Celebrity Faces: Applying CNN for Gender Detection

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Step 1: Data Exploration

In the first step, we explore our dataset, and make changes to the data, in order to prepare the d

This includes importing the necessary libraries, changing dataset values and general exploratio

```
#Import libraries
import pandas as pd
import numpy as np
import cv2
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf

from sklearn.metrics import f1_score
from keras.applications.inception_v3 import InceptionV3, preprocess_input
from keras import optimizers
from keras.models import Model
from keras.layers import Dropout, Dense, GlobalAveragePooling2D, Input
from keras.callbacks import ModelCheckpoint
from keras.preprocessing.image import ImageDataGenerator, img_to_array, load_img
from keras.utils import np_utils

from IPython.core.display import display
from PIL import Image

plt.style.use('ggplot')
%matplotlib inline
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.
We recommend you upgrade now or ensure your notebook will continue to use TensorFlow 1.x via the

```
Using TensorFlow backend.
```

```
# Mount Google Drive to access data
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?clien

Enter your authorization code:
··········
Mounted at /content/gdrive
```

```
# Unzip image folder to access image data, and store it in new
# folder (img_align_celeba)

import zipfile
with zipfile.ZipFile('gdrive/My Drive/M3_Group_Assignment/img_align_celeba.zip',
                     'r') as zip_ref:
    zip_ref.extractall('img_align_celeba')
```

```
# Set variables
root_folder = 'gdrive/My Drive/M3_Group_Assignment/'
img_folder = 'img_align_celeba/img_align_celeba/'

#Memory limitation, so we use a reduced amount of data, to train and validate.
train_size = 10000
val_size = 2000

#We set test-size as 2.000
test_size = 2000

#Predefine image size
img_width = 178
img_height = 218

#Set batch_size to 16, to reduce memory.
#Too large batch-size can negatively affect accuracy.
batch_size = 16

#Set epochs as 20
n_epochs = 20
```

```
#Import the dataset that includes the attribute for each picture
data_attr = pd.read_csv(root_folder + 'list_attr_celeba.csv')
data_attr.set_index('image_id', inplace=True)
data_attr.replace(to_replace=-1, value=0, inplace=True) #replace -1 by 0
data_attr.shape
data_attr.head()
```

image_id	5_o_Clock_Shadow	Arched_Eyebrows	Attractive	Bags_Under_Eyes	Ba
000001.jpg	0	1	1	0	
000002.jpg	0	0	0	1	
000003.jpg	0	0	0	0	
000004.jpg	0	0	1	0	
000005.jpg	0	1	1	0	

```
#We now print a list of available attributes, to get an insight of the
#possible attributes in the dataset.
for i, j in enumerate(data_attr.columns):
    print(i, j)
```

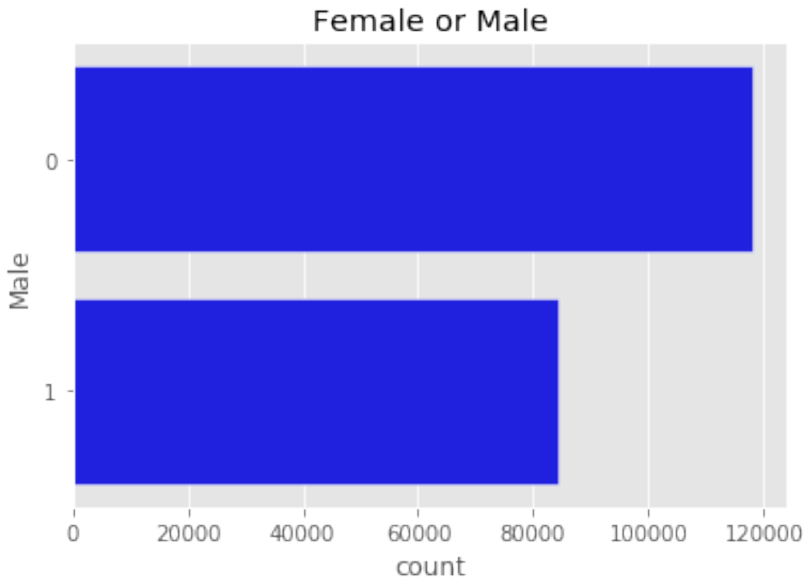
```
0 5_o_Clock_Shadow
1 Arched_Eyebrows
2 Attractive
3 Bags_Under_Eyes
4 Bald
5 Bangs
6 Big_Lips
7 Big_Nose
8 Black_Hair
9 Blond_Hair
10 Blurry
11 Brown_Hair
12 Bushy_Eyebrows
13 Chubby
14 Double_Chin
15 Eyeglasses
16 Goatee
17 Gray_Hair
18 Heavy_Makeup
19 High_Cheekbones
20 Male
21 Mouth_Slightly_Open
22 Mustache
23 Narrow_Eyes
24 No_Beard
25 Oval_Face
26 Pale_Skin
27 Pointy_Nose
28 Receding_Hairline
29 Rosy_Cheeks
30 Sideburns
31 Smiling
32 Straight_Hair
33 Wavy_Hair
34 Wearing_Earrings
35 Wearing_Hat
36 Wearing_Lipstick
37 Wearing_Necklace
38 Wearing_Necktie
39 Young
```

```
#First we want to see an example of one picture, and we therefore print
#an example of a picture. We just chose a random picture.
#We also try to print some attributes, to see if they match the picture.
#In this case we check for 'Bald', 'Male' and 'Young'.
ex_pic = img_folder + '000409.jpg'
img = load_img(ex_pic)
plt.grid(False)
plt.imshow(img)
data_attr.loc[ex_pic.split('/')[-1]][['Bald','Male','Young']] #some attributes
```

```
Bald     0
Male     1
Young    1
Name: 000409.jpg, dtype: int64
```

```
# To get an insight of the data distribution of male and female pictures
# we print a barchart with true/false labels for 'Male'.
# False values = Females
# True values = Males
plt.title('Female or Male')
sns.set_style('whitegrid')
sns.countplot(y='Male', data=data_attr, color="b")

plt.show()
```



Step 2: Split Dataset into Training, Validation and Test

For this step we divide our dataset into three subsets of the dataframe, which is training, validat
execution, we limit our splits as:

- Training: 20.000 images
- Validation: 5.000 images
- Test: 5.000 images

This way we train our data on ~66% of the dataset, validate on ~17% of the dataset and test on

The splitting of the data is predefined in the 'list_eval_partition.csv' dataset.

```
# We import the predefined partition data, where
# partition: 0 = training
# partition: 1 = validation
# partition: 2 = test
data_partition = pd.read_csv(root_folder + 'list_eval_partition.csv')
data_partition.head()
```

	image_id	partition
0	000001.jpg	0
1	000002.jpg	0
2	000003.jpg	0
3	000004.jpg	0
4	000005.jpg	0

```
# We display the distribution of train, validation and test in the
# predefined dataset.
data_partition['partition'].value_counts().sort_index()
```

```
0    162770
1     19867
2     19962
Name: partition, dtype: int64
```

```
# We add the column 'Male' from data_attr dataframe, to identify gender on
# each partition, and print out the first five values.
# The number of images needs to be balanced, in order to get a good performance
# for the model
data_partition.set_index('image_id', inplace=True)
data_par_attr = data_partition.join(data_attr['Male'], how='inner')
data_par_attr.head()
```

	partition	Male
image_id		
000001.jpg	0	0
000002.jpg	0	0
000003.jpg	0	1
000004.jpg	0	0
000005.jpg	0	0

```
#Now we create some functions, to be used later in the notebook.

#We make a function to reshape the images, after they have been processed
#through the generate_data function, which is defined below this function.
def load_reshape_img(fname):
    img = load_img(fname)
    x = img_to_array(img)/255.
    x = x.reshape((1,) + x.shape)

    return x

#The generate_data function generates data based on a partition, attributes and
#samples. This is done by generating data on train and validation and on test.
def generate_data(partition, attr, num_samples):
    '''
    partition
        0 -> train
        1 -> validation
        2 -> test

    '''

    dataframe = data_par_attr[(data_par_attr['partition'] == partition)
                           & (data_par_attr[attr] == 0)].sample(int(num_samples/
    dataframe = pd.concat([dataframe,
                      data_par_attr[(data_par_attr['partition'] == partition)
                                 & (data_par_attr[attr] == 1)].sample(int(num_s

