

```
# Set seeds for reproducibility
import random
random.seed(0)

import numpy as np
np.random.seed(0)

import tensorflow as tf
tf.random.set_seed(0)

import os
import json
from zipfile import ZipFile
from PIL import Image

!pip install kaggle

Requirement already satisfied: kaggle in /usr/local/lib/python3.10/dist-packages (1.5.16)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.10/dist-packages (from kaggle) (1.16.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.10/dist-packages (from kaggle) (2024.2.2)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.10/dist-packages (from kaggle) (2.8.2)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from kaggle) (2.31.0)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from kaggle) (4.66.2)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.10/dist-packages (from kaggle) (8.0.4)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-packages (from kaggle) (2.0.7)
Requirement already satisfied: bleach in /usr/local/lib/python3.10/dist-packages (from kaggle) (6.1.0)
Requirement already satisfied: webencodings in /usr/local/lib/python3.10/dist-packages (from bleach->kaggle) (0.5.1)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.10/dist-packages (from python-slugify->kaggle) (1.3)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->kaggle) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->kaggle) (3.7)

kaggle_credentials = json.load(open("kaggle.json"))

# setup Kaggle API key as environment variables
os.environ['KAGGLE_USERNAME'] = kaggle_credentials["username"]
os.environ['KAGGLE_KEY'] = kaggle_credentials["key"]

!kaggle datasets download -d vipoooool/new-plant-diseases-dataset

Downloading new-plant-diseases-dataset.zip to /content
... resuming from 349175808 bytes (2548533379 bytes left) ...
100% 2.70G/2.70G [00:14<00:00, 199MB/s]
100% 2.70G/2.70G [00:14<00:00, 181MB/s]

lls

drive          'new plant diseases dataset(augmented)'  new-plant-diseases-dataset.zip
kaggle.json    'New Plant Diseases Dataset(Augmented)'  test

# Unzip the downloaded dataset
with ZipFile("new-plant-diseases-dataset.zip", 'r') as zip_ref:
    zip_ref.extractall()

lls

drive          'new plant diseases dataset(augmented)'  new-plant-diseases-dataset.zip
kaggle.json    'New Plant Diseases Dataset(Augmented)'  test
```

Importing Libraries

```
import tensorflow as tf
from tensorflow.keras.layers import Dense, Conv2D, MaxPool2D, Flatten, Dropout
from tensorflow.keras.models import Sequential
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras import layers, models
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

DATA PREPROCESSING

Training Image

```

training_set = tf.keras.utils.image_dataset_from_directory(
    '/content/New Plant Diseases Dataset(Augmented)/New Plant Diseases Dataset(Augmented)/train',
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=32,
    image_size=(128, 128),
    shuffle=True,
    seed=None,
    validation_split=None,
    subset=None,
    interpolation="bilinear",
    follow_links=False,
    crop_to_aspect_ratio=False
)

Found 70295 files belonging to 38 classes.

```

VALIDATION IMAGE

```

validation_set = tf.keras.utils.image_dataset_from_directory(
    '/content/New Plant Diseases Dataset(Augmented)/New Plant Diseases Dataset(Augmented)/valid',
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=32,
    image_size=(128, 128),
    shuffle=True,
    seed=None,
    validation_split=None,
    subset=None,
    interpolation="bilinear",
    follow_links=False,
    crop_to_aspect_ratio=False
)

Found 17572 files belonging to 38 classes.

```

✓ BUILD MODEL

```

my_model = tf.keras.models.Sequential()

my_model.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, padding='same', activation='relu', input_shape=[128, 128, 3]))
my_model.add(tf.keras.layers.Conv2D(filters=32, kernel_size=3, activation='relu'))
my_model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

my_model.add(tf.keras.layers.Conv2D(filters=64, kernel_size=3, padding='same', activation='relu'))
my_model.add(tf.keras.layers.Conv2D(filters=64, kernel_size=3, activation='relu'))
my_model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

my_model.add(tf.keras.layers.Conv2D(filters=128, kernel_size=3, padding='same', activation='relu'))
my_model.add(tf.keras.layers.Conv2D(filters=128, kernel_size=3, activation='relu'))
my_model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

my_model.add(tf.keras.layers.Conv2D(filters=256, kernel_size=3, padding='same', activation='relu'))
my_model.add(tf.keras.layers.Conv2D(filters=256, kernel_size=3, activation='relu'))
my_model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

my_model.add(tf.keras.layers.Conv2D(filters=512, kernel_size=3, padding='same', activation='relu'))
my_model.add(tf.keras.layers.Conv2D(filters=512, kernel_size=3, activation='relu'))
my_model.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))

my_model.add(tf.keras.layers.Dropout(0.25)) # avoid underfitting

my_model.add(tf.keras.layers.Flatten())
my_model.add(tf.keras.layers.Dense(units=1500, activation='relu'))

my_model.add(tf.keras.layers.Dropout(0.4)) #To avoid overfitting

#Output Layer
my_model.add(tf.keras.layers.Dense(units=38, activation='softmax'))

```

COMPLILING || TRAINING

```
my_model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001) ,loss='categorical_crossentropy', metrics=['accuracy'])

my_model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 128, 128, 32)	896
conv2d_1 (Conv2D)	(None, 126, 126, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_2 (Conv2D)	(None, 63, 63, 64)	18496
conv2d_3 (Conv2D)	(None, 61, 61, 64)	36928
max_pooling2d_1 (MaxPoolin g2D)	(None, 30, 30, 64)	0
conv2d_4 (Conv2D)	(None, 30, 30, 128)	73856
conv2d_5 (Conv2D)	(None, 28, 28, 128)	147584
max_pooling2d_2 (MaxPoolin g2D)	(None, 14, 14, 128)	0
conv2d_6 (Conv2D)	(None, 14, 14, 256)	295168
conv2d_7 (Conv2D)	(None, 12, 12, 256)	590080
max_pooling2d_3 (MaxPoolin g2D)	(None, 6, 6, 256)	0
conv2d_8 (Conv2D)	(None, 6, 6, 512)	1180160
conv2d_9 (Conv2D)	(None, 4, 4, 512)	2359808
max_pooling2d_4 (MaxPoolin g2D)	(None, 2, 2, 512)	0
dropout (Dropout)	(None, 2, 2, 512)	0
flatten (Flatten)	(None, 2048)	0
dense (Dense)	(None, 1500)	3073500
dropout_1 (Dropout)	(None, 1500)	0
dense_1 (Dense)	(None, 38)	57038
=====		
Total params: 7842762 (29.92 MB)		
Trainable params: 7842762 (29.92 MB)		
Non-trainable params: 0 (0.00 Byte)		

```
training_history = my_model.fit(x=training_set,validation_data=validation_set,epochs=15)

Epoch 1/15
2197/2197 [=====] - 178s 76ms/step - loss: 1.3585 - accuracy: 0.5993 - val_loss: 0.5001 - val_accuracy: 0.
Epoch 2/15
2197/2197 [=====] - 162s 73ms/step - loss: 0.4533 - accuracy: 0.8557 - val_loss: 0.2891 - val_accuracy: 0.
Epoch 3/15
2197/2197 [=====] - 161s 73ms/step - loss: 0.2623 - accuracy: 0.9160 - val_loss: 0.3160 - val_accuracy: 0.
Epoch 4/15
2197/2197 [=====] - 162s 74ms/step - loss: 0.1837 - accuracy: 0.9406 - val_loss: 0.2627 - val_accuracy: 0.
Epoch 5/15
2197/2197 [=====] - 160s 73ms/step - loss: 0.1384 - accuracy: 0.9534 - val_loss: 0.1387 - val_accuracy: 0.
Epoch 6/15
2197/2197 [=====] - 161s 73ms/step - loss: 0.1081 - accuracy: 0.9644 - val_loss: 0.2453 - val_accuracy: 0.
Epoch 7/15
2197/2197 [=====] - 158s 72ms/step - loss: 0.0843 - accuracy: 0.9725 - val_loss: 0.1351 - val_accuracy: 0.
Epoch 8/15
2197/2197 [=====] - 160s 73ms/step - loss: 0.0752 - accuracy: 0.9750 - val_loss: 0.1149 - val_accuracy: 0.
Epoch 9/15
2197/2197 [=====] - 161s 73ms/step - loss: 0.0640 - accuracy: 0.9793 - val_loss: 0.1353 - val_accuracy: 0.
Epoch 10/15
2197/2197 [=====] - 162s 74ms/step - loss: 0.0573 - accuracy: 0.9816 - val_loss: 0.1115 - val_accuracy: 0.
Epoch 11/15
2197/2197 [=====] - 162s 74ms/step - loss: 0.0533 - accuracy: 0.9829 - val_loss: 0.1271 - val_accuracy: 0.
```

```
Epoch 12/15
2197/2197 [=====] - 163s 74ms/step - loss: 0.0437 - accuracy: 0.9860 - val_loss: 0.2143 - val_accuracy: 0.
Epoch 13/15
2197/2197 [=====] - 162s 73ms/step - loss: 0.0416 - accuracy: 0.9870 - val_loss: 0.1156 - val_accuracy: 0.
Epoch 14/15
2197/2197 [=====] - 160s 73ms/step - loss: 0.0382 - accuracy: 0.9879 - val_loss: 0.0960 - val_accuracy: 0.
Epoch 15/15
2197/2197 [=====] - 161s 73ms/step - loss: 0.0371 - accuracy: 0.9881 - val_loss: 0.1088 - val_accuracy: 0.
```

✓ EVALUATION OF THE MODEL

```
#Training set Accuracy
train_loss, train_acc = my_model.evaluate(training_set)
print('Training accuracy:', train_acc)

2197/2197 [=====] - 55s 25ms/step - loss: 0.0213 - accuracy: 0.9941
Training accuracy: 0.9940536022186279

# Image Parameters
img_size = 224
batch_size = 32

#Validation set Accuracy
val_loss, val_acc = my_model.evaluate(validation_set)
print('Validation accuracy:', val_acc)

550/550 [=====] - 14s 24ms/step - loss: 0.1088 - accuracy: 0.9711
Validation accuracy: 0.9710903763771057
```

✓ VISUALISATION TOOLS

```
training_history.history
0.2622852027416229,
0.1837005615234375,
0.13837198913097382,
0.10814646631479263,
0.08430405706167221,
0.07515065371990204,
0.0639662817120552,
0.057262271642684937,
0.05332052335143089,
0.043691739439964294,
0.041633713990449905,
0.038166094571352005,
0.03713954985141754],
'accuracy': [0.5993313789367676,
0.855665385723114,
0.9159968495368958,
0.9406074285507202,
0.9534390568733215,
0.9644213914871216,
0.972544252872467,
0.9750195741653442,
0.9793015122413635,
0.9816203117370605,
0.9829148650169373,
0.9860302805900574,
0.9869834184646606,
0.9879223108291626,
0.9881499409675598],
'val_loss': [0.5001130700111389,
0.2891317903995514,
0.31596770882606506,
0.26269352436065674,
0.13868436217308044,
0.2452743500471115,
0.13508851826190948,
0.11488883942365646,
0.13528084754943848,
0.11148218810558319,
0.12714561820030212,
0.21434347331523895,
0.1155521422624588,
0.0960436537861824,
0.10882437229156494],
'val_accuracy': [0.8420214056968689,
0.908490777015686,
0.8964261412620544,
```

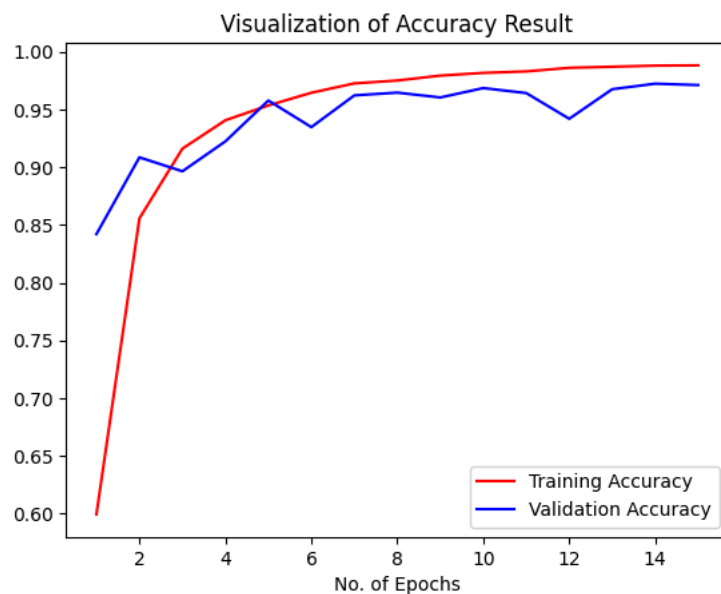
```
0.934008119313109,
0.9621556997299194,
0.9645458459854126,
0.9603345990180969,
0.9684725403785706,
0.9641475081443787,
0.9418962001800537,
0.9675050973892212,
0.9722854495048523,
0.9710903763771057]]}
```

```
import json
with open('training_hist.json','w') as f:
    json.dump(training_history.history,f)
```

```
print(training_history.history.keys())
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
epochs = [i for i in range(1,16)]
plt.plot(epochs,training_history.history['accuracy'],color='red',label='Training Accuracy')
plt.plot(epochs,training_history.history['val_accuracy'],color='blue',label='Validation Accuracy')
plt.xlabel('No. of Epochs')
plt.title('Visualization of Accuracy Result')
plt.legend()
plt.show()
```



