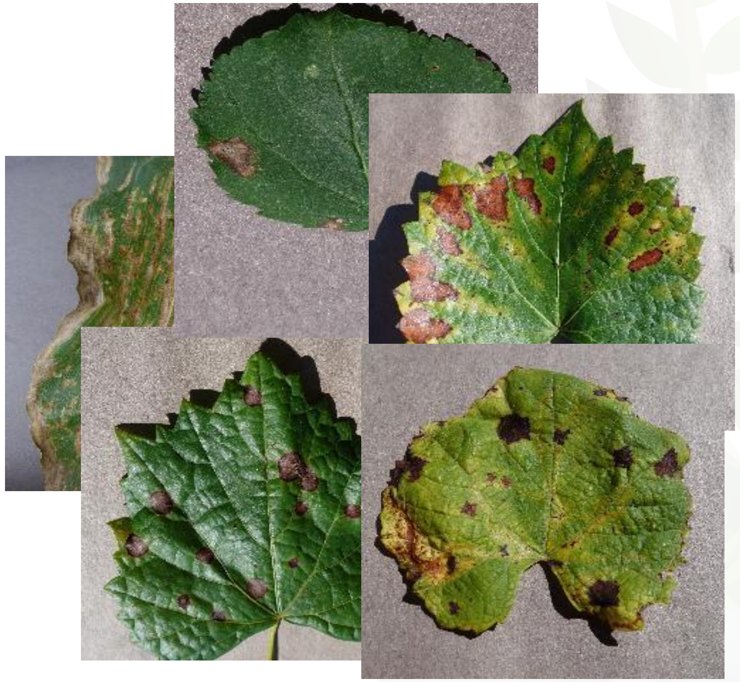
Introduction

- Agriculture is one of the major industries of today's society.
- Plants, like all living things, are prone to diseases.
- It varies with seasons and plant types.
- External conditions or living organisms can cause diseases. Nutritional deficit, heat, flooding, and freezing are some examples of external agents that cause non-infectious or abiotic diseases.
- Plant pathogens like fungi, bacteria, viruses, and algae cause biotic diseases.
- Disease occurs when all three factors of Disease Triangle are present concurrently.



Problem Addressed

- Disease prevents the growth of plants.
  - Affect quality of the crop.
  - Reduce final yield.



- Farmers need to –
  - Monitor the field regularly.
  - Detect disease early.
  - Identify the disease.
  - Know about the severity of the disease.
  - Determine the extent of damage.

aGROdet and Smart Village

- 3:4 billion people live in rural areas.
- Majority of villages lack technology, innovation, energy, and industry.
- Modernization of villages with Internet connectivity, smart agriculture, smart healthcare, smart grid, and education is required.
- Financial backbone of a smart village is agriculture industry.
- Agriculture is one of the most important areas of research for smart villages.
- Plant disease is a major challenge for sustainable agriculture.
- aGROdet automatically and accurately detects plant diseases and estimates damage.
- It can work off-line.
- No expert service is needed.
- We hope that aGROdet will help farmers take proper control measures and save time, money, and secondary plant losses.

Related Prior Works

Works	Year	Disease Type	Damage Estimation
Ji et al.	2020	Crop Leaf Diseases	Yes
Mohanty et al.	2016	Multi Crop Disease	No
Ji et al.	2020	Grape Leaf Diseases	No
Wang	2022	Fragrant Pear Diseases	No
Ozguven et al.	2019	Sugar Beet Leaf Spot Diseases	No
Pallagani et al.	2019	Multi Disease	No
Sun et al.	2020	Maize Leaf Blight Disease	No
Xavier et al.	2019	Ramularia Leaf Blight Cotton Disease	No
Saleem et al.	2020	Multi Crop Disease	No
Current Paper	**2022**	**Multi Disease**	**Yes**

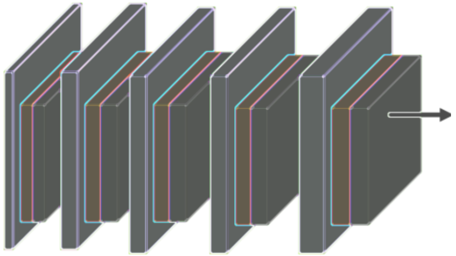
Used AI/ML Models in Related Prior Works

- K-Nearest Neighbors (KNN)
- Non-Parametric Classifiers from multi-spectral imagery of an UAV
- Support Vector Machines
- UNET
- InceptionV3, ResNet50, GoogleNet, AlexNet
- Shallow CNN
- Faster CNN
- Mask RCNN
- YOLO V3
- Single Shot MultiBox Detector (SSD) Model.

Proposed Solution of the Current Paper - aGROdet

- Detect plant diseases.
- Estimate corresponding leaf damage.

- Identification of the disease -
  - Convolutional neural network-based method.
- Estimation of the severity of leaf damage –
  - Pixel-based thresholding method.

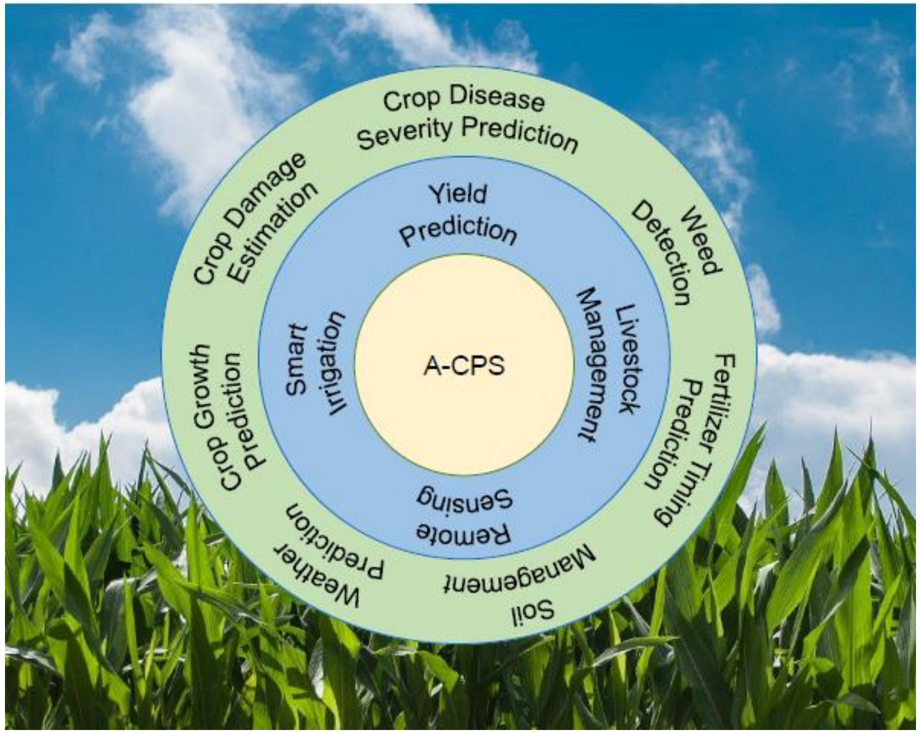


- Regular monitoring of fields and checking conditions of the plants through aGROdet can detect the disease early.

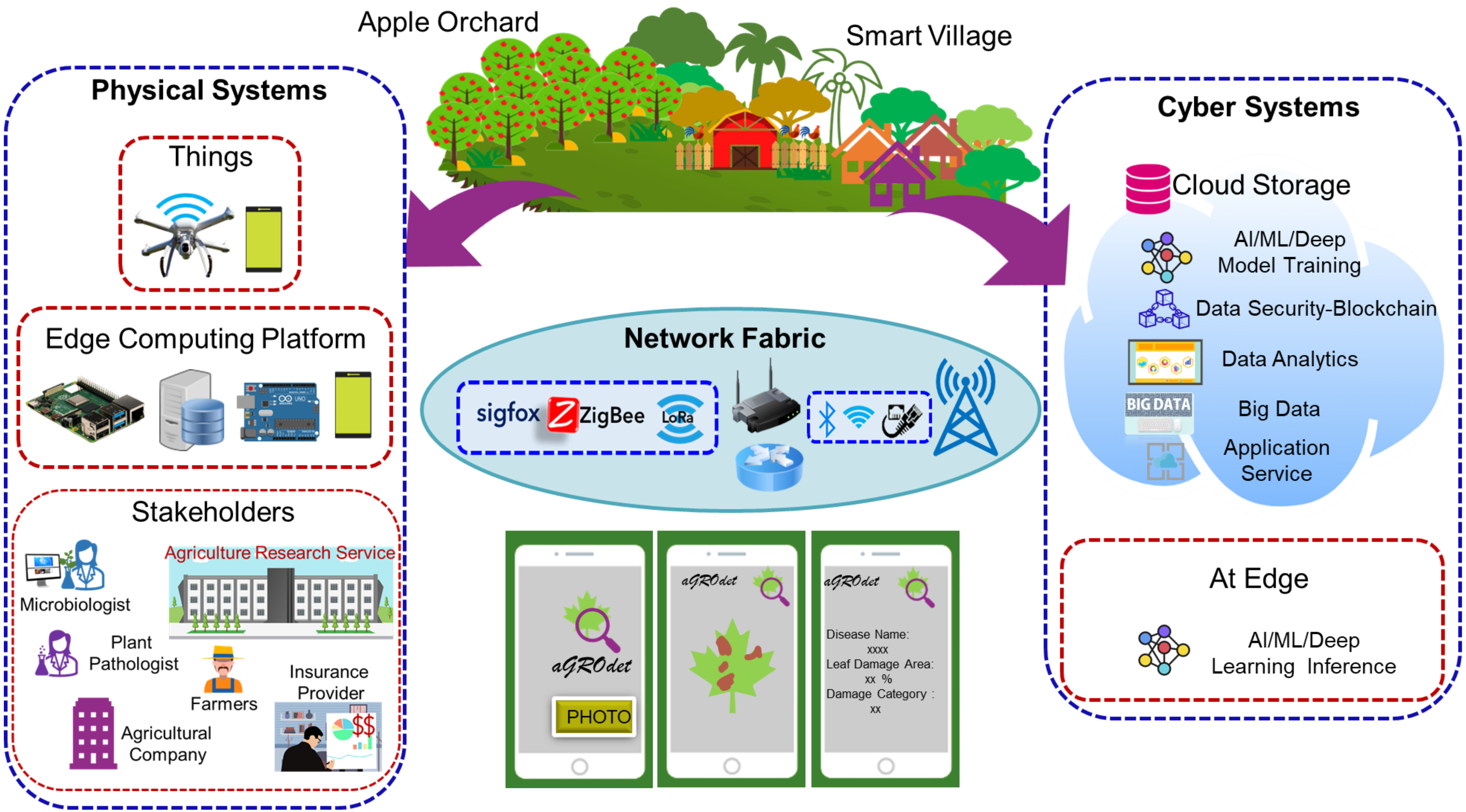
aGROdet - Proposed Method

- Fully Automatic Method
- Accessible through Mobile App (Not included in the Paper)
- As majority of the manifestation of plant disease on leaves, damage is estimated for leaves.

- Three parts of the solution –
  - Proposed A-CPS.
  - Detection of Plant Disease.
  - Estimation of the severity of leaf damage .

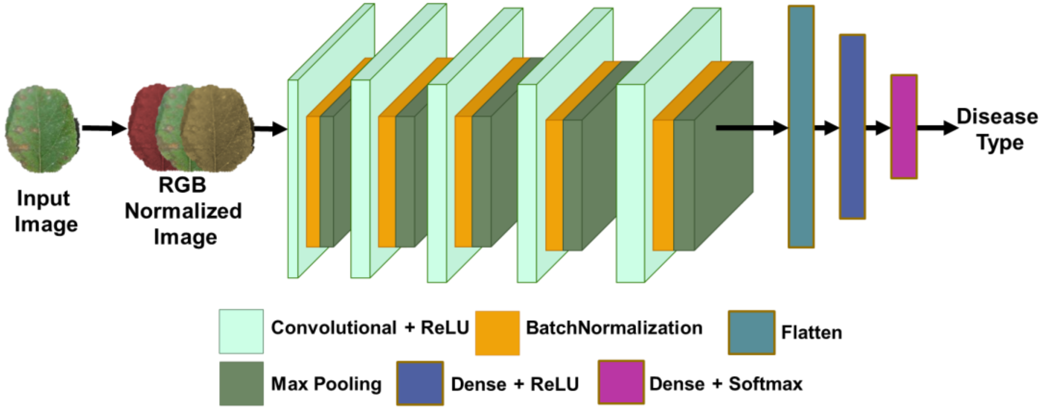


Proposed A-CPS



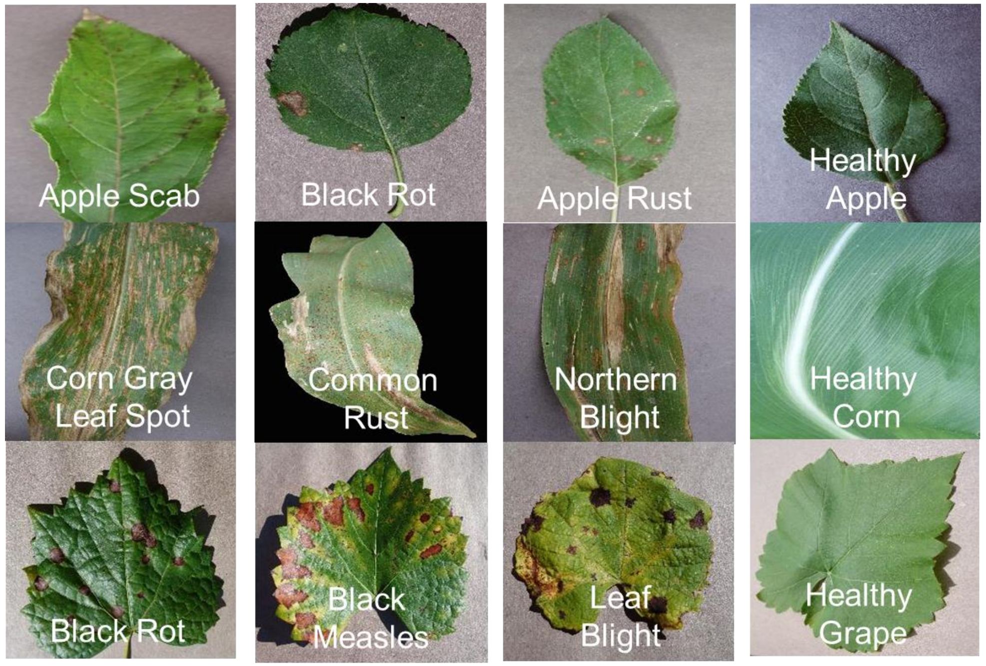
Plant Disease Detection

- CNN-based method for identifying plant diseases from images of leaves.
- Multi-class image classification problem.
- Model learns to label images through supervised learning.
- Predicts the label of an unknown image.
- The model learns the features of the labeled images during training and classifies the unknown and unlabeled images with a confidence score.



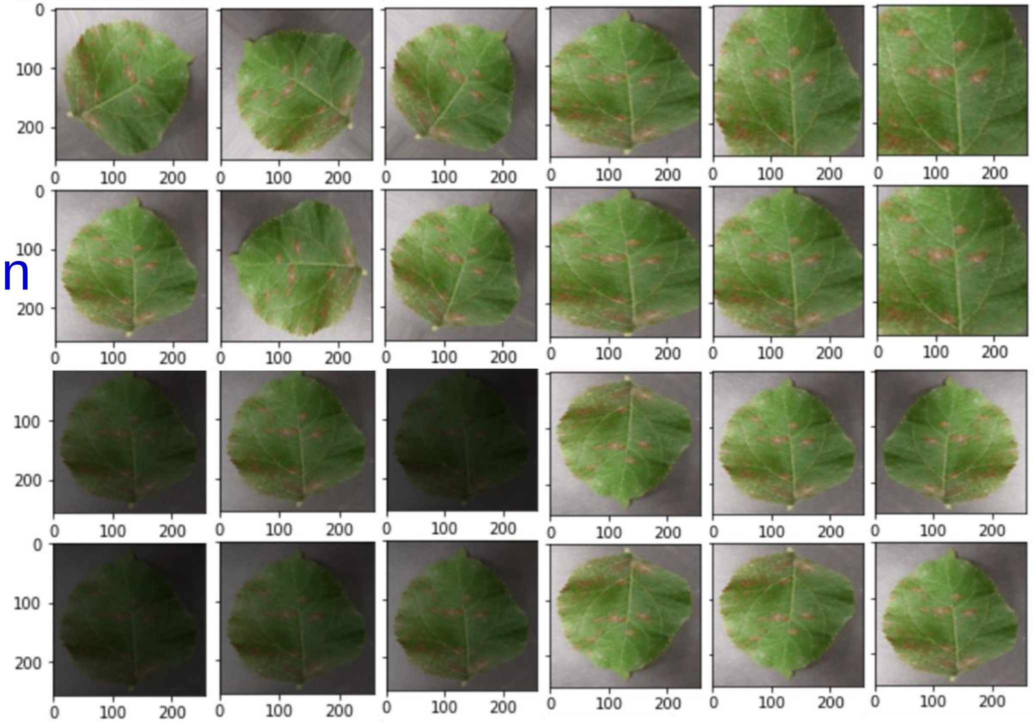
- 5 convolutional blocks.
- Each block - Convolutional layer with ReLU activation + BatchNormalization layer + MaxPooling layer.
- Number of Filters – 32, 64, 64, 64, 128.
- Final layers: Flatten + Dense with ReLU + Dense with Softmax.

Dataset Processing



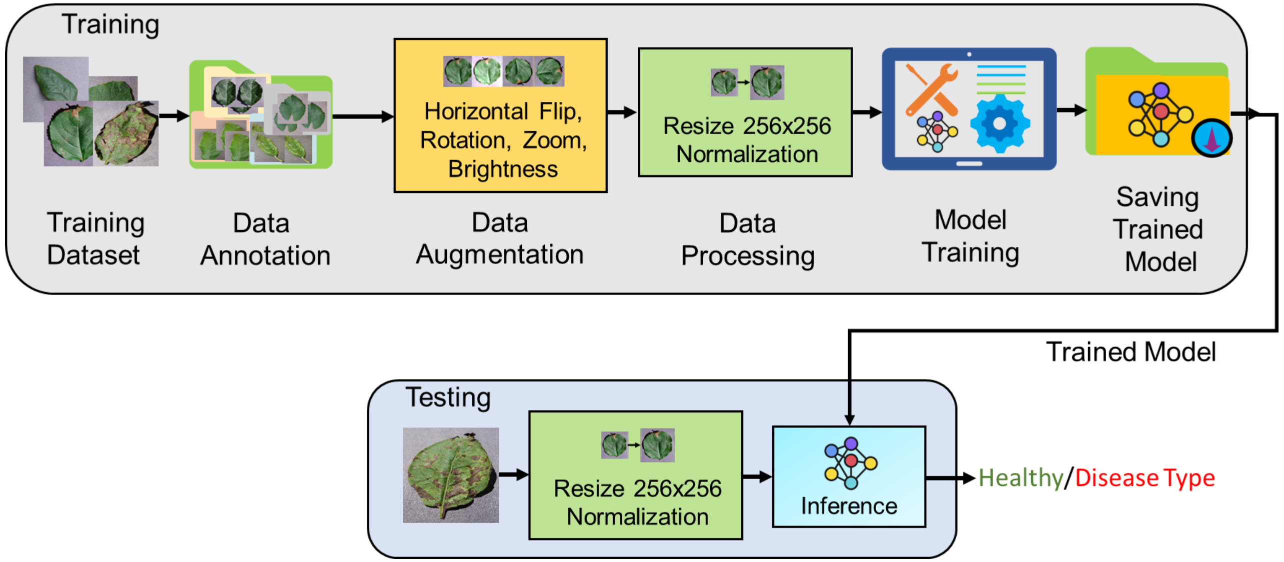
- 55, 448 images of 39 different classes.
- 38 classes related to plants' leaves.
- 1 class for images with no leaves.
- 49, 886 images used for training and validation.
- 5, 562 images for testing. the method.
- 80% - 20% distribution for training and validation.

Data Augmentation



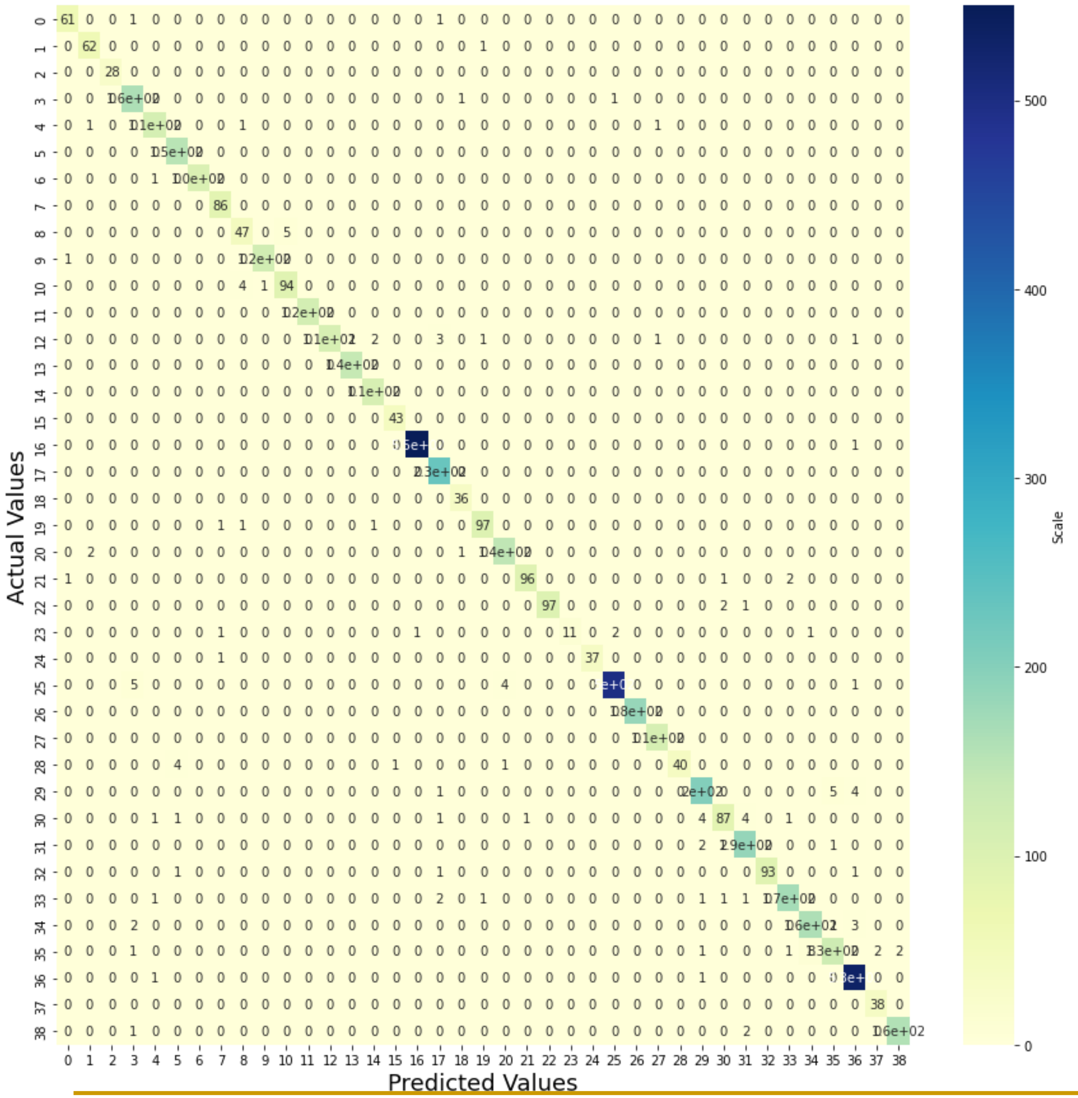
- Data augmented on the fly
- Rotation, Zoom, Brightness, Horizontal Flip.

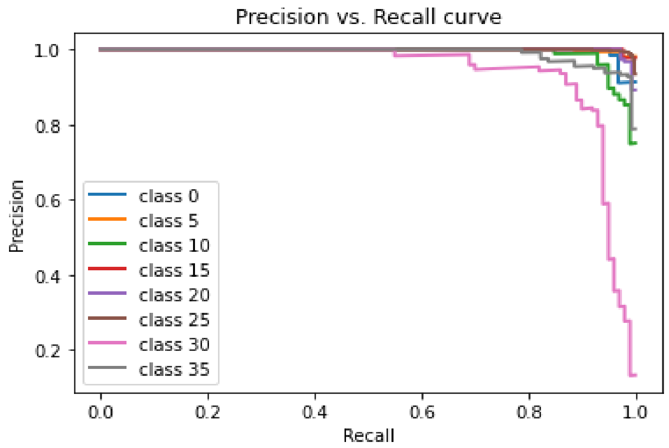
Plant Disease Detection Workflow

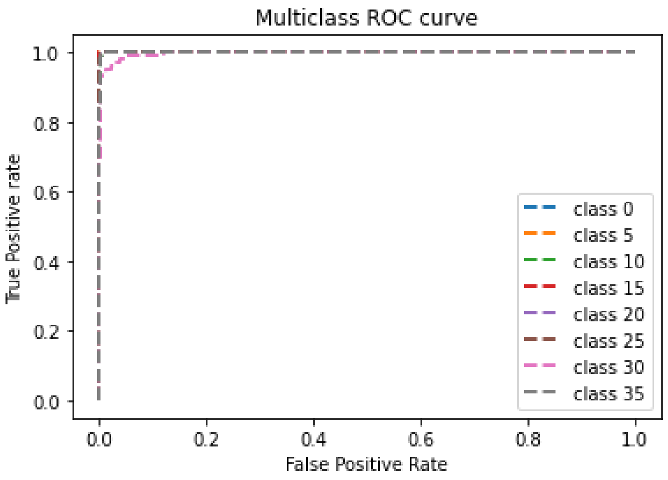


- The augmented and preprocessed data is used for training the network.
- Adam optimizer with an initial learning rate of 0.001.
- Model trained for 75 epochs.
- Model trained with and without a reduced learning rate of factor 0.1.
- Trained model is saved for future inference.
- Model evaluated using unseen 5, 562 images.
- Implemented in Keras with TensorFlow back end.

Performance Evaluation of Disease Detection







- Results are for Training without reduced learning rate.
- Classes are denoted by numbers instead of the class names to fit into the space.

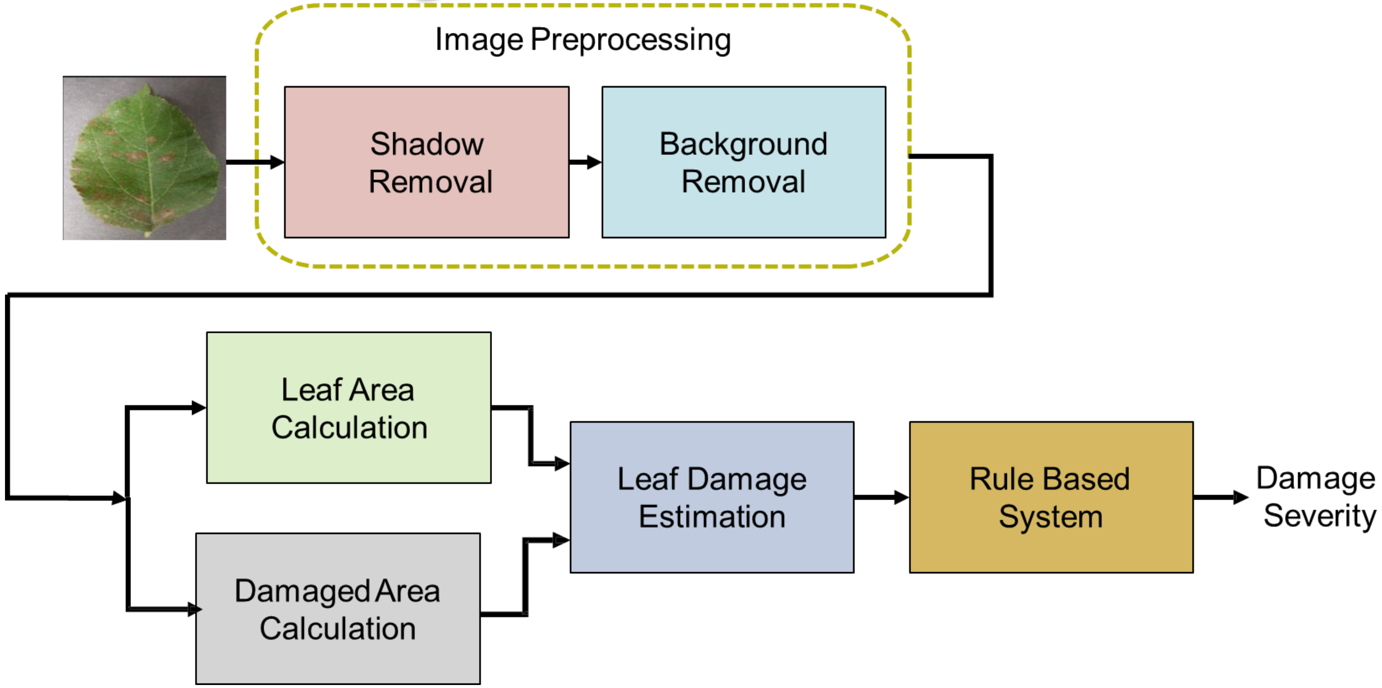
Results for Disease Detection Network

Training Type	Accuracy (%)		
	Training	Validation	Testing
Without reduced learning rate	97.62	97.42	97.68
With reduced learning rate	98.89	98.41	98.58

Works	Disease Type	Accuracy (%)	Damage Estimation
Ji et al. [12]	Multi Disease	86.70	Yes
Mohanty et al. [22]	Multi Disease	99.35	No
Ji et al. [13]	Single	98.57	No
Wang [37]	Single	96.26	No
Ozguven et al. [26]	Single	95.48	No
Pallagani et al. [27]	Multi Disease	99.24	No
Current paper	Multi Disease	98.58	Yes

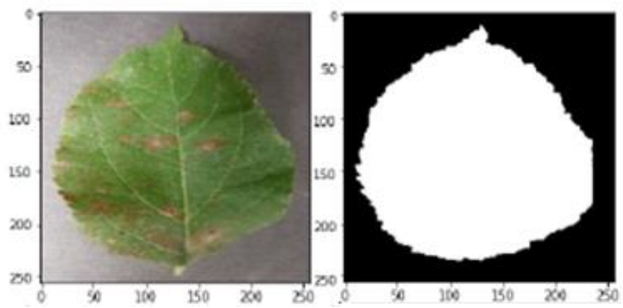
Leaf Damage Severity Estimation

- To estimate leaf damage severity –
  - Leaf area and damage area are calculated.
  - Ratio of these two areas gives the percentage of leaf damage.
  - Finally, a rule-based system predicts the damage severity.

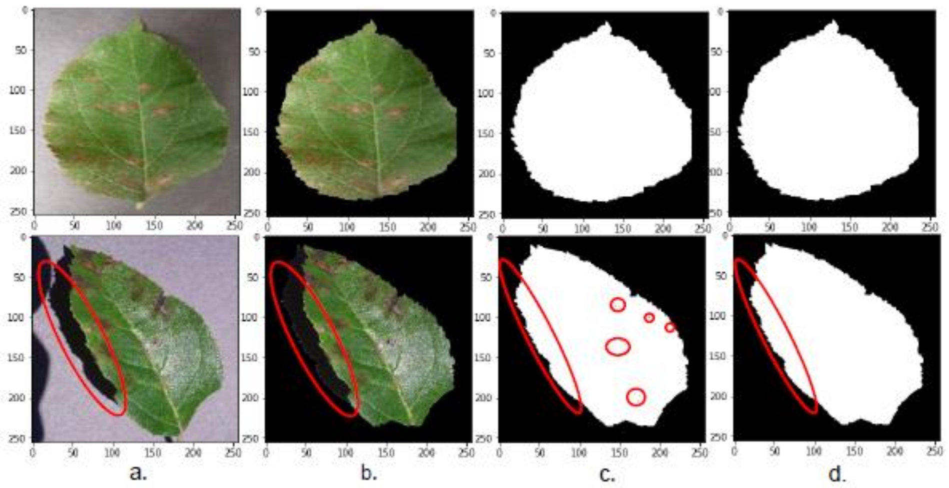


Leaf Area Detection

- First leaf area is detected.
- Next a mask is created for the leaf. Background segmentation and thresholding used to create the mask.
- Finally, the area of the mask is calculated to obtain the leaf area.



Leaf Area Detection



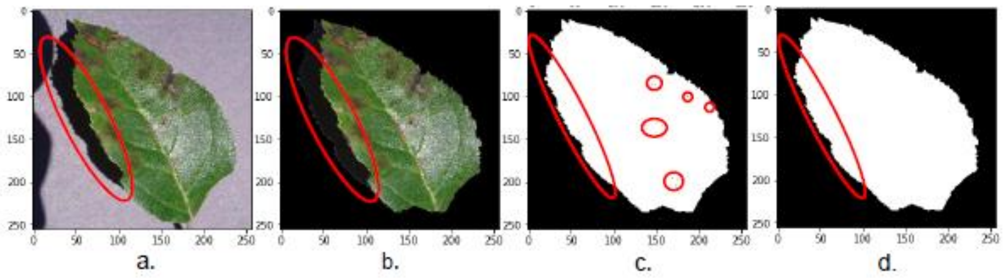
Leaf Area Detection by Creating Leaf Mask.

a. Input Image
b. Background Segmentation
c. Mask Creation for the Leaf
d. Noise Reduction from the Mask. Red large ovals show the shadow around the foreground object and small circles highlight the shadows on the foreground object.

- Background Segmentation:
- GrabCut algorithm for Background Segmentation.
- A large rectangle of size 226x226 is drawn over 256x256 image to ensure that the whole foreground object or leaf stays within the Region of Interest (ROI).
- Once the ROI is defined, the GrabCut algorithm applies a Gaussian Mixture Model (GMM) to the ROI.
- Foreground pixels are segmented from the background pixels by minimizing a cost function, which is the summation of the weights of the cut edges.
- Iterated the process 5 times to segment the leaf from its background.
- After segmentation, background pixels are turned black for the next step of processing

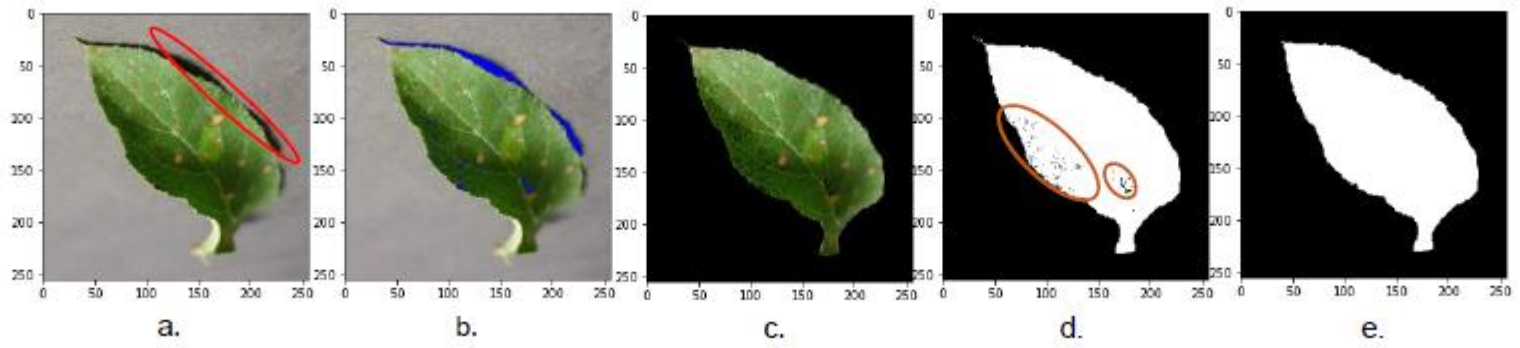
Leaf Area Detection: On-leaf Shadow Removal

- Shadows can be present on and around the leaves.
- They have an impact on accurate leaf detection.
- Outer shadow (red ovals) increases the leaf area.
- On-leaf shadows (red circles) hinder the creation of a perfect mask for the leaf.
- **Leaf Mask Creation-**
  - Leaf images of RGB color space is transformed to HSV color space.
  - Thresholding is performed over black color as c.
  - As the foreground object, a leaf, is our object of interest, the mask is inverted.



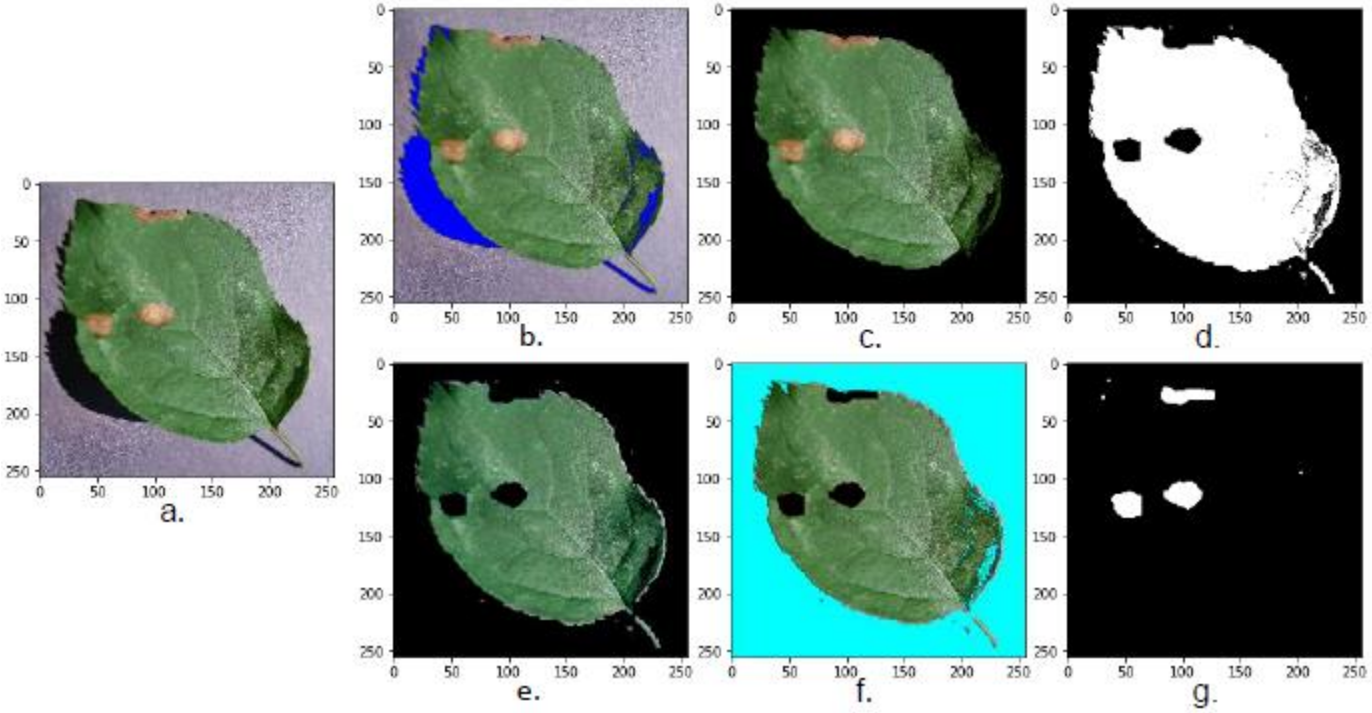
- **On-leaf Shadow Removal** -
  - But several masks have noise due to specular reflection and shadows on the leaf. This noise has been shown in small red circles in c.
  - Hence, the largest contour, selected from the foreground image, is drawn over the mask as in d.
  - It gives a perfect on-leaf noise-free mask for the leaf.
  - Still, it has outer shadow.

Around the Leaf Shadow Removal



- Around the leaf shadows have been removed before background segmentation.
- As in b, pixel-based thresholding is performed to select the shadow.
- The area around the leaf shadow part is then segmented from the foreground leaf during background segmentation, as in c.
- It is removed through contour selection during final mask generation as in d.
- Finally, the final mask is made noise free in e.

Damage Area Detection



Start

↓

Detection of Shadow around the Leaf

↓

Shadow Removal

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Leaf Mask Creation

↓

Merging of Mask and Input Image

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Recoloration of Black Background

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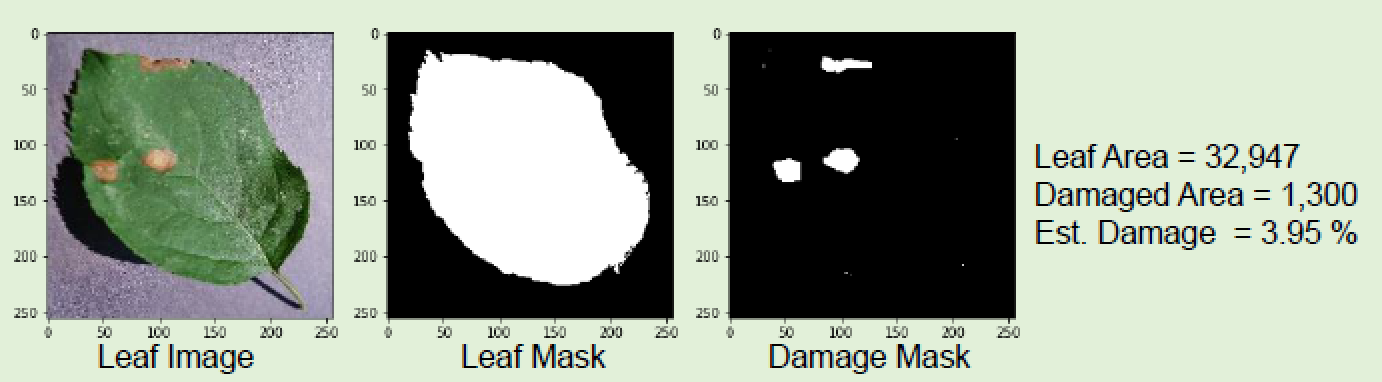
Damage Mask Creation

Leaf Damage Estimation

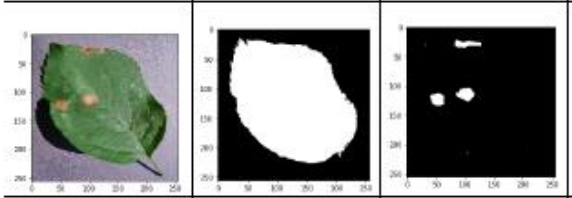
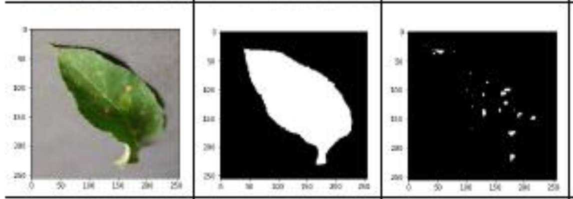
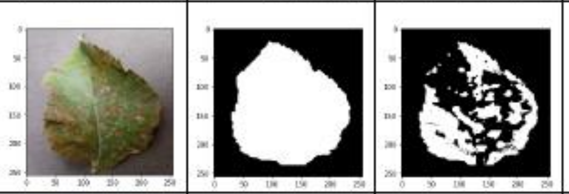
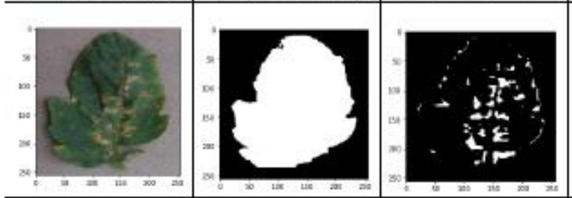
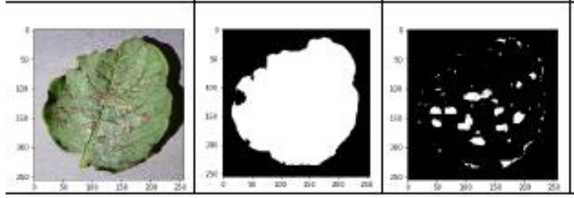


Damage Severity Grade Scale

Estimated Damage (%)	Damage Severity Grade
0	Healthy
>0 and <=5	1
>5 and <=10	2
>10 and <=25	3
>25 and <=50	4
> 50	5

- A rule-based system decides the severity of the damage to the leaf.
- As per the table, the damage severity grade of the damaged leaf in the above figure is Gr-1 as the damage is between 0 and 5%.

Results of Leaf Damage Estimation

Image	Leaf Mask	Damage Mask	Estimated Damage (%)	Damage Severity Grade
			3.95	1
			2.97	1
			53.49	5
			10.69	3
			9.49	2

- Achieved-
  - Damage estimation by aGROdet is not affected as damage masks even in the presence of shadows.
  - When there is some specular reflection in the image, aGROdet can still correctly estimates the damage of leaves.
  - No experiment for corn leaf images in the dataset as whole leaf is not visible.

- Limitations –
  - For variegated plants (e.g., Abelia, Azalia, Boxwood, Cape Jasmine, Hydrangea, and Lilac)- healthy leaves have other colors (yellow or white) damage estimation is not correct.
  - It takes yellow color as the abiotic stress.

Conclusions

- A novel method, aGROdet, has been proposed for plant disease detection and leaf damage estimation.
- aGROdet has a very high success rate in detecting disease and estimating leaf damage.
- Even when there are shadows in the image, aGROdet accurately calculates the damage.
- aGROdet accurately estimates damage, even in the presence of some specular reflection.
- aGROdet has been built for single leaf image. But, when the images are taken with a cell phone camera or UAV, there will be several leaves in the same image. Hence, a single leaf image needs to be detected from the shot image before applying aGROdet.

Future Work

- Now, aGROdet detects single leaves disease. In real life, when the images are taken with  , there will be several leaves in the same image. Hence, a single leaf image needs to be detected from the shot image before applying aGROdet.
- Inclusion of variegated leaves' damage estimates would be a good addition.
- Extent of damage is another area that needs attention.
- Here, only the top of the leaves are considered. In the future, other parts of the plants affected by disease need to be considered too.
- More work on the removal of shadows and specular reflections is needed.
- Inclusion of damage estimation in the presence of the pest would be an interesting task too.
- More publicly available datasets will be an important addition to this research.

Thank You !!