In [1]:
```
cd C:\Users\harsha.teja\Desktop\myg\ADVANCED DEEP\Main Project
```

```
C:\Users\harsha.teja\Desktop\myg\ADVANCED DEEP\Main Project
```

Perform Facial Recognition with Deep Learning in Keras Using CNN by Harsha Teja Bolla

Project 2

DESCRIPTION

Facial recognition is a biometric alternative that measures unique characteristics of a human face. Applications available today include flight check in, tagging friends and family members in photos, and “tailored” advertising. You are a computer vision engineer who needs to develop a face recognition programme with deep convolutional neural networks. Objective: Use a deep convolutional neural network to perform facial recognition using Keras. Dataset Details: ORL face database composed of 400 images of size 112 x 92. There are 40 people, 10 images per person. The images were taken at different times, lighting and facial expressions. The faces are in an upright position in frontal view, with a slight left-right rotation. Link to the Dataset: https://www.dropbox.com/s/i7uzp5yxk7wruva/ORL_faces.npz?dl=0 Prerequisites: Keras Scikit Learn Steps to be followed:

1. Input the required libraries
2. Load the dataset after loading the dataset, you have to normalize every image.
3. Split the dataset
4. Transform the images to equal sizes to feed in CNN
5. Build a CNN model that has 3 main layers:

i. Convolutional Layer ii. Pooling Layer iii. Fully Connected Layer

1. Train the model
2. Plot the result
3. Iterate the model until the accuracy is above 90%

In [2]:
```
# importing the libraries
from __future__ import division, print_function
import numpy as np
import argparse
import pandas as pd
import cv2
from tensorflow.keras.applications import imagenet_utils
from tensorflow.keras.applications.inception_v3 import preprocess_input
from tensorflow.keras.preprocessing.image import img_to_array
from tensorflow.keras.preprocessing.image import load_img
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow import keras
import cv2
from glob import glob
import os
from warnings import filterwarnings
filterwarnings('ignore')
```

```
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,LeakyReLU,PReLU,ELU,Dropout,Activation,Max
from tensorflow.keras.layers import InputLayer,Dense,Dropout
from tensorflow.keras import layers
from tensorflow.keras.optimizers import Adam,RMSprop,SGD,Adagrad
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from sklearn.utils import shuffle
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.layers import Input,InputLayer,Dense,Dropout
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import layers
from tensorflow.keras.optimizers import Adam,RMSprop,SGD,Adagrad
from sklearn.preprocessing import LabelBinarizer
from sklearn.model_selection import train_test_split
```

```
C:\Users\harsha.teja\Anaconda3\envs\deeplearning\lib\site-packages\numpy\_distributo
r_init.py:32: UserWarning: loaded more than 1 DLL from .libs:
C:\Users\harsha.teja\Anaconda3\envs\deeplearning\lib\site-packages\numpy\.libs\libop
enblas.NOIJJG62EMASZI6NYURL6JBKM4EVBGM7.gfortran-win_amd64.dll
C:\Users\harsha.teja\Anaconda3\envs\deeplearning\lib\site-packages\numpy\.libs\libop
enblas.PYQHXLVVQ7VESDPUVUADXEVJOBGHJPAY.gfortran-win_amd64.dll
  stacklevel=1)
```

import numpy as np import torch import torchvision import matplotlib.pyplot as plt from time import time from torchvision import datasets, transforms from torch import nn, optim

version of pytorch

print(torch.**version**)

In [3]:

```
import numpy as np
data = np.load('ORL_faces.npz')
```

import numpy as np

data = np.load('ORL_faces.npz', allow_pickle=True) lst = data.files

for item in lst: print(item) print(data[item])

In [4]:

```
data.files
```

Out[4]:

```
['testY', 'testX', 'trainX', 'trainY']
```

In [5]:

```
X_train= data['trainX']
X_test  = data['testX']
y_train = data['trainY']
y_test = data['testY']
```

In [6]:

```
X_train= np.array(X_train,dtype="float32")
y_train=np.array(y_train)
X_test= np.array(X_test,dtype="float32")
y_test=np.array(y_test)
```

In [7]:

```
X_train= X_train/255
X_test  = X_test/255
```

In [8]:
```
print(X_train.shape)
y_train.shape
```

```
(240, 10304)
```

Out[8]:
```
(240,)
```

In [ ]:

X_train= tf.reshape(X_train, [-1, img_shape[0], img_shape[1], channels]) X_test = tf.reshape(X_test, [-1, img_shape[0], img_shape[1], channels])

In [9]:
```
X_train.shape
```

Out[9]:
```
(240, 10304)
```

In [10]:
```
print("unique target number:",np.unique(data['trainY']))
```

```
unique target number: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19]
```

y_train = tf.keras.utils.to_categorical(y_train, num_classes=20, dtype='float32') y_test = tf.keras.utils.to_categorical(y_test, num_classes=20, dtype='float32')

In [ ]:

In [11]:
```
X_train_img=np.reshape(X_train,(X_train.shape[0],112,-1))
print ("Reshaped Image of X_Train_img is: ", X_train_img.shape, "\n")
#plt.imshow(x_train[30]
```

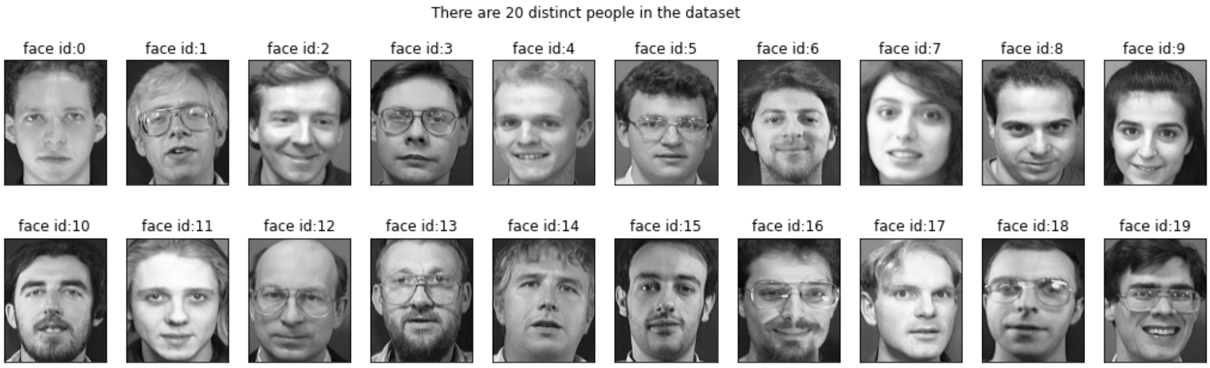
```
Reshaped Image of X_Train_img is:  (240, 112, 92)
```

In [12]:
```
X_test_img=np.reshape(X_test,(X_test.shape[0],112,92))
print ("Reshaped Image of X_Test_img is: ", X_test_img.shape, "\n")
```

```
Reshaped Image of X_Test_img is:  (160, 112, 92)
```

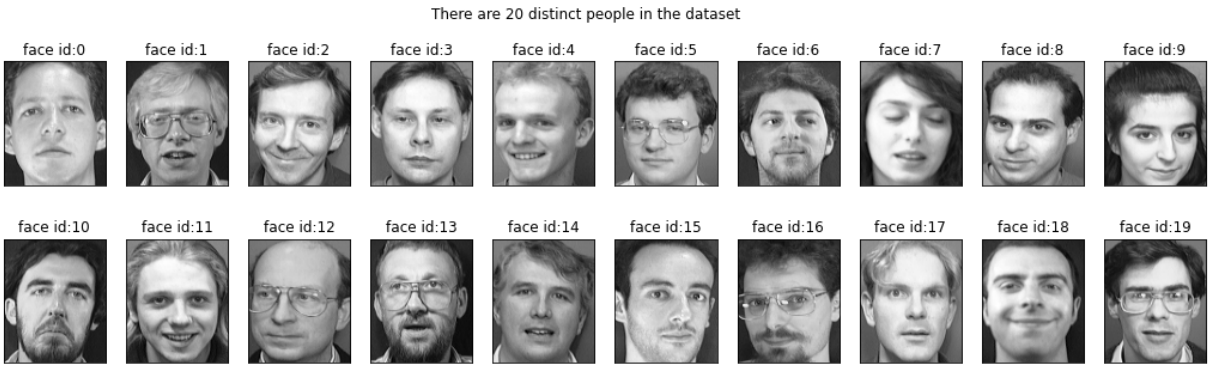
In [ ]:

In [13]:
```
def show_20_distinct_people(images, unique_ids):
  #Creating 2*10 subplots in  18x5 figure size
  fig, axarr=plt.subplots(nrows=2, ncols=10, figsize=(18, 5))

  #For easy iteration flattened 2X10 subplots matrix to 20 array
  axarr=axarr.flatten()

  #iterating over user ids
  for unique_id in unique_ids:
    image_index=unique_id*12
    axarr[unique_id].imshow(images[image_index], cmap='gray')
    axarr[unique_id].set_xticks([])
    axarr[unique_id].set_yticks([])
    axarr[unique_id].set_title("face id:{}".format(unique_id))
    plt.suptitle("There are 20 distinct people in the dataset")

show_20_distinct_people(X_train_img, np.unique(data['trainY']))
```



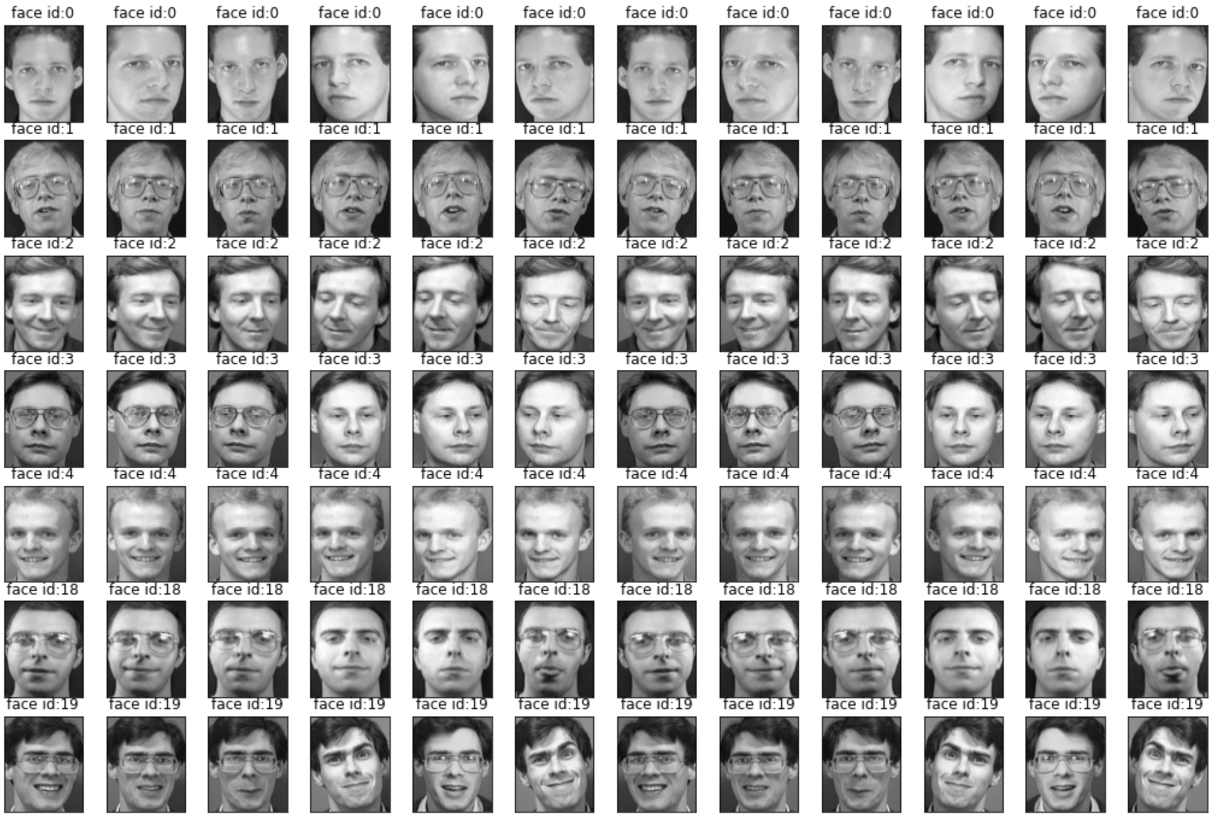
In [14]:

```
def show_16_distinct_people(images, unique_ids):
  #Creating 2*10 subplots in  18x5 figure size
  fig, axarr=plt.subplots(nrows=2, ncols=10, figsize=(18, 5))

  #For easy iteration flattened 2X10 subplots matrix to 20 array
  axarr=axarr.flatten()

  #iterating over user ids
  for unique_id in unique_ids:
    image_index=unique_id*8
    axarr[unique_id].imshow(images[image_index], cmap='gray')
    axarr[unique_id].set_xticks([])
    axarr[unique_id].set_yticks([])
    axarr[unique_id].set_title("face id:{}".format(unique_id))
    plt.suptitle("There are 20 distinct people in the dataset")

show_16_distinct_people(X_test_img, np.unique(data['testY']))
```



In [16]:

```
def show_12_faces_of_n_subject(images, subject_ids):
    cols=12
    rows=(len(subject_ids)*12)/cols
    rows=int(rows)

    fig, axarr=plt.subplots(nrows=rows, ncols=cols, figsize=(18,12))
    #axarr=axarr.flatten()

    for i, subject_id in enumerate(subject_ids):
        for j in range(cols):
            image_index=subject_id*12 + j
            axarr[i,j].imshow(images[image_index], cmap="gray")
            axarr[i,j].set_xticks([])
            axarr[i,j].set_yticks([])
            axarr[i,j].set_title("face id:{}".format(subject_id))

show_12_faces_of_n_subject(images=X_train_img, subject_ids=[0, 1, 2 , 3, 4, 18, 19])
```

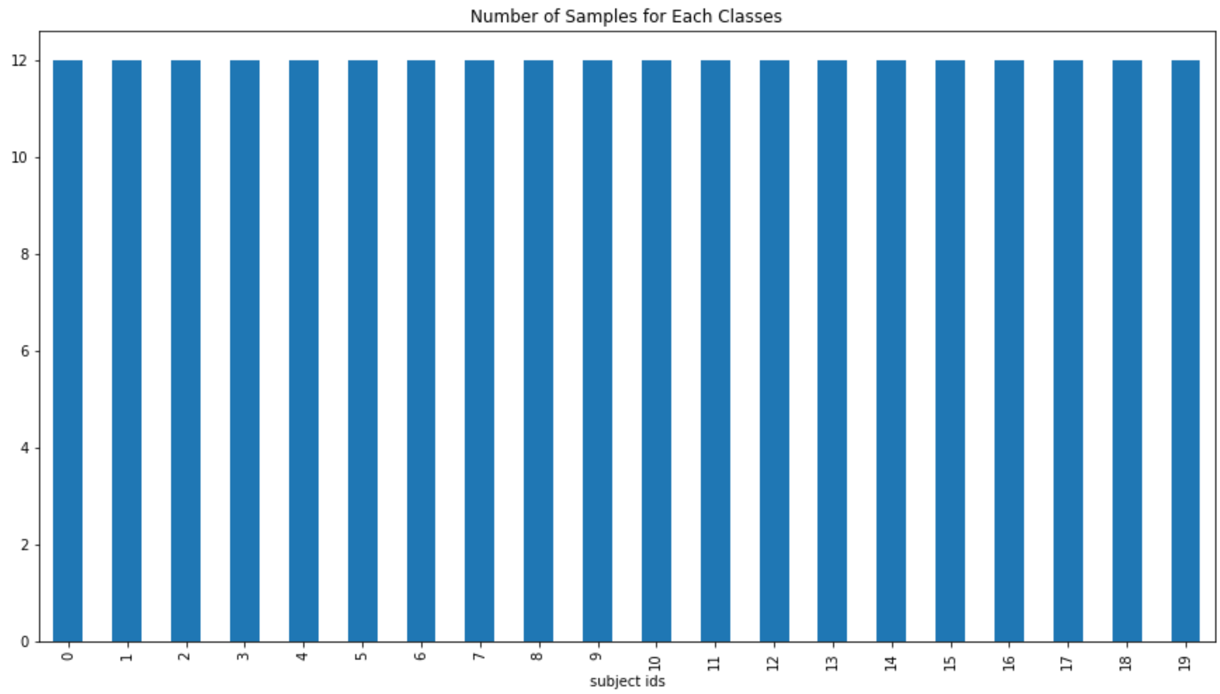


In [17]:

```python
def show_8_faces_of_n_subject(images, subject_ids):
    cols=8
    rows=(len(subject_ids)*8)/cols
    rows=int(rows)

    fig, axarr=plt.subplots(nrows=rows, ncols=cols, figsize=(12,10))
    #axarr=axarr.flatten()

    for i, subject_id in enumerate(subject_ids):
        for j in range(cols):
            image_index=subject_id*8 + j
            axarr[i,j].imshow(images[image_index], cmap="gray")
            axarr[i,j].set_xticks([])
            axarr[i,j].set_yticks([])
            axarr[i,j].set_title("face id:{}".format(subject_id))

show_8_faces_of_n_subject(images=X_test_img, subject_ids=[0, 1, 2 , 3, 4, 18, 19])
```

In [18]:
```
y_frame=pd.DataFrame()
y_frame['subject ids']=y_train
y_frame.groupby(['subject ids']).size().plot.bar(figsize=(15,8),title="Number of Sam
```

Out[18]: `<matplotlib.axes._subplots.AxesSubplot at 0x2516e0ba860>`



In [19]:
```
X_train.shape
```

Out[19]: (240, 10304)

In [20]:
```
X_train=  np.array([np.reshape(i, (112, 92, 1)) for i in X_train])
X_test=  np.array([np.reshape(i, (112, 92, 1)) for i in X_test])
```

y_train_final = tf.keras.utils.to_categorical(y_train, num_classes=20, dtype='float32') y_test_final = tf.keras.utils.to_categorical(y_test, num_classes=20, dtype='float32')

y_train = tf.keras.utils.to_categorical(y_train, num_classes=20, dtype='float32') y_test= tf.keras.utils.to_categorical(y_test, num_classes=20, dtype='float32')

In [21]:
```
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(240, 112, 92, 1)
(160, 112, 92, 1)
(240,)
(160,)
```

In [22]:
```
 X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, test_size=0
```

In [23]:
```
X_valid.shape
```

Out[23]: (48, 112, 92, 1)

input_shape = (img_height,img_width)

model = Sequential() model.add(Conv2D(32,(5,5),input_shape=(112,92,1),padding='same', activation='relu'))#3x3 is default model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(64,(5,5), activation='relu')) model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Dense(32, activation='relu'))

model.add(Dense(32, activation='relu'))

model.add(Flatten())

model.add(Dense(32, activation='relu'))

model.add(BatchNormalization()) model.add(Dropout(.4)) model.add(Dense(20, activation='softmax'))

Model summary

model.summary()

model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

In [24]:
```
# Set Parameters
```

```
batchSize = 12
epochs = 200
tf.random.set_seed(2507)
np.random.seed(2507)

# Initialising the CNN
classifier = tf.keras.models.Sequential()

# Step 1 - Convolution  #No of Feature Maps, Filter, color image with channel,
classifier.add(tf.keras.layers.Conv2D(32, (3, 3), input_shape = (112, 92, 1), activa

# Step 2 - Pooling
classifier.add(tf.keras.layers.MaxPooling2D(pool_size = (2, 2)))

# Adding a second convolutional layer
classifier.add(tf.keras.layers.Conv2D(64, (3, 3), activation = 'relu'))
classifier.add(tf.keras.layers.MaxPooling2D(pool_size = (2, 2)))

# Adding a second convolutional layer
classifier.add(tf.keras.layers.Conv2D(128, (3, 3), activation = 'relu'))
classifier.add(tf.keras.layers.MaxPooling2D(pool_size = (2, 2)))

# Step 3 - Flattening
classifier.add(tf.keras.layers.Flatten())
#classifier.add(tf.keras.layers.GlobalAveragePooling2D())

# Step 4 - Full connection
classifier.add(tf.keras.layers.Dense(units = 512, activation = 'relu'))
classifier.add(tf.keras.layers.Dropout(0.25))
classifier.add(tf.keras.layers.Dense(units = 256, activation = 'relu'))
classifier.add(tf.keras.layers.Dropout(0.25))
classifier.add(tf.keras.layers.Dense(units = 128, activation = 'relu'))
classifier.add(tf.keras.layers.Dropout(0.25))
classifier.add(tf.keras.layers.Dense(units = 64, activation = 'relu'))
classifier.add(tf.keras.layers.Dense(units = 20, activation = 'softmax'))
classifier.summary()
# Compiling the CNN
#classifier.compile(optimizer = "Adam" , loss = 'categorical_crossentropy', metrics
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 110, 90, 32)       320
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 55, 45, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 53, 43, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 26, 21, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 24, 19, 128)       73856
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 12, 9, 128)        0
_________________________________________________________________
flatten (Flatten)            (None, 13824)             0
_________________________________________________________________
dense (Dense)                (None, 512)               7078400
_________________________________________________________________
dropout (Dropout)            (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 256)               131328
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 128)               32896
_________________________________________________________________
```

```
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_3 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_4 (Dense)              (None, 20)                1300
=================================================================
Total params: 7,344,852
Trainable params: 7,344,852
Non-trainable params: 0
_________________________________________________________________
```

In [25]:
```
aug=ImageDataGenerator(featurewise_center=False,
    samplewise_center=False,
    featurewise_std_normalization=False,
    samplewise_std_normalization=False,
    zca_whitening=False,
    zca_epsilon=1e-06,
    rotation_range=20,
    width_shift_range=0.2,
    height_shift_range=0.2,
    brightness_range=None,
    shear_range=0.15,
    zoom_range=0.15,
    channel_shift_range=0.0,
    fill_mode='nearest',
    cval=0.1,
    horizontal_flip=True,
    vertical_flip=False,
    rescale=None,
    preprocessing_function=None,
    data_format=None,
    validation_split=0.0,
    dtype=None)
```

In [26]:
```
optimizer=Adam(lr=0.0001)
```

In [27]:
```
classifier.compile(loss='sparse_categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

In [28]:
```
from keras.callbacks import EarlyStopping

earlystop = EarlyStopping(monitor = 'val_loss',min_delta = 0,patience = 3, verbose =
```

```
Using TensorFlow backend.
```

h = classifier.fit(X_train, y_train, batch_size=32, epochs=epochs,verbose=1,validation_split=0.2)

In [29]:
```
#Custom Callback

class MyThresholdCallBack(tf.keras.callbacks.Callback):
    def __init__(self,cl):
        super(MyThresholdCallBack, self).__init__()
        self.cl = cl

    def on_epoch_end(self, epoch, logs=None):
        test_score = logs["val_accuracy"]
        train_score = logs["accuracy"]

        if test_score > train_score and test_score > self.cl:
        #if test_score > self.cl:
            self.model.stop_training = True
```

In [30]:
```
X_valid.shape
```

Out[30]: (48, 112, 92, 1)

In [31]:
```
myR2ScoreMonitor = MyThresholdCallBack(cl=0.90)
```

In [32]:
```
bs =32
epochs=100
```

In [ ]:
```
#callbacks=[myR2ScoreMonitor])
```

In [60]:
```
h = classifier.fit(X_train, y_train, batch_size=32,
        epochs=epochs,verbose=1,steps_per_epoch=len(X_train) // bs,
    validation_data=(X_valid,y_valid),
    validation_steps=len(X_valid) // bs)
```

```
Train on 192 samples, validate on 48 samples
Epoch 1/100
192/192 [==============================] - 3s 14ms/sample - loss: 0.3248 - accuracy:
0.8854 - val_loss: 0.1330 - val_accuracy: 0.9688
Epoch 2/100
192/192 [==============================] - 3s 14ms/sample - loss: 0.2067 - accuracy:
0.9115 - val_loss: 0.2164 - val_accuracy: 0.8750
Epoch 3/100
192/192 [==============================] - 3s 13ms/sample - loss: 0.2058 - accuracy:
0.9271 - val_loss: 0.1998 - val_accuracy: 0.9062
Epoch 4/100
192/192 [==============================] - 3s 13ms/sample - loss: 0.1881 - accuracy:
0.9635 - val_loss: 0.2110 - val_accuracy: 0.8438
Epoch 5/100
192/192 [==============================] - 2s 13ms/sample - loss: 0.1730 - accuracy:
0.9531 - val_loss: 0.1758 - val_accuracy: 0.9062
Epoch 6/100
192/192 [==============================] - 3s 13ms/sample - loss: 0.1379 - accuracy:
0.9479 - val_loss: 0.1022 - val_accuracy: 0.9062
Epoch 7/100
192/192 [==============================] - 3s 13ms/sample - loss: 0.1210 - accuracy:
0.9635 - val_loss: 0.0850 - val_accuracy: 0.9062
Epoch 8/100
192/192 [==============================] - 3s 14ms/sample - loss: 0.0602 - accuracy:
0.9948 - val_loss: 0.0665 - val_accuracy: 0.9375
Epoch 9/100
192/192 [==============================] - 2s 13ms/sample - loss: 0.0488 - accuracy:
0.9896 - val_loss: 0.0261 - val_accuracy: 1.0000
Epoch 10/100
192/192 [==============================] - 2s 13ms/sample - loss: 0.0969 - accuracy:
0.9688 - val_loss: 0.0348 - val_accuracy: 0.9688
Epoch 11/100
192/192 [==============================] - 2s 13ms/sample - loss: 0.1085 - accuracy:
0.9635 - val_loss: 0.0819 - val_accuracy: 0.9688
Epoch 12/100
192/192 [==============================] - 2s 13ms/sample - loss: 0.0853 - accuracy:
0.9740 - val_loss: 0.0627 - val_accuracy: 0.9375
Epoch 13/100
192/192 [==============================] - 2s 13ms/sample - loss: 0.0893 - accuracy:
0.9583 - val_loss: 0.0305 - val_accuracy: 1.0000
Epoch 14/100
192/192 [==============================] - 3s 15ms/sample - loss: 0.0934 - accuracy:
0.9688 - val_loss: 0.0894 - val_accuracy: 0.9688
Epoch 15/100
192/192 [==============================] - 3s 15ms/sample - loss: 0.1171 - accuracy:
0.9635 - val_loss: 0.0374 - val_accuracy: 1.0000
Epoch 16/100
192/192 [==============================] - 3s 14ms/sample - loss: 0.0405 - accuracy:
0.9896 - val_loss: 0.0487 - val_accuracy: 1.0000
Epoch 17/100
192/192 [==============================] - 3s 13ms/sample - loss: 0.0947 - accuracy:
0.9583 - val_loss: 0.1936 - val_accuracy: 0.9375
```

```
Epoch 18/100
192/192 [==============================] - 3s 15ms/sample - loss: 0.0605 - accuracy:
0.9740 - val_loss: 0.3005 - val_accuracy: 0.9375
Epoch 19/100
192/192 [==============================] - 2s 13ms/sample - loss: 0.0531 - accuracy:
0.9792 - val_loss: 0.1253 - val_accuracy: 0.9688
Epoch 20/100
192/192 [==============================] - 3s 14ms/sample - loss: 0.0320 - accuracy:
0.9844 - val_loss: 0.0370 - val_accuracy: 0.9688
Epoch 21/100
192/192 [==============================] - 3s 14ms/sample - loss: 0.0721 - accuracy:
0.9740 - val_loss: 0.1978 - val_accuracy: 0.9375
Epoch 22/100
192/192 [==============================] - 3s 14ms/sample - loss: 0.0105 - accuracy:
1.0000 - val_loss: 0.1531 - val_accuracy: 0.9375
Epoch 23/100
192/192 [==============================] - 3s 14ms/sample - loss: 0.0122 - accuracy:
1.0000 - val_loss: 0.1417 - val_accuracy: 0.9375
Epoch 24/100
192/192 [==============================] - 3s 16ms/sample - loss: 0.0355 - accuracy:
0.9896 - val_loss: 0.2137 - val_accuracy: 0.9688
Epoch 25/100
192/192 [==============================] - 3s 15ms/sample - loss: 0.0260 - accuracy:
0.9896 - val_loss: 0.0514 - val_accuracy: 0.9688
Epoch 26/100
192/192 [==============================] - 3s 15ms/sample - loss: 0.0361 - accuracy:
0.9896 - val_loss: 0.0541 - val_accuracy: 0.9688
Epoch 27/100
192/192 [==============================] - 3s 16ms/sample - loss: 0.0335 - accuracy:
0.9896 - val_loss: 0.1361 - val_accuracy: 0.9688
Epoch 28/100
192/192 [==============================] - 3s 15ms/sample - loss: 0.0323 - accuracy:
0.9896 - val_loss: 0.0938 - val_accuracy: 0.9375
Epoch 29/100
192/192 [==============================] - 3s 17ms/sample - loss: 0.0248 - accuracy:
0.9948 - val_loss: 0.0715 - val_accuracy: 0.9375
Epoch 30/100
192/192 [==============================] - 3s 16ms/sample - loss: 0.0247 - accuracy:
0.9896 - val_loss: 0.0481 - val_accuracy: 0.9688
Epoch 31/100
192/192 [==============================] - 3s 17ms/sample - loss: 0.0160 - accuracy:
0.9948 - val_loss: 0.1388 - val_accuracy: 0.9688
Epoch 32/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0854 - accuracy:
0.9792 - val_loss: 0.1364 - val_accuracy: 0.9375
Epoch 33/100
192/192 [==============================] - 3s 17ms/sample - loss: 0.0897 - accuracy:
0.9844 - val_loss: 0.1218 - val_accuracy: 0.9375
Epoch 34/100
192/192 [==============================] - 3s 17ms/sample - loss: 0.0332 - accuracy:
0.9844 - val_loss: 0.1302 - val_accuracy: 0.9375
Epoch 35/100
192/192 [==============================] - 3s 18ms/sample - loss: 0.0561 - accuracy:
0.9792 - val_loss: 0.0613 - val_accuracy: 0.9688
Epoch 36/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.1791 - accuracy:
0.9635 - val_loss: 0.2166 - val_accuracy: 0.9062
Epoch 37/100
192/192 [==============================] - 3s 18ms/sample - loss: 0.0714 - accuracy:
0.9792 - val_loss: 0.1730 - val_accuracy: 0.9062
Epoch 38/100
192/192 [==============================] - 3s 18ms/sample - loss: 0.0582 - accuracy:
0.9792 - val_loss: 0.0960 - val_accuracy: 0.9375
Epoch 39/100
192/192 [==============================] - 3s 16ms/sample - loss: 0.0321 - accuracy:
0.9844 - val_loss: 0.1014 - val_accuracy: 0.9375
Epoch 40/100
192/192 [==============================] - 4s 21ms/sample - loss: 0.0518 - accuracy:
0.9844 - val_loss: 0.0834 - val_accuracy: 0.9375
```

```
Epoch 41/100
192/192 [==============================] - 5s 23ms/sample - loss: 0.0325 - accuracy:
0.9896 - val_loss: 0.0758 - val_accuracy: 0.9375
Epoch 42/100
192/192 [==============================] - 4s 20ms/sample - loss: 0.0300 - accuracy:
0.9948 - val_loss: 0.1064 - val_accuracy: 0.9375
Epoch 43/100
192/192 [==============================] - 4s 21ms/sample - loss: 0.0174 - accuracy:
0.9948 - val_loss: 0.0937 - val_accuracy: 0.9688
Epoch 44/100
192/192 [==============================] - 4s 22ms/sample - loss: 0.0203 - accuracy:
0.9948 - val_loss: 0.1059 - val_accuracy: 0.9375
Epoch 45/100
192/192 [==============================] - 4s 22ms/sample - loss: 0.0351 - accuracy:
0.9844 - val_loss: 0.0361 - val_accuracy: 0.9688
Epoch 46/100
192/192 [==============================] - 4s 23ms/sample - loss: 0.0203 - accuracy:
0.9948 - val_loss: 0.0089 - val_accuracy: 1.0000
Epoch 47/100
192/192 [==============================] - 4s 23ms/sample - loss: 0.0370 - accuracy:
0.9948 - val_loss: 0.0993 - val_accuracy: 0.9062
Epoch 48/100
192/192 [==============================] - 5s 25ms/sample - loss: 0.0674 - accuracy:
0.9844 - val_loss: 0.0489 - val_accuracy: 0.9688
Epoch 49/100
192/192 [==============================] - 5s 25ms/sample - loss: 0.0321 - accuracy:
0.9896 - val_loss: 0.0417 - val_accuracy: 0.9688
Epoch 50/100
192/192 [==============================] - 4s 21ms/sample - loss: 0.0087 - accuracy:
1.0000 - val_loss: 0.0889 - val_accuracy: 0.9375
Epoch 51/100
192/192 [==============================] - 3s 18ms/sample - loss: 0.0286 - accuracy:
0.9896 - val_loss: 0.2507 - val_accuracy: 0.9062
Epoch 52/100
192/192 [==============================] - 4s 20ms/sample - loss: 0.0658 - accuracy:
0.9740 - val_loss: 0.1084 - val_accuracy: 0.9375
Epoch 53/100
192/192 [==============================] - 4s 18ms/sample - loss: 0.0179 - accuracy:
0.9948 - val_loss: 0.0839 - val_accuracy: 0.9375
Epoch 54/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0662 - accuracy:
0.9844 - val_loss: 0.0171 - val_accuracy: 1.0000
Epoch 55/100
192/192 [==============================] - 3s 17ms/sample - loss: 0.0506 - accuracy:
0.9844 - val_loss: 0.0733 - val_accuracy: 0.9375
Epoch 56/100
192/192 [==============================] - 5s 25ms/sample - loss: 0.0443 - accuracy:
0.9896 - val_loss: 0.1196 - val_accuracy: 0.9375
Epoch 57/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0459 - accuracy:
0.9844 - val_loss: 0.1248 - val_accuracy: 0.9375
Epoch 58/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0175 - accuracy:
1.0000 - val_loss: 0.1496 - val_accuracy: 0.9375
Epoch 59/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0398 - accuracy:
0.9896 - val_loss: 0.1049 - val_accuracy: 0.9375
Epoch 60/100
192/192 [==============================] - 3s 16ms/sample - loss: 0.0557 - accuracy:
0.9948 - val_loss: 0.0609 - val_accuracy: 0.9688
Epoch 61/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0072 - accuracy:
1.0000 - val_loss: 0.0521 - val_accuracy: 0.9688
Epoch 62/100
192/192 [==============================] - 4s 18ms/sample - loss: 0.0126 - accuracy:
0.9948 - val_loss: 0.0382 - val_accuracy: 0.9688
Epoch 63/100
192/192 [==============================] - 3s 17ms/sample - loss: 0.0125 - accuracy:
1.0000 - val_loss: 0.0305 - val_accuracy: 0.9688
```

```
Epoch 64/100
192/192 [==============================] - 4s 22ms/sample - loss: 0.0091 - accuracy:
0.9948 - val_loss: 0.1509 - val_accuracy: 0.9375
Epoch 65/100
192/192 [==============================] - 4s 21ms/sample - loss: 0.0064 - accuracy:
0.9948 - val_loss: 0.2493 - val_accuracy: 0.9375
Epoch 66/100
192/192 [==============================] - 4s 18ms/sample - loss: 0.0334 - accuracy:
0.9948 - val_loss: 0.2291 - val_accuracy: 0.9375
Epoch 67/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0191 - accuracy:
0.9948 - val_loss: 0.2851 - val_accuracy: 0.9375
Epoch 68/100
192/192 [==============================] - 4s 22ms/sample - loss: 0.0219 - accuracy:
0.9948 - val_loss: 0.2722 - val_accuracy: 0.9375
Epoch 69/100
192/192 [==============================] - 4s 23ms/sample - loss: 0.0051 - accuracy:
1.0000 - val_loss: 0.2241 - val_accuracy: 0.9375
Epoch 70/100
192/192 [==============================] - 5s 24ms/sample - loss: 0.0074 - accuracy:
1.0000 - val_loss: 0.1504 - val_accuracy: 0.9375
Epoch 71/100
192/192 [==============================] - 4s 18ms/sample - loss: 0.0015 - accuracy:
1.0000 - val_loss: 0.1934 - val_accuracy: 0.9375
Epoch 72/100
192/192 [==============================] - 3s 18ms/sample - loss: 0.0070 - accuracy:
0.9948 - val_loss: 0.2090 - val_accuracy: 0.9375
Epoch 73/100
192/192 [==============================] - 3s 18ms/sample - loss: 9.7366e-04 - accur
acy: 1.0000 - val_loss: 0.2124 - val_accuracy: 0.9375
Epoch 74/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0052 - accuracy:
1.0000 - val_loss: 0.2043 - val_accuracy: 0.9375
Epoch 75/100
192/192 [==============================] - 3s 18ms/sample - loss: 0.0016 - accuracy:
1.0000 - val_loss: 0.1985 - val_accuracy: 0.9375
Epoch 76/100
192/192 [==============================] - 3s 18ms/sample - loss: 0.0012 - accuracy:
1.0000 - val_loss: 0.1976 - val_accuracy: 0.9375
Epoch 77/100
192/192 [==============================] - 3s 18ms/sample - loss: 0.0055 - accuracy:
0.9948 - val_loss: 0.2408 - val_accuracy: 0.9375
Epoch 78/100
192/192 [==============================] - 4s 20ms/sample - loss: 0.0242 - accuracy:
0.9896 - val_loss: 0.2657 - val_accuracy: 0.9375
Epoch 79/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0032 - accuracy:
1.0000 - val_loss: 0.2669 - val_accuracy: 0.9375
Epoch 80/100
192/192 [==============================] - 3s 17ms/sample - loss: 0.0028 - accuracy:
1.0000 - val_loss: 0.1874 - val_accuracy: 0.9375
Epoch 81/100
192/192 [==============================] - 3s 16ms/sample - loss: 0.0023 - accuracy:
1.0000 - val_loss: 0.1618 - val_accuracy: 0.9375
Epoch 82/100
192/192 [==============================] - 3s 17ms/sample - loss: 0.0043 - accuracy:
1.0000 - val_loss: 0.1598 - val_accuracy: 0.9375
Epoch 83/100
192/192 [==============================] - 3s 18ms/sample - loss: 0.0032 - accuracy:
1.0000 - val_loss: 0.1487 - val_accuracy: 0.9375
Epoch 84/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0165 - accuracy:
0.9948 - val_loss: 0.1692 - val_accuracy: 0.9375
Epoch 85/100
192/192 [==============================] - 4s 20ms/sample - loss: 0.0035 - accuracy:
1.0000 - val_loss: 0.1943 - val_accuracy: 0.9375
Epoch 86/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0075 - accuracy:
0.9948 - val_loss: 0.2384 - val_accuracy: 0.9375
```

```
Epoch 87/100
192/192 [==============================] - 4s 19ms/sample - loss: 0.0027 - accuracy:
1.0000 - val_loss: 0.2776 - val_accuracy: 0.9375
Epoch 88/100
192/192 [==============================] - 4s 20ms/sample - loss: 0.0062 - accuracy:
0.9948 - val_loss: 0.0806 - val_accuracy: 0.9688
Epoch 89/100
192/192 [==============================] - 4s 19ms/sample - loss: 9.6955e-04 - accur
acy: 1.0000 - val_loss: 0.0335 - val_accuracy: 0.9688
Epoch 90/100
192/192 [==============================] - 4s 21ms/sample - loss: 0.0227 - accuracy:
0.9948 - val_loss: 0.0294 - val_accuracy: 0.9688
Epoch 91/100
192/192 [==============================] - 4s 20ms/sample - loss: 0.0156 - accuracy:
0.9896 - val_loss: 0.1430 - val_accuracy: 0.9375
Epoch 92/100
192/192 [==============================] - 5s 25ms/sample - loss: 0.0285 - accuracy:
0.9948 - val_loss: 0.2703 - val_accuracy: 0.9375
Epoch 93/100
192/192 [==============================] - 5s 24ms/sample - loss: 0.0169 - accuracy:
0.9948 - val_loss: 0.2368 - val_accuracy: 0.9375
Epoch 94/100
192/192 [==============================] - 4s 23ms/sample - loss: 0.0212 - accuracy:
0.9948 - val_loss: 0.1672 - val_accuracy: 0.9375
Epoch 95/100
192/192 [==============================] - 5s 26ms/sample - loss: 0.0214 - accuracy:
0.9948 - val_loss: 0.1462 - val_accuracy: 0.9375
Epoch 96/100
192/192 [==============================] - 6s 29ms/sample - loss: 0.0045 - accuracy:
1.0000 - val_loss: 0.1259 - val_accuracy: 0.9375
Epoch 97/100
192/192 [==============================] - 4s 23ms/sample - loss: 0.0508 - accuracy:
0.9844 - val_loss: 0.1242 - val_accuracy: 0.9375
Epoch 98/100
192/192 [==============================] - 5s 24ms/sample - loss: 0.0128 - accuracy:
1.0000 - val_loss: 0.0953 - val_accuracy: 0.9375
Epoch 99/100
192/192 [==============================] - 5s 24ms/sample - loss: 0.0112 - accuracy:
0.9948 - val_loss: 0.1617 - val_accuracy: 0.9375
Epoch 100/100
192/192 [==============================] - 5s 24ms/sample - loss: 0.0136 - accuracy:
1.0000 - val_loss: 0.2174 - val_accuracy: 0.9375
```

In [61]:

```
# training accuracy after final epoch
h.history['accuracy'][-1]
```

Out[61]: 1.0

In [62]:

```
# test accuracy after final epoch
h.history['val_accuracy'][-1]
```

Out[62]: 0.9375

In [63]:

```
trainloss,train_acc=classifier.evaluate(X_train, y_train,verbose=0)
testlossloss,test_acc=classifier.evaluate(X_valid, y_valid,verbose=0)
print("train:%3f,Test:%3f"%(train_acc,test_acc))
```

```
train:1.000000,Test:0.958333
```

In [64]:

```
print('test loss',testlossloss)
print('accuracy',test_acc*100)
```

```
test loss 0.2184815804939717
accuracy 95.83333134651184
```

In [65]:

```
loss_train,train_acc=classifier.evaluate(X_train, y_train,verbose=0)
loss_test,test_acc=classifier.evaluate(X_valid, y_valid,verbose=0)
```

```
print("train_accurcy:%.3f,Testaccury:%.3f"%(train_acc,test_acc*100))
print("loss_train:%.3f,loss_acctest:%.3f"%(loss_train,loss_test))
```

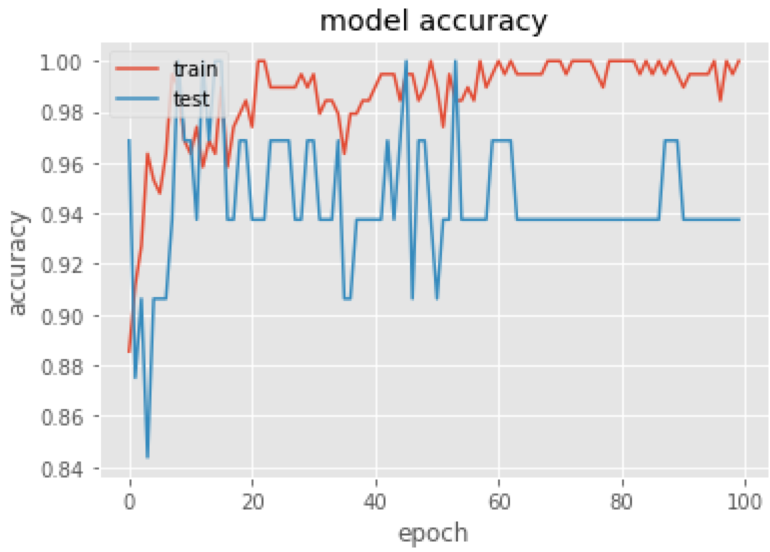
```
train_accurcy:1.000,Testaccury:95.833
loss_train:0.000,loss_acctest:0.218
```

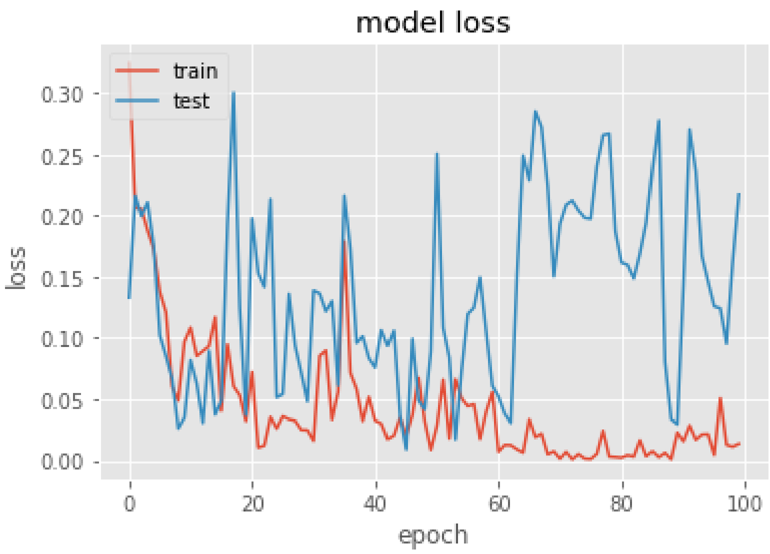
In [66]:

```
plt.figure(figsize =(6,6))
plt.plot(h.history['accuracy'])
plt.plot(h.history['val_accuracy'])
plt.title('Model Accury')
plt.ylabel('accuracy')
plt.xlabel('epcho')
plt.legend(['train','test'],loc = 'upper left')
plt.show()
```

In [67]:

```
# summarize history for accuracy
plt.plot(h.history['accuracy'])
plt.plot(h.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(h.history['loss'])
plt.plot(h.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```





In [68]:
```
predicted1 =np.array( classifier.predict_classes(X_test))
```

In [69]:
```
print("accuracy : ",accuracy_score(y_test,predicted1)*100)
```

```
accuracy :  94.375
```

In [70]:
```
prediction = classifier.predict_classes(X_test)


print("accuracy : ",accuracy_score(y_test,prediction)*100)
```

```
accuracy :  94.375
```

In [71]:
```
from keras.utils import np_utils

y_test1 = np_utils.to_categorical(y_test, 20)
```

In [72]:
```
ynew= classifier.predict_classes(X_test)


print("accuracy : ",accuracy_score(y_test,ynew)*100)
```

```
accuracy :  94.375
```

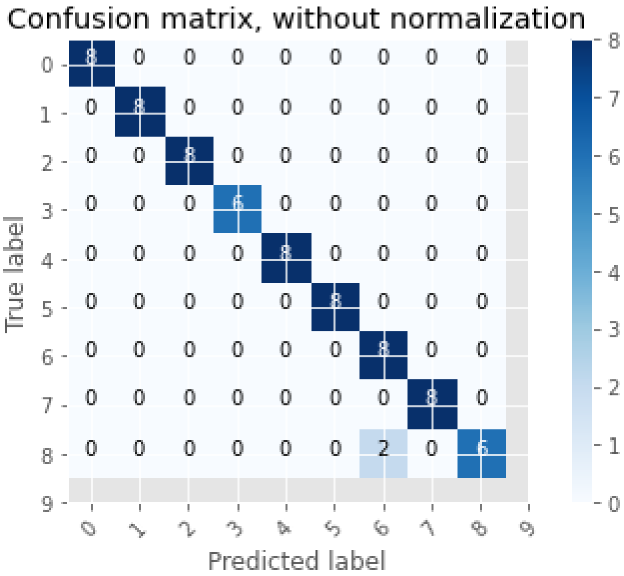
In [73]:
```
cnf_matrix=confusion_matrix(np.array(y_test), ynew)
import itertools
```

In [74]:
```
def plot_confusion_matrix(cm, classes,
```

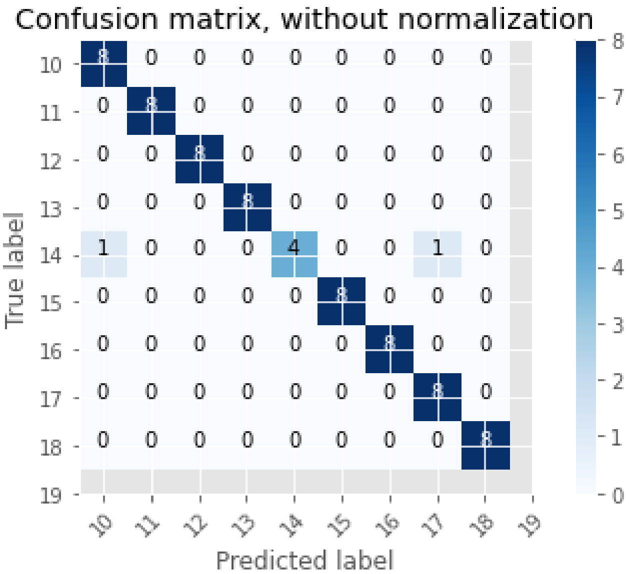
```
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        #print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    #print(cm)
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.show()


print('Confusion matrix, without normalization')
print(cnf_matrix)

plt.figure()
plot_confusion_matrix(cnf_matrix[1:10,1:10], classes=[0,1,2,3,4,5,6,7,8,9],
                      title='Confusion matrix, without normalization')

plt.figure()
plot_confusion_matrix(cnf_matrix[11:20,11:20], classes=[10,11,12,13,14,15,16,17,18,1
                      title='Confusion matrix, without normalization')

print("Confusion matrix:\n%s" % confusion_matrix(np.array(y_test), ynew))
print(classification_report(np.array(y_test), ynew))
```

```
Confusion matrix, without normalization
[[7 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0]
 [0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 6 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0]
 [0 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 6 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0]
 [2 0 0 0 0 0 0 0 0 0 0 1 0 0 0 4 0 0 1 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8 0 0 0]
```

```
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8]]
Confusion matrix, without normalization
```




```
Confusion matrix, without normalization
```




```
Confusion matrix:
[[7 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0]
 [0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 6 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0]
 [0 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 8 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 2 0 6 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 8 0 0 0 0 0]
 [2 0 0 0 0 0 0 0 0 0 0 1 0 0 0 4 0 0 1 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 8]]
              precision    recall  f1-score   support

           0       0.78      0.88      0.82         8
```

```
           1       1.00      1.00      1.00         8
           2       1.00      1.00      1.00         8
           3       1.00      1.00      1.00         8
           4       1.00      0.75      0.86         8
           5       1.00      1.00      1.00         8
           6       1.00      1.00      1.00         8
           7       0.80      1.00      0.89         8
           8       1.00      1.00      1.00         8
           9       1.00      0.75      0.86         8
          10       1.00      1.00      1.00         8
          11       0.89      1.00      0.94         8
          12       1.00      1.00      1.00         8
          13       1.00      1.00      1.00         8
          14       1.00      1.00      1.00         8
          15       1.00      0.50      0.67         8
          16       1.00      1.00      1.00         8
          17       0.80      1.00      0.89         8
          18       0.80      1.00      0.89         8
          19       1.00      1.00      1.00         8

    accuracy                           0.94       160
   macro avg       0.95      0.94      0.94       160
weighted avg       0.95      0.94      0.94       160
```

In [75]:

```python
from sklearn.metrics import confusion_matrix
confusion_matrix(y_test,prediction)
```

Out[75]:

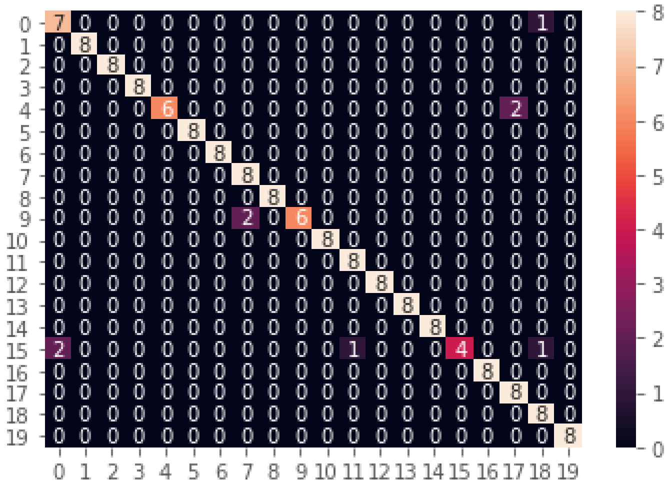
```
array([[7, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0],
       [0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 6, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 0, 0],
       [0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 2, 0, 6, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8, 0, 0, 0, 0, 0],
       [2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 4, 0, 0, 1, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8, 0, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8, 0],
       [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 8]],
      dtype=int64)
```

In [76]:

```python
import seaborn as sns
c = confusion_matrix(y_test,prediction)
sns.heatmap(c,annot = True)
```

Out[76]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x25104312080>
```



In [77]:
```
#predictios
classifier.save('FaceRecognition.tf2')
```

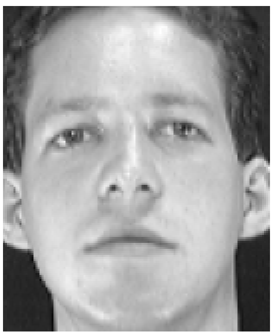
```
INFO:tensorflow:Assets written to: FaceRecognition.tf2\assets
```

In [78]:
```
predictions = classifier.predict(X_test)
```

In [79]:
```
def plot_image(i, predictions, trueLabel, img):
  predictions_array, true_label, image = predictions[i], trueLabel[i], img[i]
  plt.xticks([])
  plt.yticks([])
  #plt.imshow(x_test_edited[0].reshape(112,92))
  plt.imshow(image.reshape(112,92), cmap="gray")
  actual_label = np.argmax(true_label)
  predicted_label = np.argmax(predictions_array)
  # print("True Label: ",y_test_final[1],"\n")
  # print("Prediction: ", predictions[1], "\n")
  print("Actual Label is: ", actual_label)
  print("Predicted Label is: ", predicted_label)
  if predicted_label == actual_label:
    color = "blue"
  else:
    color = "red"
  plt.xlabel("Face ID {} predicted matches {:2.0f}% to ({})".format(predicted_label,
```

In [80]:
```
i = 0
plt.figure(figsize=(6,3))
plot_image(i, predictions, y_test, X_test)
```

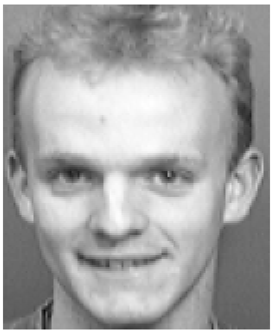
```
Actual Label is:  0
Predicted Label is:  0
```



Face ID 0 predicted matches 96% to (0)

In [81]:
```
j = 34
plt.figure(figsize=(6,3))
plot_image(j, predictions, y_test, X_test)
```

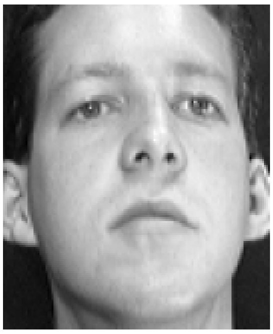
```
Actual Label is:  0
Predicted Label is:  4
```



Face ID 4 predicted matches 100% to (0)

In [83]:
```
k = 2
plt.figure(figsize=(6,3))
plot_image(k, predictions,  y_test, X_test)
```

```
Actual Label is:  0
Predicted Label is:  0
```



Face ID 0 predicted matches 84% to (0)

by Harsha Teja Bolla

In [ ]: