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

```
Requirement already satisfied: numpy<2.0,>=1.16.0 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: astunparse==1.6.3 in /usr/local/lib/python3.6/dist-package
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.6/dist-packages (frc
Requirement already satisfied: grpcio>=1.8.6 in /usr/local/lib/python3.6/dist-packages (f
Requirement already satisfied: protobuf>=3.8.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: keras-preprocessing>=1.1.0 in /usr/local/lib/python3.6/dis
Collecting tensorboard<2.3.0,>=2.2.0
  Downloading https://files.pythonhosted.org/packages/1d/74/0a6fcb206dcc72a6da9a62dd81784
     |████████████████████████████████| 3.0MB 56.2MB/s
Requirement already satisfied: absl-py>=0.7.0 in /usr/local/lib/python3.6/dist-packages (
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: setuptools in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/lib/python3.6/
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/local/lib/python3
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.6/dist-package
Requirement already satisfied: google-auth<2,>=1.6.3 in /usr/local/lib/python3.6/dist-pac
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.6/dist-
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.6/dist-package
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.6/dist-packages (fr
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in /usr/local/lib/
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.6/dist-pac
Requirement already satisfied: rsa<5,>=3.1.4; python_version >= "3.6" in /usr/local/lib/p
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/python3.6/dist-pa
Requirement already satisfied: importlib-metadata; python_version < "3.8" in /usr/local/l
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in /usr/local/lib/python3.6/dist-pack
Requirement already satisfied: typing-extensions>=3.6.4; python_version < "3.8" in /usr/l
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.6/dist-packages (from
Installing collected packages: tensorflow-estimator, tensorboard, tensorflow
  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
Successfully installed tensorboard-2.2.2 tensorflow-2.2.0 tensorflow-estimator-2.2.0
Collecting keras==2.3.1
  Downloading https://files.pythonhosted.org/packages/ad/fd/6bfe87920d7f4fd475acd28500a42
     |████████████████████████████████| 378kB 2.1MB/s
Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: keras-preprocessing>=1.0.5 in /usr/local/lib/python3.6/dis
Requirement already satisfied: scipy>=0.14 in /usr/local/lib/python3.6/dist-packages (frc
Collecting keras-applications>=1.0.6
  Downloading https://files.pythonhosted.org/packages/71/e3/19762fdfc62877ae9102edf6342d7
     |████████████████████████████████| 51kB 5.1MB/s
Requirement already satisfied: h5py in /usr/local/lib/python3.6/dist-packages (from keras
Requirement already satisfied: pyyaml in /usr/local/lib/python3.6/dist-packages (from ker
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.6/dist-packages (fr
Installing collected packages: keras-applications, keras
  Found existing installation: Keras 2.4.3
    Uninstalling Keras-2.4.3:
      Successfully uninstalled Keras-2.4.3
Successfully installed keras-2.3.1 keras-applications-1.0.8
```

Saving...

Segmentation of Indian Traffic

```
!pip install PyDrive
```

```
Requirement already satisfied: PyDrive in /usr/local/lib/python3.6/dist-packages (1.3.1)
Requirement already satisfied: oauth2client>=4.0.0 in /usr/local/lib/python3.6/dist-packa
Requirement already satisfied: google-api-python-client>=1.2 in /usr/local/lib/python3.6/
Requirement already satisfied: PyYAML>=3.0 in /usr/local/lib/python3.6/dist-packages (frc
Requirement already satisfied: pyasn1>=0.1.7 in /usr/local/lib/python3.6/dist-packages (f
Requirement already satisfied: pyasn1-modules>=0.0.5 in /usr/local/lib/python3.6/dist-pac
Requirement already satisfied: httplib2>=0.9.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: rsa>=3.1.4 in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: six>=1.6.1 in /usr/local/lib/python3.6/dist-packages (from
Requirement already satisfied: google-auth-httplib2>=0.0.3 in /usr/local/lib/python3.6/di
Requirement already satisfied: uritemplate<4dev,>=3.0.0 in /usr/local/lib/python3.6/dist-
Requirement already satisfied: google-auth>=1.4.1 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: setuptools>=40.3.0 in /usr/local/lib/python3.6/dist-packag
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/python3.6/dist-pa
```

```
from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials
```

```
auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)
```

```
downloaded = drive.CreateFile({'id':"1iQ93IWVdR6dZ6W7RahbLq166u-6ADelJ"})
downloaded.GetContentFile('data.zip')
```

```
!unzip data.zip
```

```
  inflating: data/mask/422/0003353_gtFine_polygons.json
  inflating: data/mask/422/0003620_gtFine_polygons.json
  inflating: data/mask/422/0003814_gtFine_polygons.json
  inflating: data/mask/422/0004826_gtFine_polygons.json
  inflating: data/mask/422/0005835_gtFine_polygons.json
  inflating: data/mask/422/0006760_gtFine_polygons.json
  inflating: data/mask/422/0007176_gtFine_polygons.json
  inflating: data/mask/422/0007298_gtFine_polygons.json
  inflating: data/mask/422/0007361_gtFine_polygons.json
  inflating: data/mask/422/0007442_gtFine_polygons.json
  inflating: data/mask/422/0007743_gtFine_polygons.json
  inflating: data/mask/422/0007889_gtFine_polygons.json
  inflating: data/mask/422/0008035_gtFine_polygons.json
   creating: data/mask/423/
  inflating: data/mask/423/frame0007_gtFine_polygons.json
  inflating: data/mask/423/frame0999_gtFine_polygons.json
  inflating: data/mask/423/frame12699_gtFine_polygons.json
  inflating: data/mask/423/frame5607_gtFine_polygons.json
  inflating: data/mask/423/frame7487_gtFine_polygons.json
  inflating: data/mask/423/frame7987_gtFine_polygons.json
  inflating: data/mask/423/frame8397_gtFine_polygons.json
  inflating: data/mask/423/frame8847_gtFine_polygons.json
  inflating: data/mask/423/frame9927_gtFine_polygons.json
   creating: data/mask/424/
  inflating: data/mask/424/frame0349_gtFine_polygons.json
  inflating: data/mask/424/frame0499_gtFine_polygons.json
  inflating: data/mask/424/frame0799_gtFine_polygons.json
  inflating: data/mask/424/frame0924_gtFine_polygons.json
  inflating: data/mask/424/frame1149_gtFine_polygons.json
   creating: data/mask/426/
  inflating: data/mask/426/0000000_gtFine_polygons.json
  inflating: data/mask/426/0000343_gtFine_polygons.json
```

```
          inflating: data/mask/426/0000454_gtFine_polygons.json
          inflating: data/mask/426/0000639_gtFine_polygons.json
           creating: data/mask/428/
          inflating: data/mask/428/frame0359_gtFine_polygons.json
          inflating: data/mask/428/frame0839_gtFine_polygons.json
          inflating: data/mask/428/frame0959_gtFine_polygons.json
          inflating: data/mask/428/frame1079_gtFine_polygons.json
          inflating: data/mask/428/frame1199_gtFine_polygons.json
          inflating: data/mask/428/frame1319_gtFine_polygons.json
          inflating: data/mask/428/frame1439_gtFine_polygons.json
          inflating: data/mask/428/frame1559_gtFine_polygons.json
          inflating: data/mask/428/frame1679_gtFine_polygons.json
          inflating: data/mask/428/frame1799_gtFine_polygons.json
          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
```

```
import math
from PIL import Image, ImageDraw
from PIL import ImagePath
import pandas as pd
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
import tensorflow
os.environ['TF_FORCE_GPU_ALLOW_GROWTH'] = 'true'
```

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

Saving...

```
|    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

```
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

    image = list()
    json = list()

    scenes = os.listdir(os.path.join(root_dir,'images'))

    for scene in scenes:

        if scene == '.DS_Store':
            continue

        image_frames = os.listdir(os.path.join(root_dir,'images',scene))
        image_frames.sort()
        image_frames = [ str(os.path.join(root_dir,'images',scene,i)) for i in image_frames]

        mask_frames = os.listdir(os.path.join(root_dir,'mask',scene))
        mask_frames.sort()
        mask_frames = [ str(os.path.join(root_dir,'mask',scene,i)) for i in mask_frames]

        image.extend(image_frames)
        json.extend(mask_frames)

    data_df = pd.DataFrame(list(zip(image, json)), columns =['image', 'json'])

    return data_df


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

	image	json
0	data/images/224/frame1127_leftImg8bit.jpg	data/mask/224/frame1127_gtFine_polygons.json
1	data/images/224/frame1365_leftImg8bit.jpg	data/mask/224/frame1365_gtFine_polygons.json
2	data/images/224/frame1796_leftImg8bit.jpg	data/mask/224/frame1796_gtFine_polygons.json

```
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
            return False
    return True


grader_1(data_df)
```

```
True
```

2. Structure of sample Json file

- 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

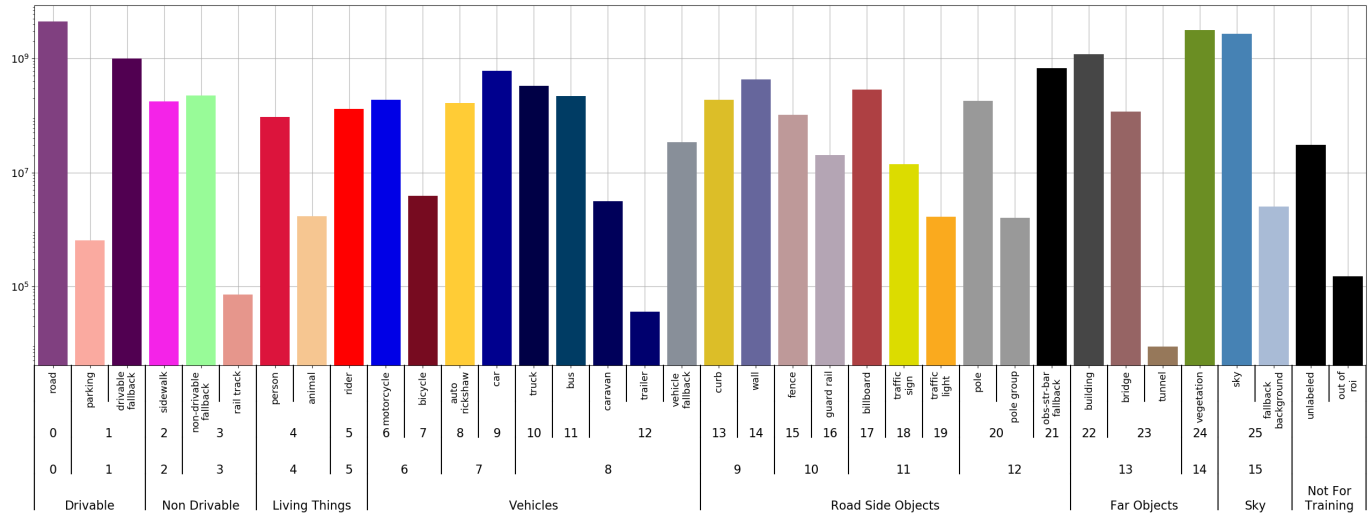
Compute the unique labels

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

Saving...

```
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

    json_path = data_df['json']

    unique_labels =list([])

    for path in json_path:
```

```
        with open(path) as f:
            data = json.load(f)
            for obj in data['objects']:
                unique_labels.append(obj['label'])

    return unique_labels


unique_labels = return_unique_labels(data_df)


unique_labels = set(unique_labels)
```




```
label_clr = {'road':10, 'parking':20, 'drivable fallback':20,'sidewalk':30,'non-drivable fallb
                        'person':50, 'animal':50, 'rider':60, 'motorcycle':70, 'bicycle':70, '
                        'car':80, 'truck':90, 'bus':90, 'vehicle fallback':90, 'trailer':90, '
                        'curb':100, 'wall':100, 'fence':110,'guard rail':110, 'billboard':120,
                        'traffic light':120, 'pole':130, 'polegroup':130, 'obs-str-bar-fallbac
                        'bridge':140,'tunnel':140, 'vegetation':150, 'sky':160, 'fallback back
                        'out of roi':0, 'ego vehicle':170, 'ground':180,'rectification border'
                    'train':200}


len(set(label_clr.values()))
```

```
21
```

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

Saving...

```
grader_2(unique_labels)
```

```
True
```

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

3. Extracting the polygons from the json files

```
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 vertice
    # 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 vertextlist[i] are corresponds to the same object, one represen
    # the other represents the location

    # width of the image
    # height of the image


    with open(file, 'r') as f:
        data = json.load(f)
    h = data['imgHeight']
    w = data['imgWidth']

    label = list([])
    vertexlist = list([])

    for obj in data['objects']:
        curr_vertices = list([])
        label.append(obj['label'])
        for vertex in obj['polygon']:
            curr_vertices.append((vertex[0], vertex[1]))
        vertexlist.append(curr_vertices)

    return w, h, label, vertexlist



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(labels,list) and isinstance(vertexlist[0],list) and isinstance(ve

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

```
True
```

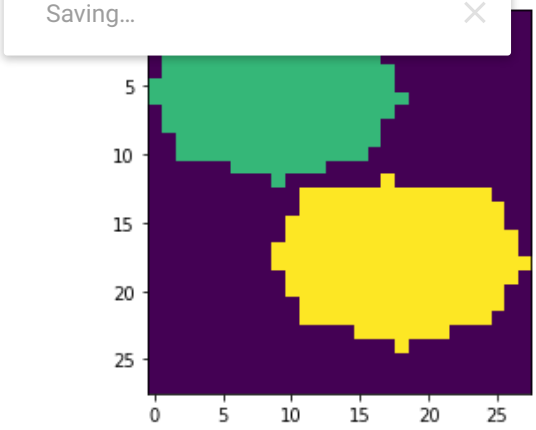
Saving...

4. Creating Image segmentations by drawing set of polygons

Example

```
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
x2 = [ ((math.cos(th) + 2) *9, (math.sin(th) + 3) *6) for th in [i * (2 * math.pi) / side for

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
plt.imshow(img[:,:,0])
print(img.shape)
print(img[:,:,0]//10)
im = Image.fromarray(img[:,:,0])
im.save("test_image.png")
```

```
(28, 28, 3)
[[0 0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0]
 [0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0]
 [2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0]
 [2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0]
 [0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0]
 [0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0]
 [0 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0]
 [0 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 2 2 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 2 0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0]
 [0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0]
 [0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3]
 [0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0]
 [0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 3 3 3 3 3 3 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 3 3 3 3 3 3 3 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 3 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0]]
```

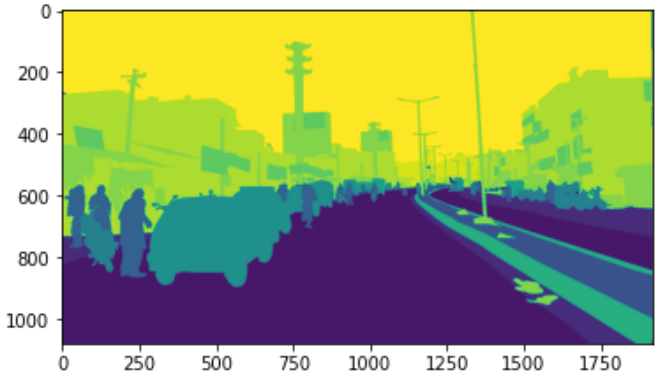


```
def compute_masks(data_df):
    # after you have computed the vertexlist plot that polygone in image like this

    # 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/framenumber_gtFi

    # 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']= ma

    root = 'data'
    mask_folder = 'output'
    mask = list([])
    for file in data_df['json']:

        _, _, scene, img_name = file.split('/')
        img_name = img_name[:-5]

        w, h, labels, vertexlist = get_poly(file)

        img = Image.new("RGB", (w,h))
        img2 = ImageDraw.Draw(img)

        for i,j in zip(labels, vertexlist):
            if len(j)<2:
                continue
            img2.polygon(j, fill=label_clr[i])


        img = np.array(img)
        im = Image.fromarray(img[:,:,0])

        if not os.path.exists(os.path.join(root,mask_folder,scene)):
            os.makedirs(os.path.join(root,mask_folder,scene))

        path = str(os.path.join(root,mask_folder,scene,img_name+'.png'))
        im.save(path)
        mask.append(path)

    data_df['mask'] = mask

    return data_df


  ply('data/mask/201/frame0029_gtFine_polygons.json')
```

Saving...

```
img2 = ImageDraw.Draw(img)

for i,j in zip(labels, vertexlist):

    img2.polygon(j, fill=label_clr[i])

img=np.array(img)

im = Image.fromarray(img[:,:,0])

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

```
im.save("test_image.png")
```

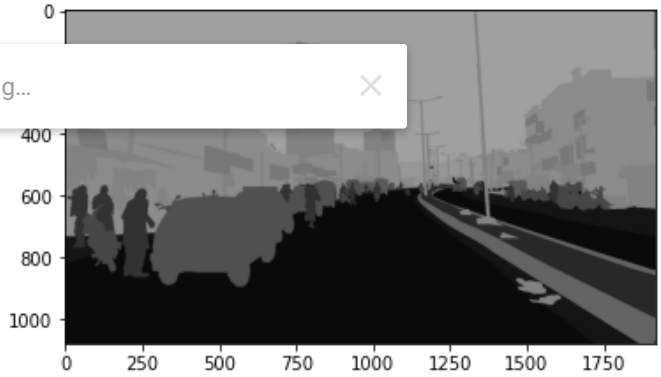



```
data_df = compute_masks(data_df)
data_df.head()
```

	image	json	
0	data/images/224/frame1127_leftImg8bit.jpg	data/mask/224/frame1127_gtFine_polygons.json	data/output/224/fra
1	data/images/224/frame1365_leftImg8bit.jpg	data/mask/224/frame1365_gtFine_polygons.json	data/output/224/fra
2	data/images/224/frame1796_leftImg8bit.jpg	data/mask/224/frame1796_gtFine_polygons.json	data/output/224/fra
3	data/images/224/frame2227_leftImg8bit.jpg	data/mask/224/frame2227_gtFine_polygons.json	data/output/224/fra
4	data/images/224/frame2452_leftImg8bit.jpg	data/mask/224/frame2452_gtFine_polygons.json	data/output/224/fra

```
def grader_3():
    url = "https://i.imgur.com/4XSUlHk.png"
    url_response = urllib.request.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]
```

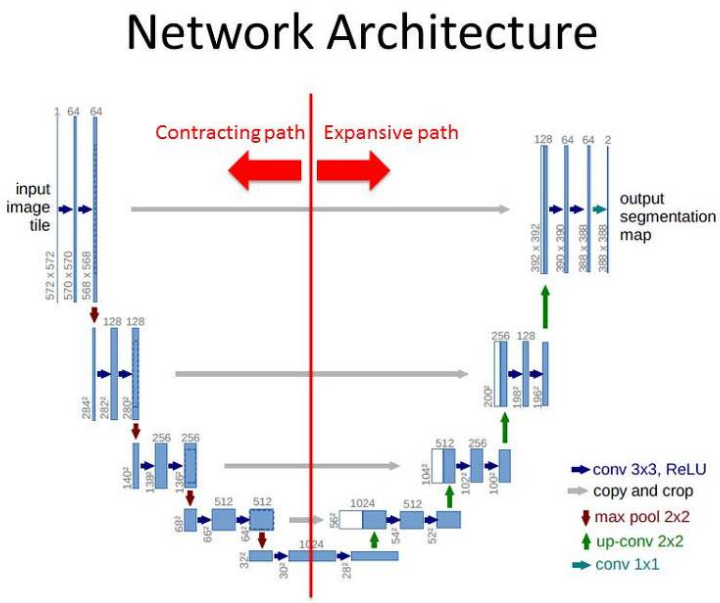



```
data_df = pd.read_csv('preprocessed_data.csv')
```

```
X_data = data_df['image']
Y_data = data_df['mask']
```

Task 2: Applying Unet to segment the images

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



*

* As a part of this assignment we won't writingt this whole architecture, rather we will be

* 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 c

* Check the reference notebook in which we have solved one end to end case study of image fo

* The number of channels in the output will depend on the number of classes in your data, si

* **This is where we want you to explore, how do you featurize your created segmentation map n**

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

Saving...

Task 2.1: Dice loss

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

1) Formulation Dice loss = 1 - sum(Y_true*Y_pred)/sum(Y_true*2 + Y_pred**2)

2) Range = 0 (perfect overlap) to 1 (no overlap)

3) It is inspired from Dice coefficient which is A.intersection(B)/ A.Union(B). The numerator is concerned with the common activations between our prediction and target mask, where as the denominator is concerned with the quantity of activations in each mask separately.

4) Since, it is computed for each class separately I think classes with smallest occureces are also paid attention.

```
pip install -U segmentation-models
```

```
Collecting segmentation-models
  Downloading https://files.pythonhosted.org/packages/da/b9/4a183518c21689a56b834eaaa45ca
Collecting efficientnet==1.0.0
  Downloading https://files.pythonhosted.org/packages/97/82/f3ae07316f0461417dc54affab6e8
Requirement already satisfied, skipping upgrade: keras-applications<=1.0.8,>=1.0.7 in /us
Collecting image-classifiers==1.0.0
  Downloading https://files.pythonhosted.org/packages/81/98/6f84720e299a4942ab80df5f76ab9
Requirement already satisfied, skipping upgrade: scikit-image in /usr/local/lib/python3.6
Requirement already satisfied, skipping upgrade: h5py in /usr/local/lib/python3.6/dist-pa
Requirement already satisfied, skipping upgrade: numpy>=1.9.1 in /usr/local/lib/python3.6
Requirement already satisfied, skipping upgrade: networkx>=2.0 in /usr/local/lib/python3.
Requirement already satisfied, skipping upgrade: PyWavelets>=0.4.0 in /usr/local/lib/pyth
Requirement already satisfied, skipping upgrade: matplotlib!=3.0.0,>=2.0.0 in /usr/local/
Requirement already satisfied, skipping upgrade: imageio>=2.3.0 in /usr/local/lib/python3
Requirement already satisfied, skipping upgrade: scipy>=0.19.0 in /usr/local/lib/python3.
Requirement already satisfied, skipping upgrade: pillow>=4.3.0 in /usr/local/lib/python3.
Requirement already satisfied, skipping upgrade: six in /usr/local/lib/python3.6/dist-pac
Requirement already satisfied, skipping upgrade: decorator>=4.3.0 in /usr/local/lib/pytho
Requirement already satisfied, skipping upgrade: cycler>=0.10 in /usr/local/lib/python3.6
Requirement already satisfied, skipping upgrade: kiwisolver>=1.0.1 in /usr/local/lib/pyth
Requirement already satisfied, skipping upgrade: python-dateutil>=2.1 in /usr/local/lib/p
Requirement already satisfied, skipping upgrade: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1
Installing collected packages: efficientnet, image-classifiers, segmentation-models
Successfully installed efficientnet-1.0.0 image-classifiers-1.0.0 segmentation-models-1.0
```

Task 2.2: Training Unet

```
* 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 segmen
```

Saving...

```
import segmentation_models as sm
from segmentation_models.metrics import iou_score
from segmentation_models import Unet
from keras.callbacks import Callback, LearningRateScheduler, TensorBoard, EarlyStopping, Model

# sm.set_framework('tf.keras')
tensorflow.keras.backend.set_image_data_format('channels_last')
```

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

```
sm.__version__
```

```
'1.0.1'
```

```
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))


def denormalize(x):
    """Scale image to range 0..1 for correct plot"""
    x_max = np.percentile(x, 98)
    x_min = np.percentile(x, 2)
    x = (x - x_min) / (x_max - x_min)
    x = x.clip(0, 1)
    return x


def visualize(**images):
    """PLot images in one row."""
    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())
        plt.imshow(image)
    plt.show()


# 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()
```



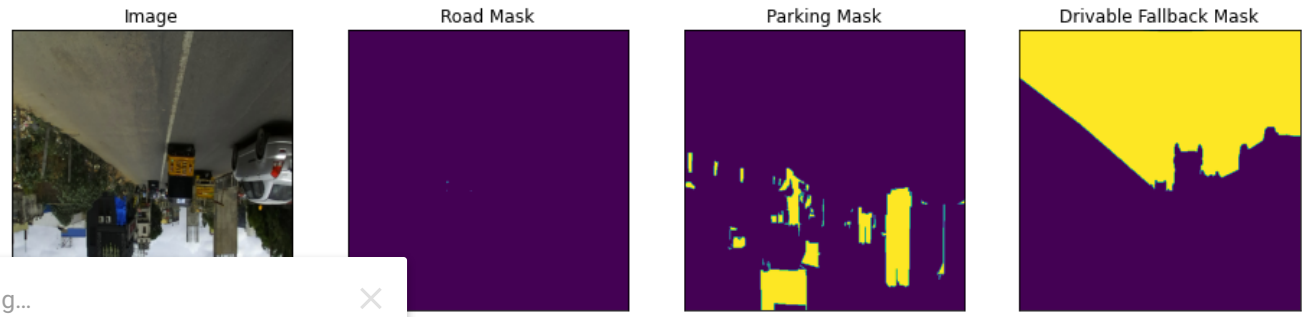
```
#     return mask

class Dataset:
    # we will be modifying this CLASSES according to your data/problems
    label_clr = {'road':10, 'parking':20, 'drivable fallback':20,'sidewalk':30,'non-drivable f
                         'person':50, 'animal':50, 'rider':60, 'motorcycle':70, 'bicycle':70, '
                         'car':80, 'truck':90, 'bus':90, 'vehicle fallback':90, 'trailer':90, '
                         'curb':100, 'wall':100, 'fence':110,'guard rail':110, 'billboard':120,
                         'traffic light':120, 'pole':130, 'polegroup':130, 'obs-str-bar-fallbac
                         'bridge':140,'tunnel':140, 'vegetation':150, 'sky':160, 'fallback back
                         'out of roi':0, 'ego vehicle':170, 'ground':180,'rectification border'
                    'train':200}
```

```
        # the parameters needs to changed based on your requirements
        # here we are collecting the file_names because in our dataset, both our images and maks w
        # ex: fil_name.jpg   file_name.mask.jpg
        def __init__(self, image_paths, mask_paths, w, h, dataset_type):


            self.images_fps   = [i for i in image_paths]
            # the paths of segmentation images
            self.masks_fps    = [i for i in mask_paths]
            # giving labels for each class
            self.class_values = list(set(self.label_clr.values()))
            # image width
            self.w = 512
            # image height
            self.h = 512
            # dataset is train or test
            self.dataset_type = dataset_type

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

            image_mask  = cv2.imread(self.masks_fps[i], cv2.IMREAD_UNCHANGED)
            image_mask = cv2.resize(image_mask,(self.w,self.h),interpolation=cv2.INTER_NEAREST)
            image_masks = [(image_mask == v) for v in self.class_values]
            image_mask = np.stack(image_masks, axis=-1).astype('float')

            if self.dataset_type == 'train':
                a = np.random.uniform()
                if a<0.2:
                    image = aug2.augment_image(image)
                    image_mask = aug2.augment_image(image_mask)
                elif a<0.4:
                    image = aug3.augment_image(image)
                    image_mask = aug3.augment_image(image_mask)
                elif a<0.6:
                    image = aug4.augment_image(image)
                    image_mask = aug4.augment_image(image_mask)
                elif a<0.8:
                    image = aug5.augment_image(image)
                    image_mask = image_mask
                else:
                    image = aug6.augment_image(image)
                    image_mask = aug6.augment_image(image_mask)
```



```
        def __len__(self):
            return len(self.images_fps)


    class Dataloder(tensorflow.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)


from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_data, Y_data, test_size=0.1, random_stat


train_dataset = Dataset(X_train, y_train, w, h, 'train')
test_dataset  = Dataset(X_test, y_test, w, h, 'test')


train_dataloader = Dataloder(train_dataset, batch_size=8, shuffle=True)
test_dataloader = Dataloder(test_dataset, batch_size=8, shuffle=True)


image, mask = train_dataset[4]

visualize(
    image=image,
    road_mask=mask[..., 0].squeeze(),
    parking_mask=mask[..., 1].squeeze(),
    drivable_fallback_mask=mask[..., 2].squeeze(),
)
```




```
import keras
import datetime


model1 = Unet('resnet34', encoder_weights='imagenet', classes=21, activation='softmax', input_
optim = keras.optimizers.Adam(learning_rate=0.0001)
focal_loss = sm.losses.cce_dice_loss
model1.compile(optim, focal_loss, metrics=[sm.metrics.IOUScore(threshold=0.5)])
```

```
Downloading data from https://github.com/qubvel/classification_models/releases/download/0
85524480/85521592 [==============================] - 4s 0us/step
```

```
print(image.shape, mask.shape)
```

```
(512, 512, 3) (512, 512, 21)
```

```
log_dir="logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
callbacks = [
    ModelCheckpoint('./best_model_Unet.h5', save_weights_only=True, save_best_only=True, \
                                        mode='max', monitor='val_iou_score'),
    ReduceLROnPlateau(monitor='val_iou_score', min_lr=0.000001,patience=2),
    EarlyStopping(monitor='val_loss', mode='min', patience=3, verbose=1),
    TensorBoard(log_dir=log_dir,histogram_freq=1, write_graph=True)
]
```

```
def display_sample(display_list):
    """
    Show side-by-side an input image,
    the ground truth and the prediction.
    """
    plt.figure(figsize=(15,15))
    title = ['Input Image', 'True Mask', 'Predicted Mask']
    for i in range(len(display_list)):
        plt.subplot(1, len(display_list), i+1)
        plt.title(title[i])
        plt.imshow(tensorflow.keras.preprocessing.image.array_to_img(display_list[i]))
        plt.axis('off')
    plt.show()
```

```
history = model1.fit_generator(train_dataloader, steps_per_epoch=len(train_dataloader), epochs
```

```
Epoch 1/10
450/450 [==============================] - 495s 1s/step - loss: 0.8770 - iou_score: 0.376
Epoch 2/10
450/450 [==============================] - 485s 1s/step - loss: 0.7070 - iou_score: 0.503
Epoch 3/10
450/450 [==============================] - 467s 1s/step - loss: 0.6044 - iou_score: 0.583
Epoch 4/10
450/450 [==============================] - 462s 1s/step - loss: 0.5458 - iou_score: 0.633
Epoch 5/10
450/450 [==============================] - 463s 1s/step - loss: 0.5420 - iou_score: 0.638
Epoch 6/10
450/450 [==============================] - 469s 1s/step - loss: 0.5306 - iou_score: 0.652
Epoch 7/10
450/450 [==============================] - 468s 1s/step - loss: 0.5279 - iou_score: 0.655
```

Saving...

```
==============] - 468s 1s/step - loss: 0.5301 - iou_score: 0.653
450/450 [==============================] - 464s 1s/step - loss: 0.5291 - iou_score: 0.654
Epoch 10/10
450/450 [==============================] - 463s 1s/step - loss: 0.5285 - iou_score: 0.654
Epoch 00010: early stopping
```

```
model1.load_weights('best_model_Unet.h5')
```

```
scores = model1.evaluate_generator(test_dataloader)
metrics=[sm.metrics.IOUScore(threshold=0.5)]
print("Loss: {:.5}".format(scores[0]))
for metric, value in zip(metrics, scores[1:]):
```

```
print("mean {}: {:.5}".format(metric.__name__, value))
```

```
Loss: 0.5301
mean iou_score: 0.61182
```

```
n = 5
ids = np.random.choice(np.arange(len(test_dataset)), size=n)

for i in ids:

    image, actual_mask = test_dataset[i]
    image = np.expand_dims(image, axis=0)
    prediction = model1.predict(image)
    prediction = np.argmax(prediction, axis=-1)
    prediction = np.squeeze(prediction, axis = 0)
    actual_mask = np.argmax(actual_mask, axis=-1)

    visualize(image=denormalize(image.squeeze()), gt_mask=actual_mask.squeeze(),pr_mask=predic
```

Saving...

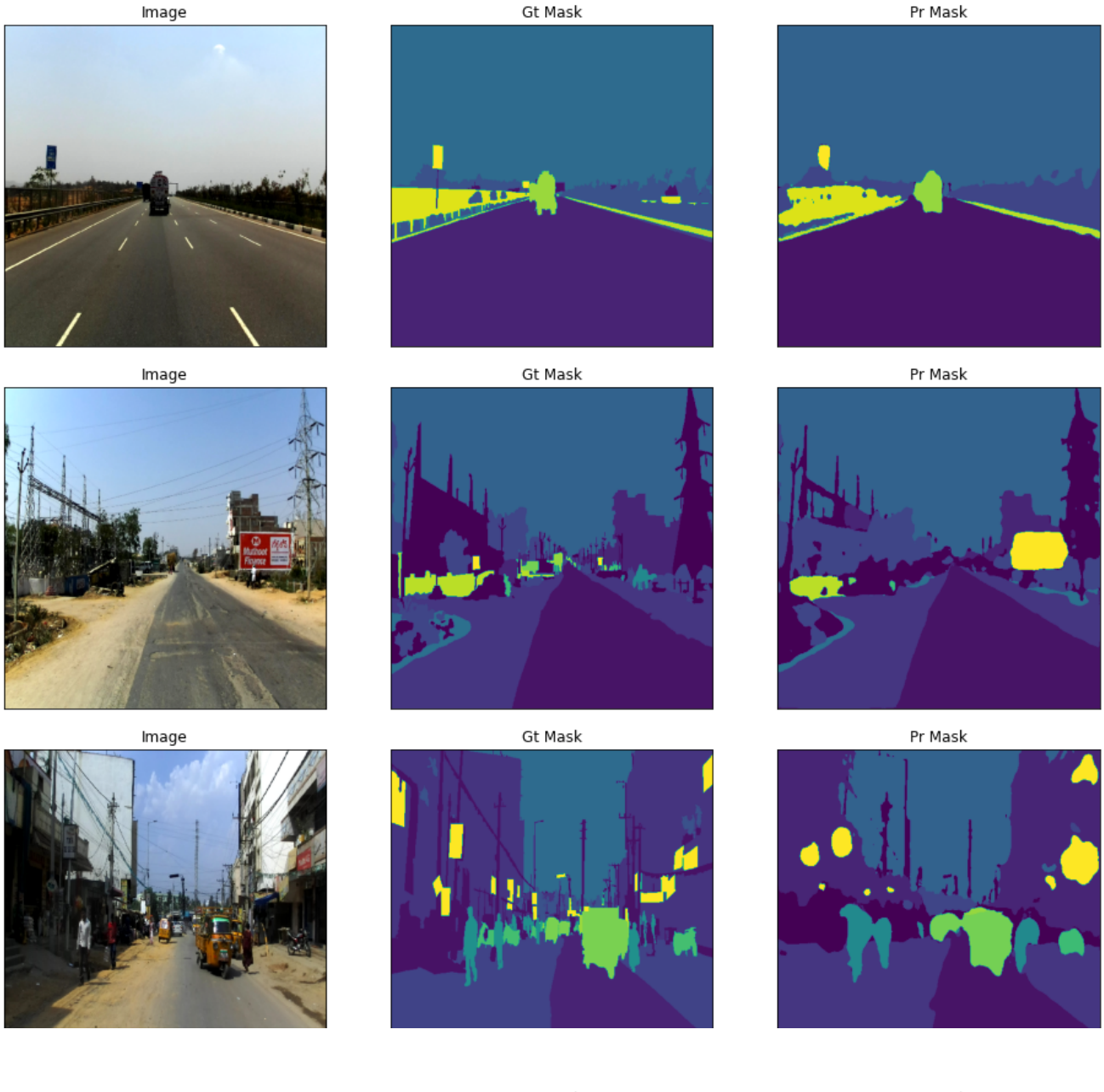
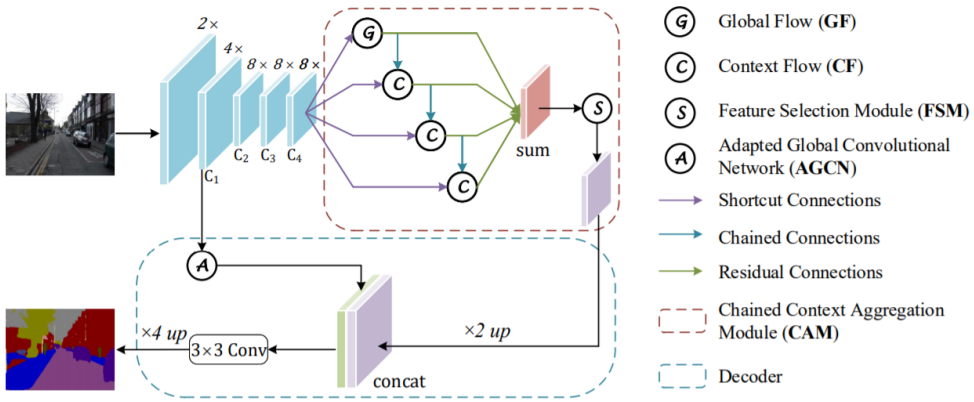


Image Gt Mask Pr Mask

Task 3: Training CANet

```
import tensorflow
# tf.compat.v1.enable_eager_execution()
# from tensorflow import keras
from tensorflow.keras.layers import *
                                    ing import image
                                    ort Model, load_model
from tensorflow.keras.layers import UpSampling2D
from tensorflow.keras.layers import MaxPooling2D, GlobalAveragePooling2D
from tensorflow.keras.layers import concatenate
from tensorflow.keras.layers import Multiply
from tensorflow.keras.callbacks import Callback, EarlyStopping, ModelCheckpoint, ReduceLROnPla
from tensorflow.keras import backend as K
from tensorflow.keras.layers import Input, Add, Dense, Activation, ZeroPadding2D, BatchNormali
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.utils import plot_model
from tensorflow.keras.initializers import glorot_uniform
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 devide the whole architecture can be devided 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 heigths are 4x times less than the original image
    - C_2 width and heigths are 8x times less than the original image
    - C_3 width and heigths are 8x times less than the original image
    - C_4 width and heigths 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 covolutional 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 covolutional layers will be $[8,8,16]$ and the number of filters in the parallel conv layer will also be 16.
    - **y block of C_3**: the number filters in the covolutional 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 covolutional 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(tensorflow.keras.layers.Layer):
    def __init__(self, kernel=3, filters=[4,4,8], stride=4, name="conv block"):
        super().__init__(name=name)
        self.F1, self.F2, self.F3 = filters
        self.kernel = kernel
        self.stride = stride
        self.block_name = name

    def build(self, data):
        self.cov1 = Conv2D(filters=self.F1, kernel_size=(1,1), strides=(1, 1), padding='valid'
        self.cov2 = Conv2D(filters=self.F2, kernel_size=(self.kernel,self.kernel), strides=(se
        self.cov3 = Conv2D(filters=self.F3, kernel_size=(1,1), strides=(1, 1), padding='valid'
        self.cov4 = Conv2D(filters=self.F3, kernel_size=(self.kernel,self.kernel), strides=(se
        self.bn1 = BatchNormalization(axis=-1)
        self.bn2 = BatchNormalization(axis=-1)
        self.bn3 = BatchNormalization(axis=-1)
        self.bn4 = BatchNormalization(axis=-1)
        self.relu1 = Activation('relu')
        self.relu2 = Activation('relu')
        self.relu3 = Activation('relu')
        self.relu4 = Activation('relu')
        self.add = Add()

    def call(self, data):
        # write the architecutre that was mentioned above

        X = self.cov1(data)
        X = self.bn1(X)
        X = self.relu1(X)

        X = self.cov2(X)
        X = self.bn2(X)
        X = self.relu2(X)

        X = self.cov3(X)
        X = self.bn3(X)
        X = self.relu3(X)

        Y = self.cov4(data)
        Y = self.bn4(Y)
        Y = self.relu4(Y)

        return output
```



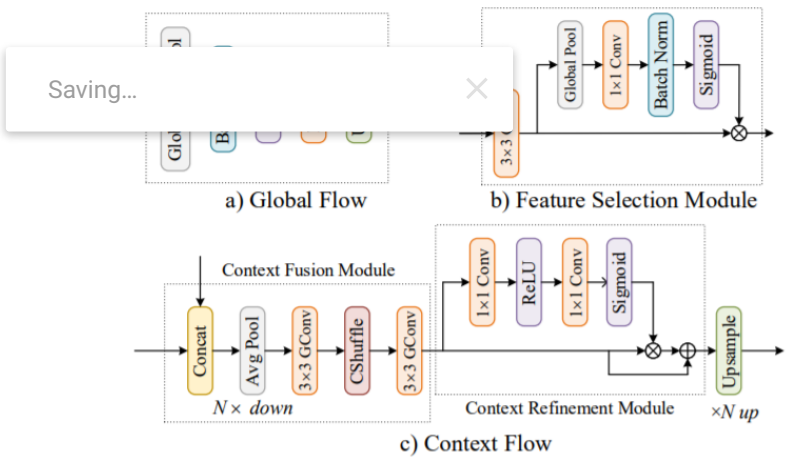
```
A = convolutional_block(name = "C1_conv_block", kernel=3, filters=[4,4,8], stride=2)(np.zeros(
A.shape
```

```
WARNING:tensorflow:Layer C1_conv_block is casting an input tensor from dtype float64 to t

If you intended to run this layer in float32, you can safely ignore this warning. If in d

To change all layers to have dtype float64 by default, call `tf.keras.backend.set_floatx(
```

```
TensorShape([3, 128, 128, 81])
```

```
class identity_block(tensorflow.keras.layers.Layer):

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

    def build(self,shapes):
        self.cov1 = Conv2D(filters=self.F1, kernel_size=(1,1), strides=(1, 1), padding='valid'
        self.cov2 = Conv2D(filters=self.F2, kernel_size=(3,3), strides=(1, 1), padding='same',
        self.cov3 = Conv2D(filters=self.F3, kernel_size=(1,1), strides=(1, 1), padding='same',
        self.bn1 = BatchNormalization(axis=-1)
        self.bn2 = BatchNormalization(axis=-1)
        self.bn3 = BatchNormalization(axis=-1)
        self.actv1 = Activation('relu')
        self.actv2 = Activation('relu')
        self.actv3 = Activation('relu')

        self.add = Add()

    def call(self, data):
        # write the architecutre that was mentioned above

        X = self.cov1(data)
        X = self.bn1(X)
        X = self.actv1(X)

        X = self.cov2(X)
        X = self.bn2(X)
        X = self.actv2(X)

        X = self.cov3(X)
        X = self.bn3(X)
        X = self.actv3(X)

        output = self.add([X,data])

        return output
```

- The output of the C_4 will be passed to 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 willl apply global avg pooling which results in (#, 1, 1, number_of_filters) then applying BN, RELU, $1 * 1$ Conv layer sequentially which results a matrix (#, 1, 1, number_of_filters). Finally apply upsampling / conv2d transpose to make the output same as the input dimensions (#, input_height, input_width, 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 concatination we will be applying Average pooling which reduces the size of feature map by $N\times$ 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 $\bigotimes \sigma((1 \times 1)conv(relu((1 \times 1)conv(X))))) \bigoplus X$, here $\bigoplus$ is elementwise addition and $\bigotimes$ is elementwise multiplication
  - Finally apply upsampling / conv2d transpose to make the output same as the input dimensions (#, input_height, input_width, 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)


```
class global_flow(tensorflow.keras.layers.Layer):
    def __init__(self, name="global_flow", filters=32):
        super().__init__(name=name)
        self.filters = filters

    def build(self, shapes):

        # here data is a TensorShape
        self.avgpool = AveragePooling2D(1,(shapes[1],shapes[1]),data_format='channels_last')
        self.bn = BatchNormalization(axis=-1)
        self.actv = Activation('relu')
        self.cov = Conv2D(filters=32, kernel_size=(1,1), strides=(1, 1), padding='valid', name
        self.upsample = UpSampling2D(size=(shapes[1],shapes[1]), data_format='channels_last',
```

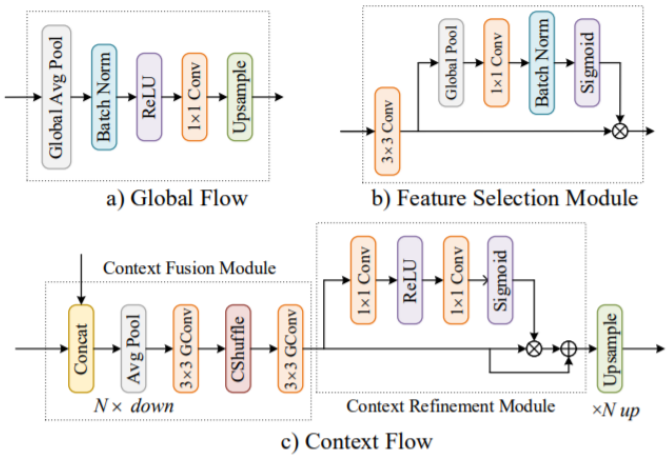
```
        self.upsample = UpSampling2D(size=(shapes[1],shapes[1]), data_format='channels_last',

    def call(self, data):
        # implement the global flow operation

        X = self.avgpool(data)
        X = self.bn(X)
        X = self.actv(X)
        X = self.cov(X)
        X = self.upsample(X)

        #print(X.shape)
        return X


class context_flow(tensorflow.keras.layers.Layer):
    def __init__(self, name="context_flow"):
        super().__init__(name=name)

    def build(self, shapes):

        self.avgpool = AveragePooling2D(pool_size=(2, 2), strides=(2,2), padding='valid', data
        self.concat = Concatenate(axis = -1)
        self.cov1 = Conv2D(filters=shapes[1][-1], kernel_size=(3,3), strides=(1, 1), padding='
        self.cov2 = Conv2D(filters=shapes[1][-1], kernel_size=(3,3), strides=(1, 1), padding='
        self.cov3 = Conv2D(filters=shapes[1][-1], kernel_size=(1,1), strides=(1, 1), padding='
        self.cov4 = Conv2D(filters=shapes[1][-1], kernel_size=(1,1), strides=(1, 1), padding='
        self.relu = Activation('relu')
        self.sigmoid = Activation('sigmoid')
        self.multiply = Multiply()
        self.add = Add()
        self.upsample = UpSampling2D(size=(2,2), data_format='channels_last', interpolation='b

    def call(self, data):
        # here X will a list of two elements
        INP, FLOW = data[0], data[1]
        # implement the context flow as mentioned in the above cell

        X = self.concat([INP,FLOW])
        X = self.avgpool(X)
        X = self.cov1(X)
        X = self.cov2(X)


        Y = self.cov3(X)
        Y = self.relu(Y)
        Y = self.cov4(Y)
        Y = self.sigmoid(Y)
```



```
        Z = self.add([X,Z])

        output = self.upsample(Z)
        #print(output.shape)
        return output
```

- 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) respectivly 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 mechanisum, 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.

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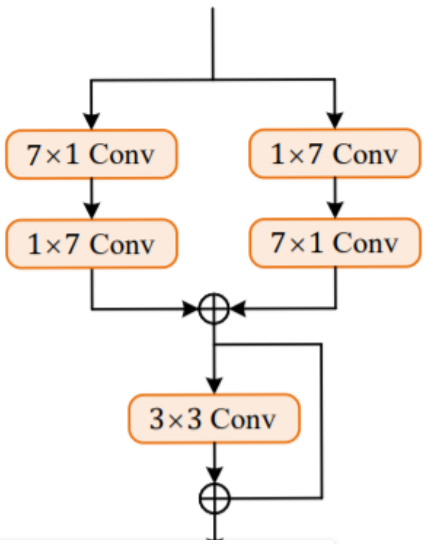
ooling as interpolation technique

- Example:
  - Assume the matrix shape of the input is (64,64,32) then after upsampling it will be (128,128,32)

```
class fsm(tensorflow.keras.layers.Layer):
    def __init__(self, name="feature_selection"):
        super().__init__(name=name)

    def build(self, shapes):

        self.cov1 = Conv2D(filters=shapes[-1], kernel_size=(3,3), strides=(1, 1), padding='sam
        self.cov2 = Conv2D(filters=32, kernel_size=(1,1), strides=(1, 1), padding='valid', nam
```

```
        self.globalAvgPool = GlobalAveragePooling2D(data_format='channels_last')
        self.bn = BatchNormalization(axis=-1)
        self.sigmoid = Activation('sigmoid')
        self.multiply = Multiply()
        self.upsampl = UpSampling2D(size=(2,2), data_format='channels_last', interpolation='bi

    def call(self, data):
        # implement the FSM modules based on image in the above cells


        X = self.cov1(data)

        X = self.globalAvgPool(X)

        X = tensorflow.reshape(X,shape=(-1,1,1,X.shape[1]))

        X = self.cov2(X)

        X = self.bn(X)

        X = self.sigmoid(X)

        output = self.multiply([data,X])

        FSM_Conv_T = self.upsampl(output)

        return FSM_Conv_T
```

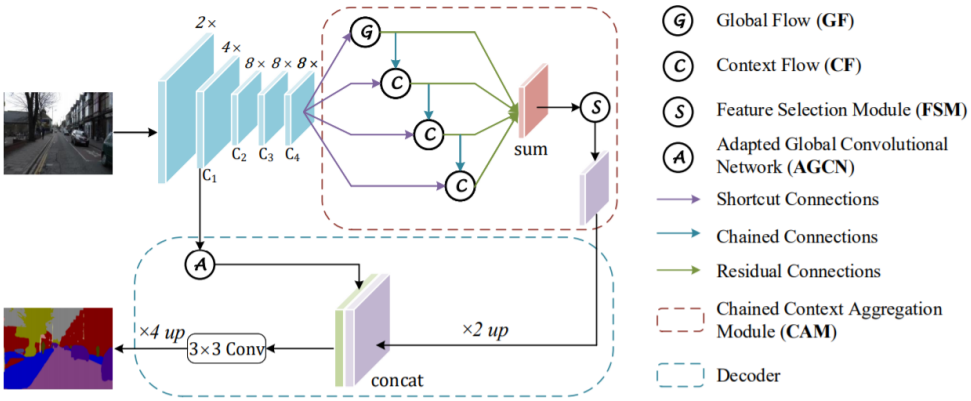
- **Adapted Global Convolutional Network (AGCN)**:



b) AGCN

  - AGCN will get the input from the output of the "conv block" of C_1
  - 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)

```
class agcn(tensorflow.keras.layers.Layer):
    def __init__(self, name="global_conv_net"):
        super().__init__(name=name)

    def build(self, shapes):
        self.cov1 = Conv2D(filters=shapes[-1], kernel_size=(7,1), strides=(1, 1), padding='sam
        self.cov2 = Conv2D(filters=shapes[-1], kernel_size=(1,7), strides=(1, 1), padding='sam
        self.cov3 = Conv2D(filters=shapes[-1], kernel_size=(1,7), strides=(1, 1), padding='sam
        self.cov4 = Conv2D(filters=shapes[-1], kernel_size=(7,1), strides=(1, 1), padding='sam
        self.cov5 = Conv2D(filters=shapes[-1], kernel_size=(3,3), strides=(1, 1), padding='sam
        self.add = Add()


    def call(self, data):
        # please implement the above mentioned architecture
        # print(data.shape)

        X = self.cov1(data)
        X = self.cov2(X)
        # print(X.shape)

        Y = self.cov3(data)
        Y = self.cov4(Y)
         #print(Y.shape)

        Z = self.add([X,Y])
        output = self.cov5(Z)

        output = self.add([Z,output])

        return output
```



- er we get the AGCN it will get concatinated with the FSM output
- If we observe the shapes both AGCN and FSM will have same height and weight
- we will be concatinating both these outputs over the last axis
- The concatinated 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 concatination 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)

```
_input = Input(shape=(512,512,3))

 Stage 1
 = Conv2D(64, (3, 3), name='conv1', padding="same", kernel_initializer=glorot_uniform(seed=0))
 = BatchNormalization(axis=3, name='bn_conv1')(X)
 = Activation('relu')(X)
 = MaxPooling2D((2, 2), strides=(2, 2))(X)

 write the complete architecutre


1 = convolutional_block(name = "C1_conv_block", kernel=3, filters=[4,4,8], stride=2)(X)
O_AGCN = C1
 print('C1')
 print(X.shape)
 print('-'*50)
1 = identity_block(name = "C1_id_block1", kernel=3, filters=[4,4,8], stride=1)(C1)
1 = identity_block(name = "C1_id_block2", kernel=3, filters=[4,4,8], stride=1)(C1)
 print(X.shape)

 print('\nC2')
 C2 and ID2
2 =convolutional_block(name = "C2_conv_block", kernel=3, filters=[8,8,16], stride=2)(C1)
 print(X.shape)
 print('-'*50)
2 = identity_block(name = "C2_id_block1", kernel=3, filters=[8,8,16], stride=1)(C2)
2 = identity_block(name = "C2_id_block2", kernel=3, filters=[8,8,16], stride=1)(C2)
2 = identity_block(name = "C2_id_block3", kernel=3, filters=[8,8,16], stride=1)(C2)

 print(X.shape)

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3 =convolutional_block(name = "C3_conv_block", kernel=3, filters=[16,16,32], stride=1)(C2)
 print(X.shape)
 print('-'*50)
3 = identity_block(name = "C3_id_block1", kernel=3, filters=[16,16,32], stride=1)(C3)
3 = identity_block(name = "C3_id_block2", kernel=3, filters=[16,16,32], stride=1)(C3)
3 = identity_block(name = "C3_id_block3", kernel=3, filters=[16,16,32], stride=1)(C3)
3 = identity_block(name = "C3_id_block4", kernel=3, filters=[16,16,32], stride=1)(C3)
3 = identity_block(name = "C3_id_block5", kernel=3, filters=[16,16,32], stride=1)(C3)
C3 = identity_block(name = "C3_id_block7", kernel=3, filters=[16,16,32], stride=1)(C3)
 print(X.shape)

 print('\nC4')
 C4 and ID4
```

```
4 = convolutional_block(name = "C4_conv_block4", kernel=3, filters=[32,32,64], stride=1)(C3)
print(X.shape)
print('-'*50)
4 = identity_block(name = "C4_id_block1", kernel=3, filters=[32,32,64], stride=1)(C4)
4 = identity_block(name = "C4_id_block2", kernel=3, filters=[32,32,64], stride=1)(C4)
C4 = identity_block(name = "C4_id_block3", kernel=3, filters=[32,32,64], stride=1)(C4)
C4 = identity_block(name = "C4_id_block4", kernel=3, filters=[32,32,64], stride=1)(C4)


rint('C4 shape ',C4.shape)

F = global_flow(name = 'global_flow', filters = 32)(C4)
rint('GF shape ',GF.shape)

F1 = context_flow(name = 'context_flow1')((C4,GF))
F2 = context_flow(name = 'context_flow2')((C4,CF1))
F3 = context_flow(name = 'context_flow3')((C4,CF2))

UM = Add()([GF, CF1, CF2, CF3])
rint('SUM shape ',SUM.shape)


SM_Conv_T = fsm()(SUM)
rint('FSM_Conv_T shape', FSM_Conv_T.shape)

GCN_op = agcn()(TO_AGCN)
rint('AGCN_op shape',AGCN_op.shape)

inal_op = Concatenate(axis = -1)([FSM_Conv_T, AGCN_op])

inal_op = Conv2D(filters=21, kernel_size=(3,3), strides=(1, 1), padding='same', activation='re

inal_op  = UpSampling2D(size=(4,4), data_format='channels_last', name='OP_UP_SAMPL', interpola

inal_op = Activation('softmax')(final_op)


odel = Model(inputs = X_input, outputs = final_op)

odel.summary()
```

C2_conv_block (convolutional_bl	(None, 64, 64, 16)	2160	C1_id_block2[0][0]
C2_id_block1 (identity_block)	(None, 64, 64, 16)	992	C2_conv_block[0][0]
C2_id_block2 (identity_block)	(None, 64, 64, 16)	992	C2_id_block1[0][0]
C2_id_block3 (identity_block)	(None, 64, 64, 16)	992	C2_id_block2[0][0]
_bl	(None, 64, 64, 32)	8160	C2_id_block3[0][0]
C3_id_block1 (identity_block)	(None, 64, 64, 32)	3648	C3_conv_block[0][0]
C3_id_block2 (identity_block)	(None, 64, 64, 32)	3648	C3_id_block1[0][0]
C3_id_block3 (identity_block)	(None, 64, 64, 32)	3648	C3_id_block2[0][0]
C3_id_block4 (identity_block)	(None, 64, 64, 32)	3648	C3_id_block3[0][0]
C3_id_block5 (identity_block)	(None, 64, 64, 32)	3648	C3_id_block4[0][0]
C4_conv_block4 (convolutional_b	(None, 64, 64, 64)	31680	C3_id_block5[0][0]
C4_id_block1 (identity_block)	(None, 64, 64, 64)	13952	C4_conv_block4[0][0]

```
C4_id_block2 (identity_block)   (None, 64, 64, 64)   13952       C4_id_block1[0][0]
global_flow (global_flow)       (None, 64, 64, 32)   2336        C4_id_block2[0][0]
context_flow1 (context_flow)    (None, 64, 64, 32)   39040       C4_id_block2[0][0]
                                                                 global_flow[0][0]
context_flow2 (context_flow)    (None, 64, 64, 32)   39040       C4_id_block2[0][0]
                                                                 context_flow1[0][0]
context_flow3 (context_flow)    (None, 64, 64, 32)   39040       C4_id_block2[0][0]
                                                                 context_flow2[0][0]
add_1 (Add)                     (None, 64, 64, 32)   0           global_flow[0][0]
                                                                 context_flow1[0][0]
                                                                 context_flow2[0][0]
                                                                 context_flow3[0][0]
feature_selection (fsm)         (None, 128, 128, 32) 10432       add_1[0][0]
global_conv_net (agcn)          (None, 128, 128, 8)  2408        C1_conv_block[0][0]
concatenate (Concatenate)       (None, 128, 128, 40) 0           feature_selection[0][0]
                                                                 global_conv_net[0][0]
OP_CONV2 (Conv2D)               (None, 128, 128, 21) 7581        concatenate[0][0]
OP_UP_SAMPL (UpSampling2D)      (None, 512, 512, 21) 0           OP_CONV2[0][0]
activation_5 (Activation)       (None, 512, 512, 21) 0           OP_UP_SAMPL[0][0]
==================================================================================================
Total params: 238,781
Trainable params: 236,333
Non-trainable params: 2,448
```

- If you observe the arcitecture 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

```
def modify_lr_rate(epoch, lr):
    '''
        this function modifies learning rate
    '''

    if (epoch+1)%3 == 0: # REDUCE ACCURACY BY 10% IF EPOCH IS MULTIPLE OF 3
        lr = lr/10
        print('lr decreased :{} '.format(lr))
        return lr
```



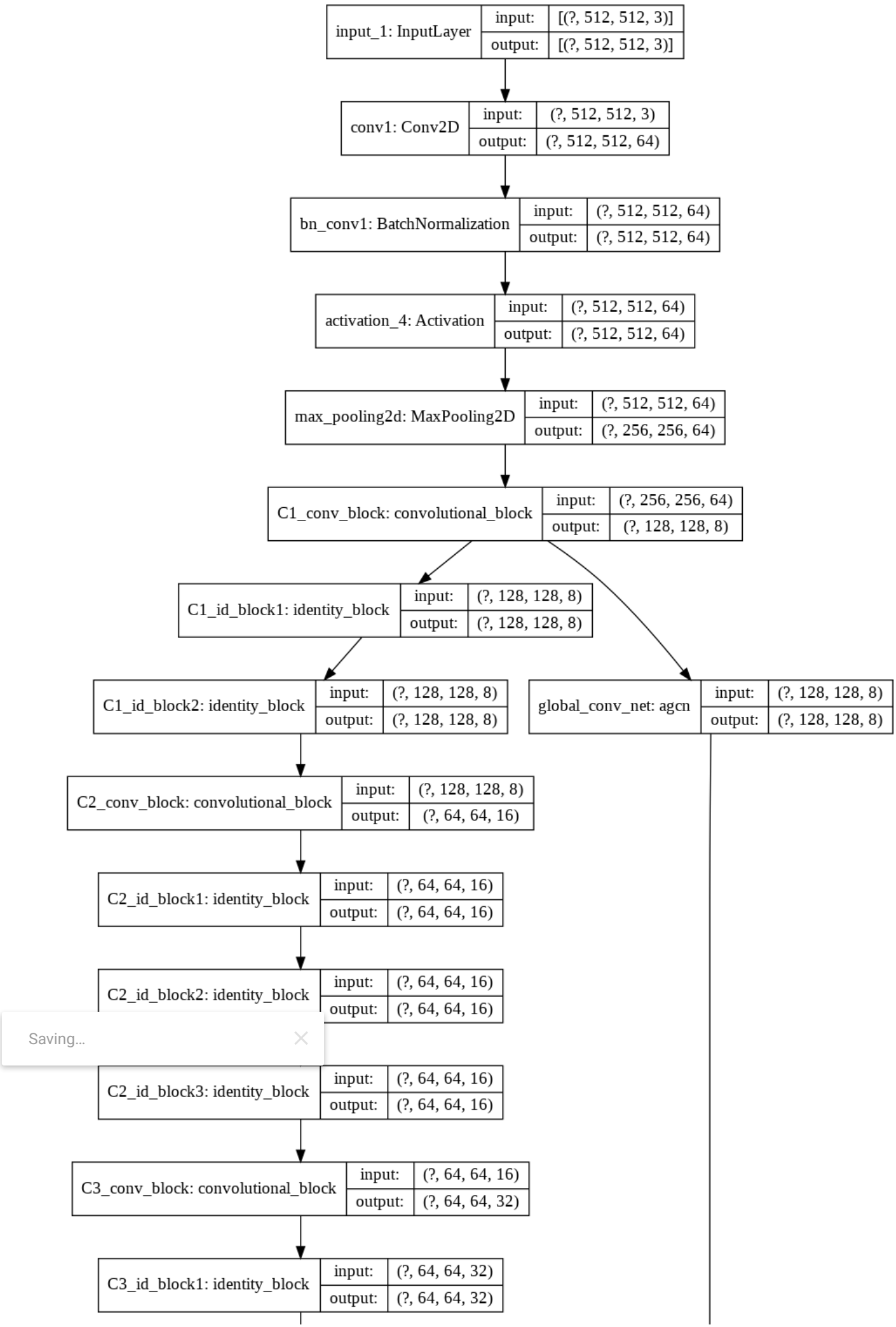
```
lrschedule = LearningRateScheduler(modify_lr_rate)


log_dir="logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
callbacks = [
    ModelCheckpoint('./best_model_Canet.h5', save_weights_only=True, save_best_only=True, \
                                    mode='min', monitor='val_iou_score'),
    TensorBoard(log_dir=log_dir,histogram_freq=1, write_graph=True)
]


optim = tensorflow.keras.optimizers.Adam(learning_rate=0.0001)
```

```
focal_loss = sm.losses.cce_dice_loss
model.compile(optimizer = optim, loss=focal_loss, metrics=[sm.metrics.IOUScore(threshold=0.5)]


tensorflow.keras.utils.plot_model(model, to_file='caNet.png', show_shapes=True)
```


input_1: InputLayer
input: [(?, 512, 512, 3)]
output: [(?, 512, 512, 3)]
conv1: Conv2D
input: (?, 512, 512, 3)
output: (?, 512, 512, 64)
bn_conv1: BatchNormalization
input: (?, 512, 512, 64)
output: (?, 512, 512, 64)
activation_4: Activation
input: (?, 512, 512, 64)
output: (?, 512, 512, 64)
max_pooling2d: MaxPooling2D
input: (?, 512, 512, 64)
output: (?, 256, 256, 64)
C1_conv_block: convolutional_block
input: (?, 256, 256, 64)
output: (?, 128, 128, 8)
C1_id_block1: identity_block
input: (?, 128, 128, 8)
output: (?, 128, 128, 8)
C1_id_block2: identity_block
input: (?, 128, 128, 8)
output: (?, 128, 128, 8)
global_conv_net: agcn
input: (?, 128, 128, 8)
output: (?, 128, 128, 8)
C2_conv_block: convolutional_block
input: (?, 128, 128, 8)
output: (?, 64, 64, 16)
C2_id_block1: identity_block
input: (?, 64, 64, 16)
output: (?, 64, 64, 16)
C2_id_block2: identity_block
input: (?, 64, 64, 16)
output: (?, 64, 64, 16)
C2_id_block3: identity_block
input: (?, 64, 64, 16)
output: (?, 64, 64, 16)
C3_conv_block: convolutional_block
input: (?, 64, 64, 16)
output: (?, 64, 64, 32)
C3_id_block1: identity_block
input: (?, 64, 64, 32)
output: (?, 64, 64, 32)

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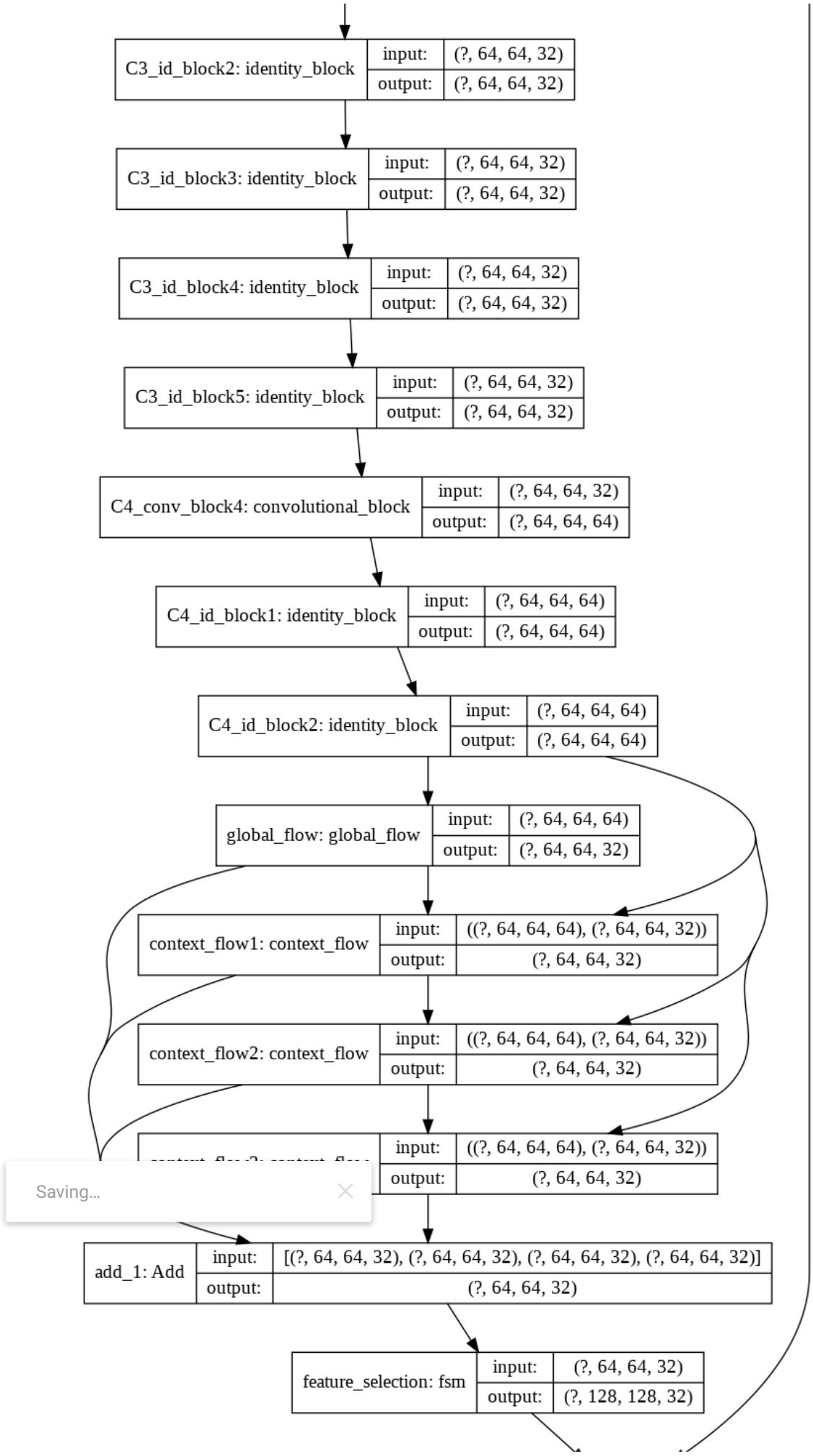


```
history = model.fit_generator(train_dataloader, steps_per_epoch = len(train_dataloader), epoch
```

```
WARNING:tensorflow:From <ipython-input-61-6b9e9c4a4896>:1: Model.fit_generator (from tens
Instructions for updating:
Please use Model.fit, which supports generators.
WARNING:tensorflow:Model failed to serialize as JSON. Ignoring... Layer convolutional_blc
Epoch 1/10
450/450 [==============================] - 507s 1s/step - loss: 0.9823 - iou_score: 0.188
Epoch 2/10
450/450 [==============================] - 509s 1s/step - loss: 0.9181 - iou_score: 0.294
Epoch 3/10
450/450 [==============================] - 494s 1s/step - loss: 0.8952 - iou_score: 0.323
Epoch 4/10
450/450 [==============================] - 493s 1s/step - loss: 0.8736 - iou_score: 0.337
Epoch 5/10
450/450 [==============================] - 494s 1s/step - loss: 0.8542 - iou_score: 0.355
Epoch 6/10
450/450 [==============================] - 496s 1s/step - loss: 0.8400 - iou_score: 0.366
Epoch 7/10
450/450 [==============================] - 487s 1s/step - loss: 0.8310 - iou_score: 0.370
Epoch 8/10
450/450 [==============================] - 489s 1s/step - loss: 0.8226 - iou_score: 0.376
Epoch 9/10
450/450 [==============================] - 492s 1s/step - loss: 0.8157 - iou_score: 0.383
Epoch 10/10
450/450 [==============================] - 489s 1s/step - loss: 0.8029 - iou_score: 0.395
```

```
model.load_weights('best_model_Canet.h5')


scores = model.evaluate_generator(test_dataloader)
metrics=[sm.metrics.IOUScore(threshold=0.5)]
print("Loss: {:.5}".format(scores[0]))
for metric, value in zip(metrics, scores[1:]):
    print("mean {}: {:.5}".format(metric.__name__, value))


n = 5
ids = np.random.choice(np.arange(len(test_dataset)), size=n)

for i in ids:

    image, actual_mask = test_dataset[i]
    image = np.expand_dims(image, axis=0)
    prediction = model.predict(image)
    prediction = np.argmax(prediction, axis=-1)
    prediction = np.squeeze(prediction, axis = 0)
    actual_mask = np.argmax(actual_mask, axis=-1)

    visualize(image=denormalize(image.squeeze()), gt_mask=actual_mask.squeeze(),pr_mask=predic
```