

**EECE 5640 - High Performance Computing**  
**Final Project Report**

Topic:

**Acceleration of Aerial Image Classification through frameworks using GPU**

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## **ABSTRACT**

Our main aim is to train the Convolution Model with Massachusetts Road Dataset and to provide the difference in the time taken between TensorFlow, and Py Torch based on Single and Multi GPU system.

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## **LIST OF ABBREVIATIONS**

<b>CNN</b>	Convolution Neural Network
<b>Res NN</b>	Residual Neural Network
<b>HBM</b>	High Bandwidth Memory
<b>IOU</b>	Intersection Over Union
<b>CoWoS</b>	Chip on Wafer on Substrate

## **CHAPTER - I**

### **1.1 INTRODUCTION:**

Aerial Imagery Road Segmentation is a difficult task. Other challenges that prevent current models from segmenting sharp road boundaries that extend from one end of the image to the other include obstruction from nearby trees, shadows from adjacent buildings, varying texture and color of roads, and road class imbalance (due to relatively few road image pixels). In the machine learning and computer vision communities, high-quality aerial photography datasets permit comparisons of existing approaches and contribute to growing interest in aerial imagery applications.

### **1.2 DATSET OVERVIEW:**

There are 1171 aerial photographs of Massachusetts in the Massachusetts Roads Dataset amounting to 10.96 GB. Each image has a resolution of 1500x1500 pixels and covers a total area of 2.25 square kilometers. We divided the data into three sets: a training set of 1108 images, a validation set of 14 images, and a test set of 49 images at random. The dataset spans over 2600 square kilometers and includes a wide range of urban, suburban, and rural areas. The test set alone covers a total area of 110 square kilometers in size. Road centerlines from the OpenStreetMap project were approached to create the target maps. The labels were created with a line thickness of 7 pixels and no smoothing. All imagery is rescaled to 1 pixel per square meter resolution.

### **1.3 MODEL TRAINING:**

For categorizing the pixels of an aerial image with semantic labels, we study the use of CNN systems trained on aligned aerial photographs and possibly outdated maps. We demonstrate how deep neural networks running on contemporary GPUs can be utilized to learn highly discriminative image characteristics quickly. Then, for training neural networks that are partially resilient to incomplete and poorly registered target mappings, we offer novel loss functions. Finally, we offer two methods for improving our system's predictions by giving structure to the neural network outputs.

### **1.4 MODEL ARCHITECTURE:**

The goal of semantic image segmentation is to assign a class to each pixel in a picture that represents anything. Unet architecture, which has undergone a variety of changes, has produced the greatest results for this assignment. The basic concept is that it consists of a few convolution blocks that extract deep and diverse types of image information, followed by deconvolution or up sample blocks that restore the input image's original shape. We also have several skip-connections after each convolution layer, which help the network remember the initial image and prevent fading gradients.

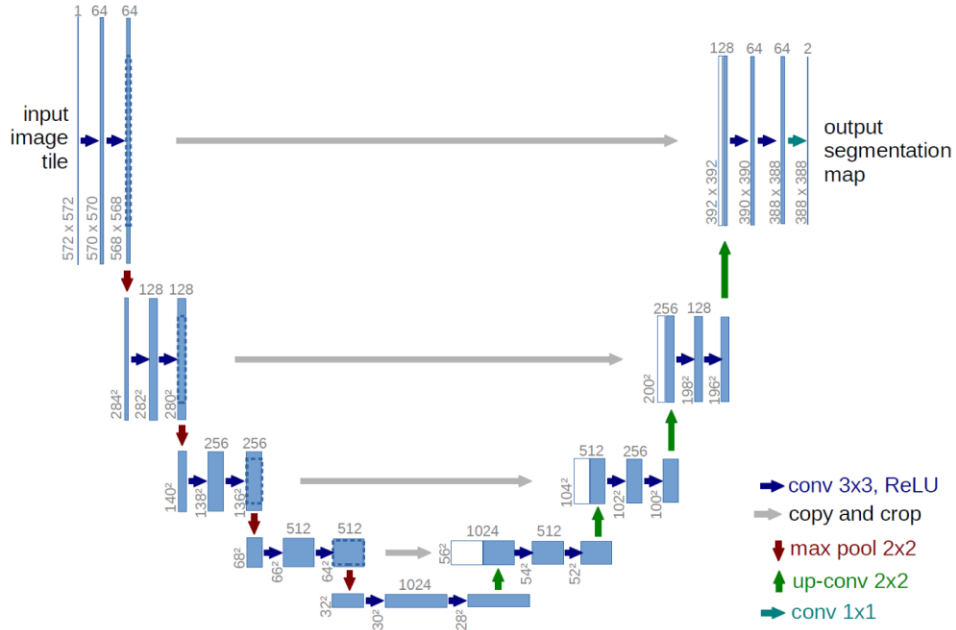


Fig 1: PyTorch U-Net architecture from Ronneberger et al. (2015)

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	[(None, 256, 256, 3)]	0	
block1_conv1 (Conv2D)	(None, 256, 256, 64)	1792	input_2[0][0]
batch_normalization_19 (Batch Normalization)	(None, 256, 256, 64)	256	block1_conv1[0][0]
activation_19 (Activation)	(None, 256, 256, 64)	0	batch_normalization_19[0][0]
block1_conv2 (Conv2D)	(None, 256, 256, 64)	36928	activation_19[0][0]
batch_normalization_20 (Batch Normalization)	(None, 256, 256, 64)	256	block1_conv2[0][0]
activation_20 (Activation)	(None, 256, 256, 64)	0	batch_normalization_20[0][0]
max_pooling2d_3 (MaxPooling2D)	(None, 128, 128, 64)	0	activation_20[0][0]
block2_conv1 (Conv2D)	(None, 128, 128, 128)	73856	max_pooling2d_3[0][0]
batch_normalization_21 (Batch Normalization)	(None, 128, 128, 128)	512	block2_conv1[0][0]
activation_21 (Activation)	(None, 128, 128, 128)	0	batch_normalization_21[0][0]
block2_conv2 (Conv2D)	(None, 128, 128, 128)	147584	activation_21[0][0]
batch_normalization_22 (Batch Normalization)	(None, 128, 128, 128)	512	block2_conv2[0][0]
activation_22 (Activation)	(None, 128, 128, 128)	0	batch_normalization_22[0][0]
max_pooling2d_4 (MaxPooling2D)	(None, 64, 64, 128)	0	activation_22[0][0]
block3_conv1 (Conv2D)	(None, 64, 64, 256)	295168	max_pooling2d_4[0][0]
batch_normalization_23 (Batch Normalization)	(None, 64, 64, 256)	1024	block3_conv1[0][0]
activation_23 (Activation)	(None, 64, 64, 256)	0	batch_normalization_23[0][0]
block3_conv2 (Conv2D)	(None, 64, 64, 256)	590080	activation_23[0][0]
batch_normalization_24 (Batch Normalization)	(None, 64, 64, 256)	1024	block3_conv2[0][0]
activation_24 (Activation)	(None, 64, 64, 256)	0	batch_normalization_24[0][0]
block3_conv3 (Conv2D)	(None, 64, 64, 256)	590080	activation_24[0][0]
batch_normalization_25 (Batch Normalization)	(None, 64, 64, 256)	1024	block3_conv3[0][0]
activation_25 (Activation)	(None, 64, 64, 256)	0	batch_normalization_25[0][0]

block4_conv1 (Conv2D)	(None, 32, 32, 512)	1188160	max_pooling2d_5[0][0]
batch_normalization_26 (BatchNo	(None, 32, 32, 512)	2048	block4_conv1[0][0]
activation_26 (Activation)	(None, 32, 32, 512)	0	batch_normalization_26[0][0]
block4_conv2 (Conv2D)	(None, 32, 32, 512)	2359808	activation_26[0][0]
batch_normalization_27 (BatchNo	(None, 32, 32, 512)	2048	block4_conv2[0][0]
activation_27 (Activation)	(None, 32, 32, 512)	0	batch_normalization_27[0][0]
block4_conv3 (Conv2D)	(None, 32, 32, 512)	2359808	activation_27[0][0]
batch_normalization_28 (BatchNo	(None, 32, 32, 512)	2048	block4_conv3[0][0]
activation_28 (Activation)	(None, 32, 32, 512)	0	batch_normalization_28[0][0]
Conv2DTranspose_UP2 (Conv2DTran	(None, 64, 64, 256)	524544	activation_28[0][0]
batch_normalization_29 (BatchNo	(None, 64, 64, 256)	1024	Conv2DTranspose_UP2[0][0]
activation_29 (Activation)	(None, 64, 64, 256)	0	batch_normalization_29[0][0]
concatenate_3 (Concatenate)	(None, 64, 64, 512)	0	activation_29[0][0] activation_25[0][0]
conv2d_7 (Conv2D)	(None, 64, 64, 256)	1179904	concatenate_3[0][0]
batch_normalization_30 (BatchNo	(None, 64, 64, 256)	1024	conv2d_7[0][0]
activation_30 (Activation)	(None, 64, 64, 256)	0	batch_normalization_30[0][0]
conv2d_8 (Conv2D)	(None, 64, 64, 256)	590080	activation_30[0][0]
batch_normalization_31 (BatchNo	(None, 64, 64, 256)	1024	conv2d_8[0][0]
activation_31 (Activation)	(None, 64, 64, 256)	0	batch_normalization_31[0][0]
Conv2DTranspose_UP3 (Conv2DTran	(None, 128, 128, 128)	131200	activation_31[0][0]
batch_normalization_32 (BatchNo	(None, 128, 128, 128)	512	Conv2DTranspose_UP3[0][0]
activation_32 (Activation)	(None, 128, 128, 128)	0	batch_normalization_32[0][0]
concatenate_4 (Concatenate)	(None, 128, 128, 256)	0	activation_32[0][0] activation_22[0][0]
conv2d_9 (Conv2D)	(None, 128, 128, 128)	295040	concatenate_4[0][0]
conv2d_9 (Conv2D)	(None, 128, 128, 128)	295040	concatenate_4[0][0]
batch_normalization_33 (BatchNo	(None, 128, 128, 128)	512	conv2d_9[0][0]
activation_33 (Activation)	(None, 128, 128, 128)	0	batch_normalization_33[0][0]
conv2d_10 (Conv2D)	(None, 128, 128, 128)	147584	activation_33[0][0]
batch_normalization_34 (BatchNo	(None, 128, 128, 128)	512	conv2d_10[0][0]
activation_34 (Activation)	(None, 128, 128, 128)	0	batch_normalization_34[0][0]
Conv2DTranspose_UP4 (Conv2DTran	(None, 256, 256, 64)	32832	activation_34[0][0]
batch_normalization_35 (BatchNo	(None, 256, 256, 64)	256	Conv2DTranspose_UP4[0][0]
activation_35 (Activation)	(None, 256, 256, 64)	0	batch_normalization_35[0][0]
concatenate_5 (Concatenate)	(None, 256, 256, 128)	0	activation_35[0][0] activation_20[0][0]
conv2d_11 (Conv2D)	(None, 256, 256, 64)	73792	concatenate_5[0][0]
batch_normalization_36 (BatchNo	(None, 256, 256, 64)	256	conv2d_11[0][0]
activation_36 (Activation)	(None, 256, 256, 64)	0	batch_normalization_36[0][0]
conv2d_12 (Conv2D)	(None, 256, 256, 64)	36928	activation_36[0][0]
batch_normalization_37 (BatchNo	(None, 256, 256, 64)	256	conv2d_12[0][0]
activation_37 (Activation)	(None, 256, 256, 64)	0	batch_normalization_37[0][0]
conv2d_13 (Conv2D)	(None, 256, 256, 1)	577	activation_37[0][0]
=====			
Total params: 10,663,873			
Trainable params: 10,655,809			
Non-trainable params: 8,064			

Fig 2. TensorFlow Convolution model

## 1.5 DATA AUGMENTATION:

Translation invariant - Convolutional Neural Networks are known to be sensitive to rotation. The U-Net model is extremely powerful, and it could easily learn all of the training photos; nevertheless, we want it to understand patterns and generalize well to new images. That is why, during the training, we chose to artificially supplement our dataset in order to better represent the geometry of the roads. The limited number of photographs in the training set with diagonal roadways is the most intuitive example that validates such a strategy. Diagonal streets should

eventually be caught well by supplying rotated versions of all the training photographs from various angles. We imported augmentation libraries for every case.

## **1.6 WORKLOADS:**

Both the workloads were executed using CNN model, with **40 Epochs** and the **Batch size** as **16**. The difference between the frameworks based on Single GPU and Multi-GPU's performances was produced.

1. TensorFlow: (tf\_road.ipynb) - It uses TensorFlow U-net model to train the images. We trained the model on a single GPU and it took almost 33 minutes to complete and with Multi GPU, the training was done under 11 minutes.
2. Py Torch: (pytorch.ipynb) - The second model is designed with Py Torch Resnet-50. It took us almost 1h 31 minutes 15 seconds to execute the model on Single GPU whereas Multi GPU trained under 35 minutes.

## CHAPTER - II

### 2.1 PLATFORM:

For **Single GPU execution**, Kaggle's NVIDIA TESLA P100 was used.

For **Multi-GPU execution**, we used Google Cloud Platform (GCP) with NVIDIA P100 GPU (4 Nos).

### 2.1.1 PLATFORM SPECIFICATIONS:

#### 2.1.1.1 NVIDIA TESLA P100:



Fig 3. Pascal GP100 SM Unit



Double-Precision Performance	4.7 teraFLOPS
Single-Precision Performance	9.3 teraFLOPS
Half-Precision Performance	18.7 teraFLOPS
PCIe x16 Interconnect Bandwidth	32 GB/s
CoWoS HBM2 Stacked Memory Capacity	16 GB or 12 GB
CoWoS HBM2 Stacked Memory Bandwidth	732 GB/s or 549 GB/s

Table 1. P100 Specifications

### **2.1.2 GOOGLE CLOUD:**

Google cloud provides NVIDIA K80, P100, P4, T4, V100, and A100 GPUs. It optimally balances the processor, memory, high performance disk, and up to 8 GPUs per instance for your individual workload.

#### **2.1.2.1 GOOGLE CLOUD INSTANCE CREATION:**

To use GCP, instance must be created, and we have configured with NVIDIA TESLA P100 with 4GPU's located at USA-Oregon region.

The screenshot shows the 'Machine configuration' section of a Google Cloud Platform VM instance creation page. At the top, the 'Region' is set to 'us-west1 (Oregon)' and the 'Zone' is 'us-west1-b', both marked as permanent. Below this, the 'Machine family' is set to 'GPU', which is highlighted in blue. The description states it is 'Optimized for machine learning, high performance computing, and visualization workloads'. The 'GPU type' is 'NVIDIA Tesla P100' and the 'Number of GPUs' is '4'. There is an unchecked checkbox for 'Enable Virtual Workstation (NVIDIA GRID)'. The 'Series' is 'N1', described as 'Powered by Intel Skylake CPU platform or one of its predecessors'. The 'Machine type' is 'n1-standard-4 (4 vCPU, 15 GB memory)'. At the bottom, a summary bar shows 'vCPU' as 4 and 'Memory' as 15 GB, accompanied by a stack of blue disks icon.

Fig 4. VM instance creation for multi-GPU in Google Cloud Platform

## **2.2 AERIAL IMAGE and BINARY MAP:**

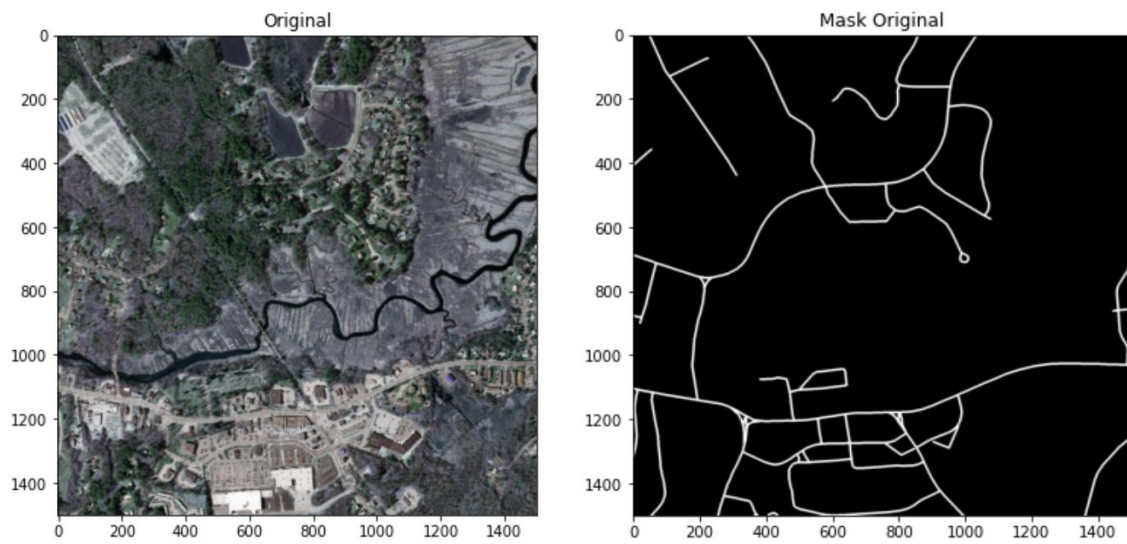


Fig 5. A sample aerial image (left) and a binary map (right) showing road locations.

## **CHAPTER - III**

### **3. EXPERIMENTS**

#### **3.1 TENSORFLOW WITH SINGLE GPU:**

**Total GPU runtime: 33 min 32seconds**

**Platform : Kaggle**

**GPU : NVIDIA Tesla P100**

#### **TRAINING OUTPUT:**

Epoch 1/40 70/70 [=====] -loss: 0.8097 - dice\_coef: 0.1903 -  
val\_loss: 0.8448 - val\_dice\_coef: 0.1552

Epoch 2/40 70/70 [=====] - loss: 0.6551 - dice\_coef: 0.3450 -  
val\_loss: 0.8999 - val\_dice\_coef: 0.1001

Epoch 3/40 70/70 [=====] - loss: 0.5070 - dice\_coef: 0.4930 -  
val\_loss: 0.9644 - val\_dice\_coef: 0.0356

Epoch 4/40 70/70 [=====] - loss: 0.4390 - dice\_coef: 0.5610  
- val\_loss: 0.9870 - val\_dice\_coef: 0.0130

Epoch 5/40 70/70 [=====] - loss: 0.4000 - dice\_coef: 0.6000 -  
val\_loss: 0.9937 - val\_dice\_coef: 0.0063

Epoch 6/40 70/70 [=====] - loss: 0.3741 - dice\_coef: 0.6259  
- val\_loss: 0.9880 - val\_dice\_coef: 0.0120

Epoch 7/40 70/70 [=====] - loss: 0.3528 - dice\_coef: 0.6472  
- val\_loss: 0.9877 - val\_dice\_coef: 0.0123

Epoch 8/40 70/70 [=====] - loss: 0.3369 - dice\_coef: 0.6632 -  
val\_loss: 0.7176 - val\_dice\_coef: 0.2824

Epoch 9/40 70/70 [=====] - loss: 0.3268 - dice\_coef: 0.6732  
- val\_loss: 0.3963 - val\_dice\_coef: 0.6037

Epoch 10/40 70/70 [=====] - loss: 0.3185 - dice\_coef: 0.6815  
- val\_loss: 0.3809 - val\_dice\_coef: 0.6191

Epoch 11/40 70/70 [=====] - loss: 0.3090 - dice\_coef: 0.6910  
- val\_loss: 0.3423 - val\_dice\_coef: 0.6577

Epoch 12/40 70/70 [=====] - loss: 0.2983 - dice\_coef: 0.7017  
- val\_loss: 0.3517 - val\_dice\_coef: 0.6483

Epoch 13/40 70/70 [=====] - loss: 0.2924 - dice\_coef: 0.7077  
- val\_loss: 0.3468 - val\_dice\_coef: 0.6532

Epoch 14/40 70/70 [=====] - loss: 0.2846 - dice\_coef: 0.7154  
- val\_loss: 0.3521 - val\_dice\_coef: 0.6479

Epoch 15/40 70/70 [=====] - loss: 0.2793 - dice\_coef: 0.7208  
- val\_loss: 0.3373 - val\_dice\_coef: 0.6627

Epoch 16/40 70/70 [=====] - loss: 0.2736 - dice\_coef: 0.7265  
- val\_loss: 0.3160 - val\_dice\_coef: 0.6840

Epoch 17/40 70/70 [=====] - loss: 0.2655 - dice\_coef: 0.7345  
- val\_loss: 0.3500 - val\_dice\_coef: 0.6500

Epoch 18/40 70/70 [=====] - loss: 0.2619 - dice\_coef: 0.7381  
- val\_loss: 0.3172 - val\_dice\_coef: 0.6828

Epoch 19/40 70/70 [=====] - loss: 0.2573 - dice\_coef: 0.7427  
- val\_loss: 0.3623 - val\_dice\_coef: 0.6377

Epoch 20/40 70/70 [=====] - loss: 0.2545 - dice\_coef: 0.7455  
- val\_loss: 0.3469 - val\_dice\_coef: 0.6531

Epoch 21/40 70/70 [=====] - loss: 0.2485 - dice\_coef: 0.7515  
- val\_loss: 0.3688 - val\_dice\_coef: 0.6312

Epoch 22/40 70/70 [=====] - loss: 0.2486 - dice\_coef: 0.7514  
- val\_loss: 0.3300 - val\_dice\_coef: 0.6700

Epoch 23/40 70/70 [=====] - loss: 0.2434 - dice\_coef: 0.7566  
- val\_loss: 0.3583 - val\_dice\_coef: 0.6417

Epoch 24/40 70/70 [=====] - loss: 0.2349 - dice\_coef: 0.7651  
- val\_loss: 0.4138 - val\_dice\_coef: 0.5862

Epoch 25/40 70/70 [=====] - loss: 0.2288 - dice\_coef: 0.7712  
- val\_loss: 0.3668 - val\_dice\_coef: 0.6332

Epoch 26/40 70/70 [=====] - loss: 0.2251 - dice\_coef: 0.7749  
- val\_loss: 0.3453 - val\_dice\_coef: 0.6547

Epoch 27/40 70/70 [=====] - loss: 0.2238 - dice\_coef: 0.7762  
- val\_loss: 0.3461 - val\_dice\_coef: 0.6539

Epoch 28/40 70/70 [=====] - loss: 0.2214 - dice\_coef: 0.7786  
- val\_loss: 0.3559 - val\_dice\_coef: 0.6441

Epoch 29/40 70/70 [=====] - loss: 0.2194 - dice\_coef: 0.7806  
- val\_loss: 0.3962 - val\_dice\_coef: 0.6038

Epoch 30/40 70/70 [=====] - loss: 0.2158 - dice\_coef: 0.7842  
- val\_loss: 0.4111 - val\_dice\_coef: 0.5889

Epoch 31/40 70/70 [=====] - loss: 0.2106 - dice\_coef: 0.7894  
- val\_loss: 0.4142 - val\_dice\_coef: 0.5858

Epoch 32/40 70/70 [=====] - loss: 0.2079 - dice\_coef: 0.7921  
- val\_loss: 0.3801 - val\_dice\_coef: 0.6199

Epoch 33/40 70/70 [=====] - loss: 0.2049 - dice\_coef: 0.7952  
- val\_loss: 0.3914 - val\_dice\_coef: 0.6086

Epoch 34/40 70/70 [=====] - loss: 0.2036 - dice\_coef: 0.7964  
- val\_loss: 0.4106 - val\_dice\_coef: 0.5894

Epoch 35/40 70/70 [=====] - loss: 0.2045 - dice\_coef: 0.7955  
- val\_loss: 0.3579 - val\_dice\_coef: 0.6421

Epoch 36/40 70/70 [=====] - loss: 0.2033 - dice\_coef: 0.7967  
- val\_loss: 0.3298 - val\_dice\_coef: 0.6702

Epoch 37/40 70/70 [=====] - loss: 0.2034 - dice\_coef: 0.7966  
- val\_loss: 0.3237 - val\_dice\_coef: 0.6763

Epoch 38/40 70/70 [=====] - loss: 0.2009 - dice\_coef: 0.7991  
- val\_loss: 0.3544 - val\_dice\_coef: 0.6456

Epoch 39/40 70/70 [=====] - loss: 0.1980 - dice\_coef: 0.8020  
- val\_loss: 0.3454 - val\_dice\_coef: 0.6546

Epoch 40/40 70/70 [=====] - loss: 0.1936 - dice\_coef: 0.8065  
- val\_loss: 0.3275 - val\_dice\_coef: 0.6725

**Wall time: 33min 32s**

### **3.2 PY TORCH WITH SINGLE GPU:**

**Total GPU runtime: 1h 31min 15s**

**Platform : Kaggle**

**GPU : NVIDIA Tesla P100**

#### **TRAINING OUTPUT:**

Epoch: 0

train: 100% ██████████ 70/70 [dice\_loss - 0.02844, iou\_score - 0.9485]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05899, iou\_score - 0.8925]

Model saved!

Epoch: 1

train: 100% ██████████ 70/70 [dice\_loss - 0.02951, iou\_score - 0.9465]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05886, iou\_score - 0.8927]

Model saved!

Epoch: 2

train: 100% ██████████ 70/70 [1.91s/it, dice\_loss - 0.03021, iou\_score - 0.9451]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05861, iou\_score - 0.8932]

Model saved!

Epoch: 3

train: 100% ██████████ 70/70 [dice\_loss - 0.02894, iou\_score - 0.9475]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05872, iou\_score - 0.893]

Epoch: 4

train: 100% ██████████ 70/70 [dice\_loss - 0.02921, iou\_score - 0.9471]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05883, iou\_score - 0.8928]

Epoch: 5

train: 100% ██████████ 70/70 [dice\_loss - 0.02818, iou\_score - 0.949]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05886, iou\_score - 0.8927]

Epoch: 6

train: 100% ██████████ 70/70 [dice\_loss - 0.02918, iou\_score - 0.9471]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05877, iou\_score - 0.8929]

Epoch: 7

train: 100% ██████████ 70/70 [dice\_loss - 0.02982, iou\_score - 0.9459]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05909, iou\_score - 0.8923]

Epoch: 8

train: 100% ██████████ 70/70 [dice\_loss - 0.02929, iou\_score - 0.9468]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05877, iou\_score - 0.8929]

Epoch: 9

train: 100% ██████████ 70/70 [dice\_loss - 0.02913, iou\_score - 0.9471]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05904, iou\_score - 0.8923]

Epoch: 10

train: 100% ██████████ 70/70 [dice\_loss - 0.02867, iou\_score - 0.9481]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05894, iou\_score - 0.8926]

Epoch: 11

train: 100% ██████████ 70/70 [dice\_loss - 0.02795, iou\_score - 0.9494]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05887, iou\_score - 0.8927]

Epoch: 12

train: 100% ██████████ 70/70 [dice\_loss - 0.0291, iou\_score - 0.9473]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05893, iou\_score - 0.8925]

Epoch: 13

train: 100% ██████████ 70/70 [dice\_loss - 0.02967, iou\_score - 0.9462]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05914, iou\_score - 0.8922]

Epoch: 14

train: 100% ██████████ 70/70 [dice\_loss - 0.02811, iou\_score - 0.9492]

valid: 100% ██████████ 14/14 [dice\_loss - 0.0588, iou\_score - 0.8928]

Epoch: 15

train: 100% ██████████ 70/70 [dice\_loss - 0.02965, iou\_score - 0.9462]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05894, iou\_score - 0.8926]

Epoch: 16

train: 100% ██████████ 70/70 [dice\_loss - 0.02903, iou\_score - 0.9474]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05908, iou\_score - 0.8923]

Epoch: 17

train: 100% ██████████ 70/70 [dice\_loss - 0.0286, iou\_score - 0.9482]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05883, iou\_score - 0.8928]

Epoch: 18

train: 100% ██████████ 70/70 [dice\_loss - 0.02926, iou\_score - 0.9469]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05881, iou\_score - 0.8928]

Epoch: 19

train: 100% ██████████ 70/70 [dice\_loss - 0.02834, iou\_score - 0.9487]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05885, iou\_score - 0.8927]

Epoch: 20

train: 100% ██████████ 70/70 [dice\_loss - 0.0292, iou\_score - 0.9471]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05877, iou\_score - 0.8929]

Epoch: 21

train: 100% ██████████ 70/70 [dice\_loss - 0.02905, iou\_score - 0.9473]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05922, iou\_score - 0.8921]

Epoch: 22

train: 100% ██████████ 70/70 [dice\_loss - 0.02883, iou\_score - 0.9478]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05879, iou\_score - 0.8928]

Epoch: 23

train: 100% ██████████ 70/70 [dice\_loss - 0.02825, iou\_score - 0.9488]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05892, iou\_score - 0.8926]



Epoch: 24

train: 100% ██████████ 70/70 [dice\_loss - 0.02942, iou\_score - 0.9466]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05896, iou\_score - 0.8925]

Epoch: 25

train: 100% ██████████ 70/70 [dice\_loss - 0.02936, iou\_score - 0.9467]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05894, iou\_score - 0.8925]

Epoch: 26

train: 100% ██████████ 70/70 [dice\_loss - 0.0285, iou\_score - 0.9484]

valid: 100% ██████████ 14/14 [dice\_loss - 0.0589, iou\_score - 0.8927]

Epoch: 27

train: 100% ██████████ 70/70 [dice\_loss - 0.02886, iou\_score - 0.9477]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05874, iou\_score - 0.8929]

Epoch: 28

train: 100% ██████████ 70/70 [dice\_loss - 0.02893, iou\_score - 0.9475]

valid: 100% ██████████ 14/14 [dice\_loss - 0.059, iou\_score - 0.8925]

Epoch: 29

train: 100% ██████████ 70/70 [dice\_loss - 0.02799, iou\_score - 0.9493]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05867, iou\_score - 0.8931]

Epoch: 30

train: 100% ██████████ 70/70 [dice\_loss - 0.02955, iou\_score - 0.9464]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05914, iou\_score - 0.8922]

Epoch: 31

train: 100% ██████████ 70/70 [dice\_loss - 0.03025, iou\_score - 0.9451]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05875, iou\_score - 0.8929]

Epoch: 32

train: 100% ██████████ 70/70 [dice\_loss - 0.02814, iou\_score - 0.9491]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05904, iou\_score - 0.8924]

Epoch: 33

train: 100% ██████████ 70/70 [dice\_loss - 0.02923, iou\_score - 0.947]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05917, iou\_score - 0.8921]

Epoch: 34

train: 100% ██████████ 70/70 [dice\_loss - 0.02986, iou\_score - 0.9458]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05881, iou\_score - 0.8928]

Epoch: 35

train: 100% ██████████ 70/70 [dice\_loss - 0.02968, iou\_score - 0.9461]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05898, iou\_score - 0.8925]

Epoch: 36

train: 100% ██████████ 70/70 [dice\_loss - 0.02907, iou\_score - 0.9473]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05885, iou\_score - 0.8928]

Epoch: 37

train: 100% ██████████ 70/70 [dice\_loss - 0.02873, iou\_score - 0.9479]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05888, iou\_score - 0.8927]

Epoch: 38

train: 100% ██████████ 70/70 [dice\_loss - 0.02922, iou\_score - 0.947]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05915, iou\_score - 0.8921]

Epoch: 39

train: 100% ██████████ 70/70 [dice\_loss - 0.02807, iou\_score - 0.9492]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05886, iou\_score - 0.8927]

**Wall time: 1h 31min 15s**

### **3.3 TENSORFLOW WITH MULTI GPU:**

**Total GPU runtime: 10 min 7 seconds**

**Platform : Google Cloud Platform**

**GPU : NVIDIA Tesla P100**

#### **TRAINING OUTPUT:**

Epoch 1/40 70/70 [=====] -loss: 0.8347 - dice\_coef: 0.1453 -  
val\_loss: 0.8488 - val\_dice\_coef: 0.1592

Epoch 2/40 70/70 [=====] - loss: 0.6651 - dice\_coef: 0.3450 -  
val\_loss: 0.8899 - val\_dice\_coef: 0.1071

Epoch 3/40 70/70 [=====] - loss: 0.5320 - dice\_coef: 0.4450 -  
val\_loss: 0.9744 - val\_dice\_coef: 0.0256

Epoch 4/40 70/70 [=====] - loss: 0.4960 - dice\_coef: 0.5620  
- val\_loss: 0.9890 - val\_dice\_coef: 0.0160

Epoch 5/40 70/70 [=====] - loss: 0.4310 - dice\_coef: 0.6000 -  
val\_loss: 0.9347 - val\_dice\_coef: 0.0033

Epoch 6/40 70/70 [=====] - loss: 0.3491 - dice\_coef: 0.6239  
- val\_loss: 0.9850 - val\_dice\_coef: 0.0110

Epoch 7/40 70/70 [=====] - loss: 0.3578 - dice\_coef: 0.6473  
- val\_loss: 0.9827 - val\_dice\_coef: 0.0153

Epoch 8/40 70/70 [=====] - loss: 0.3489 - dice\_coef: 0.6633 -  
val\_loss: 0.7076 - val\_dice\_coef: 0.2834

Epoch 9/40 70/70 [=====] - loss: 0.3167 - dice\_coef: 0.6732  
- val\_loss: 0.3163 - val\_dice\_coef: 0.6057

Epoch 10/40 70/70 [=====] - loss: 0.3345 - dice\_coef: 0.6817  
- val\_loss: 0.3819 - val\_dice\_coef: 0.6181

Epoch 11/40 70/70 [=====] - loss: 0.3005 - dice\_coef: 0.6910  
- val\_loss: 0.3423 - val\_dice\_coef: 0.6577

Epoch 12/40 70/70 [=====] - loss: 0.2924 - dice\_coef: 0.7027  
- val\_loss: 0.3507 - val\_dice\_coef: 0.6473

Epoch 13/40 70/70 [=====] - loss: 0.2924 - dice\_coef: 0.7067  
- val\_loss: 0.3568 - val\_dice\_coef: 0.6522

Epoch 14/40 70/70 [=====] - loss: 0.2736 - dice\_coef: 0.7154  
- val\_loss: 0.3521 - val\_dice\_coef: 0.6479

Epoch 15/40 70/70 [=====] - loss: 0.2683 - dice\_coef: 0.7308  
- val\_loss: 0.3363 - val\_dice\_coef: 0.6626

Epoch 16/40 70/70 [=====] - loss: 0.2886 - dice\_coef: 0.7165  
- val\_loss: 0.3170 - val\_dice\_coef: 0.6830

Epoch 17/40 70/70 [=====] - loss: 0.2755 - dice\_coef: 0.7445  
- val\_loss: 0.3580 - val\_dice\_coef: 0.6510

Epoch 18/40 70/70 [=====] - loss: 0.2919 - dice\_coef: 0.7381  
- val\_loss: 0.3182 - val\_dice\_coef: 0.6818

Epoch 19/40 70/70 [=====] - loss: 0.2273 - dice\_coef: 0.7227  
- val\_loss: 0.3523 - val\_dice\_coef: 0.6378

Epoch 20/40 70/70 [=====] - loss: 0.2845 - dice\_coef: 0.7445  
- val\_loss: 0.3369 - val\_dice\_coef: 0.6521

Epoch 21/40 70/70 [=====] - loss: 0.2585 - dice\_coef: 0.7515  
- val\_loss: 0.3788 - val\_dice\_coef: 0.6322

Epoch 22/40 70/70 [=====] - loss: 0.2436 - dice\_coef: 0.7504  
- val\_loss: 0.3350 - val\_dice\_coef: 0.6705

Epoch 23/40 70/70 [=====] - loss: 0.2674 - dice\_coef: 0.7576  
- val\_loss: 0.3563 - val\_dice\_coef: 0.6407

Epoch 24/40 70/70 [=====] - loss: 0.2899 - dice\_coef: 0.7651  
- val\_loss: 0.4137 - val\_dice\_coef: 0.5852

Epoch 25/40 70/70 [=====] - loss: 0.2338 - dice\_coef: 0.7712  
- val\_loss: 0.3668 - val\_dice\_coef: 0.6332

Epoch 26/40 70/70 [=====] - loss: 0.2151 - dice\_coef: 0.7749  
- val\_loss: 0.3453 - val\_dice\_coef: 0.6547

Epoch 27/40 70/70 [=====] - loss: 0.2568 - dice\_coef: 0.7762  
- val\_loss: 0.3461 - val\_dice\_coef: 0.6539

Epoch 28/40 70/70 [=====] - loss: 0.2784 - dice\_coef: 0.7786  
- val\_loss: 0.3559 - val\_dice\_coef: 0.6441

Epoch 29/40 70/70 [=====] - loss: 0.2204 - dice\_coef: 0.7806  
- val\_loss: 0.3962 - val\_dice\_coef: 0.6038

Epoch 30/40 70/70 [=====] - loss: 0.2153 - dice\_coef: 0.7842  
- val\_loss: 0.4111 - val\_dice\_coef: 0.5889

Epoch 31/40 70/70 [=====] - loss: 0.2006 - dice\_coef: 0.7894  
- val\_loss: 0.4142 - val\_dice\_coef: 0.5858

Epoch 32/40 70/70 [=====] - loss: 0.2079 - dice\_coef: 0.7921  
- val\_loss: 0.3801 - val\_dice\_coef: 0.6199

Epoch 33/40 70/70 [=====] - loss: 0.2349 - dice\_coef: 0.7952  
- val\_loss: 0.3914 - val\_dice\_coef: 0.6086

Epoch 34/40 70/70 [=====] - loss: 0.2036 - dice\_coef: 0.7964  
- val\_loss: 0.4106 - val\_dice\_coef: 0.5894

Epoch 35/40 70/70 [=====] - loss: 0.2245 - dice\_coef: 0.7855  
- val\_loss: 0.3589 - val\_dice\_coef: 0.6321

Epoch 36/40 70/70 [=====] - loss: 0.2023 - dice\_coef: 0.7957  
- val\_loss: 0.3298 - val\_dice\_coef: 0.6702

Epoch 37/40 70/70 [=====] - loss: 0.2135 - dice\_coef: 0.7946  
- val\_loss: 0.3237 - val\_dice\_coef: 0.6763

Epoch 38/40 70/70 [=====] - loss: 0.2009 - dice\_coef: 0.7981  
- val\_loss: 0.3444 - val\_dice\_coef: 0.6446

Epoch 39/40 70/70 [=====] - loss: 0.1980 - dice\_coef: 0.8120  
- val\_loss: 0.3444 - val\_dice\_coef: 0.6526

Epoch 40/40 70/70 [=====] - loss: 0.1866 - dice\_coef: 0.8155  
- val\_loss: 0.3575 - val\_dice\_coef: 0.675

**Wall time: 10 minutes 7s**

### **3.4 PY TORCH WITH MULTI GPU:**

**Total GPU runtime: 34 min 2 seconds**

**Platform : Google Cloud Platform**

**GPU : NVIDIA Tesla P100**

Epoch: 0

train: 100% [██████████] 70/70 [dice\_loss - 0.02844, iou\_score - 0.9485]

valid: 100% [██████████] 14/14 [dice\_loss - 0.05899, iou\_score - 0.8925]

Model saved!

Epoch: 1

train: 100% ██████████ 70/70 [dice\_loss - 0.02951, iou\_score - 0.9465]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05886, iou\_score - 0.8927]

Model saved!

Epoch: 2

train: 100% ██████████ 70/70 [1.91s/it, dice\_loss - 0.03021, iou\_score - 0.9451]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05861, iou\_score - 0.8932]

Model saved!

Epoch: 3

train: 100% ██████████ 70/70 [dice\_loss - 0.02894, iou\_score - 0.9475]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05872, iou\_score - 0.893]

Epoch: 4

train: 100% ██████████ 70/70 [dice\_loss - 0.02921, iou\_score - 0.9471]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05883, iou\_score - 0.8928]

Epoch: 5

train: 100% ██████████ 70/70 [dice\_loss - 0.02818, iou\_score - 0.949]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05886, iou\_score - 0.8927]

Epoch: 6

train: 100% ██████████ 70/70 [dice\_loss - 0.02918, iou\_score - 0.9471]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05877, iou\_score - 0.8929]

Epoch: 7

train: 100% ██████████ 70/70 [dice\_loss - 0.02982, iou\_score - 0.9459]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05909, iou\_score - 0.8923]

Epoch: 8

train: 100% ██████████ 70/70 [dice\_loss - 0.02929, iou\_score - 0.9468]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05877, iou\_score - 0.8929]

Epoch: 9

train: 100% ██████████ 70/70 [dice\_loss - 0.02913, iou\_score - 0.9471]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05904, iou\_score - 0.8923]

Epoch: 10

train: 100% ██████████ 70/70 [dice\_loss - 0.02867, iou\_score - 0.9481]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05894, iou\_score - 0.8926]

Epoch: 11

train: 100% ██████████ 70/70 [dice\_loss - 0.02795, iou\_score - 0.9494]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05887, iou\_score - 0.8927]

Epoch: 12

train: 100% ██████████ 70/70 [dice\_loss - 0.0291, iou\_score - 0.9473]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05893, iou\_score - 0.8925]

Epoch: 13

train: 100% ██████████ 70/70 [dice\_loss - 0.02967, iou\_score - 0.9462]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05914, iou\_score - 0.8922]

Epoch: 14

train: 100% ██████████ 70/70 [dice\_loss - 0.02811, iou\_score - 0.9492]

valid: 100% ██████████ 14/14 [dice\_loss - 0.0588, iou\_score - 0.8928]

Epoch: 15

train: 100% ██████████ 70/70 [dice\_loss - 0.02965, iou\_score - 0.9462]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05894, iou\_score - 0.8926]

Epoch: 16

train: 100% ██████████ 70/70 [dice\_loss - 0.02903, iou\_score - 0.9474]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05908, iou\_score - 0.8923]

Epoch: 17

train: 100% ██████████ 70/70 [dice\_loss - 0.0286, iou\_score - 0.9482]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05883, iou\_score - 0.8928]

Epoch: 18

train: 100% ██████████ 70/70 [dice\_loss - 0.02926, iou\_score - 0.9469]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05881, iou\_score - 0.8928]

Epoch: 19

train: 100% ██████████ 70/70 [dice\_loss - 0.02834, iou\_score - 0.9487]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05885, iou\_score - 0.8927]

Epoch: 20

train: 100% ██████████ 70/70 [dice\_loss - 0.0292, iou\_score - 0.9471]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05877, iou\_score - 0.8929]

Epoch: 21

train: 100% ██████████ 70/70 [dice\_loss - 0.02905, iou\_score - 0.9473]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05922, iou\_score - 0.8921]

Epoch: 22

train: 100% ██████████ 70/70 [dice\_loss - 0.02883, iou\_score - 0.9478]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05879, iou\_score - 0.8928]

Epoch: 23

train: 100% ██████████ 70/70 [dice\_loss - 0.02825, iou\_score - 0.9488]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05892, iou\_score - 0.8926]

Epoch: 24

train: 100% ██████████ 70/70 [dice\_loss - 0.02942, iou\_score - 0.9466]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05896, iou\_score - 0.8925]

Epoch: 25

train: 100% ██████████ 70/70 [dice\_loss - 0.02936, iou\_score - 0.9467]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05894, iou\_score - 0.8925]

Epoch: 26

train: 100% ██████████ 70/70 [dice\_loss - 0.0285, iou\_score - 0.9484]

valid: 100% ██████████ 14/14 [dice\_loss - 0.0589, iou\_score - 0.8927]



Epoch: 27

train: 100% ██████████ 70/70 [dice\_loss - 0.02886, iou\_score - 0.9477]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05874, iou\_score - 0.8929]

Epoch: 28

train: 100% ██████████ 70/70 [dice\_loss - 0.02893, iou\_score - 0.9475]

valid: 100% ██████████ 14/14 [dice\_loss - 0.059, iou\_score - 0.8925]

Epoch: 29

train: 100% ██████████ 70/70 [dice\_loss - 0.02799, iou\_score - 0.9493]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05867, iou\_score - 0.8931]

Epoch: 30

train: 100% ██████████ 70/70 [dice\_loss - 0.02955, iou\_score - 0.9464]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05914, iou\_score - 0.8922]

Epoch: 31

train: 100% ██████████ 70/70 [dice\_loss - 0.03025, iou\_score - 0.9451]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05875, iou\_score - 0.8929]

Epoch: 32

train: 100% ██████████ 70/70 [dice\_loss - 0.02814, iou\_score - 0.9491]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05904, iou\_score - 0.8924]

Epoch: 33

train: 100% ██████████ 70/70 [dice\_loss - 0.02923, iou\_score - 0.947]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05917, iou\_score - 0.8921]

Epoch: 34

train: 100% ██████████ 70/70 [dice\_loss - 0.02986, iou\_score - 0.9458]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05881, iou\_score - 0.8928]

Epoch: 35

train: 100% ██████████ 70/70 [dice\_loss - 0.02918, iou\_score - 0.9161]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05798, iou\_score - 0.8825]

Epoch: 36

train: 100% ██████████ 70/70 [dice\_loss - 0.02917, iou\_score - 0.9373]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05875, iou\_score - 0.8428]

Epoch: 37

train: 100% ██████████ 70/70 [dice\_loss - 0.02863, iou\_score - 0.9479]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05788, iou\_score - 0.8827]