Precision Recall Fscore

```
class_name = validation_set.class_names
print(class_name)
```

```
['Apple__Apple_scab', 'Apple__Black_rot', 'Apple__Cedar_apple_rust', 'Apple__healthy', 'Blueberry__healthy', 'Cherry_(includin
```

```
test_set = tf.keras.utils.image_dataset_from_directory(
    '/content/New Plant Diseases Dataset(Augmented)/New Plant Diseases Dataset(Augmented)/valid',
    labels="inferred",
    label_mode="categorical",
    class_names=None,
    color_mode="rgb",
    batch_size=1,
    image_size=(128, 128),
    shuffle=False,
    seed=None,
    validation_split=None,
    subset=None,
    interpolation="bilinear",
    follow_links=False,
    crop_to_aspect_ratio=False
)
```

```
Found 17572 files belonging to 38 classes.
```

```
y_pred = my_model.predict(test_set)
predicted_categories = tf.argmax(y_pred, axis=1)
```

17572/17572 [=====] - 55s 3ms/step

```
true_categories = tf.concat([y for x, y in test_set], axis=0)
Y_true = tf.argmax(true_categories, axis=1)
```

```
from sklearn.metrics import confusion_matrix, classification_report
cm = confusion_matrix(Y_true, predicted_categories)
```

```
# Precision Recall Fscore
```

```
print(classification_report(Y_true, predicted_categories, target_names=class_name))
```

	precision	recall	f1-score	support
Apple__Apple_scab	0.97	0.96	0.97	504
Apple__Black_rot	0.99	0.98	0.98	497
Apple__Cedar_apple_rust	0.97	0.99	0.98	440
Apple__healthy	0.99	0.95	0.97	502
Blueberry__healthy	0.97	0.98	0.97	454
Cherry_(including_sour)__Powdery_mildew	0.92	0.99	0.96	421
Cherry_(including_sour)__healthy	0.99	0.99	0.99	456
Corn_(maize)__Cercospora_leaf_spot Gray_leaf_spot	0.96	0.90	0.93	410
Corn_(maize)__Common_rust	1.00	0.99	0.99	477
Corn_(maize)__Northern_Leaf_Blight	0.94	0.94	0.94	477
Corn_(maize)__healthy	0.93	1.00	0.96	465
Grape__Black_rot	0.97	1.00	0.98	472
Grape__Esca_(Black_Measles)	1.00	0.97	0.99	480
Grape__Leaf_blight_(Isariopsis_Leaf_Spot)	1.00	0.99	0.99	430
Grape__healthy	0.98	1.00	0.99	423
Orange__Haunglongbing_(Citrus_greening)	1.00	0.96	0.98	503
Peach__Bacterial_spot	0.98	0.96	0.97	459
Peach__healthy	0.99	0.98	0.98	432
Pepper,_bell__Bacterial_spot	0.98	0.98	0.98	478
Pepper,_bell__healthy	0.97	0.97	0.97	497
Potato__Early_blight	1.00	0.97	0.98	485
Potato__Late_blight	0.94	0.98	0.96	485
Potato__healthy	0.99	0.94	0.97	456
Raspberry__healthy	0.95	0.99	0.97	445
Soybean__healthy	0.99	0.97	0.98	505
Squash__Powdery_mildew	0.99	0.97	0.98	434
Strawberry__Leaf_scorch	1.00	0.97	0.99	444
Strawberry__healthy	0.99	0.99	0.99	456
Tomato__Bacterial_spot	0.98	0.95	0.96	425
Tomato__Early_blight	0.88	0.96	0.92	480
Tomato__Late_blight	0.91	0.95	0.93	463
Tomato__Leaf_Mold	0.96	0.99	0.97	470
Tomato__Septoria_leaf_spot	0.97	0.89	0.93	436
Tomato__Spider_mites Two-spotted_spider_mite	0.97	0.98	0.98	435
Tomato__Target_Spot	0.96	0.93	0.95	457
Tomato__Tomato_Yellow_Leaf_Curl_Virus	0.97	1.00	0.98	490
Tomato__Tomato_mosaic_virus	0.99	1.00	0.99	448
Tomato__healthy	1.00	0.99	0.99	481
accuracy			0.97	17572
macro avg	0.97	0.97	0.97	17572
weighted avg	0.97	0.97	0.97	17572

✓ Confusion Matrix Visualise

```
plt.figure(figsize=(40, 40))
sns.heatmap(cm, annot=True, annot_kws={"size": 15})
```

```
plt.xlabel('Predicted Class', fontsize = 25)
plt.ylabel('Actual Class', fontsize = 25)
plt.title('Plant Disease Prediction Confusion Matrix', fontsize = 30)
plt.show()
```

Heatmap visualization of a Confusion Matrix for Heart Disease Prediction. The X-axis represents the Predicted Class (0 to 37) and the Y-axis represents the Actual Class (0 to 37). The color scale indicates the frequency of instances, ranging from 0 (dark purple) to 400 (light yellow). The diagonal elements are high, indicating good prediction accuracy. The off-diagonal elements show the number of misclassifications.

```
my_model.save('/content/drive/MyDrive/trained_plant_disease.keras')
```