

Importing necessary libraries

```
In [1]: 1 import matplotlib.pyplot as plt
2 import numpy as np
3 from livelossplot import PlotLossesKeras
4 import seaborn as sns
5 sns.set_theme(context='poster')
6 sns.set_context("paper")
7 %matplotlib inline
8
9 from keras.models import Sequential, Input, Model
10 from keras.layers import Dense, Dropout, Flatten
11 from keras.layers import Conv2D, MaxPooling2D
12 from keras.layers.advanced_activations import ReLU
13 from tensorflow.keras.utils import to_categorical
14 from sklearn.model_selection import train_test_split
```

Loading data from file

```
In [2]: 1 data = np.load("ORL_faces.npz")
2 for i, lst in zip(range(4), data.files):
3     if i==0:
4         testY = data[lst]
5     elif i==1:
6         testX = data[lst]
7     elif i==2:
8         trainX = data[lst]
9     else:
10        trainY = data[lst]
11
12 trainX = trainX.reshape((240,112,92))
13 testX = testX.reshape((160,112,92))
14
15 print("Training data shape :", trainX.reshape((240,112,92)).shape, trainY.shape)
16 print("Test data shape :", testX.reshape((160,112,92)).shape, testY.shape)
```

```
Training data shape : (240, 112, 92) (240,)
Test data shape : (160, 112, 92) (160,)
```

Unique classes from train set

```
In [3]: 1 classes = np.unique(trainY)
2 nClasses = len(classes)
3 print('Total number of classes : ', classes)
4 print('Classes : ', nClasses)
```

```
Total number of classes : [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19]
Classes : 20
```

Display the first image in training and test data

```
In [4]: 1 plt.subplot(121)
2 plt.imshow(trainX[0,:,:], cmap='gray')
3 plt.title("Train Data - Ground Truth : {}".format(trainY[0]))
4
5 plt.subplot(122)
6 plt.imshow(testX[0,:,:], cmap='gray')
7 plt.title("Test Data - Ground Truth : {}".format(testY[0]))
8
9 plt.show()
```



```
In [5]: 1 # Reshaping array and scaling pixel values to feed into the model
```

```
In [6]: 1 trainX = trainX.reshape(-1,112,92,1)
2 testX = testX.reshape(-1,112,92,1)
3
4 trainX = trainX/255
5 testX = testX/255
6
7
```

Change the labels from categorical to one-hot encoding

```
In [7]: 1 trainY_one_hot = to_categorical(trainY)
2 testY_one_hot = to_categorical(testY)
3
4 # Display the change for category label using one-hot encoding
5 print('Original label:', trainY[0])
6 print('After conversion to one-hot:', trainY_one_hot[0])
```

Original label: 0

After conversion to one-hot: [1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]

```
In [8]: 1 print(np.random.choice(np.ravel(np.where(trainY==0)),size=3,replace=False))
```

[4 6 0]

Splitting train data into training and validation set

In [18]:

```
1 #train_X,valid_X,train_label,valid_label = train_test_split(trainX, trainY_one_hot,
2
3 '''
4 Splitting training data into train and validation. 3 random images were choosen fro
5 '''
6 def vaidation_data_index():
7     uniq_label = np.unique(trainY)
8     lst = []
9     for val in uniq_label:
10         rand = np.random.choice(np.ravel(np.where(trainY==val)),size=3,replace=False)
11         lst+=(list(rand))
12     return lst
13
14 validation_list = vaidation_data_index()
15
16 train_X = np.delete(trainX,validation_list,axis=0)
17 train_label = np.delete(trainY_one_hot,validation_list,axis=0)
18 valid_X = trainX[validation_list]
19 valid_label = trainY_one_hot[validation_list]
```

Build Model

```
In [10]: 1 model = Sequential()
2 model.add(Conv2D(64,kernel_size=(3,3),input_shape=(112,92,1),padding='same'))
3 model.add(ReLU())
4 model.add(MaxPooling2D((2,2),padding='same'))
5
6 model.add(Conv2D(64,kernel_size=(3,3),padding='same'))
7 model.add(ReLU())
8 model.add(MaxPooling2D((2,2),padding='same'))
9
10 model.add(Flatten())
11 model.add(Dense(128,activation='relu'))
12 model.add(Dropout(0.40))
13 model.add(Dense(20,activation='softmax'))
14
15 model.compile(loss='categorical_crossentropy',optimizer='Adam',metrics=['accuracy'])
16 model.summary()
```

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|--------------------------------|---------------------|---------|
| ===== | | |
| conv2d (Conv2D) | (None, 112, 92, 64) | 640 |
| re_lu (ReLU) | (None, 112, 92, 64) | 0 |
| max_pooling2d (MaxPooling2D) | (None, 56, 46, 64) | 0 |
| conv2d_1 (Conv2D) | (None, 56, 46, 64) | 36928 |
| re_lu_1 (ReLU) | (None, 56, 46, 64) | 0 |
| max_pooling2d_1 (MaxPooling2D) | (None, 28, 23, 64) | 0 |
| flatten (Flatten) | (None, 41216) | 0 |
| dense (Dense) | (None, 128) | 5275776 |
| dropout (Dropout) | (None, 128) | 0 |
| dense_1 (Dense) | (None, 20) | 2580 |
| ===== | | |
| Total params: 5,315,924 | | |
| Trainable params: 5,315,924 | | |
| Non-trainable params: 0 | | |

Fitting the model on train data

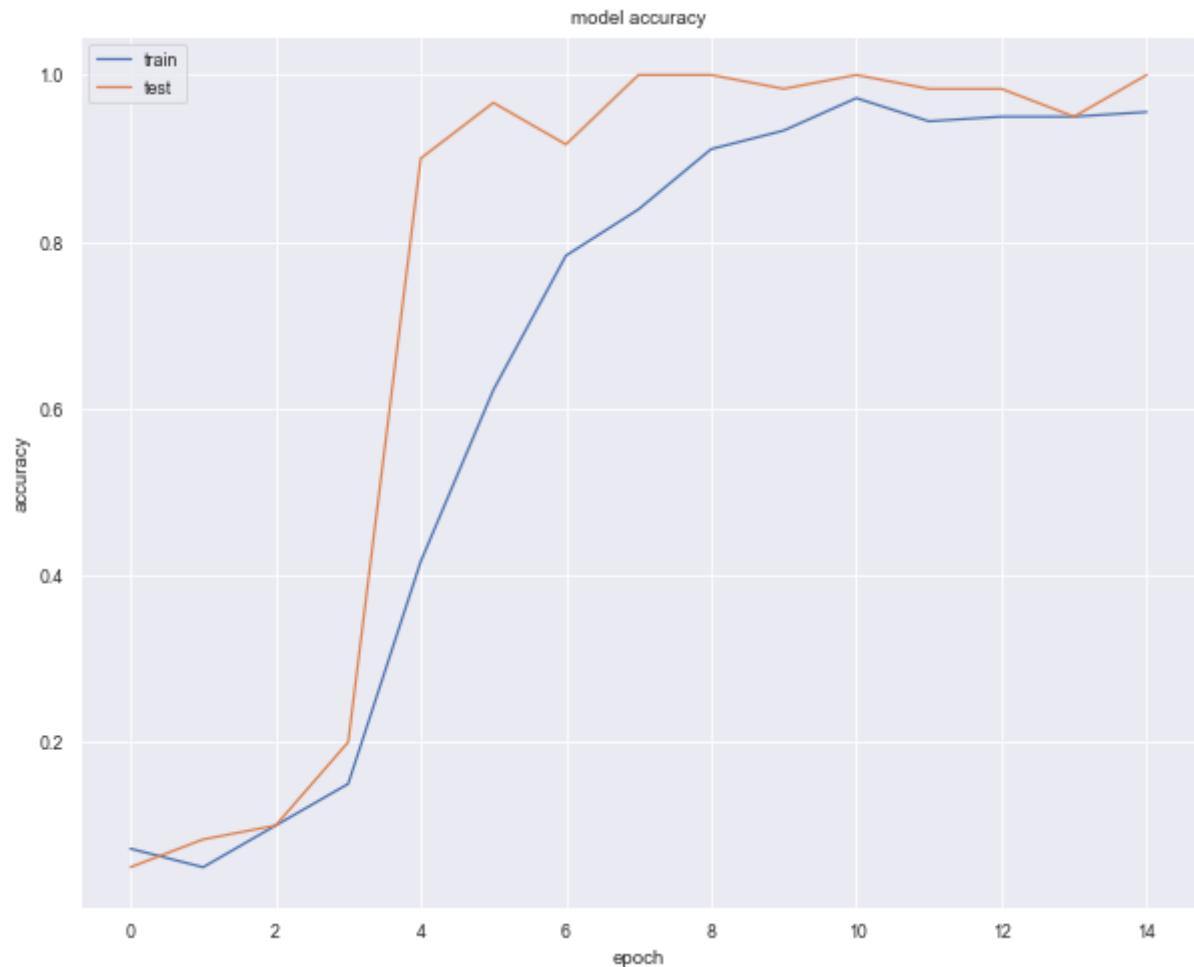
```
In [11]: 1 trained_model = model.fit(train_X,train_label,batch_size=10,epochs=15,validation_da
```

```
Epoch 1/15
18/18 [=====] - 3s 158ms/step - loss: 3.1338 - accuracy: 0.07
22 - val_loss: 2.9937 - val_accuracy: 0.0500
Epoch 2/15
18/18 [=====] - 3s 151ms/step - loss: 2.9943 - accuracy: 0.05
00 - val_loss: 2.9741 - val_accuracy: 0.0833
Epoch 3/15
18/18 [=====] - 3s 151ms/step - loss: 2.9522 - accuracy: 0.10
00 - val_loss: 2.8655 - val_accuracy: 0.1000
Epoch 4/15
18/18 [=====] - 3s 160ms/step - loss: 2.7169 - accuracy: 0.15
00 - val_loss: 2.3886 - val_accuracy: 0.2000
Epoch 5/15
18/18 [=====] - 3s 158ms/step - loss: 2.0256 - accuracy: 0.41
67 - val_loss: 1.4184 - val_accuracy: 0.9000
Epoch 6/15
18/18 [=====] - 3s 157ms/step - loss: 1.2370 - accuracy: 0.62
22 - val_loss: 0.6555 - val_accuracy: 0.9667
Epoch 7/15
18/18 [=====] - 3s 157ms/step - loss: 0.7684 - accuracy: 0.78
33 - val_loss: 0.4537 - val_accuracy: 0.9167
Epoch 8/15
18/18 [=====] - 3s 158ms/step - loss: 0.5432 - accuracy: 0.83
89 - val_loss: 0.2077 - val_accuracy: 1.0000
Epoch 9/15
18/18 [=====] - 3s 162ms/step - loss: 0.3554 - accuracy: 0.91
11 - val_loss: 0.1010 - val_accuracy: 1.0000
Epoch 10/15
18/18 [=====] - 3s 162ms/step - loss: 0.2479 - accuracy: 0.93
33 - val_loss: 0.0842 - val_accuracy: 0.9833
Epoch 11/15
18/18 [=====] - 3s 160ms/step - loss: 0.1409 - accuracy: 0.97
22 - val_loss: 0.0336 - val_accuracy: 1.0000
Epoch 12/15
18/18 [=====] - 3s 158ms/step - loss: 0.1687 - accuracy: 0.94
44 - val_loss: 0.0584 - val_accuracy: 0.9833
Epoch 13/15
18/18 [=====] - 3s 159ms/step - loss: 0.1342 - accuracy: 0.95
00 - val_loss: 0.0583 - val_accuracy: 0.9833
Epoch 14/15
18/18 [=====] - 3s 161ms/step - loss: 0.1606 - accuracy: 0.95
00 - val_loss: 0.1153 - val_accuracy: 0.9500
Epoch 15/15
18/18 [=====] - 3s 161ms/step - loss: 0.1614 - accuracy: 0.95
56 - val_loss: 0.0443 - val_accuracy: 1.0000
```

Summarize history for accuracy and Loss over the epochs

In [15]:

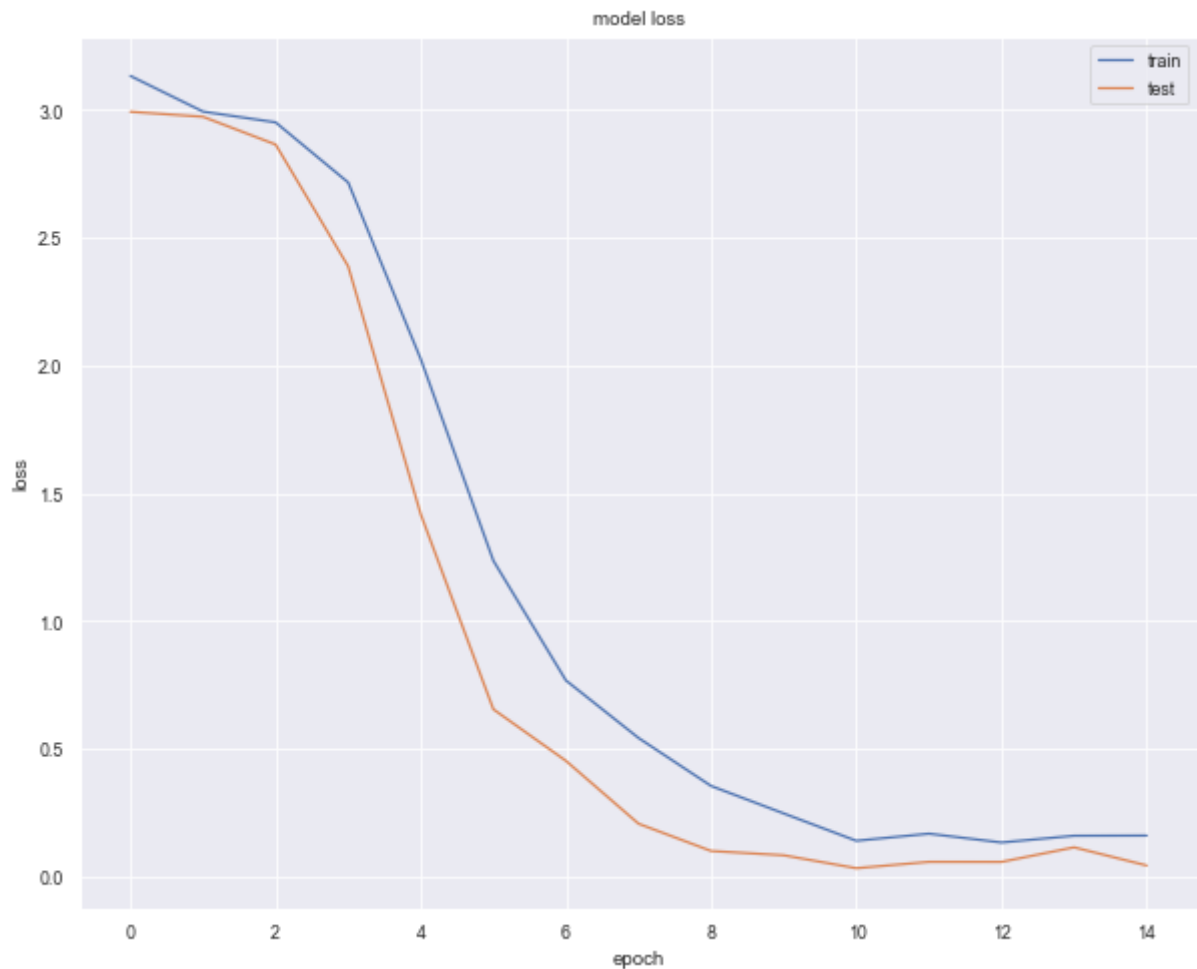
```
1 # summarize history for accuracy
2 plt.figure(figsize=(10,8))
3 plt.plot(trained_model.history['accuracy'])
4 plt.plot(trained_model.history['val_accuracy'])
5 plt.title('model accuracy')
6 plt.ylabel('accuracy')
7 plt.xlabel('epoch')
8 plt.legend(['train', 'test'], loc='upper left')
9 plt.show()
10 plt.savefig("Model_Accuracy.jpeg")
```



<Figure size 432x288 with 0 Axes>

In [16]:

```
1 # summarize history for loss
2 plt.figure(figsize=(10,8))
3 plt.plot(trained_model.history['loss'])
4 plt.plot(trained_model.history['val_loss'])
5 plt.title('model loss')
6 plt.ylabel('loss')
7 plt.xlabel('epoch')
8 plt.legend(['train', 'test'], loc='upper right')
9 plt.show()
10 plt.savefig("Model_Loss.jpeg")
```



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Predication on test data set and checking the acuracy

In [17]:

```
1 prediction = model.evaluate(testX,testY_one_hot,verbose=0)
2 print("Test Loss : ",round(prediction[0],4))
3 print(r"Test Accuracy (%age): ",round(prediction[1]*100,4))
```

Test Loss : 0.1683

Test Accuracy (%age): 96.25

