Submitted by Navneet Das 3433 Comp A

***'
Mini Project 2 Deep Learning
Gender and Age Detection: predict if a person is a male or female and also their age from the Photo images
'***

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import os
from PIL import Image, ImageOps
from sklearn.model_selection import train_test_split

from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Activation, Dropout, Flatten, Dense
from keras import optimizers
from keras.preprocessing.image import ImageDataGenerator
import tensorflow as tf
```

In [2]:
```
images = []
ages = []
genders = []

for i in os.listdir('../input/utkface-new/crop_part1/')[0:8000]:
    split = i.split('_')
    ages.append(int(split[0]))
    genders.append(int(split[1]))
    images.append(Image.open('../input/utkface-new/crop_part1/' + i))
```

In [3]:
```
images = pd.Series(list(images), name = 'Images')
ages = pd.Series(list(ages), name = 'Ages')
genders = pd.Series(list(genders), name = 'Genders')

df = pd.concat([images, ages, genders], axis=1)
df
```

Out[3]:

	Images	Ages	Genders
0	<PIL.JpegImagePlugin.JpegImageFile image mode=...	26	0
1	<PIL.JpegImagePlugin.JpegImageFile image mode=...	21	1
2	<PIL.JpegImagePlugin.JpegImageFile image mode=...	17	1
3	<PIL.JpegImagePlugin.JpegImageFile image mode=...	76	0
4	<PIL.JpegImagePlugin.JpegImageFile image mode=...	18	1
...	...	...	...
7995	<PIL.JpegImagePlugin.JpegImageFile image mode=...	3	0
7996	<PIL.JpegImagePlugin.JpegImageFile image mode=...	28	0
7997	<PIL.JpegImagePlugin.JpegImageFile image mode=...	10	0
7998	<PIL.JpegImagePlugin.JpegImageFile image mode=...	8	1
7999	<PIL.JpegImagePlugin.JpegImageFile image mode=...	22	0

8000 rows × 3 columns

In [4]:
```
display(df['Images'][0])
print(df['Ages'][0], df['Genders'][0])
```

```
26 0
```

In [5]:
```
display(df['Images'][1])
print(df['Ages'][1], df['Genders'][1])
```

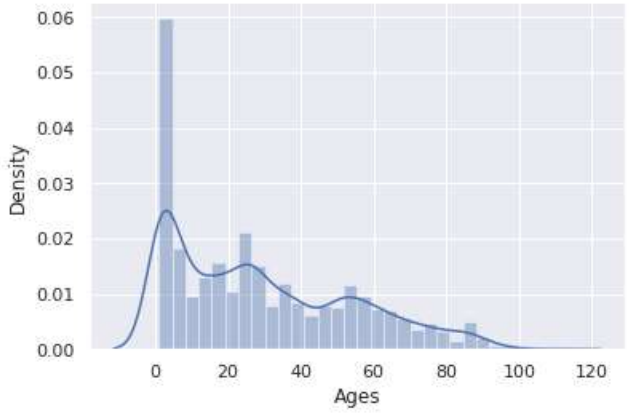
```
21 1
```

So 0 corresponds to male, 1 corresponds to female.

In [6]:
```
sns.set_theme()
sns.distplot(df['Ages'],kde=True, bins=30)
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a d
recated function and will be removed in a future version. Please adapt your code to use either `displot`
(a figure-level function with similar flexibility) or `histplot` (an axes-level function for histogram
s).
  warnings.warn(msg, FutureWarning)
```

Out[6]:
```
<AxesSubplot:xlabel='Ages', ylabel='Density'>
```



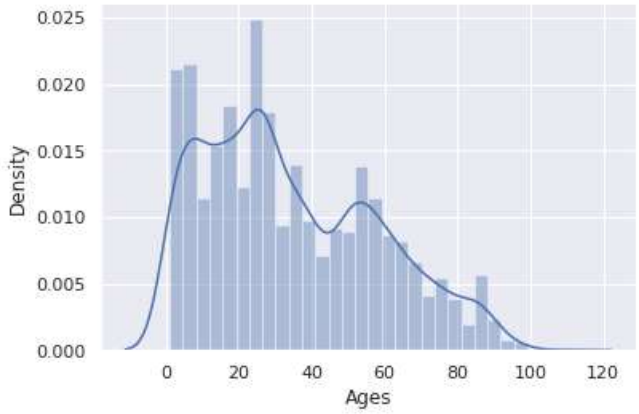
Too many faces of people between 0 and 4 years old. The model would fit too well to these ages and not enough to the other ages. To resolve this I'm only going to include a third of the images between these ages.

In [7]:
```
under4s = []

for i in range(len(df)):
    if df['Ages'].iloc[i] <= 4:
        under4s.append(df.iloc[i])
under4s = pd.DataFrame(under4s)
under4s = under4s.sample(frac=0.3)

df = df[df['Ages'] > 4]

df = pd.concat([df, under4s], ignore_index = True)
```

In [8]:
```
sns.distplot(df['Ages'],kde=True, bins=30)
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a d
recated function and will be removed in a future version. Please adapt your code to use either `displot`
(a figure-level function with similar flexibility) or `histplot` (an axes-level function for histogram
s).
  warnings.warn(msg, FutureWarning)
```

Out[8]: <AxesSubplot:xlabel='Ages', ylabel='Density'>



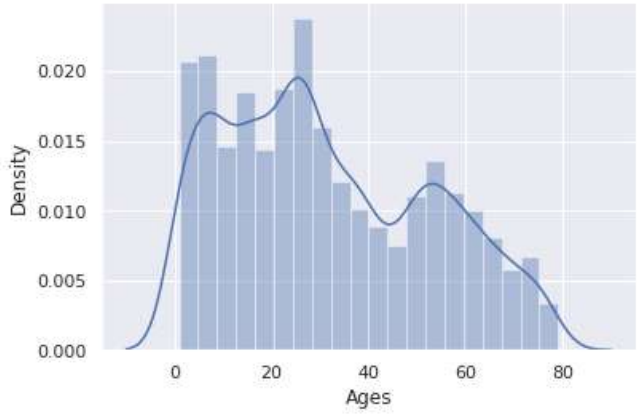
This looks much better! The dataframe is more representative of the population now. However, there aren't many images of people over 80, which would cause the model to not train well enough on those ages. It's best to just remove over 80s and only have a model that can predict the ages of people under 80.

In [9]:
```
df = df[df['Ages'] < 80]
```

In [10]:
```
sns.distplot(df['Ages'],kde=True, bins=20)
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a d
recated function and will be removed in a future version. Please adapt your code to use either `displot`
(a figure-level function with similar flexibility) or `histplot` (an axes-level function for histogram
s).
  warnings.warn(msg, FutureWarning)
```

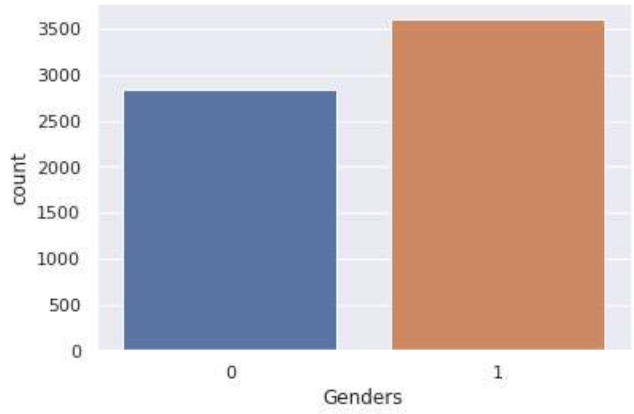
Out[10]:
```
<AxesSubplot:xlabel='Ages', ylabel='Density'>
```



In [11]:
```
sns.countplot(df['Genders'])
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following va
able as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and pass
ing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

Out[11]:
```
<AxesSubplot:xlabel='Genders', ylabel='count'>
```

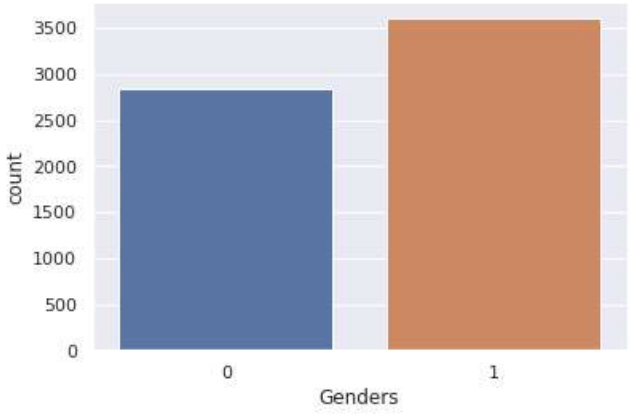


Not sure what 3 corresponds to - both genders, no gender, unknown, or just an error in the data entry? To be safe, I am going to remove any rows where gender equals 3.

