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

```
Mounted at /content/gdrive
```

```
! pip install -U git+https://github.com/qubvel/efficientnet
! pip install tensorflow-addons
```

```
Collecting git+https://github.com/qubvel/efficientnet
  Cloning https://github.com/qubvel/efficientnet to /tmp/pip-req-build-4par1m8n
  Running command git clone -q https://github.com/qubvel/efficientnet /tmp/pip-req-build-4par1m8n
Collecting keras_applications<=1.0.8,>=1.0.7
  Downloading Keras_Applications-1.0.8-py3-none-any.whl (50 kB)
     |████████████████████████████████| 50 kB 3.3 MB/s
Requirement already satisfied: scikit-image in /usr/local/lib/python3.7/dist-packages (from efficientnet==1.1.1) (0.1
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.7/dist-packages (from keras_applications<=1.0.8
Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages (from keras_applications<=1.0.8,>=1.0.7
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/dist-packages (from h5py->keras_applicatic
Requirement already satisfied: scipy>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientne
Requirement already satisfied: imageio>=2.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficient
Requirement already satisfied: PyWavelets>=1.1.1 in /usr/local/lib/python3.7/dist-packages (from scikit-image->effici
Requirement already satisfied: pillow!=7.1.0,!=7.1.1,>=4.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-i
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image
Requirement already satisfied: networkx>=2.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientn
Requirement already satisfied: tifffile>=2019.7.26 in /usr/local/lib/python3.7/dist-packages (from scikit-image->effi
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (fr
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0,>=
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0,>=2.0.0
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1->m
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.1->matplot
Building wheels for collected packages: efficientnet
  Building wheel for efficientnet (setup.py) ... done
  Created wheel for efficientnet: filename=efficientnet-1.1.1-py3-none-any.whl size=18447 sha256=38b62afadb424f4e2799
  Stored in directory: /tmp/pip-ephem-wheel-cache-ub320vd9/wheels/11/69/85/814d64d694c96db0eef17b718042d644a1e54f1139
Successfully built efficientnet
Installing collected packages: keras-applications, efficientnet
Successfully installed efficientnet-1.1.1 keras-applications-1.0.8
```

```
Collecting tensorflow-addons
  Downloading tensorflow_addons-0.16.1-cp37-cp37m-manylinux_2_12_x86_64.manylinux2010_x86_64.whl (1.1 MB)
     |████████████████████████████████| 1.1 MB 5.1 MB/s
Requirement already satisfied: typeguard>=2.7 in /usr/local/lib/python3.7/dist-packages (from tensorflow-addons) (2.7
Installing collected packages: tensorflow-addons
Successfully installed tensorflow-addons-0.16.1
```

```
!unzip /content/gdrive/MyDrive/Faces/Faces.zip -d /content/gdrive/MyDrive/Faces/
```

```
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5692.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5693.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5694.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5695.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5696.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5697.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5698.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5699.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/57.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/570.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5700.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5701.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5702.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5703.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5704.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5705.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5706.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5707.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5708.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5709.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/571.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5710.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5711.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5712.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5713.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5714.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5715.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5716.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5717.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5718.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5719.jpg
  inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/572.jpg
```

```
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5720.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5721.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5722.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5723.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5724.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5725.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5726.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5727.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5728.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5729.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/573.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5730.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5731.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5732.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5733.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5734.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5735.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5736.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5737.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5738.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5739.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/574.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5740.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5741.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5742.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5743.jpg
inflating: /content/gdrive/MyDrive/Faces/Faces/val/Real/5744.jpg
```

```
import os
import keras.backend as K
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image_dataset_from_directory
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras.models import load_model, Model, Sequential
from tensorflow.keras.layers import Input, Dense, Flatten, Dropout, InputSpec, Layer, BatchNormalization
from tensorflow.keras.layers import AveragePooling2D, AveragePooling1D, MaxPooling2D, MaxPooling1D
from tensorflow_addons.layers import SpatialPyramidPooling2D
```

```
from efficientnet.tfkeras import EfficientNetB2 #EfficientNetB0, EfficientNetB1, EfficientNetB2
efficient_net = EfficientNetB2(
    weights = 'imagenet',
    input_shape = (224, 224, 3),
    include_top = False,
)

model = Sequential()
model.add(efficient_net)
model.add(SpatialPyramidPooling2D([1, 2, 4]))
model.add(Flatten(name="flatten"))
model.add(Dense(units = 2, activation = 'softmax'))
model.summary()
```

```
Downloading data from https://github.com/Callidior/keras-applications/releases/download/efficientnet/efficientnet-b2_
31940608/31936256 [==============================] - 0s 0us/step
31948800/31936256 [==============================] - 0s 0us/step
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnet-b2 (Functional  (None, 7, 7, 1408)       7768562
 )

 spatial_pyramid_pooling2d (  (None, 21, 1408)         0
 SpatialPyramidPooling2D)

 flatten (Flatten)           (None, 29568)             0

 dense (Dense)               (None, 2)                 59138

=================================================================
Total params: 7,827,700
Trainable params: 7,760,132
Non-trainable params: 67,568
_________________________________________________________________
```

```
model.compile(optimizer = Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])
```

```
train_path = '/content/gdrive/MyDrive/Faces/Faces/train'
val_path = '/content/gdrive/MyDrive/Faces/Faces/val'


checkpoint_filepath = '/content/gdrive/MyDrive/model_checkpoint/'
print('Creating Directory: ' + checkpoint_filepath)
os.makedirs(checkpoint_filepath, exist_ok=True)
```

```
Creating Directory: /content/gdrive/MyDrive/model_checkpoint/
```

```
custom_callbacks = [
    EarlyStopping(
        monitor = 'val_loss',
        mode = 'min',
        patience = 10,
        verbose = 1
    ),
    ModelCheckpoint(
        filepath = os.path.join(checkpoint_filepath, 'SPP2_EfficientNetB2_CELEB.h5'),
        monitor = 'val_loss',
        mode = 'min',
        verbose = 1,
        save_best_only = True
    )
]


train_datagen = ImageDataGenerator(
    rescale = 1/255,
    rotation_range = 10,
    width_shift_range = 0.1,
    height_shift_range = 0.1,
    shear_range = 0.2,
    zoom_range = 0.1,
    horizontal_flip = True,
```

```
    fill_mode = 'nearest'
)
train_generator = train_datagen.flow_from_directory(
    directory = train_path,
    target_size = (224,224),
    color_mode = "rgb",
    class_mode = "categorical",
    batch_size = 32,
    shuffle = True
)

val_datagen = ImageDataGenerator(
    rescale = 1/255    #rescale the tensor values to [0,1]
)
val_generator = val_datagen.flow_from_directory(
    directory = val_path,
    target_size = (224,224),
    color_mode = "rgb",
    class_mode = "categorical",
    batch_size = 32,
    shuffle = True
)
```

```
Found 80383 images belonging to 2 classes.
Found 20109 images belonging to 2 classes.
```

```
len(train_generator)
```

```
2512
```

```
num_epochs = 20
```

```
H = model.fit(
    train_generator,
```

```
    epochs = num_epochs,
    steps_per_epoch = len(train_generator),
    validation_data = val_generator,
    validation_steps = len(val_generator),
    callbacks = custom_callbacks
)
print(H.history)
```

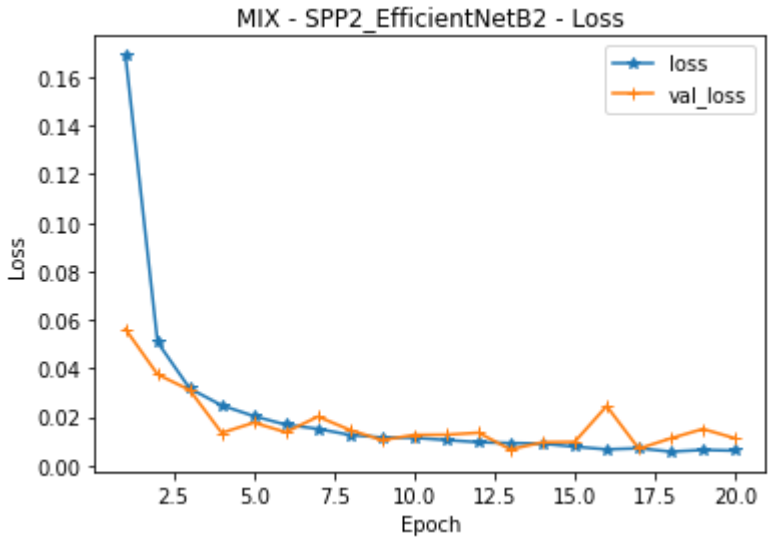
```
Epoch 1/20
2512/2512 [==============================] - ETA: 0s - loss: 0.1689 - accuracy: 0.9296
Epoch 1: val_loss improved from inf to 0.05613, saving model to /content/gdrive/MyDrive/model_checkpoint/SPP2_Efficie
2512/2512 [==============================] - 29046s 12s/step - loss: 0.1689 - accuracy: 0.9296 - val_loss: 0.0561 - v
Epoch 2/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0508 - accuracy: 0.9817
Epoch 2: val_loss improved from 0.05613 to 0.03747, saving model to /content/gdrive/MyDrive/model_checkpoint/SPP2_Eff
2512/2512 [==============================] - 1342s 534ms/step - loss: 0.0508 - accuracy: 0.9817 - val_loss: 0.0375 -
Epoch 3/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0317 - accuracy: 0.9889
Epoch 3: val_loss improved from 0.03747 to 0.03104, saving model to /content/gdrive/MyDrive/model_checkpoint/SPP2_Eff
2512/2512 [==============================] - 1341s 534ms/step - loss: 0.0317 - accuracy: 0.9889 - val_loss: 0.0310 -
Epoch 4/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0247 - accuracy: 0.9912
Epoch 4: val_loss improved from 0.03104 to 0.01336, saving model to /content/gdrive/MyDrive/model_checkpoint/SPP2_Eff
2512/2512 [==============================] - 1341s 534ms/step - loss: 0.0247 - accuracy: 0.9912 - val_loss: 0.0134 -
Epoch 5/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0203 - accuracy: 0.9931
Epoch 5: val_loss did not improve from 0.01336
2512/2512 [==============================] - 1339s 533ms/step - loss: 0.0203 - accuracy: 0.9931 - val_loss: 0.0176 -
Epoch 6/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0167 - accuracy: 0.9944
Epoch 6: val_loss did not improve from 0.01336
2512/2512 [==============================] - 1338s 533ms/step - loss: 0.0167 - accuracy: 0.9944 - val_loss: 0.0137 -
Epoch 7/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0150 - accuracy: 0.9949
Epoch 7: val_loss did not improve from 0.01336
2512/2512 [==============================] - 1334s 531ms/step - loss: 0.0150 - accuracy: 0.9949 - val_loss: 0.0201 -
Epoch 8/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0125 - accuracy: 0.9956
Epoch 8: val_loss did not improve from 0.01336
2512/2512 [==============================] - 1333s 531ms/step - loss: 0.0125 - accuracy: 0.9956 - val_loss: 0.0146 -
```

```
Epoch 9/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0115 - accuracy: 0.9959
Epoch 9: val_loss improved from 0.01336 to 0.01037, saving model to /content/gdrive/MyDrive/model_checkpoint/SPP2_Eff
2512/2512 [==============================] - 1355s 539ms/step - loss: 0.0115 - accuracy: 0.9959 - val_loss: 0.0104 -
Epoch 10/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0114 - accuracy: 0.9962
Epoch 10: val_loss did not improve from 0.01037
2512/2512 [==============================] - 1330s 529ms/step - loss: 0.0114 - accuracy: 0.9962 - val_loss: 0.0125 -
Epoch 11/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0104 - accuracy: 0.9964
Epoch 11: val_loss did not improve from 0.01037
2512/2512 [==============================] - 1336s 532ms/step - loss: 0.0104 - accuracy: 0.9964 - val_loss: 0.0126 -
Epoch 12/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0095 - accuracy: 0.9968
Epoch 12: val_loss did not improve from 0.01037
2512/2512 [==============================] - 1330s 529ms/step - loss: 0.0095 - accuracy: 0.9968 - val_loss: 0.0134 -
Epoch 13/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0092 - accuracy: 0.9969
Epoch 13: val_loss improved from 0.01037 to 0.00655, saving model to /content/gdrive/MyDrive/model_checkpoint/SPP2_Ef
2512/2512 [==============================] - 1321s 526ms/step - loss: 0.0092 - accuracy: 0.9969 - val_loss: 0.0065 -
Epoch 14/20
2512/2512 [==============================] - ETA: 0s - loss: 0.0089 - accuracy: 0.9970
Epoch 14: val_loss did not improve from 0.00655
2512/2512 [==============================] - 1330s 529ms/step - loss: 0.0089 - accuracy: 0.9970 - val_loss: 0.0095 -
Epoch 15/20
```

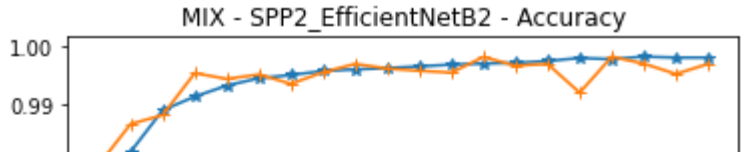
```
import matplotlib.pyplot as plt
acc = H.history['accuracy']
val_acc = H.history['val_accuracy']
loss = H.history['loss']
val_loss = H.history['val_loss']
```

```
import matplotlib.pyplot as plt
epochs = range(1, len(acc) + 1)
plt.plot(epochs, H.history['loss'], label='loss', marker="*")
plt.plot(epochs, H.history['val_loss'], label='val_loss', marker="+")
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('MIX - SPP2_EfficientNetB2 - Loss')
```

```
plt.legend()
plt.show()
```




```
plt.plot(epochs, H.history['accuracy'], label='accuracy', marker="*")
plt.plot(epochs, H.history['val_accuracy'], label='val_accuracy', marker="+")
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.title('MIX - SPP2_EfficientNetB2 - Accuracy')
plt.legend()
plt.show()
```



Testing

```
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

```
test_path = '/content/gdrive/MyDrive/Faces/Faces/test'
test_datagen = ImageDataGenerator(
    rescale = 1/255    #rescale the tensor values to [0,1]
)

test_generator = test_datagen.flow_from_directory(
    directory = test_path,
    classes=['Real', 'Fake'],
    target_size = (224,224),
    color_mode = "rgb",
    class_mode = None,
    batch_size = 1,
    shuffle = False
)
```

```
Found 35210 images belonging to 2 classes.
```

```
new_model = load_model('/content/gdrive/MyDrive/model_checkpoint/SPP2_EfficientNetB2_CELEB.h5',
                       custom_objects={'SpatialPyramidPooling2D': SpatialPyramidPooling2D})
```

```
test_generator.reset()
preds = new_model.predict(test_generator, verbose = 1)
```

```
35210/35210 [==============================] - 5898s 167ms/step
```

```
print(preds)
```

```
[[1.9016923e-11 1.0000000e+00]
 [1.4797415e-04 9.9985206e-01]
 [6.1296082e-01 3.8703918e-01]
 ...
 [8.4168476e-01 1.5831526e-01]
 [1.0000000e+00 1.3908271e-08]
 [9.9999690e-01 3.0525805e-06]]
```

```
from keras.utils import np_utils
from imutils import paths
import numpy as np
import pickle
from sklearn.preprocessing import LabelEncoder
import os

path_reals = list(paths.list_images('/content/gdrive/MyDrive/Faces/Faces/test/Real'))
labels_real = []

for path_real in path_reals:
    label2 = path_real.split(os.path.sep)[-2]
    labels_real.append(label2)

path_fakes = list(paths.list_images('/content/gdrive/MyDrive/Faces/Faces/test/Fake'))
labels_fake = []

for path_fake in path_fakes:
    label3 = path_fake.split(os.path.sep)[-2]
    labels_fake.append(label3)

labels_test = labels_real + labels_fake


print(labels_test[2])
```

```
print(labels_test[30000])
```

```
    Real
    Fake
```

```
le = LabelEncoder()
labels_test = le.fit_transform(labels_test)
labels_test = np_utils.to_categorical(labels_test, 2)

f = open('/content/gdrive/MyDrive/le.pickle', "wb")
f.write(pickle.dumps(le))
f.close()


print(labels_test[2])
print(labels_test[30000])
```

```
    [0. 1.]
    [1. 0.]
```

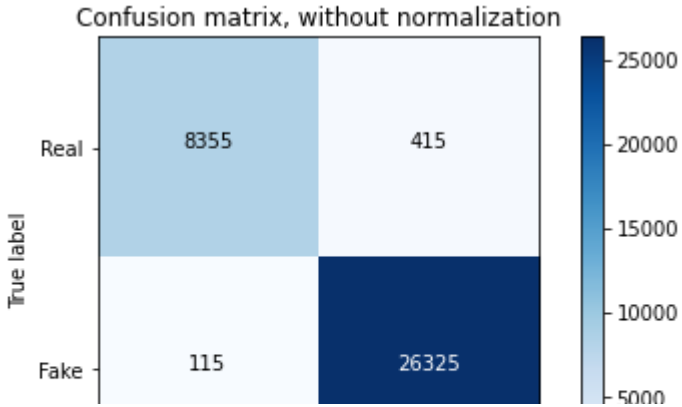
```
from sklearn.metrics import classification_report

test = np.argmin(labels_test, axis=1)
pred = np.argmin(preds, axis=1)
print(classification_report(test, pred, target_names=le.classes_, digits = 5))
```

```
                  precision    recall  f1-score   support

            Fake    0.98642   0.95268   0.96926      8770
            Real    0.98448   0.99565   0.99003     26440

        accuracy                        0.98495     35210
       macro avg    0.98545   0.97417   0.97965     35210
    weighted avg    0.98496   0.98495   0.98486     35210
```

```
from sklearn.metrics import confusion_matrix
cnf_matrix = confusion_matrix(test, pred)
```

```
print(cnf_matrix)
import matplotlib.pyplot as plt
import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1, keepdims = True)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.5f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt), horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")
    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

class_names = ['Real', 'Fake']
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')
plt.show()
```

```
[[ 8355   415]
 [  115 26325]]
```




```
from sklearn.metrics import auc, roc_curve
fpr, tpr, _ = roc_curve(test, pred, pos_label=1)

fnr = 1 - tpr
fpr_eer = fpr[np.nanargmin(np.absolute((fnr - fpr)))]
fnr_eer = fnr[np.nanargmin(np.absolute((fnr - fpr)))]
eer = min(fpr_eer, fnr_eer)
print("tpr = ", tpr)
print("fpr = ", fpr)
print("eer = ", eer)
```

```
tpr =  [0.         0.99565053 1.        ]
fpr =  [0.         0.04732041 1.        ]
eer =  0.004349470499243613
```

```
test = np.argmin(labels_test, axis=1)
true = preds[:, 0]
print(true)
```

```
[1.9016923e-11 1.4797415e-04 6.1296082e-01 ... 8.4168476e-01 1.0000000e+00
 9.9999690e-01]
```

```
from sklearn.metrics import auc, roc_curve
```

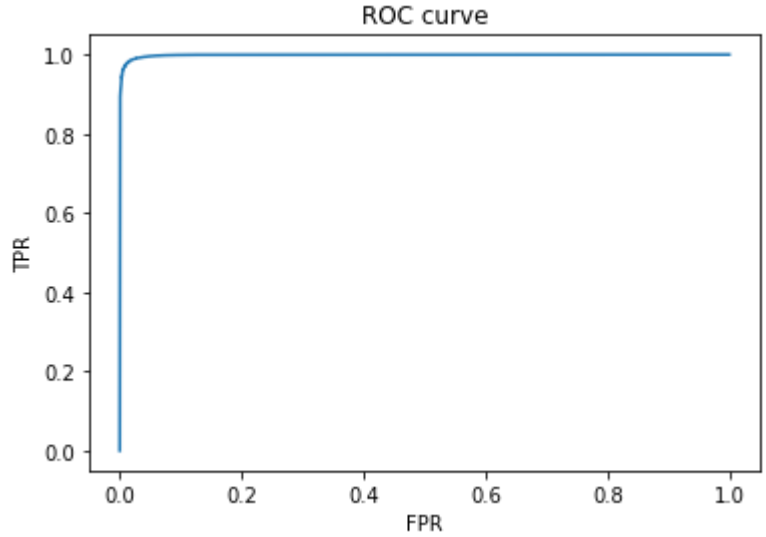
```
import matplotlib.pyplot as plt
from itertools import cycle

fpr, tpr, threshold = roc_curve(test, true, pos_label=1)
fnr = 1 - tpr
fpr_eer = fpr[np.nanargmin(np.absolute((fnr - fpr)))]
fnr_eer = fnr[np.nanargmin(np.absolute((fnr - fpr)))]
eer_threshold = threshold[np.nanargmin(np.absolute((fnr - fpr)))]
eer = min(fpr_eer, fnr_eer)
print("threshold at eer = ", eer_threshold)
print("eer = ", eer)

plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve (area = %0.4f)' % auc(fpr, tpr))
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC')
plt.legend(loc="lower right")
plt.show()
```

```
threshold at eer =  0.9881343
eer =  0.016187594553706552
```

```
import numpy as np

from scipy import interpolate

import matplotlib.pyplot as plt

from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score


def cal_metric(groundTruth, predicted):
    fpr, tpr, thresholds = roc_curve(groundTruth, predicted)
    y = (tpr)
    x = (fpr)
    z = tpr + fpr
    tpr = tpr.reshape((tpr.shape[0], 1))
    fpr = fpr.reshape((fpr.shape[0], 1))
    xnew = np.arange(0, 1, 0.0000001)
    func = interpolate.interp1d(x, y)
    # frr = fpr
    ynew = func(xnew)

    znew = abs(xnew + ynew - 1)

    eer = xnew[np.argmin(znew)]
    print('EER =', eer)
    # interpolate thresholds
    func_2 = interpolate.interp1d(x, thresholds)
    thresholds_new = func_2(xnew)

    print("Threshold at eer: {}".format(thresholds_new[np.argmin(znew)]))

    FPR = {"TPR(1.%)": 0.01, "TPR(.5%)": 0.005}

    TPRs = {"TPR(1.%)": 0.01, "TPR(.5%)": 0.005}
```

```
        for i, (key, value) in enumerate(FPR.items()):
            index = np.argwhere(xnew == value)

            score = ynew[index]

            TPRs[key] = float(np.squeeze(score))
        #       print(key, score)

        auc = roc_auc_score(groundTruth, predicted)
        print('AUC = ', auc)
        print ('TPRs = ', TPRs)
        if 1:
            plt.plot(xnew, ynew)
            plt.title("ROC curve")
            plt.xlabel("FPR")
            plt.ylabel("TPR")
            plt.show()

        return eer, TPRs, auc, {'x': xnew, 'y': ynew}


    cal_metric(test, true)
```

```
EER = 0.0161916
Threshold at eer: 0.988134245732069
AUC =  0.9987174851689763
TPRs =  {'TPR(1.%)': 0.974234114977307, 'TPR(.5%)': 0.9614920574886535}
```




```
(0.0161916,
 {'TPR(.5%)': 0.9614920574886535, 'TPR(1.%)': 0.974234114977307},
 0.9987174851689763,
 {'x': array([0.000000e+00, 1.000000e-07, 2.000000e-07, ..., 9.999997e-01,
         9.999998e-01, 9.999999e-01]),
  'y': array([0.00000000e+00, 2.49257287e-04, 4.98514574e-04, ...,
         1.00000000e+00, 1.00000000e+00, 1.00000000e+00])})
```