Epoch: 38

train: 100% ██████████ 70/70 [dice\_loss - 0.01922, iou\_score - 0.9347]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05905, iou\_score - 0.8911]

Epoch: 39

train: 100% ██████████ 70/70 [dice\_loss - 0.02707, iou\_score - 0.9392]

valid: 100% ██████████ 14/14 [dice\_loss - 0.05786, iou\_score - 0.8917]

**Wall time: 34 min 2 s**

**TENSORFLOW OUTPUT:**

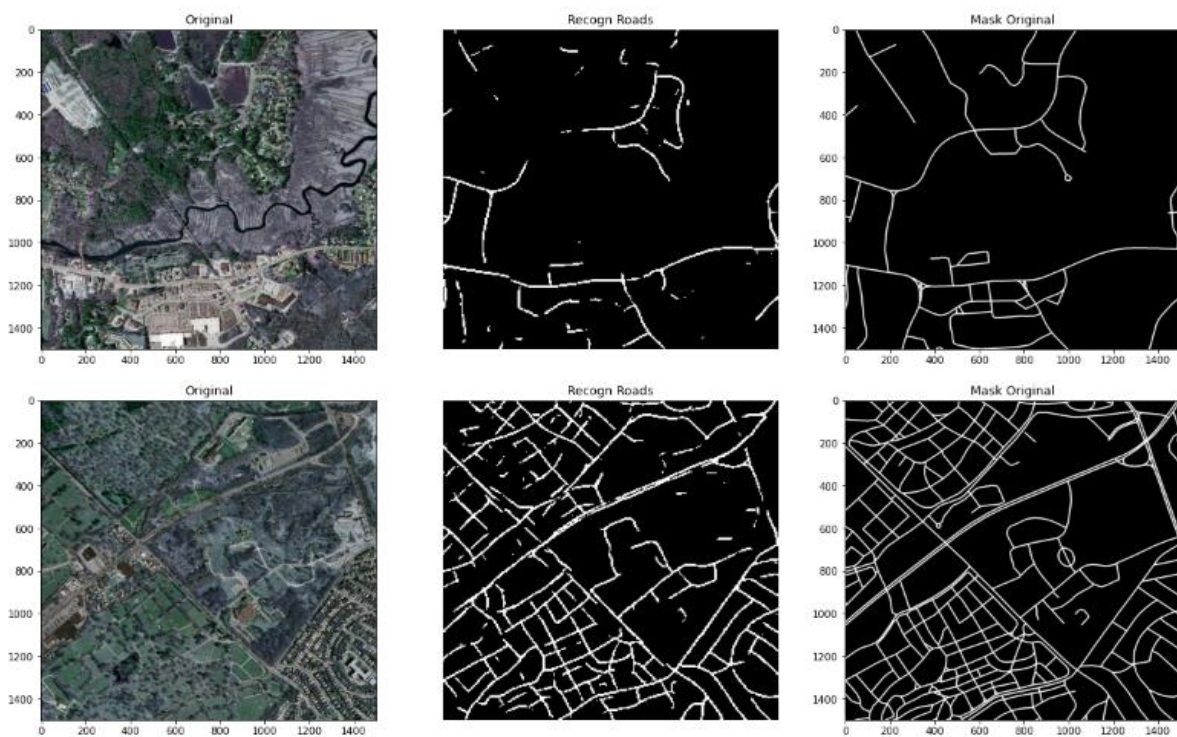


Fig 6. TensorFlow Output

**PYTORCH OUTPUT:**

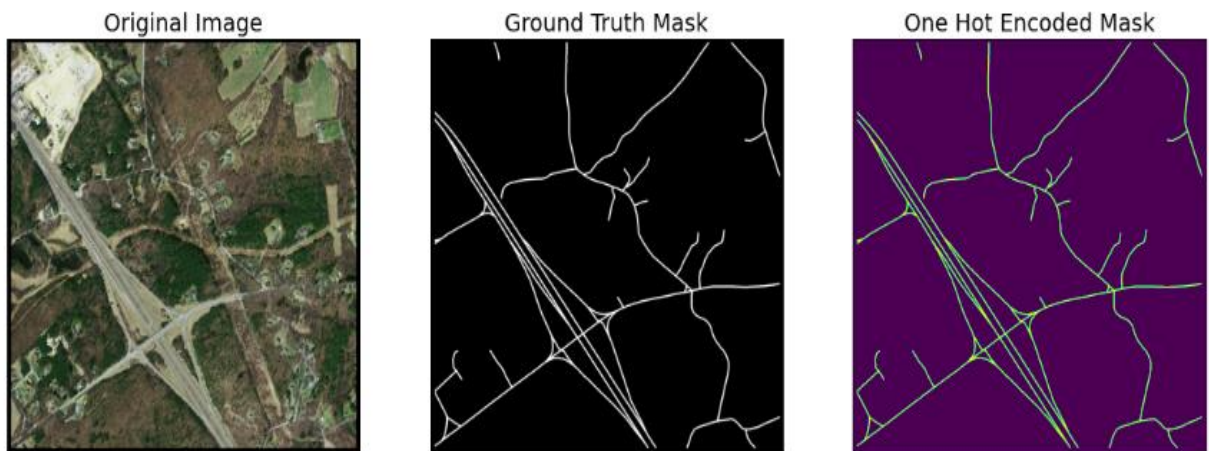


Fig 7. Py Torch Output

## **CHAPTER - IV**

### **4.1 CONCLUSION AND DISCUSSION:**

Based on the above results, it is concluded that the TensorFlow is faster than PyTorch when used with Convolution Neural Networks on both Single and Multi GPU. On challenging real-world road and building detection datasets, we demonstrated that our patch-based system for learning to classify aerial images with deep neural networks can produce good results. The findings reveal that deep networks outperform shallow networks and that convolutional networks outperform networks with other forms of connection.

### **4.2 GIT HUB**

**Code and Datasets:** [bit.ly/hpcproject5640goutham](https://bit.ly/hpcproject5640goutham)

### **4.3 REFERENCES**

#### **For UNET: CNN**

#### **U-Net: Convolutional Networks for Biomedical Image Segmentation**

Olaf Ronneberger, Philipp Fischer, Thomas Brox

#### **DATASET:**

Machine Learning for Aerial Image Labeling by Volodymyr Mnih

#### **P100 SPECIFICATIONS:**

<https://images.nvidia.com/content/pdf/tesla/whitepaper/pascal-architecture-whitepaper.pdf>

#### **AERIAL IMAGE LABELING:**

```
@phdthesis{MnihThesis,  
  author = {Volodymyr Mnih},  
  title = {Machine Learning for Aerial Image Labeling},  
  school = {University of Toronto},  
  year = {2013}  
}
```