Project-2

April 25, 2023

```
[1]: import numpy as np
     import os
     import pandas as pd
     import cv2
     from tqdm import tqdm
     import io
     from keras.layers import Input, Lambda, Dense, Flatten
     from keras.models import Model
     from keras.applications.vgg16 import VGG16
     from keras.applications.vgg16 import preprocess_input
     from keras.preprocessing import image
     from keras.preprocessing.image import ImageDataGenerator
     from keras.models import Sequential
     import numpy as np
     from glob import glob
     import matplotlib.pyplot as plt
     import warnings
     import seaborn as sns
     import matplotlib.pyplot as plt
     from sklearn.utils import shuffle # Shuffle arrays or sparse matrices in a_{\sqcup}
      ⇔consistent way
     from sklearn.model_selection import train_test_split
     from tensorflow.keras.utils import to_categorical
     from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
      →Dropout
     from tensorflow.keras.models import Sequential, load_model
     from sklearn.metrics import classification_report, confusion_matrix
     import warnings as wr
     wr.filterwarnings('ignore')
```

```
[2]: labels = ['Glioma', 'Meningioma', 'Notumor', 'Pituitary']
IMG_SIZE = [224, 224]
```

```
[3]: #Training Dataset
     X_train = []
     #Training Labels
     Y_train = []
     img_size=224
     for i in labels:
         dataset_path = os.path.join('dataset', 'Training', i)
         for j in tqdm(os.listdir(dataset_path)):
             image = cv2.imread(os.path.join(dataset path, j))
             image = cv2.resize(image, (img_size, img_size))
             X_train.append(image)
             Y_train.append(i)
     for i in labels:
         dataset_path = os.path.join('dataset', 'Testing', i) # Join two or more_
      ⇒pathname components
         for j in tqdm(os.listdir(dataset_path)):
             image = cv2.imread(os.path.join(dataset_path, j))
             image = cv2.resize(image, (img_size, img_size))
             X_train.append(image)
             Y_train.append(i)
     #Converting list into array
     X_train = np.array(X_train)
     Y_train = np.array(Y_train)
              | 1321/1321 [00:02<00:00, 440.58it/s]
    100%
    100%|
              | 1339/1339 [00:04<00:00, 313.06it/s]
    100%|
              | 1595/1595 [00:03<00:00, 424.49it/s]
              | 1457/1457 [00:04<00:00, 306.82it/s]
    100%|
    100%|
              | 300/300 [00:00<00:00, 365.94it/s]
              | 306/306 [00:00<00:00, 485.90it/s]
    100%|
              | 405/405 [00:00<00:00, 737.65it/s]
    100%|
    100%|
              | 300/300 [00:00<00:00, 458.54it/s]
[4]: #Training dataset size
    X_train.shape
[4]: (7023, 224, 224, 3)
[5]: # Shuffling data
     X_train, Y_train = shuffle(X_train, Y_train, random_state=42)
```

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[6]: #After shuffling sample size remains same
X_train.shape

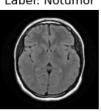
[6]: (7023, 224, 224, 3)

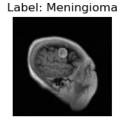
[7]: grid_w = 4
    grid_h = 4
    f, ax = plt.subplots(grid_w, grid_h)
    f.set_size_inches(8, 8)

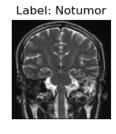
image_index = 0
    for i in range(0, grid_w):
        for j in range(0, grid_h):
            ax[i][j].axis('off')
            ax[i][j].set_title('Label: '+Y_train[image_index])
            ax[i][j].imshow(X_train[image_index])
            image_index += 1

plt.subplots_adjust(left=0, bottom=0, right=1, top=1, wspace=0.2, hspace=0.55)
```

Label: Notumor





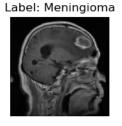


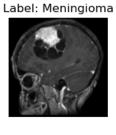


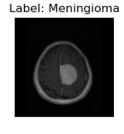




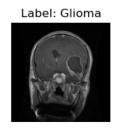


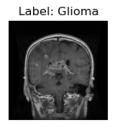
















Label: Notumor

```
[8]: X_train, X_test, Y_train, Y_test = train_test_split(X_train, Y_train, ___
      →test_size=0.2, random_state=42)
```

```
[9]: y_train_new = []
     #y_valid_new = []
     y_test_new = []
     for i in Y_train:
         y_train_new.append(labels.index(i))
     Y_train = to_categorical(y_train_new)
```

[11]: vgg16 = VGG16(input_shape=IMG_SIZE + [3], weights='imagenet', include_top=False)
for layer in vgg16.layers:
 layer.trainable = False

[12]: x = Flatten()(vgg16.output)
prediction = Dense(4, activation='softmax')(x)
CNN_model = Model(inputs=vgg16.input, outputs=prediction)

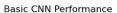
[13]: CNN_model.summary()

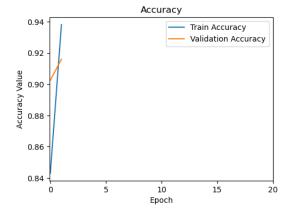
Model: "model"

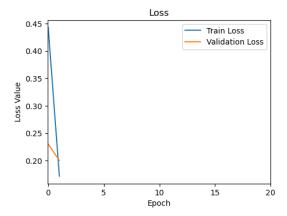
Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168

```
block3_conv2 (Conv2D)
                                 (None, 56, 56, 256)
                                                          590080
                                                          590080
      block3_conv3 (Conv2D)
                                 (None, 56, 56, 256)
                                 (None, 28, 28, 256)
      block3_pool (MaxPooling2D)
                                                          0
      block4 conv1 (Conv2D)
                                 (None, 28, 28, 512)
                                                          1180160
      block4 conv2 (Conv2D)
                                 (None, 28, 28, 512)
                                                          2359808
      block4_conv3 (Conv2D)
                                 (None, 28, 28, 512)
                                                          2359808
      block4_pool (MaxPooling2D)
                                 (None, 14, 14, 512)
      block5_conv1 (Conv2D)
                                 (None, 14, 14, 512)
                                                          2359808
      block5_conv2 (Conv2D)
                                 (None, 14, 14, 512)
                                                          2359808
      block5_conv3 (Conv2D)
                                 (None, 14, 14, 512)
                                                          2359808
                                 (None, 7, 7, 512)
      block5_pool (MaxPooling2D)
                                 (None, 25088)
      flatten (Flatten)
      dense (Dense)
                                 (None, 4)
                                                          100356
     ______
     Total params: 14,815,044
     Trainable params: 100,356
     Non-trainable params: 14,714,688
[14]: CNN_model.compile(
       loss='categorical_crossentropy',
       optimizer='adam',
       metrics=['accuracy']
[15]: # Model Scaling
     X_train_scaled = X_train.astype('float32')
     X_test_scaled = X_test.astype('float32')
     X_train_scaled /= 255
     X test scaled \neq 255
```

```
[16]: model_training = CNN_model.fit(x=X_train_scaled, y=Y_train,
                      validation_data=(X_test_scaled, Y_test),
                      batch_size=32,
                      epochs=2,
                      verbose=1)
    Epoch 1/2
    accuracy: 0.8430 - val_loss: 0.2302 - val_accuracy: 0.9025
    accuracy: 0.9382 - val_loss: 0.2004 - val_accuracy: 0.9160
[21]: f, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
     t = f.suptitle('Basic CNN Performance', fontsize=12)
     f.subplots_adjust(top=0.85, wspace=0.3)
     epoch_list = list(range(1,21))
     ax1.plot(model_training.history['accuracy'], label='Train Accuracy')
     ax1.plot(model_training.history['val_accuracy'], label='Validation Accuracy')
     ax1.set_xticks(np.arange(0, 21, 5))
     ax1.set_ylabel('Accuracy Value')
     ax1.set_xlabel('Epoch')
     ax1.set_title('Accuracy')
     11 = ax1.legend(loc="best")
     ax2.plot(model training.history['loss'], label='Train Loss')
     ax2.plot(model_training.history['val_loss'], label='Validation Loss')
     ax2.set_xticks(np.arange(0, 21, 5))
     ax2.set_ylabel('Loss Value')
     ax2.set_xlabel('Epoch')
     ax2.set title('Loss')
     12 = ax2.legend(loc="best")
```

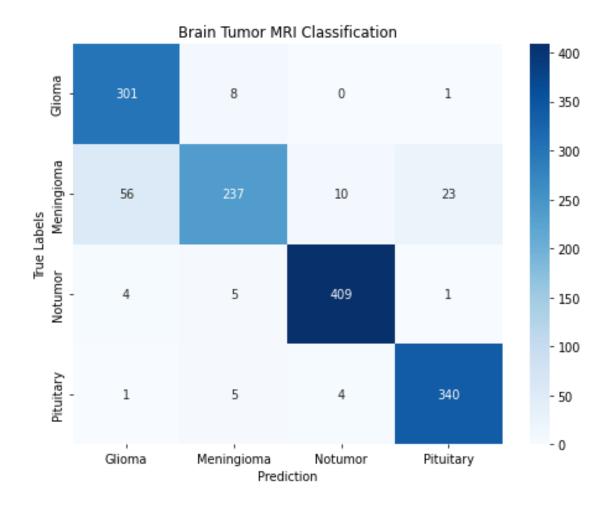






```
[23]: # Getting model predictions
  test_predictions = CNN_model.predict(X_test_scaled)
  preds = np.argmax(test_predictions, axis=1)
  actual_label = np.argmax(Y_test, axis=1)
  print(classification_report(actual_label, preds))
```

```
44/44 [======== ] - 177s 4s/step
                         recall f1-score
             precision
                                           support
          0
                 0.83
                           0.97
                                    0.90
                                               310
                 0.93
                           0.73
                                    0.82
          1
                                               326
          2
                 0.97
                           0.98
                                    0.97
                                               419
          3
                 0.93
                           0.97
                                    0.95
                                               350
   accuracy
                                    0.92
                                              1405
                                    0.91
                                              1405
  macro avg
                 0.91
                           0.91
weighted avg
                 0.92
                           0.92
                                    0.91
                                              1405
```

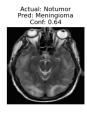


```
[25]: grid_w = 5
     grid_h = 5
     f, ax = plt.subplots(grid_w, grid_h)
     f.set_size_inches(15, 15)
     image_index = 0
     for i in range(0, grid_w):
         for j in range(0, grid_h):
            actual = actual_label[image_index]
            predicted = preds[image_index]
            confidence = round(test_predictions[image_index][predicted], 2)
             ax[i][j].axis('off')
             ax[i][j].set_title('Actual: '+labels[actual]+'\nPred:__
      ax[i][j].imshow(X_test[image_index])
             image_index += 1
     plt.subplots_adjust(left=0, bottom=0, right=1, top=1, wspace=0.5, hspace=0.55)
```

Actual: Notumor Pred: Notumor Conf: 1.0



Actual: Pituitary Pred: Pituitary Conf: 1.0

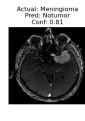


Actual: Pituitary Pred: Pituitary Conf: 1.0





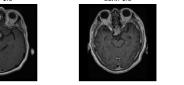
Actual: Notumor Pred: Notumor Conf: 1.0



Actual: Pituitary Pred: Notumor Conf: 0.53



Actual: Glioma Pred: Glioma Conf: 0.99



Actual: Glioma A Pred: Meningioma F Conf: 0.64



Actual: Notumor Pred: Notumor Conf: 1.0



Actual: Notumor Pred: Notumor Conf: 1.0



Actual: Notumor Pred: Notumor Conf: 1.0

Actual: Pituitary Pred: Pituitary Conf: 1.0



Actual: Notumor Pred: Notumor Conf: 0.99



Actual: Pituitary Pred: Pituitary Conf: 0.99



Actual: Glioma Pred: Glioma Conf: 0.97



Actual: Notumor Pred: Notumor Conf: 1.0



Actual: Meningioma Pred: Meningioma Conf: 0.74



Actual: Notumor Pred: Notumor Conf: 1.0



Actual: Notumor Pred: Notumor Conf: 0.99



Actual: Notumor Pred: Notumor Conf: 0.98



Actual: Pituitary Pred: Pituitary Conf: 0.99



Actual: Notumor Pred: Notumor Conf: 1.0



ituitary Pred: Not : 0.99 Conf: 1







[]: