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

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

```
!unzip '/content/gdrive/MyDrive/Colab Notebooks/archive (1).zip' -d data #unzipping data
```

Streaming output truncated to the last 5000 lines.

```
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_0_20170109004755204.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_0_20170111182452832.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_1_20170103230340961.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_1_20170104011329697.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_1_20170104165020320.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_1_20170108230211421.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_2_20170104022134829.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_2_20170104023010725.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_2_20170104172537171.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_2_20170104201443273.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_2_20170104204327523.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_2_20170105164106036.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_2_20170105172720493.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_2_20170108224608753.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_2_20170109140259136.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_3_20170104220713478.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_3_20170104235039092.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_3_20170104235537715.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_3_20170104235729572.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_3_20170105000852573.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_3_20170105001226421.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_3_20170105002136348.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_3_20170109141950796.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_4_20170103182156641.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_4_20170103230336761.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_4_20170103230444089.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/34_1_4_20170104165941169.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170103182703466.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104165411001.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104172415386.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104181243711.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104183524965.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104183852983.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104200553297.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104201044970.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104201217450.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104201328371.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104201512505.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104201742041.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104202556995.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104203145138.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104204813467.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170104210200460.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105161456219.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105162448427.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105163316787.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105163921171.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105163947659.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105164824674.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105164841588.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105165146660.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105172434989.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105172445389.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105172518557.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170105172523741.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170108224654643.jpg.chip.jpg
  inflating: data/utkface_aligned_cropped/crop_part1/35_0_0_20170108235715593.jpg.chip.jpg
```

```
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
import cv2
from keras.models import Sequential,load_model,Model
from keras.layers import Conv2D,MaxPool2D,Dense,Dropout,BatchNormalization,Flatten,Input, MaxPooling2D, concatenate
from sklearn.model_selection import train_test_split
from keras.models import Sequential
from tensorflow.keras.utils import load_img
from tqdm.notebook import tqdm
from tensorflow.keras.optimizers import Adam
```

```
path = "/content/data/UTKFace"   #sepersting data labels
image_paths = []
age_labels = []
gender_labels = []
```

```
for filename in tqdm(os.listdir(path)):
    image_path = os.path.join(path, filename)
    temp = filename.split('_')
    age = int(temp[0])
    gender = int(temp[1])
    image_paths.append(image_path)
    age_labels.append(age)
    gender_labels.append(gender)
```

100% 23708/23708 [00:00<00:00, 281580.77it/s]

```
df = pd.DataFrame() #converting labels into dataframe
df['image'], df['age'], df['gender'] = image_paths, age_labels, gender_labels
df.head()
```

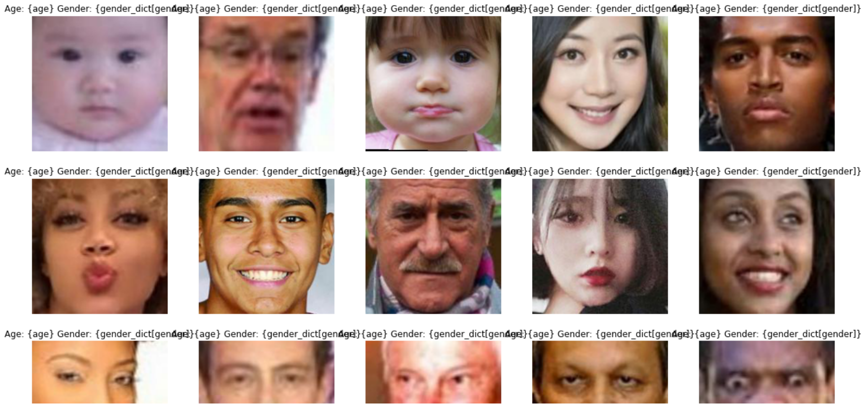
	image	age	gender
0	/content/data/UTKFace/1_1_2_20161219221943799....	1	1
1	/content/data/UTKFace/78_0_0_20170116233355259...	78	0
2	/content/data/UTKFace/4_1_0_20170109190824547....	4	1
3	/content/data/UTKFace/25_1_2_20170104021935245...	25	1
4	/content/data/UTKFace/26_0_1_20170113134356512...	26	0

```
df.shape
```

```
(23708, 3)
```

```
gender_dict = {0:'Male', 1:'Female'}
```

```
plt.figure(figsize=(20, 20))  #loading first 25 images with there age and gender
files = df.iloc[0:25]

for index, file, age, gender in files.itertuples():
    plt.subplot(5, 5, index+1)
    img = load_img(file)
    img = np.array(img)
    plt.imshow(img)
    plt.title("Age: {age} Gender: {gender_dict[gender]}")
    plt.axis('off')
```



```
from PIL import Image
def extract_features(images):  #extraxting features from images
    features = []
    for image in tqdm(images):
        img = load_img(image, grayscale=True)
        img = img.resize((128,128), Image.ANTIALIAS)
        img = np.array(img)
        features.append(img)

    features = np.array(features)
    # ignore this step if using RGB
    features = features.reshape(len(features),128,128, 1) #reshape them into (128,128)
    return features
```

```
X1 = extract_features(df['image']) #defining image features as our X1
```

100% 23708/23708 [00:37<00:00, 446.74it/s]

```
/usr/local/lib/python3.9/dist-packages/keras/utils/image_utils.py:409: UserWarning: grayscale is deprecated. Please use color_mode =
  warnings.warn(
```

```
X1.shape
```

```
(23708, 128, 128, 1)
```

```
X1 = X1/255.0
```

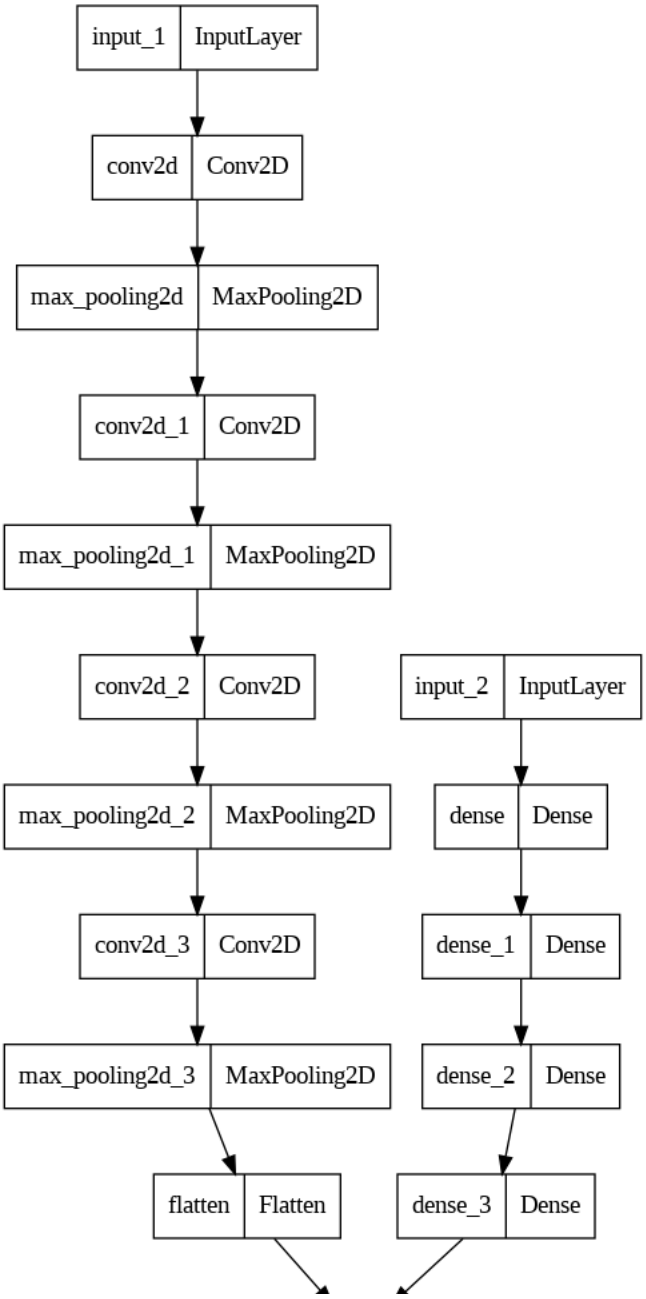
```
X2 = np.array(df['age']) #defining our second input of age
```

```
y = np.array(df['gender'])#defining our label
```

```
inputs = Input(shape=((128,128, 1))) #image input CNN model
conv_1 = Conv2D(32, kernel_size=(3, 3), activation='relu') (inputs)
maxp_1 = MaxPooling2D(pool_size=(2, 2)) (conv_1)
conv_2 = Conv2D(64, kernel_size=(3, 3), activation='relu') (maxp_1)
maxp_2 = MaxPooling2D(pool_size=(2, 2)) (conv_2)
conv_3 = Conv2D(128, kernel_size=(3, 3), activation='relu') (maxp_2)
maxp_3 = MaxPooling2D(pool_size=(2, 2)) (conv_3)
conv_4 = Conv2D(256, kernel_size=(3, 3), activation='relu') (maxp_3)
maxp_4 = MaxPooling2D(pool_size=(2, 2)) (conv_4)
conv_5 = Conv2D(512, kernel_size=(3, 3), activation='relu') (maxp_4)
maxp_5 = MaxPooling2D(pool_size=(2, 2)) (conv_5)
flatten = Flatten()(maxp_4)

inp_num = Input(shape=(1,)) #age input structure
x = Dense(256, activation='relu')(inp_num)
x2 = Dense(128, activation='relu')(x)
x3 = Dense(64, activation='relu')(x2)
out_num = Dense(32, activation='relu')(x3)

merged = concatenate([flatten, out_num]) #merging both inputs

dropout_1 = Dropout(0.2) (merged) #defining dropouts

out = Dense(1, activation='sigmoid', name='gender_out') (dropout_1) #last layer of output

model = Model([inputs, inp_num], out) #defining model inputs and outputs

model.compile(loss=['binary_crossentropy'], optimizer=Adam( lr = 1e-4 ), metrics=['accuracy']) #compiling model

model.summary()
```

```
WARNING:absl:`lr` is deprecated, please use `learning_rate` instead, or use the legacy optimizer, e.g.,tf.keras.optimizers.legacy.A
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to                     
==================================================================================================
 input_1 (InputLayer)           [(None, 128, 128, 1  0           []                               
                                )]                                                                
                                                                                                  
 conv2d (Conv2D)                (None, 126, 126, 32  320         ['input_1[0][0]']                
                                )                                                                 
                                                                                                  
 max_pooling2d (MaxPooling2D)   (None, 63, 63, 32)   0           ['conv2d[0][0]']                 
                                                                                                  
 conv2d_1 (Conv2D)              (None, 61, 61, 64)   18496       ['max_pooling2d[0][0]']          
                                                                                                  
 max_pooling2d_1 (MaxPooling2D)  (None, 30, 30, 64)  0           ['conv2d_1[0][0]']               
                                                                                                  
 conv2d_2 (Conv2D)              (None, 28, 28, 128)  73856       ['max_pooling2d_1[0][0]']        
                                                                                                  
 input_2 (InputLayer)           [(None, 1)]          0           []                               
                                                                                                  
 max_pooling2d_2 (MaxPooling2D)  (None, 14, 14, 128)  0          ['conv2d_2[0][0]']               
                                                                                                  
 dense (Dense)                  (None, 256)          512         ['input_2[0][0]']                
                                                                                                  
 conv2d_3 (Conv2D)              (None, 12, 12, 256)  295168      ['max_pooling2d_2[0][0]']        
                                                                                                  
 dense_1 (Dense)                (None, 128)          32896       ['dense[0][0]']                  
                                                                                                  
 max_pooling2d_3 (MaxPooling2D)  (None, 6, 6, 256)   0           ['conv2d_3[0][0]']               
                                                                                                  
 dense_2 (Dense)                (None, 64)           8256        ['dense_1[0][0]']                
                                                                                                  
 flatten (Flatten)              (None, 9216)         0           ['max_pooling2d_3[0][0]']        
                                                                                                  
 dense_3 (Dense)                (None, 32)           2080        ['dense_2[0][0]']                
                                                                                                  
 concatenate (Concatenate)      (None, 9248)         0           ['flatten[0][0]',                
                                                                  'dense_3[0][0]']                
                                                                                                  
 dropout (Dropout)              (None, 9248)         0           ['concatenate[0][0]']            
                                                                                                  
 gender_out (Dense)             (None, 1)            9249        ['dropout[0][0]']                
                                                                                                  
==================================================================================================
Total params: 440,833
Trainable params: 440,833
Non-trainable params: 0
__________________________________________________________________________________________________
```

```
from tensorflow.keras.utils import plot_model
plot_model(model) #plotting model structure
```



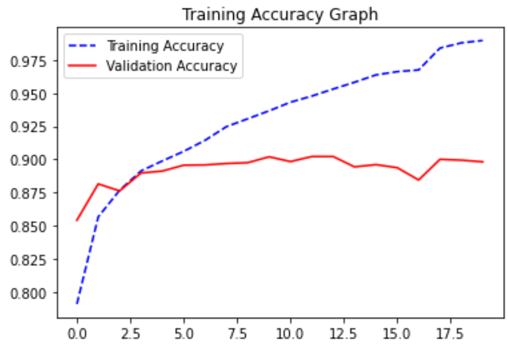

```
from keras.callbacks import Callback, ModelCheckpoint, ReduceLROnPlateau, TensorBoard
# Learning Rate Reducer
learn_control = ReduceLROnPlateau(monitor='val_accuracy', patience=5,
                                  verbose=1,factor=0.2, min_lr=1e-4)


# Checkpoint
filepath="weights.best.hdf5"
checkpoint = ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1, save_best_only=True, mode='max')


history = model.fit(
    x = [X1,X2], #inputs
    y = y, #output
    batch_size = 32,
    epochs=20,
    validation_split = 0.2, #validation data
    callbacks=[learn_control, checkpoint]
)
```

```
Epoch 1/20
593/593 [==============================] - ETA: 0s - loss: 0.4384 - accuracy: 0.7908
Epoch 1: val_accuracy improved from -inf to 0.85407, saving model to weights.best.hdf5
593/593 [==============================] - 26s 22ms/step - loss: 0.4384 - accuracy: 0.7908 - val_loss: 0.3357 - val_accuracy: 0.8
Epoch 2/20
591/593 [============================>.] - ETA: 0s - loss: 0.3297 - accuracy: 0.8565
Epoch 2: val_accuracy improved from 0.85407 to 0.88148, saving model to weights.best.hdf5
593/593 [==============================] - 12s 20ms/step - loss: 0.3296 - accuracy: 0.8566 - val_loss: 0.2874 - val_accuracy: 0.8
Epoch 3/20
590/593 [============================>.] - ETA: 0s - loss: 0.2916 - accuracy: 0.8764
Epoch 3: val_accuracy did not improve from 0.88148
593/593 [==============================] - 11s 19ms/step - loss: 0.2911 - accuracy: 0.8767 - val_loss: 0.2930 - val_accuracy: 0.8
```

```
Epoch 4/20
590/593 [============================>.] - ETA: 0s - loss: 0.2658 - accuracy: 0.8910
Epoch 4: val_accuracy improved from 0.88148 to 0.88971, saving model to weights.best.hdf5
593/593 [==============================] - 12s 19ms/step - loss: 0.2656 - accuracy: 0.8912 - val_loss: 0.2656 - val_accuracy: 0.8
Epoch 5/20
592/593 [============================>.] - ETA: 0s - loss: 0.2449 - accuracy: 0.8988
Epoch 5: val_accuracy improved from 0.88971 to 0.89119, saving model to weights.best.hdf5
593/593 [==============================] - 12s 20ms/step - loss: 0.2448 - accuracy: 0.8988 - val_loss: 0.2668 - val_accuracy: 0.8
Epoch 6/20
592/593 [============================>.] - ETA: 0s - loss: 0.2271 - accuracy: 0.9060
Epoch 6: val_accuracy improved from 0.89119 to 0.89561, saving model to weights.best.hdf5
593/593 [==============================] - 12s 19ms/step - loss: 0.2270 - accuracy: 0.9060 - val_loss: 0.2499 - val_accuracy: 0.8
Epoch 7/20
590/593 [============================>.] - ETA: 0s - loss: 0.2078 - accuracy: 0.9145
Epoch 7: val_accuracy improved from 0.89561 to 0.89582, saving model to weights.best.hdf5
593/593 [==============================] - 11s 19ms/step - loss: 0.2079 - accuracy: 0.9144 - val_loss: 0.2473 - val_accuracy: 0.8
Epoch 8/20
591/593 [============================>.] - ETA: 0s - loss: 0.1901 - accuracy: 0.9249
Epoch 8: val_accuracy improved from 0.89582 to 0.89688, saving model to weights.best.hdf5
593/593 [==============================] - 11s 19ms/step - loss: 0.1904 - accuracy: 0.9247 - val_loss: 0.2407 - val_accuracy: 0.8
Epoch 9/20
590/593 [============================>.] - ETA: 0s - loss: 0.1745 - accuracy: 0.9306
Epoch 9: val_accuracy improved from 0.89688 to 0.89751, saving model to weights.best.hdf5
593/593 [==============================] - 11s 19ms/step - loss: 0.1744 - accuracy: 0.9307 - val_loss: 0.2692 - val_accuracy: 0.8
Epoch 10/20
591/593 [============================>.] - ETA: 0s - loss: 0.1626 - accuracy: 0.9368
Epoch 10: val_accuracy improved from 0.89751 to 0.90194, saving model to weights.best.hdf5
593/593 [==============================] - 12s 20ms/step - loss: 0.1628 - accuracy: 0.9367 - val_loss: 0.2626 - val_accuracy: 0.9
Epoch 11/20
591/593 [============================>.] - ETA: 0s - loss: 0.1488 - accuracy: 0.9432
Epoch 11: val_accuracy did not improve from 0.90194
593/593 [==============================] - 11s 19ms/step - loss: 0.1488 - accuracy: 0.9432 - val_loss: 0.2602 - val_accuracy: 0.8
Epoch 12/20
591/593 [============================>.] - ETA: 0s - loss: 0.1357 - accuracy: 0.9477
Epoch 12: val_accuracy improved from 0.90194 to 0.90215, saving model to weights.best.hdf5
593/593 [==============================] - 11s 19ms/step - loss: 0.1355 - accuracy: 0.9478 - val_loss: 0.2526 - val_accuracy: 0.9
Epoch 13/20
590/593 [============================>.] - ETA: 0s - loss: 0.1254 - accuracy: 0.9532
Epoch 13: val_accuracy did not improve from 0.90215
593/593 [==============================] - 11s 19ms/step - loss: 0.1257 - accuracy: 0.9531 - val_loss: 0.2549 - val_accuracy: 0.9
Epoch 14/20
592/593 [============================>.] - ETA: 0s - loss: 0.1101 - accuracy: 0.9583
Epoch 14: val_accuracy did not improve from 0.90215
593/593 [==============================] - 11s 19ms/step - loss: 0.1101 - accuracy: 0.9582 - val_loss: 0.2863 - val_accuracy: 0.8
Epoch 15/20
```

```
# plot results for gender
acc = history.history['accuracy'] #Training Accuracy
val_acc = history.history['val_accuracy']
epochs = range(len(acc))

plt.plot(epochs, acc, 'b', linestyle='dashed', label='Training Accuracy')
plt.plot(epochs, val_acc, 'r', label='Validation Accuracy')
plt.legend()
plt.title('Training Accuracy Graph')
plt.figure()
```

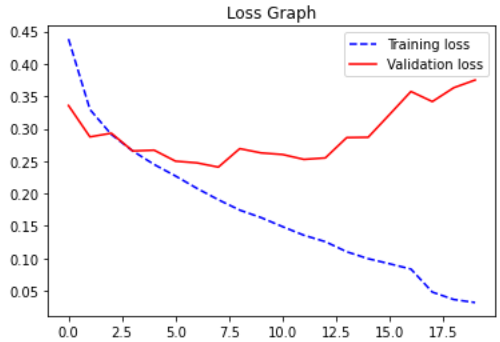
<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

```
loss = history.history['loss'] #Training loss
val_loss = history.history['val_loss']
epochs = range(len(acc))

plt.plot(epochs, loss,'b',linestyle='dashed',  label='Training loss')
plt.plot(epochs, val_loss, 'r', label='Validation loss')
plt.title('Validation Loss Graph')
plt.title('Loss Graph')
plt.legend()
plt.figure()
```

```
<Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```

```
from numpy.random import seed #ti import model as it save
seed(42)
from keras.backend import manual_variable_initialization
manual_variable_initialization(True)
import tensorflow
model = tensorflow.keras.models.load_model('/content/weights.best.hdf5') #importing model
```

```
pred= model.predict([X1,X2]) #predicting from model
```

```
741/741 [==============================] - 4s 5ms/step
```

```
pred
```

```
array([[3.5203642e-01],
       [7.2603025e-03],
       [9.4073969e-01],
       ...,
       [1.7205767e-03],
       [1.4778237e-05],
       [1.9583914e-02]], dtype=float32)
```

```
preds =np.around(pred) #rounding of the predicted value
```

```
preds
```

```
array([[0.],
       [0.],
       [1.],
       ...,
       [0.],
       [0.],
       [0.]], dtype=float32)
```

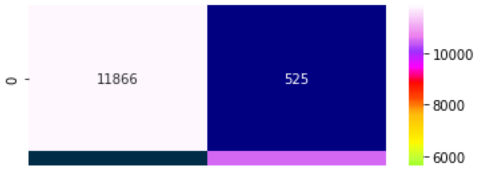
```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

report=classification_report(y , preds) #making classification report
print(report)
```

```
              precision    recall  f1-score   support

           0       0.95      0.97      0.96     12391
           1       0.97      0.95      0.96     11317

    accuracy                           0.96     23708
   macro avg       0.96      0.96      0.96     23708
weighted avg       0.96      0.96      0.96     23708
```

```
results = confusion_matrix(y, preds) #making confusion_matrix
```

```
import seaborn as sns

sns.heatmap(results, annot=True, cmap='gist_ncar', fmt='g') #plotting confusion_matrix on seaborn
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fac5a2a7c90>
```




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

roc_log = roc_auc_score(y, np.around(preds)) #predicting Auc-Roc curve
false_positive_rate, true_positive_rate, threshold = roc_curve(y, np.around(preds))
area_under_curve = auc(false_positive_rate, true_positive_rate) #calculating area under curve

plt.plot([0, 1], [0, 1], 'r--') #plotting Auc-Roc curve
plt.plot(false_positive_rate, true_positive_rate, label='AUC = {:.3f}'.format(area_under_curve))
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve')
plt.legend(loc='best')
plt.show()
#plt.savefig(ROC_PLOT_FILE, bbox_inches='tight')
plt.close()
```