Multi-output facial attribute classification.

CelebFaces Attributes Dataset (CelebA) is a large-scale face attributes dataset with more than 200K celebrity images, each with 40 attribute annotations. The images in this dataset cover large pose variations and background clutter. CelebA has large diversities, large quantities, and rich annotations, including

10,177 number of identities, 202,599 number of face images, and 5 landmark locations, 40 binary attributes annotations per image.

The aim of the project to do binary classification for three facial attributes that is:

- Gender 1 for male and 0 for not male
- Smiling 1 for smiling and 0 for not smiling
- Young 1 for young and 0 for not young

Successful conclusion would be achieving predictions that match actual attribute.

Sections of the notebook

1. Importing Necessary libraries
2. Data Exploration
3. Data Distribution
4. Batch Size, Model handle and Image size
5. Utility Funcions
6. Splitting the Dataset
7. Visualization of images
8. Normalization and data augmentation
9. Building the model
10. Training the model
11. Visualization - Training scores and Validation scores
12. Validating the model

Importing necessary libraries

In [25]:
```
#Import standard Deep Learning libraries
import numpy as np
import pandas as pd
import tensorflow as tf
import tensorflow_hub as hub
import matplotlib.pylab as plt
import seaborn as sns

#Checking tensorflow version and ensuring it is above 2.5.X to support Python 3.9
print("TF version:", tf.__version__)
print("Hub version:", hub.__version__)
```

```
TF version: 2.10.0
Hub version: 0.12.0
```

In [3]:
```
#set PATH variable to location of data set in local directory/storage.
```

```python
PATH = "D:/DL Project/"

ATTR_PATH = PATH + "list_attr_celeba.csv"
PARTITION_PATH = PATH + "list_eval_partition.csv"
IMAGES_PATH = PATH +"img_align_celeba/img_align_celeba/"
```

DATA EXPLORATION

In [4]:
```python
# Inputing CelebA dataset into DataFrame object
df = pd.merge(pd.read_csv(PARTITION_PATH), pd.read_csv(ATTR_PATH), on="image_id")
df.head()
```

Out[4]:

	image_id	partition	5_o_Clock_Shadow	Arched_Eyebrows	Attractive	Bags_Under_Eyes	Bald	Bangs	Big_Lips
0	000001.jpg	0	-1	1	1	-1	-1	-1	-1
1	000002.jpg	0	-1	-1	-1	1	-1	-1	-1
2	000003.jpg	0	-1	-1	-1	-1	-1	-1	1
3	000004.jpg	0	-1	-1	1	-1	-1	-1	-1
4	000005.jpg	0	-1	1	1	-1	-1	-1	1

5 rows × 42 columns

In [23]:
```python
df.shape
```

Out[23]:
```
(202599, 42)
```

There are total 40 image features, with image_id and parition as the other columns with 202599 unique data points

In [16]:
```python
df.describe()
```

Out[16]:

	partition	5_o_Clock_Shadow	Arched_Eyebrows	Attractive	Bags_Under_Eyes	Bald	
count	202599.000000	202599.000000	202599.000000	202599.00000	202599.000000	202599.000000	20259
mean	0.295120	-0.777728	-0.466039	0.02501	-0.590857	-0.955113	-(
std	0.636463	0.628602	0.884766	0.99969	0.806778	0.296241	(
min	0.000000	-1.000000	-1.000000	-1.00000	-1.000000	-1.000000	-
25%	0.000000	-1.000000	-1.000000	-1.00000	-1.000000	-1.000000	-
50%	0.000000	-1.000000	-1.000000	1.00000	-1.000000	-1.000000	-
75%	0.000000	-1.000000	1.000000	1.00000	-1.000000	-1.000000	-
max	2.000000	1.000000	1.000000	1.00000	1.000000	1.000000	

8 rows × 41 columns

Listing out all 40 features. But we will limit features to limit scope of the problem

In [17]:
```python
df.columns
```

Out[17]:
```
Index(['image_id', 'partition', '5_o_Clock_Shadow', 'Arched_Eyebrows',
       'Attractive', 'Bags_Under_Eyes', 'Bald', 'Bangs', 'Big_Lips',
       'Big_Nose', 'Black_Hair', 'Blond_Hair', 'Blurry', 'Brown_Hair',
       'Bushy_Eyebrows', 'Chubby', 'Double_Chin', 'Eyeglasses', 'Goatee',
       'Gray_Hair', 'Heavy_Makeup', 'High_Cheekbones', 'Male',
       'Mouth_Slightly_Open', 'Mustache', 'Narrow_Eyes', 'No_Beard',
       'Oval_Face', 'Pale_Skin', 'Pointy_Nose', 'Receding_Hairline',
       'Rosy_Cheeks', 'Sideburns', 'Smiling', 'Straight_Hair', 'Wavy_Hair',
       'Wearing_Earrings', 'Wearing_Hat', 'Wearing_Lipstick',
       'Wearing_Necklace', 'Wearing_Necktie', 'Young'],
      dtype='object')
```

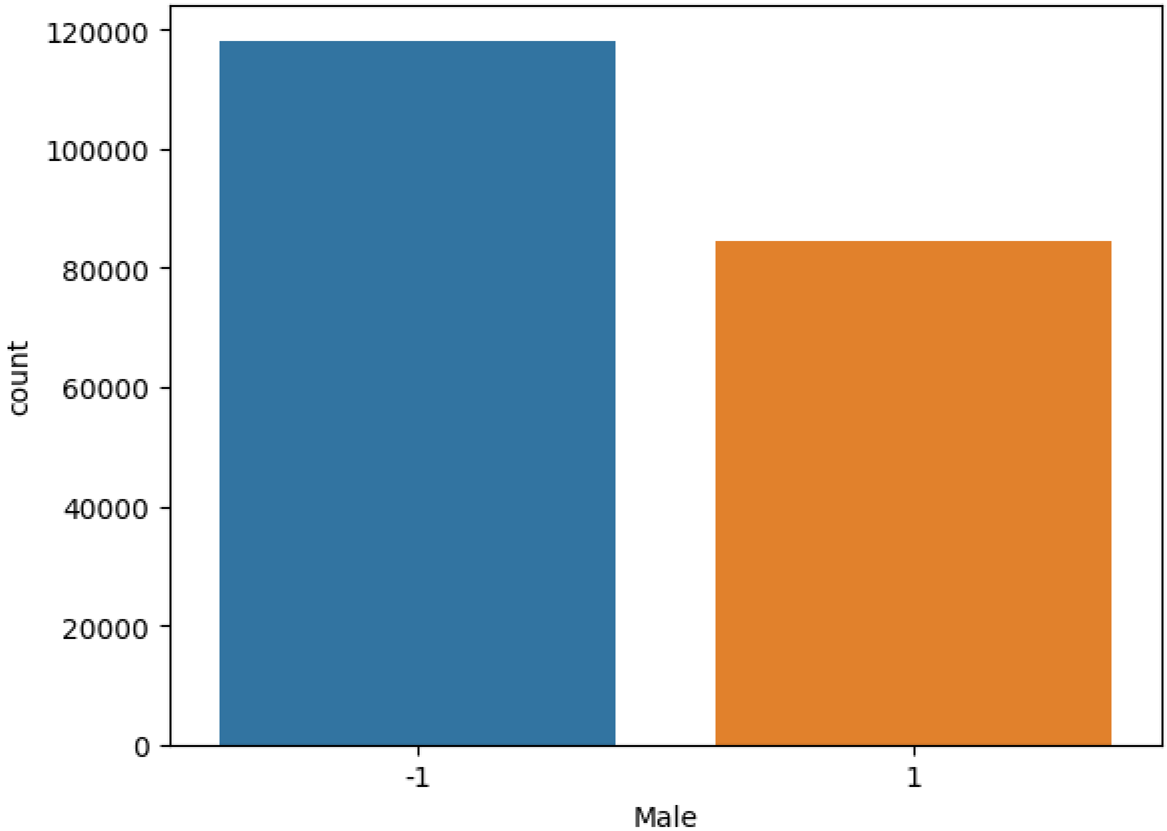
In [18]:
```
df.isnull().sum()
```

Out[18]:
```
image_id               0
partition              0
5_o_Clock_Shadow       0
Arched_Eyebrows        0
Attractive             0
Bags_Under_Eyes        0
Bald                   0
Bangs                  0
Big_Lips               0
Big_Nose               0
Black_Hair             0
Blond_Hair             0
Blurry                 0
Brown_Hair             0
Bushy_Eyebrows         0
Chubby                 0
Double_Chin            0
Eyeglasses             0
Goatee                 0
Gray_Hair              0
Heavy_Makeup           0
High_Cheekbones        0
Male                   0
Mouth_Slightly_Open    0
Mustache               0
Narrow_Eyes            0
No_Beard               0
Oval_Face              0
Pale_Skin              0
Pointy_Nose            0
Receding_Hairline      0
Rosy_Cheeks            0
Sideburns              0
Smiling                0
Straight_Hair          0
Wavy_Hair              0
Wearing_Earrings       0
Wearing_Hat            0
Wearing_Lipstick       0
Wearing_Necklace       0
Wearing_Necktie        0
Young                  0
dtype: int64
```

We can notice that all features have non zeros entries

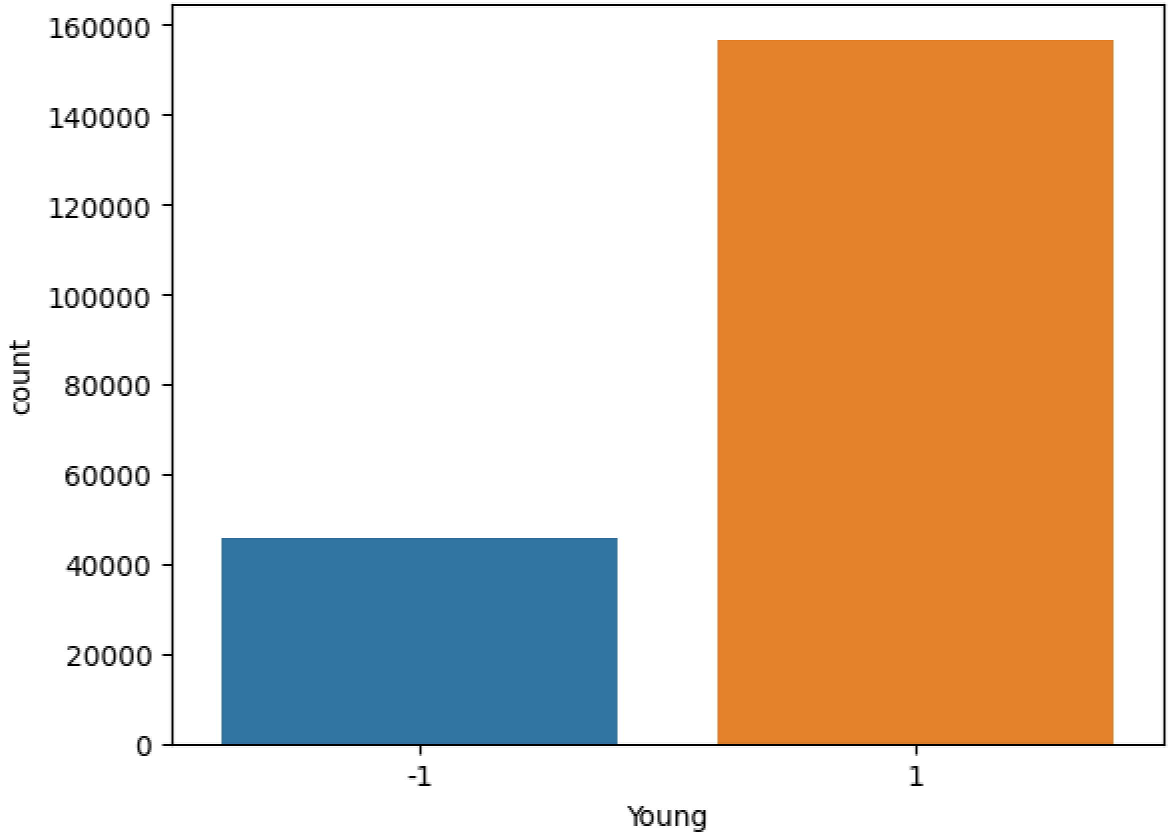
Data Distribution

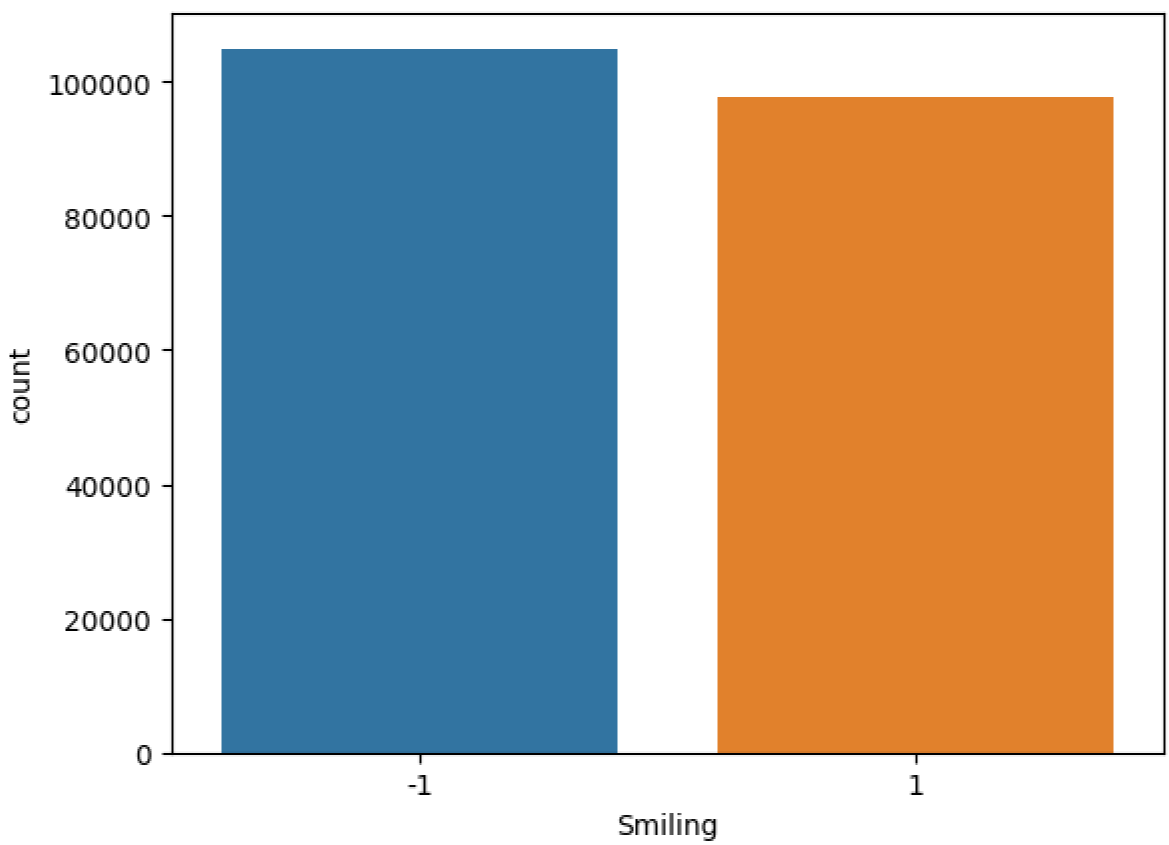
In [26]:
```
sns.countplot(data = df, x = "Male")
plt.show()
```



In [28]:
```
sns.countplot(data = df, x = "Young")
plt.show()

sns.countplot(data = df, x = "Smiling")
plt.show()
```





There are some inconsistencies in the data, for example: we can observe that there are more young samples when come to not young samples, there are more not male samples when compare to male samples and so on.

