

potato-leaf-disease-final95

March 7, 2024

IMPORTING REQUIRED LIBRARIES

```
[1]: import pandas as pd
import numpy as np
import os
import cv2
import matplotlib.pyplot as plt
import keras
import seaborn as sns
import pathlib
from pathlib import Path
import glob
import tensorflow as tf
from sklearn.model_selection import train_test_split
from tensorflow.keras.utils import to_categorical
from keras.preprocessing.image import ImageDataGenerator
```

```
[2]: data_dir='/kaggle/input/potato-leaf-disease'
root_dir='/kaggle/working/'
```

```
[3]: def countfiles(root_dir):
    for path in pathlib.Path(root_dir).iterdir():
        if path.is_dir():
            print( str(len([name for name in os.listdir(path) \
                if os.path.isfile(os.path.join(path, name))])) + " files inside the_
↪" + \
                str(path.name), 'class')
countfiles(data_dir)
```

```
1000 files inside the Potato__healthy class
1000 files inside the Potato__Late_blight class
1000 files inside the Potato__Early_blight class
```

DATASET PREPARATION

```
[11]: def data_categories(d_path):
    categories=[]      #listdir-->used to get the list of all files and_
↪directories in the specified directory
```

```

    for folder_name in os.listdir(d_path): #os.path.isdir()--->used to check
    ↪whether the specified path is an existing directory or not.
        if os.path.isdir(os.path.join(d_path,folder_name)):
            no_of_files=len(glob.glob(os.path.join(d_path, folder_name)+"/*.
    ↪JPG"))
            categories.append(np.array([folder_name,no_of_files]))
        categories.sort(key=lambda a:a[0])
        cat=np.array(categories)
        return list(cat[:, 0]),list(cat[:,1])
categories,no_of_files = data_categories("/kaggle/input/potato-leaf-disease")
print(categories)

```

```
['Potato__Early_blight', 'Potato__Late_blight', 'Potato__healthy']
```

```
[12]: print("number of categories: ", len(categories))
```

```
number of categories: 3
```

```
[13]: df = pd.DataFrame({"category": categories, "number of files": no_of_files})
df
```

```
[13]:
```

	category	number of files
0	Potato__Early_blight	1000
1	Potato__Late_blight	1000
2	Potato__healthy	1000

```
[14]: def dataset(data_path, categories, width, height):
    x = []
    y = []
    for category_idx, category in enumerate(categories):
        path = os.path.join(data_path, category)
        count = 0
        for img in os.listdir(path):
            img_array = cv2.imread(os.path.join(path,img))
            img_size = cv2.resize(img_array, (width, height))
            x.append(img_size)
            y.append(category_idx)
            count += 1
        print(f"Number of images in class {category_idx}: {count}")
    y = np.array(y)
    x = np.array(x).reshape(y.shape[0], width, height, 3)
    return x, y

```

```

x, y = dataset(data_path=data_dir, categories=['Potato__Early_blight',
    ↪'Potato__Late_blight', 'Potato__healthy'], width=100,height=100)

```

```
Number of images in class 0: 1000
```

```
Number of images in class 1: 1000
```

Number of images in class 2: 1000

```
[15]: print(f'x shape:{x.shape}')  
      print(f"y shape: {y.shape}")
```

x shape:(3000, 100, 100, 3)

y shape: (3000,)

IMAGES FROM CLASSES

```
[18]: plt.figure(figsize=(20, 10))  
      st, end = 0,500  
      for i in range(6):  
          plt.subplot(2, 3, i + 1)  
          idx = np.random.randint(st, end)  
          st = end + 1  
          end = (i + 2) * 500  
          plt.rcParams.update({'font.size':18})  
          plt.imshow(x[idx][:, :, ::-1])  
          plt.title(f"{y[idx]}--{categories[y[idx]]}")  
          plt.axis("off")  
      plt.show()
```

0-Potato_Early_blight



0-Potato_Early_blight



1-Potato_Late_blight



1-Potato_Late_blight



2-Potato_healthy



2-Potato_healthy



DATASET SPLITTING FOR TRAIN/VAL/TEST SETS

```
[19]: y=np.reshape(y,(len(y),1))  
      x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.  
      ↪1,random_state=42)
```

```

print(f"x_train: {x_train.shape}")
print(f"y_train: {y_train.shape}")
print(f"x_test: {x_test.shape}")
print(f"y_test: {y_test.shape}")

```

```

x_train: (2700, 100, 100, 3)
y_train: (2700, 1)
x_test: (300, 100, 100, 3)
y_test: (300, 1)

```

```

[20]: x_train,x_val,y_train,y_val=train_test_split(x_train,y_train,train_size=0.70)
      x_test=x_test

```

```

print(f"x_train:{x_train.shape},y_train:{y_train.shape}")
print(f"x_val: {x_val.shape},y_val:{y_val.shape}")           #70-20-10
print(f"x_test:{x_test.shape},y_test:{y_test.shape}")

```

```

x_train:(1889, 100, 100, 3),y_train:(1889, 1)
x_val: (811, 100, 100, 3),y_val:(811, 1)
x_test:(300, 100, 100, 3),y_test:(300, 1)

```

```

[21]: y_train = to_categorical(y_train)
      y_val = to_categorical(y_val)
      y_test = to_categorical(y_test)

print(f"x_train:{x_train.shape}, y_train:{y_train.shape}")
print(f"x_val:{x_val.shape}, y_val:{y_val.shape}")
print(f"x_test:{x_test.shape}, y_test:{y_test.shape}")

```

```

x_train:(1889, 100, 100, 3), y_train:(1889, 3)
x_val:(811, 100, 100, 3), y_val:(811, 3)
x_test:(300, 100, 100, 3), y_test:(300, 3)

```

DATA PREPROCESSING

```

[22]: train_generator=ImageDataGenerator(rescale=1./255,
                                         rotation_range=2,
                                         horizontal_flip=True,
                                         shear_range=0.5,
                                         zoom_range=0.7)
      val_generator=ImageDataGenerator(rescale=1./255,
                                       rotation_range=2,
                                       horizontal_flip=True,
                                       shear_range=0.5,
                                       zoom_range=0.1)
      test_generator=ImageDataGenerator(rotation_range=2,
                                        horizontal_flip=True,
                                        zoom_range=0.1)

```

```
train_generator.fit(x_train)
val_generator.fit(x_val)
test_generator.fit(x_test)
```

MODEL BUILDING-CNN

```
[23]: from keras.models import Sequential, load_model
      from keras.layers import Flatten, Dense
```

```
[42]: model = keras.Sequential([
        # Convolutional layers
        #kernels, #filters , #activation function, #input
        tf.keras.layers.Conv2D(32, (3,3), activation='relu',
        ↪input_shape=(100,100,3)),
        tf.keras.layers.Conv2D(32, (3,3), activation='relu'),
        tf.keras.layers.MaxPooling2D((2,2)),
        tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
        tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
        tf.keras.layers.MaxPooling2D((2,2)),
        tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
        tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
        tf.keras.layers.MaxPooling2D((2,2)),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(512, activation='relu'),
        tf.keras.layers.Dense(3, activation='softmax')
    ])
```

```
[43]: model.summary()
```

Model: "sequential_3"

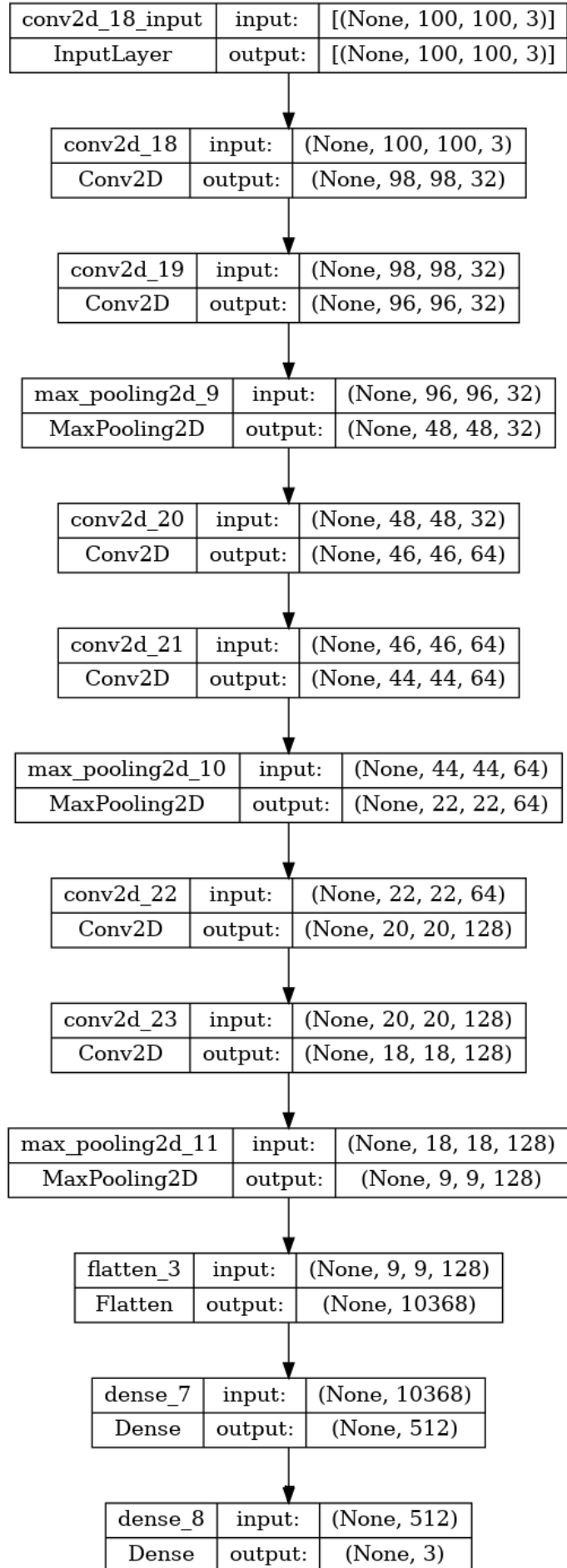
Layer (type)	Output Shape	Param #
=====		
conv2d_18 (Conv2D)	(None, 98, 98, 32)	896
conv2d_19 (Conv2D)	(None, 96, 96, 32)	9248
max_pooling2d_9 (MaxPooling 2D)	(None, 48, 48, 32)	0
conv2d_20 (Conv2D)	(None, 46, 46, 64)	18496
conv2d_21 (Conv2D)	(None, 44, 44, 64)	36928
max_pooling2d_10 (MaxPoolin g2D)	(None, 22, 22, 64)	0

conv2d_22 (Conv2D)	(None, 20, 20, 128)	73856
conv2d_23 (Conv2D)	(None, 18, 18, 128)	147584
max_pooling2d_11 (MaxPooling2D)	(None, 9, 9, 128)	0
flatten_3 (Flatten)	(None, 10368)	0
dense_7 (Dense)	(None, 512)	5308928
dense_8 (Dense)	(None, 3)	1539

```
=====
Total params: 5,597,475
Trainable params: 5,597,475
Non-trainable params: 0
-----
```

```
[44]: from tensorflow.keras.utils import plot_model
      plot_model(model, show_shapes=True, to_file='3class model.png')
```

```
[44]:
```



```
[45]: from keras.metrics import Precision, Recall
import tensorflow_addons as tfa
```

```
[46]: model.compile(optimizer='adam',
                    loss='categorical_crossentropy',
                    ↵
                    ↪metrics=[ 'accuracy', Precision(name='precision'), Recall(name='Recall'), tfa.
                    ↪metrics.F1Score(num_classes=3)])
```

```
[47]: history = model.fit(x_train,y_train, epochs=30,batch_size=100,
                           validation_data = val_generator.
                           ↪flow(x_val,y_val,batch_size=100),
                           validation_steps=200,
                           verbose=1)
history=history.history
model.save('/kaggle/working/3c_model.h5')
```

Epoch 1/30

19/19 [=====] - 6s 170ms/step - loss: 12.9609 -
accuracy: 0.4060 - precision: 0.3937 - Recall: 0.1911 - f1_score: 0.4050 -
val_loss: 1.0986 - val_accuracy: 0.3354 - val_precision: 0.0000e+00 -
val_Recall: 0.0000e+00 - val_f1_score: 0.1674

Epoch 2/30

19/19 [=====] - 1s 36ms/step - loss: 0.7701 - accuracy:
0.6548 - precision: 0.7339 - Recall: 0.5315 - f1_score: 0.6531

Epoch 3/30

19/19 [=====] - 1s 36ms/step - loss: 0.3436 - accuracy:
0.8581 - precision: 0.8688 - Recall: 0.8449 - f1_score: 0.8569

Epoch 4/30

19/19 [=====] - 1s 36ms/step - loss: 0.2577 - accuracy:
0.8999 - precision: 0.9014 - Recall: 0.8957 - f1_score: 0.8995

Epoch 5/30

19/19 [=====] - 1s 36ms/step - loss: 0.4892 - accuracy:
0.7988 - precision: 0.8145 - Recall: 0.7856 - f1_score: 0.7963

Epoch 6/30

19/19 [=====] - 1s 36ms/step - loss: 0.1956 - accuracy:
0.9201 - precision: 0.9215 - Recall: 0.9195 - f1_score: 0.9199

Epoch 7/30

19/19 [=====] - 1s 36ms/step - loss: 0.1285 - accuracy:
0.9508 - precision: 0.9518 - Recall: 0.9508 - f1_score: 0.9508

Epoch 8/30

19/19 [=====] - 1s 36ms/step - loss: 0.0910 - accuracy:
0.9656 - precision: 0.9656 - Recall: 0.9645 - f1_score: 0.9656

Epoch 9/30

19/19 [=====] - 1s 36ms/step - loss: 0.0704 - accuracy:

0.9709 - precision: 0.9714 - Recall: 0.9704 - f1_score: 0.9709

Epoch 10/30

19/19 [=====] - 1s 39ms/step - loss: 0.0428 - accuracy: 0.9846 - precision: 0.9846 - Recall: 0.9841 - f1_score: 0.9847

Epoch 11/30

19/19 [=====] - 1s 40ms/step - loss: 0.0872 - accuracy: 0.9672 - precision: 0.9682 - Recall: 0.9672 - f1_score: 0.9671

Epoch 12/30

19/19 [=====] - 1s 37ms/step - loss: 0.0625 - accuracy: 0.9799 - precision: 0.9799 - Recall: 0.9788 - f1_score: 0.9800

Epoch 13/30

19/19 [=====] - 1s 36ms/step - loss: 0.0305 - accuracy: 0.9899 - precision: 0.9899 - Recall: 0.9899 - f1_score: 0.9899

Epoch 14/30

19/19 [=====] - 1s 36ms/step - loss: 0.0197 - accuracy: 0.9936 - precision: 0.9936 - Recall: 0.9936 - f1_score: 0.9937

Epoch 15/30

19/19 [=====] - 1s 36ms/step - loss: 0.0202 - accuracy: 0.9947 - precision: 0.9947 - Recall: 0.9947 - f1_score: 0.9947

Epoch 16/30

19/19 [=====] - 1s 36ms/step - loss: 0.0105 - accuracy: 0.9979 - precision: 0.9979 - Recall: 0.9979 - f1_score: 0.9979

Epoch 17/30

19/19 [=====] - 1s 36ms/step - loss: 0.0082 - accuracy: 0.9974 - precision: 0.9974 - Recall: 0.9974 - f1_score: 0.9974

Epoch 18/30

19/19 [=====] - 1s 36ms/step - loss: 0.0050 - accuracy: 0.9995 - precision: 0.9995 - Recall: 0.9995 - f1_score: 0.9995

Epoch 19/30

19/19 [=====] - 1s 36ms/step - loss: 0.0512 - accuracy: 0.9815 - precision: 0.9820 - Recall: 0.9815 - f1_score: 0.9814

Epoch 20/30

19/19 [=====] - 1s 36ms/step - loss: 0.0711 - accuracy: 0.9756 - precision: 0.9756 - Recall: 0.9751 - f1_score: 0.9756

Epoch 21/30

19/19 [=====] - 1s 36ms/step - loss: 0.1155 - accuracy: 0.9619 - precision: 0.9619 - Recall: 0.9619 - f1_score: 0.9618

Epoch 22/30

19/19 [=====] - 1s 35ms/step - loss: 0.0400 - accuracy: 0.9846 - precision: 0.9846 - Recall: 0.9846 - f1_score: 0.9847

Epoch 23/30

19/19 [=====] - 1s 36ms/step - loss: 0.1789 - accuracy: 0.9444 - precision: 0.9449 - Recall: 0.9439 - f1_score: 0.9445

Epoch 24/30

19/19 [=====] - 1s 36ms/step - loss: 0.0652 - accuracy: 0.9756 - precision: 0.9756 - Recall: 0.9756 - f1_score: 0.9757

Epoch 25/30

19/19 [=====] - 1s 36ms/step - loss: 0.0375 - accuracy:

```

0.9862 - precision: 0.9868 - Recall: 0.9862 - f1_score: 0.9863
Epoch 26/30
19/19 [=====] - 1s 36ms/step - loss: 0.0155 - accuracy:
0.9958 - precision: 0.9958 - Recall: 0.9958 - f1_score: 0.9958
Epoch 27/30
19/19 [=====] - 1s 37ms/step - loss: 0.0063 - accuracy:
0.9989 - precision: 0.9989 - Recall: 0.9989 - f1_score: 0.9989
Epoch 28/30
19/19 [=====] - 1s 36ms/step - loss: 0.0017 - accuracy:
1.0000 - precision: 1.0000 - Recall: 1.0000 - f1_score: 1.0000
Epoch 29/30
19/19 [=====] - 1s 36ms/step - loss: 8.3512e-04 -
accuracy: 1.0000 - precision: 1.0000 - Recall: 1.0000 - f1_score: 1.0000
Epoch 30/30
19/19 [=====] - 1s 36ms/step - loss: 5.4360e-04 -
accuracy: 1.0000 - precision: 1.0000 - Recall: 1.0000 - f1_score: 1.0000

```

CNN MODEL EVALUATION

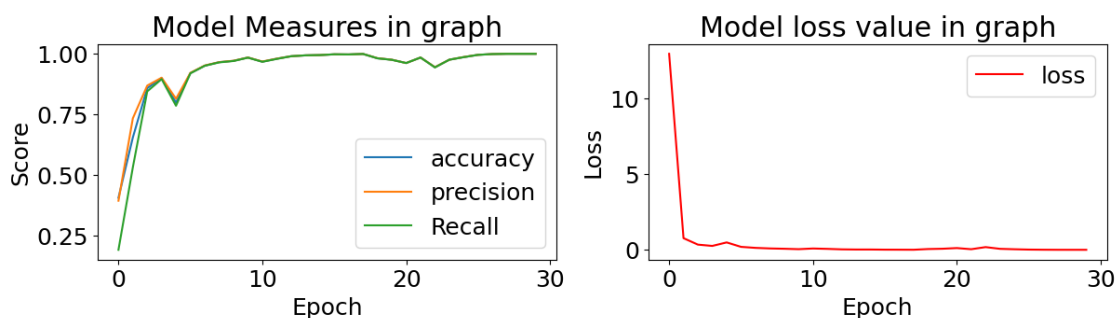
```

[55]: fig = plt.figure(figsize=(14, 3))
ax1 = fig.add_subplot(1, 2, 1)
ax1.plot(history['accuracy'])
ax1.plot(history['precision'])
ax1.plot(history["Recall"])
ax1.legend(['accuracy', 'precision', 'Recall'])
ax1.set_title('Model Measures in graph')
ax1.set_xlabel('Epoch')
ax1.set_ylabel('Score')

ax2 = fig.add_subplot(1, 2, 2)
ax2.plot(history['loss'], color='red')
ax2.legend(['loss'])
ax2.set_title('Model loss value in graph')
ax2.set_xlabel('Epoch')
ax2.set_ylabel('Loss')

plt.savefig('graph.png')
plt.show()

```



TEST SET

```
[56]: testscore=model.evaluate(x_test,y_test)
      testscore
```

```
10/10 [=====] - 0s 7ms/step - loss: 0.2006 - accuracy:
0.9567 - precision: 0.9567 - Recall: 0.9567 - f1_score: 0.9570
```

```
[56]: [0.20064330101013184,
      0.9566666483879089,
      0.9566666483879089,
      0.9566666483879089,
      array([0.9626168, 0.9353234, 0.972973 ], dtype=float32)]
```

```
[50]: print('TEST DATA')
      print('')
      print(f"Accuracy: {round(testscore[1]*100,2)}%")
      print(f"Precision: {round(testscore[2]*100,2)}%")
      print(f"Recall: {round(testscore[3]*100,2)}%")
      print(f"F1_score: {testscore[4]}")
      print(f"Loss: {testscore[0]}")
```

TEST DATA

```
Accuracy: 95.67%
Precision: 95.67%
Recall: 95.67%
F1_score: [0.9626168 0.9353234 0.972973 ]
Loss: 0.20064330101013184
```

```
[51]: from sklearn.metrics import classification_report,confusion_matrix
      from sklearn.metrics import ConfusionMatrixDisplay
```

```
[57]: y_pred=np.argmax(model.predict(x_test),axis=1)
      y_true=np.argmax(y_test,axis=1)
```

```
10/10 [=====] - 0s 4ms/step
```

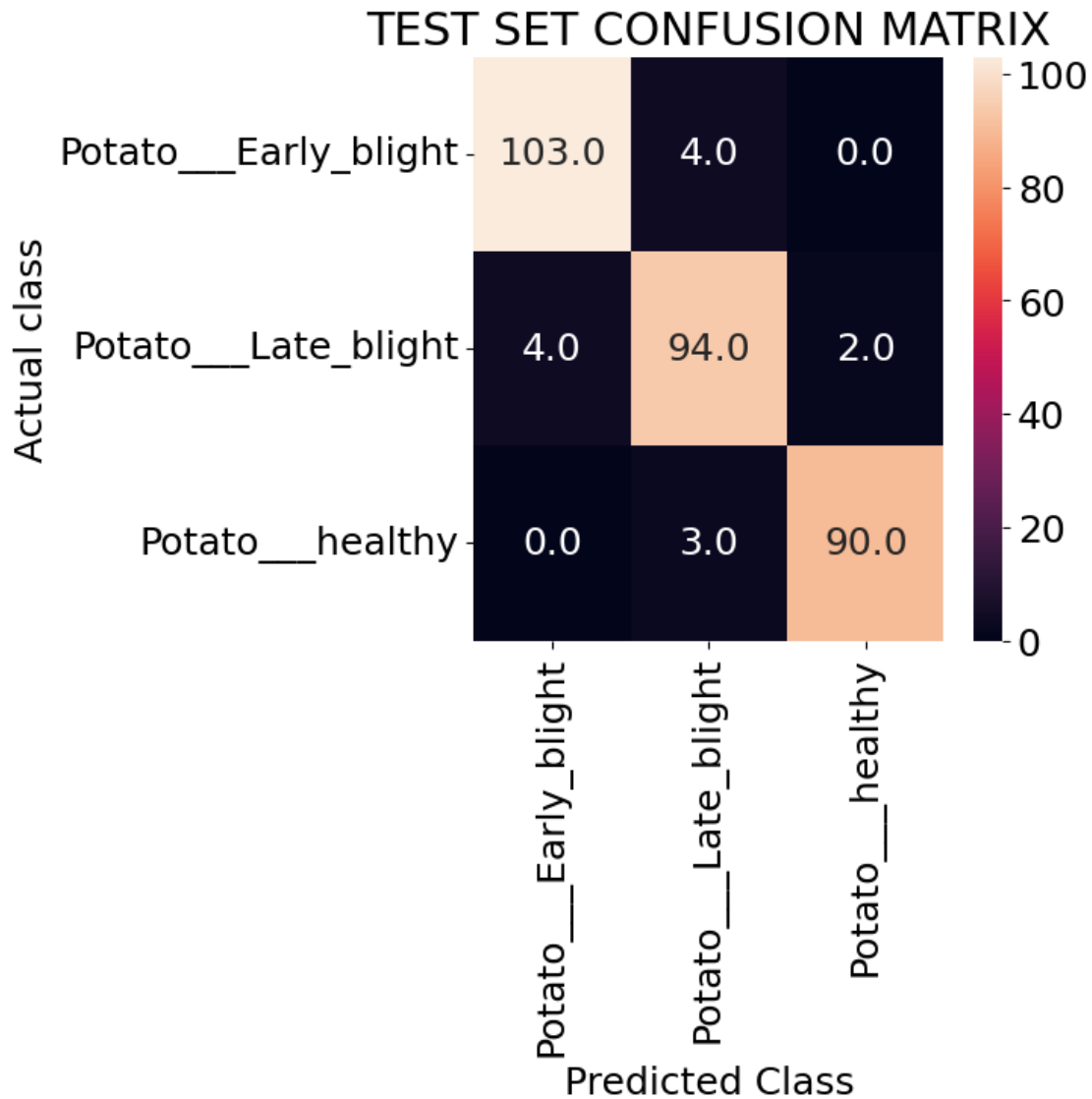
```
[58]: c_test=confusion_matrix(y_true,y_pred)
      c_test
```

```
[58]: array([[103,  4,  0],
           [ 4, 94,  2],
           [ 0,  3, 90]])
```

```
[59]: print(classification_report(y_true,y_pred,target_names=['Potato__Early_blight',
↪ 'Potato__Late_blight', 'Potato__healthy']))
```

	precision	recall	f1-score	support
Potato__Early_blight	0.96	0.96	0.96	107
Potato__Late_blight	0.93	0.94	0.94	100
Potato__healthy	0.98	0.97	0.97	93
accuracy			0.96	300
macro avg	0.96	0.96	0.96	300
weighted avg	0.96	0.96	0.96	300

```
[60]: class_names=['Potato__Early_blight', 'Potato__Late_blight',
↪ 'Potato__healthy']
plt.figure(figsize=(5,5))
sns.
↪ heatmap(c_test,annot=True,xticklabels=class_names,yticklabels=class_names,fmt='
↪ 1f')
plt.title('TEST SET CONFUSION MATRIX')
plt.xlabel("Predicted Class")
plt.ylabel("Actual class")
plt.savefig('cm test.png')
plt.show()
```



```
[61]: print(f"TEST SET")
      print('')
      for i in range(3):
          tp = c_test[i, i]
          tn = np.sum(c_test) - np.sum(c_test[i, :]) - np.sum(c_test[:, i]) +
          ↪c_test[i, i]
          fp = np.sum(c_test[:, i]) - c_test[i, i]
          fn = np.sum(c_test[i, :]) - c_test[i, i]
          print(f"Class {i}: TP={tp}, TN={tn}, FP={fp}, FN={fn}")
```

TEST SET

Class 0: TP=103, TN=189, FP=4, FN=4

Class 1: TP=94, TN=193, FP=7, FN=6
Class 2: TP=90, TN=205, FP=2, FN=3

VALIDATION SET ANALYSIS

```
[62]: valscore=model.evaluate(x_val,y_val)
      valscore
```

26/26 [=====] - 0s 8ms/step - loss: 0.1532 - accuracy:
0.9593 - precision: 0.9593 - Recall: 0.9593 - f1_score: 0.9591

```
[62]: [0.1532370150089264,
      0.9593095183372498,
      0.9593095183372498,
      0.9593095183372498,
      array([0.9726776 , 0.93761814, 0.9669118 ], dtype=float32)]
```

```
[63]: print('VALIDATION DATA')
      print('')
      print(f"Accuracy: {round(valscore[1]*100,2)}%")
      print(f"Precision: {round(valscore[2]*100,2)}%")
      print(f"Recall: {round(valscore[3]*100,2)}%")
      print(f"F1_score: {valscore[4]}")
      print(f"Loss: {valscore[0]}")
```

VALIDATION DATA

Accuracy: 95.93%
Precision: 95.93%
Recall: 95.93%
F1_score: [0.9726776 0.93761814 0.9669118]
Loss: 0.1532370150089264

```
[64]: yv_pred=np.argmax(model.predict(x_val),axis=1)
      yv_true=np.argmax(y_val,axis=1)
```

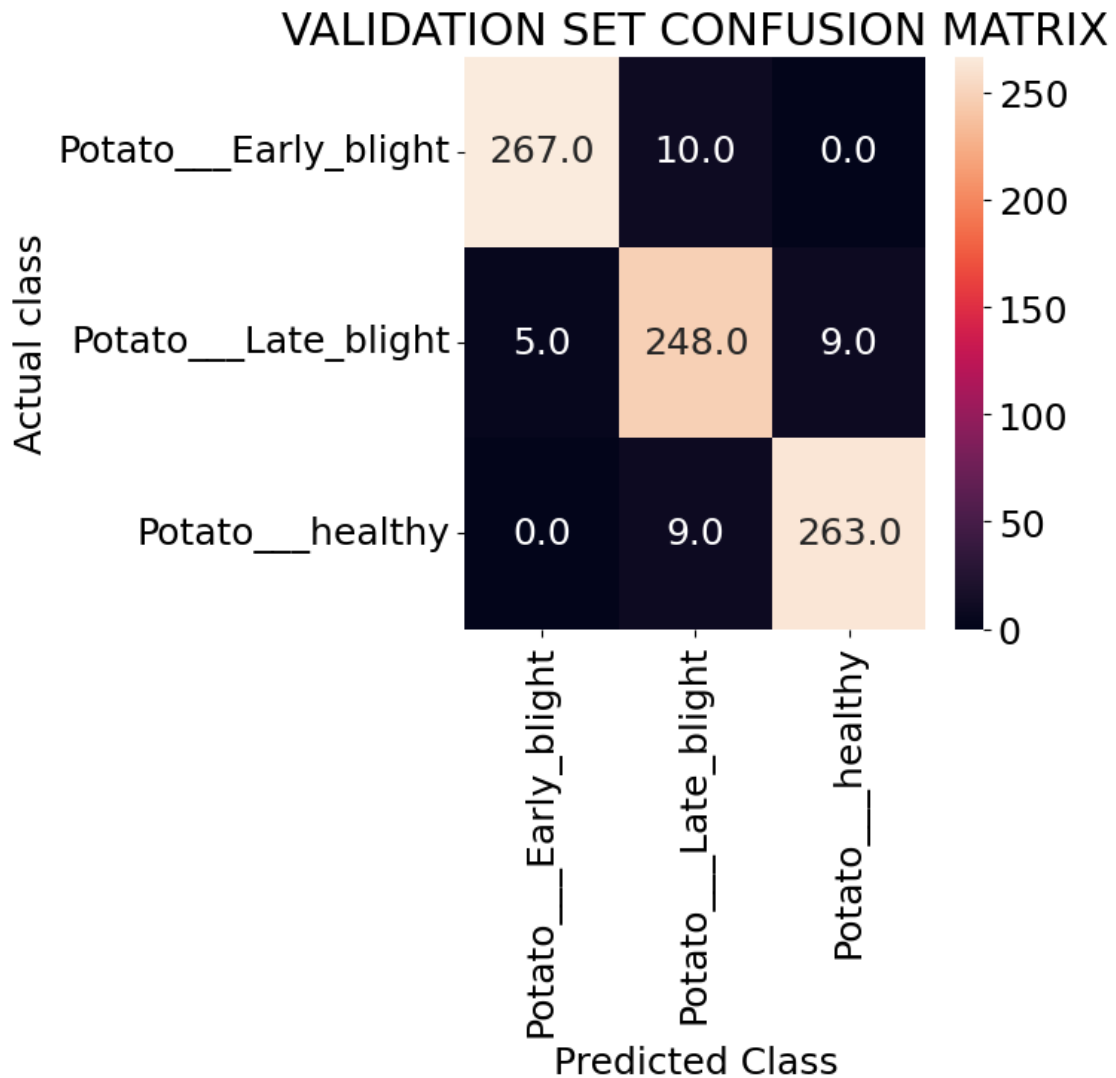
26/26 [=====] - 0s 4ms/step

```
[65]: c_val=confusion_matrix(yv_true,yv_pred)
      c_val
```

```
[65]: array([[267, 10,  0],
      [ 5, 248,  9],
      [ 0,  9, 263]])
```

```
[66]: plt.figure(figsize=(5,5))
      sns.
      ↪heatmap(c_val,annot=True,xticklabels=class_names,yticklabels=class_names,fmt='
      ↪1f')
```

```
plt.title('VALIDATION SET CONFUSION MATRIX')
plt.xlabel("Predicted Class")
plt.ylabel("Actual class")
plt.savefig('cm VAL.png')
plt.show()
```



```
[68]: print(classification_report(yv_true,yv_pred,target_names=class_names))
```

