FACE RECOGNITION WITH DEEP LEARNING IN KERAS USING CNN

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.

PRE-REQUISITES

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

6. Train the model
7. Plot the result
8. Iterate the model until the accuracy is above 90%

Step 1 : Input the required Libraries

In [28]:
```
import keras
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Dense, Flatten, Dropout
from tensorflow.keras.optimizers import Adam
from keras.callbacks import TensorBoard

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import accuracy_score
from keras.utils import np_utils
import itertools
```

Step 2 . Load the dataset after loading the dataset, you have to normalize every image.

In [29]:
```
#load dataset
data = np.load('ORL_faces.npz')

# load the "Train Images"
x_train = data['trainX']

#normalize every image
x_train = np.array(x_train,dtype='float32')/255

x_test = data['testX']
x_test = np.array(x_test,dtype='float32')/255

# load the Label of Images
y_train= data['trainY']
y_test= data['testY']

# show the train and test Data format
print('x_train : {}'.format(x_train[:]))
print('Y-train shape: {}'.format(y_train))
print('x_test shape: {}'.format(x_test.shape))
```

```
x_train : [[0.1882353  0.19215687 0.1764706  ... 0.18431373 0.18039216 0.180392
16]
 [0.23529412 0.23529412 0.24313726 ... 0.1254902  0.13333334 0.13333334]
 [0.15294118 0.17254902 0.20784314 ... 0.11372549 0.10196079 0.11372549]
 ...
 [0.44705883 0.45882353 0.44705883 ... 0.38431373 0.3764706  0.38431373]
 [0.4117647  0.4117647  0.41960785 ... 0.21176471 0.18431373 0.16078432]
 [0.45490196 0.44705883 0.45882353 ... 0.37254903 0.39215687 0.39607844]]
Y-train shape: [ 0  0  0  0  0  0  0  0  0  0  0  0  1  1  1  1  1  1  1  1  1
1  1  1
  2  2  2  2  2  2  2  2  2  2  2  2  3  3  3  3  3  3  3  3  3  3  3  3
  4  4  4  4  4  4  4  4  4  4  4  4  5  5  5  5  5  5  5  5  5  5  5  5
  6  6  6  6  6  6  6  6  6  6  6  6  7  7  7  7  7  7  7  7  7  7  7  7
  8  8  8  8  8  8  8  8  8  8  8  8  9  9  9  9  9  9  9  9  9  9  9  9
 10 10 10 10 10 10 10 10 10 10 10 10 11 11 11 11 11 11 11 11 11 11 11 11
 12 12 12 12 12 12 12 12 12 12 12 12 13 13 13 13 13 13 13 13 13 13 13 13
 14 14 14 14 14 14 14 14 14 14 14 14 15 15 15 15 15 15 15 15 15 15 15 15
 16 16 16 16 16 16 16 16 16 16 16 16 17 17 17 17 17 17 17 17 17 17 17 17
 18 18 18 18 18 18 18 18 18 18 18 18 19 19 19 19 19 19 19 19 19 19 19 19]
x_test shape: (160, 10304)
```

Step 3: Split the dataset

The dataset is splitted into two: Validation data and Train

Validation DataSet: this data set is used to minimize overfitting.If the accuracy over the training data set increases, but the accuracy over then validation data set stays the same or decreases, then you're overfitting your neural network and you should stop training.

Note: we usually use 30 percent of every dataset as the validation data but Here we only used 5 percent because the number of images in this dataset is very low.

In [30]:
```
x_train, x_valid, y_train, y_valid= train_test_split(
    x_train, y_train, test_size=.05, random_state=1234,)
```

Step 4: Transform the images to equal sizes to feed in CNN

In [36]:
```
im_rows=112
im_cols=92
batch_size=512
im_shape=(im_rows, im_cols, 1)

#change the size of images
x_train = x_train.reshape(x_train.shape[0], *im_shape,)
x_test = x_test.reshape(x_test.shape[0], *im_shape,)
x_valid = x_valid.reshape(x_valid.shape[0], *im_shape,)

print('x_train shape: {}'.format(y_train.shape[0]))
print('x_test shape: {}'.format(y_test.shape))
```

```
x_train shape: 228
x_test shape: (160,)
```

Step 5: Build CNN model: CNN have 3 main layer:

```
1-Convolotional layer

2- pooling layer

3- fully connected layer
```

we could build a new architecture of CNN by changing the number and position of layers.

In [37]:
```
#filters= the depth of output image or kernels

cnn_model= Sequential([
    Conv2D(filters=36, kernel_size=7, activation='relu', input_shape= im_shape),
    MaxPooling2D(pool_size=2),
    Conv2D(filters=54, kernel_size=5, activation='relu', input_shape= im_shape),
    MaxPooling2D(pool_size=2),
    Flatten(),
    Dense(2024, activation='relu'),
     Dropout(0.5),
    Dense(1024, activation='relu'),
    Dropout(0.5),
    Dense(512, activation='relu'),
    Dropout(0.5),
    #20 is the number of outputs
    Dense(20, activation='softmax')
])

cnn_model.compile(
    loss='sparse_categorical_crossentropy',#'categorical_crossentropy',
    optimizer=Adam(learning_rate=0.0001),
    metrics=['accuracy']
)
```

In [38]:
```
#Display the model summary
cnn_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_6 (Conv2D)            (None, 106, 86, 36)       1800      
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 53, 43, 36)        0         
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 49, 39, 54)        48654     
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 24, 19, 54)        0         
_________________________________________________________________
flatten_3 (Flatten)          (None, 24624)             0         
_________________________________________________________________
dense_12 (Dense)             (None, 2024)              49841000  
_________________________________________________________________
dropout_9 (Dropout)          (None, 2024)              0         
_________________________________________________________________
dense_13 (Dense)             (None, 1024)              2073600   
_________________________________________________________________
dropout_10 (Dropout)         (None, 1024)              0         
_________________________________________________________________
dense_14 (Dense)             (None, 512)               524800    
_________________________________________________________________
dropout_11 (Dropout)         (None, 512)               0         
_________________________________________________________________
dense_15 (Dense)             (None, 20)                10260     
=================================================================
Total params: 52,500,114
Trainable params: 52,500,114
Non-trainable params: 0
_________________________________________________________________
```

Step 6: Train the model

In [39]:
```
history=cnn_model.fit(np.array(x_train), np.array(y_train), batch_size=512,epochs
    validation_data=(np.array(x_valid),np.array(y_valid)))
```

```
Epoch 1/250
1/1 - 28s - loss: 3.0042 - accuracy: 0.0482 - val_loss: 2.9866 - val_accurac
y: 0.0000e+00
Epoch 2/250
1/1 - 1s - loss: 3.0220 - accuracy: 0.0482 - val_loss: 3.0040 - val_accurac
y: 0.0000e+00
Epoch 3/250
1/1 - 1s - loss: 3.0049 - accuracy: 0.0263 - val_loss: 3.0075 - val_accurac
y: 0.0000e+00
Epoch 4/250
1/1 - 1s - loss: 3.0315 - accuracy: 0.0570 - val_loss: 3.0117 - val_accurac
y: 0.0000e+00
Epoch 5/250
1/1 - 1s - loss: 2.9906 - accuracy: 0.0614 - val_loss: 3.0124 - val_accurac
y: 0.0000e+00
Epoch 6/250
1/1 - 1s - loss: 2.9994 - accuracy: 0.0351 - val_loss: 3.0121 - val_accurac
y: 0.0000e+00
Epoch 7/250
```

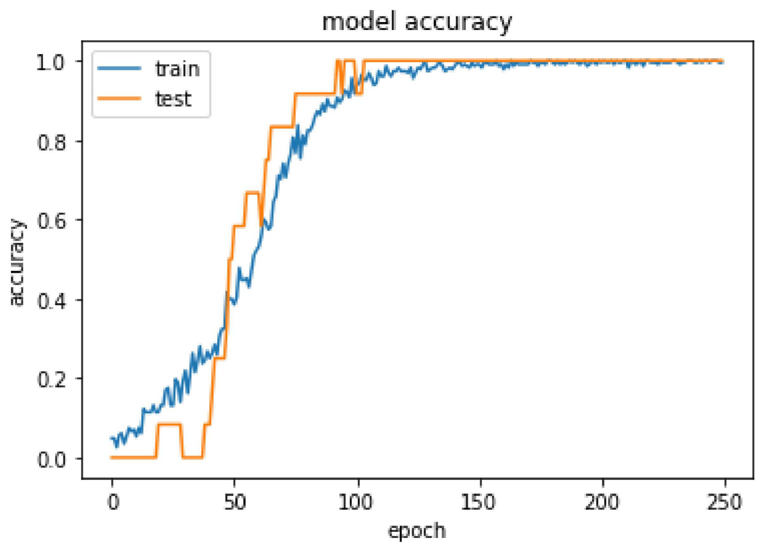
In [40]:
```
scor = cnn_model.evaluate( np.array(x_test),  np.array(y_test), verbose=0)

print('test los {:.4f}'.format(scor[0]))
print('test acc {:.4f}'.format(scor[1]))
```

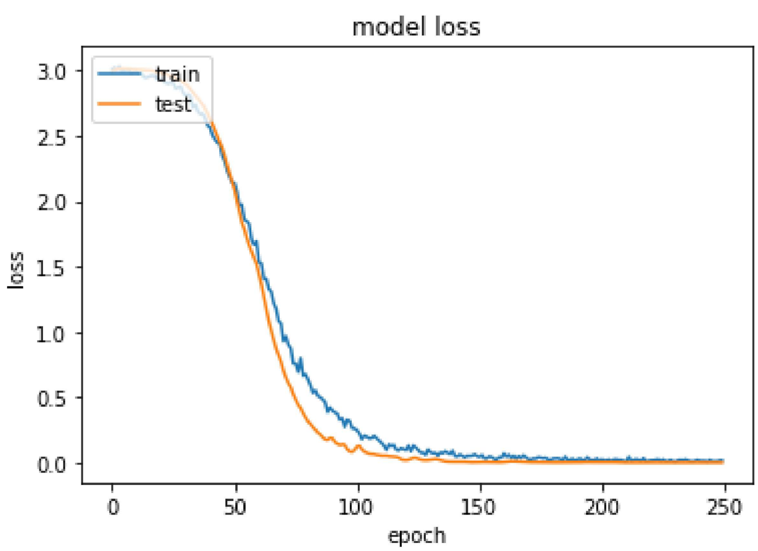
```
test los 0.3114
test acc 0.9500
```

Step 7: Plot the Results

In [44]:
```
# list all data in history
print(history.history.keys())
# summarize history for accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.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(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```





Step 8: Iterate the model until the accuracy is above 90%

In [54]:
```
predicted =np.array( cnn_model.predict(x_test))
#print(predicted)
#print(y_test)

predict_x=cnn_model.predict(x_test)
ynew=np.argmax(predict_x,axis=1)

#ynew = cnn_model.predict_classes(x_test)


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

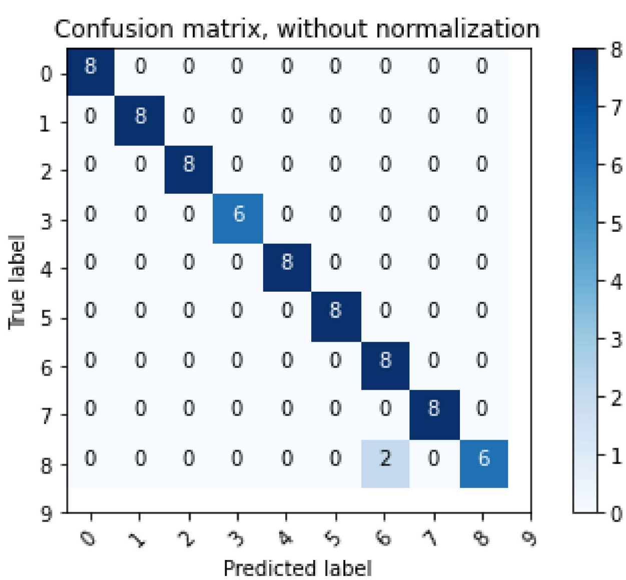
```
accuracy :  95.0 %
```

In [55]:
```
#Confusion Matrix
```

In [57]:
```
cnf_matrix=confusion_matrix(np.array(y_test), ynew)

y_test1 = np_utils.to_categorical(y_test, 20)



def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):

    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()
```

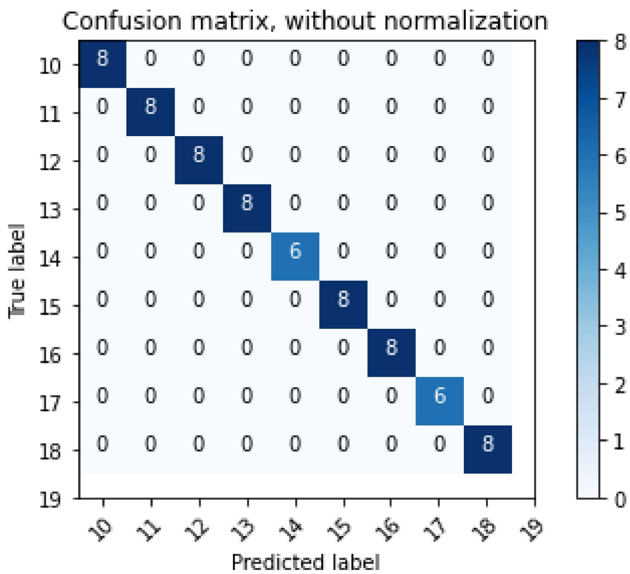
In [58]:
```python
#for classes 0-9
print('Confusion matrix, without normalization')
print(cnf_matrix)

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')
```

```
Confusion matrix, without normalization
[[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 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 0 0 0 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 2 0 0 0 0 0 0 0 6 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
```



In [59]:
```
#for classes 10-19
plt.figure()
plot_confusion_matrix(cnf_matrix[11:20,11:20], classes=[10,11,12,13,14,15,16,17,1
                      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
```




```
Confusion matrix:
[[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 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 0 0 0 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 2 0 0 0 0 0 0 0 6 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	0.80	1.00	0.89	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	0.80	1.00	0.89	8
11	1.00	1.00	1.00	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	0.75	0.86	8
16	1.00	1.00	1.00	8
17	0.80	1.00	0.89	8
18	1.00	0.75	0.86	8
19	1.00	1.00	1.00	8
accuracy			0.95	160
macro avg	0.96	0.95	0.95	160
weighted avg	0.96	0.95	0.95	160

In [ ]: