

Semantic Segmentation

Loading dataset

In [1]:

```
!gdown --id 1kHHI0xGf_t8HjQpCP_uhMAgxhfRQB04J

Downloading...
From: https://drive.google.com/uc?id=1kHHI0xGf_t8HjQpCP_uhMAgxhfRQB04J
To: /content/data.zip
2.34GB [00:25, 93.5MB/s]
```

In [2]:

```
!unzip data.zip
```

Streaming output truncated to the last 5000 lines.

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[illegible]

```
inflating: data/mask/428/frame2039_gtFine_polygons.json
inflating: data/mask/428/frame3119_gtFine_polygons.json
inflating: data/mask/428/frame3359_gtFine_polygons.json
inflating: data/mask/428/frame3479_gtFine_polygons.json
inflating: data/mask/428/frame3599_gtFine_polygons.json
inflating: data/mask/428/frame3719_gtFine_polygons.json
inflating: data/mask/428/frame3839_gtFine_polygons.json
inflating: data/mask/428/frame3959_gtFine_polygons.json
creating: data/mask/429/
inflating: data/mask/429/frame10303_gtFine_polygons.json
inflating: data/mask/429/frame13262_gtFine_polygons.json
inflating: data/mask/429/frame13699_gtFine_polygons.json
inflating: data/mask/429/frame15812_gtFine_polygons.json
inflating: data/mask/429/frame18062_gtFine_polygons.json
inflating: data/mask/429/frame18403_gtFine_polygons.json
```

In [2]:

```
# Installing keras, tensorflow and segmentation-models to compatible versions
```

```
!pip install tensorflow==2.2.0 keras==2.3.1
```

Collecting tensorflow==2.2.0

Downloading

https://files.pythonhosted.org/packages/4c/1a/0d79814736cfecc825ab8094b39648cc9c46af7af1bae839928acb73b4d/sorflow-2.2.0-cp37-cp37m-manylinux2010_x86_64.whl (516.2MB)

[REDACTED] | 516.2MB 29kB/s

Collecting keras==2.3.1

Downloading

<https://files.pythonhosted.org/packages/ad/fd/6bfe87920d7f4fd475acd28500a42482b6b84479832bdc0fe9e589a60ce/as-2.3.1-py2.py3-none-any.whl> (377kB)

[REDACTED] | 378kB 52.9MB/s

Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (1.1.0)

Collecting tensorflow-estimator<2.3.0,>=2.2.0

Downloading

https://files.pythonhosted.org/packages/a4/f5/926ae53d6a226ec0fda5208e0e581cffed895ccc89e36ba76a8e60895b7/sorflow_estimator-2.2.0-py2.py3-none-any.whl (454kB)

[REDACTED] | 460kB 60.6MB/s

Requirement already satisfied: google-pasta>=0.1.8 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (0.2.0)

Requirement already satisfied: keras-preprocessing>=1.1.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (1.1.2)

Requirement already satisfied: scipy==1.4.1; python_version >= "3" in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (1.4.1)

Collecting tensorboard<2.3.0,>=2.2.0

Downloading

<https://files.pythonhosted.org/packages/1d/74/0a6fcb206dcc72a6da9a62dd81784bfdbff5fedb099982861dc2219014f/sorboard-2.2.2-py3-none-any.whl> (3.0MB)

[REDACTED] | 3.0MB 65.9MB/s

Requirement already satisfied: astunparse==1.6.3 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (1.6.3)

Requirement already satisfied: absl-py>=0.7.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (0.10.0)

Requirement already satisfied: wrapt>=1.11.1 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (1.12.1)

Requirement already satisfied: numpy<2.0,>=1.16.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (1.19.5)

Requirement already satisfied: wheel>=0.26; python_version >= "3" in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (0.36.2)

Requirement already satisfied: protobuf>=3.8.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (3.12.4)

Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (1.15.0)

Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (3.3.0)

Requirement already satisfied: gast==0.3.3 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (0.3.3)

Requirement already satisfied: h5py<2.11.0,>=2.10.0 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (2.10.0)

Requirement already satisfied: grpcio>=1.8.6 in /usr/local/lib/python3.7/dist-packages (from tensorflow==2.2.0) (1.32.0)

Requirement already satisfied: pyyaml in /usr/local/lib/python3.7/dist-packages (from keras==2.3.1) (3.13)

Requirement already satisfied: keras-applications>=1.0.6 in /usr/local/lib/python3.7/dist-packages (from keras==2.3.1) (1.0.8)

Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/lib/python3.7/dist-packages (from tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.8.0)

Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/local/lib/python3.7/dist-packages

```

(from tensorflow<2.3.0,>=2.2.0->tensorflow==2.2.0) (0.4.3)
Requirement already satisfied: setuptools==41.0.0 in /usr/local/lib/python3.7/dist-packages (from tensorbo
oard<2.3.0,>=2.2.0->tensorflow==2.2.0) (54.1.2)
Requirement already satisfied: werkzeug==0.11.15 in /usr/local/lib/python3.7/dist-packages (from tensorbo
ard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.0.1)
Requirement already satisfied: google-auth<2,>=1.6.3 in /usr/local/lib/python3.7/dist-packages (from tens
orboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.27.1)
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.7/dist-packages (from tensor
board<2.3.0,>=2.2.0->tensorflow==2.2.0) (2.23.0)
Requirement already satisfied: markdown==2.6.8 in /usr/local/lib/python3.7/dist-packages (from tensorboar
d<2.3.0,>=2.2.0->tensorflow==2.2.0) (3.3.4)
Requirement already satisfied: requests-oauthlib==0.7.0 in /usr/local/lib/python3.7/dist-packages (from g
oogle-auth-oauthlib<0.5,>=0.4.1->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.3.0)
Requirement already satisfied: pyasn1-modules==0.2.1 in /usr/local/lib/python3.7/dist-packages (from goog
le-auth<2,>=1.6.3->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (0.2.8)
Requirement already satisfied: rsa<5,>=3.1.4; python_version >= "3.6" in /usr/local/lib/python3.7/dist-pa
ckages (from google-auth<2,>=1.6.3->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (4.7.2)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from goo
gle-auth<2,>=1.6.3->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (4.2.1)
Requirement already satisfied: certifi==2017.4.17 in /usr/local/lib/python3.7/dist-packages (from request
s<3,>=2.21.0->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (2020.12.5)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/dist-packages (from requests<3,>=
2.21.0->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.7/dist-packages (from request
s<3,>=2.21.0->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.7/dist-p
ackages (from requests<3,>=2.21.0->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (1.24.3)
Requirement already satisfied: importlib-metadata; python_version < "3.8" in
/usr/local/lib/python3.7/dist-packages (from markdown==2.6.8->tensorboard<2.3.0,>=2.2.0-
>tensorflow==2.2.0) (3.7.2)
Requirement already satisfied: oauthlib==3.0.0 in /usr/local/lib/python3.7/dist-packages (from requests-o
authlib==0.7.0->google-auth-oauthlib<0.5,>=0.4.1->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (3.1.0)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /usr/local/lib/python3.7/dist-packages (from pyasn
1-modules==0.2.1->google-auth<2,>=1.6.3->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (0.4.8)
Requirement already satisfied: typing-extensions==3.6.4; python_version < "3.8" in
/usr/local/lib/python3.7/dist-packages (from importlib-metadata; python_version < "3.8"-
>markdown==2.6.8->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (3.7.4.3)
Requirement already satisfied: zipp==0.5 in /usr/local/lib/python3.7/dist-packages (from importlib-metada
ta; python_version < "3.8"->markdown==2.6.8->tensorboard<2.3.0,>=2.2.0->tensorflow==2.2.0) (3.4.1)
Installing collected packages: tensorflow-estimator, tensorboard, tensorflow, keras
  Found existing installation: tensorflow-estimator 2.4.0
    Uninstalling tensorflow-estimator-2.4.0:
      Successfully uninstalled tensorflow-estimator-2.4.0
  Found existing installation: tensorboard 2.4.1
    Uninstalling tensorboard-2.4.1:
      Successfully uninstalled tensorboard-2.4.1
  Found existing installation: tensorflow 2.4.1
    Uninstalling tensorflow-2.4.1:
      Successfully uninstalled tensorflow-2.4.1
  Found existing installation: Keras 2.4.3
    Uninstalling Keras-2.4.3:
      Successfully uninstalled Keras-2.4.3
Successfully installed keras-2.3.1 tensorboard-2.2.2 tensorflow-2.2.0 tensorflow-estimator-2.2.0

```


In []:

```
!pip install segmentation-models==0.2.1
```

In [3]:

```

import math
from PIL import Image, ImageDraw
from PIL import ImagePath
import pandas as pd
import shutil
import os
from os import path
from tqdm import tqdm
import json
import cv2
import numpy as np
import matplotlib.pyplot as plt
import urllib

```

1. You can download the data from this link, and extract it
2. All your data will be in the folder "data"
3. Inside the data you will be having two folders

```
|--- data
|-----| ---- images
|-----| -----|----- Scene 1
|-----| -----|-----| ---- Frame 1 (image 1)
|-----| -----|-----| ---- Frame 2 (image 2)
|-----| -----|-----| ---- ...
|-----| -----|----- Scene 2
|-----| -----|-----| ---- Frame 1 (image 1)
|-----| -----|-----| ---- Frame 2 (image 2)
|-----| -----|-----| ---- ...
|-----| -----|----- .....
|-----| ---- masks
|-----| -----|----- Scene 1
|-----| -----|-----| ---- json 1 (labeled objects in image 1)
|-----| -----|-----| ---- json 2 (labeled objects in image 1)
|-----| -----|-----| ---- ...
|-----| -----|----- Scene 2
|-----| -----|-----| ---- json 1 (labeled objects in image 1)
|-----| -----|-----| ---- json 2 (labeled objects in image 1)
|-----| -----|-----| ---- ...
|-----| -----|----- .....
```

Task 1: Preprocessing

1. Get all the file name and corresponding json files

In [4]:

```
def return_file_names_df(root_dir):
    # write the code that will create a dataframe with two columns ['images', 'json']
    # the column 'image' will have path to images
    # the column 'json' will have path to json files
    scenes = []
    for l in os.listdir(root_dir + '/images'):
        scenes.append(l)
    scenes = sorted(scenes)
    images = []
    jsons = []
    for scene in scenes:
        scene_images = []
        for f in os.listdir(root_dir + '/images/' + scene):
            scene_images.append(f)
        scene_images = sorted(scene_images)

        scene_jsons = []
        for f in os.listdir(root_dir + '/mask/' + scene):
            scene_jsons.append(f)
        scene_jsons = sorted(scene_jsons)

        for img, json in zip(scene_images, scene_jsons):
            images.append('data/images/' + scene + '/' + img)
            jsons.append('data/mask/' + scene + '/' + json)

    result = dict()
    result['images'] = images
    result['json'] = jsons

    return pd.DataFrame.from_dict(result)
```

In [5]:

```
data_df = return_file_names_df('data')
data_df.head()
```


Out[5]:

	images	json
0	data/images/201/frame0029_leftImg8bit.jpg	data/mask/201/frame0029_gtFine_polygons.json
1	data/images/201/frame0299_leftImg8bit.jpg	data/mask/201/frame0299_gtFine_polygons.json
2	data/images/201/frame0779_leftImg8bit.jpg	data/mask/201/frame0779_gtFine_polygons.json
3	data/images/201/frame1019_leftImg8bit.jpg	data/mask/201/frame1019_gtFine_polygons.json
4	data/images/201/frame1469_leftImg8bit.jpg	data/mask/201/frame1469_gtFine_polygons.json

If you observe the dataframe, we can consider each row as single data point, where first feature is image and the second feature is corresponding json file

In [6]:

```
def grader_1(data_df):  
    for i in data_df.values:  
        if not (path.isfile(i[0]) and path.isfile(i[1]) and i[0][12:i[0].find('_')]==i[1][10:i[1].find('_')]):  
            return False  
    return True
```

In [7]:

```
grader_1(data_df)
```

Out[7]:

True

In [8]:

```
data_df.shape
```

Out[8]:

(4008, 2)

2. Structure of sample Json file

```
{  
  "imgHeight": 1080,  
  "imgWidth": 1920,  
  "objects": [  
    {  
      "date": "25-Jun-2019 23:13:12",  
      "deleted": 0,  
      "draw": true,  
      "id": 0,  
      "label": "sky",  
      "polygon": [  
        [  
          0.0,  
          556.1538461538462  
        ],  
        [  
          810.0,  
          565.3846153846154  
        ],  
        [  
          1374.2307692307693,  
          596.5384615384615  
        ],  
        [  
          1919.0,  
          639.2307692307692  
        ],  
        [  
          1919.0,  
          0.0  
        ],  
        [  
          0.0,  
          0.0  
        ]  
      ],  
      "user": "cvit",  
      "verified": 0  
    }  
  ],  
}
```

- Each File will have 3 attributes
 - imgHeight: which tells the height of the image
 - imgWidth: which tells the width of the image
 - objects: it is a list of objects, each object will have multiple attributes,
 - label: the type of the object
 - polygon: a list of two element lists, representing the coordinates of the polygon

Compute the unique labels

Let's see how many unique objects are there in the json file. to see how to get the object from the json file please check [this blog](#)

In [9]:

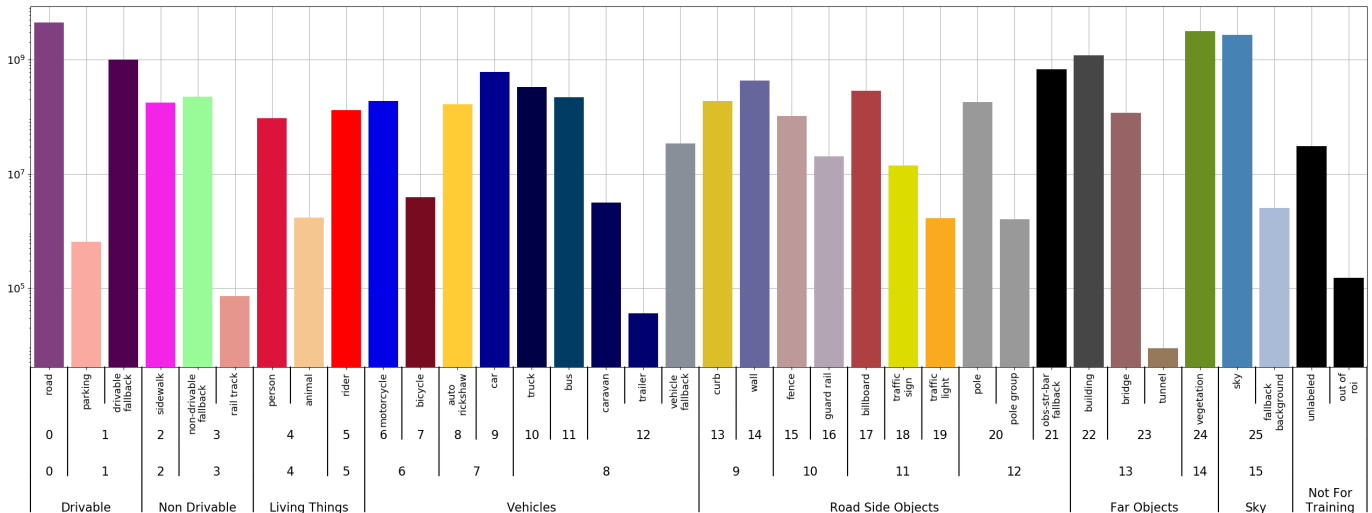
```
def return_unique_labels(data_df):  
    # for each file in the column json  
    #     read and store all the objects present in that file  
    # compute the unique objects and retrun them
```

```
# if open any json file using any editor you will get better sense of it
unique_labels = set()
for json_file in data_df['json'].values:
    f = open(json_file)
    data = json.load(f)
    for obj in data['objects']:
        unique_labels.add(obj['label'])

return unique_labels
```

In [10]:

```
unique_labels = return_unique_labels(data_df)
```



In [11]:

```
label_clr = {'road':10, 'parking':20, 'drivable fallback':20, 'sidewalk':30, 'non-drivable fallback':40, 'ra
'person':50, 'animal':50, 'rider':60, 'motorcycle':70, 'bicycle':70, 'autoricksha
'car':80, 'truck':90, 'bus':90, 'vehicle fallback':90, 'trailer':90, 'caravan':90
'traffic sign':120, 'pole':130, 'polegroup':130, 'obs-str-bar fallback':130, 'bui
'bridge':140, 'tunnel':140, 'vegetation':150, 'sky':160, 'fallback background':160
'out of roi':0, 'ego vehicle':170, 'ground':180, 'rectification border':190, \
'train':200}
```

```
CLASSES = list(np.unique(list(label_clr.values())))
```

In [12]:

```
def grader_2(unique_labels):
    if (not (set(label_clr.keys())-set(unique_labels))) and len(unique_labels) == 40:
        print("True")
    else:
        print("Flase")
```

```
grader_2(unique_labels)
```

True

* here we have given a number for each of object types, if you see we are having 21 different set of objects
 * Note that we have multiplies each object's number with 10, that is just to make different objects look differently in the segmentation map
 * Before you pass it to the models, you might need to devide the image array /10.

3. Extracting the polygons from the json files

In [13]:

```
def get_poly(file):
    # this function will take a file name as argument

    # it will process all the objects in that file and returns

    # label: a list of labels for all the objects label[i] will have the corresponding vertices in verte.
    # len(label) == number of objects in the image

    # vertexlist: it should be list of list of vertices in tuple formate
    # ex: [(x11,y11), (x12,y12), (x13,y13) .. (x1n,y1n)]
    #      [(x21,y21), (x22,y12), (x23,y23) .. (x2n,y2n)]
    #      .....
```

```

# [(xm1,ym1), (xm2,ym2), (xm3,ym3) .. (xmn,ymn)]
# len(vertexlist) == number of objects in the image

# * note that label[i] and vertexlist[i] are corresponds to the same object, one represents the type
# the other represents the location

# width of the image
# height of the image

f = open(file)
data = json.load(f)
label = []
vertexlist = []
h = data['imgHeight']
w = data['imgWidth']

for obj in data['objects']:
    polygons = obj['polygon']
    vertexObj = []
    for poly in polygons:
        if len(poly) == 2:
            vertexObj.append(tuple(poly))
    if len(vertexObj) > 1:
        label.append(obj['label'])
        vertexlist.append(vertexObj)

return w, h, label, vertexlist

```

In [14]:

```

def grader_3(file):
    w, h, labels, vertexlist = get_poly(file)
    print(len((set(labels)))==18 and len(vertexlist)==227 and w==1920 and h==1080 \
          and isinstance(vertexlist,list) and isinstance(vertexlist[0],list) and isinstance(vertexlist[0]

grader_3('data/mask/201/frame0029_gtFine_polygons.json')

True

```

4. Creating Image segmentations by drawing set of polygons

Example

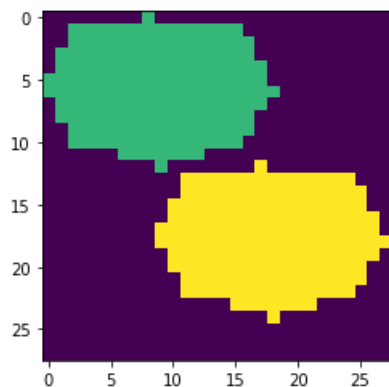
In [15]:

```

import math
from PIL import Image, ImageDraw
from PIL import ImagePath
side=8
x1 = [ ((math.cos(th) + 1) *9, (math.sin(th) + 1) * 6) for th in [i * (2 * math.pi) / side for i in range(s
x2 = [ ((math.cos(th) + 2) *9, (math.sin(th) + 3) *6) for th in [i * (2 * math.pi) / side for i in range(si
img = Image.new("RGB", (28,28))
img1 = ImageDraw.Draw(img)
# please play with the fill value
# writing the first polygon
img1.polygon(x1, fill =20)
# writing the second polygon
img1.polygon(x2, fill =30)

img=np.array(img)
# note that the filling of the values happens at the channel 1, so we are considering only the first cha
plt.imshow(img[:, :,0])
print(img.shape)
print(img[:, :,0]//10)
im = Image.fromarray(img[:, :,0])
im.save("test_image.png")

```

[illegible]

In [16]:

```
def compute_masks(data_df):
    # after you have computed the vertexlist plot that polygone in image like this

    # img = Image.new("RGB", (w, h))
    # img1 = ImageDraw.Draw(img)
    # img1.polygon(vertexlist[i], fill = label_clr[label[i]])

    # after drawing all the polygons that we collected from json file,
    # you need to store that image in the folder like this "data/output/scene/framenummer_gtFine_polygon.

    # after saving the image into disk, store the path in a list
    # after storing all the paths, add a column to the data_df['mask'] ex: data_df['mask']= mask_paths

    for json_file in data_df['json'].values:

        # Get the scene number, json file name to build path for output image
        strPath = json_file.split('.')[0]
        tokens = strPath.split('/')
        scene = tokens[2]
        name = tokens[3]
        # Make directories if not created to save image in folder structure
        if not os.path.exists('data/output'):
            os.mkdir(os.path.join('data', 'output'))
        if not os.path.exists('data/output/' + scene):
            os.mkdir(os.path.join('data/output', scene))

        imgPath = 'data/output/' + scene + '/' + name + '.png'
        w, h, labels, vertexlist = get_poly(json_file)
        img = Image.new("RGB", (w, h))
        img1 = ImageDraw.Draw(img)
        # please play with the fill value
```

```

# writing the first polygon
for i in range(len(labels)):
    img1.polygon(vertexlist[i], fill = label_clr[labels[i]])

img=np.array(img)
# note that the filling of the values happens at the channel 1, so we are considering only the fir:
im = Image.fromarray(img[:, :, 0])
im.save(imgPath)
data_df.loc[data_df['json'] == json_file, 'mask'] = imgPath
return data_df

```

In [17]:

```

data_df = compute_masks(data_df)
data_df.head()

```

Out[17]:

	images	json	mask
0	data/images/201/frame0029-leftImg8bit.jpg	data/mask/201/frame0029-gtFine-polygons.json	data/output/201/frame0029-gtFine-polygons.png
1	data/images/201/frame0299-leftImg8bit.jpg	data/mask/201/frame0299-gtFine-polygons.json	data/output/201/frame0299-gtFine-polygons.png
2	data/images/201/frame0779-leftImg8bit.jpg	data/mask/201/frame0779-gtFine-polygons.json	data/output/201/frame0779-gtFine-polygons.png
3	data/images/201/frame1019-leftImg8bit.jpg	data/mask/201/frame1019-gtFine-polygons.json	data/output/201/frame1019-gtFine-polygons.png
4	data/images/201/frame1469-leftImg8bit.jpg	data/mask/201/frame1469-gtFine-polygons.json	data/output/201/frame1469-gtFine-polygons.png

In [18]:

```

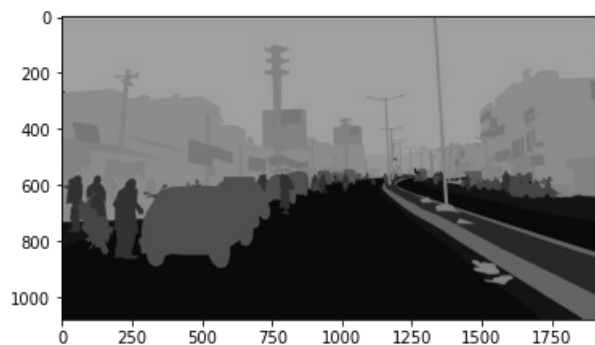
from urllib.request import urlopen
def grader_3():
    url = "https://i.imgur.com/4XSU1Hk.png"
    #url_response = urllib.request.urlopen(url)
    url_response = urlopen(url)
    img_array = np.array(bytearray(url_response.read()), dtype=np.uint8)
    img = cv2.imdecode(img_array, -1)
    my_img = cv2.imread('data/output/201/frame0029-gtFine-polygons.png')
    plt.imshow(my_img)
    print((my_img[:, :, 0]==img).all())
    print(np.unique(img))
    print(np.unique(my_img[:, :, 0]))
    data_df.to_csv('preprocessed_data.csv', index=False)
grader_3()

```

```

True
[ 0  10  20  40  50  60  70  80  90 100 120 130 140 150 160]
[ 0  10  20  40  50  60  70  80  90 100 120 130 140 150 160]

```



Data Preparation

In [19]:

```

# Import for upcoming models

import tensorflow as tf
# tf.enable_eager_execution()
import os
import numpy as np
import pandas as pd
import cv2
import matplotlib.pyplot as plt
# from hilbert import hilbertCurve
import imgaug.augmenters as iaa
import numpy as np
# import albumentations as A
os.environ['TF_FORCE_GPU_ALLOW_GROWTH'] = 'true'

```



```

from tensorflow.keras import layers
from tensorflow.keras.layers import Dense, Input, Conv2D, MaxPool2D, Activation, Dropout, Flatten, BatchNormali
from tensorflow.keras.models import Model
import random as rn
from sklearn.model_selection import train_test_split

```

In [20]:

```

data_df = pd.read_csv('preprocessed_data.csv')
data_df.head()

```

Out[20]:

	images	json	mask
0	data/images/201/frame0029_leftImg8bit.jpg	data/mask/201/frame0029_gtFine_polygons.json	data/output/201/frame0029_gtFine_polygons.png
1	data/images/201/frame0299_leftImg8bit.jpg	data/mask/201/frame0299_gtFine_polygons.json	data/output/201/frame0299_gtFine_polygons.png
2	data/images/201/frame0779_leftImg8bit.jpg	data/mask/201/frame0779_gtFine_polygons.json	data/output/201/frame0779_gtFine_polygons.png
3	data/images/201/frame1019_leftImg8bit.jpg	data/mask/201/frame1019_gtFine_polygons.json	data/output/201/frame1019_gtFine_polygons.png
4	data/images/201/frame1469_leftImg8bit.jpg	data/mask/201/frame1469_gtFine_polygons.json	data/output/201/frame1469_gtFine_polygons.png

```

* Split the data into 80:20.
* Train the UNET on the given dataset and plot the train and validation loss.
* As shown in the reference notebook plot 20 images from the test data along with its
segmentation map, predicted map.

```

In [21]:

```

# Split data into train test

X_train, X_test = train_test_split(data_df[['images', 'mask']], test_size=0.20, random_state=42)
print(X_train.shape)
print(X_test.shape)

(3206, 2)
(802, 2)

```

Generating dataset of images and masks in batches

In [22]:

```

img_h = 256
img_w = 256

```

In [23]:

```

aug2 = iaa.Fliplr(1)
aug3 = iaa.Flipud(1)
aug4 = iaa.Emboss(alpha=(1), strength=1)
aug5 = iaa.DirectedEdgeDetect(alpha=(0.8), direction=(1.0))
aug6 = iaa.Sharpen(alpha=(1.0), lightness=(1.5))

```

In [24]:

```

def visualize(**images):
    n = len(images)
    plt.figure(figsize=(16, 5))
    for i, (name, image) in enumerate(images.items()):
        plt.subplot(1, n, i + 1)
        plt.xticks([])
        plt.yticks([])
        plt.title(' '.join(name.split('_')).title())
        if i==1:
            plt.imshow(image, cmap='gray', vmax=1, vmin=0)
        else:
            plt.imshow(image)
    plt.show()

def normalize_image(mask):
    mask = mask/255
    return mask

class Dataset:

    def __init__(self, X, CLASSES, w, h, isTrainset = True):

        self.ids = list(X[:, 0])
        self.w = w
        self.h = h
        self.isTrainset = isTrainset
        # the paths of images
        self.images_fps = list(X[:, 0])

```

```

# the paths of segmentation images
self.masks_fps = list(X[:, 1])
# giving labels for each class
self.class_values = CLASSES

def __getitem__(self, i):

    # read data
    image = cv2.imread(self.images_fps[i], cv2.IMREAD_UNCHANGED)
    image = cv2.resize(image, (self.w, self.h), interpolation = cv2.INTER_AREA)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    mask = cv2.imread(self.masks_fps[i], cv2.IMREAD_UNCHANGED)
    mask = cv2.resize(mask, (self.w, self.h), interpolation = cv2.INTER_AREA)

    mask = [(mask == v) for v in self.class_values]
    mask = np.stack(mask, axis=-1).astype('float')

    if self.isTrainset:
        a = np.random.uniform()
        if a<0.2:
            image = aug2.augment_image(image)
            mask = aug2.augment_image(mask)
        elif a<0.4:
            image = aug3.augment_image(image)
            mask = aug3.augment_image(mask)
        elif a<0.6:
            image = aug4.augment_image(image)
            mask = aug4.augment_image(mask)
        elif a<0.8:
            image = aug5.augment_image(image)
            mask = mask
        else:
            image = aug6.augment_image(image)
            mask = aug6.augment_image(mask)

    return image, mask

def __len__(self):
    return len(self.ids)

class Dataloader(tf.keras.utils.Sequence):
    def __init__(self, dataset, batch_size=1, shuffle=False):
        self.dataset = dataset
        self.batch_size = batch_size
        self.shuffle = shuffle
        self.indexes = np.arange(len(dataset))

    def __getitem__(self, i):

        # collect batch data
        start = i * self.batch_size
        stop = (i + 1) * self.batch_size
        data = []
        for j in range(start, stop):
            data.append(self.dataset[j])

        batch = [np.stack(samples, axis=0) for samples in zip(*data)]

        return tuple(batch)

    def __len__(self):
        return len(self.indexes) // self.batch_size

    def on_epoch_end(self):
        if self.shuffle:
            self.indexes = np.random.permutation(self.indexes)

train_dataset = Dataset(X_train.values, CLASSES, img_w, img_h)
test_dataset = Dataset(X_test.values, CLASSES, img_w, img_h, False)

BATCH_SIZE=4
train_dataloader = Dataloader(train_dataset, BATCH_SIZE, shuffle=True)
test_dataloader = Dataloader(test_dataset, BATCH_SIZE, shuffle=True)

print(train_dataloader[0][0].shape)

```

In []:

```
print(train_dataloader[0][1].shape)
```

```
(4, 256, 256, 3)
```

```
(4, 256, 256, 21)
```

In [25]:

```
# define callback (Getting 0.4 score is also fine -> suggested by team)
```

```
from tensorflow import keras
```

```
class TerminateOnBaseline(keras.callbacks.Callback):
```

```
    """Callback that terminates training when either acc or val_acc reaches a specified baseline
    """
```

```
    def __init__(self, monitor='val_iou_score', baseline=0.45):
```

```
        super(TerminateOnBaseline, self).__init__()
```

```
        self.monitor = monitor
```

```
        self.baseline = baseline
```

```
    def on_epoch_end(self, epoch, logs=None):
```

```
        logs = logs or {}
```

```
        acc = logs.get(self.monitor)
```

```
        if acc is not None:
```

```
            if acc >= self.baseline:
```

```
                print('Epoch %d: Reached baseline, terminating training' % (epoch))
```

```
                self.model.stop_training = True
```

In [26]:

```
# Plot model metrics
```

```
def plot_model_loss_score(history):
```

```
    # Plot training & validation iou_score values
```

```
    plt.figure(figsize=(30, 5))
```

```
    plt.subplot(121)
```

```
    plt.plot(history.history['iou_score'])
```

```
    plt.plot(history.history['val_iou_score'])
```

```
    plt.title('Model iou_score')
```

```
    plt.ylabel('iou_score')
```

```
    plt.xlabel('Epoch')
```

```
    plt.legend(['Train', 'Test'], loc='upper left')
```

```
    # Plot training & validation loss values
```

```
    plt.subplot(122)
```

```
    plt.plot(history.history['loss'])
```

```
    plt.plot(history.history['val_loss'])
```

```
    plt.title('Model loss')
```

```
    plt.ylabel('Loss')
```

```
    plt.xlabel('Epoch')
```

```
    plt.legend(['Train', 'Test'], loc='upper left')
```

```
    plt.show()
```

In [27]:

```
def predict_and_compare(X_test):
```

```
    for p in X_test.values:
```

```
        #original image
```

```
        image = cv2.imread(p[0], cv2.IMREAD_UNCHANGED)
```

```
        image = cv2.resize(image, (256,256))
```

```
        image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
```

```
        #predicted segmentation map
```

```
        predicted = model.predict(image[np.newaxis,:,:,:])
```

```
        #original segmentation map
```

```
        image_mask = cv2.imread(p[1], cv2.IMREAD_UNCHANGED)
```

```
        image_mask = cv2.resize(image_mask, (256,256))
```

```
    plt.figure(figsize=(10,6))
```

```
    plt.subplot(131)
```

```
    plt.imshow(image)
```

```
    plt.subplot(132)
```

```
    plt.imshow(image_mask)
```

```
    plt.subplot(133)
```

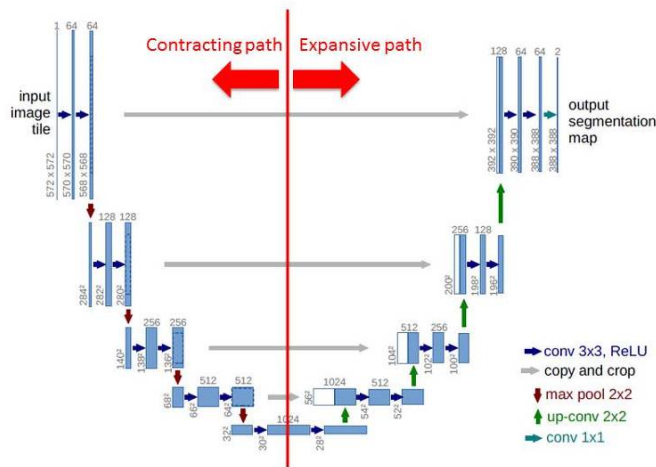
```
    plt.imshow(predicted[0,:,:,:0])
```

```
    plt.show()
```

Task 2: Applying Unet to segment the images

* please check the paper: <https://arxiv.org/abs/1505.04597>

Network Architecture



*

* As a part of this assignment we won't write this whole architecture, rather we will be doing transfer learning

* please check the library https://github.com/qubvel/segmentation_models

* You can install it like this "pip install -U segmentation_models==0.2.1", even in google colab you can install the same with "!pip install -U segmentation_models==0.2.1"

* Check the reference notebook in which we have solved one end to end case study of image forgery detection using same unet

* The number of channels in the output will depend on the number of classes in your data, since we know that we are having 21 classes, the number of channels in the output will also be 21

* **This is where we want you to explore, how do you featurize your created segmentation map note that the original map will be of (w, h, 1) and the output will be (w, h, 21) how will you calculate the loss, you can check the examples in segmentation github**

* please use the loss function that is used in the reference notebooks

Task 2.1: Dice loss

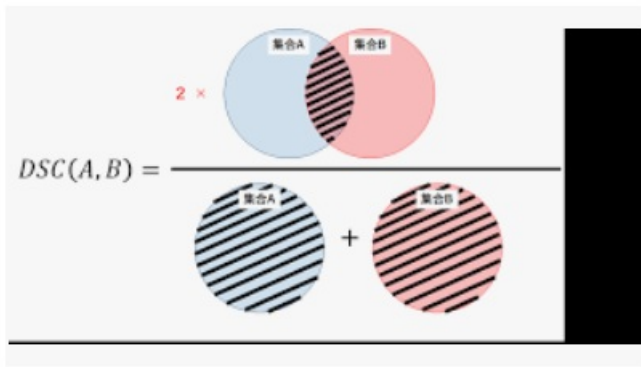
- * Explain the Dice loss
- * 1. Write the formulation
- * 2. Range of the loss function
- * 3. Interpretation of loss function
- * 4. Write your understanding of the loss function, how does it help in segmentation

Dice Loss:

This loss is based on Dice coefficient which measures the similarity of two samples by measuring the overlapping between them. If both of them are totally same, then both images will completely overlap on each other which will give dice coefficient as 1.

It can be calculated as follows.

$$Dice = \frac{2 |A \cap B|}{|A| + |B|}$$



Basically it measures the the common part between two sets per total number of elements in both sets.

In case of image segmentation, we have mask and predicted image, so (A intersection B) can be calculated by doing elementwise multiplication between two matrices and sum all elements of the resultant matrix.

|A| and |B| can be calculated either by summing the values of each matrix individually or do a suqared sum.

It takes the pixel values into account to measure the loss.

Its calculated for binary class (0,1). Thats why we can get some zeros in A * B matix as the target sample will have (0,1). Now from the non-zero values, the higher values will determine the numerator for high dice value.

The actual dice loss uses the dice coefficient as follows.

The soft dice loss is 1 - dice_coefficient. It is calculated for each class and finally averaged. So it will range from 0 to 1.

As the classes in image segmentation, there can be class imbalance, so dice index is better option than categorical cross-entropy. As in a image, there will be focused image and background, but the number pixels for background is more than that of the target picture. So the cross-entropy will predict low loss even if most of the predicted pixel value will be for background, which is not true. But as dice-loss uses intersection over union method, if there is no overlapping, it will give 0 and give high error as 1. (1 - dice index = 1 - 0 = 1)

Similarly if we predict all pixels as the target picture by ignoring the background, it will give high union value which altimately will give high error value.

Hence, Dice loss gives low error as it focuses on maximising the intersection area over foreground while minimising the Union over foreground.

$$1 - \frac{2 \sum_{pixels} y_{true} y_{pred}}{\sum_{pixels} y_{true}^2 + \sum_{pixels} y_{pred}^2}$$

Dice-loss in segmentation_model is as follows.

Creates a criterion to measure Dice loss:

$$L(\text{precision}, \text{recall}) = 1 - (1 + \beta^2) \frac{\text{precision} \cdot \text{recall}}{\beta^2 \cdot \text{precision} + \text{recall}}$$

The formula in terms of *Type I* and *Type II* errors:

$$L(tp, fp, fn) = \frac{(1 + \beta^2) \cdot tp}{(1 + \beta^2) \cdot fp + \beta^2 \cdot fn + fp}$$

where:

- tp - true positives;
- fp - false positives;
- fn - false negatives;

Parameters:

- **beta** – Float or integer coefficient for precision and recall balance.
- **class_weights** – Array (`np.array`) of class weights (`len(weights) = num_classes`).
- **class_indexes** – Optional integer or list of integers, classes to consider, if `None` all classes are used.
- **per_image** – If `True` loss is calculated for each image in batch and then averaged,
- **loss is calculated for the whole batch. (else)** –
- **smooth** – Value to avoid division by zero.

Returns:

A callable `dice_loss` instance. Can be used in `model.compile(...)` function` or combined with other losses.

Task 2.2: Training Unet

```
import segmentation_models as sm
from segmentation_models import Unet
tf.keras.backend.set_image_data_format('channels_last')
from segmentation_models.metrics import iou_score
```

In []:

```
# Creating pre-trained UNet model
model = Unet('resnet34', encoder_weights='imagenet', classes=21, activation='sigmoid', input_shape=(img_h
```

In []:

```
model.summary()
```

In []:

Model: "u-resnet34"

Layer (type)	Output Shape	Param #	Connected to
data (InputLayer)	(None, 256, 256, 3)	0	
bn_data (BatchNormalization)	(None, 256, 256, 3)	9	data[0][0]
zero_padding2d_69 (ZeroPadding2D)	(None, 262, 262, 3)	0	bn_data[0][0]
conv0 (Conv2D)	(None, 128, 128, 64)	9408	zero_padding2d_69[0][0]
bn0 (BatchNormalization)	(None, 128, 128, 64)	256	conv0[0][0]
relu0 (Activation)	(None, 128, 128, 64)	0	bn0[0][0]
zero_padding2d_70 (ZeroPadding2D)	(None, 130, 130, 64)	0	relu0[0][0]

pooling0 (MaxPooling2D)	(None, 64, 64, 64)	0	zero_padding2d_70[0][0]
stage1_unit1_bn1 (BatchNormaliz	(None, 64, 64, 64)	256	pooling0[0][0]
stage1_unit1_relu1 (Activation)	(None, 64, 64, 64)	0	stage1_unit1_bn1[0][0]
zero_padding2d_71 (ZeroPadding2	(None, 66, 66, 64)	0	stage1_unit1_relu1[0][0]
stage1_unit1_conv1 (Conv2D)	(None, 64, 64, 64)	36864	zero_padding2d_71[0][0]
stage1_unit1_bn2 (BatchNormaliz	(None, 64, 64, 64)	256	stage1_unit1_conv1[0][0]
stage1_unit1_relu2 (Activation)	(None, 64, 64, 64)	0	stage1_unit1_bn2[0][0]
zero_padding2d_72 (ZeroPadding2	(None, 66, 66, 64)	0	stage1_unit1_relu2[0][0]
stage1_unit1_conv2 (Conv2D)	(None, 64, 64, 64)	36864	zero_padding2d_72[0][0]
stage1_unit1_sc (Conv2D)	(None, 64, 64, 64)	4096	stage1_unit1_relu1[0][0]
add_33 (Add)	(None, 64, 64, 64)	0	stage1_unit1_conv2[0][0] stage1_unit1_sc[0][0]
stage1_unit2_bn1 (BatchNormaliz	(None, 64, 64, 64)	256	add_33[0][0]
stage1_unit2_relu1 (Activation)	(None, 64, 64, 64)	0	stage1_unit2_bn1[0][0]
zero_padding2d_73 (ZeroPadding2	(None, 66, 66, 64)	0	stage1_unit2_relu1[0][0]
stage1_unit2_conv1 (Conv2D)	(None, 64, 64, 64)	36864	zero_padding2d_73[0][0]
stage1_unit2_bn2 (BatchNormaliz	(None, 64, 64, 64)	256	stage1_unit2_conv1[0][0]
stage1_unit2_relu2 (Activation)	(None, 64, 64, 64)	0	stage1_unit2_bn2[0][0]
zero_padding2d_74 (ZeroPadding2	(None, 66, 66, 64)	0	stage1_unit2_relu2[0][0]
stage1_unit2_conv2 (Conv2D)	(None, 64, 64, 64)	36864	zero_padding2d_74[0][0]
add_34 (Add)	(None, 64, 64, 64)	0	stage1_unit2_conv2[0][0] add_33[0][0]
stage1_unit3_bn1 (BatchNormaliz	(None, 64, 64, 64)	256	add_34[0][0]
stage1_unit3_relu1 (Activation)	(None, 64, 64, 64)	0	stage1_unit3_bn1[0][0]
zero_padding2d_75 (ZeroPadding2	(None, 66, 66, 64)	0	stage1_unit3_relu1[0][0]
stage1_unit3_conv1 (Conv2D)	(None, 64, 64, 64)	36864	zero_padding2d_75[0][0]
stage1_unit3_bn2 (BatchNormaliz	(None, 64, 64, 64)	256	stage1_unit3_conv1[0][0]
stage1_unit3_relu2 (Activation)	(None, 64, 64, 64)	0	stage1_unit3_bn2[0][0]
zero_padding2d_76 (ZeroPadding2	(None, 66, 66, 64)	0	stage1_unit3_relu2[0][0]
stage1_unit3_conv2 (Conv2D)	(None, 64, 64, 64)	36864	zero_padding2d_76[0][0]
add_35 (Add)	(None, 64, 64, 64)	0	stage1_unit3_conv2[0][0] add_34[0][0]
stage2_unit1_bn1 (BatchNormaliz	(None, 64, 64, 64)	256	add_35[0][0]
stage2_unit1_relu1 (Activation)	(None, 64, 64, 64)	0	stage2_unit1_bn1[0][0]
zero_padding2d_77 (ZeroPadding2	(None, 66, 66, 64)	0	stage2_unit1_relu1[0][0]
stage2_unit1_conv1 (Conv2D)	(None, 32, 32, 128)	73728	zero_padding2d_77[0][0]
stage2_unit1_bn2 (BatchNormaliz	(None, 32, 32, 128)	512	stage2_unit1_conv1[0][0]
stage2_unit1_relu2 (Activation)	(None, 32, 32, 128)	0	stage2_unit1_bn2[0][0]
zero_padding2d_78 (ZeroPadding2	(None, 34, 34, 128)	0	stage2_unit1_relu2[0][0]
stage2_unit1_conv2 (Conv2D)	(None, 32, 32, 128)	147456	zero_padding2d_78[0][0]

stage2_unit1_sc (Conv2D)	(None, 32, 32, 128)	8192	stage2_unit1_relu1[0][0]
add_36 (Add)	(None, 32, 32, 128)	0	stage2_unit1_conv2[0][0] stage2_unit1_sc[0][0]
stage2_unit2_bn1 (BatchNormaliz	(None, 32, 32, 128)	512	add_36[0][0]
stage2_unit2_relu1 (Activation)	(None, 32, 32, 128)	0	stage2_unit2_bn1[0][0]
zero_padding2d_79 (ZeroPadding2	(None, 34, 34, 128)	0	stage2_unit2_relu1[0][0]
stage2_unit2_conv1 (Conv2D)	(None, 32, 32, 128)	147456	zero_padding2d_79[0][0]
stage2_unit2_bn2 (BatchNormaliz	(None, 32, 32, 128)	512	stage2_unit2_conv1[0][0]
stage2_unit2_relu2 (Activation)	(None, 32, 32, 128)	0	stage2_unit2_bn2[0][0]
zero_padding2d_80 (ZeroPadding2	(None, 34, 34, 128)	0	stage2_unit2_relu2[0][0]
stage2_unit2_conv2 (Conv2D)	(None, 32, 32, 128)	147456	zero_padding2d_80[0][0]
add_37 (Add)	(None, 32, 32, 128)	0	stage2_unit2_conv2[0][0] add_36[0][0]
stage2_unit3_bn1 (BatchNormaliz	(None, 32, 32, 128)	512	add_37[0][0]
stage2_unit3_relu1 (Activation)	(None, 32, 32, 128)	0	stage2_unit3_bn1[0][0]
zero_padding2d_81 (ZeroPadding2	(None, 34, 34, 128)	0	stage2_unit3_relu1[0][0]
stage2_unit3_conv1 (Conv2D)	(None, 32, 32, 128)	147456	zero_padding2d_81[0][0]
stage2_unit3_bn2 (BatchNormaliz	(None, 32, 32, 128)	512	stage2_unit3_conv1[0][0]
stage2_unit3_relu2 (Activation)	(None, 32, 32, 128)	0	stage2_unit3_bn2[0][0]
zero_padding2d_82 (ZeroPadding2	(None, 34, 34, 128)	0	stage2_unit3_relu2[0][0]
stage2_unit3_conv2 (Conv2D)	(None, 32, 32, 128)	147456	zero_padding2d_82[0][0]
add_38 (Add)	(None, 32, 32, 128)	0	stage2_unit3_conv2[0][0] add_37[0][0]
stage2_unit4_bn1 (BatchNormaliz	(None, 32, 32, 128)	512	add_38[0][0]
stage2_unit4_relu1 (Activation)	(None, 32, 32, 128)	0	stage2_unit4_bn1[0][0]
zero_padding2d_83 (ZeroPadding2	(None, 34, 34, 128)	0	stage2_unit4_relu1[0][0]
stage2_unit4_conv1 (Conv2D)	(None, 32, 32, 128)	147456	zero_padding2d_83[0][0]
stage2_unit4_bn2 (BatchNormaliz	(None, 32, 32, 128)	512	stage2_unit4_conv1[0][0]
stage2_unit4_relu2 (Activation)	(None, 32, 32, 128)	0	stage2_unit4_bn2[0][0]
zero_padding2d_84 (ZeroPadding2	(None, 34, 34, 128)	0	stage2_unit4_relu2[0][0]
stage2_unit4_conv2 (Conv2D)	(None, 32, 32, 128)	147456	zero_padding2d_84[0][0]
add_39 (Add)	(None, 32, 32, 128)	0	stage2_unit4_conv2[0][0] add_38[0][0]
stage3_unit1_bn1 (BatchNormaliz	(None, 32, 32, 128)	512	add_39[0][0]
stage3_unit1_relu1 (Activation)	(None, 32, 32, 128)	0	stage3_unit1_bn1[0][0]
zero_padding2d_85 (ZeroPadding2	(None, 34, 34, 128)	0	stage3_unit1_relu1[0][0]
stage3_unit1_conv1 (Conv2D)	(None, 16, 16, 256)	294912	zero_padding2d_85[0][0]
stage3_unit1_bn2 (BatchNormaliz	(None, 16, 16, 256)	1024	stage3_unit1_conv1[0][0]
stage3_unit1_relu2 (Activation)	(None, 16, 16, 256)	0	stage3_unit1_bn2[0][0]
zero_padding2d_86 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit1_relu2[0][0]

stage3_unit1_conv2 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_86[0][0]
stage3_unit1_sc (Conv2D)	(None, 16, 16, 256)	32768	stage3_unit1_relu1[0][0]
add_40 (Add)	(None, 16, 16, 256)	0	stage3_unit1_conv2[0][0] stage3_unit1_sc[0][0]
stage3_unit2_bn1 (BatchNormaliz	(None, 16, 16, 256)	1024	add_40[0][0]
stage3_unit2_relu1 (Activation)	(None, 16, 16, 256)	0	stage3_unit2_bn1[0][0]
zero_padding2d_87 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit2_relu1[0][0]
stage3_unit2_conv1 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_87[0][0]
stage3_unit2_bn2 (BatchNormaliz	(None, 16, 16, 256)	1024	stage3_unit2_conv1[0][0]
stage3_unit2_relu2 (Activation)	(None, 16, 16, 256)	0	stage3_unit2_bn2[0][0]
zero_padding2d_88 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit2_relu2[0][0]
stage3_unit2_conv2 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_88[0][0]
add_41 (Add)	(None, 16, 16, 256)	0	stage3_unit2_conv2[0][0] add_40[0][0]
stage3_unit3_bn1 (BatchNormaliz	(None, 16, 16, 256)	1024	add_41[0][0]
stage3_unit3_relu1 (Activation)	(None, 16, 16, 256)	0	stage3_unit3_bn1[0][0]
zero_padding2d_89 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit3_relu1[0][0]
stage3_unit3_conv1 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_89[0][0]
stage3_unit3_bn2 (BatchNormaliz	(None, 16, 16, 256)	1024	stage3_unit3_conv1[0][0]
stage3_unit3_relu2 (Activation)	(None, 16, 16, 256)	0	stage3_unit3_bn2[0][0]
zero_padding2d_90 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit3_relu2[0][0]
stage3_unit3_conv2 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_90[0][0]
add_42 (Add)	(None, 16, 16, 256)	0	stage3_unit3_conv2[0][0] add_41[0][0]
stage3_unit4_bn1 (BatchNormaliz	(None, 16, 16, 256)	1024	add_42[0][0]
stage3_unit4_relu1 (Activation)	(None, 16, 16, 256)	0	stage3_unit4_bn1[0][0]
zero_padding2d_91 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit4_relu1[0][0]
stage3_unit4_conv1 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_91[0][0]
stage3_unit4_bn2 (BatchNormaliz	(None, 16, 16, 256)	1024	stage3_unit4_conv1[0][0]
stage3_unit4_relu2 (Activation)	(None, 16, 16, 256)	0	stage3_unit4_bn2[0][0]
zero_padding2d_92 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit4_relu2[0][0]
stage3_unit4_conv2 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_92[0][0]
add_43 (Add)	(None, 16, 16, 256)	0	stage3_unit4_conv2[0][0] add_42[0][0]
stage3_unit5_bn1 (BatchNormaliz	(None, 16, 16, 256)	1024	add_43[0][0]
stage3_unit5_relu1 (Activation)	(None, 16, 16, 256)	0	stage3_unit5_bn1[0][0]
zero_padding2d_93 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit5_relu1[0][0]
stage3_unit5_conv1 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_93[0][0]
stage3_unit5_bn2 (BatchNormaliz	(None, 16, 16, 256)	1024	stage3_unit5_conv1[0][0]
stage3_unit5_relu2 (Activation)	(None, 16, 16, 256)	0	stage3_unit5_bn2[0][0]
zero padding2d_94 (ZeroPadding2	(None, 18, 18, 256)	0	stage3 unit5 relu2[0][0]

stage3_unit5_conv2 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_94[0][0]
add_44 (Add)	(None, 16, 16, 256)	0	stage3_unit5_conv2[0][0] add_43[0][0]
stage3_unit6_bn1 (BatchNormaliz	(None, 16, 16, 256)	1024	add_44[0][0]
stage3_unit6_relu1 (Activation)	(None, 16, 16, 256)	0	stage3_unit6_bn1[0][0]
zero_padding2d_95 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit6_relu1[0][0]
stage3_unit6_conv1 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_95[0][0]
stage3_unit6_bn2 (BatchNormaliz	(None, 16, 16, 256)	1024	stage3_unit6_conv1[0][0]
stage3_unit6_relu2 (Activation)	(None, 16, 16, 256)	0	stage3_unit6_bn2[0][0]
zero_padding2d_96 (ZeroPadding2	(None, 18, 18, 256)	0	stage3_unit6_relu2[0][0]
stage3_unit6_conv2 (Conv2D)	(None, 16, 16, 256)	589824	zero_padding2d_96[0][0]
add_45 (Add)	(None, 16, 16, 256)	0	stage3_unit6_conv2[0][0] add_44[0][0]
stage4_unit1_bn1 (BatchNormaliz	(None, 16, 16, 256)	1024	add_45[0][0]
stage4_unit1_relu1 (Activation)	(None, 16, 16, 256)	0	stage4_unit1_bn1[0][0]
zero_padding2d_97 (ZeroPadding2	(None, 18, 18, 256)	0	stage4_unit1_relu1[0][0]
stage4_unit1_conv1 (Conv2D)	(None, 8, 8, 512)	1179648	zero_padding2d_97[0][0]
stage4_unit1_bn2 (BatchNormaliz	(None, 8, 8, 512)	2048	stage4_unit1_conv1[0][0]
stage4_unit1_relu2 (Activation)	(None, 8, 8, 512)	0	stage4_unit1_bn2[0][0]
zero_padding2d_98 (ZeroPadding2	(None, 10, 10, 512)	0	stage4_unit1_relu2[0][0]
stage4_unit1_conv2 (Conv2D)	(None, 8, 8, 512)	2359296	zero_padding2d_98[0][0]
stage4_unit1_sc (Conv2D)	(None, 8, 8, 512)	131072	stage4_unit1_relu1[0][0]
add_46 (Add)	(None, 8, 8, 512)	0	stage4_unit1_conv2[0][0] stage4_unit1_sc[0][0]
stage4_unit2_bn1 (BatchNormaliz	(None, 8, 8, 512)	2048	add_46[0][0]
stage4_unit2_relu1 (Activation)	(None, 8, 8, 512)	0	stage4_unit2_bn1[0][0]
zero_padding2d_99 (ZeroPadding2	(None, 10, 10, 512)	0	stage4_unit2_relu1[0][0]
stage4_unit2_conv1 (Conv2D)	(None, 8, 8, 512)	2359296	zero_padding2d_99[0][0]
stage4_unit2_bn2 (BatchNormaliz	(None, 8, 8, 512)	2048	stage4_unit2_conv1[0][0]
stage4_unit2_relu2 (Activation)	(None, 8, 8, 512)	0	stage4_unit2_bn2[0][0]
zero_padding2d_100 (ZeroPadding	(None, 10, 10, 512)	0	stage4_unit2_relu2[0][0]
stage4_unit2_conv2 (Conv2D)	(None, 8, 8, 512)	2359296	zero_padding2d_100[0][0]
add_47 (Add)	(None, 8, 8, 512)	0	stage4_unit2_conv2[0][0] add_46[0][0]
stage4_unit3_bn1 (BatchNormaliz	(None, 8, 8, 512)	2048	add_47[0][0]
stage4_unit3_relu1 (Activation)	(None, 8, 8, 512)	0	stage4_unit3_bn1[0][0]
zero_padding2d_101 (ZeroPadding	(None, 10, 10, 512)	0	stage4_unit3_relu1[0][0]
stage4_unit3_conv1 (Conv2D)	(None, 8, 8, 512)	2359296	zero_padding2d_101[0][0]
stage4_unit3_bn2 (BatchNormaliz	(None, 8, 8, 512)	2048	stage4_unit3_conv1[0][0]
stage4_unit3_relu2 (Activation)	(None, 8, 8, 512)	0	stage4_unit3_bn2[0][0]

zero_padding2d_102 (ZeroPadding	(None, 10, 10, 512)	0	stage4_unit3_relu2[0][0]
stage4_unit3_conv2 (Conv2D)	(None, 8, 8, 512)	2359296	zero_padding2d_102[0][0]
add_48 (Add)	(None, 8, 8, 512)	0	stage4_unit3_conv2[0][0] add_47[0][0]
bn1 (BatchNormalization)	(None, 8, 8, 512)	2048	add_48[0][0]
relu1 (Activation)	(None, 8, 8, 512)	0	bn1[0][0]
decoder_stage0_upsample (UpSamp	(None, 16, 16, 512)	0	relu1[0][0]
concatenate_9 (Concatenate)	(None, 16, 16, 768)	0	decoder_stage0_upsample[0][0] stage4_unit1_relu1[0][0]
decoder_stage0_conv1 (Conv2D)	(None, 16, 16, 256)	1769472	concatenate_9[0][0]
decoder_stage0_bn1 (BatchNormal	(None, 16, 16, 256)	1024	decoder_stage0_conv1[0][0]
decoder_stage0_relu1 (Activatio	(None, 16, 16, 256)	0	decoder_stage0_bn1[0][0]
decoder_stage0_conv2 (Conv2D)	(None, 16, 16, 256)	589824	decoder_stage0_relu1[0][0]
decoder_stage0_bn2 (BatchNormal	(None, 16, 16, 256)	1024	decoder_stage0_conv2[0][0]
decoder_stage0_relu2 (Activatio	(None, 16, 16, 256)	0	decoder_stage0_bn2[0][0]
decoder_stage1_upsample (UpSamp	(None, 32, 32, 256)	0	decoder_stage0_relu2[0][0]
concatenate_10 (Concatenate)	(None, 32, 32, 384)	0	decoder_stage1_upsample[0][0] stage3_unit1_relu1[0][0]
decoder_stage1_conv1 (Conv2D)	(None, 32, 32, 128)	442368	concatenate_10[0][0]
decoder_stage1_bn1 (BatchNormal	(None, 32, 32, 128)	512	decoder_stage1_conv1[0][0]
decoder_stage1_relu1 (Activatio	(None, 32, 32, 128)	0	decoder_stage1_bn1[0][0]
decoder_stage1_conv2 (Conv2D)	(None, 32, 32, 128)	147456	decoder_stage1_relu1[0][0]
decoder_stage1_bn2 (BatchNormal	(None, 32, 32, 128)	512	decoder_stage1_conv2[0][0]
decoder_stage1_relu2 (Activatio	(None, 32, 32, 128)	0	decoder_stage1_bn2[0][0]
decoder_stage2_upsample (UpSamp	(None, 64, 64, 128)	0	decoder_stage1_relu2[0][0]
concatenate_11 (Concatenate)	(None, 64, 64, 192)	0	decoder_stage2_upsample[0][0] stage2_unit1_relu1[0][0]
decoder_stage2_conv1 (Conv2D)	(None, 64, 64, 64)	110592	concatenate_11[0][0]
decoder_stage2_bn1 (BatchNormal	(None, 64, 64, 64)	256	decoder_stage2_conv1[0][0]
decoder_stage2_relu1 (Activatio	(None, 64, 64, 64)	0	decoder_stage2_bn1[0][0]
decoder_stage2_conv2 (Conv2D)	(None, 64, 64, 64)	36864	decoder_stage2_relu1[0][0]
decoder_stage2_bn2 (BatchNormal	(None, 64, 64, 64)	256	decoder_stage2_conv2[0][0]
decoder_stage2_relu2 (Activatio	(None, 64, 64, 64)	0	decoder_stage2_bn2[0][0]
decoder_stage3_upsample (UpSamp	(None, 128, 128, 64)	0	decoder_stage2_relu2[0][0]
concatenate_12 (Concatenate)	(None, 128, 128, 128)	0	decoder_stage3_upsample[0][0] relu0[0][0]
decoder_stage3_conv1 (Conv2D)	(None, 128, 128, 32)	36864	concatenate_12[0][0]
decoder_stage3_bn1 (BatchNormal	(None, 128, 128, 32)	128	decoder_stage3_conv1[0][0]
decoder_stage3_relu1 (Activatio	(None, 128, 128, 32)	0	decoder_stage3_bn1[0][0]
decoder_stage3_conv2 (Conv2D)	(None, 128, 128, 32)	9216	decoder_stage3_relu1[0][0]
decoder_stage3_bn2 (BatchNormal	(None, 128, 128, 32)	128	decoder_stage3_conv2[0][0]

decoder_stage3_relu2	(Activation) (None, 128, 128, 32) 0	decoder_stage3_bn2[0][0]
decoder_stage4_upsample	(UpSample) (None, 256, 256, 32) 0	decoder_stage3_relu2[0][0]
decoder_stage4_conv1	(Conv2D) (None, 256, 256, 16) 4608	decoder_stage4_upsample[0][0]
decoder_stage4_bn1	(BatchNormal) (None, 256, 256, 16) 64	decoder_stage4_conv1[0][0]
decoder_stage4_relu1	(Activation) (None, 256, 256, 16) 0	decoder_stage4_bn1[0][0]
decoder_stage4_conv2	(Conv2D) (None, 256, 256, 16) 2304	decoder_stage4_relu1[0][0]
decoder_stage4_bn2	(BatchNormal) (None, 256, 256, 16) 64	decoder_stage4_conv2[0][0]
decoder_stage4_relu2	(Activation) (None, 256, 256, 16) 0	decoder_stage4_bn2[0][0]
final_conv	(Conv2D) (None, 256, 256, 21) 3045	decoder_stage4_relu2[0][0]
sigmoid	(Activation) (None, 256, 256, 21) 0	final_conv[0][0]
=====		
Total params: 24,459,054		
Trainable params: 24,441,704		
Non-trainable params: 17,350		

```

# Compile Unet model

optim = tf.keras.optimizers.Adam(0.0001)
#focal_loss = sm.losses.cce_dice_loss
focal_loss = sm.losses.dice_loss
model.compile(optim, focal_loss, metrics=[iou_score])

callback = TerminateOnBaseline()

# Fit the Unet model

history = model.fit_generator(train_dataloader, steps_per_epoch=len(train_dataloader), epochs=50,\
                             validation_data=test_dataloader,callbacks= [callback] )

Epoch 1/50
801/801 [=====] - 295s 368ms/step - loss: 0.8403 - iou_score: 0.1264 -
val_loss: 0.7884 - val_iou_score: 0.1874
Epoch 2/50
801/801 [=====] - 287s 358ms/step - loss: 0.5889 - iou_score: 0.3728 -
val_loss: 0.5983 - val_iou_score: 0.3864
Epoch 3/50
801/801 [=====] - 288s 359ms/step - loss: 0.5334 - iou_score: 0.4286 -
val_loss: 0.5793 - val_iou_score: 0.4137
Epoch 4/50
801/801 [=====] - 286s 357ms/step - loss: 0.5119 - iou_score: 0.4526 -
val_loss: 0.5736 - val_iou_score: 0.4252
Epoch 5/50
801/801 [=====] - 288s 359ms/step - loss: 0.4979 - iou_score: 0.4745 -
val_loss: 0.5741 - val_iou_score: 0.4310
Epoch 6/50
801/801 [=====] - 288s 359ms/step - loss: 0.4865 - iou_score: 0.4808 -
val_loss: 0.5601 - val_iou_score: 0.4382
Epoch 7/50
801/801 [=====] - 287s 358ms/step - loss: 0.4793 - iou_score: 0.4908 -
val_loss: 0.5747 - val_iou_score: 0.4463
Epoch 8/50
801/801 [=====] - 288s 360ms/step - loss: 0.4681 - iou_score: 0.5164 -
val_loss: 0.5674 - val_iou_score: 0.4492
Epoch 9/50
801/801 [=====] - 288s 359ms/step - loss: 0.4610 - iou_score: 0.5364 -
val_loss: 0.5577 - val_iou_score: 0.4522
Epoch 8: Reached baseline, terminating training

# IOU score and loss Vs Epoch PLOt
plot_model_loss_score(history)

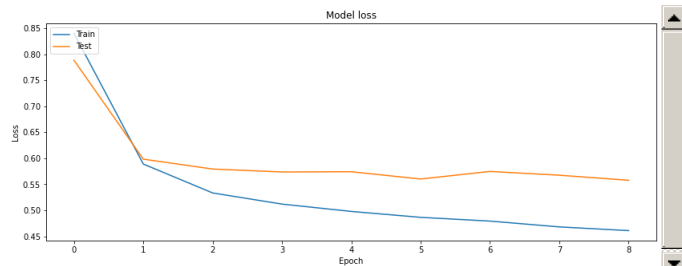
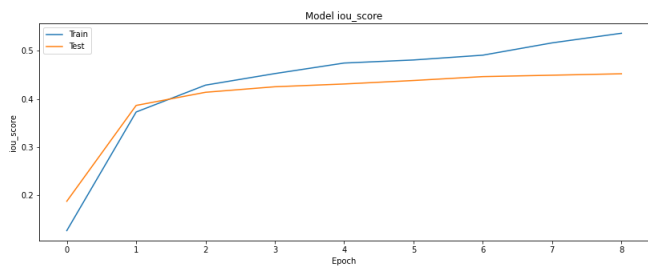
```

In []:

In []:

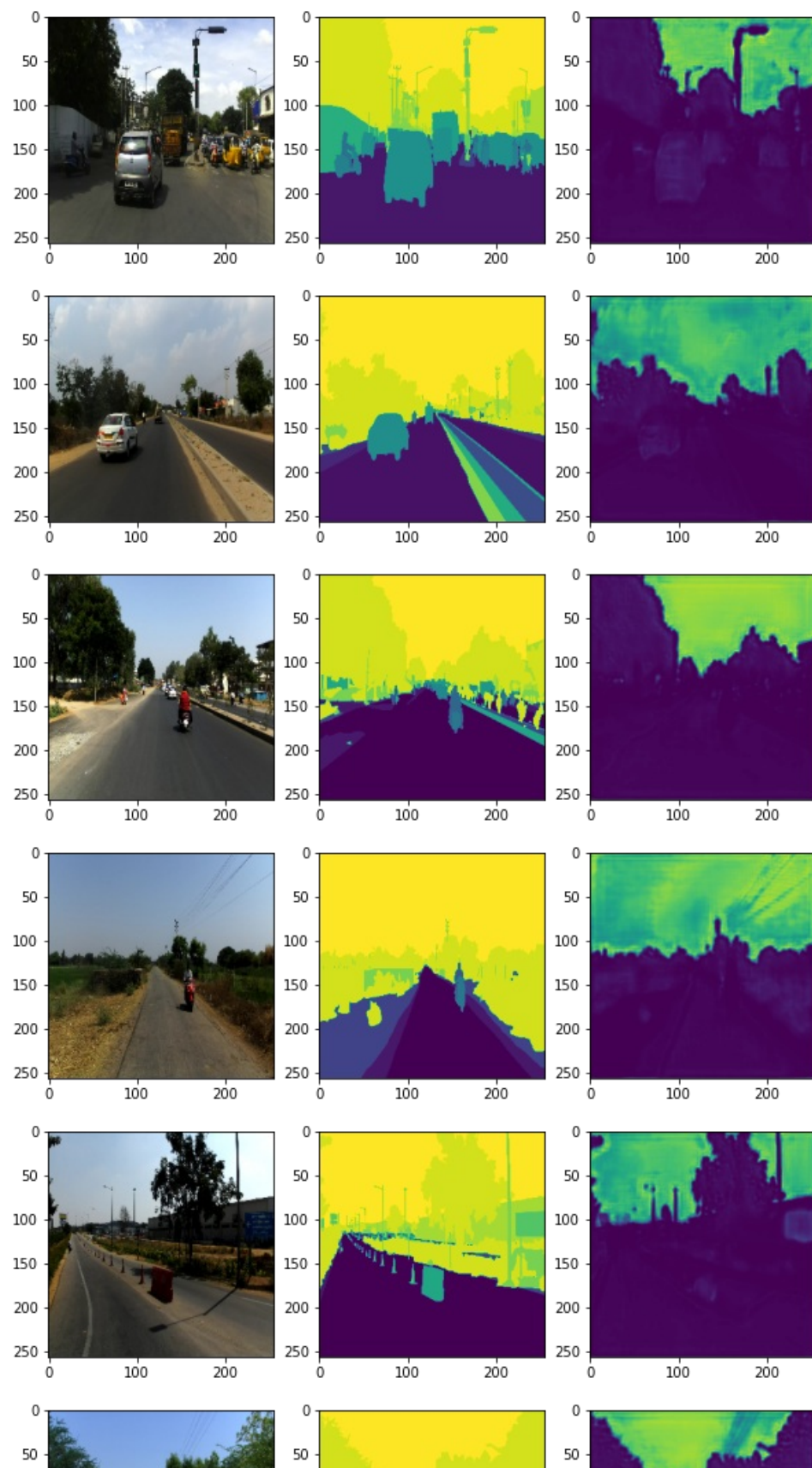
In []:

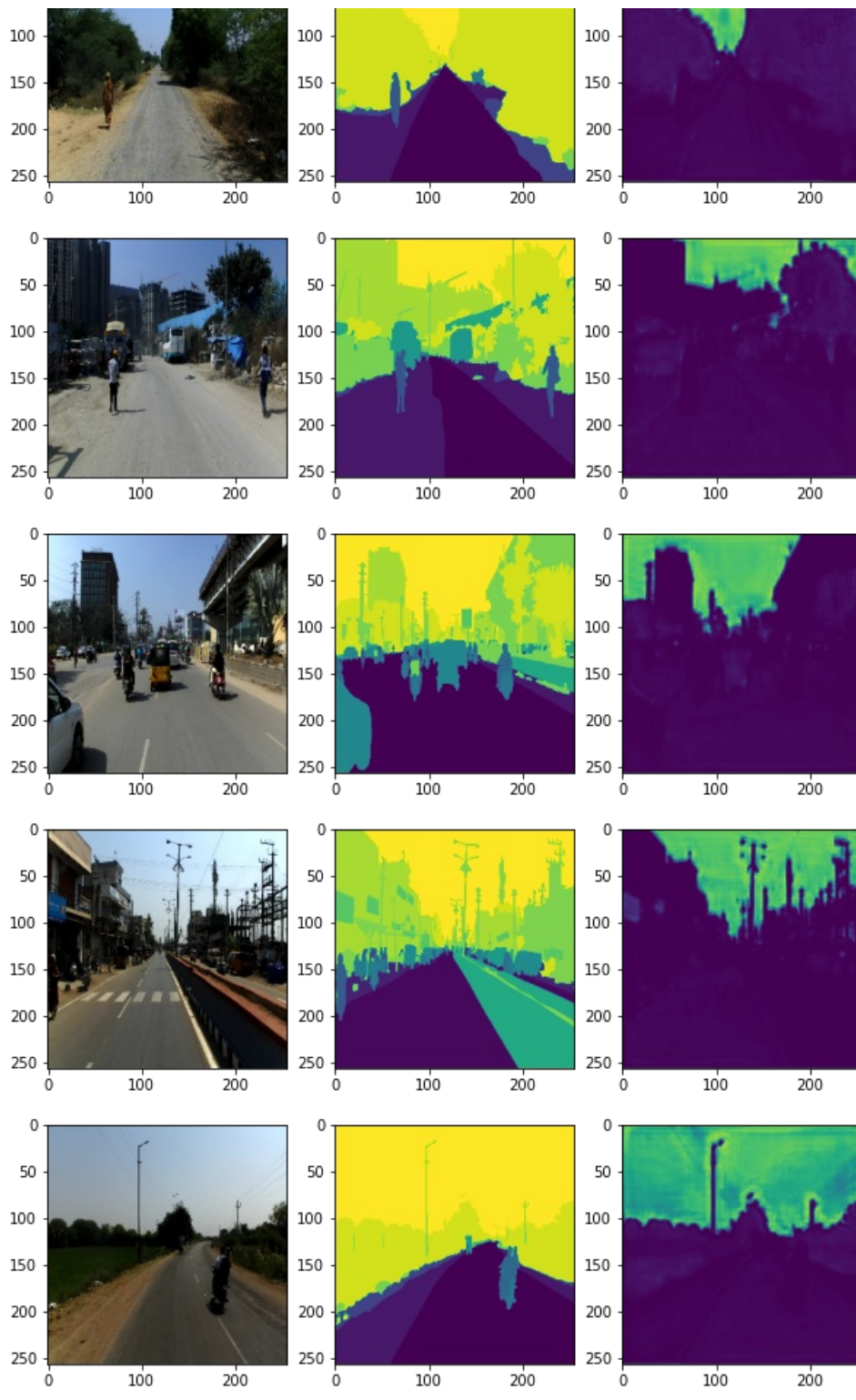
In []:



In []:

```
X_test_sample = X_test.sample(n=10)
predict_and_compare(X_test_sample)
```





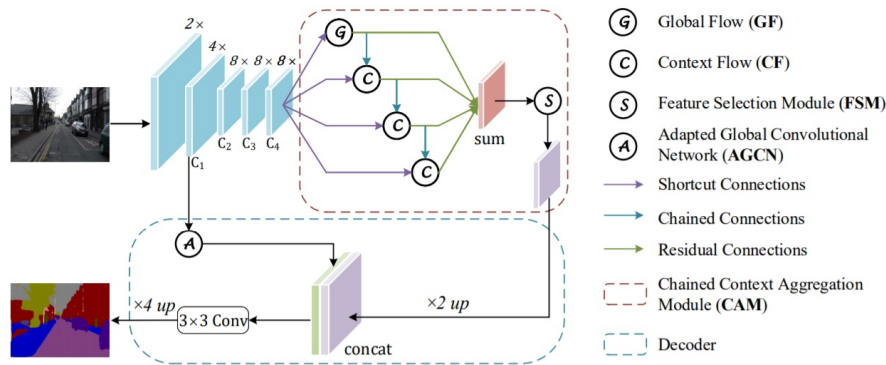
Task 3: Training CANet

In [28]:

```
import tensorflow as tf
# tf.compat.v1.enable_eager_execution()
from tensorflow.keras import keras
from tensorflow.keras.layers import *
from tensorflow.keras.preprocessing import image
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.layers import UpSampling2D
from tensorflow.keras.layers import concatenate, Reshape, Multiply, Add
from tensorflow.keras.layers import Multiply
from tensorflow.keras import regularizers
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras import backend as K
from tensorflow.keras.layers import Input, Dense, Activation, ZeroPadding2D, BatchNormalization, Flatten,
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.utils import plot_model
```

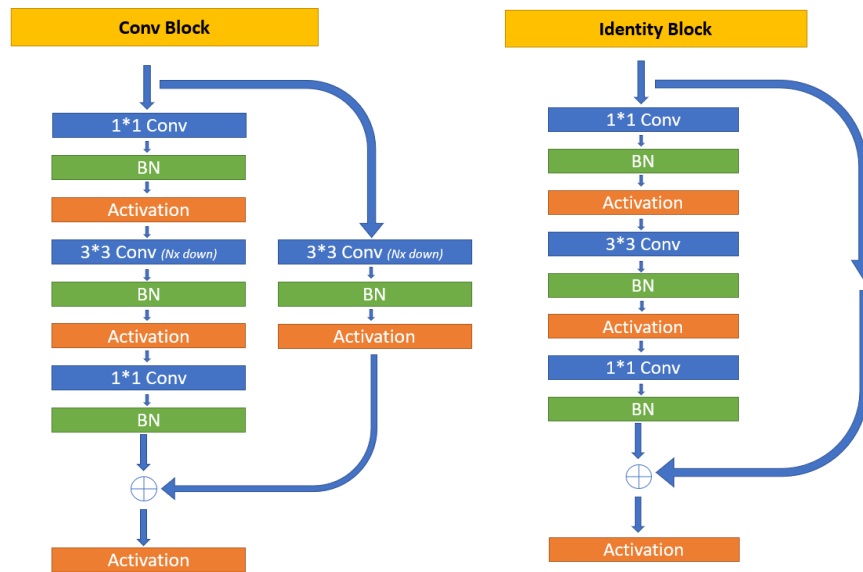
```
from tensorflow.keras.initializers import glorot_uniform, he_normal
K.set_image_data_format('channels_last')
K.set_learning_phase(1)
```


- as a part of this assignment we will be implementing the architecture based on this paper <https://arxiv.org/pdf/2002.12041.pdf>
- We will be using the custom layers concept that we used in seq-seq assignment
- You can divide the whole architecture can be divided into two parts
 1. Encoder



- 2. Decoder
- Encoder:

- The first step of the encoder is to create the channel maps [C_1 , C_2 , C_3 , C_4]
- C_1 width and heights are 4x times less than the original image
- C_2 width and heights are 8x times less than the original image
- C_3 width and heights are 8x times less than the original image
- C_4 width and heights are 8x times less than the original image
- you can reduce the dimensions by using stride parameter.
- [C_1 , C_2 , C_3 , C_4] are formed by applying a "conv block" followed by k number of "identity block". i.e the C_k feature map will single "conv block" followed by k number of "identity blocks".



- **The conv block and identity block of C_1** : the number filters in the convolutional layers will be $[4,4,8]$ and the number of filters in the parallel conv layer will also be 8.
- **The conv block and identity block of C_2** : the number filters in the convolutional layers will be $[8,8,16]$ and the number of filters in the parallel conv layer will also be 16.
- **The conv block and identity block of C_3** : the number filters in the convolutional layers will be $[16,16,32]$ and the number of filters in the parallel conv layer will also be 32.
- **The conv block and identity block of C_4** : the number filters in the convolutional layers will be $[32,32,64]$ and the number of filters in the parallel conv layer will also be 64.
- Here \oplus represents the elementwise sum

NOTE: these filters are of your choice, you can explore more options also

- Example: if your image is of size $(512, 512, 3)$
 - the output after C_1 will be $128*128*8$
 - the output after C_2 will be $64*64*16$
 - the output after C_3 will be $64*64*32$
 - the output after C_4 will be $64*64*64$

```
class convolutional_block(tf.keras.layers.Layer):
```

```

def __init__(self, kernel=3, filters=[4,4,8], stride=1, name="conv_block"):
    super().__init__(name=name)
    self.F1, self.F2, self.F3 = filters
    self.kernel = kernel
    self.stride = stride

    # First conv layer and batch normalization
    self.conv1 = Conv2D(self.F1, (1, 1), padding="same", activation='relu',
                        kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.01))
    self.bn1 = BatchNormalization()

    # Second conv layer and batch normalization
    self.conv2 = Conv2D(self.F2, (self.kernel, self.kernel), activation='relu',
                        strides = (self.stride, self.stride), padding="same",
                        kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.01))
    self.bn2 = BatchNormalization()

    # Third conv layer and batch normalization
    self.conv3 = Conv2D(self.F3, (1, 1), padding="same", activation='relu',
                        kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.01))
    self.bn3 = BatchNormalization()

    # Parallel conv layer and batch normalization
    self.conv4 = Conv2D(self.F3, (self.kernel, self.kernel), activation='relu',
                        strides = (self.stride, self.stride), padding="same",
                        kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.01))
    self.bn4 = BatchNormalization()

    self.add = Add()
    self.act_relu = Activation('relu')

def call(self, X):
    # write the architecture that was mentioned above
    conv4 = self.conv4(X)
    bn4 = self.bn4(conv4)
    relu4 = self.act_relu(bn4)

    conv1 = self.conv1(X)
    bn1 = self.bn1(conv1)
    relu1 = self.act_relu(bn1)

    conv2 = self.conv2(relu1)
    bn2 = self.bn2(conv2)
    relu2 = self.act_relu(bn2)

    conv3 = self.conv3(relu2)
    bn3 = self.bn3(conv3)

    X = self.add([bn3, relu4])
    X = self.act_relu(X)

    return X

```

In [30]:

```

class identity_block(tf.keras.layers.Layer):
    def __init__(self, kernel=3, filters=[4,4,8], name="identity_block"):
        super().__init__(name=name)
        self.F1, self.F2, self.F3 = filters
        self.kernel = kernel

        # First conv layer and batch normalization
        self.conv1 = Conv2D(self.F1, (1, 1), padding="same", activation='relu',
                            kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.01))
        self.bn1 = BatchNormalization()

        # Second conv layer and batch normalization
        self.conv2 = Conv2D(self.F2, (self.kernel, self.kernel), activation='relu', padding="same",
                            kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.01))
        self.bn2 = BatchNormalization()

        # Third conv layer and batch normalization
        self.conv3 = Conv2D(self.F3, (1, 1), padding="same", activation='relu',
                            kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.01))
        self.bn3 = BatchNormalization()

        # Parallel conv layer and batch normalization
        self.conv4 = Conv2D(self.F3, (self.kernel, self.kernel), activation='relu', padding="same",
                            kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.01))
        self.bn4 = BatchNormalization()

```

```

        kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer
self.bn4 = BatchNormalization()

self.add = Add()
self.act_relu = Activation('relu')

def call(self, X):
    # write the architecture that was mentioned above
    conv4 = self.conv4(X)

    conv1 = self.conv1(X)
    bn1 = self.bn1(conv1)
    relu1 = self.act_relu(bn1)

    conv2 = self.conv2(relu1)
    bn2 = self.bn2(conv2)
    relu2 = self.act_relu(bn2)

    conv3 = self.conv3(relu2)
    bn3 = self.bn3(conv3)

    X = self.add([bn3, conv4])
    X = self.act_relu(X)

    return X

```

In [31]:

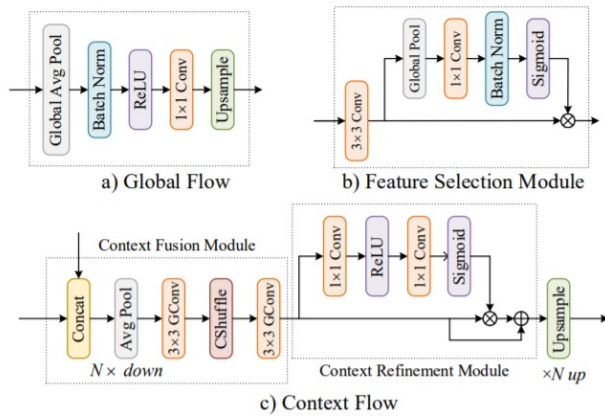
```

def build_conv_identity_block(X):
    CB1 = convolutional_block(kernel=3, filters=[4,4,8], stride=2, name="C1")(X)
    IB1 = identity_block(kernel=3, filters=[4,4,8],name='I1')(CB1)
    CB2 = convolutional_block(kernel=3, filters=[8,8,16], stride=2, name="C2")(IB1)
    IB21 = identity_block(kernel=3, filters=[8,8,16],name='I21')(CB2)
    IB22 = identity_block(kernel=3, filters=[8,8,16],name='I22')(IB21)
    CB3 = convolutional_block(kernel=3, filters=[16,16,32], stride=1, name="C3")(IB22)
    IB31 = identity_block(kernel=3, filters=[16,16,32],name='I31')(CB3)
    IB32 = identity_block(kernel=3, filters=[16,16,32],name='I32')(IB31)
    IB33 = identity_block(kernel=3, filters=[16,16,32],name='I33')(IB32)
    CB4 = convolutional_block(kernel=3, filters=[32,32,64], stride=1, name="C4")(IB33)
    IB41 = identity_block(kernel=3, filters=[32,32,64],name='I41')(CB4)
    IB42 = identity_block(kernel=3, filters=[32,32,64],name='I42')(IB41)
    IB43 = identity_block(kernel=3, filters=[32,32,64],name='I43')(IB42)
    IB44 = identity_block(kernel=3, filters=[32,32,64],name='I44')(IB43)

    return CB1, IB44

```

- The output of the C₄ will be passed to $\text{Chained Context Aggregation Module (CAM)}$



- The CAM module will have two operations names Context flow and Global flow
- **The Global flow:**
 - as shown in the above figure first we will apply **global avg pooling** which results in $(\#, 1, 1, \text{number_of_filters})$ then applying **BN**, **RELU**, $1 \times 1 \text{ Conv}$ layer sequentially which results a matrix $(\#, 1, 1, \text{number_of_filters})$. Finally apply **upsampling / conv2d transpose** to make the output same as the input dimensions $(\#, \text{input_height}, \text{input_width}, \text{number_of_filters})$
 - If you use **upsampling** then use bilinear pooling as interpolation technique
- **The Context flow:**
 - as shown in the above figure (c) the context flow will get inputs from two modules a. C₄ b. From the above flow
 - We will be **concatinating** the both inputs on the last axis.
 - After the concatenation we will be applying **Average pooling** which reduces the size of feature map by $N \times N$ times
 - In the paper it was mentioned that to apply a group convolutions, but for the assignment we will be applying the simple conv layers with kernel size (3×3)
 - We are skipping the channel shuffling
 - similarly we will be applying a simple conv layers with kernel size (3×3) consider this output is X
 - later we will get the $Y = (X \otimes \sigma(1 \times 1 \text{ conv}(\text{relu}(1 \times 1 \text{ conv}(X)))) \oplus X$, here \otimes is elementwise multiplication and \oplus is elementwise addition
 - Finally apply **upsampling / conv2d transpose** to make the output same as the input dimensions $(\#, \text{input_height}, \text{input_width}, \text{number_of_filters})$
 - If you use **upsampling** then use bilinear pooling as interpolation technique

NOTE: here N times reduction and N time increments makes the input and out shape same, you can explore with the N values, you can choose N = 2 or 4

- Example with N=2:
 - Assume the C₄ is of shape (64,64,64) then the shape of GF will be (64,64,32)
 - Assume the C₄ is of shape (64,64,64) and the shape of GF is (64,64,32) then the shape of CF1 will be (64,64,32)
 - Assume the C₄ is of shape (64,64,64) and the shape of CF1 is (64,64,32) then the shape of CF2 will be (64,64,32)
 - Assume the C₄ is of shape (64,64,64) and the shape of CF2 is (64,64,32) then the shape of CF3 will be (64,64,32)

In [32]:

```
class global_flow(tf.keras.layers.Layer):
    def __init__(self, input_x, name="global_flow"):
        super().__init__(name=name)
        self.h = input_x.shape[1]
        self.w = input_x.shape[2]
        self.globalAverage = GlobalAveragePooling2D()
        self.bn = BatchNormalization()
        self.act_relu = Activation('relu')
        self.reshape = Reshape(target_shape=(1,1,64))
        self.conv = Conv2D(64, (1,1), activation='relu', padding="same",
                           kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.01))
        self.upSample = UpSampling2D((self.h, self.w), interpolation='bilinear')

    def call(self, X):
        # implement the global flow operation
        X = self.globalAverage(X)
        X = self.bn(X)
        X = self.act_relu(X)
        X = self.reshape(X)
        X = self.conv(X)
        X = self.upSample(X)

        return X
```

In [33]:

```
class context_flow(tf.keras.layers.Layer):
```

```

def __init__(self, name="context_flow"):
    super().__init__(name=name)
    self.concatenate = Concatenate()
    self.averagePooling = AveragePooling2D((2, 2), (2, 2),padding='same')
    self.conv1 = Conv2D(64, (3,3), activation='relu', padding="same",
                        kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer
    self.conv2 = Conv2D(64, (3,3), activation='relu', padding="same",
                        kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer
    self.conv3 = Conv2D(64, (1, 1), activation='relu', padding="same",
                        kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer
    self.conv4 = Conv2D(64, (1, 1), activation='relu', padding="same",
                        kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer
    self.act_relu = Activation('relu')
    self.act_sig = Activation('sigmoid')
    self.mul = Multiply()
    self.add = Add()
    self.upSample = UpSampling2D((2, 2), interpolation='bilinear')

```

```

def call(self, X):
    # here X will a list of two elements
    INP, FLOW = X[0], X[1]

    # implement the context flow as mentioned in the above cell
    X = self.concatenate([INP, FLOW])
    X = self.averagePooling(X)
    X = self.conv1(X)
    X = self.conv2(X)
    X1 = X

    X = self.conv3(X)
    X = self.act_relu(X)
    X = self.conv4(X)
    X = self.act_sig(X)

    X = self.mul([X1 , X])
    X = self.add([X1,X])
    X = self.upSample(X)

    return X

```

In [34]:

```

def build_global_context_layers(X):
    X_list = []
    X_g = global_flow(input_x = X) (X)
    X_list.append(X_g)

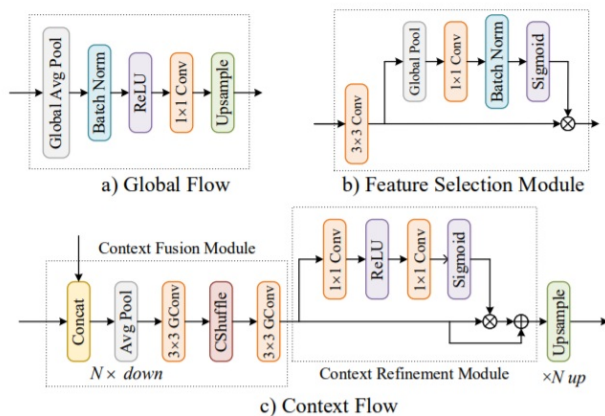
    for i in range(3):
        name = "context_flow" + str(i+1)
        X_c = context_flow(name = name) ((X, X_list[-1]))
        X_list.append(X_c)

    X = Add() (X_list)

    return X

```


- As shown in the above architecture we will be having 4 context flows
- if you have implemented correctly all the shapes of Global Flow, and 3 context flows will have the same dimension
- the output of these 4 modules will be added to get the same output matrix



- The output of after the sum, will be sent to the **Feature selection module \$FSM\$**
- Example:
 - if the shapes of GF, CF1, CF2, CF3 are (64,64,32), (64,64,32), (64,64,32), (64,64,32), (64,64,32) respectively then after the sum we will be getting (64,64,32), which will be passed to the next module.

Feature selection module:

- As part of the FSM we will be applying a conv layer (3,3) with the padding="same" so that the output and input will have same shapes
- Let call the output as X
- Pass the X to global pooling which results the matrix (#, 1, 1, number_of_channels)
- Apply \$1*1\$ conv layer, after the pooling
- the output of the \$1*1\$ conv layer will be passed to the Batch normalization layer, followed by Sigmoid activation function.
- we will be having the output matrix of shape (#, 1, 1, number_of_channels) lets call it 'Y'
- **we can interpret this as attention mechanism, i.e for each channel we will having a weight**
- the dimension of X (#, w, h, k) and output above steps Y is (#, 1, 1, k) i.e we need to multiply each channel of X will be multiplied with corresponding channel of Y
- After creating the weighted channel map we will be doing upsampling such that it will double the height and width.
- apply **upsampling** with bilinear pooling as interpolation technique
- **Example:**
 - Assume the matrix shape of the input is (64,64,32) then after upsampling it will be (128,128,32)

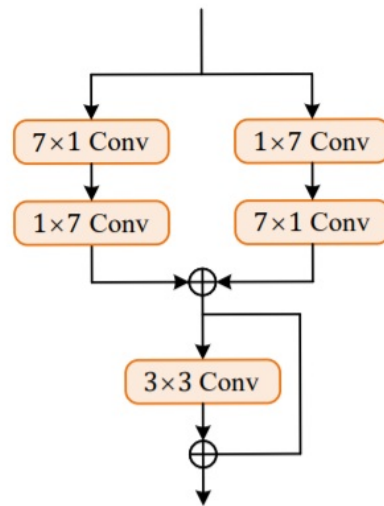
In [35]:

```
class fsm(tf.keras.layers.Layer):
    def __init__(self, name="feature_selection"):
        super().__init__(name=name)
        self.conv1 = Conv2D(32, (3,3), activation='relu', padding="same",
                             kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer)
        self.conv2 = Conv2D(32, (1,1), activation='relu', padding="same",
                             kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer)
        self.globalAveragePooling = GlobalAveragePooling2D()
        self.reshape = Reshape(target_shape= (1,1,32))
        self.bn = BatchNormalization()
        self.act_sig = Activation('sigmoid')
        self.mul = Multiply()
        self.upSample = UpSampling2D((2, 2), interpolation='bilinear')

    def call(self, X):
        # implement the FSM modules based on image in the above cells
        X = self.conv1(X)
        X1 = X
        X = self.globalAveragePooling(X)
        X = self.reshape(X)
        X = self.conv2(X)
        X = self.bn(X)
        X = self.act_sig(X)

        X = self.mul([X1, X])
        X = self.upSample(X)

    return X
```



b) AGCN

- Adapted Global Convolutional Network (AGCN):

- AGCN will get the input from the output of the "conv block" of \$C_{11}\$
- In all the above layers we will be using the padding="same" and stride=(1,1)
- so that we can have the input and output matrices of same size

- Example:

- Assume the matrix shape of the input is (128,128,32) then the output it will be (128,128,32)

In [36]:

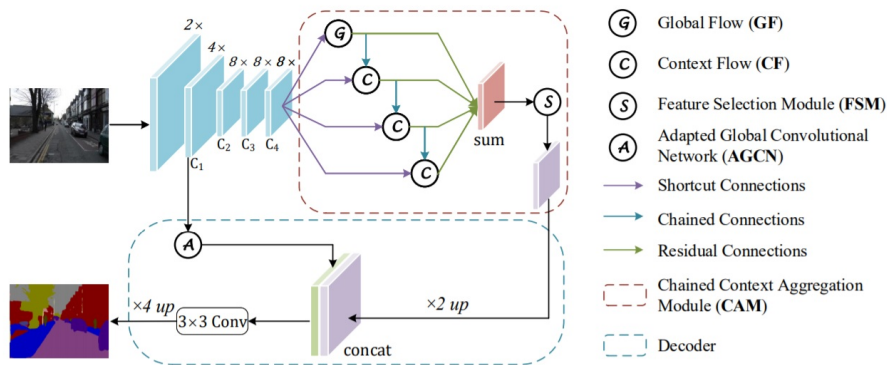
```
class agcn(tf.keras.layers.Layer):
    def __init__(self, input_x, name="global_conv_net"):
        super().__init__(name=name)
        self.filters = input_x.shape[3]
        self.conv1 = Conv2D(self.filters, (1, 7), activation='relu', padding="same",
                             kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer)
        self.conv2 = Conv2D(self.filters, (7, 1), activation='relu', padding="same",
                             kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer)
        self.conv3 = Conv2D(self.filters, (7, 1), activation='relu', padding="same",
                             kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer)
        self.conv4 = Conv2D(self.filters, (1, 7), activation='relu', padding="same",
                             kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer)
        self.conv5 = Conv2D(self.filters, (3, 3), activation='relu', padding="same",
                             kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizer)
        self.add = Add()

    def call(self, X_input):
        # please implement the above mentioned architecture
        X = self.conv1(X_input)
        X = self.conv2(X)

        X1 = self.conv3(X_input)
        X1 = self.conv4(X1)

        X = self.add([X, X1])
        X1 = X

        X = self.conv5(X)
        X = self.add([X, X1])
        return X
```



- as shown in the architecture, after we get the AGCN it will get concatenated with the FSM output
- If we observe the shapes both AGCN and FSM will have same height and weight
- we will be concatenating both these outputs over the last axis
- The concatenated output will be passed to a conv layers with filters = number of classes in our data set and the activation function = 'relu'
- we will be using padding="same" which results in the same size feature map
- If you observe the shape of matrix, it will be 4x times less than the original image
- to make it equal to the original output shape, we will do 4x times upsampling of rows and columns
- apply [upsampling](#) with bilinear pooling as interpolation technique
- Finally we will be applying sigmoid activation.
- Example:
 - Assume the matrix shape of AGCN is (128,128,32) and FSM is (128,128,32) the concatenation will make it (128, 128, 64)
 - Applying conv layer will make it (128,128,21)
 - Finally applying upsampling will make it (512, 512, 21)
 - Applying sigmoid will result in the same matrix (512, 512, 21)

Building model:

In [37]:

```
X_input = Input(shape=(256,256,3))
num_classes = len(CLASSES)

# Stage 1
X = Conv2D(64, (3, 3), name='conv1', padding="same",
           kernel_initializer=tf.keras.initializers.glorot_uniform(seed=0), kernel_regularizer=tf.keras.r
X = Dropout(0.5)(X)
X = BatchNormalization(axis=3, name='bn_conv1')(X)
X = Activation('relu')(X)
X = tf.keras.layers.MaxPooling2D((2, 2), strides=(2, 2))(X)
CB1, X = build_conv_identity_block(X)
X = build_global_context_layers(X)
X = Dropout(0.5)(X)
X = BatchNormalization(axis=3, name='bn_conv2')(X)
X = fsm()(X)
AGCN = agcn(input_x = X)(CB1)
X = Concatenate()([X, AGCN])
X = Dropout(0.5)(X)
X = BatchNormalization(axis=3, name='bn_conv3')(X)
X = Conv2D(num_classes, (3, 3), activation='relu', padding="same",
           kernel_initializer=he_normal(seed=0), kernel_regularizer=tf.keras.regularizers.l2(0.001))(X)
X = UpSampling2D((4, 4), interpolation='bilinear')(X)
X = Dropout(0.5)(X)
X = BatchNormalization(axis=3, name='bn_conv4')(X)
X_output = Activation('softmax')(X)

print(X_input.shape)
print(X.shape)

(None, 256, 256, 3)
(None, 256, 256, 21)
```

- If you observe the architecture we are creating a feature map with 2x time less width and height
- we have written the first stage of the code above.
- Write the next layers by using the custom layers we have written

In [52]:

```
# write the complete architecutre
```

```
model = Model(inputs = X_input, outputs = X_output)
```

```
model.summary()
```

```
Model: "model_2"
```

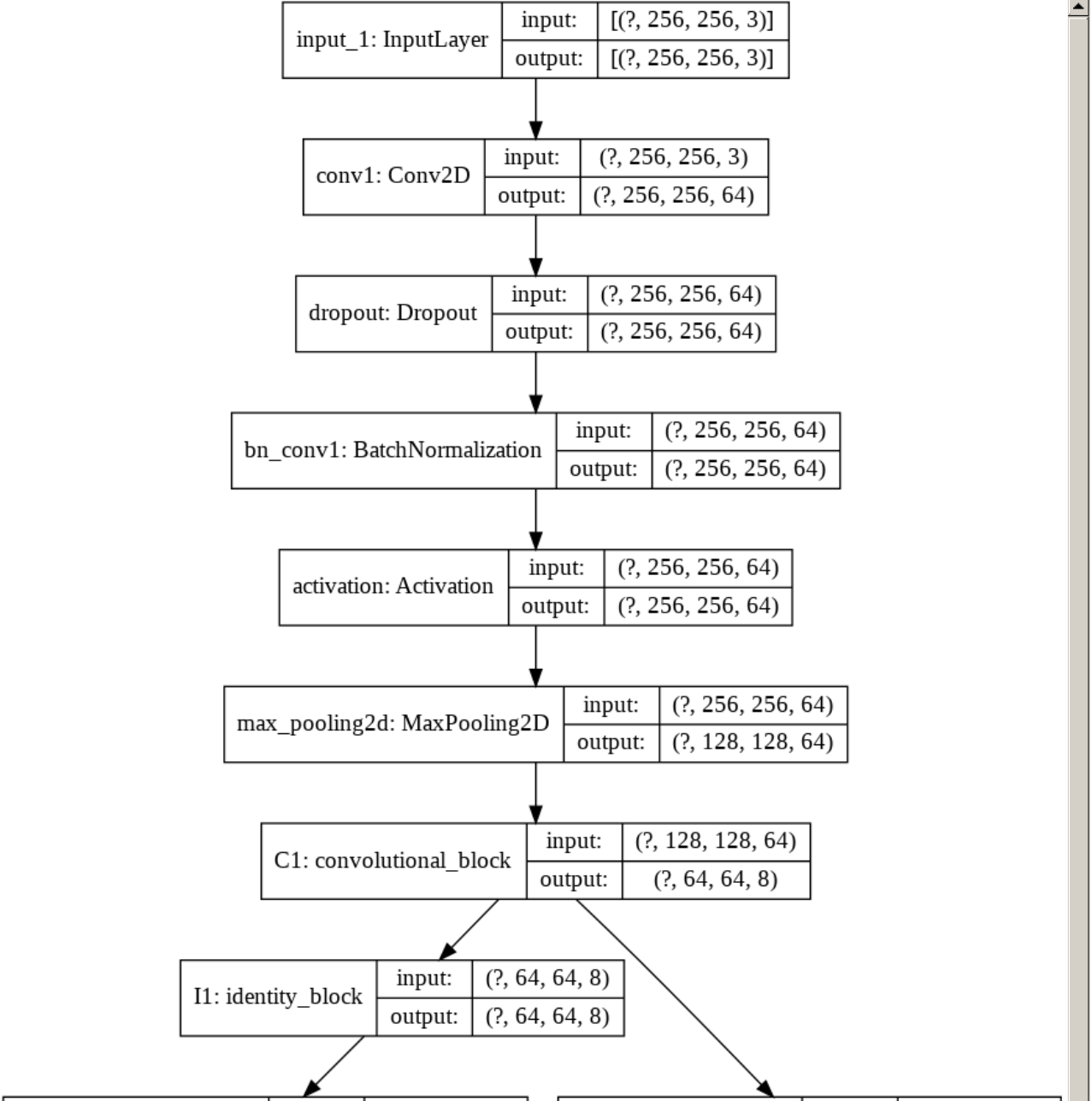
Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 256, 256, 3) 0		
conv1 (Conv2D)	(None, 256, 256, 64)	1792	input_1[0][0]
dropout (Dropout)	(None, 256, 256, 64) 0		conv1[0][0]
bn_conv1 (BatchNormalization)	(None, 256, 256, 64)	256	dropout[0][0]
activation (Activation)	(None, 256, 256, 64) 0		bn_conv1[0][0]
max_pooling2d (MaxPooling2D)	(None, 128, 128, 64) 0		activation[0][0]
C1 (convolutional_block)	(None, 64, 64, 8)	5160	max_pooling2d[0][0]
I1 (identity_block)	(None, 64, 64, 8)	872	C1[0][0]
C2 (convolutional_block)	(None, 32, 32, 16)	2160	I1[0][0]
I21 (identity_block)	(None, 32, 32, 16)	3312	C2[0][0]
I22 (identity_block)	(None, 32, 32, 16)	3312	I21[0][0]
C3 (convolutional_block)	(None, 32, 32, 32)	8160	I22[0][0]
I31 (identity_block)	(None, 32, 32, 32)	12896	C3[0][0]
I32 (identity_block)	(None, 32, 32, 32)	12896	I31[0][0]
I33 (identity_block)	(None, 32, 32, 32)	12896	I32[0][0]
C4 (convolutional_block)	(None, 32, 32, 64)	31680	I33[0][0]
I41 (identity_block)	(None, 32, 32, 64)	50880	C4[0][0]
I42 (identity_block)	(None, 32, 32, 64)	50880	I41[0][0]
I43 (identity_block)	(None, 32, 32, 64)	50880	I42[0][0]
I44 (identity_block)	(None, 32, 32, 64)	50880	I43[0][0]
global_flow (global_flow)	(None, 32, 32, 64)	4416	I44[0][0]
context_flow1 (context_flow)	(None, 32, 32, 64)	119040	I44[0][0] global_flow[0][0]
context_flow2 (context_flow)	(None, 32, 32, 64)	119040	I44[0][0] context_flow1[0][0]
context_flow3 (context_flow)	(None, 32, 32, 64)	119040	I44[0][0] context_flow2[0][0]
add_17 (Add)	(None, 32, 32, 64)	0	global_flow[0][0] context_flow1[0][0] context_flow2[0][0] context_flow3[0][0]
dropout_1 (Dropout)	(None, 32, 32, 64)	0	add_17[0][0]
bn_conv2 (BatchNormalization)	(None, 32, 32, 64)	256	dropout_1[0][0]
feature_selection (fsm)	(None, 64, 64, 32)	19648	bn_conv2[0][0]

global_conv_net (agcn)	(None, 64, 64, 32)	27296	C1[0][0]
concatenate_3 (Concatenate)	(None, 64, 64, 64)	0	feature_selection[0][0] global_conv_net[0][0]
dropout_2 (Dropout)	(None, 64, 64, 64)	0	concatenate_3[0][0]
bn_conv3 (BatchNormalization)	(None, 64, 64, 64)	256	dropout_2[0][0]
conv2d_76 (Conv2D)	(None, 64, 64, 21)	12117	bn_conv3[0][0]
up_sampling2d_5 (UpSampling2D)	(None, 256, 256, 21)	0	conv2d_76[0][0]
dropout_3 (Dropout)	(None, 256, 256, 21)	0	up_sampling2d_5[0][0]
bn_conv4 (BatchNormalization)	(None, 256, 256, 21)	84	dropout_3[0][0]
activation_23 (Activation)	(None, 256, 256, 21)	0	bn_conv4[0][0]
=====			
Total params: 720,105			
Trainable params: 717,199			
Non-trainable params: 2,906			

In [39]:

```
tf.keras.utils.plot_model(
    model, to_file='model4.png', show_shapes=True, show_layer_names=True,
    rankdir='TB')
```

Out[39]:



C2: convolutional_block	input:	(?, 64, 64, 8)
	output:	(?, 32, 32, 16)

global_conv_net: agcn	input:	(?, 64, 64, 8)
	output:	(?, 64, 64, 32)

I21: identity_block	input:	(?, 32, 32, 16)
	output:	(?, 32, 32, 16)

I22: identity_block	input:	(?, 32, 32, 16)
	output:	(?, 32, 32, 16)

C3: convolutional_block	input:	(?, 32, 32, 16)
	output:	(?, 32, 32, 32)

I31: identity_block	input:	(?, 32, 32, 32)
	output:	(?, 32, 32, 32)

I32: identity_block	input:	(?, 32, 32, 32)
	output:	(?, 32, 32, 32)

I33: identity_block	input:	(?, 32, 32, 32)
	output:	(?, 32, 32, 32)

C4: convolutional_block	input:	(?, 32, 32, 32)
	output:	(?, 32, 32, 64)

I41: identity_block	input:	(?, 32, 32, 64)
	output:	(?, 32, 32, 64)

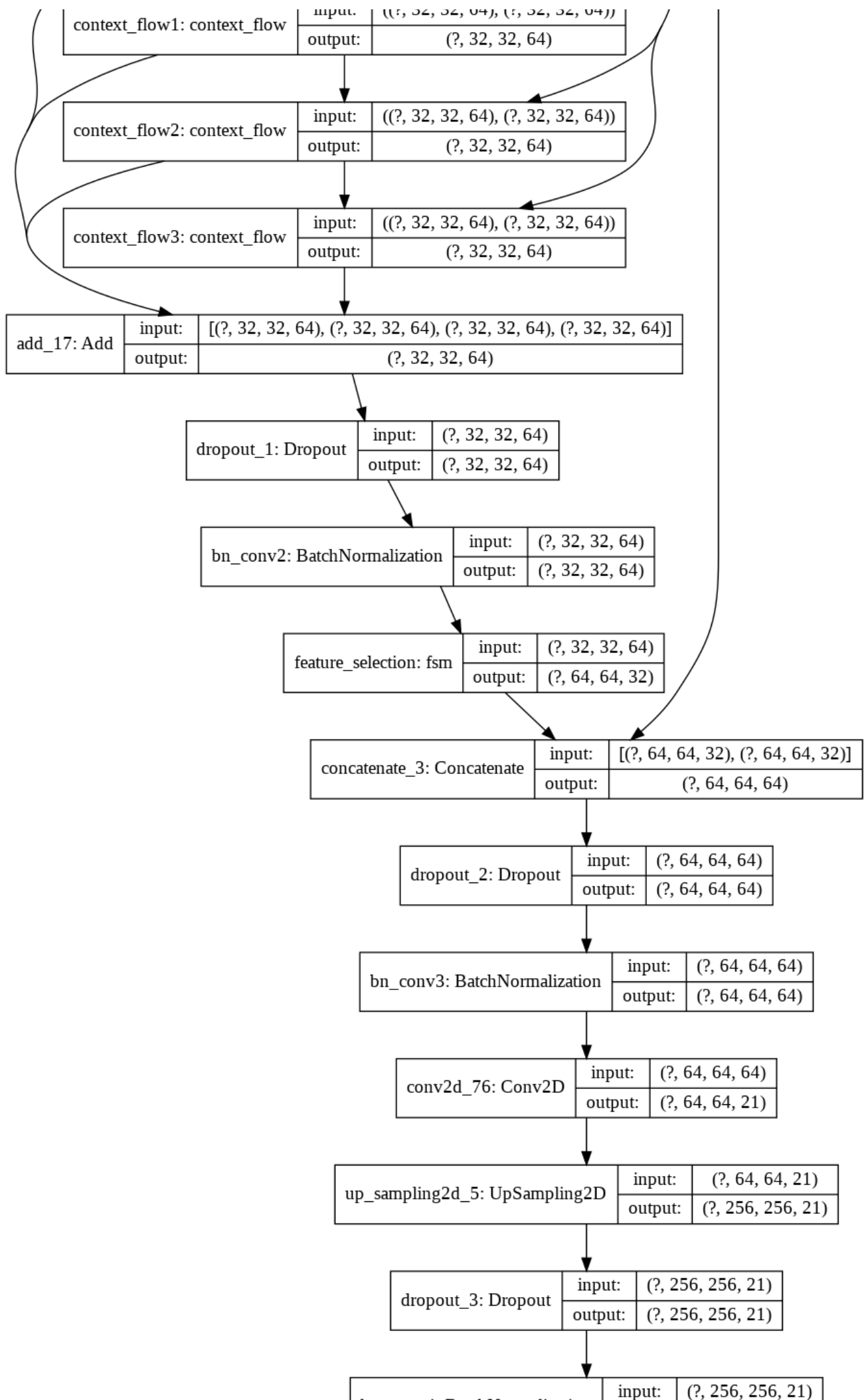
I42: identity_block	input:	(?, 32, 32, 64)
	output:	(?, 32, 32, 64)

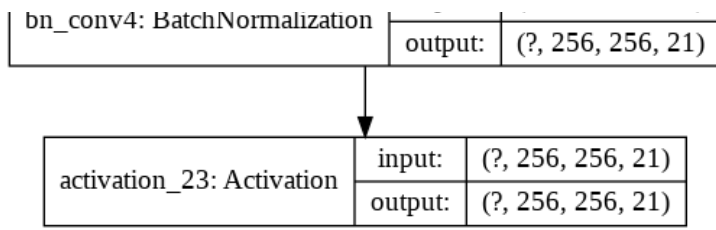
I43: identity_block	input:	(?, 32, 32, 64)
	output:	(?, 32, 32, 64)

I44: identity_block	input:	(?, 32, 32, 64)
	output:	(?, 32, 32, 64)

global_flow: global_flow	input:	(?, 32, 32, 64)
	output:	(?, 32, 32, 64)

	input:	(?, 32, 32, 64) (?, 32, 32, 64)
	output:	





Usefull tips:

- use "interpolation=cv2.INTER_NEAREST" when you are resizing the image, so that it won't mess with the number of classes
- keep the images in the square shape like \$256*256\$ or \$512*512\$
- Carefull when you are converting the (W, H) output image into (W, H, Classes)
- Even for the canet, use the segmentation model's losses and the metrics
- The goal of this assignment is make you familier in with computer vision problems, image preprocessing, building complex architectures and implementing research papers, so that in future you will be very confident in industry
- you can use the tensorboard logss to see how is yours model's training happening
- use callbacks that you have implemented in previous assignments

Things to keep in mind

- You need to train above built model and plot the train and test losses.
- Make sure there is no overfitting, you are free play with the identity blocks in C1, C2, C3, C4
- before we apply the final sigmoid activation, you can add more conv layers or BN or dropouts etc
- you are free to use any other optimizer or learning rate or weights init or regularizations

In [1]:

```
!pip install segmentation-models
```

```
Collecting segmentation-models
  Downloading
https://files.pythonhosted.org/packages/da/b9/4a183518c21689a56b834eaaa45cad242d9ec09a4360b5b10139f23c63f
mentation_models-1.0.1-py3-none-any.whl
Collecting keras-applications<=1.0.8,>=1.0.7
  Downloading
https://files.pythonhosted.org/packages/71/e3/19762fd9fc62877ae9102edf6342d71b28fbfd9dea3d2f96a882ce099b03
as_Applications-1.0.8-py3-none-any.whl (50kB)
[REDACTED] 51kB 4.3MB/s
Collecting efficientnet==1.0.0
  Downloading
https://files.pythonhosted.org/packages/97/82/f3ae07316f0461417dc54affab6e86ab188a5a22f33176d35271628b96e
icientnet-1.0.0-py3-none-any.whl
Collecting image-classifiers==1.0.0
  Downloading
https://files.pythonhosted.org/packages/81/98/6f84720e299a4942ab80df5f76ab97b7828b24d1de5e9b2cbb6073228b
ge_classifiers-1.0.0-py3-none-any.whl
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.7/dist-packages (from keras-applica
tions<=1.0.8,>=1.0.7->segmentation-models) (1.19.5)
Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages (from keras-applications<=1
.0.8,>=1.0.7->segmentation-models) (2.10.0)
Requirement already satisfied: scikit-image in /usr/local/lib/python3.7/dist-packages (from efficientnet==
1.0.0->segmentation-models) (0.16.2)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from h5py->keras-applicatio
ns<=1.0.8,>=1.0.7->segmentation-models) (1.15.0)
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from
scikit-image->efficientnet==1.0.0->segmentation-models) (3.2.2)
Requirement already satisfied: scipy>=0.19.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image
->efficientnet==1.0.0->segmentation-models) (1.4.1)
Requirement already satisfied: PyWavelets>=0.4.0 in /usr/local/lib/python3.7/dist-packages (from scikit-i
mage->efficientnet==1.0.0->segmentation-models) (1.1.1)
Requirement already satisfied: networkx>=2.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image
->efficientnet==1.0.0->segmentation-models) (2.5)
Requirement already satisfied: pillow>=4.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image
->efficientnet==1.0.0->segmentation-models) (7.0.0)
Requirement already satisfied: imageio>=2.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-imag
e->efficientnet==1.0.0->segmentation-models) (2.4.1)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matpl
otlib!=3.0.0,>=2.0.0->scikit-image->efficientnet==1.0.0->segmentation-models) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotl
ib!=3.0.0,>=2.0.0->scikit-image->efficientnet==1.0.0->segmentation-models) (1.3.1)
Requirement already satisfied: pyparsing!=2.0.4,!2.1.2,!2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-pa
ckages (from matplotlib!=3.0.0,>=2.0.0->scikit-image->efficientnet==1.0.0->segmentation-models) (2.4.7)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3
.0.0,>=2.0.0->scikit-image->efficientnet==1.0.0->segmentation-models) (0.10.0)
Requirement already satisfied: decorator>=4.3.0 in /usr/local/lib/python3.7/dist-packages (from networkx>
=2.0->scikit-image->efficientnet==1.0.0->segmentation-models) (4.4.2)
Installing collected packages: keras-applications, efficientnet, image-classifiers, segmentation-models
Successfully installed efficientnet-1.0.0 image-classifiers-1.0.0 keras-applications-1.0.8 segmentation-
models-1.0.1
```

```
import segmentation_models
iou = segmentation_models.metrics.IOUScore(class_weights=None, class_indexes=None, threshold=0.5, per_image=True)

Segmentation Models: using `keras` framework.
Using TensorFlow backend.
```

```
# Learning rate scheduler function
def scheduler(epoch, lr):
    if epoch > 0 and epoch % 3 == 0:
        lr = 0.9 * lr
        print('Reducing learning rate by 10%.')

    return lr
```

```
lrScheduler = tf.keras.callbacks.LearningRateScheduler(scheduler)
```

```
# Compile CANET model

optim = tf.keras.optimizers.Adam(0.0001, clipvalue=0.5)
model.compile(optimizer = optim, loss = 'categorical_crossentropy', metrics = [iou])
```

```
# Load data
```

```
train_dataset = Dataset(X_train.values, CLASSES, img_w, img_h)
test_dataset = Dataset(X_test.values, CLASSES, img_w, img_h, False)
```

```
BATCH_SIZE=8
train_dataloader = Dataloader(train_dataset, BATCH_SIZE, shuffle=True)
test_dataloader = Dataloader(test_dataset, BATCH_SIZE, shuffle=True)
```

```
print(train_dataloader[0][0].shape)
print(train_dataloader[0][1].shape)
```

```
(8, 256, 256, 3)
(8, 256, 256, 21)
```

In [45]:

```
callback = TerminateOnBaseline(baseline= 0.35)
```

In [54]:

```
# Fit the CANET model
```

```
history = model.fit_generator(train_dataloader, steps_per_epoch=len(train_dataloader), epochs=50,\
                             validation_data=test_dataloader,callbacks= [callback, lrScheduler] )
```

```
Epoch 1/50
400/400 [=====] - 305s 763ms/step - loss: 1.7216 - iou_score: 0.2705 -
val_loss: 1.5095 - val_iou_score: 0.2662 - lr: 1.0000e-04
Epoch 2/50
400/400 [=====] - 305s 762ms/step - loss: 1.6903 - iou_score: 0.2728 -
val_loss: 1.2862 - val_iou_score: 0.3033 - lr: 1.0000e-04
Epoch 3/50
400/400 [=====] - 306s 764ms/step - loss: 1.6829 - iou_score: 0.2740 -
val_loss: 1.3056 - val_iou_score: 0.3048 - lr: 1.0000e-04
Reducing learning rate by 10%.
Epoch 4/50
400/400 [=====] - 305s 762ms/step - loss: 1.6754 - iou_score: 0.2744 -
val_loss: 1.2758 - val_iou_score: 0.3072 - lr: 9.0000e-05
Epoch 5/50
400/400 [=====] - 306s 765ms/step - loss: 1.6693 - iou_score: 0.2754 -
val_loss: 1.2484 - val_iou_score: 0.3083 - lr: 9.0000e-05
Epoch 6/50
400/400 [=====] - 303s 759ms/step - loss: 1.6589 - iou_score: 0.2759 -
val_loss: 1.3112 - val_iou_score: 0.3037 - lr: 9.0000e-05
Reducing learning rate by 10%.
Epoch 7/50
400/400 [=====] - 303s 758ms/step - loss: 1.6533 - iou_score: 0.2767 -
val_loss: 1.2471 - val_iou_score: 0.3083 - lr: 8.1000e-05
Epoch 8/50
400/400 [=====] - 305s 763ms/step - loss: 1.6433 - iou_score: 0.2767 -
val_loss: 1.2373 - val_iou_score: 0.3098 - lr: 8.1000e-05
Epoch 9/50
400/400 [=====] - 305s 762ms/step - loss: 1.6572 - iou_score: 0.2773 -
val_loss: 1.3013 - val_iou_score: 0.3004 - lr: 8.1000e-05
Reducing learning rate by 10%.
Epoch 10/50
400/400 [=====] - 306s 766ms/step - loss: 1.6454 - iou_score: 0.2777 -
val_loss: 1.2717 - val_iou_score: 0.3075 - lr: 7.2900e-05
Epoch 11/50
400/400 [=====] - 311s 777ms/step - loss: 1.6360 - iou_score: 0.2781 -
val_loss: 1.2615 - val_iou_score: 0.3057 - lr: 7.2900e-05
Epoch 12/50
400/400 [=====] - 307s 768ms/step - loss: 1.6328 - iou_score: 0.2777 -
val_loss: 1.2031 - val_iou_score: 0.3104 - lr: 7.2900e-05
Reducing learning rate by 10%.
Epoch 13/50
400/400 [=====] - 311s 777ms/step - loss: 1.6419 - iou_score: 0.2787 -
val_loss: 1.1965 - val_iou_score: 0.3122 - lr: 6.5610e-05
Epoch 14/50
400/400 [=====] - 302s 755ms/step - loss: 1.6266 - iou_score: 0.2793 -
val_loss: 1.2002 - val_iou_score: 0.3112 - lr: 6.5610e-05
Epoch 15/50
400/400 [=====] - 299s 747ms/step - loss: 1.6304 - iou_score: 0.2789 -
val_loss: 1.2009 - val_iou_score: 0.3128 - lr: 6.5610e-05
Reducing learning rate by 10%.
Epoch 16/50
400/400 [=====] - 300s 750ms/step - loss: 1.6308 - iou_score: 0.2791 -
val_loss: 1.2119 - val_iou_score: 0.3131 - lr: 5.9049e-05
Epoch 17/50
400/400 [=====] - 300s 750ms/step - loss: 1.6265 - iou_score: 0.2793 -
val loss: 1.2424 - val iou score: 0.3050 - lr: 5.9049e-05
```



```
Epoch 18/50
400/400 [=====] - 300s 751ms/step - loss: 1.6262 - iou_score: 0.2795 -
val_loss: 1.1969 - val_iou_score: 0.3137 - lr: 5.9049e-05
Reducing learning rate by 10%.
Epoch 19/50
400/400 [=====] - 300s 751ms/step - loss: 1.6210 - iou_score: 0.2799 -
val_loss: 1.1928 - val_iou_score: 0.3139 - lr: 5.3144e-05
Epoch 20/50
400/400 [=====] - 297s 743ms/step - loss: 1.6186 - iou_score: 0.2799 -
val_loss: 1.1922 - val_iou_score: 0.3135 - lr: 5.3144e-05
Epoch 21/50
400/400 [=====] - 298s 745ms/step - loss: 1.6153 - iou_score: 0.2799 -
val_loss: 1.1901 - val_iou_score: 0.3147 - lr: 5.3144e-05
Reducing learning rate by 10%.
Epoch 22/50
400/400 [=====] - 299s 747ms/step - loss: 1.6184 - iou_score: 0.2796 -
val_loss: 1.1690 - val_iou_score: 0.3143 - lr: 4.7830e-05
Epoch 23/50
400/400 [=====] - 300s 751ms/step - loss: 1.6138 - iou_score: 0.2800 -
val_loss: 1.1719 - val_iou_score: 0.3145 - lr: 4.7830e-05
Epoch 24/50
400/400 [=====] - 306s 765ms/step - loss: 1.6153 - iou_score: 0.2804 -
val_loss: 1.1746 - val_iou_score: 0.3145 - lr: 4.7830e-05
Reducing learning rate by 10%.
Epoch 25/50
400/400 [=====] - 306s 766ms/step - loss: 1.6109 - iou_score: 0.2805 -
val_loss: 1.1797 - val_iou_score: 0.3131 - lr: 4.3047e-05
Epoch 26/50
400/400 [=====] - 307s 768ms/step - loss: 1.6230 - iou_score: 0.2804 -
val_loss: 1.1686 - val_iou_score: 0.3151 - lr: 4.3047e-05
Epoch 27/50
400/400 [=====] - 309s 772ms/step - loss: 1.6167 - iou_score: 0.2807 -
val_loss: 1.1775 - val_iou_score: 0.3136 - lr: 4.3047e-05
Reducing learning rate by 10%.
Epoch 28/50
400/400 [=====] - 313s 782ms/step - loss: 1.6168 - iou_score: 0.2806 -
val_loss: 1.1701 - val_iou_score: 0.3139 - lr: 3.8742e-05
Epoch 29/50
400/400 [=====] - 312s 780ms/step - loss: 1.6089 - iou_score: 0.2809 -
val_loss: 1.1684 - val_iou_score: 0.3149 - lr: 3.8742e-05
Epoch 30/50
400/400 [=====] - 310s 774ms/step - loss: 1.6046 - iou_score: 0.2812 -
val_loss: 1.1905 - val_iou_score: 0.3121 - lr: 3.8742e-05
Reducing learning rate by 10%.
Epoch 31/50
400/400 [=====] - 308s 771ms/step - loss: 1.6232 - iou_score: 0.2812 -
val_loss: 1.1513 - val_iou_score: 0.3159 - lr: 3.4868e-05
Epoch 32/50
400/400 [=====] - 303s 758ms/step - loss: 1.6124 - iou_score: 0.2807 -
val_loss: 1.1565 - val_iou_score: 0.3138 - lr: 3.4868e-05
Epoch 33/50
400/400 [=====] - 302s 755ms/step - loss: 1.6026 - iou_score: 0.2811 -
val_loss: 1.1550 - val_iou_score: 0.3155 - lr: 3.4868e-05
Reducing learning rate by 10%.
Epoch 34/50
400/400 [=====] - 304s 759ms/step - loss: 1.6217 - iou_score: 0.2810 -
val_loss: 1.1607 - val_iou_score: 0.3146 - lr: 3.1381e-05
Epoch 35/50
400/400 [=====] - 300s 750ms/step - loss: 1.6144 - iou_score: 0.2812 -
val_loss: 1.1735 - val_iou_score: 0.3137 - lr: 3.1381e-05
Epoch 36/50
400/400 [=====] - 299s 747ms/step - loss: 1.6199 - iou_score: 0.2812 -
val_loss: 1.1577 - val_iou_score: 0.3155 - lr: 3.1381e-05
Reducing learning rate by 10%.
Epoch 37/50
400/400 [=====] - 299s 747ms/step - loss: 1.6059 - iou_score: 0.2814 -
val_loss: 1.1532 - val_iou_score: 0.3145 - lr: 2.8243e-05
Epoch 38/50
400/400 [=====] - 309s 772ms/step - loss: 1.5935 - iou_score: 0.2812 -
val_loss: 1.1725 - val_iou_score: 0.3131 - lr: 2.8243e-05
Epoch 39/50
400/400 [=====] - 298s 746ms/step - loss: 1.6022 - iou_score: 0.2813 -
val_loss: 1.1570 - val_iou_score: 0.3148 - lr: 2.8243e-05
Reducing learning rate by 10%.
Epoch 40/50
400/400 [=====] - 298s 744ms/step - loss: 1.6014 - iou_score: 0.2815 -
val loss: 1.1596 - val iou score: 0.3147 - lr: 2.5419e-05
```

```

Epoch 41/50
400/400 [=====] - 300s 750ms/step - loss: 1.6020 - iou_score: 0.2816 -
val_loss: 1.1463 - val_iou_score: 0.3165 - lr: 2.5419e-05
Epoch 42/50
400/400 [=====] - 300s 750ms/step - loss: 1.6056 - iou_score: 0.2816 -
val_loss: 1.1588 - val_iou_score: 0.3150 - lr: 2.5419e-05
Reducing learning rate by 10%.
Epoch 43/50
400/400 [=====] - 299s 748ms/step - loss: 1.6093 - iou_score: 0.2814 -
val_loss: 1.1558 - val_iou_score: 0.3146 - lr: 2.2877e-05
Epoch 44/50
400/400 [=====] - 299s 747ms/step - loss: 1.6026 - iou_score: 0.2813 -
val_loss: 1.1529 - val_iou_score: 0.3162 - lr: 2.2877e-05
Epoch 45/50
400/400 [=====] - 300s 750ms/step - loss: 1.6093 - iou_score: 0.2819 -
val_loss: 1.1746 - val_iou_score: 0.3118 - lr: 2.2877e-05
Reducing learning rate by 10%.
Epoch 46/50
400/400 [=====] - 297s 742ms/step - loss: 1.5882 - iou_score: 0.2818 -
val_loss: 1.1594 - val_iou_score: 0.3152 - lr: 2.0589e-05
Epoch 47/50
400/400 [=====] - 298s 746ms/step - loss: 1.5991 - iou_score: 0.2819 -
val_loss: 1.1362 - val_iou_score: 0.3156 - lr: 2.0589e-05
Epoch 48/50
400/400 [=====] - 300s 751ms/step - loss: 1.5979 - iou_score: 0.2821 -
val_loss: 1.1639 - val_iou_score: 0.3145 - lr: 2.0589e-05
Reducing learning rate by 10%.
Epoch 49/50
400/400 [=====] - 300s 749ms/step - loss: 1.5962 - iou_score: 0.2815 -
val_loss: 1.1396 - val_iou_score: 0.3165 - lr: 1.8530e-05
Epoch 50/50
400/400 [=====] - 296s 740ms/step - loss: 1.6006 - iou_score: 0.2817 -
val_loss: 1.1472 - val_iou_score: 0.3154 - lr: 1.8530e-05

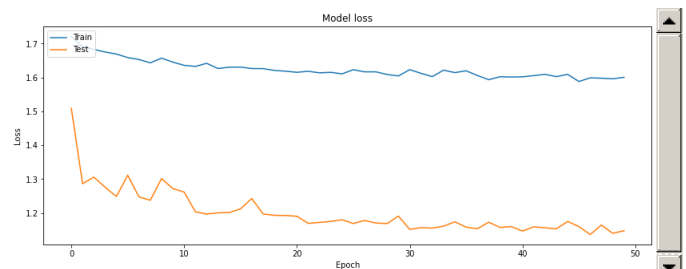
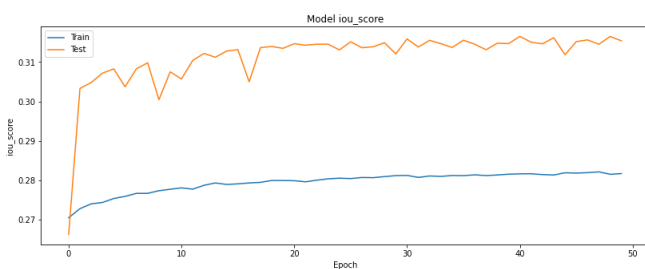
```

In [55]:

```

# IOU score and loss Vs Epoch PLOT
plot_model_loss_score(history)

```

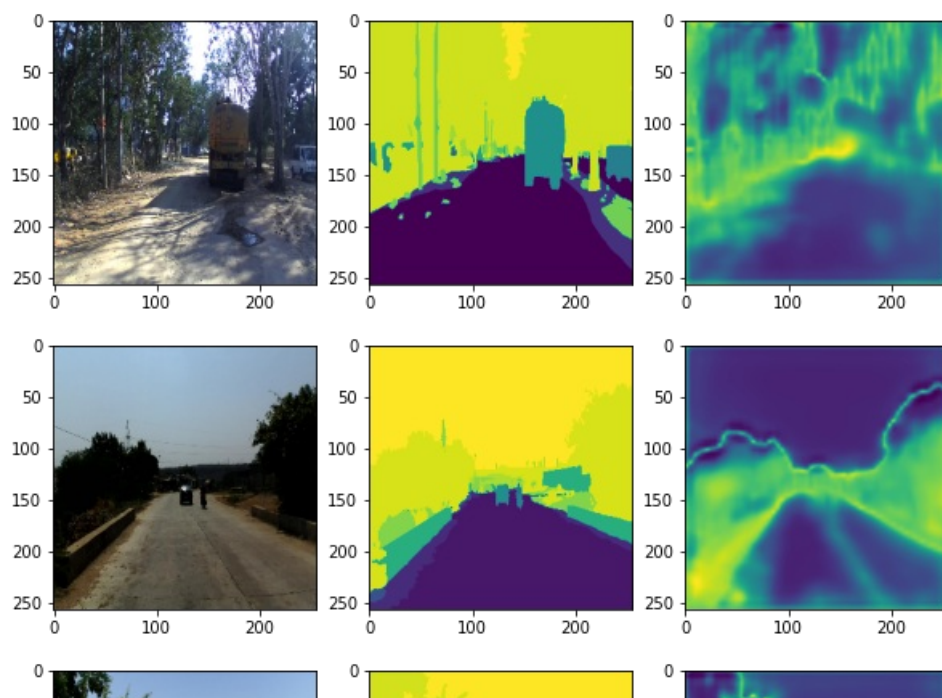


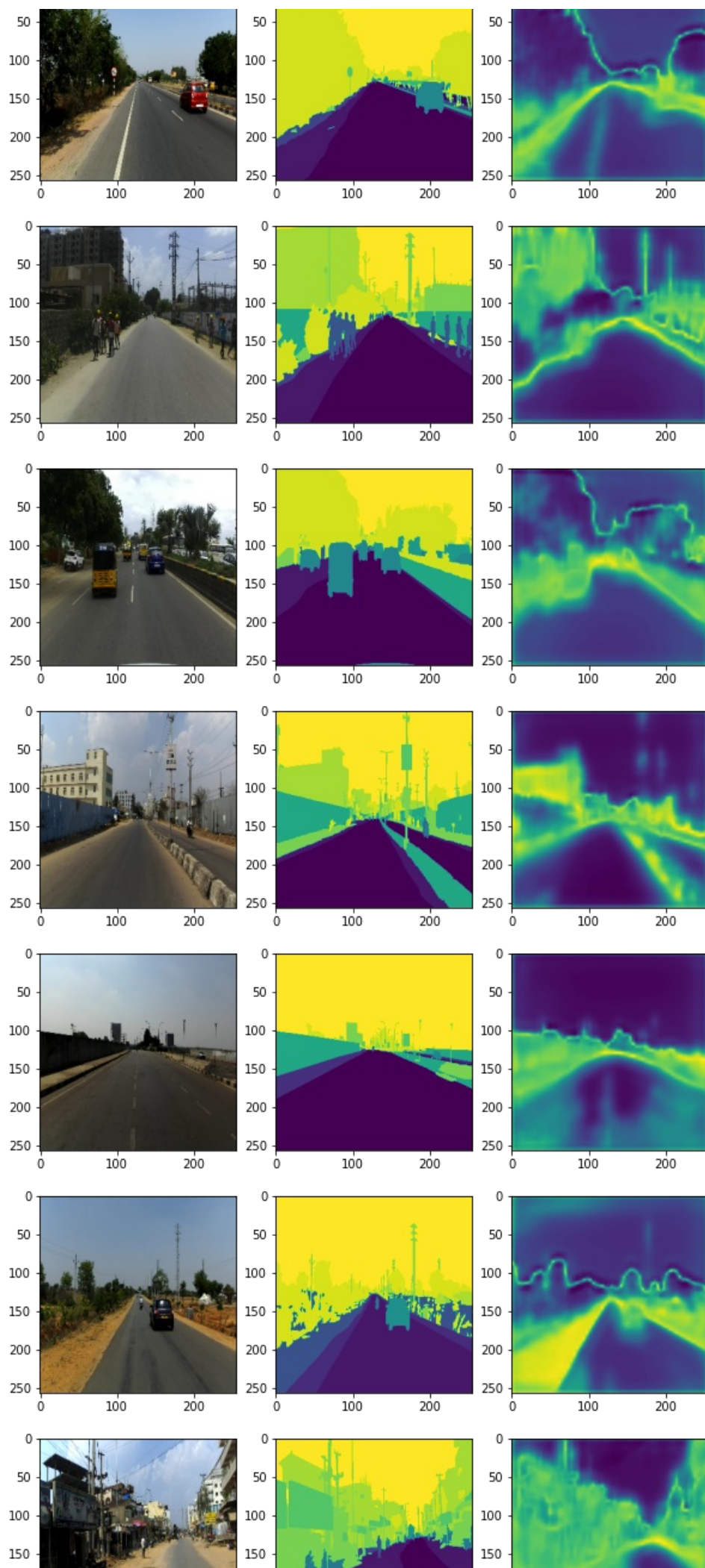
In [56]:

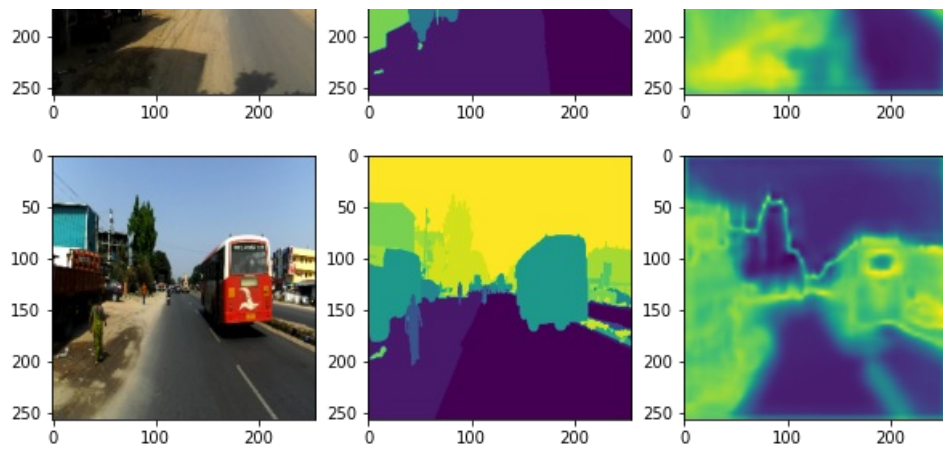
```

X_test_sample = X_test.sample(n=10)
predict_and_compare(X_test_sample)

```







We have got 0.45 and 0.31 IOU validation scores for UNET and CANET models and predicted/coded the 10 randomly selected images from validation set to check the model performance.