In [1]:

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

In [2]:

```
# 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
```

In [3]:

```
# 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, ROTA
#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
#MAXPOOLING2D PERFORMS DOWNSAMPLING, REDUCING DIMENSIONALITY OF DATA, CAPTU
#DENSE REPRESENTS FULLY CONNECTED LAYER USED IN FINAL STAGES OF MODEL FOR C
#FLATTEN FLATTENS MULTI-DIMENSIONAL OUTPUT OF CONVO LAYERS INTO A SINGLE VE

from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
#DROPOUT LAYER RANDOMLY DROPS CERTAIN PERCENTAGE OF NEURONS DURING TRAINING
#ACTIVATION LAYER APPLIES ACTIVATION FUNCTION (LIKE RELU) FOR NON-LINEARITY
#BATCHNORMALIZATION NORMALIZES ACTIVATIONS OF PREVIOUS LAYER, IMPROVING TRA
from tensorflow.keras.layers import Activation, BatchNormalization, Dropout
#REGULARIZERS PENSLIZE MODEL FOR OVERLY COMPLEX WEIGHTS, HELPING TO PREVENT
#REGULARIZERS FUNCTIONS LIKE L1 AND L2 REGULARIZATION
from tensorflow.keras import regularizers
#IGNORE WARNINGS
import warnings
warnings.filterwarnings("ignore")
print ('modules loaded')
```

```
modules loaded
```

In [4]:

```
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 SU
#RESULT OF THIS FUNCTION CALL IS STORED IN VARIABLE FOLDS
```

In [5]:

```
#ITERATE OVER EACH ELEMENT IN FOLD LIST
for fold in folds:
    #os.path.join FUNC FROM OS LIBRARY, IT COMBINES BASE PATH(test_file) W
    #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 FIL
    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
```

Out[5]:

	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 × 2 columns

In [6]:

```
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
```

Out[6]:

	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 × 2 columns

In [7]:

```
#VALID DATAFRAME WILL CONTAIN A PORTION OF DATA, WILL HAVE SAME STRUCTURE A
#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 T
#SHUFFLE THE DATA BEFORE SPLITTING TO ENSURE TRAINING & TESTING REPRESENT A
#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_
```

In [8]:

```
#ASSIGNS VALUE 16 TO BATCH SIZE, USED TO DEFINE NO. OF IMAGES PROCESSED DU
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 &
tr_gen = ImageDataGenerator()
#CREATES SEPARATE INSTANCE FOR PREPROCESSING TESTING DATA WITHOUT AUGMENTA
ts_gen = ImageDataGenerator()
```

In [9]:

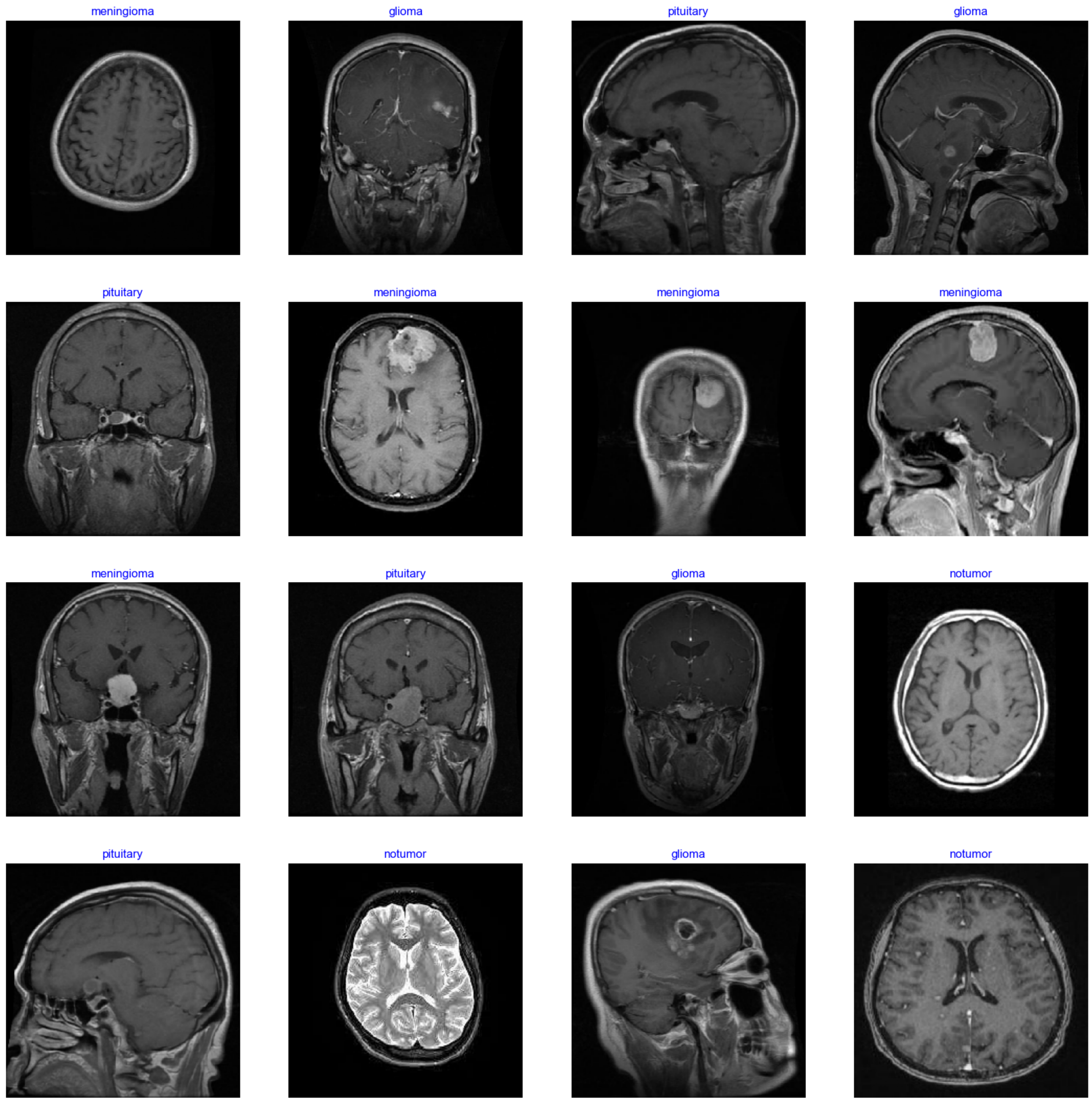
```
#GENERATORS ACT AS PIPELINES TO AUTOMATICALLY LOAD, PREPROCESS, AND AUGMEN
train_gen = tr_gen.flow_from_dataframe( data, x_col= 'filepaths', y_col= '
test_gen = tr_gen.flow_from_dataframe( test_df, x_col= 'filepaths', y_col=
valid_gen = tr_gen.flow_from_dataframe( valid_df, x_col= 'filepaths', y_co
```

```
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.
```

In [10]:

```
#RETREIVES DICTIONARY NAMES class_indices FROM train_gen (TRAINING DATA GEI
#WHICH MAPS CLASS LABELS TO CORRESPONDING INTEGER INDICES USED FOR ONE-HOT
gen_dictionary = train_gen.class_indices
#LINE CREATES LIST NAMED classes; LIST FUNC CONVERT THE KEYS OF DICTIONARY
classes = list(gen_dictionary.keys())
#USES NEXT FUNC TO RETRIEVE BATCH OF DATA FROM train_gen (TRAINING DATA GEI
#BY CALLING NEXT ON THIS GENERATOR, YOU'RE ESSENTIALLY FETCHING NEXT BATCH(
#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 S
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 INI
    #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
plt.show();
```



In [11]:

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

In [12]:

```
#DEFINES A CNN USING TENSORFLOW LIBRARY
#tf.keras.applications.VGG16 IMPORTS VGG16 ARCHITECTURE; IT IS A POPULAR PI
#include_top=False ARG SPECIFIES NOT TO INCLUDE TOP (CLASSIFICATION) LAYERS
#weights="imagenet" LOADS PRE-TRAINED WEIGHTS FROM ImageNet DATASET INTO VG
#input_shape=image_shape DEFINES EXPECTED INPUT SHAPE FOR MODEL
#pooling_'max' SPECIFIES TYPE OF POOLING OPERATION TO USE AT END OF PRE-TRA
base_model = tf.keras.applications.VGG16(include_top= False, weights= "imag
#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 CEL
    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
    #activity_regularizer=regularizers.l1(0.006) APPLIES L1 REGULARIZATION
    #activation='relu' SPECIFIES ACTIVATION FUNCTION FOR LAYER WHICH IS SET
    Dense(256, kernel_regularizer= regularizers.l2(0.016), activity_regular
                bias_regularizer= regularizers.l1(0.006), activation= 'relu
    #ACTIVATION FUNC SET TO SOFTMAX; SOFTMAX ACTIVATION USED FOR MULTICLASS
    Dense(class_count, activation= 'softmax')
])


#Adamax SPECIFIES OPTIMIZER USED FOR TRAINING; IT IS CHOSEN WITH LEARNING R
#OPTIMIZER DETERMINES HOW MODELS UPDATES ITS INTERNAL WEIGHTS BASED ON ERRO
#loss FUNC TO MEASURE MODEL'S PERFORMANCE DURING TRAINING; CATEGORICAL CROS
model.compile(Adamax(learning_rate= 0.001), loss= 'categorical_crossentropy
#PRINT SUMMARY OF MODEL ARCH, NO. OF LAYERS, SHAPES N TOTAL NO. OF PARAMETE
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
_________________________________________________________________
```

In [13]:

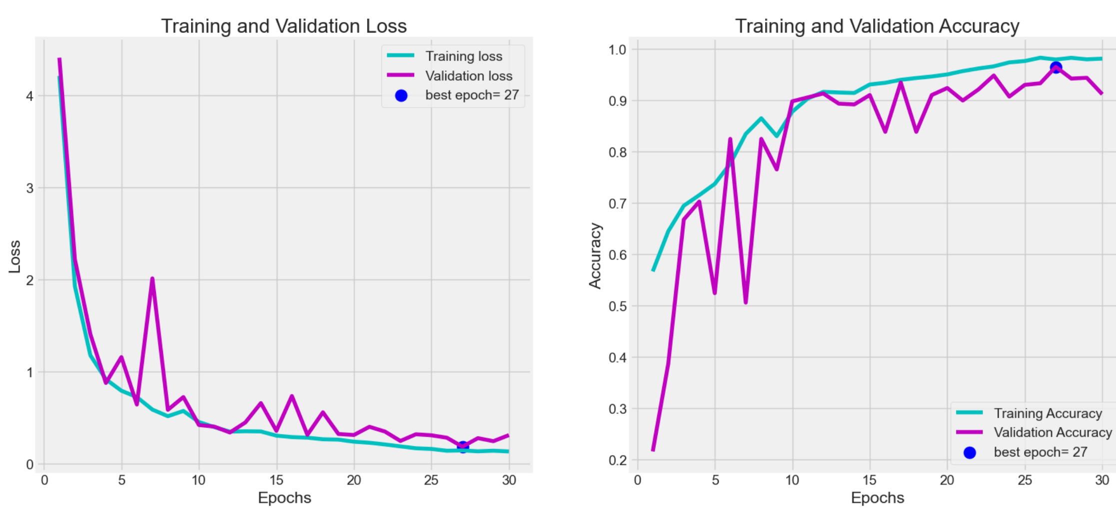
```
#EPOCH FOR SINGLE PASS THROUGH ENTIRE TRAINING DATASET
#MODEL WILL GO THROUGH TRAINING DATA 30 TIMES
epochs = 30
#VERBOSE = 1: CONTROLS VERBOSITY. SETTING IT TO 1 PROVIDES LIMITED OUTPUT A
#SETTING IT TO 2 PROVIDES MORE DETAILED OUTPUT
#SETTING IT TO 0 PROVIDES NO OUTPUT
history = model.fit(x = train_gen, epochs = epochs, verbose = 1, validatio
```

```
Epoch 1/30
357/357 [==============================] - 7366s 21s/step - loss: 4.2084
- accuracy: 0.5662 - val_loss: 4.4053 - val_accuracy: 0.2153
Epoch 2/30
357/357 [==============================] - 10385s 29s/step - loss: 1.9281
- accuracy: 0.6444 - val_loss: 2.2191 - val_accuracy: 0.3863
Epoch 3/30
357/357 [==============================] - 14035s 39s/step - loss: 1.1772
- accuracy: 0.6942 - val_loss: 1.4063 - val_accuracy: 0.6672
Epoch 4/30
357/357 [==============================] - 9123s 26s/step - loss: 0.9175
- accuracy: 0.7148 - val_loss: 0.8770 - val_accuracy: 0.7023
Epoch 5/30
357/357 [==============================] - 29103s 82s/step - loss: 0.7934
- accuracy: 0.7367 - val_loss: 1.1577 - val_accuracy: 0.5237
Epoch 6/30
357/357 [==============================] - 14861s 42s/step - loss: 0.7245
- accuracy: 0.7761 - val_loss: 0.6432 - val_accuracy: 0.8244
Epoch 7/30
357/357 [==============================] - 13272s 37s/step - loss: 0.5888
- accuracy: 0.8342 - val_loss: 2.0121 - val_accuracy: 0.5053
Epoch 8/30
357/357 [==============================] - 14056s 39s/step - loss: 0.5168
- accuracy: 0.8647 - val_loss: 0.5864 - val_accuracy: 0.8244
Epoch 9/30
357/357 [==============================] - 12155s 34s/step - loss: 0.5739
- accuracy: 0.8298 - val_loss: 0.7246 - val_accuracy: 0.7649
Epoch 10/30
357/357 [==============================] - 7929s 22s/step - loss: 0.4539
- accuracy: 0.8775 - val_loss: 0.4217 - val_accuracy: 0.8977
Epoch 11/30
357/357 [==============================] - 6336s 18s/step - loss: 0.3986
- accuracy: 0.9032 - val_loss: 0.4035 - val_accuracy: 0.9053
Epoch 12/30
357/357 [==============================] - 6451s 18s/step - loss: 0.3494
- accuracy: 0.9161 - val_loss: 0.3401 - val_accuracy: 0.9130
Epoch 13/30
357/357 [==============================] - 9565s 27s/step - loss: 0.3534
- accuracy: 0.9149 - val_loss: 0.4493 - val_accuracy: 0.8931
Epoch 14/30
357/357 [==============================] - 8650s 24s/step - loss: 0.3513
- accuracy: 0.9140 - val_loss: 0.6593 - val_accuracy: 0.8916
Epoch 15/30
357/357 [==============================] - 7101s 20s/step - loss: 0.3062
- accuracy: 0.9305 - val_loss: 0.3583 - val_accuracy: 0.9099
Epoch 16/30
357/357 [==============================] - 10521s 29s/step - loss: 0.2904
- accuracy: 0.9338 - val_loss: 0.7362 - val_accuracy: 0.8382
```

```
Epoch 17/30
357/357 [==============================] - 9838s 28s/step - loss: 0.2841
- accuracy: 0.9396 - val_loss: 0.3149 - val_accuracy: 0.9344
Epoch 18/30
357/357 [==============================] - 10691s 30s/step - loss: 0.2669
- accuracy: 0.9431 - val_loss: 0.5591 - val_accuracy: 0.8382
Epoch 19/30
357/357 [==============================] - 10542s 30s/step - loss: 0.2629
- accuracy: 0.9461 - val_loss: 0.3241 - val_accuracy: 0.9099
Epoch 20/30
357/357 [==============================] - 10596s 30s/step - loss: 0.2403
- accuracy: 0.9501 - val_loss: 0.3129 - val_accuracy: 0.9237
Epoch 21/30
357/357 [==============================] - 10616s 30s/step - loss: 0.2290
- accuracy: 0.9566 - val_loss: 0.4019 - val_accuracy: 0.8992
Epoch 22/30
357/357 [==============================] - 10532s 30s/step - loss: 0.2105
- accuracy: 0.9617 - val_loss: 0.3506 - val_accuracy: 0.9206
Epoch 23/30
357/357 [==============================] - 11604s 33s/step - loss: 0.1896
- accuracy: 0.9659 - val_loss: 0.2484 - val_accuracy: 0.9481
Epoch 24/30
357/357 [==============================] - 10417s 29s/step - loss: 0.1691
- accuracy: 0.9736 - val_loss: 0.3208 - val_accuracy: 0.9069
Epoch 25/30
357/357 [==============================] - 10650s 30s/step - loss: 0.1617
- accuracy: 0.9762 - val_loss: 0.3097 - val_accuracy: 0.9298
Epoch 26/30
357/357 [==============================] - 10971s 31s/step - loss: 0.1420
- accuracy: 0.9827 - val_loss: 0.2835 - val_accuracy: 0.9328
Epoch 27/30
357/357 [==============================] - 8324s 23s/step - loss: 0.1455
- accuracy: 0.9792 - val_loss: 0.1863 - val_accuracy: 0.9649
Epoch 28/30
357/357 [==============================] - 3271s 9s/step - loss: 0.1362 -
accuracy: 0.9825 - val_loss: 0.2787 - val_accuracy: 0.9420
Epoch 29/30
357/357 [==============================] - 3250s 9s/step - loss: 0.1425 -
accuracy: 0.9795 - val_loss: 0.2460 - val_accuracy: 0.9435
Epoch 30/30
357/357 [==============================] - 3263s 9s/step - loss: 0.1348 -
accuracy: 0.9809 - val_loss: 0.3117 - val_accuracy: 0.9115
```

In [14]:
```
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')
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_lab
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_lab
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.tight_layout
```

Out[14]:
```
<function matplotlib.pyplot.tight_layout(*, pad=1.08, h_pad=None, w_pad=N
one, rect=None)>
```



In [15]:

```
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 [==============================] - 844s 2s/step - loss: 0.9267 -
accuracy: 0.9706
41/41 [==============================] - 96s 2s/step - loss: 0.3117 - acc
uracy: 0.9115
41/41 [==============================] - 98s 2s/step - loss: 0.2676 - acc
uracy: 0.9268
```

In [16]:

```
#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
y_pred = np.argmax(preds, axis = 1)
```

```
41/41 [==============================] - 97s 2s/step
```

In [17]:

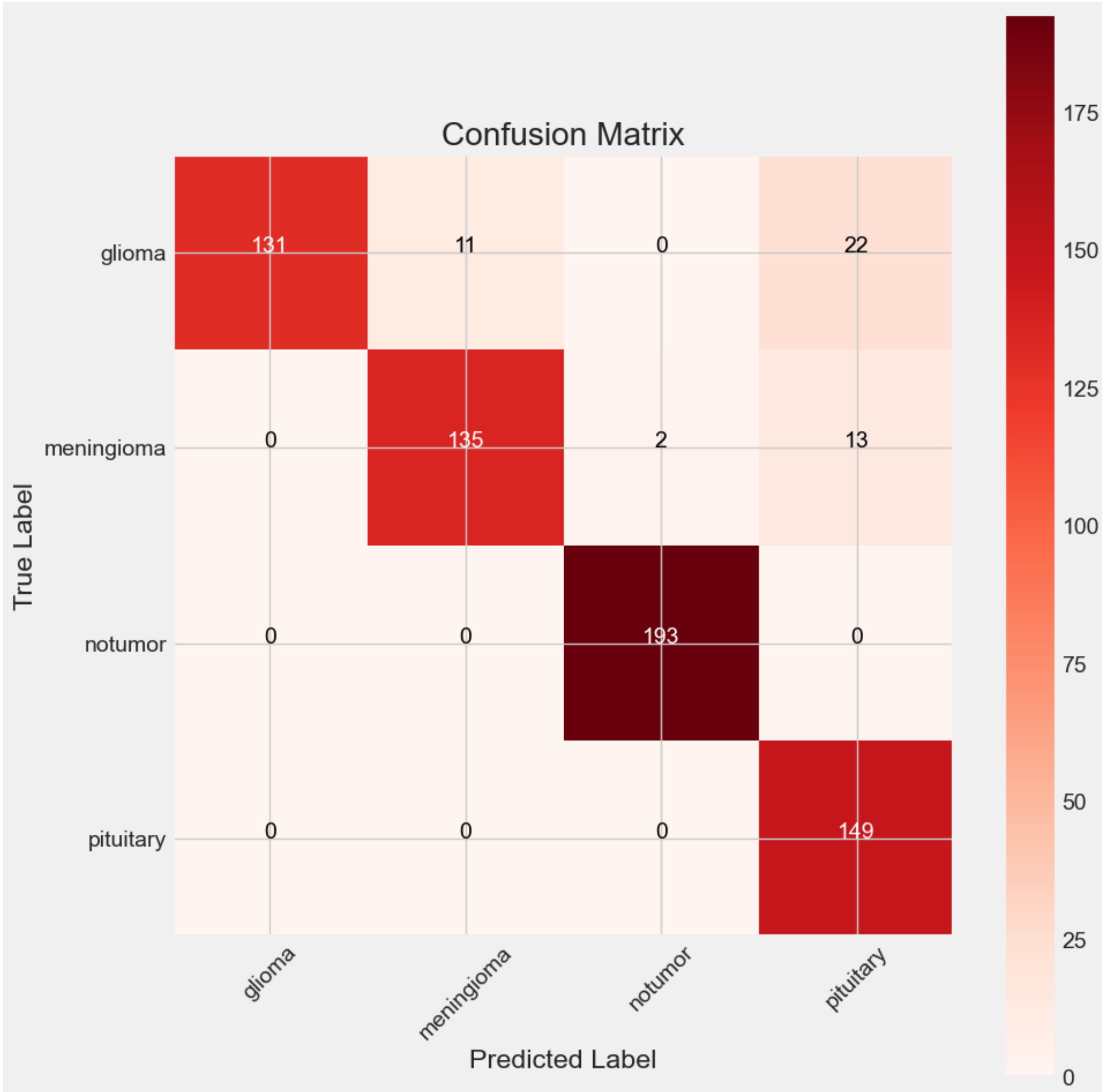
```
#CREATE CONFUSION MATRIX TO EVALUATE PERFORMANCE ON TEST DATA
#RETRIEVES A DICT class_indices, MAPS INT LABELS
g_dict = test_gen.class_indices
#CREATES A LIST NAMED CLASSES, CONVERT KEYS FROM DICT INTO LIST; INT LABEL
classes = list(g_dict.keys())
#CONFUSION MATRIX CREATED; TAKES 2 ARG
#COMPARES 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
```

Out[17]:

```
array([[131,  11,   0,  22],
       [  0, 135,   2,  13],
       [  0,   0, 193,   0],
       [  0,   0,   0, 149]], dtype=int64)
```

In [18]:

```
#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 PL
plt.colorbar()
#IMPROVE READABILITY, CREATE ARRAY OF EVENLY SPACED VAL WITHIN SPECIFIED R
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
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 CON
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'
#HIGH VALUES: WHITE TEXT ON DARK BACKGROUND, LOW VALUES: BLACK TEXT ON LLI
#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
131
11
0
22
0
135
2
13
0
0
193
0
0
0
0
149
175
150
125
100
75
50
25
0