Batch Size, Model handle and Image size

Batch size is the number of samples that will be passed through to the network at one time.

Model Handle is the common terminology used to denote pre-trained weights in tensorflow hub environment and takes input string to load pre-trained weights.

Image size is usually defined as the size of vector that input network layers expect

In [5]:
```
#Adjust batch size accordingly to computational resources available, we have choosen 128 accordi
BATCH_SIZE = 128
#MODEL_HANDLE is the variable in which we are saving pretrained weights from Efficientnet_v2 used
MODEL_HANDLE = "https://tfhub.dev/google/imagenet/efficientnet_v2_imagenet21k_ft1k_b0/feature_vec

#Image size of 224,224,3 is the input required for Efficientnet, and Efficientnet V2 expects a fe
IMAGE_SIZE = (224, 224)
```

Utility functions to preprocess, load and preprocess images and building dataset with relevant features only

This section of code builds utility functions that help build dataset from the original dataframe and select 3 features out of the total 40 features.

In [6]:
```
# Preprocess_image is used to resize all images into 224 X 224 pixels
def preprocess_image(image):
    image = tf.image.decode_jpeg(image, channels=3)
    image = tf.image.resize(image, IMAGE_SIZE)
    return image

# load_and_preprocess
def load_and_preprocess_image(path):
    image = tf.io.read_file(path)
    return preprocess_image(image)

# load_and_preprocess_from_path_label function
def load_and_preprocess_from_path_label(path, male, smiling, young):
    images = load_and_preprocess_image(path)
    return images, male, smiling, young
'''
build_data_from_df utilizes the above funcions to build dataset from the original Dataframe of Ce
that are out of scope of defined problem statement.
'''
def build_dataset_from_df(df):
    ds = tf.data.Dataset.from_tensor_slices((
        [IMAGES_PATH + image_id for image_id in df["image_id"]],
        list(df["Male"].replace(-1, 0)),
        list(df["Smiling"].replace(-1, 0)),
        list(df["Young"].replace(-1, 0))
    ))
    ds = ds.map(load_and_preprocess_from_path_label)
    ds = ds.shuffle(buffer_size=1000)
    ds = ds.repeat()
    ds = ds.batch(BATCH_SIZE)
    ds = ds.prefetch(buffer_size=tf.data.AUTOTUNE)
    return ds
```

Splitting the dataset

Spliting the dataset into training and validation set based on data from "partition" column.
0 --> Training data 1 --> Validation data 2 --> Testing data

In [8]:
```
# train_ds and val_ds are the new Dataframe objects containing attributes- young, smiling and mal

train_df = df.loc[df["partition"] == 0]
train_ds = build_dataset_from_df(train_df)

val_df = df.loc[df["partition"] == 1]
val_ds = build_dataset_from_df(val_df)
```

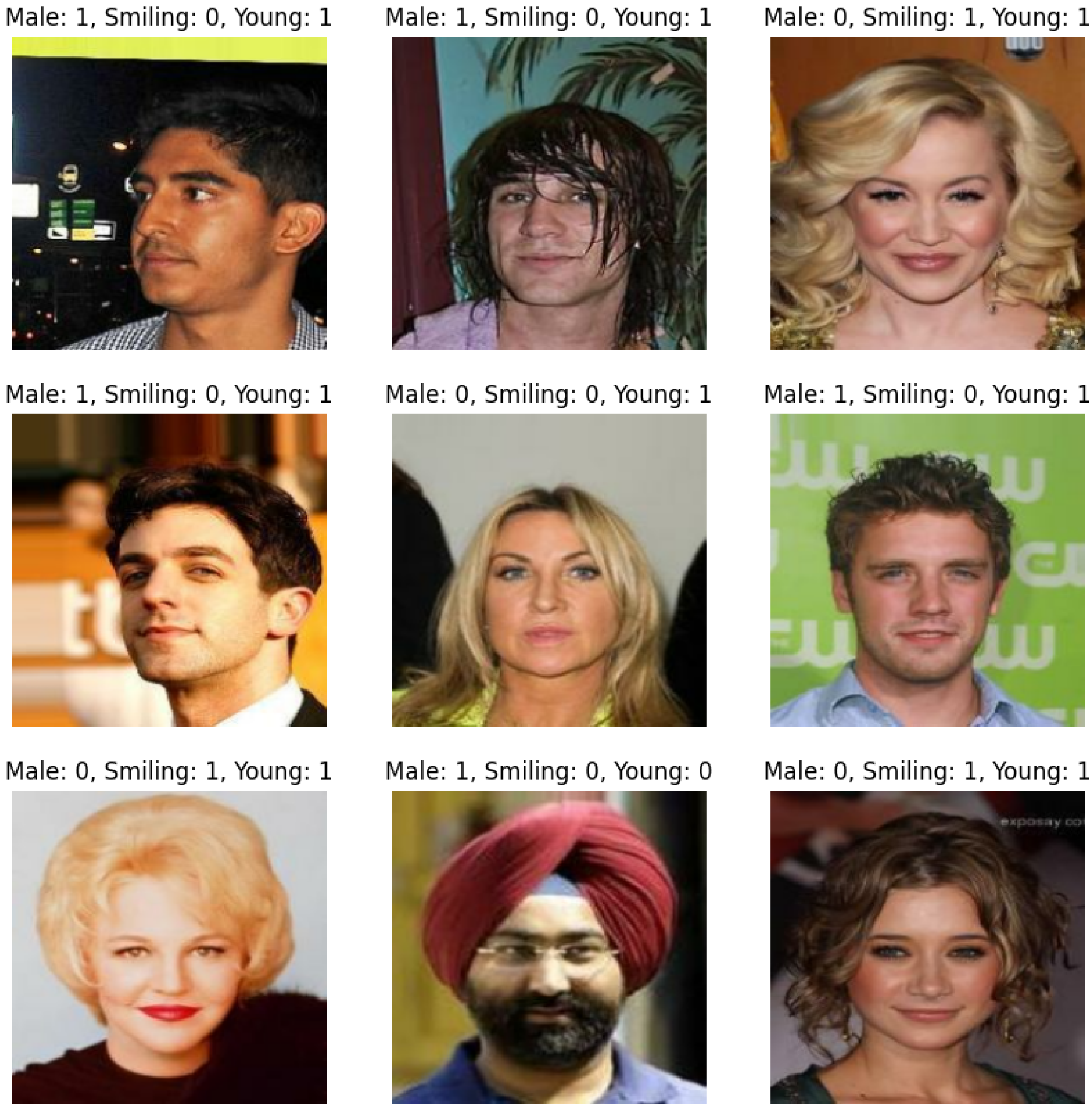
In [9]:
```
# Printing size of the labels with attribute
for image, male, smiling, young in train_ds.take(1):
    print("Image dimension: ", image.numpy().shape)
    print("Shape of Gender feature vector: ", male.shape)
    print("Shape of Smiling feature vector:", smiling.shape)
    print("Shape of Young vector", young.shape)
```

```
Image dimension:  (128, 224, 224, 3)
Shape of Gender feature vector:  (128,)
Shape of Smiling feature vector: (128,)
Shape of Young vector (128,)
```

Visualization of images with their actual facial attributes

Plotting images with their corresponding features

In [11]:
```
image, male, smiling, young = next(iter(train_ds))
plt.figure(figsize=(10, 10))
for i in range(9):
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(image[i].numpy().astype("uint8"))
    s = f"Male: {male[i].numpy()}, Smiling: {smiling[i].numpy()}, Young: {young[i].numpy()}"
    plt.title(s)
    plt.axis("off")
```



Normalization and data augmentation layers to remove inconsistencies in data set

To address the problem of data inconsistency observed in data visualization section, we have to use image segmentation to produce variations of images that are treated as new images so as to increase the number of labeled data the model sees.

But to computational limitations that we have choosen to not use image/data augmentation but it is recommended to achieve higher accuracies

In [12]:

```
normalization_layer = tf.keras.layers.Rescaling(1. / 255)
preprocessing_model = tf.keras.Sequential([normalization_layer])

#Disabling data augmentation due to computational restrictions
#
do_data_augmentation = False
```

```
if do_data_augmentation:
    preprocessing_model.add(tf.keras.layers.RandomRotation(0.2))
    preprocessing_model.add(tf.keras.layers.RandomTranslation(0, 0.2))
    preprocessing_model.add(tf.keras.layers.RandomTranslation(0.2, 0))
    preprocessing_model.add(tf.keras.layers.RandomZoom(0.2, 0.2))
    preprocessing_model.add(tf.keras.layers.RandomFlip(mode="horizontal"))

train_ds = train_ds.map(lambda images, male, smiling, young:
                        (preprocessing_model(images), (male, smiling, young)))

val_ds = val_ds.map(lambda images, male, smiling, young:
                    (normalization_layer(images), (male, smiling, young)))
```

Building the Model

In [13]:

```
#Fine tuning set to false due to computational restrictions as code was run on local machine
do_fine_tuning = False
input = tf.keras.Input(shape=IMAGE_SIZE + (3,))
x = hub.KerasLayer(MODEL_HANDLE, trainable=do_fine_tuning)(input)
x = tf.keras.layers.Dropout(rate=0.2)(x)
x = tf.keras.layers.Dense(128, activation="relu")(x)

#Out_male, out_smiling, and out_young
out_male = tf.keras.layers.Dense(1, kernel_regularizer=tf.keras.regularizers.l2(0.0001), activat
out_smiling = tf.keras.layers.Dense(1, kernel_regularizer=tf.keras.regularizers.l2(0.0001), acti
out_young = tf.keras.layers.Dense(1, kernel_regularizer=tf.keras.regularizers.l2(0.0001), activa

model = tf.keras.Model( inputs = input, outputs = [out_male, out_smiling, out_young])
model.summary()
```

```
WARNING:tensorflow:Please fix your imports. Module tensorflow.python.training.tracking.data_structures has been moved to tensorflow.python.trackable.data_structures. The old module will be deleted in version 2.11.
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to                     
==================================================================================================
 input_1 (InputLayer)           [(None, 224, 224, 3  0           []                               
                                )]                                                                
                                                                                                  
 keras_layer (KerasLayer)       (None, 1280)         5919312     ['input_1[0][0]']                
                                                                                                  
 dropout (Dropout)              (None, 1280)         0           ['keras_layer[0][0]']            
                                                                                                  
 dense (Dense)                  (None, 128)          163968      ['dropout[0][0]']                
                                                                                                  
 male (Dense)                   (None, 1)            129         ['dense[0][0]']                  
                                                                                                  
 smiling (Dense)                (None, 1)            129         ['dense[0][0]']                  
                                                                                                  
 young (Dense)                  (None, 1)            129         ['dense[0][0]']                  
                                                                                                  
==================================================================================================
Total params: 6,083,667
Trainable params: 164,355
Non-trainable params: 5,919,312
__________________________________________________________________________________________________
```

Model summary:

As we can observe, there are 6.08 million parameters with total trainable parameters being 164,355. Total non-trainable parameters are 5.9 million.

In [14]:
```
# Using Binary Crossentropy because we aim to do binary classification of each of the defined
model.compile(
    loss = {
        "male": tf.keras.losses.BinaryCrossentropy(),
        "smiling": tf.keras.losses.BinaryCrossentropy(),
        "young": tf.keras.losses.BinaryCrossentropy()
    },
```

```python
# Using accuracy metrics
    metrics = {
        "male": 'accuracy',
        "smiling": 'accuracy',
        "young": 'accuracy'
    },
    optimizer = tf.keras.optimizers.Adam(learning_rate=0.001)
)
```

Training the model

In [13]:

```python
steps_per_epoch = len(train_df) // BATCH_SIZE
validation_steps = len(val_df) // BATCH_SIZE
hist = model.fit(
    train_ds,
    epochs=3, steps_per_epoch=steps_per_epoch,
    validation_data=val_ds,
    validation_steps=validation_steps).history
```

```
Epoch 1/3
1271/1271 [==============================] - 3847s 3s/step - loss: 0.8622 - male_loss: 0.1247 - smiling_loss: 0.4109 - young_loss: 0.3261 - male_accuracy: 0.9520 - smiling_accuracy: 0.8099 - young_accuracy: 0.8640 - val_loss: 0.7642 - val_male_loss: 0.0855 - val_smiling_loss: 0.3507 - val_young_loss: 0.3275 - val_male_accuracy: 0.9666 - val_smiling_accuracy: 0.8498 - val_young_accuracy: 0.8594
Epoch 2/3
1271/1271 [==============================] - 3746s 3s/step - loss: 0.7929 - male_loss: 0.1054 - smiling_loss: 0.3796 - young_loss: 0.3073 - male_accuracy: 0.9593 - smiling_accuracy: 0.8276 - young_accuracy: 0.8724 - val_loss: 0.7478 - val_male_loss: 0.0798 - val_smiling_loss: 0.3391 - val_young_loss: 0.3285 - val_male_accuracy: 0.9695 - val_smiling_accuracy: 0.8509 - val_young_accuracy: 0.8605
Epoch 3/3
1271/1271 [==============================] - 3747s 3s/step - loss: 0.7708 - male_loss: 0.0989 - smiling_loss: 0.3695 - young_loss: 0.3019 - male_accuracy: 0.9621 - smiling_accuracy: 0.8332 - young_accuracy: 0.8746 - val_loss: 0.7404 - val_male_loss: 0.0783 - val_smiling_loss: 0.3316 - val_young_loss: 0.3302 - val_male_accuracy: 0.9683 - val_smiling_accuracy: 0.8533 - val_young_accuracy: 0.8595
```

In [23]:

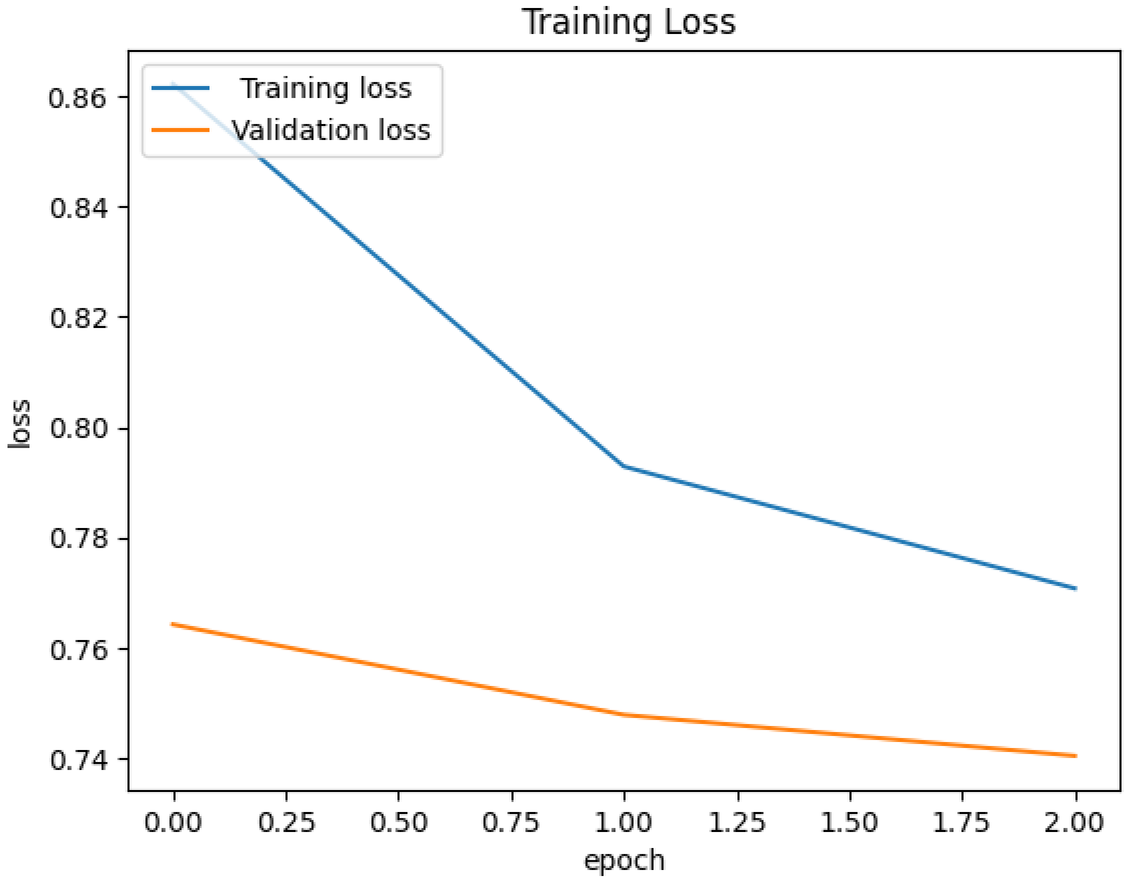
```python
hist
```

Out[23]:
```
{'loss': [0.8621907830238342, 0.7928568124771118, 0.7707589864730835],
 'male_loss': [0.12472067028284073, 0.10539133846759796, 0.09892390668392181],
 'smiling_loss': [0.41085001826286316,
  0.37964698672294617,
  0.3695099353790283],
 'young_loss': [0.3260566294193268, 0.3073425889015198, 0.3018992841243744],
 'male_accuracy': [0.9520493149757385, 0.9592840075492859, 0.9620869159698486],
 'smiling_accuracy': [0.8098999261856079,
  0.8276086449623108,
  0.8331591486930847],
 'young_accuracy': [0.8639727830886841, 0.872393786907196, 0.8746373653411865],
 'val_loss': [0.7642360329627991, 0.7478486895561218, 0.7404118180274963],
 'val_male_loss': [0.08553789556026459,
  0.07982660830020905,
  0.07828792184591293],
 'val_smiling_loss': [0.35069721937179565,
  0.3391178250312805,
  0.3315522372722626],
 'val_young_loss': [0.3274909555912018,
  0.32845795154571533,
  0.33016806840896606],
 'val_male_accuracy': [0.9665826559066772,
  0.969506025314331,
  0.9682963490486145],
 'val_smiling_accuracy': [0.8498488068580627,
  0.8509072661399841,
  0.8532761931419373],
 'val_young_accuracy': [0.859375, 0.8604838848114014, 0.8595262169837952]}
```

Visualization of Training and Validation graphs

Plotting training and validation accuracy scores

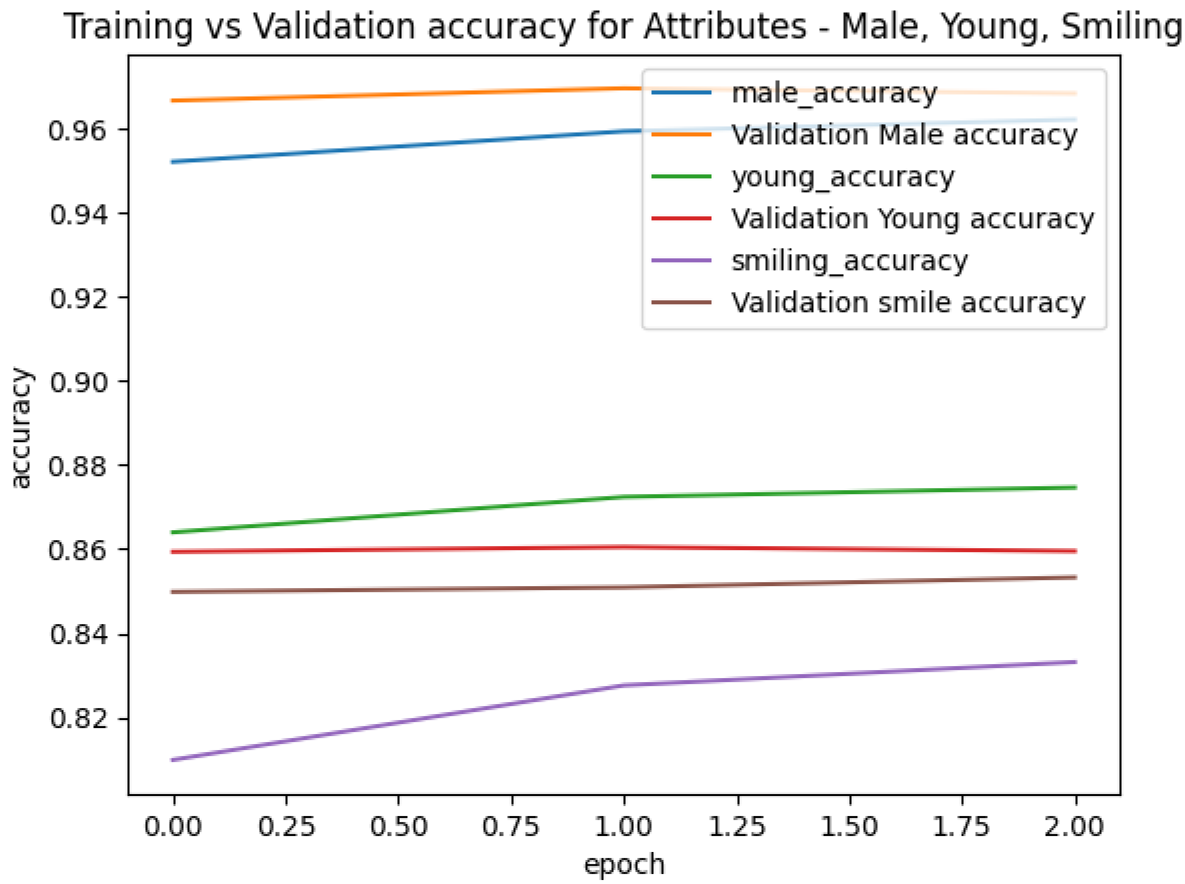
In [26]:
```
plt.plot(hist["loss"])
plt.plot(hist["val_loss"])
plt.title(' Training Loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend([' Training loss', 'Validation loss'], loc='upper left')
plt.show()
```



In [28]:

```
# Using Matplotlib to plot accuracy values from hist dictionary with corresponding epochs
plt.plot(hist['male_accuracy'])
plt.plot(hist['val_male_accuracy'])
plt.plot(hist['young_accuracy'])
plt.plot(hist['val_young_accuracy'])
plt.plot(hist['smiling_accuracy'])
plt.plot(hist['val_smiling_accuracy'])
plt.plot

plt.title('Training vs Validation accuracy for Attributes - Male, Young, Smiling')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['male_accuracy', 'Validation Male accuracy', 'young_accuracy', 'Validation Young accu
plt.show()
```



Testing

Taking a random image from constructed dataset and predicting probability of person in the picture being Male, Young and Smiling and then doing binary classification to give a 0 or 1 to indicate presence of attribute.

In [30]:
```
x, y = next(iter(val_ds))
image = x[0, :, :, :]
plt.imshow(image)
plt.axis('off')
plt.show()

prediction_scores = model.predict(np.expand_dims(image, axis=0))
for i, label in enumerate(["Male", "Smiling", "Young"]):
    pred = prediction_scores[i][0][0]
    print(f"{label}: actual {y[i][0]}, predicted {1 if pred > 0.5 else 0} ({format(pred, '.4f')})
```

```
1/1 [==============================] - 0s 47ms/step
Male: actual 1, predicted 1 (0.9998)
Smiling: actual 0, predicted 0 (0.1421)
Young: actual 1, predicted 1 (0.9257)
```

In [31]:

```
x, y = next(iter(val_ds))
image = x[0, :, :, :]
plt.imshow(image)
plt.axis('off')
plt.show()

prediction_scores = model.predict(np.expand_dims(image, axis=0))
for i, label in enumerate(["Male", "Smiling", "Young"]):
    pred = prediction_scores[i][0][0]
    print(f"{label}: actual {y[i][0]}, predicted {1 if pred > 0.5 else 0} ({format(pred, '.4f')})
```

```
1/1 [==============================] - 0s 49ms/step
Male: actual 1, predicted 1 (0.9970)
Smiling: actual 0, predicted 0 (0.0738)
Young: actual 1, predicted 1 (0.8993)
```

In [32]:
```python
x, y = next(iter(val_ds))
image = x[0, :, :, :]
plt.imshow(image)
plt.axis('off')
plt.show()

prediction_scores = model.predict(np.expand_dims(image, axis=0))
for i, label in enumerate(["Male", "Smiling", "Young"]):
    pred = prediction_scores[i][0][0]
    print(f"{label}: actual {y[i][0]}, predicted {1 if pred > 0.5 else 0} ({format(pred, '.4f')}
```

```
1/1 [==============================] - 0s 51ms/step
Male: actual 1, predicted 1 (0.7063)
Smiling: actual 1, predicted 0 (0.1964)
Young: actual 1, predicted 1 (0.7718)
```

References:

Used for code and model architecture:

https://www.kaggle.com/code/cbrincoveanu/transfer-learning-and-multi-output-tutorial
https://www.kaggle.com/code/dpamgautam/face-recognition-gender-detection-inceptionv3
https://www.kaggle.com/code/ky2019/starter-celebfaces-attributes-celeba-b5421ae1-e
https://www.kaggle.com/code/bulentorun/pytorchdeepcnn-classifying-images-with-deep-cnn
https://tfhub.dev/google/collections/efficientnet/1
https://datasets.activeloop.ai/docs/ml/datasets/celeba-dataset/
https://towardsdatascience.com/real-time-multi-facial-attribute-detection-using-transfer-learning-and-haar-cascades-with-fastai-47ff59e36df0

In [ ]: