313326985_206172686-nosearchoutput

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1 Assignment 2

1.1 Id numbers and names

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1.2 Imports

[ ]:
```
!pip install tensorflow
```

```
Requirement already satisfied: tensorflow in /usr/local/lib/python3.7/dist-
packages (2.8.0+zzzcolab20220506162203)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (0.25.0)
Collecting tf-estimator-nightly==2.8.0.dev2021122109
  Downloading tf_estimator_nightly-2.8.0.dev2021122109-py2.py3-none-any.whl (462
kB)
     |                 | 462 kB 5.3 MB/s
Requirement already satisfied: absl-py>=0.4.0 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (1.0.0)
Requirement already satisfied: libclang>=9.0.1 in /usr/local/lib/python3.7/dist-
packages (from tensorflow) (14.0.1)
Requirement already satisfied: typing-extensions>=3.6.6 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (4.2.0)
Requirement already satisfied: opt-einsum>=2.3.2 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (3.3.0)
Requirement already satisfied: flatbuffers>=1.12 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (2.0)
Requirement already satisfied: astunparse>=1.6.0 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.7/dist-
packages (from tensorflow) (3.1.0)
Requirement already satisfied: termcolor>=1.1.0 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (1.1.0)
Requirement already satisfied: protobuf>=3.9.2 in /usr/local/lib/python3.7/dist-
```

```
packages (from tensorflow) (3.17.3)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (1.46.1)
Requirement already satisfied: tensorboard<2.9,>=2.8 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (2.8.0)
Requirement already satisfied: keras-preprocessing>=1.1.1 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (1.1.2)
Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.7/dist-
packages (from tensorflow) (1.14.1)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-
packages (from tensorflow) (57.4.0)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.7/dist-
packages (from tensorflow) (1.15.0)
Requirement already satisfied: gast>=0.2.1 in /usr/local/lib/python3.7/dist-
packages (from tensorflow) (0.5.3)
Requirement already satisfied: numpy>=1.20 in /usr/local/lib/python3.7/dist-
packages (from tensorflow) (1.21.6)
Requirement already satisfied: google-pasta>=0.1.1 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (0.2.0)
Requirement already satisfied: keras<2.9,>=2.8.0rc0 in
/usr/local/lib/python3.7/dist-packages (from tensorflow) (2.8.0)
Requirement already satisfied: wheel<1.0,>=0.23.0 in
/usr/local/lib/python3.7/dist-packages (from astunparse>=1.6.0->tensorflow)
(0.37.1)
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/dist-
packages (from h5py>=2.9.0->tensorflow) (1.5.2)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.7/dist-
packages (from tensorboard<2.9,>=2.8->tensorflow) (3.3.7)
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in
/usr/local/lib/python3.7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow)
(0.4.6)
Requirement already satisfied: werkzeug>=0.11.15 in
/usr/local/lib/python3.7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow)
(1.0.1)
Requirement already satisfied: requests<3,>=2.21.0 in
/usr/local/lib/python3.7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow)
(2.23.0)
Requirement already satisfied: tensorboard-data-server<0.7.0,>=0.6.0 in
/usr/local/lib/python3.7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow)
(0.6.1)
Requirement already satisfied: google-auth<3,>=1.6.3 in
/usr/local/lib/python3.7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow)
(1.35.0)
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in
/usr/local/lib/python3.7/dist-packages (from tensorboard<2.9,>=2.8->tensorflow)
(1.8.1)
Requirement already satisfied: pyasn1-modules>=0.2.1 in
/usr/local/lib/python3.7/dist-packages (from google-
```

```
auth<3,>=1.6.3->tensorboard<2.9,>=2.8->tensorflow) (0.2.8)
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.7/dist-
packages (from google-auth<3,>=1.6.3->tensorboard<2.9,>=2.8->tensorflow) (4.8)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from google-
auth<3,>=1.6.3->tensorboard<2.9,>=2.8->tensorflow) (4.2.4)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/usr/local/lib/python3.7/dist-packages (from google-auth-
oauthlib<0.5,>=0.4.1->tensorboard<2.9,>=2.8->tensorflow) (1.3.1)
Requirement already satisfied: importlib-metadata>=4.4 in
/usr/local/lib/python3.7/dist-packages (from
markdown>=2.6.8->tensorboard<2.9,>=2.8->tensorflow) (4.11.3)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.7/dist-
packages (from importlib-
metadata>=4.4->markdown>=2.6.8->tensorboard<2.9,>=2.8->tensorflow) (3.8.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in
/usr/local/lib/python3.7/dist-packages (from pyasn1-modules>=0.2.1->google-
auth<3,>=1.6.3->tensorboard<2.9,>=2.8->tensorflow) (0.4.8)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-
packages (from requests<3,>=2.21.0->tensorboard<2.9,>=2.8->tensorflow) (2.10)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/usr/local/lib/python3.7/dist-packages (from
requests<3,>=2.21.0->tensorboard<2.9,>=2.8->tensorflow) (1.24.3)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.7/dist-packages (from
requests<3,>=2.21.0->tensorboard<2.9,>=2.8->tensorflow) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.7/dist-packages (from
requests<3,>=2.21.0->tensorboard<2.9,>=2.8->tensorflow) (2021.10.8)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.7/dist-
packages (from requests-oauthlib>=0.7.0->google-auth-
oauthlib<0.5,>=0.4.1->tensorboard<2.9,>=2.8->tensorflow) (3.2.0)
Installing collected packages: tf-estimator-nightly
Successfully installed tf-estimator-nightly-2.8.0.dev2021122109
```

[ ]:

```
import numpy as np
import os
import seaborn as sns
import pandas as pd
import cv2
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow.keras.layers import Input, Dense, Flatten, Conv2D,␣
↪MaxPooling2D, Dropout, BatchNormalization, Lambda, Subtract, MaxPool2D
from tensorflow.keras.models import Model, Sequential, load_model, save_model
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping,␣
↪ReduceLROnPlateau
```

```
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.regularizers import l2
from tensorflow.keras import backend as K
import random
import itertools
import joblib
import time
```

[ ]:
```
# tf.test.is_gpu_available(
#     cuda_only=False, min_cuda_compute_capability=None
# )

# tf.config.list_physical_devices('GPU')
```

1.3 Data set - Labeled Faces in the Wild

The "Labeled Faces in the Wild-a" image collection is a database of labeled, face images intended for studying Face Recognition in unconstrained images.

1.3.1 Download the dataset

[ ]:
```
# The url provided in the work instructions
url = "https://drive.google.com/file/d/1p1wjaqpTh_5RHfJu4vUh8JJCdKwYMHCp/view?
↪usp=sharing"
```

[ ]:
```
# Download the dataset from the url
!wget -q --load-cookies /tmp/cookies.txt "https://docs.google.com/uc?
↪export=download&confirm=$(wget --quiet --save-cookies /tmp/cookies.txt␣
↪--keep-session-cookies --no-check-certificate 'https://docs.google.com/uc?
↪export=download&id=1p1wjaqpTh_5RHfJu4vUh8JJCdKwYMHCp' -O- | sed -rn 's/.
↪*confirm=([0-9A-Za-z_]+).*/\1\n/p')&id=1p1wjaqpTh_5RHfJu4vUh8JJCdKwYMHCp" -O␣
↪LFW-a && rm -rf /tmp/cookies.txt
!unzip -q LFW-a && rm LFW-a
```

[ ]:
```
DATAPATH = './lfw2/lfw2/'
```

1.3.2 Train and Test sets

We used the training set and the test set attached to the instructions. In addition, we produce a validation set which will be 20% of the training set (and the rest will be the training set).

[ ]:
```
# Download the train and test meta data
!wget http://vis-www.cs.umass.edu/lfw/pairsDevTrain.txt
!wget http://vis-www.cs.umass.edu/lfw/pairsDevTest.txt
```

```
--2022-05-17 19:50:17--  http://vis-www.cs.umass.edu/lfw/pairsDevTrain.txt
Resolving vis-www.cs.umass.edu (vis-www.cs.umass.edu)… 128.119.244.95
Connecting to vis-www.cs.umass.edu (vis-www.cs.umass.edu)|128.119.244.95|:80…
connected.
HTTP request sent, awaiting response… 200 OK
Length: 56579 (55K) [text/plain]
Saving to: 'pairsDevTrain.txt'

pairsDevTrain.txt   100%[===================>]  55.25K  --.-KB/s    in 0.09s

2022-05-17 19:50:17 (594 KB/s) - 'pairsDevTrain.txt' saved [56579/56579]

--2022-05-17 19:50:17--  http://vis-www.cs.umass.edu/lfw/pairsDevTest.txt
Resolving vis-www.cs.umass.edu (vis-www.cs.umass.edu)… 128.119.244.95
Connecting to vis-www.cs.umass.edu (vis-www.cs.umass.edu)|128.119.244.95|:80…
connected.
HTTP request sent, awaiting response… 200 OK
Length: 26002 (25K) [text/plain]
Saving to: 'pairsDevTest.txt'

pairsDevTest.txt    100%[===================>]  25.39K  --.-KB/s    in 0.05s

2022-05-17 19:50:18 (545 KB/s) - 'pairsDevTest.txt' saved [26002/26002]
```

[ ]:
```
# global seed
seed = 10
random.seed(seed)
np.random.seed(seed)
tf.random.set_seed(seed)
```

[ ]:
```
# Save image paths in data frame
def read_data(path):
  match_pairs = pd.DataFrame(columns=['Name1', 'Image1', 'Name2', 'Image2',␣
↪'Label'])
  mismatch_pairs= pd.DataFrame(columns=['Name1', 'Image1', 'Name2', 'Image2',␣
↪'Label'])
  with open(path) as f:
      for line in f:
          row = line.split()
          if len(row) == 3:
            data_to_append = {}
            row[1] = f'{DATAPATH}{row[0]}/{row[0]}_{str(row[1]).rjust(4, "0")}.
↪jpg'
            row[2] = f'{DATAPATH}{row[0]}/{row[0]}_{str(row[2]).rjust(4, "0")}.
↪jpg'
            for i in range(len(match_pairs.columns)):
```

```
            if i == 2:
              data_to_append[match_pairs.columns[i]] = row[0]
            elif i == 3:
              data_to_append[match_pairs.columns[i]] = row[2]
            elif i == 4:
              data_to_append[match_pairs.columns[i]] = 'same'
            else:
              data_to_append[match_pairs.columns[i]] = row[i]
          match_pairs = match_pairs.append(data_to_append, ignore_index =␣
↪True)
        elif len(row) == 4:
          data_to_append = {}
          row[1] = f'{DATAPATH}{row[0]}/{row[0]}_{str(row[1]).rjust(4, "0")}.
↪jpg'
          row[3] = f'{DATAPATH}{row[2]}/{row[2]}_{str(row[3]).rjust(4, "0")}.
↪jpg'
          for i in range(len(mismatch_pairs.columns)):
            if i == 4:
              data_to_append[match_pairs.columns[i]] = 'different'
            else:
              data_to_append[mismatch_pairs.columns[i]] = row[i]
          mismatch_pairs = mismatch_pairs.append(data_to_append, ignore_index␣
↪= True)
  return pd.concat([match_pairs, mismatch_pairs]).reset_index(drop=True)
```

[ ]:
```
# Split the data into train, validation and test sets
# The validation set is 20% of training set
def split_train_validation_test():
  train_validation = read_data('./pairsDevTrain.txt')
  test = read_data('./pairsDevTest.txt')

  seed = 10
  random.seed(seed)
  np.random.seed(seed)
  tf.random.set_seed(seed)

  validation = train_validation.sample(frac = 0.2)
  train = train_validation.drop(validation.index)

  return train, validation, test
```

[ ]:
```
def load_image(image_path):
    img = cv2.imread(image_path)/255
    img = (cv2.resize(img, (105, 105)))
    return img
```

```
[ ]: def load_X(meta_data):
       X1 = []
       X2 = []
       for index, row in meta_data.iterrows():
         image1 = load_image(row['Image1'])
         X1.append(image1)
         image2 = load_image(row['Image2'])
         X2.append(image2)


       return np.array([[x1, x2] for x1, x2 in zip(X1, X2)])
```

```
[ ]: def load_Y(meta_data):
       Y = pd.DataFrame(meta_data['Label'].copy())
       Y['Label'].replace({"same":1, "different":0}, inplace=True)

       return Y.to_numpy()
```

```
[ ]: def load_X_Y(train, validation, test):
       X_train = load_X(train)
       X_val = load_X(validation)
       X_test = load_X(test)
       Y_train = load_Y(train)
       Y_val = load_Y(validation)
       Y_test = load_Y(test)


       return X_train, Y_train, X_val, Y_val, X_test, Y_test
```

```
[ ]: train, validation, test = split_train_validation_test()
     X_train, Y_train, X_val, Y_val, X_test, Y_test = load_X_Y(train, validation,␣
      ↪test)
```

1.3.3 Analysis of the dataset

size, number of examples – in total and per class – for the train and test sets, etc.

The dataset contains a total of 3200 samples. Where each smaple contains two images, and each sample is labeled as 'same' or 'different'. * There are 2200 samples in the training set, 1100 of them are labeled as 'same' and 1100 of them are labeled as 'different'. * There are 1000 samples in the test set, 500 of which are labeled as 'same' and 500 of which are labeled as 'different'.

We splitted the train set into train and validation sets (the validation set contains 20% if the train set).

```
[ ]: peoples = os.listdir(DATAPATH)
     peoples_images = [len(os.listdir(f'{DATAPATH}/{people}')) for people in peoples]
```

Total:

```
[ ]: print("The dataset contains images of " + str(len(peoples)) + " peoples")
     print("The dataset contains a total of " + str(np.sum(peoples_images)) + "␣
     ↪images")
     print("Each pesron has an average " + str(np.round(np.mean(peoples_images),3))␣
     ↪+ " +- " + str(np.round(np.std(peoples_images),3)) + " images")
```

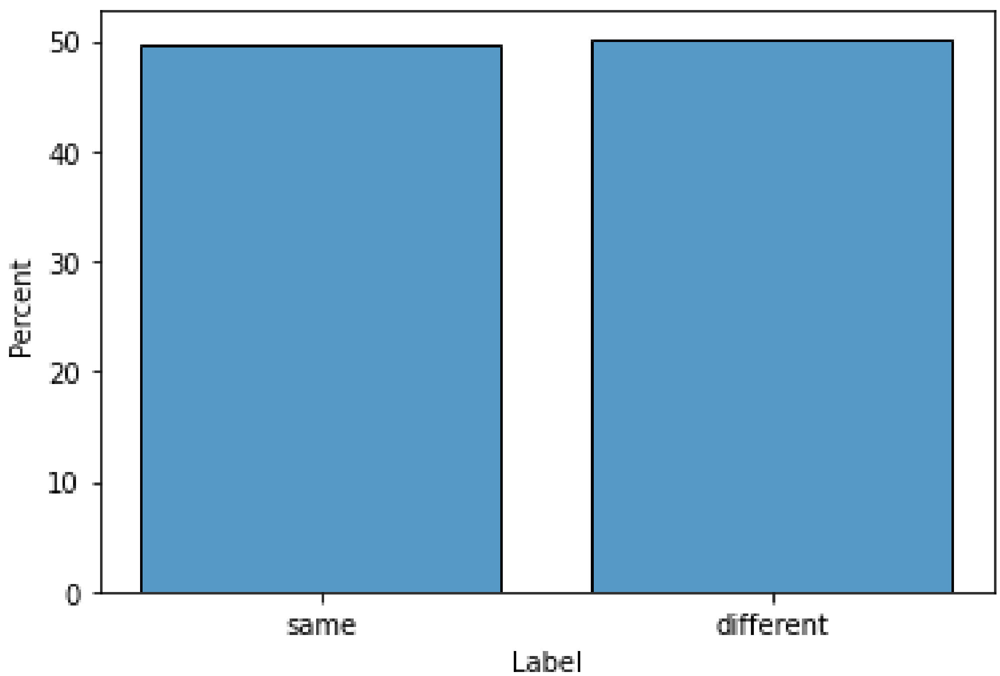
```
The dataset contains images of 5749 peoples
The dataset contains a total of 13233 images
Each pesron has an average 2.302 +- 9.016 images
```

Training set:

```
[ ]: print("The training set contains " + str(train.shape[0]) + " examples")
     print("The training set contains " + str(train[train['Label'] == 'same'].
     ↪count()[0]) + " match examples - class 'same'")
     print("The training set contains " + str(train[train['Label'] == 'different'].
     ↪count()[0]) + " mismatch examples - class 'different'")
     sns.histplot(data=train, x="Label", stat="percent", shrink=.8)
```

```
The training set contains 1760 examples
The training set contains 876 match examples - class 'same'
The training set contains 884 mismatch examples - class 'different'
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc58cec1090>
```

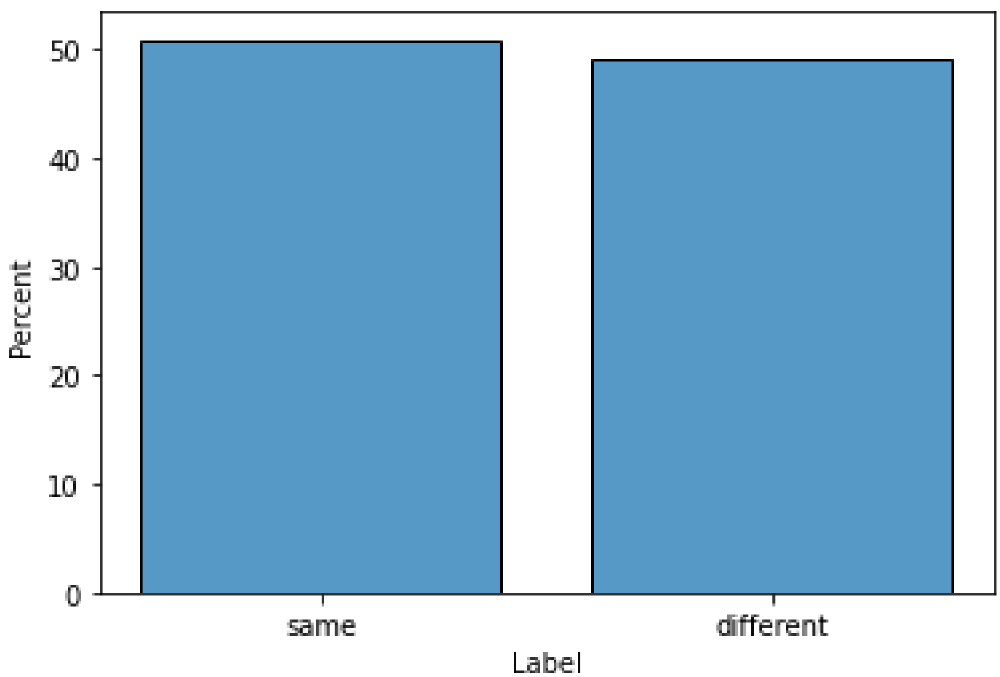


Validation set:

```
[ ]: print("The validation set contains " + str(validation.shape[0]) + " examples")
print("The validation set contains " + str(validation[validation['Label'] ==␣
↪'same'].count()[0]) + " match examples - class 'same'")
print("The validation set contains " + str(validation[validation['Label'] ==␣
↪'different'].count()[0]) + " mismatch examples - class 'different'")
sns.histplot(data=validation, x="Label", stat="percent", shrink=.8)
```

```
The validation set contains 440 examples
The validation set contains 224 match examples - class 'same'
The validation set contains 216 mismatch examples - class 'different'
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc58cd94150>
```



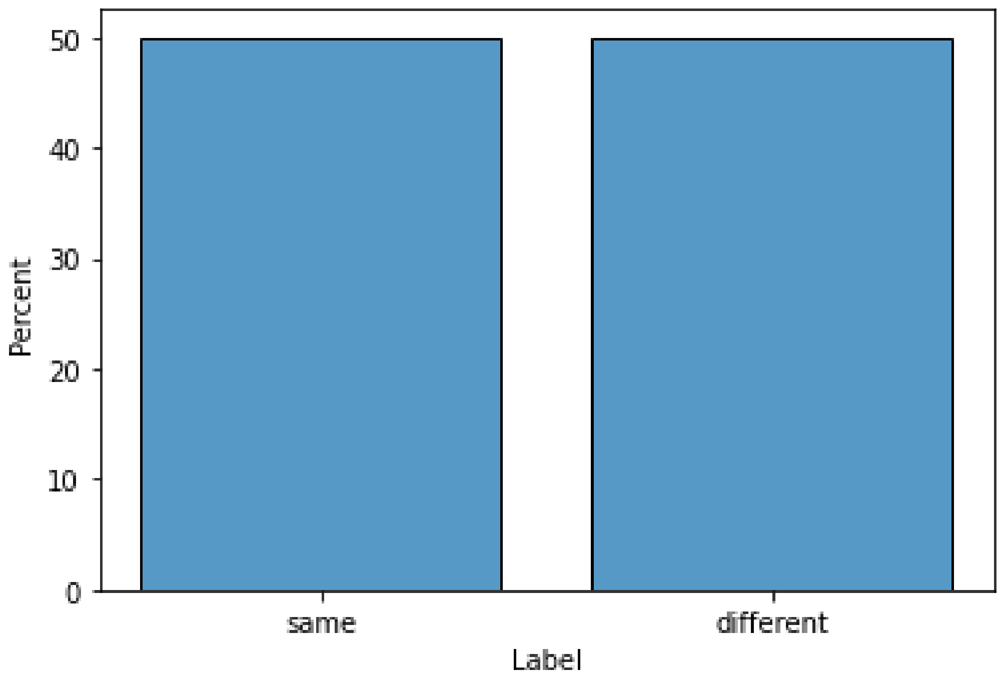
Test set:

```
[ ]: print("The test set contains " + str(test.shape[0]) + " examples")
print("The test set contains " + str(test[test['Label'] == 'same'].count()[0])␣
↪+ " match examples - class 'same'")
print("The test set contains " + str(test[test['Label'] == 'different'].
↪count()[0]) + " mismatch examples - class 'different'")
sns.histplot(data=test, x="Label", stat="percent", shrink=.8)
```

```
The test set contains 1000 examples
The test set contains 500 match examples - class 'same'
```

```
The test set contains 500 mismatch examples - class 'different'
```

[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc58c8c1890>



[ ]:
```
sample_same1 = train[train['Label'] == 'same'].sample()
sample_same2 = train[train['Label'] == 'same'].sample()
sample_different1 = train[train['Label'] == 'different'].sample()
sample_different2 = train[train['Label'] == 'different'].sample()
```

Examples of 'same' images:

[ ]:
```
img11 = cv2.imread(sample_same1['Image1'].values[0])
img21 = cv2.imread(sample_same1['Image2'].values[0])
img12 = cv2.imread(sample_same2['Image1'].values[0])
img22 = cv2.imread(sample_same2['Image2'].values[0])

fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,10))
for i, img in enumerate([img11, img21]):
  ax[i].axis('off')
  ax[i].imshow(img)

fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,10))
for i, img in enumerate([img12, img22]):
  ax[i].axis('off')
  ax[i].imshow(img)
```

Examples of 'different' images:

```
[ ]: img11 = cv2.imread(sample_different1['Image1'].values[0])
     img21 = cv2.imread(sample_different1['Image2'].values[0])
     img12 = cv2.imread(sample_different2['Image1'].values[0])
     img22 = cv2.imread(sample_different2['Image2'].values[0])

     fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,10))
     for i, img in enumerate([img11, img21]):
       ax[i].axis('off')
       ax[i].imshow(img)
```

```
fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(10,10))
for i, img in enumerate([img12, img22]):
  ax[i].axis('off')
  ax[i].imshow(img)
```

1.4 Siamese network

1.4.1 Our architecture:

We reconstructed the architecture from the paper:

We first created a Siamese network consist of two Convolutional Neural Networks that are joined towards the end. The goal of this part is to constracting the feature vectors.

Each CNN has 4 conventional layers and 1 fully connected layer. Then we combined both networks to a single output by a distance layer. In this part we compare between the two vectors.

- There are 2 input layers of 105x105x3 that represent 2 images to compare.
- For all CNN layers (except the last layer) we used 'l2' **kernel regularizer** with regularization factor of $2e - 4$ and perform batch normalization.
- In the last layer (fully connected) we used 'l2' **kernel regularizer** with regularization factor of $2e - 3$.
- Then, we connected both networks with one more layer - the L1 distance vector, on which we performed a **dropout** of 0.3, wihch created the Siamese network, using "**sigmoid**" activation function.

Parameters Initialization:

- We initialized the weights of the **kernel initializer** in all layers to a normal distribution with mean of 0 and standard deviation of 10^{-2}, as discribed in the paper.
- We initialized the **bias** with mean of 0.5 and standard deviation of 10^{-2}, as discribed in the paper. We performed it on all layers except the first layer, since no bias in the first layer might be more beneficial when the layer is very large and the data is distributed uniformly as in our case.

Early Stopping:

We used early stopping that will stop the training when the monitor metric of validation loss stops to improve with a **delta** (minimum change) of 0.01 and **patience** (number of epochs without improvments) of 6.

We also used **batch normalization** on each layer exept the fully connected one.

Loss Function:

binary_crossentropy - in the paper they also used the loss function of cross-entropy since the L1 distance between the feature vectors combined with the sigmoid activation which maps onto the interval of [0, 1], and makes it very natural choise.

[ ]:
```
# global seed
seed = 10
random.seed(seed)
np.random.seed(seed)
tf.random.set_seed(seed)
```

[ ]:
```
def kernel_initializer(shape, dtype=None):
    """
    Initializing weights for the siamese model. useing the keras random_normal␣
↪function.
    returns a tensor with normal distribution of weights
    """
```

```
    return K.random_normal(shape, mean=0.0, stddev=0.01, dtype=dtype, seed=seed)


def bias_initializer(shape, dtype=None):
    """
    Initializing biases for the siamese model. useing the keras random_normal␣
 ↪function.
    return a tensor with normal distribution of weights
    """
    return K.random_normal(shape, mean=0.5, stddev=0.01, seed=seed)
```

[ ]:
```
def siamese_model(input_shape):
    """
    Building the CNN network that will use in the siamese model according to␣
 ↪the architecture used in the paper.
    """
    model = Sequential()

    model.add(Conv2D(64, (10, 10), activation='relu',␣
 ↪input_shape=input_shape,kernel_initializer=kernel_initializer,kernel_regularizer=l2(2e-4)))
    model.add(BatchNormalization())
    model.add(MaxPooling2D())
    model.add(Conv2D(128, (7, 7),␣
 ↪activation='relu',kernel_initializer=kernel_initializer,bias_initializer=bias_initializer,k
    model.add(BatchNormalization())
    model.add(MaxPooling2D())
    model.add(Conv2D(128, (4, 4),␣
 ↪activation='relu',kernel_initializer=kernel_initializer,bias_initializer=bias_initializer,k
    model.add(BatchNormalization())
    model.add(MaxPooling2D())
    model.add(Conv2D(256, (4, 4),␣
 ↪activation='relu',kernel_initializer=kernel_initializer,bias_initializer=bias_initializer,k
    model.add(BatchNormalization())

    model.add(Flatten())
    model.add(Dense(4096,␣
 ↪activation='sigmoid',kernel_initializer=kernel_initializer,bias_initialize

    return model
```

Number of layers, dimenstions and filters, as well as total parameters:

[ ]:
```
input_shape = X_train[0].shape[1:]
siamese_model(input_shape).summary()
print("input size: " + str(input_shape))
```

```
Model: "sequential"
```

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 96, 96, 64)        19264

 batch_normalization (BatchN  (None, 96, 96, 64)       256
 ormalization)

 max_pooling2d (MaxPooling2D  (None, 48, 48, 64)       0
 )

 conv2d_1 (Conv2D)           (None, 42, 42, 128)       401536

 batch_normalization_1 (Batc  (None, 42, 42, 128)      512
 hNormalization)

 max_pooling2d_1 (MaxPooling  (None, 21, 21, 128)      0
 2D)

 conv2d_2 (Conv2D)           (None, 18, 18, 128)       262272

 batch_normalization_2 (Batc  (None, 18, 18, 128)      512
 hNormalization)

 max_pooling2d_2 (MaxPooling  (None, 9, 9, 128)        0
 2D)

 conv2d_3 (Conv2D)           (None, 6, 6, 256)         524544

 batch_normalization_3 (Batc  (None, 6, 6, 256)        1024
 hNormalization)

 flatten (Flatten)           (None, 9216)              0

 dense (Dense)               (None, 4096)              37752832

=================================================================
Total params: 38,962,752
Trainable params: 38,961,600
Non-trainable params: 1,152
_________________________________________________________________
input size: (105, 105, 3)
```

[ ]:
```
def get_siamese_model(input_shape, parameters):
    """
    Building the siamese model using the CNN network we built
    """
```

```
    left_input = Input(input_shape)
    right_input = Input(input_shape)

    # get the cnn network
    model = siamese_model(input_shape)

    encoded_l = model(left_input)
    encoded_r = model(right_input)

    # Combining the 2 CNN's with a new layer
    L1_layer = Lambda(lambda tensors: K.abs(tensors[0] - tensors[1]))
    L1_siamese_distance = L1_layer([encoded_l, encoded_r])
    L1_siamese_distance = Dropout(parameters['dropout'])(L1_siamese_distance)

    output = Dense(1,␣
↪activation='sigmoid',bias_initializer=bias_initializer)(L1_siamese_distance)

    my_model = Model(inputs=[left_input, right_input], outputs=output)
    my_model.compile(loss='binary_crossentropy',␣
↪optimizer=Adam(learning_rate=parameters['learning_rate']),␣
↪metrics=['accuracy'])

    return my_model
```

[ ]:
```
def fit_model(build_model, training_set, validation_set, early_stop, delta,␣
↪patience, use_cache=False, parameters=None):
    """
    Train the model using a training set and validation set.
    Using early stopping to monitor the validation loss with delta (minimum␣
↪change) of 0.01 and patience (number of epochs without improvments) of 6
    """

    # Here we save the model and the model history to a faster runtime while␣
↪testing multiple parameters
    os.makedirs('./my_models', exist_ok=True)
    model_params = ''
    if parameters is not None:
        model_params = '_'.join(str(key) + '_' + str(value) for key, value in␣
↪parameters.items())

    model_name = build_model.__name__[4:] + '_' + model_params
    model_history_path = './my_models/' + model_name + '_history.sav'
    model_path = './my_models/' + model_name + '.h5'

    # if use cache is true then we check if the model is exist and use it␣
↪instead of fitting again
```

```
    if use_cache and os.path.exists(model_history_path):
        model_history = joblib.load(model_history_path)
        print(model_path, "loaded from cache")
    else:
      print(model_path, "doesn't exist, building")
      callbacks = []
      if early_stop:
          early_stopping = EarlyStopping(monitor='val_loss', min_delta=delta,␣
↪patience=patience, mode='auto', verbose=1)
          callbacks.append(early_stopping)

      checkpoint = ModelCheckpoint(model_path, monitor='val_loss',␣
↪save_best_only=True, mode='auto')
      callbacks.append(checkpoint)

      # Transpose performed to fit the data to the input
      x_train, y_train = training_set
      x_val, y_val = validation_set
      transposed_x_train = x_train.transpose((1,0,2,3,4))
      transposed_x_val = x_val.transpose((1,0,2,3,4))
      input_shape = x_train[0].shape[1:]

      model = build_model(input_shape, parameters=parameters)
      model_history = model.fit([transposed_x_train[0], transposed_x_train[1]],␣
↪y_train, batch_size=parameters['batch_size'], epochs=parameters['epochs'],
                validation_data=([transposed_x_val[0], transposed_x_val[1]],␣
↪y_val),
                callbacks=callbacks,
                verbose=1)
      model_history = model_history.history

      joblib.dump(model_history, model_history_path)
      model.save(model_path)

      print("Saved model: " + model_name)

    model = tf.keras.models.load_model(model_path,␣
↪custom_objects={'bias_initializer': bias_initializer, 'kernel_initializer':␣
↪kernel_initializer, 'tf': tf})


    return model, model_history
```

1.5 Analysis of our architecture's performance

Convergence times, final loss and accuracy on the test set and holdout set:

```
[ ]: # Global parameters
EARLY_STOP = True
DELTA = 0.01
PATIENCE = 6
```

```
[ ]: def run(build_model, parameters):
    """
    Get the model to fit and its parameters and fit it.
    Measure the fitting time.
    """
    start_time = time.time()
    my_siamese_model, my_siamese_history = fit_model(build_model, (X_train,␣
 ↪Y_train),(X_val, Y_val), early_stop=EARLY_STOP, delta=DELTA,␣
 ↪patience=PATIENCE, use_cache=False, parameters=parameters)
    end_time = time.time()
    total_time = end_time - start_time

    return my_siamese_model, my_siamese_history, total_time


def evaluate(trained_model, x_set, y_set):
    """
    Returns the model prediction statistics (loss and accuracy) on the data
    """
    x = x_set.transpose((1, 0, 2, 3, 4))
    results = trained_model.evaluate([x[0], x[1]], y_set)

    return results
```

We decided to use a validation set since the data is not very big so its better to use it. We divide it to 80% training and 20% valitation which performed well. After we performed a hyperparameters search we found our best parameters to be: - learning rate: 0.00005 - batch size: 32 - epochs: 30 - dropout: 0.3

```
[ ]: # Use the best parameters we found in experiments to fit and evaluate the model
best_parameters = {'learning_rate': 0.00005, 'dropout': 0.3, 'epochs': 30,␣
 ↪'batch_size': 32}
my_siamese_model, my_siamese_history, total_time = run(get_siamese_model,␣
 ↪best_parameters)

seed = 10
random.seed(seed)
np.random.seed(seed)
tf.random.set_seed(seed)

train = evaluate(my_siamese_model, X_train, Y_train)
validation = evaluate(my_siamese_model, X_val, Y_val)
```

```
test = evaluate(my_siamese_model, X_test, Y_test)
```

```
./my_models/siamese_model_learning_rate_5e-05_dropout_0.3_epochs_30_batch_size_3
2.h5 doesn't exist, building
Epoch 1/30
55/55 [==============================] - 24s 388ms/step - loss: 7.9500 -
accuracy: 0.6341 - val_loss: 7.7507 - val_accuracy: 0.5091
Epoch 2/30
55/55 [==============================] - 16s 300ms/step - loss: 7.1596 -
accuracy: 0.8881 - val_loss: 7.2088 - val_accuracy: 0.5182
Epoch 3/30
55/55 [==============================] - 17s 305ms/step - loss: 6.5028 -
accuracy: 0.9773 - val_loss: 6.6711 - val_accuracy: 0.6227
Epoch 4/30
55/55 [==============================] - 16s 299ms/step - loss: 5.9227 -
accuracy: 0.9955 - val_loss: 6.1288 - val_accuracy: 0.7136
Epoch 5/30
55/55 [==============================] - 16s 299ms/step - loss: 5.4031 -
accuracy: 1.0000 - val_loss: 5.6210 - val_accuracy: 0.7386
Epoch 6/30
55/55 [==============================] - 16s 299ms/step - loss: 4.9264 -
accuracy: 1.0000 - val_loss: 5.1528 - val_accuracy: 0.7477
Epoch 7/30
55/55 [==============================] - 16s 301ms/step - loss: 4.4835 -
accuracy: 1.0000 - val_loss: 4.7216 - val_accuracy: 0.7568
Epoch 8/30
55/55 [==============================] - 17s 301ms/step - loss: 4.0711 -
accuracy: 1.0000 - val_loss: 4.3240 - val_accuracy: 0.7636
Epoch 9/30
55/55 [==============================] - 17s 302ms/step - loss: 3.6888 -
accuracy: 1.0000 - val_loss: 3.9593 - val_accuracy: 0.7773
Epoch 10/30
55/55 [==============================] - 17s 303ms/step - loss: 3.3336 -
accuracy: 1.0000 - val_loss: 3.6175 - val_accuracy: 0.7841
Epoch 11/30
55/55 [==============================] - 17s 301ms/step - loss: 3.0048 -
accuracy: 1.0000 - val_loss: 3.3053 - val_accuracy: 0.7795
Epoch 12/30
55/55 [==============================] - 16s 299ms/step - loss: 2.7028 -
accuracy: 1.0000 - val_loss: 3.0159 - val_accuracy: 0.7818
Epoch 13/30
55/55 [==============================] - 16s 300ms/step - loss: 2.4254 -
accuracy: 1.0000 - val_loss: 2.7512 - val_accuracy: 0.7773
Epoch 14/30
55/55 [==============================] - 16s 300ms/step - loss: 2.1714 -
accuracy: 1.0000 - val_loss: 2.5069 - val_accuracy: 0.7727
Epoch 15/30
```

```
55/55 [==============================] - 17s 301ms/step - loss: 1.9395 -
accuracy: 1.0000 - val_loss: 2.2888 - val_accuracy: 0.7841
Epoch 16/30
55/55 [==============================] - 16s 300ms/step - loss: 1.7286 -
accuracy: 1.0000 - val_loss: 2.0876 - val_accuracy: 0.7864
Epoch 17/30
55/55 [==============================] - 17s 301ms/step - loss: 1.5379 -
accuracy: 1.0000 - val_loss: 1.9051 - val_accuracy: 0.7955
Epoch 18/30
55/55 [==============================] - 16s 299ms/step - loss: 1.3653 -
accuracy: 1.0000 - val_loss: 1.7436 - val_accuracy: 0.7795
Epoch 19/30
55/55 [==============================] - 17s 303ms/step - loss: 1.2089 -
accuracy: 1.0000 - val_loss: 1.5987 - val_accuracy: 0.7864
Epoch 20/30
55/55 [==============================] - 17s 302ms/step - loss: 1.0685 -
accuracy: 1.0000 - val_loss: 1.4621 - val_accuracy: 0.7795
Epoch 21/30
55/55 [==============================] - 17s 302ms/step - loss: 0.9426 -
accuracy: 1.0000 - val_loss: 1.3470 - val_accuracy: 0.7795
Epoch 22/30
55/55 [==============================] - 17s 301ms/step - loss: 0.8311 -
accuracy: 1.0000 - val_loss: 1.2431 - val_accuracy: 0.7909
Epoch 23/30
55/55 [==============================] - 17s 302ms/step - loss: 0.7302 -
accuracy: 1.0000 - val_loss: 1.1444 - val_accuracy: 0.7841
Epoch 24/30
55/55 [==============================] - 17s 303ms/step - loss: 0.6406 -
accuracy: 1.0000 - val_loss: 1.0661 - val_accuracy: 0.7818
Epoch 25/30
55/55 [==============================] - 16s 299ms/step - loss: 0.5617 -
accuracy: 1.0000 - val_loss: 0.9878 - val_accuracy: 0.7841
Epoch 26/30
55/55 [==============================] - 17s 301ms/step - loss: 0.4921 -
accuracy: 1.0000 - val_loss: 0.9291 - val_accuracy: 0.7795
Epoch 27/30
55/55 [==============================] - 17s 301ms/step - loss: 0.4303 -
accuracy: 1.0000 - val_loss: 0.8748 - val_accuracy: 0.7886
Epoch 28/30
55/55 [==============================] - 17s 301ms/step - loss: 0.3763 -
accuracy: 1.0000 - val_loss: 0.8283 - val_accuracy: 0.7818
Epoch 29/30
55/55 [==============================] - 17s 302ms/step - loss: 0.3288 -
accuracy: 1.0000 - val_loss: 0.7921 - val_accuracy: 0.7818
Epoch 30/30
55/55 [==============================] - 17s 302ms/step - loss: 0.2874 -
accuracy: 1.0000 - val_loss: 0.7450 - val_accuracy: 0.7909
Saved model:
```

```
siamese_model_learning_rate_5e-05_dropout_0.3_epochs_30_batch_size_32
55/55 [==============================] - 5s 83ms/step - loss: 0.2668 - accuracy:
1.0000
14/14 [==============================] - 2s 84ms/step - loss: 0.7450 - accuracy:
0.7909
32/32 [==============================] - 3s 107ms/step - loss: 0.8487 -
accuracy: 0.7080
```

Here we see the results of the convergence time, loss and accuracy of our Siamese model on the train, validation and test

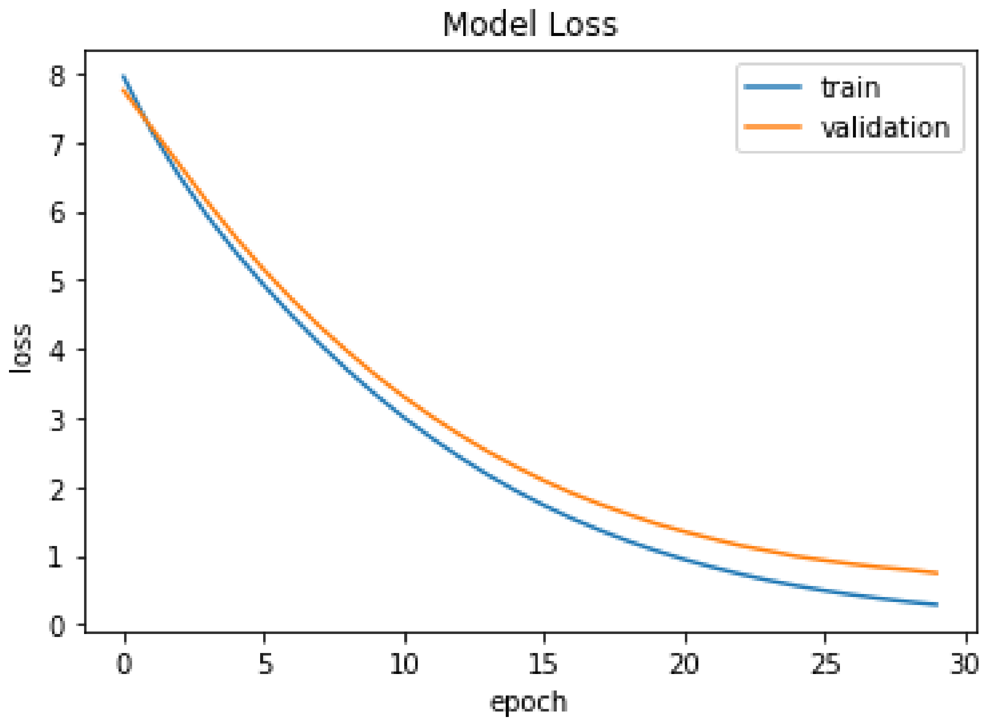
[ ]:
```
print("Model fitting time: " + str(total_time) + " seconds")
print("Results:")
print("Train -> loss: " + str(train[0]) + ", accuracy percentage: " +␣
↪str(train[1] * 100) + "%")
print("Validation -> loss: " + str(validation[0]) + ", accuracy percentage: " +␣
↪str(validation[1] * 100) + "%")
print("Test -> loss: " + str(test[0]) + ", accuracy percentage: " + str(test[1]␣
↪* 100) + "%")
```