In [12]:
```
df = df[df['Genders'] != 3]
sns.countplot(df['Genders'])
```

```
/opt/conda/lib/python3.7/site-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following va
able as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and pass
ing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

Out[12]: <AxesSubplot:xlabel='Genders', ylabel='count'>



In [13]:
```
x = []
y = []

for i in range(len(df)):
    df['Images'].iloc[i] = df['Images'].iloc[i].resize((200,200), Image.ANTIALIAS)
    ar = np.asarray(df['Images'].iloc[i])
    x.append(ar)
    agegen = [int(df['Ages'].iloc[i]), int(df['Genders'].iloc[i])]
    y.append(agegen)
x = np.array(x)
```

```
/opt/conda/lib/python3.7/site-packages/pandas/core/indexing.py:670: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.h
tml#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  iloc._setitem_with_indexer(indexer, value)
```

In [14]:
```
y_age = df['Ages']
y_gender = df['Genders']

x_train_age, x_test_age, y_train_age, y_test_age = train_test_split(x, y_age, test_size=0.2, stratify=y_a
x_train_gender, x_test_gender, y_train_gender, y_test_gender = train_test_split(x, y_gender, test_size=0.
```

I will create two individual models - one to predict age and one to predict gender. The age model should be capable of returning continuous values which I will round to the nearest integer, and the gender model should return a binary result.

In [15]:

```
agemodel = Sequential()
agemodel.add(Conv2D(32, (3,3), activation='relu', input_shape=(200, 200, 3)))
agemodel.add(MaxPooling2D((2,2)))
agemodel.add(Conv2D(64, (3,3), activation='relu'))
agemodel.add(MaxPooling2D((2,2)))
agemodel.add(Conv2D(128, (3,3), activation='relu'))
agemodel.add(MaxPooling2D((2,2)))
agemodel.add(Flatten())
agemodel.add(Dense(64, activation='relu'))
agemodel.add(Dropout(0.5))
agemodel.add(Dense(1, activation='relu'))

agemodel.compile(loss='mean_squared_error',
            optimizer=optimizers.Adam(lr=0.0001))

genmodel = Sequential()
genmodel.add(Conv2D(32, (3,3), activation='relu', input_shape=(200, 200, 3)))
genmodel.add(MaxPooling2D((2,2)))
genmodel.add(Conv2D(64, (3,3), activation='relu'))
genmodel.add(MaxPooling2D((2,2)))
genmodel.add(Conv2D(128, (3,3), activation='relu'))
genmodel.add(MaxPooling2D((2,2)))
genmodel.add(Flatten())
genmodel.add(Dense(64, activation='relu'))
genmodel.add(Dropout(0.5))
genmodel.add(Dense(1, activation='sigmoid'))

genmodel.compile(loss='binary_crossentropy',
            optimizer=optimizers.Adam(lr=0.0001),
            metrics=['accuracy'])
```

In [16]:

```
datagen = ImageDataGenerator(
      rescale=1./255., width_shift_range = 0.1, height_shift_range = 0.1, horizontal_flip = True)

test_datagen = ImageDataGenerator(rescale=1./255)

train1 = datagen.flow(x_train_age, y_train_age, batch_size=32)

test1 = test_datagen.flow(
        x_test_age, y_test_age,
        batch_size=32)

history1 = agemodel.fit(train1, epochs=50, shuffle=True, validation_data=test1)
```

```
Epoch 1/50
161/161 [==============================] - 44s 253ms/step - loss: 706.2857 - val_loss: 452.0310
Epoch 2/50
161/161 [==============================] - 41s 255ms/step - loss: 493.1964 - val_loss: 403.0540
Epoch 3/50
161/161 [==============================] - 42s 262ms/step - loss: 439.5375 - val_loss: 419.8955
Epoch 4/50
161/161 [==============================] - 41s 257ms/step - loss: 382.1004 - val_loss: 328.3317
Epoch 5/50
161/161 [==============================] - 41s 256ms/step - loss: 376.2793 - val_loss: 306.8690
Epoch 6/50
161/161 [==============================] - 41s 255ms/step - loss: 378.7557 - val_loss: 298.7830
Epoch 7/50
161/161 [==============================] - 42s 258ms/step - loss: 353.1836 - val_loss: 364.5480
Epoch 8/50
161/161 [==============================] - 41s 257ms/step - loss: 350.4301 - val_loss: 273.9537
Epoch 9/50
161/161 [==============================] - 41s 257ms/step - loss: 347.8215 - val_loss: 281.0771
Epoch 10/50
161/161 [==============================] - 41s 257ms/step - loss: 316.9603 - val_loss: 322.0839
Epoch 11/50
161/161 [==============================] - 42s 260ms/step - loss: 321.0114 - val_loss: 257.4635
Epoch 12/50
161/161 [==============================] - 42s 259ms/step - loss: 307.2590 - val_loss: 299.9180
Epoch 13/50
161/161 [==============================] - 41s 256ms/step - loss: 308.6267 - val_loss: 329.4791
Epoch 14/50
161/161 [==============================] - 42s 261ms/step - loss: 314.8022 - val_loss: 245.9729
Epoch 15/50
161/161 [==============================] - 41s 257ms/step - loss: 301.3866 - val_loss: 255.6889
Epoch 16/50
161/161 [==============================] - 41s 258ms/step - loss: 287.3217 - val_loss: 238.2000
Epoch 17/50
161/161 [==============================] - 41s 258ms/step - loss: 299.2067 - val_loss: 226.4820
Epoch 18/50
161/161 [==============================] - 42s 261ms/step - loss: 293.4950 - val_loss: 219.9284
Epoch 19/50
161/161 [==============================] - 41s 258ms/step - loss: 268.2615 - val_loss: 218.2262
Epoch 20/50
161/161 [==============================] - 41s 254ms/step - loss: 284.8218 - val_loss: 234.8680
Epoch 21/50
161/161 [==============================] - 41s 258ms/step - loss: 267.3226 - val_loss: 216.5874
Epoch 22/50
161/161 [==============================] - 42s 260ms/step - loss: 280.1753 - val_loss: 238.4909
Epoch 23/50
161/161 [==============================] - 41s 257ms/step - loss: 269.4055 - val_loss: 200.0749
Epoch 24/50
161/161 [==============================] - 41s 256ms/step - loss: 262.5218 - val_loss: 221.6551
Epoch 25/50
161/161 [==============================] - 42s 260ms/step - loss: 275.6070 - val_loss: 198.7766
Epoch 26/50
161/161 [==============================] - 42s 259ms/step - loss: 266.5272 - val_loss: 221.8195
Epoch 27/50
161/161 [==============================] - 41s 257ms/step - loss: 254.4120 - val_loss: 199.4566
Epoch 28/50
161/161 [==============================] - 41s 256ms/step - loss: 252.5054 - val_loss: 193.0954
Epoch 29/50
161/161 [==============================] - 42s 259ms/step - loss: 267.9600 - val_loss: 196.8834
Epoch 30/50
161/161 [==============================] - 41s 258ms/step - loss: 241.8575 - val_loss: 187.8295
Epoch 31/50
161/161 [==============================] - 41s 256ms/step - loss: 241.0621 - val_loss: 183.0156
Epoch 32/50
161/161 [==============================] - 42s 259ms/step - loss: 238.2132 - val_loss: 189.9071
Epoch 33/50
161/161 [==============================] - 41s 256ms/step - loss: 238.4509 - val_loss: 193.3439
Epoch 34/50
161/161 [==============================] - 41s 257ms/step - loss: 230.6079 - val_loss: 197.5394
Epoch 35/50
161/161 [==============================] - 41s 255ms/step - loss: 252.5103 - val_loss: 177.1196
Epoch 36/50
161/161 [==============================] - 42s 260ms/step - loss: 248.8367 - val_loss: 190.6460
```

```
Epoch 37/50
161/161 [==============================] - 41s 254ms/step - loss: 238.1350 - val_loss: 222.1548
Epoch 38/50
161/161 [==============================] - 41s 257ms/step - loss: 232.1687 - val_loss: 171.6752
Epoch 39/50
161/161 [==============================] - 41s 257ms/step - loss: 227.3713 - val_loss: 180.7836
Epoch 40/50
161/161 [==============================] - 42s 260ms/step - loss: 229.9505 - val_loss: 167.7247
Epoch 41/50
161/161 [==============================] - 41s 257ms/step - loss: 229.1870 - val_loss: 221.3032
Epoch 42/50
161/161 [==============================] - 42s 257ms/step - loss: 232.8839 - val_loss: 166.4539
Epoch 43/50
161/161 [==============================] - 41s 255ms/step - loss: 228.9473 - val_loss: 161.2658
Epoch 44/50
161/161 [==============================] - 42s 260ms/step - loss: 222.0279 - val_loss: 185.0128
Epoch 45/50
161/161 [==============================] - 41s 256ms/step - loss: 219.0961 - val_loss: 160.4378
Epoch 46/50
161/161 [==============================] - 41s 253ms/step - loss: 221.8582 - val_loss: 174.0324
Epoch 47/50
161/161 [==============================] - 41s 256ms/step - loss: 212.9477 - val_loss: 159.7157
Epoch 48/50
161/161 [==============================] - 42s 259ms/step - loss: 220.9071 - val_loss: 189.6833
Epoch 49/50
161/161 [==============================] - 42s 257ms/step - loss: 232.4877 - val_loss: 160.9419
Epoch 50/50
161/161 [==============================] - 41s 253ms/step - loss: 212.5144 - val_loss: 153.1291
```

In [17]:

```
datagen = ImageDataGenerator(
      rescale=1./255., width_shift_range = 0.1, height_shift_range = 0.1, horizontal_flip = True)

test_datagen = ImageDataGenerator(rescale=1./255)

train2 = datagen.flow(x_train_gender, y_train_gender, batch_size=64)

test2 = test_datagen.flow(
        x_test_gender, y_test_gender,
        batch_size=64)

history2 = genmodel.fit(train2, epochs=50, shuffle=True, validation_data=test2)
```

```
0.3459 - val_accuracy: 0.8502
Epoch 45/50
81/81 [==============================] - 40s 495ms/step - loss: 0.3489 - accuracy: 0.8388 - val_loss:
0.3409 - val_accuracy: 0.8463
Epoch 46/50
81/81 [==============================] - 40s 495ms/step - loss: 0.3607 - accuracy: 0.8433 - val_loss:
0.3385 - val_accuracy: 0.8494
Epoch 47/50
81/81 [==============================] - 40s 489ms/step - loss: 0.3515 - accuracy: 0.8444 - val_loss:
0.3429 - val_accuracy: 0.8502
Epoch 48/50
81/81 [==============================] - 40s 497ms/step - loss: 0.3520 - accuracy: 0.8401 - val_loss:
0.3361 - val_accuracy: 0.8556
Epoch 49/50
81/81 [==============================] - 40s 496ms/step - loss: 0.3475 - accuracy: 0.8469 - val_loss:
0.3392 - val_accuracy: 0.8470
Epoch 50/50
81/81 [==============================] - 40s 495ms/step - loss: 0.3502 - accuracy: 0.8380 - val_loss:
0.3420 - val_accuracy: 0.8564
```

Now to evaluate the models I am going to use some external images of celebrities. These celebrities are of a variety of ages and genders.

In [30]:
```
def process_and_predict(file):
    im = Image.open(file)
    width, height = im.size
    if width == height:
        im = im.resize((200,200), Image.ANTIALIAS)
    else:
        if width > height:
            left = width/2 - height/2
            right = width/2 + height/2
            top = 0
            bottom = height
            im = im.crop((left,top,right,bottom))
            im = im.resize((200,200), Image.ANTIALIAS)
        else:
            left = 0
            right = width
            top = 0
            bottom = width
            im = im.crop((left,top,right,bottom))
            im = im.resize((200,200), Image.ANTIALIAS)

    ar = np.asarray(im)
    ar = ar.astype('float32')
    ar /= 255.0
    ar = ar.reshape(-1, 200, 200, 3)

    age = agemodel.predict(ar)
    gender = np.round(genmodel.predict(ar))
    if gender == 0:
        gender = 'male'
    elif gender == 1:
        gender = 'female'

    print('Age:', int(age), '\n Gender:', gender)
    return im.resize((300,300), Image.ANTIALIAS)
```

In [43]:
```
process_and_predict('../input/celebrities2/alyson.jpg')
```

```
Age: 36
 Gender: female
```

Out[43]:

In [46]:
```
process_and_predict('../input/celebrities2/david.jpg')
```

```
Age: 61
 Gender: male
```

Out[46]:

In [48]:
```
process_and_predict('../input/celebrities2/gaten.jpg')
```

```
Age: 38
 Gender: male
```

Out[48]:

In [50]:
```
process_and_predict('../input/celebrities2/jack.jpg')
```

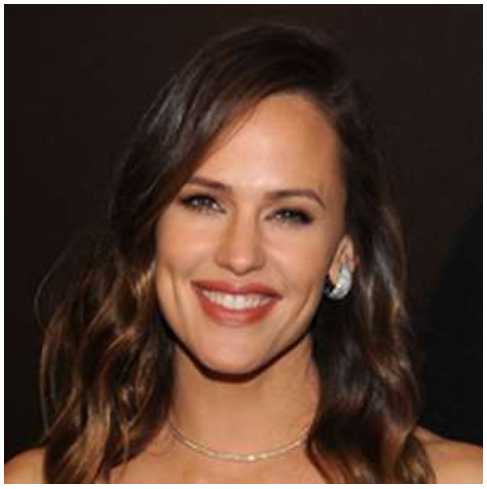
```
Age: 14
 Gender: female
```

Out[50]:

In [52]:
```
process_and_predict('../input/celebrities2/jennifer.jpg')
```

```
Age: 28
 Gender: female
```

Out[52]:



In [53]:
```
process_and_predict('../input/celebrities2/jenniferlaw.jpg')
```

```
Age: 47
 Gender: female
```

Out[53]:

In [57]:
```
process_and_predict('../input/celebrities2/meryl.jpg')
```

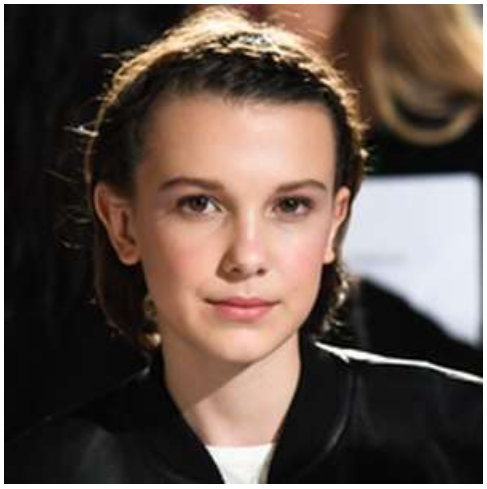
```
Age: 64
 Gender: female
```

Out[57]:

In [58]:
```
process_and_predict('../input/celebrities2/millie.jpg')
```

```
Age: 13
 Gender: female
```

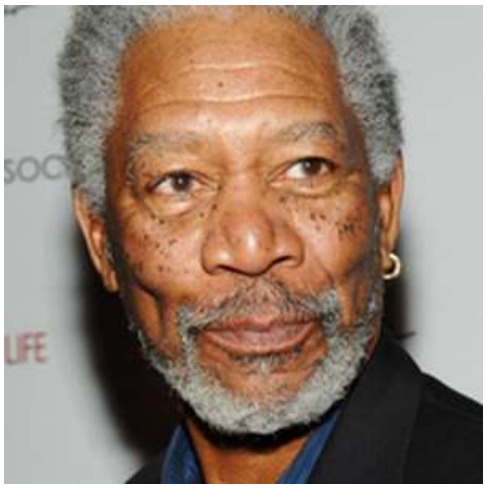
Out[58]:



In [59]:
```
process_and_predict('../input/celebrities2/morgan.jpg')
```

```
Age: 86
 Gender: male
```

Out[59]:



In [60]:
```
process_and_predict('../input/celebrities2/oprah.jpg')
```

```
Age: 42
 Gender: female
```

Out[60]:

In [63]:
```
process_and_predict('../input/celebrities2/tom.jpg')
```

```
Age: 51
 Gender: male
```

Out[63]:

In [65]:
```
process_and_predict('../input/celebrities2/winona.jpg')
```

```
Age: 26
 Gender: female
```

Out[65]: