Common Task 1. Electron/photon classification

Datasets:

https://cernbox.cern.ch/index.php/s/AtBT8y4MiQYFcgc (photons)

https://cernbox.cern.ch/index.php/s/FbXw3V4XNyYB3oA (electrons)

Description: 32x32 matrices (two channels - hit energy and time) for two classes of particles electrons and photons impinging on a calorimeter Please use a deep learning method of your choice to achieve the highest possible classification on this dataset (we ask that you do it both in Keras/Tensorflow and in PyTorch). Please provide a Jupyter notebook that shows your solution. The model yousubmit should have a ROC AUC score of at least 0.80.

Downloading the datasets from the links provided:

```
!wget https://cernbox.cern.ch/index.php/s/AtBT8y4MiQYFcgc/download -O photons.hdf5
!wget https://cernbox.cern.ch/index.php/s/FbXw3V4XNyYB3oA/download -O electrons.hdf5
```

```
--2022-04-04 15:41:23--  https://cernbox.cern.ch/index.php/s/AtBT8y4MiQYFcgc/download
Resolving cernbox.cern.ch (cernbox.cern.ch)... 128.142.170.17, 188.184.97.72, 137.138.12
Connecting to cernbox.cern.ch (cernbox.cern.ch)|128.142.170.17|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 119703858 (114M) [application/octet-stream]
Saving to: ‘photons.hdf5’

photons.hdf5        100%[===================>] 114.16M   121MB/s    in 0.9s

Last-modified header invalid -- time-stamp ignored.
2022-04-04 15:41:26 (121 MB/s) - ‘photons.hdf5’ saved [119703858/119703858]

--2022-04-04 15:41:26--  https://cernbox.cern.ch/index.php/s/FbXw3V4XNyYB3oA/download
Resolving cernbox.cern.ch (cernbox.cern.ch)... 128.142.170.17, 188.184.97.72, 137.138.12
Connecting to cernbox.cern.ch (cernbox.cern.ch)|128.142.170.17|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 128927319 (123M) [application/octet-stream]
Saving to: ‘electrons.hdf5’

electrons.hdf5      100%[===================>] 122.95M   119MB/s    in 1.0s

Last-modified header invalid -- time-stamp ignored.
2022-04-04 15:41:29 (119 MB/s) - ‘electrons.hdf5’ saved [128927319/128927319]
```

Setting up the imports:

```
import numpy as np
```

```
import tensorflow as tf
import h5py
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score, roc_curve, auc

print(tf.__version__)
```

```
2.8.0
```

Get the data from the downloaded HDF5 files and combine the loaded datasets:

```
X_electron = np.array(h5py.File("electrons.hdf5",'r').get(name="X")[()])
y_electron = np.array(h5py.File("electrons.hdf5",'r').get(name="y")[()])
X_photon = np.array(h5py.File("photons.hdf5",'r').get(name="X")[()])
y_photon = np.array(h5py.File("photons.hdf5",'r').get(name="y")[()])

X_particles = np.concatenate((X_electron,X_photon),axis=0)
y_particles = np.concatenate((y_electron,y_photon),axis=0)
print(X_particles.shape,y_particles.shape)

del X_electron
del X_photon
del y_electron
del y_photon

index = np.random.permutation(len(y_particles))
X_particles, y_particles = X_particles[index][:,:,:,0].reshape((-1,32*32)), y_particles[index
```

```
(498000, 32, 32, 2) (498000,)
```

Splitting the data into training and testing sets (I have split it in 80-20 as per instructions):

```
X_train, X_test, y_train, y_test = train_test_split( X_particles, y_particles, random_state=4

del X_particles
del y_particles

#X_train, X_test, y_train, y_test = train_test_split( X_train_m, y_train_m, random_state=48,
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((398400, 1024), (99600, 1024), (398400,), (99600,))
```

Defining the VGG model:

```
model = tf.keras.applications.VGG16(
          include_top=True,
          weights=None,
          input_shape=(32,32,1),
          classes=1,
          classifier_activation='sigmoid'
)
```

Defining a CNN model:

```
model = tf.keras.models.Sequential([
  tf.keras.layers.Dense(512, activation = 'relu', input_shape= (32*32,)),
  tf.keras.layers.Dropout(0.5),
  tf.keras.layers.Dense(512, activation = 'relu'),
  tf.keras.layers.Dropout(0.5),
  tf.keras.layers.Dense(512, activation = 'relu'),
  tf.keras.layers.Dropout(0.5),
  tf.keras.layers.Dense(512, activation = 'relu'),
  tf.keras.layers.Dropout(0.5),
  tf.keras.layers.Dense(1, activation = 'sigmoid')
])
```

Get model summary:

```
model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_26 (Dense)            (None, 512)               524800

 dropout_23 (Dropout)        (None, 512)               0

 dense_27 (Dense)            (None, 512)               262656

 dropout_24 (Dropout)        (None, 512)               0

 dense_28 (Dense)            (None, 256)               131328

 dropout_25 (Dropout)        (None, 256)               0

 dense_29 (Dense)            (None, 256)               65792

 dropout_26 (Dropout)        (None, 256)               0

 dense_30 (Dense)            (None, 256)               65792

 dropout_27 (Dropout)        (None, 256)               0
```

```
 dense_31 (Dense)            (None, 256)               65792

 dropout_28 (Dropout)        (None, 256)               0

 dense_32 (Dense)            (None, 256)               65792

 dropout_29 (Dropout)        (None, 256)               0

 dense_33 (Dense)            (None, 1)                 257

=================================================================
Total params: 1,182,209
Trainable params: 1,182,209
Non-trainable params: 0
_________________________________________________________________
```

Defining callbacks:

```
filepath="classifier_weights2-improvement-{epoch:02d}-{val_accuracy:.2f}.hdf5"
checkpoint1 = tf.keras.callbacks.ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1,
callbacks_list = [checkpoint1]
```

Compiling the model and fitting it with testing data:

```
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.001),loss='binary_crossentro
history = model.fit(X_train,  y_train,
                    validation_split=0.2,
                    epochs=20,
                    callbacks=callbacks_list
)
```

```
Epoch 7/20
9953/9960 [============================>.] - ETA: 0s - loss: 0.5729 - accuracy: 0.714
Epoch 7: val_accuracy did not improve from 0.72594
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5730 - accuracy:
Epoch 8/20
9954/9960 [============================>.] - ETA: 0s - loss: 0.5727 - accuracy: 0.715
Epoch 8: val_accuracy did not improve from 0.72594
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5726 - accuracy:
Epoch 9/20
9956/9960 [============================>.] - ETA: 0s - loss: 0.5723 - accuracy: 0.716
Epoch 9: val_accuracy did not improve from 0.72594
9960/9960 [==============================] - 50s 5ms/step - loss: 0.5723 - accuracy:
Epoch 10/20
9960/9960 [==============================] - ETA: 0s - loss: 0.5726 - accuracy: 0.716
Epoch 10: val_accuracy improved from 0.72594 to 0.72608, saving model to classifier_w
9960/9960 [==============================] - 50s 5ms/step - loss: 0.5726 - accuracy:
Epoch 11/20
9954/9960 [============================>.] - ETA: 0s - loss: 0.5721 - accuracy: 0.717
Epoch 11: val_accuracy did not improve from 0.72608
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5721 - accuracy:
```

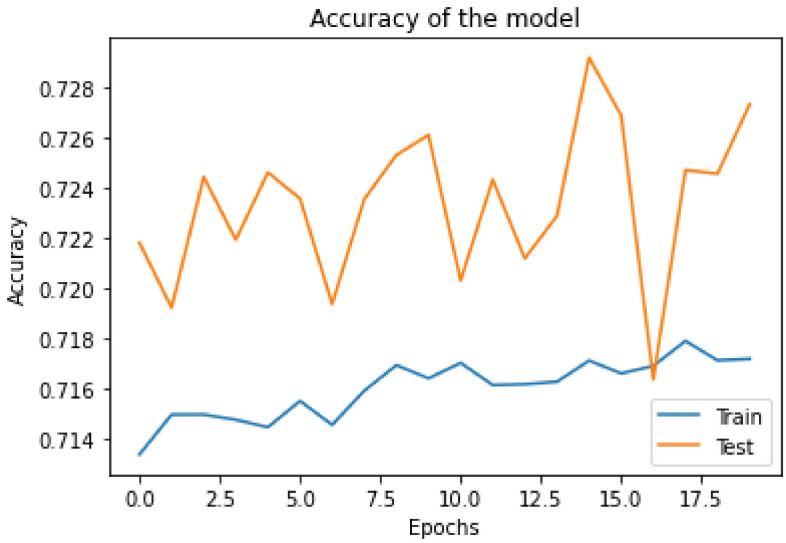
```
Epoch 12/20
9957/9960 [============================>.] - ETA: 0s - loss: 0.5722 - accuracy: 0.716
Epoch 12: val_accuracy did not improve from 0.72608
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5721 - accuracy:
Epoch 13/20
9956/9960 [============================>.] - ETA: 0s - loss: 0.5721 - accuracy: 0.716
Epoch 13: val_accuracy did not improve from 0.72608
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5721 - accuracy:
Epoch 14/20
9958/9960 [============================>.] - ETA: 0s - loss: 0.5720 - accuracy: 0.716
Epoch 14: val_accuracy did not improve from 0.72608
9960/9960 [==============================] - 50s 5ms/step - loss: 0.5720 - accuracy:
Epoch 15/20
9958/9960 [============================>.] - ETA: 0s - loss: 0.5717 - accuracy: 0.717
Epoch 15: val_accuracy improved from 0.72608 to 0.72915, saving model to classifier_w
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5717 - accuracy:
Epoch 16/20
9960/9960 [==============================] - ETA: 0s - loss: 0.5721 - accuracy: 0.716
Epoch 16: val_accuracy did not improve from 0.72915
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5721 - accuracy:
Epoch 17/20
9958/9960 [============================>.] - ETA: 0s - loss: 0.5720 - accuracy: 0.716
Epoch 17: val_accuracy did not improve from 0.72915
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5720 - accuracy:
Epoch 18/20
9954/9960 [============================>.] - ETA: 0s - loss: 0.5714 - accuracy: 0.717
Epoch 18: val_accuracy did not improve from 0.72915
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5715 - accuracy:
Epoch 19/20
9958/9960 [============================>.] - ETA: 0s - loss: 0.5722 - accuracy: 0.717
Epoch 19: val_accuracy did not improve from 0.72915
9960/9960 [==============================] - 50s 5ms/step - loss: 0.5723 - accuracy:
Epoch 20/20
9949/9960 [============================>.] - ETA: 0s - loss: 0.5717 - accuracy: 0.717
Epoch 20: val_accuracy did not improve from 0.72915
9960/9960 [==============================] - 51s 5ms/step - loss: 0.5717 - accuracy:
```

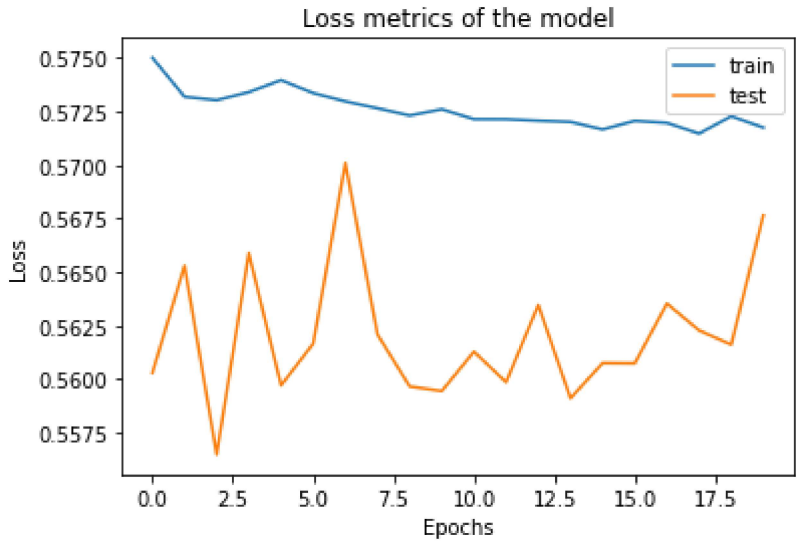
Plotting the results:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Accuracy of the model')
plt.ylabel('Accuracy')
plt.xlabel('Epochs')
plt.legend(['Train', 'Test'], loc='lower right')
plt.show()

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Loss metrics of the model')
plt.ylabel('Loss')
plt.xlabel('Epochs')
```

```
plt.legend(['train', 'test'], loc='upper right')
plt.show()
```





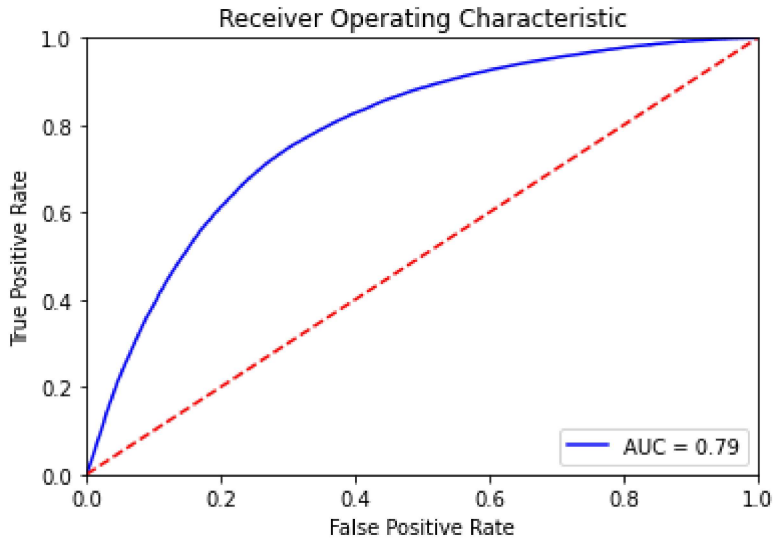
Check the performance of the model on predictions:

```
best_epoch=np.argmax(history.history['val_accuracy'])
best_acc=np.max(history.history['val_accuracy'])
model.load_weights('/content/classifier_weights2-improvement-15-0.73.hdf5')
predictions = model.predict(X_test)
print("ROC AUC:")
roc_auc_score(y_test, predictions)
```

```
ROC AUC:
0.7853177911179511
```

Classification Report and ROC AUC score:

```
fpr, tpr, thresholds = roc_curve(y_test, predictions)
roc_auc = auc(fpr, tpr)
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



The model that I have used here is a linear Neural Network and achieved almost 0.80 ROC AUC score. Due to the high volume of the dataset using a pre-trained model like VGG or ResNet has been difficult due to the limitations of the online resources provided in colab but could theoretically achieve higher ROC AUC score.

References :

1. Examining Electron and Photon Classification Using Convolutional Neural Networks Jonah Warner, Research Assistant Department of Physics, Carnegie Mellon University, Pittsburgh 15213
2. End-to-End Event Classification of High-Energy Physics Data M Andrews , M Paulini , S Gleyzer , B Poczos
3. Calorimetry with Deep Learning: Particle Classification, Energy Regression, and Simulation for High-Energy Physics Federico Carminati, Gulrukh Khattak, Maurizio Pierini CERN
4. Electron/Photon Ambiguity Resolution Using Neural networks For ATLAS Experiment Nutthawara Buatthaisong, Khon Kaen University, Thailand