CSE Computer Vision Assignment 3

Name : Arka Sarkar
Roll Number : 2018222

In [1]:
```python
from google.colab import drive
drive.mount('/gdrive')
```

```
Mounted at /gdrive
```

In [3]:
```python
%cd /gdrive/MyDrive/CV_Assignment3
```

```
/gdrive/MyDrive/CV_Assignment3
```

Checking for GPU device

In [1]:
```python
import tensorflow as tf
device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  raise SystemError('GPU device not found')
print('Found GPU at: {}'.format(device_name))
```

```
---------------------------------------------------------------------------
SystemError                               Traceback (most recent call last)
<ipython-input-1-d1680108c58e> in <module>
      2 device_name = tf.test.gpu_device_name()
      3 if device_name != '/device:GPU:0':
----> 4   raise SystemError('GPU device not found')
      5 print('Found GPU at: {}'.format(device_name))

SystemError: GPU device not found
```

In [2]:
```
!nvidia-smi
```

```
'nvidia-smi' is not recognized as an internal or external command,
operable program or batch file.
```

Importing Dependencies

In [3]:
```python
import numpy as np
from IPython.display import Image
import pandas as pd
import matplotlib.pyplot as plt
from tqdm import tqdm
import copy
import pickle
import cv2
import csv
from keras.preprocessing import image
from keras.utils import layer_utils
import numpy as np
import os
import skimage.io as io
import skimage.transform as trans
import numpy as np
from keras.models import *
from keras.layers import *
from keras.optimizers import *
from keras.callbacks import ModelCheckpoint, LearningRateScheduler
from keras import backend as keras
import random
from sklearn.metrics import jaccard_score
```

Original MNIST Dataset

MNIST Handwritten Digit Classification Dataset
It is a dataset of 60,000 small square 28×28 pixel grayscale images of handwritten single digits between 0 and 9. The task is to classify a given image of a handwritten digit into one of 10 classes representing integer values from 0 to 9, inclusively

In [442]:
```python
train_df = pd.read_csv("dataset/mnist_train.csv")
test_df = pd.read_csv("dataset/mnist_test.csv")
```

In [443]:
```python
train_df
```

Out[443]:

	label	1x1	1x2	1x3	1x4	1x5	1x6	1x7	1x8	1x9	...	28x19	28x20	28x21	28x22	28x23	28x24	28x25	28x26	28x27	28x28
0	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
2	4	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	1	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	9	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
59995	8	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
59996	3	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
59997	5	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
59998	6	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
59999	8	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

60000 rows × 785 columns

In [444]:
```python
train = np.array(train_df)
test = np.array(test_df)

Y_train = np.zeros((train.shape[0], 10))
X_train = []
Y_test = np.zeros((test.shape[0], 10))
X_test = []

for i in range(train.shape[0]):
    X_train.append(train[i,1:])
    Y_train[i,train[i,0]] = 1

for i in range(test.shape[0]):
    X_test.append(test[i,1:])
    Y_test[i,test[i,0]] = 1

X_train = np.array(X_train)
X_test = np.array(X_test)
print("Testing X Shape : ", X_test.shape)
print("Training X Shape : ", X_train.shape)
print("Testing Y Shape : ",Y_test.shape)
print("Training Y Shape : ",Y_train.shape)
```

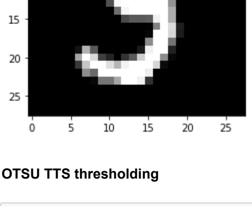
```
Testing X Shape :  (10000, 784)
Training X Shape :  (60000, 784)
Testing Y Shape :  (10000, 10)
Training Y Shape :  (60000, 10)
```

sample MNIST image

In [445]:
```python
idx = 10
sample = X_train[idx].reshape((28,28))
print(Y_train[idx])
plt.imshow(sample, cmap = "gray")
```

```
[0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
```

Out[445]:
```
<matplotlib.image.AxesImage at 0x234700acd88>
```



OTSU TTS thresholding

In [446]:
```python
def otsu_tts(img):
    img = img.reshape((28,28))
    min_cost = float('inf')
    threshold = 0

    for i in range(1,256):
        v0 = img[img < i]
        s0 = np.sum((v0 - np.mean(v0))**2)
        w0 = len(img[img < i])
        v1 = img[img >= i]
        s1 = np.sum((v1 - np.mean(v1))**2)
        w1 = len(img[img >= i])

        cost = s0 + s1
        if(cost < min_cost):
            min_cost = cost
            threshold = i

    return threshold

def select_foreground(img, s = 0):
    if(s == 0):
        m,n = img.shape

        m0 = int(0.15*m)
        n0 = int(0.15*n)
        c0 = 0
        c1 = 0
        for i in range(m//2 - m0, m//2 + m0):
            for j in range(n//2 - n0, n//2 + n0):
                if(img[i,j] == 0):
                    c0 = c0 + 1
                else:
                    c1 = c1 + 1
        if(c0 > c1):
            return 0
        else :
            return 1
    else :

        m,n = img.shape

        m0 = 10
        n0 = 10
        c0 = 0
        c1 = 0
        for i in range(m):
            for j in range(n):
                if (i < m0):
                    if(img[i,j] == 0):
                        c0 = c0 + 1
                    else:
                        c1 = c1 + 1

                elif (i > m-m0):
                    if(img[i,j] == 0):
                        c0 = c0 + 1
                    else:
                        c1 = c1 + 1
                elif (j < n0):
                    if(img[i,j] == 0):
                        c0 = c0 + 1
                    else:
                        c1 = c1 + 1
                elif (j > n-n0):
                    if(img[i,j] == 0):
                        c0 = c0 + 1
                    else:
                        c1 = c1 + 1

        if(c0 > c1):
            return 0
        else :
            return 1
```

Question 1

Perform the following on MNIST dataset to build three new datasets:

1. Obtain foreground segmentation masks for images in MNIST dataset using TSS-based threshold [Q1, Assignment 1]. In this way, you have rough groundtruth masks required to build a new foreground segmentation dataset. [1 Mark]
   Note: The pre-existing labels are of no use here. The goal of the dataset is just to extract the foreground.
2. Obtain tight groundtruth circles around the foreground segmentation masks obtained in (a). In this way, you can build a new dataset of 10 classes for performing classification with circlization (circular localization). You can use existing libraries for generating the tight circles. [1 Mark]
3. Randomly concatenate 4 images and their corresponding groundtruths obtained in (a),along with the pre-existing labels, in a 2x2 manner to develop new images and semantic segmentation groundtruths, respectively. In this way, you have a new dataset of 10 classes for performing semantic segmentation. [2 Marks]

part (a)

In [ ]:
```python
# run only once
# making the training set
fg_masks_train = []
for i in tqdm(range(len(X_train)), position = 0, desc = "Progress : "):
    thres = otsu_tts(X_train[i])
    img = X_train[i].reshape((28,28))
    mask = copy.deepcopy(img)
    mask[mask<thres] = 0
    mask[mask > thres] = 1
    fg_masks_train.append(mask.flatten())
```

Saving the dataset in a .csv file.

In [ ]:
```python
with open('dataset/Q1fg_mask_train.csv', 'a+', newline ='') as f:
    write = csv.writer(f)
    write.writerows(fg_masks_train)
```

In [ ]:
```python
# run only once
# making the testing set

fg_masks_test = []
for i in tqdm(range(len(X_test)), position = 0, desc = "Progress : "):
    thres = otsu_tts(X_test[i])
    img = X_test[i].reshape((28,28))
    mask = copy.deepcopy(img)
    mask[mask<thres] = 0
    mask[mask > thres] = 1
    fg_masks_test.append(mask.flatten())
```

Saving the dataset in a .csv file.

In [ ]:
```python
with open('dataset/Q1fg_mask_test.csv', 'a+', newline ='') as f:
    write = csv.writer(f)
    write.writerows(fg_masks_test)
```

In [447]:
```python
idx  = 10
sample_x = np.array(pd.read_csv('dataset/mnist_train.csv'))[idx,1:].reshape((28,28))
sample_y = np.array(pd.read_csv('dataset/Q1fg_mask_train.csv', header = None))[idx].reshape((28,28))
```

In [448]:
```python
fig=plt.figure(figsize=(8, 8))
columns = 2
rows = 1
fig.add_subplot(rows, columns, 1)
plt.imshow(sample_x, cmap = 'gray')
plt.title("Original Image")
fig.add_subplot(rows, columns, 2)
plt.imshow(sample_y, cmap = 'gray')
plt.title("Foreground Mask")
fig.tight_layout()
plt.show()
```

part (b)

In [ ]:
```python
X_train = pd.read_csv("dataset/Q1fg_mask_train.csv", header = None)
X_test = pd.read_csv("dataset/Q1fg_mask_test.csv", header= None)
y_label_train = np.array(pd.read_csv("dataset/mnist_train.csv"))[:,0]
y_label_test = np.array(pd.read_csv("dataset/mnist_test.csv"))[:,0]
X_train = np.array(X_train)
X_test = np.array(X_test)
```

Writing the MNIST images into disc

In [ ]:
```python
#code for saving the original images
#run once
X_orig_train = np.array(pd.read_csv("dataset/mnist_train.csv"))[:,1:]

for i in tqdm(range(len(X_orig_train)), position = 0, desc = "Progress : "):
    img = X_orig_train[i].reshape((28,28))
    cv2.imwrite('dataset/mnist_images/train/' + str(i) + '.png', img )
```

```
Progress : 100%|██████████| 60000/60000 [08:52<00:00, 112.63it/s]
```

In [ ]:
```python
#code for saving the original images
#run once
X_orig_test = np.array(pd.read_csv("dataset/mnist_test.csv"))[:,1:]
for i in tqdm(range(len(X_orig_test)), position = 0, desc = "Progress : "):
    img = X_orig_test[i].reshape((28,28))
    cv2.imwrite('dataset/mnist_images/test/' + str(i) + '.png', img )
```

```
Progress : 100%|██████████| 10000/10000 [01:29<00:00, 111.89it/s]
```

Writing the MNIST foreground images obtained in (a) into disc

In [ ]:
```python
#code for saving the fg images
#run once


for i in tqdm(range(len(X_train)), position = 0, desc = "Progress : "):
    img = X_train[i].reshape((28,28))*255
    cv2.imwrite('dataset/mnist_images_fg/train/' + str(i) + '.png', img )
```

```
Progress : 100%|██████████| 60000/60000 [09:06<00:00, 109.83it/s]
```

In [ ]:
```python
#code for saving the fg images
#run once
for i in tqdm(range(len(X_test)), position = 0, desc = "Progress : "):
    img = X_test[i].reshape((28,28))*255
    cv2.imwrite('dataset/mnist_images_fg/test/' + str(i) + '.png', img )
```

```
Progress : 100%|██████████| 10000/10000 [01:27<00:00, 114.41it/s]
```

Center Radius Dataset

Dataset columns : 'label','x','y', 'radius'
Dataset Size : (n_samples, 4)
'label' : labels of the image ranging from 0 to 9.
'x' : normalsed x coordinate for the bounding circle.
'y' : normalsed y coordinate for the bounding circle.
'radius' : normalsed radius coordinate for the bounding circle.

In [ ]:
```python
# making the center radius dataset
center_radius_dataset_train = []

for i in tqdm(range(60000)):
    img = cv2.imread('dataset/mnist_images_fg/train/' + str(i) + '.png',cv2.IMREAD_GRAYSCALE)
    cnts = cv2.findContours(img, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)[-2]
    (x,y), radius = cv2.minEnclosingCircle(cnts[0])
    center_x = round(int(x)/28,2)
    center_y = round(int(y)/28,2)
    radius = round(int(radius)/(28/(2)**0.5),2)
    center_radius_dataset_train.append([y_label_train[i],center_x, center_y, radius])
```

```
100%|████████████████████████████████████████████████████████████████████████████████| 60000/60000 [00:36<0
0:00, 1632.94it/s]
```

Saving the dataset in a .csv file.

In [ ]:
```python
with open('dataset/Q1b_center_rad_train.csv', 'a+', newline ='') as f:
    write = csv.writer(f)
    write.writerow(['label','x','y', 'radius'])
    write.writerows(center_radius_dataset_train)
```

In [ ]:
```python
center_radius_dataset_test = []

for i in tqdm(range(10000)):
    img = cv2.imread('dataset/mnist_images_fg/test/' + str(i) + '.png',cv2.IMREAD_GRAYSCALE)
    cnts = cv2.findContours(img, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)[-2]
    (x,y), radius = cv2.minEnclosingCircle(cnts[0])
    center_x = round(int(x)/28,2)
    center_y = round(int(y)/28,2)
    radius = round(int(radius)/(28/(2)**0.5),2)
    center_radius_dataset_test.append([y_label_test[i],center_x, center_y, radius])
```

```
100%|████████████████████████████████████████████████████████████████████████████████| 10000/10000 [00:06<0
0:00, 1594.78it/s]
```

Saving the dataset in a .csv file.

In [ ]:
```python
with open('dataset/Q1b_center_rad_test.csv', 'a+', newline ='') as f:
    write = csv.writer(f)
    write.writerow(['label','x','y', 'radius'])
    write.writerows(center_radius_dataset_test)
```

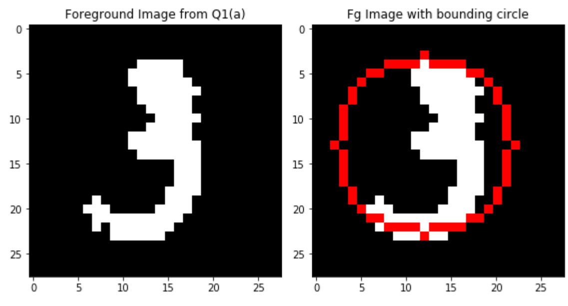
Sample Visualization

In [125]:
```python
idx  = 10
sample_x = np.array(pd.read_csv('dataset/mnist_train.csv'))[idx,1:].reshape((28,28))
sample_y = np.array(pd.read_csv('dataset/Q1b_center_rad_train.csv'))[idx]
```

In [126]:
```python
img = cv2.imread('dataset/mnist_images_fg/train/' + str(idx) + '.png')
label = sample_y[0]
x = int(round(sample_y[1]*28))
y = int(round(sample_y[2]*28))
center_coordinates = (x, y)
color = (255, 0, 0)
thickness = 1
radius  = int(round(sample_y[3]*28/(2)**0.5))
sample_y = cv2.circle(img, center_coordinates, radius, color, thickness)
```

In [129]:
```python
img = cv2.imread('dataset/mnist_images_fg/train/' + str(idx) + '.png')
```

In [133]:
```python
fig=plt.figure(figsize=(8, 8))
columns = 2
rows = 1
fig.add_subplot(rows, columns, 1)
plt.imshow(img, cmap = 'gray')
plt.title("Foreground Image from Q1(a)")
fig.add_subplot(rows, columns, 2)
plt.imshow(sample_y)
plt.title("Fg Image with bounding circle")
fig.tight_layout()
plt.show()
```



part (c)

In [459]:
```python
X_train = np.array(pd.read_csv("dataset/mnist_train.csv"))[:,1:]
X_test = np.array(pd.read_csv("dataset/mnist_test.csv"))[:,1:]
y_label_train = np.array(pd.read_csv("dataset/mnist_train.csv"))[:,0] + 1
y_label_test = np.array(pd.read_csv("dataset/mnist_test.csv"))[:,0] + 1
y_train = np.array(pd.read_csv("dataset/Q1fg_mask_train.csv", header = None))
y_test = np.array(pd.read_csv("dataset/Q1fg_mask_test.csv", header = None))
y_train[y_train >=1 ] = 1
y_test[y_test >=1 ] = 1
```

Segmentation Dataset

In this datasset each pixel has an label associated with it, which is to predicted by the model in Q4.
Dataset Size : (n_samples, 56,56,1)

number of classes = 11

Classes :

- class 0 : background class
- class 1 : number 0
- class 2 : number 1
- class 3 : number 2
- class 4 : number 3
- class 5 : number 4
- class 6 : number 5
- class 7 : number 6
- class 8 : number 7
- class 9 : number 8
- class 10 : number 9

In [460]:
```python
# Creating the training Set
q4_dataset_x_train = []
q4_dataset_y_train = []

indexes = np.arange(60000)
while(len(indexes) > 0):
    e1 = random.choice(indexes)
    indexes = np.delete(indexes, np.where(indexes == e1)[0][0])
    e2 = random.choice(indexes)
    indexes = np.delete(indexes, np.where(indexes == e2)[0][0])
    e3 = random.choice(indexes)
    indexes = np.delete(indexes, np.where(indexes == e3)[0][0])
    e4 = random.choice(indexes)
    indexes = np.delete(indexes, np.where(indexes == e4)[0][0])


    img1, y1 = X_train[e1].reshape((28,28)), y_train[e1].reshape((28,28))*y_label_train[e1]
    img2, y2 = X_train[e2].reshape((28,28)), y_train[e2].reshape((28,28))*y_label_train[e2]
    img3, y3 = X_train[e3].reshape((28,28)), y_train[e3].reshape((28,28))*y_label_train[e3]
    img4, y4 = X_train[e4].reshape((28,28)), y_train[e4].reshape((28,28))*y_label_train[e4]

    final_img = np.zeros((56,56))
    final_seg = np.zeros((56,56))
    final_img[0:28,0:28] = img1
    final_img[0:28,28:] = img2
    final_img[28:,0:28] = img3
    final_img[28:,28:] = img4

    final_seg[0:28,0:28] = y1
    final_seg[0:28 ,28:] = y2
    final_seg[28:,0:28] = y3
    final_seg[28:,28:] = y4

    q4_dataset_x_train.append(final_img.flatten())
    q4_dataset_y_train.append(final_seg.flatten())

q4_dataset_x_train = np.array(q4_dataset_x_train)
q4_dataset_y_train = np.array(q4_dataset_y_train)
```

Saving the dataset in a .csv file.

In [ ]:
```python
with open('dataset/question4/Q1image_segmentation_train_x.csv', 'a+', newline ='') as f:
    write = csv.writer(f)
    write.writerows(q4_dataset_x_train)
with open('dataset/question4/Q1image_segmentation_train_y.csv', 'a+', newline ='') as f:
    write = csv.writer(f)
    write.writerows(q4_dataset_y_train)
```

In [461]:
```python
# Creating the Test Set
q4_dataset_x_test = []
q4_dataset_y_test = []

indexes = np.arange(10000)
while(len(indexes) > 0):
    e1 = random.choice(indexes)
    indexes = np.delete(indexes, np.where(indexes == e1)[0][0])
    e2 = random.choice(indexes)
    indexes = np.delete(indexes, np.where(indexes == e2)[0][0])
    e3 = random.choice(indexes)
    indexes = np.delete(indexes, np.where(indexes == e3)[0][0])
    e4 = random.choice(indexes)
    indexes = np.delete(indexes, np.where(indexes == e4)[0][0])


    img1, y1 = X_test[e1].reshape((28,28)), y_test[e1].reshape((28,28))*y_label_test[e1]
    img2, y2 = X_test[e2].reshape((28,28)), y_test[e2].reshape((28,28))*y_label_test[e2]
    img3, y3 = X_test[e3].reshape((28,28)), y_test[e3].reshape((28,28))*y_label_test[e3]
    img4, y4 = X_test[e4].reshape((28,28)), y_test[e4].reshape((28,28))*y_label_test[e4]

    final_img = np.zeros((56,56))
    final_seg = np.zeros((56,56))
    final_img[0:28,0:28] = img1
    final_img[0:28,28:] = img2
    final_img[28:,0:28] = img3
    final_img[28:,28:] = img4

    final_seg[0:28,0:28] = y1
    final_seg[0:28 ,28:] = y2
    final_seg[28:,0:28] = y3
    final_seg[28:,28:] = y4

    q4_dataset_x_test.append(final_img.flatten())
    q4_dataset_y_test.append(final_seg.flatten())

q4_dataset_x_test = np.array(q4_dataset_x_test)
q4_dataset_y_test = np.array(q4_dataset_y_test)
```

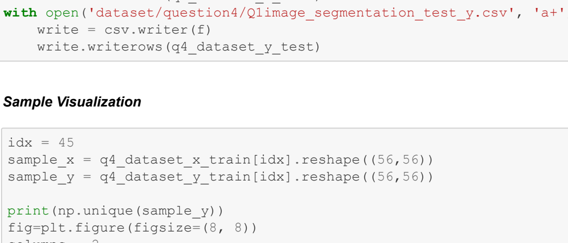
Saving the dataset in a .csv file.

In [ ]:
```python
with open('dataset/question4/Q1image_segmentation_test_x.csv', 'a+', newline ='') as f:
    write = csv.writer(f)
    write.writerows(q4_dataset_x_test)
with open('dataset/question4/Q1image_segmentation_test_y.csv', 'a+', newline ='') as f:
    write = csv.writer(f)
    write.writerows(q4_dataset_y_test)
```

Sample Visualization

In [463]:
```python
idx = 45
sample_x = q4_dataset_x_train[idx].reshape((56,56))
sample_y = q4_dataset_y_train[idx].reshape((56,56))

print(np.unique(sample_y))
fig=plt.figure(figsize=(8, 8))
columns = 2
rows = 1
fig.add_subplot(rows, columns, 1)
plt.imshow(sample_x, cmap = 'gray')
plt.title("Image")
fig.add_subplot(rows, columns, 2)
plt.imshow(sample_y, cmap = 'gray')
plt.title("Segmentation")
fig.tight_layout()
plt.show()
```

```
[ 0.  1.  3.  7. 10.]
```



**The segmentation map as each pixel has an associated label with it ranging from 0 to 10.
Thus the background is 0 hence black and rest other number are positive values , thus denoting different shades of gray. Like in this example the segmentation of 6 will have all labels as 7 and segmentation of 9 will have all labels as 10. Thus 9 being more brighter than 6**

Question 2

Train a DL network from scratch for performing **foreground extraction** on the new dataset obtained in Q1 (a). Report your test performance using Jaccard similarity. [3 Marks]

In [114]:
```python
X_train_df = pd.read_csv("dataset/mnist_train.csv")
X_test_df = pd.read_csv("dataset/mnist_test.csv")


y_train_df = pd.read_csv("dataset/Q1fg_mask_train.csv", header = None)
y_test_df = pd.read_csv("dataset/Q1fg_mask_test.csv", header= None)
```

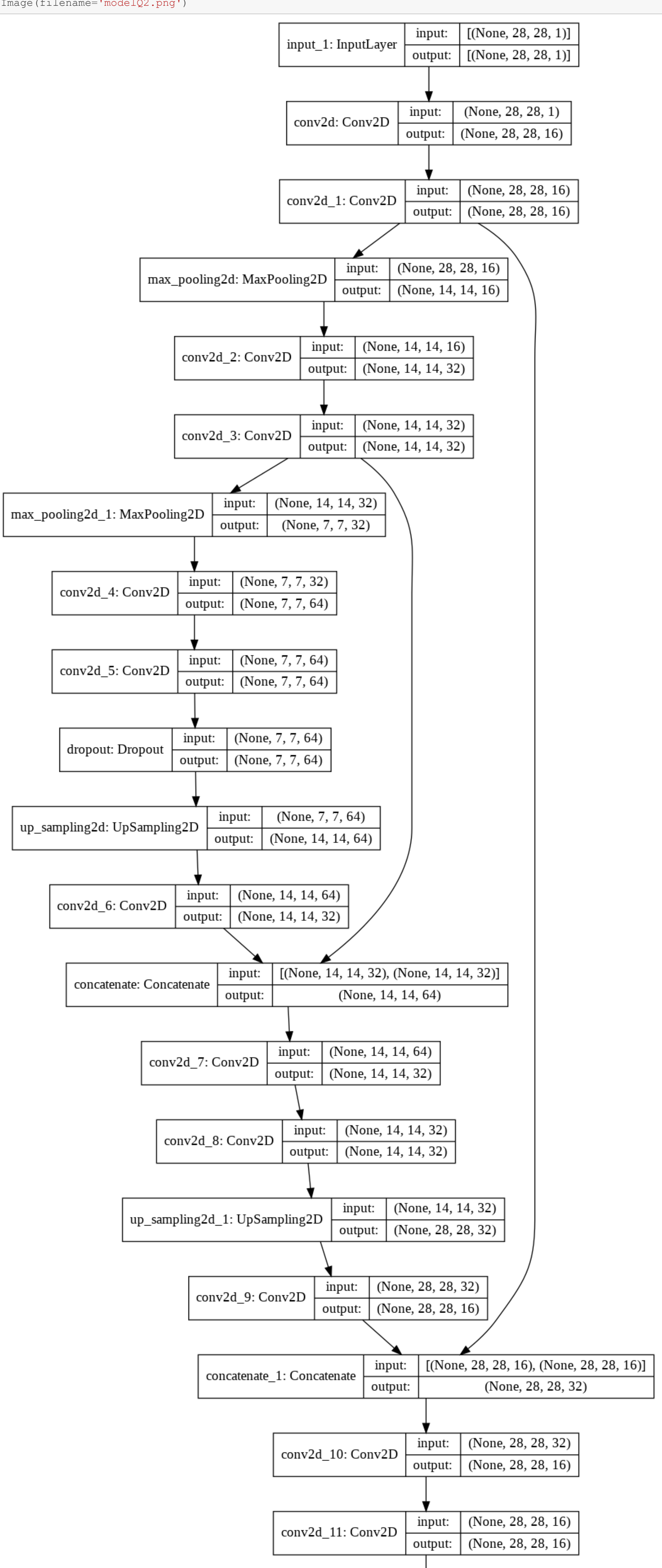
In [115]:
```python
X_train = np.array(X_train_df)[:,1:]
X_test = np.array(X_test_df)[:,1:]
y_train = np.array(y_train_df)
y_test = np.array(y_test_df)


X_train = X_train.reshape((X_train.shape[0], 28,28,1))
X_test = X_test.reshape((X_test.shape[0], 28,28,1))
y_train = y_train.reshape((y_train.shape[0], 28,28,1))
y_test = y_test.reshape((y_test.shape[0], 28,28,1))

print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(60000, 28, 28, 1)
(10000, 28, 28, 1)
(60000, 28, 28, 1)
(10000, 28, 28, 1)
```

Defining the Model

The Architecture of the model

```
In [112]: Image(filename='modelQ2.png')
Out[112]:
```




```python
In [ ]: def SkipNet(input_shape = (28,28,1) ):

    inputs = Input(input_shape)
    conv1 = Conv2D(16, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(inputs)
    conv1 = Conv2D(16, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(conv1)
    pool1 = MaxPooling2D(pool_size=(2, 2))(conv1)

    conv2 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(pool1)
    conv2 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(conv2)
    pool2 = MaxPooling2D(pool_size=(2, 2))(conv2)

    conv3 = Conv2D(64, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(pool2)
    conv3 = Conv2D(64, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(conv3)
    drop3 = Dropout(0.2)(conv3)

    up4 = Conv2D(32, 2, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(UpSampling2D(size = (2,2))(drop3))
    merge4 = concatenate([conv2,up4], axis = 3)
    conv4 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(merge4)
    conv4 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(conv4)

    up5 = Conv2D(16, 2, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(UpSampling2D(size = (2,2))(conv4))
    merge5 = concatenate([conv1,up5], axis = 3)
    conv5 = Conv2D(16, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(merge5)
    conv5 = Conv2D(16, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(conv5)
    conv5 = Conv2D(2, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(conv5)
    conv6 = Conv2D(1, 1, activation = 'sigmoid')(conv5)

    model = Model(inputs = inputs, outputs = conv6, name = "SkipNet")

    model.compile(optimizer = Adam(lr = 1e-4), loss = 'binary_crossentropy', metrics = ['accuracy'])

    model.summary()

    return model
```

Training from sratch

Parameters :

- Optimizer : Adam optimization algorithm
- loss : Binary Crossentropy
- Learning Rate : 0.0001
- epochs : 20
- batch size : 256
- metrics : accuracy

```python
In [ ]: model = SkipNet()
model.fit(X_train, y_train, epochs = 20, batch_size = 256)
```

```
Model: "SkipNet"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_3 (InputLayer)            [(None, 28, 28, 1)]  0
__________________________________________________________________________________________________
conv2d_28 (Conv2D)              (None, 28, 28, 16)   160         input_3[0][0]
__________________________________________________________________________________________________
conv2d_29 (Conv2D)              (None, 28, 28, 16)   2320        conv2d_28[0][0]
__________________________________________________________________________________________________
max_pooling2d_4 (MaxPooling2D)  (None, 14, 14, 16)   0           conv2d_29[0][0]
__________________________________________________________________________________________________
conv2d_30 (Conv2D)              (None, 14, 14, 32)   4640        max_pooling2d_4[0][0]
__________________________________________________________________________________________________
conv2d_31 (Conv2D)              (None, 14, 14, 32)   9248        conv2d_30[0][0]
__________________________________________________________________________________________________
max_pooling2d_5 (MaxPooling2D)  (None, 7, 7, 32)     0           conv2d_31[0][0]
__________________________________________________________________________________________________
conv2d_32 (Conv2D)              (None, 7, 7, 64)     18496       max_pooling2d_5[0][0]
__________________________________________________________________________________________________
conv2d_33 (Conv2D)              (None, 7, 7, 64)     36928       conv2d_32[0][0]
__________________________________________________________________________________________________
dropout_2 (Dropout)             (None, 7, 7, 64)     0           conv2d_33[0][0]
__________________________________________________________________________________________________
up_sampling2d_4 (UpSampling2D)  (None, 14, 14, 64)   0           dropout_2[0][0]
__________________________________________________________________________________________________
conv2d_34 (Conv2D)              (None, 14, 14, 32)   8224        up_sampling2d_4[0][0]
__________________________________________________________________________________________________
concatenate_4 (Concatenate)     (None, 14, 14, 64)   0           conv2d_31[0][0]
                                                                 conv2d_34[0][0]
__________________________________________________________________________________________________
conv2d_35 (Conv2D)              (None, 14, 14, 32)   18464       concatenate_4[0][0]
__________________________________________________________________________________________________
conv2d_36 (Conv2D)              (None, 14, 14, 32)   9248        conv2d_35[0][0]
__________________________________________________________________________________________________
up_sampling2d_5 (UpSampling2D)  (None, 28, 28, 32)   0           conv2d_36[0][0]
__________________________________________________________________________________________________
conv2d_37 (Conv2D)              (None, 28, 28, 16)   2064        up_sampling2d_5[0][0]
__________________________________________________________________________________________________
concatenate_5 (Concatenate)     (None, 28, 28, 32)   0           conv2d_29[0][0]
                                                                 conv2d_37[0][0]
__________________________________________________________________________________________________
conv2d_38 (Conv2D)              (None, 28, 28, 16)   4624        concatenate_5[0][0]
__________________________________________________________________________________________________
conv2d_39 (Conv2D)              (None, 28, 28, 16)   2320        conv2d_38[0][0]
__________________________________________________________________________________________________
conv2d_40 (Conv2D)              (None, 28, 28, 2)    290         conv2d_39[0][0]
__________________________________________________________________________________________________
conv2d_41 (Conv2D)              (None, 28, 28, 1)    3           conv2d_40[0][0]
==================================================================================================
Total params: 117,029
Trainable params: 117,029
Non-trainable params: 0
__________________________________________________________________________________________________
Epoch 1/20
235/235 [==============================] - 6s 19ms/step - loss: 3.5798 - accuracy: 0.7989
Epoch 2/20
235/235 [==============================] - 5s 19ms/step - loss: 0.1691 - accuracy: 0.8628
Epoch 3/20
235/235 [==============================] - 5s 19ms/step - loss: 0.1423 - accuracy: 0.9515
Epoch 4/20
235/235 [==============================] - 5s 19ms/step - loss: 0.1299 - accuracy: 0.9627
Epoch 5/20
235/235 [==============================] - 5s 19ms/step - loss: 0.1230 - accuracy: 0.9687
Epoch 6/20
235/235 [==============================] - 5s 19ms/step - loss: 0.1173 - accuracy: 0.9735
Epoch 7/20
235/235 [==============================] - 5s 19ms/step - loss: 0.1116 - accuracy: 0.9779
Epoch 8/20
235/235 [==============================] - 5s 19ms/step - loss: 0.1076 - accuracy: 0.9805
Epoch 9/20
235/235 [==============================] - 5s 19ms/step - loss: 0.1028 - accuracy: 0.9834
Epoch 10/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0992 - accuracy: 0.9855
Epoch 11/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0963 - accuracy: 0.9875
Epoch 12/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0936 - accuracy: 0.9882
Epoch 13/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0915 - accuracy: 0.9893
Epoch 14/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0892 - accuracy: 0.9901
Epoch 15/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0874 - accuracy: 0.9906
Epoch 16/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0856 - accuracy: 0.9910
Epoch 17/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0839 - accuracy: 0.9917
Epoch 18/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0821 - accuracy: 0.9921
Epoch 19/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0805 - accuracy: 0.9922
Epoch 20/20
235/235 [==============================] - 5s 19ms/step - loss: 0.0790 - accuracy: 0.9924
Out[ ]: <tensorflow.python.keras.callbacks.History at 0x7f65bc06c0d0>
```

Saving the weights

```python
In [ ]: model.save('ModelZoo/FgExtractor')
```

```
INFO:tensorflow:Assets written to: ModelZoo/FgExtractor/assets
```

Loading the weights

```python
In [116]: from tensorflow import keras
model = keras.models.load_model('ModelZoo/FgExtractor')
```

Evaluating on the test set

```python
In [117]: y_pred = model.predict(X_test)
y_pred[y_pred < 0.5] = 0
y_pred[y_pred >= 0.5] = 1
```

```python
In [118]: idx = 15
img = np.squeeze(X_test[idx])
pred = np.squeeze(y_pred[idx])
y = np.squeeze(y_test[idx])
fig=plt.figure(figsize=(10, 10))
columns = 3
rows = 1
fig.add_subplot(rows, columns, 1)
plt.imshow(img, cmap = 'gray')
plt.title("Original Image")
fig.add_subplot(rows, columns, 2)
plt.imshow(pred, cmap = "gray")
plt.title("Predicted Foreground map")
fig.add_subplot(rows, columns, 3)
plt.imshow(y, cmap = "gray")
plt.title("Ground truth Foreground map")
fig.tight_layout()
plt.show()
```

Calculating the jaccard Similarity

```python
In [122]: avg_jacc_score = 0
for i in range(len(y_pred)):
    jc = jaccard_score(y_test[i].flatten(), y_pred[i].flatten(), average = 'binary')
    avg_jacc_score+=jc
avg_jacc_score/=len(y_pred)
print("Average \033[1m Jaccard Similarity \033[0m on the Test set :", avg_jacc_score)
```

```
Average  Jaccard Similarity  on the Test set : 0.9517986598096035
```

Question 3

Train a DL network from scratch for performing classification with circlization on the new dataset obtained in Q1 (b). Report your test performance using Jaccard Similarity. [4 Marks]
Note: If the classification is already wrong, the Jaccard Similarity score will become zero.

Reading the Dataset

```python
In [4]: X_train_df = pd.read_csv("dataset/mnist_train.csv")
X_test_df = pd.read_csv("dataset/mnist_test.csv")
Y_train_df =  pd.read_csv("dataset/Q1b_center_rad_train.csv")
Y_test_df = pd.read_csv("dataset/Q1b_center_rad_test.csv")
```

```python
In [5]: Y_train_df
Out[5]:
```

	label	x	y	radius
0	5	0.46	0.50	0.66
1	0	0.46	0.46	0.51
2	4	0.46	0.46	0.56
3	1	0.50	0.50	0.51
4	9	0.54	0.57	0.45
...	...	...	...	...
59995	8	0.50	0.54	0.56
59996	3	0.43	0.46	0.56
59997	5	0.50	0.50	0.66
59998	6	0.46	0.39	0.56
59999	8	0.57	0.54	0.56

60000 rows × 4 columns

```python
In [6]: train_names = np.arange(60000).astype(str)
train_labels = Y_train_df.label.values
train_coor = Y_train_df[['x', 'y', 'radius']].values

test_names = np.arange(10000).astype(str)
test_labels = Y_test_df.label.values
test_coor = Y_test_df[['x', 'y', 'radius']].values
```

```python
In [7]: X_train = np.array(X_train_df)[:,1:]
X_test = np.array(X_test_df)[:,1:]
```

Creating the tf records

```python
In [8]: AUTO = tf.data.experimental.AUTOTUNE
BATCH_SIZE = 32

@tf.function
def preprocess_train(image_name, label, coor):
    image = tf.io.read_file('dataset/mnist_images/train/'+image_name + ".png")
    image = tf.image.decode_png(image, channels=1)

    return image, {'label': label, 'coor': coor}

@tf.function
def preprocess_test(image_name, label, coor):
    image = tf.io.read_file('dataset/mnist_images/test/'+image_name + ".png")
    image = tf.image.decode_png(image, channels=1)

    return image, {'label': label, 'coor': coor}

trainloader = tf.data.Dataset.from_tensor_slices((train_names, train_labels, train_coor))
testloader = tf.data.Dataset.from_tensor_slices((test_names, test_labels, test_coor))

trainloader = (
    trainloader
    .map(preprocess_train, num_parallel_calls=AUTO)
    .shuffle(1024)
    .batch(BATCH_SIZE)
    .prefetch(AUTO)
)

testloader = (
    testloader
    .map(preprocess_test, num_parallel_calls=AUTO)
    .batch(BATCH_SIZE)
    .prefetch(AUTO)
)
```

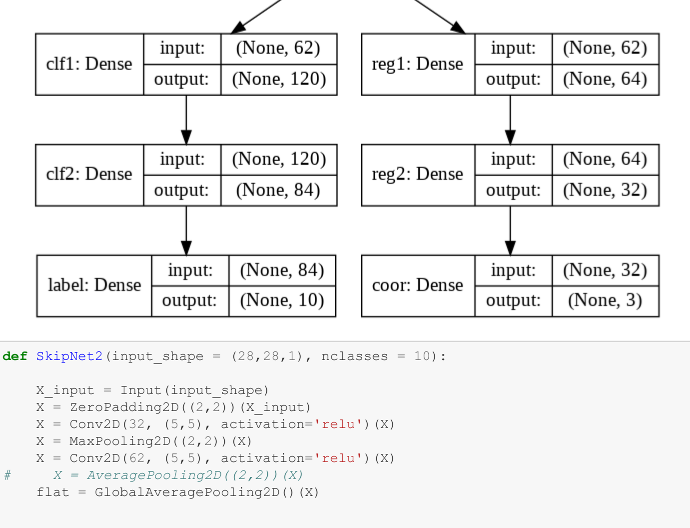
To calculate the discrete points inside the circle given the radius and center

```python
In [9]: def points_in_circle_np(radius, x0=0, y0=0):
    """
    To get all the logical points in a circle.

    Arguments
    ----------
    radius : Radius of the circle, int.
    x0 : x-coordinate of the center, int.
    y0 : y-coordinate of the center, int.

    """
    x_ = np.arange(x0 - radius - 1, x0 + radius + 1, dtype=int)
    y_ = np.arange(y0 - radius - 1, y0 + radius + 1, dtype=int)
    x, y = np.where((x_[:,np.newaxis] - x0)**2 + (y_ - y0)**2 <= radius**2)
    list_ = []
    for x, y in zip(x_[x], y_[y]):
        list_.append((x,y))
    return list_
```

Defining the Model

The Architecture of the model

```python
In [10]: Image(filename='modelQ3.png')
Out[10]:
```




```python
In [11]: def SkipNet2(input_shape = (28,28,1), nclasses = 10):

    X_input = Input(input_shape)
    X = ZeroPadding2D((2,2))(X_input)
    X = Conv2D(32, (5,5), activation='relu')(X)
    X = MaxPooling2D((2,2))(X)
    X = Conv2D(62, (5,5), activation='relu')(X)
#     X = AveragePooling2D((2,2))(X)
    flat = GlobalAveragePooling2D()(X)


    clf = Dense(120, activation = 'relu', name  = 'clf1')(flat)

    clf = Dense(84, activation = 'relu', name = 'clf2')(clf)

    clf = Dense(10, activation = 'softmax', name = 'label')(clf)

    reg = Dense(64, activation='relu', name = 'reg1')(flat)
    reg = Dense(32, activation='relu', name = 'reg2')(reg)
    reg = Dense(3, activation='sigmoid', name='coor')(reg)

    model =  Model(inputs=X_input, outputs=[clf, reg], name = "MyObjectDetectionNet")

    return model
```

```python
In [12]: model = SkipNet2()
model.summary()
```

```
Model: "MyObjectDetectionNet"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            [(None, 28, 28, 1)]  0
__________________________________________________________________________________________________
zero_padding2d (ZeroPadding2D)  (None, 32, 32, 1)    0           input_1[0][0]
__________________________________________________________________________________________________
conv2d (Conv2D)                 (None, 28, 28, 32)   832         zero_padding2d[0][0]
__________________________________________________________________________________________________
max_pooling2d (MaxPooling2D)    (None, 14, 14, 32)   0           conv2d[0][0]
__________________________________________________________________________________________________
conv2d_1 (Conv2D)               (None, 10, 10, 62)   49662       max_pooling2d[0][0]
__________________________________________________________________________________________________
global_average_pooling2d (Globa (None, 62)           0           conv2d_1[0][0]
__________________________________________________________________________________________________
clf1 (Dense)                    (None, 120)          7560        global_average_pooling2d[0][0]
__________________________________________________________________________________________________
reg1 (Dense)                    (None, 64)           4032        global_average_pooling2d[0][0]
__________________________________________________________________________________________________
clf2 (Dense)                    (None, 84)           10164       clf1[0][0]
__________________________________________________________________________________________________
reg2 (Dense)                    (None, 32)           2080        reg1[0][0]
__________________________________________________________________________________________________
label (Dense)                   (None, 10)           850         clf2[0][0]
__________________________________________________________________________________________________
coor (Dense)                    (None, 3)            99          reg2[0][0]
==================================================================================================
Total params: 75,279
Trainable params: 75,279
Non-trainable params: 0
__________________________________________________________________________________________________
```

```python
In [13]: losses = {'label': 'sparse_categorical_crossentropy',
          'coor': 'mse'}

loss_weights = {'label': 1.0,
               'coor': 1.0}
model.compile('adam', loss=losses, loss_weights=loss_weights, metrics=['acc'])
```

Training from sratch

Parameters :

- Optimizer : Adam optimization algorithm
- loss : Sparse Categorical Crossentropy and MSE
- epochs : 30
- batch size : 32
- metrics : accuracy

```python
In [77]: model.fit(trainloader,epochs=20)
```

```
Epoch 1/20
1875/1875 [==============================] - 108s 58ms/step - loss: 0.2904 - label_loss: 0.2828 - coor_loss: 0.0075 - label_acc: 0.9113 - coor_acc: 0.53223s - loss: 0.2971 - label_loss: 0.2894 - coor_loss: 0.0077 - label_
Epoch 2/20
1875/1875 [==============================] - 97s 52ms/step - loss: 0.0731 - label_loss: 0.0703 - coor_loss: 0.0027 - label_acc: 0.9779 - coor_acc: 0.6741
Epoch 3/20
1875/1875 [==============================] - 82s 44ms/step - loss: 0.0561 - label_loss: 0.0535 - coor_loss: 0.0026 - label_acc: 0.9832 - coor_acc: 0.6978 7s - l
Epoch 4/20
1875/1875 [==============================] - 83s 44ms/step - loss: 0.0443 - label_loss: 0.0418 - coor_loss: 0.0025 - label_acc: 0.9870 - coor_acc: 0.7044 2s - loss: 0.0443 - label_loss: 0.0418 - coor_loss: 0.0025 - label_acc:
Epoch 5/20
1875/1875 [==============================] - 90s 48ms/step - loss: 0.0393 - label_loss: 0.0369 - coor_loss: 0.0024 - label_acc: 0.9881 - coor_acc: 0.7119 - ETA: 4s - loss: 0.0398 - label_loss: 0.0374 - coor_loss: 0.0024 - label_acc: 0.9879  - ETA: 2s - loss: 0.0395 - label_loss: 0.0371 - coor_loss: 0.0024
Epoch 6/20
1875/1875 [==============================] - 89s 47ms/step - loss: 0.0333 - label_loss: 0.0310 - coor_loss: 0.0024 - label_acc: 0.9903 - coor_acc: 0.7089 3s - loss: 0.0333 - label_loss: 0.0309 - coor_loss: 0.0023
Epoch 7/20
1875/1875 [==============================] - 94s 50ms/step - loss: 0.0293 - label_loss: 0.0270 - coor_loss: 0.0023 - label_acc: 0.9916 - coor_acc: 0.7134 8s - l
Epoch 8/20
1875/1875 [==============================] - 93s 50ms/step - loss: 0.0269 - label_loss: 0.0246 - coor_loss: 0.0023 - label_acc: 0.9923 - coor_acc: 0.7171
Epoch 9/20
1875/1875 [==============================] - 89s 48ms/step - loss: 0.0243 - label_loss: 0.0220 - coor_loss: 0.0023 - label_acc: 0.9930 - coor_acc: 0.7236 5s - loss: 0.0243 - label_loss: 0.0221 - coor_loss: 0.0022 - label_acc: 0.9929 - c - ETA: 4s - loss: 0.0243 - label_loss:
Epoch 10/20
1875/1875 [==============================] - 93s 49ms/step - loss: 0.0213 - label_loss: 0.0191 - coor_loss: 0.0022 - label_acc: 0.9940 - coor_acc: 0.7214 2s - loss: 0.0214 - label_loss: 0.0192 - coor_loss: 0.0022 - label_a
Epoch 11/20
1875/1875 [==============================] - 95s 51ms/step - loss: 0.0201 - label_loss: 0.0179 - coor_loss: 0.0022 - label_acc: 0.9945 - coor_acc: 0.7282
Epoch 12/20
1875/1875 [==============================] - 77s 41ms/step - loss: 0.0222 - label_loss: 0.0200 - coor_loss: 0.0022 - label_acc: 0.9936 - coor_acc: 0.7246
Epoch 13/20
1875/1875 [==============================] - 80s 42ms/step - loss: 0.0171 - label_loss: 0.0149 - coor_loss: 0.0022 - label_acc: 0.9954 - coor_acc: 0.7289
Epoch 14/20
1875/1875 [==============================] - 86s 46ms/step - loss: 0.0175 - label_loss: 0.0153 - coor_loss: 0.0022 - label_acc: 0.9949 - coor_acc: 0.7307
Epoch 15/20
1875/1875 [==============================] - 88s 47ms/step - loss: 0.0160 - label_loss: 0.0139 - coor_loss: 0.0022 - label_acc: 0.9961 - coor_acc: 0.7305
Epoch 16/20
1875/1875 [==============================] - 89s 47ms/step - loss: 0.0149 - label_loss: 0.0128 - coor_loss: 0.0021 - label_acc: 0.9962 - coor_acc: 0.7314 5s - loss: 0.0152 - label_loss: 0
Epoch 17/20
1875/1875 [==============================] - 94s 50ms/step - loss: 0.0150 - label_loss: 0.0128 - coor_loss: 0.0021 - label_acc: 0.9960 - coor_acc: 0.7298 4s - loss: 0.0147 - label_loss: 0.0126 - coor_loss: 0.0021 - label_acc: 0.9960 - coor_acc: 0.72 - ETA: 4s - loss: 0.0148 - label_loss: 0.0127 -
Epoch 18/20
1875/1875 [==============================] - 96s 51ms/step - loss: 0.0162 - label_loss: 0.0141 - coor_loss: 0.0021 - label_acc: 0.9958 - coor_acc: 0.7327
Epoch 19/20
1875/1875 [==============================] - 93s 50ms/step - loss: 0.0142 - label_loss: 0.0121 - coor_loss: 0.0021 - label_acc: 0.9962 - coor_acc: 0.7290 10s - loss: 0.0142 - label_loss: 0.0121 - coor_loss: 0.0021 - label_acc: - ETA: 8s - loss: 0.0141 - label_loss: 0.0120 - coor_loss: 0.0021 - la - ETA: 5s - loss: 0.0140 - label_loss: 0.01
Epoch 20/20
1875/1875 [==============================] - 89s 47ms/step - loss: 0.0137 - label_loss: 0.0116 - coor_loss: 0.0021 - label_acc: 0.9963 - coor_acc: 0.7332
Out[77]: <tensorflow.python.keras.callbacks.History at 0x1b260139048>
```

Saving the weights

```python
In [78]: model.save('ModelZoo/ObjectLocalizer')
```

```
WARNING:tensorflow:From C:\Users\Asus\Anaconda3\lib\site-packages\tensorflow\python\training\tracking\tracking.py:111: Model.state_updates (from tensorflow.python.keras.engine.training) is deprecated and will be removed in a future version.
Instructions for updating:
This property should not be used in TensorFlow 2.0, as updates are applied automatically.
WARNING:tensorflow:From C:\Users\Asus\Anaconda3\lib\site-packages\tensorflow\python\training\tracking\tracking.py:111: Layer.updates (from tensorflow.python.keras.engine.base_layer) is deprecated and will be removed in a future version.
Instructions for updating:
This property should not be used in TensorFlow 2.0, as updates are applied automatically.
INFO:tensorflow:Assets written to: ModelZoo/ObjectLocalizer\assets
```

Loading the weights

```
In [14]: from tensorflow import keras
         model = keras.models.load_model('ModelZoo/ObjectLocalizer')
```

Evaluating on the test set

```
In [15]: y_pred,y_coor = model.predict(testloader)
```

```
In [16]: y_pred[y_pred < 0.5] = 0
         y_pred[y_pred >=0.5] = 1
         y_pred = np.argmax(y_pred, axis = 1)
         y_pred

Out[16]: array([7, 2, 1, ..., 4, 5, 6], dtype=int64)
```

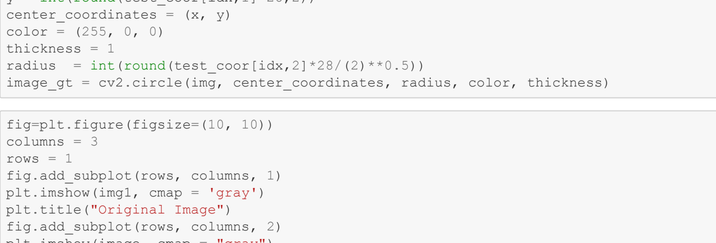
```
In [17]: print(y_coor)
         y_coor[:,0] = y_coor[:,0]*28
         y_coor[:,1] = y_coor[:,1]*28
         y_coor[:,2] = y_coor[:,2]*28/(2)**0.5

[[0.47272468 0.57472044 0.526576  ]
 [0.51313406 0.4295074  0.5609449 ]
 [0.49180645 0.44644102 0.46394607]
 ...
 [0.563763   0.5231803  0.49714106]
 [0.55173963 0.52794296 0.54207116]
 [0.45740402 0.3839616  0.44101104]]
```

```
In [51]: idx = 448
         img1 = X_test[idx].reshape(28,28)
```

```
In [52]: img = cv2.imread('dataset/mnist_images/test/' + str(idx) + '.png')
         x = y_coor[idx,0]
         y = y_coor[idx,1]
         center_coordinates = (x, y)
         color = (255, 0, 0)
         thickness = 1
         radius  = int(round(y_coor[idx,2]))
         image = cv2.circle(img, center_coordinates, radius, color, thickness)
```

```
In [53]: img = cv2.imread('dataset/mnist_images/test/' + str(idx) + '.png')
         x = int(round(test_coor[idx,0]*28,2))
         y = int(round(test_coor[idx,1]*28,2))
         center_coordinates = (x, y)
         color = (255, 0, 0)
         thickness = 1
         radius  = int(round(test_coor[idx,2]*28/(2)**0.5))
         image_gt = cv2.circle(img, center_coordinates, radius, color, thickness)
```

```
In [54]: fig=plt.figure(figsize=(10, 10))
         columns = 3
         rows = 1
         fig.add_subplot(rows, columns, 1)
         plt.imshow(img1, cmap = 'gray')
         plt.title("Original Image")
         fig.add_subplot(rows, columns, 2)
         plt.imshow(image, cmap = "gray")
         plt.title("Predicted Bounding Circle")
         fig.add_subplot(rows, columns, 3)
         plt.imshow(image_gt, cmap = "gray")
         plt.title("Ground Truth Bounding Circle")
         fig.tight_layout()
         plt.show()
```



Jaccard Similarity

Jaccard Similarity computes the intersection of two binary marks BM1 and BM2 divided by the union of BW1 and BW2.

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

where A,B are the two binary masks.

```
In [61]: def jaccard_similarity(binary_mask1, binary_mask2):
             """
             Returns the jaccard similarity score for 2 binary masks.

             Arguments
             ---------
             binary_mask1 : list of all the points in mask A.
             binary_mask2 : list of all the points in mask B.

             Returns
             -------
             IOU : Jaccard Similarity of the two masks.
             """

             intersection = len(list(set(binary_mask1).intersection(set(binary_mask2))))
             union = len(set(binary_mask1).union(set(binary_mask2)))
             if(union == 0):
                 return 0
             return float(intersection) / union
```

Calculating the average jaccard score

We would be calculating the jaccard score into two parts :

1. Calculating the jaccard scores on the input image and the predicted circle.
2. Calculating the jaccard scores on the Ground truth circle and the predicted circle.

1. Calculating the jaccard scores on the input image and the predicted circle.

```
In [64]: j_score=  0

         for i in tqdm(range(len(X_test)),position = 0, desc = "Progress : "):
             img = X_test[i].reshape(28,28)
             idxs = np.where(img > 0)
             x = idxs[0]
             y = idxs[1]
             pixels = [(i,j) for (i,j) in zip(x,y)]
             c_x = round(y_coor[i,0])
             c_y = round(y_coor[i,1])
             rad = int(round(y_coor[i,2]))
             y_p = y_pred[i]
             y_t = test_labels[i]
             if(y_p == y_t):
                 points_circle = points_in_circle_np(rad,c_x,c_y)
                 score = jaccard_similarity(points_circle,pixels)
                 j_score+=score
             else:
                 j_score+=0

         avg_jacc_score = j_score/(len(X_test))
         print("The \033[1m average jaccard score on input image and predicted circle \033[0m is : ", avg_jacc_s
core)

Progress : 100%|██████████████████████████████████████████████| 10000/10000 [00:23<
00:00, 432.69it/s]

The  average jaccard score on input image and predicted circle  is :  0.39441413368874534
```

2. Calculating the jaccard scores on the Ground truth cicles and the predicted circle.

```
In [63]: j_score=  0

         for i in tqdm(range(len(X_test)),position = 0, desc = "Progress : "):
             x,y,r = test_coor[i]
             x = round(x*28)
             y = round(y*28)
             r = int(round(r*28/(2)**0.5))

             c_x = round(y_coor[i,0])
             c_y = round(y_coor[i,1])
             rad = int(round(y_coor[i,2]))
             y_p = y_pred[i]
             y_t = test_labels[i]
             if(y_p == y_t):
                 points_circle = points_in_circle_np(rad,c_x,c_y)
                 gt_circle = points_in_circle_np(r,x,y)
                 score = jaccard_similarity(gt_circle,points_circle)
                 j_score+=score
             else:
                 j_score+=0

         avg_jacc_score = j_score/(len(X_test))
         print("The \033[1m average jaccard score on Ground truth Circle and predicted circle \033[0m is : ", av
g_jacc_score)

Progress : 100%|██████████████████████████████████████████████| 10000/10000 [00:08<0
0:00, 1179.43it/s]

The  average jaccard score on Ground truth Circle and predicted circle  is :  0.8457513813013228
```

Question 4

Train a DL network from scratch for performing semantic segmentation on the new dataset obtained in Q1 (c). Report your test performance using Jaccard Similarity. [4 Marks]

```
In [135]: X_train_df = pd.read_csv("dataset/question4/Q1image_segmentation_train_x.csv", header = None)
          y_train_df = pd.read_csv("dataset/question4/Q1image_segmentation_train_y.csv", header= None)
          X_test_df = pd.read_csv("dataset/question4/Q1image_segmentation_test_x.csv", header = None)
          y_test_df = pd.read_csv("dataset/question4/Q1image_segmentation_test_y.csv", header= None)
```

```
In [136]: X_train = np.array(X_train_df).astype(int)
          y_train_orig = np.array(y_train_df).astype(int)
          X_test = np.array(X_test_df).astype(int)
          y_test_orig = np.array(y_test_df).astype(int)
```

```
In [137]: X_train = X_train.reshape((X_train.shape[0], 56,56,1))
          y_train_orig = y_train_orig.reshape((y_train_orig.shape[0], 56,56,1))
          X_test = X_test.reshape((X_test.shape[0], 56,56,1))
          y_test_orig = y_test_orig.reshape((y_test_orig.shape[0], 56,56,1))
```

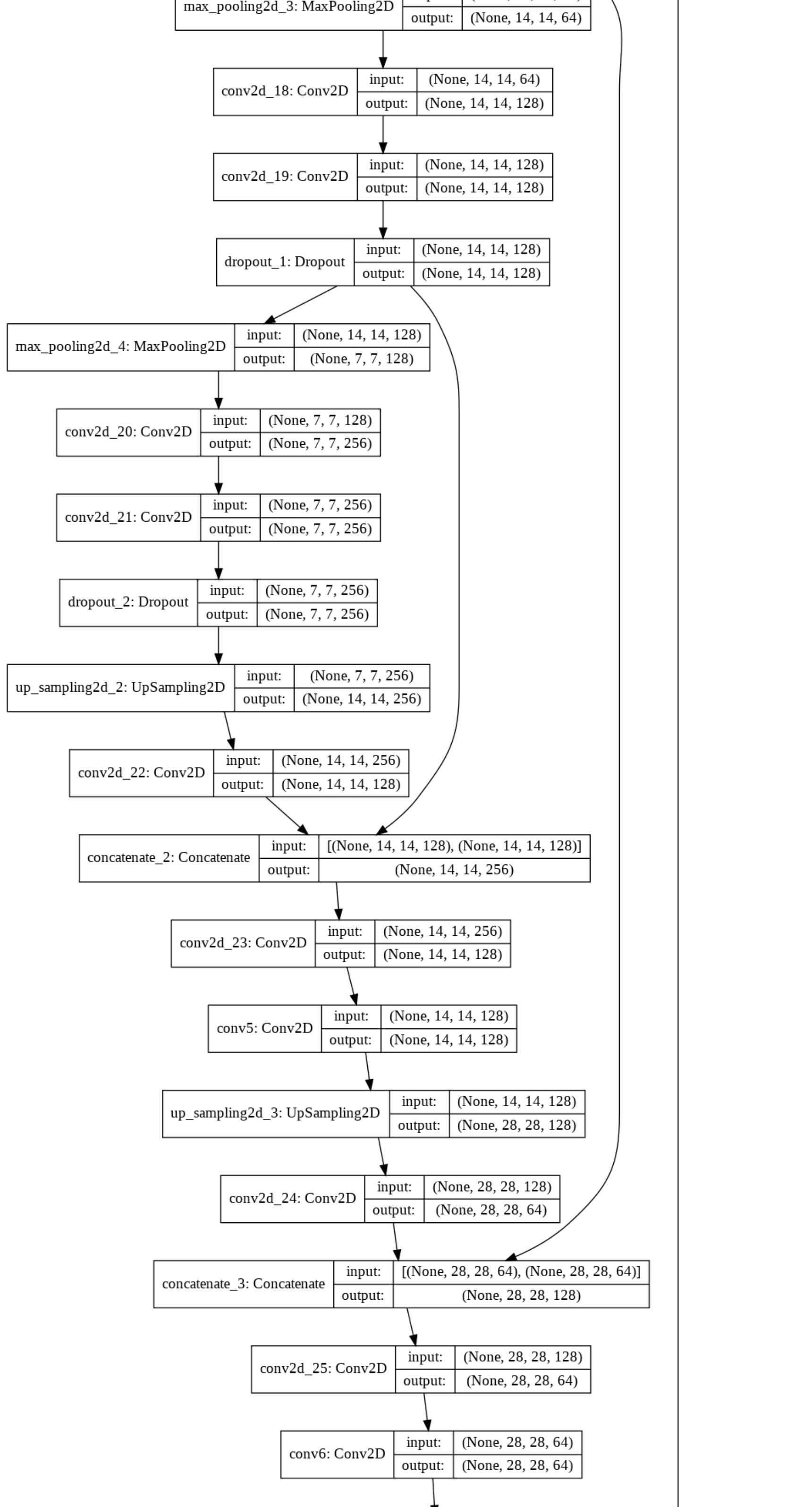
```
In [ ]: #To load the train set (takes a lot of RAM)

        y_train = np.zeros((y_train_orig.shape[0], 56,56,11), dtype = int)

        for i in tqdm(range(y_train.shape[0]), position = 0, desc = "Progress :"):
            for j in range(y_train.shape[1]):
                for k in range(y_train.shape[2]):
                    y_train[i,j,k,y_train_orig[i,j,k,0]] = 1


        print(X_train.shape)
        print(y_train.shape)

Progress :: 100%|██████████| 15000/15000 [00:31<00:00, 476.48it/s]
Progress :: 100%|██████████| 2500/2500 [00:05<00:00, 473.46it/s]
```

```
In [138]: #To load the test set (takes a lot of RAM)

          y_test = np.zeros((y_test_orig.shape[0], 56,56,11), dtype = int)

          for i in tqdm(range(y_test.shape[0]), position = 0, desc = "Progress :"):
              for j in range(y_test.shape[1]):
                  for k in range(y_test.shape[2]):
                      y_test[i,j,k,y_test_orig[i,j,k,0]] = 1
          print(X_test.shape)
          print(y_test.shape)

Progress :: 100%|██████████████████████████████████████████████████| 2500/2500 [00:08<
00:00, 281.93it/s]

(2500, 56, 56, 1)
(2500, 56, 56, 11)
```

Defining the Model

The Architecture of the model

```
In [124]: Image(filename='modelQ4.png')

Out[124]:
```




```
In [ ]: def SkipNet3(input_shape = (56,56,1) ):

            inputs = Input(input_shape)
            conv1 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(inpu
ts)
            conv1 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(conv
1)
            pool1 = MaxPooling2D(pool_size=(2, 2))(conv1)

            conv2 = Conv2D(64, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(pool
1)
            conv2 = Conv2D(64, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(conv
2)
            pool2 = MaxPooling2D(pool_size=(2, 2))(conv2)

            conv3 = Conv2D(128, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(poo
l2)
            conv3 = Conv2D(128, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(con
v3)
            drop3 = Dropout(0.2)(conv3)
            pool3 = MaxPooling2D(pool_size=(2, 2))(drop3)

            conv4 = Conv2D(256, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(poo
l3)
            conv4 = Conv2D(256, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(con
v4)
            drop4 = Dropout(0.2)(conv4)


            up5 = Conv2D(128, 2, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(UpSam
pling2D(size = (2,2))(drop4))
            merge5 = concatenate([drop3,up5], axis = 3)
            conv5 = Conv2D(128, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(mer
ge5)
            conv5 = Conv2D(128, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal', nam
e = 'conv5')(conv5)

            up6 = Conv2D(64, 2, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(UpSamp
ling2D(size = (2,2))(conv5))
            merge6 = concatenate([conv2,up6], axis = 3)
            conv6 = Conv2D(64, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(merg
e6)
            conv6 = Conv2D(64, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal', name
 = 'conv6')(conv6)

            up7 = Conv2D(32, 2, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(UpSamp
ling2D(size = (2,2))(conv6))
            merge7 = concatenate([conv1,up7], axis = 3)
            conv7 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(merg
e7)
            conv7 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')(conv
7)
            conv7 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal', name
 = 'conv7')(conv7)
            conv8 = Conv2D(11, 1, activation = 'softmax')(conv7)

            model = Model(inputs = inputs, outputs = conv8, name = "SkipNet3")

            model.compile(optimizer = Adam(lr = 1e-3), loss = 'categorical_crossentropy', metrics = ['accuracy'
])

            model.summary()

            return model
```

```
In [ ]: model = SkipNet3()

Model: "SkipNet3"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_2 (InputLayer)            [(None, 56, 56, 1)]  0
__________________________________________________________________________________________________
conv2d_16 (Conv2D)              (None, 56, 56, 32)   320         input_2[0][0]
__________________________________________________________________________________________________
conv2d_17 (Conv2D)              (None, 56, 56, 32)   9248        conv2d_16[0][0]
__________________________________________________________________________________________________
max_pooling2d_3 (MaxPooling2D)  (None, 28, 28, 32)   0           conv2d_17[0][0]
__________________________________________________________________________________________________
conv2d_18 (Conv2D)              (None, 28, 28, 64)   18496       max_pooling2d_3[0][0]
__________________________________________________________________________________________________
conv2d_19 (Conv2D)              (None, 28, 28, 64)   36928       conv2d_18[0][0]
__________________________________________________________________________________________________
max_pooling2d_4 (MaxPooling2D)  (None, 14, 14, 64)   0           conv2d_19[0][0]
__________________________________________________________________________________________________
conv2d_20 (Conv2D)              (None, 14, 14, 128)  73856       max_pooling2d_4[0][0]
__________________________________________________________________________________________________
conv2d_21 (Conv2D)              (None, 14, 14, 128)  147584      conv2d_20[0][0]
__________________________________________________________________________________________________
dropout_2 (Dropout)             (None, 14, 14, 128)  0           conv2d_21[0][0]
__________________________________________________________________________________________________
max_pooling2d_5 (MaxPooling2D)  (None, 7, 7, 128)    0           dropout_2[0][0]
__________________________________________________________________________________________________
conv2d_22 (Conv2D)              (None, 7, 7, 256)    295168      max_pooling2d_5[0][0]
__________________________________________________________________________________________________
conv2d_23 (Conv2D)              (None, 7, 7, 256)    590080      conv2d_22[0][0]
__________________________________________________________________________________________________
dropout_3 (Dropout)             (None, 7, 7, 256)    0           conv2d_23[0][0]
__________________________________________________________________________________________________
up_sampling2d_3 (UpSampling2D)  (None, 14, 14, 256)  0           dropout_3[0][0]
__________________________________________________________________________________________________
conv2d_24 (Conv2D)              (None, 14, 14, 128)  131200      up_sampling2d_3[0][0]
__________________________________________________________________________________________________
concatenate_3 (Concatenate)     (None, 14, 14, 256)  0           dropout_2[0][0]
                                                                 conv2d_24[0][0]
__________________________________________________________________________________________________
conv2d_25 (Conv2D)              (None, 14, 14, 128)  295040      concatenate_3[0][0]
__________________________________________________________________________________________________
conv5 (Conv2D)                  (None, 14, 14, 128)  147584      conv2d_25[0][0]
__________________________________________________________________________________________________
up_sampling2d_4 (UpSampling2D)  (None, 28, 28, 128)  0           conv5[0][0]
__________________________________________________________________________________________________
conv2d_26 (Conv2D)              (None, 28, 28, 64)   32832       up_sampling2d_4[0][0]
__________________________________________________________________________________________________
concatenate_4 (Concatenate)     (None, 28, 28, 128)  0           conv2d_19[0][0]
                                                                 conv2d_26[0][0]
__________________________________________________________________________________________________
conv2d_27 (Conv2D)              (None, 28, 28, 64)   73792       concatenate_4[0][0]
__________________________________________________________________________________________________
conv6 (Conv2D)                  (None, 28, 28, 64)   36928       conv2d_27[0][0]
__________________________________________________________________________________________________
up_sampling2d_5 (UpSampling2D)  (None, 56, 56, 64)   0           conv6[0][0]
__________________________________________________________________________________________________
conv2d_28 (Conv2D)              (None, 56, 56, 32)   8224        up_sampling2d_5[0][0]
__________________________________________________________________________________________________
concatenate_5 (Concatenate)     (None, 56, 56, 64)   0           conv2d_17[0][0]
                                                                 conv2d_28[0][0]
__________________________________________________________________________________________________
conv2d_29 (Conv2D)              (None, 56, 56, 32)   18464       concatenate_5[0][0]
__________________________________________________________________________________________________
conv2d_30 (Conv2D)              (None, 56, 56, 32)   9248        conv2d_29[0][0]
__________________________________________________________________________________________________
conv7 (Conv2D)                  (None, 56, 56, 32)   9248        conv2d_30[0][0]
__________________________________________________________________________________________________
conv2d_31 (Conv2D)              (None, 56, 56, 11)   363         conv7[0][0]
==================================================================================================
Total params: 1,934,603
Trainable params: 1,934,603
Non-trainable params: 0
__________________________________________________________________________________________________
```

