# 深度学习大作业：使用预训练的神经网络预测人民币面额

## 1.将VGG16卷积基实例化

In [1]:

```
from keras.applications import VGG16
```

```
Using TensorFlow backend.
```

In [2]:

```
conv_base = VGG16(weights='imagenet',
                  include_top = False)
```

In [3]:

```
conv_base.summary()
```

```
Model: "vgg16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_1 (InputLayer)         (None, None, None, 3)     0         
_________________________________________________________________
block1_conv1 (Conv2D)        (None, None, None, 64)    1792      
_________________________________________________________________
block1_conv2 (Conv2D)        (None, None, None, 64)    36928     
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, None, None, 64)    0         
_________________________________________________________________
block2_conv1 (Conv2D)        (None, None, None, 128)   73856     
_________________________________________________________________
block2_conv2 (Conv2D)        (None, None, None, 128)   147584    
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, None, None, 128)   0         
_________________________________________________________________
block3_conv1 (Conv2D)        (None, None, None, 256)   295168    
_________________________________________________________________
block3_conv2 (Conv2D)        (None, None, None, 256)   590080    
_________________________________________________________________
block3_conv3 (Conv2D)        (None, None, None, 256)   590080    
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, None, None, 256)   0         
_________________________________________________________________
block4_conv1 (Conv2D)        (None, None, None, 512)   1180160   
_________________________________________________________________
block4_conv2 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block4_conv3 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, None, None, 512)   0         
_________________________________________________________________
block5_conv1 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block5_conv2 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block5_conv3 (Conv2D)        (None, None, None, 512)   2359808   
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, None, None, 512)   0         
=================================================================
Total params: 14,714,688
Trainable params: 14,714,688
Non-trainable params: 0
_________________________________________________________________
```

# 不使用数据增强

# 2.使用预训练的卷积基提取特征

In [4]:

```
import os
import numpy as np
from keras.preprocessing.image import ImageDataGenerator

base_dir = 'RMB'

train_dir = os.path.join(base_dir, 'train')
validation_dir = os.path.join(base_dir, 'validation')
test_dir = os.path.join(base_dir, 'test')

datagen = ImageDataGenerator(rescale=1./255)
batch_size = 20

def extract_features(directory, sample_count):
    features = np.zeros(shape=(sample_count, 8, 8, 512))
    labels = np.zeros(shape=(sample_count))
    generator = datagen.flow_from_directory(
        directory,
#         target_size=(150, 150),
        batch_size=batch_size,
        class_mode='binary')
    i = 0
    for inputs_batch, labels_batch in generator:
        features_batch = conv_base.predict(inputs_batch)
        features[i * batch_size : (i + 1) * batch_size] = features_batch
        labels[i * batch_size : (i + 1) * batch_size] = labels_batch
        i += 1
        if i * batch_size >= sample_count:
            # Note that since generators yield data indefinitely in a loop,
            # we must `break` after every image has been seen once.
            break
    return features, labels

train_features, train_labels = extract_features(train_dir, 40)
validation_features, validation_labels = extract_features(validation_dir, 20)
test_features, test_labels = extract_features(test_dir, 20)
```

```
Found 40 images belonging to 2 classes.
Found 20 images belonging to 2 classes.
Found 20 images belonging to 2 classes.
```

In [5]:

```
train_features = np.reshape(train_features, (40, 8 * 8 * 512))
validation_features = np.reshape(validation_features, (20, 8 * 8 * 512))
test_features = np.reshape(test_features, (20, 8 * 8 * 512))
```

# 3.定义并训练密集链接分类器

In [6]:

```
from keras import models
from keras import layers
from keras import optimizers

model = models.Sequential()
model.add(layers.Dense(256, activation='relu', input_dim=8 * 8 * 512))
model.add(layers.Dropout(0.3))
# model.add(layers.Dropout(0.5))
model.add(layers.Dense(1, activation='sigmoid'))

model.compile(optimizer=optimizers.RMSprop(lr=2e-5),
              loss='binary_crossentropy',
              metrics=['acc'])

history = model.fit(train_features, train_labels,
                    epochs=30,
                    batch_size=10,
                    validation_data=(validation_features, validation_labels))
```

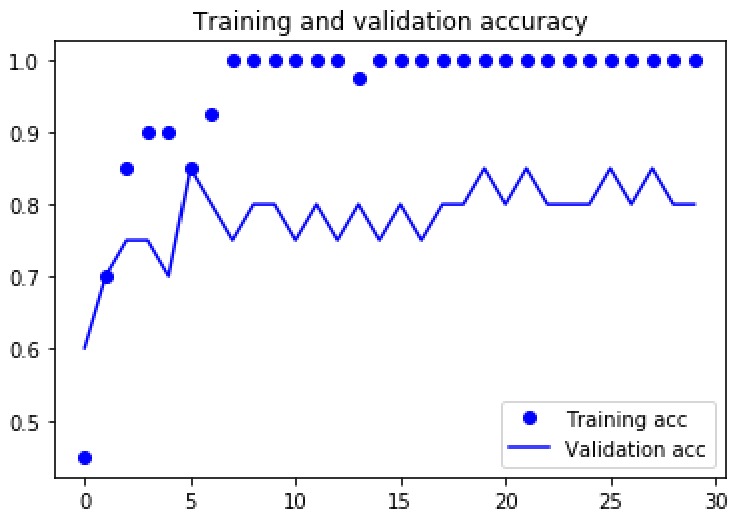
```
WARNING:tensorflow:From D:\programming_software_install\Anaconda3\lib\site-packages
\tensorflow_core\python\ops\nn_impl.py:183: where (from tensorflow.python.ops.array_
ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
Train on 40 samples, validate on 20 samples
Epoch 1/30
40/40 [==============================] - 1s 22ms/step - loss: 0.9066 - acc: 0.4500 -
val_loss: 0.6638 - val_acc: 0.6000
Epoch 2/30
40/40 [==============================] - 1s 18ms/step - loss: 0.6172 - acc: 0.7000 -
val_loss: 0.6057 - val_acc: 0.7000
Epoch 3/30
40/40 [==============================] - 1s 21ms/step - loss: 0.4520 - acc: 0.8500 -
val_loss: 0.5790 - val_acc: 0.7500
Epoch 4/30
40/40 [==============================] - 1s 22ms/step - loss: 0.3832 - acc: 0.9000 -
val_loss: 0.5674 - val_acc: 0.7500
Epoch 5/30
40/40 [==============================] - 1s 20ms/step - loss: 0.3637 - acc: 0.9000 -
val_loss: 0.5548 - val_acc: 0.7000
Epoch 6/30
40/40 [==============================] - 1s 20ms/step - loss: 0.3440 - acc: 0.8500 -
val_loss: 0.5190 - val_acc: 0.8500
Epoch 7/30
40/40 [==============================] - 1s 22ms/step - loss: 0.3206 - acc: 0.9250 -
val_loss: 0.4981 - val_acc: 0.8000
Epoch 8/30
40/40 [==============================] - 1s 20ms/step - loss: 0.1964 - acc: 1.0000 -
val_loss: 0.5424 - val_acc: 0.7500
Epoch 9/30
40/40 [==============================] - 1s 24ms/step - loss: 0.2126 - acc: 1.0000 -
val_loss: 0.4715 - val_acc: 0.8000
Epoch 10/30
40/40 [==============================] - 1s 25ms/step - loss: 0.2098 - acc: 1.0000 -
val_loss: 0.4685 - val_acc: 0.8000
Epoch 11/30
40/40 [==============================] - 1s 25ms/step - loss: 0.1666 - acc: 1.0000 -
val_loss: 0.4792 - val_acc: 0.7500
Epoch 12/30
```

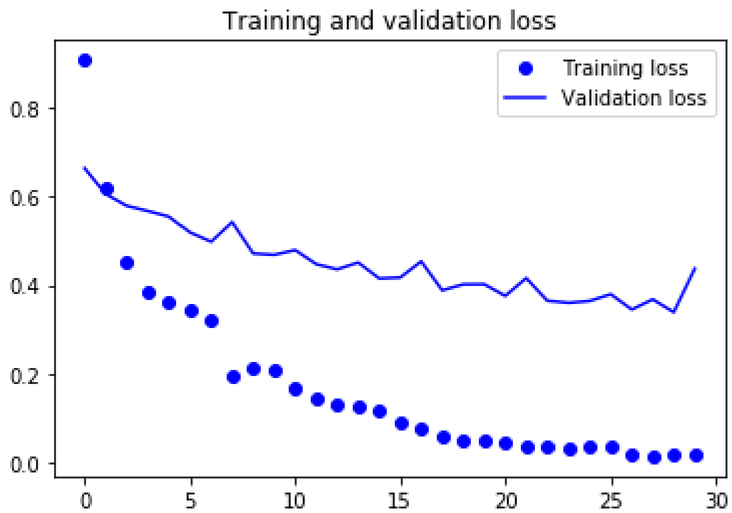
```
40/40 [==============================] - 1s 20ms/step - loss: 0.1459 - acc: 1.0000 -
val_loss: 0.4475 - val_acc: 0.8000
Epoch 13/30
40/40 [==============================] - 1s 19ms/step - loss: 0.1326 - acc: 1.0000 -
val_loss: 0.4358 - val_acc: 0.7500
Epoch 14/30
40/40 [==============================] - 1s 19ms/step - loss: 0.1277 - acc: 0.9750 -
val_loss: 0.4512 - val_acc: 0.8000
Epoch 15/30
40/40 [==============================] - 1s 19ms/step - loss: 0.1208 - acc: 1.0000 -
val_loss: 0.4153 - val_acc: 0.7500
Epoch 16/30
40/40 [==============================] - 1s 18ms/step - loss: 0.0925 - acc: 1.0000 -
val_loss: 0.4174 - val_acc: 0.8000
Epoch 17/30
40/40 [==============================] - 1s 19ms/step - loss: 0.0792 - acc: 1.0000 -
val_loss: 0.4537 - val_acc: 0.7500
Epoch 18/30
40/40 [==============================] - 1s 19ms/step - loss: 0.0611 - acc: 1.0000 -
val_loss: 0.3885 - val_acc: 0.8000
Epoch 19/30
40/40 [==============================] - 1s 22ms/step - loss: 0.0494 - acc: 1.0000 -
val_loss: 0.4019 - val_acc: 0.8000
Epoch 20/30
40/40 [==============================] - 1s 22ms/step - loss: 0.0496 - acc: 1.0000 -
val_loss: 0.4023 - val_acc: 0.8500
Epoch 21/30
40/40 [==============================] - 1s 20ms/step - loss: 0.0446 - acc: 1.0000 -
val_loss: 0.3759 - val_acc: 0.8000
Epoch 22/30
40/40 [==============================] - 1s 21ms/step - loss: 0.0383 - acc: 1.0000 -
val_loss: 0.4161 - val_acc: 0.8500
Epoch 23/30
40/40 [==============================] - 1s 18ms/step - loss: 0.0375 - acc: 1.0000 -
val_loss: 0.3651 - val_acc: 0.8000
Epoch 24/30
40/40 [==============================] - 1s 18ms/step - loss: 0.0320 - acc: 1.0000 -
val_loss: 0.3602 - val_acc: 0.8000
Epoch 25/30
40/40 [==============================] - 1s 21ms/step - loss: 0.0379 - acc: 1.0000 -
val_loss: 0.3646 - val_acc: 0.8000
Epoch 26/30
40/40 [==============================] - 1s 20ms/step - loss: 0.0361 - acc: 1.0000 -
val_loss: 0.3797 - val_acc: 0.8500
Epoch 27/30
40/40 [==============================] - 1s 18ms/step - loss: 0.0197 - acc: 1.0000 -
val_loss: 0.3452 - val_acc: 0.8000
Epoch 28/30
40/40 [==============================] - 1s 18ms/step - loss: 0.0154 - acc: 1.0000 -
val_loss: 0.3681 - val_acc: 0.8500
Epoch 29/30
40/40 [==============================] - 1s 18ms/step - loss: 0.0198 - acc: 1.0000 -
val_loss: 0.3391 - val_acc: 0.8000
Epoch 30/30
40/40 [==============================] - 1s 22ms/step - loss: 0.0201 - acc: 1.0000 -
val_loss: 0.4376 - val_acc: 0.8000
```

# 4.作图分析

In [7]:

```
import matplotlib.pyplot as plt

acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```




不使用数据增强的模型过拟合很快，验证准确率在80%左右

# 数据增强

# 5.在卷积基上添加有个密集连接分类器

In [67]:

```
conv_base = VGG16(weights='imagenet',
                  include_top = False,
                  input_shape=(150,300,3))
```

In [68]:

```
from keras import models
from keras import layers

model = models.Sequential()
model.add(conv_base)
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dense(1, activation='sigmoid'))
```

In [69]:

```
print('This is the number of trainable weights '
      'before freezing the conv base:', len(model.trainable_weights))
```

```
This is the number of trainable weights before freezing the conv base: 30
```

In [70]:

```
# 冻结卷积基
conv_base.trainable = False
```

In [ ]:

```
?layers.Flatten
```

In [71]:

```
print('This is the number of trainable weights '
      'after freezing the conv base:', len(model.trainable_weights))
```

```
This is the number of trainable weights after freezing the conv base: 4
```

# 6.利用冻结的卷积基端到端的训练模型

In [86]:

```
from keras.preprocessing.image import ImageDataGenerator

import os
import numpy as np
from keras.preprocessing.image import ImageDataGenerator
from keras import models
from keras import layers
from keras import optimizers

base_dir = 'RMB'

train_dir = os.path.join(base_dir, 'train')
validation_dir = os.path.join(base_dir, 'validation')
test_dir = os.path.join(base_dir, 'test')

train_datagen = ImageDataGenerator(
      rescale=1./255,
      rotation_range=40,
      width_shift_range=0.2,
      height_shift_range=0.2,
      shear_range=0.2,
      zoom_range=0.2,
      horizontal_flip=True,
      fill_mode='nearest')

# Note that the validation data should not be augmented!
test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
        # This is the target directory
        train_dir,
        # All images will be resized to 150x150
        target_size=(150, 300),
        batch_size=10,
        # Since we use binary_crossentropy loss, we need binary labels
        class_mode='binary')

validation_generator = test_datagen.flow_from_directory(
        validation_dir,
        target_size=(150, 300),
        batch_size=10,
        class_mode='binary')

model.compile(loss='binary_crossentropy',
              optimizer=optimizers.RMSprop(lr=2e-5),
              metrics=['acc'])

history = model.fit_generator(
      train_generator,
      steps_per_epoch=4,  # 40/10=4
      epochs=30,
      validation_data=validation_generator,
      validation_steps=2)  # 20/10=2
```

```
Found 40 images belonging to 2 classes.
Found 20 images belonging to 2 classes.
Epoch 1/30
4/4 [==============================] - 10s 3s/step - loss: 0.4983 - acc: 0.7250 - va
l_loss: 0.5309 - val_acc: 0.8500
```

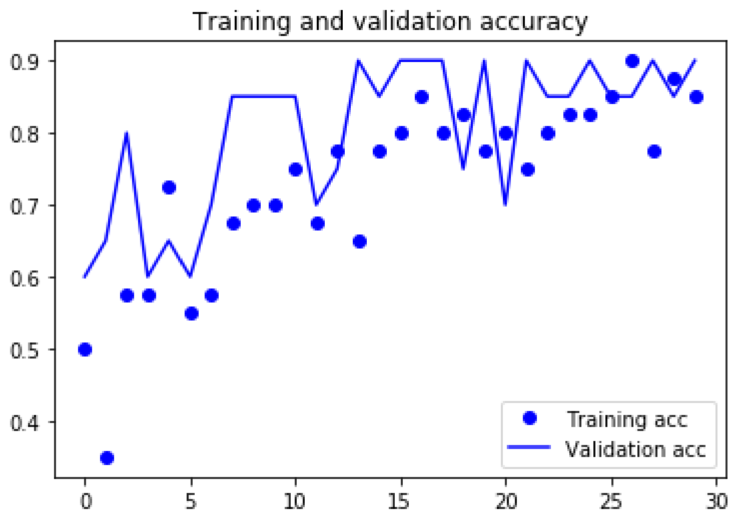
```
Epoch 2/30
4/4 [==============================] - 9s 2s/step - loss: 0.3863 - acc: 0.9500 - val
_loss: 0.4963 - val_acc: 0.8500
Epoch 3/30
4/4 [==============================] - 9s 2s/step - loss: 0.4130 - acc: 0.9000 - val
_loss: 0.3735 - val_acc: 0.8500
Epoch 4/30
4/4 [==============================] - 9s 2s/step - loss: 0.4684 - acc: 0.8000 - val
_loss: 0.4199 - val_acc: 0.8500
Epoch 5/30
4/4 [==============================] - 9s 2s/step - loss: 0.4285 - acc: 0.8250 - val
_loss: 0.3742 - val_acc: 0.8500
Epoch 6/30
4/4 [==============================] - 9s 2s/step - loss: 0.4281 - acc: 0.8000 - val
_loss: 0.4188 - val_acc: 0.8500
Epoch 7/30
4/4 [==============================] - 9s 2s/step - loss: 0.3745 - acc: 0.9500 - val
_loss: 0.3599 - val_acc: 0.8500
Epoch 8/30
4/4 [==============================] - 9s 2s/step - loss: 0.3713 - acc: 0.9250 - val
_loss: 0.4884 - val_acc: 0.8500
Epoch 9/30
4/4 [==============================] - 9s 2s/step - loss: 0.4812 - acc: 0.7500 - val
_loss: 0.3460 - val_acc: 0.8500
Epoch 10/30
4/4 [==============================] - 9s 2s/step - loss: 0.3836 - acc: 0.9250 - val
_loss: 0.5165 - val_acc: 0.8000
Epoch 11/30
4/4 [==============================] - 9s 2s/step - loss: 0.4876 - acc: 0.7500 - val
_loss: 0.4878 - val_acc: 0.9000
Epoch 12/30
4/4 [==============================] - 9s 2s/step - loss: 0.4094 - acc: 0.9250 - val
_loss: 0.5558 - val_acc: 0.9000
Epoch 13/30
4/4 [==============================] - 9s 2s/step - loss: 0.3929 - acc: 0.9250 - val
_loss: 0.3510 - val_acc: 0.8500
Epoch 14/30
4/4 [==============================] - 9s 2s/step - loss: 0.4267 - acc: 0.8000 - val
_loss: 0.3783 - val_acc: 0.8500
Epoch 15/30
4/4 [==============================] - 9s 2s/step - loss: 0.4903 - acc: 0.7250 - val
_loss: 0.4892 - val_acc: 0.8500
Epoch 16/30
4/4 [==============================] - 9s 2s/step - loss: 0.3959 - acc: 0.8750 - val
_loss: 0.5783 - val_acc: 0.8500
Epoch 17/30
4/4 [==============================] - 9s 2s/step - loss: 0.3667 - acc: 0.9250 - val
_loss: 0.2927 - val_acc: 0.8500
Epoch 18/30
4/4 [==============================] - 9s 2s/step - loss: 0.3357 - acc: 0.9250 - val
_loss: 0.3319 - val_acc: 0.8500
Epoch 19/30
4/4 [==============================] - 9s 2s/step - loss: 0.3802 - acc: 0.8750 - val
_loss: 0.3748 - val_acc: 0.9000
Epoch 20/30
4/4 [==============================] - 9s 2s/step - loss: 0.3698 - acc: 0.8500 - val
_loss: 0.3591 - val_acc: 0.8500
Epoch 21/30
4/4 [==============================] - 9s 2s/step - loss: 0.3461 - acc: 0.8500 - val
_loss: 0.5043 - val_acc: 0.8000
Epoch 22/30
```

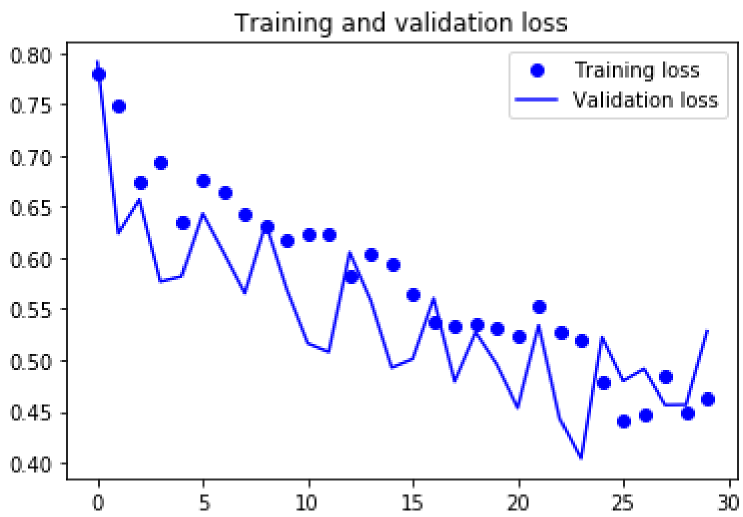
```
4/4 [==============================] - 10s 2s/step - loss: 0.3758 - acc: 0.8750 - va
l_loss: 0.3844 - val_acc: 0.8500
Epoch 23/30
4/4 [==============================] - 9s 2s/step - loss: 0.3390 - acc: 0.9000 - val
_loss: 0.4559 - val_acc: 0.9000
Epoch 24/30
4/4 [==============================] - 9s 2s/step - loss: 0.3153 - acc: 0.9000 - val
_loss: 0.4981 - val_acc: 0.8500
Epoch 25/30
4/4 [==============================] - 9s 2s/step - loss: 0.3246 - acc: 0.9500 - val
_loss: 0.3254 - val_acc: 0.8000
Epoch 26/30
4/4 [==============================] - 9s 2s/step - loss: 0.3695 - acc: 0.9250 - val
_loss: 0.4693 - val_acc: 0.9000
Epoch 27/30
4/4 [==============================] - 9s 2s/step - loss: 0.2785 - acc: 0.9500 - val
_loss: 0.3909 - val_acc: 0.7500
Epoch 28/30
4/4 [==============================] - 9s 2s/step - loss: 0.4136 - acc: 0.7750 - val
_loss: 0.3878 - val_acc: 0.8500
Epoch 29/30
4/4 [==============================] - 9s 2s/step - loss: 0.3193 - acc: 0.9500 - val
_loss: 0.4350 - val_acc: 0.7500
Epoch 30/30
4/4 [==============================] - 9s 2s/step - loss: 0.3147 - acc: 0.8750 - val
_loss: 0.5196 - val_acc: 0.8500
```

# 7.作图分析

In [73]:

```
import matplotlib.pyplot as plt
acc = history.history['acc']
val_acc = history.history['val_acc']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(len(acc))

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```




使用数据增强的模型过拟合情况要好一些，验证准确率接近90%

# 8.使用测试集测试模型

In [87]:

```
test_generator = test_datagen.flow_from_directory(
        test_dir,
        target_size=(150, 300),
        batch_size=10,
        class_mode='binary')

test_loss, test_acc = model.evaluate_generator(test_generator, steps=2)
print('test acc:', test_acc)
```

```
Found 20 images belonging to 2 classes.
test acc: 0.8999999761581421
```

# 9.使用模型预测图片

In [25]:

```
# 保存模型
# model.save('RMB_data_augmentation.h5')
```

In [55]:

```
# 导入保存的模型
from keras.models import load_model
# model = load_model('RMB_data_augmentation.h5')
```

In [75]:

```
# 读取图片
import matplotlib.pyplot as plt
import matplotlib.image as mpimg # mpimg 用于读取图片
test_img = mpimg.imread('test_50.jpg')
```

In [76]:

```
plt.imshow(test_img)
plt.show()
```

In [77]:

```
test_img.shape
```

Out[77]:

```
(221, 449, 3)
```

In [78]:

```
import cv2
test_img = cv2.resize(test_img, (300, 150))
plt.imshow(test_img)
plt.show()
test_img.shape
```


Out[78]:

```
(150, 300, 3)
```

In [79]:

```
test_img = test_img.reshape(1,150,300,3)
test_img.shape
```

Out[79]:

```
(1, 150, 300, 3)
```

In [80]:

```
model.predict(test_img)
```

Out[80]:

```
array([[0.9835865]], dtype=float32)
```

In [81]:

```
model.predict_classes(test_img)
```

Out[81]:

```
array([[1]])
```

In [82]:

```
test_img = mpimg.imread('test_20.jpg')
import cv2
test_img = cv2.resize(test_img,(300,150))
plt.imshow(test_img)
plt.show()
test_img.shape
```

Out[82]:

(150, 300, 3)

In [83]:

```
test_img = test_img.reshape(1,150,300,3)
test_img.shape
```

Out[83]:

(1, 150, 300, 3)

In [84]:

```
model.predict(test_img)
```

Out[84]:

array([[3.184825e-08]], dtype=float32)

In [85]:

```
model.predict_classes(test_img)
```

Out[85]:

array([[0]])

# 9.总结

使用数据增强的模型识别出了图像的类别

- 0 - 20元
- 1 - 50元

In [ ]:

```

```