

▼ Segmentation of Indian Traffic

```
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 urllib.request
```

```
from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

```
!pip install pyunpack
!pip install patool
```

```
Collecting pyunpack
  Downloading pyunpack-0.2.2-py2.py3-none-any.whl (3.8 kB)
Collecting entrypoint2
  Downloading entrypoint2-1.0-py3-none-any.whl (9.8 kB)
Collecting easyprocess
  Downloading EasyProcess-1.1-py3-none-any.whl (8.7 kB)
Installing collected packages: entrypoint2, easyprocess, pyunpack
Successfully installed easyprocess-1.1 entrypoint2-1.0 pyunpack-0.2.2
Collecting patool
  Downloading patool-1.12-py2.py3-none-any.whl (77 kB)
    |████████████████████████████████████████████████████████████████████████████████| 77 kB 6.2 MB/s
Installing collected packages: patool
Successfully installed patool-1.12
```

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

```
Collecting segmentation-models
  Downloading segmentation_models-1.0.1-py3-none-any.whl (33 kB)
Collecting keras-applications<=1.0.8,>=1.0.7
  Downloading Keras_Applications-1.0.8-py3-none-any.whl (50 kB)
    |████████████████████████████████████████| 50 kB 8.4 MB/s
Collecting efficientnet==1.0.0
  Downloading efficientnet-1.0.0-py3-none-any.whl (17 kB)
Collecting image-classifiers==1.0.0
  Downloading image_classifiers-1.0.0-py3-none-any.whl (19 kB)
Requirement already satisfied: scikit-image in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.7/dist-packages
```

```
Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages (from k
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.0 in /usr/local/lib/python3.7/
Requirement already satisfied: imageio>=2.3.0 in /usr/local/lib/python3.7/dist-packag
Requirement already satisfied: scipy>=1.0.1 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: tifffile>=2019.7.26 in /usr/local/lib/python3.7/dist-p
Requirement already satisfied: PyWavelets>=1.1.1 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: pillow!=7.1.0,!7.1.1,>=4.3.0 in /usr/local/lib/pythor
Requirement already satisfied: networkx>=2.0 in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: pyparsing!=2.0.4,!2.1.2,!2.1.6,>=2.0.1 in /usr/local
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (fr
Installing collected packages: keras-applications, image-classifiers, efficientnet, s
Successfully installed efficientnet-1.0.0 image-classifiers-1.0.0 keras-applications-
```

```
from zipfile import ZipFile
```

```
from pyunpack import Archive
```

```
#Reference: https://thispointer.com/python-how-to-unzip-a-file-extract-single-multiple-or-
```

```
with ZipFile('/content/drive/MyDrive/Segmentation/data-002.zip', 'r') as zipObj:
```

```
    # Extract all the contents of zip file in current directory
```

```
    zipObj.extractall()
```

```
!pip install git+https://github.com/qubvel/segmentation_models
```

```
Collecting git+https://github.com/qubvel/segmentation\_models
```

```
  Cloning https://github.com/qubvel/segmentation\_models to /tmp/pip-req-build-f66jhdc
```

```
  Running command git clone -q https://github.com/qubvel/segmentation\_models /tmp/pi
```

```
  Running command git submodule update --init --recursive -q
```

```
Requirement already satisfied: keras_applications<=1.0.8,>=1.0.7 in /usr/local/lib/py
```

```
Requirement already satisfied: image-classifiers==1.0.0 in /usr/local/lib/python3.7/c
```

```
Requirement already satisfied: efficientnet==1.0.0 in /usr/local/lib/python3.7/dist-p
```

```
Requirement already satisfied: scikit-image in /usr/local/lib/python3.7/dist-packages
```

```
Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages (from k
```

```
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.7/dist-packages
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```
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/dist-packa
```

```
Requirement already satisfied: tifffile>=2019.7.26 in /usr/local/lib/python3.7/dist-p
```

```
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.0 in /usr/local/lib/python3.7/
```

```
Requirement already satisfied: pillow!=7.1.0,!7.1.1,>=4.3.0 in /usr/local/lib/pythor
```

```
Requirement already satisfied: PyWavelets>=1.1.1 in /usr/local/lib/python3.7/dist-pac
```

```
Requirement already satisfied: imageio>=2.3.0 in /usr/local/lib/python3.7/dist-packag
```

```
Requirement already satisfied: scipy>=1.0.1 in /usr/local/lib/python3.7/dist-packages
```

```
Requirement already satisfied: networkx>=2.0 in /usr/local/lib/python3.7/dist-package
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```
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-pac
```

```
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages
```

```
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-
```

```
Requirement already satisfied: pyparsing!=2.0.4,!2.1.2,!2.1.6,>=2.0.1 in /usr/local
```

```
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (fr
```

```

import warnings
warnings.filterwarnings('ignore')

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 seaborn as sns
import urllib
from sklearn.model_selection import train_test_split
import imgaug.augmenters as iaa
import gc
import tensorflow as tf
import math
from PIL import Image, ImageDraw
from PIL import ImagePath
import segmentation_models as sm
from segmentation_models.metrics import iou_score
from segmentation_models import Unet

```

Segmentation Models: using `keras` framework.

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

```
os.chdir('/gdrive/My Drive/Image_Segmentation/segmentation')
os.listdir()
```

```
['data',
 'Preprocessing.csv',
 'logs',
 'Model_save',
 'Segmentation_Assignment.ipynb',
 'tf_ckpts',
 'Copy of Segmentation_Assignment.ipynb',
 'test_image.png',
 'Preprocessing_2.csv',
 'preprocessed_data.csv',
 'Reference_Pretrained_Unet.ipynb',
 'model4.png',
 'model.png',
 'Model_save_CANET',
 'best_model_CANET.hdf5',
 'best_model_CANET.h5']
```

```
# First check both image and Mask folder contains same number of sub-folder with same name
image_sub_folder = sorted(os.listdir('data/images'))
mask_sub_folder = sorted(os.listdir('data/mask'))
print('Length of image folder',len(image_sub_folder))
print('Length of image folder',len(mask_sub_folder))
print('Both Image and Mask contains same folder names - ',image_sub_folder == (mask_sub_fo
```

```
Length of image folder 143
Length of image folder 143
Both Image and Mask contains same folder names - True
```

```

def return_file_names_df():
    directory_images = 'data/images'
    directory_mask = 'data/mask'
    image_folders = sorted(os.listdir('data/images'))
    mask_folders = sorted(os.listdir('data/mask'))
    all_image_files = []
    folder_number_image = []
    for i in image_folders:
        image_files = sorted(os.listdir(directory_images + '/' + i))
        length_1 = [i]*len(image_files)
        all_image_files = all_image_files + image_files
        folder_number_image = folder_number_image + length_1
    all_json_files = []
    folder_number_json = []
    for j in mask_folders:
        json_files = sorted(os.listdir(directory_mask + '/' + j))
        length_2 = [j]*len(json_files)
        all_json_files = all_json_files + json_files
        folder_number_json = folder_number_json + length_2
    all_image_paths = []
    all_json_paths = []
    for k in range(len(folder_number_image)):
        image_path = directory_images + '/' + folder_number_image[k] + '/' + all_image_files[k]
        json_path = directory_mask + '/' + folder_number_json[k] + '/' + all_json_files[k]
        all_image_paths.append(image_path)
        all_json_paths.append(json_path)
    data_df = pd.DataFrame({'image' : all_image_paths, 'json' : all_json_paths})
    return data_df

```

```

data_df = return_file_names_df()
data_df.head()

```

	image	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

```

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][

```

```

        return False
    return True

```

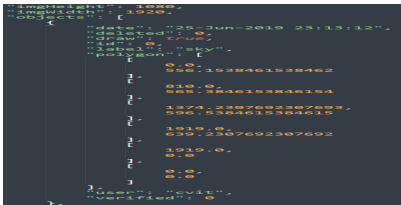
```
grader_1(data_df)
```

```
True
```

```
data_df.shape
```

```
(4008, 2)
```

▼ 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](#)

```

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
    all_attributes = [] # storing all attributes
    all_labels = [] # stroing all label values of each row

    for i in tqdm(range(data_df.shape[0])):
        f = open(data_df.json[i],)
        data = json.load(f)

```

```
for j in data['objects']:
    all_attributes.append(j)
f.close()
```

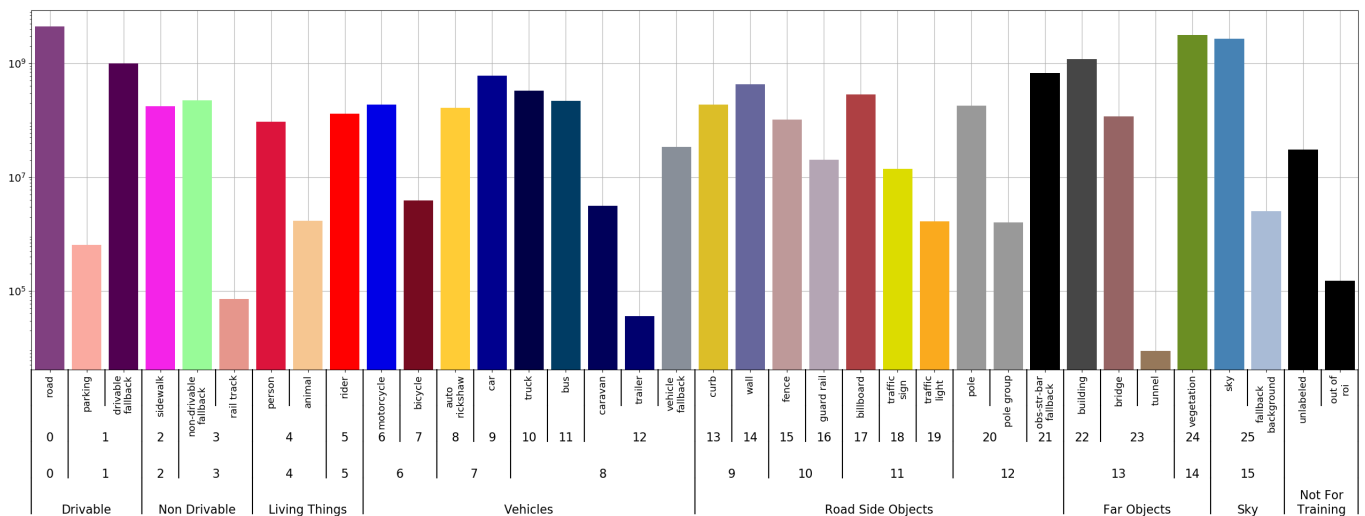
```
# to get unique label count
for k in tqdm(range(len(all_attributes))):
    all_labels.append( all_attributes[k]['label'])
```

```
# get unique
unique_labels = list(set(all_labels))
print('Number of unique labels ',len(unique_labels))
```

```
return unique_labels
```

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

```
100%|██████████| 4008/4008 [00:28<00:00, 141.53it/s]
100%|██████████| 434321/434321 [00:00<00:00, 1719253.23it/s]
Number of unique labels 40
```



```
label_clr = {'road':10, 'parking':20, 'drivable fallback':20,'sidewalk':30,'non-drivable f
'person':50, 'animal':50, 'rider':60, 'motorcycle':70, 'bicycle':7
'car':80, 'truck':90, 'bus':90, 'vehicle fallback':90, 'trailer':9
'curb':100, 'wall':100, 'fence':110,'guard rail':110, 'billboard':
'traffic light':120, 'pole':130, 'polegroup':130, 'obs-str-bar-fal
'bridge':140,'tunnel':140, 'vegetation':150, 'sky':160, 'fallback
'out of roi':0, 'ego vehicle':170, 'ground':180,'rectification bor
'train':200}
```

```
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 diff
 * Note that we have multiplies each object's number with 10, that is just to make differ
 * 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):
    f0 = open(file, 'r')
    f1 = json.load(f0)
    f0.close()
    w = f1['imgWidth']
    h = f1['imgHeight']
    labels = []
    vertexlist_0 = []
    for i in f1['objects']:
        labels.append(i.get('label', -1))
        vertexlist_0.append(i.get('polygon', -1))
    vertexlist = []
    for i in vertexlist_0:
        k = []
        for j in i:
            k.append(tuple(j))
        vertexlist.append(k)
    return w, h, labels, vertexlist
```

```
w, h, labels, vertexlist = get_poly('data/mask/201/frame0029_gtFine_polygons.json')
```

```
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 isinstanc
```

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

```
True
```

```
image_meta_data = {}
for i in tqdm(data_df['json']):
    w, h, labels, vertexlist = get_poly(i)
    image_meta_data[i] = [w, h, labels, vertexlist]
```


100%|██████████| 4008/4008 [00:52<00:00, 75.94it/s]

```
output_folders = data_df['json'].apply(lambda x : '/'.join(x.split('/')[0:3]).replace('mask', 'seg'))
for i in output_folders:
    os.makedirs(i, exist_ok = True)
```

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

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


100%|██████████| 4008/4008 [03:15<00:00, 20.51it/s]

	image	json	
0	data/images/201/frame0029_leftImg8bit.jpg	data/mask/201/frame0029_gtFine_polygons.json	dat
1	data/images/201/frame0299_leftImg8bit.jpg	data/mask/201/frame0299_gtFine_polygons.json	dat
2	data/images/201/frame0779_leftImg8bit.jpg	data/mask/201/frame0779_gtFine_polygons.json	dat

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

100%|██████████| 4008/4008 [03:16<00:00, 20.40it/s]

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

```
#daving the final dataframe to a csv file
data_df.to_csv('preprocessed_data.csv', index=False)
```

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

▼ Task 2: Applying Unet to segment the images

Channels Last

. Image data is represented in a three-dimensional array where the last channel represen



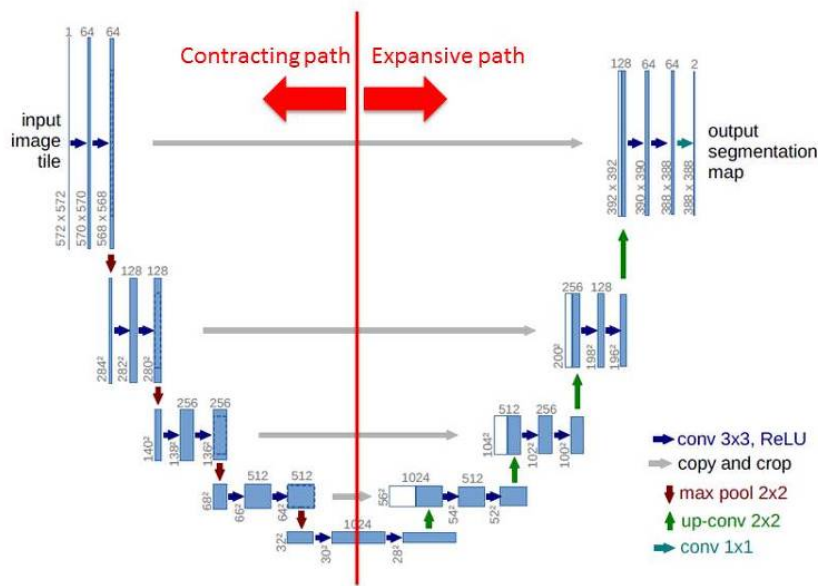
Channels First

Image data is represented in a three-dimensional array where the first channel represent



* 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

* 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 goog

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

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

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

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

```
!pip install tensorflow==2.2.0
```

```
Collecting tensorflow==2.2.0
```

```
  Downloading https://files.pythonhosted.org/packages/3d/be/679ce5254a8c8d07470efb4a/
```

```
  | 516.2MB 31kB/s
```

```
Requirement already satisfied: scipy==1.4.1; python_version >= "3" in /usr/local/lib/
```

```
Requirement already satisfied: absl-py>=0.7.0 in /usr/local/lib/python3.6/dist-packag
```

```
Requirement already satisfied: wheel>=0.26; python_version >= "3" in /usr/local/lib/p
```

```
Requirement already satisfied: keras-preprocessing>=1.1.0 in /usr/local/lib/python3.6
```

```
Collecting tensorboard<2.3.0,>=2.2.0
```

```
  Downloading https://files.pythonhosted.org/packages/1d/74/0a6fcb206dcc72a6da9a62dd/
```

```

| 3.0MB 39.7MB/s
Requirement already satisfied: google-pasta>=0.1.8 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: gast==0.3.3 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: numpy<2.0,>=1.16.0 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: wrapt>=1.11.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: protobuf>=3.8.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: grpcio>=1.8.6 in /usr/local/lib/python3.6/dist-packages
Collecting tensorflow-estimator<2.3.0,>=2.2.0
  Downloading https://files.pythonhosted.org/packages/a4/f5/926ae53d6a226ec0fda5208e6
| 460kB 37.0MB/s
Requirement already satisfied: astunparse==1.6.3 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: h5py<2.11.0,>=2.10.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: google-auth-oauthlib<0.5,>=0.4.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: werkzeug>=0.11.15 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: setuptools>=41.0.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: tensorboard-plugin-wit>=1.6.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: google-auth<2,>=1.6.3 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: importlib-metadata; python_version < "3.8" in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: rsa<5,>=3.1.4; python_version >= "3" in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: cachetools<5.0,>=2.0.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: urllib3!=1.25.0,!1.25.1,<1.26,>=1.21.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.6/dist-packages (from importlib-metadata)
Requirement already satisfied: pyasn1>=0.1.3 in /usr/local/lib/python3.6/dist-packages (from google-auth)
Installing collected packages: tensorboard, tensorflow-estimator, tensorflow
  Found existing installation: tensorboard 2.3.0
    Uninstalling tensorboard-2.3.0:
      Successfully uninstalled tensorboard-2.3.0
  Found existing installation: tensorflow-estimator 2.3.0
    Uninstalling tensorflow-estimator-2.3.0:
      Successfully uninstalled tensorflow-estimator-2.3.0
  Found existing installation: tensorflow 2.3.0
    Uninstalling tensorflow-2.3.0:
      Successfully uninstalled tensorflow-2.3.0
Successfully installed tensorboard-2.2.2 tensorflow-2.2.0 tensorflow-estimator-2.2.0

```

```
!pip install keras==2.3.1
```

```

Collecting keras==2.3.1
  Downloading https://files.pythonhosted.org/packages/ad/fd/6bfe87920d7f4fd475acd2856
| 378kB 2.8MB/s
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: keras-preprocessing>=1.0.5 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: scipy>=0.14 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: six>=1.9.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied: h5py in /usr/local/lib/python3.6/dist-packages (from keras)
Collecting keras-applications>=1.0.6
  Downloading https://files.pythonhosted.org/packages/71/e3/19762fd6c62877ae9102edf63

```

```

|████████████████████████████████████████████████████████████████████████████████| 51kB 5.9MB/s
Requirement already satisfied: pyyaml in /usr/local/lib/python3.6/dist-packages (from
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

```

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

```

Collecting segmentation-models==0.2.1
  Downloading https://files.pythonhosted.org/packages/10/bf/253c8834014a834cacf2384c7
|████████████████████████████████████████████████████████████████████████████████| 51kB 1.7MB/s
Requirement already satisfied, skipping upgrade: keras>=2.2.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: keras-applications>=1.0.7 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: scikit-image in /usr/local/lib/python3.6/dist-packages
Collecting image-classifiers==0.2.0
  Downloading https://files.pythonhosted.org/packages/de/32/a1e74e03f74506d1e4b46bb27
|████████████████████████████████████████████████████████████████████████████████| 81kB 4.3MB/s
Requirement already satisfied, skipping upgrade: pyyaml in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: six>=1.9.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: h5py in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: keras-preprocessing>=1.0.5 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: scipy>=0.14 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: numpy>=1.9.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: PyWavelets>=0.4.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: networkx>=2.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: matplotlib!=3.0.0,>=2.0.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: imageio>=2.3.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: pillow>=4.3.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: decorator>=4.3.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: cycycler>=0.10 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: pyparsing!=2.0.4,!2.1.2,!2.1.6,>=2.1.0 in /usr/local/lib/python3.6/dist-packages
Requirement already satisfied, skipping upgrade: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages
Installing collected packages: image-classifiers, segmentation-models
Successfully installed image-classifiers-0.2.0 segmentation-models-0.2.1

```

```

# install required Package
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, Model
from tensorflow.keras.layers import Dense, Input, Conv2D, MaxPool2D, Activation, Dropout, Flatten
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, LearningRateScheduler

```

```

from tensorflow.keras.models import Model
import random as rn

# here dir_path is the route directory where all the images and segmentation maps are ther
dir_path = "data/images/"
dir_path_output = "data/output/"
file_names = set()
file_names_output = set()
for folder in tqdm(os.listdir(dir_path)):

    dir_paths = "data/images/" +str(folder)
    for i in os.listdir(dir_paths):
        path= (i.split('.')[0].split('_')[0])
        file_names.add(str(folder) +str('/')+path)

for folder in tqdm(os.listdir(dir_path_output)):
    dir_paths = "data/output/" +str(folder)
    for i in os.listdir(dir_paths):
        path= (i.split('.')[0].split('_')[0])
        file_names_output.add(str(folder) +str('/')+path)

100%|██████████| 143/143 [00:20<00:00, 6.89it/s]
100%|██████████| 143/143 [00:18<00:00, 7.78it/s]

print('Total_number of unique files', len(file_names))
print('Total_number of unique files- Output Mask folder', len(file_names_output))

Total_number of unique files 4008
Total_number of unique files- Output Mask folder 4008

from sklearn.model_selection import train_test_split
X_train, X_test = train_test_split(list(file_names), test_size=0.20, random_state=42)

X_train[:5]

['237/frame52930',
 '376/frame1866',
 '333/frame0389',
 '236/frame36799',
 '417/0002149']

# install required Package
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, Model
from tensorflow.keras.layers import Dense, Input, Conv2D, MaxPool2D, Activation, Dropout, Flatten
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, LearningRateScheduler

from tensorflow.keras.models import Model
import random as rn

# we are importing the pretrained unet from the segmentation models
# https://github.com/qubvel/segmentation_models
import segmentation_models as sm

tf.keras.backend.set_image_data_format('channels_last')
```

Using TensorFlow backend.

```
/usr/local/lib/python3.6/dist-packages/classification_models/resnext/__init__.py:4: l
warnings.warn('Current ResNext models are deprecated, '
```

```
# import imgaug.augmenters as iaa
# For the assignment choose any 4 augmentation techniques
# check the imgaug documentations for more augmentations
aug2 = iaa.Fliplr(1)
aug3 = iaa.Flipud(1)
aug4 = iaa.Emboss(alpha=(1), strength=1)
aug5 = iaa.DirectedEdgeDetect(alpha=(0.8), direction=(1.0))
```

```
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:
    # we will be modifying this CLASSES according to your data/problems
    #CLASSES = class_values
    CLASSES = list(np.unique(list(label_clr.values()))))
    #classes=CLASSES

    # the parameters needs to changed based on your requirements
    # here we are collecting the file_names because in our dataset, both our images and ma
    # ex: fil_name.jpg    file_name.mask.jpg
    def __init__(self, images_dir,images_dir_mask ,file_names,classes):
        print(classes)

        self.ids = file_names
        # the paths of images
        self.images_fps = [os.path.join(images_dir, image_id+'_leftImg8bit.jpg') for ima
        # the paths of segmentation images
        self.masks_fps = [os.path.join(images_dir_mask, image_id+"_gtFine_polygons.png"
        # giving labels for each class
        #self.class_values = [self.CLASSES.index(cls) for cls in classes]
        self.class_values = CLASSES
        print(self.class_values)

    def __getitem__(self, i):

        # read data
        #print('Reading a data')

        image = cv2.imread(self.images_fps[i], cv2.IMREAD_UNCHANGED)
        image = cv2.resize(image, (256, 256),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, (256, 256),interpolation=cv2.INTER_AREA)

        image_mask = mask

        image_masks = [(image_mask == v) for v in self.class_values]
        image_mask = np.stack(image_masks, axis=-1).astype('float')
        #print('MASK',image_mask.shape)

        if self.isTest == False:
            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)
            else:
                image = aug5.augment_image(image)
                #image_mask = image_mask

```

```

        return image, image_mask

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

class Dataloder(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)]
        #print(type(batch))

        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)

# Dataset for train images
CLASSES = list(np.unique(list(label_clr.values()))))
train_dataset = Dataset(dir_path,dir_path_output,X_train, classes=CLASSES,isTest=False)
test_dataset = Dataset(dir_path,dir_path_output,X_test, classes=CLASSES,isTest=True)


[0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180,
[0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180,
[0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180,
[0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, 120, 130, 140, 150, 160, 170, 180,

```



```

# CANET
train_dataloader = Dataloder(train_dataset, batch_size=32, shuffle=True)
test_dataloader = Dataloder(test_dataset, batch_size=32, shuffle=True)

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

```

```
(32, 256, 256, 3)
```

```
print(test_dataloader[0][0].shape)
```

```
(32, 256, 256, 3)
```

```
print(train_dataloader)
```

```
print(test_dataloader)
```

```
<__main__.Dataloder object at 0x7f0d30234898>
```

```
<__main__.Dataloder object at 0x7f0d30234940>
```

▼ 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 se



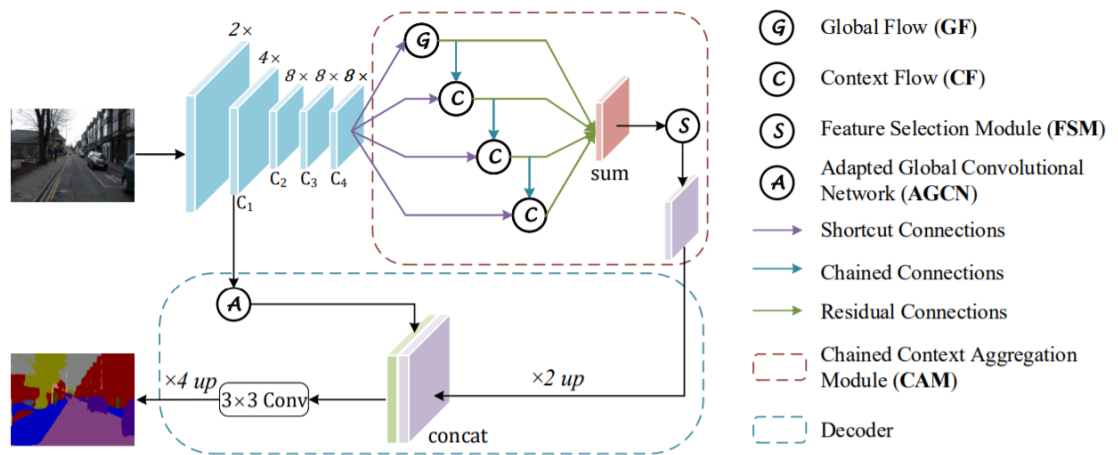
▼ Task 3: Training CANet

```
import tensorflow as tf
# tf.compat.v1.enable_eager_execution()
from tensorflow 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 MaxPooling2D, GlobalAveragePooling2D
from tensorflow.keras.layers import concatenate
from tensorflow.keras.layers import Multiply
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras import backend as K
from tensorflow.keras.layers import Input, Add, Dense, Activation, ZeroPadding2D, BatchNor
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.utils import plot_model
from tensorflow.keras.initializers import glorot_uniform
from tensorflow.keras.activations import relu
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



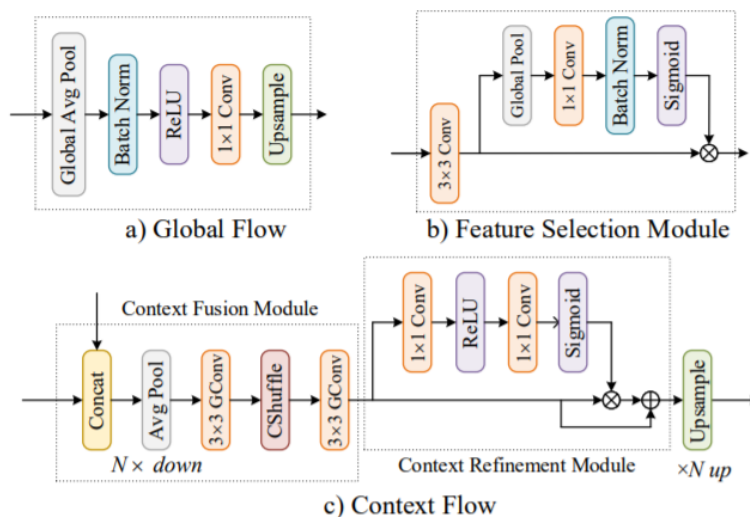
- Encoder:

- 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 SC_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 SC_1 will be $128 \times 128 \times 8$
 - the output after SC_2 will be $64 \times 64 \times 16$
 - the output after SC_3 will be $64 \times 64 \times 32$
 - the output after SC_4 will be $64 \times 64 \times 64$
- The output of the C_4 will be passed to Chained Context Aggregation Module (CAM)

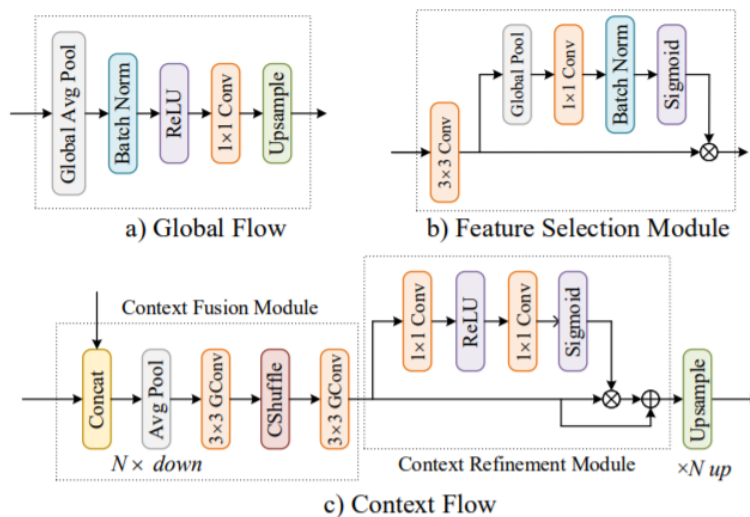


- The CAM module will have two operations names Context flow and Global flow
- **The Global flow:**
 - as shown in the above figure first we will apply [global avg pooling](#) which results in $(\#, 1, 1, \text{number_of_filters})$ then applying [BN](#), [RELU](#), 1×1 Conv layer sequentially which results 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. C_4 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 $N \times$ 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 $Y = (X \otimes \sigma((1 \times 1)conv(\text{relu}((1 \times 1)conv(X)))))) \oplus X$, here \oplus is elementwise addition and \otimes 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 $(64,64,32)$
- 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



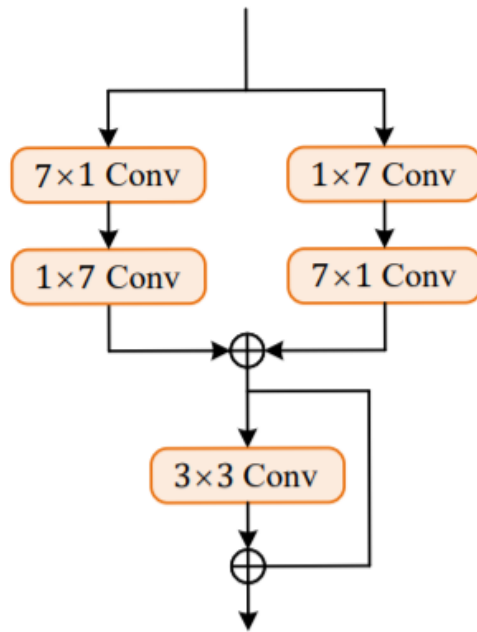
* The output of after the sum, will

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.

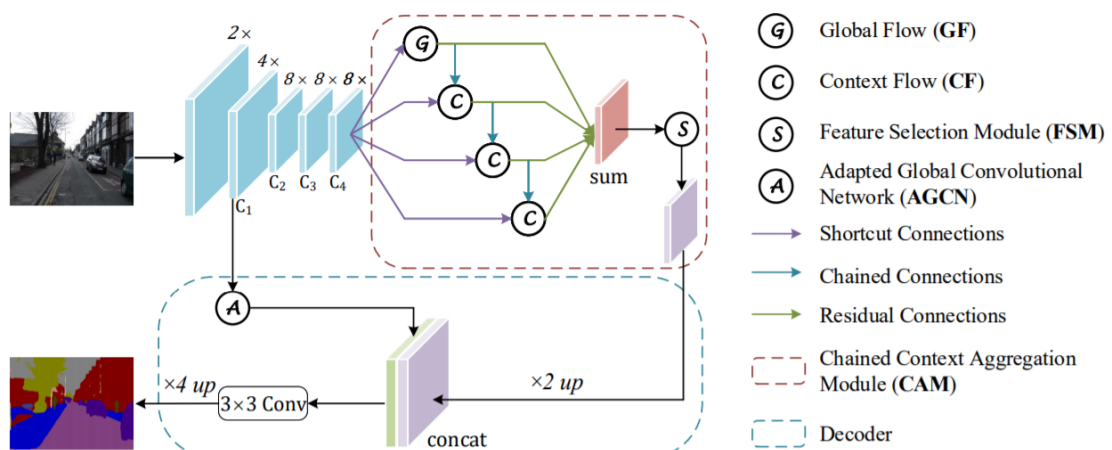
Feature selection module:

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



b) AGCN

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



- 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)
- 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

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

BEST TRY

```
# tf.compat.v1.enable_eager_execution()
from tensorflow import keras
import tensorflow as tf
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 MaxPooling2D, GlobalAveragePooling2D
from tensorflow.keras.layers import concatenate
from tensorflow.keras.layers import Multiply
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, LearningRateScheduler

from tensorflow.keras import backend as K
from tensorflow.keras.layers import Input, Add, Dense, Activation, ZeroPadding2D, BatchNormalization
from tensorflow.keras.models import Model, load_model
from tensorflow.keras.utils import plot_model
from tensorflow.keras.initializers import glorot_uniform
from tensorflow.keras.activations import relu
K.set_image_data_format('channels_last')
K.set_learning_phase(1)
# from tensorflow.keras.layers.core import Lambda

inputs = Input((256,256,3))
# Layer before C1
conv1 = Conv2D(64, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_normal')
n1 = BatchNormalization()(conv1)
n1 = Activation('relu')(n1)
x1 = MaxPooling2D((2,2), strides = (2,2))(n1)
print(x1.shape)

(None, 128, 128, 64)

class convolutional_block(tf.keras.Model):
    def __init__(self, kernel_size, filters, stride, layer = 1):
        super().__init__()
        F = filters
        k1 = kernel_size
```

```
s1= stride

#initializse the layers
#C1 layer
if layer == 1:
    #set 1
    self.conv2a = tf.keras.layers.Conv2D(F, (1, 1),activation = 'relu',padding='same
    self.bn2a = tf.keras.layers.BatchNormalization()
    self.at2a = tf.keras.layers.Activation('relu')

    #set 2
    self.conv2b = tf.keras.layers.Conv2D(F, k1,activation = 'relu',strides=s1,paddin
    self.bn2b = tf.keras.layers.BatchNormalization()
    self.at2b = tf.keras.layers.Activation('relu')

    #set 3
    self.conv2c = tf.keras.layers.Conv2D(F, (1,1),activation = 'relu',strides=1,padd
    self.bn2c = tf.keras.layers.BatchNormalization()

    #set 4
    self.conv2d = tf.keras.layers.Conv2D(F, k1,activation = 'relu',strides=s1,paddin
    self.bn2d = tf.keras.layers.BatchNormalization()
    self.at2d = tf.keras.layers.Activation('relu')

# C2 layer

if layer == 2:
    #set 1
    self.conv2a = tf.keras.layers.Conv2D(F, (1, 1),activation = 'relu',padding='same
    self.bn2a = tf.keras.layers.BatchNormalization()
    self.at2a = tf.keras.layers.Activation('relu')

    #set 2
    self.conv2b = tf.keras.layers.Conv2D(F, k1,activation = 'relu',strides=s1,paddin
    self.bn2b = tf.keras.layers.BatchNormalization()
    self.at2b = tf.keras.layers.Activation('relu')

    #set 3
    self.conv2c = tf.keras.layers.Conv2D(F, (1,1),activation = 'relu',strides=1,padd
    self.bn2c = tf.keras.layers.BatchNormalization()

    #set 4
    self.conv2d = tf.keras.layers.Conv2D(F, k1,activation = 'relu',strides=s1,paddin
    self.bn2d = tf.keras.layers.BatchNormalization()
    self.at2d = tf.keras.layers.Activation('relu')

# C3 layer
if layer == 3:
    #set 1
    self.conv2a = tf.keras.layers.Conv2D(F, (1, 1),activation = 'relu',padding='same
    self.bn2a = tf.keras.layers.BatchNormalization()
    self.at2a = tf.keras.layers.Activation('relu')

    #set 2
    self.conv2b = tf.keras.layers.Conv2D(F, k1,activation = 'relu',strides=1,padding
```

```

self.bn2b = tf.keras.layers.BatchNormalization()
self.at2b = tf.keras.layers.Activation('relu')

#set 3
self.conv2c = tf.keras.layers.Conv2D(F, (1,1),activation = 'relu',strides=1,padd
self.bn2c = tf.keras.layers.BatchNormalization()

#set 4
self.conv2d = tf.keras.layers.Conv2D(F, k1,activation = 'relu',strides=1,padding
self.bn2d = tf.keras.layers.BatchNormalization()
self.at2d = tf.keras.layers.Activation('relu')

# C4 layer
if layer == 4:
    #set 1
    self.conv2a = tf.keras.layers.Conv2D(F, (1, 1),activation = 'relu',padding='same
    self.bn2a = tf.keras.layers.BatchNormalization()
    self.at2a = tf.keras.layers.Activation('relu')

    #set 2
    self.conv2b = tf.keras.layers.Conv2D(F, k1,activation = 'relu',strides=1,padding
    self.bn2b = tf.keras.layers.BatchNormalization()
    self.at2b = tf.keras.layers.Activation('relu')

    #set 3
    self.conv2c = tf.keras.layers.Conv2D(F, (1,1),activation = 'relu',strides=1,padd
    self.bn2c = tf.keras.layers.BatchNormalization()

    #set 4
    self.conv2d = tf.keras.layers.Conv2D(F, k1,activation = 'relu',strides=1,padding
    self.bn2d = tf.keras.layers.BatchNormalization()
    self.at2d = tf.keras.layers.Activation('relu')

def call(self, x):
    # write the architecutre that was mentioned above
    x = float(x)

    x_parellel = x
    x = self.conv2a(x)

    x = self.bn2a(x)
    x = self.at2a (x)

    x = self.conv2b(x)
    x = self.bn2b(x)
    x = self.at2b(x)
    x = self.conv2c(x)
    x = self.bn2c(x)

    x_i = self.conv2d(x_parellel)
    x_i = self.bn2d(x_i)
    x_i = self.at2d(x_i)

```

```

y1 = Add()([x,x_i])
conv_layer_output = Activation('relu')(y1)
#print('Conv layer',conv_layer_output.shape)

return tf.nn.relu(y1)

```

```
#####
```

```

class identity_block(tf.keras.layers.Layer):
    def __init__(self, kernel_size, filters, stride):
        super().__init__() # https://stackoverflow.com/a/27134600/4084039
        F = filters
        k1= kernel_size
        s1= stride

        #self.con_block_1 = convolutional_block(kernel_size,f1,s1,l1)
        #self.con_block_2 = convolutional_block(kernel_size,f2,s1,l2)
        #self.con_block_3 = convolutional_block(kernel_size,f3,s1,l3)
        #self.con_block_4 = convolutional_block(kernel_size,f4,s1,l4)
        self.conv2a_i = tf.keras.layers.Conv2D(F, (1, 1),activation = 'relu',padding='same',st
        self.bn2a_i = tf.keras.layers.BatchNormalization()
        self.at2a_i = tf.keras.layers.Activation('relu')

        #set 2
        self.conv2b_i = tf.keras.layers.Conv2D(F, k1,activation = 'relu',strides=1,padding='sa
        self.bn2b_i = tf.keras.layers.BatchNormalization()
        self.at2b_i = tf.keras.layers.Activation('relu')

        #set 3
        self.conv2c_i = tf.keras.layers.Conv2D(F, (1,1),activation = 'relu',strides=1,padding=
        self.bn2c_i = tf.keras.layers.BatchNormalization()

        #set 4
        self.conv2d_i = tf.keras.layers.Conv2D(F, (1,1),activation = 'relu',strides=1,padding=
        self.bn2d_i = tf.keras.layers.BatchNormalization()
        self.at2d_i = tf.keras.layers.Activation('relu')

    def call(self, x):
        #c1 = self.con_block_1(input)
        x_parellel = x
        #print('shape parellel', x_parellel.shape)
        x = self.conv2a_i(x)
        x = self.bn2a_i(x)
        x = self.at2a_i (x)

        x = self.conv2b_i(x)
        x = self.bn2b_i(x)
        x = self.at2b_i(x)
        x = self.conv2c_i(x)
        x = self.bn2c_i(x)
        #print('shape X main', x.shape)

```

```

#x_i = self.conv2d_i(x_parellel)
#x_i = self.bn2d_i(x_i)
#x_i = self.at2d_i(x_i)

y1 = Add()(x,x_parellel)
conv_layer_output = Activation('relu')(y1)
#print('Conv layer',conv_layer_output.shape)
return conv_layer_output

```

```

class global_flow(tf.keras.layers.Layer):
    def __init__(self, filters):
        F = filters
        super().__init__() # https://stackoverflow.com/a/27134600/4084039
        #self.identity_block_new = identity_block(kernel_size, filters, stride, layers)
        self.glo_avg_pool = GlobalAveragePooling2D()
        self.btch_norm = BatchNormalization()
        self.activation_glo = Activation('relu')
        self.con_glo = Conv2D(F, 1, activation = 'relu', padding = 'same', kernel_initializer
        self.upsampling_glo = UpSampling2D(size=(32, 32), interpolation='bilinear')

    def call(self, input):
        #c1 = self.identity_block_new(input)
        c2 = self.glo_avg_pool(input)
        c3 = self.btch_norm(c2)
        c4 = self.activation_glo (c3)
        reshape_glo = Reshape(( 1,1,64))(c4)
        conv_glob = self.con_glo(reshape_glo)
        up_samp = self.upsampling_glo(conv_glob)

        #print('shape of Global layer',up_samp.shape)
        return up_samp

```

```

class CFM(tf.keras.layers.Layer):
    def __init__(self, kernel_size, filters, stride):
        f4= filters
        super().__init__() # https://stackoverflow.com/a/27134600/4084039
        #self.global_flow_new = global_flow(kernel_size, filters, stride, layers)
        self.Avg_avg_pool = AveragePooling2D(pool_size=(2, 2))
        self.conv_context_1 = Conv2D(f4, kernel_size, activation = 'relu', padding = 'same', k
        self.conv_context_2 = Conv2D(f4, kernel_size, activation = 'relu', padding = 'same', k
        self.conv_context_3 = Conv2D(f4, kernel_size, activation = 'relu', padding = 'same', k
        self.conv_context_4 = Conv2D(f4, kernel_size, activation = 'relu', padding = 'same', k
        self.activation_context_1 = Activation('relu')
        self.activation_context_2 = Activation('sigmoid')
        self.upsampling_context = UpSampling2D(size=(2, 2), interpolation='bilinear')

```

```
def call(self, input1):
```

```
##### CONTEXT FLOW 1 ###
```

```
concat_val = Concatenate(axis = 3)(input1)
```

```

avg_pool    = self.Avg_avg_pool(concat_val)
conv_1      = self.conv_context_1(avg_pool)
conv_2      = self.conv_context_2(conv_1)

##CONTEXT REFINEMENT MODULE
conv_3      = self.conv_context_3(conv_2)
activation_new = self.activation_context_1 (conv_3)
conv_4      = self.conv_context_4(activation_new)
activation_sig = self.activation_context_2 (conv_4)

mul  = Multiply()([conv_2,activation_sig ])
add_layer = Add()([mul,conv_2])
context_flow_1_result = self.upsampling_context(add_layer)

#print('shape of Context_fusion_1 module shape ',context_flow_1_result.shape)

CFM_result  = context_flow_1_result

return CFM_result

```

```

class FSM(tf.keras.layers.Layer):
    def __init__(self, filters):
        f4 = filters
        super().__init__() # https://stackoverflow.com/a/27134600/4084039
        #self.CFM = CFM(kernel_size, filters, stride, layers)
        self.glo_avg_pool = GlobalAveragePooling2D()
        self.btch_norm    = BatchNormalization()
        self.activation_fsm = Activation('sigmoid')
        self.con_fsm = Conv2D(f4, 1, activation = 'relu', padding = 'same', kernel_initializer
        self.upsampling_fsm = UpSampling2D(size=(2, 2), interpolation='bilinear')

    def call(self, input):
        #c1  = self.CFM (input)
        con_1 = self.con_fsm(input)
        c2 = self.glo_avg_pool(con_1)
        reshape_fsm = Reshape(( 1,1,32))(c2)
        c3 = self.btch_norm(reshape_fsm)
        c4 = self.activation_fsm (c3)
        mul_fsm = Multiply()([con_1,c4])

        ##x2 up(Upsampling after FSM)
        fsm_result = self.upsampling_fsm(mul_fsm)

        #print('shape of Feature Selection Module',fsm_result.shape)
        return fsm_result

```

Adapted Global Convolutional Network (AGCN)

```

class AGCN(tf.keras.layers.Layer):
    def __init__(self, kernel_size, filters):
        f1 = filters
        super().__init__() # https://stackoverflow.com/a/27134600/4084039
        #self.FSM = FSM(kernel_size, filters, stride, layers)
        self.activation_agcn = Activation('softmax')
        self.con_AGCN_1 = Conv2D(f1, (7,1), activation = 'relu', padding = 'same', kernel_init
        self.con_AGCN_2 = Conv2D(f1, (1,7), activation = 'relu', padding = 'same', kernel_init
        self.con_AGCN_3 = Conv2D(f1, (1,7), activation = 'relu', padding = 'same', kernel_init
        self.con_AGCN_4 = Conv2D(f1, (7,1), activation = 'relu', padding = 'same', kernel_init
        self.con_AGCN_5 = Conv2D(f1, kernel_size, activation = 'relu', padding = 'same', kerne
        #self.con_AGCN_6 = Conv2D(classes, kernel_size, activation = 'relu', padding = 'same',

        self.upsampling_agcn = UpSampling2D(size=(4, 4), interpolation='bilinear')

    def call(self, input):
        #c1 = self.FSM(input)

        #Left Layer
        c2 = self.con_AGCN_1(input)
        c3 = self.con_AGCN_2(c2)

        #Right Layer
        c4 = self.con_AGCN_3(input)
        c5 = self.con_AGCN_4(c4)

        #Combine left and right
        add_agcn = Add()([c3,c5])
        c6 = self.con_AGCN_5(add_agcn)
        add_agcn_new = Add()([add_agcn,c6])
        #print('shape of ',add_agcn_new.shape)

        #print('Adapted Global Convolutional Network',add_agcn_new.shape)
        return add_agcn_new

```

Adapted Global Convolutional Network (AGCN)

```

class CA_NET(tf.keras.Model):
    def __init__(self):

        super().__init__() # https://stackoverflow.com/a/27134600/4084039
        #self.FSM = FSM(kernel_size, filters, stride, layers)
        self.model = convolutional_block(kernel_size = 3, filters = 8, stride = 2, layer =1)
        self.ident_1 = identity_block(kernel_size = 3, filters = 8, stride = 2)
        self.model_2 = convolutional_block(kernel_size = 3, filters = 16, stride = 2, layer =2)
        self.ident_2_1 = identity_block(kernel_size = 3, filters = 16, stride = 2)
        self.ident_2_2 = identity_block(kernel_size = 3, filters = 16, stride = 2)
        self.model_3 = convolutional_block(kernel_size = 3, filters = 32, stride = 2, layer =3)
        self.ident_3_1 = identity_block(kernel_size = 3, filters = 32, stride = 2)
        self.ident_3_2 = identity_block(kernel_size = 3, filters = 32, stride = 2)
        self.ident_3_3 = identity_block(kernel_size = 3, filters = 32, stride = 2)

```



```

self.model_4 = convolutional_block(kernel_size = 3, filters = 64, stride = 2, layer = 3)
self.ident_4_1 = identity_block(kernel_size = 3, filters = 64, stride = 2)
self.ident_4_2 = identity_block(kernel_size = 3, filters = 64, stride = 2)
self.ident_4_3 = identity_block(kernel_size = 3, filters = 64, stride = 2)
self.ident_4_4 = identity_block(kernel_size = 3, filters = 64, stride = 2)
self.model_5 = global_flow(filters = 64)
self.model_6 = CFM(kernel_size = 3, filters=64, stride=1)
self.model_7 = CFM(kernel_size = 3, filters=64, stride=1)
self.model_8 = CFM(kernel_size = 3, filters=64, stride=1)
self.model_9 = FSM(filters=32)
self.model_10 = AGCN(filters=32, kernel_size=3)
self.class_conv = Conv2D(21, 3, activation = 'relu', padding = 'same', kernel_initializer =
self.upsampling_final = UpSampling2D(size=(4, 4), interpolation='bilinear')
self.activation_final = Activation('softmax')
self.con_1 = Conv2D(64, 3, activation = 'relu', padding = 'same', kernel_initializer =
self.batch_1 = BatchNormalization()
self.activa_1 = Activation('relu')
self.max_1 = MaxPooling2D((2,2), strides = (2,2))

```

```
def call(self, input):
```

```

    output_1 = self.model(input)
    iden_output_1 = self.ident_1(output_1)
    output_2 = self.model_2(iden_output_1)
    iden_output_2_1 = self.ident_2_1(output_2)
    iden_output_2_2 = self.ident_2_2(iden_output_2_1)
    output_3 = self.model_3(iden_output_2_2)
    iden_output_3_1 = self.ident_3_1(output_3)
    iden_output_3_2 = self.ident_3_2(iden_output_3_1)
    iden_output_3_3 = self.ident_3_3(iden_output_3_2)
    output_4 = self.model_4(iden_output_3_3)
    iden_output_4_1 = self.ident_4_1(output_4)
    iden_output_4_2 = self.ident_4_2(iden_output_4_1)
    iden_output_4_3 = self.ident_4_3(iden_output_4_2)
    iden_output_4_4 = self.ident_4_4(iden_output_4_3)

    output_5 = self.model_5(iden_output_4_4)

    output_6 = self.model_6([output_5, iden_output_4_4])
    output_7 = self.model_7([output_6, iden_output_4_4])
    output_8 = self.model_8([output_7, iden_output_4_4])

    # Add all context fusion
    Add_context_fusion = Add()([output_8, output_7, output_6, output_5])

    #Feature Selection Module
    output_9 = self.model_9(Add_context_fusion)

    output_10 = self.model_10(output_1)
    concat_fsm_agcn = concatenate([output_9, output_10], axis = 3)
    class_1 = self.class_conv(concat_fsm_agcn)
    print(class_1.shape)
    up_sampling = self.upsampling_final(class_1)
    activation = self.activation_final(up_sampling)

```

```
print('CANET',activation.shape)
return activation
```

#C1 layer and 1 identity layer

```
model = convolutional_block(kernel_size = 3, filters = 8, stride = 2, layer =1)
output_1 = model(x1)
ident_1 = identity_block(kernel_size = 3, filters = 8, stride = 2)
iden_output_1 = ident_1(output_1)
```

##C2 layer and 2 identity layer

```
model_2 = convolutional_block(kernel_size = 3, filters = 16, stride = 2, layer =2)
output_2 = model_2(iden_output_1)
ident_2_1 = identity_block(kernel_size = 3, filters = 16, stride = 2)
ident_output_2_1 = ident_2_1(output_2)
ident_2_2 = identity_block(kernel_size = 3, filters = 16, stride = 2)
ident_output_2_2 = ident_2_2(ident_output_2_1)
```

##C3 layer and 3 identity layer

```
model_3 = convolutional_block(kernel_size = 3, filters = 32, stride = 2, layer =3)
output_3 = model_3(iden_output_2_2)
ident_3_1 = identity_block(kernel_size = 3, filters = 32, stride = 2)
ident_output_3_1 = ident_3_1(output_3)
ident_3_2 = identity_block(kernel_size = 3, filters = 32, stride = 2)
ident_output_3_2 = ident_3_2(ident_output_3_1)
ident_3_3 = identity_block(kernel_size = 3, filters = 32, stride = 2)
ident_output_3_3 = ident_3_3(ident_output_3_2)
```

##C4 layer and 4 identity layer

```
model_4 = convolutional_block(kernel_size = 3, filters = 64, stride = 2, layer =3)
output_4 = model_4(iden_output_3_3)
ident_4_1 = identity_block(kernel_size = 3, filters = 64, stride = 2)
ident_output_4_1 = ident_4_1(output_4)
ident_4_2 = identity_block(kernel_size = 3, filters = 64, stride = 2)
ident_output_4_2 = ident_4_2(ident_output_4_1)
ident_4_3 = identity_block(kernel_size = 3, filters = 64, stride = 2)
ident_output_4_3 = ident_4_3(ident_output_4_2)
ident_4_4 = identity_block(kernel_size = 3, filters = 64, stride = 2)
ident_output_4_4 = ident_4_4(ident_output_4_3)
```

Global_Flow

```
model_5 = global_flow(filters = 64)
output_5 = model_5(ident_output_4_4)
```

Context Fusion Module

```
model_6 = CFM(kernel_size = 3, filters=64,stride=1)
output_6 = model_6([output_5,ident_output_4_4])
model_7 = CFM(kernel_size = 3, filters=64,stride=1)
output_7 = model_7([output_6,ident_output_4_4])
```

```

model_8 = CFM(kernel_size = 3, filters=64, stride=1)
output_8 = model_8([output_7, ident_output_4_4])

# Add all context fusion
Add_context_fusion = Add()([output_8, output_7, output_6, output_5])

#Feature Selection Module
model_9 = FSM(filters=32)
output_9 = model_9(Add_context_fusion)
print('FSM----->', output_9.shape)

model_10 = AGCN(filters=32, kernel_size=3)
output_10 = model_10(output_1)

#model_10 = Conv2D(32, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_
concat_fsm_agcn = concatenate([output_9, output_10], axis = 3)
class_1 = Conv2D(21, 3, activation = 'relu', padding = 'same', kernel_initializer = 'he_no
print(class_1.shape)
up_sampling = UpSampling2D(size=(4, 4), interpolation='bilinear')(class_1)
activation = Activation('softmax')(up_sampling)

    FSM-----> (None, 64, 64, 32)
    (None, 64, 64, 21)

'''ca_net = CA_NET()
block = ca_net(x1)
model_canet = Model(inputs=inputs, outputs= block)'''

os.environ['PYTHONHASHSEED'] = '0'

##https://keras.io/getting-started/faq/#how-can-i-obtain-reproducible-results-using-keras-
## Have to clear the session. If you are not clearing, Graph will create again and again a
## Variables will also set to some value from before session
tf.keras.backend.clear_session()

## Set the random seed values to regenerate the model.
np.random.seed(0)
rn.seed(0)
model_canet = Model(inputs=inputs, outputs= activation)

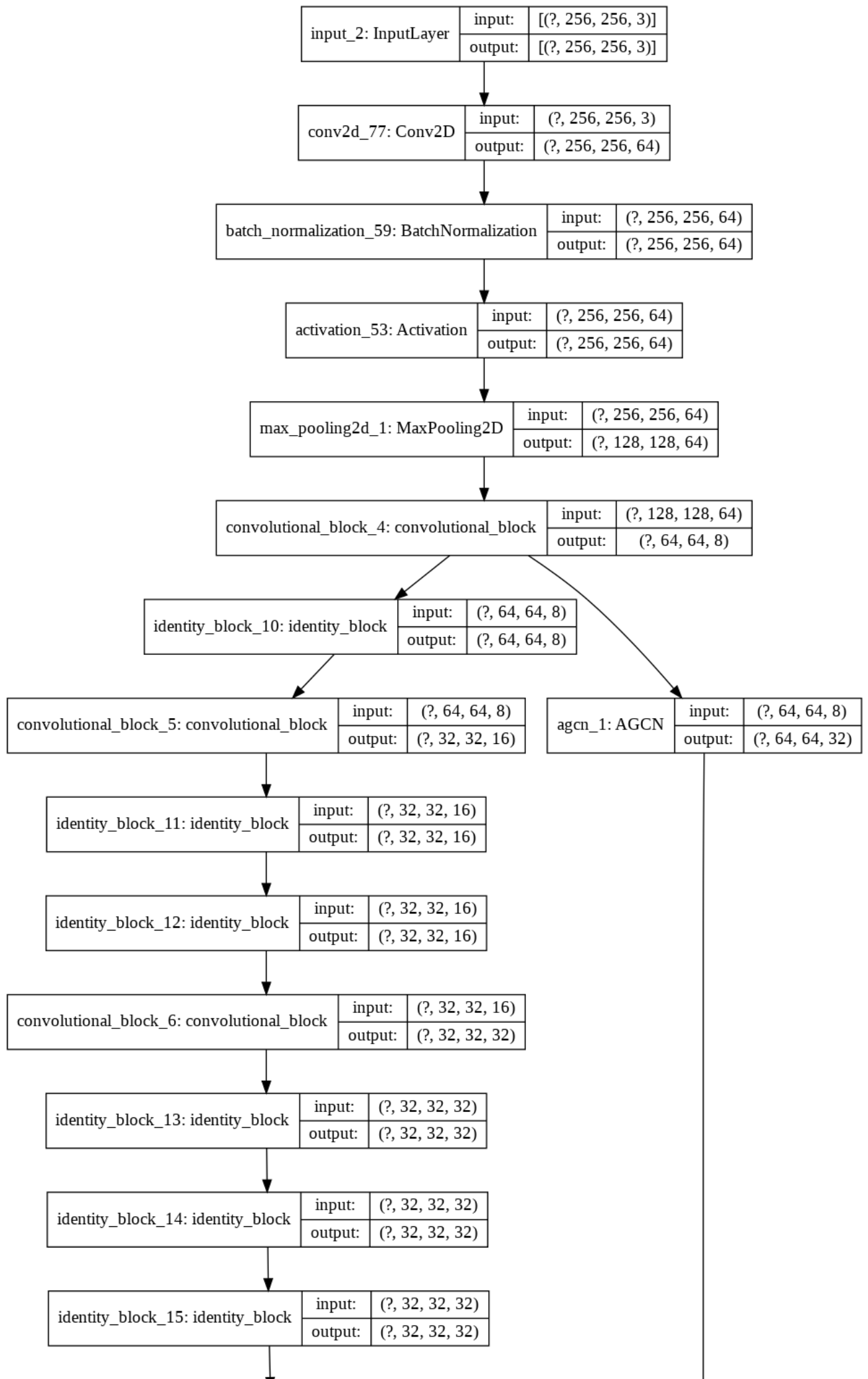
model_canet.summary()

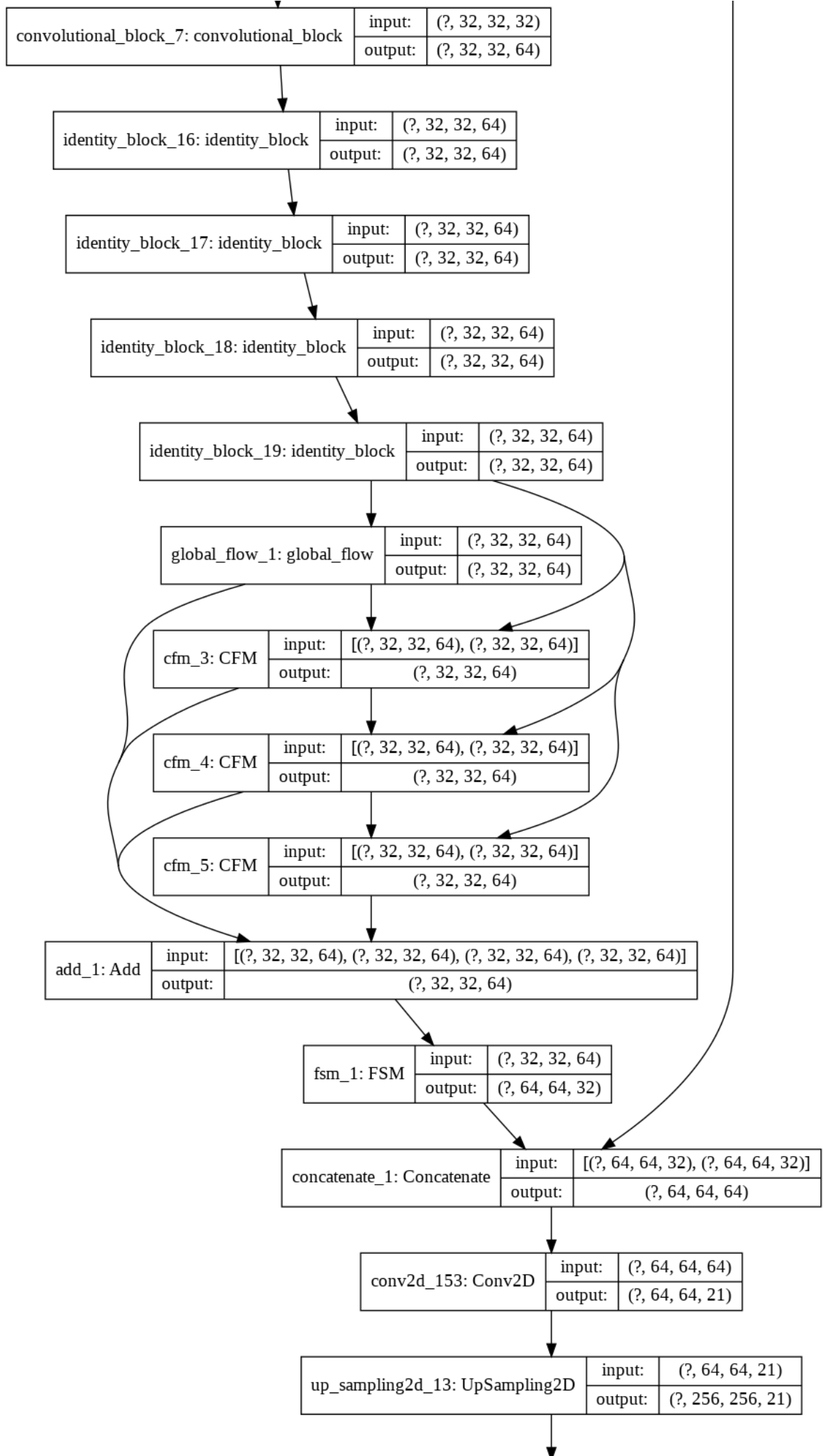
```

Layer (type)	Output Shape	Param #	Connected to
convolutional_block_1 (convolut	(None, 32, 32, 16)	4160	identity_block[0]
identity_block_1 (identity_bloc	(None, 32, 32, 16)	3056	convolutional_blo
identity_block_2 (identity_bloc	(None, 32, 32, 16)	3056	identity_block_1[0]
convolutional_block_2 (convolut	(None, 32, 32, 32)	16000	identity_block_2[0]
identity_block_3 (identity_bloc	(None, 32, 32, 32)	11744	convolutional_blo
identity_block_4 (identity_bloc	(None, 32, 32, 32)	11744	identity_block_3[0]

identity_block_5 (identity_block)	(None, 32, 32, 32)	11744	identity_block_4[0]
convolutional_block_3 (convolutional_block)	(None, 32, 32, 64)	62720	identity_block_5[0]
identity_block_6 (identity_block)	(None, 32, 32, 64)	46016	convolutional_block_3[0]
identity_block_7 (identity_block)	(None, 32, 32, 64)	46016	identity_block_6[0]
identity_block_8 (identity_block)	(None, 32, 32, 64)	46016	identity_block_7[0]
identity_block_9 (identity_block)	(None, 32, 32, 64)	46016	identity_block_8[0]
global_flow (global_flow)	(None, 32, 32, 64)	4416	identity_block_9[0]
cfm (CFM)	(None, 32, 32, 64)	184576	global_flow[0][0] identity_block_9[0]
cfm_1 (CFM)	(None, 32, 32, 64)	184576	cfm[0][0] identity_block_9[0]
cfm_2 (CFM)	(None, 32, 32, 64)	184576	cfm_1[0][0] identity_block_9[0]
add (Add)	(None, 32, 32, 64)	0	cfm_2[0][0] cfm_1[0][0] cfm[0][0] global_flow[0][0]
fsm (FSM)	(None, 64, 64, 32)	2208	add[0][0]
agcn (AGCN)	(None, 64, 64, 32)	27296	convolutional_block_3[0]
concatenate (Concatenate)	(None, 64, 64, 64)	0	fsm[0][0] agcn[0][0]
conv2d_76 (Conv2D)	(None, 64, 64, 21)	12117	concatenate[0][0]
up_sampling2d_6 (UpSampling2D)	(None, 256, 256, 21)	0	conv2d_76[0][0]
activation_52 (Activation)	(None, 256, 256, 21)	0	up_sampling2d_6[0]
=====			
Total params: 916,845			
Trainable params: 913,213			
Non-trainable params: 3,632			

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





activation_105: Activation	input:	(?, 256, 256, 21)
	output:	(?, 256, 256, 21)

```
import segmentation_models as sm
from segmentation_models.metrics import iou_score
from segmentation_models import Unet
import keras
```

```

ACCURACY_THRESHOLD_test = 0.8
class myCallback(tf.keras.callbacks.Callback):
    def __init__(self):
        '''check'''

    def on_train_begin(self, logs={}):
        ## on begin of training, we are creating a instance variable called history
        ## it is a dict with keys [loss, acc, val_loss, val_acc]
        '''self.history={'loss': [], 'IOU_Score': [], 'val_loss': [], 'Val_IOU_Score': []}'''
        self.best_val_iou = 0
        #self.model.save = model.save

    def on_epoch_end(self, epoch, logs=None):
        #print(logs.get('loss'))
        #print(logs.get('iou_score'))
        #print(logs.get('val_iou_score'))

        #print(self.best_val_iou)

        print(f"epoch: {epoch}, train_acc: {logs['iou_score']}, valid_acc: {logs['val_iou_

        if logs['val_iou_score'] > self.best_val_iou :
            print('Model accuarcy improved from {} to {}'.format(self.best_val_iou, logs['val_
            self.model.save_weights("best_model_CANET_NEW.h5", overwrite=True)
            self.best_val_iou = logs['val_iou_score']

        else:
            print('Model not improved from {}'.format(self.best_val_iou))

        if(logs.get('val_iou_score') >= ACCURACY_THRESHOLD_test and logs.get('iou_score')
            print("\nReached %2.2f%% accuracy, so stopping training!!" %(ACCURACY_THRESHOLD_
            self.model.stop_training = True

        #print('\n***'*50)

```

```
early_stop_iou_scores = myCallback()
```

```

# https://github.com/qubvel/segmentation\_models
import segmentation_models as sm
from segmentation_models.metrics import iou_score
from segmentation_models import Unet

```



```
import keras
```

```
focal_loss = sm.losses.cce_dice_loss
```

```
# actually total_loss can be imported directly from library, above example just show you
```

```
# total_loss = sm.losses.binary_focal_dice_loss
```

```
# or total_loss = sm.losses.categorical_focal_dice_loss
```

```
model_canet.compile(optimizer = 'adam', loss=focal_loss, metrics=[iou_score])
```

```
history = model_canet.fit_generator(train_dataloader, epochs=200,  
                                   validation_data=test_dataloader, callbacks = [early_st
```

```
Epoch 1/200
```

```
100/100 [=====] - ETA: 0s - loss: 2.0307 - iou_score: 0.00
```

```
Model accuracy improved from 0 to 0.07771468162536621
```

```
100/100 [=====] - 340s 3s/step - loss: 2.0307 - iou_score
```

```
Epoch 2/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.9901 - iou_score: 0.00
```

```
Model accuracy improved from 0.07771468162536621 to 0.08111810684204102
```

```
100/100 [=====] - 337s 3s/step - loss: 1.9901 - iou_score
```

```
Epoch 3/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.9827 - iou_score: 0.00
```

```
Model accuracy improved from 0.08111810684204102 to 0.09183380752801895
```

```
100/100 [=====] - 337s 3s/step - loss: 1.9827 - iou_score
```

```
Epoch 4/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.9713 - iou_score: 0.00
```

```
Model not improved from 0.09183380752801895
```

```
100/100 [=====] - 330s 3s/step - loss: 1.9713 - iou_score
```

```
Epoch 5/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.9392 - iou_score: 0.00
```

```
Model not improved from 0.09183380752801895
```

```
100/100 [=====] - 333s 3s/step - loss: 1.9392 - iou_score
```

```
Epoch 6/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.8908 - iou_score: 0.00
```

```
Model accuracy improved from 0.09183380752801895 to 0.20672382414340973
```

```
100/100 [=====] - 334s 3s/step - loss: 1.8908 - iou_score
```

```
Epoch 7/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.7890 - iou_score: 0.20
```

```
Model accuracy improved from 0.20672382414340973 to 0.3305586576461792
```

```
100/100 [=====] - 336s 3s/step - loss: 1.7890 - iou_score
```

```
Epoch 8/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.7421 - iou_score: 0.30
```

```
Model not improved from 0.3305586576461792
```

```
100/100 [=====] - 337s 3s/step - loss: 1.7421 - iou_score
```

```
Epoch 9/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.7186 - iou_score: 0.30
```

```
Model not improved from 0.3305586576461792
```

```
100/100 [=====] - 338s 3s/step - loss: 1.7186 - iou_score
```

```
Epoch 10/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.7010 - iou_score: 0.30
```

```
Model not improved from 0.3305586576461792
```

```
100/100 [=====] - 337s 3s/step - loss: 1.7010 - iou_score
```

```
Epoch 11/200
```

```
100/100 [=====] - ETA: 0s - loss: 1.6908 - iou_score: 0.30
```

```
Model accuracy improved from 0.3305586576461792 to 0.3341962695121765
```

```
100/100 [=====] - 339s 3s/step - loss: 1.6908 - iou_score
```

```

Epoch 12/200
100/100 [=====] - ETA: 0s - loss: 1.6766 - iou_score: 0.3
Model not improved from 0.3341962695121765
100/100 [=====] - 337s 3s/step - loss: 1.6766 - iou_score
Epoch 13/200
100/100 [=====] - ETA: 0s - loss: 1.6777 - iou_score: 0.3
Model not improved from 0.3341962695121765
100/100 [=====] - 335s 3s/step - loss: 1.6777 - iou_score
Epoch 14/200
100/100 [=====] - ETA: 0s - loss: 1.6704 - iou_score: 0.3
Model accuracy improved from 0.3341962695121765 to 0.33432522416114807
100/100 [=====] - 335s 3s/step - loss: 1.6704 - iou_score

```

```

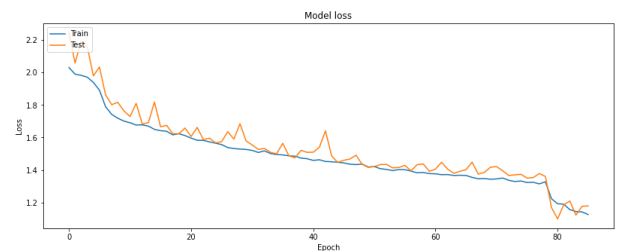
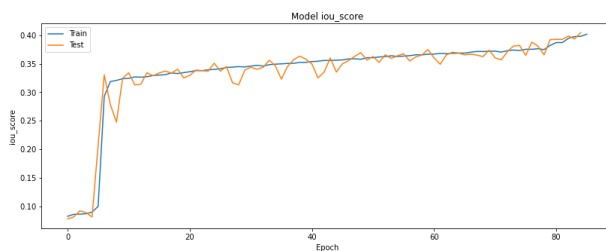
# Plot training & validation iou_score values
plt.figure(figsize=(30, 5))
plt.subplot(121)
plt.plot(history.history['iou_score'])
plt.plot(history.history['val_iou_score'])
plt.title('Model iou_score')
plt.ylabel('iou_score')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')

```

```

# 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()

```



```

for p, i in enumerate(X_train):
    #original image

    #image = cv2.imread(list(X_test['image'])[p], cv2.IMREAD_UNCHANGED)
    image = cv2.imread(os.path.join(dir_path, i+'_leftImg8bit.jpg'), cv2.IMREAD_UNCHANGED)
    image = cv2.resize(image, (256,256),interpolation = cv2.INTER_NEAREST)

```