

Severstal: Steel Defect Detection



1.0 Business Problem

1.1 Description

Severstal is leading the charge in efficient steel mining and production. With over 50K employees, 5K clients, and 25K products, this company has produced 11.8 Million tonnes of steel, 4.7 Million tonnes of coal and 11 Million tonnes of iron core pellets in 2019 which justifies its dominance in the steel industry.

We know that steel is one of the most important and most widely used building materials of modern times due to its impressive properties like durability, thermal conductivity, resistance to natural and man-made wear and most importantly it is resistant to corrosion which makes the material ubiquitous around the world. In order to make steel production more efficient without compromising the quality, Severstal wants to leverage the advances of Artificial Intelligence like computer vision to identify defects in delicate flat steel sheets. These sheets are produced from a sequence of manufacturing processes that involves heating, rolling, drying and cutting

Off lately, Severstal is using images generated from high frequency cameras to power a defect detection algorithm and Severstal is expecting the AI engineers to improve the algorithm to detect defects with high precision.

Credits: Kaggle

Problem Statement

- Detect and localize the surface defects on a steel sheet provided the image of steel sheets.
- Classify the detected surface defects into one or multiple classes among class values [1, 2, 3, 4]

1.2 Sources/Useful Links

- Source : [\(https://www.kaggle.com/c/severstal-steel-defect-detection/overview\)](https://www.kaggle.com/c/severstal-steel-defect-detection/overview)

Useful Links

- References :
- [\(https://forums.fast.ai/t/understanding-the-dice-coefficient/5838\)](https://forums.fast.ai/t/understanding-the-dice-coefficient/5838)
- [\(https://www.kaggle.com/wh1tezzz/correct-dice-metrics-for-this-competition\)](https://www.kaggle.com/wh1tezzz/correct-dice-metrics-for-this-competition)
- [\(https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/\)](https://lmb.informatik.uni-freiburg.de/people/ronneber/u-net/)
- [\(https://www.kaggle.com/go1dfish/clear-mask-visualization-and-simple-eda\)](https://www.kaggle.com/go1dfish/clear-mask-visualization-and-simple-eda)
- [\(https://www.kaggle.com/cdeotte/keras-unet-with-eda\)](https://www.kaggle.com/cdeotte/keras-unet-with-eda)
- [\(https://stanford.edu/~shervine/blog/keras-how-to-generate-data-on-the-fly.\)](https://stanford.edu/~shervine/blog/keras-how-to-generate-data-on-the-fly)

1.3 Real world/Business Objectives and Constraints

1. No strict latency concerns but defect identification and localization should not take a long time. In an ideal situation it is desirable to match with the frequency of cameras.
2. Interpretability can be obtained in the form of probability values for each of 4 class labels.

2.0 Machine Learning Problem

2.1 Data

2.1.1 Data Overview

The data folder (size 2GB in total) provided by Severstal contains the following:

- train_images/ - folder of training images
- test_images/ - folder of test images (you are segmenting and classifying these images)
- train.csv - training annotations which provide segments for defects (ClassId = [1, 2, 3, 4])
- sample_submission.csv - a sample submission file in the correct format, with each ImageId repeated 4 times, one for each of the 4 defect classes

2.1.2 Example Data point

Sample train image



train_csv data point

ImageId	ClassId	EncodedPixels
0 0002cc93b.jpg	1	29102 12 29346 24 29602 24 29858 24 30114 24 3...

2.2 Mapping the real world problem to an ML problem

2.2.1 Type of Machine Learning Problem

- This is an image segmentation and a classification problem to predict, localize the defects and then classify the detected defects

2.2.2 Performance Metric

- Dice coefficient.
- <https://forums.fast.ai/t/understanding-the-dice-coefficient/5838>
(<https://forums.fast.ai/t/understanding-the-dice-coefficient/5838>)
- https://en.wikipedia.org/wiki/S%C3%B8rensen%E2%80%93Dice_coefficient
(https://en.wikipedia.org/wiki/S%C3%B8rensen%E2%80%93Dice_coefficient)

2.3 Train, CV and Test construction

- Training images will be split randomly into train & CV in the ratio 85:15.
- Testing images will be used for predictions.

3.0 Exploratory Data Analysis

Importing all the modules

In [0]:

```
import warnings
warnings.filterwarnings("ignore")
from datetime import datetime
import pandas as pd
import numpy as np
from numpy import asarray
import matplotlib.pyplot as plt
%matplotlib notebook
%matplotlib inline
import seaborn as sns
from sklearn import metrics
import pickle
from tqdm import tqdm
import math
import random
import os
import cv2
from collections import Counter
from os import listdir
from matplotlib import image
from matplotlib import pyplot
from PIL import Image
from collections import defaultdict
from sklearn.model_selection import train_test_split
import tensorflow as tf
from keras import backend as K
from keras.losses import binary_crossentropy
from keras.layers import UpSampling2D, Conv2D, Activation, LeakyReLU, BatchNormalization, Input, Conv2DTranspose, Dropout
from keras.layers.pooling import MaxPooling2D, GlobalMaxPool2D
from keras import Model
from keras.preprocessing.image import ImageDataGenerator, array_to_img, img_to_array, load_img
from keras.callbacks import EarlyStopping, ReduceLROnPlateau, ModelCheckpoint, LearningRateScheduler, Callback
from keras.optimizers import Adam
from tqdm import tqdm_notebook
from keras.layers.pooling import MaxPooling2D
from keras.layers.merge import concatenate, add
```

The default version of TensorFlow in Colab will switch to TensorFlow 2.x on the 27th of March, 2020.