    # for Train and Validation
    if partition != 2:
        x_ = np.array([load_reshape_img(img_folder + fname) for fname in datafra
        x_ = x_.reshape(x_.shape[0], 218, 178, 3)
        y_ = np_utils.to_categorical(dataframe[attr],2)
    # for Test
    else:
        x_ = []
        y_ = []

        for index, target in dataframe.iterrows():
            im = cv2.imread(img_folder + index)
            im = cv2.resize(cv2.cvtColor(im, cv2.COLOR_BGR2RGB), (img_width, img
            im = np.expand_dims(im, axis =0)
            x_.append(im)
            y_.append(target[attr])

    return x_, y_
```

Step 3: Pre-processing images: Data Augmentation

In order to be able to make better predictions, we process the images with modifications to the etc. the images. The model will this way learn from these different variations, resulting in better

Below is an image example on how a picture will look like after data augmentation.

```
# We generate image generator for data augmentation with
# the ImageDataGenerator function below
dataGenerator =  ImageDataGenerator(
  rotation_range=40,
  width_shift_range=0.3,
  height_shift_range=0.3,
  shear_range=0.3,
  zoom_range=0.3,
  horizontal_flip=True
)

# We use ex_pic as example for the data augmentation
img = load_img(ex_pic)
x = img_to_array(img)/255.
x = x.reshape((1,) + x.shape)

# We then plot 10 augmented images of the loaded image to see the behavior of
# the data augmentation
plt.figure(figsize=(20,10))
plt.suptitle('Example Data Augmentation', fontsize=26)

i = 0
for batch in dataGenerator.flow(x, batch_size=1):
    plt.subplot(3, 5, i+1)
    plt.grid(False)
    plt.imshow( batch.reshape(218, 178, 3))

    if i == 9:
        break
    i += 1

plt.show()
```

Example Data Augme

```
# Define the train data
x_train, y_train = generate_data(0, 'Male', train_size)

# Train - Data Preparation for data augmentation
train_datagen =  ImageDataGenerator(
  preprocessing_function=preprocess_input,
  rotation_range=40,
  width_shift_range=0.3,
  height_shift_range=0.3,
  shear_range=0.3,
  zoom_range=0.3,
  horizontal_flip=True,
)

#fitting the model
train_datagen.fit(x_train)

train_generator = train_datagen.flow(
x_train, y_train,
batch_size=batch_size,
)
```

```
# Define validation Data
x_valid, y_valid = generate_data(1, 'Male', val_size)
```

Step 4: Build the Model - Gender Recognition

In this step we build the model for the Gender detection through image recognition.

First we apply a non-neural model to our dataset, to see how it scores on predicting gender on i

We apply the Google-made InceptionV3 transfer-learning model. On top of this layer-architectur
performance within our problem-scope.

We then train the model through a number of epochs.

Lastly in this step, we plot the loss function value and accuracy through the different epochs, ar

```
#import necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA

#We define our target label as the Gender column (male or not)
target = data_attr['Male'];
#define our dataset
data_pca = pd.read_csv(root_folder + 'list_attr_celeba.csv')
#We remove the male and image_id from the dataset to predict the Male column.
#image_id holds no attributes, so this is removed
data_pca.drop(['Male', 'image_id'], inplace=True, axis=1)

#print data to check values
target.head()
data_pca.head()

#Define our training and test data, with test_size of 20%.
train_attr, test_attr, train_target, test_target = train_test_split(data_pca, ta


#We use standardscaler to scale our data, and fit on train data.
scaler = StandardScaler()
scaler.fit(train_attr)
```

```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

```
#Apply transform to training and testset
train_attr = scaler.transform(train_attr)
test_attr = scaler.transform(test_attr)
```

```
#Create PCA on training data and print number of appropriate components
pca = PCA(.95)
pca.fit(train_attr)
pca.n_components_
```

```
34
```

```
#Transform the pca to training and testset
train_attr = pca.transform(train_attr)
test_attr = pca.transform(test_attr)
```

```
#import logistic regression
from sklearn.linear_model import LogisticRegression

logisticRegr = LogisticRegression(solver='lbfgs')

#Fit logistic regression on training attributes and target.
logisticRegr.fit(train_attr, train_target)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
#Predict on the first 10 rows of our dataset.
logisticRegr.predict(test_attr[0:10])
```

```
array([1, 0, 1, 0, 0, 0, 0, 1, 1, 0])
```

```
#print the score of our logistic regression prediction.
logisticRegr.score(test_attr, test_target)
```

```
0.93215695952616
```

```
# Import InceptionV3 Model
# The inceptionV3 is a Google made transfer-learning model, which is the most
# popular model for image recognition, and is trained on over 1 million pictures
inc_model = InceptionV3(weights= root_folder + 'inception_v3_weights_tf_dim_orde
                        include_top=False,
                        input_shape=(img_height, img_width, 3))

#Print the number of layers in the architecture. We did outcomment the summary
#function, to save space (it takes a lot of space to print 311 layers)
print("number of layers:", len(inc_model.layers))
#inc_model.summary()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend

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WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend

number of layers: 311
```

```
#We add our custom layers to fit the model to our problem-scope

x = inc_model.output
#Add GlovalAveragePooling2D to apply a two-dimensional output to the
#kernel-size, to produce a tensor with dimensions.
x = GlobalAveragePooling2D()(x)
#We add a Dense layer which is a linear operation in which every input is
#connected to every output by a weight
x = Dense(1024, activation="relu")(x)
#Add dropout layer, to add 'braindamage' to prevent overfitting
x = Dropout(0.5)(x)
#Add second Dense layer
x = Dense(512, activation="relu")(x)
#Define prediction as the full-model, with a Dense-layer
#and 'sigmoid' as activation, because of the binary problem-statement.
predictions = Dense(2, activation="sigmoid")(x)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 -
```

```
# creating the final model with inc_model.input as input and
#our defined predictions as output.
model_ = Model(inputs=inc_model.input, outputs=predictions)

# Lock initial layers to do not be trained
for layer in model_.layers[:52]:
    layer.trainable = False

# compile the model
model_.compile(optimizer='adam'
                    , loss='binary_crossentropy'
                    , metrics=['accuracy'])
```

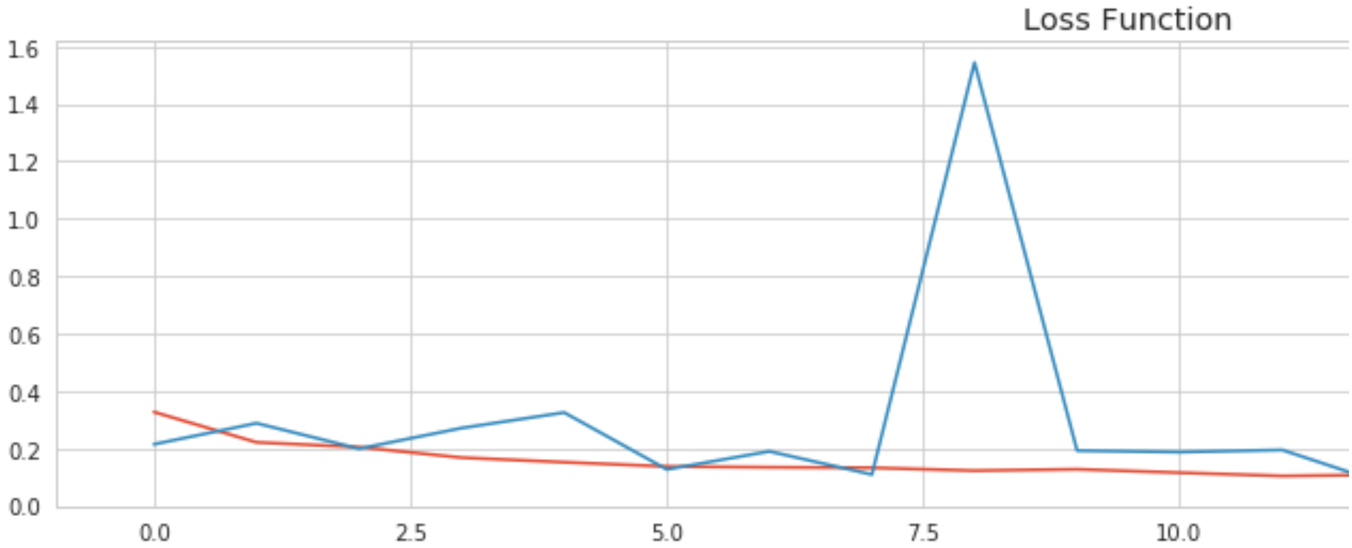
```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimiz

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow_co
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
```

```
#We use ModelCheckpoint to create a filepath, which later will save the best
#model from the training session.
checkpointer = ModelCheckpoint(filepath='weights.best.inc.male.hdf5',
                               verbose=1, save_best_only=True)


#We execute our training session, and store it as hist variable.
# We calculate steps_per_epoch as train_size divided by batch_size, to ensure
# that we train on all data in each epoch.
# We use 20 epochs to get a proper amount of epochs for the training session,
# which then stores the best model for the test session through the callback.
hist = model_.fit_generator(train_generator
                     , validation_data = (x_valid, y_valid)
                      , steps_per_epoch= train_size/batch_size
                      , epochs= n_epochs
                      , callbacks=[checkpointer]
                      , verbose=1
                    )
```

