LEAVES CLASSIFICATION

CV A & C

9th February 2024

Meet the Team

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Training

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Amar Ma’ruf

Exploratory Data Analysis

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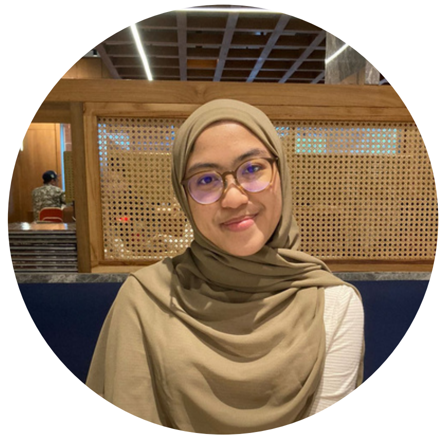
Training

Moch Ardhi Kurniawan



Mahdia Aliyya Nuha Kiswanto

Deployment

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Background & Problem Analysis

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Modelling

Muhammad Fatih Zuhdy

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Data Preparation & Problem Analysis

Fatah Abdul Jalil

Background & Problem Statement

The agricultural sector is currently grappling with challenges like climate change, pest infestations, and environmental stressors, necessitating innovative solutions for ensuring food security and sustainable crop production, especially for the upcoming challenges associated with quality food.

One crucial facet is early detection of plant health issues, prompting the development of an efficient leaf classification system capable of categorizing leaves as healthy, sick, or withered (dead).

This system, driven by advanced image analysis and machine learning, aims to empower farmers with a rapid and reliable tool for crop assessment. Therefore, the urgency of implementing such a solution is evident in its potential to transform agricultural practices, ensuring a more resilient and productive future for global food production.

Objectives & Scope

The objectives of this agricultural solution theough the classification of leaves include:

1. Early Detection: Enable farmers to identify plant health issues at their early stages, facilitating timely intervention.

2. Resource Optimization & Cost-Effectiveness: Contribute to efficient resource management by aiding farmers in optimizing inputs such as water, fertilizers, and pesticides, which in turn saves farmers from spending unnecessary treatments and interventions.

3. Global Food Security: Contribute to global food security by improving crop productivity and minimizing losses in the face of increasing demands and changing environmental conditions.

Data Collection & Preparation

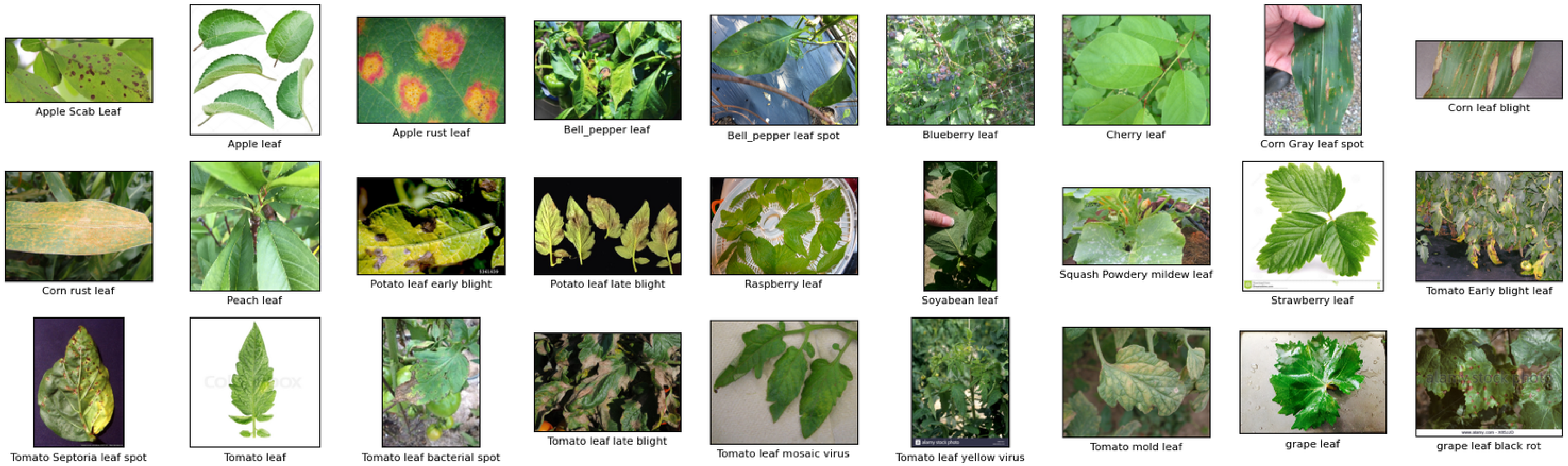
kaggle

Dataset Information:

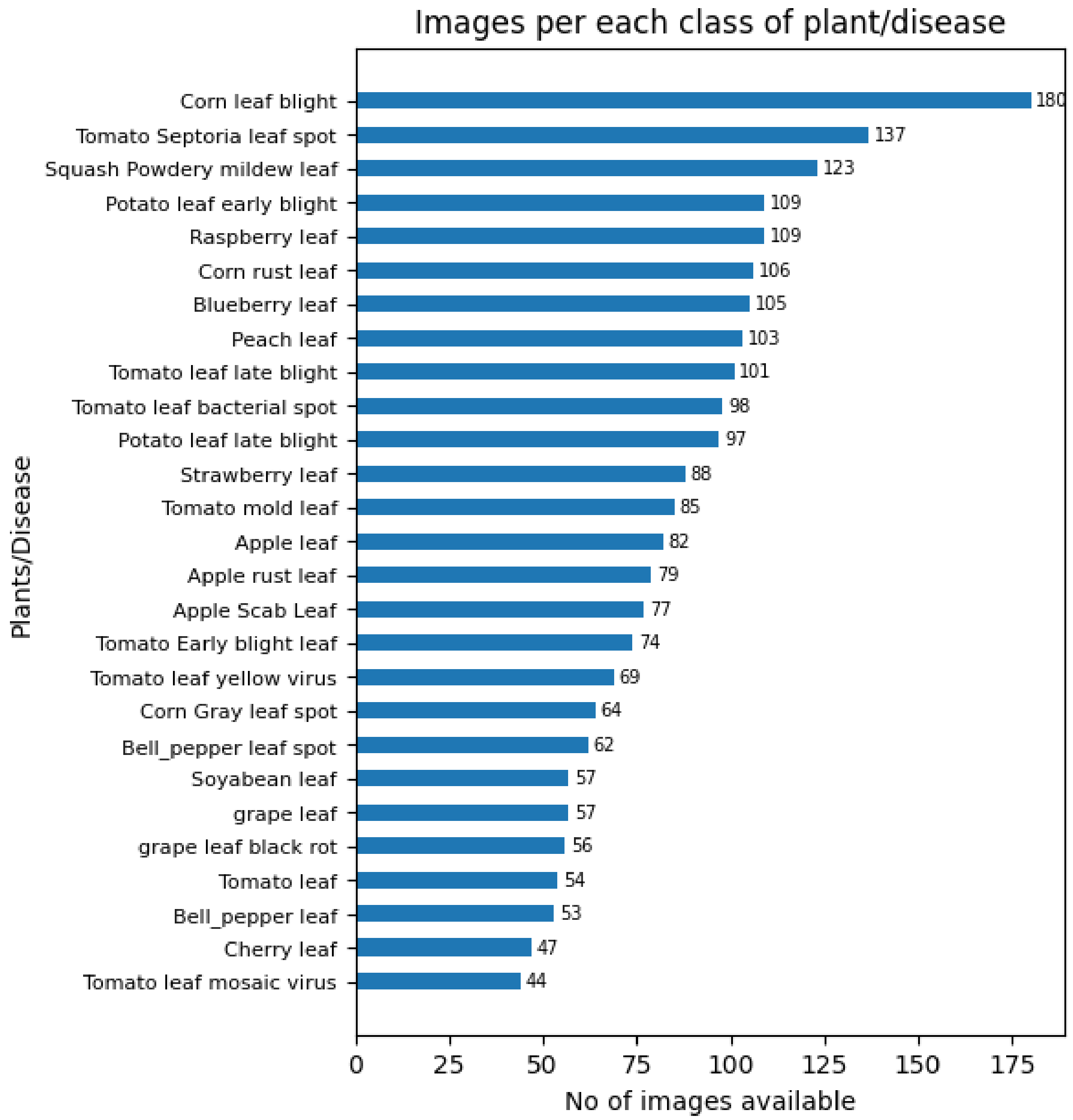
This dataset was about a condition that india recently had because they experience loses 35% of the annual crop yield due to plant disease. This dataset provides some information about the condition of healthy and diseased leaf.

Dataset Description:

- This dataset was divided into 2 partition **Train** and **Test**
- Every partition has **27 classes** that represent every leaf conditions.
- Every class **DO NOT HAVE** same number of images.



Plant Doc Dataset



Data Collection & Preparation

Dataset Distribution:

