part_1

Model building: Brain MRI Segmentation

apart from using pretrained model, we will also train some model from scrach so

```
so in model building stage we will use UNET models as they are popular for the sematic segmantation for the medical problem.
here we mainly focus on UNET and try to use different different variation of UNET for example - Unet with resnet34, etc.
so instead of creating architecture for all and train from scratch which is too much time consuming
we will use consept of transfer learning .
for the context - transfer learning : is a concept where previously trained model is reused to solve the similar type of problem. h
so there is libary "segmantation model" which provides multiple pretrained model with different-2 variation of UNET .
to install this library and see how it work - click me
there are multiple backbone(variation) and with some research
we have listed our priorities as follows which we train our tasks:
1. UNET with resnet34 (basemodel)
2. UNET with inceptionv3
3. UNet with EfficientNet
4. UNet with senet154
5. UNet with senet
```

that we can compare what is diffence among them.(in next upcoming notebook)

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→ 1. Dependencies

```
# import pickle
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from os import path
import cv2
import os
import re
import random
import pdb
import seaborn as sns
import tensorflow as tf
import keras
!pip install -U segmentation-models==1.0.1
from keras.utils.layer utils import get source inputs
import segmentation models as sm
sm.set framework('tf.keras')
tf.keras.backend.set image data format('channels last')
from segmentation models import Unet
from segmentation models.metrics import iou score
from segmentation models.losses import DiceLoss
import pickle
     Looking in indexes: <a href="https://pypi.org/simple">https://us-python.pkg.dev/colab-wheels/public/simple/</a>
     Collecting segmentation-models==1.0.1
       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 5.5 MB/s
     Collecting image-classifiers==1.0.0
       Downloading image_classifiers-1.0.0-py3-none-any.whl (19 kB)
     Collecting efficientnet==1.0.0
       Downloading efficientnet-1.0.0-py3-none-any.whl (17 kB)
```

```
Requirement already satisfied: scikit-image in /usr/local/lib/python3.7/dist-packages (from efficientnet==1.0.0->segmentation-m
Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages (from keras-applications<=1.0.8,>=1.0.7->segmenta
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.7/dist-packages (from keras-applications<=1.0.8,>=1.0.7->
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/dist-packages (from h5py->keras-applications<=1.0.8,
Requirement already satisfied: scipy>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==1.0.0->
Requirement already satisfied: imageio>=2.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==1.0.0
Requirement already satisfied: tifffile>=2019.7.26 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==
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Requirement already satisfied: pillow!=7.1.0,!=7.1.1,>=4.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->effi
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficien
Requirement already satisfied: PyWavelets>=1.1.1 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==1.
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0,>=2.0.0->sci
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from matplot
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0,>=2.0.0->
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0,>=2.0.0->scikit-i
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1->matplotlib!
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from python-dateutil>=2.1->matplotlib!=3.0.0
Installing collected packages: keras-applications, image-classifiers, efficientnet, segmentation-models
Successfully installed efficientnet-1.0.0 image-classifiers-1.0.0 keras-applications-1.0.8 segmentation-models-1.0.1
Segmentation Models: using `keras` framework.
```

Streaming output truncated to the last 5000 lines.

inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7294 19890104/TCGA DU 7294 19890104 9 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 1.tif inflating: lgg-mri-segmentation/kaggle_3m/TCGA_DU_7298_19910324/TCGA_DU_7298_19910324_10.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 10 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 11.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 11 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 12.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 12 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 13.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 13 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 14.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 14 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 15.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 15 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 16.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 16 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 17.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 17 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 18.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 18 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 19.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 19 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 1 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 2.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 20.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 20 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 21.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 21 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 22.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 22 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 23.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 23 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 24.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 24 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 25.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 25 mask.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 26.tif inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 26 mask.tif inflating: lgg-mri-segmentation/kaggle_3m/TCGA_DU_7298_19910324/TCGA_DU_7298_19910324_27.tif

```
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 27 mask.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 28.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 28 mask.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 29.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 29 mask.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 2 mask.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 3.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 30.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 30 mask.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 31.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 31 mask.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 32.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 32 mask.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 3 mask.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 4.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 4 mask.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 5.tif
inflating: lgg-mri-segmentation/kaggle 3m/TCGA DU 7298 19910324/TCGA DU 7298 19910324 5 mask.tif
```

▼ 2. data loading

```
# pdb.set trace()
        if path.isdir(sub_dir):
            for j in os.listdir(sub_dir):
                  img_dir.append(str(sub_dir+j))
    #
                if "mask" in j :
                    mask_img_url.append(str(sub_dir+j))
    # pdb.set trace()
   img_url = [re.sub("_mask","", i) for i in mask_img_url]
    df["image"] = img url
   df["mask"] = mask img url
    return df
main dir = "/content/kaggle 3m/"
data = return_file_name(main_dir)
    checking all file if path is correct
.....
b = True
for i in range(data.shape[0]):
    if not path.isfile(data["image"][i]):
        b = False
    elif not path.isfile(data["mask"][i]):
        b = False
print(b)
     True
data.head()
```

	image	mask
0	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA
1	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA
2	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA
3	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA
4	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA	/content/kaggle_3m/TCGA_HT_7855_19951020/TCGA
data.shape		
(3929, 2)		

▼ 4. Data Preprocessing

In data this stage: we will analyse, filter and transforming data so that algorithm can understand and work with the preprocessed data.

So, as the popular saying goes, "if garbage goes in, garbage comes out". model will only work successfully if data going into machine is high quality.

when we get data from real world scenarios, these is high chances that it contains noice data and missing value.

in this case, we are using the LGG Segmentation Dataset.

▼ 4.1 Data cleaning and filtering

while doing EDA we observe there are some images which doesn't contain any information(black image) so we will remove those images

```
data.shape
     (3929, 2)
def garbage_img_prepross(df):
        finding image which doesn't have much infomation
        here we choose 30 as pixel value threshhold all img which maximum pixel value
        is less that 30 considered to be garbage image
    thres = 30
   temp img = []
    for i in df["image"]:
        val = np.max(cv2.imread(i))
        if val <thres:
            temp_img.append(i)
    temp img = np.array(temp img)
    df = df[~df["image"].isin(temp_img)]
    return df, temp_img
```

```
data, temp img = garbage img prepross(data)
print("we got total {} image which doesn't contains information, so in order to prepross, we removed it from data".format(len(temp im
     we got total 89 image which doesn't contains information, so in order to prepross, we removed it from data
data.shape
     (3840, 2)
# # visulization garbase images which having less information (max picxel val < 30)
\# r = 3
# fig,axis = plt.subplots(r, c, figsize=(16,10))
# p = 0
# for j in range(r):
      for i in range(c):
          axis[j,i].imshow(cv2.imread(temp img[63-p]))
          p +=1
```

these image in our train data doesn't have any information so as next move we will remove it from our train data so that our model learn better

NOW, going ahead, we resizes of all images(will done in data pipeline), remove garbage images, now our data is ready for next task - (data pipeline, augmentation, modeling)

```
# data.to_pickle("preprocessed_data.pkl")
# data = pd.read_pickle("/content/preprocessed_data.pkl")
```

▼ Data Pipeline

```
from sklearn.model selection import train test split
  X train, X test = train test split(data, test size=0.20, random state=42)
  X train = X train.reset index(drop=True)
  X test = X test.reset index(drop=True)
  # def preprocess test img(test):
        te img = []
        for i in range(test.shape[0]):
            image = cv2.imread(test[i], cv2.IMREAD UNCHANGED)
            image = cv2.resize(image, (256,256))
            image = preprocess input(image)
            pdb.set trace()
  #
            te img.append(image)
  #
        return np.array(te img)
  # X test1 = preprocess test img(X test["image"])

▼ image generator

  # 1. creating image generator - through url
  from tensorflow.keras.preprocessing.image import ImageDataGenerator
  datagen=ImageDataGenerator(rescale=1./255.,
                             rotation_range=0.2, zoom_range=0.1, horizontal_flip=True,
                                  width_shift_range=0.05,
                                  height_shift_range=0.05,
                                  shear_range=0.05, fill_mode='nearest')
```

```
mask datagen=ImageDataGenerator(rescale=1./255.,
                           rotation_range=0.2, zoom_range=0.1, horizontal flip=True,
                                width shift range=0.05,
                                height shift range=0.05,
                                shear range=0.05, fill mode='nearest')
val datagen=ImageDataGenerator(rescale=1./255. )
val mask datagen=ImageDataGenerator(rescale=1./255. )
BATCH SIZE = 16
train generator=datagen.flow from dataframe(dataframe=X train, x col='image',
                                            color mode = 'rgb', class mode=None,
                                            target size=(256,256), batch size=BATCH SIZE,
                                            seed=42, shuffle=True)
train mask generator = mask datagen.flow from dataframe(dataframe=X train,
                                                                    x col='mask',
                                                                    batch size=BATCH SIZE,
                                                                    class mode=None,
                                                                    target size=(256, 256),
                                                                    seed=42,
                                                                    color mode='grayscale')
val image generator = val datagen.flow from dataframe(dataframe=X test, x col='image',
                                                batch size=BATCH SIZE, seed=42,
                                                shuffle=True, color mode='rgb',
                                                class mode=None, target size=(256,256))
val_mask_generator = val_mask_datagen.flow_from_dataframe(dataframe=X_test, x_col='mask',
                                                batch_size=BATCH_SIZE, seed=42,
                                                shuffle=True, color mode='grayscale',
```

```
class_mode=None,target_size=(256,256))
```

```
def data iterator(image generator, mask generator):
    while True:
       X, Y = next(image generator), next(mask generator)
       vield X, Y
def data generator(train image generator, train mask generator, val image generator, val mask generator):
    return data iterator(train image generator, train mask generator), data iterator(val image generator, val mask generator)
train data loader, val data loader = data generator(train generator, train mask generator, val image generator, val mask generator)
     Found 3072 validated image filenames.
     Found 3072 validated image filenames.
     Found 768 validated image filenames.
     Found 768 validated image filenames.
train generator.n//BATCH SIZE, val image generator.n//BATCH SIZE
     (192, 48)
# !rm -rf ./logs/
```

→ callbacks

%load_ext tensorboard

```
# define callbacks for learning rate scheduling and best checkpoints saving
import datetime
from tensorflow.keras.callbacks import ModelCheckpoint
```

```
def create_callback_lists(name = ""):
      filepath='best model with {}.h5'.format(name)
      checkpoint = ModelCheckpoint(filepath=filepath, monitor='val iou score', verbose=1, save best only=True, mode='max')
      learning rt = tf.keras.callbacks.ReduceLROnPlateau(monitor='val iou score', min lr=0.0001,patience=1, verbose=1)
      # !rm -rf ./logs/
      log dir="logs/fit/" + datetime.datetime.now().strftime("%Y-%m-%d-%H %M")
      early stop callback = tf.keras.callbacks.EarlyStopping(monitor='val loss', patience=3)
      tensorboard callback = tf.keras.callbacks.TensorBoard(log dir=log dir, histogram freg=1, write graph=True)
      return [early stop callback, tensorboard callback, checkpoint]
  callback list = create callback lists()

▼ drive connect

  from google.colab import drive
```

```
drive.mount('/content/drive')
     Mounted at /content/drive
```

→ 5. Modeling

▼ Base line model

```
# loading unet model with backbone - resnet34
model = sm.Unet('resnet34', encoder_weights="imagenet", classes=1,
```

```
activation='sigmoid',encoder freeze=True, input shape=(256, 256,3))
```

Epoch 10/10

```
optim = tf.keras.optimizers.Adam(learning rate = .006)
callback list = create callback lists(name = "resnet34 UNET")
loss = DiceLoss()#sm.losses.bce jaccard loss
model.compile(optim, loss, metrics=[iou score])
# with different augmentation techinique
# train data loader, val data loader = data generator(train generator, train mask generator, val image generator, val mask generator)
callback list = create callback lists("baseline unet")
history = model.fit(train data loader, steps per epoch=192, epochs=10,
            validation data = val data loader, validation steps = 48,
            initial epoch = 0, use multiprocessing = True )#callbacks = callback list,
   Epoch 1/10
   Epoch 2/10
   Epoch 3/10
   Epoch 4/10
   Epoch 5/10
   192/192 [============= ] - 81s 420ms/step - loss: 0.2167 - iou score: 0.6539 - val loss: 0.9994 - val iou score
   Epoch 6/10
   192/192 [============== ] - 82s 426ms/step - loss: 0.2149 - iou score: 0.6599 - val loss: 0.2782 - val iou score
   Epoch 7/10
   Epoch 8/10
   192/192 [============= ] - 81s 421ms/step - loss: 0.1709 - iou score: 0.7147 - val loss: 0.2033 - val iou score
   Epoch 9/10
```

192/192 [=============] - 82s 430ms/step - loss: 0.1623 - iou score: 0.7297 - val loss: 0.2393 - val iou score

```
history = model.fit(train data loader, steps per epoch=192, epochs=5,
        validation data = val data loader, validation steps = 48,
        initial epoch = 0, use multiprocessing = True )#callbacks = callback list,
  Epoch 1/5
  Epoch 2/5
  192/192 [============= ] - 86s 450ms/step - loss: 0.1626 - iou score: 0.7270 - val loss: 0.1853 - val iou score
  Epoch 3/5
  Epoch 4/5
  Epoch 5/5
  history = model.fit(train data loader, steps per epoch=192, epochs=5,
        validation data = val data loader, validation steps = 48,
        initial epoch = 0, use multiprocessing = True )#callbacks = callback list,
  Epoch 1/5
  Epoch 2/5
  192/192 [============= ] - 83s 434ms/step - loss: 0.1449 - iou score: 0.7512 - val loss: 0.1548 - val iou score
  Epoch 3/5
  Epoch 4/5
  Epoch 5/5
```

```
initial_epoch = 10, callbacks = callback_list,use_multiprocessing = True )#callbacks = callback_list,
```

```
Epoch 11/15
Epoch 11: val iou score did not improve from 0.71187
Epoch 12/15
Epoch 12: val iou score improved from 0.71187 to 0.74025, saving model to best model with baseline unet.hdf5
Epoch 13/15
Epoch 13: val iou score improved from 0.74025 to 0.74189, saving model to best model with baseline unet.hdf5
Epoch 14/15
Epoch 14: val iou score improved from 0.74189 to 0.74702, saving model to best model with baseline unet.hdf5
Epoch 15/15
Epoch 15: val iou score improved from 0.74702 to 0.75386, saving model to best model with baseline unet.hdf5
192/192 [============= ] - 96s 499ms/step - loss: 0.1347 - iou score: 0.7662 - val loss: 0.1460 - val iou score
```

saving and loading model in drive

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

# model.save_weights("/content/drive/MyDrive/imp document/unet_res_model.hdf5")
# model.load_weights("/content/drive/MyDrive/imp document/unet_res_model.hdf5")
```

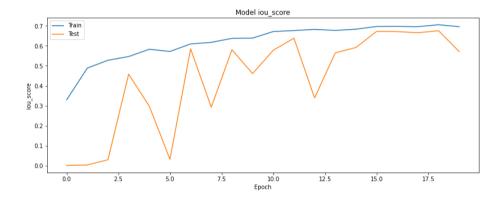
```
train data loader, val data loader = data generator(train generator, train mask generator, val image generator, val mask generator)
callback list = create callback lists("baseline unet")
history = model.fit(train data loader, steps per epoch=384, epochs=20,
        validation data = val data loader, validation steps = 96,
        initial epoch = 0, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
  Epoch 1/20
  Epoch 1: val iou score improved from -inf to 0.00048, saving model to best model with baseline unet.hdf5
  Epoch 2/20
  Epoch 2: val iou score improved from 0.00048 to 0.00269, saving model to best model with baseline unet.hdf5
  Epoch 3/20
  Epoch 3: val iou score improved from 0.00269 to 0.02921, saving model to best model with baseline unet.hdf5
  Epoch 4/20
  Epoch 4: val iou score improved from 0.02921 to 0.45811, saving model to best model with baseline unet.hdf5
  Epoch 5/20
  Epoch 5: val iou score did not improve from 0.45811
  Epoch 6/20
  Epoch 6: val iou score did not improve from 0.45811
  Epoch 7/20
  Epoch 7: val iou score improved from 0.45811 to 0.58481, saving model to best_model_with_baseline_unet.hdf5
  Epoch 8/20
  Epoch 8: val iou score did not improve from 0.58481
```

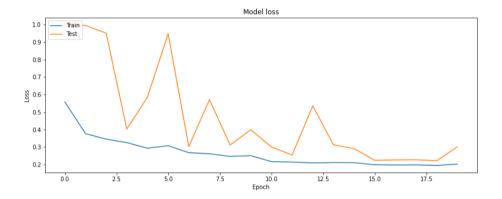
with different augmentation techinique - 20 epochs

```
Epoch 9/20
 Epoch 9: val iou score did not improve from 0.58481
 Epoch 10/20
 Epoch 10: val iou score did not improve from 0.58481
 Epoch 11/20
 Epoch 11: val iou score did not improve from 0.58481
 Epoch 12/20
 Epoch 12: val iou score improved from 0.58481 to 0.63858, saving model to best model with baseline unet.hdf5
 Epoch 13/20
 Epoch 13: val iou score did not improve from 0.63858
 Epoch 14/20
 Epoch 14: val iou score did not improve from 0.63858
 Epoch 15/20
# Plot training & validation iou score values
```

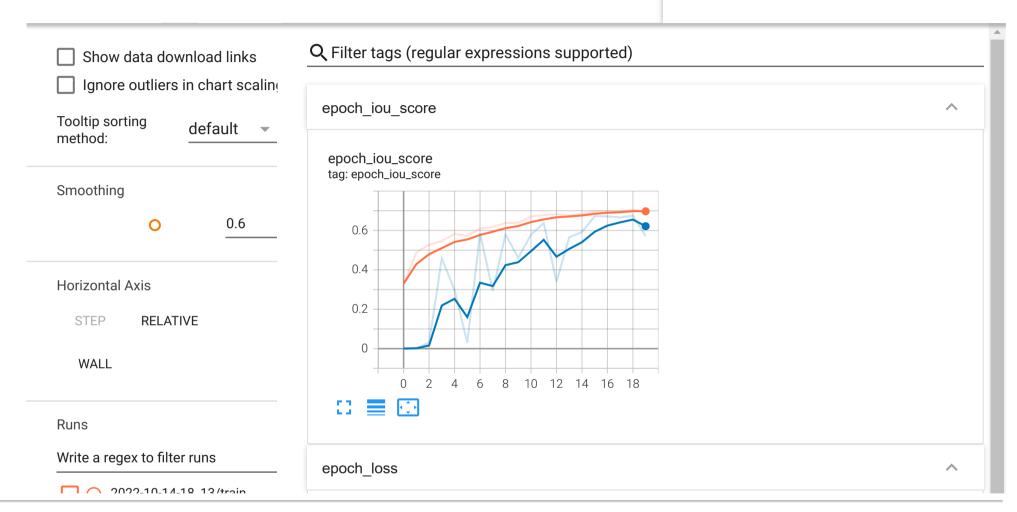
```
# Plot training & validation iou_score values
plt.figure(figsize=(30, 5))
plt.subplot(121)
plt.plot(history.history['iou_score'])
plt.plot(history.history['val_iou_score'])
plt.title('Model iou_score')
plt.ylabel('iou_score')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
# Plot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





loading tensorboard
%tensorboard --logdir logs/fit



with different augmentation techinique
train_data_loader, val_data_loader = data_generator(train_generator, train_mask_generator, val_image_generator, val_mask_generator)
callback_list = create_callback_lists("baseline_unet")

history = model.fit(train_data_loader, steps_per_epoch=384, epochs=40,

validation_data = val_data_loader, validation_steps = 96, initial_epoch = 0, callbacks = callback_list,use_multiprocessing = True)#callbacks = callback_list,

```
Epoch 1/40
Epoch 1: val iou score improved from -inf to 0.00004, saving model to best model with baseline unet.hdf5
Epoch 2/40
Epoch 2: val iou score did not improve from 0.00004
Epoch 3/40
Epoch 3: val iou score improved from 0.00004 to 0.32058, saving model to best model with baseline unet.hdf5
Epoch 4/40
Epoch 4: val iou score improved from 0.32058 to 0.54698, saving model to best model with baseline unet.hdf5
Epoch 5/40
Epoch 5: val iou score did not improve from 0.54698
Epoch 6/40
Epoch 6: val iou score improved from 0.54698 to 0.61231, saving model to best model with baseline unet.hdf5
Epoch 7/40
Epoch 7: val iou score improved from 0.61231 to 0.61754, saving model to best model with baseline unet.hdf5
Epoch 8/40
Epoch 8: val iou score did not improve from 0.61754
Epoch 9/40
Epoch 9: val iou score did not improve from 0.61754
```

```
Epoch 10/40
Epoch 10: val iou score did not improve from 0.61754
Epoch 11/40
Epoch 11: val iou score improved from 0.61754 to 0.64517, saving model to best model with baseline unet.hdf5
Epoch 12/40
Epoch 12: val iou score did not improve from 0.64517
Epoch 13/40
Epoch 13: val iou score did not improve from 0.64517
Epoch 14/40
Epoch 14: val iou score improved from 0.64517 to 0.66384, saving model to best model with baseline unet.hdf5
```

history = model.fit(train_dataloader, steps_per_epoch=len(train_dataloader), epochs=20, validation_data=test_dataloader, callbacks =

```
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
```

history = model.fit(train_dataloader, steps_per_epoch=len(train_dataloader), epochs=20, validation_data=test_dataloader, callbacks =

model.save_weights("model_case_2.h5")

history = model.fit(train_dataloader, steps_per_epoch=len(train_dataloader), epochs=20, validation_data=test_dataloader, callbacks =

```
Epoch 1/20
Epoch 2/20
Epoch 3/20
Epoch 4/20
Epoch 5/20
Epoch 6/20
Epoch 7/20
Epoch 8/20
Epoch 9/20
Epoch 10/20
Epoch 11/20
Epoch 12/20
```

```
Epoch 13/20
Epoch 14/20
Epoch 15/20
Epoch 16/20
Epoch 17/20
Epoch 18/20
Epoch 19/20
Epoch 20/20
```

hyperparameter tuning

for hyperparameter tuning we have choosen 100 image only so that we can better analysis which loss, matrix, optimiser is better.

```
from tensorflow.keras.models import clone_model

tf.random.set_seed(22)
tf.keras.backend.clear_session()

# model = clone_model(model_t)
model = sm.Unet('resnet34', encoder_weights="imagenet", classes=1, activation='sigmoid',encoder_freeze=True, input_shape=(256, 256,3)

optim = tf.keras.optimizers.Adam()
focal_loss = DiceLoss()#sm.losses.bce_jaccard_loss
```

```
model.compile(optim, focal_loss, metrics=[iou_score])
```

diceloss + ADAM

model.fit(train_dataloader, steps_per_epoch=len(train_dataloader), epochs=50, validation_data=test_dataloader)

```
Epoch 1/50
Epoch 2/50
Epoch 3/50
Epoch 4/50
Epoch 5/50
Epoch 6/50
Epoch 7/50
Epoch 8/50
Epoch 9/50
Epoch 10/50
12/12 [============== ] - 2s 190ms/step - loss: 0.5545 - iou score: 0.3090 - val loss: 0.9327 - val iou score:
Epoch 11/50
Epoch 12/50
Epoch 13/50
Epoch 14/50
Epoch 15/50
Epoch 16/50
Epoch 17/50
```

```
Epoch 18/50
12/12 [=============== ] - 2s 193ms/step - loss: 0.4821 - iou score: 0.3760 - val loss: 0.7225 - val iou score:
Epoch 19/50
Epoch 20/50
Epoch 21/50
Epoch 22/50
Epoch 23/50
Epoch 24/50
Epoch 25/50
Epoch 26/50
Epoch 27/50
Epoch 28/50
Frach 20/F0
```

got val_iou score = .38 with 1000 images

diceloss + ADAM

```
Epoch 5/50
Epoch 6/50
Epoch 7/50
Epoch 8/50
12/12 [============== ] - 2s 190ms/step - loss: 0.3237 - iou score: 0.5379 - val loss: 0.5700 - val iou score:
Epoch 9/50
Epoch 10/50
Epoch 11/50
Epoch 12/50
Epoch 13/50
Epoch 14/50
Epoch 15/50
Epoch 16/50
Epoch 17/50
Epoch 18/50
Epoch 19/50
Epoch 20/50
Epoch 21/50
Epoch 22/50
Epoch 23/50
Epoch 24/50
Epoch 25/50
```

got val_iou score = .41 with 100 images and epch = 100

performance is not increasing after some extent

```
# diceloss + ADAM
```

model.fit(train_dataloader, steps_per_epoch=len(train_dataloader), epochs=10,validation_data=test_dataloader)

```
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
<keras.callbacks.History at 0x7f5090271fd0>
```

```
# diceloss + ADAM
model.fit(train dataloader, steps per epoch=len(train dataloader), epochs=10, validation data=test dataloader
 Epoch 1/10
 Epoch 2/10
 Epoch 3/10
 Epoch 4/10
 Epoch 5/10
 Epoch 6/10
 Epoch 7/10
 Epoch 8/10
 Epoch 9/10
 Epoch 10/10
 <keras.callbacks.History at 0x7efdc7dbc950>
# diceloss + ADAM + .0001
model.fit(train dataloader, steps per epoch=len(train dataloader), epochs=10, validation data=test dataloader
 Epoch 1/10
 Epoch 2/10
 Epoch 3/10
```

```
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
<keras.callbacks.History at 0x7efdcd2fdad0>
# diceloss + ADAM + .1
model.fit(train dataloader, steps per epoch=len(train dataloader), epochs=10, validation data=test dataloader
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
```

Epoch 4/10

```
<keras.callbacks.History at 0x7efdcdff0550>
# diceloss + ADAM + .01
model.fit(train dataloader, steps per epoch=len(train dataloader), epochs=10,validation data=test dataloader
 Epoch 1/10
 Epoch 2/10
 Epoch 3/10
 Epoch 4/10
 Epoch 5/10
 Epoch 6/10
 Epoch 7/10
 Epoch 8/10
 Epoch 9/10
 Epoch 10/10
 <keras.callbacks.History at 0x7efdcfde7d90>
# jaccard + sgd
model.fit(train dataloader, steps per epoch=len(train dataloader), epochs=10,validation data=test dataloader
 Epoch 1/10
 Epoch 2/10
```

```
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
Epoch 9/10
Epoch 10/10
<keras.callbacks.History at 0x7f001b0e02d0>
```

jaccard

4

```
model.fit(train_dataloader, steps_per_epoch=len(train_dataloader), epochs=10,validation_data=test_dataloader
```

```
Epoch 1/10
Epoch 2/10
Epoch 3/10
Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
```

```
Epoch 9/10
Epoch 10/10
# diceloss
callback list = [checkpoint, learning rt]
# model.load weights("/content/model segmentation.h5")
history = model.fit(train dataloader, steps per epoch=len(train dataloader), epochs=10, validation data=test dataloader
 Epoch 1/10
Epoch 2/10
Epoch 3/10
 Epoch 4/10
Epoch 5/10
Epoch 6/10
Epoch 7/10
Epoch 8/10
 Epoch 9/10
 Epoch 10/10
```

4

▼ 5.2 model - inceptionv3_unet

```
# loading unet model with backbone - resnet34
model = sm.Unet('inceptionv3', encoder weights="imagenet", classes=1,
             activation='sigmoid',encoder freeze=True, input shape=(256, 256,3))
    Downloading data from https://github.com/fchollet/deep-learning-models/releases/download/v0.5/inception v3 weights tf dim order
    87910968/87910968 [=========== ] - 7s Ous/step
callback list = create callback lists(name = "inceptionv3 UNET")
optim = tf.keras.optimizers.Adam()
loss = DiceLoss()#sm.losses.bce jaccard loss
model.compile(optim, loss, metrics=[iou score])
train data loader, val data loader = data generator(train generator, train mask generator, val image generator, val mask generator)
callback list = create callback lists("inceptionv3 unet")
history = model.fit(train data loader, steps per epoch=384, epochs=20,
                validation data = val data loader, validation steps = 96,
                initial epoch = 0, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
    Epoch 1/20
    Epoch 1: val iou score improved from -inf to 0.25847, saving model to best model with inceptionv3 unet.hdf5
    384/384 [============ ] - 93s 194ms/step - loss: 0.5105 - iou score: 0.3743 - val loss: 0.6090 - val iou sco
    Epoch 2/20
    Epoch 2: val iou score improved from 0.25847 to 0.55838, saving model to best model with inceptionv3 unet.hdf5
    Epoch 3/20
```

```
Epoch 3: val iou score improved from 0.55838 to 0.56096, saving model to best model with inceptionv3 unet.hdf5
Epoch 4/20
Epoch 4: val iou score improved from 0.56096 to 0.60582, saving model to best model with inceptionv3 unet.hdf5
384/384 [=================== ] - 130s 339ms/step - loss: 0.2837 - iou score: 0.5943 - val loss: 0.2772 - val iou sc
Epoch 5/20
Epoch 5: val iou score did not improve from 0.60582
Epoch 6/20
Epoch 6: val iou score did not improve from 0.60582
Epoch 7/20
Epoch 7: val iou score did not improve from 0.60582
Epoch 8/20
Epoch 8: val iou score improved from 0.60582 to 0.65729, saving model to best model with inceptionv3 unet.hdf5
Epoch 9/20
Epoch 9: val iou score did not improve from 0.65729
Epoch 10/20
Epoch 10: val iou score did not improve from 0.65729
Epoch 11/20
Epoch 11: val iou score improved from 0.65729 to 0.69145, saving model to best model with inceptionv3 unet.hdf5
Epoch 12/20
Epoch 12: val iou score did not improve from 0.69145
384/384 [============== ] - 76s 197ms/step - loss: 0.1855 - iou_score: 0.7154 - val_loss: 0.2209 - val_iou_sco
Epoch 13/20
```

```
# 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()
```

Model iou score Model loss

loading tensorboard
%tensorboard --logdir logs/fit

```
history = model3.fit(train_data_loader, steps_per_epoch=384, epochs=20,
validation_data = val_data_loader, validation_steps = 96,
initial_epoch = 0, callbacks = callback_list,use_multiprocessing = True )#callbacks = callback_list,
```

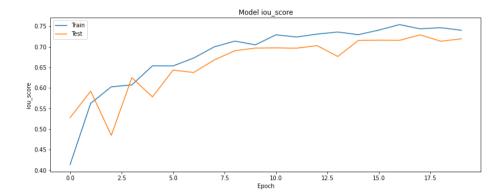
```
Epoch 1/20
Epoch 1: val iou score improved from -inf to 0.52775, saving model to best model with efficientnetb1 UNET.hdf5
Epoch 2/20
Epoch 2: val iou score improved from 0.52775 to 0.59215, saving model to best_model_with_efficientnetb1_UNET.hdf5
Epoch 3/20
Epoch 3: val iou score did not improve from 0.59215
Epoch 4/20
Epoch 4: val iou score improved from 0.59215 to 0.62494, saving model to best model with efficientnetb1 UNET.hdf5
Epoch 5/20
Epoch 5: val iou score did not improve from 0.62494
Epoch 6/20
Epoch 6: val iou score improved from 0.62494 to 0.64332, saving model to best model with efficientnetb1 UNET.hdf5
Epoch 7/20
Epoch 7: val iou score did not improve from 0.64332
Epoch 8/20
Epoch 8: val iou score improved from 0.64332 to 0.66788, saving model to best model with efficientnetb1 UNET.hdf5
Epoch 9/20
Epoch 9: val_iou_score improved from 0.66788 to 0.69038, saving model to best_model_with_efficientnetb1_UNET.hdf5
```

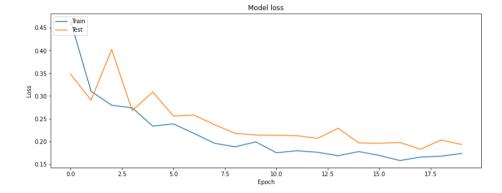
```
Epoch 10/20
  Epoch 10: val iou score improved from 0.69038 to 0.69692, saving model to best model with efficientnetb1 UNET.hdf5
  Epoch 11/20
  Epoch 11: val iou score improved from 0.69692 to 0.69732, saving model to best model with efficientnetb1 UNET.hdf5
  384/384 [============ ] - 84s 218ms/step - loss: 0.1749 - iou score: 0.7291 - val loss: 0.2135 - val iou sco
  Epoch 12/20
  Epoch 12: val iou score did not improve from 0.69732
  Epoch 13/20
  Epoch 13: val iou score improved from 0.69732 to 0.70276, saving model to best model with efficientnetb1 UNET.hdf5
  384/384 [============ ] - 80s 207ms/step - loss: 0.1761 - iou score: 0.7308 - val loss: 0.2067 - val iou sco
  Epoch 14/20
  Epoch 14: val iou score did not improve from 0.70276
  L 4F/20
# Plot training & validation iou score values
```

```
# 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')

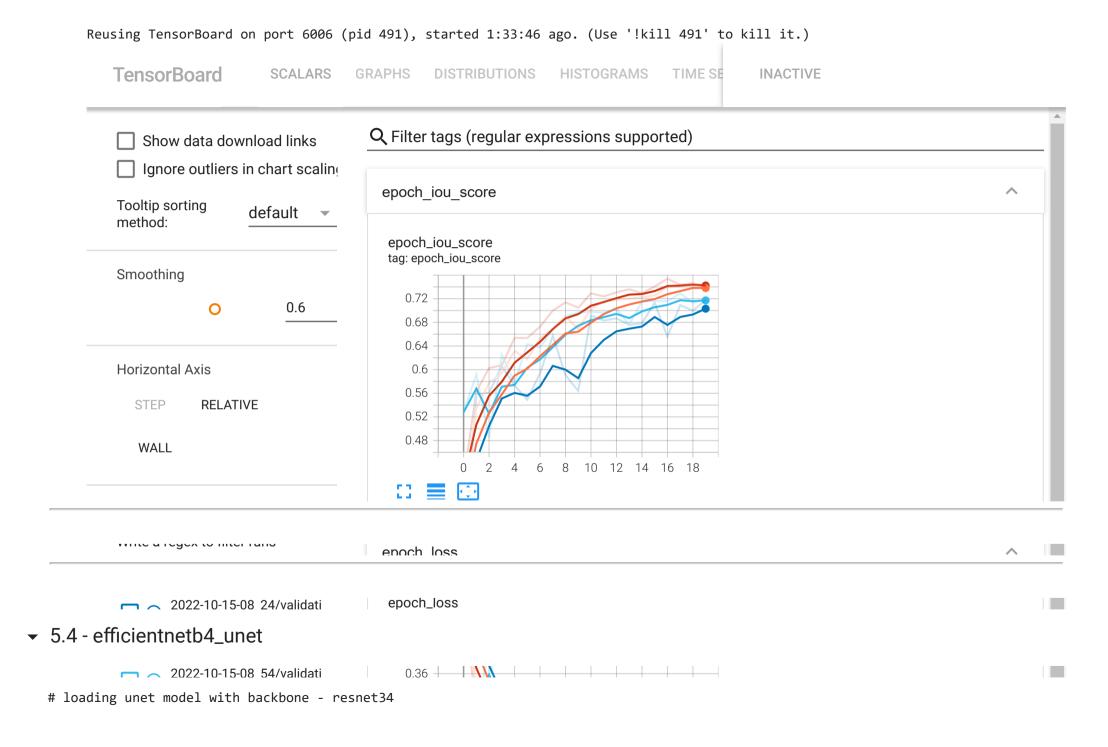
# Plot training & validation loss values
plt.subplot(122)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
```

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





loading tensorboard
%tensorboard --logdir logs/fit



```
model4 = sm.Unet('efficientnetb4', encoder weights="imagenet", classes=1,
         activation='sigmoid',encoder freeze=True, input shape=(256, 256,3))
   Downloading data from https://github.com/Callidior/keras-applications/releases/download/efficientnet/efficientnet-b4 weights tf
   callback list = create callback lists(name = "efficientnetb4 unet")
optim = tf.keras.optimizers.Adam()
loss = DiceLoss()#sm.losses.bce jaccard loss
model4.compile(optim, loss, metrics=[iou_score])
%%time
history = model4.fit(train data loader, steps per epoch=192, epochs=10,
           validation data = val data loader, validation steps = 48,
           initial epoch = 0, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
   Epoch 1/10
   Epoch 1: val iou score improved from -inf to 0.14672, saving model to best model with efficientnetb4 unet.hdf5
   Epoch 2/10
   Epoch 2: val iou score improved from 0.14672 to 0.64450, saving model to best model with efficientnetb4 unet.hdf5
   Epoch 3/10
   Epoch 3: val iou score improved from 0.64450 to 0.66512, saving model to best model with efficientnetb4 unet.hdf5
   Epoch 4/10
   192/192 [============= ] - ETA: 0s - loss: 0.1837 - iou score: 0.6989
   Epoch 4: val iou score improved from 0.66512 to 0.67102, saving model to best model with efficientnetb4 unet.hdf5
   Epoch 5/10
```

```
Epoch 5: val iou score improved from 0.67102 to 0.69105, saving model to best model with efficientnetb4 unet.hdf5
  Epoch 6/10
  Epoch 6: val iou score improved from 0.69105 to 0.71631, saving model to best model with efficientnetb4 unet.hdf5
  Epoch 7/10
  Epoch 7: val iou score improved from 0.71631 to 0.73004, saving model to best model with efficientnetb4 unet.hdf5
  Epoch 8/10
  Epoch 8: val iou score did not improve from 0.73004
  Epoch 9/10
  Epoch 9: val iou score did not improve from 0.73004
  Epoch 10/10
  Epoch 10: val iou score did not improve from 0.73004
  # model4.save weights("/content/drive/MyDrive/dl model save/efficientnetb4 unet 72.h5")
%%time
history = model4.fit(train data loader, steps per epoch=192, epochs=20,
        validation_data = val_data_loader, validation steps = 48.
        initial epoch = 10, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
  Epoch 11/20
  Epoch 11: val iou score improved from 0.73004 to 0.74522, saving model to best model with efficientnetb4 unet.hdf5
  Epoch 12/20
```

```
Epoch 12: val iou score improved from 0.74522 to 0.75033, saving model to best model with efficientnetb4 unet.hdf5
Epoch 13/20
Epoch 13: val iou score improved from 0.75033 to 0.76586, saving model to best model with efficientnetb4 unet.hdf5
Epoch 14/20
Epoch 14: val iou score improved from 0.76586 to 0.76823, saving model to best model with efficientnetb4 unet.hdf5
Epoch 15/20
Epoch 15: val iou score improved from 0.76823 to 0.77001, saving model to best model with efficientnetb4 unet.hdf5
Epoch 16/20
Epoch 16: val iou score improved from 0.77001 to 0.77651, saving model to best model with efficientnetb4 unet.hdf5
Epoch 17/20
Epoch 17: val iou score did not improve from 0.77651
Epoch 18/20
192/192 [============ ] - ETA: 0s - loss: 0.1042 - iou score: 0.8141
Epoch 18: val iou score improved from 0.77651 to 0.77720, saving model to best model with efficientnetb4 unet.hdf5
Epoch 19/20
Epoch 19: val iou score did not improve from 0.77720
Epoch 20/20
Epoch 20: val iou score did not improve from 0.77720
CPU times: user 14min 34s, sys: 8min 11s, total: 22min 46s
Wall time: 18min 45s
```

callback_list = create_callback_lists(name = "efficientnetb4_unet")
optim = tf.keras.optimizers.Adam(learning_rate = 0.006)

```
Epoch 24/40
Epoch 25/40
Epoch 26/40
Epoch 27/40
Epoch 28/40
Epoch 29/40
Epoch 30/40
Epoch 31/40
Epoch 32/40
192/192 [============= ] - 92s 481ms/step - loss: 0.0893 - iou score: 0.8379 - val loss: 0.1152 - val iou score
Epoch 33/40
Epoch 34/40
Epoch 35/40
```

```
Epoch 36/40
 Epoch 37/40
 Epoch 38/40
 Epoch 39/40
 Epoch 40/40
 # model4
model4.save weights("efficientnetb4 unet 79.hdf5")
# 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.subplot(122)

plt.ylabel('Loss')
plt.xlabel('Epoch')

plt.show()

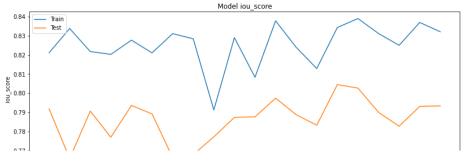
plt.title('Model loss')

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

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

Plot training & validation loss values

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



```
0.13 | Wain | Test | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 | 0.
```

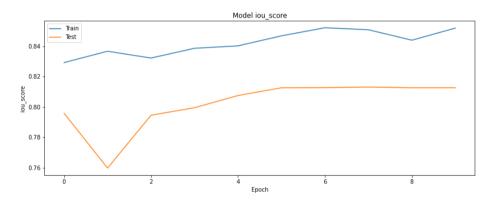
```
S 011
callback list = create callback lists(name = "efficientnetb4 unet")
optim = tf.keras.optimizers.Adam(learning rate = 0.008)
loss = DiceLoss()#sm.losses.bce jaccard loss
model4.compile(optim, loss, metrics=[iou score])
model4.load weights("/content/drive/MyDrive/dl model save/efficientnetb4 unet 79.h5")
# model4.save weights("efficientnetb4 unet 79.h5")
%%time
history = model4.fit(train data loader, steps per epoch=192, epochs=10,
             validation_data = val_data_loader, validation steps = 48.
             initial epoch = 0, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
   Epoch 1/10
   Epoch 1: val iou score improved from -inf to 0.79579, saving model to best model with efficientnetb4 unet.h5
   Epoch 2/10
   192/192 [============ ] - ETA: 0s - loss: 0.0898 - iou score: 0.8367
   Epoch 2: val iou score did not improve from 0.79579
   Epoch 3/10
```

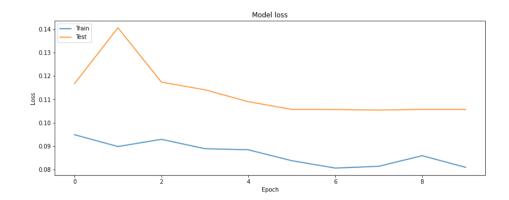
```
Epoch 4/10
Epoch 4: val iou score improved from 0.79579 to 0.79948, saving model to best model with efficientnetb4 unet.h5
Epoch 5/10
Epoch 5: val iou score improved from 0.79948 to 0.80749, saving model to best model with efficientnetb4 unet.h5
Epoch 6/10
Epoch 6: val iou score improved from 0.80749 to 0.81259, saving model to best model with efficientnetb4 unet.h5
Epoch 7/10
Epoch 7: val iou score improved from 0.81259 to 0.81269, saving model to best model with efficientnetb4 unet.h5
Epoch 8/10
Epoch 8: val iou score improved from 0.81269 to 0.81308, saving model to best model with efficientnetb4 unet.h5
Epoch 9/10
Epoch 9: val iou score did not improve from 0.81308
Epoch 10/10
Epoch 10: val iou score did not improve from 0.81308
CPU times: user 14min 36s, sys: 7min 53s, total: 22min 30s
Wall time: 18min 19s
```

```
# 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()
```





%%time

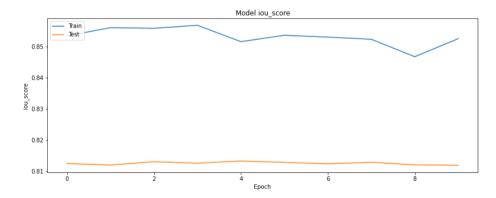
```
history = model4.fit(train_data_loader, steps_per_epoch=192, epochs=50,
validation_data = val_data_loader, validation_steps = 48,
initial epoch = 40, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
```

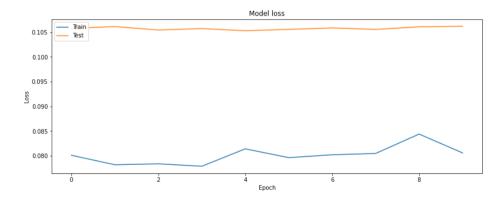
```
Epoch 43/50
Epoch 43: val_iou_score did not improve from 0.81308
Epoch 44/50
Epoch 44: val iou score did not improve from 0.81308
Epoch 45/50
Epoch 45: val iou score improved from 0.81308 to 0.81323, saving model to best model with efficientnetb4 unet.h5
Epoch 46/50
Epoch 46: val iou score did not improve from 0.81323
Epoch 47/50
Epoch 47: val iou score did not improve from 0.81323
Epoch 48/50
Epoch 48: val iou score did not improve from 0.81323
Epoch 49/50
Epoch 49: val iou score did not improve from 0.81323
Epoch 50/50
Epoch 50: val iou score did not improve from 0.81323
CPU times: user 14min 21s, sys: 9min 36s, total: 23min 58s
Wall time: 19min 57s
```

model4.save_weights("/content/drive/MyDrive/dl_model_save/efficientnetb4_unet_81.h5")

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()
```





```
callback_list = create_callback_lists(name = "efficientnetb4_unet")
optim = tf.keras.optimizers.Adam(learning_rate = 0.008)
loss = DiceLoss()#sm.losses.bce_jaccard_loss
```

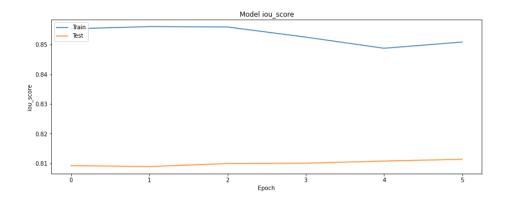
```
model4.compile(optim, loss, metrics=[iou score])
model4.load weights("/content/best model with efficientnetb4 unet.h5")
%%time
history = model4.fit(train data loader, steps per epoch=192, epochs=57,
          validation data = val data loader, validation steps = 48,
          initial epoch = 50, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
  Epoch 51/57
  192/192 [============ ] - ETA: 0s - loss: 0.0869 - iou score: 0.8423
  Epoch 51: val iou score improved from -inf to 0.76627, saving model to best model with efficientnetb4 unet.h5
  Epoch 52/57
  Epoch 52: val iou score improved from 0.76627 to 0.77983, saving model to best model with efficientnetb4 unet.h5
  Epoch 53/57
  Epoch 53: val iou score improved from 0.77983 to 0.80219, saving model to best model with efficientnetb4 unet.h5
  Epoch 54/57
  Epoch 54: val iou score improved from 0.80219 to 0.80394, saving model to best model with efficientnetb4 unet.h5
  Epoch 55/57
  192/192 [============= ] - ETA: 0s - loss: 0.0861 - iou score: 0.8438
  Epoch 55: val iou score improved from 0.80394 to 0.80464, saving model to best model with efficientnetb4 unet.h5
  Epoch 56/57
  Epoch 56: val iou score improved from 0.80464 to 0.80532, saving model to best model with efficientnetb4 unet.h5
  Epoch 57/57
  Epoch 57: val iou score improved from 0.80532 to 0.80556, saving model to best model with efficientnetb4 unet.h5
```

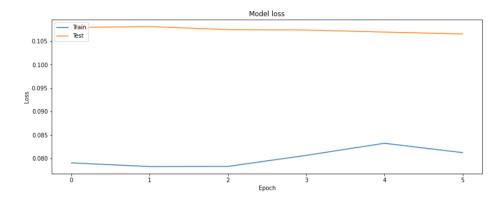
```
CPU times: user 10min 21s, sys: 5min 46s, total: 16min 8s
   Wall time: 13min 34s
%%time
callback list = create callback lists(name = "efficientnetb4 unet")
history = model4.fit(train data loader, steps per epoch=192, epochs=60,
            validation data = val data loader, validation steps = 48,
            initial epoch = 57, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
   Epoch 58/60
   Epoch 58: val iou score improved from -inf to 0.80629, saving model to best model with efficientnetb4 unet.h5
   Epoch 59/60
   Epoch 59: val iou score improved from 0.80629 to 0.80656, saving model to best model with efficientnetb4 unet.h5
   Epoch 60/60
   Epoch 60: val iou score improved from 0.80656 to 0.80777, saving model to best model with efficientnetb4 unet.h5
   CPU times: user 4min 24s, sys: 3min 1s, total: 7min 26s
   Wall time: 6min 2s
%%time
callback list = create callback lists(name = "efficientnetb4 unet")
history = model4.fit(train data loader, steps per epoch=192, epochs=66,
            validation data = val data loader, validation steps = 48,
            initial epoch = 60, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
   Epoch 61/66
   Epoch 61: val_iou_score improved from -inf to 0.80925, saving model to best_model_with_efficientnetb4_unet.h5
```

```
Epoch 62/66
  Epoch 62: val iou score did not improve from 0.80925
  Epoch 63/66
  Epoch 63: val iou score improved from 0.80925 to 0.80994, saving model to best model with efficientnetb4 unet.h5
  Epoch 64/66
  Epoch 64: val iou score improved from 0.80994 to 0.81007, saving model to best model with efficientnetb4 unet.h5
  Epoch 65/66
  Epoch 65: val iou score improved from 0.81007 to 0.81078, saving model to best model with efficientnetb4 unet.h5
  Epoch 66/66
  Epoch 66: val iou score improved from 0.81078 to 0.81137, saving model to best model with efficientnetb4 unet.h5
  CPU times: user 8min 49s, sys: 4min 49s, total: 13min 39s
  Wall time: 11min 22s
# 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()
```





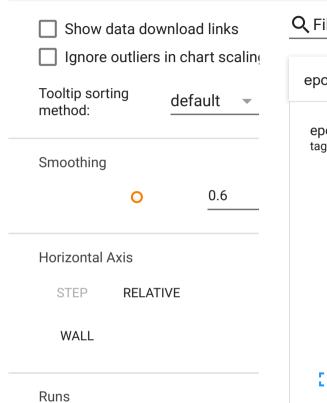
```
Epoch 67/70
192/192 [============= ] - ETA: 0s - loss: 0.0767 - iou score: 0.8591
Epoch 67: val iou score did not improve from 0.81137
Epoch 68/70
Epoch 68: val iou score did not improve from 0.81137
Epoch 69/70
Epoch 69: val iou score did not improve from 0.81137
Epoch 70/70
Epoch 70: val iou score did not improve from 0.81137
```

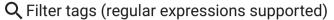
4

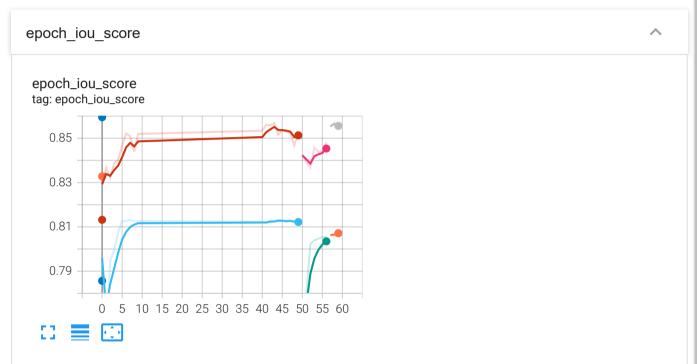
tensorboard

loading tensorboard
%tensorboard --logdir logs/fit

TensorBoard SCALARS GRAPHS DISTRIBUTIONS HISTOGRAMS TIME SE INACTIVE







highest accuracy got is .81 IOU score

▼ 20 epoch result

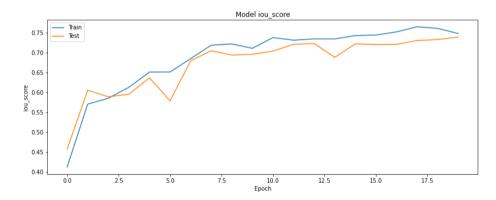
history = model4.fit(train_data_loader, steps_per_epoch=384, epochs=20, validation_data = val_data_loader, validation_steps = 96,

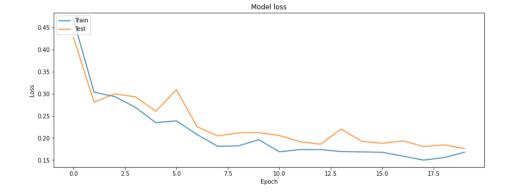
```
Epoch 1/20
Epoch 1: val iou score improved from -inf to 0.45757, saving model to best model with efficientnetb4 unet.hdf5
Epoch 2/20
Epoch 2: val iou score improved from 0.45757 to 0.60541, saving model to best model with efficientnetb4 unet.hdf5
Epoch 3/20
Epoch 3: val iou score did not improve from 0.60541
Epoch 4/20
Epoch 4: val iou score did not improve from 0.60541
Epoch 5/20
Epoch 5: val iou score improved from 0.60541 to 0.63673, saving model to best model with efficientnetb4 unet.hdf5
Epoch 6/20
Epoch 6: val iou score did not improve from 0.63673
Epoch 7/20
Epoch 7: val iou score improved from 0.63673 to 0.67931, saving model to best model with efficientnetb4 unet.hdf5
Epoch 8/20
Epoch 8: val iou score improved from 0.67931 to 0.70483, saving model to best model with efficientnetb4 unet.hdf5
Epoch 9/20
Epoch 9: val iou score did not improve from 0.70483
Epoch 10/20
```

```
Epoch 10: val iou score did not improve from 0.70483
   384/384 [============ ] - 125s 324ms/step - loss: 0.1961 - iou score: 0.7109 - val loss: 0.2121 - val iou sc
   Epoch 11/20
   Epoch 11: val iou score did not improve from 0.70483
   Epoch 12/20
   Epoch 12: val iou score improved from 0.70483 to 0.72098, saving model to best model with efficientnetb4 unet.hdf5
   Epoch 13/20
   Epoch 13: val iou score improved from 0.72098 to 0.72286, saving model to best model with efficientnetb4 unet.hdf5
   384/384 [============= ] - 123s 321ms/step - loss: 0.1736 - iou score: 0.7346 - val loss: 0.1858 - val iou sc
   Epoch 14/20
   Epoch 14: val iou score did not improve from 0.72286
   Epoch 15/20
model4.load weights("/content/best model with efficientnetb4 unet.hdf5")
history = model4.fit(train data loader, steps per epoch=384, epochs=1,
           validation data = val data loader, validation steps = 96,
           initial epoch = 0, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
   Epoch 1: val iou score improved from 0.73766 to 0.74307, saving model to best model with efficientnetb4 unet.hdf5
   # 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()
```





loading tensorboard
%tensorboard --logdir logs/fit

TensorBoard SCALARS GRAPHS DISTRIBUTIONS HISTOGRAMS TIME SE INACTIVE



▼ 5.5 senet154_unet

```
0.10
# loading unet model with backbone - resnet34
model = sm.Unet('senet154', encoder weights="imagenet", classes=1,
         activation='sigmoid',encoder freeze=True, input shape=(256, 256,3))
   Downloading data from <a href="https://github.com/qubvel/classification-models/releases/download/0.0.1/senet154">https://github.com/qubvel/classification-models/releases/download/0.0.1/senet154</a> imagenet 1000 no top.h5
   callback list = create callback lists(name = "senet154 unet")
optim = tf.keras.optimizers.Adam()
loss = DiceLoss()#sm.losses.bce jaccard loss
model.compile(optim, loss, metrics=[iou score])
history = model.fit(train data loader, steps per epoch=192, epochs=20,
            validation data = val data loader, validation steps = 48,
            initial epoch = 0, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
   Epoch 1/20
   Epoch 1: val iou score improved from -inf to 0.27342, saving model to best model with senet154 unet.hdf5
   Epoch 2/20
   Epoch 2: val iou score improved from 0.27342 to 0.65832, saving model to best model with senet154 unet.hdf5
   Epoch 3/20
   Epoch 3: val iou score did not improve from 0.65832
   Epoch 4/20
```

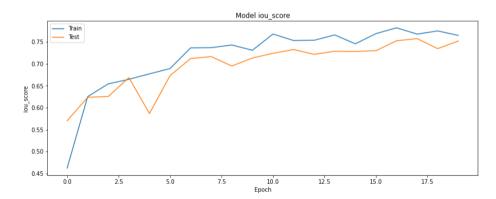
```
Epoch 5/20
  Epoch 5: val iou score did not improve from 0.75427
  Epoch 6/20
  Epoch 6: val iou score improved from 0.75427 to 0.78345, saving model to best model with senet154 unet.hdf5
  Epoch 7/20
  8/192 [>.....] - ETA: 5:16 - loss: 0.1453 - iou score: 0.7569
history = model.fit(train data loader, steps per epoch=384, epochs=20,
       validation data = val data loader, validation steps = 96,
       initial epoch = 0, callbacks = callback list, use multiprocessing = True )#callbacks = callback list,
  Epoch 1/20
  Epoch 1: val iou score improved from -inf to 0.57017, saving model to best model with senet154 unet.hdf5
  Epoch 2/20
  Epoch 2: val iou score improved from 0.57017 to 0.62372, saving model to best model with senet154 unet.hdf5
  Epoch 3/20
  Epoch 3: val iou score improved from 0.62372 to 0.62558, saving model to best model with senet154 unet.hdf5
  Epoch 4/20
  Epoch 4: val iou score improved from 0.62558 to 0.66856, saving model to best model with senet154 unet.hdf5
  Epoch 5/20
  Epoch 5: val iou score did not improve from 0.66856
  Epoch 6/20
```

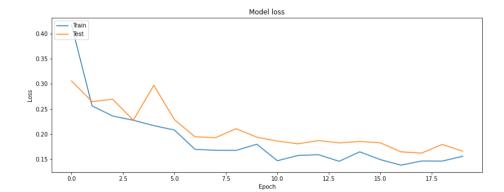
Epoch 4: val iou score improved from 0.65832 to 0.75427, saving model to best model with senet154 unet.hdf5

```
Epoch 6: val iou score improved from 0.66856 to 0.67313, saving model to best model with senet154 unet.hdf5
Epoch 7/20
Epoch 7: val iou score improved from 0.67313 to 0.71207, saving model to best model with senet154 unet.hdf5
Epoch 8/20
Epoch 8: val iou score improved from 0.71207 to 0.71651, saving model to best_model_with_senet154_unet.hdf5
Epoch 9/20
Epoch 9: val iou score did not improve from 0.71651
Epoch 10/20
Epoch 10: val iou score did not improve from 0.71651
Epoch 11/20
Epoch 11: val iou score improved from 0.71651 to 0.72404, saving model to best model with senet154 unet.hdf5
Epoch 12/20
Epoch 12: val iou score improved from 0.72404 to 0.73258, saving model to best model with senet154 unet.hdf5
Epoch 13/20
Epoch 13: val iou score did not improve from 0.73258
Epoch 14/20
Epoch 14: val iou score did not improve from 0.73258
Epoch 15/20
```

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()
```





loading tensorboard
%tensorboard --logdir logs/fit



▼ performance table

```
from prettytable import PrettyTable
x = PrettyTable()
x.field names = ["Model", "Backbon", "loss", "val loss", "IOU score", "val IOU score", "epoch"]
x.add rows(
        ["UNET", "resnet 34", .1951, .2221, .70, .67,20],
        ["UNET", "inceptionv3", .1657, .2066, .74, .69, 20],
        ["UNET", "effiecientnetb1", .1654, .1827, .74, .72, 20],
        ["UNET", "efficientnetb4", .1678, .1760, .74, .73, 20],
        ["UNET", "senet154",.1466, .1624, .76, .75, 20],
print(x)
                                        | val loss | IOU score | val IOU score | epoch
       Model
                   Backbon
                                  loss
                  resnet 34
                                 0.1951
                                           0.2221
                                                                                    20
        UNET |
                                                        0.7
                                                                      0.67
                 inceptionv3
                                           0.2066
        UNET
                                 0.1657
                                                        0.74
                                                                      0.69
                                                                                    20
               effiecientnetb1
```

0.1827

0.1624

0.176

0.74

0.74

0.76

0.72

0.73

0.75

20

20

20

0.1654

0.1678

0.1466

Note: will be continue in part2

UNET |

UNET

UNET

efficientnetb4

senet154

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