

### Group Members:

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### Models Used:

Model 01 : CNN – Convolutional Neural Network

Model 02: RNN – Recurrent Neural Network

### **CNN Model**

### Codes:

### **Training & Validation**

```
import tensorflow as tf
import numpy as np
import pandas as pd
import seaborn as sns
```

```
Training & Validation
                                                                   + Code + Markdown
    import tensorflow as tf
    from tensorflow.keras.utils import image_dataset_from_directory
    dataset_directory = 'Plant disease detection Dataset'
    train_directroy = 'Plant disease detection Dataset/TRAIN'
    valid_directory = 'Plant disease detection Dataset/VALID'
    train_dataset = image_dataset_from_directory(
        train_directroy,
labels="inferred",
        label_mode="categorical",
        color_mode="rgb",
        batch_size=32,
        image_size=(256, 256),
        shuffle=True,
        validation_split=None, # data used for validation/test
        interpolation="bilinear",
        follow_links=False,
```

```
# Load the validation dataset
val_dataset = image_dataset_from_directory(
    valid_directory,
    labels="inferred",
    label_mode="categorical",
    color_mode="rgb",
    batch_size=32,
    image_size=(256, 256),
    shuffle=True,
    seed=42,
    validation_split=None,#
    interpolation="bilinear",
    follow_links=False,
```

### **Output:**

```
Found 410 files belonging to 2 classes.
Found 355 files belonging to 2 classes.
```

```
for x,y in train_dataset :
    print(x,x.shape)
    print(y,y.shape)
    break
```

```
tf.Tensor(
[[[[116.71484 96.71484 89.71484]
   [124.577896 104.577896 97.577896]
   [126.34276 106.34276 99.34276]
   ...
[149.97382 121.2328 115.10332 ]
   [148.54515 119.54515 113.54515 ]
   [148.78125 118.37789 113.079575]]
  [[132.5653 112.565315 105.565315]
[134.20634 112.57158 106.1165 ]
[127.59004 104.59004 98.59004 ]
   [141.51192 116.32832 109.32832 ]
   [142.48044 115.48044 108.48044 ]
   [142.1684 115.168396 108.168396]]
  [[129.33652 106.33652 100.33652 ]
[120.41837 97.41837 91.41837 ]
[116.45804 93.45804 87.45804 ]
   [138.27737 113.27737 106.27737 ]
   [132.24353 107.24353 100.24353 ]
[136.72968 111.72968 104.72968 ]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]], shape=(32, 2), dtype=float32) (32, 2)
```

```
def resize_image(image, label):
    image = tf.image.resize(image, (256, 256))
    return image, label

train_dataset = train_dataset.map(resize_image)
    val_dataset = val_dataset.map(resize_image)
```

```
Building Model

from tensorflow.keras.layers import Dense,Conv2D,MaxPool2D,Flatten,Dropout
from tensorflow.keras.models import Sequential

model = Sequential()

model.add(Conv2D(filters=32,kernel_size=3,padding='same',activation='relu',input_shape=[256,256,3]))
model.add(Conv2D(filters=32,kernel_size=3,activation='relu'))
model.add(MaxPool2D(pool_size=2,strides=2))

c:\Users\hema2\anaconda3\Lib\site-packages\keras\src\layers\convolutional\base_conv.py:99: UserWarning: Do not pass an `input_sh super().__init__(
```

```
model.add(Conv2D(filters=64,kernel_size=3,padding='same',activation='relu',input_shape=[256,256,3]))
model.add(Conv2D(filters=64,kernel_size=3,activation='relu'))
model.add(MaxPool2D(pool_size=2,strides=2))

model.add(Conv2D(filters=128,kernel_size=3,padding='same',activation='relu',input_shape=[256,256,3]))
model.add(Conv2D(filters=128,kernel_size=3,activation='relu'))
model.add(MaxPool2D(pool_size=2,strides=2))

model.add(Conv2D(filters=256,kernel_size=3,padding='same',activation='relu',input_shape=[256,256,3]))
model.add(Conv2D(filters=256,kernel_size=3,activation='relu'))
model.add(MaxPool2D(pool_size=2,strides=2))

model.add(Dropout(0.25)) #to avoid overfitting
```

```
model.add(Flatten())

model.add(Dense(units=1024,activation='relu'))

model.add(Dropout(0.40)) #to avoid overfitting

Output layer

model.add(Dense(units=1,activation='sigmoid',))
```

```
compiling

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

model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 256, 256, 32)	896
conv2d_1 (Conv2D)	(None, 254, 254, 32)	9,248
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_2 (Conv2D)	(None, 127, 127, 64)	18,496
conv2d_3 (Conv2D)	(None, 125, 125, 64)	36,928
max_pooling2d_1 (MaxPooling2D)	(None, 62, 62, 64)	0
conv2d_4 (Conv2D)	(None, 62, 62, 128)	73,856
conv2d_5 (Conv2D)	(None, 60, 60, 128)	147,584
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_6 (Conv2D)	(None, 30, 30, 256)	295,168
conv2d_7 (Conv2D)	(None, 28, 28, 256)	590,080
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 256)	0
dropout (Dropout)	(None, 14, 14, 256)	0
flatten (Flatten)	(None, 50176)	0
dense (Dense)	(None, 1024)	51,381,248
dropout_1 (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 1)	1,025

Total params: 52,554,529 (200.48 MB)

Trainable params: 52,554,529 (200.48 MB)

Non-trainable params: 0 (0.00 B)

```
Model Training
    history = model.fit(
       epochs=5,
       validation_data=val_dataset)
 Epoch 1/5
 13/13
                          — 597s 45s/step - accuracy: 0.8638 - loss: 0.4281 - val_accuracy: 0.9268 - val_loss: 0.3217
 Epoch 2/5
                         — 545s 41s/step - accuracy: 0.8787 - loss: 0.3886 - val_accuracy: 0.9268 - val_loss: 0.3164
 13/13 -
 Epoch 3/5
                          - 519s 41s/step - accuracy: 0.8666 - loss: 0.4031 - val_accuracy: 0.9268 - val_loss: 0.3117
 13/13
                           - 460s 35s/step - accuracy: 0.8981 - loss: 0.3538 - val_accuracy: 0.9268 - val_loss: 0.3070
Epoch 5/5
13/13
                           462s 35s/step - accuracy: 0.8707 - loss: 0.3927 - val_accuracy: 0.9268 - val_loss: 0.3036
```

# To the above when there loss is increasing from 1st to next step

```
1.Chose small learning rate (Default :0.001 eg :- change it to 0.0001)
```

2. There may be underfitting, so increase the number of neurons

3.Add more convolution layer to extract more feachture from images.

```
model.add(Conv2D(filters=512,kernel_size=3,padding='same',activation='relu',
input_shape=[256,256,3]))
model.add(Conv2D(filters=512,kernel_size=3,padding='same'activation='relu'))
model.add(MaxPool2D(pool_size=2,strides=2))
```

### **Model Evalution**

```
>
        history.history ##uncomment to print training history
     {'accuracy': [0.8878048658370972,
      0.8878048658370972,
      0.8878048658370972,
      0.8878048658370972,
      0.8878048658370972],
      'loss': [0.38396719098091125,
       0.37482762336730957,
      0.37138935923576355,
      0.36888575553894043,
      0.3658979535102844],
      'val accuracy': [0.9267605543136597,
      0.9267605543136597,
      0.9267605543136597,
       0.9267605543136597,
      0.9267605543136597],
      'val_loss': [0.3216615319252014,
      0.3164416551589966,
      0.31168046593666077,
      0.306998610496521,
       0.3035570979118347]}
```

# **Acuracy Visualization**

```
import numpy as np
x = np.array([1]) # x has shape (1,)
y = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10]) # y has shape (10,)

# Reshape x to match the shape of y
x = np.full_like(y, x) # x now has shape (10,)

# Now you can perform operations on x and y
result = x + y
```

```
import matplotlib.pyplot as plt

train_acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

# Create a figure and axis object
fig, ax = plt.subplots()

# Plot the training accuracy vs. epochs
ax.plot(range(1, len(train_acc) + 1), train_acc, label='Training Accuracy')

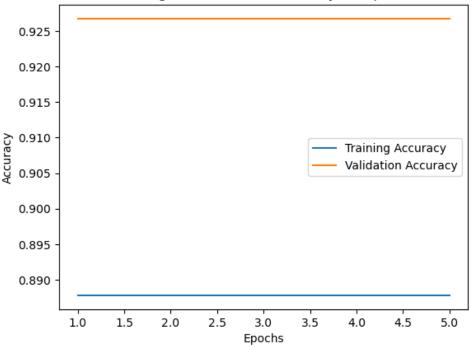
# Plot the validation accuracy vs. epochs
ax.plot(range(1, len(val_acc) + 1), val_acc, label='Validation Accuracy')

# Set the title and labels
ax.set_title('Training and Validation Accuracy vs. Epochs')
ax.set_xlabel('Epochs')
ax.set_ylabel('Accuracy')

# Add a legend
ax.legend()

# Show the plot
plt.show()
```





# test\_directory = 'Plant disease detection Dataset/TEST' test\_dataset = image\_dataset\_from\_directory( test\_directory, labels="inferred", label\_mode="categorical", color\_mode="rgb", batch\_size=32, image\_size=(256, 256), shuffle=True, seed=42, validation\_split=None, interpolation="bilinear", follow\_links=False, Found 410 files belonging to 2 classes.

```
y_pred =model.predict(test_dataset)

. 13/13 — 53s 3s/step
```

```
y_pred,y_pred.shape
[34]
    (array([[0.82840735, 0.17159258],
            [0.82840735, 0.17159258],
            [0.82840735, 0.17159258],
            [0.82840735, 0.17159258],
            [0.82840735, 0.17159258],
            [0.82840735, 0.17159258],
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            [0.82840735, 0.17159258],
            [0.82840735, 0.17159258],
            [0.82840735, 0.17159258],
            [0.82840735, 0.17159258]], dtype=float32),
     (410, 2))
```

```
predicted_catg = tf.cast(tf.greater(y_pred[:, 1], 0.5), tf.bool)
                                             print(predicted_catg)
tf.Tensor(
[False False False
              False False False False False False False False False False False
              False False False False False False False False False False False
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              False False False False False False False False False False False
                     False False False False False False False False False False
```

```
true_catg =tf.concat([y for x,y in test_dataset],axis=0)
   true_catg
<tf.Tensor: shape=(410, 2), dtype=float32, numpy=
array([[0., 1.],
       [1., 0.],
       [1., 0.],
       [0., 1.],
       [1., 0.],
       [1., 0.],
       [1., 0.],
       [1., 0.],
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       [1., 0.],
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       [1., 0.],
       [1., 0.],
       [1., 0.],
       [1., 0.],
```

```
import os
   class_name=test_dataset.class_names
   class_name
['Diseased', 'Healthy']
   from sklearn.metrics import classification_report
   print(classification_report (y_true,predicted_catg,target_names=class_name))
             precision
                          recall f1-score
                                             support
   Diseased
                  0.89
                            1.00
                                      0.94
    Healthy
                  0.00
                            0.00
                                      0.00
                                                  46
   accuracy
                                      0.89
                                                 410
                  0.44
                            0.50
                                      0.47
                                                 410
  macro avg
                  0.79
                            0.89
                                                 410
weighted avg
                                      0.84
```

```
for i in range(83):
    print(all_labels[np.argmax(y_test[i])], "-",all_labels[np.argmax(y_pred[i])])
Diseased - Diseased
Healthy - Diseased
Diseased - Diseased
Healthy - Diseased
Diseased - Diseased
Healthy - Diseased
Diseased - Diseased
Diseased - Diseased
Diseased - Diseased
Diseased - Diseased
Healthy - Diseased
Diseased - Diseased
```

```
from sklearn.metrics import classification_report,confusion_matrix cn= confusion_matrix (y_true,predicted_catg) cn.shape

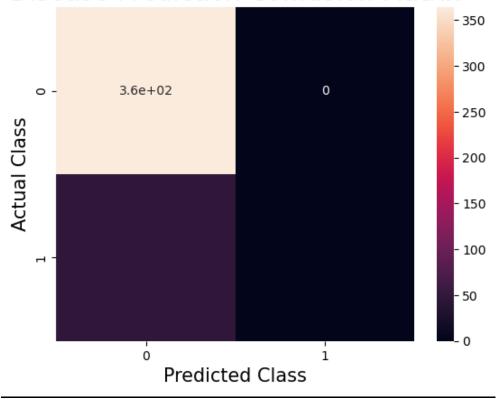
[41]

**Confusion matrix visuals

import matplotlib.pyplot as plt sns.heatmap(cn,annot=True) plt.xlabel("Predicted class",fontsize=15) plt.ylabel("Actual Class",fontsize=15) plt.title("Disease Prediction Confusion Matrix",fontsize=20) plt.show()

[42]
```

# Disease Prediction Confusion Matrix



```
model.save("trained_model_plant_disease111.h5")
model.save("trained_model_111.keras")#for moreoption: search in web tf save model_
warning:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)
```

### **CNN: Prediction**

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.utils import image_dataset_from_directory
from tensorflow.keras.preprocessing.image import load_img
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 256, 256, 32)	896
conv2d_1 (Conv2D)	(None, 254, 254, 32)	9,248
<pre>max_pooling2d (MaxPooling2D)</pre>	(None, 127, 127, 32)	0
conv2d_2 (Conv2D)	(None, 127, 127, 64)	18,496
conv2d_3 (Conv2D)	(None, 125, 125, 64)	36,928
<pre>max_pooling2d_1 (MaxPooling2D)</pre>	(None, 62, 62, 64)	0
conv2d_4 (Conv2D)	(None, 62, 62, 128)	73,856
conv2d_5 (Conv2D)	(None, 60, 60, 128)	147,584
max_pooling2d_2 (MaxPooling2D)	(None, 30, 30, 128)	0
conv2d_6 (Conv2D)	(None, 30, 30, 256)	295,168
conv2d_7 (Conv2D)	(None, 28, 28, 256)	590,080
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 256)	0
dropout (Dropout)	(None, 14, 14, 256)	0
flatten (Flatten)	(None, 50176)	0
dense (Dense)	(None, 1024)	51,381,248
dropout_1 (Dropout)	(None, 1024)	0
dense_1 (Dense)	(None, 1)	1,025
dense_2 (Dense)	(None, 2)	4

```
Total params: 105,109,068 (400.96 MB)

Trainable params: 52,554,533 (200.48 MB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 52,554,535 (200.48 MB)
```

```
Data Visualization

!pip install opencv-python

Collecting opencv-python
   Using cached opencv_python-4.10.0.84-cp37-abi3-win_amd64.whl.metadata (20 kB)
Requirement already satisfied: numpy>=1.21.2 in c:\users\hema2\anaconda3\lib\site-packages (from opencv-python)
Using cached opencv_python-4.10.0.84-cp37-abi3-win_amd64.whl (38.8 MB)
Installing collected packages: opencv-python
Successfully installed opencv-python-4.10.0.84
```

```
import cv2
image_path ="Plant disease detection Dataset\TEST\Diseased\1013.jpeg"

#Read image
img=cv2.imread(image_path)
img=cv2.cvtColor(img,cv2.COLOR_BGR2RGB) #converting BGR to RGB

#Display image
plt.imshow(img)
plt.tittle("Test Image")
plt.xticks([])
plt.ytricks([])
plt.show
```

```
##Testing Model
image =tf.keras.preprocessing.image.load_img(image_path,target_size
=(256,256))
input_arr =tf.keras.preprocessing.image.img_to_array(image)
input_arr =np.array([input_arr])  # converting sigle image to a batch
print(input_arr.shape)
```

```
prediction =model.predict(input_arr)
prediction,prediction.shape
```

```
result_index =np.argmax(prediction)
result_index
class_name =['Healthy','Diseased']
```

```
#Displaying the Result of Test image
model_prediction =class_name[result_index]
plt.imshow(img)
plt.tittle(f"Prediction :{model_prediction}")
plt.xticks([])
plt.ytricks([])
plt.show()
```

### Model 2:RNN

```
# -*- coding: utf-8 -*-
"""Untitled15.ipynb
Automatically generated by Colab.
Original file is located at
    https://colab.research.google.com/drive/1j7lgHxYK0VOswFJHyFs96cmFvaFmIzIi
from google.colab import drive
drive.mount('/content/drive')
!ls /content/drive/MyDrive/DL_project/Plant-disease-detection-Dataset
# Commented out IPython magic to ensure Python compatibility.
# %cd
# %pwd /content/drive/MyDrive/DL_project
import os
os.listdir(".")
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import VGG16
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Flatten, TimeDistributed
from tensorflow.keras.optimizers import Adam
train_datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)
```

```
train_generator = train_datagen.flow_from_directory(
    '/content/drive/MyDrive/DL project/Plant-disease-detection-Dataset',
    target size=(224, 224),
    batch_size=32,
    class mode='binary',
    subset='training')
validation_generator = train_datagen.flow_from_directory(
    '/content/drive/MyDrive/DL_project/Plant-disease-detection-Dataset',
    target_size=(224, 224),
    batch_size=32,
    class mode='binary',
    subset='validation')
cnn base = VGG16(weights='imagenet', include top=False, input shape=(224, 224,
3))
model = Sequential()
model.add(cnn base)
model.add(Flatten())
model.compile(optimizer=Adam(lr=0.0001), loss='binary_crossentropy',
metrics=['accuracy'])
history = model.fit(
    train_generator,
    steps_per_epoch=train_generator.samples // 32,
    validation_data=validation_generator,
    validation steps=validation generator.samples // 32,
    epochs=10)
loss, accuracy = model.evaluate(validation generator)
print(f'Validation Accuracy: {accuracy*100:.2f}%')
```

### Outputs:

```
Epoch 1/20
    /usr/local/lib/python3.10/dist-packages/keras/src/trainers/data_adapters/py_dataset_adapter.py:121: UserWarning: Your `PyDataset` class should call `s ^ 🗸 😅 🗐 🗓
₹ 10/10 -
     self. warn if super not called()
                              - 311s 26s/step - accuracy: 0.7266 - loss: 0.5742 - val accuracy: 0.8438 - val loss: 0.4616 - learning rate: 1.0000e-04
     Epoch 2/20
                             - 3:13 22s/step - accuracy: 0.9375 - loss: 0.1920/usr/lib/python3.10/contextlib.py:153: UserWarning: Your input ran out of data; interrupting training. Mak
     1/10 ---
      self.gen.throw(typ, value, traceback)
                              33s 1s/step - accuracy: 0.9375 - loss: 0.1920 - val accuracy: 0.7647 - val loss: 0.5216 - learning rate: 1.0000e-04
                              – 230s 23s/step - accuracy: 0.9057 - loss: 0.2186 - val_accuracy: 0.6562 - val_loss: 0.6416 - learning_rate: 1.0000e-04
     10/10 -
     Epoch 4/20
                              – 30s 1s/step - accuracy: 0.9062 - loss: 0.1782 - val_accuracy: 0.7059 - val_loss: 0.5396 - learning_rate: 1.0000e-04
     10/10 -
     Epoch 5/20
                              – 248s 25s/step - accuracy: 0.9115 - loss: 0.1755 - val_accuracy: 0.7344 - val_loss: 0.5034 - learning_rate: 2.0000e-05
     10/10 -
     Epoch 6/20
     10/10 -
                              16s 1s/step - accuracy: 0.8889 - loss: 0.2434 - val_accuracy: 0.8235 - val_loss: 0.4544 - learning rate: 2.0000e-05
     Epoch 7/20
                              = 227s 22s/step - accuracy: 0.9132 - loss: 0.1803 - val_accuracy: 0.7656 - val_loss: 0.4528 - learning_rate: 2.0000e-05
     10/10 -
     Epoch 8/20
                              - 29s 1s/step - accuracy: 0.9062 - loss: 0.2181 - val accuracy: 0.7647 - val loss: 0.4702 - learning rate: 2.0000e-05
     Epoch 9/20
     10/10 -
                              – 223s 22s/step - accuracy: 0.9380 - loss: 0.1312 - val_accuracy: 0.5312 - val_loss: 0.8126 - learning_rate: 2.0000e-05
     Epoch 10/20
     10/10 -
                              - 30s 1s/step - accuracy: 0.9062 - loss: 0.1650 - val_accuracy: 0.6471 - val_loss: 0.5898 - learning_rate: 2.0000e-05
     Epoch 11/20
                              = 232s 23s/step - accuracy: 0.9246 - loss: 0.1684 - val_accuracy: 0.5625 - val_loss: 0.8105 - learning_rate: 1.0000e-05
     10/10 -
     Epoch 12/20
                              - 30s 1s/step - accuracy: 0.9062 - loss: 0.1525 - val accuracy: 0.4706 - val loss: 0.7808 - learning rate: 1.0000e-05
     10/10 -
                           49s 15s/step - accuracy: 0.8315 - loss: 0.4074
     Validation Accuracy: 82.72%
```