

```

In [1]: from scipy import io as sio
import tensorflow as tf
import numpy as np
import keras
from keras.models import Sequential, Input, Model
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras.layers.normalization import BatchNormalization
from keras.layers.advanced_activations import LeakyReLU

import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

#step 1 loading and preprocessing EMNIST dataset

mat = sio.loadmat('emnist-letters.mat')
data = mat['dataset']

# this type of sample did not work as the other way of splitting so I pass for now
x_train, x_test, y_train, y_test = train_test_split(data['train'][0,0]['images'][0,0],
                                                    data['train'][0,0]['images'][0,0],
                                                    test_size=0.2)

#
rate=42
random_s

#define what the training and testing data are

x_train = data['train'][0,0]['images'][0,0]

```

```

y_train = data['train'][0,0]['labels'][0,0]
x_test = data['test'][0,0]['images'][0,0]
y_test = data['test'][0,0]['labels'][0,0]

#I did not use cross-validation by now since it was not that important in this case
_train = data['test'][0,0]['labels'][0,0]
#using cross validation
val_start = x_train.shape[0] - x_test.shape[0]
_val = x_train[val_start:x_train.shape[0]]
_val = y_train[val_start:y_train.shape[0]]
_train = x_train[0:val_start]
_train = y_train[0:val_start]

#reshape the arrays into image

x_train = x_train.reshape( (x_train.shape[0], 28, 28), order='F')


_train.shape, y_train.shape

_test.shape, y_test.shape


_train = x_train[..., tf.newaxis]
_test = x_test[..., tf.newaxis]

_train.shape

_test.shape

p.min(x_train), np.max(x_train)

```

```

#x_train = x_train / 255.
#x_test=x_test/255

#p.min(x_train), np.max(x_train)
#x_train = x_train.reshape( (x_train.shape[0], 28, 28), order='F')

#y_train = y_train.reshape( (y_train.shape[0], 28, 28), order='F')'''
x_test = x_test.reshape( (x_test.shape[0], 28, 28), order='F')

#number of unique classes
classes = np.unique(y_train)
nClasses = len(classes)
print('Total number of outputs : ', nClasses)
print('Output classes : ', classes)

print('train shape', x_train.shape)
print('test shape', x_test.shape)

```

Using TensorFlow backend.

```

Total number of outputs : 26
Output classes : [ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 1
8 19 20 21 22 23 24
25 26]
train shape (124800, 28, 28)
test shape (20800, 28, 28)

```

```

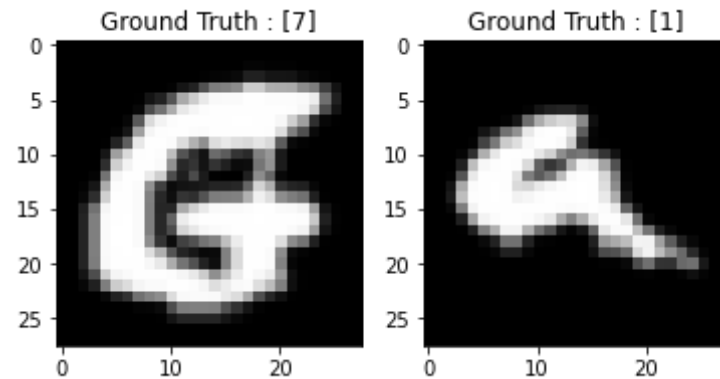
In [2]: # Display the image in training data
plt.subplot(121)
plt.imshow(x_train[1,:,:], cmap='gray')
plt.title("Ground Truth : {}".format(y_train[1]))

# Display the first image in testing data
plt.subplot(122)

```

```
plt.imshow(x_test[0,:], cmap='gray')
plt.title("Ground Truth : {}".format(y_test[0]))
```

Out[2]: Text(0.5, 1.0, 'Ground Truth : [1]')



```
In [3]: #reshaping the training and testing data
x_train = x_train.reshape(-1, 28,28, 1)
x_test = x_test.reshape(-1, 28,28, 1)
x_train.shape, x_test.shape
```

Out[3]: ((124800, 28, 28, 1), (20800, 28, 28, 1))

```
In [4]: #converting the data from int8 to float32

x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train = x_train / 255.
x_test = x_test / 255.
```

```
In [5]: #need to convert the class label data in one encoding vector.
#So let's convert the training and testing labels into one-hot encoding
vectors
```

```
from keras.utils import to_categorical
y_train_one_hot = to_categorical(y_train)
y_test_one_hot = to_categorical(y_test)
```

```
# Display the change for category label using one-hot encoding
print('Original label:', y_train[3])
print('After conversion to one-hot:', y_train_one_hot[0])

#from sklearn.model_selection import train_test_split
#x_train,valid_X,train_label,valid_label=train_test_split(x_train, y_train_one_hot, test_size=0.2, random_state=13)

#x_train.shape,valid_X.shape,train_label.shape,valid_label.shape
```

```
Original label: [15]
After conversion to one-hot: [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
0. 0. 0. 0. 0. 0. 0. 0. 0. 1.
0. 0. 0.]
```

```
In [6]: batch_size = 64
epochs = 13
num_classes = 26
```

```
In [7]: #built the model

model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),activation='linear',input_shape=(28,28,1),padding='same'))
model.add(LeakyReLU(alpha=0.1))
model.add(MaxPooling2D((2, 2),padding='same'))
model.add(Conv2D(64, (3, 3), activation='linear',padding='same'))
model.add(LeakyReLU(alpha=0.1))
model.add(MaxPooling2D(pool_size=(2, 2),padding='same'))
model.add(Conv2D(128, (3, 3), activation='linear',padding='same'))
model.add(LeakyReLU(alpha=0.1))
model.add(MaxPooling2D(pool_size=(2, 2),padding='same'))
model.add(Flatten())
model.add(Dense(128, activation='linear'))
model.add(LeakyReLU(alpha=0.1))
model.add(Dense(num_classes+1, activation='softmax'))
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(),metrics=['accuracy'])
```

```
model.summary()
```

```
'''Let's visualize the layers that you created in the above step by using the summary function. This will show some parameters (weights and biases) in each layer and also the total parameters in your model'''
```

```
#train the model/fitting
```

```
model_train = model.fit(x_train, y_train_one_hot, batch_size=batch_size, epochs=epochs, verbose =1)  
#no validation set needed for now validation_data=(valid_X, valid_label))
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 28, 28, 32)	320
leaky_re_lu_1 (LeakyReLU)	(None, 28, 28, 32)	0
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 32)	0
conv2d_2 (Conv2D)	(None, 14, 14, 64)	18496
leaky_re_lu_2 (LeakyReLU)	(None, 14, 14, 64)	0
max_pooling2d_2 (MaxPooling2D)	(None, 7, 7, 64)	0
conv2d_3 (Conv2D)	(None, 7, 7, 128)	73856
leaky_re_lu_3 (LeakyReLU)	(None, 7, 7, 128)	0
max_pooling2d_3 (MaxPooling2D)	(None, 4, 4, 128)	0
flatten_1 (Flatten)	(None, 2048)	0

dense_1 (Dense)	(None, 128)	262272
leaky_re_lu_4 (LeakyReLU)	(None, 128)	0
dense_2 (Dense)	(None, 27)	3483

Total params: 358,427
 Trainable params: 358,427
 Non-trainable params: 0

Epoch 1/13
 124800/124800 [=====] - 208s 2ms/step - loss: 0.3779 - accuracy: 0.8778
 Epoch 2/13
 124800/124800 [=====] - 208s 2ms/step - loss: 0.1880 - accuracy: 0.9355
 Epoch 3/13
 124800/124800 [=====] - 195s 2ms/step - loss: 0.1565 - accuracy: 0.9446
 Epoch 4/13
 124800/124800 [=====] - 182s 1ms/step - loss: 0.1350 - accuracy: 0.95101s -
 Epoch 5/13
 124800/124800 [=====] - 178s 1ms/step - loss: 0.1191 - accuracy: 0.9555
 Epoch 6/13
 124800/124800 [=====] - 168s 1ms/step - loss: 0.1062 - accuracy: 0.9597
 Epoch 7/13
 124800/124800 [=====] - 166s 1ms/step - loss: 0.0959 - accuracy: 0.9625
 Epoch 8/13
 124800/124800 [=====] - 165s 1ms/step - loss: 0.0876 - accuracy: 0.9644
 Epoch 9/13
 124800/124800 [=====] - 185s 1ms/step - loss: 0.0789 - accuracy: 0.9675
 Epoch 10/13
 124800/124800 [=====] - 183s 1ms/step - loss: 0.0752 - accuracy: 0.9688

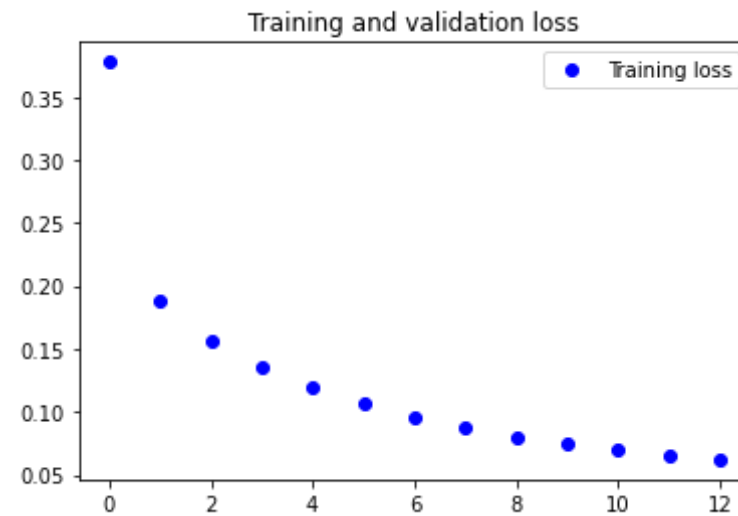
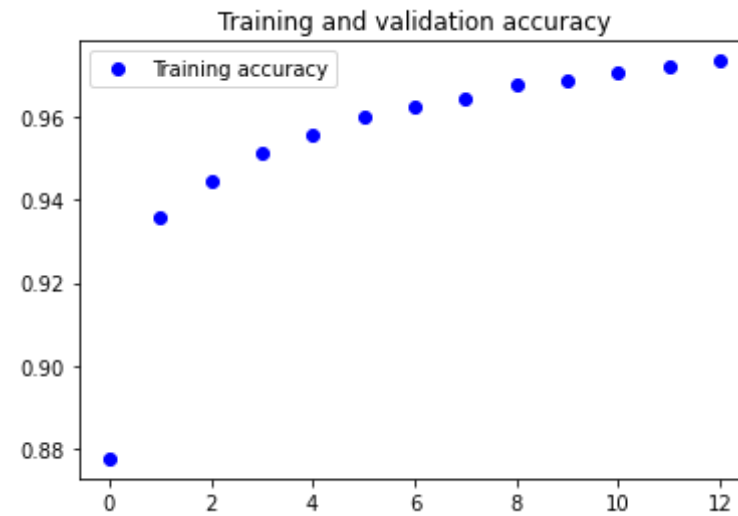
```
Epoch 11/13
124800/124800 [=====] - 182s 1ms/step - loss:
0.0693 - accuracy: 0.9706
Epoch 12/13
124800/124800 [=====] - 185s 1ms/step - loss:
0.0657 - accuracy: 0.9718
Epoch 13/13
124800/124800 [=====] - 189s 2ms/step - loss:
0.0622 - accuracy: 0.9733
```

```
In [8]: #test evaluation
test_eval = model.evaluate(x_test, y_test_one_hot, verbose=0)
print('Test loss:', test_eval[0])
print('Test accuracy:', test_eval[1])
```

```
Test loss: 0.24865888032202707
Test accuracy: 0.938605785369873
```

```
In [9]: #now we analyse our model and see what can be done to make it better

accuracy = model_train.history['accuracy']
#val_acc = model_train.history['val_accuracy']
loss = model_train.history['loss']
#val_loss = model_train.history['val_loss']
epochs = range(len(accuracy))
plt.plot(epochs, accuracy, 'bo', label='Training accuracy')
#plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochs, loss, 'bo', label='Training loss')
#plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
```

```
In [16]: #dropout
batch_size = 64
epochs = 2
num_classes = 26
```

```
In [17]: #CNN with the drop out layer
```

```

model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),activation='linear',padding='same',input_shape=(28,28,1)))
model.add(LeakyReLU(alpha=0.1))
model.add(MaxPooling2D((2, 2),padding='same'))
model.add(Dropout(0.25))
model.add(Conv2D(64, (3, 3), activation='linear',padding='same'))
model.add(LeakyReLU(alpha=0.1))
model.add(MaxPooling2D(pool_size=(2, 2),padding='same'))
model.add(Dropout(0.25))
model.add(Conv2D(128, (3, 3), activation='linear',padding='same'))
model.add(LeakyReLU(alpha=0.1))
model.add(MaxPooling2D(pool_size=(2, 2),padding='same'))
model.add(Dropout(0.4))
model.add(Flatten())
model.add(Dense(128, activation='linear'))
model.add(LeakyReLU(alpha=0.1))
model.add(Dropout(0.3))
model.add(Dense(num_classes+1, activation='softmax'))
model.compile(loss=keras.losses.categorical_crossentropy, optimizer=keras.optimizers.Adam(),metrics=['accuracy'])
model_train_dropout = model.fit(x_train, y_train_one_hot, batch_size=batch_size,epochs=epochs,verbose=1)

```

'''We add a dropout layer to overcome the problem of overfitting to some extent. Dropout randomly turns off a fraction of neurons during the training process, reducing the dependency on the training set by some amount.

How many fractions of neurons you want to turn off is decided by a hyperparameter, which can be tuned accordingly.

This way, turning off some neurons will not allow the network to memorize the training data since not all the neurons will be active at the same time and the inactive neurons will not be able to learn anything.'''

Epoch 1/2

124800/124800 [=====] - 208s 2ms/step - loss: 0.5960 - accuracy: 0.8099

Epoch 2/2

124800/124800 [=====] - 225s 2ms/step - loss: 0.3037 - accuracy: 0.9000

Out[17]: 'We add a dropout layer to overcome the problem of overfitting to some extent. Dropout randomly turns off a fraction of neurons during the training process, reducing the dependency on the training set by some amount.\nHow many fractions of neurons you want to turn off is decided by a hyperparameter, which can be tuned accordingly.\nThis way, turning off some neurons will not allow the network to memorize the training data since not all the neurons will be active at the same time and the inactive neurons will not be able to learn anything.'

```
In [29]: #model summary
model.summary()

#now we analyse our model and see what can be done to make it better

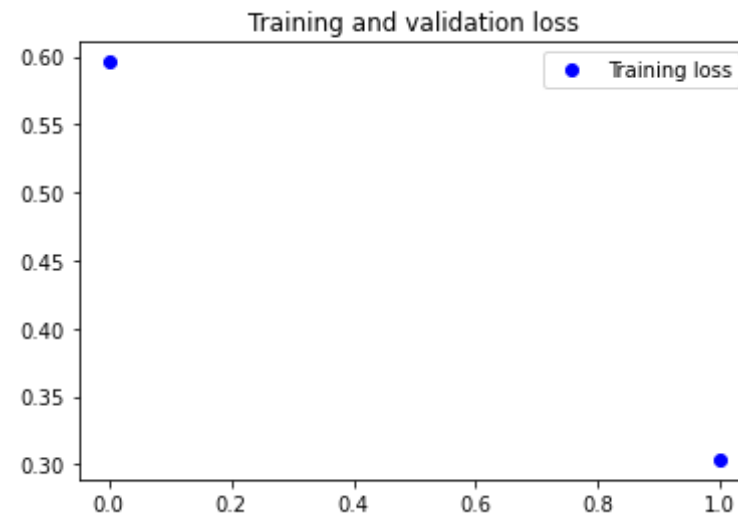
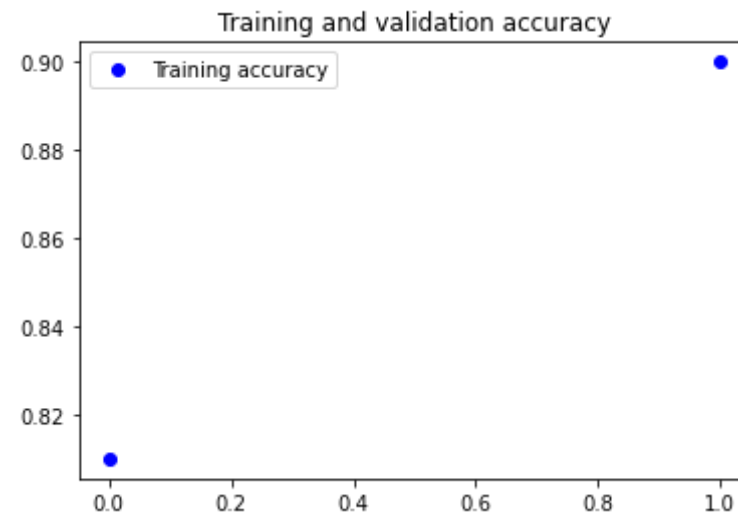
accuracy = model_train_dropout.history['accuracy']
#val_acc = model_train.history['val_accuracy']
loss = model_train_dropout.history['loss']
#val_loss = model_train.history['val_loss']
epochs = range(len(accuracy))
plt.plot(epochs, accuracy, 'bo', label='Training accuracy')
#plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochs, loss, 'bo', label='Training loss')
#plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()

#save the model to use for testing
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_13 (Conv2D)	(None, 28, 28, 32)	320
leaky_re_lu_17 (LeakyReLU)	(None, 28, 28, 32)	0
max_pooling2d_13 (MaxPooling)	(None, 14, 14, 32)	0
dropout_13 (Dropout)	(None, 14, 14, 32)	0
conv2d_14 (Conv2D)	(None, 14, 14, 64)	18496
leaky_re_lu_18 (LeakyReLU)	(None, 14, 14, 64)	0
max_pooling2d_14 (MaxPooling)	(None, 7, 7, 64)	0
dropout_14 (Dropout)	(None, 7, 7, 64)	0
conv2d_15 (Conv2D)	(None, 7, 7, 128)	73856
leaky_re_lu_19 (LeakyReLU)	(None, 7, 7, 128)	0
max_pooling2d_15 (MaxPooling)	(None, 4, 4, 128)	0
dropout_15 (Dropout)	(None, 4, 4, 128)	0
flatten_5 (Flatten)	(None, 2048)	0
dense_9 (Dense)	(None, 128)	262272
leaky_re_lu_20 (LeakyReLU)	(None, 128)	0
dropout_16 (Dropout)	(None, 128)	0
dense_10 (Dense)	(None, 27)	3483
Total params: 358,427		

Trainable params: 358,427
Non-trainable params: 0



```
In [30]: model.save("epic_let_read.model")
```

```
In [31]: new_model = tf.keras.models.load_model("epic_let_read.model")
```

```
In [32]: prediktions = new_model.predict(x_test)
print(prediktions)
```

```
[[1.2393689e-06 9.2087340e-01 8.9413326e-05 ... 3.9757852e-04
 3.4936613e-05 6.1814341e-04]
 [1.2356492e-09 9.9693751e-01 3.0252834e-06 ... 8.4265207e-07
 2.5167697e-06 3.3734898e-06]
 [6.6081758e-11 9.9269682e-01 3.5546526e-07 ... 1.1386664e-08
 2.4139798e-08 3.6830606e-06]
 ...
 [7.4849111e-12 1.1405632e-05 3.9312499e-07 ... 7.0474493e-06
 1.6392974e-08 9.9944478e-01]
 [3.8649004e-09 1.2394096e-04 7.3254792e-05 ... 7.2232610e-06
 3.1839065e-06 9.9828905e-01]
 [5.6445500e-14 2.4358385e-06 2.4650814e-07 ... 5.2607788e-06
 9.4131170e-10 9.9993896e-01]]
```

```
In [33]: print(np.argmax(prediktions[6452]))
```

```
12
```

```
In [ ]:
```

```
In [34]: test_eval = model.evaluate(x_test, y_test_one_hot, verbose=1)
```

```
20800/20800 [=====] - 8s 398us/step
```

```
In [35]: print('Test loss:', test_eval[0])
print('Test accuracy:', test_eval[1])
```

```
Test loss: 0.21073072996581546
Test accuracy: 0.927307665348053
```

```
In [36]: predicted_classes = model.predict(x_test)
```

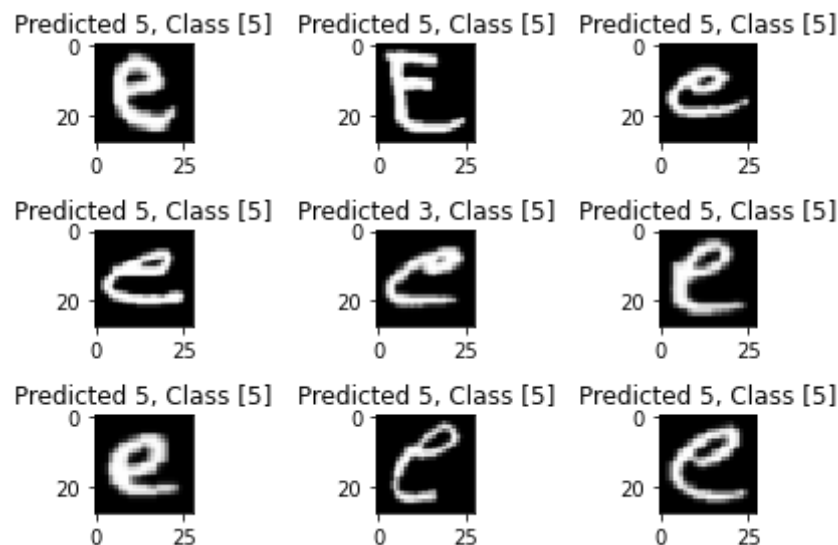
```
In [37]: #need to use argmax function to find the one prediction with the highest probability
predicted_classes = np.argmax(np.round(predicted_classes),axis=1)
```

```
In [38]: predicted_classes.shape, y_test.shape
```

```
Out[38]: ((20800,), (20800, 1))
```

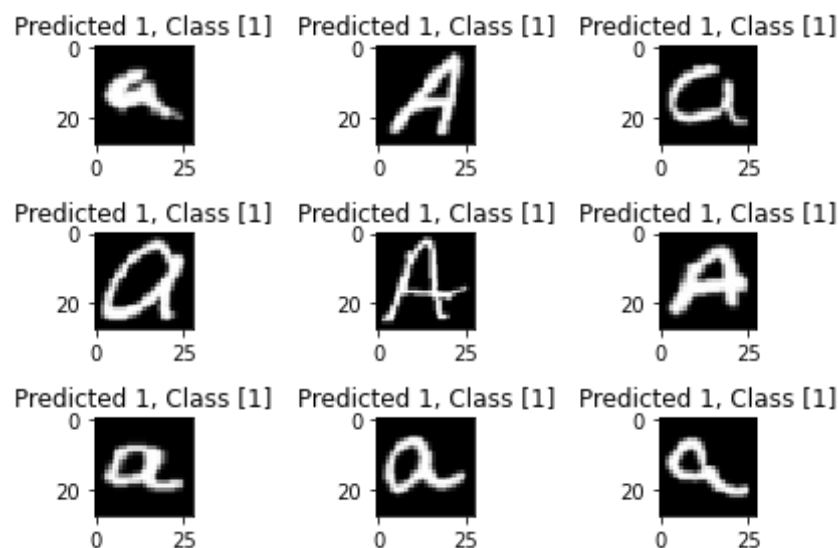
```
In [39]: correct = np.where(predicted_classes[3422]==y_test)[0]
print ("Found %d correct labels" % len(correct))
for i, correct in enumerate(correct[:9]):
    plt.subplot(3,3,i+1)
    plt.imshow(x_test[correct].reshape(28,28), cmap='gray', interpolation='none')
    plt.title("Predicted {}, Class {}".format(predicted_classes[correct], y_test[correct]))
plt.tight_layout()
```

Found 800 correct labels



```
In [40]: #now for the incorrect ones
incorrect = np.where(predicted_classes[3422]!=y_test)[0]
print ("Found %d incorrect labels" % len(incorrect))
for i, incorrect in enumerate(incorrect[:9]):
    plt.subplot(3,3,i+1)
    plt.imshow(x_test[incorrect].reshape(28,28), cmap='gray', interpolation='none')
    plt.title("Predicted {}, Class {}".format(predicted_classes[incorrect], y_test[incorrect]))
plt.tight_layout()
```

Found 20000 incorrect labels



```
In [41]: '''Classification report will help us in identifying the misclassified
classes in more detail.
You will be able to observe for which class the model performed bad out
of the given 26 classes'''
```

```
from sklearn.metrics import classification_report
target_names = ["Class {}".format(i) for i in range(num_classes+1)]
```



```
print(classification_report(y_test, predicted_classes, target_names=target_names))
```

	precision	recall	f1-score	support
Class 0	0.00	0.00	0.00	0
Class 1	0.93	0.92	0.93	800
Class 2	0.99	0.95	0.97	800
Class 3	0.96	0.94	0.95	800
Class 4	0.97	0.92	0.94	800
Class 5	0.95	0.95	0.95	800
Class 6	0.99	0.94	0.96	800
Class 7	0.90	0.75	0.82	800
Class 8	0.94	0.93	0.94	800
Class 9	0.67	0.85	0.75	800
Class 10	0.97	0.92	0.95	800
Class 11	0.99	0.92	0.96	800
Class 12	0.79	0.61	0.69	800
Class 13	0.98	0.97	0.98	800
Class 14	0.94	0.96	0.95	800
Class 15	0.91	0.99	0.95	800
Class 16	0.98	0.98	0.98	800
Class 17	0.83	0.84	0.84	800
Class 18	0.98	0.92	0.95	800
Class 19	0.97	0.98	0.98	800
Class 20	0.94	0.98	0.96	800
Class 21	0.95	0.93	0.94	800
Class 22	0.93	0.93	0.93	800
Class 23	0.99	0.97	0.98	800
Class 24	0.97	0.95	0.96	800
Class 25	0.95	0.97	0.96	800
Class 26	0.98	0.98	0.98	800
accuracy			0.92	20800
macro avg	0.90	0.89	0.89	20800
weighted avg	0.94	0.92	0.93	20800

```
c:\users\serem1\appdata\local\programs\python\python38\lib\site-packages\sklearn\metrics\_classification.py:1221: UndefinedMetricWarning:
```

```
Recall and F-score are ill-defined and being set to 0.0 in labels with no true samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

In []:

In []: