性别识别：逻辑回归

案例代码

In [76]:

```
import pandas as pd  #导入库
MasterFile=pd.read_csv('F:/大三（上）/深度学习/TASK2.1：AI可以为颜值打分/FaceScore.csv')
#读入参考文件
print(MasterFile.shape)  #打印数组维度
MasterFile.head()        #打印前五个
```

(24, 2)

Out[76]:

	Filename	Rating
0	ftw (1).jpg	4.083333
1	mtw (2).jpg	3.666667
2	mtw (3).jpg	1.916667
3	mtw (4).jpg	2.416667
4	mtw (5).jpg	3.166667

准备X数据

In [77]:

```
import numpy as np
from PIL import Image

FileNames=MasterFile['Filename']
N=len(FileNames)
IMSIZE=128            #设置随机种子
X=np.zeros([N,IMSIZE,IMSIZE,3])  #返回一个和文件图片一致的用0填充的矩阵
for i in range(N):    #循环导入文件
    MyFile=FileNames[i]
    Im=Image.open('F:/大三（上）/深度学习/TASK2.1：AI可以为颜值打分/image/'+MyFile)
    Im=Im.resize([IMSIZE,IMSIZE])  #图像的缩放
    Im=np.array(Im)/255
    X[i,]=Im
```

准备Y数据

In [78]:

```
Y=np.zeros([N,2])
for i in range(N):
    gender=FileNames[i][0]
    if gender=='m':
        Y[i,0]=1
    else:
```

```
    else:
        Y[i,1]=1
```

切分：Training+Validation

In [79]:

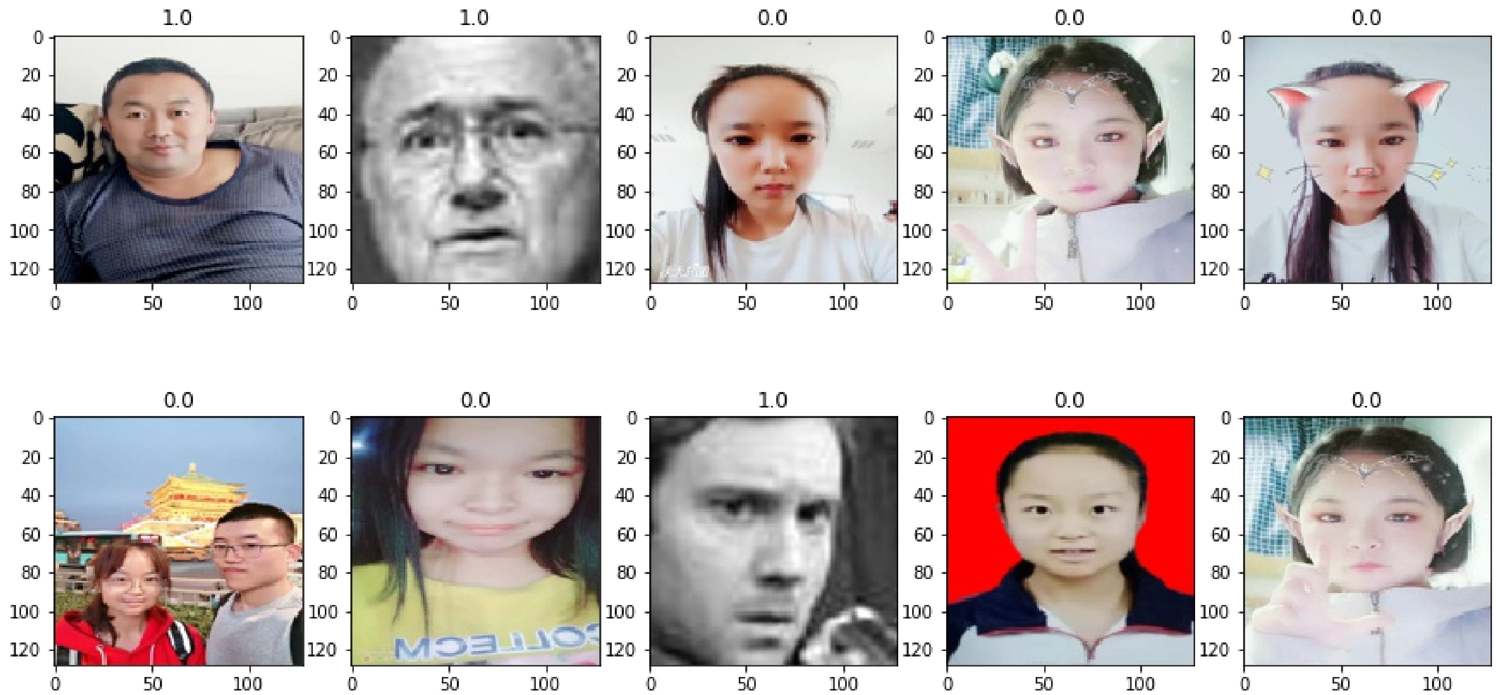
```
from sklearn.model_selection import train_test_split  #构造训练集和测试集
X0,X1,Y0,Y1=train_test_split(X,Y,test_size=0.5,random_state=0)
```

数据展示

In [80]:

```
plt.figure()             #导入绘图库
fig,ax=plt.subplots(2,5)      #2行5列
fig.set_figheight(7.5)
fig.set_figwidth(15)
ax=ax.flatten()
for i in range(10):        #展示10张照片的性别
    ax[i].imshow(X0[i,:,:,:])
    ax[i].set_title(Y0[i,0])
```

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



逻辑回归：模型设计

In [81]:

```
from keras.layers import Dense, Flatten, Input      #导入keras模型库
from keras.layers import BatchNormalization, Conv2D,MaxPooling2D
from keras import Model

input_layer=Input([IMSIZE,IMSIZE,3])  #输入数组矩阵
x=input_layer
#x=BatchNormalization()(x)
#x=Conv2D(10,[2,2],activation='relu')(x)
#x=MaxPooling2D([16,16])(x)
```

```
x=Flatten()(x)              #返回一维数组
x=Dense(2,activation='softmax')(x)  #激活神经元
output_layer=x              #输出性别
model=Model(input_layer,output_layer)  #建立模型
model.summary()             #描述模型统计变量
```

```
Model: "functional_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_4 (InputLayer)         [(None, 128, 128, 3)]     0
_________________________________________________________________
flatten_3 (Flatten)          (None, 49152)             0
_________________________________________________________________
dense_3 (Dense)              (None, 2)                 98306
=================================================================
Total params: 98,306
Trainable params: 98,306
Non-trainable params: 0
_________________________________________________________________
```

输入层为长度为128x128x3的矩阵，消耗了49152个参数，乘以2，再加上截距项，一共消耗了98306个参数.

In [82]:

```
from keras.optimizers import Adam
model.compile(loss='categorical_crossentropy',optimizer=Adam(lr=0.01),metrics=['accuracy'])
#极大似然估计；设置学习速率为0.01；计算精度。
```

