IMAGE-BASED CROP LEAF DISEASE AUTOMATIC IDENTIFICATION USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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Abstract

Globally, crop leaf diseases have been an enormous burden on farmers and a major threat to food security. The latest breakthrough in machine learning paved the way for automatic identification of crop leaf diseases. Using the PlantVillage dataset consisted of 35, 263 images, a convolutional neural network was trained to identify 19 crop-disease class labels. The trained model yielded an overall **accuracy of 98.742%, mean recall of 88.431%, mean precision of 89.073%**, and **mean F1-Score of 88.408%** on 5-fold cross-validation, demonstrating the feasibility of this approach. The proposed convolutional neural network model provides great potential and direction in related crop disease control and machine learning studies.

Introduction

9.7B

World's Population by 2050

70%

Increase in Food Production

40-50%

Total Crop Loss

The Problem

- MANUAL CHECKING
- ONE-SIZE-FITS-ALL SOLUTION

Objectives

The general objective of the study is to develop a model that will identify crop leaf diseases using Convolutional Neural Network (CNN). Specifically, the study aims to achieve the following:

01

To train the model using Convolutional Neural Network (CNN) with crop-diseases labeled data from PlantVillage dataset

02

To validate the model's performance using K-Fold Stratified Cross-Validation

03

To compute for performance evaluation metrics for the created model and to accurately identify the crop leaf diseases test dataset.

With the development of modern technology, it is important for us to incorporate modern technology to the main source of our economic growth, as well as our daily food.

Scope

To create a model for classifying crop leaf diseases

Limitation

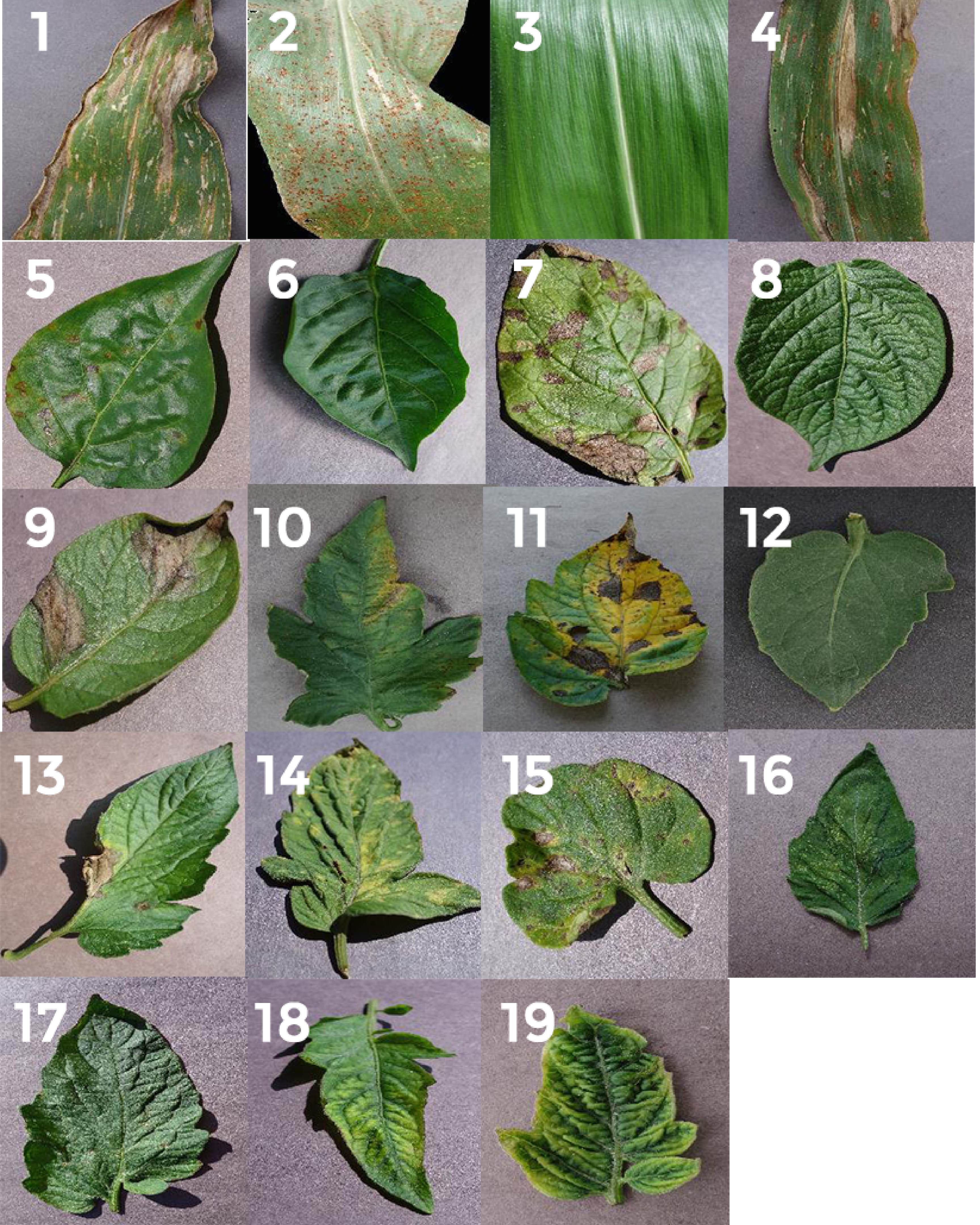
1) Corn Gray Leaf Spot, 2) Corn Common Rust, 3) Corn healthy, 4) Corn Northern Leaf Blight, 5) Bell Pepper Bacterial Spot, 6) Bell Pepper Healthy, 7) Potato Early Blight, 8) Potato Healthy, 9) Potato Late Blight, 10) Tomato Bacterial Spot, 11) Tomato Early Blight, 12) Tomato Healthy, 13) Tomato Late Blight, 14) Tomato Leaf Mold, 15) Tomato Septoria Leaf Spot, 16) Tomato Two Spotted Spider Mite, 17) Tomato Target Spot, 18) Tomato Mosaic Virus, and 19) Tomato Yellow Leaf Curl Virus.

Methodology

Materials

Laptop with specifications: Intel Pentium Dual Core 4th Gen Processor @ 2.1 Ghz, 2 GB DDR3 RAM, Linux 16.04 Operating System.

Development Tools



Dataset Description

35,263

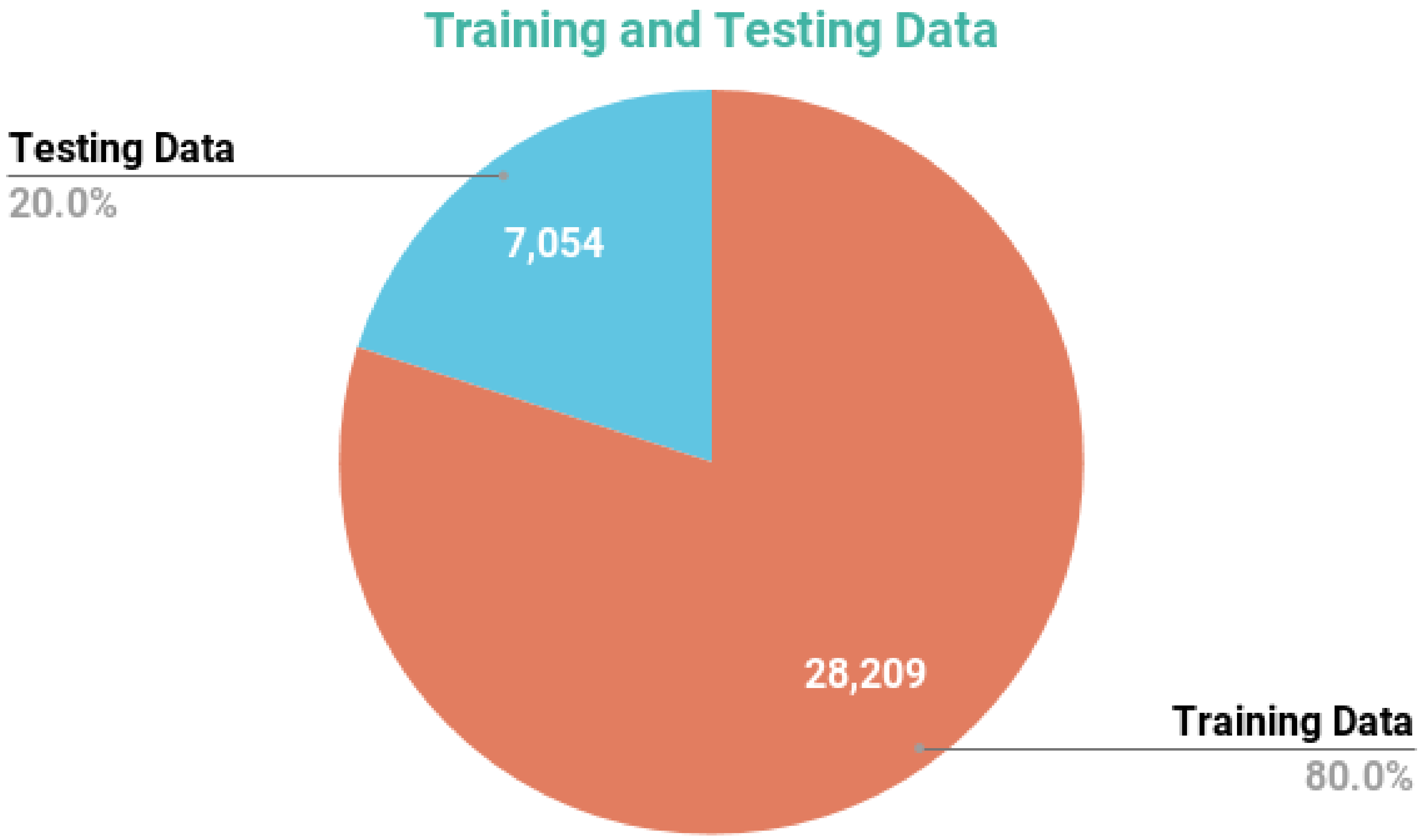
Crop-Disease labeled images were obtained from Kaggle.com

1)Corn Gray Leaf Spot, 2)Corn Common Rust, 3)Corn healthy, 4)Corn Northern Leaf Blight, 5)Bell Pepper Bacterial Spot, 6)Bell Pepper Healthy, 7)Potato Early Blight, 8)Potato Healthy, 9)Potato Late Blight, 10)Tomato Bacterial Spot, 11)Tomato Early Blight, 12)Tomato Healthy, 13)Tomato Late Blight, 14)Tomato Leaf Mold, 15)Tomato Septoria Leaf Spot, 16)Tomato Two Spotted Spider Mite, 17)Tomato Target Spot, 18)Tomato Mosaic Virus, and 19)Tomato Yellow Leaf Curl Virus.

Dataset Division

80-20 Train-Test Split

28,209 images are allotted for the training dataset and 7,054 is allocated for testing dataset



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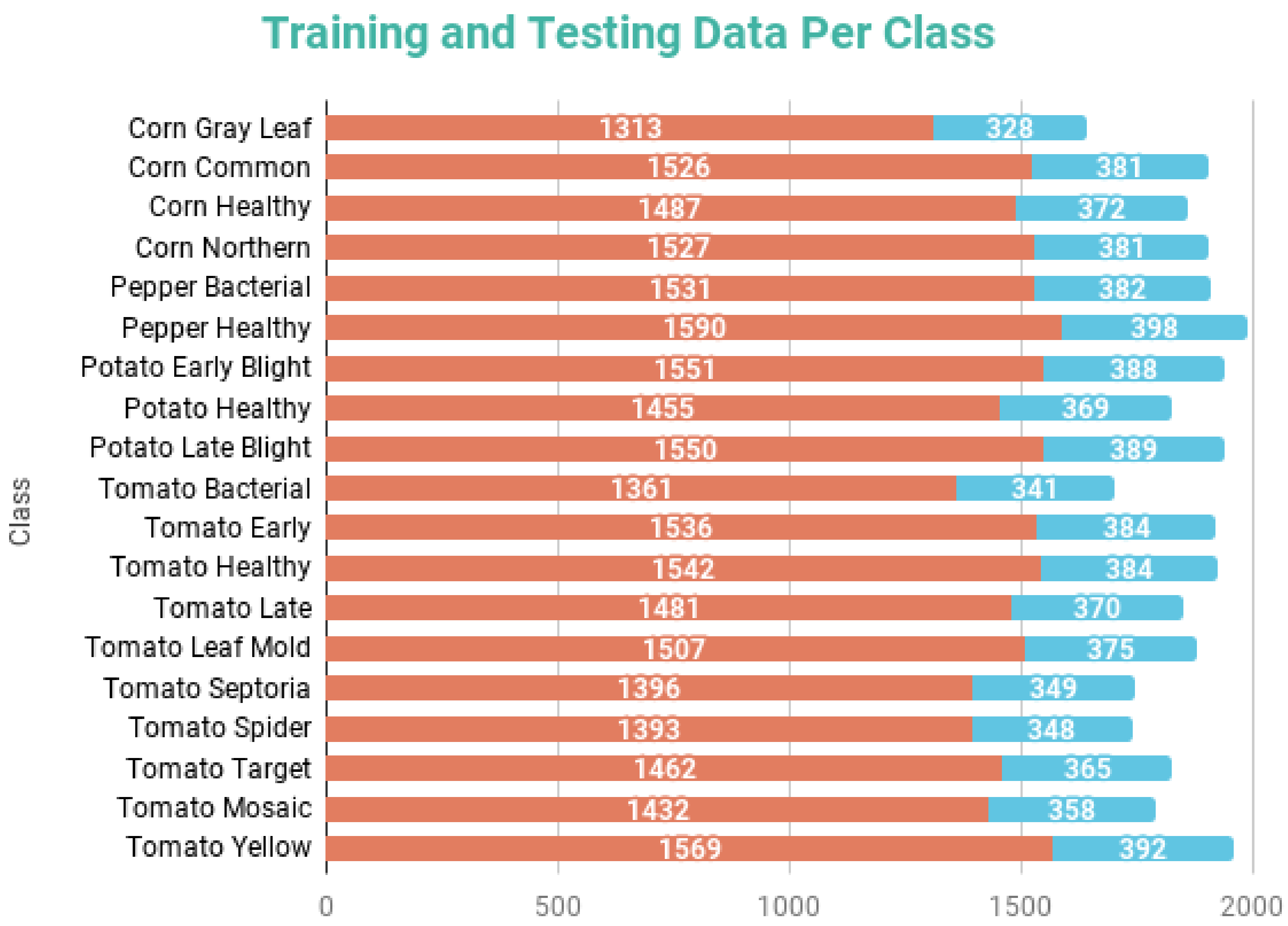


Image Enhancement

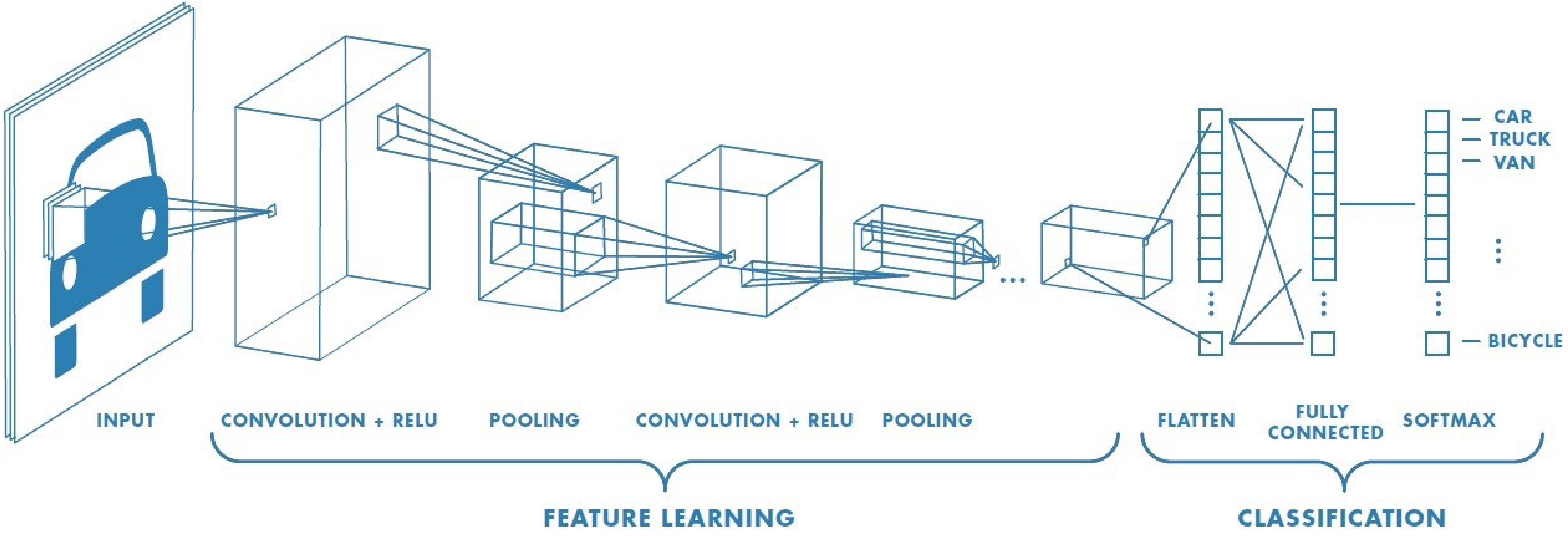
Conversion to 3-channel BGR color image

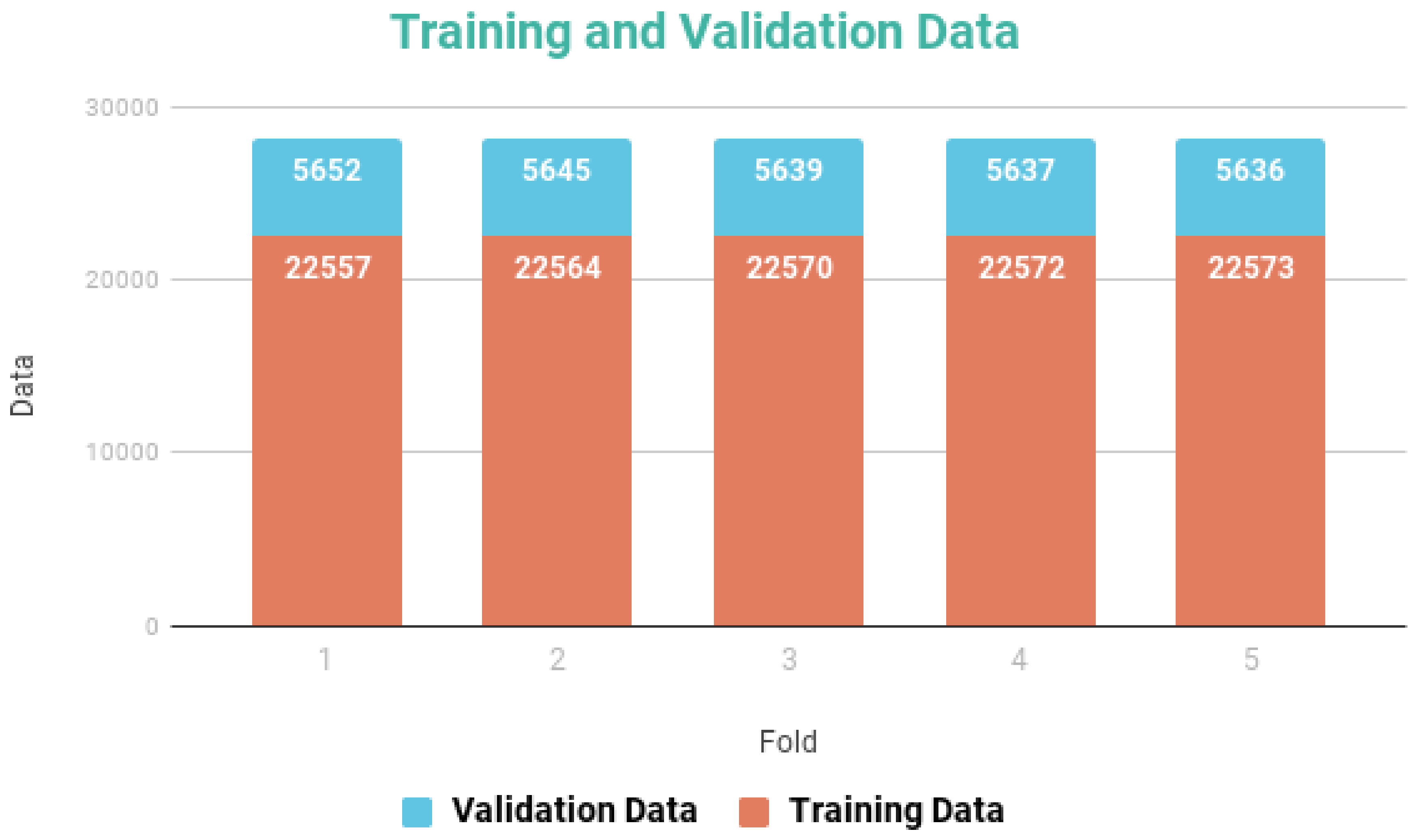
Resizing of images to 50x50 pixels

Convolutional Neural Network (CNN)

The following hyperparameters were used in all model setup:

- Learning Rate: 1e-3
- Optimizer: Adam
- Loss: Categorical Cross-Entropy
- Epoch: 12
- Solver Type: Batch Gradient Descent





5-Fold Cross-Validation

Stratified k-fold cross-validation approach was implemented in rearranging the data.

Evaluation Metrics

Used to determine the performance of the CNN classifier

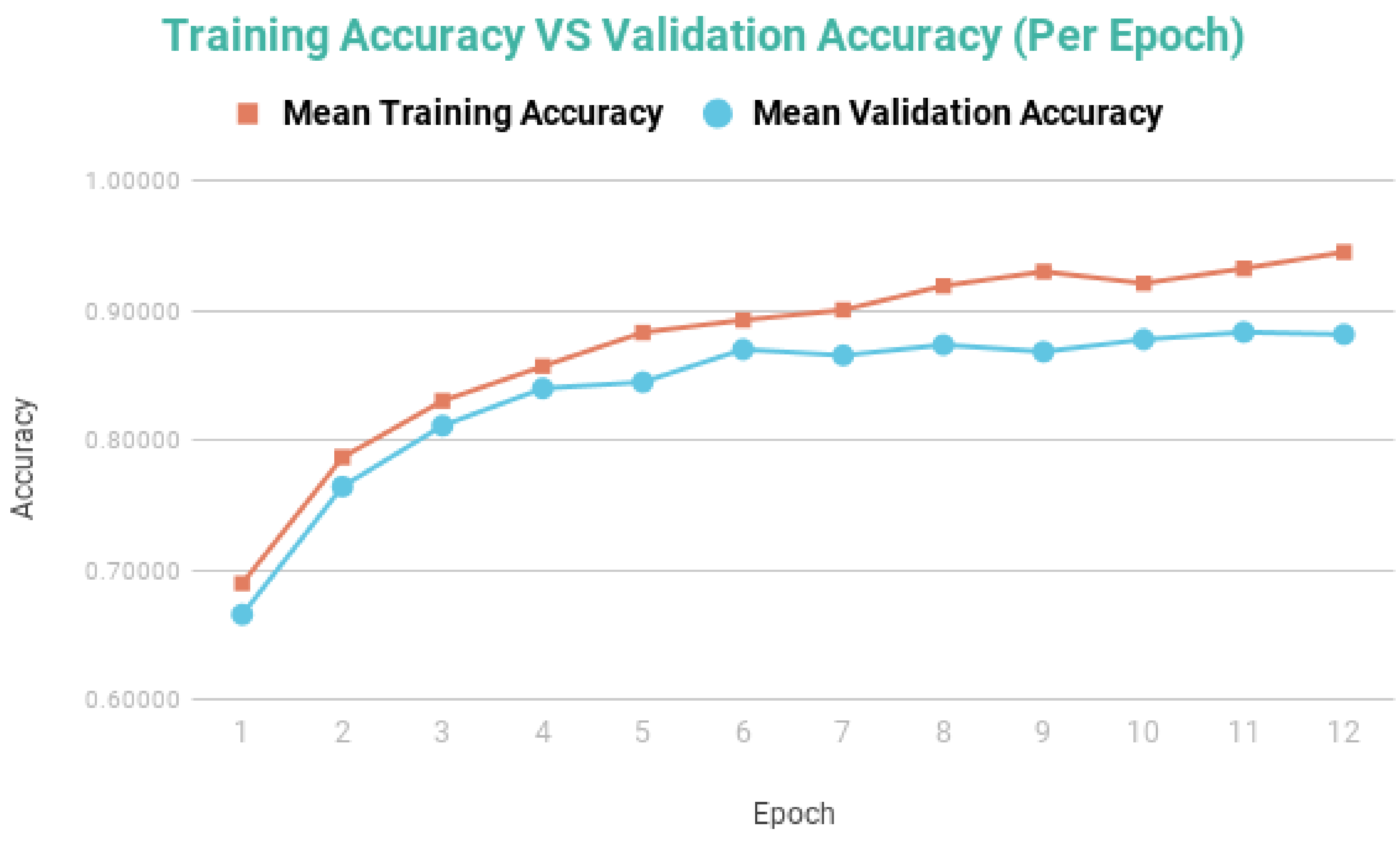
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

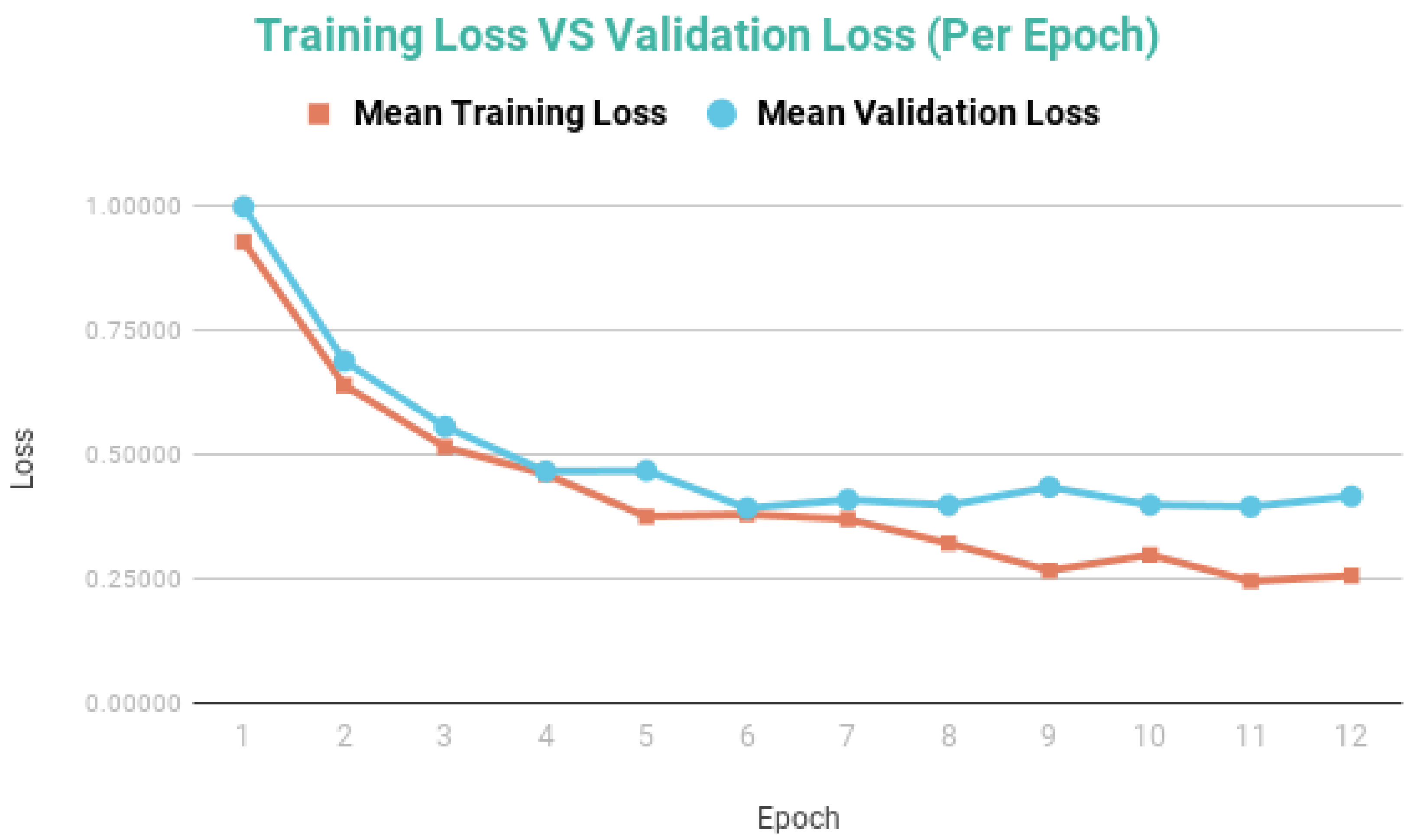
$$Recall = \frac{TP}{TP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$F1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

Results and Discussion



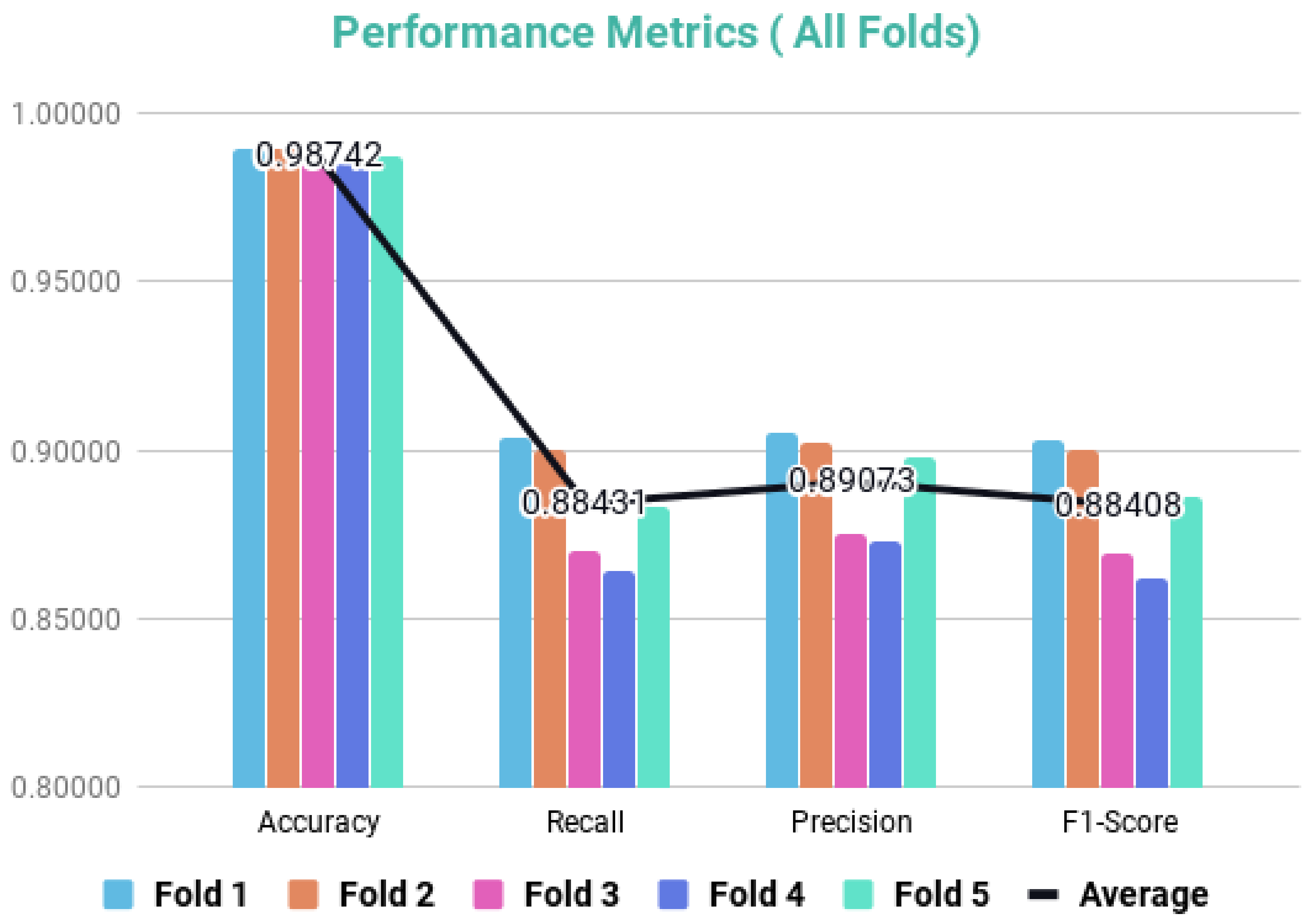


Training Phase

The training and validation accuracies and loss per epoch were recorded

The CNN classifier is tested using 20%(7054) of the Dataset

Afterwards, various evaluation metrics were computed from the performance of the classifier across all folds



It is perceived that Fold 1 yielded the highest value for the computed metrics; having 98.93% for accuracy, 90.35% for recall, 90.56% for precision, and 90.28% for f1-score.

Confusion Matrix, Accuracy and F1-Score of Fold 1

TABLE I

FOLD 1 CONFUSION MATRIX , ACCURACY AND F1-SCORE

Class Label	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	AC	FS
1	298	0	3	18	0	0	0	0	2	0	4	0	3	0	0	0	0	0	0	98.75%	87.64%
2	1	380	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	99.95%	99.60%
3	0	1	371	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	99.89%	99.06%
4	43	0	3	332	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	98.97%	90.58%
5	0	0	0	0	343	6	10	2	2	1	6	0	1	1	9	0	1	0	0	98.79%	89.43%
6	0	0	0	0	10	359	0	8	0	1	0	0	0	2	18	0	0	0	0	99.17%	92.88%
7	0	0	0	0	1	0	375	0	7	0	0	0	3	0	2	0	0	0	0	99.52%	95.90%
8	0	0	0	0	1	1	0	352	3	0	0	0	0	0	0	4	8	0	0	99.31%	93.86%
9	0	0	0	0	1	0	1	13	343	1	4	0	5	0	6	13	2	0	0	98.89%	90.26%
10	1	0	0	0	0	0	0	1	0	313	6	0	2	0	2	0	4	0	12	99.36%	93.57%
11	3	0	0	1	10	6	0	2	2	7	296	0	9	5	7	12	8	1	15	97.46%	77.58%
12	0	0	0	0	0	0	0	0	0	0	0	379	0	0	0	0	5	0	0	99.70%	97.42%
13	6	0	0	1	4	1	4	2	6	2	46	3	280	1	8	3	1	1	1	98.15%	81.75%
14	0	0	0	0	4	1	1	0	0	0	8	5	2	328	12	11	0	2	1	99.01%	90.85%
15	0	0	0	0	7	0	3	0	5	0	5	3	5	9	290	8	11	2	1	98.09%	81.80%
16	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	332	7	4	2	97.73%	81.37%
17	0	0	0	0	1	0	0	1	1	0	2	4	0	0	4	81	271	0	0	97.90%	79.23%
18	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	2	1	353	0	99.77%	97.91%
19	0	1	0	0	3	0	0	0	0	3	1	0	0	1	1	2	0	0	380	99.34%	94.52%
																				98.93%	90.28%

Legend: 1-Corn Gray Leaf Spot, 2-Corn Common Rust, 3-Corn healthy, 4-Corn Northern Leaf Blight, 5-Bell Pepper Bacterial Spot, 6-Bell Pepper Healthy, 7-Potato Early Blight, 8-Potato Healthy, 9-Potato Late Blight, 10-Tomato Bacterial Spot, 11-Tomato Early Blight, 12-Tomato Healthy, 13-Tomato Late Blight, 14-Tomato Leaf Mold, 15-Tomato Septoria Leaf Spot, 16-Tomato Two Spotted Spider Mite, 17-Tomato Target Spot, 18-Tomato Mosaic Virus, 19-Tomato Yellow Leaf Curl Virus, AC-Accuracy, and FS-F1-Score.

(a) Tomato Early Blight

(b) Tomato Yellow Leaf Curl Virus

(c) Bell Pepper Bacterial Spot

(d) Tomato Two Spotted Spider Mite

Fig. 9. Image comparision of Tomato Early Bright,Tomato Yellow Leaf Curl Virus, Bell Pepper Bacterial Spot, and Tomato Two Spotted Spider Mite

Tomato Early Bright class performed the lowest; with 97.46% Accuracy and 77.58% F1-Score.

In contrast, Corn Common Rust performs well in determining its true positives and false positive. Covering all class labels, it only classified 2 false positive; having 99.95% accuracy and 99.60% F1-Score.

On average, Corn Healthy class label yielded the highest overall accuracy (99.922%), mean recall (99.731%), mean precision (98.883%), and mean f1-score (99.304%)

(a) Tomato Septoria Leaf Spot (b) Tomato Leaf Mold

Fig. 9. Image comparision of Tomato Septoria Leaf and Tomato Leaf Mold

On the other hand, Tomato Septoria Leaf Spot produced the lowest computed value for overall accuracy, mean recall, mean precision, and mean f1-score– 97.392%, 70.716%, 78.547%, and 72.884%, respectively

TABLE II

SUMMARY OF OVERALL ACCURACY, MEAN RECALL, MEAN PRECISION, AND MEAN F1-SCORE PER CLASS LABEL

Class Label	Accuracy	Recall	Precision	F1-Score
Corn Gray Leaf Spot (328)	98.824%	87.927%	88.063%	87.858%
Corn Common Rust (381)	99.874%	98.740%	99.063%	98.896%
Corn Healthy (372)	99.922%	99.731%	98.883%	99.304%
Corn Northern Leaf Blight (381)	99.025%	91.076%	91.823%	91.380%
Pepper Bacterial Spot (382)	98.377%	83.717%	87.873%	85.173%
Pepper Healthy (398)	99.043%	91.457%	92.705%	91.940%
Potato Early Blight (388)	99.389%	96.392%	93.361%	94.835%
Potato Healthy (369)	98.905%	94.201%	88.418%	90.719%
Potato Late Blight (389)	98.538%	90.797%	85.438%	87.928%
Tomato Bacterial Spot (341)	98.960%	85.337%	93.655%	89.119%
Tomato Early Blight (384)	97.088%	76.406%	75.165%	74.971%
Tomato Healthy (384)	99.733%	97.708%	97.671%	97.683%
Tomato Late Blight (370)	97.662%	75.081%	81.344%	77.935%
Tomato Leaf Mold (375)	98.459%	88.053%	85.591%	86.579%
Tomato Septoria Leaf Spot (349)	97.392%	70.716%	78.547%	72.884%
Tomato Spider Mites (348)	98.215%	85.172%	82.086%	83.184%
Tomato Target Spot (365)	98.061%	78.904%	84.601%	81.403%
Tomato Mosaic Virus (358)	99.356%	95.196%	93.756%	94.215%
Tomato Yellow Leaf Curl Virus (392)	99.267%	93.571%	94.337%	93.750%
	98.742%	88.431%	89.073%	88.408%

In summary, we noted that the overall accuracy of the CNN classifier ranges from 97%-99%. Also, we observed that the mean recall, mean precision and mean f1-score span from 72%-99%.

Conclusion

With the use of the PlantVillage dataset, an overall accuracy of 98.742%, mean recall of 88.431%, mean precision of 89.073%, and mean F1-Score of 88.408% were computed from the performance of the classifier across all folds.

Future Works and Recommendations

The images used to train and to test the created models are from the PlantVillage dataset only. Additional datasets from different sources and different environment setups would improve the performance of the model.
The model in this study can be used in creating a web-based or a mobile application where users can capture or input a leaf image and know if the crop is healthy or infected by a crop leaf disease.

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