Apple Foliar Disease Detector

Preserving Apple Health

Introduction

Setting the Stage: AFD Detector's Introduction

Introduction:

- **Foliar diseases:** Delicate whispers of nature's challenges, prompting us to nurture and protect the orchards.
- **Safeguarding apple orchards:** Detecting foliar disease early to protect production and ensure the overall health of our apples.
- **Bringing technology to the orchard:** We use digital image processing to analyze apple leaf images and spot foliar diseases accurately.

Motivation

Uncovering the Need: AFD Detector’s Importance in Apple Farming

Motivation:

- **Apple as top 5 global fruit:** A leading global fruit, cultivated across vast acres of orchards.
- **Orchard care made tough:** Manually it's hard to know which plants are sick, what diseases each leaf has, what pesticides to spray and where to spray.
- **Revolutionizes orchard care:** Automating disease detection. Leveraging drone or satellite images.

Focus

Key Objectives and Scope: Defining the AFD Detector’s Role in Orchard Health

Focus:

- **Leaf Classification:** Main challenge involves precisely categorizing apple leaves into six distinct disease classes. This task forms the foundation for effective orchard management, ensuring timely and targeted interventions.
- **Key Objectives:** Maximize efficiency and save pesticides by precisely targeting affected trees and ultimately enhancing production.

Dataset

Data Source and Insights: Unpacking the AFD Detector's Dataset

Dataset:

- **Plant Pathology 2021 :** A competition on Kaggle. The main objective of the competition is to identify the category of foliar diseases in apple trees.
- **Unveiling Dataset:** The dataset comprises "train.csv" with image IDs and disease labels and 18,632 images for model training and evaluation.

Dataset: Snapshot

complex

rust

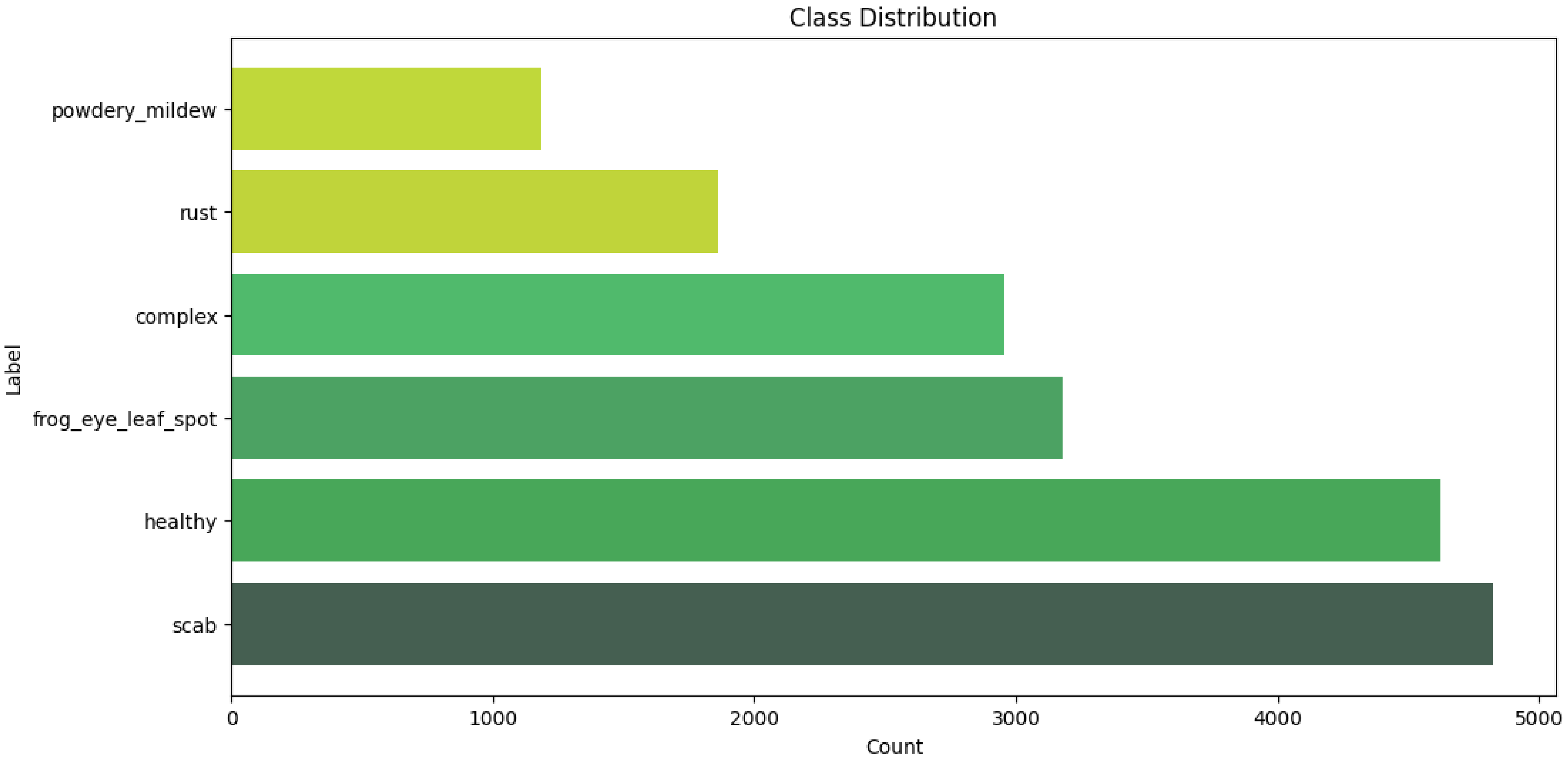
frog_eye_leaf_spot complex

scab

complex

powdery_mildew

Dataset: Class Distribution



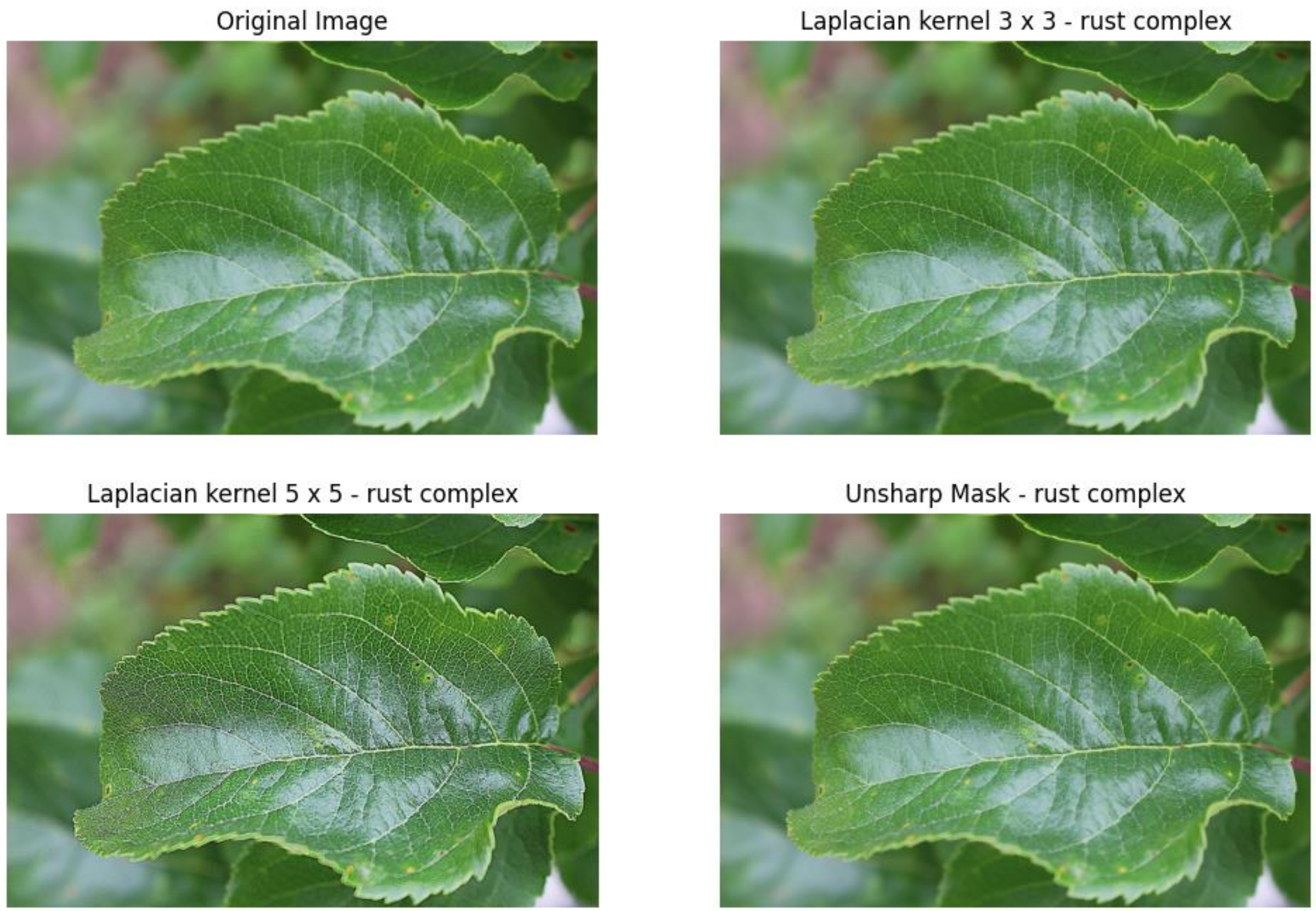
Preprocessing

Image Data Preparation: Preprocessing AFD Detector's Dataset

Preprocessing:

- **Preprocessing in Image Classification:** Preprocessing is a vital step in refining raw leaf images for optimal input into our classification model.
- **Sharpening:** Enhances image clarity and feature definition by accentuating edges.
- **Histogram Equalization:** Balances image contrast by redistributing pixel intensities.

Preprocessing: Sharpening



Preprocessing: Hist Equalization

Original

Original Image - scab

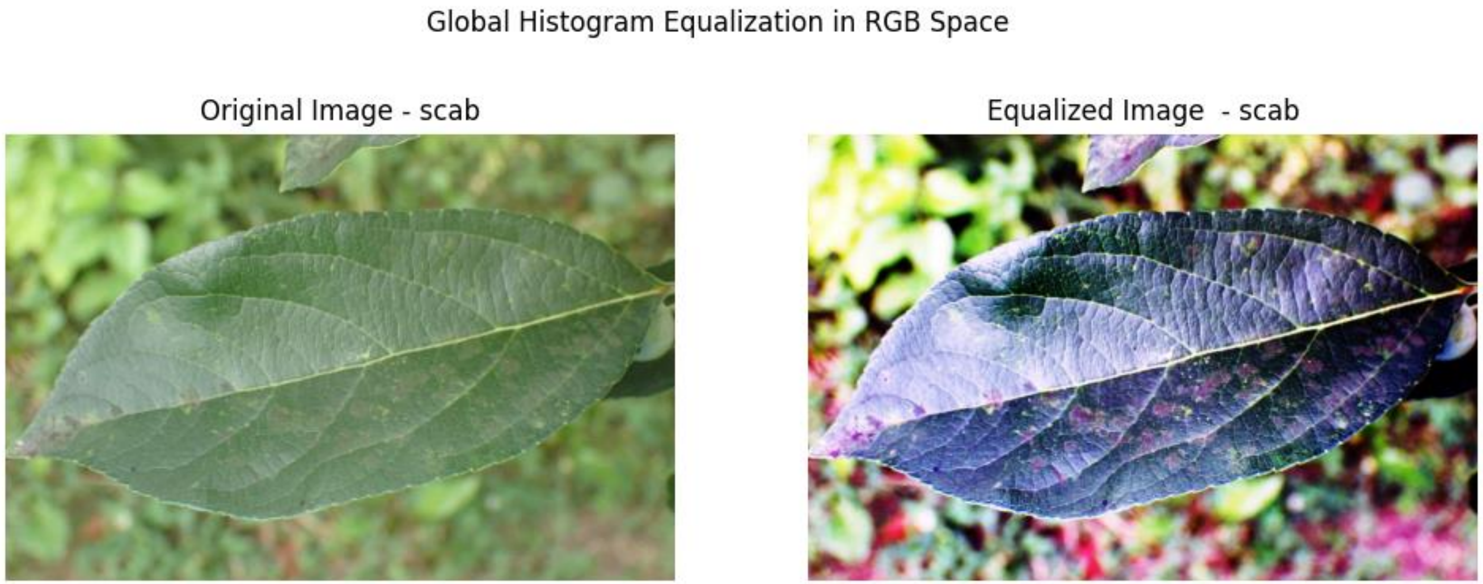
Global

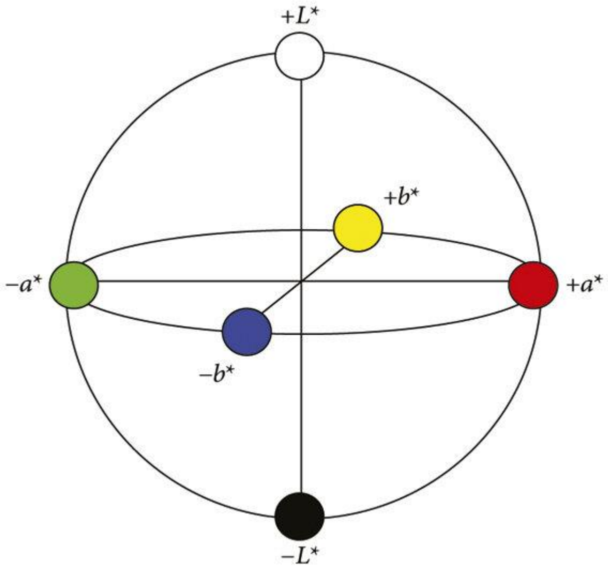
Equalized Image - scab

Local

Equalized Image - scab

Preprocessing: RGB vs LAB





Models

ML Models: Choosing AFD Detector’s Learning Model for Predictions

Models:

Aspect	CNNs	SVMs
Type of Algorithm	Neural Network	Linear Classifier
Architecture	Deep, hierarchical	Single-layer or kernel
Feature Learning	Automated	Requires Engineering
Data Type	Often used for images	General data types
Non-linearity	Inherently nonlinear	Linear or kernel trick
Interpretability	Less interpretable	More interpretable
Scalability	Resource-intensive	Efficient for high-D data
Transfer Learning	Effective	Limited

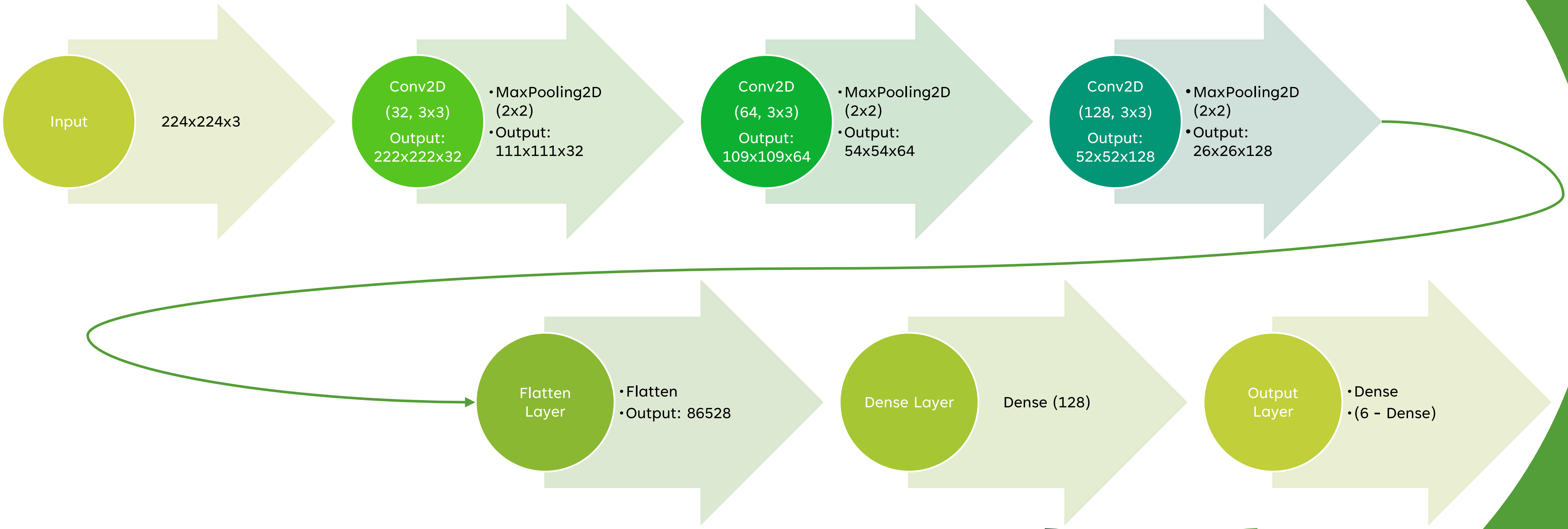
CNN

Convolutional Neural Networks: AFD Detector's Learning Model

CNN:

- **Convolutional Neural Networks:** Artificial Neural network architectures designed for image and grid-like data processing, automatically extracting features and modeling complex relationships in data.
- **Sequential CNN:** A neural network with a sequential layer arrangement, proficient at extracting intricate image features, widely employed in computer vision applications.

CNN: Architecture



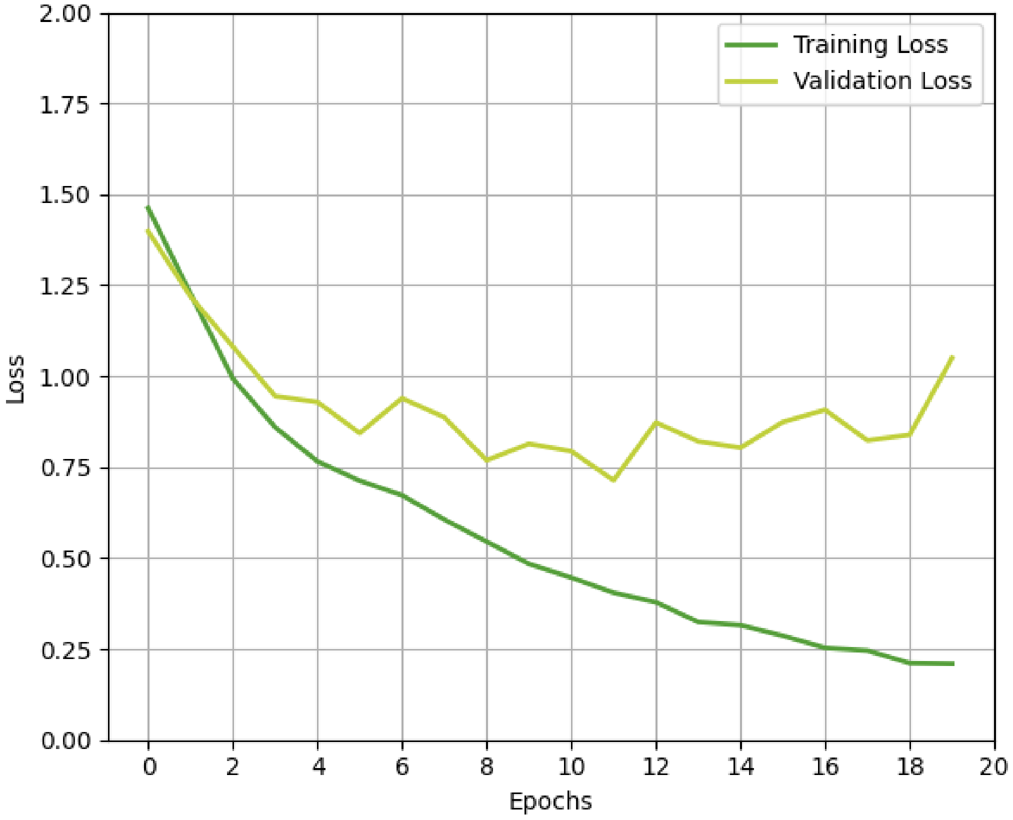
CNN: Architecture

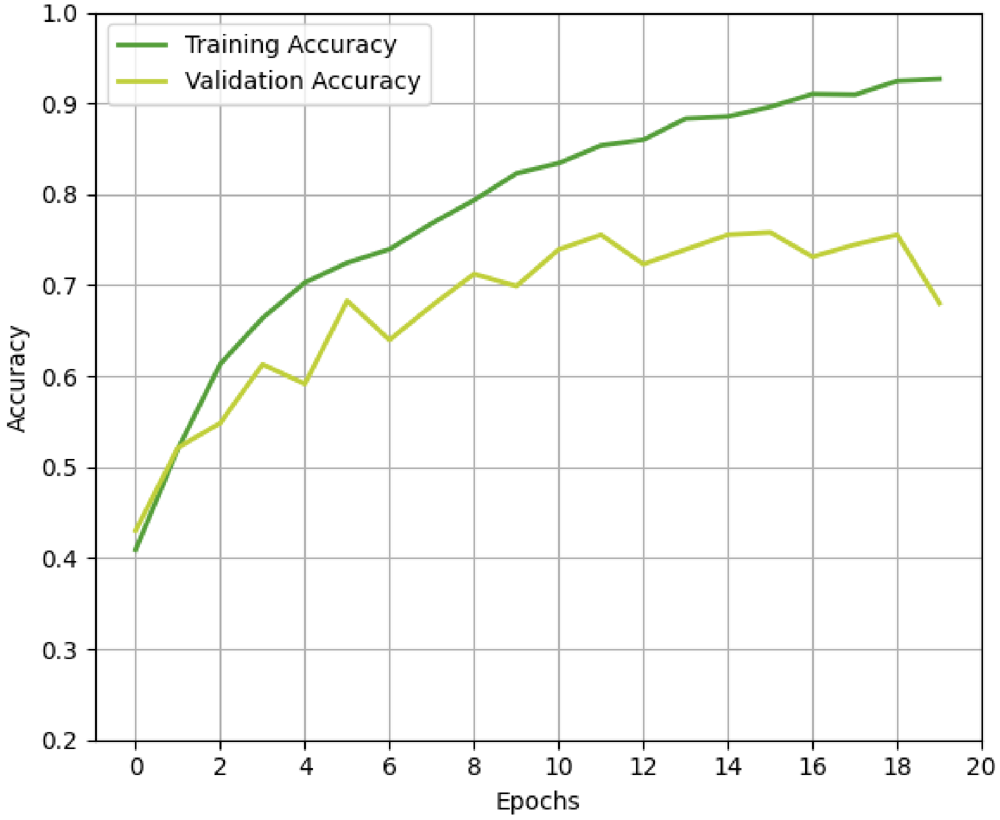
Layer	Type	Filter/Pool	Filters/Neuron	Activation	Output Shape
Input	Input	224x224	-	-	224x224x3
Conv2D	Convolutional	3x3	32	ReLU	222x222x32
MaxPooling2D	Max Pooling	2x2	-	-	111x111x32
Conv2D	Convolutional	3x3	64	ReLU	109x109x64
MaxPooling2D	Max Pooling	2x2	-	-	54x54x64
Conv2D	Convolutional	3x3	128	ReLU	52x52x128
MaxPooling2D	Max Pooling	2x2	-	-	26x26x128
Flatten	Flatten	-	-	-	86528
Dense	Fully Connected	-	128	ReLU	128
Dense	Fully Connected	-	6	Softmax	6 - Output

Evaluation

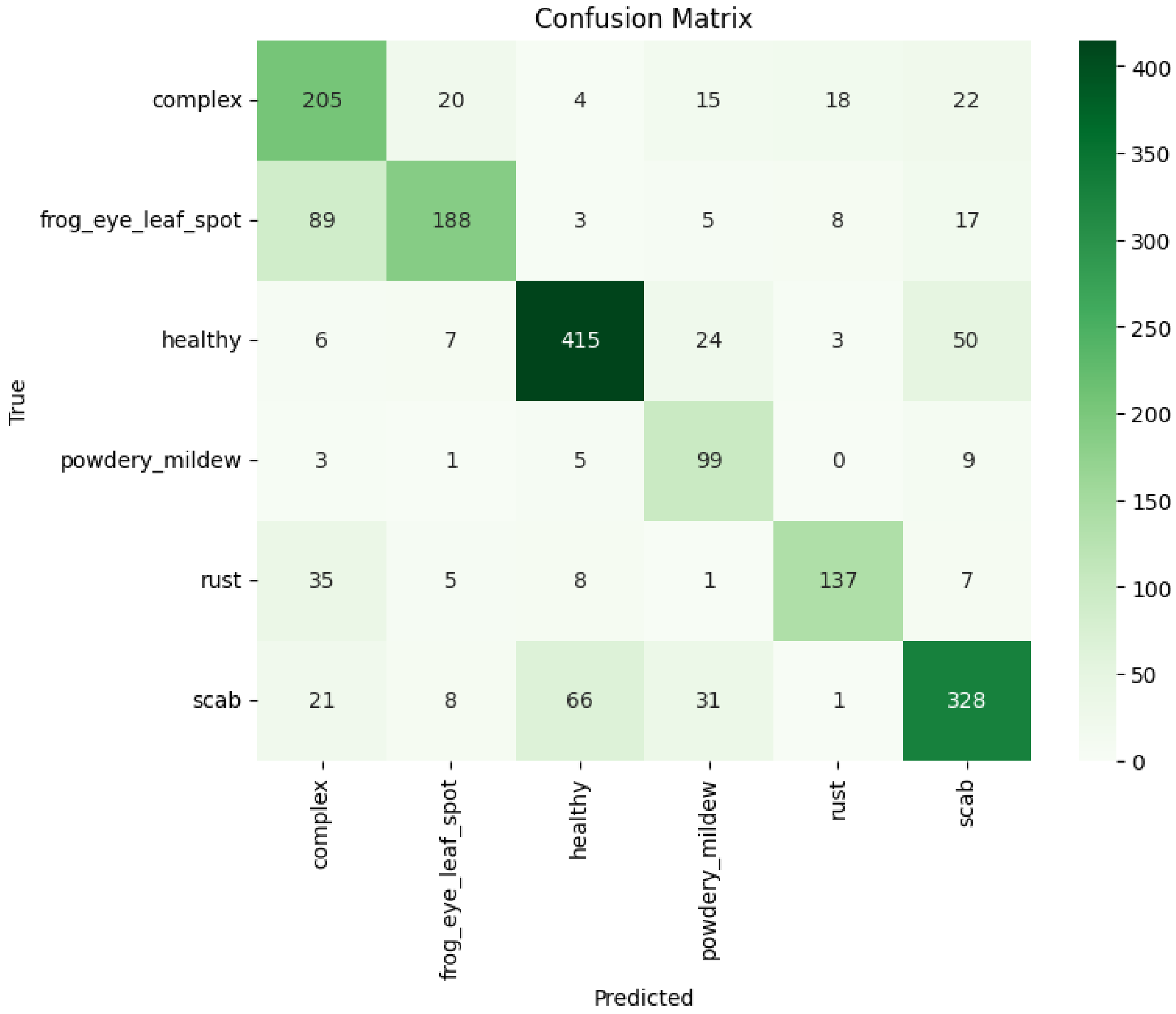
Evaluating CNN: Analyzing AFD Detector's Performance

Evaluation: Loss and Accuracy





Evaluation: Confusion Matrix



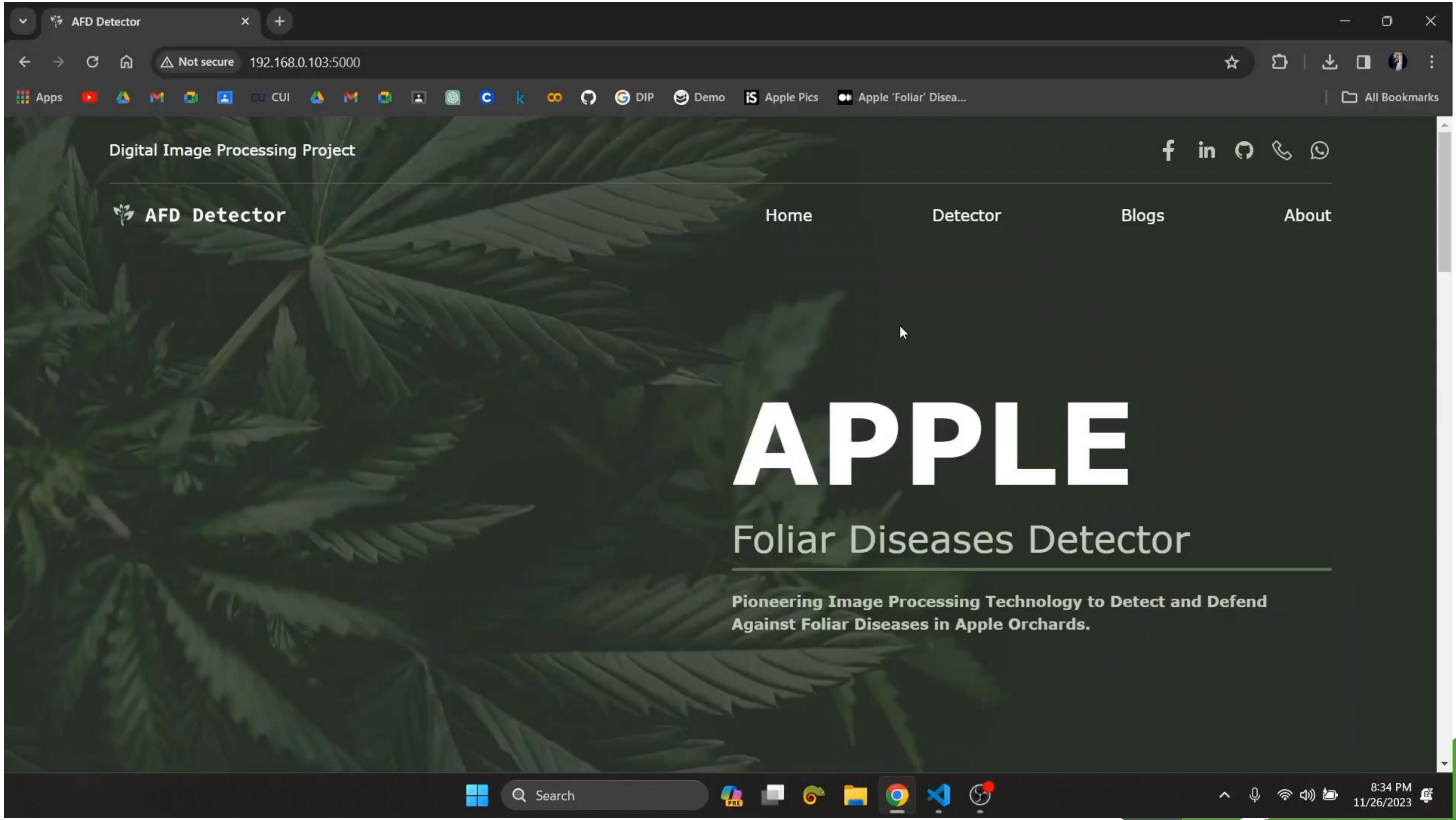
Evaluation: Report

Class	Precision	Recall	F1-Score	Support	Correct
complex	0.57	0.72	0.64	284	205
frog_eye_leaf_spot	0.82	0.61	0.70	310	188
healthy	0.83	0.82	0.83	505	418
powdery_mildew	0.57	0.85	0.68	117	99
rust	0.82	0.71	0.76	193	137
scab	0.76	0.72	0.74	455	328
Accuracy			0.74	1864	
Macro Avg	0.73	0.74	0.72	1864	
Weighted Avg	0.75	0.74	0.74	1864	

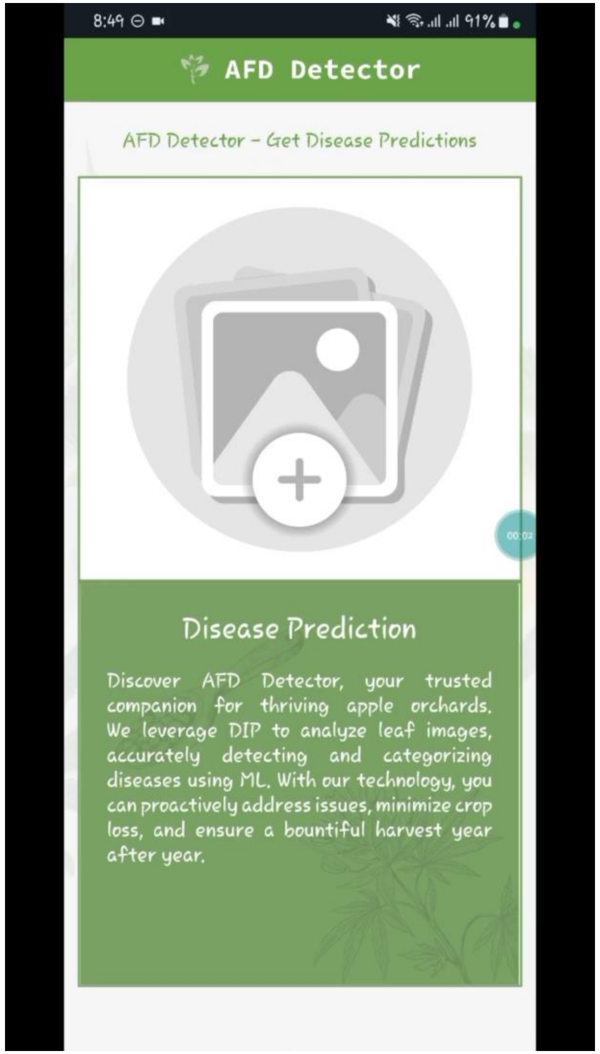
Usage

Usage and Testing: AFD Detector’s Performance at Realtime Testing

Usage: Website



Usage: Mobile App



Technologies

Listing Technologies Utilized: AFD Detector’s Backbone Technologies

Technologies:

- DIP and ML Model:
- Website:
- Mobile App:

Conclusion

Listing Technologies Utilized: AFD Detector’s Backbone Technologies

Conclusion:

- **In conclusion:** From discussing the challenges of manual care to introducing the vision of automated detection using digital image processing.
- **Looking ahead:** Our vision is to integrate advanced detection algorithm into pesticide spraying drones or bots to spray specific pesticides only on affected trees.

Thank You!

I deeply appreciate your engagement during my recent presentation.