Project

April 25, 2022

[5]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import random
import time

import os,shutil
import os.path
from pathlib import Path
import glob

from PIL import Image
from keras.preprocessing import image
from keras.applications.vgg16 import preprocess_input, decode_predictions
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator, array_to_img,␣
↪img_to_array, load_img

from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from keras.utils.np_utils import to_categorical
from sklearn.model_selection import train_test_split
from keras import regularizers
from sklearn.preprocessing import LabelEncoder

from sklearn.metrics import confusion_matrix, accuracy_score,␣
↪classification_report, roc_auc_score, roc_curve
from sklearn.model_selection import GridSearchCV, cross_val_score
from sklearn.metrics import mean_squared_error, r2_score

from tensorflow.keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Conv2D,␣
↪MaxPool2D,MaxPooling2D,\
Bidirectional,LSTM, GlobalAveragePooling2D,␣
↪Convolution2D,AveragePooling2D,Input, \
GlobalMaxPooling2D,Activation,BatchNormalization
```

```python
from keras import models
from keras import layers
from keras import Input
from keras import regularizers, optimizers
from keras.models import Model
import tensorflow as tf
from keras.models import load_model
from keras.regularizers import l1,l2,L1L2
from tensorflow.keras import regularizers
np.random.seed(123)
```

0.1 Business Problem

Our aim is in this project is to image classification about Mars. Images collected by Curiosity Rover which launched Nov. 26, 2011 and landed on Mars at Aug. 5, 2012.
Curiosity set out to answer the question: Did Mars ever have the right environmental conditions to support small life forms called microbes? We are going to classify images collected by curiosity rover to help future projects. Our aim to make machine learning model and deploy at the future rovers to make future rover more effective decisions with artificial intelligence depend on mission.

0.2 Business Value

In this project, NASA or any other space companies who work on mars can find image classification model about mars. This could help the business to deploy our machine learning model on the future rovers to make better and better decisions by itself. NASA has two future missions shows on website; first Mars Sample Return, second ExoMars 2022 Rover and Surface Platform. Our model could deploy on that missions.

[64]:
```python
## Opening label informations.
with open ('Labels Information.txt','r') as rd:
    lst = [str(line) for line in rd]
lst
```

```
---------------------------------------------------------------------------
FileNotFoundError                         Traceback (most recent call last)
<ipython-input-64-c521e7dfb516> in <module>
      1 ## Opening label informations.
----> 2 with open ('Labels Information.txt','r') as rd:
      3     lst = [str(line) for line in rd]
      4 lst

FileNotFoundError: [Errno 2] No such file or directory: 'Labels Information.txt
```

[ ]:
```python
ls
```

[6]:
```python
# Looking train data.
train_df = pd.read_csv(r'C:\Users\AI\Desktop\mars_image/Train_CSV.csv')
```

```
train_df
```

[6]:

```
                                              JPG  LABELS
0     calibrated/0077ML0005780000102730I01_DRCL.JPG      15
1     calibrated/0072MR0005610170103642E01_DRCL.JPG       8
2     calibrated/0069MR0004130000103477I01_DRCL.JPG      21
3     calibrated/0154ML0008510010104492E01_DRCL.JPG       8
4     calibrated/0019MR0000530000100138C00_DRCL.JPG       8
…                                               …     …
3741  calibrated/0163ML0008760050104602D01_DRCL.JPG      10
3742  calibrated/0072MR0005620000103655E01_DRCL.JPG       8
3743  calibrated/0066ML0003650000102517M00_DRCL.JPG      21
3744  calibrated/0157ML0008550020104531I01_DRCL.JPG       8
3745  calibrated/0057ML0002640010102297E01_DRCL.JPG       8

[3746 rows x 2 columns]
```

[7]:

```
test_df = pd.read_csv(r'C:\Users\AI\Desktop\mars_image/Test_CSV.csv')
test_df
```

[7]:

```
                                              JPG  LABELS
0     calibrated/0830MR0036510000500684E01_DRCL.JPG       7
1     calibrated/0640MH0002640000203781I01_DRCL.JPG      24
2     calibrated/0647MH0003250050203806E01_DRCL.JPG       9
3     calibrated/0844MR0037590000501001I01_DRCL.JPG       7
4     calibrated/0618MR0026460020401253I01_DRCL.JPG      11
…                                               …     …
1300  calibrated/0571MH0002590000201894I01_DRCL.JPG      24
1301  calibrated/0840ML0037090000401385I01_DRCL.JPG      17
1302  calibrated/0868MH0003900000302200I01_DRCL.JPG      10
1303  calibrated/0568MH0002630000201882E01_DRCL.JPG      24
1304  calibrated/0613MH0003900000203392I01_DRCL.JPG      10

[1305 rows x 2 columns]
```

[8]:

```
valid_df = pd.read_csv(r'C:\Users\AI\Desktop\mars_image/Validation_CSV.csv')
valid_df
```

[8]:

```
                                              JPG  LABELS
0     calibrated/0292MH0002810020103587C00_DRCL.JPG       5
1     calibrated/0270MH0002530050102760I01_DRCL.JPG       5
2     calibrated/0549MH0002620000201566E01_DRCL.JPG      24
3     calibrated/0229MR0009720000202913E01_DRCL.JPG       0
4     calibrated/0292MH0002810020103613C00_DRCL.JPG       5
…                                               …     …
1635  calibrated/0486MR0011580000302944E01_DRCL.JPG       0
1636  calibrated/0506MH0002240020200655I01_DRCL.JPG       8
```

```
1637   calibrated/0229MR0010840000202939I01_DRCL.JPG      16
1638   calibrated/0229MR0009760000202918I01_DRCL.JPG      18
1639   calibrated/0270MH0002530050102767E01_DRCL.JPG       5

[1640 rows x 2 columns]
```

[ ]:
```
# Looking an example image.
from matplotlib.pyplot import imshow
fpath=r'C:\Users\AI\Desktop\mars_image/images/0003ML0000000110100031E01_DRCL.
↪JPG'
img=plt.imread(fpath)
print (img.shape)
imshow(img)
```

[ ]:
```
train_df['JPG'] = [i.split('/')[1] for i in train_df['JPG']]
```

0.3 Data Understanding

[ ]:
```
cd images
```

0.3.1 Understanding Label Classes

Alpha Particle X-Ray Spectrometer (APXS) When it is placed right next to a rock or soil surface, it uses two kinds of radiation to measure the amounts and types of chemical elements that are present.

[88]:
```
Image.open(r"0032MR0000870010100789I01_DRCL.JPG")
```

[88]:

Alpha Particle X-Ray Spectrometer Calibration Target Objects with known properties that act as reference points to help scientists fine-tune observations not only from imagers but also other science instruments

[87]:
```
Image.open(r"0179MH0002170010102506I01_DRCL.JPG")
```

[87]:

Chemcam Calibration target The Chemistry and Camera tool is known as ChemCam. ChemCam's laser, camera and spectrograph work together to identify the chemical and mineral composition of rocks and soils.

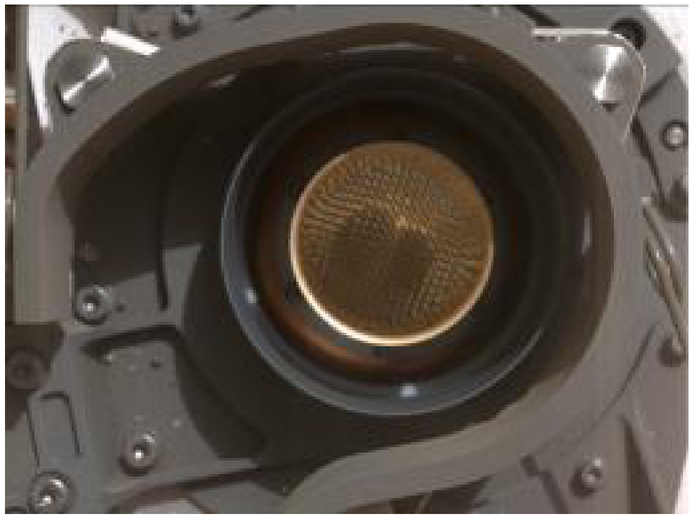
[86]:
```
Image.open(r"0050ML0002300250102173E01_DRCL.JPG")
```

[86]:

Chemin inlet open The Chemistry and Mineralogy instrument, or CheMin for short, performs chemical analysis of powdered rock samples to identify the types and amounts of different minerals that are present.

[85]:
```
Image.open(r"0036MH0000510030100058E01_DRCL.JPG")
```

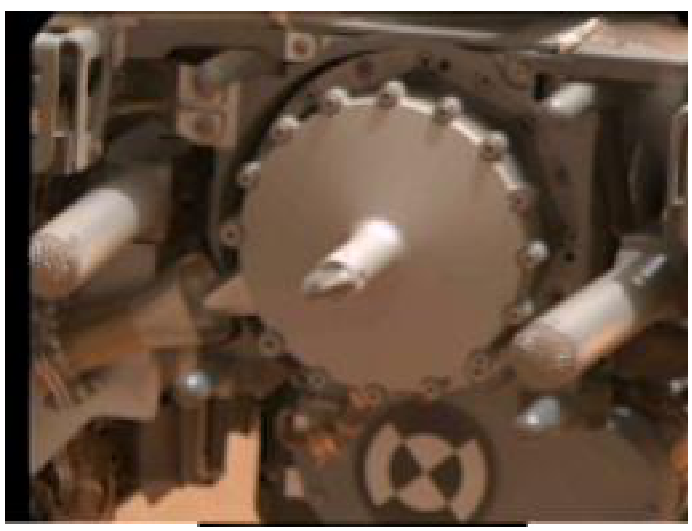
[85]:



Drill When the rover needs to drill to soil it uses this tool.

[84]:
```
Image.open(r"0173MR0008970000201801I01_DRCL.JPG")
```

[84]:



Drill holes Drill holes opened from curiosity rover.

[65]:
```
Image.open(r"0180MH0001490020102528C00_DRCL.JPG")
```

[65]:

Dust Removal Tool(DRT) front The robot's Dust Removal Tool (DRT) has brushed a section of the target, prepping it for drilling.

[66]:
```
Image.open(r"0150MR0007360000201220E01_DRCL.JPG")
```

[66]:

Drt side

[67]:
```
Image.open(r"0150MR0007370000201221E01_DRCL.JPG")
```

[67]:

Ground Mars surface ground.

[68]:
```
Image.open(r"0017ML0000500200100233B00_DRCL.JPG")
```

[68]:

Horizon Instances from mars horizon.

[69]:
```
Image.open(r"0017ML0000500030100216C00_DRCL.JPG")
```

[69]:

Inlet Instances from inside of the rover.

[70]:
```
Image.open(r"0093MH0001290030101088E01_DRCL.JPG")
```

[70]:

Mars Hand Lens Imager(MAHLI) The Mars Hand Lens Imager, called MAHLI, is the rover's version of the magnifying hand lens that geologists usually carry with them into the field. MAHLI's close-up images reveal the minerals and textures in rock surfaces

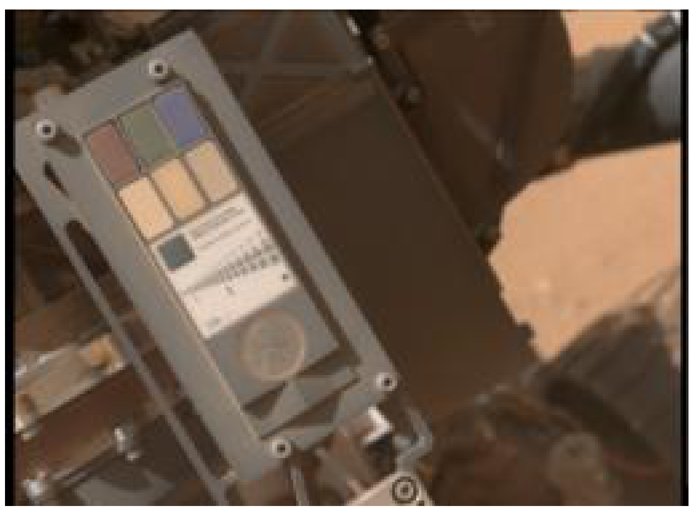
[71]:
```
Image.open(r"0032MR0000760020100776I01_DRCL.JPG")
```

[71]:

MAHLI Calibration Target The MAHLI calibration target includes color chips, a metric standardized bar graphic, a penny, and a stair-step pattern for depth calibration. The MAHLI adjustable-focus, color camera is one of the tools on the turret at the end of Curiosity's robotic arm. Its calibration target is attached to the rover at the arm's shoulder joint.

[72]:
```
Image.open(r"0034MH0000470030100045E01_DRCL.JPG")
```

[72]:



MASTCAM The Mast Camera, or Mastcam for short, takes color images and color video footage of the Martian terrain. The images can be stitched together to create panoramas of the landscape around the rover.

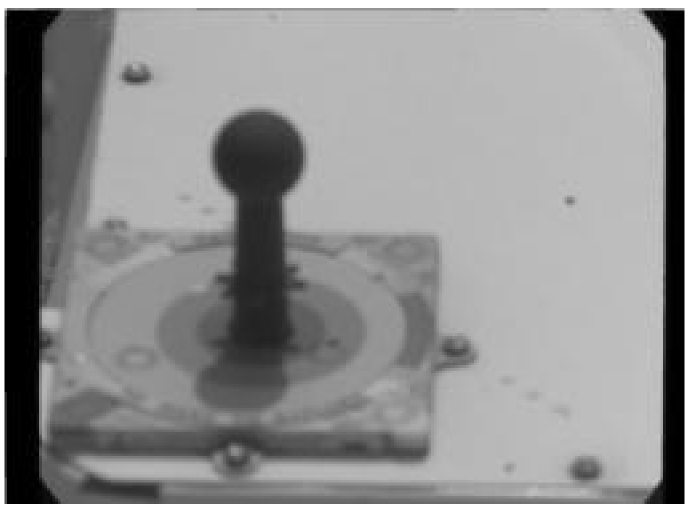
[73]:
```
Image.open(r"0177MH0002260000102364C00_DRCL.JPG")
```

[73]:

MASTCAM Calibration Target The primary calibration target for Mastcam, a pair of zoomable cameras aboard NASA's Perseverance Mars rover, features color swatches used by scientists to fine-tune the cameras' settings. The object in the center, known as a shadow post, helps scientists check the color of the sky to calibrate for lighting conditions.

[74]:
```python
Image.open(r"0013MR0000020060100034D01_DRCL.JPG")
```

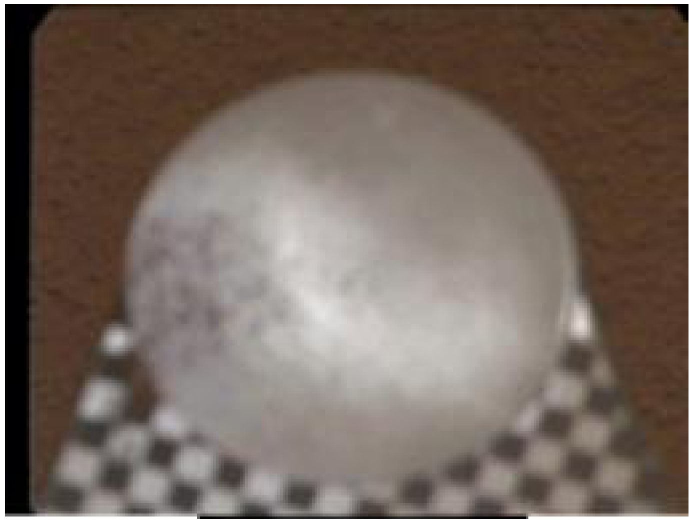
[74]:



Observation tray This is the small tray at the rover which rover put samples for observation.

[75]:
```python
Image.open(r"0078MR0005850080103904I01_DRCL.JPG")
```

[75]:



Portion Box It is small boxes at the rover for store.

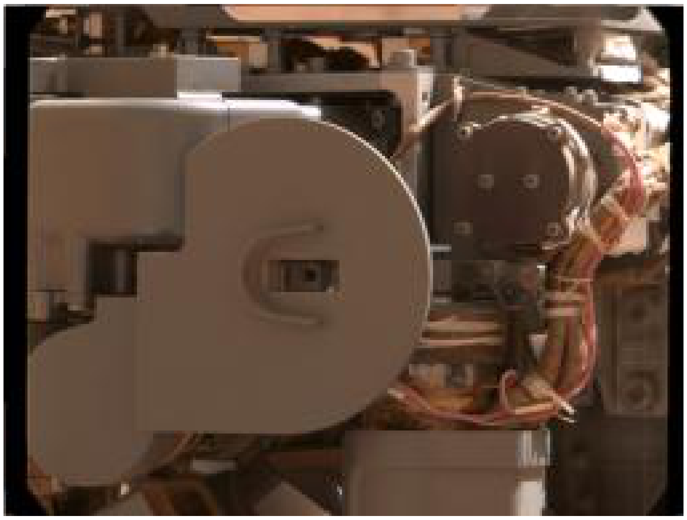
[76]:
```
Image.open(r"0173MR0009030000201807E01_DRCL.JPG")
```

[76]:

Portion tube

[77]:
```
Image.open(r"0073MR0003910010103663E01_DRCL.JPG")
```

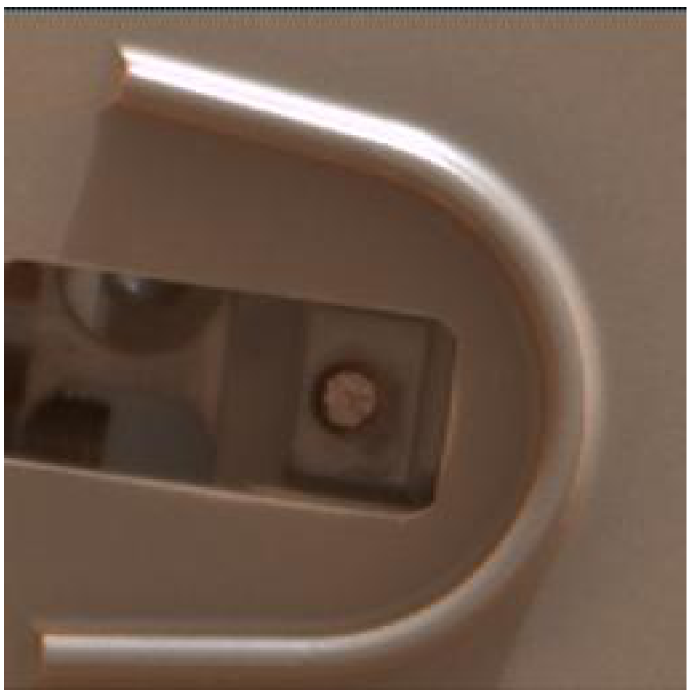
[77]:



Portion tube opening

[78]:
```
Image.open(r"0173MR0008930000201797C00_DRCL.JPG")
```

[78]:



Rems uv sensor The Rover Environmental Monitoring Station is nicknamed REMS, and it contains all the weather instruments needed to provide daily and seasonal reports on meteorological conditions around the rover.

[79]:
```python
Image.open(r"0154MH0000950010101443C00_DRCL.JPG")
```
[79]:

Rover rear deck

[80]:
```python
Image.open(r"0044MR0002011450102524E01_DRCL.JPG")
```
[80]:

Scoop

[81]:
```python
Image.open(r"0069MR0004130000103477I01_DRCL.JPG")
```
[81]:

Turret The turret at the end of Curiosity's robotic arm holds five devices. On the left (downhill) edge of the turret in this view is the percussive drill for collecting powdered samples from rock interiors. On the edge toward the camera is a brush device named Dust Removal Tool. Farther to the right is the Mars Hand Lens Imager. Not visible in this view are the Alpha Particle X-ray Spectrometer and a multi-purpose device named Collection and Handling for In-situ Martian Rock Analysis (CHIMRA), which includes a soil scoop and a set of chambers and labyrinths for sieving, sorting and portioning samples of rock powder or soil for delivery to analytical instruments.

[82]:
```
Image.open(r"0065ML0003350000102429I01_DRCL.JPG")
```

[82]:

Wheel Examples from wheels of rover.

[83]:
```
Image.open(r"0085MH0001130000100975E01_DRCL.JPG")
```

[83]:

0.4 Data Preparation

[9]:
```
#First data cleaning.
sdir=r'C:\Users\AI\Desktop\mars_image/images'

# convet LABELS column values to strings whic are required.
train_df['LABELS']=train_df['LABELS'].apply(lambda x: str(x))
test_df['LABELS']=test_df['LABELS'].apply(lambda x: str(x))
valid_df['LABELS']=valid_df['LABELS'].apply(lambda x: str(x))

# remove 'calibrated' from each of the filenames
train_df['JPG']=train_df['JPG'].apply(lambda x: os.path.split(x)[1])
test_df['JPG']=test_df['JPG'].apply(lambda x: os.path.split(x)[1])
valid_df['JPG']=valid_df['JPG'].apply(lambda x: os.path.split(x)[1])

# for  dataframes make column JPG a full path to the image
train_df['JPG']=train_df['JPG'].apply(lambda x: os.path.join(sdir,x))
test_df['JPG']=test_df['JPG'].apply(lambda x: os.path.join(sdir,x))
valid_df['JPG']=valid_df['JPG'].apply(lambda x: os.path.join(sdir,x))
```

[10]:
```
# Looking labels distribution.
train_df['LABELS'].value_counts(normalize=True)
```

[10]:
```
8     0.625467
9     0.059797
23    0.047517
21    0.044314
10    0.044047
```

```
14    0.026962
15    0.022691
17    0.019487
24    0.018420
20    0.015216
3     0.012547
5     0.009610
13    0.009610
12    0.008542
0     0.008009
4     0.005072
16    0.004805
2     0.004004
11    0.003737
19    0.003203
18    0.002136
7     0.002136
1     0.001602
6     0.001068
Name: LABELS, dtype: float64
```

[11]:

```
#Concating all 3 dataframes and splitting to prevent error at the modeling.␣
↪Because we have missings at the validation dataframe.
df=pd.concat([train_df, valid_df, test_df], axis=0).reset_index(drop=True)
print (df.head())
print (len(df))
```

```
                                                  JPG LABELS
0  C:\Users\AI\Desktop\mars_image/images\0077ML00…     15
1  C:\Users\AI\Desktop\mars_image/images\0072MR00…      8
2  C:\Users\AI\Desktop\mars_image/images\0069MR00…     21
3  C:\Users\AI\Desktop\mars_image/images\0154ML00…      8
4  C:\Users\AI\Desktop\mars_image/images\0019MR00…      8
6691
```

[12]:

```
#Splitting.
train_split=.6
valid_split=.2
dummy_split=valid_split/(1-train_split)
train_df, dummy_df=train_test_split(df, train_size=train_split, shuffle=True,␣
↪random_state=123)
valid_df, test_df=train_test_split(dummy_df, train_size=dummy_split,␣
↪shuffle=True, random_state=123)
print('train_df length: ', len(train_df), '  test_df length: ', len(test_df), '␣
↪ valid_df length: ', len(valid_df))

# make sure each dataframe has all the classes
```

```
tr_count=len(list(train_df['LABELS'].unique()))
te_count=len(list(test_df['LABELS'].unique()))
v_count=len(list(valid_df['LABELS'].unique()))
print (' train_df classes: ', tr_count, '  test_df classes: ', te_count, ' ␣
↪valid_df classes: ', v_count)
print (train_df['LABELS'].value_counts())
print(test_df['LABELS'].value_counts())
```

```
train_df length:  4014   test_df length:  1339   valid_df length:  1338
 train_df classes:  24   test_df classes:  24   valid_df classes:  24
8     1610
24     609
5      294
9      217
10     179
21     120
23     110
3      107
14      94
7       93
17      86
15      67
12      65
0       56
16      52
13      45
6       44
20      38
19      35
4       29
2       20
1       17
11      16
18      11
Name: LABELS, dtype: int64
8     525
24    205
5     112
9      60
10     54
21     48
23     37
7      34
12     31
3      29
17     27
14     26
16     24
```

```
15      22
20      18
19      16
4       16
0       13
6       12
18       9
13       9
1        5
2        4
11       3
Name: LABELS, dtype: int64
```

[13]:

```python
#Limiting number of samples per class up to 100 for solution imbalance.
sample_list=[]
max_size= 100
groups=train_df.groupby('LABELS')
for label in train_df['LABELS'].unique():
    group=groups.get_group(label)
    sample_count=len(group)
    if sample_count> max_size:
        samples=group.sample(max_size, replace=False, weights=None,␣
 ↪random_state=123, axis=0).reset_index(drop=True)
    else:
        samples=group.sample(frac=1.0, replace=False, random_state=123, axis=0).
 ↪reset_index(drop=True)

    sample_list.append(samples)
train_df=pd.concat(sample_list, axis=0).reset_index(drop=True)
print (len(train_df))
print (train_df['LABELS'].value_counts())
```

```
1568
24     100
10     100
23     100
8      100
9      100
3      100
5      100
21     100
14      94
7       93
17      86
15      67
12      65
0       56
```

```
16      52
13      45
6       44
20      38
19      35
4       29
2       20
1       17
11      16
18      11
Name: LABELS, dtype: int64
```

[14]:
```
#Making directories to save augmented images.
working_dir=r'./'
aug_dir=os.path.join(working_dir, 'aug')
sdir=r'../input/mars-surface-and-curiosity-image-set-nasa/Mars Surface and␣
↪Curiosity Image/images'
if os.path.isdir(aug_dir):
    shutil.rmtree(aug_dir)
os.mkdir(aug_dir)
for label in train_df['LABELS'].unique():
    dir_path=os.path.join(aug_dir,label)
    os.mkdir(dir_path)
print(os.listdir(aug_dir))
```

```
['0', '1', '10', '11', '12', '13', '14', '15', '16', '17', '18', '19', '2',
'20', '21', '23', '24', '3', '4', '5', '6', '7', '8', '9']
```

[15]:
```
#Creaing augmented images and store in aug directories.
target=100
gen=ImageDataGenerator(horizontal_flip=True, vertical_flip=True,␣
↪rotation_range=20, width_shift_range=.2,
                              height_shift_range=.2, zoom_range=.2)
groups=train_df.groupby('LABELS')
for label in train_df['LABELS'].unique():
    group=groups.get_group(label)
    sample_count=len(group)
    if sample_count< target:
        aug_img_count=0
        delta=target-sample_count
        target_dir=os.path.join(aug_dir, label)
        aug_gen=gen.flow_from_dataframe( group,  x_col='JPG', y_col=None,␣
↪target_size=(256,256), class_mode=None, batch_size=1,
                                         shuffle=False, save_to_dir=target_dir,␣
↪save_prefix='aug-',save_format='jpg')
        while aug_img_count<delta:
            images=next(aug_gen)
            aug_img_count += len(images)
```

```
Found 93 validated image filenames.
Found 94 validated image filenames.
Found 35 validated image filenames.
Found 86 validated image filenames.
Found 20 validated image filenames.
Found 29 validated image filenames.
Found 11 validated image filenames.
Found 38 validated image filenames.
Found 56 validated image filenames.
Found 52 validated image filenames.
Found 16 validated image filenames.
Found 45 validated image filenames.
Found 67 validated image filenames.
Found 17 validated image filenames.
Found 65 validated image filenames.
Found 44 validated image filenames.
```

[16]:
```python
#Creating aug dataframe and concating with train dataframe.
aug_fpaths=[]
aug_labels=[]
classlist=os.listdir(aug_dir)
for klass in classlist:
    classpath=os.path.join(aug_dir, klass)
    flist=os.listdir(classpath)
    for f in flist:
        fpath=os.path.join(classpath,f)
        aug_fpaths.append(fpath)
        aug_labels.append(klass)
Fseries=pd.Series(aug_fpaths, name='JPG')
Lseries=pd.Series(aug_labels, name='LABELS')
aug_df=pd.concat([Fseries, Lseries], axis=1)
print ('Length of aug_df: ', len(aug_df))
print (aug_df.head())
print()

train_df=pd.concat([train_df,aug_df], axis=0).reset_index(drop=True)
train_df=train_df.sample(frac=1.0, replace=False, random_state=123, axis=0).
 ↪reset_index(drop=True)

print ('Length of train_df is: ', len(train_df))
print (train_df.head())
print (train_df['LABELS'].value_counts())
```

```
Length of aug_df:  832
                          JPG LABELS
0   ./aug\0\aug-_0_2628891.jpg      0
1  ./aug\0\aug-_10_1760835.jpg      0
2  ./aug\0\aug-_11_7256916.jpg      0
```

```
3  ./aug\0\aug-_12_3189018.jpg      0
4  ./aug\0\aug-_13_5031126.jpg      0

Length of train_df is:  2400
                                                JPG LABELS
0  C:\Users\AI\Desktop\mars_image/images\0172MR00…      2
1                        ./aug\2\aug-_15_3119123.jpg      2
2  C:\Users\AI\Desktop\mars_image/images\0076MR00…      8
3                       ./aug\11\aug-_11_1575142.jpg     11
4                       ./aug\20\aug-_22_6010346.jpg     20
24    100
7     100
16    100
1     100
14    100
15    100
17    100
4     100
23    100
18    100
11    100
2     100
3     100
8     100
13    100
9     100
10    100
12    100
20    100
6     100
0     100
21    100
19    100
5     100
Name: LABELS, dtype: int64
```

[17]:

```
#Creating train test and validation sets.
height=256
width=256
channels=3
batch_size=40
img_shape=(height, width, channels)
img_size=(height, width)
length=len(test_df)
test_batch_size=sorted([int(length/n) for n in range(1,length+1) if length % n␣
 ↪==0 and length/n<=80],reverse=True)[0]
test_steps=int(length/test_batch_size)
```

```
print ( 'test batch size: ' ,test_batch_size, '  test steps: ', test_steps)
def scalar(img):
    #img=img/127.5-1
    return img
trgen=ImageDataGenerator(preprocessing_function=scalar, horizontal_flip=True)
tvgen=ImageDataGenerator(preprocessing_function=scalar)
sdir=r'../input/mars-surface-and-curiosity-image-set-nasa/Mars Surface and␣
↪Curiosity Image/images'
train_gen=trgen.flow_from_dataframe( train_df, x_col='JPG', y_col='LABELS',␣
↪target_size=img_size, class_mode='categorical',
                                    color_mode='rgb', shuffle=True,␣
↪batch_size=batch_size)
test_gen=tvgen.flow_from_dataframe( test_df, x_col='JPG', y_col='LABELS',␣
↪target_size=img_size, class_mode='categorical',
                                    color_mode='rgb', shuffle=False,␣
↪batch_size=test_batch_size)
valid_gen=tvgen.flow_from_dataframe( valid_df, x_col='JPG', y_col='LABELS',␣
↪target_size=img_size, class_mode='categorical',
                                    color_mode='rgb', shuffle=True,␣
↪batch_size=batch_size)
classes=list(train_gen.class_indices.keys())
class_count=len(classes)
train_steps=int(len(train_gen.labels)/batch_size)
valid_steps = int(len(valid_gen.labels)/batch_size)
```

```
test batch size:  13   test steps:  103
Found 2400 validated image filenames belonging to 24 classes.
Found 1339 validated image filenames belonging to 24 classes.
Found 1338 validated image filenames belonging to 24 classes.
```

[95]:

```
#Creating support function for evaluation.
def evaluation(test_gen, preds, print_code, save_dir, subject):
    class_dict=test_gen.class_indices
    labels= test_gen.labels
    file_names= test_gen.filenames
    error_list=[]
    true_class=[]
    pred_class=[]
    prob_list=[]
    new_dict={}
    error_indices=[]
    y_pred=[]
    for key,value in class_dict.items():
        new_dict[value]=key             # dictionary {integer of class number:␣
↪string of class name}
    # store new_dict as a text fine in the save_dir
    classes=list(new_dict.values())     # list of string of class names
```

```
    errors=0
    for i, p in enumerate(preds):
        pred_index=np.argmax(p)
        true_index=labels[i]  # labels are integer values
        if pred_index != true_index: # a misclassification has occurred
            error_list.append(file_names[i])
            true_class.append(new_dict[true_index])
            pred_class.append(new_dict[pred_index])
            prob_list.append(p[pred_index])
            error_indices.append(true_index)
            errors=errors + 1
        y_pred.append(pred_index)

    y_true= np.array(labels)
    y_pred=np.array(y_pred)

    if len(classes)<= 30:
        # create a confusion matrix
        cm = confusion_matrix(y_true, y_pred )
        length=len(classes)
        if length<8:
            fig_width=8
            fig_height=8
        else:
            fig_width= int(length * .5)
            fig_height= int(length * .5)
        plt.figure(figsize=(fig_width, fig_height))
        sns.heatmap(cm, annot=True, vmin=0, fmt='g', cmap='Blues', cbar=False)
        plt.xticks(np.arange(length)+.5, classes, rotation= 90)
        plt.yticks(np.arange(length)+.5, classes, rotation=0)
        plt.xlabel("Predicted")
        plt.ylabel("Actual")
        plt.title("Confusion Matrix")
        plt.show()

    clr = classification_report(y_true, y_pred, target_names=classes, digits= 4)
    ("Confusion Matrix:\n----------------------\n", cm)
    print("Classification Report:\n----------------------\n", clr)v
```

[ ]:
```
# # lst=[]
# # for i in range(0,25):
# #     lst.append(train_df['JPG'][i])
# for i in train_df['LABELS'].unique():
#     with open(train_df['JPG'][i], 'rb') as file:
#         img = Image.open(file)
#         img.show()
```

0.5 Modeling

0.5.1 First Model

[18]:
```
model = Sequential()
model.add(Conv2D(32, (3, 3), padding='same',
                 input_shape=(256,256,3)))
model.add(Activation('relu'))
model.add(Conv2D(32, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(Conv2D(64, (3, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(24, activation='sigmoid'))
model.compile(loss="binary_crossentropy",metrics=["accuracy"])
```

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

[19]:
```
history = model.fit(train_gen,
                              steps_per_epoch=20,
                              epochs=30,
                              validation_data=valid_gen,
                              validation_steps=20)
```

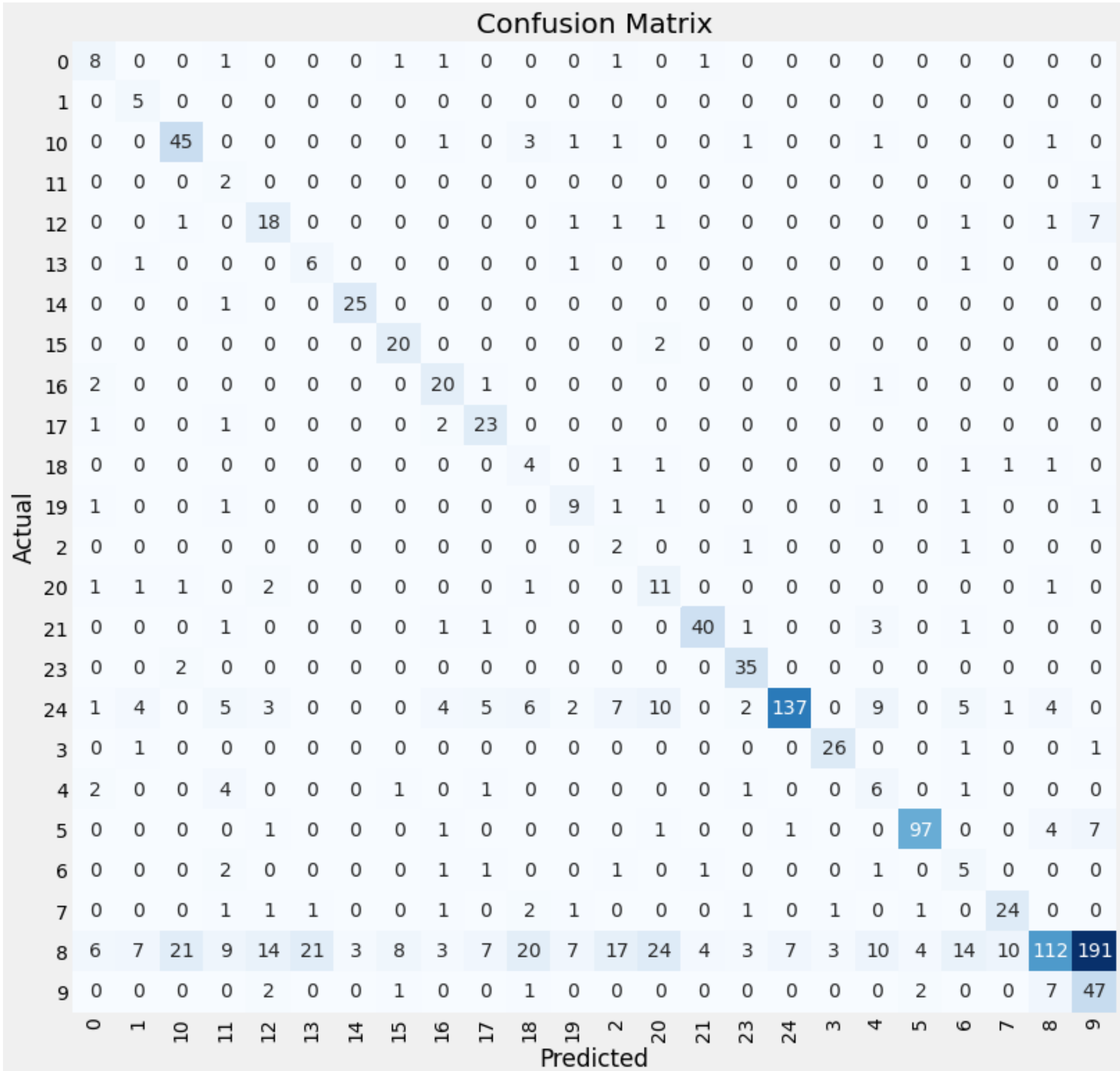
```
Epoch 1/30
20/20 [==============================] - 82s 4s/step - loss: 9.4837 - accuracy:
0.0800 - val_loss: 0.6480 - val_accuracy: 0.1150
Epoch 2/30
20/20 [==============================] - 79s 4s/step - loss: 0.2556 - accuracy:
0.1075 - val_loss: 0.5319 - val_accuracy: 0.1850
Epoch 3/30
20/20 [==============================] - 78s 4s/step - loss: 0.8552 - accuracy:
0.1138 - val_loss: 0.5765 - val_accuracy: 0.1400
Epoch 4/30
20/20 [==============================] - 81s 4s/step - loss: 0.8278 - accuracy:
0.1513 - val_loss: 0.5523 - val_accuracy: 0.1275
Epoch 5/30
20/20 [==============================] - 79s 4s/step - loss: 0.4701 - accuracy:
```

```
0.1988 - val_loss: 0.5054 - val_accuracy: 0.1513
Epoch 6/30
20/20 [==============================] - 79s 4s/step - loss: 0.2113 - accuracy:
0.3075 - val_loss: 0.2293 - val_accuracy: 0.2738
Epoch 7/30
20/20 [==============================] - 79s 4s/step - loss: 0.1690 - accuracy:
0.3575 - val_loss: 0.1235 - val_accuracy: 0.3212
Epoch 8/30
20/20 [==============================] - 79s 4s/step - loss: 0.2426 - accuracy:
0.3587 - val_loss: 0.1268 - val_accuracy: 0.3587
Epoch 9/30
20/20 [==============================] - 79s 4s/step - loss: 0.1462 - accuracy:
0.4350 - val_loss: 0.1498 - val_accuracy: 0.2975
Epoch 10/30
20/20 [==============================] - 79s 4s/step - loss: 0.1490 - accuracy:
0.4600 - val_loss: 0.0936 - val_accuracy: 0.5063
Epoch 11/30
20/20 [==============================] - 79s 4s/step - loss: 0.1223 - accuracy:
0.5300 - val_loss: 0.3193 - val_accuracy: 0.4187
Epoch 12/30
20/20 [==============================] - 78s 4s/step - loss: 0.3305 - accuracy:
0.4925 - val_loss: 0.1041 - val_accuracy: 0.4200
Epoch 13/30
20/20 [==============================] - 79s 4s/step - loss: 0.0962 - accuracy:
0.6363 - val_loss: 0.0843 - val_accuracy: 0.6913
Epoch 14/30
20/20 [==============================] - 79s 4s/step - loss: 0.0903 - accuracy:
0.6675 - val_loss: 0.1079 - val_accuracy: 0.4363
Epoch 15/30
20/20 [==============================] - 79s 4s/step - loss: 0.0819 - accuracy:
0.6925 - val_loss: 0.1066 - val_accuracy: 0.4363
Epoch 16/30
20/20 [==============================] - 79s 4s/step - loss: 0.2793 - accuracy:
0.5888 - val_loss: 0.1038 - val_accuracy: 0.4775
Epoch 17/30
20/20 [==============================] - 79s 4s/step - loss: 0.1267 - accuracy:
0.6475 - val_loss: 0.1086 - val_accuracy: 0.5288
Epoch 18/30
20/20 [==============================] - 79s 4s/step - loss: 0.0633 - accuracy:
0.7638 - val_loss: 0.0876 - val_accuracy: 0.5312
Epoch 19/30
20/20 [==============================] - 80s 4s/step - loss: 0.3817 - accuracy:
0.5900 - val_loss: 0.1039 - val_accuracy: 0.5088
Epoch 20/30
20/20 [==============================] - 79s 4s/step - loss: 0.0731 - accuracy:
0.7625 - val_loss: 0.1093 - val_accuracy: 0.5288
Epoch 21/30
20/20 [==============================] - 80s 4s/step - loss: 0.0530 - accuracy:
```

```
0.8338 - val_loss: 0.1102 - val_accuracy: 0.5000
Epoch 22/30
20/20 [==============================] - 79s 4s/step - loss: 0.0555 - accuracy:
0.8125 - val_loss: 0.0731 - val_accuracy: 0.7287
Epoch 23/30
20/20 [==============================] - 79s 4s/step - loss: 0.0582 - accuracy:
0.7987 - val_loss: 0.1708 - val_accuracy: 0.5250
Epoch 24/30
20/20 [==============================] - 80s 4s/step - loss: 0.5107 - accuracy:
0.6762 - val_loss: 0.1003 - val_accuracy: 0.5312
Epoch 25/30
20/20 [==============================] - 81s 4s/step - loss: 0.0498 - accuracy:
0.8388 - val_loss: 0.0890 - val_accuracy: 0.5688
Epoch 26/30
20/20 [==============================] - 81s 4s/step - loss: 0.0427 - accuracy:
0.8512 - val_loss: 0.0898 - val_accuracy: 0.5863
Epoch 27/30
20/20 [==============================] - 81s 4s/step - loss: 0.0433 - accuracy:
0.8562 - val_loss: 0.0837 - val_accuracy: 0.6787
Epoch 28/30
20/20 [==============================] - 80s 4s/step - loss: 0.0877 - accuracy:
0.7950 - val_loss: 0.0748 - val_accuracy: 0.7700
Epoch 29/30
20/20 [==============================] - 80s 4s/step - loss: 0.0437 - accuracy:
0.8575 - val_loss: 0.1051 - val_accuracy: 0.5437
Epoch 30/30
20/20 [==============================] - 79s 4s/step - loss: 0.0661 - accuracy:
0.8200 - val_loss: 0.0886 - val_accuracy: 0.6388
```

[86]:

```
print_code=10
preds=model.predict(test_gen)
print_info(test_gen, preds, print_code, working_dir, subject)
```




```
Classification Report:
----------------------
```

	precision	recall	f1-score	support
0	0.3636	0.6154	0.4571	13
1	0.2632	1.0000	0.4167	5
10	0.6429	0.8333	0.7258	54
11	0.0714	0.6667	0.1290	3
12	0.4390	0.5806	0.5000	31
13	0.2143	0.6667	0.3243	9
14	0.8929	0.9615	0.9259	26
15	0.6452	0.9091	0.7547	22
16	0.5714	0.8333	0.6780	24
17	0.5897	0.8519	0.6970	27

```
          18     0.1081    0.4444    0.1739         9
          19     0.4091    0.5625    0.4737        16
           2     0.0625    0.5000    0.1111         4
          20     0.2157    0.6111    0.3188        18
          21     0.8696    0.8333    0.8511        48
          23     0.7778    0.9459    0.8537        37
          24     0.9448    0.6683    0.7829       205
           3     0.8667    0.8966    0.8814        29
           4     0.1875    0.3750    0.2500        16
           5     0.9327    0.8661    0.8981       112
           6     0.1562    0.4167    0.2273        12
           7     0.6667    0.7059    0.6857        34
           8     0.8550    0.2133    0.3415       525
           9     0.1843    0.7833    0.2984        60

    accuracy                         0.5429      1339
   macro avg     0.4971    0.6975    0.5315      1339
weighted avg     0.7591    0.5429    0.5552      1339
```

[86]: 5.42942494398805e-15

0.5.2 Second Model

[97]:
```python
model2 = Sequential([
  layers.Conv2D(32, 3, padding='same', activation='relu',
             input_shape=(256 ,256,  3)),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Dense(5, activation='relu')

])


model2.summary()
```

```
Model: "sequential_5"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_16 (Conv2D)          (None, 256, 256, 32)      896


 max_pooling2d_14 (MaxPoolin  (None, 128, 128, 32)     0
 g2D)
```

```
 conv2d_17 (Conv2D)          (None, 128, 128, 32)      9248

 max_pooling2d_15 (MaxPoolin  (None, 64, 64, 32)       0
 g2D)

 conv2d_18 (Conv2D)          (None, 64, 64, 64)        18496

 max_pooling2d_16 (MaxPoolin  (None, 32, 32, 64)       0
 g2D)

 dense_9 (Dense)             (None, 32, 32, 5)         325

=================================================================
Total params: 28,965
Trainable params: 28,965
Non-trainable params: 0
_________________________________________________________________
```

[98]:

```
model2.add(layers.Flatten())
model2.add(layers.Dense(24, activation='softmax'))

model2.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_16 (Conv2D)          (None, 256, 256, 32)      896

 max_pooling2d_14 (MaxPoolin  (None, 128, 128, 32)     0
 g2D)

 conv2d_17 (Conv2D)          (None, 128, 128, 32)      9248

 max_pooling2d_15 (MaxPoolin  (None, 64, 64, 32)       0
 g2D)

 conv2d_18 (Conv2D)          (None, 64, 64, 64)        18496

 max_pooling2d_16 (MaxPoolin  (None, 32, 32, 64)       0
 g2D)

 dense_9 (Dense)             (None, 32, 32, 5)         325

 flatten_4 (Flatten)         (None, 5120)              0

 dense_10 (Dense)            (None, 24)                122904
```

```
=================================================================
Total params: 151,869
Trainable params: 151,869
Non-trainable params: 0
_________________________________________________________________
```

[99]:
```python
model2.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

[100]:
```python
history = model2.fit(train_gen,
                              steps_per_epoch=train_steps,
                              epochs=30,
                              validation_data=valid_gen,
                              validation_steps=valid_steps)
```

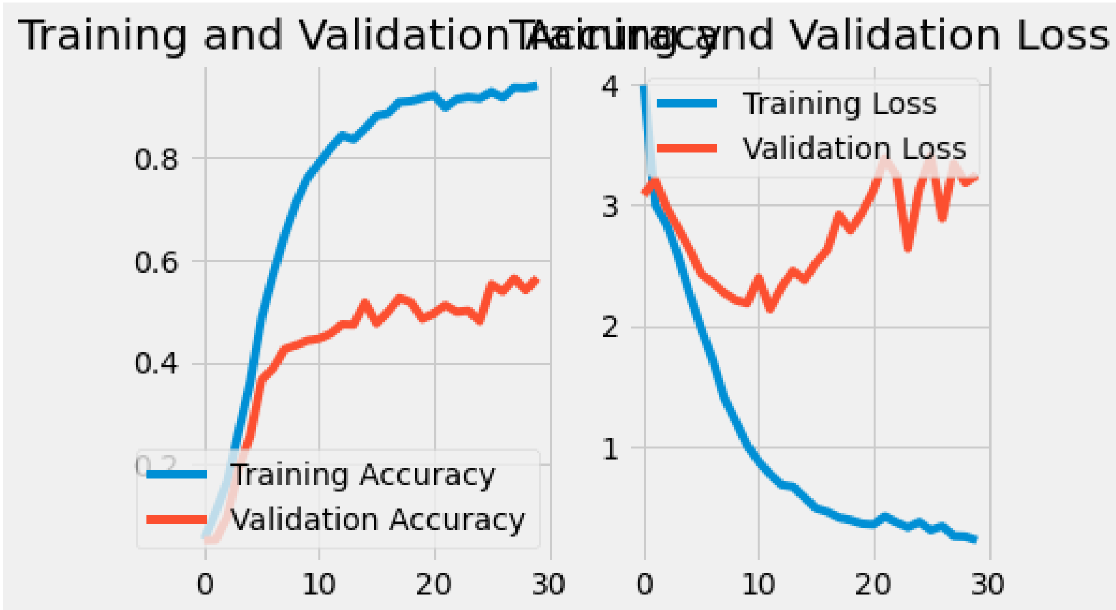
```
Epoch 1/30
60/60 [==============================] - 62s 1s/step - loss: 3.9908 - accuracy:
0.0538 - val_loss: 3.0855 - val_accuracy: 0.0515
Epoch 2/30
60/60 [==============================] - 59s 986ms/step - loss: 3.0019 -
accuracy: 0.1067 - val_loss: 3.2084 - val_accuracy: 0.0523
Epoch 3/30
60/60 [==============================] - 59s 977ms/step - loss: 2.8404 -
accuracy: 0.1667 - val_loss: 2.9780 - val_accuracy: 0.0970
Epoch 4/30
60/60 [==============================] - 59s 976ms/step - loss: 2.5768 -
accuracy: 0.2642 - val_loss: 2.8079 - val_accuracy: 0.1909
Epoch 5/30
60/60 [==============================] - 59s 982ms/step - loss: 2.2627 -
accuracy: 0.3600 - val_loss: 2.6301 - val_accuracy: 0.2553
Epoch 6/30
60/60 [==============================] - 59s 990ms/step - loss: 1.9781 -
accuracy: 0.4867 - val_loss: 2.4302 - val_accuracy: 0.3652
Epoch 7/30
60/60 [==============================] - 59s 977ms/step - loss: 1.7209 -
accuracy: 0.5713 - val_loss: 2.3583 - val_accuracy: 0.3871
Epoch 8/30
60/60 [==============================] - 59s 977ms/step - loss: 1.4077 -
accuracy: 0.6471 - val_loss: 2.2732 - val_accuracy: 0.4250
Epoch 9/30
60/60 [==============================] - 59s 984ms/step - loss: 1.2139 -
accuracy: 0.7113 - val_loss: 2.2140 - val_accuracy: 0.4326
Epoch 10/30
60/60 [==============================] - 59s 982ms/step - loss: 1.0129 -
accuracy: 0.7600 - val_loss: 2.1872 - val_accuracy: 0.4417
Epoch 11/30
60/60 [==============================] - 61s 1s/step - loss: 0.8787 - accuracy:
```

```
0.7883 - val_loss: 2.3992 - val_accuracy: 0.4455
Epoch 12/30
60/60 [==============================] - 60s 1s/step - loss: 0.7728 - accuracy:
0.8179 - val_loss: 2.1379 - val_accuracy: 0.4553
Epoch 13/30
60/60 [==============================] - 59s 983ms/step - loss: 0.6851 -
accuracy: 0.8425 - val_loss: 2.3228 - val_accuracy: 0.4735
Epoch 14/30
60/60 [==============================] - 59s 987ms/step - loss: 0.6695 -
accuracy: 0.8350 - val_loss: 2.4561 - val_accuracy: 0.4727
Epoch 15/30
60/60 [==============================] - 60s 1s/step - loss: 0.5808 - accuracy:
0.8558 - val_loss: 2.3801 - val_accuracy: 0.5159
Epoch 16/30
60/60 [==============================] - 59s 980ms/step - loss: 0.4909 -
accuracy: 0.8808 - val_loss: 2.5224 - val_accuracy: 0.4750
Epoch 17/30
60/60 [==============================] - 59s 990ms/step - loss: 0.4618 -
accuracy: 0.8858 - val_loss: 2.6324 - val_accuracy: 0.4977
Epoch 18/30
60/60 [==============================] - 59s 988ms/step - loss: 0.4146 -
accuracy: 0.9079 - val_loss: 2.9197 - val_accuracy: 0.5250
Epoch 19/30
60/60 [==============================] - 60s 998ms/step - loss: 0.3939 -
accuracy: 0.9096 - val_loss: 2.7895 - val_accuracy: 0.5167
Epoch 20/30
60/60 [==============================] - 59s 985ms/step - loss: 0.3640 -
accuracy: 0.9154 - val_loss: 2.9344 - val_accuracy: 0.4841
Epoch 21/30
60/60 [==============================] - 59s 984ms/step - loss: 0.3572 -
accuracy: 0.9208 - val_loss: 3.1203 - val_accuracy: 0.4947
Epoch 22/30
60/60 [==============================] - 59s 985ms/step - loss: 0.4237 -
accuracy: 0.8975 - val_loss: 3.3886 - val_accuracy: 0.5106
Epoch 23/30
60/60 [==============================] - 59s 990ms/step - loss: 0.3753 -
accuracy: 0.9133 - val_loss: 3.2455 - val_accuracy: 0.4977
Epoch 24/30
60/60 [==============================] - 60s 1s/step - loss: 0.3327 - accuracy:
0.9175 - val_loss: 2.6431 - val_accuracy: 0.5000
Epoch 25/30
60/60 [==============================] - 60s 1s/step - loss: 0.3788 - accuracy:
0.9146 - val_loss: 3.1344 - val_accuracy: 0.4795
Epoch 26/30
60/60 [==============================] - 60s 1s/step - loss: 0.3102 - accuracy:
0.9279 - val_loss: 3.4059 - val_accuracy: 0.5515
Epoch 27/30
60/60 [==============================] - 59s 986ms/step - loss: 0.3443 -
```

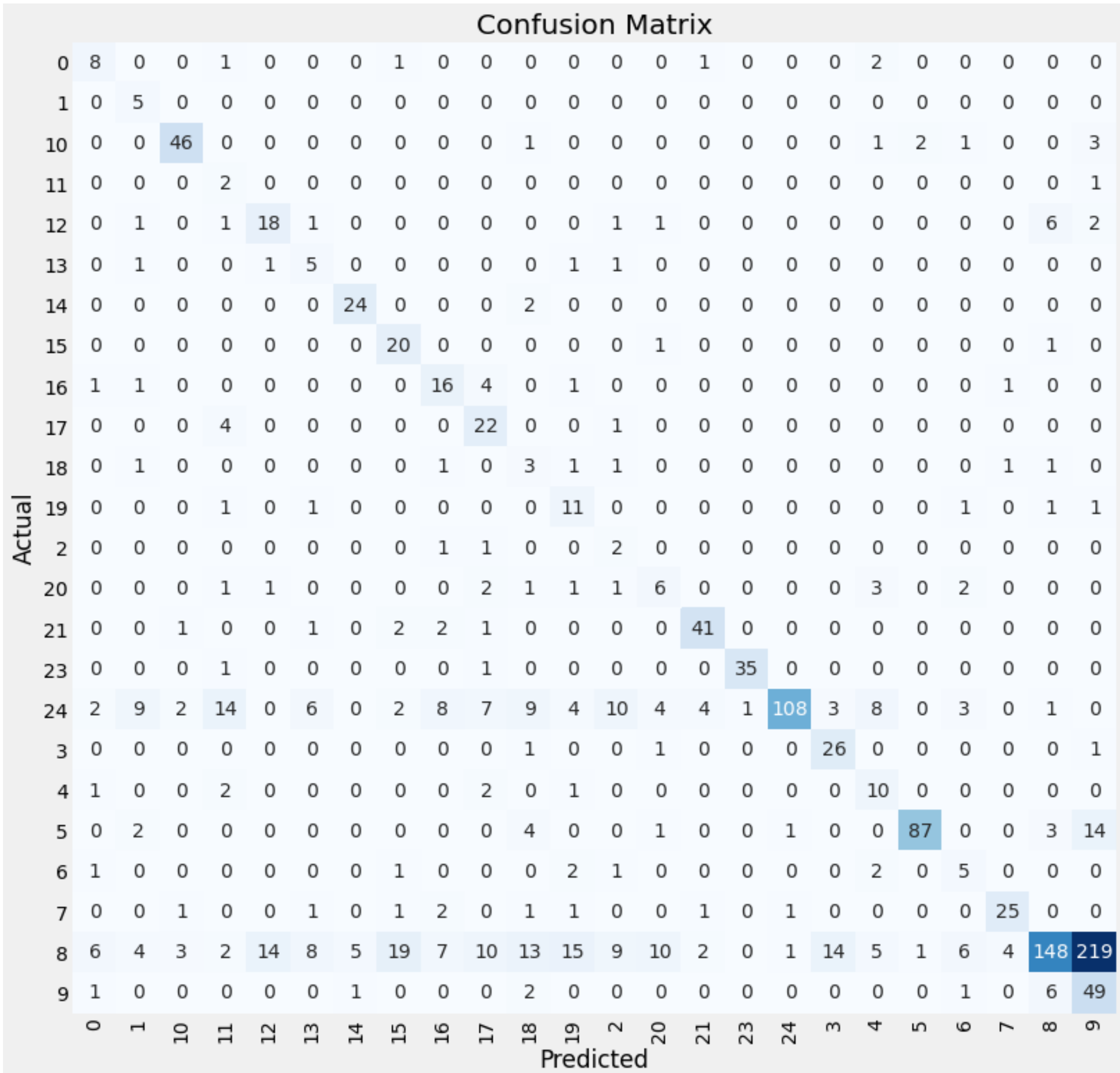
```
accuracy: 0.9167 - val_loss: 2.8909 - val_accuracy: 0.5379
Epoch 28/30
60/60 [==============================] - 59s 986ms/step - loss: 0.2617 -
accuracy: 0.9358 - val_loss: 3.3429 - val_accuracy: 0.5629
Epoch 29/30
60/60 [==============================] - 62s 1s/step - loss: 0.2584 - accuracy:
0.9350 - val_loss: 3.1842 - val_accuracy: 0.5402
Epoch 30/30
60/60 [==============================] - 60s 995ms/step - loss: 0.2267 -
accuracy: 0.9404 - val_loss: 3.2488 - val_accuracy: 0.5636
```

[106]:

```
epochs = 30
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(6,4))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



[103]:
```
print_code=10
preds=model2.predict(test_gen)
print_info(test_gen, preds, print_code, working_dir, subject)
```



Classification Report:

----

	precision	recall	f1-score	support
0	0.4000	0.6154	0.4848	13
1	0.2083	1.0000	0.3448	5
10	0.8679	0.8519	0.8598	54
11	0.0690	0.6667	0.1250	3
12	0.5294	0.5806	0.5538	31
13	0.2174	0.5556	0.3125	9
14	0.8000	0.9231	0.8571	26
15	0.4348	0.9091	0.5882	22
16	0.4324	0.6667	0.5246	24
17	0.4400	0.8148	0.5714	27

```
          18       0.0811    0.3333    0.1304         9
          19       0.2895    0.6875    0.4074        16
           2       0.0741    0.5000    0.1290         4
          20       0.2500    0.3333    0.2857        18
          21       0.8367    0.8542    0.8454        48
          23       0.9722    0.9459    0.9589        37
          24       0.9730    0.5268    0.6835       205
           3       0.6047    0.8966    0.7222        29
           4       0.3226    0.6250    0.4255        16
           5       0.9667    0.7768    0.8614       112
           6       0.2632    0.4167    0.3226        12
           7       0.8065    0.7353    0.7692        34
           8       0.8862    0.2819    0.4277       525
           9       0.1690    0.8167    0.2800        60

    accuracy                         0.5392      1339
   macro avg       0.4956    0.6797    0.5196      1339
weighted avg       0.7819    0.5392    0.5700      1339
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-103-adef6f047b34> in <module>
      1 print_code=10
      2 preds=model2.predict(test_gen)
----> 3 print_info(test_gen, preds, print_code, working_dir, subject)

<ipython-input-83-bbf9a1b25e07> in print_info(test_gen, preds, print_code,␣
 ↪save_dir, subject)
     52         ("Confusion Matrix:\n----------------------\n", cm)
     53         print("Classification Report:\n----------------------\n", clr)
---> 54     return acc/100

TypeError: unsupported operand type(s) for /: 'list' and 'int'
```

0.5.3 Third Model

[24]:
```
model3 = Sequential([
  layers.Conv2D(32, (3,3), padding='same', activation='relu',
                input_shape=(256,256,3 )),
  layers.MaxPooling2D(),
  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),
  layers.Dropout(0.2),
```

```
    layers.Flatten(),
    layers.Dense(128,activation='relu'),
  layers.Dense(24, activation='softmax'),
])


model3.summary()
```

```
Model: "sequential_2"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_7 (Conv2D)           (None, 256, 256, 32)      896

 max_pooling2d_5 (MaxPooling  (None, 128, 128, 32)     0
 2D)

 conv2d_8 (Conv2D)           (None, 128, 128, 32)      9248

 max_pooling2d_6 (MaxPooling  (None, 64, 64, 32)       0
 2D)

 conv2d_9 (Conv2D)           (None, 64, 64, 64)        18496

 max_pooling2d_7 (MaxPooling  (None, 32, 32, 64)       0
 2D)

 dropout_3 (Dropout)         (None, 32, 32, 64)        0

 flatten_2 (Flatten)         (None, 65536)             0

 dense_4 (Dense)             (None, 128)               8388736

 dense_5 (Dense)             (None, 24)                3096

=================================================================
Total params: 8,420,472
Trainable params: 8,420,472
Non-trainable params: 0
_________________________________________________________________
```

[25]:
```
model3.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

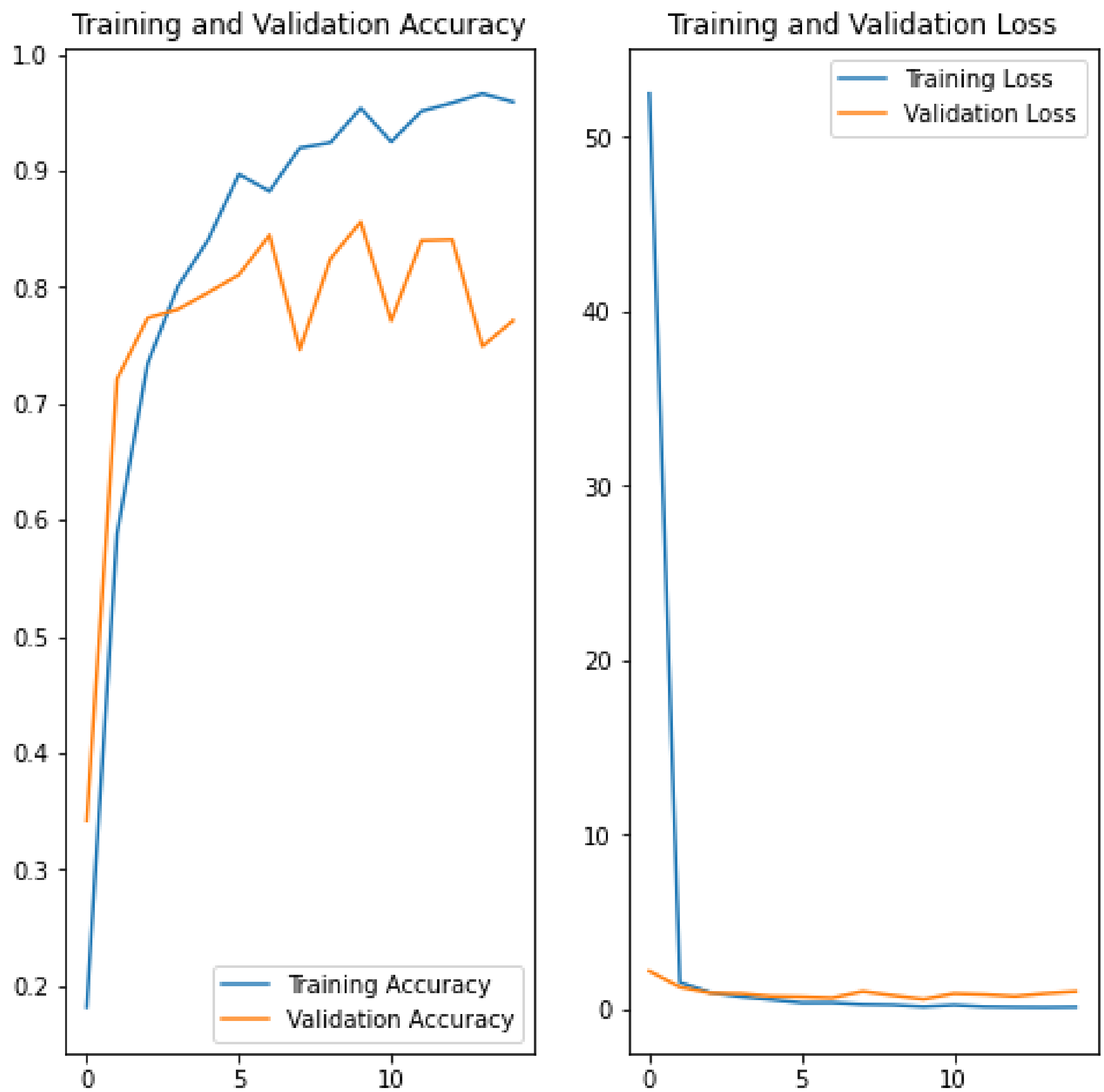
[26]:
```
history = model3.fit(train_gen,
                              steps_per_epoch=train_steps,
                              epochs=15,
                              validation_data=valid_gen,
                              validation_steps=valid_steps)
```

```
Epoch 1/15
60/60 [==============================] - 60s 993ms/step - loss: 52.4538 -
accuracy: 0.1813 - val_loss: 2.1978 - val_accuracy: 0.3417
Epoch 2/15
60/60 [==============================] - 59s 988ms/step - loss: 1.5550 -
accuracy: 0.5883 - val_loss: 1.2869 - val_accuracy: 0.7212
Epoch 3/15
60/60 [==============================] - 59s 984ms/step - loss: 0.9703 -
accuracy: 0.7342 - val_loss: 0.9433 - val_accuracy: 0.7735
Epoch 4/15
60/60 [==============================] - 60s 993ms/step - loss: 0.7292 -
accuracy: 0.8008 - val_loss: 0.9167 - val_accuracy: 0.7811
Epoch 5/15
60/60 [==============================] - 59s 987ms/step - loss: 0.5685 -
accuracy: 0.8413 - val_loss: 0.7575 - val_accuracy: 0.7955
Epoch 6/15
60/60 [==============================] - 60s 993ms/step - loss: 0.3896 -
accuracy: 0.8971 - val_loss: 0.7254 - val_accuracy: 0.8106
Epoch 7/15
60/60 [==============================] - 59s 992ms/step - loss: 0.3936 -
accuracy: 0.8825 - val_loss: 0.6623 - val_accuracy: 0.8447
Epoch 8/15
60/60 [==============================] - 60s 993ms/step - loss: 0.2924 -
accuracy: 0.9196 - val_loss: 1.0389 - val_accuracy: 0.7462
Epoch 9/15
60/60 [==============================] - 63s 1s/step - loss: 0.2648 - accuracy:
0.9242 - val_loss: 0.8039 - val_accuracy: 0.8242
Epoch 10/15
60/60 [==============================] - 65s 1s/step - loss: 0.1619 - accuracy:
0.9538 - val_loss: 0.5909 - val_accuracy: 0.8561
Epoch 11/15
60/60 [==============================] - 63s 1s/step - loss: 0.2603 - accuracy:
0.9250 - val_loss: 0.9150 - val_accuracy: 0.7712
Epoch 12/15
60/60 [==============================] - 64s 1s/step - loss: 0.1581 - accuracy:
0.9513 - val_loss: 0.8598 - val_accuracy: 0.8402
Epoch 13/15
60/60 [==============================] - 63s 1s/step - loss: 0.1369 - accuracy:
0.9583 - val_loss: 0.7543 - val_accuracy: 0.8409
Epoch 14/15
60/60 [==============================] - 64s 1s/step - loss: 0.1283 - accuracy:
0.9663 - val_loss: 0.9203 - val_accuracy: 0.7492
```

```
Epoch 15/15
60/60 [==============================] - 65s 1s/step - loss: 0.1404 - accuracy:
0.9592 - val_loss: 1.0371 - val_accuracy: 0.7712
```

[35]:

```
epochs = 15
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']

loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs_range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')

plt.subplot(1, 2, 2)
plt.plot(epochs_range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



[36]:
```
test_x, test_y = next(test_gen)
```

[37]:
```
results_test = model.evaluate(test_x, test_y)
```

```
1/1 [==============================] - 0s 195ms/step - loss: 5.5437 - accuracy:
0.3846
```

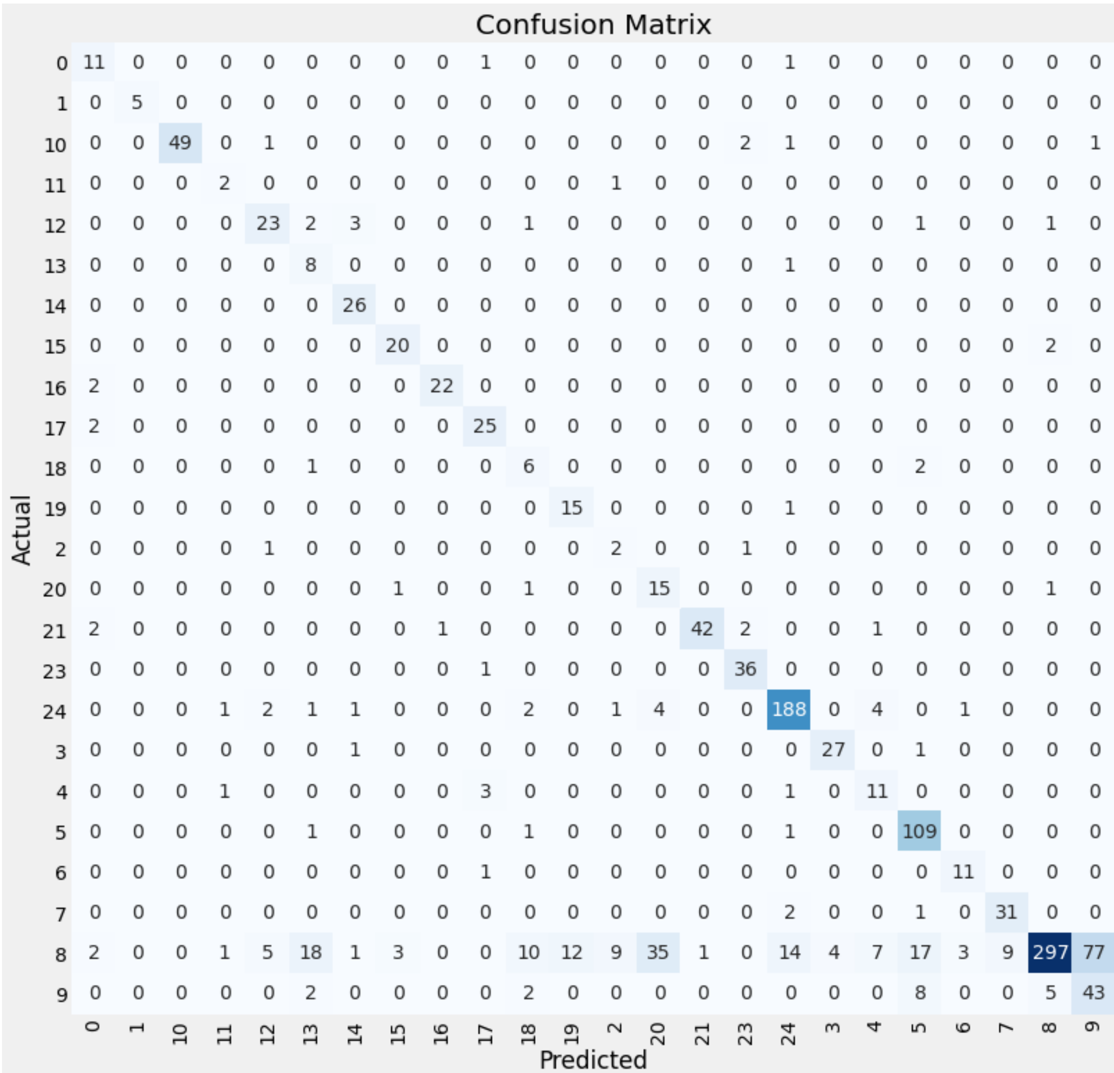
[38]:
```
results_test
```

[38]:
```
[5.5437092781066895, 0.38461539149284363]
```

Classification Report

[96]:

```
print_code=10
preds=model3.predict(test_gen)
acc=print_info( test_gen, preds, print_code, working_dir, subject )
```




```
Classification Report:
----------------------
              precision    recall  f1-score   support

           0     0.5789    0.8462    0.6875        13
           1     1.0000    1.0000    1.0000         5
          10     1.0000    0.9074    0.9515        54
          11     0.4000    0.6667    0.5000         3
          12     0.7188    0.7419    0.7302        31
          13     0.2424    0.8889    0.3810         9
```

```
          14     0.8125    1.0000    0.8966        26
          15     0.8333    0.9091    0.8696        22
          16     0.9565    0.9167    0.9362        24
          17     0.8065    0.9259    0.8621        27
          18     0.2609    0.6667    0.3750         9
          19     0.5556    0.9375    0.6977        16
           2     0.1538    0.5000    0.2353         4
          20     0.2778    0.8333    0.4167        18
          21     0.9767    0.8750    0.9231        48
          23     0.8780    0.9730    0.9231        37
          24     0.8952    0.9171    0.9060       205
           3     0.8710    0.9310    0.9000        29
           4     0.4783    0.6875    0.5641        16
           5     0.7842    0.9732    0.8685       112
           6     0.7333    0.9167    0.8148        12
           7     0.7750    0.9118    0.8378        34
           8     0.9706    0.5657    0.7148       525
           9     0.3554    0.7167    0.4751        60

    accuracy                         0.7647      1339
   macro avg     0.6798    0.8420    0.7278      1339
weighted avg     0.8535    0.7647    0.7787      1339
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-96-07b07dd0de34> in <module>
      1 print_code=10
      2 preds=model3.predict(test_gen)
----> 3 acc=print_info( test_gen, preds, print_code, working_dir, subject )

<ipython-input-83-bbf9a1b25e07> in print_info(test_gen, preds, print_code,␣
↪save_dir, subject)
     52     ("Confusion Matrix:\n----------------------\n", cm)
     53     print("Classification Report:\n----------------------\n", clr)
---> 54     return acc/100

TypeError: unsupported operand type(s) for /: 'list' and 'int'
```

0.6 Conclusion

For this project tried 3 different convolutional neural network(CNN) model basic to complex and got best result at the and as 76% accuracy predicted is true. What this mean is model will 24% predict wrong. It looks like not good but not bad too.

0.7 Future Work

We can work on our model overall shapes to get better result.

We can gather more images about mars to get better data.(which is a little problem in this dataset)

We can try more complex models to get better result.