Importing Libraries

```
#IMPORT LIB

# FIRST WE'LL IMPORT THE SYSTEM LIBRARIES
import os
import itertools
import pathlib
from PIL import Image
import time
import shutil

# THEN IMPORT THE DATA HANDLING TOOLS
import numpy as np
import pandas as pd
import cv2
import seaborn as sns
sns.set_style('darkgrid')
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
import matplotlib.pyplot as plt

# THEN IMPORT DL LIBRARIES
import tensorflow as tf
from tensorflow import keras
#SEQUENTIAL CLASS FOR CREATING NEURAL NETWORK MODELS IN TENSORFLOW
#ALLOWS TO DEFINE A SEQUENTIAL STACK OF LAYERS
from tensorflow.keras.models import Sequential
#IMPORTED ADAMS AND ADAMAX OPTIMIZER
#ITERATIVELY ADJUST THE WEIGHTS OF NETWORK'S CONNECTIONS
#TO MINIMIZE A LOSS FUNCTION & IMPROVE MODEL'S PERFORMANCE
from tensorflow.keras.optimizers import Adam, Adamax
#IMAGE DATAGEN FOR AUGMENTING & PREPARING IMAGE DATA AS RANDOME FLIPS,
ROTATIONS, SCALING
#PREVENTS OVERFITTING
from tensorflow.keras.preprocessing.image import ImageDataGenerator
#IMPORTING ESSENTIAL LAYERS USED TO BUILD A CNN MODEL
#CONV2D LAYER PERFORMS CONVOLUTIONAL OPERATIONS, CORE BUILDING BLOCK
OF CNN & EXTRACTS FEATURES FROM IMAGE
#MAXPOOLING2D PERFORMS DOWNSAMPLING, REDUCING DIMENSIONALITY OF DATA,
CAPTURING SPATIAL INFO
#DENSE REPRESENTS FULLY CONNECTED LAYER USED IN FINAL STAGES OF MODEL
FOR CLASSIFICATION OR REGRESSION TASKS
#FLATTEN FLATTENS MULTI-DIMENSIONAL OUTPUT OF CONVO LAYERS INTO A
SINGLE VECTOR FOR FEEDING

from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten,
Dense
#DROPOUT LAYER RANDOMLY DROPS CERTAIN PERCENTAGE OF NEURONS DURING
TRAINING TO PREVENT OVERFITTING
```

```
#ACTIVATION LAYER APPLIES ACTIVATION FUNCTION (LIKE RELU) FOR NON-
LINEARITY INTO NETWORK
#BATCHNORMALIZATION NORMALIZES ACTIVATIONS OF PREVIOUS LAYER,
IMPROVING TRAINING SPEED & STABILITY
from tensorflow.keras.layers import Activation, BatchNormalization,
Dropout
#REGULARIZERS PENSLIZE MODEL FOR OVERLY COMPLEX WEIGHTS, HELPING TO
PREVENT OVERFIITING
#REGULARIZERS FUNCTIONS LIKE L1 AND L2 REGULARIZATION
from tensorflow.keras import regularizers
#IGNORE WARNINGS
import warnings
warnings.filterwarnings("ignore")
print ('modules loaded')
```

```
modules loaded
```

```
test_file = 'C:\\Users\\KIIT\\Downloads\\Testing'
labels = []
#EMPLTY LIST LABELS TO STORE LABELS
filepaths = []
#CREATES ANOTHER EMPTY LIST, TO STORE COMPLETE FILE PATHS
folds = os.listdir(test_file)
#OS LIBRARY HAS ALREADY BEEN IMPORTED
#os.listdir(test_file) FUNCTION CALL RETRIEVES A LIST OF FILENEAMES
AND SUBDIRECTORY NAMES WITHIN DIRECTORY
#RESULT OF THIS FUNCTION CALL IS STORED IN VARIABLE FOLDS

#ITERATE OVER EACH ELEMENT IN FOLD LIST
for fold in folds:
    #os.path.join FUNC FROM OS LIBRARY, IT COMBINES BASE
PATH(test_file) WITH CURRENT FOLDER NAME (fold) & CREATES COMPLETE
PATH TO CURRENT SUBFOLDER
    #RESULT STORED IN VARIABLE FOLDPATH
    foldpath = os.path.join(test_file, fold)
    #os.listdir WITH FOLDPATH
    filelist = os.listdir(foldpath)
    #STARTS ANOTHER NESTED FOR LOOP THAT ITERATES OVER EACH ELEMENT IN
FILELIST
    for file in filelist:
        #COMBINES SUBFOLDER (FOLDPATH) WITH FILENAME (FILE)
        filepath = os.path.join(foldpath, file)
        #APPEND FILEPATH TO FILEPATHS LIST WITHIN TESTING DIRECTORY
        filepaths.append(filepath)
        #APPENDS CURRENT FOLDER NAME (FOLD) TO LABELS LIST
        labels.append(fold)
#FILESERIES CREATED  FROM FILEPATHS LIST, HOLD FILEPATHS AS PANDAS
SERIES
FileSeries = pd.Series(filepaths, name = 'filepaths')
#LABELSERIES CREATED FROM LABELS LIST, HOLD LABELS AS PANDAS SERIES
```

```
LabelSeries = pd.Series(labels, name = 'labels')
#CONCATENATE THESE 2 SERIES INTO SINGLE DATAFRAME DT
#AXIS ARG SPECIFIES IT TO HAPPEN IN COLUMNS
dt = pd.concat([FileSeries, LabelSeries], axis = 'columns')
dt
```

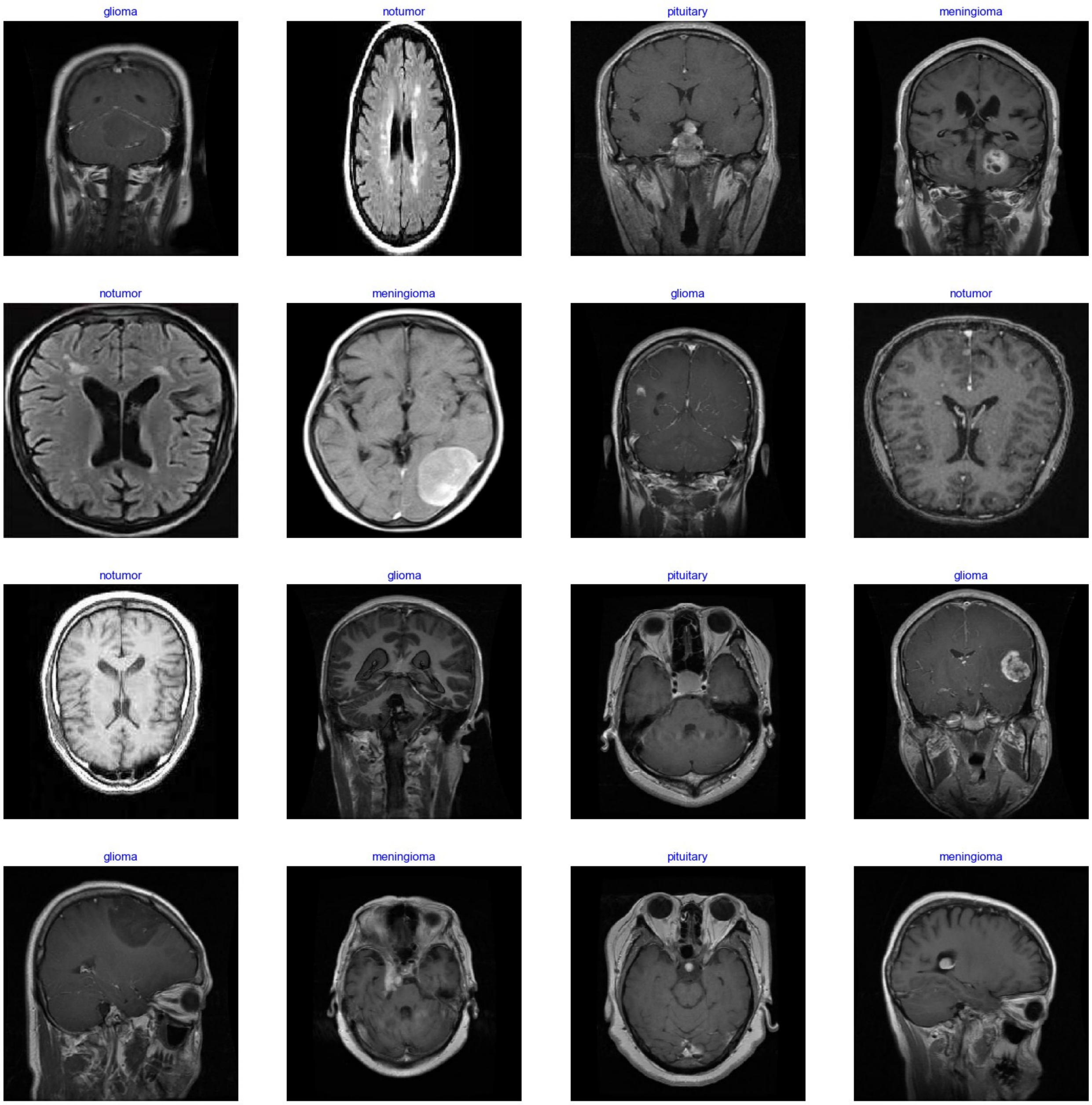
```
                                              filepaths     labels
0     C:\Users\KIIT\Downloads\Testing\glioma\Te-glTr...     glioma
1     C:\Users\KIIT\Downloads\Testing\glioma\Te-glTr...     glioma
2     C:\Users\KIIT\Downloads\Testing\glioma\Te-glTr...     glioma
3     C:\Users\KIIT\Downloads\Testing\glioma\Te-glTr...     glioma
4     C:\Users\KIIT\Downloads\Testing\glioma\Te-glTr...     glioma
...                                                 ...        ...
1306  C:\Users\KIIT\Downloads\Testing\pituitary\Te-p...  pituitary
1307  C:\Users\KIIT\Downloads\Testing\pituitary\Te-p...  pituitary
1308  C:\Users\KIIT\Downloads\Testing\pituitary\Te-p...  pituitary
1309  C:\Users\KIIT\Downloads\Testing\pituitary\Te-p...  pituitary
1310  C:\Users\KIIT\Downloads\Testing\pituitary\Te-p...  pituitary

[1311 rows x 2 columns]
```

```
train_file = 'C:\\Users\\KIIT\\Downloads\\Training'
filepaths = []
labels = []

folds = os.listdir(train_file)
for fold in folds:
    foldpath = os.path.join(train_file, fold)
    filelist = os.listdir(foldpath)
    for file in filelist:
        fpath = os.path.join(foldpath, file)
        filepaths.append(fpath)
        labels.append(fold)
FileSeries = pd.Series(filepaths, name= 'filepaths')
LabelSeries = pd.Series(labels, name='labels')
data = pd.concat([FileSeries, LabelSeries], axis= 1)
data
```

```
                                              filepaths     labels
0     C:\Users\KIIT\Downloads\Training\glioma\Tr-glT...     glioma
1     C:\Users\KIIT\Downloads\Training\glioma\Tr-glT...     glioma
2     C:\Users\KIIT\Downloads\Training\glioma\Tr-glT...     glioma
3     C:\Users\KIIT\Downloads\Training\glioma\Tr-glT...     glioma
4     C:\Users\KIIT\Downloads\Training\glioma\Tr-glT...     glioma
...                                                 ...        ...
5707  C:\Users\KIIT\Downloads\Training\pituitary\Tr-...  pituitary
5708  C:\Users\KIIT\Downloads\Training\pituitary\Tr-...  pituitary
5709  C:\Users\KIIT\Downloads\Training\pituitary\Tr-...  pituitary
5710  C:\Users\KIIT\Downloads\Training\pituitary\Tr-...  pituitary
5711  C:\Users\KIIT\Downloads\Training\pituitary\Tr-...  pituitary
```

```
[5712 rows x 2 columns]

#VALID DATAFRAME WILL CONTAIN A PORTION OF DATA, WILL HAVE SAME
STRUCTURE AS ORIGINAL DATAFRAME dt
#TESTING DATAFRAME WILL CONTAIN REMAINING PORTION OF DATA
#DT IS DATAFRAME CREATED CONTAINING FILPATHS & LABELS
#TRAIN SIZE - 0.5; ITS SET TO 0.5, WHICH MEANS 50% OF DATA WILL
ALLOCATED TO TRAINING SET. REMAINING 50% WILL BE USED FOR TESTING SET
#SHUFFLE THE DATA BEFORE SPLITTING TO ENSURE TRAINING & TESTING
REPRESENT A GOOD CROSS-SECTION & REDUCCE BIAS
#SET A SEED FOR RANDOM NUMBER GENERATOR USED FOR SHUFFLING DATA
#SETTING A SEED ENSURES WE GET SAME SPLIT
valid_df,test_df =
train_test_split(dt,train_size=0.5,shuffle=True,random_state=123)

#ASSIGNS VALUE 16 TO BATCH SIZE, USED TO DEFINE NO. OF IMAGES
PROCESSED DURING TRAINING & VALIDATION
batch_size=16
#CREATES A TUPLE CONTAINING HEIGHT N WIDTH IN PIXELS
image_size = (224,224)
#ASSIGNS YOUR IMAGE TO HAVE 3 COLOR CHANNELS (RGB)
channels = 3
#COMBINES IMAGE HEIGHT, WIDTH, & NO. OF CHANNELS INTO A SINGLE TUBLE
image_shape=(image_size[0],image_size[1],channels)  #224*224*3
#CREATES AN INSTANCE AND ASSIGNS IT TO tr_gen; USED FOR DATA
AUGMENTATION & PREPROCESSING DURING TRAINING
tr_gen = ImageDataGenerator()
#CREATES SEPARATE INSTANCE FOR PREPROCESSING TESTING DATA WITHOUT
AUGMENTATION
ts_gen = ImageDataGenerator()

#GENERATORS ACT AS PIPELINES TO AUTOMATICALLY LOAD, PREPROCESS, AND
AUGMENT YOUR IMAGES BASED ON PARAMETERS
train_gen = tr_gen.flow_from_dataframe( data, x_col= 'filepaths',
y_col= 'labels', target_size= image_size, class_mode= 'categorical',
color_mode= 'rgb', shuffle= True,batch_size= batch_size)
test_gen = tr_gen.flow_from_dataframe( test_df, x_col= 'filepaths',
y_col= 'labels', target_size= image_size, class_mode= 'categorical',
color_mode= 'rgb', shuffle= False ,batch_size= batch_size)
valid_gen = tr_gen.flow_from_dataframe( valid_df, x_col= 'filepaths',
y_col= 'labels', target_size= image_size, class_mode= 'categorical',
color_mode= 'rgb', shuffle= True,batch_size= batch_size)

Found 5712 validated image filenames belonging to 4 classes.
Found 656 validated image filenames belonging to 4 classes.
Found 655 validated image filenames belonging to 4 classes.

#RETREIVES DICTIONARY NAMES class_indices FROM train_gen (TRAINING
DATA GENERATOR)
```

```python
#WHICH MAPS CLASS LABELS TO CORRESPONDING INTEGER INDICES USED FOR
ONE-HOT ENCODING
gen_dictionary = train_gen.class_indices
#LINE CREATES LIST NAMED classes; LIST FUNC CONVERT THE KEYS OF
DICTIONARY INTO LIST
classes = list(gen_dictionary.keys())
#USES NEXT FUNC TO RETRIEVE BATCH OF DATA FROM train_gen (TRAINING
DATA GENERATOR)
#BY CALLING NEXT ON THIS GENERATOR, YOU'RE ESSENTIALLY FETCHING NEXT
BATCHOF IMAGES & LABELS
#IMAGES & LABELS WILL BE A NUMPY ARRAY
images,labels = next(train_gen)
#THE FOLLOWING LINE CREATES MATPLOTLIB FIGURE OBJECT
#plt.figure FUNC USED TO CREATE NEW FIG WINDOW FOR PLOTTING
#figsize ARG SETS WIGTH & HEIGHT OF FIGURE WINDOW IN INCHES; SET TO
LARGE SIZE OF (20,20) INCHES
plt.figure(figsize = (20,20))

#ITERATES 16 TIMES; CREATES A SUBPLOT FROM MATPLOTLIB
#ARGUMENTS SPECIFY A GRID LAYOUT OF 4 ROWS & 4 COLUMNS
#i+1 ENSURES SUBPLOTS ARE FILLED IN ROW-MAJOR ORDER
for i in range(16):
    plt.subplot(4,4,i+1)
    #i-th IMAGE RETRIEVED FROM IMAGES ARRAY & PERFORMS NORMALIZATION
    #IMAGE DATA STORED AS INT VALUE BWTN 0 AND 255
    #RESULTANT IMAGE STORED IN IMAGE VARIABLE
    image = images[i]/255
    #DISPLAYS NORMALIZED IMAGE (image) ON CURRENT SUBPLOT
    plt.imshow(image)
    #FIND INDEX OF MAXIMUM VALUE, WHICH CORRESPONDS TO THE PREDICTED
CLASS
    #INDEX OF PREDICTED CLASS IS STORED IN INDEX VARIABLE
    index = np.argmax(labels[i])
    #RETRIEVES ACTUAL CLASS LABEL NAME CORRESPONDING TO PREDICTED
CLASS INDEX
    #USES classes LIST & ACCESSES ELEMENT AT INDEX
    class_name= classes[index]
    #SET TITLE OF CURRENT SUBPLOT USING plt.title FUNC
    #SET TO class_name WITH BLUE COLOR AND FONT SIZE TO 12
    plt.title(class_name,color='blue',fontsize=12)
    #HIDE AXIS LABELS & TICKS OF CURRENT SUBPLOT;
    plt.axis('off')
#AFTER LOOP ENDS, LINE DISPLAYS ENTIRE FIG WINDOW CONTAINING GRID OF
IMAGES & THEIR PREDICTED CLASS LABELS USING plt.show
plt.show();
```




```
#RETRIEVES NO. OF CLASSES  FROM TRAINING DATA GENERATOR TO DEFINE
OUTPUT LAYER OF IMAGE CLASSIFICATION MODEL
image_size = (224, 224)
channels = 3
image_shape = (image_size[0], image_size[1], channels)
class_count = len(list(train_gen.class_indices.keys()))

#DEFINES A CNN USING TENSORFLOW LIBRARY
#tf.keras.applications.VGG16 IMPORTS VGG16 ARCHITECTURE; IT IS A
POPULAR PRE-TRAINED CNN MODEL THAT HAS BEEN TRAINED ON MASSIVE IMAGE
DATASET (ImageNet)
#include_top=False ARG SPECIFIES NOT TO INCLUDE TOP (CLASSIFICATION)
```

```
LAYERS OF MODEL
#weights="imagenet" LOADS PRE-TRAINED WEIGHTS FROM ImageNet DATASET
INTO VGG16 MODEL, WEIGHTS CAPTURE VALUABLE IMAGE FEATURES LEARNED FROM
LARGE DATASET
#input_shape=image_shape DEFINES EXPECTED INPUT SHAPE FOR MODEL
#pooling_'max' SPECIFIES TYPE OF POOLING OPERATION TO USE AT END OF
PRE-TRAINED VGG16 MODEL; SET TO 'max' FOR MAX POOLING
base_model = tf.keras.applications.VGG16(include_top= False, weights=
"imagenet", input_shape= image_shape, pooling= 'max')
#DEFINES SEQUENTIAL MODEL TO BUILT CNN
model = Sequential([
    #REFERS TO PRE-TRAINED VGG16 ADDED AS FIRST LAYER IN SEQ MODEL
    base_model,
    #LAYER INTRODUCES DROPOUT WITH RATE OF 0.45; DROPOUT RANDOMLY
DROPS CERTAIN PERCENTAGE OF NEURONS DURING TRAINING TO PREVENT
OVERFITTING
    Dropout(rate= 0.45, seed= 123),
    #APPLIES BATCH NORM TO IMPROVE SPEED N STABILITY
    BatchNormalization(axis= -1, momentum= 0.99, epsilon= 0.001),
    #DENSE LAYER FULLY CONNECTED LAYER WITH 256 NEURONS
    #kernel_regularizer=regularizers.l2(0.016) APPLIES L2
REGULARIZATION TO KERNELS OF LAYER TO PREVENT OVERFITTING
    #activity_regularizer=regularizers.l1(0.006) APPLIES L1
REGULARIZATION TO ACTIVATIONS OF LAYERS TO PREVENT OVERFITTING
    #activation='relu' SPECIFIES ACTIVATION FUNCTION FOR LAYER WHICH
IS SET TO 'relu' (RECTIFIES LINEAR UNIT)
    Dense(256, kernel_regularizer= regularizers.l2(0.016),
activity_regularizer= regularizers.l1(0.006),
                bias_regularizer= regularizers.l1(0.006), activation=
'relu'),
    #ACTIVATION FUNC SET TO SOFTMAX; SOFTMAX ACTIVATION USED FOR
MULTICLASS CLASSIFICATION PROBLEMS AS IT OUTPUTS A PROBABILITY
DISTRIBUTION FOR EACH CLASS
    Dense(class_count, activation= 'softmax')
])


#Adamax SPECIFIES OPTIMIZER USED FOR TRAINING; IT IS CHOSEN WITH
LEARNING RATE OF 0.01
#OPTIMIZER DETERMINES HOW MODELS UPDATES ITS INTERNAL WEIGHTS BASED ON
ERROR
#loss FUNC TO MEASURE MODEL'S PERFORMANCE DURING TRAINING; CATEGORICAL
CROSS ENTROPY MEAURES DIFF BTWN PREDICTED PROBABILITY DISTRIBUTION
(FROM SOFTMAX ACTV) AND LABELS
model.compile(Adamax(learning_rate= 0.001), loss=
'categorical_crossentropy', metrics= ['accuracy'])
#PRINT SUMMARY OF MODEL ARCH, NO. OF LAYERS, SHAPES N TOTAL NO. OF
PARAMETERS
```

```
model.summary()
Model: "sequential_1"

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 vgg16 (Functional)          (None, 512)               14714688

 dropout (Dropout)           (None, 512)               0

 batch_normalization (BatchN  (None, 512)              2048
 ormalization)

 dense (Dense)               (None, 256)               131328

 dense_1 (Dense)             (None, 4)                 1028

=================================================================
Total params: 14,849,092
Trainable params: 14,848,068
Non-trainable params: 1,024
_________________________________________________________________

#EPOCH FOR SINGLE PASS THROUGH ENTIRE TRAINING DATASET
#MODEL WILL GO THROUGH TRAINING DATA 30 TIMES
epochs = 30
#VERBOSE = 1: CONTROLS VERBOSITY. SETTING IT TO 1 PROVIDES LIMITED
OUTPUT AFTER EACH EPOCH, INCLUDING EPOCH NUMBER, LOSS VALUE, ACCURACY
#SETTING IT TO 2 PROVIDES MORE DETAILED OUTPUT
#SETTING IT TO 0 PROVIDES NO OUTPUT
history = model.fit(x = train_gen, epochs = epochs, verbose = 1,
validation_data = valid_gen, shuffle = False)

Epoch 1/30
357/357 [==============================] - 5113s 14s/step - loss:
3.9938 - accuracy: 0.5630 - val_loss: 5.4684 - val_accuracy: 0.4748
Epoch 2/30
357/357 [==============================] - 6295s 18s/step - loss:
1.8092 - accuracy: 0.6691 - val_loss: 1.8914 - val_accuracy: 0.4427
Epoch 3/30
357/357 [==============================] - 5265s 15s/step - loss:
1.1464 - accuracy: 0.7265 - val_loss: 1.5692 - val_accuracy: 0.3908
Epoch 4/30
357/357 [==============================] - 5909s 17s/step - loss:
0.9058 - accuracy: 0.7491 - val_loss: 0.8007 - val_accuracy: 0.7908
Epoch 5/30
357/357 [==============================] - 6428s 18s/step - loss:
0.7714 - accuracy: 0.7948 - val_loss: 0.9397 - val_accuracy: 0.7115
Epoch 6/30
```

```
357/357 [==============================] - 7053s 20s/step - loss:
0.6652 - accuracy: 0.8150 - val_loss: 0.6314 - val_accuracy: 0.8198
Epoch 7/30
357/357 [==============================] - 6678s 19s/step - loss:
0.5718 - accuracy: 0.8463 - val_loss: 1.3331 - val_accuracy: 0.5008
Epoch 8/30
357/357 [==============================] - 6408s 18s/step - loss:
0.5252 - accuracy: 0.8589 - val_loss: 1.8736 - val_accuracy: 0.8580
Epoch 9/30
357/357 [==============================] - 6497s 18s/step - loss:
0.5006 - accuracy: 0.8631 - val_loss: 0.6241 - val_accuracy: 0.8214
Epoch 10/30
357/357 [==============================] - 6013s 17s/step - loss:
0.4554 - accuracy: 0.8799 - val_loss: 0.5810 - val_accuracy: 0.8641
Epoch 11/30
357/357 [==============================] - 5569s 16s/step - loss:
0.3857 - accuracy: 0.9081 - val_loss: 0.4187 - val_accuracy: 0.8962
Epoch 12/30
357/357 [==============================] - 3575s 10s/step - loss:
0.3761 - accuracy: 0.9079 - val_loss: 0.4278 - val_accuracy: 0.8977
Epoch 13/30
357/357 [==============================] - 3493s 10s/step - loss:
0.3570 - accuracy: 0.9156 - val_loss: 1.0463 - val_accuracy: 0.7557
Epoch 14/30
357/357 [==============================] - 3536s 10s/step - loss:
0.3333 - accuracy: 0.9242 - val_loss: 0.3615 - val_accuracy: 0.9069
Epoch 15/30
357/357 [==============================] - 3504s 10s/step - loss:
0.3324 - accuracy: 0.9221 - val_loss: 0.5538 - val_accuracy: 0.8290
Epoch 16/30
357/357 [==============================] - 3877s 11s/step - loss:
0.2872 - accuracy: 0.9349 - val_loss: 0.8265 - val_accuracy: 0.9298
Epoch 17/30
357/357 [==============================] - 5283s 15s/step - loss:
0.2649 - accuracy: 0.9454 - val_loss: 0.2912 - val_accuracy: 0.9359
Epoch 18/30
357/357 [==============================] - 5333s 15s/step - loss:
0.2412 - accuracy: 0.9508 - val_loss: 0.2796 - val_accuracy: 0.9481
Epoch 19/30
357/357 [==============================] - 5646s 16s/step - loss:
0.2362 - accuracy: 0.9547 - val_loss: 0.3916 - val_accuracy: 0.9420
Epoch 20/30
357/357 [==============================] - 5798s 16s/step - loss:
0.2220 - accuracy: 0.9555 - val_loss: 0.3901 - val_accuracy: 0.9053
Epoch 21/30
357/357 [==============================] - 5674s 16s/step - loss:
0.2051 - accuracy: 0.9639 - val_loss: 0.2442 - val_accuracy: 0.9450
Epoch 22/30
357/357 [==============================] - 6002s 17s/step - loss:
```

```
0.1724 - accuracy: 0.9718 - val_loss: 0.4081 - val_accuracy: 0.8885
Epoch 23/30
357/357 [==============================] - 5867s 16s/step - loss:
0.1663 - accuracy: 0.9736 - val_loss: 0.7625 - val_accuracy: 0.9389
Epoch 24/30
357/357 [==============================] - 5712s 16s/step - loss:
0.1528 - accuracy: 0.9804 - val_loss: 0.1892 - val_accuracy: 0.9664
Epoch 25/30
357/357 [==============================] - 5294s 15s/step - loss:
0.1545 - accuracy: 0.9771 - val_loss: 0.1757 - val_accuracy: 0.9679
Epoch 26/30
357/357 [==============================] - 5496s 15s/step - loss:
0.1258 - accuracy: 0.9862 - val_loss: 0.6178 - val_accuracy: 0.9023
Epoch 27/30
357/357 [==============================] - 5597s 16s/step - loss:
0.1369 - accuracy: 0.9811 - val_loss: 0.4787 - val_accuracy: 0.8748
Epoch 28/30
357/357 [==============================] - 3623s 10s/step - loss:
0.1326 - accuracy: 0.9828 - val_loss: 0.2688 - val_accuracy: 0.9542
Epoch 29/30
357/357 [==============================] - 3544s 10s/step - loss:
0.1099 - accuracy: 0.9907 - val_loss: 0.3821 - val_accuracy: 0.9664
Epoch 30/30
357/357 [==============================] - 3513s 10s/step - loss:
0.1186 - accuracy: 0.9867 - val_loss: 0.1884 - val_accuracy: 0.9710
```

```
epochs = 10
history = model.fit(x = train_gen, epochs = epochs, verbose = 1,
validation_data = valid_gen, shuffle = False)
```

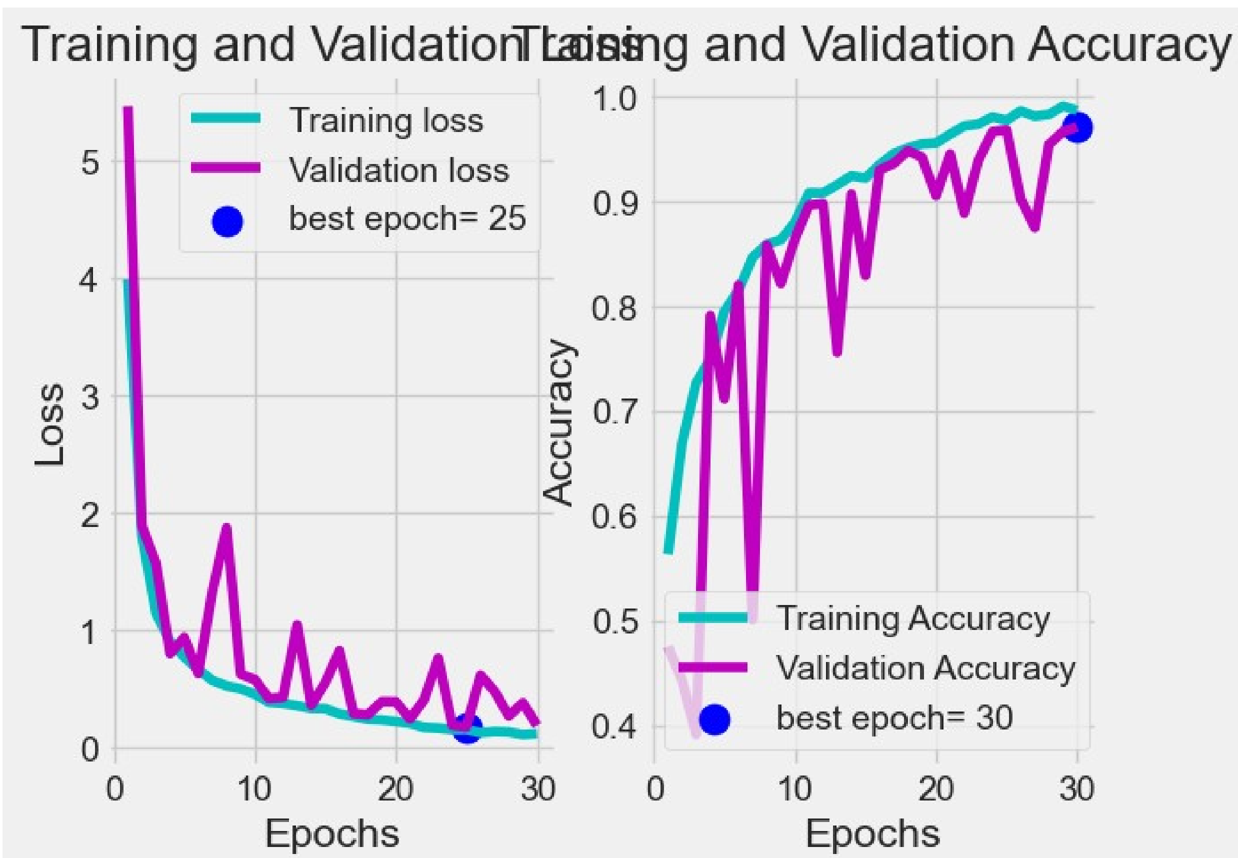
```
tr_acc = history.history['accuracy']
tr_loss = history.history['loss']
val_acc = history.history['val_accuracy']
val_loss = history.history['val_loss']
index_loss = np.argmin(val_loss)
val_lowest = val_loss[index_loss]
index_acc = np.argmax(val_acc)
acc_highest = val_acc[index_acc]
Epochs = [i+1 for i in range(len(tr_acc))]
loss_label = f'best epoch= {str(index_loss + 1)}'
acc_label = f'best epoch= {str(index_acc + 1)}'
plt.figure(figsize= (20, 8))
plt.style.use('fivethirtyeight')
```

```
<Figure size 2000x800 with 0 Axes>
```

```
plt.subplot(1, 2, 1)
plt.plot(Epochs, tr_loss, 'c', label= 'Training loss')
plt.plot(Epochs, val_loss, 'm', label= 'Validation loss')
plt.scatter(index_loss + 1, val_lowest, s= 150, c= 'blue', label=
```

```
loss_label)
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(Epochs, tr_acc, 'c', label= 'Training Accuracy')
plt.plot(Epochs, val_acc, 'm', label= 'Validation Accuracy')
plt.scatter(index_acc + 1 , acc_highest, s= 150, c= 'blue', label=
acc_label)
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout
```

```
<function matplotlib.pyplot.tight_layout(*, pad=1.08, h_pad=None,
w_pad=None, rect=None)>
```




```
train_score = model.evaluate(train_gen ,  verbose = 1)
valid_score = model.evaluate(valid_gen ,  verbose = 1)
test_score = model.evaluate(test_gen ,  verbose = 1)
```

```
357/357 [==============================] - 1546s 4s/step - loss:
0.1388 - accuracy: 0.9965
41/41 [==============================] - 186s 5s/step - loss: 0.1884 -
accuracy: 0.9710
41/41 [==============================] - 188s 5s/step - loss: 0.3629 -
accuracy: 0.9771
```

```
#ACCURACY ON TRAINING DATA IS 99.6% AND ON TEST DATA IS
#USE TRAINED MODEL TO GENERATE PREDICTIONS ON TEST DATA
preds = model.predict(test_gen)
#np.argmax FINDS INDEX OF LARGEST ELEMENT ALONG GIVEN AXIS IN ARRAY
#axis = 1 SPECIFIES WE'RE FINDING MAX VAL ALONG FIRST AXIS, CONVERTS
MODEL'S PROBABILITY INTO PREDICTED CLASS LABELS
y_pred = np.argmax(preds, axis = 1)
```

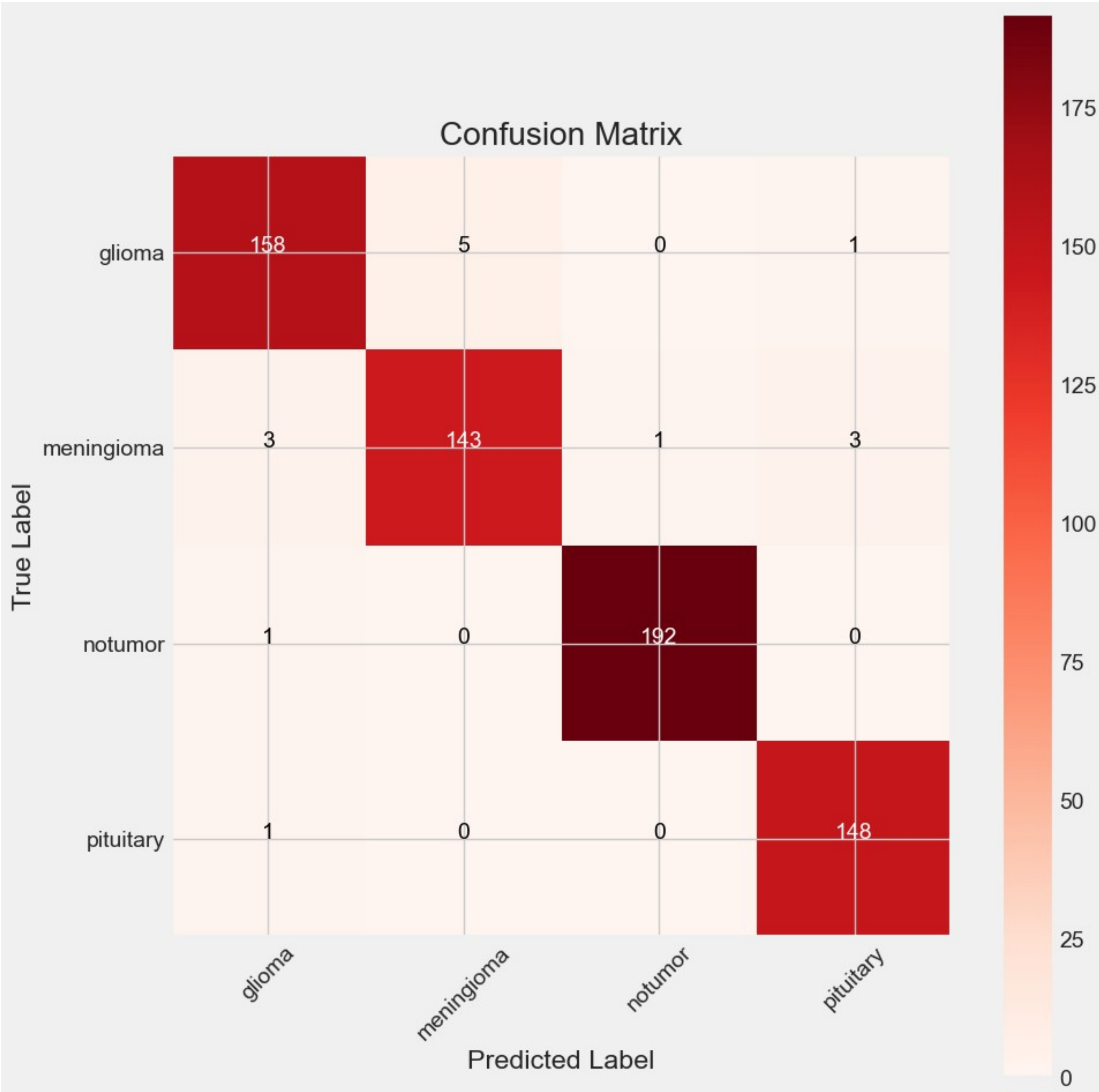
```
41/41 [==============================] - 191s 5s/step
```

```
#CREATE CONFUSION MATRIX TO EVALUATE PERFORMANCE ON TEST DATA
#RETRIEVES A DICT class_indices, MAPS INT LABELS
g_dict = test_gen.class_indices
#CREATES A LIST NAMED CLASSES, CONVERT KEYS FROM DICT INTO LIST; INT
LABELS TO CLASSES
classes = list(g_dict.keys())
#CONFUSION MATRIX CREATED; TAKES 2 ARG
#COMPARES ACTUAL CLASS LABELS WITH PREDICTED CLASS LABELS FOR TEST
DATA
#CORRECT CLASSIFICATION: HIGH VALUES ON DIAGONAL
cm = confusion_matrix(test_gen.classes, y_pred)
cm
```

```
array([[158,   5,   0,   1],
       [  3, 143,   1,   3],
       [  1,   0, 192,   0],
       [  1,   0,   0, 148]], dtype=int64)
```

```
#CREATE FIG WINDOW
#VISUALIZATION OF CONFUSION MATRIX USING MATPLOTLIB
plt.figure(figsize= (10, 10))
#DISPLAY DATA, SPECIFY RESAMPLING MATHOD USED TO DISPLAY IMAGE
#nearest ASSIGNS NEAREST COLOR FROM COLORMAP TO EACH PIXEL
plt.imshow(cm, interpolation= 'nearest', cmap= plt.cm.Reds)
plt.title('Confusion Matrix')
#DISPLAY MAPPING BTWN VALUES IN CONFUSION MATRIX & COLORS USED IN
IMAGE PLOT; HELPS INTERPRET COLOR INTENSITY IN IMAGE
plt.colorbar()
#IMPROVE READABILITY, CREATE ARRAY OF EVENLY SPACED VAL WITHIN
SPECIFIED RANGE (0 to len(classes)-1)
tick_marks = np.arange(len(classes))
#X-AXIS LABELS OF CM PLOT
#ROTATES AXIS TO 45% TO PREVENT OVERLAPPING OF LONG CLS NAMES
```

```
plt.xticks(tick_marks, classes, rotation= 45)
#Y-AXIS LABELS OF CM PLOT
plt.yticks(tick_marks, classes)
#DEFINES THRESHOLD VALUE, CALC MAX VALUE IN CM & DIVIDES IT BY 2, USED
TO DETERMINE TEXT COLOR FOR ANNOTATIONS
thresh = cm.max() / 2.
#START ITERATING
#range(cm.shape[0]) CREATES SEQ OF NUMBERS FROM 0 TO NO. OF ROWS IN CM
#range(cm.shape[1]) CREATES SEQ OF NUMBERS FROM 0 TO NO. OF COLUMNS IN
CONFUSION MATRIX MINUS 1
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, cm[i, j], horizontalalignment= 'center', color=
'white' if cm[i, j] > thresh else 'black')
#HIGH VALUES: WHITE TEXT ON DARK BACKGROUND, LOW VALUES: BLACK TEXT ON
LLIGHT BACKGROUND
#ADJUST SPACING BTWN PLOT ELEMENTS TO AVOID OVERLAPPING
plt.tight_layout()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```


Confusion Matrix
True Label
Predicted Label
glioma
meningioma
notumor
pituitary
158
5
0
1
3
143
1
3
1
0
192
0
1
0
0
148
175
150
125
100
75
50
25
0

```
#-----
```