In [ ]:

```
pip install segmentation-models
```

```
Collecting segmentation-models
  Downloading segmentation_models-1.0.1-py3-none-any.whl (33 kB)
Collecting image-classifiers==1.0.0
  Downloading image_classifiers-1.0.0-py3-none-any.whl (19 kB)
Collecting keras-applications<=1.0.8,>=1.0.7
  Downloading Keras_Applications-1.0.8-py3-none-any.whl (50 kB)
     |████████████████████████████████| 50 kB 4.1 MB/s
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-models)
(0.16.2)
Requirement already satisfied: numpy>=1.9.1 in /usr/local/lib/python3.7/dist-packages (from keras-applications<=1.0.8,>=1.0.7->segmen
tation-models) (1.19.5)
Requirement already satisfied: h5py in /usr/local/lib/python3.7/dist-packages (from keras-applications<=1.0.8,>=1.0.7->segmentation-m
odels) (3.1.0)
Requirement already satisfied: cached-property in /usr/local/lib/python3.7/dist-packages (from h5py->keras-applications<=1.0.8,>=1.0.
7->segmentation-models) (1.5.2)
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==
1.0.0->segmentation-models) (3.2.2)
Requirement already satisfied: scipy>=0.19.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==1.0.0->segme
ntation-models) (1.4.1)
Requirement already satisfied: PyWavelets>=0.4.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==1.0.0->s
egmentation-models) (1.1.1)
Requirement already satisfied: imageio>=2.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==1.0.0->segm
entation-models) (2.4.1)
Requirement already satisfied: networkx>=2.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==1.0.0->segme
ntation-models) (2.6.3)
Requirement already satisfied: pillow>=4.3.0 in /usr/local/lib/python3.7/dist-packages (from scikit-image->efficientnet==1.0.0->segme
ntation-models) (7.1.2)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0,>=2.0.0->scikit-im
age->efficientnet==1.0.0->segmentation-models) (1.3.2)
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 matplotlib!=3
.0.0,>=2.0.0->scikit-image->efficientnet==1.0.0->segmentation-models) (2.4.7)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0,>=2.0.0->scikit-image->
efficientnet==1.0.0->segmentation-models) (0.10.0)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-packages (from matplotlib!=3.0.0,>=2.0.0->scikit
-image->efficientnet==1.0.0->segmentation-models) (2.8.2)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from cycler>=0.10->matplotlib!=3.0.0,>=2.0.0->scikit-im
age->efficientnet==1.0.0->segmentation-models) (1.15.0)
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
```

In [ ]:

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import os
import pickle
import matplotlib.patches as patches
import re
import random
from sklearn.model_selection import train_test_split
import cv2
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.utils import plot_model
from PIL import Image
import tensorflow as tf
import keras
from keras import backend as K
from keras.models import Model,load_model
from keras.regularizers import l2
import datetime
%load_ext tensorboard
import segmentation_models
from segmentation_models import Unet
from segmentation_models import get_preprocessing
import imgaug.augmenters as iaa
import segmentation_models as sm
sm.set_framework('tf.keras')
```

```
sm.framework()
from tensorflow.keras.losses import binary_crossentropy
from tqdm import tqdm
```

```
Segmentation Models: using `keras` framework.
```

In [ ]:

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

```
Mounted at /content/drive
```

In [ ]:

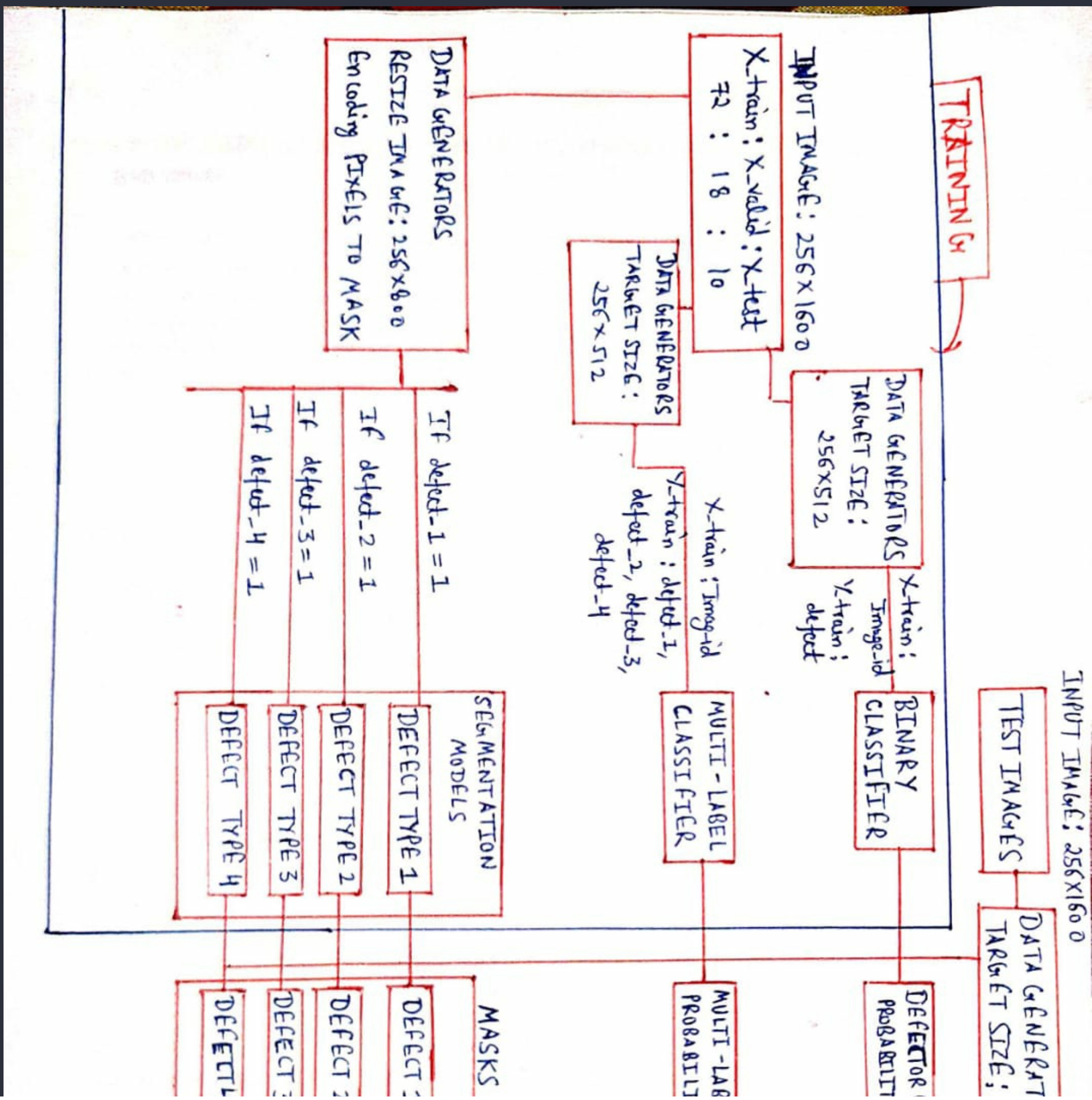
```
test_image=[i for i in os.listdir('/content/drive//My Drive/Steel_Detection /test_images')]
```

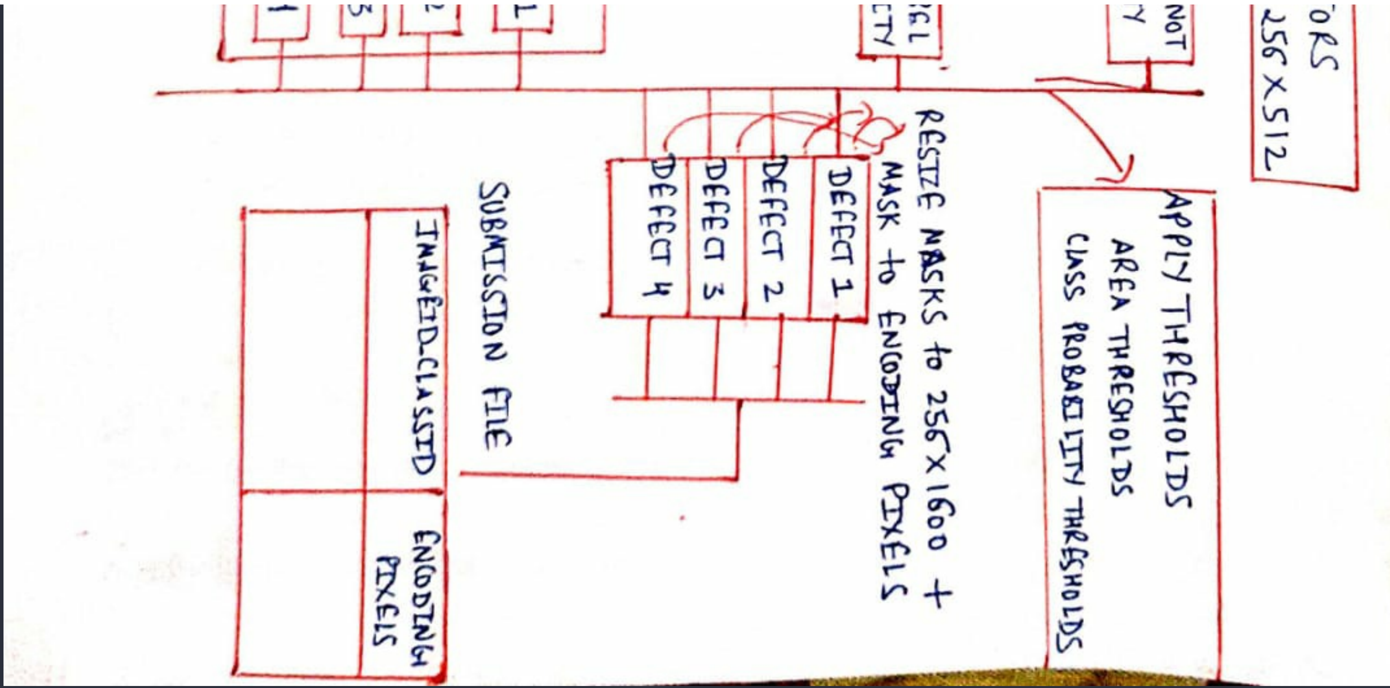
In [ ]:

```
len(test_image)
```

```
5516
```

Final Pipeline





- Binary Classifier trained with all Images with 1 output probability i.e. [defect] which tells whether whether Image have defect or not while Multi-label Classifier trained only with Images with defect. Multi-label Classifier have 4 output probability i.e. [defect_1,defect_2,defect_3,defect_4].
- Segmentation models are trained on each defect separately and predicts mask for each defect. Overall,we have 4 segment models i.e. one for each defect. There are total 6 models that are saved and later uses area threshold and class probability (different for each defect, depending on particular defect mask area and class probability).
- At last Encoded Pixels for test images are predicted and submitted. While training one must take care that proper data is fed to each model in the network which will help to reduce loss.

In [ ]:

```
def f1_score(y_true, y_pred):
    #https://aakashgoel12.medium.com/how-to-add-user-defined-function-get-f1-score-in-keras-metrics-3013f979ce0d
    #https://stackoverflow.com/questions/43547402/how-to-calculate-f1-macro-in-keras
    true_positives=K.sum(K.round(K.clip(y_true*y_pred,0,1)))    #calculates number of true positives
    possible_positives=K.sum(K.round(K.clip(y_true,0,1)))       #calculates number of actual positives
    predicted_positives=K.sum(K.round(K.clip(y_pred,0,1)))

    #K.epsilon takes care of non-zero divisions
    #was modified by adding the constant epsilon, in order to avoid division by 0. Thus NaN will not be computed.
    precision=true_positives/(predicted_positives +K.epsilon())
    recall=true_positives/(possible_positives+K.epsilon())
    f1_val=2*(precision*recall)/(precision+recall+K.epsilon())
    return f1_val
```

In [ ]:

```
#https://stackoverflow.com/questions/31273652/how-to-calculate-dice-coefficient-for-measuring-accuracy-of-image-segmentation-i
def dice_coef(y_true,y_pred):
    y_true_f=tf.reshape(tf.dtypes.cast(y_true, tf.float32),[-1])
    y_pred_f=tf.reshape(tf.dtypes.cast(y_pred, tf.float32),[-1])
    intersection=tf.reduce_sum(y_true_f*y_pred_f)
    return (2. * intersection + 1.) / (tf.reduce_sum(y_true_f) + tf.reduce_sum(y_pred_f) + 1.)

#https://stackoverflow.com/questions/49785133/keras-dice-coefficient-loss-function-is-negative-and-increasing-with-epochs
def dice_loss(y_true, y_pred):
    y_true_f = tf.reshape(y_true, [-1])
    y_pred_f = tf.reshape(y_pred, [-1])
    return (1-dice_coefficient(y_true, y_pred))
```

```
#defining function for calculation of loss function: binary cross entropy + dice loss
def bce_dice_loss(y_true, y_pred):
    y_true_f = tf.reshape(y_true, [-1])
    y_pred_f = tf.reshape(y_pred, [-1])
    return binary_crossentropy(y_true, y_pred) + (1-dice_coef(y_true, y_pred))
```

In [ ]:

```
def sum_pixel(i):
    return sum([int(k) for k in i.split(' ')[1::2]])
```

In [ ]:

```
#Reference: https://www.kaggle.com/paulorzp/rle-functions-run-lenght-encode-decode
def mask2rle(img):
    pixels= img.T.flatten()
    pixels = np.concatenate([[0], pixels, [0]])
    runs = np.where(pixels[1:] != pixels[:-1])[0] + 1
    runs[1::2] -= runs[::2]
    return ' '.join(str(x) for x in runs)
```

In [ ]:

```
# Implementing custom data generator
#https://towardsdatascience.com/implementing-custom-data-generators-in-keras-de56f013581c
class test_DataGenerator(keras.utils.all_utils.Sequence):

  def __init__(self,dataframe,batch_size=1,shuffle=False,preprocess=None,info={}):
    self.batch_size = batch_size
    self.df = dataframe
    self.indices = self.df.index.tolist()
    self.preprocess = preprocess
    self.shuffle = shuffle
    self.on_epoch_end()

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

  def __getitem__(self, index):
    index = self.index[index * self.batch_size:(index + 1) * self.batch_size]
    batch = [self.indices[k] for k in index]

    X= self.__get_data(batch)
    return X

  def on_epoch_end(self):
    self.index = np.arange(len(self.indices))
    if self.shuffle == True:
      np.random.shuffle(self.index)

  def __get_data(self, batch):
    X = np.empty((self.batch_size,256,800,3),dtype=np.float32) # image place-holders


    for i, id in enumerate(batch):
      X[i,] = Image.open('/content/drive//My Drive/Steel_Detection /test_images/' + str(self.
df['image_id'].loc[id])).resize((800,256))



      # preprocess input
    if self.preprocess!=None: X = self.preprocess(X)

    return X
```

In [ ]:

```
binary=load_model('/content/drive//My Drive/Steel_Detection /binary_Xception_2.h5',custom_obj
ects={'f1_score':f1_score})
multi=load_model('/content/drive//My Drive/Steel_Detection /multi_label.h5',custom_objects={'
f1_score':f1_score})
segment_1=load_model('/content/drive//My Drive/Steel_Detection /segmentation_defect_1.h5',cus
```

```
tom_objects={'bce_dice_loss':bce_dice_loss,'dice_coef':dice_coef})
segment_2=load_model('/content/drive//My Drive/Steel_Detection /segmentation_defect_2.h5',cus
tom_objects={'bce_dice_loss':bce_dice_loss,'dice_coef':dice_coef})
segment_3=load_model('/content/drive//My Drive/Steel_Detection /segmentation_defect_3.h5',cus
tom_objects={'bce_dice_loss':bce_dice_loss,'dice_coef':dice_coef})
segment_4=load_model('/content/drive//My Drive/Steel_Detection /segmentation_defect_4.h5',cus
tom_objects={'bce_dice_loss':bce_dice_loss,'dice_coef':dice_coef})
```

- Loading all saved models.

In [ ]:

```
test_folder_path='/content/drive//My Drive/Steel_Detection /test_images'
```

In [ ]:

```
def threshold(X):
  t=[]

  for i in range(len(X)):

    if sum_pixel(X['rle_1'].iloc[i])>=300 and sum_pixel(X['rle_1'].iloc[i])<=13500 and X['defe
ct'].iloc[i]>=0.4 and X['defect_1'].iloc[i]>=0.5:
      t.append([X['image_id'].iloc[i]+'_1',X['rle_1'].iloc[i]])
    else:
      t.append([X['image_id'].iloc[i]+'_1',''])

    if sum_pixel(X['rle_2'].iloc[i])>=500 and sum_pixel(X['rle_2'].iloc[i])<=9000 and X['defec
t'].iloc[i]>=0.4 and X['defect_2'].iloc[i]>=0.5:
      t.append([X['image_id'].iloc[i]+'_2',X['rle_2'].iloc[i]])
    else:
      t.append([X['image_id'].iloc[i]+'_2',''])

    if sum_pixel(X['rle_3'].iloc[i])>=900 and sum_pixel(X['rle_3'].iloc[i])<=140000 and X['def
ect'].iloc[i]>=0.5 and X['defect_3'].iloc[i]>=0.6:
      t.append([X['image_id'].iloc[i]+'_3',X['rle_3'].iloc[i]])
    else:
      t.append([X['image_id'].iloc[i]+'_3',''])

    if sum_pixel(X['rle_4'].iloc[i])>=2400 and sum_pixel(X['rle_4'].iloc[i])<=120000 and X['de
fect'].iloc[i]>=0.4 and X['defect_4'].iloc[i]>=0.5:
      t.append([X['image_id'].iloc[i]+'_4',X['rle_4'].iloc[i]])
    else:
      t.append([X['image_id'].iloc[i]+'_4',''])

  df=pd.DataFrame(t,columns=['imageid_classid','rle'])
  return df
```

- Depending on mask area(plot drawn in EDA) and class probability thresholds are decided for each defects respectively.

In [ ]:

```
def predict(X):

   preprocess=get_preprocessing('efficientnetb5')
   datagen=ImageDataGenerator(rescale=1./255)
   data_generator=datagen.flow_from_dataframe(dataframe=X,
                                              directory=test_folder_path,
                                              x_col="image_id",
                                              class_mode=None,
                                              target_size=(256,512),
                                              batch_size=1,
                                              shuffle=False)
   a=[]

   pred_binary=binary.predict_generator(data_generator)
   pred_multi=multi.predict_generator(data_generator)
   classify =pd.DataFrame(pred_multi,columns=['defect_1','defect_2','defect_3','defect_4'])
   classify['defect']=pred_binary
   classify['image_id']=X['image_id']
```

```
    batch=test_DataGenerator(X,preprocess=preprocess)
    pred_1=segment_1.predict_generator(batch)
    pred_2=segment_2.predict_generator(batch)
    pred_3=segment_3.predict_generator(batch)
    pred_4=segment_4.predict_generator(batch)
    for i in range(len(pred_1)):
      v1=mask2rle(np.array((Image.fromarray((pred_1[i][:,:,0])>=0.5)).resize((1600,256))).asty
pe(int))
      v2=mask2rle(np.array((Image.fromarray((pred_2[i][:,:,0])>=0.5)).resize((1600,256))).asty
pe(int))
      v3=mask2rle(np.array((Image.fromarray((pred_3[i][:,:,0])>=0.5)).resize((1600,256))).asty
pe(int))
      v4=mask2rle(np.array((Image.fromarray((pred_4[i][:,:,0])>=0.5)).resize((1600,256))).asty
pe(int))
      a.append([X.image_id.iloc[i],v1,v2,v3,v4])
    segment=pd.DataFrame(a,columns=['image_id','rle_1','rle_2','rle_3','rle_4'])

    df=classify.merge(segment,on=['image_id'])

    df1=threshold(df)
    return df1
```

- First compute binary and multi-label classification later use segmentation model and after checking thresholds for each defect finally predicts Encoded pixels for each image id and class id .

Prediction on Unseen given Test data

In [ ]:

```
test=pd.DataFrame(test_image,columns=['image_id'])
test1=test[0:20]
test1=test1.reset_index().drop('index',axis=1)
data=predict(test1)
data
```

```
Found 20 validated image filenames.
```

	imageid_classid	rle
0	dc5acf74b.jpg_1	
1	dc5acf74b.jpg_2	
2	dc5acf74b.jpg_3	
3	dc5acf74b.jpg_4	
4	d9411a571.jpg_1	
...	...	...
75	dc74717d9.jpg_4	
76	d82a63ce0.jpg_1	
77	d82a63ce0.jpg_2	
78	d82a63ce0.jpg_3	395799 19 396055 19 396295 43 396551 43 396802...
79	d82a63ce0.jpg_4	

80 rows × 2 columns

In [ ]:

```
a=[]
b=[]
for i in data.imageid_classid.values:
  k,l=i.split('_')
  a.append(k)
  b.append(l)
```

In [ ]:

```
df=pd.DataFrame(columns=['image_Id','class_Id','EncodedPixels'])
df['image_id']=a
```

```
df['class_id']=b
df['EncodedPixels']=data.rle.values
df.drop(['image_Id','class_Id'],axis=1,inplace=True)
```

In [ ]:

```
#https://www.analyticsvidhya.com/blog/2020/03/pivot-table-pandas-python/
df1=pd.pivot_table(df,values='EncodedPixels',index='image_id',columns='class_id',aggfunc=np.s
um).astype(str)
df1=df1.reset_index()
df1.columns=['image_id','rle_1','rle_2','rle_3','rle_4']
df1
```

	image_id	rle_1	rle_2	rle_3	rle_4
0	d118e5d28.jpg			46829 8 47085 8 47338 23 47594 23 47844 29 481...	
1	d28f267cd.jpg			208022 9 208278 9 208520 28 208776 28 209029 3...	
2	d37025202.jpg				
3	d3b616a4d.jpg	355842 10 356098 10 356353 47 356609 47 356865...			
4	d49797229.jpg			58428 44 58684 44 58929 59 59185 59 59438 62 5...	
5	d723c8b84.jpg				
6	d7a14c445.jpg			355535 6 355548 16 355791 6 355804 16 355913 5...	
7	d8073b1f7.jpg				
8	d82a63ce0.jpg			395799 19 396055 19 396295 43 396551 43 396802...	
9	d898dbda6.jpg				
10	d899cba2b.jpg			262814 99 263070 99 263247 11 263269 2 263279 ...	
11	d8beae3f0.jpg			137329 4 137585 4 137785 63 138041 63 138290 7...	
12	d8d24f9d5.jpg			90743 78 90999 78 91238 124 91494 124 91671 16...	
13	d9411a571.jpg				
14	da8392b29.jpg				
15	db406c510.jpg				
16	dc108224f.jpg			293930 13 293975 20 294048 52 294186 13 294231...	
17	dc5acf74b.jpg				
18	dc5d220aa.jpg			44 23 300 23 553 33 809 33 1062 40 1318 40 157...	
19	dc74717d9.jpg			35471 14 35515 9 35727 14 35771 9 35981 21 360...	

In [ ]:

```
def plot_mask(d):
  d=d.reset_index().drop('index',axis=1)
  test_folder_path='/content/drive//My Drive/Steel_Detection /test_images/'
  # Create figure and axes
  fig,ax=plt.subplots(d.shape[0],5,figsize=(17,8))
  for i in range(d.shape[0]):
    image_id=d['image_id'][i]
    rle_1=d['rle_1'][i]
    rle_2=d['rle_2'][i]
    rle_3=d['rle_3'][i]
    rle_4=d['rle_4'][i]
    im=Image.open(test_folder_path+str(image_id))
    ax[i,0].imshow(im)
    ax[i,0].set_title(image_id)

    mask=rle2mask(rle_1)
    ax[i,1].imshow(mask)
    ax[i,1].set_title("Defect_1")

    mask=rle2mask(rle_2)
    ax[i,2].imshow(mask)
    ax[i,2].set_title("Defect_2")

    mask=rle2mask(rle_3)
    ax[i,3].imshow(mask)
    ax[i,3].set_title("Defect_3")

    mask=rle2mask(rle_4)
    ax[i,4].imshow(mask)
```

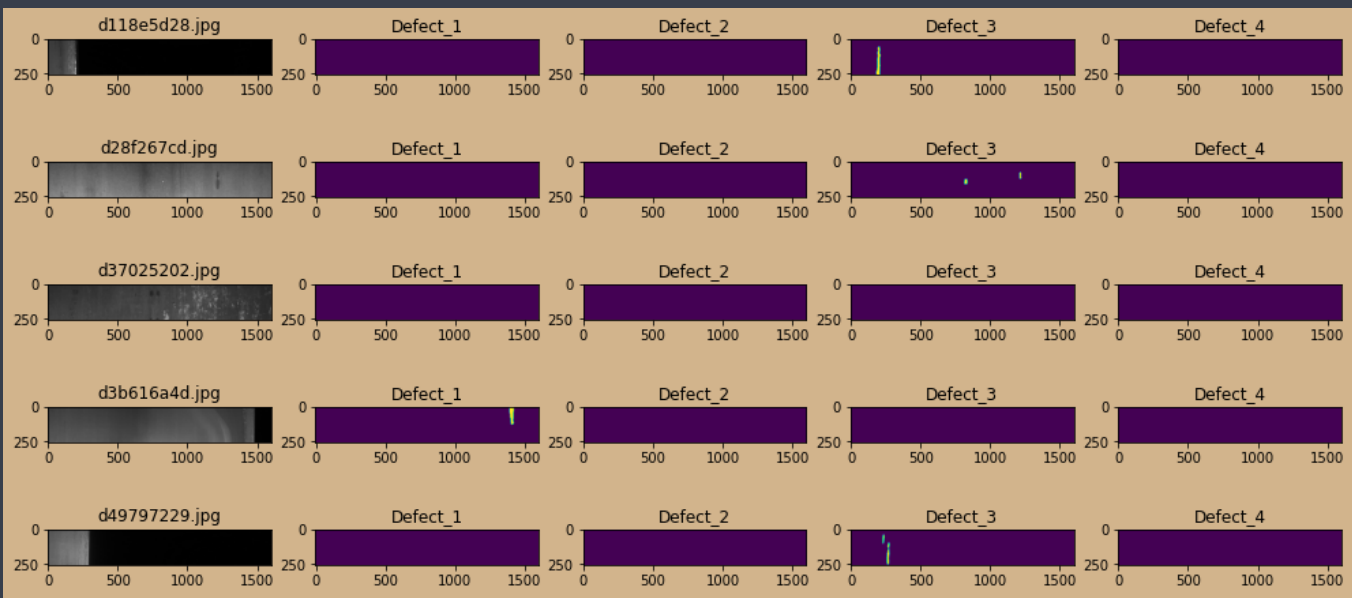
```
    ax[i,4].imshow(mask)
    ax[i,4].set_title("Defect_4")

  fig.set_facecolor("tan")
  plt.show()
```

In [ ]:

```
def rle2mask(rle):
    # CONVERT RLE TO MASK
    if (pd.isnull(rle))|(rle=='')|(rle=='-1'):
        return np.zeros((256,1600) ,dtype=np.uint8)

    height= 256
    width = 1600
    mask= np.zeros( width*height ,dtype=np.uint8)

    array = np.asarray([int(x) for x in rle.split()])
    starts = array[0::2]-1
    lengths = array[1::2]
    for index, start in enumerate(starts):
        mask[int(start):int(start+lengths[index])] = 1

    return mask.reshape( (height,width), order='F' )
```

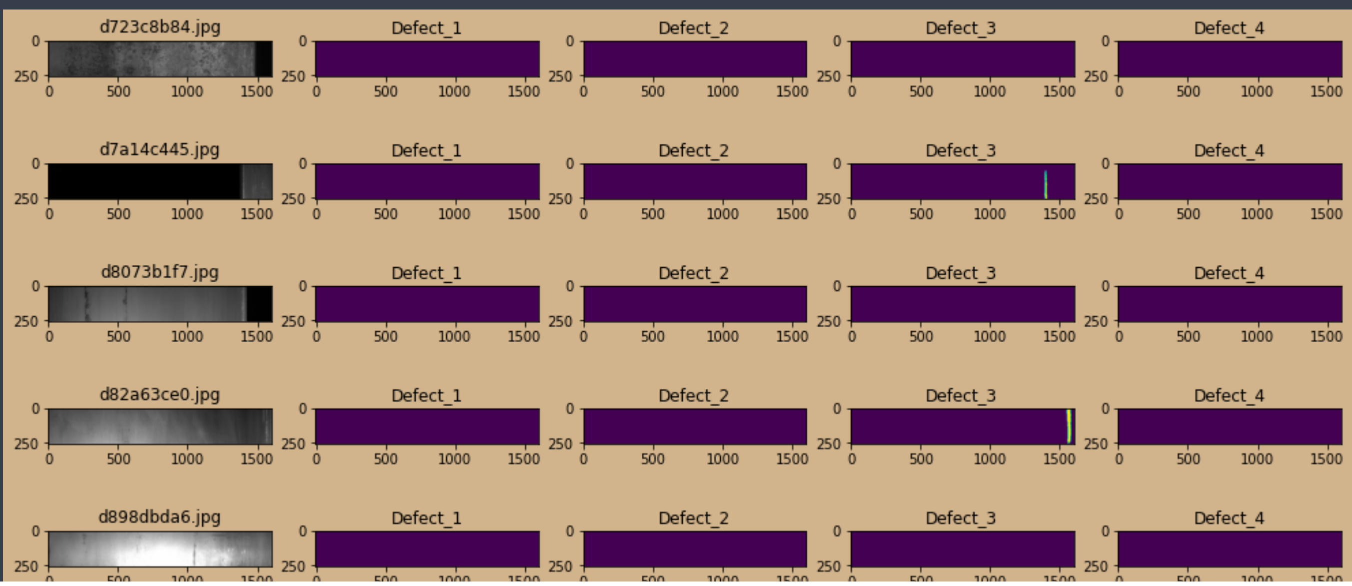
In [ ]:

```
plot_mask(df1[0:5])
```



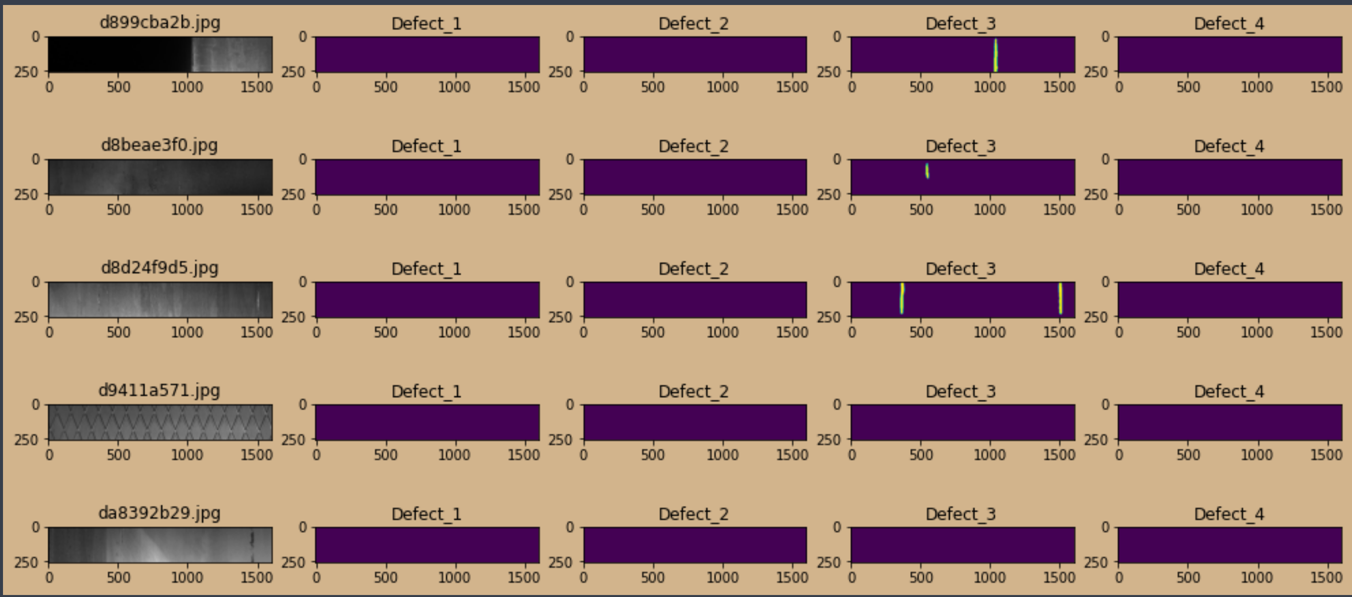
In [ ]:

```
plot_mask(df1[5:10])
```



In [ ]:

```
plot_mask(df1[10:15])
```



In [ ]:

```
plot_mask(df1[15:20])
```