Plant Disease Detection

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INTRODUCTION

Leaf Dataset

Goal :

- Recognize the leaf
- Recognize any disease

DATASET

- color
- grayscale
- segmented

54,305 images per folder

38 directories - 14 plants → 25 directories - 5 plants

Apple___Apple_scab	Apple___Black_rot	Apple___Cedar_apple_rust	Apple___healthy	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Corn_(maize)___Common_rust_	Corn_(maize)___healthy	Corn_(maize)___Northern_Leaf_Blight	Grape___Black_rot	Grape___Esca_(Black_Measles)
Grape___healthy	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	Potato___Early_blight	Potato___healthy	Potato___Late_blight
Tomato___Bacterial_spot	Tomato___Early_blight	Tomato___healthy	Tomato___Late_blight	Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot	Tomato___Spider_mites Two-spotted_spider_mite	Tomato___Target_Spot	Tomato___Tomato_mosaic_virus	Tomato___Tomato_Yellow_Leaf_Curl_Virus

THE IMAGES


Apple healthy


Grape black rot

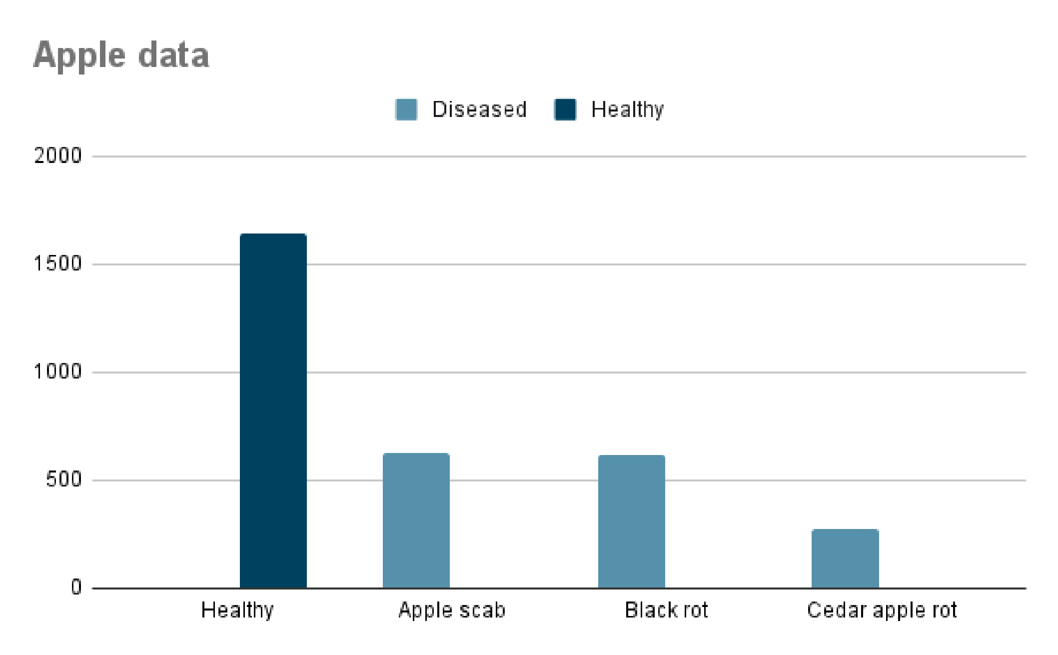

Corn northern leaf blight

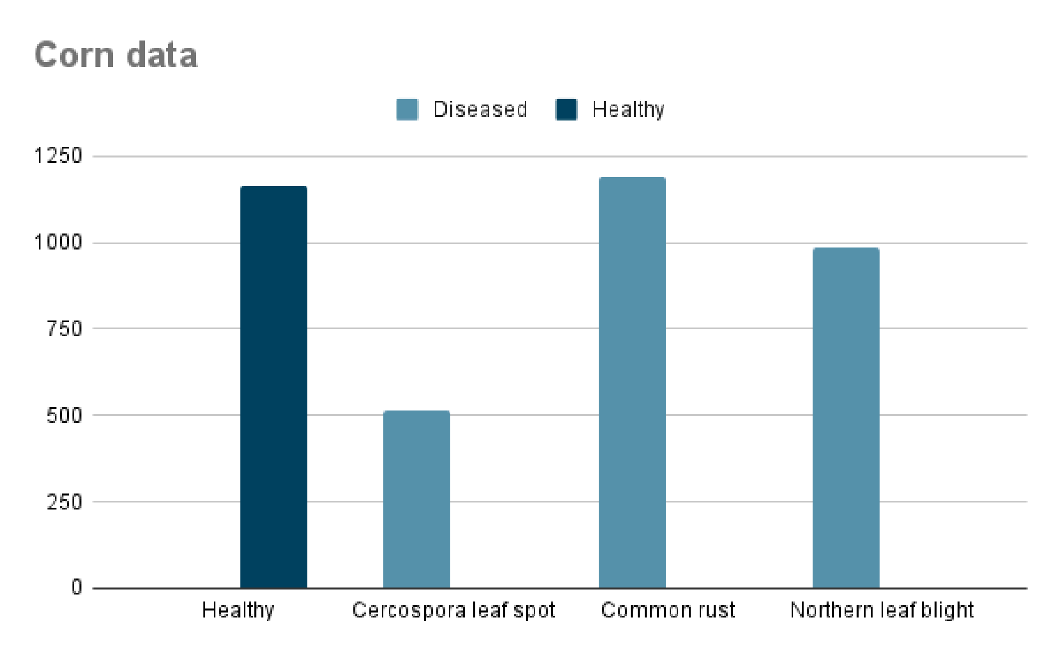

Potato early blight

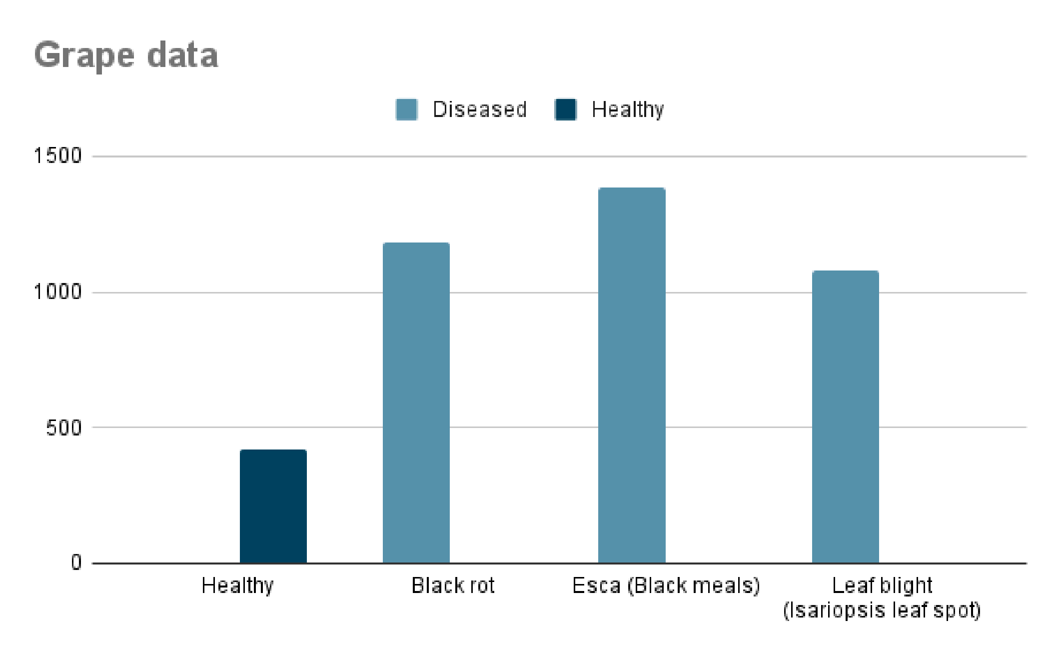

Tomato healthy

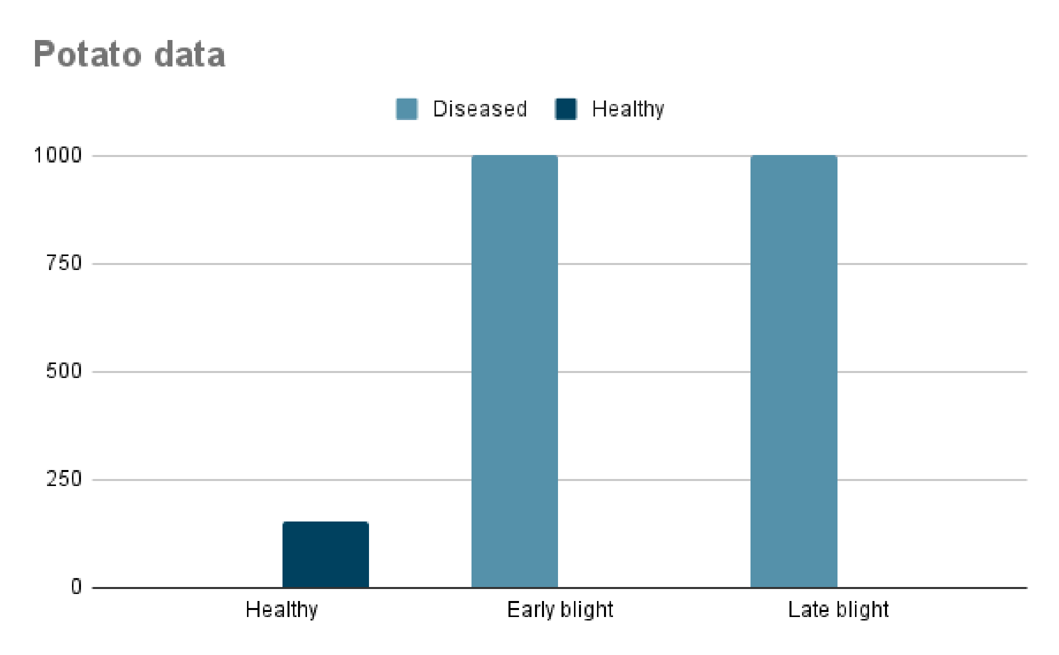
After keeping 5 plants (apple, grape, corn, potato and tomato) : **31,397** images

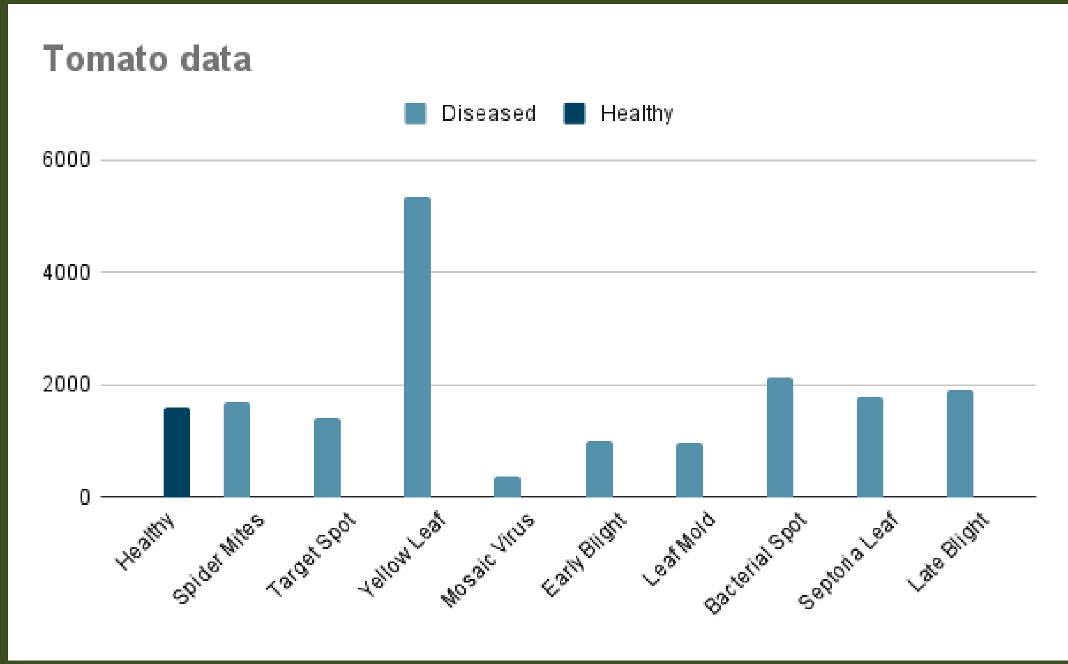
NUMBER OF IMAGES PER DATA



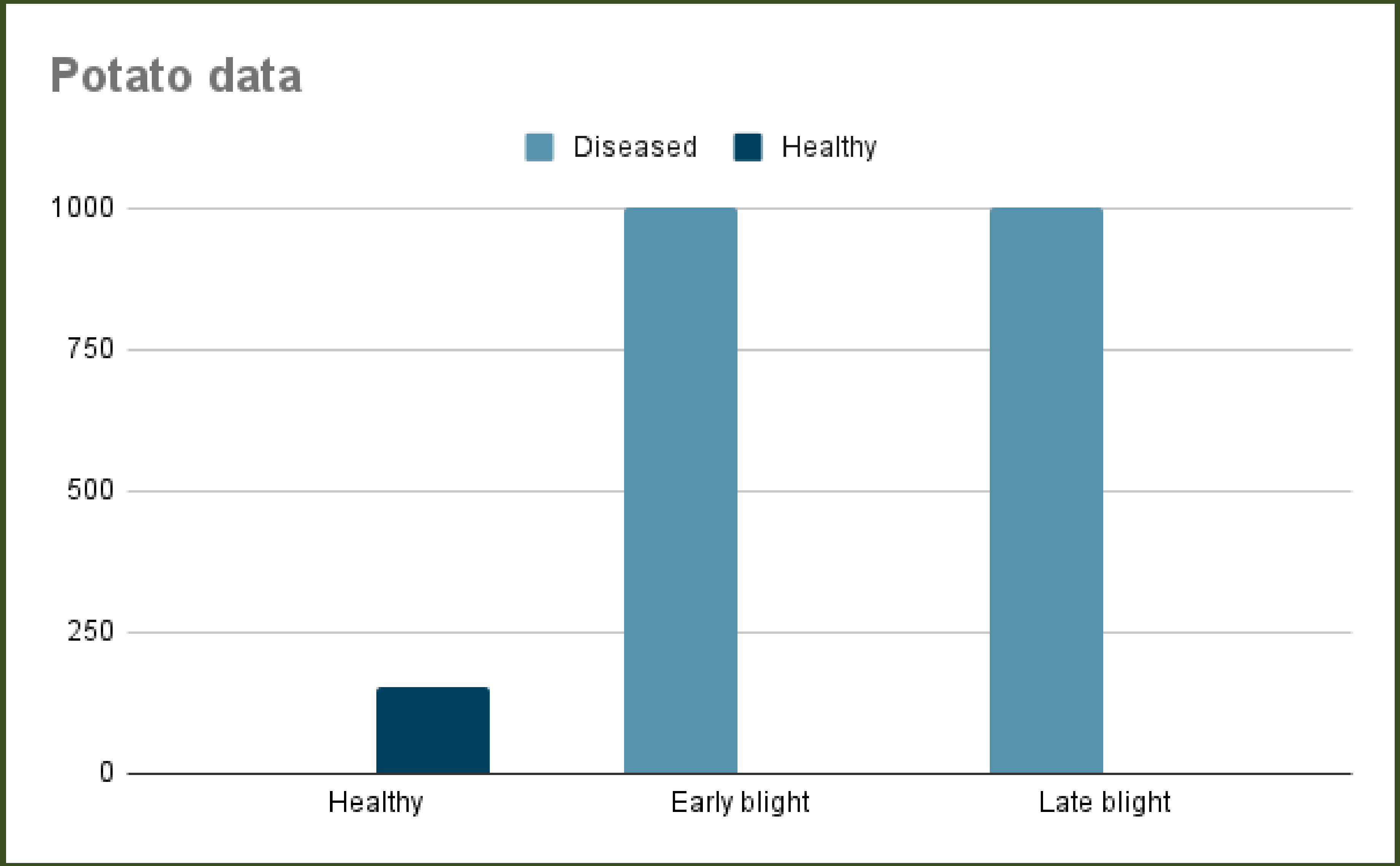








NUMBER OF IMAGES PER DATA

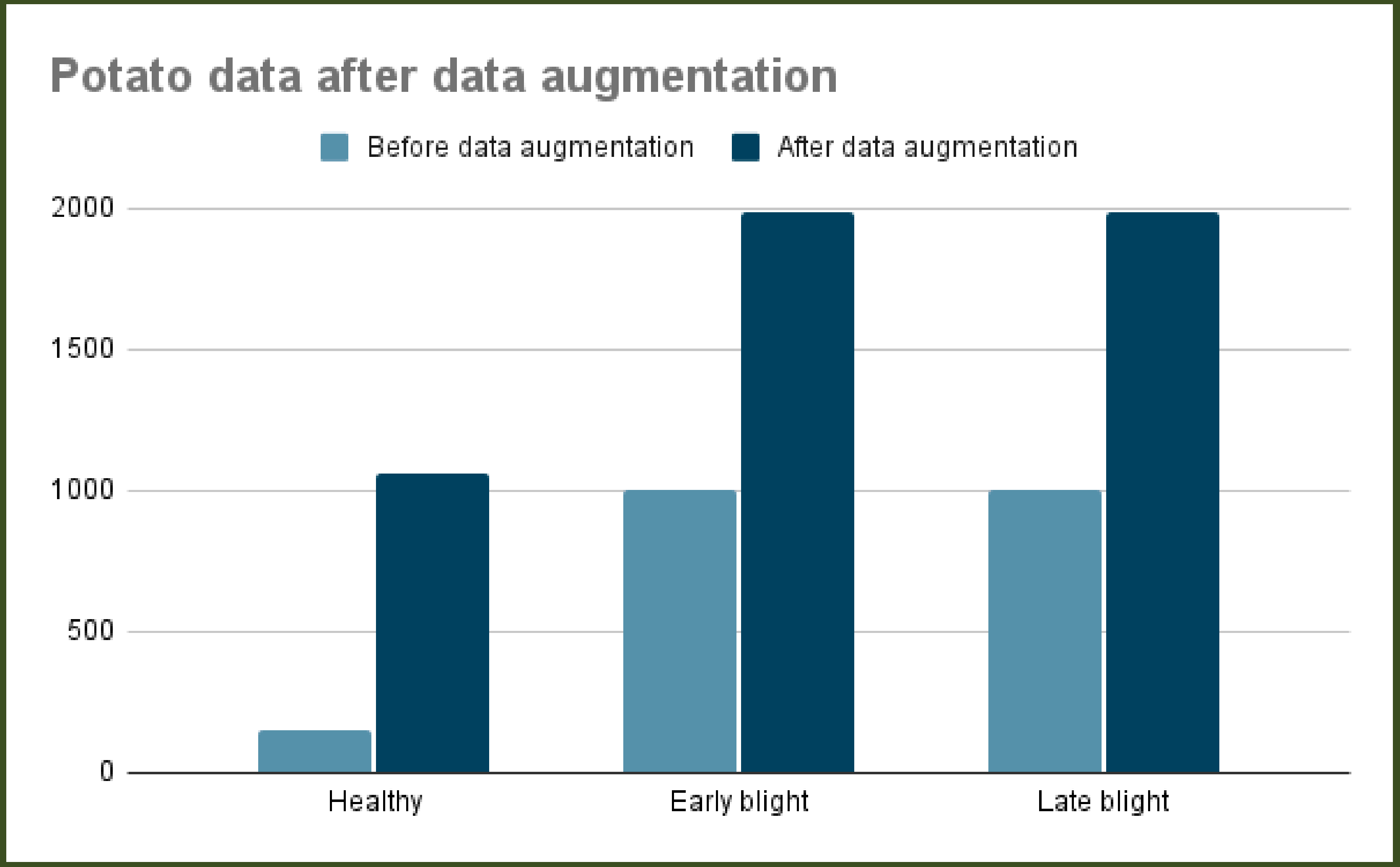


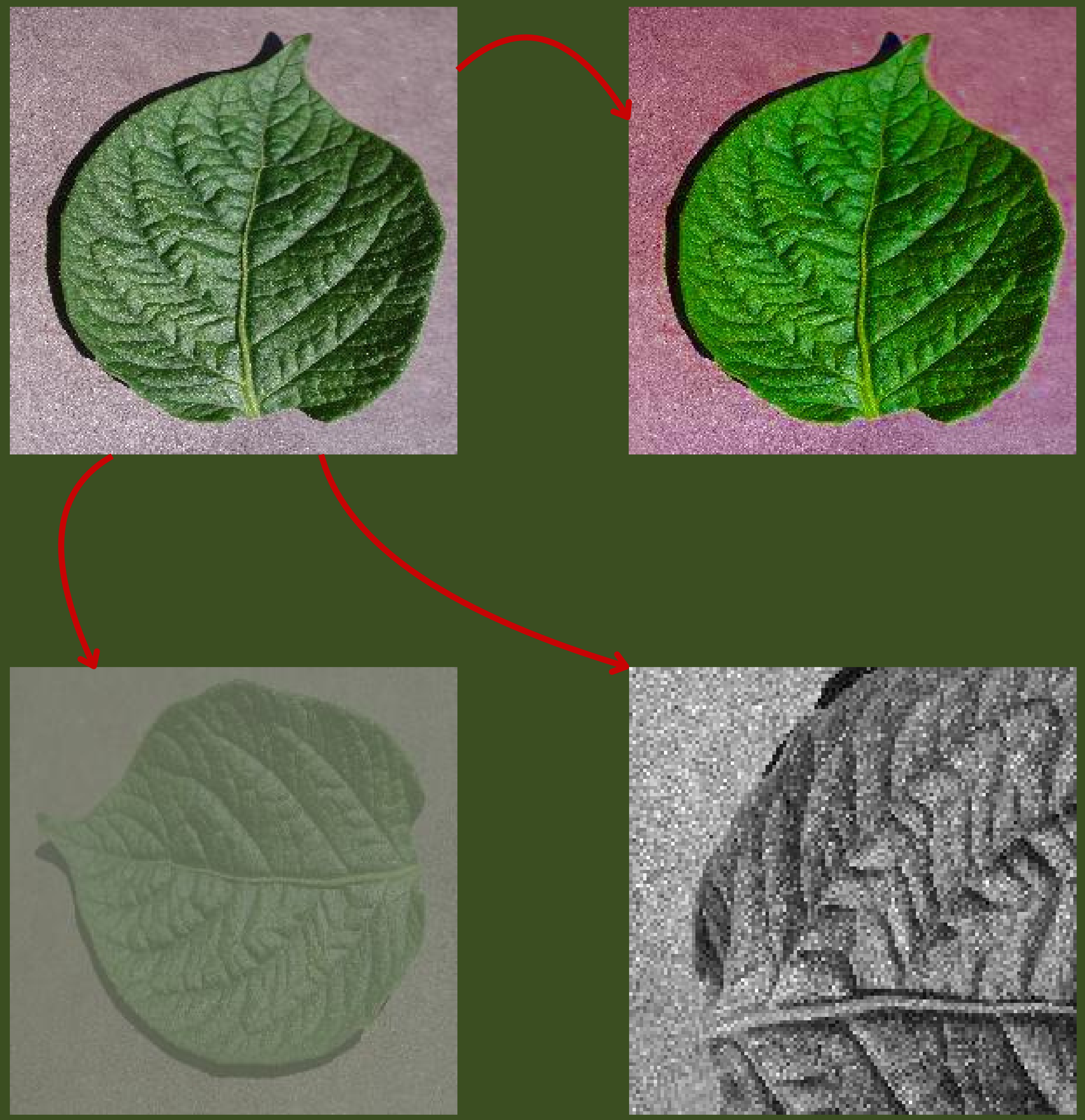
Imbalanced data + not enough data

DATA AUGMENTATION

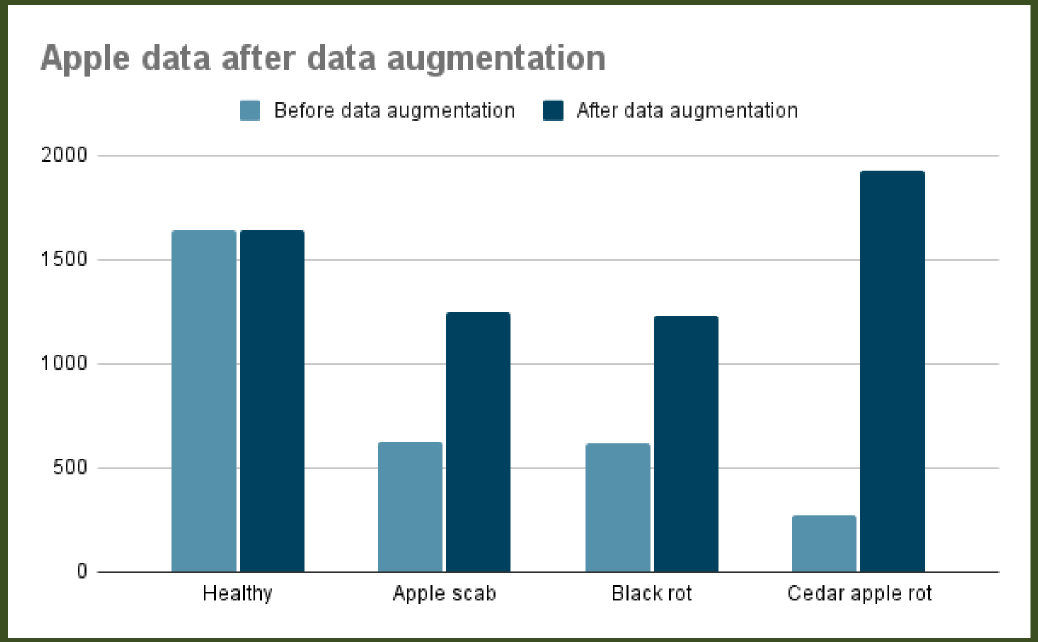
Duplicate images and modify them

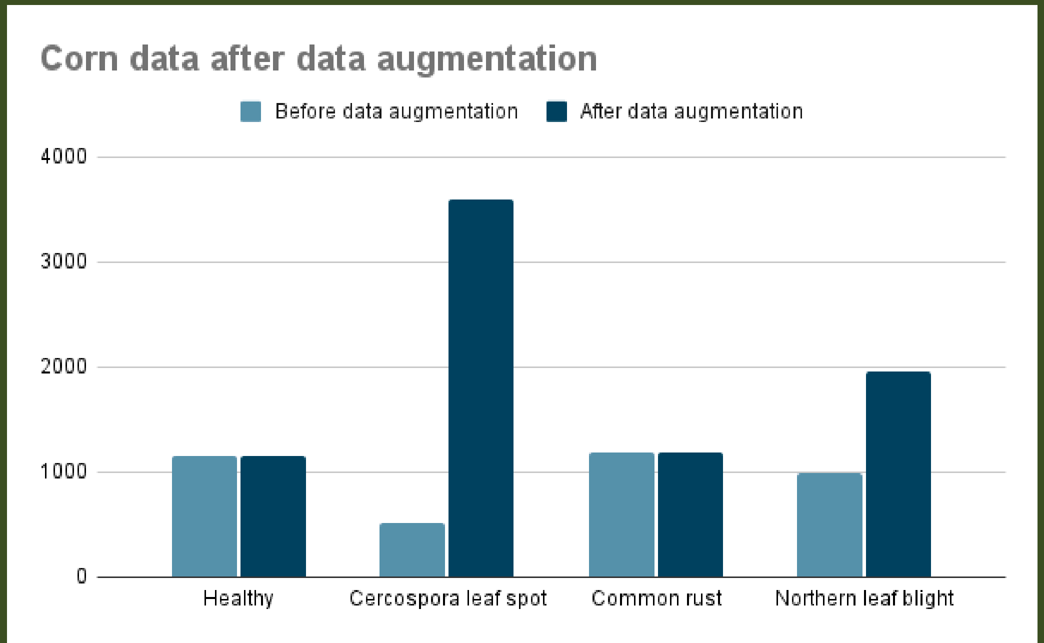
-> Balance population between each class

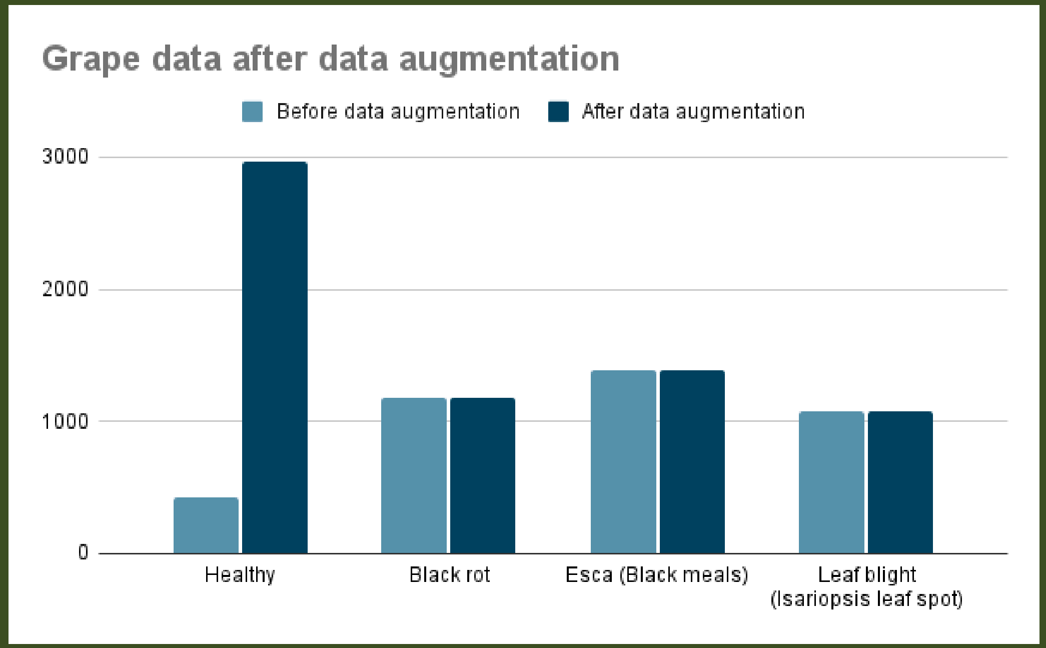


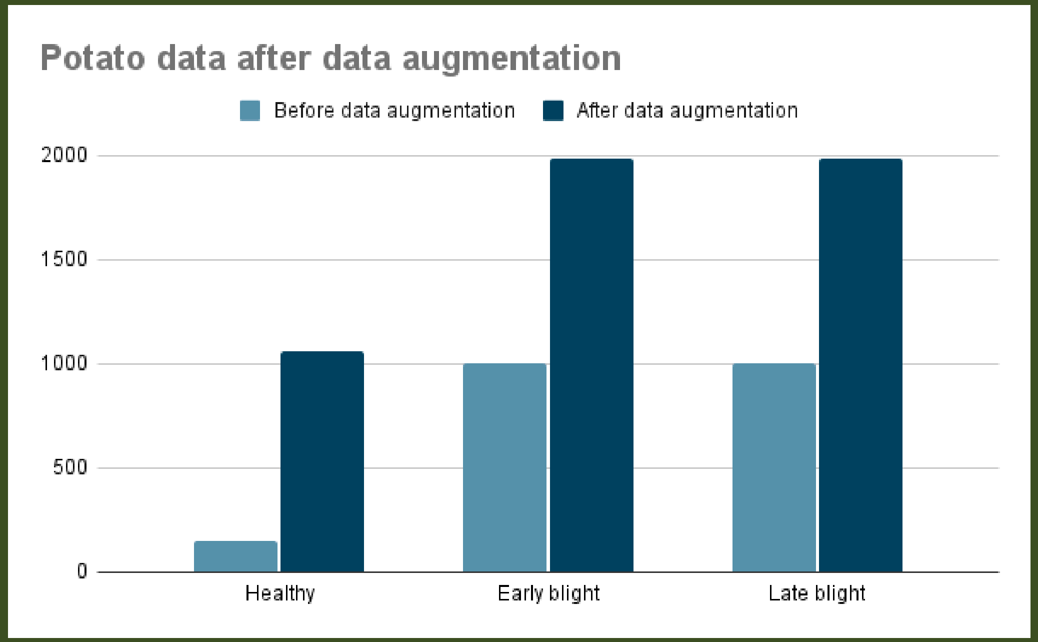


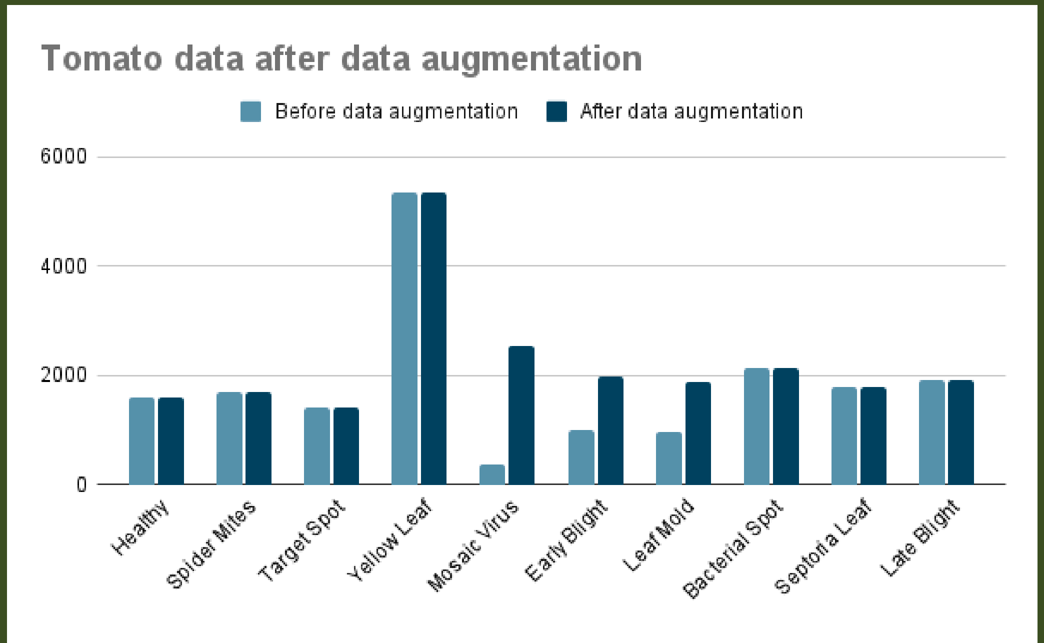
DATA AUGMENTATION







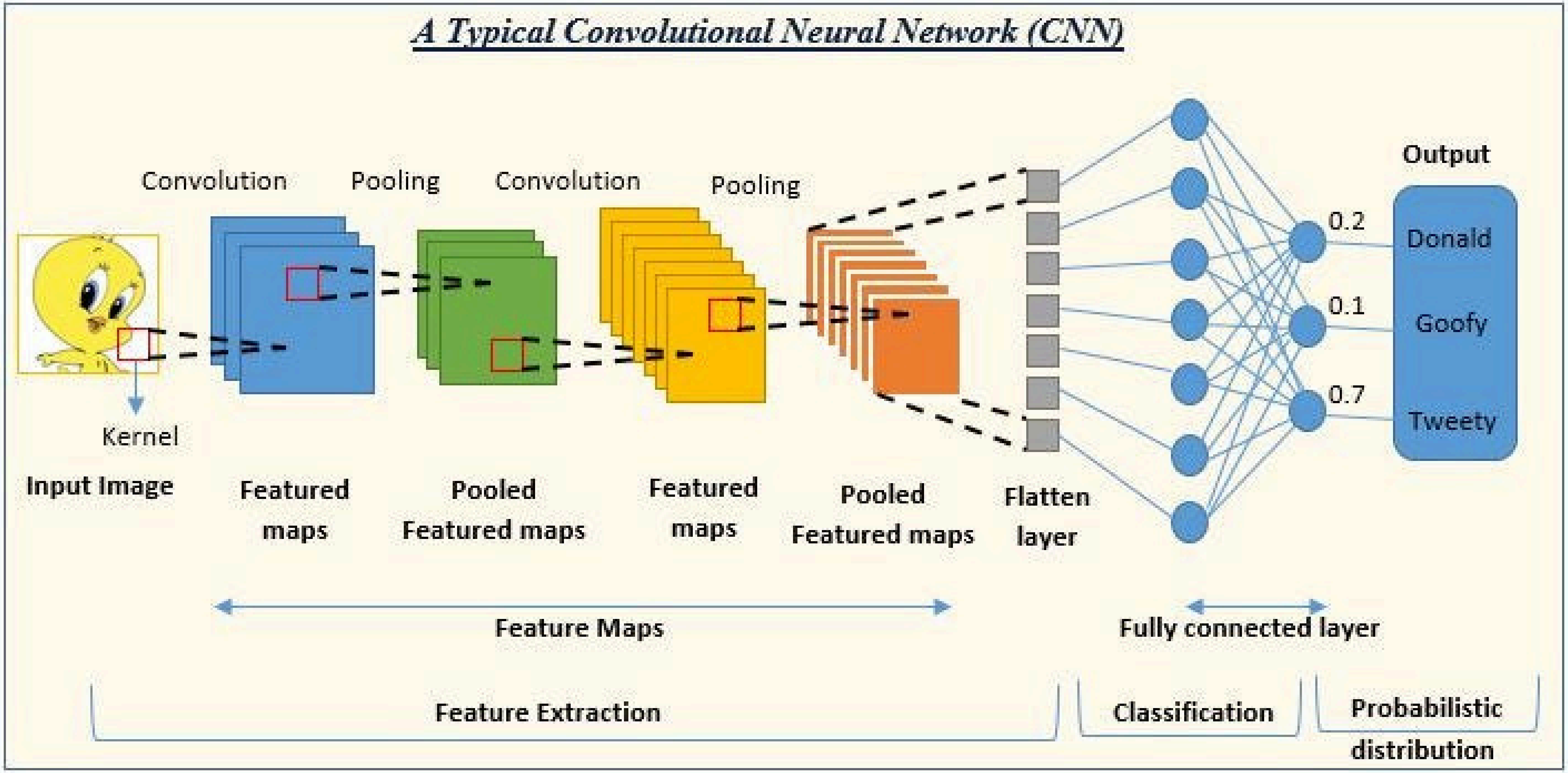




After data augmentation: **47,871** images

47,621 : for train and test

250 : for test during presentation


A Typical Convolutional Neural Network (CNN)
Convolution
Pooling
Convolution
Pooling
Output
0.2
Donald
0.1
Goofy
0.7
Tweety
Kernel
Input Image
Featured maps
Pooled Featured maps
Featured maps
Pooled Featured maps
Flatten layer
Feature Maps
Fully connected layer
Feature Extraction
Classification
Probabilistic distribution

Our model

Kernel number -> number of images based on one

2 hidden layers

```
model = Sequential([
        Conv2D(32, (3, 3), activation='relu', input_shape=(256, 256,
3)),
        MaxPooling2D((2, 2)),
        Conv2D(64, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Flatten(),
        Dense(256, activation='relu'),
        Dense(len(label_encoder.classes_), activation='softmax')
    ])
```

Keep the max pixel from the 2x2 matrix

Filter size: 3x3 matrix
-> matrix multiplication with the image

Our model

Neurons activate when the value is >0

```
model = Sequential([
        Conv2D(32, (3, 3), activation='relu', input_shape=(256, 256,
3)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(256, activation='relu'),
    Dense(len(label_encoder.classes_), activation='softmax')
])
```

converts raw scores (logits) into probabilities
-> multiple classes

```
Model compiled.
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_6 (Conv2D)           (None, 254, 254, 32)      896

 max_pooling2d_6 (MaxPooling  (None, 127, 127, 32)     0
 2D)

 conv2d_7 (Conv2D)           (None, 125, 125, 64)      18496

 max_pooling2d_7 (MaxPooling  (None, 62, 62, 64)       0
 2D)

 flatten_3 (Flatten)         (None, 246016)            0

 dense_6 (Dense)             (None, 256)               62980352

 dense_7 (Dense)             (None, 25)                6425

=================================================================
Total params: 63,006,169
Trainable params: 63,006,169
Non-trainable params: 0
```

```
_________________________________________________________________
Total params: 63,006,169
Trainable params: 63,006,169
Non-trainable params: 0
```

Our model

Optimizer function

```
model.compile(optimizer='adam',loss='categorical_crossentropy',
metrics=['accuracy'])
```

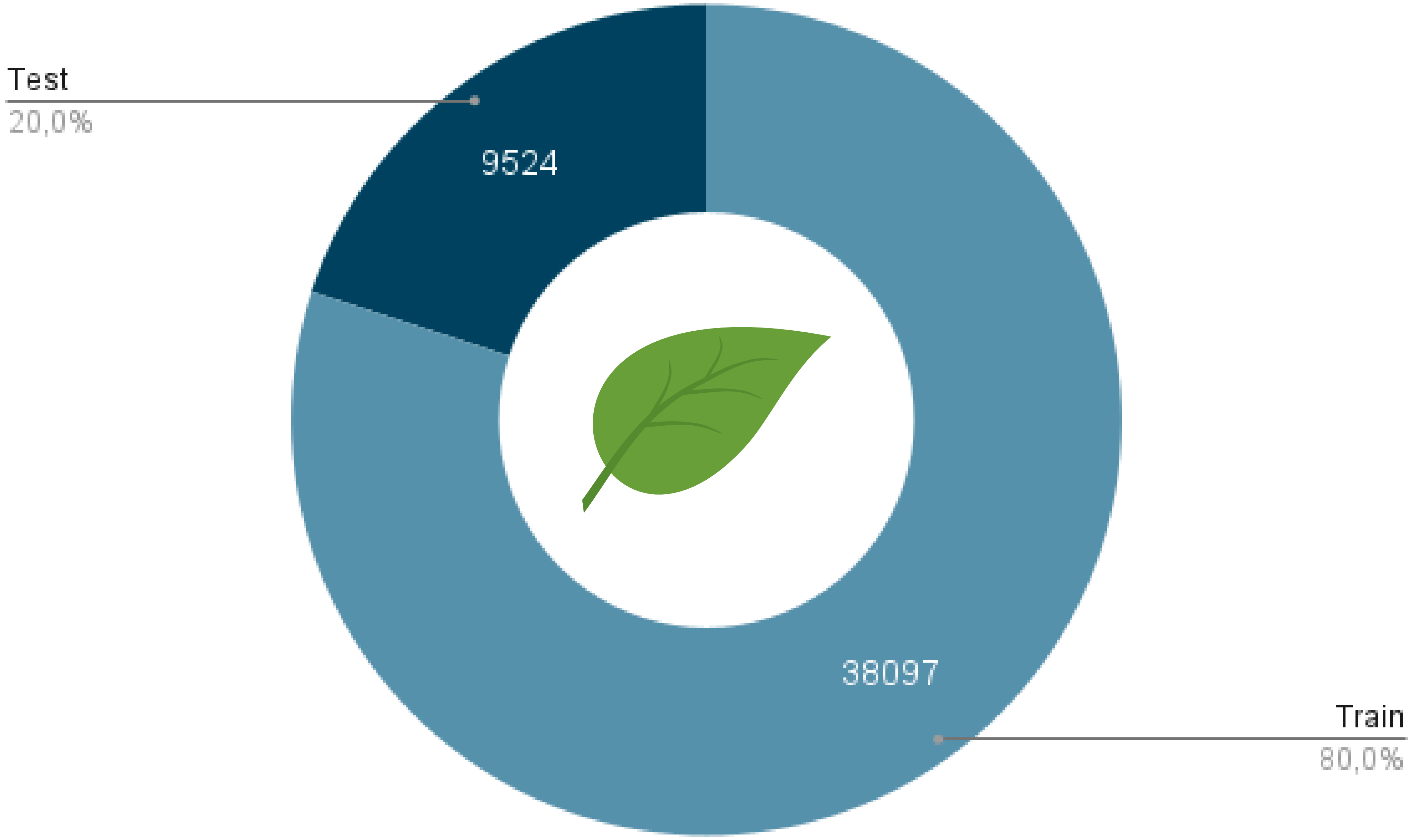
Loss function to optimize

We chose Adam because
"ADAM IS THE BEST"

- Mohammed A. Shehab

Splitting data

47,621 images



TRAINING

Model 0

Model 1

25,000 images = 1000 per class

Same parameters

no charts or graphics

charts and graphics like the confusion matrix

Model 2

47,621 images = entire dataset

charts and graphics like the confusion matrix

Model 3

47,621 images = entire dataset

charts and graphics like the confusion matrix

Simpliest data processing before training

TRAINING

- 10 epochs : 10 full cycle where the model processes all the training data once
  -> to minimize loss and maximize accuracy
- early stop: if the accuracy start going down we stop the training
  -> to prevent overfitting and save compututional ressources
- 10 versions of each model = 10 trains with same parameters but different seed
  -> to take the best seed with the highest accuracy

TRAINING

First trains (model 0 and 1)

```
model = Sequential([
            Conv2D(32, (3, 3), activation='relu', input_shape=(256, 256,
3)),
        MaxPooling2D((2, 2)),
        Conv2D(64, (3, 3), activation='relu'),
        MaxPooling2D((2, 2)),
        Flatten(),
        Dense(256, activation='relu'),
        Dense(len(label_encoder.classes_), activation='softmax')
    ])
```

Model:

- without specifying a seed
- One Convolutional layer with 32 3x3 kernel images (and with an input shape equal to the size of the dataset's images)
- A dimension reduction of this layer by taking the max of 2x2 subsets of these kernel images
- Another Convolutional layer with 64 3x3 kernel images
- Another dimension reduction of this layer by taking the max of 2x2 subsets of these kernel images

Accuracy: aproximatively 80% without seed and 86% with the best seed

TRAINING

Overfit so we tried to create less complex models

Test accuracy	Train accuracy
86%	94%

We did 3 different tests:

- Reducing the number of kernel images to 16 instead of 32 and 32 instead of 64: we got a test accuracy of 0.81, which is very similar to the unseeded precedent.
- Keeping the first hidden layer with 32 kernel images of size 4x4, but removing the second layer of CNN: the test accuracy diminished to 0.76, and with a greater gap between the test accuracy and the train accuracy.
- Keeping the first hidden layer, this time with 16 kernel images of size 3x3, and removing the second layer of CNN: the test accuracy dropped to 0.37 at its best, while still having a train accuracy of 94%.

Modifications failed to reduce overfitting

TRAINING

Model 2:

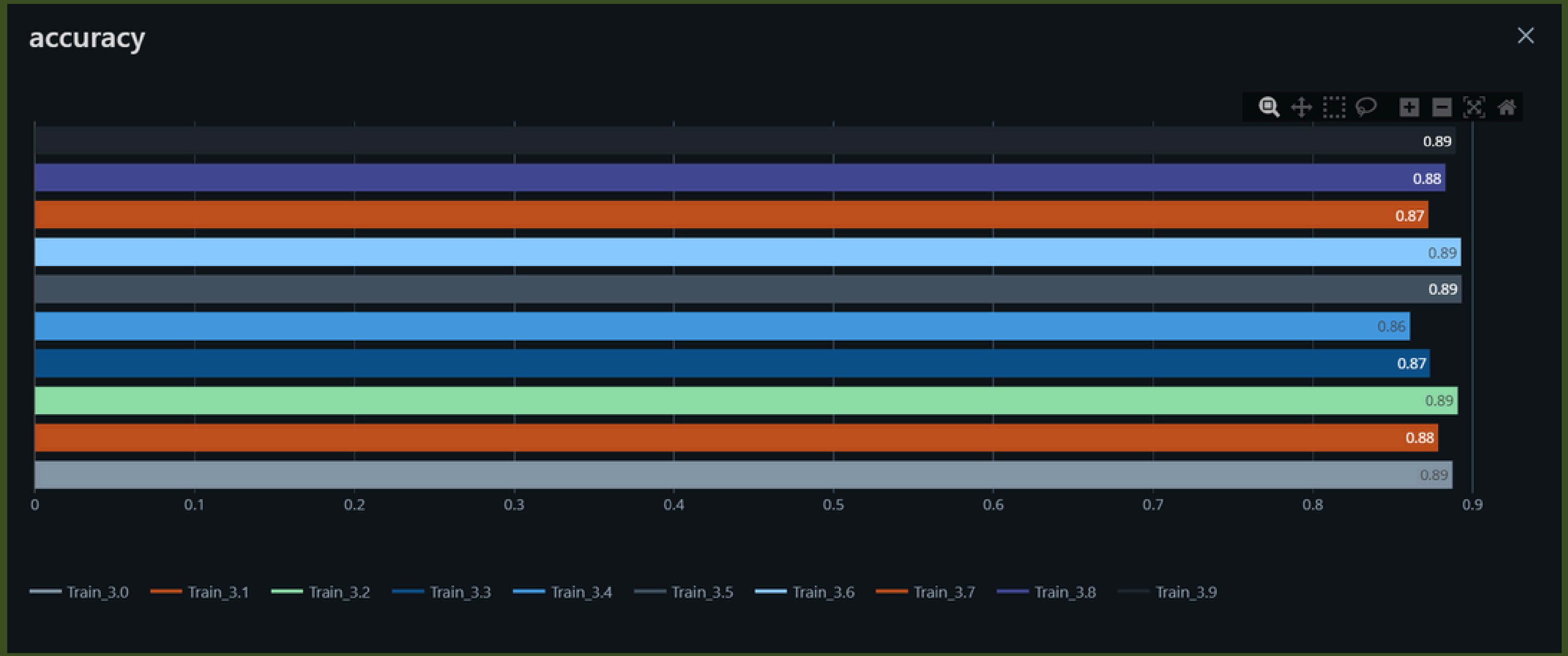
- Changed the method of data loading
- Loaded the whole dataset (more than 1000 images for each class)

Accuracy increased: almost 88%

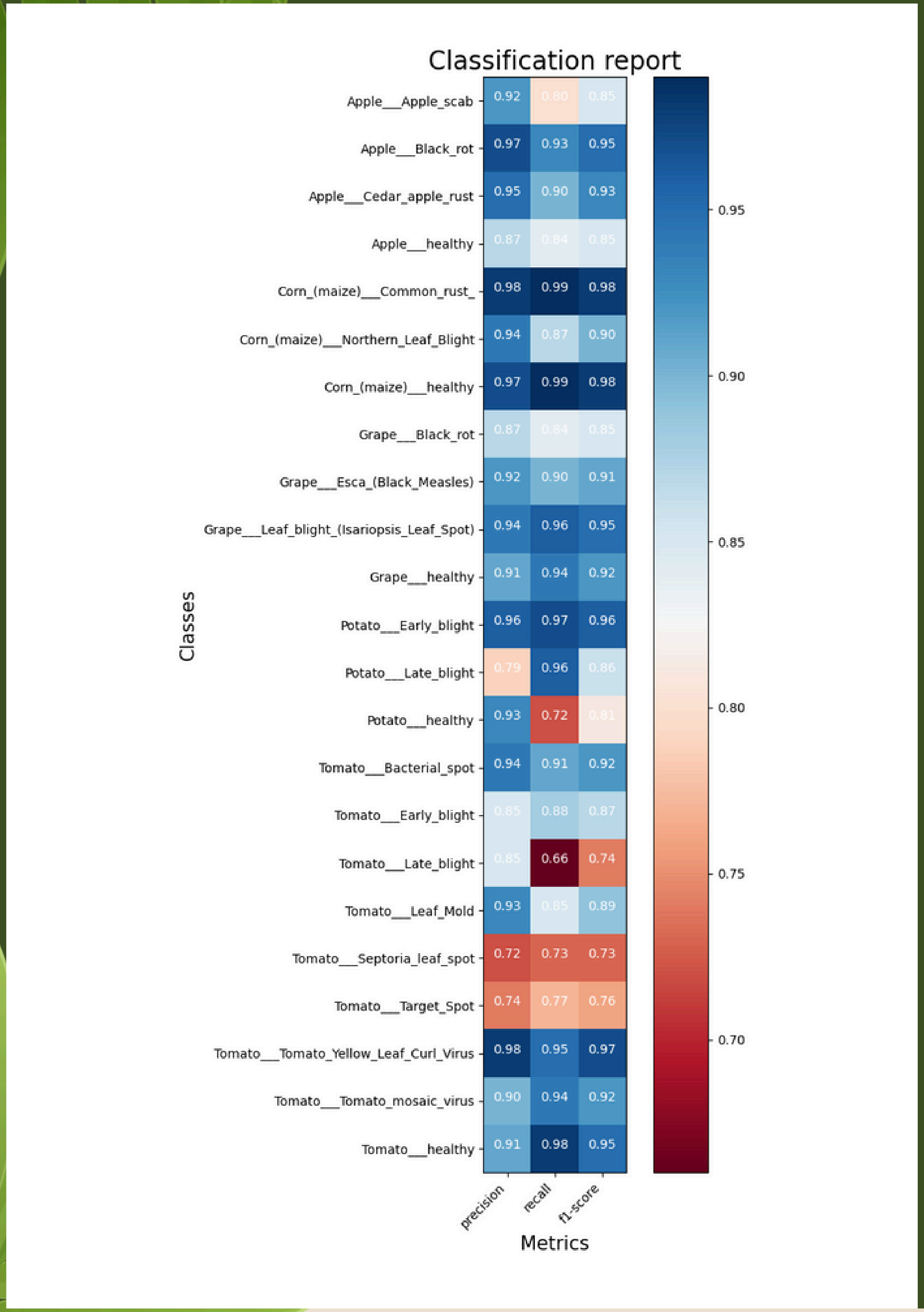
Model 3:

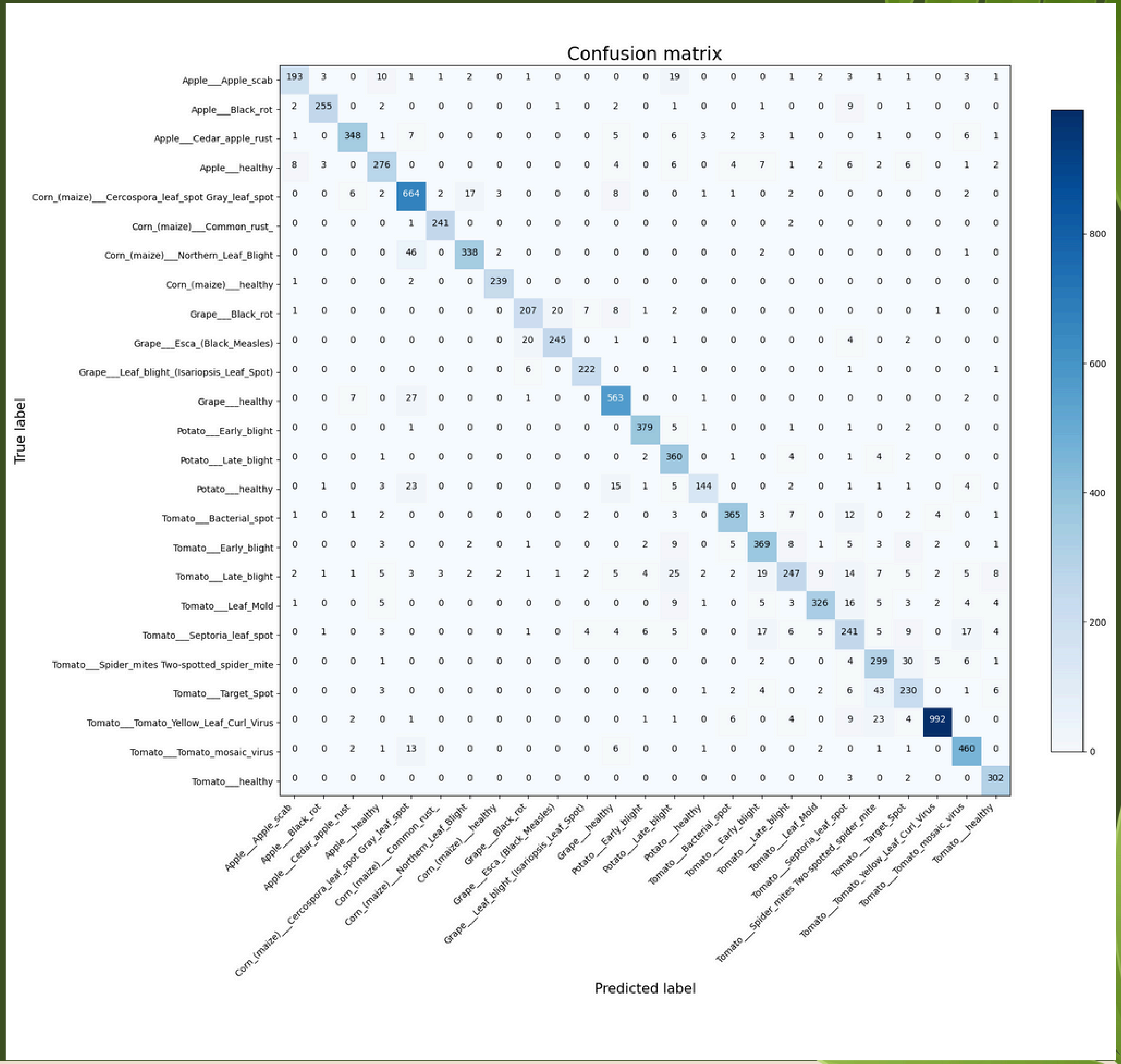
- Trained with GPU
- Changed some precessing before the training

Accuracy increased: 89%



RESULTS


Classification report
Classes
Metrics
precision
recall
f1-score
Apple___Apple_scab
Apple___Black_rot
Apple___Cedar_apple_rust
Apple___healthy
Corn_(maize)___Common_rust_
Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy


Confusion matrix
True label
Predicted label
Apple___Apple_scab
Apple___Black_rot
Apple___Cedar_apple_rust
Apple___healthy
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Corn_(maize)___Common_rust_
Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
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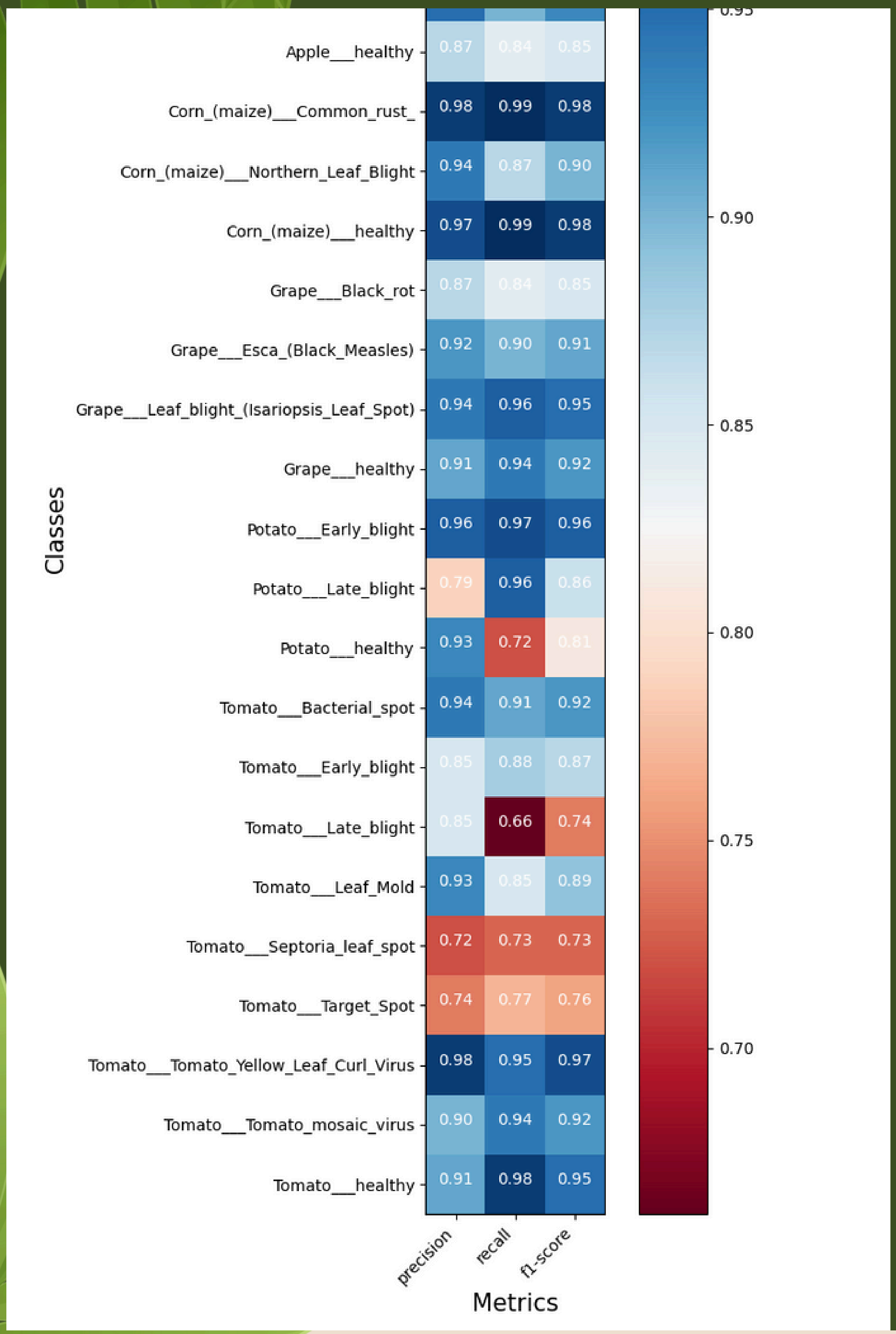
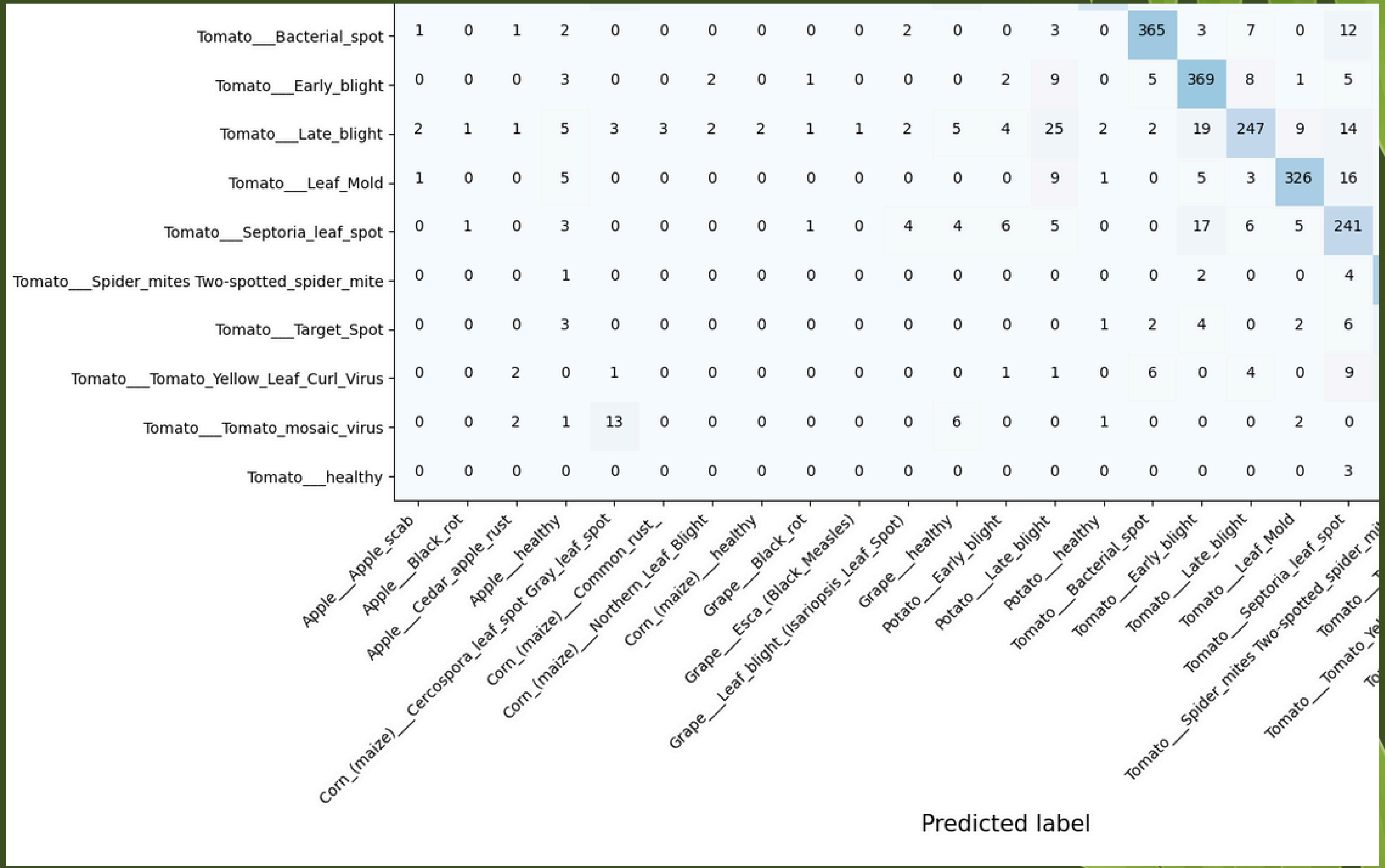
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Spider_mites Two-spotted_spider_mite
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy

RESULTS


Apple___healthy 0.87 0.84 0.85
Corn_(maize)___Common_rust_ 0.98 0.99 0.98
Corn_(maize)___Northern_Leaf_Blight 0.94 0.87 0.90
Corn_(maize)___healthy 0.97 0.99 0.98
Grape___Black_rot 0.87 0.84 0.85
Grape___Esca_(Black_Measles) 0.92 0.90 0.91
Grape___Leaf_blight_(Isariopsis_Leaf_Spot) 0.94 0.96 0.95
Grape___healthy 0.91 0.94 0.92
Potato___Early_blight 0.96 0.97 0.96
Potato___Late_blight 0.79 0.96 0.86
Potato___healthy 0.93 0.72 0.81
Tomato___Bacterial_spot 0.94 0.91 0.92
Tomato___Early_blight 0.85 0.88 0.87
Tomato___Late_blight 0.85 0.66 0.74
Tomato___Leaf_Mold 0.93 0.85 0.89
Tomato___Septoria_leaf_spot 0.72 0.73 0.73
Tomato___Target_Spot 0.74 0.77 0.76
Tomato___Tomato_Yellow_Leaf_Curl_Virus 0.98 0.95 0.97
Tomato___Tomato_mosaic_virus 0.90 0.94 0.92
Tomato___healthy 0.91 0.98 0.95
Classes
0.90
0.85
0.80
0.75
0.70
precision
recall
f1-score
Metrics


Tomato___Bacterial_spot 1 0 1 2 0 0 0 0 0 0 2 0 0 3 0 365 3 7 0 12
Tomato___Early_blight 0 0 0 3 0 0 2 0 1 0 0 0 2 9 0 5 369 8 1 5
Tomato___Late_blight 2 1 1 5 3 3 2 2 1 1 2 5 4 25 2 2 19 247 9 14
Tomato___Leaf_Mold 1 0 0 5 0 0 0 0 0 0 0 0 0 9 1 0 5 3 326 16
Tomato___Septoria_leaf_spot 0 1 0 3 0 0 0 0 1 0 4 4 6 5 0 0 17 6 5 241
Tomato___Spider_mites Two-spotted_spider_mite 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0 4
Tomato___Target_Spot 0 0 0 3 0 0 0 0 0 0 0 0 0 0 1 2 4 0 2 6
Tomato___Tomato_Yellow_Leaf_Curl_Virus 0 0 2 0 1 0 0 0 0 0 0 0 1 1 0 6 0 4 0 9
Tomato___Tomato_mosaic_virus 0 0 2 1 13 0 0 0 0 0 0 6 0 0 1 0 0 0 2 0
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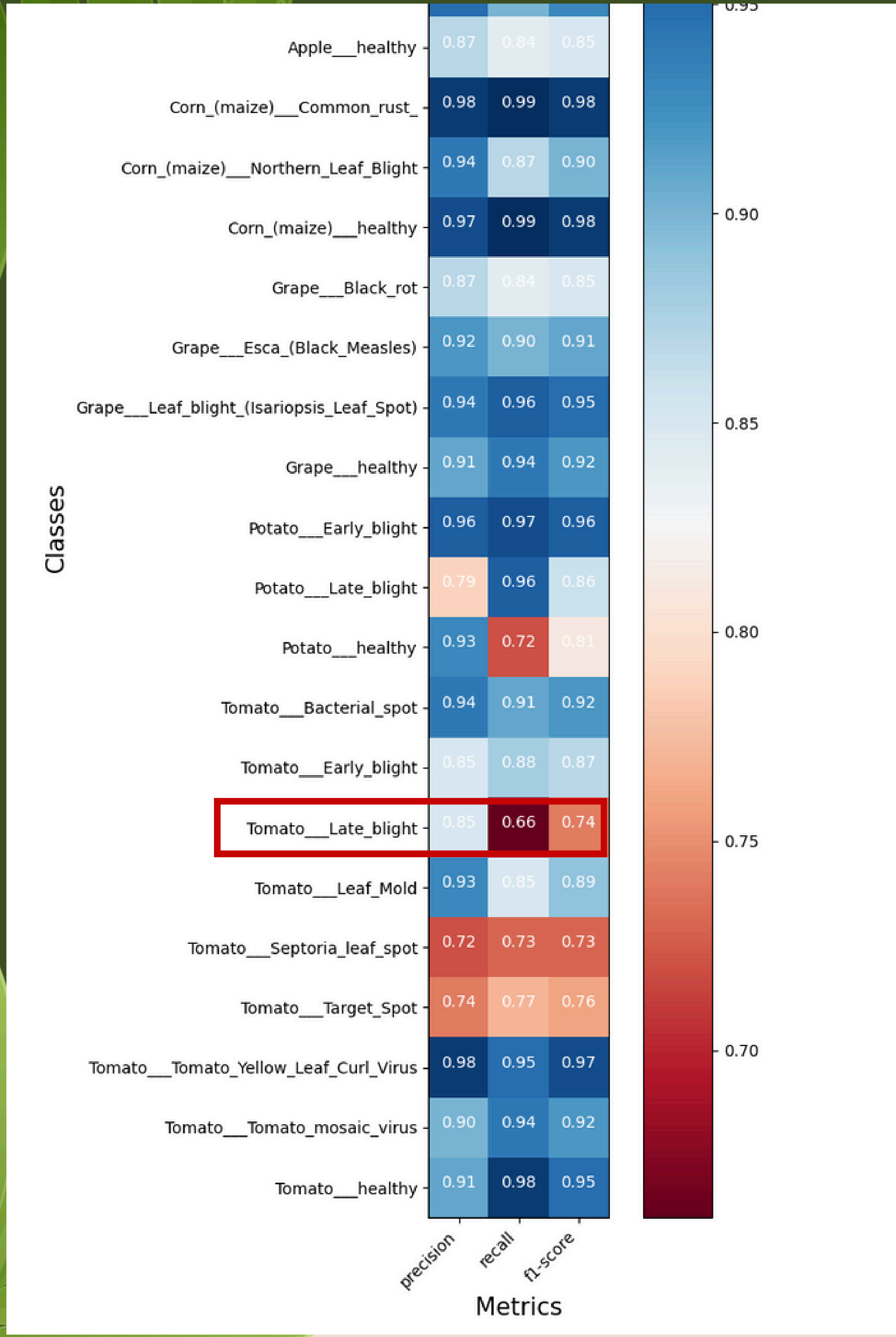
Grape___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Predicted label

RESULTS



Apple___healthy 0.87 0.84 0.85
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Tomato___Target_Spot 0.74 0.77 0.76
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Tomato___Tomato_mosaic_virus 0.90 0.94 0.92
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recall
f1-score
Metrics
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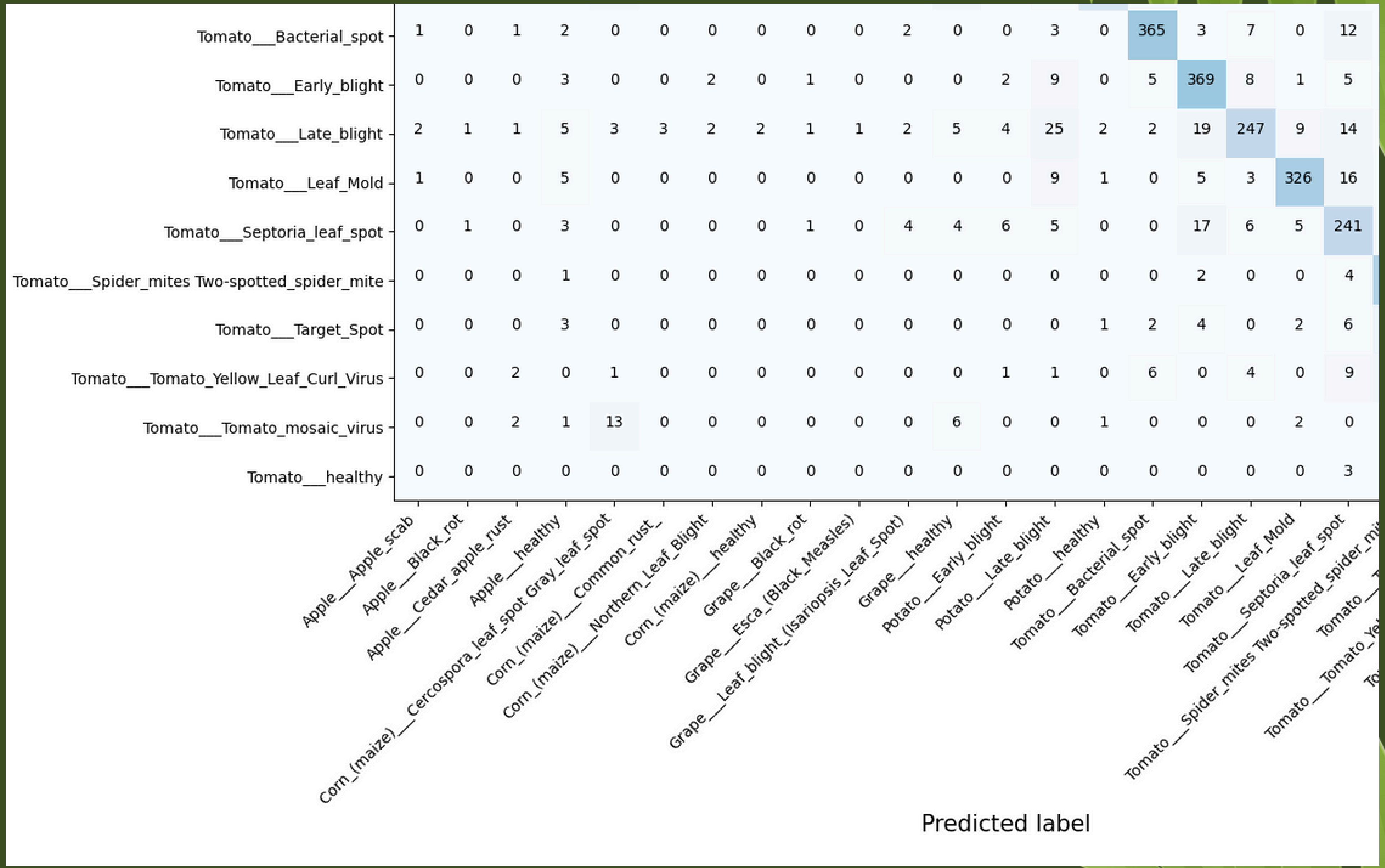

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Tomato___Target_Spot 0 0 0 3 0 0 0 0 0 0 0 0 0 0 1 2 4 0 2 6
Tomato___Tomato_Yellow_Leaf_Curl_Virus 0 0 2 0 1 0 0 0 0 0 0 0 1 1 0 6 0 4 0 9
Tomato___Tomato_mosaic_virus 0 0 2 1 13 0 0 0 0 0 0 6 0 0 1 0 0 0 2 0
Tomato___healthy 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3
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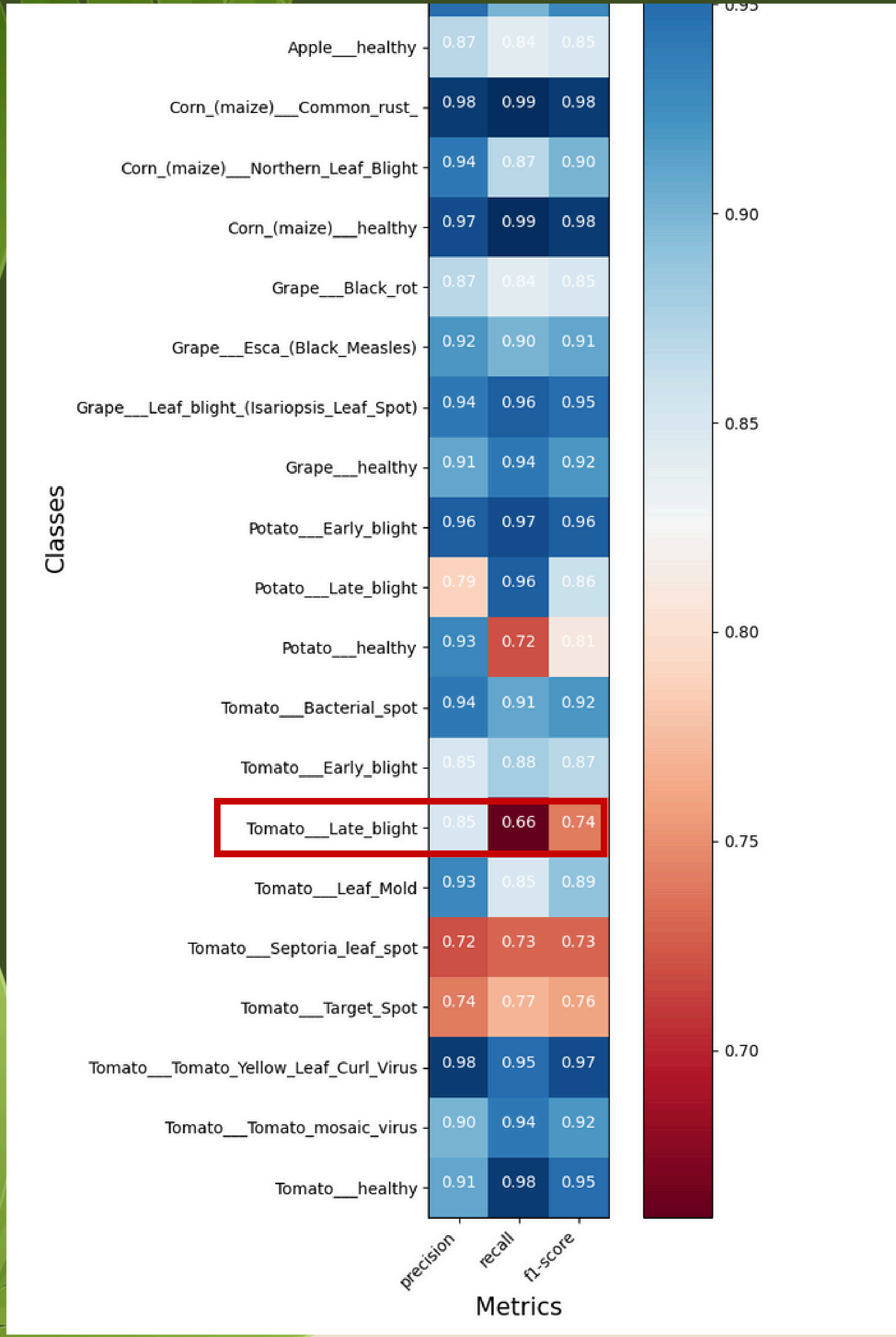
Predicted label

RESULTS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Corn_(maize)___healthy 0.97 0.99 0.98
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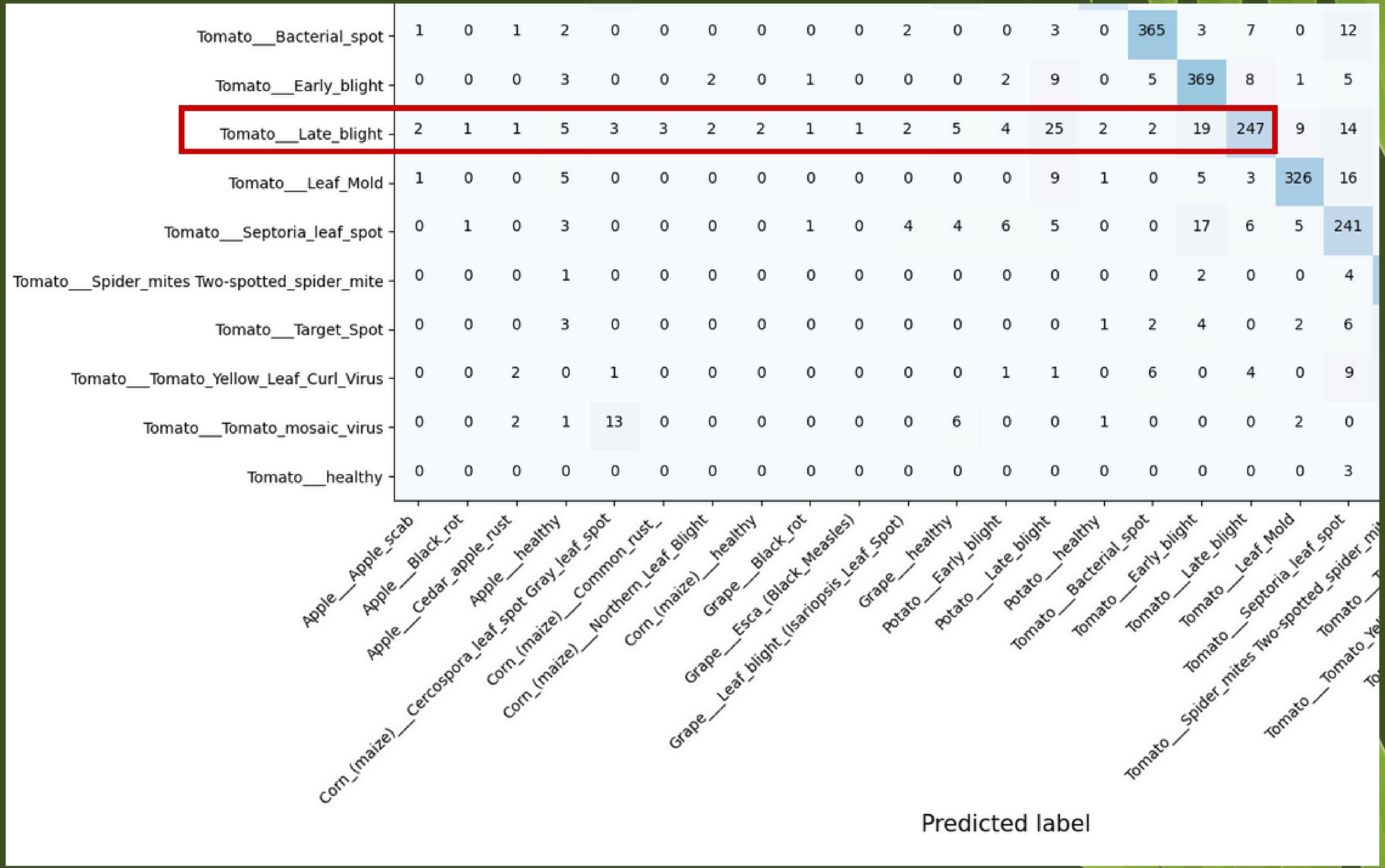
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Tomato___Target_Spot 0 0 0 3 0 0 0 0 0 0 0 0 0 0 1 2 4 0 2 6
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Tomato___healthy 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3
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Apple___Black_rot
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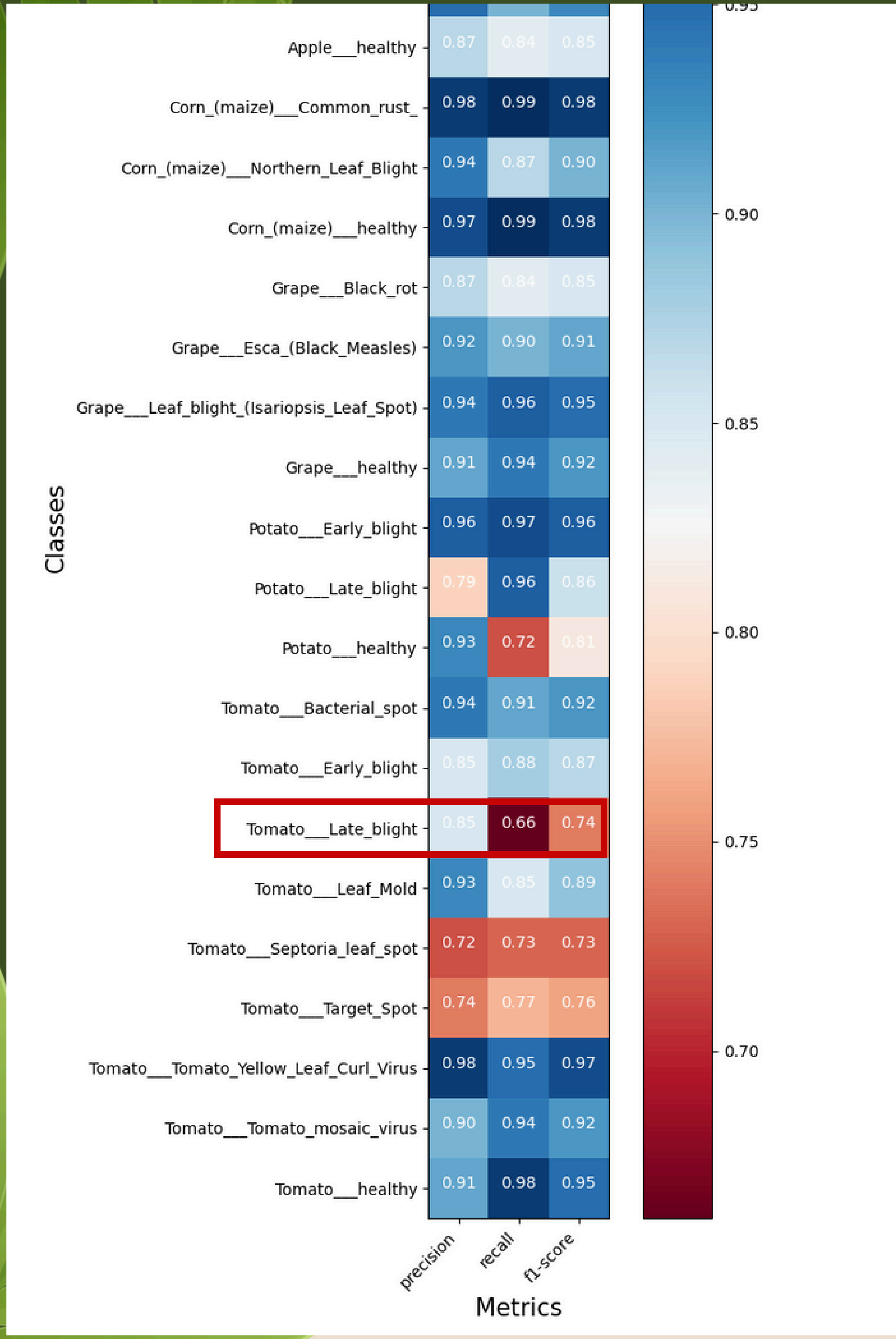
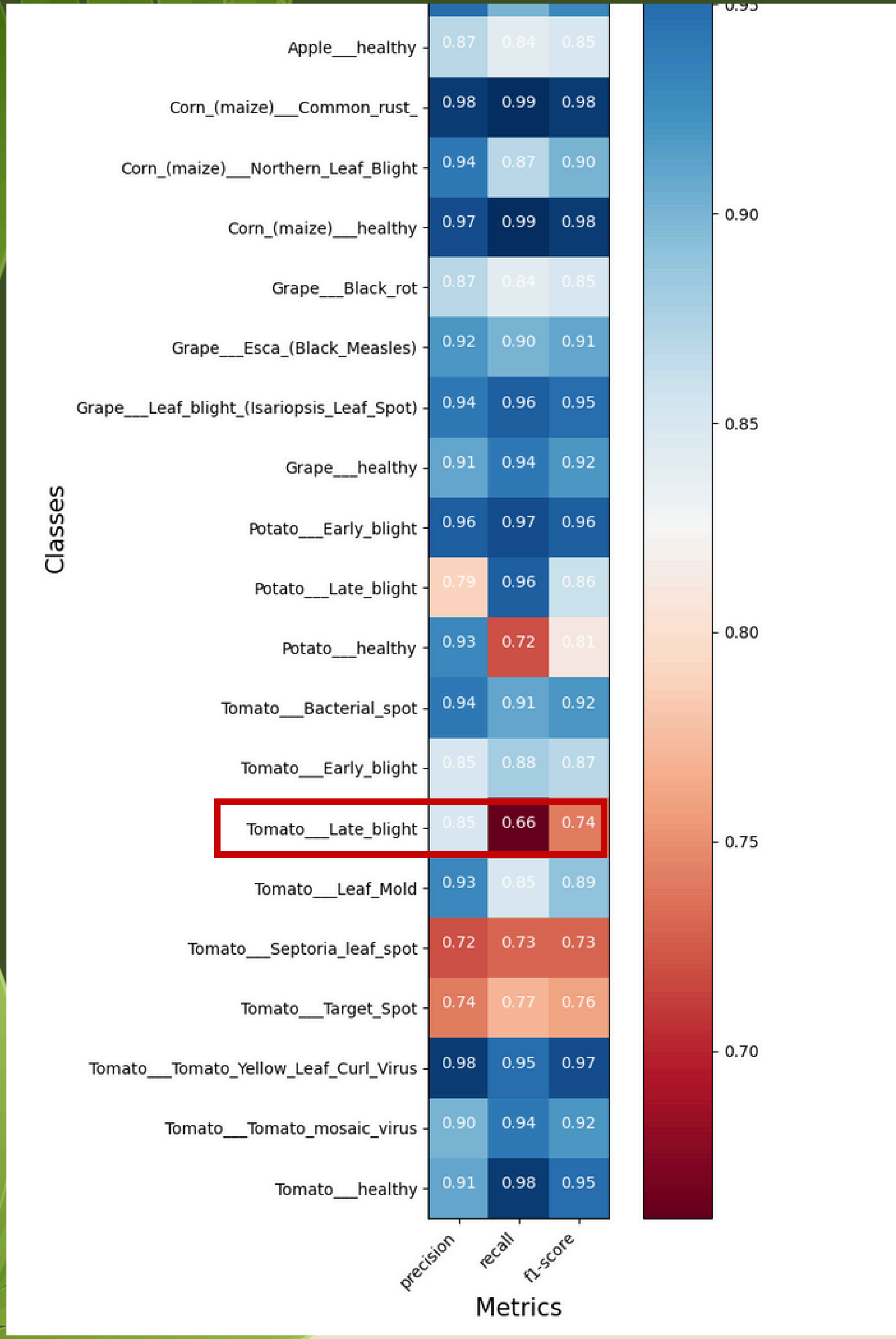
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Predicted label

RESULTS

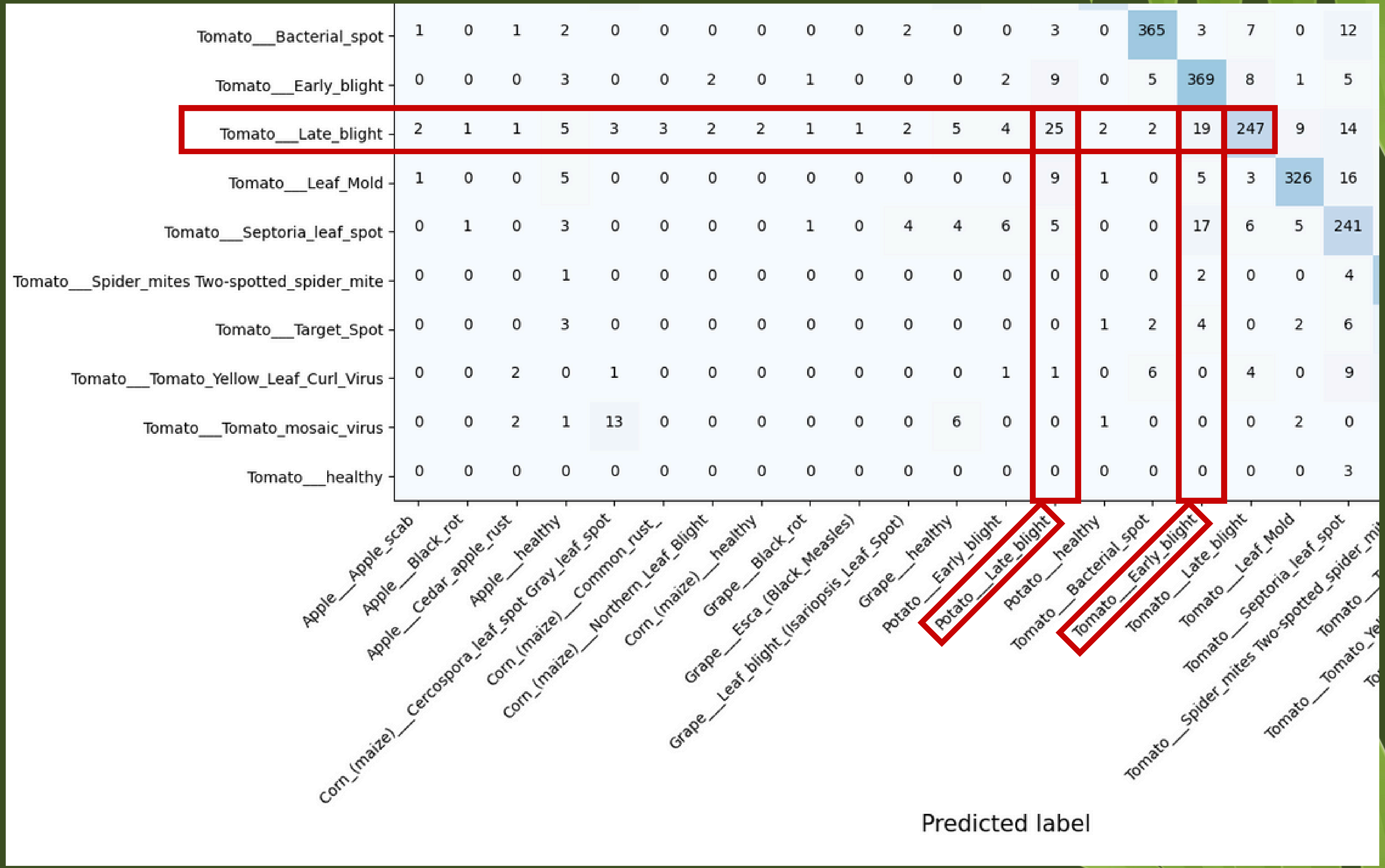

Apple___healthy
Corn_(maize)___Common_rust_
Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy
Classes
precision
recall
f1-score
Metrics
0.90
0.85
0.80
0.75
0.70


Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Spider_mites Two-spotted_spider_mite
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy
Apple___Apple_scab
Apple___Black_rot
Apple___Cedar_apple_rust
Apple___healthy
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Corn_(maize)___Common_rust_
Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Predicted label

RESULTS

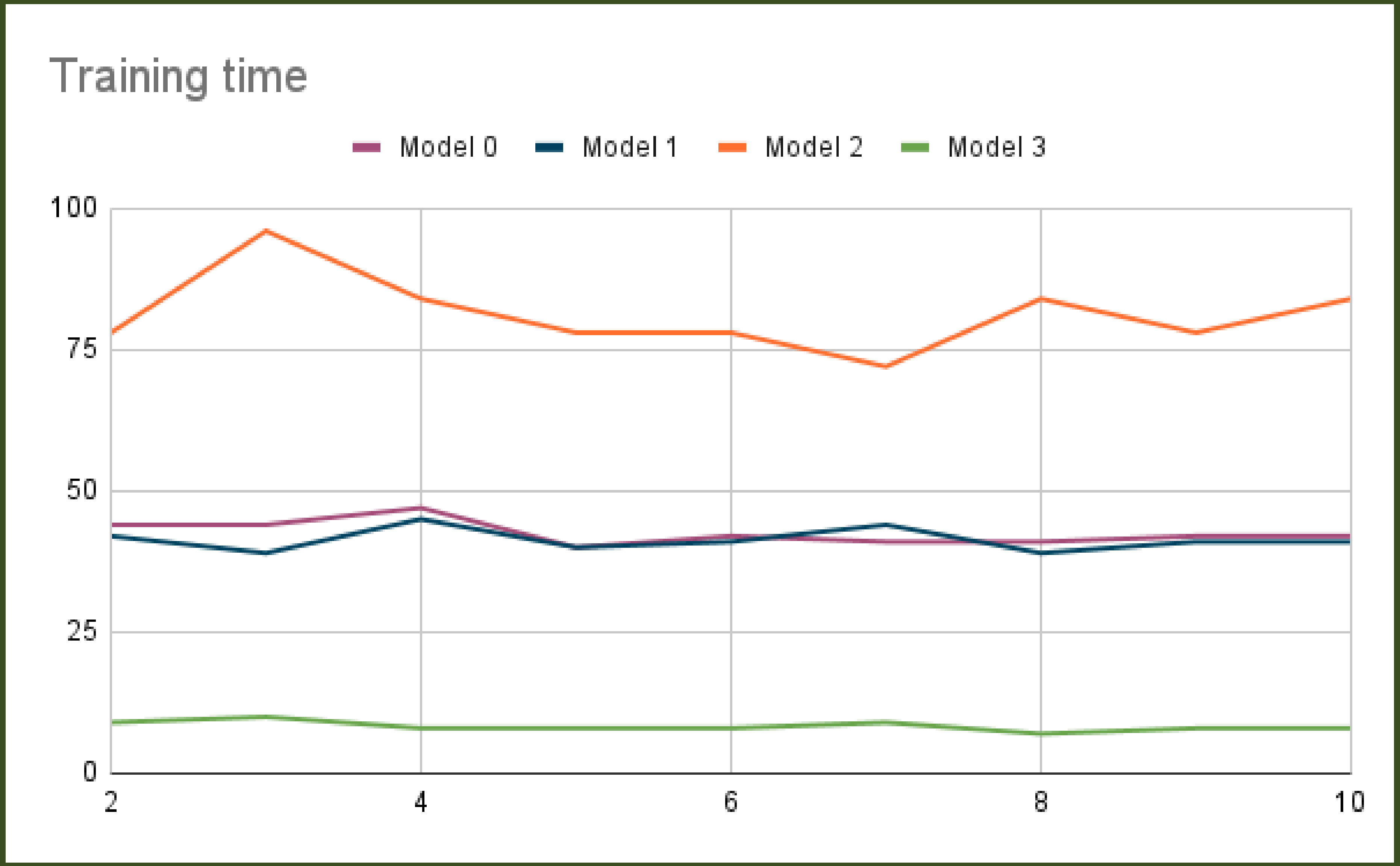


Classes
Metrics
precision
recall
f1-score
Apple___healthy
Corn_(maize)___Common_rust_
Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy



Predicted label
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot
Tomato___Spider_mites Two-spotted_spider_mite
Tomato___Target_Spot
Tomato___Tomato_Yellow_Leaf_Curl_Virus
Tomato___Tomato_mosaic_virus
Tomato___healthy
Apple___Apple_scab
Apple___Black_rot
Apple___Cedar_apple_rust
Apple___healthy
Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
Corn_(maize)___Common_rust_
Corn_(maize)___Northern_Leaf_Blight
Corn_(maize)___healthy
Grape___Black_rot
Grape___Esca_(Black_Measles)
Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
Grape___healthy
Potato___Early_blight
Potato___Late_blight
Potato___healthy
Tomato___Bacterial_spot
Tomato___Early_blight
Tomato___Late_blight
Tomato___Leaf_Mold
Tomato___Septoria_leaf_spot

DIFFICULTIES ENCOUNTERED

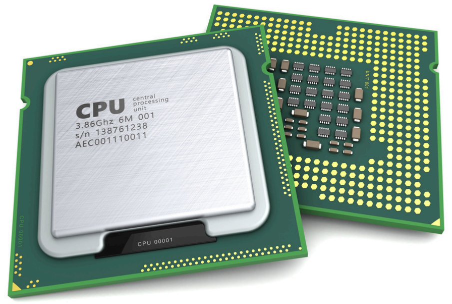


⟹ 1725 minutes or 28h and 45 minutes

DIFFICULTIES ENCOUNTERED

Training the model on a GPU

By default, tensorflow uses the **CPU**



But **GPU** is performant for **matrix multiplication,** so training our models will take less time


```
with tf.device('/GPU:0'):
    history = model.fit(train_data,
                        epochs=10,
                        validation_data=val_data,
                        callbacks=[checkpoint_callback, early_stopping_callback])
```

DIFFICULTIES ENCOUNTERED

Training the model on a GPU

Install compatible versions of CUDA and CUDNN

Anaconda - python 3.8 virtual environment

install CUDA and CUDNN in the environment from the versions that we already installed on the computer

Install tensorflow in the environment

Install all other useful libraries like mlflow

Demonstration !