

IBM Machine Learning

Course 5: Deep Learning

Topic: English Handwritten Characters

1. Introduction

We will work on the handwritten English dataset, which consists of 3410 images. The characters include 0-9, A-Z and a-z. 62 classes in total and each image is map to only one label. The objective is to classify the images to the correct label. The dataset can be found in this link: <https://www.kaggle.com/dnu/vulgate/english-handwritten-characters-dataset?select=mn>

2. Exploratory Data Analysis

2.1 import the data

```
In [141]: ## import the library
import numpy as np
import pandas as pd
import matplotlib.image as mpimg
import matplotlib.pyplot as plt

from PIL import Image
import keras
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation, Flatten
from tensorflow.keras.layers import Conv2D, MaxPooling2D
from tensorflow.keras.optimizers import Adam, SGD, RMSprop
import warnings

warnings.filterwarnings('ignore')
```

```
In [142]: ## load the data label
df=pd.read_csv("data/english.csv")
```

```
In [143]: ## the first 5 rows in the label file
df.head()
```

```
Out[143]:
```

	image	label
0	img/img001-001.png	0
1	img/img001-002.png	0
2	img/img001-003.png	0
3	img/img001-004.png	0
4	img/img001-005.png	0

```
In [144]: ## As describe in introduction, there 3410 records.
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3410 entries, 0 to 3409
Data columns (total 2 columns):
 #   Column      Non-Null Count  Dtype
---  ---
 0   image      3410 non-null    object
 1   label      3410 non-null    object
dtypes: object(2)
memory usage: 13.4+ KB
```

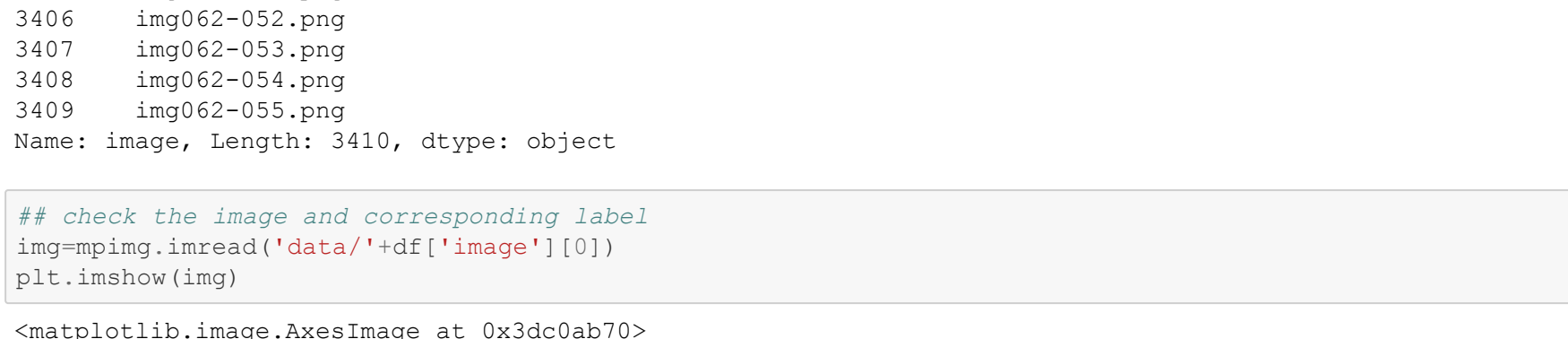
```
In [145]: ## Process the image column
df['image']=df['image'].str.split('/').str[1]
df['image']
```

```
Out[145]:
```

0	img001-001.png
1	img001-002.png
2	img001-003.png
3	img001-004.png
4	img001-005.png
...	...
3405	img062-051.png
3406	img062-052.png
3407	img062-053.png
3408	img062-054.png
3409	img062-055.png
Name: image, length: 3410, dtype: object	

```
In [146]: ## check the image and corresponding label
img=mpimg.imread('data/'+df['image'][0])
plt.imshow(img)
```

```
Out[146]: <matplotlib.image.AxesImage at 0x3dc0ab70>
```



```
In [147]: df['label'][0]
```

```
Out[147]: '0'
```

2.2 convert each image to 2D array

From the image we can see that each image have 900 pixels in height and 1200 pixels in width. We have 3409 images. If we use the original dimension, it will need a few GB memory, we will compress and convert each image to an array of size(30, 40)

```
In [148]: from sklearn.preprocessing import LabelEncoder

# before resize
image=Image.open('data/'+df['image'][0]).convert('L')
```

```
In [149]: print(image.format)
print(image.size)
print(image.mode)
```

```
None
(1200, 900)
L
```

```
In [150]: # after resize
new_image=image.resize((40,30))
plt.imshow(new_image)
```

```
Out[150]: <matplotlib.image.AxesImage at 0x3d9596a0>
```

```
In [151]: # the size
np.asarray(new_image).shape
```

```
Out[151]: (30, 40)
```

```
In [152]: # create the dataset for the pixel value of each image
l=[]
for image in df['image']:
    rawData=np.asarray(image.open('data/'+image).convert('L')).resize((40,30))
    l.append(rawData)
```

```
In [153]: # convert to numpy array
len(l)
X=np.array(l)
X.shape
```

```
Out[153]: (3410, 30, 40)
```

```
In [154]: # create the data for label
y=df['label']
```

```
In [155]: # creating instance of labelencoder
labelencoder = LabelEncoder()

# Assigning numerical values
y=labelencoder.fit_transform(y)
```

2.3 Data preprocessing

```
In [156]: # Let's make everything float and scale
X=X.astype('float32')
X/=255
```

2.4 Data splitted into training and test

```
In [157]: from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(X, y,
                                                    stratify=y,
                                                    test_size=0.25)
```

```
In [158]: x_train.shape
```

```
Out[158]: (2557, 30, 40)
```

3. Build Model

3.1 Get a baseline performance using Random Forest

```
In [159]: ## flatten our data
x_train_flat=x_train.reshape(len(x_train), -1)
x_test_flat=x_test.reshape(len(x_test), -1)
```

```
In [160]: ## the size of training
print('x_train_flat shape:', x_train_flat.shape)

x_train_flat shape: (2557, 1200)
```

```
In [161]: ## the size of testing
print('x_test_flat shape:', x_test_flat.shape)

x_test_flat shape: (853, 1200)
```

```
In [162]: import datetime
#used to help some of the timing functions
now = datetime.datetime.now
```

```
In [163]: from sklearn.metrics import confusion_matrix, precision_recall_curve, roc_auc_score, roc_curve, accuracy_score
from sklearn.ensemble import RandomForestClassifier

## Train the RF Model
t = now()
rf_model = RandomForestClassifier(n_estimators=200)
rf_model.fit(x_train_flat, y_train)
print("Training time: %s" % (now() - t))

Training time: 0:00:02.186125
```

```
In [164]: # Make predictions on the test set - both "hard" predictions, and the scores (percent of trees voting yes)
y_pred_class_rf = rf_model.predict(x_test_flat)
y_pred_prob_rf = rf_model.predict_proba(x_test_flat)

print('accuracy is {:.3f}'.format(accuracy_score(y_test,y_pred_class_rf)))

accuracy is 0.449
```

```
In [165]: confusion_matrix(y_test,y_pred_class_rf)
```

```
Out[165]: array([[ 4, 0, 0, ..., 0, 0, 0],
 [ 0, 10, 0, ..., 0, 0, 0],
 [ 0, 0, 10, ..., 0, 0, 0],
 ...,
 [ 0, 0, 0, ..., 4, 0, 1],
 [ 0, 0, 0, ..., 1, 5, 0],
 [ 0, 0, 1, ..., 1, 0, 5]], dtype=int64)
```

As we can see above, the training time is long and the accuracy is quite low(less than 50%)

3.2 Build a full connected neural network

```
In [166]: num_classes = len(set(y))

y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)
```

```
In [167]: model_1=Sequential()
model_1.add(Dense(100,input_shape=(1200,), activation='sigmoid'))
model_1.add(Dense(62,activation='softmax'))
```

```
In [168]: model_1.summary()
```

```
Model: "sequential_9"
```

Layer (type)	Output Shape	Param #
dense_10 (Dense)	(None, 100)	120100
dense_11 (Dense)	(None, 62)	6262
Total params: 126,362		
Trainable params: 126,362		
Non-trainable params: 0		


```

In [69]: # Compile the model with Optimizer, Loss Function and Metrics
optimizer = keras.optimizers.Adam(lr=0.0005)
model.compile(optimizer=optimizer, loss='categorical_crossentropy', metrics=['accuracy'])
train_hist = model.fit(x=train_flat, y=train, validation_data=(x_test_flat, y_test), epochs=200)

print('Training time: %s' % (now() - t))

Epoch 1/200
80/80 [=====] - 0s 1ms/step - loss: 4.1787 - accuracy: 0.0160 - val_loss: 4.1254 - val_accuracy: 0.0211
Epoch 2/200
80/80 [=====] - 0s 2ms/step - loss: 4.1243 - accuracy: 0.0235 - val_loss: 4.1042 - val_accuracy: 0.0457
Epoch 3/200
80/80 [=====] - 0s 1ms/step - loss: 4.0929 - accuracy: 0.0305 - val_loss: 4.0581 - val_accuracy: 0.0352
Epoch 4/200
80/80 [=====] - 0s 1ms/step - loss: 4.0302 - accuracy: 0.0372 - val_loss: 4.0225 - val_accuracy: 0.0399
Epoch 5/200
80/80 [=====] - 0s 1ms/step - loss: 3.9689 - accuracy: 0.0571 - val_loss: 3.9600 - val_accuracy: 0.0715
Epoch 6/200
80/80 [=====] - 0s 1ms/step - loss: 3.9033 - accuracy: 0.0755 - val_loss: 3.9012 - val_accuracy: 0.0680
Epoch 7/200
80/80 [=====] - 0s 1ms/step - loss: 3.8236 - accuracy: 0.1060 - val_loss: 3.8078 - val_accuracy: 0.0797
Epoch 8/200
80/80 [=====] - 0s 2ms/step - loss: 3.7624 - accuracy: 0.1279 - val_loss: 3.7249 - val_accuracy: 0.1020
Epoch 9/200
80/80 [=====] - 0s 2ms/step - loss: 3.6869 - accuracy: 0.1486 - val_loss: 3.7252 - val_accuracy: 0.1313
Epoch 10/200
80/80 [=====] - 0s 1ms/step - loss: 3.6252 - accuracy: 0.1658 - val_loss: 3.6671 - val_accuracy: 0.1348
Epoch 11/200
80/80 [=====] - 0s 1ms/step - loss: 3.5523 - accuracy: 0.1979 - val_loss: 3.6011 - val_accuracy: 0.1676
Epoch 12/200
80/80 [=====] - 0s 1ms/step - loss: 3.4790 - accuracy: 0.2081 - val_loss: 3.5933 - val_accuracy: 0.1524
Epoch 13/200
80/80 [=====] - 0s 1ms/step - loss: 3.4214 - accuracy: 0.2276 - val_loss: 3.4947 - val_accuracy: 0.1381
Epoch 14/200
80/80 [=====] - 0s 1ms/step - loss: 3.3563 - accuracy: 0.2464 - val_loss: 3.4636 - val_accuracy: 0.1676
Epoch 15/200
80/80 [=====] - 0s 1ms/step - loss: 3.2975 - accuracy: 0.2538 - val_loss: 3.4078 - val_accuracy: 0.2286
Epoch 16/200
80/80 [=====] - 0s 1ms/step - loss: 3.2486 - accuracy: 0.2663 - val_loss: 3.3459 - val_accuracy: 0.2005
Epoch 17/200
80/80 [=====] - 0s 1ms/step - loss: 3.1863 - accuracy: 0.2914 - val_loss: 3.2713 - val_accuracy: 0.2169
Epoch 18/200
80/80 [=====] - 0s 1ms/step - loss: 3.1430 - accuracy: 0.2804 - val_loss: 3.2718 - val_accuracy: 0.2450
Epoch 19/200
80/80 [=====] - 0s 1ms/step - loss: 3.0859 - accuracy: 0.3125 - val_loss: 3.2537 - val_accuracy: 0.2392
Epoch 20/200
80/80 [=====] - 0s 1ms/step - loss: 3.0384 - accuracy: 0.3269 - val_loss: 3.2062 - val_accuracy: 0.2579
Epoch 21/200
80/80 [=====] - 0s 1ms/step - loss: 3.0062 - accuracy: 0.3273 - val_loss: 3.1845 - val_accuracy: 0.2567
Epoch 22/200
80/80 [=====] - 0s 1ms/step - loss: 2.9514 - accuracy: 0.3359 - val_loss: 3.1596 - val_accuracy: 0.2521
Epoch 23/200
80/80 [=====] - 0s 1ms/step - loss: 2.9149 - accuracy: 0.3465 - val_loss: 3.1335 - val_accuracy: 0.2403
Epoch 24/200
80/80 [=====] - 0s 1ms/step - loss: 2.8736 - accuracy: 0.3531 - val_loss: 3.1048 - val_accuracy: 0.2755
Epoch 25/200
80/80 [=====] - 0s 1ms/step - loss: 2.8418 - accuracy: 0.3559 - val_loss: 3.0870 - val_accuracy: 0.2755
Epoch 26/200
80/80 [=====] - 0s 1ms/step - loss: 2.8027 - accuracy: 0.3582 - val_loss: 3.0549 - val_accuracy: 0.2767
Epoch 27/200
80/80 [=====] - 0s 1ms/step - loss: 2.7672 - accuracy: 0.3696 - val_loss: 3.0457 - val_accuracy: 0.2614
Epoch 28/200
80/80 [=====] - 0s 1ms/step - loss: 2.7379 - accuracy: 0.3766 - val_loss: 3.0259 - val_accuracy: 0.2532
Epoch 29/200
80/80 [=====] - 0s 1ms/step - loss: 2.7097 - accuracy: 0.3817 - val_loss: 3.0080 - val_accuracy: 0.3118
Epoch 30/200
80/80 [=====] - 0s 1ms/step - loss: 2.6711 - accuracy: 0.3817 - val_loss: 2.9578 - val_accuracy: 0.2884
Epoch 31/200
80/80 [=====] - 0s 1ms/step - loss: 2.6403 - accuracy: 0.3954 - val_loss: 2.9005 - val_accuracy: 0.2755
Epoch 32/200
80/80 [=====] - 0s 1ms/step - loss: 2.6155 - accuracy: 0.3989 - val_loss: 2.9317 - val_accuracy: 0.3107
Epoch 33/200
80/80 [=====] - 0s 1ms/step - loss: 2.5904 - accuracy: 0.4048 - val_loss: 2.8780 - val_accuracy: 0.3025
Epoch 34/200
80/80 [=====] - 0s 1ms/step - loss: 2.5607 - accuracy: 0.4095 - val_loss: 2.8480 - val_accuracy: 0.3036
Epoch 35/200
80/80 [=====] - 0s 1ms/step - loss: 2.5370 - accuracy: 0.3989 - val_loss: 2.8850 - val_accuracy: 0.3154
Epoch 36/200
80/80 [=====] - 0s 1ms/step - loss: 2.5103 - accuracy: 0.4247 - val_loss: 2.8910 - val_accuracy: 0.3025
Epoch 37/200
80/80 [=====] - 0s 1ms/step - loss: 2.4762 - accuracy: 0.4204 - val_loss: 2.8483 - val_accuracy: 0.3200
Epoch 38/200
80/80 [=====] - 0s 1ms/step - loss: 2.4574 - accuracy: 0.4251 - val_loss: 2.8940 - val_accuracy: 0.2814
Epoch 39/200
80/80 [=====] - 0s 1ms/step - loss: 2.4368 - accuracy: 0.4216 - val_loss: 2.8132 - val_accuracy: 0.3236
Epoch 40/200
80/80 [=====] - 0s 1ms/step - loss: 2.4204 - accuracy: 0.4357 - val_loss: 2.8085 - val_accuracy: 0.3294
Epoch 41/200
80/80 [=====] - 0s 1ms/step - loss: 2.3908 - accuracy: 0.4341 - val_loss: 2.8070 - val_accuracy: 0.3210
Epoch 42/200
80/80 [=====] - 0s 1ms/step - loss: 2.3757 - accuracy: 0.4361 - val_loss: 2.7840 - val_accuracy: 0.3239
Epoch 43/200
80/80 [=====] - 0s 1ms/step - loss: 2.3523 - accuracy: 0.4501 - val_loss: 2.7610 - val_accuracy: 0.3212
Epoch 44/200
80/80 [=====] - 0s 1ms/step - loss: 2.3358 - accuracy: 0.4505 - val_loss: 2.751 - val_accuracy: 0.3306
Epoch 45/200
80/80 [=====] - 0s 1ms/step - loss: 2.3184 - accuracy: 0.4580 - val_loss: 2.7678 - val_accuracy: 0.3236
Epoch 46/200
80/80 [=====] - 0s 1ms/step - loss: 2.2922 - accuracy: 0.4564 - val_loss: 2.7532 - val_accuracy: 0.3411
Epoch 47/200
80/80 [=====] - 0s 1ms/step - loss: 2.2790 - accuracy: 0.4540 - val_loss: 2.7175 - val_accuracy: 0.3294
Epoch 48/200
80/80 [=====] - 0s 1ms/step - loss: 2.2617 - accuracy: 0.4627 - val_loss: 2.7255 - val_accuracy: 0.3306
Epoch 49/200
80/80 [=====] - 0s 1ms/step - loss: 2.2471 - accuracy: 0.4724 - val_loss: 2.7612 - val_accuracy: 0.3306
Epoch 50/200
80/80 [=====] - 0s 1ms/step - loss: 2.2327 - accuracy: 0.4685 - val_loss: 2.8070 - val_accuracy: 0.3341
Epoch 51/200
80/80 [=====] - 0s 1ms/step - loss: 2.2081 - accuracy: 0.4732 - val_loss: 2.8080 - val_accuracy: 0.3318
Epoch 52/200
80/80 [=====] - 0s 1ms/step - loss: 2.1967 - accuracy: 0.4767 - val_loss: 2.8664 - val_accuracy: 0.3494
Epoch 53/200
80/80 [=====] - 0s 1ms/step - loss: 2.1778 - accuracy: 0.4814 - val_loss: 2.680 - val_accuracy: 0.3646
Epoch 54/200
80/80 [=====] - 0s 1ms/step - loss: 2.1605 - accuracy: 0.4842 - val_loss: 2.6784 - val_accuracy: 0.3458
Epoch 55/200
80/80 [=====] - 0s 1ms/step - loss: 2.1482 - accuracy: 0.4869 - val_loss: 2.6780 - val_accuracy: 0.3458
Epoch 56/200
80/80 [=====] - 0s 1ms/step - loss: 2.1289 - accuracy: 0.4842 - val_loss: 2.6663 - val_accuracy: 0.3505
Epoch 57/200
80/80 [=====] - 0s 1ms/step - loss: 2.1158 - accuracy: 0.4955 - val_loss: 2.7195 - val_accuracy: 0.3376
Epoch 58/200
80/80 [=====] - 0s 1ms/step - loss: 2.0992 - accuracy: 0.5025 - val_loss: 2.6999 - val_accuracy: 0.3505
Epoch 59/2
```

```

        model_2.add(Activation('relu'))
        model_2.add(Conv2D(32, (3, 4), padding='same',
                             input_shape=input_shape))
        model_2.add(Activation('relu'))
        model_2.add(MaxPooling2D(pool_size=(3, 4)))
        model_2.add(Dropout(0.25))

        model_2.add(Conv2D(64, (3, 3), padding='same'))
        model_2.add(Activation('relu'))
        model_2.add(Conv2D(64, (3, 3)))
        model_2.add(Activation('relu'))
        model_2.add(MaxPooling2D(pool_size=(2, 2)))
        model_2.add(Dropout(0.25))

        model_2.add(Flatten())
        model_2.add(Dense(512))
        model_2.add(Activation('relu'))
        model_2.add(Dropout(0.5))
        model_2.add(Dense(num_classes))
        model_2.add(Activation('softmax'))

```

```
In [174]: model_2.summary()
```

```
Model: "sequential_10"
```

layer (type)	Output Shape	Param #
conv2d_15 (Conv2D)	(None, 30, 40, 32)	416
activation_17 (Activation)	(None, 30, 40, 32)	0
conv2d_16 (Conv2D)	(None, 30, 40, 32)	12320

activation_18 (Activation)	(None, 10, 40, 32)	0
max_pooling2d_5 (MaxPooling2D)	(None, 10, 10, 32)	0
dropout_8 (Dropout)	(None, 10, 10, 32)	0
conv2d_17 (Conv2D)	(None, 10, 10, 64)	18496
activation_19 (Activation)	(None, 10, 10, 64)	0
conv2d_18 (Conv2D)	(None, 8, 8, 64)	36928
activation_20 (Activation)	(None, 8, 8, 64)	0

max_pooling2d_6 (MaxPooling2D)	(None, 4, 4, 64)	0
dropout_9 (Dropout)	(None, 4, 4, 64)	0
flatten_3 (Flatten)	(None, 1024)	0
dense_12 (Dense)	(None, 512)	524800
activation_21 (Activation)	(None, 512)	0
dropout_10 (Dropout)	(None, 512)	0

```

dense_13 (Dense)                (None, 62)                31806
activation_22 (Activation)       (None, 62)                0
=====
Total params: 624,766
Trainable params: 624,766
Non-trainable params: 0
=====

```

```

In [175]: batch_size = 32

          # initiate RMSprop optimizer

```

```
opt_2 = keras.optimizers.RMSprop(lr=0.0005)

# Let's train the model using RMSprop
model_2.compile(loss='categorical_crossentropy',
                optimizer=opt_2,
                metrics=['accuracy'])
```

In [176]: `x_train=x_train.reshape((x_train.shape[0],)*input_shape)`
`x_test=x_test.reshape((x_test.shape[0],)*input_shape)`

In [179]: `t = now()`
`train = 0`
`for i in range(10):`

```

model.compile(optimizer=adam,
              loss=loss,
              metrics=[accuracy],
              batch_size=batch_size,
              epochs=30,
              validation_data=(x_test, y_test),
              shuffle=True)

print('Training time: %s' % (now() - t))

Epoch 1/30
0.0000 - val_loss: 1.6700 - val_accuracy: 0.6100 - 6s 70ms/step - loss: 1.2305 - accuracy: 0.6277 - val_loss:
1.1017 - val_accuracy: 0.6917
Epoch 2/30
0.0000 - val_loss: 1.0500 - val_accuracy: 0.7200 - 5s 67ms/step - loss: 1.1552 - accuracy: 0.6461 - val_loss:
1.0788 - val_accuracy: 0.6917

```

```

80/80 (=====) - 5s 67ms/step - loss: 1.0053 - accuracy: 0.6899 - val_loss:
1.0145 - val_accuracy: 0.7069
Epoch 4/30
80/80 (=====) - 5s 68ms/step - loss: 0.9633 - accuracy: 0.7004 - val_loss:
0.9579 - val_accuracy: 0.7128
Epoch 5/30
80/80 (=====) - 6s 72ms/step - loss: 0.8756 - accuracy: 0.7223 - val_loss:
0.9342 - val_accuracy: 0.7280
Epoch 6/30
80/80 (=====) - 5s 69ms/step - loss: 0.8299 - accuracy: 0.7368 - val_loss:
0.9239 - val_accuracy: 0.7245
Epoch 7/30

```

```

=====
80/80 [====] - 6s 58ma/step - loss: 0.7681 - accuracy: 0.7450 - val_loss:
0.8713 - val_accuracy: 0.7351
Epoch: 8/30
=====
80/80 [====] - 6s 59ma/step - loss: 0.7284 - accuracy: 0.7673 - val_loss:
0.8713 - val_accuracy: 0.7444
Epoch: 9/30
=====
80/80 [====] - 6s 58ma/step - loss: 0.6916 - accuracy: 0.7888 - val_loss:
0.8722 - val_accuracy: 0.7515
Epoch: 10/30
=====
80/80 [====] - 6s 70ms/step - loss: 0.6348 - accuracy: 0.8045 - val_loss:
0.8240 - val_accuracy: 0.7597
Epoch: 11/30
=====
80/80 [====] - 6s 71ms/step - loss: 0.5816 - accuracy: 0.8080 - val_loss:

```

```

0.9016 - val_accuracy: 0.7339
Epoch 12/20
80/80 [=====] - 6s 71ms/step - loss: 0.5470 - accuracy: 0.8162 - val_loss:
0.8006 - val_accuracy: 0.7655
Epoch 13/20
80/80 [=====] - 5s 67ms/step - loss: 0.5308 - accuracy: 0.8314 - val_loss:
0.8131 - val_accuracy: 0.7620
Epoch 14/20
80/80 [=====] - 5s 68ms/step - loss: 0.5298 - accuracy: 0.8197 - val_loss:
0.7980 - val_accuracy: 0.7585
Epoch 15/20
80/80 [=====] - 5s 68ms/step - loss: 0.4866 - accuracy: 0.8346 - val_loss:

```

```
Epoch 16/30
80/80 [=====] - 5s 68ms/step - loss: 0.4581 - accuracy: 0.8479 - val_loss:
0.8092 - val_accuracy: 0.7796
Epoch 17/30
80/80 [=====] - 5s 68ms/step - loss: 0.4099 - accuracy: 0.8612 - val_loss:
0.8092 - val_accuracy: 0.7644
Epoch 18/30
80/80 [=====] - 5s 68ms/step - loss: 0.4255 - accuracy: 0.8557 - val_loss:
0.8055 - val_accuracy: 0.7691
Epoch 19/30
80/80 [=====] - 5s 69ms/step - loss: 0.3849 - accuracy: 0.8686 - val_loss:
0.7738 - val_accuracy: 0.7855
```

```
Epoch 20/30
80/80 [=====] - 5s 68ms/step - loss: 0.3844 - accuracy: 0.8580 - val_loss:
0.7779 - val_accuracy: 0.7737
Epoch 21/30
80/80 [=====] - 5s 68ms/step - loss: 0.3509 - accuracy: 0.8627 - val_loss:
0.7604 - val_accuracy: 0.7831
Epoch 22/30
80/80 [=====] - 6s 71ms/step - loss: 0.3509 - accuracy: 0.8619 - val_loss:
0.8023 - val_accuracy: 0.7761
Epoch 23/30
80/80 [=====] - 6s 70ms/step - loss: 0.3437 - accuracy: 0.8627 - val_loss:
0.7478 - val_accuracy: 0.7876
Epoch 24/30
```

```

80/80 [=====] - 6s 70ms/step - loss: 0.3078 - accuracy: 0.8882 - val_loss:
0.7346 - val_accuracy: 0.7866
Rpeh 25/30
80/80 [=====] - 5s 68ms/step - loss: 0.3088 - accuracy: 0.8901 - val_loss:
0.8130 - val_accuracy: 0.7643
Rpeh 26/30
80/80 [=====] - 6s 69ms/step - loss: 0.2950 - accuracy: 0.8921 - val_loss:
0.8197 - val_accuracy: 0.7691
Rpeh 27/30
80/80 [=====] - 6s 70ms/step - loss: 0.2802 - accuracy: 0.9042 - val_loss:
0.7880 - val_accuracy: 0.7749
Rpeh 28/30
80/80 [=====] - 5s 68ms/step - loss: 0.2687 - accuracy: 0.9034 - val_loss:

```

```

0.8032 - val_accuracy: 0.7866
Epoch 29/30
=====
- Ss 68ms/step - loss: 0.2654 - accuracy: 0.9147 - val_loss:
0.8050 - val_accuracy: 0.7866
0.8331 - val_accuracy: 0.7866
Epoch 30/30
=====
- Ss 68ms/step - loss: 0.2674 - accuracy: 0.9081 - val_loss:
0.8297 - val_accuracy: 0.7937
Training time: 0:02:47.210564

In [180]: score = model_2.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
```

```
Test score: 0.8297411799430847
Test accuracy: 0.79366946025993347
```

4. Conclusion

This task involves in recognizing hand written english characters. There are more than 60 categories. We know that it is more difficult compared to MNIST digit data classification. For example, z may look like e and 50 on. From the analysis above, we found that convolution neural network can achieve very high accuracy for image classification. Each pixel can be treated as one feature. The relative location and value of each pixel is very important for image. The final accuracy in test set is close to 80% while the training accuracy

