

REPORT – LETTUCE LEAVES DISEASE CLASSIFICATION

Introduction

The aim of this project is to classify different types of diseases affecting lettuce leaves using machine learning techniques.

Dataset

The dataset was created by modifying an existing dataset and adding more images from google to it.

The following classes are there in the dataset :

Bacterial

Downy mildew

Healthy

Potassium deficiency

Nitrogen deficiency

Phosphorous deficiency

Powdery mildew

Septoria blight

Model Architecture

A big constraint was the small size of the dataset. Many other pretrained models were tried but good results were not observed . The following mentioned model recorded the best accuracy.

The model architecture used for classification consists of two convolutional layers followed by max-pooling layers to extract features from the images.

The output from the convolutional layers is flattened and passed through a dense layer with ReLU activation.

Finally, a softmax layer is used to predict the probability distribution over the classes.

The images are loaded from the directory and resized to a desired width and height. Preprocessing involves scaling the pixel values to the range [0, 1].

Training

The dataset is split into training and testing sets using a 90-10 split.

The model is compiled with the Adam optimizer and sparse categorical cross-entropy loss function.

Early stopping is applied to prevent overfitting, monitoring the validation accuracy with a patience of 15 epochs.

Results

A validation accuracy of **70 %** was observed for the code in this project.

Other models were also tried: Resnet50 - 44% Mobilenet - 36%

For the custom model prepared in the project the following are the evaluation details:

```
Epoch 1/100
6/6 [=====] - 19s 3s/step - loss: 6.1684 - accuracy: 0.1850 - val_loss:
2.1718 - val_accuracy: 0.2000
Epoch 2/100
6/6 [=====] - 15s 3s/step - loss: 2.0464 - accuracy: 0.1503 - val_loss:
1.8755 - val_accuracy: 0.2000
Epoch 3/100
6/6 [=====] - 18s 3s/step - loss: 1.7722 - accuracy: 0.3642 - val_loss:
1.4092 - val_accuracy: 0.4500
Epoch 4/100
6/6 [=====] - 17s 3s/step - loss: 1.2752 - accuracy: 0.5607 - val_loss:
1.2986 - val_accuracy: 0.3500
Epoch 5/100
6/6 [=====] - 16s 3s/step - loss: 0.8157 - accuracy: 0.6994 - val_loss:
1.2750 - val_accuracy: 0.3500
Epoch 6/100
6/6 [=====] - 17s 3s/step - loss: 0.5303 - accuracy: 0.8035 - val_loss:
1.2038 - val_accuracy: 0.6000
Epoch 7/100
6/6 [=====] - 17s 3s/step - loss: 0.4256 - accuracy: 0.8439 - val_loss:
1.1882 - val_accuracy: 0.5000
Epoch 8/100
6/6 [=====] - 16s 3s/step - loss: 0.3527 - accuracy: 0.8613 - val_loss:
1.1486 - val_accuracy: 0.6000
Epoch 9/100
```

6/6 [=====] - 17s 3s/step - loss: 0.1738 - accuracy: 0.9538 - val_loss: 1.2154 - val_accuracy: 0.6500
Epoch 10/100
6/6 [=====] - 17s 3s/step - loss: 0.1758 - accuracy: 0.9480 - val_loss: 1.1930 - val_accuracy: 0.6500
Epoch 11/100
6/6 [=====] - 17s 3s/step - loss: 0.2012 - accuracy: 0.9422 - val_loss: 1.0364 - val_accuracy: 0.6000
Epoch 12/100
6/6 [=====] - 18s 3s/step - loss: 0.1130 - accuracy: 0.9711 - val_loss: 1.2620 - val_accuracy: 0.5500
Epoch 13/100
6/6 [=====] - 17s 3s/step - loss: 0.0688 - accuracy: 0.9769 - val_loss: 1.3597 - val_accuracy: 0.5500
Epoch 14/100
6/6 [=====] - 17s 3s/step - loss: 0.0725 - accuracy: 0.9827 - val_loss: 1.0578 - val_accuracy: 0.7000
Epoch 15/100
6/6 [=====] - 17s 3s/step - loss: 0.0774 - accuracy: 0.9711 - val_loss: 1.0671 - val_accuracy: 0.6000
Epoch 16/100
6/6 [=====] - 16s 3s/step - loss: 0.0415 - accuracy: 0.9827 - val_loss: 1.3355 - val_accuracy: 0.5500
Epoch 17/100
6/6 [=====] - 16s 3s/step - loss: 0.0310 - accuracy: 0.9827 - val_loss: 1.2414 - val_accuracy: 0.6000
Epoch 18/100
6/6 [=====] - 17s 3s/step - loss: 0.0360 - accuracy: 0.9827 - val_loss: 1.2579 - val_accuracy: 0.6000
Epoch 19/100
6/6 [=====] - 17s 3s/step - loss: 0.0667 - accuracy: 0.9884 - val_loss: 1.2788 - val_accuracy: 0.6500
Epoch 20/100
6/6 [=====] - 16s 3s/step - loss: 0.0195 - accuracy: 0.9942 - val_loss: 1.4793 - val_accuracy: 0.5500
Epoch 21/100
6/6 [=====] - 16s 3s/step - loss: 0.0566 - accuracy: 0.9827 - val_loss: 0.9934 - val_accuracy: 0.6000
Epoch 22/100
6/6 [=====] - 16s 3s/step - loss: 0.0381 - accuracy: 0.9769 - val_loss: 1.2077 - val_accuracy: 0.5500
Epoch 23/100
6/6 [=====] - 17s 3s/step - loss: 0.0207 - accuracy: 0.9827 - val_loss: 1.2105 - val_accuracy: 0.5500
Epoch 24/100
6/6 [=====] - 16s 3s/step - loss: 0.0185 - accuracy: 0.9884 - val_loss: 1.3159 - val_accuracy: 0.6500
Epoch 25/100
6/6 [=====] - 17s 3s/step - loss: 0.0331 - accuracy: 0.9884 - val_loss: 1.6429 - val_accuracy: 0.6000
Epoch 26/100
6/6 [=====] - 18s 3s/step - loss: 0.0906 - accuracy: 0.9827 - val_loss: 1.3872 - val_accuracy: 0.5500
Epoch 27/100
6/6 [=====] - 17s 3s/step - loss: 0.1648 - accuracy: 0.9595 - val_loss: 1.2500 - val_accuracy: 0.5500
Epoch 28/100
6/6 [=====] - 17s 3s/step - loss: 0.1321 - accuracy: 0.9884 - val_loss: 1.8565 - val_accuracy: 0.5500

Epoch 29/100

6/6 [=====] - 17s 3s/step - loss: 0.1479 - accuracy: 0.9595 - val_loss: 1.4462 - val_accuracy: 0.5500

1/1 [=====] - 0s 384ms/step - loss: 1.0578 - accuracy: 0.7000

Test Accuracy: 0.699999988079071

1/1 [=====] - 1s 617ms/step

Actual Labels: [1 3 6 1 7 0 5 3 4 7 6 5 1 0 4 2 1 2 1 6]

Predicted Labels: [3 3 6 1 1 2 5 3 5 7 6 5 1 0 5 2 1 0 1 6]

Example Predictions:

Actual Label: 1



Predicted Label: 1



Actual Label: 3



Predicted Label: 3

