In [1]:
```
import os
os.environ['KMP_DUPLICATE_LIB_OK']='True'
DATASETS_FOLDER = 'datasets'
if not os.path.isdir(DATASETS_FOLDER):
    os.mkdir(DATASETS_FOLDER)
    os.environ['FUEL_DATA_PATH']='./datasets/'
```

In [2]:
```
import numpy as np
np.random.seed(7100)  # for reproducibility

import warnings
warnings.filterwarnings('ignore',category=FutureWarning)
import tensorflow as tf

from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation, Flatte
from tensorflow.keras.layers import Conv2D, MaxPooling2D, MaxPooling3D
from tensorflow.keras.constraints import MaxNorm
from tensorflow.keras.optimizers import SGD
from tensorflow.keras import utils

from skimage.transform import resize
import matplotlib.pylab as plt
from lfw_fuel import lfw
```

Crop and downsample function

In [3]:
```
def crop_and_downsample(originalX, downsample_size=32):
    """
    Starts with a 250 x 250 image.
    Crops to 128 x 128 around the center.
    Downsamples the image to (downsample_size) x (downsample_size).
    Returns an image with dimensions (channel, width, height).
    """
    current_dim = 250
    target_dim = 128
    margin = int((current_dim - target_dim)/2)
    left_margin = margin
    right_margin = current_dim - margin

    # newim is shape (6, 128, 128)
    newim = originalX[:, left_margin:right_margin, left_margin:right_m

    # This transpose is mainly useful for plotting with color:
    # Put the images in standard dimension order
    # (width, height, channels)
    sized1 = newim[0:3,:,:]
    sized1 = np.transpose(sized1,(1,2,0))

    sized2 = newim[3:6,:,:]
    sized2 = np.transpose(sized2,(1,2,0))

    # resized are shape (feature_width, feature_height, 3)
    feature_width = feature_height = downsample_size
    resized1 = resize(sized1, (feature_width, feature_height), order=3
    resized2 = resize(sized2, (feature_width, feature_height), order=3

    # re-packge into a new X entry
    newX = np.concatenate([resized1,resized2], axis=2)

    return newX

a = 0
```

Load the data from LFW web

There are three dataset options: * Original * Funneling * Deep Funneling

We choose Deep Funneling dataset

In [4]:
```
# Load the data, shuffled and split between train and test sets
(X_train_original, y_train_original), (X_test_original, y_test_origina
```

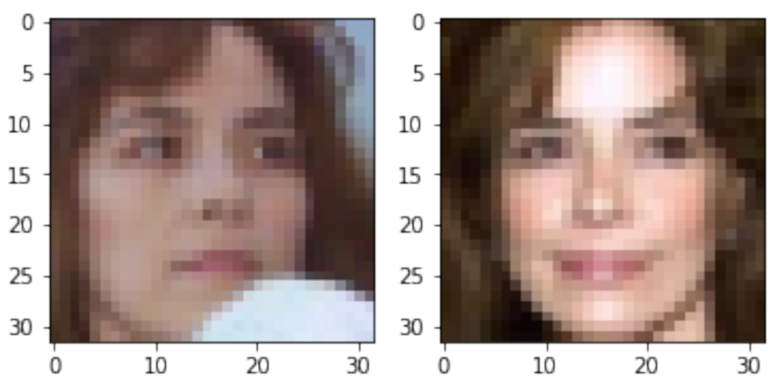
Transform raw pictures

In [5]:
```
# Start with 32*32 picture size
ds = 32
X_train = np.asarray([crop_and_downsample(x, downsample_size=ds) for x
X_test  = np.asarray([crop_and_downsample(x, downsample_size=ds) for x
y_train = y_train_original
y_test  = y_test_original
```

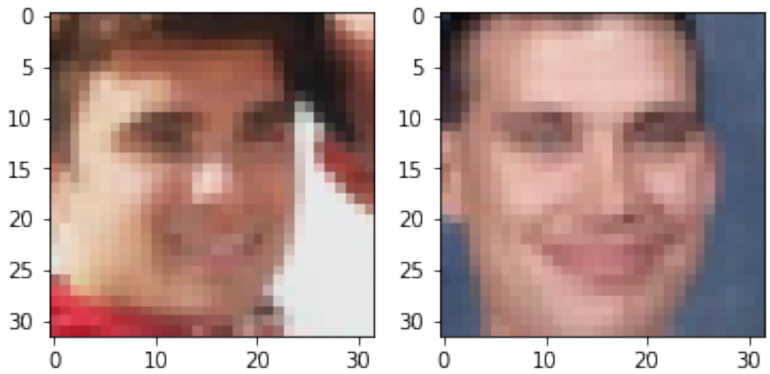
Check Individual Datapoint

Make sure we read the data in correctly

In [6]:
```
# datapoint 1
fig = plt.figure()
ax1, ax2 = [fig.add_subplot(1,2,i+1) for i in range(2)]
ax1.imshow(X_train[6,:,:,0:3])
ax2.imshow(X_train[6,:,:,3:6])
plt.show()
```



In [7]:
```
# datapoint 2
fig = plt.figure()
ax1, ax2 = [fig.add_subplot(1,2,i+1) for i in range(2)]
ax1.imshow(X_test[12,:,:,0:3])
ax2.imshow(X_test[12,:,:,3:6])
plt.show()
```



In [8]:
```
print(y_train.shape)
print("Zeros: %d"%(np.sum(y_train==0)))
print("Ones: %d"%(np.sum(y_train==1)))
```

```
(2200, 1)
Zeros: 1100
Ones: 1100
```

Build Baseline Model

- Input
- Conv1: 32 feature, 3*3 kernel size
- Conv2: 64 feature, 3*3 kernel size
- Pooling1: 2*2
- Dropout1: 0.2
- FullConnect
- Dropout2: 0.5
- Output

In [9]:

```
# Baseline Model

base_model = Sequential()

# Input and first convolutional layer
base_model.add(Conv2D(32, (3,3),
                 input_shape=(ds,ds,6),
                 padding='same',
                 data_format='channels_last',
                 activation='relu'))

# Second convolutional layer
base_model.add(Conv2D(64, (3,3),
                 padding='same',
                 data_format='channels_last',
                 activation='relu'))

# Pooling layer 1
base_model.add(AveragePooling2D(pool_size=(2,2),
                          data_format='channels_last'))

# Dropout after pooling 1
base_model.add(Dropout(0.2))

# Flatten layer.
base_model.add(Flatten())

# Fully connected layer
base_model.add(Dense(128, activation='relu',kernel_constraint=MaxNorm(

# Dropout set to 50%.
base_model.add(Dropout(0.5))

# Output layer with 2 units (Y/N) (sigmoid activation function)
base_model.add(Dense(1, activation='sigmoid'))

print(base_model.summary())
```

```
WARNING:tensorflow:From /Users/nosam/anaconda3/lib/python3.7/site-pac
kages/tensorflow/python/ops/init_ops.py:1251: calling VarianceScaling
.__init__ (from tensorflow.python.ops.init_ops) with dtype is depreca
ted and will be removed in a future version.
Instructions for updating:
Call initializer instance with the dtype argument instead of passing
it to the constructor
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 32, 32, 32)        1760
```

```
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 32, 32, 64)        18496     
_________________________________________________________________
average_pooling2d (AveragePo (None, 16, 16, 64)        0         
_________________________________________________________________
dropout (Dropout)            (None, 16, 16, 64)        0         
_________________________________________________________________
flatten (Flatten)            (None, 16384)             0         
_________________________________________________________________
dense (Dense)                (None, 128)               2097280   
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129       
=================================================================
Total params: 2,117,665
Trainable params: 2,117,665
Non-trainable params: 0
_________________________________________________________________
None
```

In [10]:
```
# Compile model:
base_model.compile(loss='binary_crossentropy', optimizer='adam', metri
```

```
WARNING:tensorflow:From /Users/nosam/anaconda3/lib/python3.7/site-pac
kages/tensorflow/python/ops/nn_impl.py:180: add_dispatch_support.<loc
als>.wrapper (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
```

In [11]:
```
epochs = 25
batch_size = 128

base_CNN = base_model.fit(X_train, y_train,
           batch_size=batch_size,
           epochs=epochs,
           verbose=1,
           validation_data=(X_test, y_test))
```

```
Train on 2200 samples, validate on 1000 samples
Epoch 1/25
2200/2200 [==============================] - 6s 3ms/sample - loss: 0.
7164 - binary_accuracy: 0.5086 - val_loss: 0.6863 - val_binary_accura
cy: 0.5720
Epoch 2/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
6756 - binary_accuracy: 0.5818 - val_loss: 0.6515 - val_binary_accura
cy: 0.6570
```

```
Epoch 3/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
6496 - binary_accuracy: 0.6305 - val_loss: 0.6285 - val_binary_accura
cy: 0.6490
Epoch 4/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
6296 - binary_accuracy: 0.6518 - val_loss: 0.6138 - val_binary_accura
cy: 0.6830
Epoch 5/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
6059 - binary_accuracy: 0.6936 - val_loss: 0.6004 - val_binary_accura
cy: 0.6900
Epoch 6/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
5991 - binary_accuracy: 0.6941 - val_loss: 0.5978 - val_binary_accura
cy: 0.6860
Epoch 7/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
5800 - binary_accuracy: 0.6927 - val_loss: 0.5992 - val_binary_accura
cy: 0.6770
Epoch 8/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
5685 - binary_accuracy: 0.7127 - val_loss: 0.5790 - val_binary_accura
cy: 0.6970
Epoch 9/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
5398 - binary_accuracy: 0.7305 - val_loss: 0.5830 - val_binary_accura
cy: 0.6990
Epoch 10/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
5203 - binary_accuracy: 0.7382 - val_loss: 0.6486 - val_binary_accura
cy: 0.6390
Epoch 11/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
5015 - binary_accuracy: 0.7564 - val_loss: 0.6016 - val_binary_accura
cy: 0.6860
Epoch 12/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
4928 - binary_accuracy: 0.7709 - val_loss: 0.5980 - val_binary_accura
cy: 0.6810
Epoch 13/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
4677 - binary_accuracy: 0.7686 - val_loss: 0.5944 - val_binary_accura
cy: 0.6800
Epoch 14/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
4293 - binary_accuracy: 0.7995 - val_loss: 0.6100 - val_binary_accura
cy: 0.6770
Epoch 15/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
```

```
4194 - binary_accuracy: 0.8100 - val_loss: 0.6117 - val_binary_accura
cy: 0.6840
Epoch 16/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
4029 - binary_accuracy: 0.8232 - val_loss: 0.5649 - val_binary_accura
cy: 0.7280
Epoch 17/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
3744 - binary_accuracy: 0.8395 - val_loss: 0.6114 - val_binary_accura
cy: 0.7030
Epoch 18/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
3535 - binary_accuracy: 0.8500 - val_loss: 0.5944 - val_binary_accura
cy: 0.7000
Epoch 19/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
3247 - binary_accuracy: 0.8700 - val_loss: 0.6088 - val_binary_accura
cy: 0.7030
Epoch 20/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
3127 - binary_accuracy: 0.8659 - val_loss: 0.6125 - val_binary_accura
cy: 0.7090
Epoch 21/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
2818 - binary_accuracy: 0.8914 - val_loss: 0.6370 - val_binary_accura
cy: 0.7080
Epoch 22/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
2673 - binary_accuracy: 0.8927 - val_loss: 0.6142 - val_binary_accura
cy: 0.7160
Epoch 23/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
2576 - binary_accuracy: 0.9023 - val_loss: 0.6491 - val_binary_accura
cy: 0.6860
Epoch 24/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
2556 - binary_accuracy: 0.9018 - val_loss: 0.7037 - val_binary_accura
cy: 0.6950
Epoch 25/25
2200/2200 [==============================] - 5s 2ms/sample - loss: 0.
2368 - binary_accuracy: 0.9077 - val_loss: 0.6610 - val_binary_accura
cy: 0.7030
```

In [12]:
```
res1 = base_model.predict(X_train)
res2 = base_model.predict(X_test)
```

In [13]:
```
print("Training Data:")
print("Zeros: %d"%(np.sum(res1<0.5)))
print("Ones: %d"%(np.sum(res1>0.5)))
print("\n")
print("Testing Data:")
print("Zeros: %d"%(np.sum(res2<0.5)))
print("Ones: %d"%(np.sum(res2>0.5)))
```

```
Training Data:
Zeros: 1116
Ones: 1084


Testing Data:
Zeros: 527
Ones: 473
```

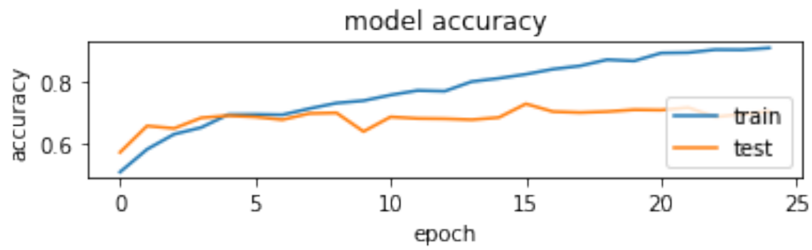
In [14]:
```
score = base_model.evaluate(X_test, y_test, verbose=0)
print('Baseline Test accuracy: {0:%}'.format(score[1]))
```

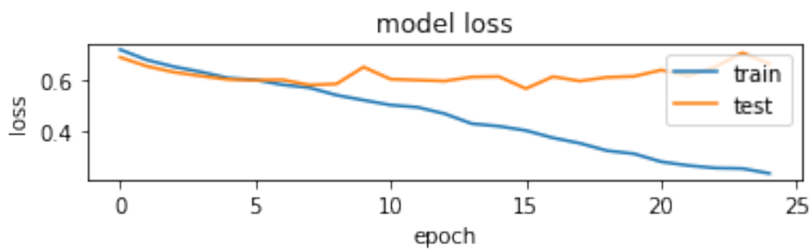
```
Baseline Test accuracy: 70.300001%
```

In [15]:
```
plt.subplot(3,1,1)
plt.plot(base_CNN.history['binary_accuracy'])
plt.plot(base_CNN.history['val_binary_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')

plt.subplot(3,1,3)
plt.plot(base_CNN.history['loss'])
plt.plot(base_CNN.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')

plt.show()
```





In [16]:

```
modelA = Sequential()

# Input and first convolutional layer
modelA.add(Conv2D(32, (5,5),
                  input_shape=(ds,ds,6),
                  padding='same',
                  data_format='channels_last',
                  activation='relu'))

# Second convolutional layer
modelA.add(Conv2D(64, (5,5),
                  padding='same',
                  data_format='channels_last',
                  activation='relu'))

# Pooling layer 1
modelA.add(AveragePooling2D(pool_size=(2,2),
                            data_format='channels_last'))

# Dropout after pooling 1
modelA.add(Dropout(0.2))

# Flatten layer.
modelA.add(Flatten())

# Fully connected layer
modelA.add(Dense(128, activation='relu',kernel_constraint=MaxNorm(3)))

# Dropout set to 50%.
modelA.add(Dropout(0.5))

# Output layer with 2 units (Y/N) (sigmoid activation function)
modelA.add(Dense(1, activation='sigmoid'))

print(modelA.summary())
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)           (None, 32, 32, 32)        4832
_________________________________________________________________
conv2d_3 (Conv2D)           (None, 32, 32, 64)        51264
_________________________________________________________________
average_pooling2d_1 (Average (None, 16, 16, 64)       0
_________________________________________________________________
dropout_2 (Dropout)         (None, 16, 16, 64)        0
_________________________________________________________________
flatten_1 (Flatten)         (None, 16384)             0
_________________________________________________________________
```

```
dense_2 (Dense)              (None, 128)               2097280
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
Total params: 2,153,505
Trainable params: 2,153,505
Non-trainable params: 0
_________________________________________________________________
None
```

In [17]:

```
# Compile model:
modelA.compile(loss='binary_crossentropy', optimizer='adam', metrics=[
```

In [18]:

```
epochs = 25
batch_size = 128

modelA_CNN = modelA.fit(X_train, y_train,
           batch_size=batch_size,
           epochs=epochs,
           verbose=1,
           validation_data=(X_test, y_test))
```

```
Train on 2200 samples, validate on 1000 samples
Epoch 1/25
2200/2200 [==============================] - 9s 4ms/sample - loss: 0.
7250 - binary_accuracy: 0.5159 - val_loss: 0.6944 - val_binary_accura
cy: 0.5000
Epoch 2/25
2200/2200 [==============================] - 8s 4ms/sample - loss: 0.
6946 - binary_accuracy: 0.5036 - val_loss: 0.6929 - val_binary_accura
cy: 0.5430
Epoch 3/25
2200/2200 [==============================] - 8s 4ms/sample - loss: 0.
6933 - binary_accuracy: 0.5050 - val_loss: 0.6907 - val_binary_accura
cy: 0.5030
Epoch 4/25
2200/2200 [==============================] - 8s 4ms/sample - loss: 0.
6866 - binary_accuracy: 0.5291 - val_loss: 0.6830 - val_binary_accura
cy: 0.5660
Epoch 5/25
2200/2200 [==============================] - 8s 4ms/sample - loss: 0.
6746 - binary_accuracy: 0.5768 - val_loss: 0.6719 - val_binary_accura
cy: 0.5820
Epoch 6/25
2200/2200 [==============================] - 8s 4ms/sample - loss: 0.
6715 - binary_accuracy: 0.5818 - val_loss: 0.6725 - val_binary_accura
cy: 0.5690
```

```
Epoch 7/25
2200/2200 [==============================] - 8s 4ms/sample - loss: 0.
6671 - binary_accuracy: 0.5768 - val_loss: 0.6654 - val_binary_accura
cy: 0.5800
Epoch 8/25
2200/2200 [==============================] - 8s 4ms/sample - loss: 0.
6495 - binary_accuracy: 0.6141 - val_loss: 0.6568 - val_binary_accura
cy: 0.6290
Epoch 9/25
2200/2200 [==============================] - 8s 4ms/sample - loss: 0.
6395 - binary_accuracy: 0.6336 - val_loss: 0.6280 - val_binary_accura
cy: 0.6350
Epoch 10/25
2200/2200 [==============================] - 8s 4ms/sample - loss: 0.
6274 - binary_accuracy: 0.6564 - val_loss: 0.5988 - val_binary_accura
cy: 0.6850
Epoch 11/25
2200/2200 [==============================] - 9s 4ms/sample - loss: 0.
6009 - binary_accuracy: 0.6868 - val_loss: 0.5995 - val_binary_accura
cy: 0.6800
Epoch 12/25
2200/2200 [==============================] - 9s 4ms/sample - loss: 0.
6032 - binary_accuracy: 0.6859 - val_loss: 0.6024 - val_binary_accura
cy: 0.6830
Epoch 13/25
2200/2200 [==============================] - 9s 4ms/sample - loss: 0.
5958 - binary_accuracy: 0.6900 - val_loss: 0.5877 - val_binary_accura
cy: 0.6910
Epoch 14/25
2200/2200 [==============================] - 9s 4ms/sample - loss: 0.
5535 - binary_accuracy: 0.7277 - val_loss: 0.5673 - val_binary_accura
cy: 0.7010
Epoch 15/25
2200/2200 [==============================] - 10s 4ms/sample - loss: 0
.5464 - binary_accuracy: 0.7305 - val_loss: 0.5782 - val_binary_accur
acy: 0.6960
Epoch 16/25
2200/2200 [==============================] - 11s 5ms/sample - loss: 0
.5135 - binary_accuracy: 0.7509 - val_loss: 0.5612 - val_binary_accur
acy: 0.7060
Epoch 17/25
2200/2200 [==============================] - 10s 5ms/sample - loss: 0
.5156 - binary_accuracy: 0.7459 - val_loss: 0.5770 - val_binary_accur
acy: 0.6930
Epoch 18/25
2200/2200 [==============================] - 10s 5ms/sample - loss: 0
.4984 - binary_accuracy: 0.7609 - val_loss: 0.5712 - val_binary_accur
acy: 0.7020
Epoch 19/25
2200/2200 [==============================] - 10s 5ms/sample - loss: 0
```

```
.4618 - binary_accuracy: 0.7805 - val_loss: 0.5690 - val_binary_accur
acy: 0.7040
Epoch 20/25
2200/2200 [==============================] - 10s 5ms/sample - loss: 0
.4449 - binary_accuracy: 0.7864 - val_loss: 0.5695 - val_binary_accur
acy: 0.7150
Epoch 21/25
2200/2200 [==============================] - 11s 5ms/sample - loss: 0
.4272 - binary_accuracy: 0.7986 - val_loss: 0.6437 - val_binary_accur
acy: 0.6720
Epoch 22/25
2200/2200 [==============================] - 10s 5ms/sample - loss: 0
.4170 - binary_accuracy: 0.8095 - val_loss: 0.6158 - val_binary_accur
acy: 0.6860
Epoch 23/25
2200/2200 [==============================] - 11s 5ms/sample - loss: 0
.4038 - binary_accuracy: 0.8150 - val_loss: 0.6130 - val_binary_accur
acy: 0.6950
Epoch 24/25
2200/2200 [==============================] - 11s 5ms/sample - loss: 0
.3704 - binary_accuracy: 0.8305 - val_loss: 0.6330 - val_binary_accur
acy: 0.6820
Epoch 25/25
2200/2200 [==============================] - 10s 5ms/sample - loss: 0
.3385 - binary_accuracy: 0.8473 - val_loss: 0.6474 - val_binary_accur
acy: 0.7000
```

In [19]:

```
res1 = modelA.predict(X_train)
res2 = modelA.predict(X_test)
```

In [20]:

```
print("Training Data:")
print("Zeros: %d"%(np.sum(res1<0.5)))
print("Ones: %d"%(np.sum(res1>0.5)))
print("\n")
print("Testing Data:")
print("Zeros: %d"%(np.sum(res2<0.5)))
print("Ones: %d"%(np.sum(res2>0.5)))
```

```
Training Data:
Zeros: 1095
Ones: 1105


Testing Data:
Zeros: 534
Ones: 466
```

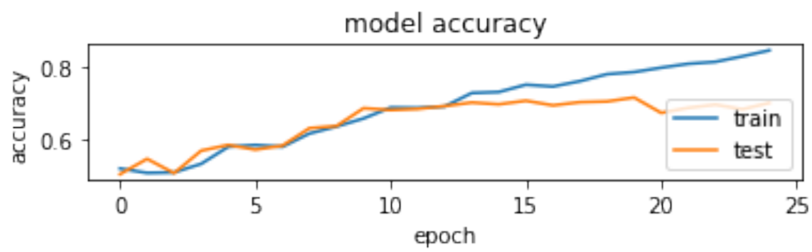
In [21]:
```
score = modelA.evaluate(X_test, y_test, verbose=0)
print('modelA Test accuracy: {0:%}'.format(score[1]))
```

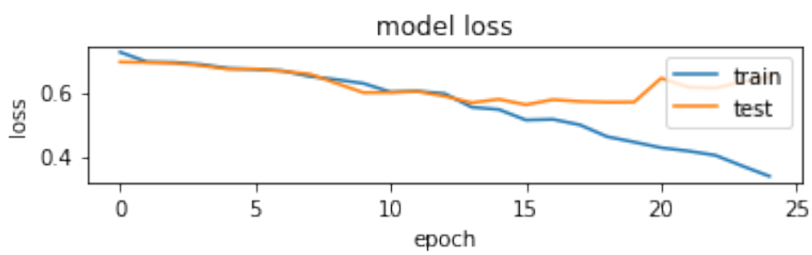
```
modelA Test accuracy: 69.999999%
```

In [22]:
```
plt.subplot(3,1,1)
plt.plot(modelA_CNN.history['binary_accuracy'])
plt.plot(modelA_CNN.history['val_binary_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')

plt.subplot(3,1,3)
plt.plot(modelA_CNN.history['loss'])
plt.plot(modelA_CNN.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')

plt.show()
```





In [23]:

```
modelB = Sequential()

# Input and first convolutional layer
modelB.add(Conv2D(32, (7,7),
                  input_shape=(ds,ds,6),
                  padding='same',
                  data_format='channels_last',
                  activation='relu'))

# Second convolutional layer
modelB.add(Conv2D(64, (7,7),
                  padding='same',
                  data_format='channels_last',
                  activation='relu'))

# Pooling layer 1
modelB.add(AveragePooling2D(pool_size=(2,2),
                            data_format='channels_last'))

# Dropout after pooling 1
modelB.add(Dropout(0.2))

# Flatten layer.
modelB.add(Flatten())

# Fully connected layer
modelB.add(Dense(128, activation='relu',kernel_constraint=MaxNorm(3)))

# Dropout set to 50%.
modelB.add(Dropout(0.5))

# Output layer with 2 units (Y/N) (sigmoid activation function)
modelB.add(Dense(1, activation='sigmoid'))

print(modelB.summary())
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (Conv2D)            (None, 32, 32, 32)        9440
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 32, 32, 64)        100416
_________________________________________________________________
average_pooling2d_2 (Average (None, 16, 16, 64)        0
_________________________________________________________________
dropout_4 (Dropout)          (None, 16, 16, 64)        0
_________________________________________________________________
flatten_2 (Flatten)          (None, 16384)             0
_________________________________________________________________
```

```
dense_4 (Dense)              (None, 128)               2097280
_________________________________________________________________
dropout_5 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 129
=================================================================
Total params: 2,207,265
Trainable params: 2,207,265
Non-trainable params: 0
_________________________________________________________________
None
```

In [24]:

```
# Compile model:
modelB.compile(loss='binary_crossentropy', optimizer='adam', metrics=[
```

In [25]:

```
epochs = 25
batch_size = 128

modelB_CNN = modelB.fit(X_train, y_train,
           batch_size=batch_size,
           epochs=epochs,
           verbose=1,
           validation_data=(X_test, y_test))
```

```
Train on 2200 samples, validate on 1000 samples
Epoch 1/25
2200/2200 [==============================] - 15s 7ms/sample - loss: 0
.7179 - binary_accuracy: 0.4950 - val_loss: 0.6895 - val_binary_accur
acy: 0.5620
Epoch 2/25
2200/2200 [==============================] - 14s 6ms/sample - loss: 0
.6823 - binary_accuracy: 0.5505 - val_loss: 0.6764 - val_binary_accur
acy: 0.5580
Epoch 3/25
2200/2200 [==============================] - 14s 6ms/sample - loss: 0
.6852 - binary_accuracy: 0.5482 - val_loss: 0.7093 - val_binary_accur
acy: 0.5360
Epoch 4/25
2200/2200 [==============================] - 14s 6ms/sample - loss: 0
.6724 - binary_accuracy: 0.5895 - val_loss: 0.6439 - val_binary_accur
acy: 0.6620
Epoch 5/25
2200/2200 [==============================] - 14s 6ms/sample - loss: 0
.6588 - binary_accuracy: 0.6245 - val_loss: 0.6374 - val_binary_accur
acy: 0.6670
Epoch 6/25
2200/2200 [==============================] - 14s 6ms/sample - loss: 0
.6492 - binary_accuracy: 0.6259 - val_loss: 0.6187 - val_binary_accur
acy: 0.6490
```

```
Epoch 7/25
2200/2200 [==============================] - 15s 7ms/sample - loss: 0
.6272 - binary_accuracy: 0.6559 - val_loss: 0.6094 - val_binary_accur
acy: 0.6790
Epoch 8/25
2200/2200 [==============================] - 16s 7ms/sample - loss: 0
.6240 - binary_accuracy: 0.6586 - val_loss: 0.6066 - val_binary_accur
acy: 0.6800
Epoch 9/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.6242 - binary_accuracy: 0.6505 - val_loss: 0.6441 - val_binary_accur
acy: 0.6120
Epoch 10/25
2200/2200 [==============================] - 19s 8ms/sample - loss: 0
.5980 - binary_accuracy: 0.6855 - val_loss: 0.5825 - val_binary_accur
acy: 0.7050
Epoch 11/25
2200/2200 [==============================] - 20s 9ms/sample - loss: 0
.5864 - binary_accuracy: 0.6950 - val_loss: 0.5843 - val_binary_accur
acy: 0.7140
Epoch 12/25
2200/2200 [==============================] - 19s 9ms/sample - loss: 0
.5659 - binary_accuracy: 0.7141 - val_loss: 0.6659 - val_binary_accur
acy: 0.6380
Epoch 13/25
2200/2200 [==============================] - 20s 9ms/sample - loss: 0
.5691 - binary_accuracy: 0.7095 - val_loss: 0.5713 - val_binary_accur
acy: 0.6970
Epoch 14/25
2200/2200 [==============================] - 19s 8ms/sample - loss: 0
.5441 - binary_accuracy: 0.7245 - val_loss: 0.5677 - val_binary_accur
acy: 0.7150
Epoch 15/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0
.5206 - binary_accuracy: 0.7514 - val_loss: 0.6433 - val_binary_accur
acy: 0.6540
Epoch 16/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.5147 - binary_accuracy: 0.7509 - val_loss: 0.5686 - val_binary_accur
acy: 0.7200
Epoch 17/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.4686 - binary_accuracy: 0.7723 - val_loss: 0.5632 - val_binary_accur
acy: 0.7090
Epoch 18/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.4446 - binary_accuracy: 0.7941 - val_loss: 0.5719 - val_binary_accur
acy: 0.7130
Epoch 19/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
```

```
.4140 - binary_accuracy: 0.8086 - val_loss: 0.5621 - val_binary_accur
acy: 0.7220
Epoch 20/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0
.4133 - binary_accuracy: 0.8182 - val_loss: 0.5941 - val_binary_accur
acy: 0.7090
Epoch 21/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0
.3986 - binary_accuracy: 0.8227 - val_loss: 0.5830 - val_binary_accur
acy: 0.7300
Epoch 22/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0
.3567 - binary_accuracy: 0.8414 - val_loss: 0.6037 - val_binary_accur
acy: 0.7130
Epoch 23/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0
.3099 - binary_accuracy: 0.8705 - val_loss: 0.6107 - val_binary_accur
acy: 0.7160
Epoch 24/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0
.2754 - binary_accuracy: 0.8832 - val_loss: 0.6547 - val_binary_accur
acy: 0.7060
Epoch 25/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0
.2590 - binary_accuracy: 0.8918 - val_loss: 0.6686 - val_binary_accur
acy: 0.7040
```

In [26]:

```
res1 = modelB.predict(X_train)
res2 = modelB.predict(X_test)
```

In [27]:

```
print("Training Data:")
print("Zeros: %d"%(np.sum(res1<0.5)))
print("Ones: %d"%(np.sum(res1>0.5)))
print("\n")
print("Testing Data:")
print("Zeros: %d"%(np.sum(res2<0.5)))
print("Ones: %d"%(np.sum(res2>0.5)))
```

```
Training Data:
Zeros: 1167
Ones: 1033


Testing Data:
Zeros: 598
Ones: 402
```

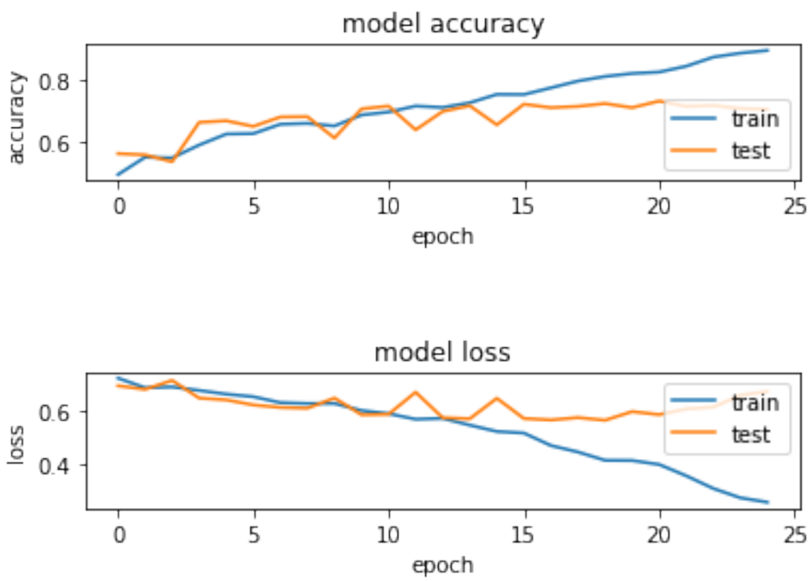
In [28]:
```
score = modelB.evaluate(X_test, y_test, verbose=0)
print('modelB Test accuracy: {0:%}'.format(score[1]))
```

```
modelB Test accuracy: 70.400000%
```

In [29]:
```
plt.subplot(3,1,1)
plt.plot(modelB_CNN.history['binary_accuracy'])
plt.plot(modelB_CNN.history['val_binary_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')

plt.subplot(3,1,3)
plt.plot(modelB_CNN.history['loss'])
plt.plot(modelB_CNN.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')

plt.show()
```



Build More Complex Model

Compare baseline, modelA and modelB, we find that overall modelA is the best model(less underfitting). So we build more complex model on top of modelA

Model C:

- Input
- Conv1: 32 feature, 5*5 kernel size
- Conv2: 64 feature, 5*5 kernel size
- Pooling1: 2*2
- Dropout1: 0.2
- Conv3: 128 feature, 5*5 kernel size
- Pooling2: 2*2
- Dropout2: 0.2
- FullConnect
- Dropout3: 0.5
- Output

In [30]:
```
# modelC

modelC = Sequential()

# Input and first convolutional layer
modelC.add(Conv2D(32, (5,5),
                  input_shape=(ds,ds,6),
                  padding='same',
                  data_format='channels_last',
                  activation='relu'))

# Second convolutional layer
modelC.add(Conv2D(64, (5,5),
                  padding='same',
                  data_format='channels_last',
                  activation='relu'))

# Pooling layer 1
modelC.add(AveragePooling2D(pool_size=(2,2),
                            data_format='channels_last'))

# Dropout after pooling 1
modelC.add(Dropout(0.2))

# Third convolutional layer
modelC.add(Conv2D(128, (5,5),
                  padding='same'
```

```
                   padding='same',
                   data_format='channels_last',
                   activation='relu'))

# Pooling layer 2
modelC.add(AveragePooling2D(pool_size=(2,2),
                            data_format='channels_last'))

# Dropout after pooling 2
modelC.add(Dropout(0.2))

# Flatten layer.
modelC.add(Flatten())

# Fully connected layer
modelC.add(Dense(128, activation='relu',kernel_constraint=MaxNorm(3)))

# Dropout set to 50%.
modelC.add(Dropout(0.5))

# Output layer with 2 units (Y/N) (sigmoid activation function)
modelC.add(Dense(1, activation='sigmoid'))

print(modelC.summary())
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
conv2d_6 (Conv2D)           (None, 32, 32, 32)        4832
_________________________________________________________________
conv2d_7 (Conv2D)           (None, 32, 32, 64)        51264
_________________________________________________________________
average_pooling2d_3 (Average (None, 16, 16, 64)       0
_________________________________________________________________
dropout_6 (Dropout)         (None, 16, 16, 64)        0
_________________________________________________________________
conv2d_8 (Conv2D)           (None, 16, 16, 128)       204928
_________________________________________________________________
average_pooling2d_4 (Average (None, 8, 8, 128)        0
_________________________________________________________________
dropout_7 (Dropout)         (None, 8, 8, 128)         0
_________________________________________________________________
flatten_3 (Flatten)         (None, 8192)              0
_________________________________________________________________
dense_6 (Dense)             (None, 128)               1048704
_________________________________________________________________
dropout_8 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_7 (Dense)             (None, 1)                 129
=================================================================
```

```
Total params: 1,309,857
Trainable params: 1,309,857
Non-trainable params: 0
_________________________________________________________________
None
```

In [31]:
```
# Compile model:
modelC.compile(loss='binary_crossentropy', optimizer='adam', metrics=[
```

In [32]:
```
epochs = 25
batch_size = 128

modelC_CNN = modelC.fit(X_train, y_train,
           batch_size=batch_size,
           epochs=epochs,
           verbose=1,
           validation_data=(X_test, y_test))
```

```
Train on 2200 samples, validate on 1000 samples
Epoch 1/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.6990 - binary_accuracy: 0.4818 - val_loss: 0.6931 - val_binary_accur
acy: 0.5000
Epoch 2/25
2200/2200 [==============================] - 16s 7ms/sample - loss: 0
.6932 - binary_accuracy: 0.4977 - val_loss: 0.6928 - val_binary_accur
acy: 0.5060
Epoch 3/25
2200/2200 [==============================] - 15s 7ms/sample - loss: 0
.6894 - binary_accuracy: 0.5350 - val_loss: 0.6872 - val_binary_accur
acy: 0.5400
Epoch 4/25
2200/2200 [==============================] - 15s 7ms/sample - loss: 0
.6878 - binary_accuracy: 0.5500 - val_loss: 0.6687 - val_binary_accur
acy: 0.6230
Epoch 5/25
2200/2200 [==============================] - 15s 7ms/sample - loss: 0
.6643 - binary_accuracy: 0.5941 - val_loss: 0.6386 - val_binary_accur
acy: 0.6390
Epoch 6/25
2200/2200 [==============================] - 15s 7ms/sample - loss: 0
.6488 - binary_accuracy: 0.6336 - val_loss: 0.6237 - val_binary_accur
acy: 0.6560
Epoch 7/25
2200/2200 [==============================] - 16s 7ms/sample - loss: 0
.6421 - binary_accuracy: 0.6295 - val_loss: 0.6169 - val_binary_accur
acy: 0.6860
Epoch 8/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0
```

```
.6435 - binary_accuracy: 0.6309 - val_loss: 0.6115 - val_binary_accur
acy: 0.6800
Epoch 9/25
2200/2200 [==============================] - 21s 9ms/sample - loss: 0
.6139 - binary_accuracy: 0.6573 - val_loss: 0.6155 - val_binary_accur
acy: 0.6670
Epoch 10/25
2200/2200 [==============================] - 23s 11ms/sample - loss:
0.5989 - binary_accuracy: 0.6845 - val_loss: 0.5847 - val_binary_accu
racy: 0.6890
Epoch 11/25
2200/2200 [==============================] - 24s 11ms/sample - loss:
0.5859 - binary_accuracy: 0.6945 - val_loss: 0.5723 - val_binary_accu
racy: 0.7070
Epoch 12/25
2200/2200 [==============================] - 21s 9ms/sample - loss: 0
.5847 - binary_accuracy: 0.6918 - val_loss: 0.5877 - val_binary_accur
acy: 0.6990
Epoch 13/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0
.5602 - binary_accuracy: 0.7173 - val_loss: 0.5627 - val_binary_accur
acy: 0.7180
Epoch 14/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.5605 - binary_accuracy: 0.7159 - val_loss: 0.5628 - val_binary_accur
acy: 0.7030
Epoch 15/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.5309 - binary_accuracy: 0.7286 - val_loss: 0.5547 - val_binary_accur
acy: 0.7210
Epoch 16/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.5244 - binary_accuracy: 0.7286 - val_loss: 0.5815 - val_binary_accur
acy: 0.7010
Epoch 17/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.5037 - binary_accuracy: 0.7523 - val_loss: 0.6131 - val_binary_accur
acy: 0.6810
Epoch 18/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.4909 - binary_accuracy: 0.7564 - val_loss: 0.5689 - val_binary_accur
acy: 0.7130
Epoch 19/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.4914 - binary_accuracy: 0.7605 - val_loss: 0.5551 - val_binary_accur
acy: 0.7170
Epoch 20/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0
.4599 - binary_accuracy: 0.7795 - val_loss: 0.6063 - val_binary_accur
acy: 0.7020
```

```
Epoch 21/25
2200/2200 [==============================] - 22s 10ms/sample - loss: 0.4515 - binary_accuracy: 0.7882 - val_loss: 0.6424 - val_binary_accuracy: 0.6810
Epoch 22/25
2200/2200 [==============================] - 19s 9ms/sample - loss: 0.4518 - binary_accuracy: 0.7918 - val_loss: 0.6162 - val_binary_accuracy: 0.7240
Epoch 23/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0.4136 - binary_accuracy: 0.8041 - val_loss: 0.6017 - val_binary_accuracy: 0.7150
Epoch 24/25
2200/2200 [==============================] - 18s 8ms/sample - loss: 0.3993 - binary_accuracy: 0.8150 - val_loss: 0.6171 - val_binary_accuracy: 0.7080
Epoch 25/25
2200/2200 [==============================] - 17s 8ms/sample - loss: 0.4171 - binary_accuracy: 0.8023 - val_loss: 0.6260 - val_binary_accuracy: 0.7000
```

In [33]:

```
res1 = modelC.predict(X_train)
res2 = modelC.predict(X_test)
```

In [34]:

```
print("Training Data:")
print("Zeros: %d"%(np.sum(res1<0.5)))
print("Ones: %d"%(np.sum(res1>0.5)))
print("\n")
print("Testing Data:")
print("Zeros: %d"%(np.sum(res2<0.5)))
print("Ones: %d"%(np.sum(res2>0.5)))
```

```
Training Data:
Zeros: 1235
Ones: 965


Testing Data:
Zeros: 584
Ones: 416
```

In [35]:

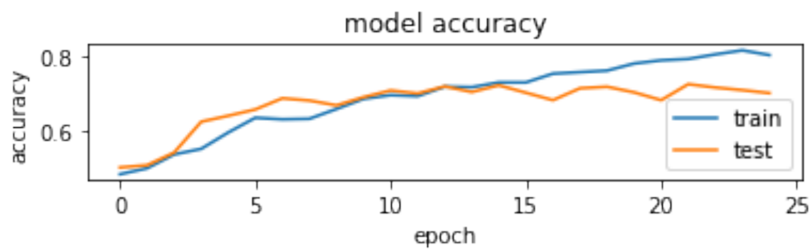
```
score = modelC.evaluate(X_test, y_test, verbose=0)
print('modelC Test accuracy: {0:%}'.format(score[1]))
```

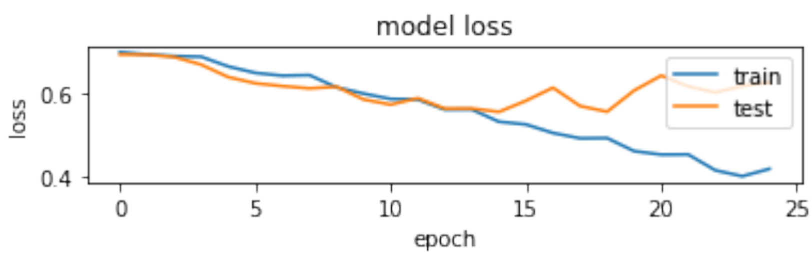
```
modelC Test accuracy: 69.999999%
```

In [36]:
```
plt.subplot(3,1,1)
plt.plot(modelC_CNN.history['binary_accuracy'])
plt.plot(modelC_CNN.history['val_binary_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='lower right')

plt.subplot(3,1,3)
plt.plot(modelC_CNN.history['loss'])
plt.plot(modelC_CNN.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper right')

plt.show()
```





Final Best Model

We experiment batch_size value: 32, 64, 128, 256 And we find, batch_size=128 is the best So we use callback function to find the best model on top of modelC

In [37]:
```
from tensorflow.keras.callbacks import ModelCheckpoint
# Define a checkpoint to save the data
checkpoint_name = 'weights.best.hdf5'
checkpoint = ModelCheckpoint(checkpoint_name, monitor='val_binary_accu
callbacks_list = [checkpoint]
```

In [38]:
```
# Train the model
final_CNN = modelC.fit(X_train, y_train,
           batch_size=128,
           epochs=100,
           verbose=1,
           validation_data=(X_test, y_test),
           callbacks=callbacks_list)
```

```
Train on 2200 samples, validate on 1000 samples
Epoch 1/100
2176/2200 [============================>.] - ETA: 0s - loss: 0.3833 -
binary_accuracy: 0.8258
Epoch 00001: val_binary_accuracy improved from -inf to 0.69400, savin
g model to weights.best.hdf5
2200/2200 [==============================] - 15s 7ms/sample - loss: 0
.3838 - binary_accuracy: 0.8250 - val_loss: 0.6055 - val_binary_accur
acy: 0.6940
Epoch 2/100
2176/2200 [============================>.] - ETA: 0s - loss: 0.3529 -
binary_accuracy: 0.8415
Epoch 00002: val_binary_accuracy improved from 0.69400 to 0.71200, sa
ving model to weights.best.hdf5
2200/2200 [==============================] - 15s 7ms/sample - loss: 0
.3522 - binary_accuracy: 0.8418 - val_loss: 0.6078 - val_binary_accur
acy: 0.7120
Epoch 3/100
2176/2200 [============================>.] - ETA: 0s - loss: 0.3178 -
binary_accuracy: 0.8566
```

In [39]:
```
# Load wights file of the best model :
wights_file = 'weights.best.hdf5'
best_CNN = modelC.load_weights(wights_file) # load it
modelC.compile(loss='binary_crossentropy', optimizer='adam', metrics=[
```

In [40]:
```
score = modelC.evaluate(X_test, y_test, verbose=0)
print('Best CNN Model Test accuracy: {0:%}'.format(score[1]))
```

```
Best CNN Model Test accuracy: 72.799999%
```

In [41]:
```
# Make predictions
predictions = modelC.predict(X_test)
```

In [42]:
```
predictions
```

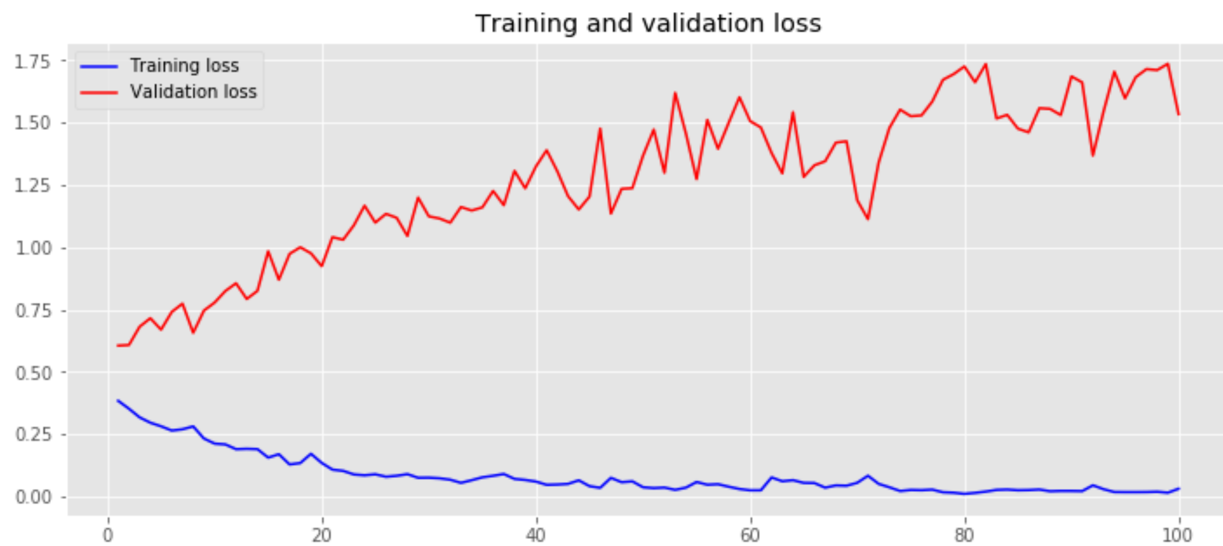
Out[42]:
```
array([[3.36706936e-01],
       [6.15119934e-05],
       [9.56135035e-01],
       [2.48032808e-03],
       [1.13038272e-01],
       [9.98085678e-01],
       [3.25866759e-01],
       [9.54843640e-01],
       [1.00000000e+00],
       [8.95335317e-01],
       [3.47958922e-01],
       [2.16363668e-02],
       [1.44955635e-01],
       [9.99999881e-01],
       [2.69778967e-02],
       [7.69262195e-01],
       [9.07015562e-01],
       [9.99962389e-01],
       [5.96199572e-01],
       [9.99930978e-01],
```

In [43]:
```
plt.style.use('ggplot')

def plot_history(history):
    loss = history.history['loss']
    val_loss = history.history['val_loss']
    x = range(1, len(loss) + 1)

    plt.figure(figsize=(12, 5))
    plt.plot(x, loss, 'b', label='Training loss')
    plt.plot(x, val_loss, 'r', label='Validation loss')
    plt.title('Training and validation loss')
    plt.legend()
    plt.show()


plot_history(final_CNN)
```



End