逻辑回归：建立模型

In [83]:

```
model.fit(X0,Y0,           #模型实现
        validation_data=[X1,Y1],
        batch_size=500,
        epochs=100)
```

```
Epoch 1/100
1/1 [==============================] - 0s 67ms/step - loss: 0.5296 - accuracy: 0.6667 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 2/100
1/1 [==============================] - 0s 18ms/step - loss: 118.6905 - accuracy: 0.7500 - val_loss: 0.00
00e+00 - val_accuracy: 0.0000e+00
Epoch 3/100
1/1 [==============================] - 0s 18ms/step - loss: 64.5663 - accuracy: 0.7500 - val_loss: 0.000
0e+00 - val_accuracy: 0.0000e+00
Epoch 4/100
1/1 [==============================] - 0s 17ms/step - loss: 3.9412 - accuracy: 0.8333 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 5/100
1/1 [==============================] - 0s 18ms/step - loss: 43.1873 - accuracy: 0.3333 - val_loss: 0.000
0e+00 - val_accuracy: 0.0000e+00
Epoch 6/100
1/1 [==============================] - 0s 17ms/step - loss: 1.3010 - accuracy: 0.9167 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 7/100
1/1 [==============================] - 0s 17ms/step - loss: 33.0379 - accuracy: 0.7500 - val_loss: 0.000
0e+00 - val_accuracy: 0.0000e+00
Epoch 8/100
```

```
1/1 [==============================] - 0s 19ms/step - loss: 42.6818 - accuracy: 0.7500 - val_loss: 0.000
0e+00 - val_accuracy: 0.0000e+00
Epoch 9/100
1/1 [==============================] - 0s 17ms/step - loss: 32.6142 - accuracy: 0.7500 - val_loss: 0.000
0e+00 - val_accuracy: 0.0000e+00
Epoch 10/100
1/1 [==============================] - 0s 19ms/step - loss: 6.9708 - accuracy: 0.8333 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 11/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 12/100
1/1 [==============================] - 0s 17ms/step - loss: 3.3560 - accuracy: 0.9167 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 13/100
1/1 [==============================] - 0s 17ms/step - loss: 12.7735 - accuracy: 0.7500 - val_loss: 0.000
0e+00 - val_accuracy: 0.0000e+00
Epoch 14/100
1/1 [==============================] - 0s 19ms/step - loss: 9.2676 - accuracy: 0.8333 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 15/100
1/1 [==============================] - 0s 17ms/step - loss: 2.7084 - accuracy: 0.9167 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 16/100
1/1 [==============================] - 0s 19ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 17/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 18/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 19/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 20/100
1/1 [==============================] - 0s 16ms/step - loss: 1.9610 - accuracy: 0.9167 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 21/100
1/1 [==============================] - 0s 17ms/step - loss: 3.3035 - accuracy: 0.8333 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 22/100
1/1 [==============================] - 0s 20ms/step - loss: 0.4413 - accuracy: 0.9167 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 23/100
1/1 [==============================] - 0s 18ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 24/100
1/1 [==============================] - 0s 18ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 25/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 26/100
1/1 [==============================] - 0s 18ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 27/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 28/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
```

```
Epoch 29/100
1/1 [==============================] - 0s 19ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 30/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 31/100
1/1 [==============================] - 0s 18ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 32/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 33/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 34/100
1/1 [==============================] - 0s 22ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 35/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 36/100
1/1 [==============================] - 0s 18ms/step - loss: 3.4769e-07 - accuracy: 1.0000 - val_loss: 0.0
000e+00 - val_accuracy: 0.0000e+00
Epoch 37/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0236 - accuracy: 1.0000 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 38/100
1/1 [==============================] - 0s 18ms/step - loss: 0.0785 - accuracy: 0.9167 - val_loss: 0.0000
e+00 - val_accuracy: 0.0000e+00
Epoch 39/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 40/100
1/1 [==============================] - 0s 22ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 41/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 42/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 43/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 44/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 45/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 46/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 47/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 48/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 49/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
```

```
0000e+00 - val_accuracy: 0.0000e+00
Epoch 50/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 51/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 52/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 53/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 54/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 55/100
1/1 [==============================] - 0s 25ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 56/100
1/1 [==============================] - 0s 23ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 57/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 58/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 59/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 60/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 61/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 62/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 63/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 64/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 65/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 66/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 67/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 68/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 69/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 70/100
```

```
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 71/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 72/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 73/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 74/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 75/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 76/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 77/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 78/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 79/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 80/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 81/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 82/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 83/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 84/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 85/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 86/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 87/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 88/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 89/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 90/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
```

```
0000e+00 - val_accuracy: 0.0000e+00
Epoch 91/100
1/1 [==============================] - 0s 15ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 92/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 93/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 94/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 95/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 96/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 97/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 98/100
1/1 [==============================] - 0s 18ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 99/100
1/1 [==============================] - 0s 17ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
Epoch 100/100
1/1 [==============================] - 0s 16ms/step - loss: 0.0000e+00 - accuracy: 1.0000 - val_loss: 0.
0000e+00 - val_accuracy: 0.0000e+00
```

Out[83]:

```
<tensorflow.python.keras.callbacks.History at 0x1fa01f76808>
```

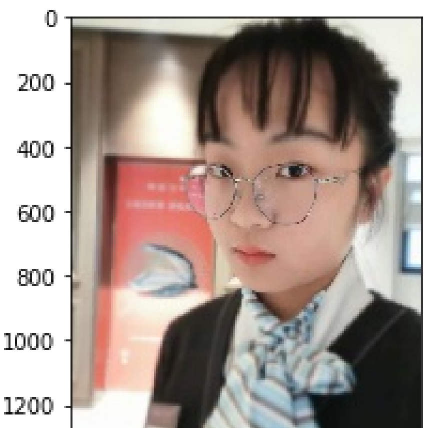
模型预测：性别识别

In [84]:

```
MyPic=Image.open('F:/图片/刘嘉玲/一张严肃的照片.jpg')  #导入测试照片
plt.imshow(MyPic)                          #打印该照片
MyPic=MyPic.resize((IMSIZE,IMSIZE))                  #图片缩放
MyPic=np.array(MyPic)/255                  #构建数组
MyPic=MyPic.reshape((1,IMSIZE,IMSIZE,3))          # 改变数组的形状
model.predict(MyPic)
```

Out[84]:

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



这里看预测识别还是准确的，精准度为1。

自己编写的模型

In [31]:

```
import os
filePath = 'F:/大三（上）/机器学习/3.实践作业/3.实践作业/二分类图'
items = os.listdir(filePath)
```

In [32]:

```
#为了避免有不是jpg格式的文件，有临时文件时可能会有问题，多做一步
namelist=[]
for name in items:
    if name.endswith(".jpg"):
        namelist.append(name)
```

In [33]:

```
len(namelist)
```

Out[33]:

350

In [34]:

```
namelist[0] #355表示图片编号，后面的35表示人的类别
```

Out[34]:

'0_male.jpg'

In [35]:

```
#需要将类别（输出）拆解出来
namelist[0][:-4].split("_")
```

Out[35]:

['0', 'male']

读取图片，将图片作为特征X，将人的类别作为输出Y

In [36]:

```
from PIL import Image
import numpy as np
X=np.empty((0,4096))
n_pixels=64
for i in namelist:
    img=np.array(Image.open('F:/大三（上）/机器学习/4.实践作业/4.2实践作业/二分类图/'+i).convert('L'), 'f')
    img_new=img.reshape(1,4096)
    X=np.vstack((X,img_new))
```

In [37]:

```
X.shape
```

Out[37]:

```
(350, 4096)
```

In [38]:

```
X[:5]
```

Out[38]:

```
array([[ 77.,  91., 104., ...,  25.,  15.,  30.],
       [ 68.,  39.,  43., ...,   0.,  13.,   0.],
       [ 25.,  47., 192., ...,  12.,  54.,  39.],
       [ 75.,  11.,  58., ...,   7.,  64.,  25.],
       [ 10., 165., 246., ...,   4.,   0.,   1.]])
```

In [39]:

```
y=[]
for i in namelist:
    people=i[:-4].split("_")[1]
    y.append(people)
```

In [40]:

```
y=np.array(y)
y
```

Out[40]:

```
array(['male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'female', 'female', 'female', 'female', 'female',
```

```
       'male', 'male', 'female', 'female', 'female', 'female', 'female',
       'female', 'female', 'female', 'female', 'female', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'female', 'female',
       'female', 'female', 'female', 'female', 'female', 'female',
       'female', 'female', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'female', 'female', 'female', 'female', 'female',
       'female', 'female', 'female', 'female', 'female', 'male', 'male',
       'male', 'male', 'male', 'male', 'male', 'male', 'male', 'male',
       'male', 'male', 'female', 'female', 'female', 'female', 'female',
       'female', 'female', 'female', 'female', 'female', 'male'],
      dtype='<U6')
```

划分训练集和测试集

In [41]:

```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.01)
```

In [42]:

```python
X_train.shape
```

Out[42]:

```
(346, 4096)
```

In [43]:

```python
X_test.shape
```

Out[43]:

```
(4, 4096)
```

构建KNN模型

In [50]:

```python
#训练模型
from sklearn import neighbors
from sklearn import metrics

KNN_model = neighbors.KNeighborsClassifier(n_neighbors =4, metric = 'minkowski', p = 2)
KNN_model.fit(X_train, y_train)
```

Out[50]:

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=4, p=2,
                     weights='uniform')
```

In [51]:

```python
#在测试集上验证
```

```
y_predict=KNN_model.predict(X_test) #输出分类结果
```

In [52]:

```
y_predict_prob=KNN_model.predict_proba(X_test)
y_predict_prob
```

Out[52]:

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

In [56]:

```
y_predict
```

Out[56]:

```
array(['male', 'male', 'male', 'male'], dtype='<U6')
```

In [57]:

```
y_test
```

Out[57]:

```
array(['male', 'male', 'male', 'male'], dtype='<U6')
```

从上面预测结果来看，预测非常准确