	precision	recall	f1-score	support
Potato__Early_blight	0.98	0.96	0.97	277
Potato__Late_blight	0.93	0.95	0.94	262
Potato__healthy	0.97	0.97	0.97	272

accuracy			0.96	811
macro avg	0.96	0.96	0.96	811
weighted avg	0.96	0.96	0.96	811

```
[69]: print(f"VALIDATION SET")
print('')
for i in range(3):
    tp = c_val[i, i]
    tn = np.sum(c_val) - np.sum(c_val[i, :]) - np.sum(c_val[:, i]) + c_val[i, i]
    fp = np.sum(c_val[:, i]) - c_val[i, i]
    fn = np.sum(c_val[i, :]) - c_val[i, i]
    print(f"Class {i}: TP={tp}, TN={tn}, FP={fp}, FN={fn}")
```

VALIDATION SET

Class 0: TP=267, TN=529, FP=5, FN=10

Class 1: TP=248, TN=530, FP=19, FN=14

Class 2: TP=263, TN=530, FP=9, FN=9

IMAGE PREDICTIONS WITH PERCENTAGES

```
[71]: plt.figure(figsize=(30, 30))
plt.subplots_adjust(wspace=0.3, hspace=0.3)
for i in range(20):
    idx = np.random.randint(len(y))
    img, true_class = x[idx], categories[y[idx].squeeze()]

    # predict class probabilities for the current image
    probs = model.predict(img[None, :, :, :])[0]
    pred_class = categories[np.argmax(probs)]
    max_prob = np.max(probs)*100
    plt.rcParams.update({'font.size':18})
    plt.subplot(5, 4, i + 1)
    plt.imshow(img[:, :, :-1])
    plt.title(f"Predicted: {pred_class}\nActual: {true_class}\n\
↪matching_Percentage: {round(max_prob)}%")
    plt.axis("off")
plt.show()
```

```
1/1 [=====] - 0s 20ms/step
1/1 [=====] - 0s 21ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 20ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 25ms/step
1/1 [=====] - 0s 23ms/step
1/1 [=====] - 0s 19ms/step
1/1 [=====] - 0s 19ms/step
```


1/1 [=====] - 0s 20ms/step
 1/1 [=====] - 0s 19ms/step
 1/1 [=====] - 0s 22ms/step
 1/1 [=====] - 0s 22ms/step
 1/1 [=====] - 0s 21ms/step
 1/1 [=====] - 0s 22ms/step
 1/1 [=====] - 0s 21ms/step
 1/1 [=====] - 0s 20ms/step
 1/1 [=====] - 0s 20ms/step
 1/1 [=====] - 0s 20ms/step
 1/1 [=====] - 0s 38ms/step

Predicted: Potato__Late_blight
 Actual: Potato__Late_blight
 matching_Percentage: 100%



Predicted: Potato__healthy
 Actual: Potato__healthy
 matching_Percentage: 100%



Predicted: Potato__healthy
 Actual: Potato__healthy
 matching_Percentage: 100%



Predicted: Potato__Late_blight
 Actual: Potato__Late_blight
 matching_Percentage: 100%



Predicted: Potato__Early_blight
 Actual: Potato__Early_blight
 matching_Percentage: 100%



Predicted: Potato__Early_blight
 Actual: Potato__Early_blight
 matching_Percentage: 100%



Predicted: Potato__Late_blight
 Actual: Potato__Late_blight
 matching_Percentage: 100%



Predicted: Potato__Late_blight
 Actual: Potato__Late_blight
 matching_Percentage: 100%



Predicted: Potato__healthy
 Actual: Potato__healthy
 matching_Percentage: 100%



Predicted: Potato__Late_blight
 Actual: Potato__Late_blight
 matching_Percentage: 100%



Predicted: Potato__Late_blight
 Actual: Potato__Late_blight
 matching_Percentage: 100%



Predicted: Potato__Early_blight
 Actual: Potato__Early_blight
 matching_Percentage: 100%



Predicted: Potato__healthy
 Actual: Potato__healthy
 matching_Percentage: 100%



Predicted: Potato__healthy
 Actual: Potato__healthy
 matching_Percentage: 100%



Predicted: Potato__Early_blight
 Actual: Potato__Early_blight
 matching_Percentage: 100%



Predicted: Potato__Early_blight
 Actual: Potato__Early_blight
 matching_Percentage: 100%



Predicted: Potato__Early_blight
 Actual: Potato__Early_blight
 matching_Percentage: 100%



Predicted: Potato__Early_blight
 Actual: Potato__Early_blight
 matching_Percentage: 100%



Predicted: Potato__healthy
 Actual: Potato__healthy
 matching_Percentage: 100%



Predicted: Potato__Late_blight
 Actual: Potato__Late_blight
 matching_Percentage: 100%