```
Model fitting time: 510.3927946090698 seconds
Results:
Train -> loss: 0.2668054401874542, accuracy percentage: 100.0%
Validation -> loss: 0.7450321316719055, accuracy percentage: 79.09091114997864%
Test -> loss: 0.8486946821212769, accuracy percentage: 70.80000042915344%
```

Graphs describing the loss on the training set throughout the training process:

[ ]:
```
def plot_loss(model_history):
    """
    Plotting the loss on the train and validation sets
    """
    plt.plot(model_history['loss'])
    plt.plot(model_history['val_loss'])
    plt.title('Model Loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['train', 'validation'], loc='upper right')
    plt.show()
```

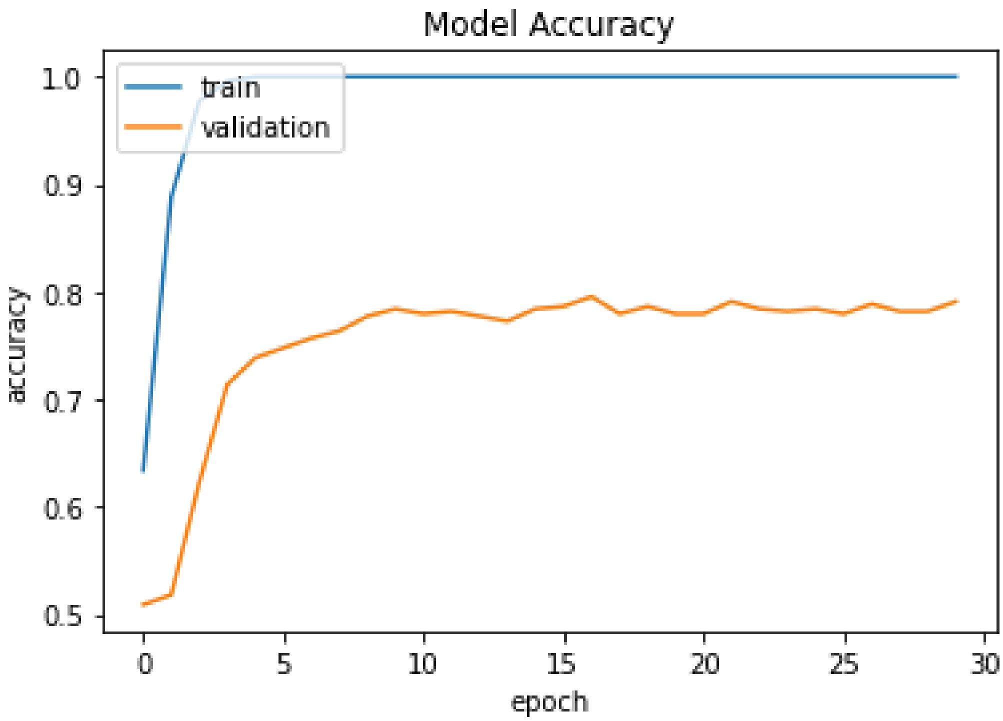
[ ]:
```
plot_loss(my_siamese_history)
```



We can see the loss function is a reducing for each epoch, and the validation set predicted the loss well

[ ]:
```
def plot_accuracy(model_history):
    """
    Plotting the accuracy on the train and validation sets
    """
    plt.plot(model_history['accuracy'])
    plt.plot(model_history['val_accuracy'])
    plt.title('Model Accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    plt.legend(['train', 'validation'], loc='upper left')
    plt.show()
```

[ ]:
```
plot_accuracy(my_siamese_history)
```



This figure shows the the accuracy of the training set and validation for each epoch. We can see that the accuracy of the validation set stop improving significantlly in about 10 epochs, but as we saw in the model loss function plot, it's loss was continued to decrease.

Performance when experimenting with the various parameters:

```
[ ]: def clear_session(model):
         """
         Clearing the session to removes all the nodes left over from previous␣
      ↪models,
         freeing memory and preventing slowdown during hyperparameter search
         """
         del model
         tf.keras.backend.clear_session()
```

```
[ ]: def find_best_params():
         """
         Performing hyperparameters search to find the best parameters for the model␣
      ↪
         """
         learning_rate = [0.001, 0.00001, 0.00005]
         dropout = [0.3, 0.4]
         epochs = [10, 20, 30]
         batch_size = [32, 64]
```

```
    combinations_list = list(itertools.product(learning_rate, dropout, epochs,␣
↪batch_size))

    params_names = ['learning_rate', 'dropout', 'epochs', 'batch_size']

    best_parameters = {}
    best_accuracy = 0

    for combination in combinations_list:
        seed = 10
        random.seed(seed)
        np.random.seed(seed)
        tf.random.set_seed(seed)

        # Creating different combiniation of parameters to fit the model
        parameters = {params_names[i]: combination[i] for i in␣
↪range(len(combination))}
        siamese_model, _ = fit_model(get_siamese_model, (X_train, Y_train),␣
↪(X_val, Y_val),
                                     early_stop=EARLY_STOP, delta=DELTA,␣
↪patience=PATIENCE, use_cache=True, parameters=parameters)
        transposed_x_val = X_val.transpose((1,0,2,3,4))
        loss, accuracy = siamese_model.evaluate([transposed_x_val[0],␣
↪transposed_x_val[1]], Y_val, verbose=0)
        clear_session(siamese_model)
        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_parameters = parameters
        print("parameters: " + str(parameters) + ", loss: " + str(loss) + ",␣
↪accuracy: " + str(accuracy*100) + "%")

    return best_parameters
```

[ ]:
```
best_parameters = find_best_params()
print("Best parameters: " + str(best_parameters))
```

parameters: {'learning_rate': 0.001, 'dropout': 0.3, 'epochs': 10, 'batch_size': 32}, loss: 1.2630672454833984, accuracy: 69.09090876579285% parameters: {'learning_rate': 0.001, 'dropout': 0.3, 'epochs': 10, 'batch_size': 64}, loss: 1.26186203956604, accuracy: 64.31818008422852% parameters: {'learning_rate': 0.001, 'dropout': 0.3, 'epochs': 20, 'batch_size': 32}, loss: 1.4682191610336304, accuracy: 67.27272868156433% parameters: {'learning_rate': 0.001, 'dropout': 0.3, 'epochs': 20, 'batch_size': 64}, loss: 1.385820984840393, accuracy: 59.54545736312866% parameters: {'learning_rate': 0.001, 'dropout': 0.3, 'epochs': 30, 'batch_size': 32}, loss: 1.516265869140625, accuracy: 66.36363863945007% parameters: {'learning_rate': 0.001, 'dropout': 0.3, 'epochs': 30, 'batch_size': 64}, loss: 1.3292211294174194, accuracy: 66.13636612892151% parameters: {'learning_rate': 0.001, 'dropout': 0.4, 'epochs': 10, 'batch_size': 32}, loss: 1.4739246368408203, accuracy: 65.45454263687134% parameters: {'learning_rate': 0.001, 'dropout': 0.4, 'epochs': 10, 'batch_size': 64}, loss: 1.4168723821640015, accuracy: 65.90909361839294% parameters: {'learning_rate': 0.001, 'dropout': 0.4, 'epochs': 20, 'batch_size': 32}, loss: 1.5186843872070312, accuracy: 66.8181836605072% parameters: {'learning_rate': 0.001, 'dropout': 0.4, 'epochs': 20, 'batch_size': 64}, loss: 1.3498518466949463, accuracy: 68.86363625526428% parameters: {'learning_rate': 0.001, 'dropout': 0.4, 'epochs': 30, 'batch_size': 32}, loss: 1.818779706954956, accuracy: 64.99999761581421% parameters: {'learning_rate': 0.001, 'dropout': 0.4, 'epochs': 30, 'batch_size': 64}, loss: 1.7412759065628052, accuracy: 67.72727370262146% parameters: {'learning_rate': 1e-05, 'dropout': 0.3, 'epochs': 10, 'batch_size': 32}, loss: 6.886650085449219, accuracy: 74.09090995788574% parameters: {'learning_rate': 1e-05, 'dropout': 0.3, 'epochs': 10, 'batch_size': 64}, loss: 7.356791019439697, accuracy: 71.36363387107849% parameters: {'learning_rate': 1e-05, 'dropout': 0.3, 'epochs': 20, 'batch_size': 32}, loss: 5.585606575012207, accuracy: 74.54545497894287% parameters: {'learning_rate': 1e-05, 'dropout': 0.3, 'epochs': 20, 'batch_size': 64}, loss: 6.434811592102051, accuracy: 74.77272748947144% parameters: {'learning_rate': 1e-05, 'dropout': 0.3, 'epochs': 30, 'batch_size': 32}, loss: 4.377230167388916, accuracy: 75.90909004211426% parameters: {'learning_rate': 1e-05, 'dropout': 0.3, 'epochs': 30, 'batch_size': 64}, loss: 5.568629741668701, accuracy: 74.77272748947144% parameters: {'learning_rate': 1e-05, 'dropout': 0.4, 'epochs': 10, 'batch_size': 32}, loss: 6.966867446899414, accuracy: 75.0% parameters: {'learning_rate': 1e-05, 'dropout': 0.4, 'epochs': 10, 'batch_size': 64}, loss: 7.4068498611450195, accuracy: 71.36363387107849% parameters: {'learning_rate': 1e-05, 'dropout': 0.4, 'epochs': 20, 'batch_size': 32}, loss: 5.7469916343688965, accuracy: 76.36363506317139% parameters: {'learning_rate': 1e-05, 'dropout': 0.4, 'epochs': 20, 'batch_size': 64}, loss: 6.5396294593811035, accuracy: 74.3181824684143% parameters: {'learning_rate': 1e-05, 'dropout': 0.4, 'epochs': 30, 'batch_size': 32}, loss: 4.595505714416504, accuracy: 75.45454502105713% parameters: {'learning_rate': 1e-05, 'dropout': 0.4, 'epochs': 30, 'batch_size': 64}, loss: 5.721138000488281, accuracy: 74.77272748947144% parameters: {'learning_rate': 5e-05, 'dropout': 0.3, 'epochs': 10, 'batch_size': 32}, loss: 3.6951475143432617, accuracy: 76.13636255264282% parameters: {'learning_rate': 5e-05, 'dropout': 0.3, 'epochs': 10, 'batch_size': 64}, loss: 4.668642997741699, accuracy: 72.95454740524292% parameters: {'learning_rate': 5e-05, 'dropout': 0.3, 'epochs': 20, 'batch_size': 32}, loss: 1.550892949104309, accuracy: 77.04545259475708% parameters: {'learning_rate': 5e-05, 'dropout': 0.3, 'epochs': 20, 'batch_size': 64}, loss: 2.3958675861358643, accuracy: 76.13636255264282% parameters: {'learning_rate': 5e-05, 'dropout': 0.3, 'epochs': 30, 'batch_size': 32}, loss: 0.7450321316719055, accuracy: 79.09091114997864% parameters: {'learning_rate': 5e-05, 'dropout': 0.3, 'epochs': 30, 'batch_size': 64}, loss: 1.2844340801239014, accuracy: 77.49999761581421% parameters: {'learning_rate': 5e-05, 'dropout': 0.4, 'epochs': 10, 'batch_size': 32}, loss: 3.9075188636779785, accuracy: 78.18182110786438% parameters: {'learning_rate': 5e-05, 'dropout': 0.4, 'epochs': 10, 'batch_size': 64}, loss: 4.879052639007568, accuracy: 72.72727489471436% parameters: {'learning_rate': 5e-05, 'dropout': 0.4, 'epochs': 20, 'batch_size': 32}, loss: 1.7015209197998047, accuracy: 77.49999761581421% parameters: {'learning_rate': 5e-05, 'dropout': 0.4, 'epochs': 20, 'batch_size': 64}, loss: 2.643259048461914, accuracy: 75.6818175315857% parameters: {'learning_rate': 5e-05, 'dropout': 0.4, 'epochs': 30, 'batch_size': 32}, loss: 0.8528352379798889, accuracy: 78.86363863945007% parameters: {'learning_rate': 5e-05, 'dropout': 0.4, 'epochs': 30, 'batch_size': 64}, loss: 1.4677842855453491, accuracy: 76.36363506317139%

Best parameters: {'learning_rate': 5e-05, 'dropout': 0.3, 'epochs': 30, 'batch_size': 32}

Best parameters:

- learning_rate - 0.00005
- dropout - 0.3
- epochs - 30
- batch_size - 32

Examples of accurate and misclassifications:

[ ]:
```
def predict(trained_model, X):
    """
    Getting trained model an get it's predictions
    """
    x = X.transpose((1, 0, 2, 3, 4))
    x_test = [x[0], x[1]]
    predictions = trained_model.predict(x_test)

    return predictions.reshape(-1)


def generate_examples(idxs_to_example, predictions):
    """
    Show examples of images the model successfully classified and images that␣
 ↪was missed classified
    """


    for idx in idxs_to_example:
        color = 'lightgreen' if Y_test[idx] == np.around(predictions)[idx] else␣
 ↪'tomato'
        fig, ax = plt.subplots(nrows=1, ncols=2, figsize=(6,6), facecolor=color)

        fig.tight_layout()

        # Label of 'same'
        if Y_test[idx] == 1:
            t = f'model predicted same in: {predictions[idx]*100:.2f}%'
        # Label of 'different'
        if Y_test[idx] == 0:
            t = f'model predicted different in: {100 - predictions[idx] * 100:.
 ↪2f}%'
        # Check if the model classification was correct
        if Y_test[idx] == np.round(predictions[idx]):
            fig.suptitle('Correct! ' + t, fontsize=12)
        else:
            fig.suptitle('Wrong! ' + t, fontsize=12)


        for i, axis in enumerate(ax):
            ax[i].axis('off')
```

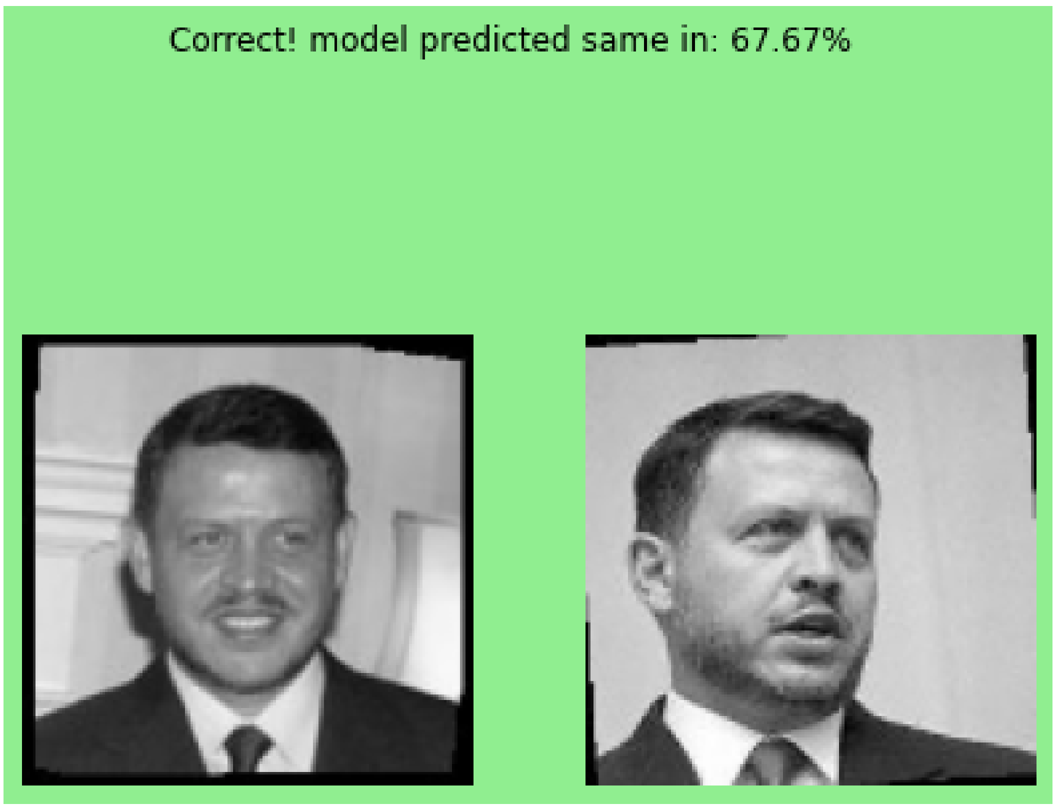
```
            ax[i].imshow(X_test.transpose((1, 0, 2, 3, 4))[i][idx])
```

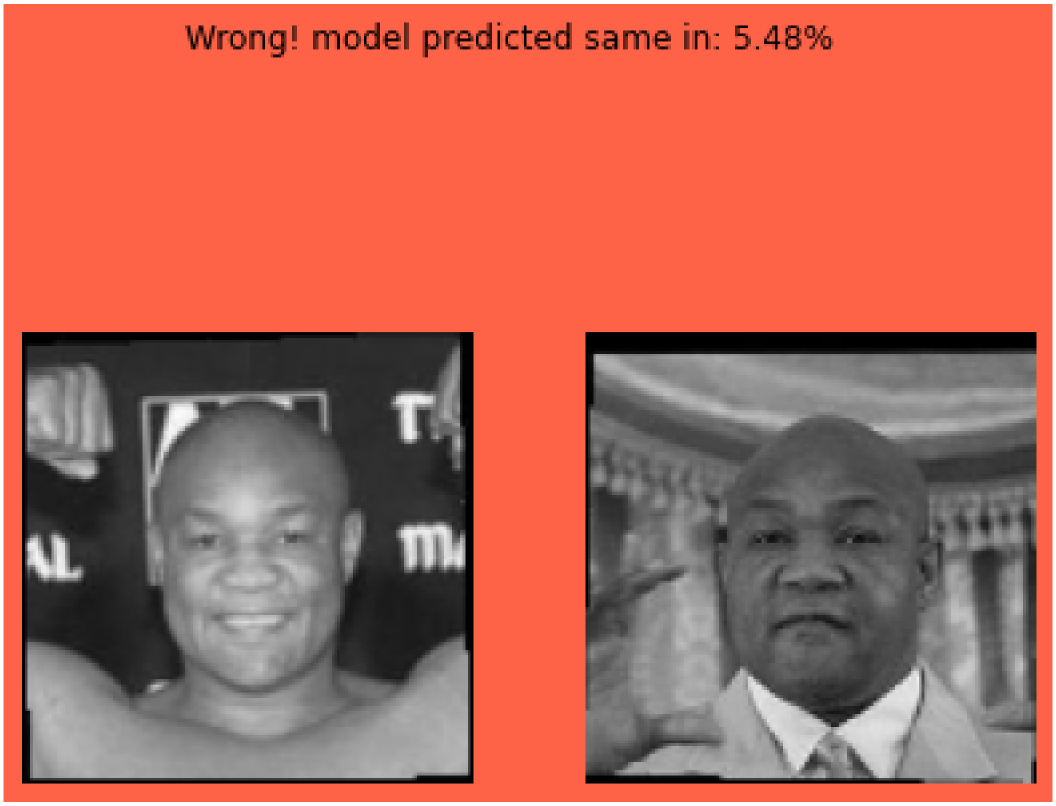
Model performance on the 'same' images:

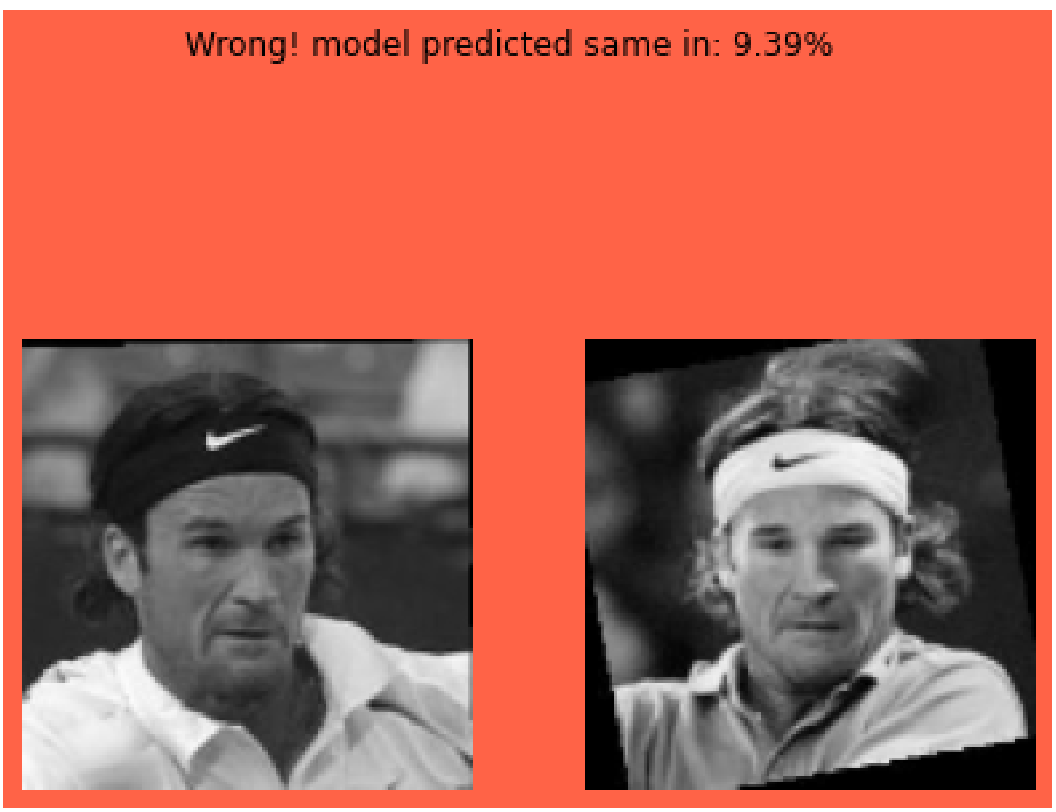
[ ]:
```
model_predictions = predict(my_siamese_model, X_test)

num_of_same_imgs = Y_test.shape[0]//2
tpr = (np.around(model_predictions)[:num_of_same_imgs].sum() /␣
 ↪num_of_same_imgs) * 100

print("The model predicted  successfully " + str(tpr) + "% out of all the␣
 ↪'same' subset in the test set")
```

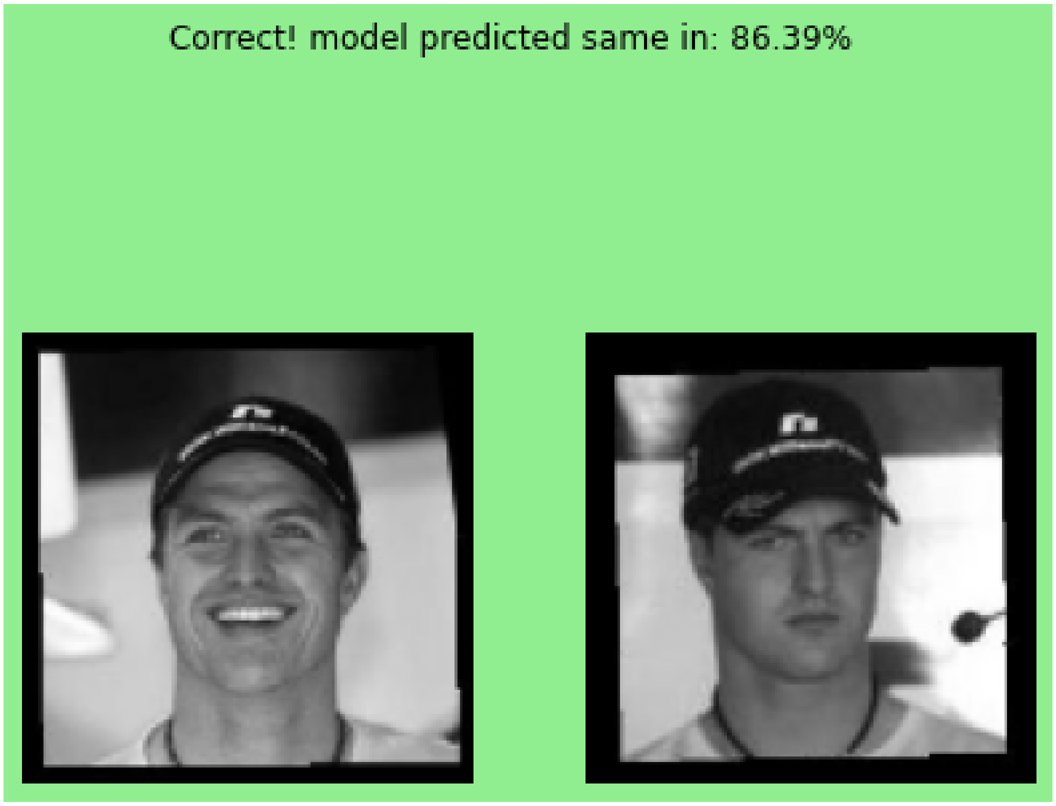
```
The model predicted  successfully 75.6% out of all the 'same' subset in the test
set
```

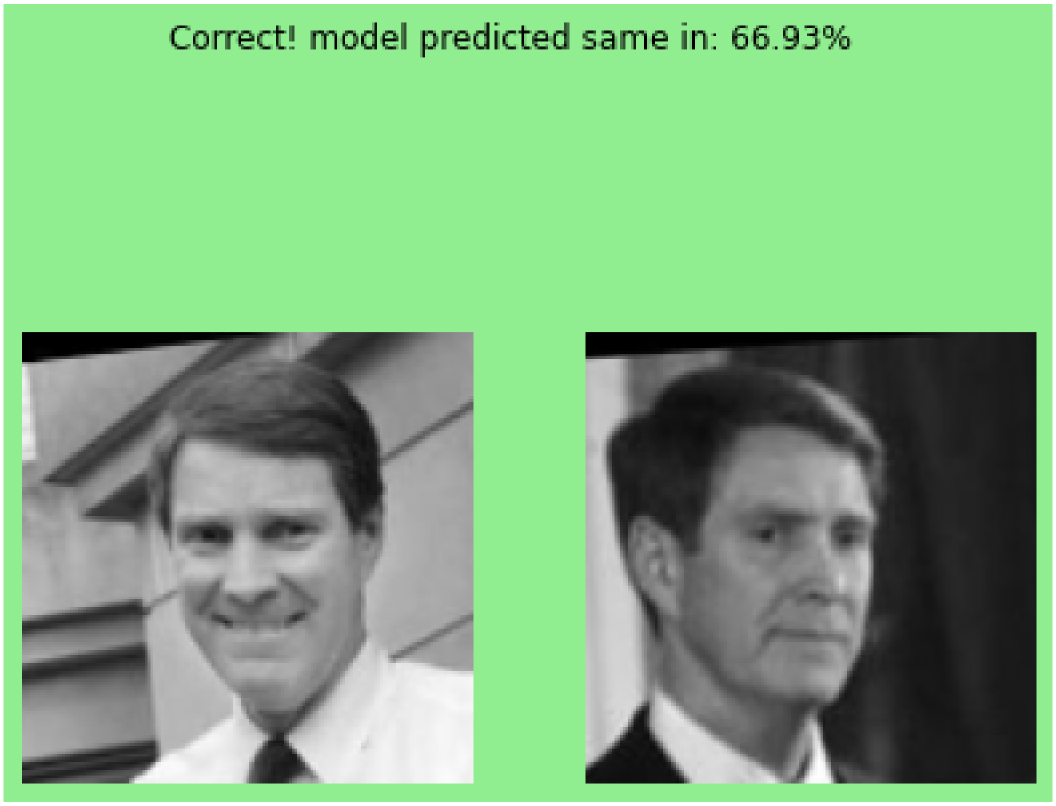
[ ]:
```
# Generate random index list for the examples
index_list = random.sample(list(range(num_of_same_imgs)), 10)
generate_examples(index_list, model_predictions)
```

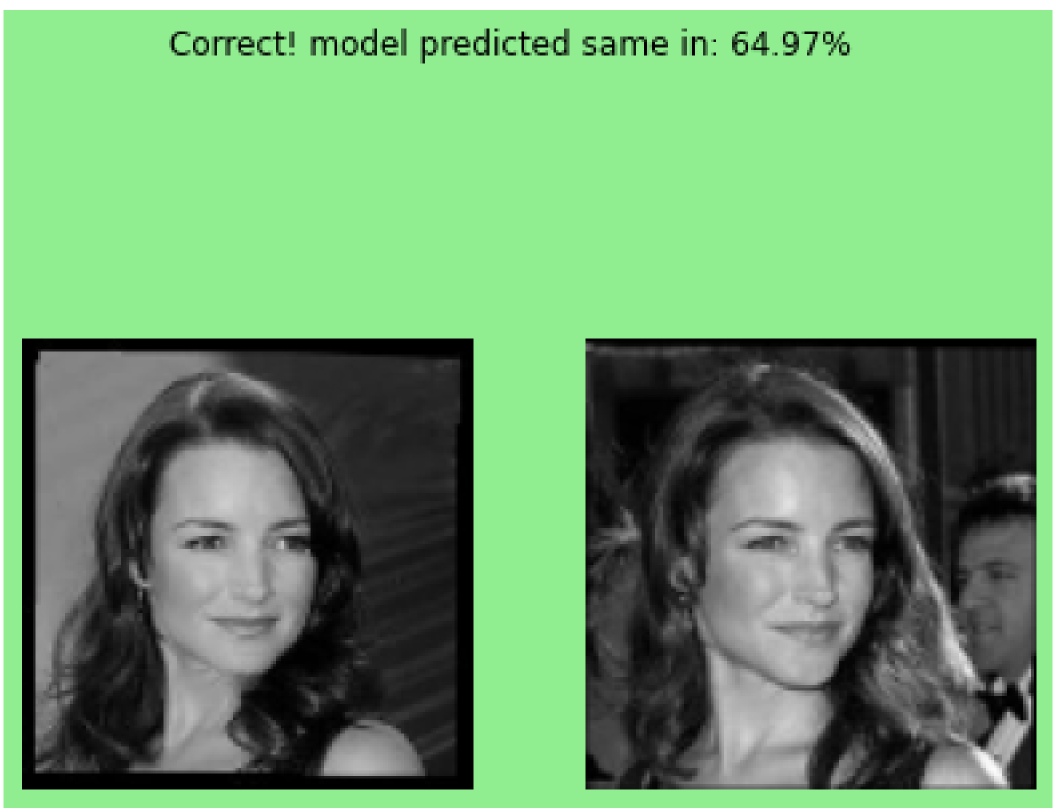


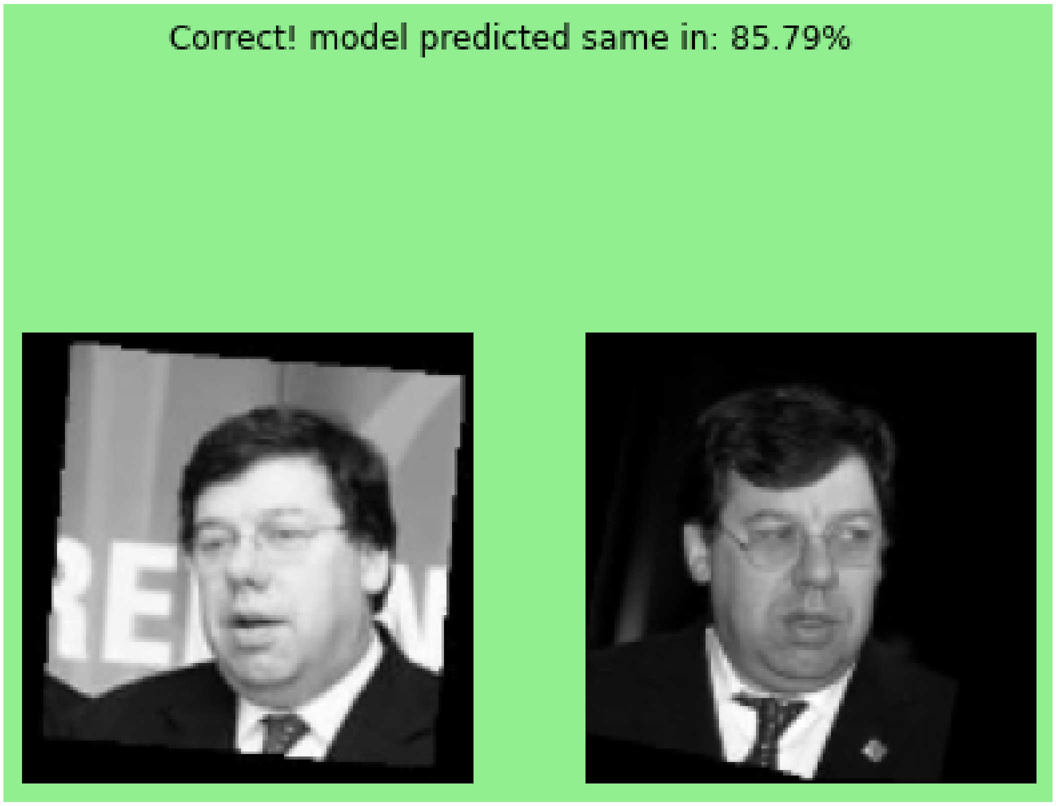

Wrong! model predicted same in: 5.48%

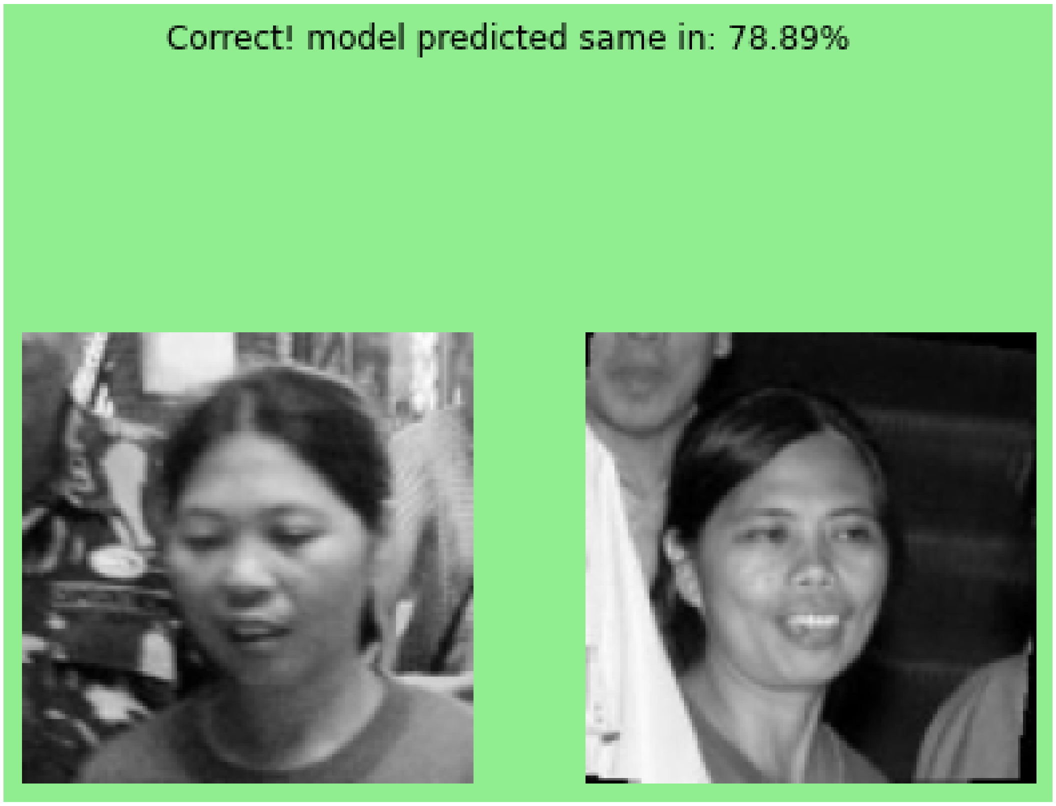

Wrong! model predicted same in: 9.39%

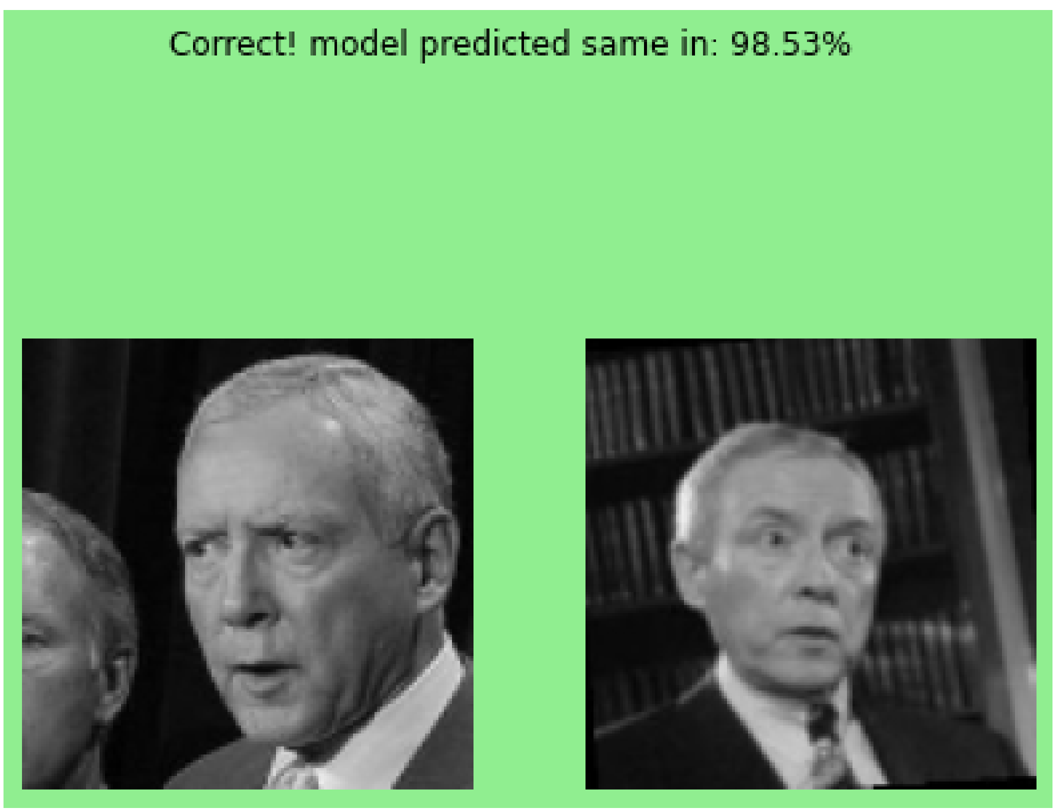

Correct! model predicted same in: 86.39%

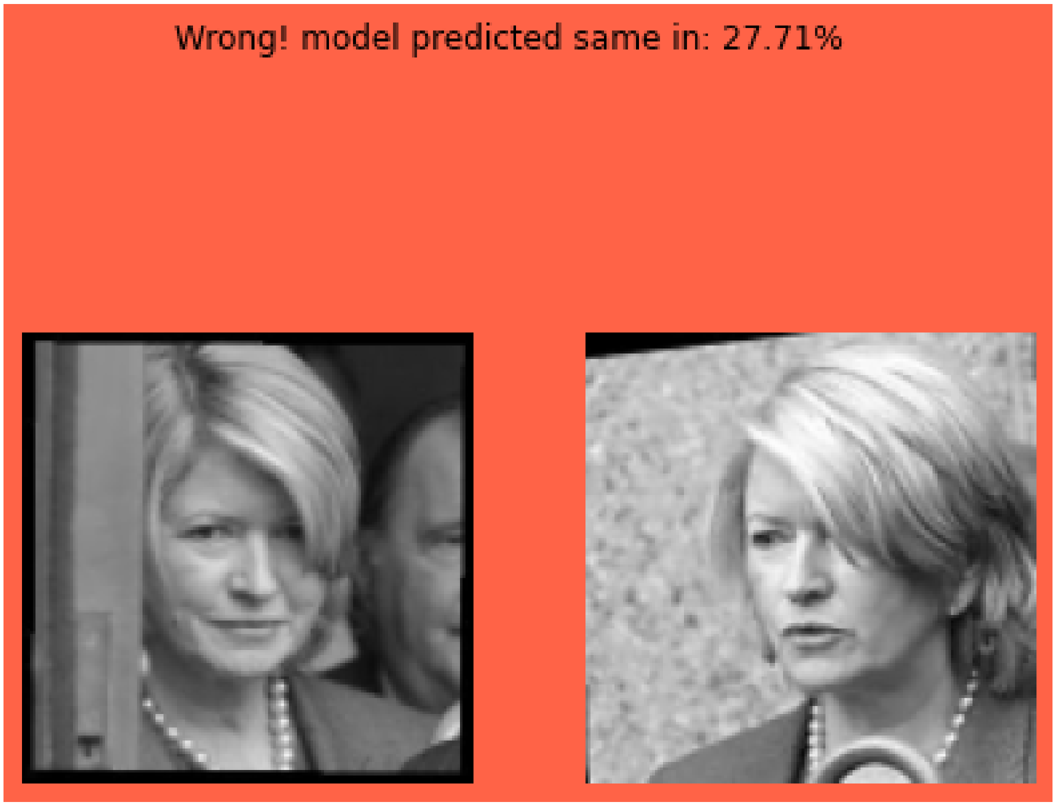

Correct! model predicted same in: 66.93%


Correct! model predicted same in: 64.97%


Correct! model predicted same in: 85.79%


Correct! model predicted same in: 78.89%


Correct! model predicted same in: 98.53%



We can see that our model able to predict well the images from the 'same' subset. There are only 3 pairs which the model did not identify as 'same':

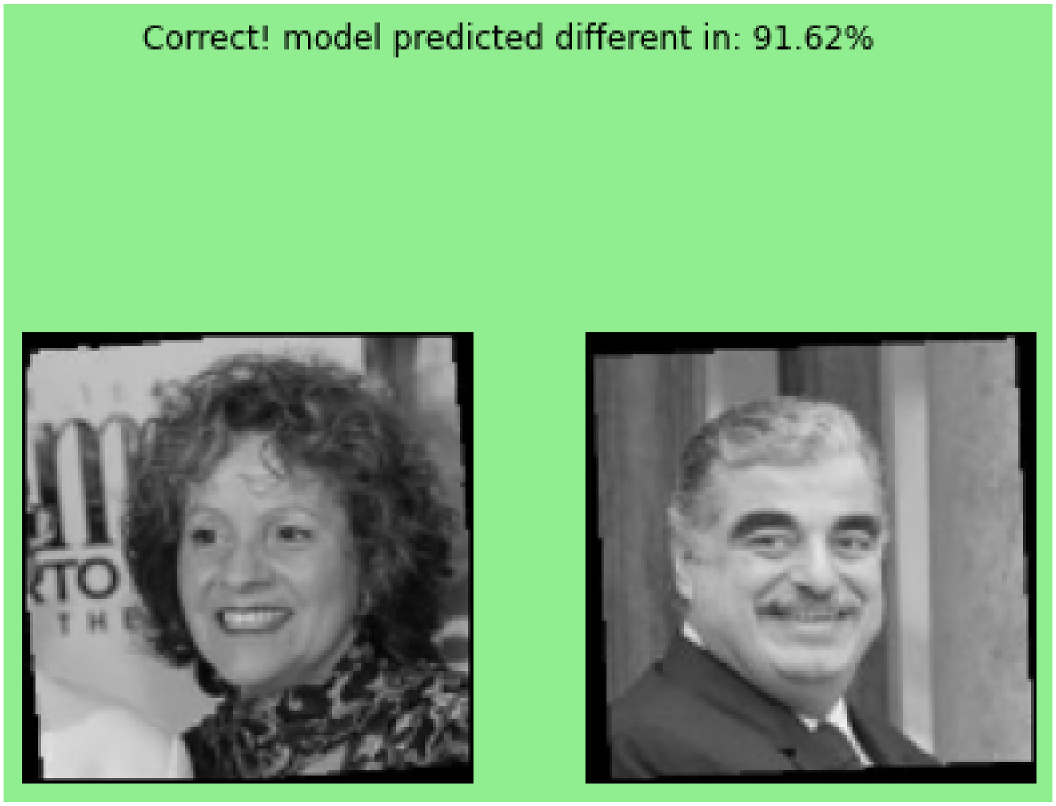
1. In the image on the left, the man raises his hands.
2. The person puts a different colored headband in each image.
3. In the left image there is a door that hides some of the face of the person.

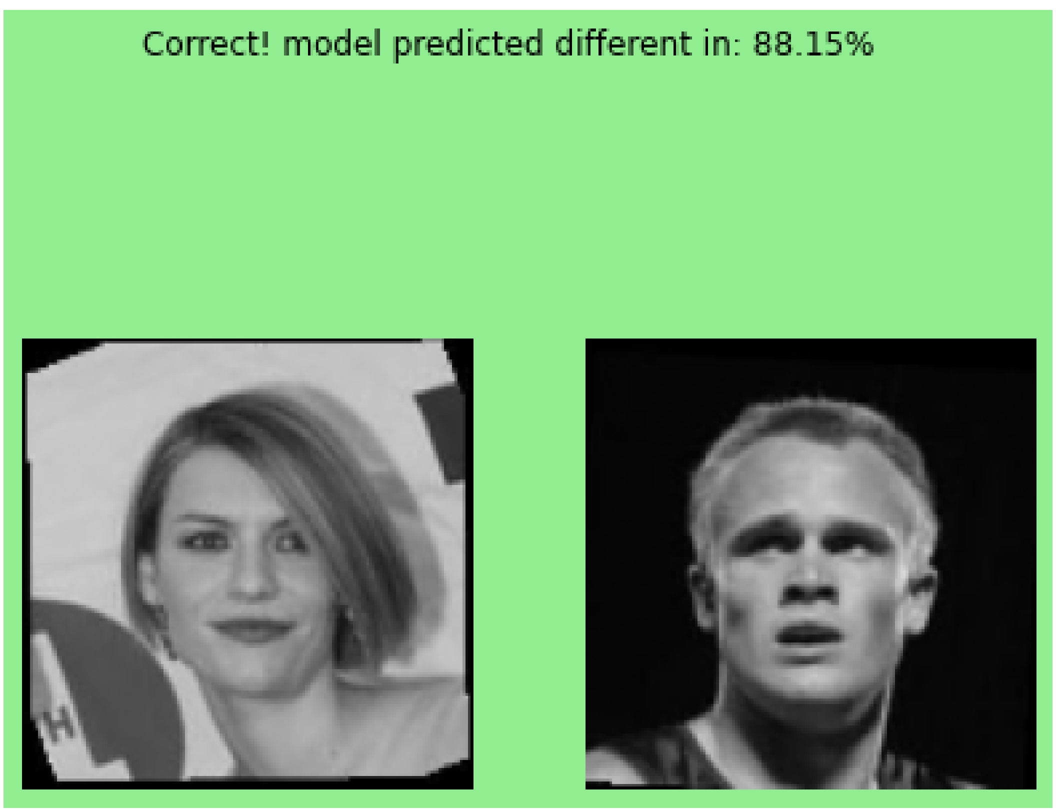
Model performance on the 'different' images:

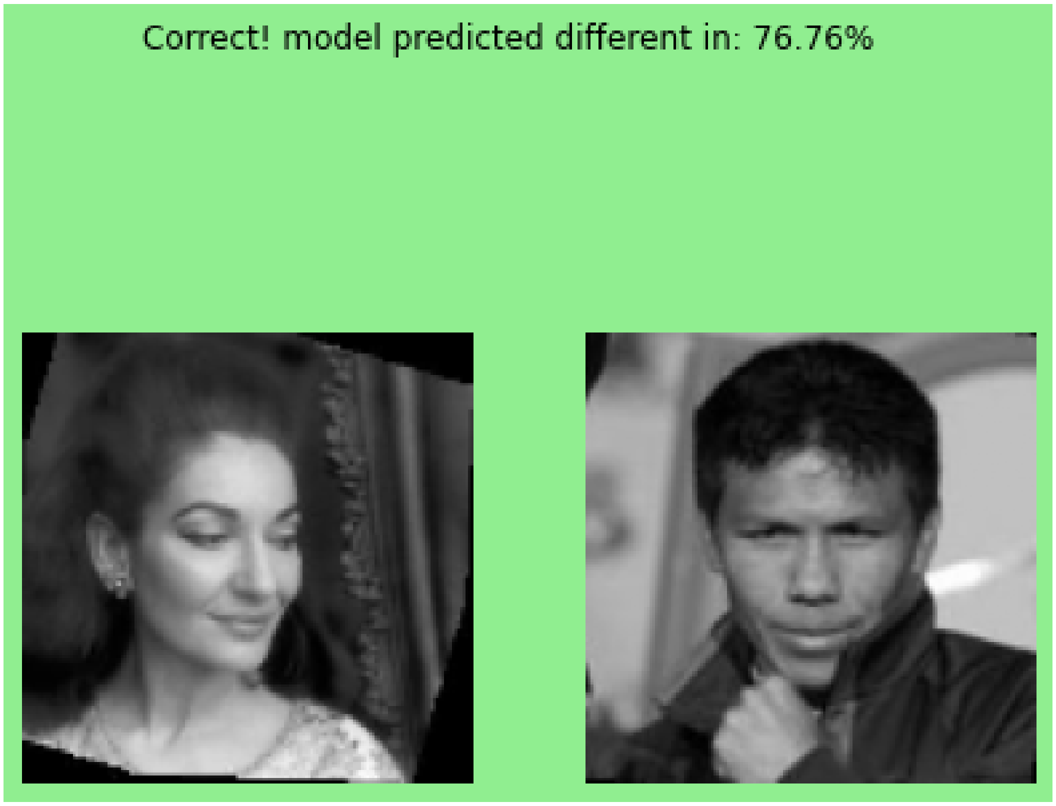
[ ]:
```
tnr = ((num_of_same_imgs - np.around(model_predictions)[num_of_same_imgs:].
 ↪sum()) / num_of_same_imgs) * 100

print("The model predicted  successfully " + str(tnr) + "% out of all the␣
 ↪'different' subset in the test set")
```

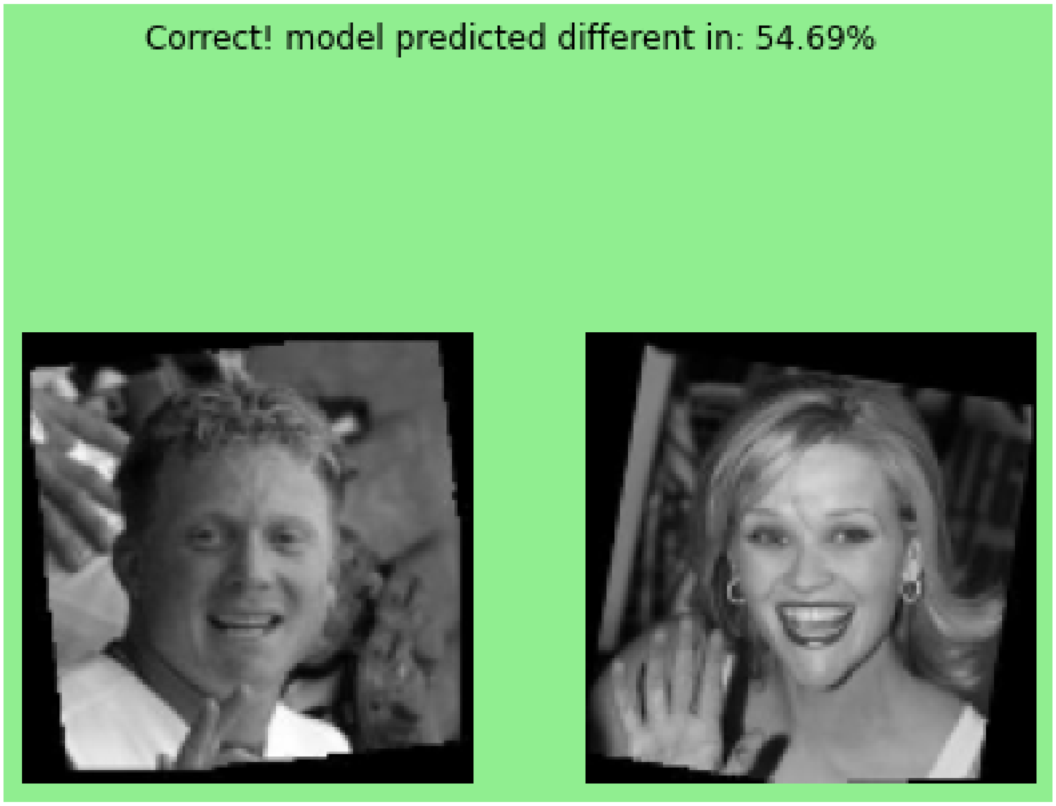
```
The model predicted  successfully 66.0% out of all the 'different' subset in the
test set
```

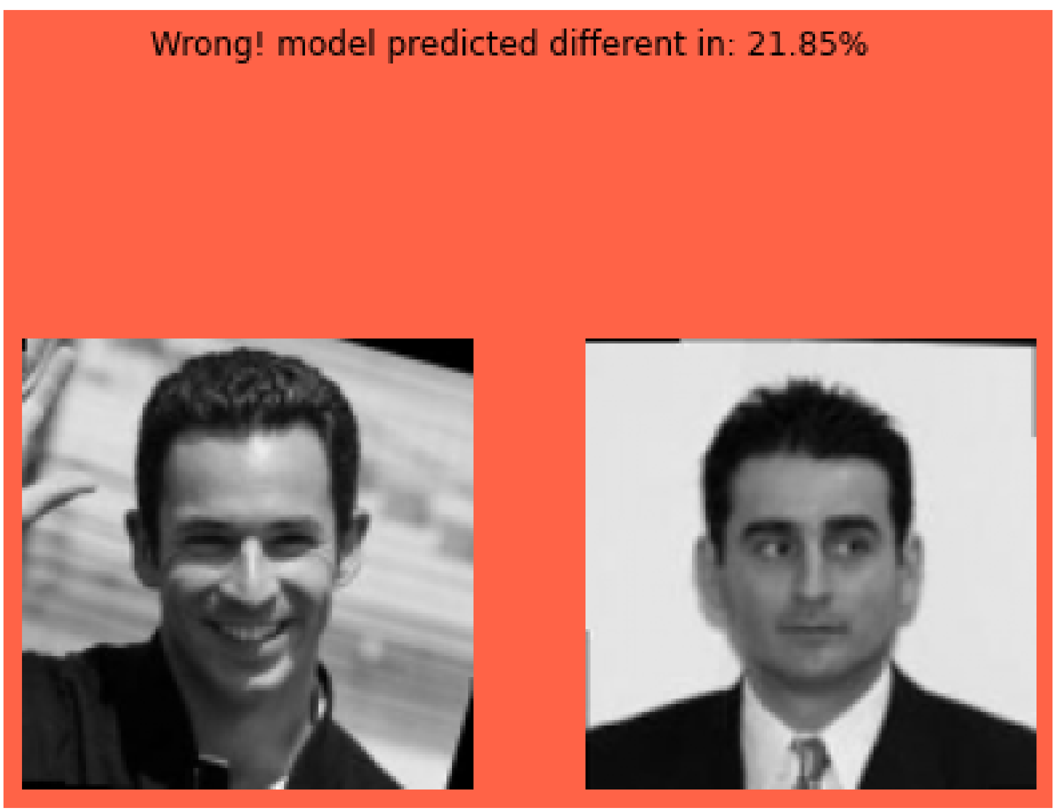
[ ]:
```
# Generate random index list for the examples
index_list = random.sample(list(range(num_of_same_imgs,Y_test.shape[0])), 10)
generate_examples(index_list, model_predictions)
```

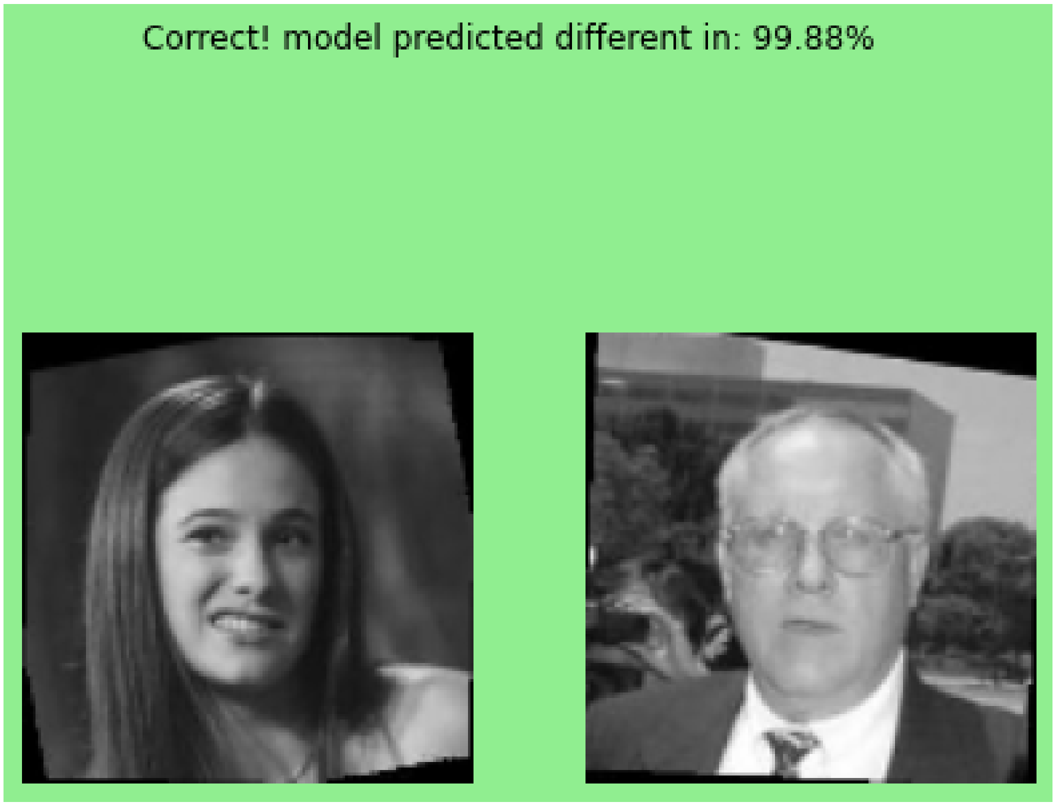

Correct! model predicted different in: 91.62%

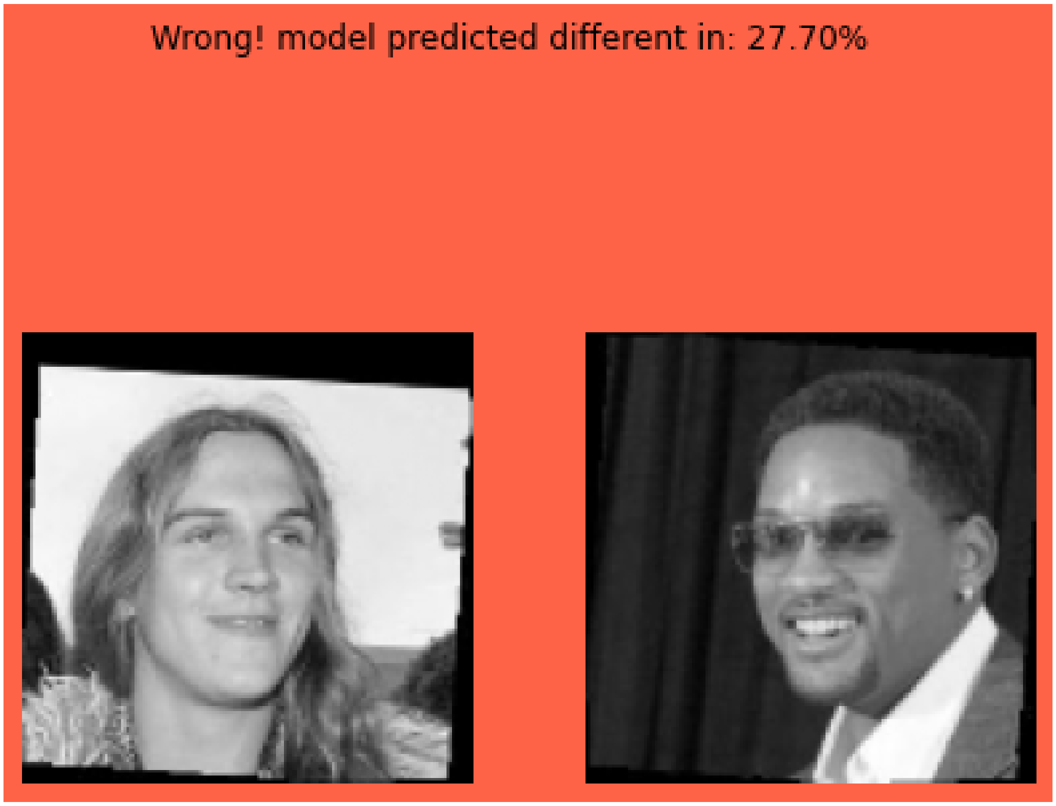

Correct! model predicted different in: 88.15%

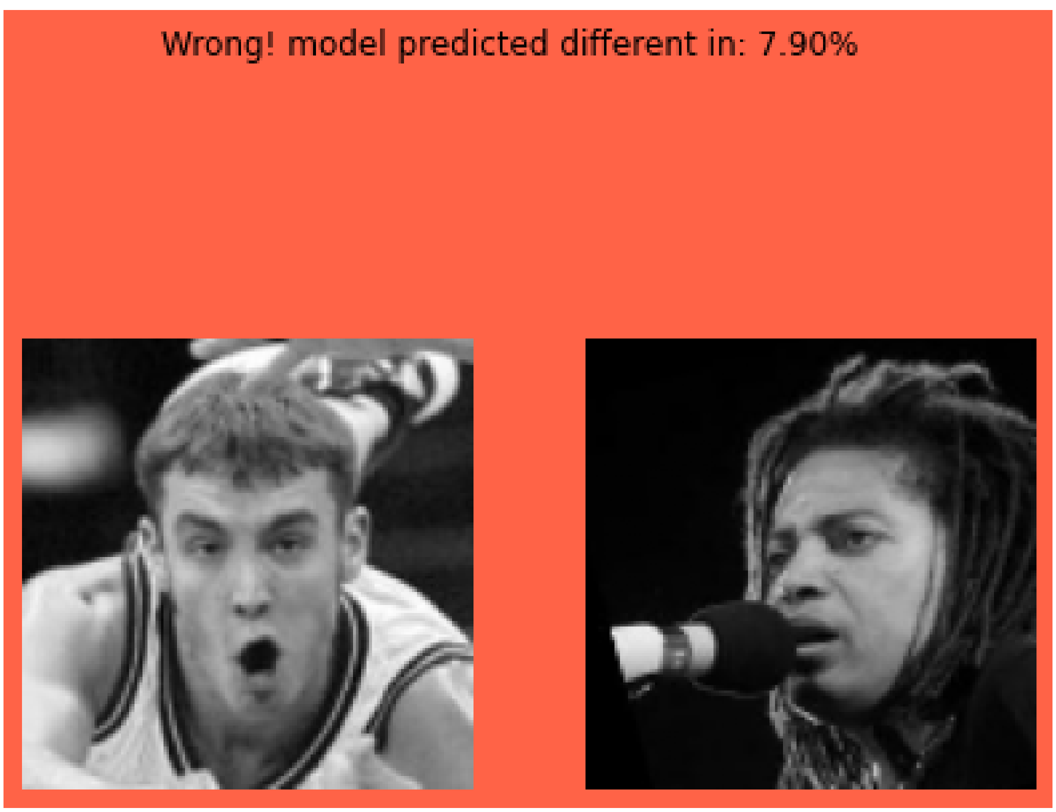

Correct! model predicted different in: 76.76%

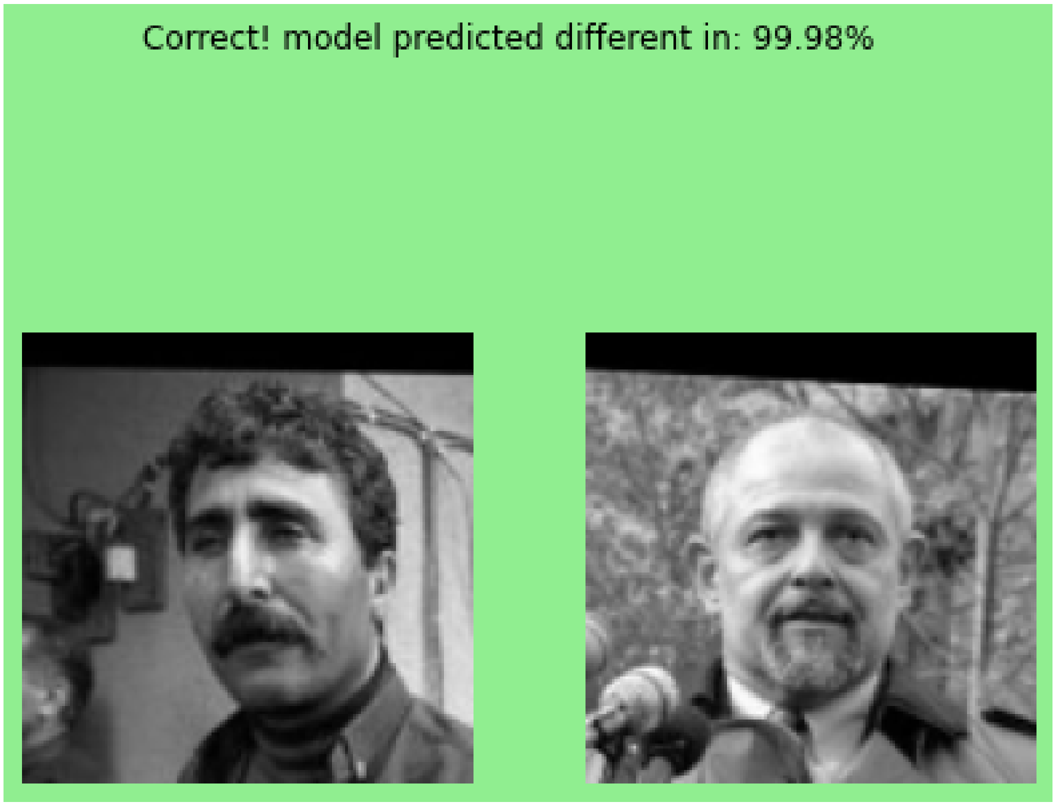

Correct! model predicted different in: 54.69%

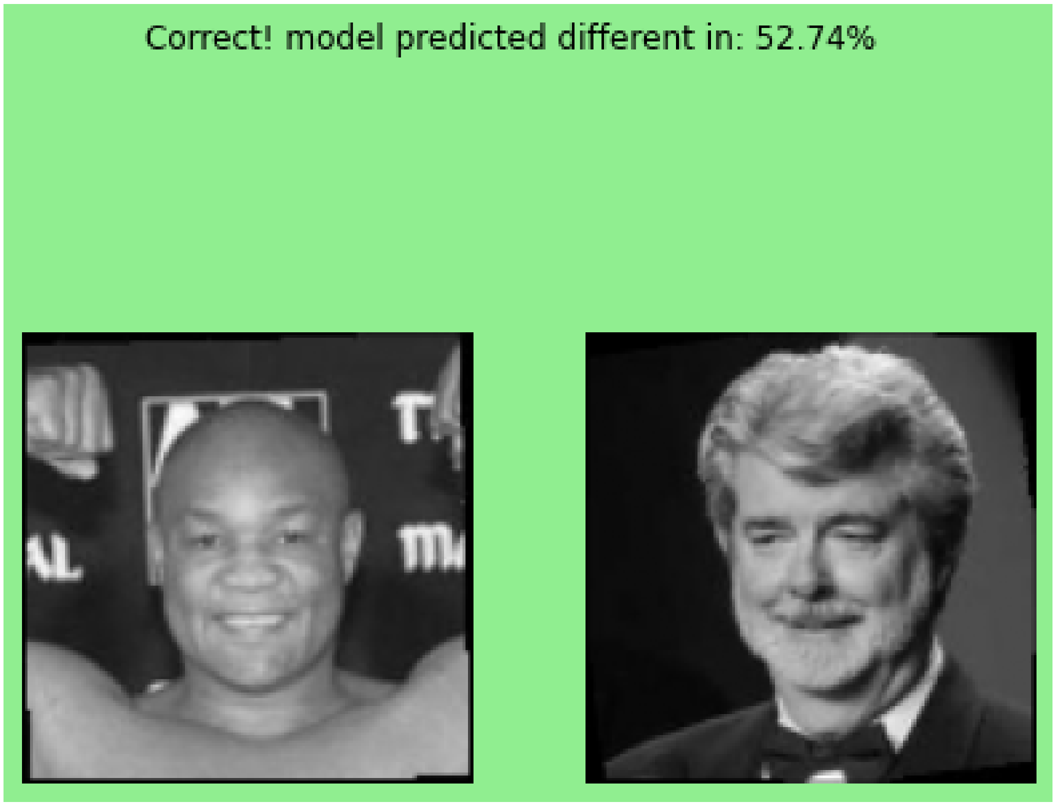

Wrong! model predicted different in: 21.85%


Correct! model predicted different in: 99.88%


Wrong! model predicted different in: 27.70%


Wrong! model predicted different in: 7.90%


Correct! model predicted different in: 99.98%



We can see that our model was less successful to predict the images from the 'different' subset. The model was particularly successful in the simplest cases, when there was one image of a man and one image of a woman. Another case where the model succeeded is when the in one picture a man has hair and in the other picture the man is bald.