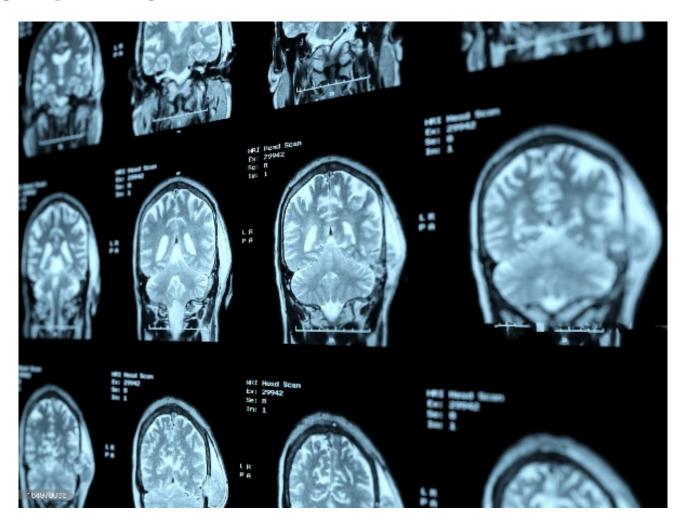
# Detection and Classification of Brain Tumor through Brain MRI Images Using Deep Learning



#### 1.Introduction

- The occurrence of brain tumor patients in India is steadily rising, more and more number of cases are reported each year in India across various age groups.
- The International Association of Cancer Registries (IARC) reported that there are over 28,000 cases of brain tumours reported in India each year and more than 24,000 people reportedly i.e. 85.72% of the total reported die due to brain tumours annually. Brain tumour's are a serious condition and in most cases fatal if not detected & treated in early stages.

#### 2. Setting Up Local Storage for Dataset

#### 2.1 Giving Access To Google Drive

In []:

```
from google.colab import drive
drive.mount('/content/gdrive/')
```

Mounted at /content/gdrive/

#### 2.2 Checking OS Version and Details

```
print("OS Version & Details: ")
!lsb_release -a
```

OS Version & Details: No LSB modules are available. Distributor ID: Ubuntu

Description: Ubuntu 18.04.5 LTS

Release: 18.04 Codename: bionic

#### 3. Importing Required Libraries

#### In []:

```
import sys
import os
import math
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
from matplotlib import rcParams
rcParams['figure.dpi'] = 300
%matplotlib inline
import seaborn as sns
import missingno as msno
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import *
from tensorflow.keras.optimizers import *
from tensorflow.keras.applications import InceptionV3
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from sklearn.model_selection import train_test_split, KFold
from sklearn.metrics import *
from PIL import Image, ImageEnhance
from tensorflow.keras.preprocessing.image import *
print(f'Tensorflow Version: {tf.__version__}.')
```

Tensorflow Version: 2.5.0.

#### 4. Setting Up the Environment

```
gpu_device_location = tpu_device_location = cpu_device_location = None
if os.environ['COLAB GPU'] == '1':
   print("Allocated GPU Runtime Details:")
   !nvidia-smi
   print()
   try:
       import pynvml
       pynvml.nvmlInit()
       handle = pynvml.nvmlDeviceGetHandleByIndex(0)
       gpu_device_name = pynvml.nvmlDeviceGetName(handle)
       if gpu_device_name not in {b'Tesla T4', b'Tesla P4', b'Tesla P100-PCIE-16GB'}:
          raise Exception("Unfortunately this instance does not have a T4, P4 or P100 GPU.
 →\nSometimes Colab allocates a Tesla K80 instead of a T4, P4 or P100.\nIf you get Tesla⊔
 →K80 then you can factory reset your runtime to get another GPUs.")
   except Exception as hardware_exception:
       print(hardware_exception, end = '\n\n')
   gpu_device_location = tf.test.gpu_device_name()
   print(f"{gpu_device_name.decode('utf-8')} is allocated sucessfully at location: ⊔
 →{gpu_device_location}")
elif 'COLAB_TPU_ADDR' in os.environ:
   tpu_device_location = f"grpc://{os.environ['COLAB_TPU_ADDR']}"
   print(f"TPU is allocated successfully at location: {tpu_device_location}.")
   resolver = tf.distribute.cluster_resolver.TPUClusterResolver(tpu_location)
   tf.config.experimental_connect_to_cluster(resolver)
   tf.tpu.experimental.initialize_tpu_system(resolver)
   tpu_strategy = tf.distribute.TPUStrategy()
else:
   cpu_device_location = "/cpu:0"
   print("GPUs and TPUs are not allocated successfully, hence runtime fallbacked to CPU.")
Allocated GPU Runtime Details:
Tue Jun 8 20:01:14 2021
+-----+
| NVIDIA-SMI 465.27
                    Driver Version: 460.32.03
                                            CUDA Version: 11.2
|-----
| GPU Name Persistence-M| Bus-Id Disp.A | Volatile Uncorr. ECC |
| Fan Temp Perf Pwr:Usage/Cap| Memory-Usage | GPU-Util Compute M. |
Off | 00000000:00:04.0 Off |
 0 Tesla T4
| N/A 57C P8 10W / 70W | OMiB / 15109MiB | 0% Default |
 ------
| Processes:
 GPU GI CI
                   PID Type Process name
                                                       GPU Memory |
                                                       Usage
```

|-----|

Tesla T4 is allocated sucessfully at location: /device:GPU:0

#### 4.1 Installation of tree Utility Using Bash.

```
%%bash
RED_COLOR='\033[0;31m'
NO_COLOR='\033[Om'
pkg_name=tree
dpkg -s $pkg_name &> /dev/null
if [ "$?" -ne "0" ]
    then
        echo "Installing tree utility..."
        apt-get autoclean
        apt-get autoremove
        apt-get install $pkg_name
        if [ "$?" -eq "0" ]
            then
                echo -e ${RED_COLOR}"tree utility installed sucessfully.\n"${NO_COLOR}
        fi
    else
        echo "tree utility is already installed."
fi
tree --version
```

```
Installing tree utility...
Reading package lists...
Building dependency tree...
Reading state information...
Reading package lists...
Building dependency tree...
Reading state information...
0 upgraded, 0 newly installed, 0 to remove and 39 not upgraded.
Reading package lists...
Building dependency tree...
Reading state information...
The following NEW packages will be installed:
  tree
0 upgraded, 1 newly installed, 0 to remove and 39 not upgraded.
Need to get 40.7 kB of archives.
After this operation, 105 kB of additional disk space will be used.
Get:1 http://archive.ubuntu.com/ubuntu bionic/universe amd64 tree amd64 1.7.0-5 [40.7 kB]
Fetched 40.7 \text{ kB} in 1s (73.4 \text{ kB/s})
Selecting previously unselected package tree.
(Reading database ... 160772 files and directories currently installed.)
Preparing to unpack .../tree_1.7.0-5_amd64.deb ...
Unpacking tree (1.7.0-5) ...
Setting up tree (1.7.0-5) ...
```

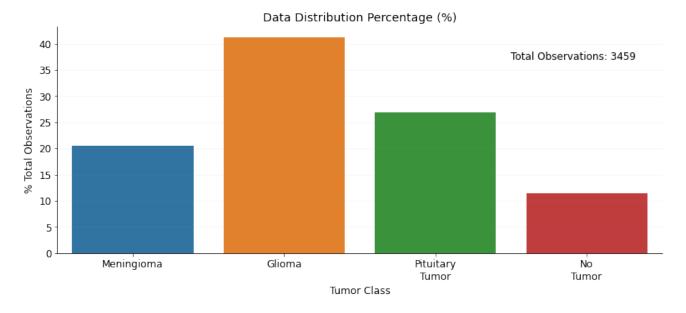
```
Processing triggers for man-db (2.8.3-2ubuntu0.1) ...
tree utility installed sucessfully.
tree v1.7.0 (c) 1996 - 2014 by Steve Baker, Thomas Moore, Francesc Rocher, Florian
Sesser, Kyosuke Tokoro
4.2 Display of File Structure
In []:
 !tree -d "gdrive/MyDrive/Deep_Learning_Course_Project"
gdrive/MyDrive/Deep_Learning_Course_Project
  Brain-Tumor-Dataset
      Brain-Tumor-Images-Mat-Files
      Testing
         No
          Yes
      Training
         glioma
         meningioma
         no_tumor
         pituitary_tumor
      Tumor-Mask
          glioma
          meningioma
          pituitary_tumor
  Model-Checkpoints
      AlexNet-CNN
      InceptionV3
      Multi-Layer-Perceptron
  Research-Papers
19 directories
4.3 Setting Up Paths to Root and Data Directories
In []:
ROOT_DIR = r"gdrive/MyDrive/Deep_Learning_Course_Project/"
DATA_ROOT_DIR = os.path.join(ROOT_DIR, "Brain-Tumor-Dataset")
TRAIN_DIR = os.path.join(DATA_ROOT_DIR, 'Training')
MASK_DIR = os.path.join(DATA_ROOT_DIR, 'Tumor-Mask')
assert os.path.isdir(ROOT_DIR) and os.path.isdir(DATA_ROOT_DIR) and os.path.
 →isdir(TRAIN_DIR) and os.path.isdir(MASK_DIR)
TUMOR_CLASS = ['meningioma', 'glioma', 'pituitary_tumor', 'no_tumor']
IMAGE_DATA_PATHS = [os.path.join(TRAIN_DIR, tumor_class) for tumor_class in TUMOR_CLASS]
MASK_DATA_PATHS = [os.path.join(MASK_DIR, tumor_name) for tumor_name in TUMOR_CLASS[:-1]]
```

# 5. Data Preprocessing and Exploratory Data Analysis

# Out []:

meningioma 708 glioma 1426 pituitary\_tumor 930 no\_tumor 395 dtype: int64

#### 5.1 Data Distribution Visualization



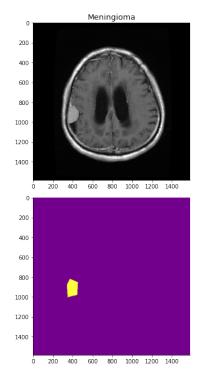
#### 5.2 Visualisation of Brain MRI Dataset

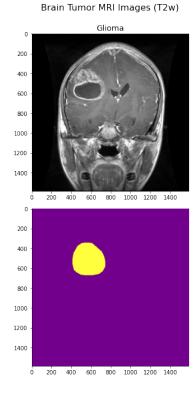
Dataset Source: https://figshare.com/articles/dataset/brain\_tumor\_dataset/1512427

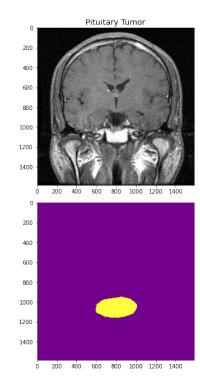
Source Code for Conversion of .mat file to .jpg: Google Colab Notebook Link

 $\label{link:https://drive.google.com/drive/folders/11QIC82FBdAyq0PUwLVNd22i-oq6lcat1?usp=sharing$ 

```
BRIGHTNESS_FACTOR = 1.7
fig, axes = plt.subplots(nrows = 2, ncols = 3, figsize = (18, 9))
axes = axes.flatten()
fig.suptitle("Brain Tumor MRI Images (T2w)", fontsize = 16, fontdict = dict(weight = __
\rightarrow'bold'), y = 1.04)
for curr_title, filename, curr_axis in zip(TUMOR_CLASS[:-1], IMAGE_DATA_PATHS[:-1], axes[:
→31):
    curr_image = Image.open(os.path.join(filename, os.listdir(filename)[2]))
    img_enhancer = ImageEnhance.Brightness(curr_image)
    curr_axis.imshow(img_enhancer.enhance(BRIGHTNESS_FACTOR))
    curr_axis.set_title(" ".join(curr_title.split('_')).title(), fontsize = 14)
for filename, curr_axis in zip(MASK_DATA_PATHS, axes[3:]):
    curr_image = Image.open(os.path.join(filename, os.listdir(filename)[2]))
    mask_enhance = ImageEnhance.Brightness(curr_image)
    curr_axis.imshow(mask_enhancer.enhance(BRIGHTNESS_FACTOR))
fig.tight_layout()
sns.despine()
```







#### 6. Development of Training, Validation & Testing Dataset

```
In []:
```

```
image_data_paths = []
for curr_path, tumor_name in zip(IMAGE_DATA_PATHS, TUMOR_CLASS):
    if os.path.exists(curr_path) and os.path.isdir(curr_path):
        image_data_paths.extend(map(lambda filename: (os.path.join(curr_path, filename),
        -tumor_name), os.listdir(curr_path)))
```

# In []:

#### Out []:

```
image_filepaths tumor_class

gdrive/MyDrive/Deep_Learning_Course_Project/Br... meningioma

gdrive/MyDrive/Deep_Learning_Course_Project/Br... meningioma

gdrive/MyDrive/Deep_Learning_Course_Project/Br... pituitary_tumor

gdrive/MyDrive/Deep_Learning_Course_Project/Br... pituitary_tumor

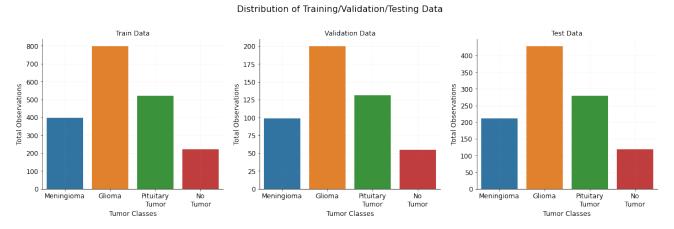
gdrive/MyDrive/Deep_Learning_Course_Project/Br... pituitary_tumor
```

# In []:

```
image_data_paths_df.info()
```

#### 6.1 Training, Validation and Testing Dataset Data Distribution Visualization

#### In []:



#### 7. Data/Image Augmentation

- Image augmentation is usually used to increase the image dataset and also to make the network more robust against translation invariance. Image augmentation is defined as creating duplicates of the original image datasets by flipping, rotating, zooming, and adjusting brightness.
- We will use data/image augmentation using ImageDataGenerator class to train the model on different types
  of combinations formed by rotation, flipping, changing the brightness etc of an image so as to increase our
  model accuracy.

```
zoom_range = 0.01,
shear_range = 0.01,
brightness_range = [0.3, 1.5],
horizontal_flip = True,
vertical_flip = True)
```

```
train_image_datagen = ImageDataGenerator(**image_datagen_kwargs)
validation_image_datagen = ImageDataGenerator(**image_datagen_kwargs)
test_image_datagen = ImageDataGenerator(**image_datagen_kwargs)
```

#### In []:

```
train_dataset = train_image_datagen.flow_from_dataframe(train_data,
                                                         x_col = 'image_filepaths',
                                                         y_col = 'tumor_class',
                                                         seed = 42,
                                                         batch_size = batch_size,
                                                         target_size = (image_size,_
→image_size),
                                                         color_mode = 'rgb')
validation_dataset = validation_image_datagen.flow_from_dataframe(validation_data,
                                                                   x_col = 'image_filepaths',
                                                                   y_col = 'tumor_class',
                                                                   seed = 42,
                                                                   batch_size = batch_size,
                                                                   target_size =
 →(image_size, image_size),
                                                                   color_mode = 'rgb')
test_dataset = test_image_datagen.flow_from_dataframe(test_data,
                                                       x_col = 'image_filepaths',
                                                       y_col = 'tumor_class',
                                                       seed = 42,
                                                       batch_size = batch_size,
                                                       target_size = (image_size,_
→image_size),
                                                       color_mode = 'rgb')
```

Found 1936 validated image filenames belonging to 4 classes. Found 485 validated image filenames belonging to 4 classes. Found 1038 validated image filenames belonging to 4 classes.

# In $[\ ]:$

```
print("Information about Training Dataset:")
print(train_dataset.class_indices)
print(train_dataset.image_shape, end = '\n\n')

print("Information about Validation Dataset:")
print(validation_dataset.class_indices)
print(validation_dataset.image_shape, end = '\n\n')
```

```
print("Information about Testing Dataset:")
print(test_dataset.class_indices)
print(test_dataset.image_shape)

Information about Training Dataset:
{'glioma': 0, 'meningioma': 1, 'no_tumor': 2, 'pituitary_tumor': 3}
(128, 128, 3)
```

Information about Validation Dataset:
{'glioma': 0, 'meningioma': 1, 'no\_tumor': 2, 'pituitary\_tumor': 3}
(128, 128, 3)

Information about Testing Dataset:

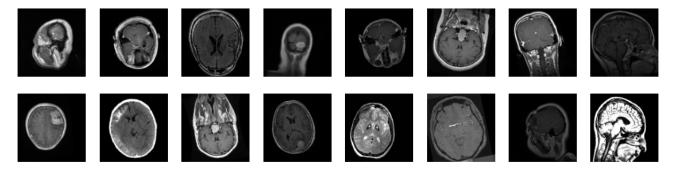
{'glioma': 0, 'meningioma': 1, 'no\_tumor': 2, 'pituitary\_tumor': 3} (128, 128, 3)

#### 7.1 Training Data Images Glimpse

# In []:

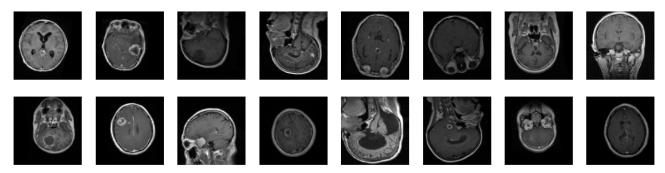
```
fig, axes = plt.subplots(nrows = 2, ncols = 8, figsize = (20, 5))
fig.suptitle("Samples from Training Set Batch", fontsize = 16, fontdict = dict(weight = 'bold'))
for curr_axis, curr_image in zip(axes.flatten(), train_dataset[0][0][:16]):
    curr_axis.imshow(tf.squeeze(curr_image), cmap = 'gray')
    curr_axis.axis(False)
```

Samples from Training Set Batch



#### 7.2 Validation Data Images Glimpse

```
fig, axes = plt.subplots(nrows = 2, ncols = 8, figsize = (20, 5))
fig.suptitle("Samples from Validation Set Batch", fontsize = 16, fontdict = dict(weight = 'bold'))
for curr_axis, curr_image in zip(axes.flatten(), validation_dataset[0][0][:16]):
    curr_axis.imshow(tf.squeeze(curr_image), cmap = 'gray')
    curr_axis.axis(False)
```

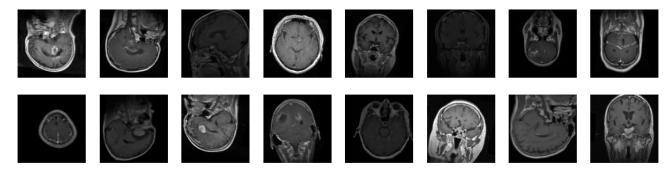


#### 7.3 Testing Data Images Glimpse

# In []:

```
fig, axes = plt.subplots(nrows = 2, ncols = 8, figsize = (20, 5))
fig.suptitle("Samples from Testing Set Batch", fontsize = 16, fontdict = dict(weight = 'bold'))
for curr_axis, curr_image in zip(axes.flatten(), test_dataset[0][0][:16]):
    curr_axis.imshow(tf.squeeze(curr_image), cmap = 'gray')
    curr_axis.axis(False)
```

Samples from Testing Set Batch



#### 8. Model Development

```
In []:
```

```
early_stopping = EarlyStopping(monitor = 'val_accuracy', patience = 10)
```

```
ROOT_CHECKPOINT_DIR_PATH = os.path.join(ROOT_DIR, "Model-Checkpoints")

MLP_CHECKPOINT_DIR_PATH = os.path.join(ROOT_CHECKPOINT_DIR_PATH, "Multi-Layer-Perceptron")

ALEXNET_CHECKPOINT_DIR_PATH = os.path.join(ROOT_CHECKPOINT_DIR_PATH, "AlexNet-CNN")

INCEPTIONV3_CHECKPOINT_DIR_PATH = os.path.join(ROOT_CHECKPOINT_DIR_PATH, "InceptionV3")
```

```
assert os.path.isdir(ROOT_CHECKPOINT_DIR_PATH) and os.path.isdir(MLP_CHECKPOINT_DIR_PATH)

→and os.path.isdir(ALEXNET_CHECKPOINT_DIR_PATH) and os.path.

→isdir(INCEPTIONV3_CHECKPOINT_DIR_PATH)
```

# In []:

```
def training_process_viz(training_stats: pd.DataFrame, **plot_kwargs) -> None:
    fig, axes = plt.subplots(ncols = 2, figsize = (15, 5))
    fig.suptitle(plot_kwargs['plot_title'], fontsize = 16, fontdict = dict(weight = __
\rightarrow'bold'), y = 1.08)
    for curr_axis, col_name in zip(axes, ['accuracy', 'loss']):
        curr_axis.grid(True, alpha = 0.3)
        curr_axis.set_title(f"Model {col_name}".title(), fontsize = 14)
        sns.lineplot(x = range(1, 1 + training_stats.shape[0]), y =__
 →training_stats[col_name], color = 'blue', ax = curr_axis)
        sns.lineplot(x = range(1, 1 + training_stats.shape[0]), y = __
 training_stats[f"val_{col_name}"], color = 'red', ax = curr_axis)
        curr axis.set xlabel("Epochs", fontsize = 12)
        curr_axis.set_ylabel(col_name.title(), fontsize = 12)
        curr_axis.tick_params(which = 'major', labelsize = 12)
        curr_axis.legend([col_name.title(), f"validation {col_name}".title()], title =_u
 →col_name.title())
    fig.tight_layout()
    sns.despine()
```

```
def confusion_matrix_viz(model, test_dataset, **plot_kwargs) -> None:
    assert isinstance(model, Sequential)
    model_preds = [np.argmax(curr_row) for curr_row in model.predict(test_dataset)]
    fig, axis = plt.subplots(figsize = (8, 6))
```

```
def generate_report(*models, test_dataset, row_indexes) -> pd.DataFrame:
    assert len(models)
    report_df = pd.DataFrame(columns = ['MAE', 'MSE', 'RMSE', 'Loss', 'Accuracy',
    'F1-Score'])
    y_hat = test_dataset.classes # y_hat = ground_truth
    for curr_index, curr_model in enumerate(models):
        assert isinstance(curr_model, Sequential)
        curr_model_loss, curr_model_accuracy = curr_model.evaluate(test_dataset)
        y_preds = [np.argmax(curr_preds) for curr_preds in curr_model.predict(test_dataset)]
        report_df.loc[curr_index] = [mean_absolute_error(y_hat, y_preds),
        deman_squared_error(y_hat, y_preds), mean_squared_error(y_hat, y_preds, squared = False),
        deman_squared_loss, curr_model_accuracy, f1_score(y_hat, y_preds, average = "micro")]
    report_df.index = row_indexes
    return report_df
```

#### 8.1 Multi-Layer Perceptron

#### 8.1.1 Development of Multi-Layer Perceptron Model

```
mlp_model = Sequential()
mlp_model.add(Flatten(input_shape = (image_size, image_size, 3), name = 'Flatten-Layer'))
mlp_model.add(Dense(2048, activation = 'relu', name = 'Hidden-Layer-1'))
mlp_model.add(Dropout(rate = 0.2, name = 'Dropout-Layer-1'))
mlp_model.add(Dense(1024, activation = 'relu', name = 'Hidden-Layer-2'))
mlp_model.add(Dropout(rate = 0.2, name = 'Dropout-Layer-2'))
mlp_model.add(Dense(512, activation = 'relu', name = 'Hidden-Layer-3'))
mlp_model.add(Dropout(rate = 0.2, name = 'Dropout-Layer-3'))
mlp_model.add(Dense(4, activation = 'softmax', name = 'Output-Layer-1'))
mlp_model.compile(optimizer = 'Adam', loss = 'categorical_crossentropy', metrics = \( \cdot \) \
```

```
Flatten-Layer (Flatten) (None, 49152)
Hidden-Layer-1 (Dense) (None, 2048)
                                  100665344
Dropout-Layer-1 (Dropout) (None, 2048)
Hidden-Layer-2 (Dense) (None, 1024)
                                  2098176
Dropout-Layer-2 (Dropout) (None, 1024)
Hidden-Layer-3 (Dense) (None, 512)
                                  524800
_____
Dropout-Layer-3 (Dropout) (None, 512)
_____
Output-Layer-1 (Dense) (None, 4)
                                  2052
______
Total params: 103,290,372
Trainable params: 103,290,372
```

Non-trainable params: 0

\_\_\_\_\_

# 8.1.2 Training and Validation of Multi-Layer Perceptron Based Model

```
with tf.device(gpu_device_location) if gpu_device_location else tpu_strategy.scope() if
→tpu_device_location else tf.device(cpu_device_location):
   mlp_train_history = mlp_model.fit(train_dataset,
                                      batch_size = batch_size,
                                      validation_data = validation_dataset,
                                      epochs = 100,
                                      callbacks = [early_stopping])
```

```
Epoch 1/100
- val_loss: 1.3696 - val_accuracy: 0.3299
Epoch 2/100
val_loss: 1.1744 - val_accuracy: 0.5629
Epoch 3/100
val_loss: 1.1415 - val_accuracy: 0.5505
Epoch 4/100
val_loss: 1.1290 - val_accuracy: 0.5670
Epoch 5/100
val_loss: 1.1370 - val_accuracy: 0.5423
Epoch 6/100
val_loss: 1.1002 - val_accuracy: 0.5773
Epoch 7/100
```

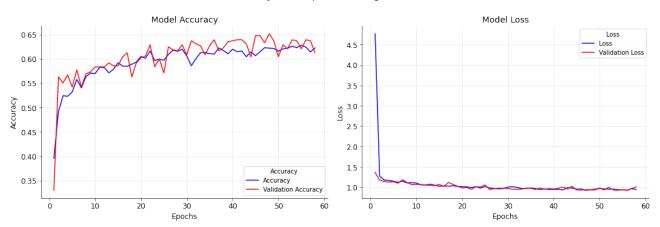
```
val_loss: 1.1865 - val_accuracy: 0.5423
Epoch 8/100
val_loss: 1.1172 - val_accuracy: 0.5691
Epoch 9/100
val_loss: 1.0647 - val_accuracy: 0.5732
Epoch 10/100
val_loss: 1.0703 - val_accuracy: 0.5835
Epoch 11/100
val_loss: 1.0690 - val_accuracy: 0.5835
Epoch 12/100
val_loss: 1.0487 - val_accuracy: 0.5835
Epoch 13/100
val_loss: 1.0513 - val_accuracy: 0.5918
Epoch 14/100
val_loss: 1.0400 - val_accuracy: 0.5856
Epoch 15/100
val_loss: 1.0699 - val_accuracy: 0.5856
Epoch 16/100
val_loss: 1.0210 - val_accuracy: 0.6041
Epoch 17/100
val_loss: 1.1187 - val_accuracy: 0.6124
Epoch 18/100
val_loss: 1.0726 - val_accuracy: 0.5629
Epoch 19/100
val_loss: 1.0249 - val_accuracy: 0.5918
Epoch 20/100
val_loss: 0.9846 - val_accuracy: 0.6021
Epoch 21/100
val_loss: 0.9933 - val_accuracy: 0.6062
Epoch 22/100
val_loss: 0.9511 - val_accuracy: 0.6289
Epoch 23/100
val_loss: 1.0133 - val_accuracy: 0.5835
Epoch 24/100
val_loss: 1.0058 - val_accuracy: 0.6000
```

```
Epoch 25/100
val_loss: 1.0592 - val_accuracy: 0.5711
Epoch 26/100
val_loss: 0.9448 - val_accuracy: 0.6247
Epoch 27/100
val_loss: 0.9680 - val_accuracy: 0.6186
Epoch 28/100
val_loss: 0.9766 - val_accuracy: 0.6165
Epoch 29/100
val_loss: 0.9779 - val_accuracy: 0.6289
Epoch 30/100
val_loss: 0.9709 - val_accuracy: 0.6082
Epoch 31/100
val_loss: 0.9550 - val_accuracy: 0.6371
Epoch 32/100
val_loss: 0.9459 - val_accuracy: 0.6309
Epoch 33/100
val_loss: 0.9566 - val_accuracy: 0.6268
Epoch 34/100
val_loss: 0.9805 - val_accuracy: 0.6082
Epoch 35/100
val_loss: 0.9733 - val_accuracy: 0.6268
Epoch 36/100
val_loss: 0.9485 - val_accuracy: 0.6392
Epoch 37/100
val_loss: 0.9829 - val_accuracy: 0.6165
Epoch 38/100
val_loss: 0.9563 - val_accuracy: 0.6227
Epoch 39/100
val_loss: 0.9691 - val_accuracy: 0.6351
Epoch 40/100
val_loss: 0.9605 - val_accuracy: 0.6371
Epoch 41/100
val_loss: 0.9770 - val_accuracy: 0.6392
Epoch 42/100
```

```
val_loss: 1.0055 - val_accuracy: 0.6392
Epoch 43/100
val_loss: 0.9579 - val_accuracy: 0.6309
Epoch 44/100
val_loss: 1.0254 - val_accuracy: 0.6041
Epoch 45/100
val_loss: 0.9354 - val_accuracy: 0.6474
Epoch 46/100
val_loss: 0.9321 - val_accuracy: 0.6474
Epoch 47/100
val_loss: 0.9412 - val_accuracy: 0.6330
Epoch 48/100
val_loss: 0.9390 - val_accuracy: 0.6515
Epoch 49/100
val_loss: 0.9330 - val_accuracy: 0.6371
Epoch 50/100
val_loss: 0.9832 - val_accuracy: 0.6041
val_loss: 0.9360 - val_accuracy: 0.6289
Epoch 52/100
val_loss: 0.9978 - val_accuracy: 0.6206
Epoch 53/100
val_loss: 0.9343 - val_accuracy: 0.6392
Epoch 54/100
val_loss: 0.9262 - val_accuracy: 0.6371
Epoch 55/100
val_loss: 0.9395 - val_accuracy: 0.6206
Epoch 56/100
val_loss: 0.9245 - val_accuracy: 0.6392
Epoch 57/100
val_loss: 0.9657 - val_accuracy: 0.6371
Epoch 58/100
val_loss: 1.0117 - val_accuracy: 0.6124
```

#### 8.1.3 Multi-Layer Perceptron Based Model Training Process Statistics

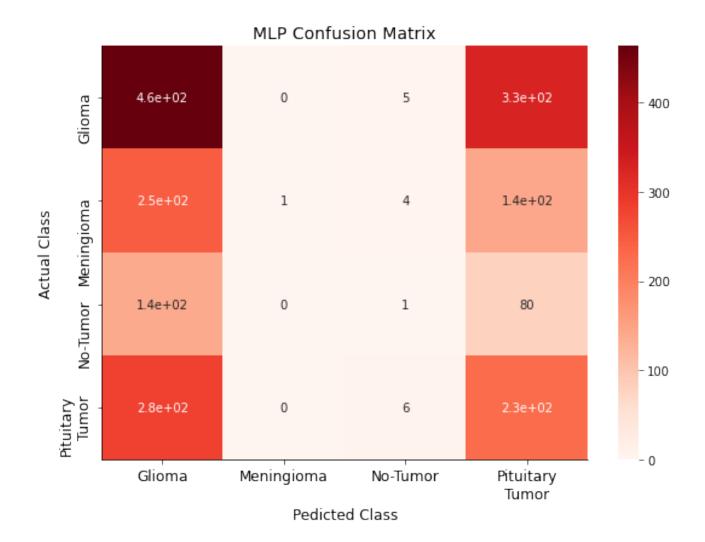
#### Multilayer Perceptron Training Statistics



# 8.1.4 Confusion Matrix for Multi-Layer Perceptron Based Model

# In []:

confusion\_matrix\_viz(mlp\_model, train\_dataset, plot\_title = "MLP Confusion Matrix")



#### 8.2 AlexNet CNN

#### 8.2.1 Develoment of AlexNet CNN Model

```
alexnet cnn = Sequential()
alexnet_cnn.add(Conv2D(96, kernel_size = 11, strides = 4, activation = 'relu', input_shape_
 alexnet_cnn.add(BatchNormalization(name = 'Batch-Normalization-1'))
alexnet_cnn.add(MaxPool2D(pool_size = 3, strides = 2, name = 'Max-Pooling-1'))
alexnet_cnn.add(Conv2D(256, kernel_size = 5, padding = 'same', activation = 'relu', name = __
 alexnet_cnn.add(BatchNormalization(name = 'Batch-Normalization-2'))
alexnet_cnn.add(MaxPool2D(pool_size = 3, strides = 2, name = 'Max-Pooling-2'))
alexnet_cnn.add(Conv2D(384, kernel_size = 3, padding = 'same', activation = 'relu', name = __
 \rightarrow 'Conv2D-3'))
alexnet_cnn.add(BatchNormalization(name = 'Batch-Normalization-3'))
alexnet_cnn.add(Conv2D(384, kernel_size = 3, padding = 'same', activation = 'relu', name = u
 \hookrightarrow 'Conv2D-4'))
alexnet cnn.add(BatchNormalization(name = 'Batch-Normalization-4'))
alexnet_cnn.add(Conv2D(256, kernel_size = 3, padding = 'same', activation = 'relu', name = 1
 \hookrightarrow 'Conv2D-5'))
alexnet_cnn.add(BatchNormalization(name = 'Batch-Normalization-5'))
alexnet_cnn.add(MaxPool2D(pool_size = 3, strides = 2, name = 'Max-Pooling-3'))
alexnet_cnn.add(Flatten(name = 'Flatten-Layer-1'))
alexnet_cnn.add(Dense(128, activation = 'relu', name = 'Hidden-Layer-1'))
alexnet_cnn.add(Dropout(rate = 0.5, name = 'Dropout-Layer-1'))
alexnet_cnn.add(Dense(64, activation = 'relu', name = 'Hidden-Layer-2'))
alexnet_cnn.add(Dropout(rate = 0.5, name = 'Dropout-Layer-2'))
alexnet_cnn.add(Dense(4, activation = 'softmax', name = 'Output-Layer'))
alexnet_cnn.compile(optimizer = 'Adam', loss = 'categorical_crossentropy', metrics = 'categorical_crossentro
 →['accuracy'])
alexnet_cnn.summary()
```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
Conv2D-1 (Conv2D)	(None, 30, 30, 96)	34944
Batch-Normalization-1 (Batch	(None, 30, 30, 96)	384
Max-Pooling-1 (MaxPooling2D)	(None, 14, 14, 96)	0
Conv2D-2 (Conv2D)	(None, 14, 14, 256)	614656
Batch-Normalization-2 (Batch	(None, 14, 14, 256)	1024
Max-Pooling-2 (MaxPooling2D)	(None, 6, 6, 256)	0
Conv2D-3 (Conv2D)	(None, 6, 6, 384)	885120
Batch-Normalization-3 (Batch	(None, 6, 6, 384)	1536
Conv2D-4 (Conv2D)	(None, 6, 6, 384)	1327488

Batch-Normalization-4 (Batch	(None, 6, 6, 384)	1536
Conv2D-5 (Conv2D)	(None, 6, 6, 256)	884992
Batch-Normalization-5 (Batch	(None, 6, 6, 256)	1024
Max-Pooling-3 (MaxPooling2D)	(None, 2, 2, 256)	0
Flatten-Layer-1 (Flatten)	(None, 1024)	0
Hidden-Layer-1 (Dense)	(None, 128)	131200
Dropout-Layer-1 (Dropout)	(None, 128)	0
Hidden-Layer-2 (Dense)	(None, 64)	8256
Dropout-Layer-2 (Dropout)	(None, 64)	0
Output-Layer (Dense)	(None, 4)	260
Total params: 3,892,420 Trainable params: 3,889,668 Non-trainable params: 2,752		

#### 8.2.2 Training and Validation of AlexNet CNN Model

```
with tf.device(gpu_device_location) if gpu_device_location else tpu_strategy.scope() if u
 →tpu_device_location else tf.device(cpu_device_location):
   alexnet_train_history = alexnet_cnn.fit(train_dataset,
                                batch_size = batch_size,
                                validation_data = validation_dataset,
                                epochs = 100,
                                callbacks = [early_stopping,_
 →alexnet_cp_callback])
Epoch 1/100
val_loss: 1.3511 - val_accuracy: 0.3361
Epoch 00001: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 2/100
val_loss: 1.4838 - val_accuracy: 0.2701
Epoch 00002: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 3/100
val_loss: 1.4569 - val_accuracy: 0.2825
```

```
Epoch 00003: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/AlexNet-CNN
Epoch 4/100
val_loss: 1.2596 - val_accuracy: 0.4433
Epoch 00004: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 5/100
val_loss: 1.9028 - val_accuracy: 0.4124
Epoch 00005: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 6/100
val_loss: 1.1000 - val_accuracy: 0.5464
Epoch 00006: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 7/100
val_loss: 1.3219 - val_accuracy: 0.5093
Epoch 00007: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/AlexNet-CNN
Epoch 8/100
val_loss: 1.0640 - val_accuracy: 0.5711
Epoch 00008: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/AlexNet-CNN
Epoch 9/100
val_loss: 1.0312 - val_accuracy: 0.6041
Epoch 00009: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 10/100
val_loss: 1.0401 - val_accuracy: 0.5711
Epoch 00010: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 11/100
val_loss: 1.3941 - val_accuracy: 0.4969
Epoch 00011: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 12/100
```

```
val_loss: 1.0185 - val_accuracy: 0.5773
Epoch 00012: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 13/100
val_loss: 1.2468 - val_accuracy: 0.5546
Epoch 00013: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 14/100
val_loss: 0.8579 - val_accuracy: 0.6639
Epoch 00014: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 15/100
val_loss: 1.0546 - val_accuracy: 0.6206
Epoch 00015: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 16/100
val_loss: 0.8214 - val_accuracy: 0.6825
Epoch 00016: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 17/100
val_loss: 0.8492 - val_accuracy: 0.6825
Epoch 00017: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 18/100
val_loss: 1.1481 - val_accuracy: 0.5320
Epoch 00018: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 19/100
val_loss: 0.8517 - val_accuracy: 0.6660
Epoch 00019: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 20/100
val_loss: 1.0671 - val_accuracy: 0.5856
```

Epoch 00020: saving model to gdrive/MyDrive/Deep\_Learning\_Course\_Project/Model-

```
Checkpoints/AlexNet-CNN
Epoch 21/100
val_loss: 0.7761 - val_accuracy: 0.6825
Epoch 00021: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 22/100
val_loss: 0.7683 - val_accuracy: 0.6845
Epoch 00022: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 23/100
val_loss: 0.8285 - val_accuracy: 0.6412
Epoch 00023: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 24/100
val_loss: 0.9983 - val_accuracy: 0.6062
Epoch 00024: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 25/100
val_loss: 0.7648 - val_accuracy: 0.6907
Epoch 00025: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 26/100
val_loss: 0.7971 - val_accuracy: 0.6701
Epoch 00026: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 27/100
val_loss: 0.7770 - val_accuracy: 0.6866
Epoch 00027: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 28/100
val_loss: 0.8068 - val_accuracy: 0.6701
Epoch 00028: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 29/100
val_loss: 0.9703 - val_accuracy: 0.5814
```

```
Epoch 00029: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/AlexNet-CNN
Epoch 30/100
val_loss: 0.9537 - val_accuracy: 0.5876
Epoch 00030: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 31/100
val_loss: 0.6383 - val_accuracy: 0.7299
Epoch 00031: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 32/100
val_loss: 0.6763 - val_accuracy: 0.7361
Epoch 00032: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 33/100
val_loss: 0.6968 - val_accuracy: 0.7196
Epoch 00033: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/AlexNet-CNN
Epoch 34/100
val_loss: 0.6255 - val_accuracy: 0.7340
Epoch 00034: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/AlexNet-CNN
Epoch 35/100
val_loss: 0.6555 - val_accuracy: 0.7361
Epoch 00035: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 36/100
val_loss: 0.8182 - val_accuracy: 0.6619
Epoch 00036: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 37/100
val_loss: 0.7252 - val_accuracy: 0.6969
Epoch 00037: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 38/100
```

```
val_loss: 1.1803 - val_accuracy: 0.5464
Epoch 00038: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 39/100
val_loss: 0.7726 - val_accuracy: 0.6887
Epoch 00039: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 40/100
val_loss: 0.7610 - val_accuracy: 0.7010
Epoch 00040: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 41/100
val_loss: 0.7677 - val_accuracy: 0.6784
Epoch 00041: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/AlexNet-CNN
Epoch 42/100
val_loss: 1.0997 - val_accuracy: 0.6268
```

 ${\tt Epoch~00042:~saving~model~to~gdrive/MyDrive/Deep\_Learning\_Course\_Project/Model-Checkpoints/AlexNet-CNN}$ 

#### 8.2.3 AlexNet CNN Model Training Process Statistics

### In []:

 $\label{training_process_viz} $$\operatorname{train_pistory.history}, \ plot_title = 'AlexNet \ CNN_{\sqcup} \hookrightarrow Training \ Stats')$$ 



#### 8.2.4 Confusion Matrix for AlexNet CNN Model

# In []:

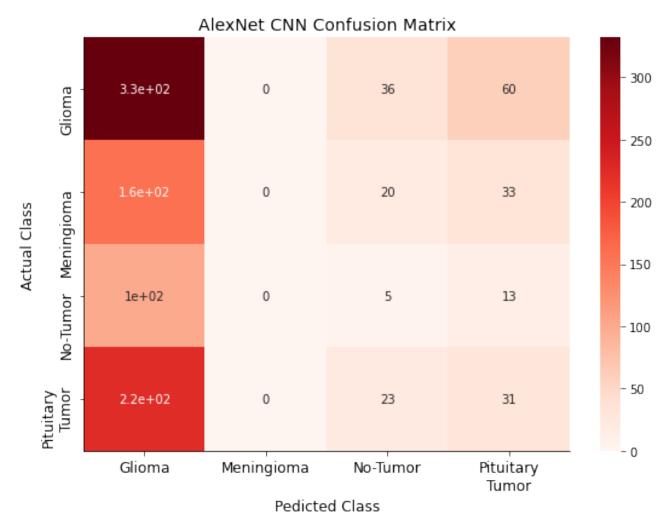
```
with tf.device(gpu_device_location) if gpu_device_location else tpu_strategy.scope() if 

→tpu_device_name else tf.device(cpu_device_location):

confusion_matrix_viz(alexnet_cnn,

test_dataset,

plot_title = "AlexNet CNN Confusion Matrix")
```



# In []:

```
alexnet_report_df = generate_report(alexnet_cnn, test_dataset = test_dataset, row_indexes = Graduate = G
```

Out []:

```
MAE MSE RMSE Loss Accuracy F1-Score AlexNet CNN 1.301541 3.205202 1.790308 1.135692 0.6079 0.382466
```

#### 8.3 Inception V3

#### 8.3.1 Developement of InceptionV3

#### In []:

#### In []:

#### Model: "sequential\_2"

Layer (type)	Output Shape	Param #
inception_v3 (Functional)	(None, 2048)	21802784
flatten (Flatten)	(None, 2048)	0
Hidden-Layer-1 (Dense)	(None, 1024)	2098176
Output-Layer (Dense)	(None, 4)	4100
Total params: 23,905,060 Trainable params: 2,102,276 Non-trainable params: 21,802	,784	

#### 8.3.2 Training and Validation of InceptionV3 Model

```
with tf.device(gpu_device_location) if gpu_device_location else tpu_strategy.scope() if_u 

tpu_device_location else tf.device(cpu_device_location):
inception_model_train_history = inception_cnn_model.fit(train_dataset,
```

```
batch_size = batch_size,
                                       validation_data =_
 →validation_dataset,
                                       epochs = 100,
                                       callbacks = [early_stopping,_
 →inceptionv3_cp_callback])
Epoch 1/100
val_loss: 0.7379 - val_accuracy: 0.7113
Epoch 00001: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 2/100
val_loss: 0.6218 - val_accuracy: 0.7979
Epoch 00002: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 3/100
val_loss: 0.6042 - val_accuracy: 0.7835
Epoch 00003: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 4/100
val_loss: 0.8480 - val_accuracy: 0.6536
Epoch 00004: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 5/100
val_loss: 0.5721 - val_accuracy: 0.7732
Epoch 00005: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 6/100
val_loss: 0.6748 - val_accuracy: 0.7485
Epoch 00006: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 7/100
val_loss: 0.5046 - val_accuracy: 0.8000
Epoch 00007: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 8/100
val_loss: 0.6136 - val_accuracy: 0.7649
```

```
Epoch 00008: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/InceptionV3
Epoch 9/100
val_loss: 0.5283 - val_accuracy: 0.7876
Epoch 00009: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 10/100
val_loss: 0.5484 - val_accuracy: 0.8000
Epoch 00010: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 11/100
val_loss: 0.4995 - val_accuracy: 0.8062
Epoch 00011: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 12/100
val_loss: 0.5364 - val_accuracy: 0.7979
Epoch 00012: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/InceptionV3
Epoch 13/100
val_loss: 0.5230 - val_accuracy: 0.7835
Epoch 00013: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/InceptionV3
Epoch 14/100
val_loss: 0.5177 - val_accuracy: 0.7979
Epoch 00014: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 15/100
val_loss: 0.5387 - val_accuracy: 0.7979
Epoch 00015: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 16/100
val_loss: 0.5662 - val_accuracy: 0.7814
Epoch 00016: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 17/100
```

```
val_loss: 0.5143 - val_accuracy: 0.7938
Epoch 00017: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 18/100
val_loss: 0.5568 - val_accuracy: 0.7959
Epoch 00018: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 19/100
val_loss: 0.4909 - val_accuracy: 0.8206
Epoch 00019: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 20/100
val_loss: 0.6110 - val_accuracy: 0.7423
Epoch 00020: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 21/100
val_loss: 0.5006 - val_accuracy: 0.7959
Epoch 00021: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 22/100
val_loss: 0.4776 - val_accuracy: 0.8206
Epoch 00022: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 23/100
val_loss: 0.4448 - val_accuracy: 0.8206
Epoch 00023: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 24/100
val_loss: 0.4913 - val_accuracy: 0.8227
Epoch 00024: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 25/100
val_loss: 0.5133 - val_accuracy: 0.8206
```

Epoch 00025: saving model to gdrive/MyDrive/Deep\_Learning\_Course\_Project/Model-

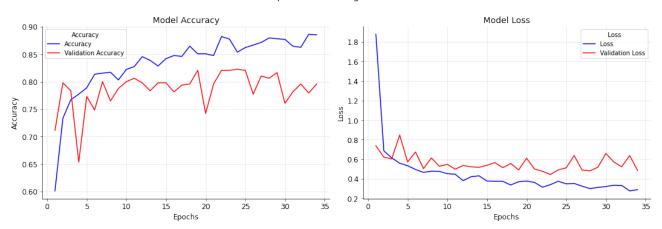
```
Checkpoints/InceptionV3
Epoch 26/100
val_loss: 0.6384 - val_accuracy: 0.7773
Epoch 00026: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 27/100
val_loss: 0.4896 - val_accuracy: 0.8103
Epoch 00027: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/InceptionV3
Epoch 28/100
val_loss: 0.4820 - val_accuracy: 0.8062
Epoch 00028: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 29/100
val_loss: 0.5193 - val_accuracy: 0.8165
Epoch 00029: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 30/100
val_loss: 0.6595 - val_accuracy: 0.7608
Epoch 00030: saving model to gdrive/MyDrive/Deep Learning Course Project/Model-
Checkpoints/InceptionV3
Epoch 31/100
val_loss: 0.5732 - val_accuracy: 0.7814
Epoch 00031: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 32/100
val_loss: 0.5237 - val_accuracy: 0.7959
Epoch 00032: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 33/100
val_loss: 0.6379 - val_accuracy: 0.7794
Epoch 00033: saving model to gdrive/MyDrive/Deep_Learning_Course_Project/Model-
Checkpoints/InceptionV3
Epoch 34/100
val_loss: 0.4858 - val_accuracy: 0.7959
```

 ${\tt Epoch~00034:~saving~model~to~gdrive/MyDrive/Deep\_Learning\_Course\_Project/Model-Checkpoints/InceptionV3}$ 

### 8.3.3 InceptionV3 Model Training Process Statistics

# In []:

#### Inception-V3 Training Statistics



#### 8.3.4 Confusion Matrix for InceptionV3 Model

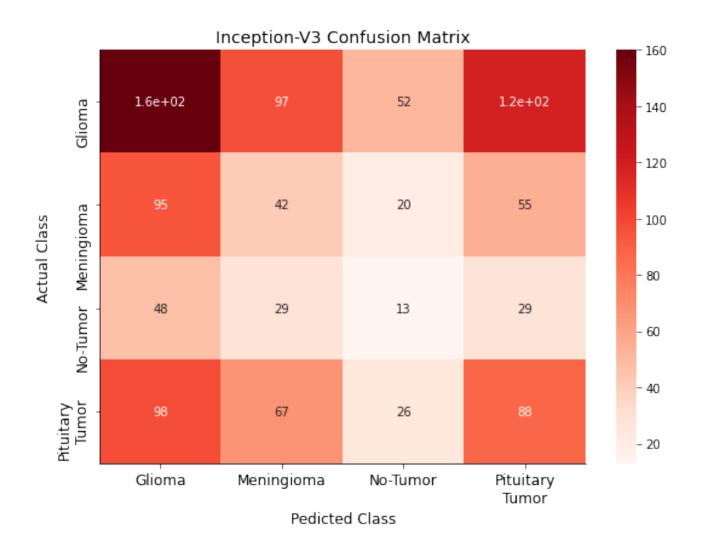
```
with tf.device(gpu_device_location) if gpu_device_location else tpu_strategy.scope() if 

tpu_device_location else tf.device(cpu_device_name):

confusion_matrix_viz(inception_cnn_model,

test_dataset,

plot_title = "Inception-V3 Confusion Matrix")
```



Out []:

MAE MSE RMSE Loss Accuracy F1-Score

InceptionV3 1.365125 3.101156 1.76101 0.452249

#### 9. Conclusions

• The **pre-trained (imagenet) InceptionV3** model has performed the best among Multi-Layer perceptron and AlexNet CNN models with an accuracy of 82.57% (Refer the following table).

0.825626

0.2842

```
final_report_df = pd.concat([mlp_report_df, alexnet_report_df, inceptionv3_report_df])
final_report_df
```

# Out []:

```
MAE
                                            MSE
                                                 ... Accuracy F1-Score
Multi-Layer-Perceptron Model
                             1.394990
                                       3.533719
                                                    0.624277
                                                              0.368979
AlexNet CNN
                             1.301541
                                       3.205202
                                                    0.607900
                                                              0.382466
InceptionV3
                             1.365125 3.101156 ...
                                                    0.825626 0.284200
```

[3 rows x 6 columns]

#### 10. Future Works

- To incorporate a Data Augmentation pipeline to efficiently generate various different variants of the iamges to make the model more roboust.
- Training process will be migrated to TPUs (Tensor Processing Units) by representing the data in TFRecord format for significant reduction in training time.
- Implementation of R-CNN to not only detect a image which has a tumor in it but to also label the location of the tumor in the image.