Training from sratch

Parameters :

- Optimizer : Adam optimization algorithm
- loss : Categorical Crossentropy
- Learning Rate : 0.001
- epochs : 50
- batch size : 512
- metrics : accuracy

```
In [ ]: model.fit(X_train, y_train, epochs = 50, batch_size = 512)

Epoch 1/50
30/30 [==============================] - 33s 1s/step - loss: 1.0161 - accuracy: 0.8415
Epoch 2/50
30/30 [==============================] - 33s 1s/step - loss: 0.4271 - accuracy: 0.8591
Epoch 3/50
30/30 [==============================] - 33s 1s/step - loss: 0.4016 - accuracy: 0.8612
Epoch 4/50
30/30 [==============================] - 33s 1s/step - loss: 0.3919 - accuracy: 0.8619
Epoch 5/50
30/30 [==============================] - 33s 1s/step - loss: 0.3854 - accuracy: 0.8625
Epoch 6/50
30/30 [==============================] - 33s 1s/step - loss: 0.3797 - accuracy: 0.8639
Epoch 7/50
30/30 [==============================] - 33s 1s/step - loss: 0.3745 - accuracy: 0.8696
Epoch 8/50
30/30 [==============================] - 33s 1s/step - loss: 0.3702 - accuracy: 0.8707
Epoch 9/50
30/30 [==============================] - 33s 1s/step - loss: 0.3666 - accuracy: 0.8713
Epoch 10/50
30/30 [==============================] - 33s 1s/step - loss: 0.3632 - accuracy: 0.8719
Epoch 11/50
30/30 [==============================] - 33s 1s/step - loss: 0.3600 - accuracy: 0.8723
Epoch 12/50
30/30 [==============================] - 33s 1s/step - loss: 0.3570 - accuracy: 0.8729
Epoch 13/50
30/30 [==============================] - 33s 1s/step - loss: 0.3542 - accuracy: 0.8737
Epoch 14/50
30/30 [==============================] - 33s 1s/step - loss: 0.3515 - accuracy: 0.8746
Epoch 15/50
30/30 [==============================] - 33s 1s/step - loss: 0.3484 - accuracy: 0.8752
Epoch 16/50
30/30 [==============================] - 33s 1s/step - loss: 0.3448 - accuracy: 0.8761
Epoch 17/50
30/30 [==============================] - 33s 1s/step - loss: 0.3401 - accuracy: 0.8777
Epoch 18/50
30/30 [==============================] - 33s 1s/step - loss: 0.3347 - accuracy: 0.8791
Epoch 19/50
30/30 [==============================] - 33s 1s/step - loss: 0.3303 - accuracy: 0.8805
Epoch 20/50
30/30 [==============================] - 33s 1s/step - loss: 0.3244 - accuracy: 0.8817
Epoch 21/50
30/30 [==============================] - 33s 1s/step - loss: 0.3171 - accuracy: 0.8836
Epoch 22/50
30/30 [==============================] - 33s 1s/step - loss: 0.3171 - accuracy: 0.8864
Epoch 23/50
30/30 [==============================] - 33s 1s/step - loss: 0.3082 - accuracy: 0.8899
Epoch 24/50
30/30 [==============================] - 33s 1s/step - loss: 0.2983 - accuracy: 0.8925
Epoch 25/50
30/30 [==============================] - 33s 1s/step - loss: 0.2878 - accuracy: 0.8957
Epoch 26/50
30/30 [==============================] - 33s 1s/step - loss: 0.2796 - accuracy: 0.8976
Epoch 27/50
30/30 [==============================] - 33s 1s/step - loss: 0.2583 - accuracy: 0.9039
Epoch 28/50
30/30 [==============================] - 33s 1s/step - loss: 0.2609 - accuracy: 0.9032
Epoch 29/50
30/30 [==============================] - 33s 1s/step - loss: 0.2361 - accuracy: 0.9108
Epoch 30/50
30/30 [==============================] - 33s 1s/step - loss: 0.2284 - accuracy: 0.9138
Epoch 31/50
30/30 [==============================] - 33s 1s/step - loss: 0.2170 - accuracy: 0.9186
Epoch 32/50
30/30 [==============================] - 33s 1s/step - loss: 0.2279 - accuracy: 0.9154
Epoch 33/50
30/30 [==============================] - 33s 1s/step - loss: 0.1973 - accuracy: 0.9271
Epoch 34/50
30/30 [==============================] - 33s 1s/step - loss: 0.1830 - accuracy: 0.9331
Epoch 35/50
30/30 [==============================] - 33s 1s/step - loss: 0.1693 - accuracy: 0.9383
Epoch 36/50
30/30 [==============================] - 33s 1s/step - loss: 0.1705 - accuracy: 0.9378
Epoch 37/50
30/30 [==============================] - 33s 1s/step - loss: 0.1540 - accuracy: 0.9442
Epoch 38/50
30/30 [==============================] - 33s 1s/step - loss: 0.1503 - accuracy: 0.9455
Epoch 39/50
30/30 [==============================] - 33s 1s/step - loss: 0.1378 - accuracy: 0.9511
Epoch 40/50
30/30 [==============================] - 33s 1s/step - loss: 0.1577 - accuracy: 0.9438
Epoch 41/50
30/30 [==============================] - 33s 1s/step - loss: 0.1235 - accuracy: 0.9573
Epoch 42/50
30/30 [==============================] - 33s 1s/step - loss: 0.1343 - accuracy: 0.9551
Epoch 43/50
30/30 [==============================] - 33s 1s/step - loss: 0.1709 - accuracy: 0.9366
Epoch 44/50
30/30 [==============================] - 33s 1s/step - loss: 0.1186 - accuracy: 0.9588
Epoch 45/50
30/30 [==============================] - 33s 1s/step - loss: 0.1108 - accuracy: 0.9628
Epoch 46/50
30/30 [==============================] - 33s 1s/step - loss: 0.0929 - accuracy: 0.9704
Epoch 47/50
30/30 [==============================] - 33s 1s/step - loss: 0.1030 - accuracy: 0.9667
Epoch 48/50
30/30 [==============================] - 33s 1s/step - loss: 0.0806 - accuracy: 0.9753
Epoch 49/50
30/30 [==============================] - 33s 1s/step - loss: 0.0661 - accuracy: 0.9806
Epoch 50/50
30/30 [==============================] - 33s 1s/step - loss: 0.0594 - accuracy: 0.9828

Out[ ]: <tensorflow.python.keras.callbacks.History at 0x7fb0b2a0fcd0>
```

Saving the weights

```
In [ ]: model.save('ModelZoo/semanticSegmentor')

INFO:tensorflow:Assets written to: ModelZoo/semanticSegmentor/assets
```

Loading the weights

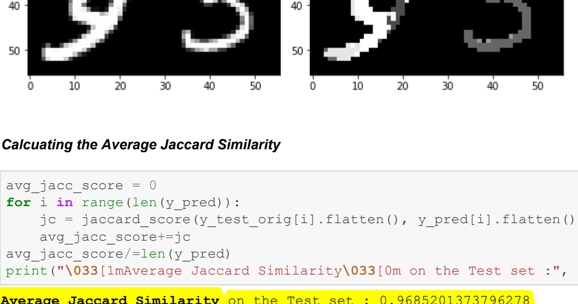
```
In [139]: from tensorflow import keras
          model = keras.models.load_model('ModelZoo/semanticSegmentor')
```

Evaluating on the test set

```
In [140]: y_pred = model.predict(X_test)
          y_pred = np.argmax(y_pred, axis = 3)
          y_pred = y_pred.reshape((y_pred.shape[0], 56,56,1))
```

```
In [156]: idx = 98
          img = np.squeeze(X_test[idx])
          sample_y = np.squeeze(y_pred[idx])
```

```
In [157]: fig=plt.figure(figsize=(8, 8))
          columns = 2
          rows = 1
          fig.add_subplot(rows, columns, 1)
          plt.imshow(img, cmap = 'gray')
          plt.title("Input Image")
          fig.add_subplot(rows, columns, 2)
          plt.imshow(sample_y, cmap = "gray")
          plt.title("Predicted Segmentation")
          fig.tight_layout()
          plt.show()
```



Calcuating the Average Jaccard Similarity

```
In [159]: avg_jacc_score = 0
          for i in range(len(y_pred)):
              jc = jaccard_score(y_test_orig[i].flatten(), y_pred[i].flatten(), average = 'micro')
              avg_jacc_score+=jc
          avg_jacc_score/=len(y_pred)
          print("\033[1mAverage Jaccard Similarity\033[0m on the Test set :", avg_jacc_score)

Average Jaccard Similarity on the Test set : 0.9685201373796278
```

$$- - - - - - - - - - - - - - - - - END - - - - - - - - - - - - - - - - -$$