Convolutional Networks for CAPTHA Recognition

I. Definition

Project Overview

The CAPTHA Recognition is inspired by the MNINST/SVHN datasets and the hateness of annoying step before logging in or browsing pages. Although this step is for security concern, it is actually not helpful since the spirl of Machine Learning. Lots of websites,including government's sites, still use the CAPTHAs. This project will reveal that even beginner as I can easily solve CAPTCHAs quickly. it is not only easy to machine to solve, but it annoy human users a lot. Based on the study :"How Good are Humans at Solving CAPTCHAs? A Large Scale Evaluation". it revealed that it is more effective for an attacker touse Mechanical Turk to solve captchas than an underground service.

Problem Statement

This problem is a classification of letters by computer vision. Use amounts of CAPTCHAs with various letters' fonts as input data. By Convolutional Netowrks, the CAPTCHAs images can't correctly predicted. Because the images are formed by numbers 0~9 and letters A~Z, the expected output will be the text of 0~9 and A~Z.

Metrics

I use the accuracy and ROC curve to measure the performance of my models. Based on the characteristics of this problem, the score of accuracy must be high. After all, in real scenario, there is no partial right. The ROC curve is to evaluate the true positive rate versus false positive rate.

II. Analysis

Data Preprocessing and Visualization

The CAPTCHAs data samples are from the https://captcha.com/captcha-examples.html A quantity of samples is 9,000. Every image is formated with 72x24 pixels and the backgrounds are all white. From a example below, the pixels grouping of white are all the same value, but the black areas are distributed with different value. these characteristics don't effect our following analysis. However, the joint between 'W' and 'J' wil be problematic, since the model may consider them as one letter.

There is a simple solution with this problem. we can use the ratio of width versus height to filter this kind feature. if the ratio large than specific value, we can divide the width into half. Futhermore, the postion of numbers and letters are almost at the center of images. Although the vertical position of each number or letter is not the same, the max height and max width of each number or letter are all the same. I can use the characteristic mentioned above to recognize and split the letters.

We can sort images into five classes, all letters, all numbers, one number three letters, two numbers two letters and three numbers one letter. The amount of five classes images are almost random and all letters are capital. Except for all numbers and all letters.In order to browse the whole datasets, I create two dictionary of letters and numbers. After spliting each image with letter and numbers, I count the number and save in dictionary. I plot the histogram to see how many the A~Z and 0~9 as below diagram. We can find that in our datasets, the distribution of letters and numbers is almost equal except for the number 0,1 and the letter O,I. it seems like the contours of 1/0 and I/O are very similar. In fact, the text shape of the I/O and 1/0 often confuse human too; therefore, there are fe of CAPCHAs contain these letters. https://www.quora.com/How-do-you-decipher-between-a-0-and-an-O-of-a-captcha. The sequence of letters and numbers are also random and there are no sign of dominant class; therefore, I can just randomly split the datasets into training/validation/testing.

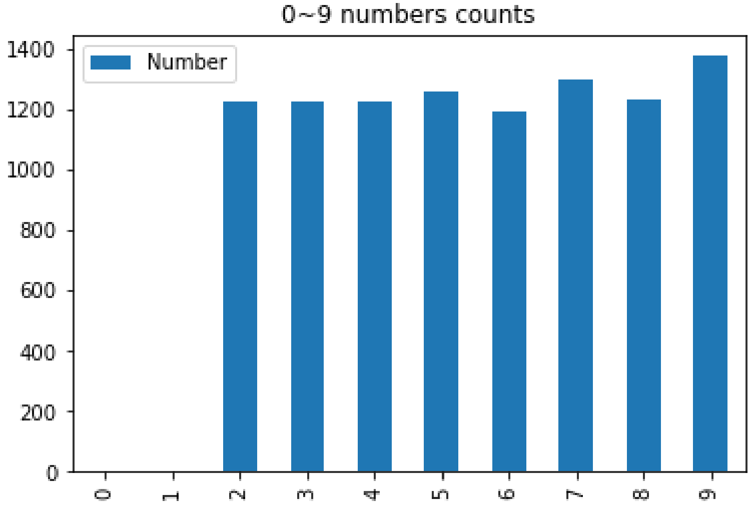
In [5]:

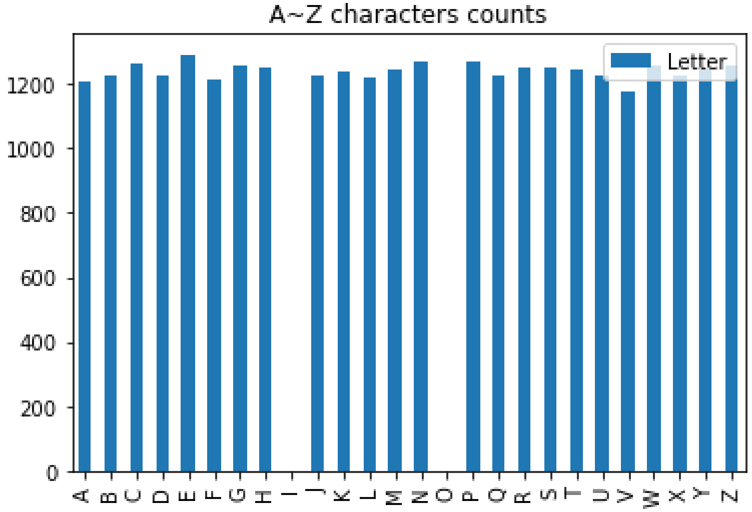
```
from IPython.display import Image
display(
#Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\2A5R.PNG'),
```

```
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\XWJE.PNG')
)
```


```
In [7]:
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f81d427978>
```



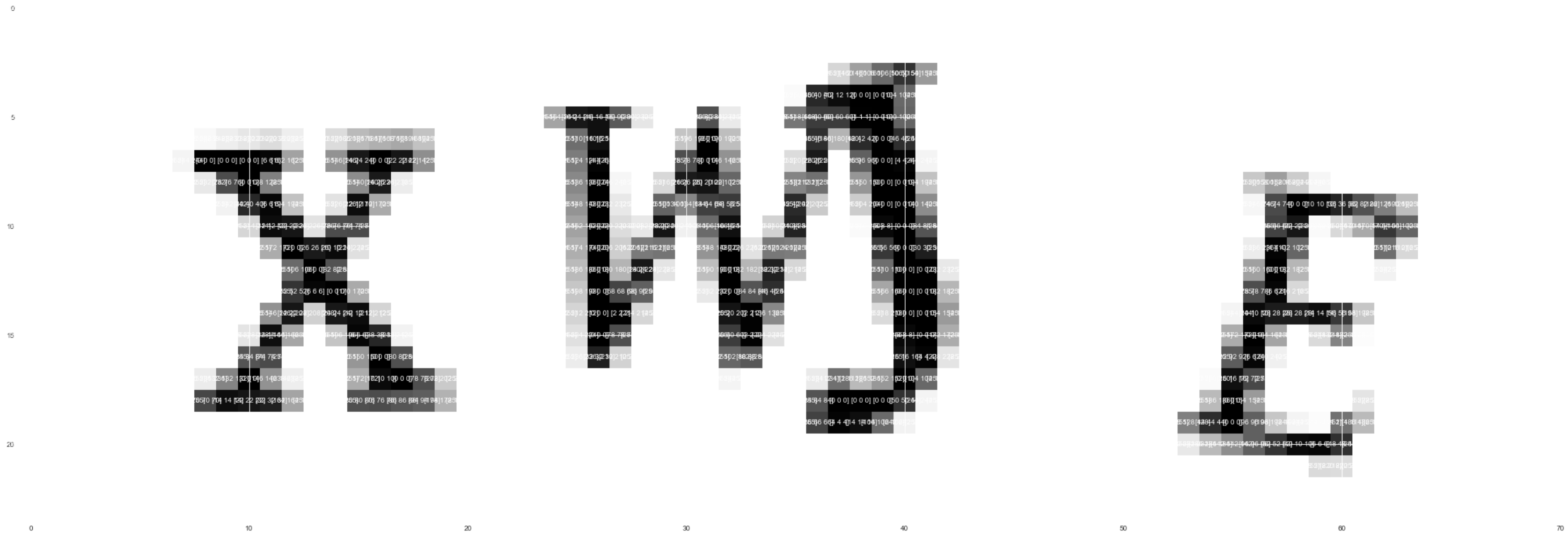



```
In [148]: import matplotlib.pyplot as plt
%matplotlib inline
```

```
import matplotlib.cm as cm
import numpy as np
from PIL import Image
import cv2

image = cv2.imread('C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\XWJE.PNG')
print (image.shape)
print (image.dtype)
fig = plt.figure(figsize = (40,40))
ax = fig.add_subplot(1,1,1)
ax.imshow(image, cmap='gray')
width= image.shape[0]
height = image.shape[1]
thresh = image.max()
print (thresh)
for x in range(width):
    for y in range(height):
        ax.annotate(str(np.round(image[x][y],2)), xy=(y,x),horizontalalignment='cente
r',verticalalignment='center',color='white' if image[x][y].any() < thresh else 'black')
```

```
(24, 72, 3)
uint8
255
```



Algorithms and Techniques

The algorithms I used is CNN and MLP(the benchmark model). I will explain each layer as follow:

Convolutional layer:

The Convolutional Neural Network(CNN) is structed from Convolutional layer at the first layer.What is Convolutional layer ? We can imagine the flash light highlight the left-up conrner area of the images pixels. The flash light is called "filter" and the hightlgiht area is called "receptive field". The operation is as below. The filter is a numpy array of weights values and The receptive field is also numpy array. The filter will slide from left-up to right-bottom. Each step dot the weights with pixels to map a new feature. These steps are all summed up then we have new feature map.

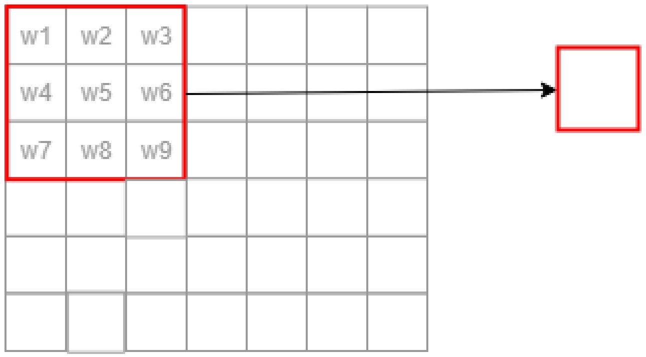
Fully Connected Layer:

The MLP model is mainly constructed by Fully Connected Layers. we can imagine the filter size is equal the image size. This layer basically takes an N dimensional input images and outputs N dimensional feature map.

Dropout Layer:

The dropout layer in neural networks is used to deal with the problem of overfitting, the idea is to drop out a random activation set in that layer. it make sure the network is not too fit to trainig dataset.

In [104]:
```
from keras.models import Model
from keras.layers import Input, Dense, Conv2D, Dropout, MaxPooling2D
display(
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-maste
r\\projects\\capstone\\CNN.png'),
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-maste
r\\projects\\capstone\\CNN1.png')
      )
```



50	50	40	30	0	0	0	0
20	50	30	0	0	0	0	0
0	30	50	30	0	0	0	0
0	0	30	50	30	0	0	0
0	0	0	30	50	30	0	0
0	0	0	0	40	50	40	0
0	0	0	0	0	40	50	50
0	0	0	0	0	0	50	50

Receptive fileds

20	20	0	0	0	0	0	0
0	20	0	0	0	0	0	0
0	0	20	0	0	0	0	0
0	0	20	20	0	0	0	0
0	0	0	0	20	0	0	0
0	0	0	0	20	20	0	0
0	0	0	0	0	0	20	20
0	0	0	0	0	0	20	20

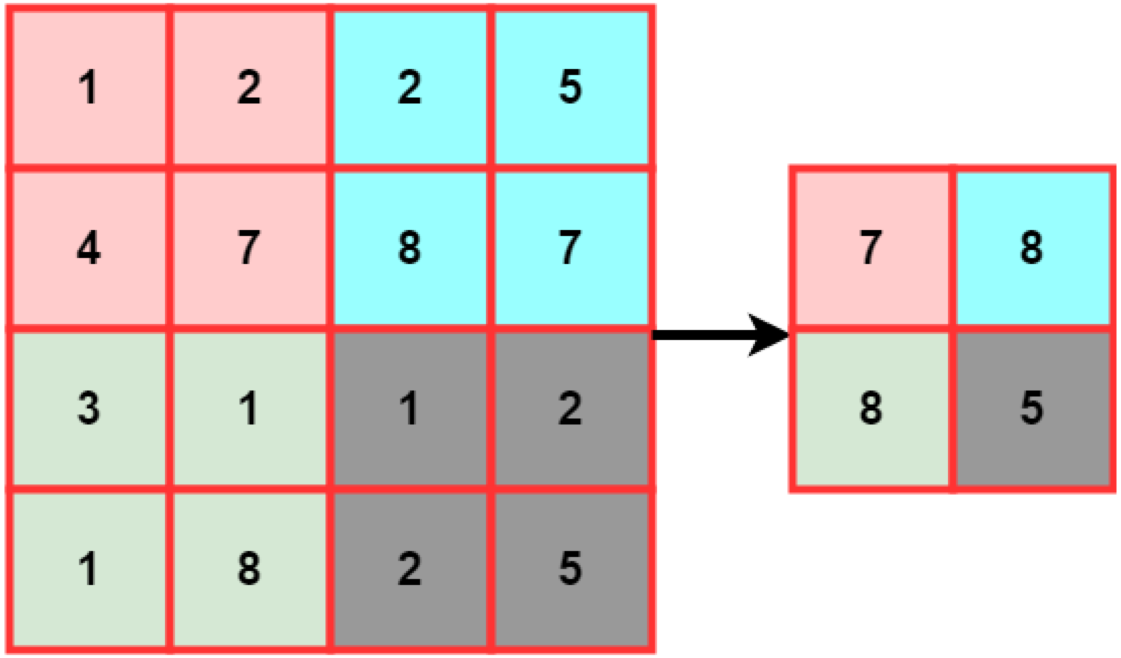
Filter

MaxPooling Layer:

The idea of MaxPooling layer is simple. As we know the specific feature in the original input volume and get a feature map from the convolutional layer. the relative relation between each pixel location is important than the actual location, so it takes a filter with size 2x2 normally and a stride of the same length. Then it applies to the input volume and outputs the maximum number in every subregion that the filter convolves around as below schematic. This layer can reduce the spatial dimension of the input volume and also control overfitting.

In [103]:

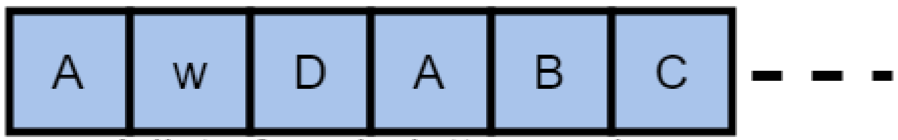
```
display(
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-maste
r\\projects\\capstone\\MaxPool.png')
     )
```



MaxPooling layer

III. Methodology

In [6]:
```
display(
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-master\\projects\\capstone\\list.png'),
)
```



A list of each_letter_region

At the data preprocessing, I use the OpenCV package to deal with my image datasets. Fisrt of all, the CPATCHAs images look like gray scale; however, I still covert images to gray scale for safty concern:

```
import cv2
image = cv2.imread(image_file)
image = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
```

Because there are still different intense black as Analysis discussed, I need to convert the images to pure black and white.

```
thresh = cv2.threshold(image, 0, 255, cv2.THRESH_BINARY_INV | cv2.THRESH_OTSU
)[1]
```

After the conversion, it will be easier to find the contours of images. However, there is a difficulty as mentioned above, the joints between letters. If we don't process trickly, it would discriminate our predict results. So the ratio of width and length of each contour must be examinated. If the the ratio is large than 1.25, the contour may contain two letter. Then the width of this contour will be cut to split into half. each letter will be append into a list of "each_letter_region". Furthermore, if and only if every letter in images are all same height and width, the critera of 1.25 is valid, which means our algorithm and model have a basic assumption that can't be broken.

```
contours = cv2.findContours(thresh.copy(), cv2.RETR_EXTERNAL, cv2.CHAIN_APPRO
X_SIMPLE)
```

```
each_letter_region = []
for contour in contours:
    (x, y, w, h) = cv2.boundingRect(contour)
    if w / h > 1.25:
        half_w = int(w / 2)
        each_letter_region.append((x, y, half_w, h))
        each_letter_region.append((x + half_w, y, half_w, h))
```

```
    else:
        each_letter_region.append((x, y, w, h))
```

After all letters are split, sort the list of each_letter_region based on the x coordinate to make sure left-to-right, so we match the right image with the right letter.

```
each_letter_region = sorted(each_letter_region, key=lambda x: x[0])
```

Finally, save each letter into one image and put same letter into same file. For example the "M" letter as below.

I use the Keras to implement my model. For flexible concern, I don't use Sequential Model as usual. I use Model class API to constrcut both MLP and CNN architectures. Therefore, as mentioned above, I import the core layers I will use in architectures:

```
from keras.models import Model
from keras.layers import Input, Flatten, Dense, Conv2D, Dropout, MaxPooling2D
```

The benchmark model MLP:

For computation efficiency, as mentioned above, my input volume resize to (25,25,1) and flatten the input size:

```
inp = Input(shape=(25,25,1))
flat = Flatten()(inp)
```

Becasue the simple complexity of images and the images are preprocessed, I use two fully connected layers with two dropout layers for overfitting prevention. The activation function are ReLU function $f(x) = \max(0, x)$, the dimensionality of the output space are 1000 and 512.

```
Dense1 = Dense(1000, activation='relu')(flat)
Drop1 = Dropout(0.2)(Dense1)
Dense2 = Dense(512, activation='relu')(Drop1)
Drop2 = Dropout(0.2)(Dense2)
```

The output layer is still fully connected layer with activation function softmax $\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$

```
Dense3 = Dense(32, activation='softmax')(Drop2)
model = Model(inp,Dense3)
```

The CNN model:

The CNN model I used is constructed by two convolutional layers with two maxpooling layers, and then flatten to one fully connected layer. Firtstly, as same as MLP model:

```
inp = Input(shape=(25,25,1))
```

Then, for convolution layers, the parameter padding is "same", which mean that the output as same as the input. The activation function is also the ReLU like MLP above. For the maxpooling layer, the parameters of pool_size and strides are (2,2) as usual.

```
conv1 = Conv2D(20, (5, 5), padding="same", activation="relu")(inp)
maxpool1 = MaxPooling2D(pool_size=(2, 2), strides=(2, 2))(conv1)
conv2 = Conv2D(50,(5,5),padding="same", activation="relu")(maxpool1)
maxpool2 = MaxPooling2D(pool_size=(2, 2), strides=(2, 2))(conv2)
```

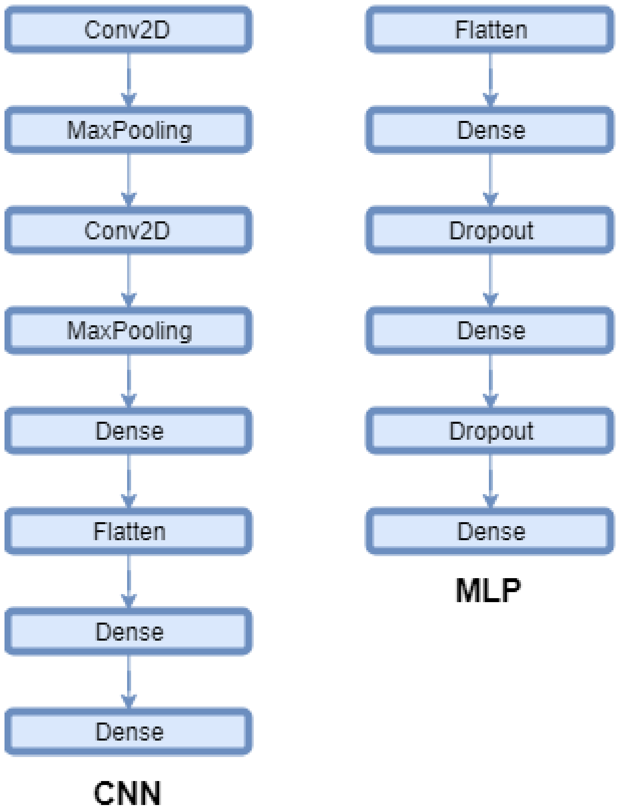
At the last layer, I expect the outputs distribution of probability of each class. Therefore, I use th e Flatten layer to convert the tridimensional tensor into a monodimensional tensor (a vector). Then use two fully connected layers like MLP above. The output activation function is also Softmax, because I want to the distribution of probability of each class.

```
flat = Flatten()(maxpool2)
dense1 = Dense(500, activation="relu")(flat)
dense2 = Dense(32, activation="softmax")(dense1)
model = Model(inp,dense2)
```

Refinement

After several training, it seems that just few steps of epochs can converge the results. From the simple two layers neural network to four layers, the result of prediction is almost the same, but the more number of the layers, the more training time.

In [29]:
```
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\flow diagram (6).png')
```



IV. Results

Model Evaluation and Validation

Firstly, from the parameters of MLP and CNN models, we can find that total parameters of the MLP are more than the total parameters of the CNN. However, if we compare the training times of 5 epochs between them, the MLP is 7.25 mins and the CNN is 17.03 mins. At view of computation efficiency, the process times of the CNN is indeed consumable than the MLP. But, we can see the prediction accuracy between them as below. the CNN is more accurate than the MLP. Compare to loss, the conversion of the CNN is quicker than the MLP. If we prolong the training epochs of the MLP to 10 steps, we can observe that the loss fuction is hard to converse, and the accuracy is not improved much.

Based the CPU concern, the 10 epochs is too time consuming; therefore, by using wrappers for the Scikit-Learn API of Keras, I tune the parameters of epochs and batch size to find the suitable parameters. As below results, we can find that the best_params are {'epochs': 3, 'batch_size': 32}.

```
best_params:  {'epochs': 3, 'batch_size': 32}

mean: 0.99604, std: 0.00034, params: {'epochs': 3, 'batch_size': 16}
mean: 0.99621, std: 0.00090, params: {'epochs': 5, 'batch_size': 16}
mean: 0.99628, std: 0.00008, params: {'epochs': 3, 'batch_size': 32}
mean: 0.99484, std: 0.00199, params: {'epochs': 5, 'batch_size': 32}
```

After confirming the parameters of models, we save the model parameters and grab some CAPTCHAs from web to see the results.

From the result, we can find that the prediction is alsmost correct. The CNN and MLP models both predict the correct answer. However, as discussed above, the datasets are images with clean background. If there are interference at backgorund, the prediction results will not good. Becasue the model can't tell the difference.

From discussion above, the distribution of letters is almost uniform except for I/O and 1/0; therefore, there is no domain element to dropout.

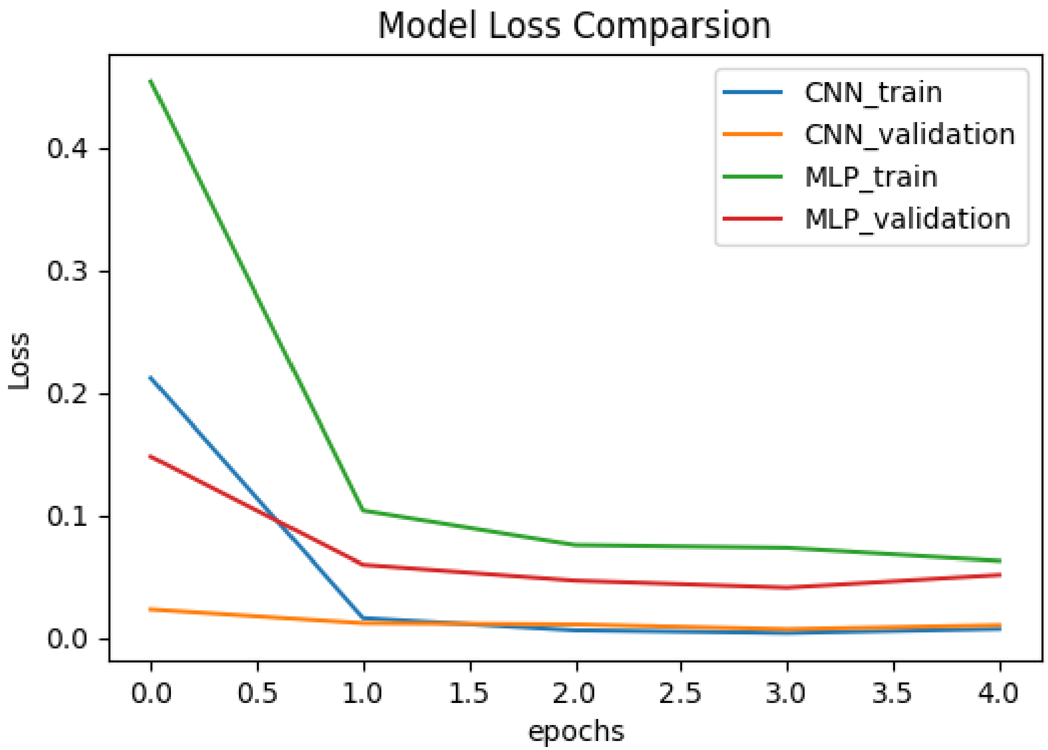
In [135]:

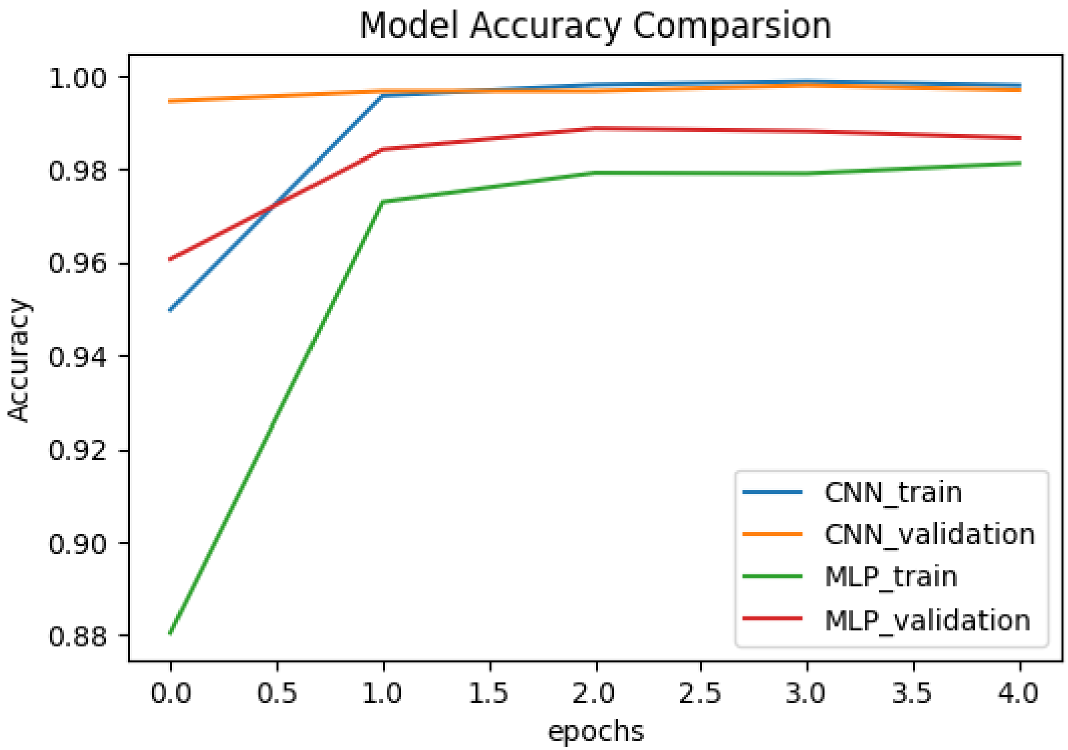
```
from keras.models import load_model
MODEL_FILENAME_CNN = "C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-master\\projects\\capstone\\CAPTCHA\\solving_captchas\\captcha_model_CNN.hdf5"
MODEL_FILENAME_MLP = "C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-master\\projects\\capstone\\CAPTCHA\\solving_captchas\\captcha_model_MLP.hdf5"
model_CNN = load_model(MODEL_FILENAME_CNN)
model_MLP = load_model(MODEL_FILENAME_MLP)
print ("MLP Model")
model_MLP.summary()
print ("\n\nCNN Model")
model_CNN.summary()
```

```
MLP Model
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_2 (InputLayer)         (None, 25, 25, 1)         0         
_________________________________________________________________
flatten_2 (Flatten)          (None, 625)               0         
_________________________________________________________________
dense_3 (Dense)              (None, 1000)              626000    
_________________________________________________________________
dropout_1 (Dropout)          (None, 1000)              0         
_________________________________________________________________
dense_4 (Dense)              (None, 512)               512512    
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_5 (Dense)              (None, 32)                16416     
=================================================================
Total params: 1,154,928
Trainable params: 1,154,928
Non-trainable params: 0
_________________________________________________________________
```

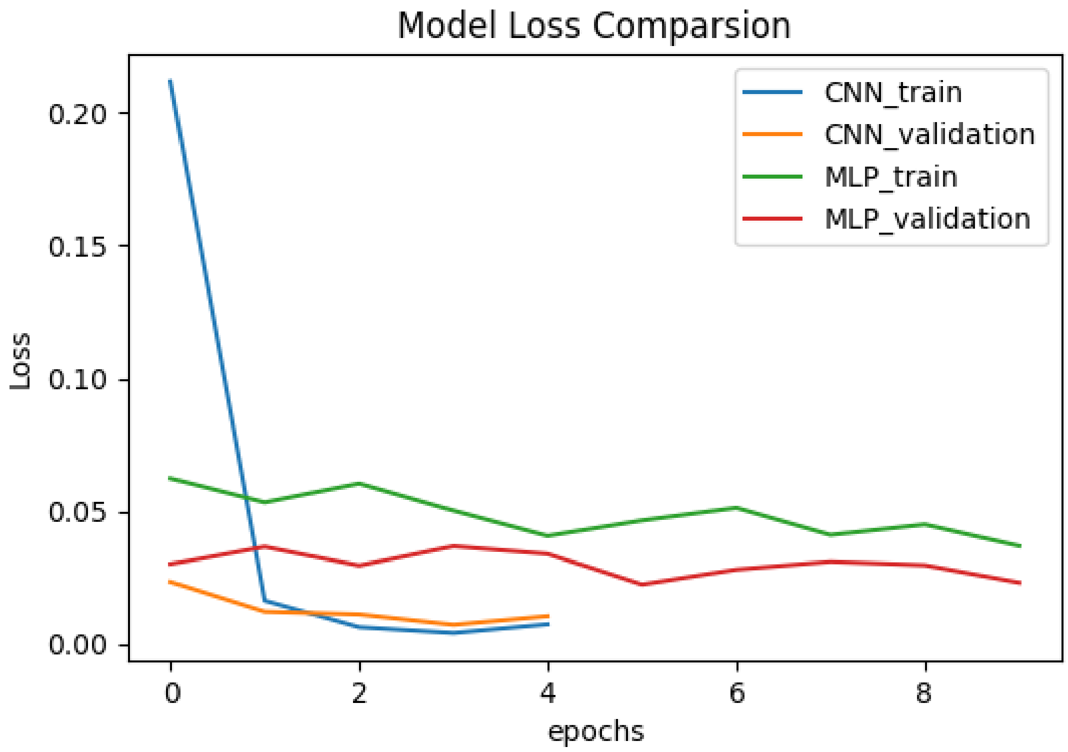
```
CNN Model
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_1 (InputLayer)         (None, 25, 25, 1)         0         
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 25, 25, 20)        520       
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 12, 12, 20)        0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 12, 12, 50)        25050     
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 6, 6, 50)          0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 1800)              0         
_________________________________________________________________
dense_1 (Dense)              (None, 500)               900500    
_________________________________________________________________
dense_2 (Dense)              (None, 32)                16032     
=================================================================
Total params: 942,102
Trainable params: 942,102
Non-trainable params: 0
_________________________________________________________________
```

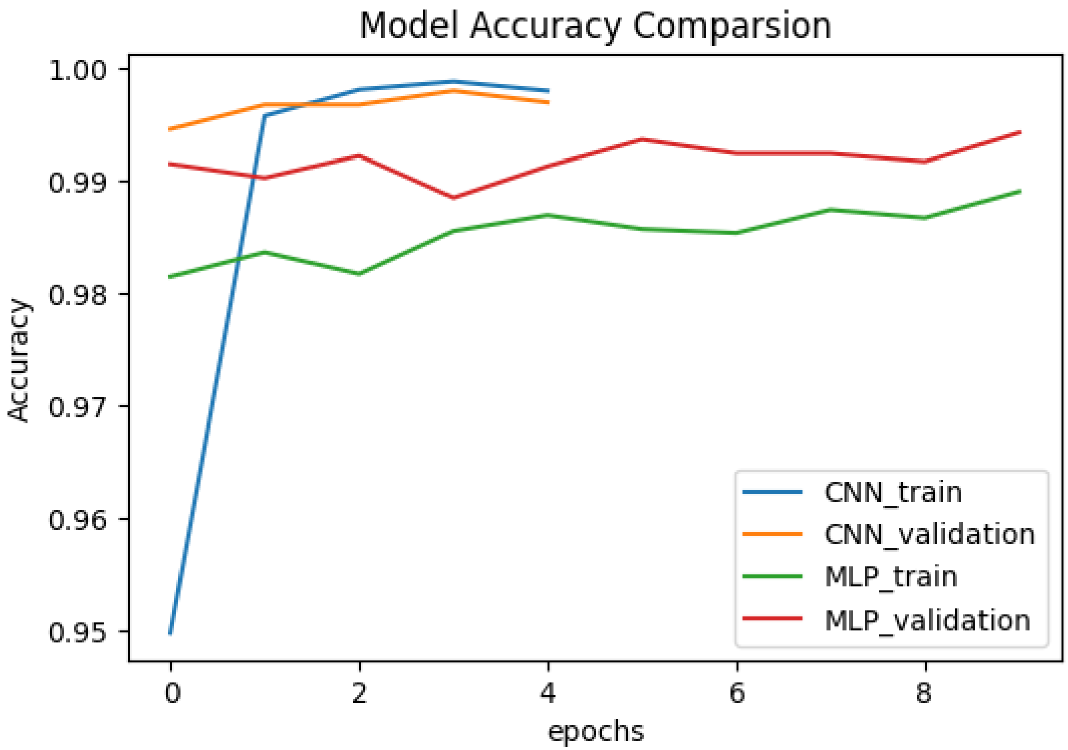
In [134]:


Model Loss Comparsion
CNN_train
CNN_validation
MLP_train
MLP_validation
0.4
0.3
0.2
0.1
0.0
Loss
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
epochs



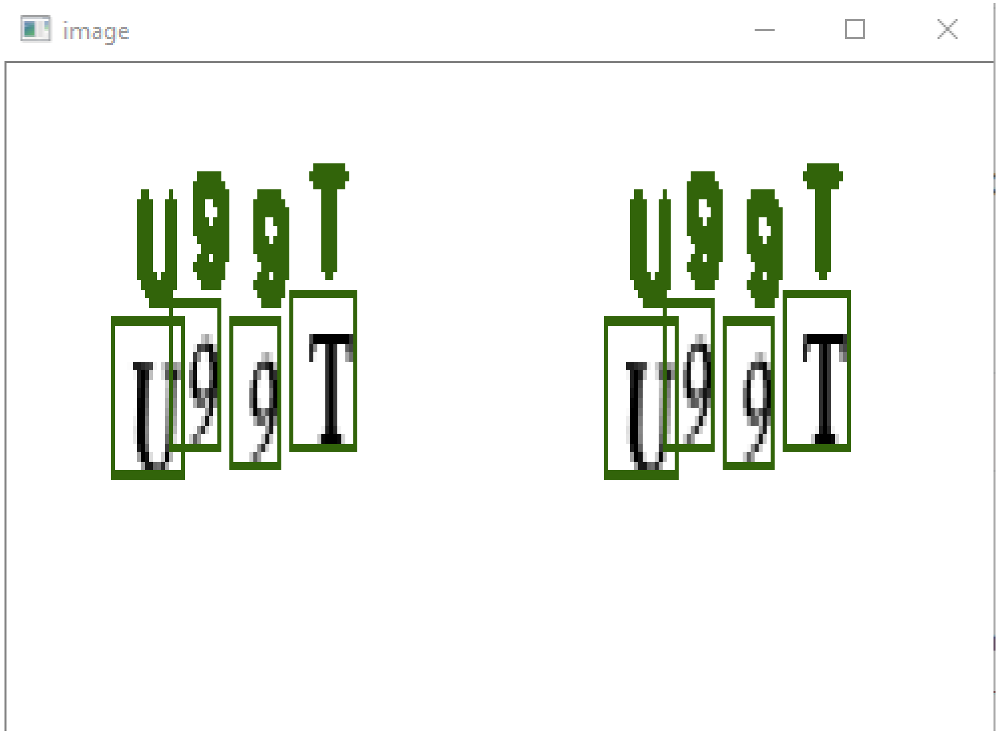
In [136]:
```
display(
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-maste
r\\projects\\capstone\\CAPTCHA\\solving_captchas\\loss.png'),
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-maste
r\\projects\\capstone\\CAPTCHA\\solving_captchas\\acc.png')
)
```


Model Loss Comparsion
CNN_train
CNN_validation
MLP_train
MLP_validation
0.20
0.15
0.10
0.05
0.00
Loss
0
2
4
6
8
epochs



In [141]:

```
display(
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-maste
r\\projects\\capstone\\result.png'),
Image(filename = 'C:\\Users\\MLUSER\\Documents\\GitHub\\Udacity\\machine-learning-maste
r\\projects\\capstone\\result1.png')
)
```



image


image

V. Conclusion

We can observe that the CNN Model is more robust than the MLP. The accuracy of the CNN Model is more accurate tham the MLP Model. However, from validation view, the prediction results of the MLP and the CNN almost the same. The reasons are is that our datasets are clean and there are no bias of distribution.

The biggest challenge I confirmed is that if we plot some black dot in the background of CAPTCHAs image, The models I constructed have diffcultity to identify the letters and segment, there is a lot of space to improve my algorithms.

However, based on research of Elie Bursztien et al[1]. The human ability of the segmentation outperform than the computers. If the background clutter consists of shapes similar to letter shapes, and the letters are connected by this clutter, the segmentation becomes nearly impossible with current software. Hence, my statement at the beginning of my proposal is vulnerable.

VI. Improvement

The CAPTCHAs can focus on segmentation to enforce the defense. for example, the static CAPTCHAs are subject to laundry attacks because they are pictures that contain the static puzzle and the user has to complete the answer to a text field outside the puzzle. That is, the solution of the CAPTCHA is static and can be transfered between nodes of a malicious infrastructure. if we transform a CAPTCHA test from astatic picture to a dynamic application. That is, the answer must be completed inside the puzzle.[2]

[1]http://web.stanford.edu/~jurafsky/burszstein_2010_captcha.pdf
[2]https://link.springer.com/content/pdf/10.1007/11909033_9.pdf

Before submitting your proposal, ask yourself. . .

- Does the proposal you have written follow a well-organized structure similar to that of the project template?
- Is each section (particularly **Solution Statement** and **Project Design**) written in a clear, concise and specific fashion? Are there any ambiguous terms or phrases that need clarification?
- Would the intended audience of your project be able to understand your proposal?
- Have you properly proofread your proposal to assure there are minimal grammatical and spelling mistakes?
- Are all the resources used for this project correctly cited and referenced?