# Potato Disease Classification Using Neural Network

Every year, farmers suffer economic losses and crop waste owing to different illnesses in potato plants. We will utilise CNN to classify images and create a smartphone app that will allow a farmer to take a picture of a plant and determine whether or not it has a disease. This project will use the following technology stack:

Model Construction: CNN, TensorFlow, Data Augmentation, and TF Dataset.

- 1) The project includes data collection, model building using Convolutional Neural Network (CNN), ML ops using TF serving, a backend server using Fast API, deployment to Google Cloud, and a mobile app in React Native.
- 2) The main problem addressed is the economic losses faced by potato farmers due to early blight and late blight diseases.
- 3) The application will classify images of potato plants as healthy or having early blight or late blight.
- 4) The data collection process involves gathering images of healthy potato plant leaves and leaves with early blight or late blight.
- 5) Data cleaning and pre-processing will be done using tf dataset and data augmentation.
- 6) Model building will be carried out using CNN, and the trained model will be exported onto the disk.

### **IMPORTNG LIBRARIES**

```
import tensorflow as tf
from tensorflow.keras import models, layers
import matplotlib.pyplot as plt
import pandas as pd
import numpy

WARNING:tensorflow:From c:\Program Files\Python311\Lib\site-packages\keras\src\losses.py:2976: The name
tf.losses.sparse_softmax_cross_entropy is deprecated. Please use
tf.compat.v1.losses.sparse_softmax_cross_entropy instead.

IMAGE_SIZE = 256
BATCH = 32
CHANNELS = 3
EPOCHS = 50
```

#### CONVERTING IMAGES TO TENSORS

```
''' For downloading dataset into tensorfolw dataset using keras '''
dataset = tf.keras.preprocessing.image dataset from directory(
    r"C:\Users\raman\Desktop\mini-projects\potato class\potato",
     shuffle = True,
     image size = (IMAGE SIZE,IMAGE SIZE),
     batch size = BATCH)
Found 2152 files belonging to 3 classes.
class names = dataset.class names
class names
              # for printing class names
['Potato Early blight', 'Potato___Late_blight', 'Potato___healthy']
len(dataset) # 68 -> represent number of batches so 68*32 will give
total length
68
for image batch,label batch in dataset.take(1):
    print(image batch.shape)
    print(label batch.numpy())
1.1.1
32 -> batches
256,256 -> dimensions
3 \rightarrow RGB
I \cap I \cap I
(32, 256, 256, 3)
[1\ 0\ 2\ 0\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 2\ 1\ 0\ 0\ 0\ 0\ 0\ 1\ 1\ 1\ 1\ 1]
\n32 -> batches\n256,256 -> dimensions\n3 -> RGB\n'
plt.figure(figsize=(10,10))
for image batch, label batch in dataset.take(1):
    for i in range(12):
        plt.subplot(3,4,i+1)
        plt.imshow(image batch[i].numpy().astype('uint8'))
        plt.title(class names[label batch[i]])
        plt.axis('off')
plt.imshow()-> to represent matrix into picture
'\nplt.imshow()-> to represent matrix into picture\n'
```

Potato\_\_Early\_blight























## **DATA SPLITTING**

```
training = 80% data
validation = 10% data
test = 10% data
'\ntraining = 80% data\nvalidation = 10% data\ntest = 10% data\n'

def
get_dataset_partition_tf(ds,train_split=0.8,val_split=0.1,test_split=0.1,shuffle=True,shuffle_size=10000):
```

```
1.1.1
    For Splitting data into training, validation and testing data
    ds size = len(ds)
    if shuffle:
        ds = ds.shuffle(shuffle size, seed=12)
    train size = int(train split*ds size)
    val size = int(val split*ds size)
    train ds = ds.take(train size)
    val ds = ds.skip(train size).take(val size)
    test ds = ds.skip(train size).skip(val size)
    return train ds , val ds , test ds
train ds , val ds , test ds = get dataset partition tf(dataset)
len(train ds) , len(val ds) , len(test ds)
(54, 6, 8)
##
train ds = train ds.cache().shuffle(1000).prefetch(buffer size =
tf.data.AUTOTUNE)
val ds = val ds.cache().shuffle(1000).prefetch(buffer size =
tf.data.AUTOTUNE)
test ds = test ds.cache().shuffle(1000).prefetch(buffer size =
tf.data.AUTOTUNE)
```

#### **PREPROCESSING**

```
resize_and_rescale = tf.keras.Sequential([
    layers.experimental.preprocessing.Resizing(IMAGE_SIZE,IMAGE_SIZE),
    layers.experimental.preprocessing.Rescaling(1.0/255)
]) ### Adding Layer for rescaling and resizing the data

WARNING:tensorflow:From c:\Program Files\Python311\Lib\site-packages\
keras\src\backend.py:873: The name tf.get_default_graph is deprecated.
Please use tf.compat.v1.get_default_graph instead.
```

```
DATA AUGMENTATION
```

```
data_augmentation = tf.keras.Sequential([
    layers.experimental.preprocessing.RandomFlip("horizontal_and_vertical"
),
        layers.experimental.preprocessing.RandomRotation(0.2)
])
## Adding 2 Data augmentation filters RandomFlip and RandomRotation
```

# MODELLING USING CONVOLUTIONAL NEURAL NETWORK

Layers. Conv2D(Filter, kernel, activation, input\_shape) -> first layer

```
Polling2D(kernel)
    Conv2D(filter, kernel, activation)
input shape = (BATCH, IMAGE SIZE, IMAGE SIZE, CHANNELS)
n classes = 3
model = models.Sequential([
    resize and rescale,
    data augmentation,
    layers.Conv2D(32,(3,3),activation="relu",input shape =
input shape),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,kernel size = (3,3),activation="relu"),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,kernel_size = (3,3),activation = "relu"),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,kernel_size = (3,3),activation = "relu"),
    layers.MaxPooling2D((2,2)),
    layers.Conv2D(64,kernel_size = (3,3),activation = "relu"),
    layers.MaxPooling2D((2,\overline{2})),
    layers.Conv2D(64, kernel size = (3,3), activation = "relu"),
    layers.MaxPooling2D((2,2)),
    layers.Flatten(),
    layers.Dense(64,activation = "relu"),
    layers.Dense(n classes,activation = "softmax")
1)
model.build(input shape = input shape)
WARNING:tensorflow:From c:\Program Files\Python311\Lib\site-packages\
keras\src\layers\pooling\max pooling2d.py:161: The name tf.nn.max pool
is deprecated. Please use tf.nn.max pool2d instead.
model.summary() # summary of neural network architecture
```

<pre>Model: "sequential_2"</pre>		
Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
<pre>sequential_1 (Sequential)</pre>	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 32)	896
<pre>max_pooling2d (MaxPooling2 D)</pre>	(32, 127, 127, 32)	0
conv2d_1 (Conv2D)	(32, 125, 125, 64)	18496
<pre>max_pooling2d_1 (MaxPoolin g2D)</pre>	(32, 62, 62, 64)	0
conv2d_2 (Conv2D)	(32, 60, 60, 64)	36928
<pre>max_pooling2d_2 (MaxPoolin g2D)</pre>	(32, 30, 30, 64)	0
conv2d_3 (Conv2D)	(32, 28, 28, 64)	36928
<pre>max_pooling2d_3 (MaxPoolin g2D)</pre>	(32, 14, 14, 64)	0
conv2d_4 (Conv2D)	(32, 12, 12, 64)	36928
<pre>max_pooling2d_4 (MaxPoolin g2D)</pre>	(32, 6, 6, 64)	0
conv2d_5 (Conv2D)	(32, 4, 4, 64)	36928
<pre>max_pooling2d_5 (MaxPoolin g2D)</pre>	(32, 2, 2, 64)	0
flatten (Flatten)	(32, 256)	0
dense (Dense)	(32, 64)	16448
dense_1 (Dense)	(32, 3)	195
Total narams: 183747 (717 76		

Total params: 183747 (717.76 KB) Trainable params: 183747 (717.76 KB) Non-trainable params: 0 (0.00 Byte)

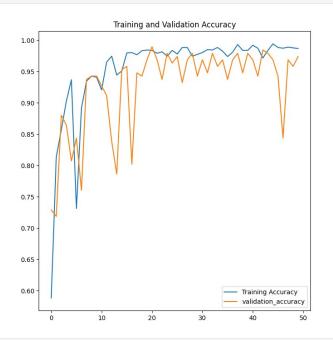
```
model.compile(
   optimizer = 'adam',
   loss = tf.keras.losses.SparseCategoricalCrossentropy(from logits =
   metrics = ['accuracy']
## keras.losses.SparseCategoricalCrossentropy
WARNING:tensorflow:From c:\Program Files\Python311\Lib\site-packages\
keras\src\optimizers\__init__.py:309: The name tf.train.Optimizer is
deprecated. Please use tf.compat.v1.train.Optimizer instead.
history = model.fit(
   train ds,
   epochs = EPOCHS,
   batch size = BATCH,
   verbose = 1,
   validation data = val ds
)
Epoch 1/50
WARNING:tensorflow:From c:\Program Files\Python311\Lib\site-packages\
keras\src\utils\tf utils.py:492: The name tf.ragged.RaggedTensorValue
is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue
instead.
WARNING:tensorflow:From c:\Program Files\Python311\Lib\site-packages\
keras\src\engine\base layer utils.py:384: The name
tf.executing_eagerly_outside_functions is deprecated. Please use
tf.compat.vl.executing eagerly outside functions instead.
accuracy: 0.5885 - val loss: 0.5505 - val accuracy: 0.7292
Epoch 2/50
- accuracy: 0.8137 - val loss: 0.6161 - val accuracy: 0.7188
Epoch 3/50
- accuracy: 0.8571 - val_loss: 0.3821 - val_accuracy: 0.8802
Epoch 4/50
- accuracy: 0.9028 - val loss: 0.3420 - val accuracy: 0.8646
Epoch 5/50
- accuracy: 0.9369 - val loss: 0.6096 - val accuracy: 0.8073
Epoch 6/50
- accuracy: 0.7315 - val_loss: 0.3622 - val accuracy: 0.8438
```

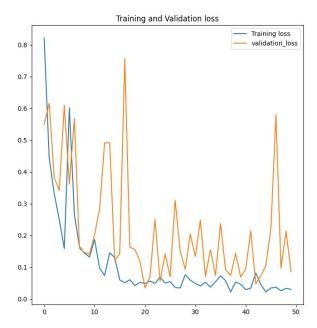
```
Epoch 7/50
- accuracy: 0.8918 - val loss: 0.5683 - val accuracy: 0.7604
Epoch 8/50
- accuracy: 0.9346 - val loss: 0.1595 - val accuracy: 0.9375
Epoch 9/50
- accuracy: 0.9427 - val loss: 0.1470 - val accuracy: 0.9427
Epoch 10/50
- accuracy: 0.9410 - val loss: 0.1416 - val accuracy: 0.9427
Epoch 11/50
- accuracy: 0.9207 - val_loss: 0.2019 - val_accuracy: 0.9271
Epoch 12/50
- accuracy: 0.9653 - val loss: 0.2838 - val accuracy: 0.9115
Epoch 13/50
- accuracy: 0.9745 - val_loss: 0.4919 - val_accuracy: 0.8385
Epoch 14/50
- accuracy: 0.9444 - val loss: 0.4919 - val accuracy: 0.7865
Epoch 15/50
- accuracy: 0.9508 - val_loss: 0.1223 - val_accuracy: 0.9531
Epoch 16/50
- accuracy: 0.9797 - val_loss: 0.1427 - val_accuracy: 0.9583
Epoch 17/50
- accuracy: 0.9803 - val loss: 0.7570 - val accuracy: 0.8021
Epoch 18/50
- accuracy: 0.9769 - val loss: 0.1635 - val accuracy: 0.9479
Epoch 19/50
- accuracy: 0.9832 - val loss: 0.1561 - val accuracy: 0.9427
Epoch 20/50
- accuracy: 0.9844 - val loss: 0.1201 - val accuracy: 0.9688
Epoch 21/50
- accuracy: 0.9838 - val_loss: 0.0357 - val_accuracy: 0.9896
Epoch 22/50
- accuracy: 0.9792 - val loss: 0.0697 - val accuracy: 0.9688
Epoch 23/50
```

```
- accuracy: 0.9815 - val loss: 0.2513 - val accuracy: 0.9375
Epoch 24/50
- accuracy: 0.9745 - val loss: 0.0565 - val accuracy: 0.9792
Epoch 25/50
- accuracy: 0.9838 - val_loss: 0.1417 - val_accuracy: 0.9635
Epoch 26/50
- accuracy: 0.9780 - val loss: 0.0705 - val accuracy: 0.9740
Epoch 27/50
- accuracy: 0.9884 - val loss: 0.3109 - val accuracy: 0.9323
Epoch 28/50
- accuracy: 0.9884 - val loss: 0.1509 - val accuracy: 0.9688
Epoch 29/50
- accuracy: 0.9745 - val loss: 0.0935 - val accuracy: 0.9792
Epoch 30/50
- accuracy: 0.9774 - val loss: 0.2052 - val accuracy: 0.9427
Epoch 31/50
- accuracy: 0.9803 - val loss: 0.1339 - val accuracy: 0.9688
Epoch 32/50
- accuracy: 0.9850 - val loss: 0.2492 - val accuracy: 0.9479
Epoch 33/50
- accuracy: 0.9844 - val loss: 0.0718 - val accuracy: 0.9792
Epoch 34/50
- accuracy: 0.9884 - val loss: 0.1556 - val accuracy: 0.9583
Epoch 35/50
- accuracy: 0.9826 - val loss: 0.0741 - val accuracy: 0.9688
Epoch 36/50
- accuracy: 0.9740 - val loss: 0.2379 - val accuracy: 0.9375
Epoch 37/50
- accuracy: 0.9809 - val loss: 0.0923 - val accuracy: 0.9688
Epoch 38/50
- accuracy: 0.9931 - val loss: 0.0747 - val_accuracy: 0.9792
Epoch 39/50
```

```
- accuracy: 0.9838 - val loss: 0.1442 - val accuracy: 0.9479
Epoch 40/50
- accuracy: 0.9838 - val_loss: 0.0696 - val accuracy: 0.9792
Epoch 41/50
54/54 [============== ] - 56s 1s/step - loss: 0.0298 -
accuracy: 0.9919 - val loss: 0.0947 - val accuracy: 0.9688
Epoch 42/50
- accuracy: 0.9873 - val loss: 0.2150 - val accuracy: 0.9427
Epoch 43/50
- accuracy: 0.9716 - val_loss: 0.0477 - val_accuracy: 0.9844
Epoch 44/50
- accuracy: 0.9838 - val loss: 0.0737 - val accuracy: 0.9792
Epoch 45/50
- accuracy: 0.9942 - val loss: 0.1055 - val accuracy: 0.9688
Epoch 46/50
- accuracy: 0.9884 - val loss: 0.2235 - val accuracy: 0.9427
Epoch 47/50
- accuracy: 0.9873 - val loss: 0.5801 - val accuracy: 0.8438
Epoch 48/50
- accuracy: 0.9890 - val loss: 0.0977 - val accuracy: 0.9688
Epoch 49/50
- accuracy: 0.9878 - val loss: 0.2137 - val_accuracy: 0.9583
Epoch 50/50
- accuracy: 0.9867 - val loss: 0.0861 - val accuracy: 0.9740
scores = model.evaluate(test ds)
accuracy: 0.9766
scores
[0.05161502584815025, 0.9765625]
history
<keras.src.callbacks.History at 0x24bfcc52b50>
history.params
{'verbose': 1, 'epochs': 50, 'steps': 54}
```

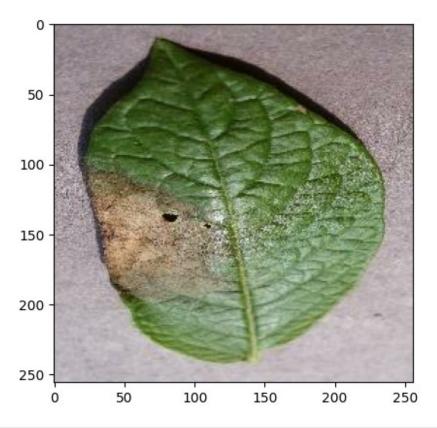
```
history.history.keys()
dict keys(['loss', 'accuracy', 'val loss', 'val accuracy'])
acc = history.history["accuracy"]
val acc= history.history["val accuracy"]
loss = historv.historv["loss"]
val loss = history.history["val loss"]
plt.figure(figsize=(17,8))
plt.subplot(1,2,1)
plt.plot(range(EPOCHS),acc,label="Training Accuracy")
plt.plot(range(EPOCHS), val acc, label = "validation accuracy")
plt.legend(loc="lower right")
plt.title("Training and Validation Accuracy")
plt.subplot(1,2,2)
plt.plot(range(EPOCHS), loss, label="Training loss")
plt.plot(range(EPOCHS), val_loss, label = "validation_loss")
plt.legend(loc="upper right")
plt.title("Training and Validation loss")
Text(0.5, 1.0, 'Training and Validation loss')
```





```
for image_batch,label_batch in test_ds.take(1):
    first_image = image_batch[0].numpy().astype("uint8")
    first_label = label_batch[0].numpy()

    print('first image to predict')
    plt.imshow(first_image)
```



## Defining functions for predicting test dataset results

def predict(model,img):
 img\_arry = tf.keras.preprocessing.image.img\_to\_array((img))
 img\_array = tf.expand\_dims(img\_arry,0) ## creating a batch
 # prediction
 prediction = model.predict(img\_array)

pred\_class = class\_names[numpy.argmax(prediction[0])]
 confidence = round(100\*(numpy.max(prediction[0])),2)
 return pred\_class , confidence

```
plt.figure(figsize = (15,15))
for images, label in test ds.take(1):
  for i in range(12):
    ax = plt.subplot(3,4,i+1)
    plt.imshow(images[i].numpy().astype('uint8'))
    pred class , confidence = predict(model,images[i])
    actual class = class names[label[i]]
    plt.title(f"Actual : {actual class}, \n Predicted :
{pred class}. \n Confidence : {confidence} %")
    plt.axis('off')
1/1 [======] - 0s 38ms/step
1/1 [======] - 0s 54ms/step
1/1 [======= ] - 0s 40ms/step
1/1 [======] - 0s 36ms/step
1/1 [=======] - 0s 39ms/step
1/1 [======] - 0s 36ms/step
1/1 [=======] - 0s 42ms/step
1/1 [======= ] - 0s 49ms/step
```

Actual : Potato \_\_Early\_blight, Predicted : Potato \_\_Early\_blight. Confidence : 96.83 %



Actual : Potato\_\_\_Late\_blight, Predicted : Potato\_\_\_Late\_blight. Confidence : 99.95 %



Actual : Potato\_\_\_Early\_blight, Predicted : Potato\_\_\_Early\_blight. Confidence : 100.0 %



Actual: Potato\_\_\_Early\_blight, Predicted: Potato\_\_\_Early\_blight.



Actual : Potato\_\_\_Late\_blight, Predicted : Potato\_\_\_Late\_blight. Confidence : 99.99 %



Actual : Potato\_\_\_Early\_blight, Predicted : Potato\_\_\_Early\_blight. Confidence : 100.0 %



Actual : Potato\_\_\_Early\_blight, Predicted : Potato\_\_\_Early\_blight. Confidence : 100.0 %



Actual: Potato\_\_\_Early\_blight, Predicted: Potato\_\_\_Early\_blight. Confidence: 100.0 %



Actual : Potato\_\_Late\_blight, Predicted : Potato\_\_Late\_blight. Confidence : 100.0 %



Actual : Potato\_\_\_Early\_blight, Predicted : Potato\_\_\_Early\_blight. Confidence : 100.0 %



Actual : Potato\_\_Late\_blight, Predicted : Potato\_\_Late\_blight. Confidence : 73.11 %



Actual : Potato\_\_\_Late\_blight, Predicted : Potato\_\_\_Early\_blight. Confidence : 56.17 %



import os

model\_version = max([int(i) for i in os.listdir(r"C:\Users\raman\
Desktop\mini-projects\potato class\models") + [0]])+1
model.save(f'Potato Disease {model\_version}')

INFO:tensorflow:Assets written to: Potato Disease 1\assets

INFO:tensorflow:Assets written to: Potato Disease 1\assets