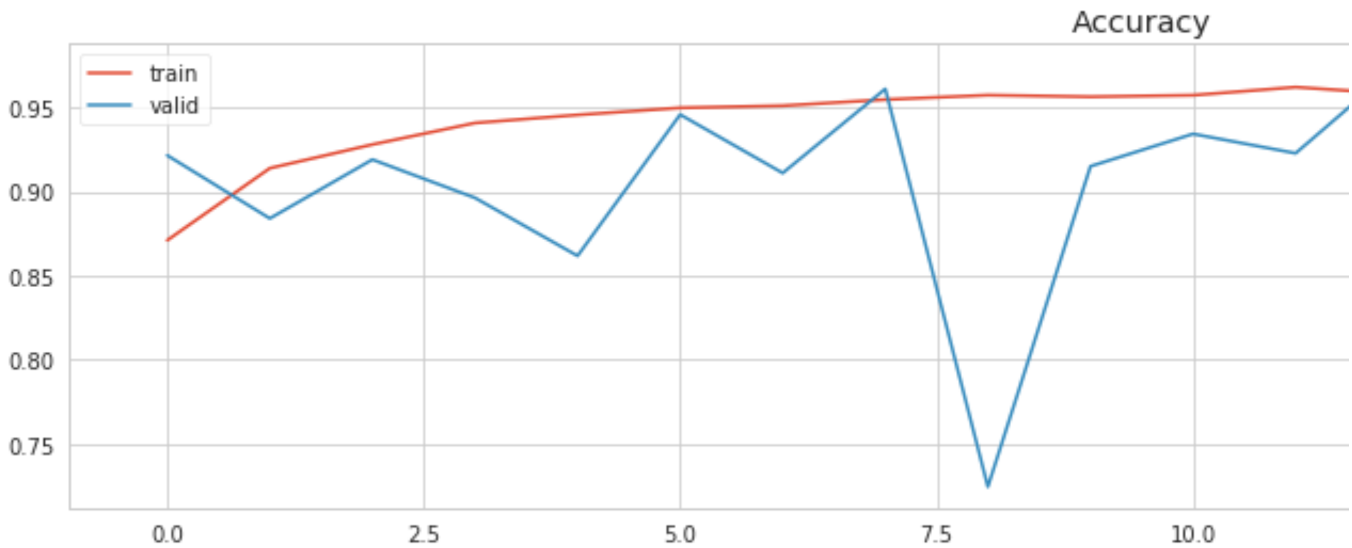
```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend

Epoch 1/20
625/625 [==============================] - 96s 154ms/step - loss: 0.3268 - a

Epoch 00001: val_loss improved from inf to 0.21431, saving model to weights.
Epoch 2/20
625/625 [==============================] - 77s 123ms/step - loss: 0.2210 - a

Epoch 00002: val_loss did not improve from 0.21431
Epoch 3/20
625/625 [==============================] - 76s 121ms/step - loss: 0.2043 - a

Epoch 00003: val_loss improved from 0.21431 to 0.19888, saving model to weig
Epoch 4/20
625/625 [==============================] - 76s 122ms/step - loss: 0.1678 - a

Epoch 00004: val_loss did not improve from 0.19888
Epoch 5/20
625/625 [==============================] - 76s 121ms/step - loss: 0.1518 - a

Epoch 00005: val_loss did not improve from 0.19888
Epoch 6/20
625/625 [==============================] - 76s 122ms/step - loss: 0.1369 - a

Epoch 00006: val_loss improved from 0.19888 to 0.12671, saving model to weig
Epoch 7/20
625/625 [==============================] - 76s 122ms/step - loss: 0.1342 - a

Epoch 00007: val_loss did not improve from 0.12671
Epoch 8/20
```

```
625/625 [==============================] - 76s 121ms/step - loss: 0.1324 - a

Epoch 00008: val_loss improved from 0.12671 to 0.10883, saving model to weig
Epoch 9/20
625/625 [==============================] - 76s 122ms/step - loss: 0.1224 - a

Epoch 00009: val_loss did not improve from 0.10883
Epoch 10/20
625/625 [==============================] - 76s 122ms/step - loss: 0.1271 - a

Epoch 00010: val_loss did not improve from 0.10883
Epoch 11/20
625/625 [==============================] - 76s 122ms/step - loss: 0.1152 - a

Epoch 00011: val_loss did not improve from 0.10883
Epoch 12/20
625/625 [==============================] - 76s 122ms/step - loss: 0.1039 - a

Epoch 00012: val_loss did not improve from 0.10883
Epoch 13/20
625/625 [==============================] - 76s 122ms/step - loss: 0.1080 - a

Epoch 00013: val_loss improved from 0.10883 to 0.07629, saving model to weig
Epoch 14/20
625/625 [==============================] - 76s 122ms/step - loss: 0.1182 - a

Epoch 00014: val_loss improved from 0.07629 to 0.07194, saving model to weig
Epoch 15/20
625/625 [==============================] - 77s 123ms/step - loss: 0.1056 - a

Epoch 00015: val_loss did not improve from 0.07194
Epoch 16/20
625/625 [==============================] - 77s 123ms/step - loss: 0.0953 - a

Epoch 00016: val_loss did not improve from 0.07194
Epoch 17/20
625/625 [==============================] - 77s 122ms/step - loss: 0.1037 - a

Epoch 00017: val_loss did not improve from 0.07194
Epoch 18/20
625/625 [==============================] - 76s 122ms/step - loss: 0.0942 - a

Epoch 00018: val_loss did not improve from 0.07194
Epoch 19/20
625/625 [==============================] - 76s 122ms/step - loss: 0.0870 - a

Epoch 00019: val_loss did not improve from 0.07194
Epoch 20/20
625/625 [==============================] - 76s 122ms/step - loss: 0.0918 - a

Epoch 00020: val_loss did not improve from 0.07194
```

```
# We plot the loss function value through epochs
plt.figure(figsize=(18, 4))
plt.plot(hist.history['loss'], label = 'train')
plt.plot(hist.history['val_loss'], label = 'valid')
plt.legend()
plt.title('Loss Function')
plt.show()
```




```
# We plot the accuracy through epochs
plt.figure(figsize=(18, 4))
plt.plot(hist.history['acc'], label = 'train')
plt.plot(hist.history['val_acc'], label = 'valid')
plt.legend()
plt.title('Accuracy')
plt.show()
```



```
# We then load in the best model, which is stored in the
# 'weights.best.inc.male.hdf5' file.
model_.load_weights('weights.best.inc.male.hdf5')


# Define the test data
x_test, y_test = generate_data(2, 'Male', test_size)

# Generate prediction
model_predictions = [np.argmax(model_.predict(feature)) for feature in x_test ]

# report test accuracy
test_accuracy = 100 * np.sum(np.array(model_predictions)==y_test) / len(model_pr
print('Model Evaluation')
print('Test accuracy: %.4f%%' % test_accuracy)
print('f1_score:', f1_score(y_test, model_predictions))
```

```
Model Evaluation
Test accuracy: 96.2500%
f1_score: 0.9617931737137035
```