A4_Final

February 3, 2023

1 Data Preprocessing

[282]:
```
import tensorflow as tf
import matplotlib.pyplot as plt
import numpy as np
import os
import pathlib
import random
```

[283]:
```
path = '/Users/richardreynard/Downloads/AY 2022/SP53:22/MA3832/Assignment4/
↪Dataset/'
data_dir = pathlib.Path(path)
```

[284]:
```
class_names = np.array([sorted(item.name for item in data_dir.glob("*"))])
class_names
```

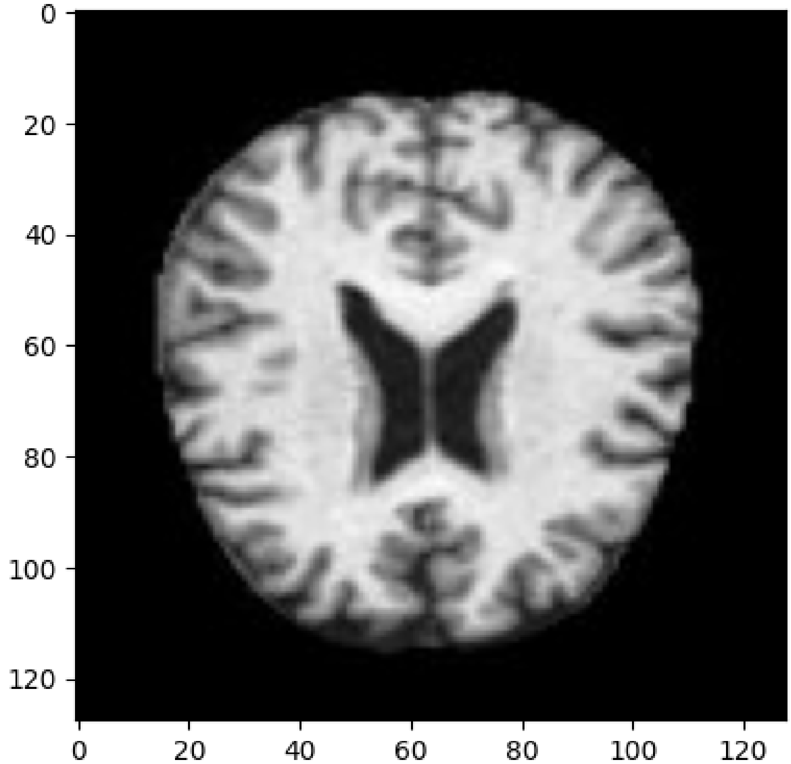
[284]:
```
array([['.DS_Store', 'Mild_Demented', 'Moderate_Demented',
        'Non_Demented', 'Very_Mild_Demented']], dtype='<U18')
```

[285]:
```
imageCount = len(list(data_dir.glob("*/*.jpg") ))
imageCount
```

[285]:
```
6400
```

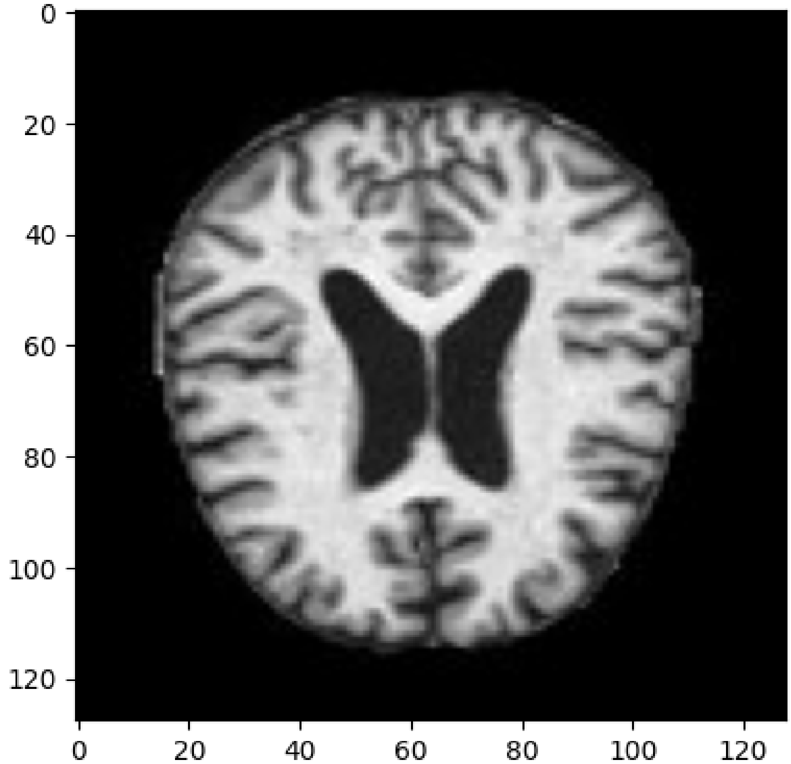
[286]:
```
import cv2
from matplotlib import pyplot as plt
non_demented_image = cv2.imread("Dataset/Non_Demented/non.jpg")
plt.imshow(non_demented_image)
```

[286]:
```
<matplotlib.image.AxesImage at 0x7fd257fb1c40>
```



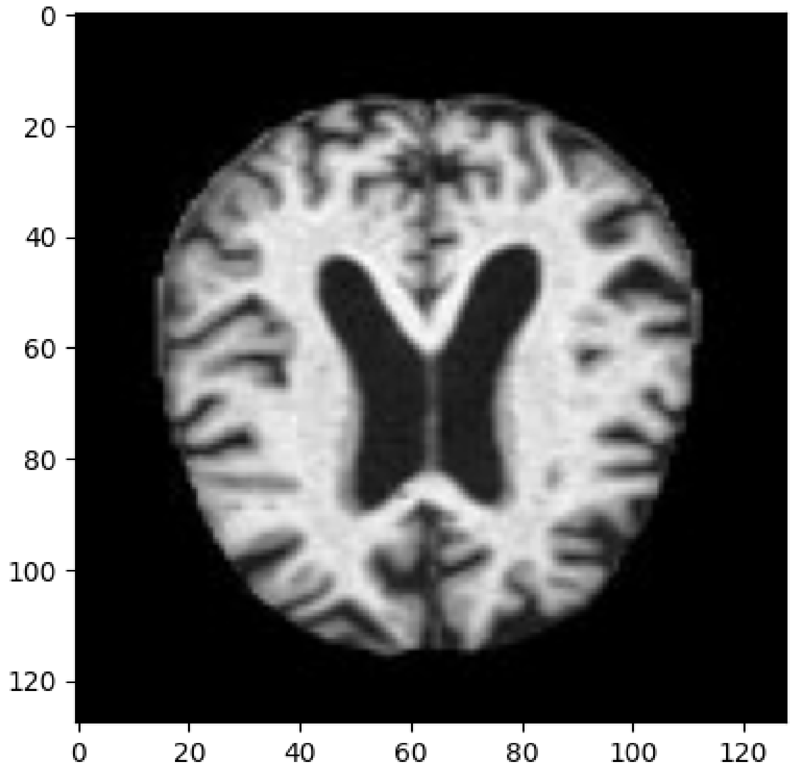
[287]:
```
very_mild_demented_image = cv2.imread("Dataset/Very_Mild_Demented/verymild.jpg")
plt.imshow(very_mild_demented_image)
```

[287]: <matplotlib.image.AxesImage at 0x7fd1da92fc10>



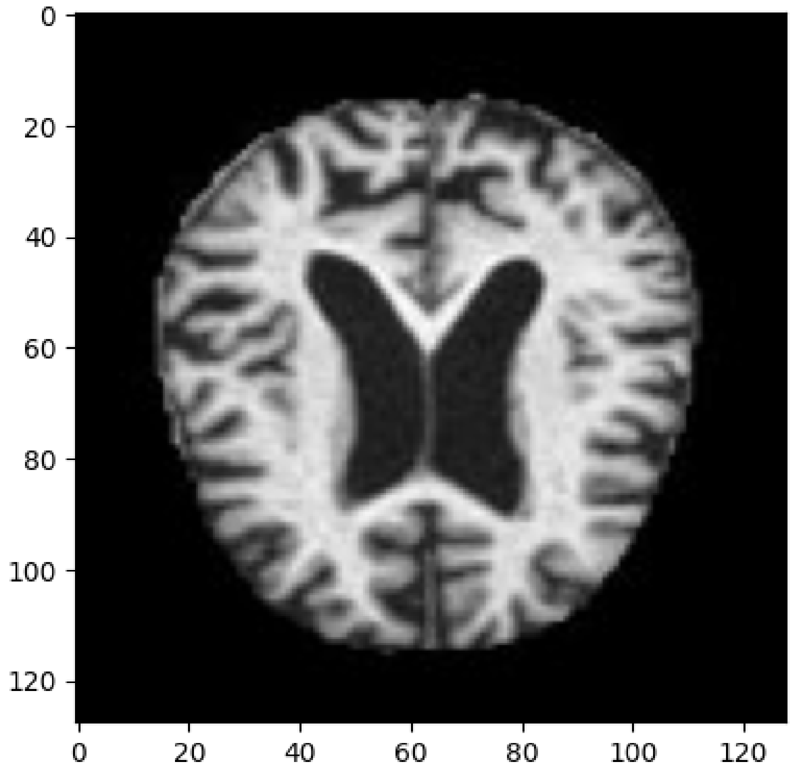
[288]:
```
mild_demented_image = cv2.imread("Dataset/Mild_Demented/mild.jpg")
plt.imshow(mild_demented_image)
```

[288]: <matplotlib.image.AxesImage at 0x7fd2b9eb8700>



[289]:
```
moderate_demented_image = cv2.imread("Dataset/Moderate_Demented/moderate.jpg")
plt.imshow(moderate_demented_image)
```

[289]: <matplotlib.image.AxesImage at 0x7fce41252700>



[296]:
```
batch_size = 32
img_height = 256
img_width = 256
```

[297]:
```
from tensorflow.keras.utils import image_dataset_from_directory
from tensorflow.keras.utils import image_dataset_from_directory

train_data = image_dataset_from_directory(
                  data_dir,
                  validation_split=0.2,
                  subset="training",
                  seed=123,
                  image_size=(img_height, img_width),
                  batch_size=batch_size)



val_data = image_dataset_from_directory(data_dir,
                                        validation_split=0.2,
                                        subset="validation",
                                        seed=123,
                                        image_size=(img_height,img_width),
                                        batch_size=batch_size)
```

```
Found 6400 files belonging to 4 classes.
Using 5120 files for training.
Found 6400 files belonging to 4 classes.
Using 1280 files for validation.
```

2 Build Model

[302]:
```
from tensorflow.keras import layers

model = tf.keras.Sequential([

   layers.Rescaling(1./255, input_shape=(img_height, img_width, 3)),

  layers.Conv2D(16, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),

  layers.Conv2D(32, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),

  layers.Conv2D(64, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),

  layers.Conv2D(128, 3, padding='same', activation='relu'),
  layers.MaxPooling2D(),

  layers.Dropout(0.5),
  layers.Flatten(),

  layers.Dense(128, activation='relu'),
  layers.Dense(4,activation="softmax")
])
```

[303]:
```
model.compile(optimizer="Adam",
            loss=tf.keras.losses.SparseCategoricalCrossentropy(),
            metrics=["accuracy"])
model.summary()
```

```
Model: "sequential_61"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 rescaling_32 (Rescaling)    (None, 256, 256, 3)       0

 conv2d_106 (Conv2D)         (None, 256, 256, 16)      448

 max_pooling2d_121 (MaxPooli  (None, 128, 128, 16)     0
 ng2D)
```

```
 conv2d_107 (Conv2D)         (None, 128, 128, 32)      4640

 max_pooling2d_122 (MaxPooli  (None, 64, 64, 32)       0
 ng2D)

 conv2d_108 (Conv2D)         (None, 64, 64, 64)        18496

 max_pooling2d_123 (MaxPooli  (None, 32, 32, 64)       0
 ng2D)

 conv2d_109 (Conv2D)         (None, 32, 32, 128)       73856

 max_pooling2d_124 (MaxPooli  (None, 16, 16, 128)      0
 ng2D)

 dropout_44 (Dropout)        (None, 16, 16, 128)       0

 flatten_44 (Flatten)        (None, 32768)             0

 dense_125 (Dense)           (None, 128)               4194432

 dense_126 (Dense)           (None, 4)                 516

=================================================================
Total params: 4,292,388
Trainable params: 4,292,388
Non-trainable params: 0
_________________________________________________________________
```

[304]:

```
epochs = 10
history = model.fit(train_data,
                    epochs=epochs,
                    validation_data=val_data,
                    batch_size=batch_size)
```

```
Epoch 1/10
160/160 [==============================] - 220s 1s/step - loss: 1.0449 -
accuracy: 0.4977 - val_loss: 0.9187 - val_accuracy: 0.5703
Epoch 2/10
160/160 [==============================] - 206s 1s/step - loss: 0.9055 -
accuracy: 0.5680 - val_loss: 0.8020 - val_accuracy: 0.6367
Epoch 3/10
160/160 [==============================] - 222s 1s/step - loss: 0.7925 -
accuracy: 0.6359 - val_loss: 0.7002 - val_accuracy: 0.7133
Epoch 4/10
160/160 [==============================] - 213s 1s/step - loss: 0.6673 -
accuracy: 0.7014 - val_loss: 0.5533 - val_accuracy: 0.7719
```

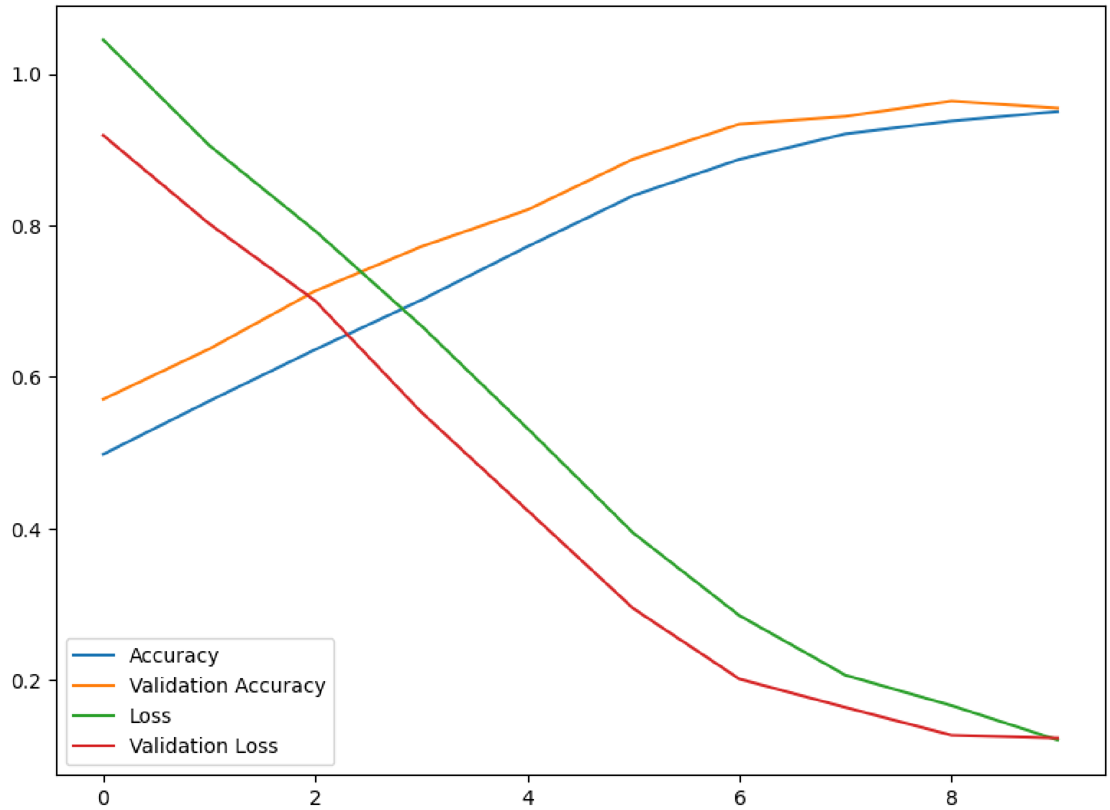
```
Epoch 5/10
160/160 [==============================] - 204s 1s/step - loss: 0.5319 -
accuracy: 0.7719 - val_loss: 0.4236 - val_accuracy: 0.8203
Epoch 6/10
160/160 [==============================] - 200s 1s/step - loss: 0.3935 -
accuracy: 0.8393 - val_loss: 0.2939 - val_accuracy: 0.8875
Epoch 7/10
160/160 [==============================] - 231s 1s/step - loss: 0.2847 -
accuracy: 0.8871 - val_loss: 0.2009 - val_accuracy: 0.9336
Epoch 8/10
160/160 [==============================] - 232s 1s/step - loss: 0.2060 -
accuracy: 0.9207 - val_loss: 0.1634 - val_accuracy: 0.9438
Epoch 9/10
160/160 [==============================] - 234s 1s/step - loss: 0.1659 -
accuracy: 0.9377 - val_loss: 0.1267 - val_accuracy: 0.9641
Epoch 10/10
160/160 [==============================] - 231s 1s/step - loss: 0.1204 -
accuracy: 0.9502 - val_loss: 0.1228 - val_accuracy: 0.9547
```

[312]:

```
acc = history.history['accuracy']
val_acc =  history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(32,32))
plt.subplot(4,3,4)
plt.plot(epochs_range,acc,label='Accuracy')
plt.plot(epochs_range,val_acc,label="Validation Accuracy")
plt.plot(epochs_range,loss,label='Loss')
plt.plot(epochs_range,val_loss,label="Validation Loss")
plt.legend()
```

[312]:

```
<matplotlib.legend.Legend at 0x7fcf999b5520>
```



3 Transfer Learning

[313]:
```
import tensorflow as tf
from keras_preprocessing.image import ImageDataGenerator
import os
import cv2
import random
from matplotlib import pyplot as plt
import pathlib
import pandas as pd
import numpy as np
```

[239]:
```
# train_dir = '/Users/richardreynard/Downloads/Dataset3/Train_Set'
# test_dir = '/Users/richardreynard/Downloads/Dataset3/Test_Set'
```

[314]:
```
train_dir = '/Users/richardreynard/Downloads/Dataset_BiT/Training Data'
test_dir = '/Users/richardreynard/Downloads/Dataset_BiT/Testing Data'
val_dir = '/Users/richardreynard/Downloads/Dataset_BiT/Validation Data'
```

[238]:
```
# from keras.preprocessing.image import ImageDataGenerator as IDG

# # Initialize image data generator
# train_gen = IDG(rescale=1/255, rotation_range=10, horizontal_flip=True,␣
↪vertical_flip=False)
# test_gen = IDG(rescale=1/255, rotation_range=10, horizontal_flip=True,␣
↪vertical_flip=False)
# valid_gen = IDG(rescale=1/255)

# # Load the datasets
# train_ds = train_gen.flow_from_directory(train_dir, shuffle=True,␣
↪batch_size=64, target_size=(256,256), class_mode='binary')
# test_ds = test_gen.flow_from_directory(train_dir, shuffle=True,␣
↪batch_size=64, target_size=(256,256), class_mode='binary')
# valid_ds = test_gen.flow_from_directory(test_dir, shuffle=True,␣
↪batch_size=32, target_size=(256,256), class_mode='binary')
```

```
Found 5120 images belonging to 4 classes.
Found 5120 images belonging to 4 classes.
Found 1280 images belonging to 4 classes.
```

[240]:
```
from keras.preprocessing.image import ImageDataGenerator as IDG

# Initialize image data generator
train_gen = IDG(rescale=1/255, rotation_range=10, horizontal_flip=True,␣
↪vertical_flip=False)
test_gen = IDG(rescale=1/255, rotation_range=10, horizontal_flip=True,␣
↪vertical_flip=False)
valid_gen = IDG(rescale=1/255)

# Load the datasets
train_ds = train_gen.flow_from_directory(train_dir, shuffle=True,␣
↪batch_size=64, target_size=(256,256), class_mode='binary')
test_ds = test_gen.flow_from_directory(test_dir, shuffle=True, batch_size=64,␣
↪target_size=(256,256), class_mode='binary')
valid_ds = test_gen.flow_from_directory(val_dir, shuffle=True, batch_size=32,␣
↪target_size=(256,256), class_mode='binary')
```

```
Found 4267 images belonging to 4 classes.
Found 1422 images belonging to 4 classes.
Found 711 images belonging to 4 classes.
```

[241]:
```
from keras.layers import Dense, GlobalAveragePooling2D as GAP, Dropout
from keras.models import load_model, Sequential

# Pre Trained Models
```

```python
from tensorflow.keras.applications import ResNet50V2, InceptionV3, Xception,␣
↪ResNet50, ResNet152V2
```

3.1 Using ResNet50V2 - Most Accurate

[242]:
```python
# Base Model
base = ResNet50V2(include_top=False, input_shape=(256,256,3))
base.trainable = False

# Model Architecture
model = tf.keras.Sequential([
    base,
    GAP(),
    Dense(1024, kernel_initializer='he_normal', activation='relu'),
    Dense(512, kernel_initializer='he_normal', activation='relu'),
    Dropout(0.4),
    Dense(4,activation="softmax"),
])


# Compile
model.compile(
    loss='sparse_categorical_crossentropy',
    optimizer=tf.keras.optimizers.Adam(learning_rate=2e-3),
    metrics=['accuracy']
)
```

[243]:
```python
epochs = 20
history = model.fit(
            train_ds,
            validation_data = valid_ds,
            epochs = epochs)
```

```
Epoch 1/20
67/67 [==============================] - 399s 6s/step - loss: 1.5325 - accuracy:
0.4870 - val_loss: 0.9243 - val_accuracy: 0.5682
Epoch 2/20
67/67 [==============================] - 413s 6s/step - loss: 0.9041 - accuracy:
0.5742 - val_loss: 0.8858 - val_accuracy: 0.5851
Epoch 3/20
67/67 [==============================] - 426s 6s/step - loss: 0.8566 - accuracy:
0.5948 - val_loss: 0.8882 - val_accuracy: 0.5767
Epoch 4/20
67/67 [==============================] - 492s 7s/step - loss: 0.8359 - accuracy:
0.6072 - val_loss: 0.8668 - val_accuracy: 0.5977
Epoch 5/20
67/67 [==============================] - 620s 9s/step - loss: 0.8000 - accuracy:
```

```
0.6307 - val_loss: 0.8594 - val_accuracy: 0.5668
Epoch 6/20
67/67 [==============================] - 469s 7s/step - loss: 0.7669 - accuracy:
0.6445 - val_loss: 0.8376 - val_accuracy: 0.6020
Epoch 7/20
67/67 [==============================] - 456s 7s/step - loss: 0.7536 - accuracy:
0.6478 - val_loss: 0.8160 - val_accuracy: 0.6188
Epoch 8/20
67/67 [==============================] - 491s 7s/step - loss: 0.7149 - accuracy:
0.6773 - val_loss: 0.8063 - val_accuracy: 0.6357
Epoch 9/20
67/67 [==============================] - 508s 8s/step - loss: 0.6793 - accuracy:
0.7003 - val_loss: 0.8001 - val_accuracy: 0.6414
Epoch 10/20
67/67 [==============================] - 497s 7s/step - loss: 0.6428 - accuracy:
0.7209 - val_loss: 0.8043 - val_accuracy: 0.6371
Epoch 11/20
67/67 [==============================] - 501s 7s/step - loss: 0.6205 - accuracy:
0.7270 - val_loss: 0.7921 - val_accuracy: 0.6385
Epoch 12/20
67/67 [==============================] - 513s 8s/step - loss: 0.6232 - accuracy:
0.7288 - val_loss: 0.7934 - val_accuracy: 0.6371
Epoch 13/20
67/67 [==============================] - 503s 8s/step - loss: 0.6022 - accuracy:
0.7413 - val_loss: 0.8621 - val_accuracy: 0.6343
Epoch 14/20
67/67 [==============================] - 513s 8s/step - loss: 0.5771 - accuracy:
0.7570 - val_loss: 0.8078 - val_accuracy: 0.6442
Epoch 15/20
67/67 [==============================] - 490s 7s/step - loss: 0.5540 - accuracy:
0.7628 - val_loss: 0.8008 - val_accuracy: 0.6582
Epoch 16/20
67/67 [==============================] - 437s 7s/step - loss: 0.5424 - accuracy:
0.7654 - val_loss: 0.7863 - val_accuracy: 0.6428
Epoch 17/20
67/67 [==============================] - 481s 7s/step - loss: 0.5419 - accuracy:
0.7628 - val_loss: 0.8347 - val_accuracy: 0.6245
Epoch 18/20
67/67 [==============================] - 487s 7s/step - loss: 0.4900 - accuracy:
0.7968 - val_loss: 0.8192 - val_accuracy: 0.6498
Epoch 19/20
67/67 [==============================] - 496s 7s/step - loss: 0.4868 - accuracy:
0.7935 - val_loss: 0.8406 - val_accuracy: 0.6568
Epoch 20/20
67/67 [==============================] - 478s 7s/step - loss: 0.4421 - accuracy:
0.8188 - val_loss: 0.7834 - val_accuracy: 0.6793
```

[244]:

```
epochs = 50
history = model.fit(
            train_ds,
            validation_data = valid_ds,
            epochs = epochs)
```

```
Epoch 1/50
67/67 [==============================] - 437s 7s/step - loss: 0.4423 - accuracy:
0.8186 - val_loss: 0.8957 - val_accuracy: 0.6245
Epoch 2/50
67/67 [==============================] - 464s 7s/step - loss: 0.4435 - accuracy:
0.8106 - val_loss: 0.8037 - val_accuracy: 0.6667
Epoch 3/50
67/67 [==============================] - 464s 7s/step - loss: 0.4367 - accuracy:
0.8275 - val_loss: 0.9119 - val_accuracy: 0.6118
Epoch 4/50
67/67 [==============================] - 445s 7s/step - loss: 0.4227 - accuracy:
0.8245 - val_loss: 0.8668 - val_accuracy: 0.6062
Epoch 5/50
67/67 [==============================] - 442s 7s/step - loss: 0.4400 - accuracy:
0.8172 - val_loss: 0.9114 - val_accuracy: 0.6146
Epoch 6/50
67/67 [==============================] - 445s 7s/step - loss: 0.4066 - accuracy:
0.8294 - val_loss: 0.8820 - val_accuracy: 0.6610
Epoch 7/50
67/67 [==============================] - 455s 7s/step - loss: 0.3823 - accuracy:
0.8423 - val_loss: 0.8471 - val_accuracy: 0.6624
Epoch 8/50
67/67 [==============================] - 470s 7s/step - loss: 0.4095 - accuracy:
0.8306 - val_loss: 0.8988 - val_accuracy: 0.6287
Epoch 9/50
67/67 [==============================] - 478s 7s/step - loss: 0.3966 - accuracy:
0.8434 - val_loss: 0.7246 - val_accuracy: 0.6920
Epoch 10/50
67/67 [==============================] - 481s 7s/step - loss: 0.3556 - accuracy:
0.8570 - val_loss: 0.8094 - val_accuracy: 0.6554
Epoch 11/50
67/67 [==============================] - 482s 7s/step - loss: 0.3332 - accuracy:
0.8688 - val_loss: 0.8156 - val_accuracy: 0.6737
Epoch 12/50
67/67 [==============================] - 498s 7s/step - loss: 0.4041 - accuracy:
0.8310 - val_loss: 0.8227 - val_accuracy: 0.6751
Epoch 13/50
67/67 [==============================] - 484s 7s/step - loss: 0.3727 - accuracy:
0.8449 - val_loss: 0.7421 - val_accuracy: 0.7032
Epoch 14/50
67/67 [==============================] - 513s 8s/step - loss: 0.3273 - accuracy:
```

```
0.8683 - val_loss: 1.0109 - val_accuracy: 0.6470
Epoch 15/50
67/67 [==============================] - 546s 8s/step - loss: 0.3265 - accuracy:
0.8688 - val_loss: 0.9632 - val_accuracy: 0.6512
Epoch 16/50
67/67 [==============================] - 484s 7s/step - loss: 0.3104 - accuracy:
0.8774 - val_loss: 0.9600 - val_accuracy: 0.6470
Epoch 17/50
67/67 [==============================] - 469s 7s/step - loss: 0.3155 - accuracy:
0.8723 - val_loss: 0.8573 - val_accuracy: 0.6821
Epoch 18/50
67/67 [==============================] - 464s 7s/step - loss: 0.2857 - accuracy:
0.8835 - val_loss: 0.7902 - val_accuracy: 0.7032
Epoch 19/50
67/67 [==============================] - 477s 7s/step - loss: 0.3040 - accuracy:
0.8777 - val_loss: 0.8240 - val_accuracy: 0.6737
Epoch 20/50
67/67 [==============================] - 464s 7s/step - loss: 0.3072 - accuracy:
0.8795 - val_loss: 1.1248 - val_accuracy: 0.6315
Epoch 21/50
67/67 [==============================] - 453s 7s/step - loss: 0.2597 - accuracy:
0.8999 - val_loss: 0.9245 - val_accuracy: 0.6962
Epoch 22/50
67/67 [==============================] - 449s 7s/step - loss: 0.2850 - accuracy:
0.8875 - val_loss: 0.9493 - val_accuracy: 0.7060
Epoch 23/50
67/67 [==============================] - 433s 6s/step - loss: 0.3066 - accuracy:
0.8749 - val_loss: 0.8603 - val_accuracy: 0.7060
Epoch 24/50
67/67 [==============================] - 437s 7s/step - loss: 0.2648 - accuracy:
0.8983 - val_loss: 0.9196 - val_accuracy: 0.6807
Epoch 25/50
67/67 [==============================] - 445s 7s/step - loss: 0.2656 - accuracy:
0.9013 - val_loss: 1.0210 - val_accuracy: 0.6610
Epoch 26/50
67/67 [==============================] - 461s 7s/step - loss: 0.2500 - accuracy:
0.9049 - val_loss: 0.8302 - val_accuracy: 0.6920
Epoch 27/50
67/67 [==============================] - 432s 6s/step - loss: 0.2547 - accuracy:
0.8938 - val_loss: 0.8668 - val_accuracy: 0.6850
Epoch 28/50
67/67 [==============================] - 426s 6s/step - loss: 0.2568 - accuracy:
0.8964 - val_loss: 0.9620 - val_accuracy: 0.6681
Epoch 29/50
67/67 [==============================] - 435s 6s/step - loss: 0.2518 - accuracy:
0.9041 - val_loss: 0.8521 - val_accuracy: 0.7018
Epoch 30/50
67/67 [==============================] - 462s 7s/step - loss: 0.2481 - accuracy:
```

```
0.8995 - val_loss: 0.9633 - val_accuracy: 0.6709
Epoch 31/50
67/67 [==============================] - 458s 7s/step - loss: 0.2333 - accuracy:
0.9058 - val_loss: 0.8234 - val_accuracy: 0.7046
Epoch 32/50
67/67 [==============================] - 461s 7s/step - loss: 0.2401 - accuracy:
0.9077 - val_loss: 0.8987 - val_accuracy: 0.7103
Epoch 33/50
67/67 [==============================] - 465s 7s/step - loss: 0.2328 - accuracy:
0.9063 - val_loss: 0.8510 - val_accuracy: 0.7004
Epoch 34/50
67/67 [==============================] - 451s 7s/step - loss: 0.2246 - accuracy:
0.9105 - val_loss: 0.9158 - val_accuracy: 0.7089
Epoch 35/50
67/67 [==============================] - 446s 7s/step - loss: 0.2418 - accuracy:
0.9070 - val_loss: 1.0032 - val_accuracy: 0.6667
Epoch 36/50
67/67 [==============================] - 451s 7s/step - loss: 0.2316 - accuracy:
0.9067 - val_loss: 1.0431 - val_accuracy: 0.6850
Epoch 37/50
67/67 [==============================] - 447s 7s/step - loss: 0.2166 - accuracy:
0.9138 - val_loss: 0.9070 - val_accuracy: 0.7328
Epoch 38/50
67/67 [==============================] - 452s 7s/step - loss: 0.2319 - accuracy:
0.9131 - val_loss: 0.9205 - val_accuracy: 0.7229
Epoch 39/50
67/67 [==============================] - 457s 7s/step - loss: 0.2477 - accuracy:
0.9041 - val_loss: 0.9027 - val_accuracy: 0.7018
Epoch 40/50
67/67 [==============================] - 447s 7s/step - loss: 0.2351 - accuracy:
0.9070 - val_loss: 0.8493 - val_accuracy: 0.7089
Epoch 41/50
67/67 [==============================] - 443s 7s/step - loss: 0.1828 - accuracy:
0.9320 - val_loss: 1.1205 - val_accuracy: 0.6934
Epoch 42/50
67/67 [==============================] - 453s 7s/step - loss: 0.1863 - accuracy:
0.9313 - val_loss: 1.0778 - val_accuracy: 0.6878
Epoch 43/50
67/67 [==============================] - 462s 7s/step - loss: 0.1897 - accuracy:
0.9266 - val_loss: 1.2172 - val_accuracy: 0.6835
Epoch 44/50
67/67 [==============================] - 444s 7s/step - loss: 0.1833 - accuracy:
0.9288 - val_loss: 1.0887 - val_accuracy: 0.6765
Epoch 45/50
67/67 [==============================] - 446s 7s/step - loss: 0.2024 - accuracy:
0.9222 - val_loss: 0.8976 - val_accuracy: 0.7173
Epoch 46/50
67/67 [==============================] - 461s 7s/step - loss: 0.1749 - accuracy:
```

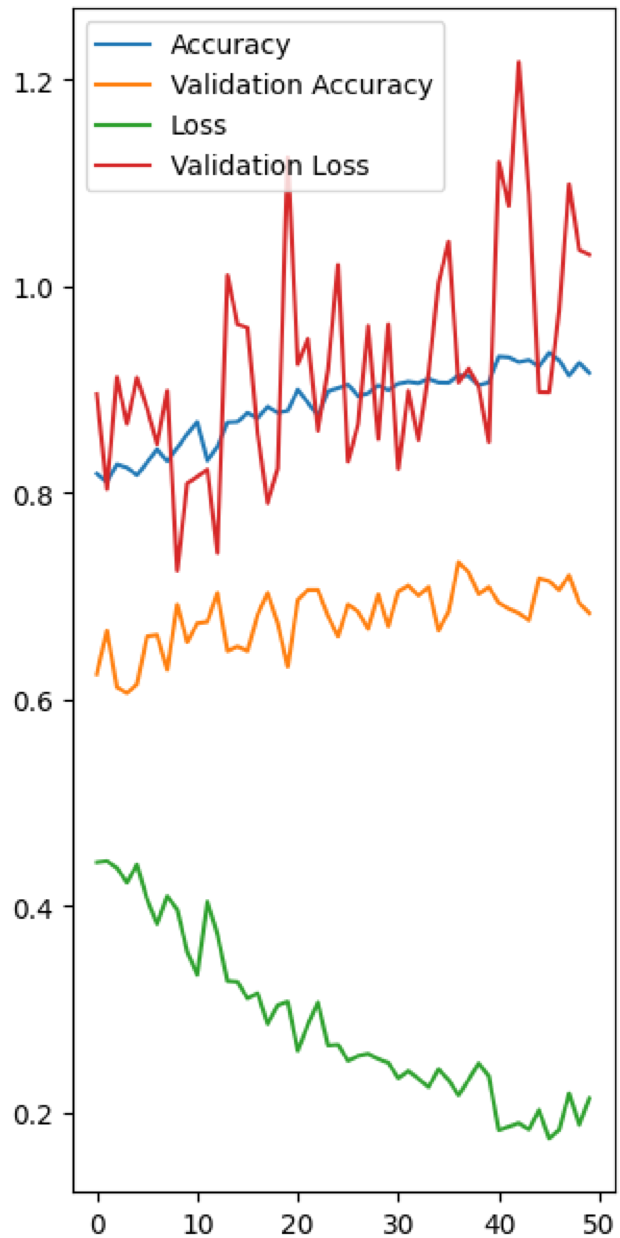
```
0.9356 - val_loss: 0.8974 - val_accuracy: 0.7145
Epoch 47/50
67/67 [==============================] - 456s 7s/step - loss: 0.1829 - accuracy:
0.9285 - val_loss: 0.9759 - val_accuracy: 0.7060
Epoch 48/50
67/67 [==============================] - 444s 7s/step - loss: 0.2186 - accuracy:
0.9135 - val_loss: 1.0988 - val_accuracy: 0.7201
Epoch 49/50
67/67 [==============================] - 444s 7s/step - loss: 0.1880 - accuracy:
0.9262 - val_loss: 1.0354 - val_accuracy: 0.6934
Epoch 50/50
67/67 [==============================] - 449s 7s/step - loss: 0.2136 - accuracy:
0.9161 - val_loss: 1.0307 - val_accuracy: 0.6835
```

[246]:

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

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

epochs_range = range(epochs)

plt.figure(figsize=(8,8))
plt.subplot(1,2,2)
plt.plot(epochs_range,acc,label='Accuracy')
plt.plot(epochs_range,val_acc,label="Validation Accuracy")
plt.plot(epochs_range,loss,label='Loss')
plt.plot(epochs_range,val_loss,label="Validation Loss")
plt.legend()
```

[246]:

```
<matplotlib.legend.Legend at 0x7fd27e9af730>
```



3.2 Using BiT - Big Transfer

[222]:
```
# import os
# import numpy as np
# import pandas as pd
# from glob import glob
# import tensorflow as tf

# ! pip install "tensorflow>=2.0.0"
```

```
# ! pip install --upgrade tensorflow-hub
# import tensorflow_hub as hub
# from IPython.display import clear_output as cls

# # Data
# from tensorflow.keras.utils import load_img, img_to_array
# from keras.preprocessing.image import ImageDataGenerator

# # Data Visualization
# import plotly.express as px
# import matplotlib.pyplot as plt

# # Model
# from keras.models import Sequential, load_model
# from keras.layers import GlobalAvgPool2D as GAP, Dense, Dropout

# # Callbacks
# from keras.callbacks import EarlyStopping, ModelCheckpoint

# # Pre-Trained Model
# from tensorflow.keras.applications import ResNet50V2
```

[224]:
```
# Check Training Data Information
train_path = '/Users/richardreynard/Downloads/Dataset_BiT/Training Data/'
class_names = sorted(os.listdir(train_path))
n_classes = len(class_names)

# Show
print(f"Total Number of Classes : {n_classes} \nClass Names : {class_names}")
```

```
Total Number of Classes : 5
Class Names : ['.DS_Store', 'Mild_Demented', 'Moderate_Demented',
'Non_Demented', 'Very_Mild_Demented']
```

[225]:
```
# # Check Testing Data Information
test_path = '/Users/richardreynard/Downloads/Dataset_BiT/Testing Data/'
class_names = sorted(os.listdir(test_path))
n_classes = len(class_names)

# Show
print(f"Total Number of Classes : {n_classes} \nClass Names : {class_names}")
```

```
Total Number of Classes : 5
Class Names : ['.DS_Store', 'Mild_Demented', 'Moderate_Demented',
'Non_Demented', 'Very_Mild_Demented']
```

[227]:
```
# Check Validation Data Information
valid_path = '/Users/richardreynard/Downloads/Dataset_BiT/Validation Data/'
class_names = sorted(os.listdir(valid_path))
n_classes = len(class_names)

# Show
print(f"Total Number of Classes : {n_classes} \nClass Names : {class_names}")
```

```
Total Number of Classes : 5
Class Names : ['.DS_Store', 'Mild_Demented', 'Moderate_Demented',
'Non_Demented', 'Very_Mild_Demented']
```

[228]:
```
# Initialize Generator
train_gen = ImageDataGenerator(rescale=1/255., rotation_range=10,␣
↪horizontal_flip=True)
valid_gen = ImageDataGenerator(rescale=1/255.)
test_gen = ImageDataGenerator(rescale=1/255)

# Load Data
train_ds = train_gen.flow_from_directory(train_path, class_mode='binary',␣
↪target_size=(256,256), shuffle=True, batch_size=32)
valid_ds = valid_gen.flow_from_directory(valid_path, class_mode='binary',␣
↪target_size=(256,256), shuffle=True, batch_size=32)
test_ds = test_gen.flow_from_directory(test_path, class_mode='binary',␣
↪target_size=(256,256), shuffle=True, batch_size=32)
```

```
Found 4267 images belonging to 4 classes.
Found 711 images belonging to 4 classes.
Found 1422 images belonging to 4 classes.
```

[229]:
```
# Import BiT model
bit_model_url = "https://tfhub.dev/google/bit/m-r50x1/1"
bit_module = hub.KerasLayer(bit_model_url)
```

[230]:
```
model = Sequential([
    bit_module,
    Dense(4, activation='softmax', kernel_initializer='zeros')
], name='bit-custom')
```

[231]:
```
BATCH_SIZE = 32
lr = 1e-3 * BATCH_SIZE/512
print(f"Learning rate : {lr}")
```

```
Learning rate : 6.25e-05
```

[232]:
```
SCHEDULE_BOUNDARIES = [
    200,
```

```
    300,
    400,
]
```

[233]:
```
lr_schedule = tf.keras.optimizers.schedules.PiecewiseConstantDecay(
    boundaries=SCHEDULE_BOUNDARIES,
    values=[
        lr,
        lr * 0.1,
        lr * 0.01,
        lr * 0.001,
    ],
)
optimizer = tf.keras.optimizers.SGD(learning_rate=lr_schedule, momentum=0.9)
```

[234]:
```
model.compile(
    loss='sparse_categorical_crossentropy',
    optimizer=optimizer,
    metrics=['accuracy']
)
```

[235]:
```
history = model.fit(train_ds, validation_data=valid_ds, epochs=4)
```

```
Epoch 1/4
134/134 [==============================] - 993s 7s/step - loss: 1.0017 -
accuracy: 0.5245 - val_loss: 0.9224 - val_accuracy: 0.5668
Epoch 2/4
134/134 [==============================] - 936s 7s/step - loss: 0.9179 -
accuracy: 0.5664 - val_loss: 0.8909 - val_accuracy: 0.5696
Epoch 3/4
134/134 [==============================] - 923s 7s/step - loss: 0.8731 -
accuracy: 0.5814 - val_loss: 0.8920 - val_accuracy: 0.5823
Epoch 4/4
134/134 [==============================] - 949s 7s/step - loss: 0.8693 -
accuracy: 0.5857 - val_loss: 0.8917 - val_accuracy: 0.5809
```

3.3 Using EfficientNetB0 - Least Efficient

[315]:
```
train_dir = '/Users/richardreynard/Downloads/Dataset_BiT/Training Data'
test_dir = '/Users/richardreynard/Downloads/Dataset_BiT/Testing Data'
val_dir = '/Users/richardreynard/Downloads/Dataset_BiT/Validation Data'
```

[316]:
```
# Initialize Generator
train_gen = ImageDataGenerator(rescale=1/255., rotation_range=10,␣
 ↪horizontal_flip=True)
valid_gen = ImageDataGenerator(rescale=1/255.)
test_gen = ImageDataGenerator(rescale=1/255)
```

```
# Load Data
train_ds = train_gen.flow_from_directory(train_path, class_mode='binary',␣
↪target_size=(256,256), shuffle=True, batch_size=32)
valid_ds = valid_gen.flow_from_directory(valid_path, class_mode='binary',␣
↪target_size=(256,256), shuffle=True, batch_size=32)
test_ds = test_gen.flow_from_directory(test_path, class_mode='binary',␣
↪target_size=(256,256), shuffle=True, batch_size=32)
```

```
Found 4267 images belonging to 4 classes.
Found 711 images belonging to 4 classes.
Found 1422 images belonging to 4 classes.
```

[317]:
```
base2 = tf.keras.applications.EfficientNetB0(include_top=False,␣
↪input_shape=(256,256,3))
base2.trainable = False
model2 = tf.keras.Sequential([
    base2,
    GAP(),
    Dense(1024, kernel_initializer='he_normal', activation='relu'),
    Dropout(0.4),
    Dense(512, kernel_initializer='he_normal', activation='relu'),
    Dropout(0.4),
    Dense(4, activation="softmax")
])


# Compile
model2.compile(
    loss='sparse_categorical_crossentropy',
    optimizer=tf.keras.optimizers.Adam(learning_rate=2e-3),
    metrics=['accuracy']
)
```

[318]:
```
epochs = 5
history = model2.fit(
            train_ds,
            validation_data = valid_ds,
            epochs = epochs)
```

```
Epoch 1/5
134/134 [==============================] - 258s 2s/step - loss: 1.1474 -
accuracy: 0.4596 - val_loss: 1.0611 - val_accuracy: 0.5007
Epoch 2/5
134/134 [==============================] - 234s 2s/step - loss: 1.0635 -
accuracy: 0.4821 - val_loss: 1.0434 - val_accuracy: 0.5007
Epoch 3/5
```

```
134/134 [==============================] - 266s 2s/step - loss: 1.0633 -
accuracy: 0.4872 - val_loss: 1.0414 - val_accuracy: 0.5007
Epoch 4/5
134/134 [==============================] - 264s 2s/step - loss: 1.0460 -
accuracy: 0.4896 - val_loss: 1.0349 - val_accuracy: 0.5007
Epoch 5/5
134/134 [==============================] - 245s 2s/step - loss: 1.0376 -
accuracy: 0.5008 - val_loss: 1.0391 - val_accuracy: 0.5007
```

[326]:
```
acc = history.history['accuracy']
val_acc =  history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs_range = range(epochs)

plt.figure(figsize=(10,8))
plt.subplot(2,2,2)
plt.plot(epochs_range,acc,label='Accuracy')
plt.plot(epochs_range,val_acc,label="Validation Accuracy")
plt.plot(epochs_range,loss,label='Loss')
plt.plot(epochs_range,val_loss,label="Validation Loss")
plt.legend()
```

[326]:
```
<matplotlib.legend.Legend at 0x7fd07539a730>
```