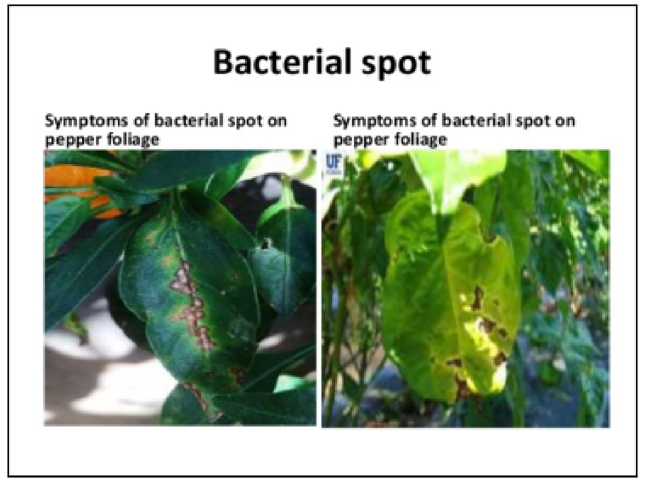
2316
Total Images

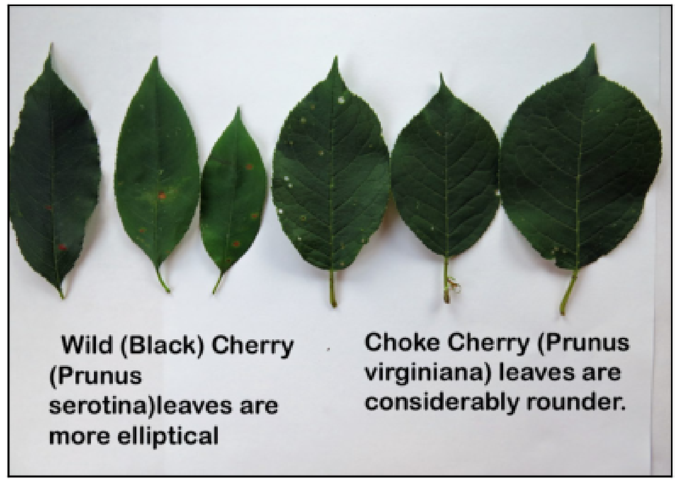
1853
Train Images

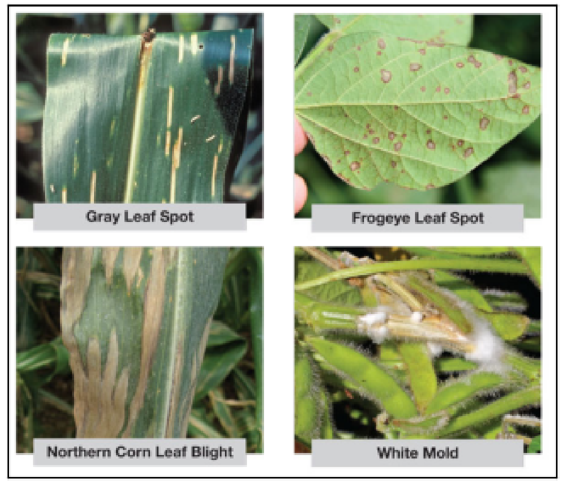
18
Broken Images

463
Test Images

7
Broken Images

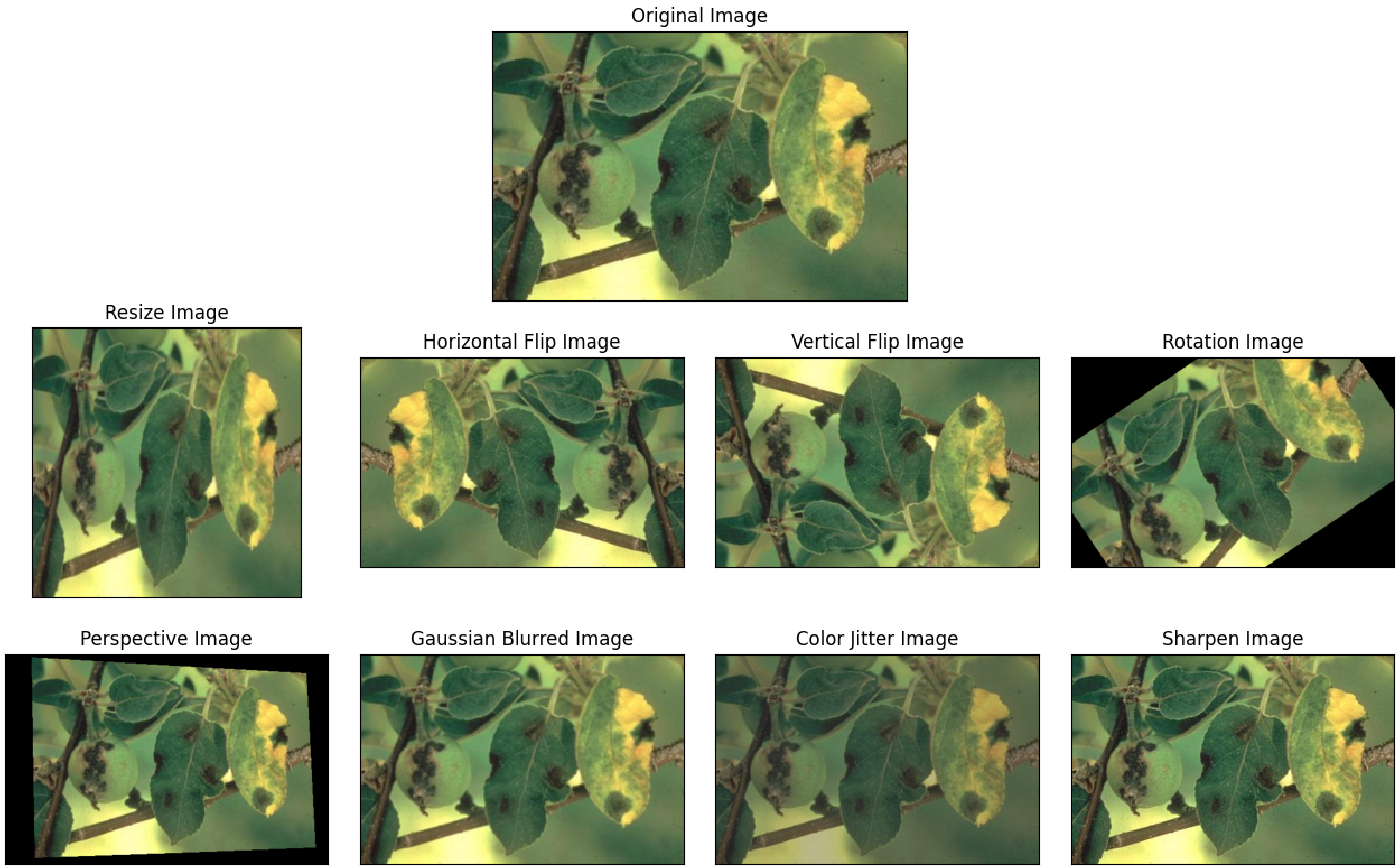






Data Augmentation:

Plant Doc Dataset



Model Development

After we did cleanse our data and add transformation process such as augmentation, next we put our data into model to train our system to identify which images belongs to **1 of 27** leaf class.

We train **1835** Images out of **2316** and the rest for the test data **456**

Classification Model

VGG 19

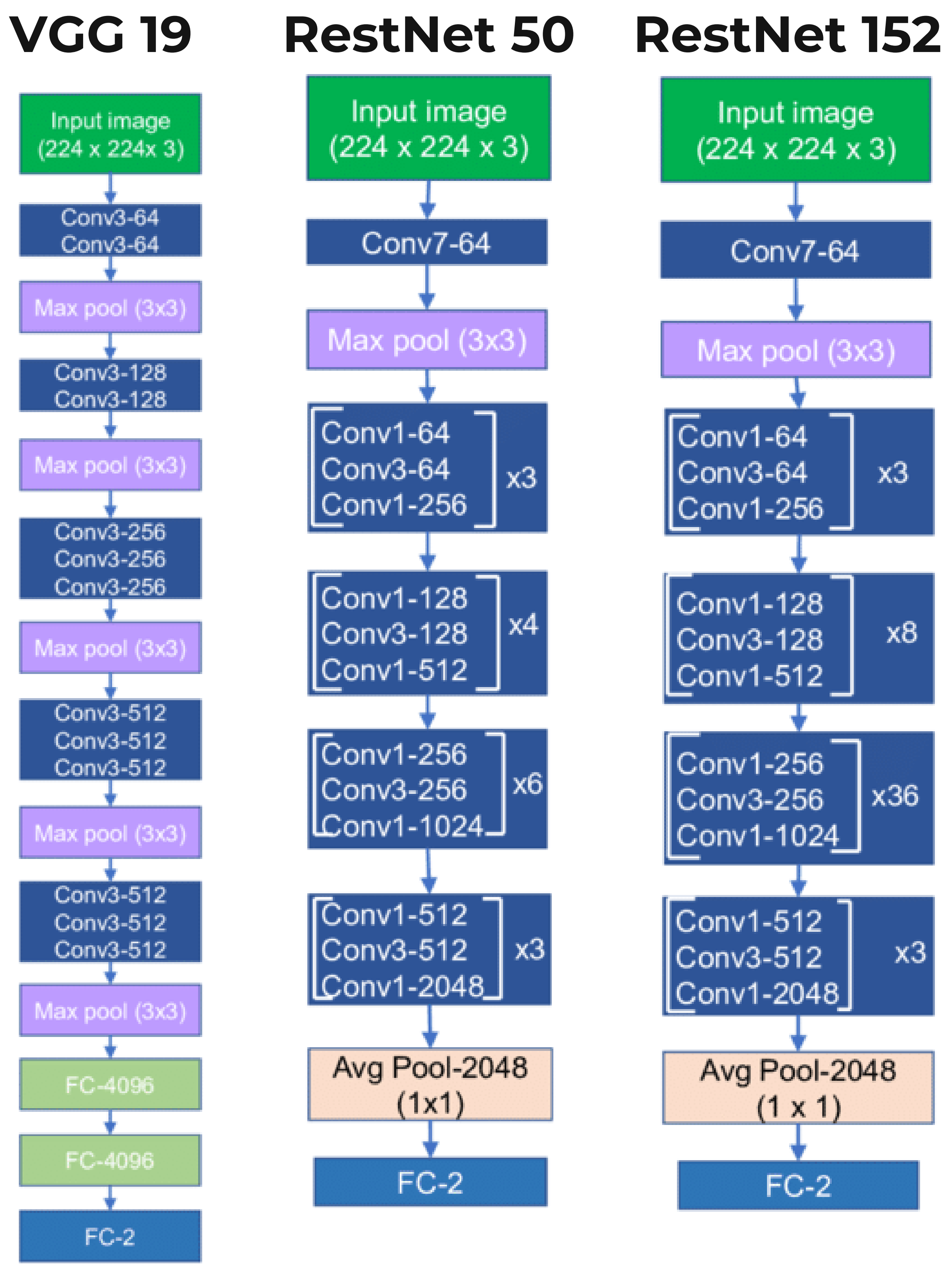
VGG-19 (Visual Geometry Group 19) is a deep convolutional neural network (CNN) architecture that was developed by the Visual Geometry Group at the University of Oxford. VGG-19 is an extended version of the original VGG-16 architecture, with 19 layers (16 convolutional layers and 3 fully connected layers).

RestNet 50

The convolutional layers in ResNet50 consist of several convolutional layers followed by batch normalization and ReLU activation. These layers are responsible for extracting features from the input image, such as edges, textures, and shapes. The convolutional layers are followed by max pooling layers, which reduce the spatial dimensions of the feature maps while preserving the most important features.

RestNet 152

Compared to its first version, ResNet152 provide comprehensive empirical evidence showing that these residual networks are easier to optimize and can gain accuracy from considerably increased depth. It is also evaluated on ImageNet dataset with a depth of up to 152 layers---8x deeper than VGG nets but still having lower complexity.



Training & Optimization

First, before deletion of bad images, no weighting classes

Model	Epoch	Optimizers	Learning Rate	Momentum	Train Loss Best	Train Acuracy Best	Validation Loss Best	Validation Accuracy Best	Testing Accuracy
RESNET50	30	SGD	0.001	0.9	0.391	87.696	1.024	68.035	58.051
		SGD	0.001	0.5	1.735	51.646	1.837	48.596	43.22
		SGD	0.001	0	2.592	33.297	2.643	36.933	25.424
		SGD	0.01	0.9	0.332	88.667	1.142	67.819	58.051
		SGD	**0.01**	**0.5**	**0.443**	**85.807**	**1.065**	**68.035**	**63.136**
		SGD	0.01	0	0.37	86.297	1.017	67.756	60.699
		ADAM	0.001	-	0.767	74.96	1.341	58.963	-
		ADAM	0.01	-	2.996	11.927	3.011	15.119	7.627
RESNET152		SGD	0.001	0.9	0.381	88.559	1.071	65.227	60.593
		SGD	0.001	0.5	1.438	60.443	1.635	53.132	50.847
		SGD	0.001	0	2.353	38.37	2.429	37.797	31.356

Training & Optimization

After deletion bad images, adding weighting classes

Model	Epoch	Optimizers	Learning Rate	Momentum	DropOut	Train Loss Best	Train Acuracy Best	Validation Loss Best	Validation Accuracy Best	Testing Accuracy
RESNET50	30	sgd	0.01	0.9	0	0.803	71.126	1.163	66.231	56.769
		sgd	0.01	0.9	0.15	0.742	74.551	1.236	62.527	58.952
		sgd	0.01	0.9	0	0.476	83.796	1.114	70.37	61.572
		sgd	0.01	0	0.15	0.484	83.415	1.045	70.588	62.445
		sgd	**0.01**	**0**	**0**	**0.334**	**89.638**	**1.094**	**65.659**	**65.678**
	50	sgd	0.01	0.9	0	0.356	87.858	1.290	61.771	60.593
RESNET152	30	sgd	0.01	0.9	0	0.577	79.5	1.293	63.834	62.882
		sgd	0.01	0.9	0.15	0.586	79.608	1.193	62.309	56.769
VGG19	30	Adam	0.0001	-	0.15	0.712	74.008	1.45	61.656	54.585
	50	Adam	0.0001	-	0.15	0.725	74.986	1.249	62.527	52.402
	30	SGD	0.001	0.9	0.15	1.073	63.948	1.319	60.131	56.332
	50	SGD	0.001	0.9	0.15	0.912	68.787	1.171	63.617	50.655
	50	SGD	0.001	0.9	0	0.829	72.099	1.273	64.147	59.322

Results

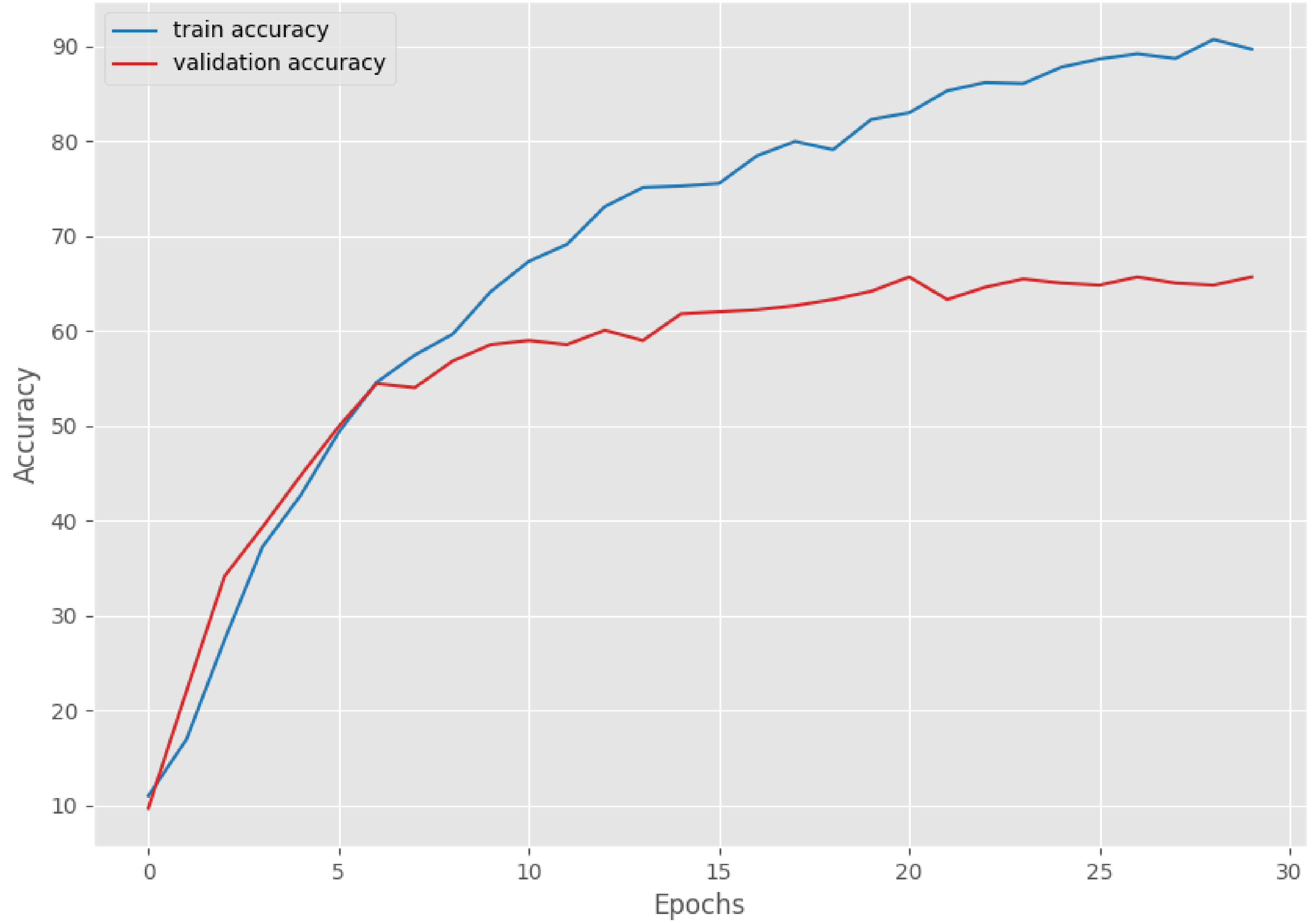
Model	Best Model Result				
	Train Accuracy	Train Loss	Validation Accuracy	Validation Loss	Test Accuracy
Resnet50	89.638	0.334	65.659	1.094	65.678
Resnet152	79.5	0.577	63.834	1.293	62.882
VGG-19	72.099	0.829	64.147	1.273	59.322

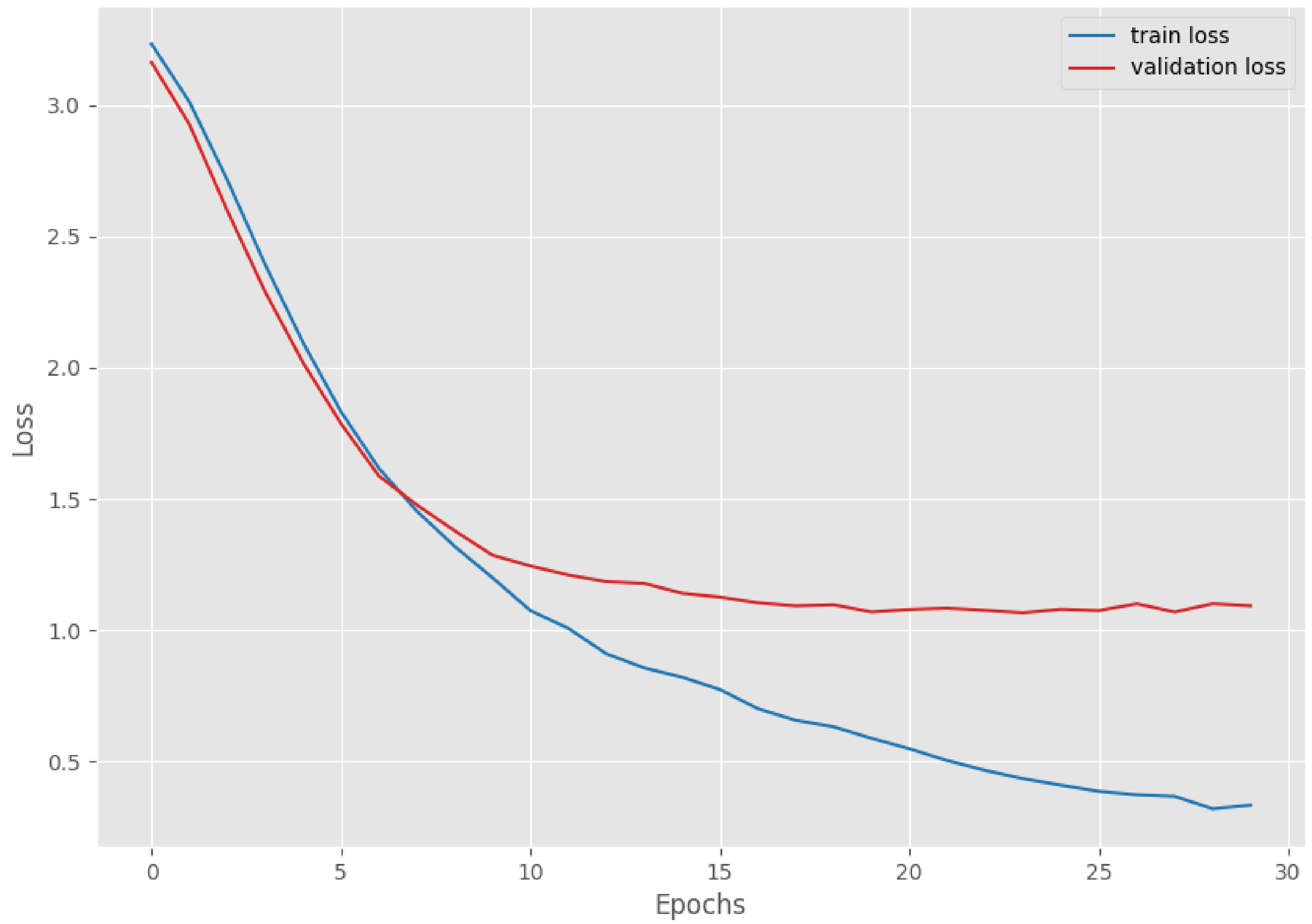
Resnet50

Best Model Result

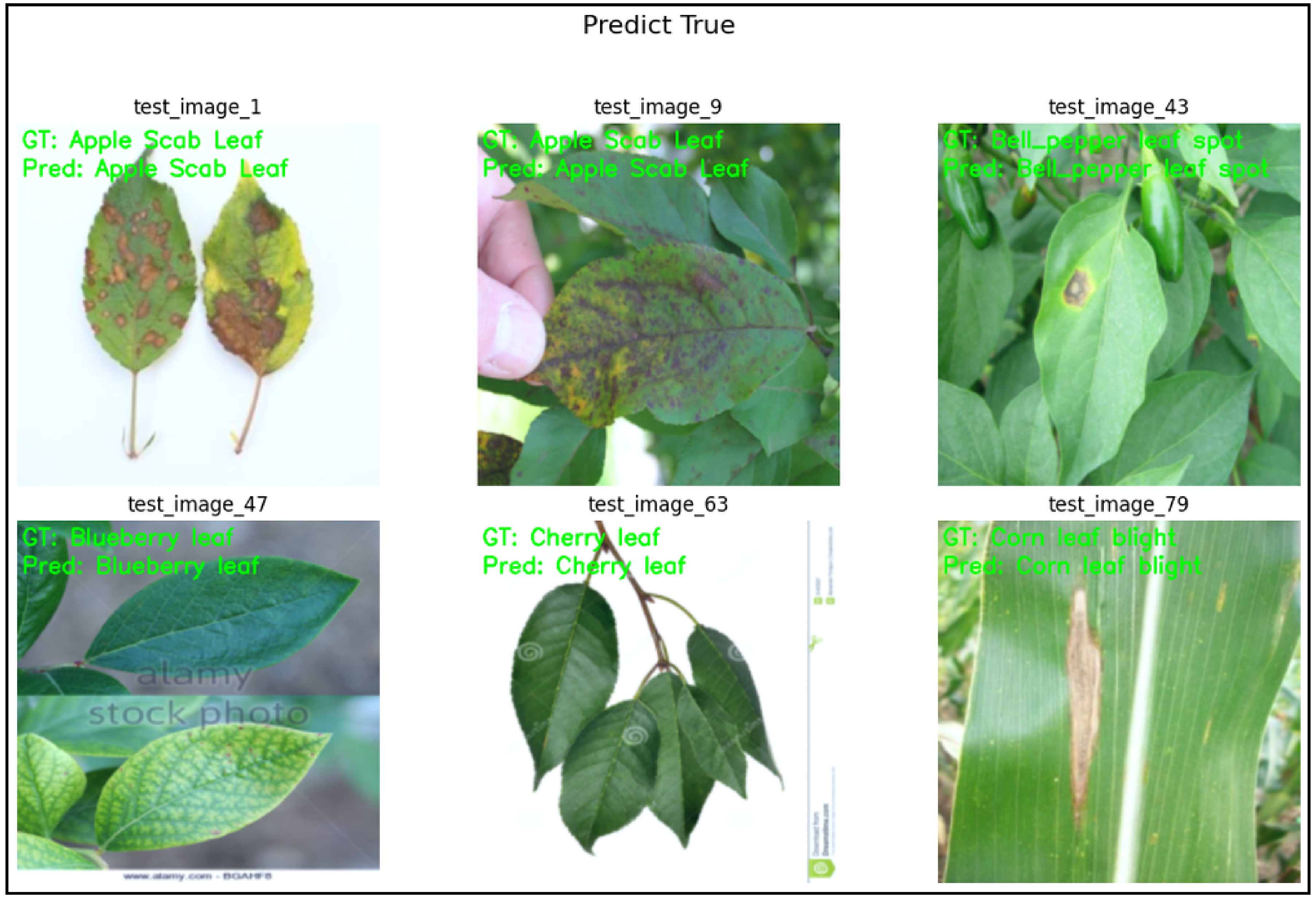
25

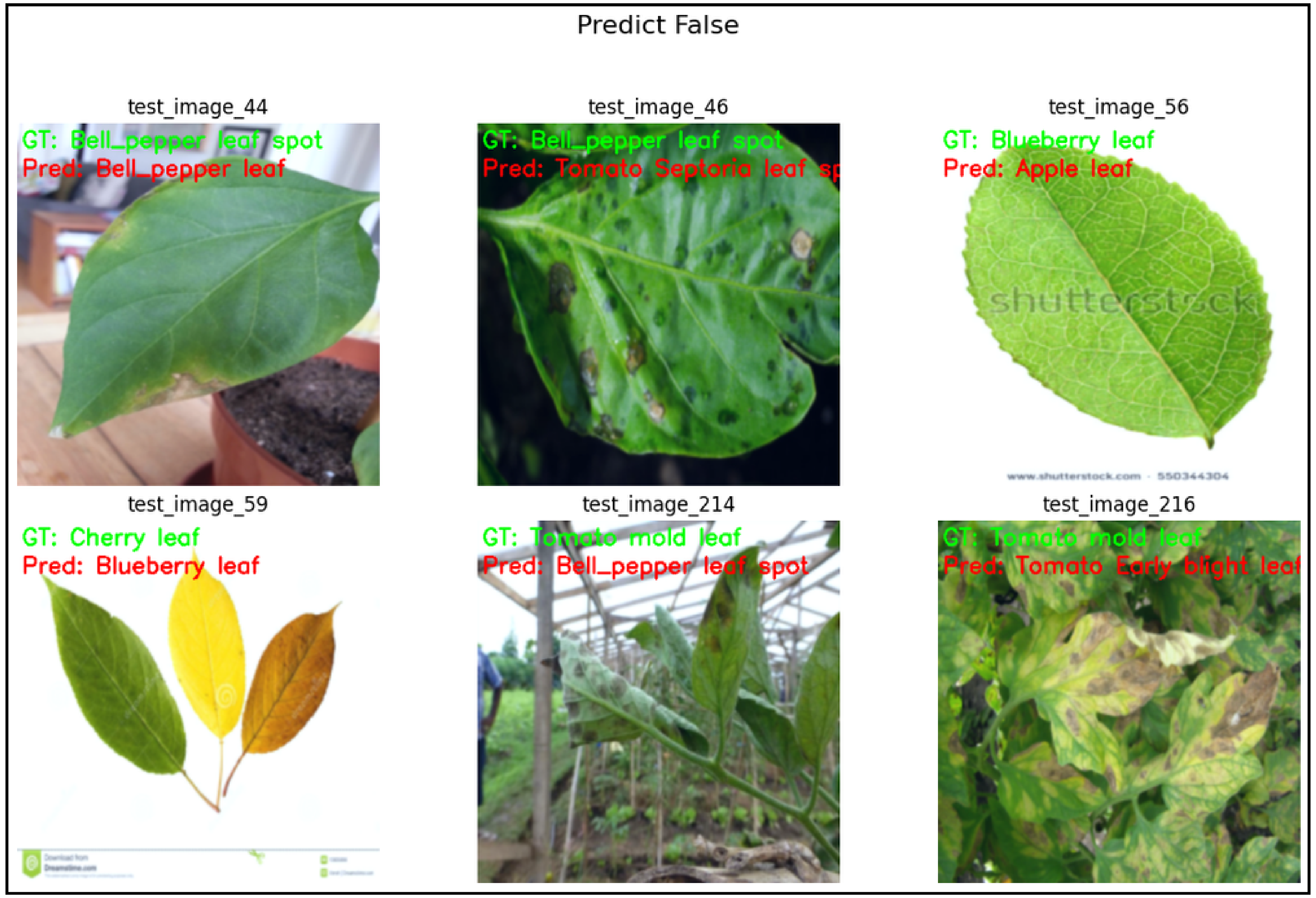
Best Model Epoch





Results


Predict True
test_image_1
GT: Apple Scab Leaf
Pred: Apple Scab Leaf
test_image_9
GT: Apple Scab Leaf
Pred: Apple Scab Leaf
test_image_43
GT: Bell_pepper leaf spot
Pred: Bell_pepper leaf spot
test_image_47
GT: Blueberry leaf
Pred: Blueberry leaf
alamy
stock photo
test_image_63
GT: Cherry leaf
Pred: Cherry leaf
test_image_79
GT: Corn leaf blight
Pred: Corn leaf blight


Predict False
test_image_44
GT: Bell_pepper leaf spot
Pred: Bell_pepper leaf
test_image_46
GT: Bell_pepper leaf spot
Pred: Tomato Septoria leaf sp
test_image_56
GT: Blueberry leaf
Pred: Apple leaf
shutterstock
test_image_59
GT: Cherry leaf
Pred: Blueberry leaf
test_image_214
GT: Tomato mold leaf
Pred: Bell_pepper leaf spot
test_image_216
GT: Tomato mold leaf
Pred: Tomato Early blight leaf

Future Improvement

LIMITATIONS:

- May be difficult to classify leaves which are covered by noisy background

FUTURE IMPROVEMENT:

- Retraining using a larger dataset to enhance testing accuracy.
- Conducting comprehensive data cleaning on images with significant noise.
- Experimenting with various models or architectures to align with the dataset.

Real-world Application

Plant disease detection system has the potential to revolutionize agricultural practices by providing farmers with timely and accurate information to better manage their crops and improve overall productivity and sustainability in agriculture.

With accessibility through their phone, farmers can take pictures of their crop leaves so they can easily detect any signs of disease or abnormalities and take actions accordingly,

https://plant-disease-detection-indonesiaai.streamlit.app/

Real-world Application

pot_late_blight.jpeg 8.8KB

Uploaded Image

Prediction:

Potato

Leaf Late Blight

89.24%

ap_rus.jpeg 13.0KB

Uploaded Image

Prediction:

Apple

Scab Leaf

61.41%

Conclusion

- Some of Images are deleted due to noises.
- We try to compare ResNet and VGG model which perform better for leaf image classification.
- There are 2 times training, before and after deleting bad images and insert weighting.
- For Training process, we use different parameter for each model such as Epoch, Optimizers, Learning Rate, Momentum.
- The highest result for training model is RestNet50 with results are Overfit.
- After testing the deployment using Streamlit, the results were quite good.

Contact Us

Don’t hesitate to contact us for further inquiries or any collaborations.

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