We recommend you [upgrade](https://www.tensorflow.org/guide/migrate) (<https://www.tensorflow.org/guide/migrate>) now or ensure your notebook will continue to use TensorFlow 1.x via the %tensorflow_version 1.x magic: [more info](https://colab.research.google.com/notebooks/tensorflow_version.ipynb) (https://colab.research.google.com/notebooks/tensorflow_version.ipynb).

Using TensorFlow backend.

3.1 Loading train csv file

In [0]:

```
#Loading the train csv file containing pixels indicating defects
train_df= pd.read_csv("/content/train.csv")
train_df.head()
```

Out[0]:

	ImageId	ClassId	EncodedPixels
0	0002cc93b.jpg	1	29102 12 29346 24 29602 24 29858 24 30114 24 3...
1	0007a71bf.jpg	3	18661 28 18863 82 19091 110 19347 110 19603 11...
2	000a4bcdd.jpg	1	37607 3 37858 8 38108 14 38359 20 38610 25 388...
3	000f6bf48.jpg	4	131973 1 132228 4 132483 6 132738 8 132993 11 ...
4	0014fce06.jpg	3	229501 11 229741 33 229981 55 230221 77 230468...

EncodedPixels columns indicate run-length encoding on the pixel values which are pairs of values that contain a start position and a run length. E.g. '1 3' implies starting at pixel 1 and running a total of 3 pixels (1,2,3).

The competition format requires a space delimited list of pairs. For example, '1 3 10 5' implies pixels 1,2,3,10,11,12,13,14 are to be included in the mask. The metric checks that the pairs are sorted, positive, and the decoded pixel values are not duplicated. The pixels are numbered from top to bottom, then left to right: 1 is pixel (1,1), 2 is pixel (2,1), etc.

In [0]:

```
print(train_df.shape)
```

(7095, 3)

- There are 7095 datapoints or steel sheet images containing defects

3.2 Checking for NaN

In [0]:

```
# train data
nan_rows = train_df[train_df.isnull().any(axis=1)]
nan_rows
```

Out[0]:

	ImageId	ClassId	EncodedPixels

- There are no NaN's

3.3 Analysing train & test image folders

3.3.1 Number of train & test images

In [0]:

```
train_count= 0
test_count= 0

for filename in.listdir('train_images'):
    #counting number of images in train folder
    train_count+=1
for filename in.listdir('test_images'):
    #counting number of images in test folder
    test_count+=1

print("Number of images in the train folder: ",train_count)
print("Number of images in the test folder: ",test_count)
print('---'*100)

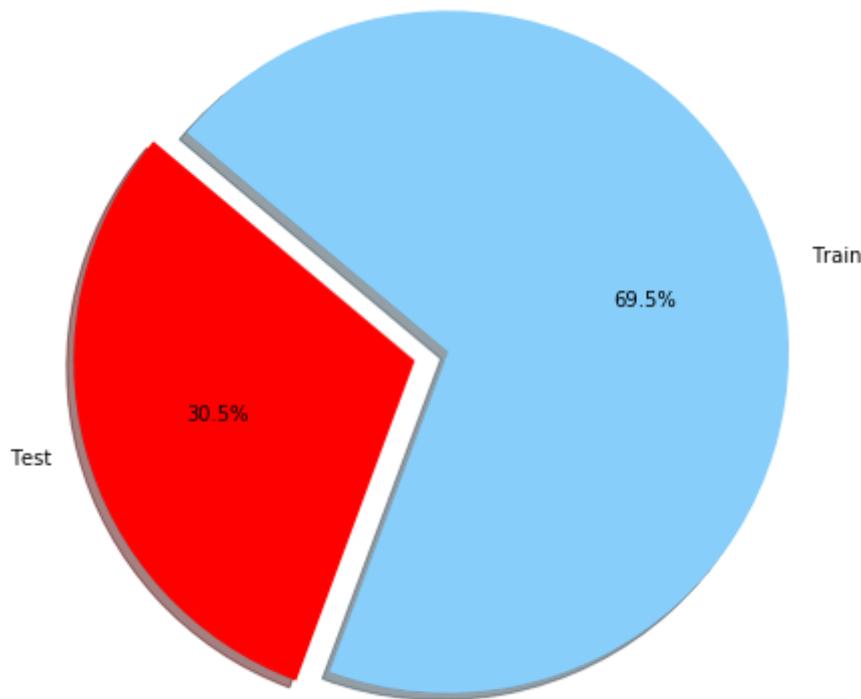
#Pie-chart https://pythonspot.com/matplotlib-pie-chart/
# Data to plot
labels = 'Test', 'Train'
sizes = [test_count,train_count]
colors = ['red','lightskyblue']
explode = (0.1, 0)  # explode 1st slice

# Plot
plt.figure(figsize=(7,7))
plt.pie(sizes, explode=explode, labels=labels, colors=colors,
autopct='%1.1f%%', shadow=True, startangle=140)

plt.axis('equal')
plt.show()
```

Number of images in the train folder: 12568

Number of images in the test folder: 5506



Looks like there is difference in image count in train folder & the imgaeID in train.csv

In [0]:

```
print("Number of images in the train folder which do not have defects are:",(train_coun  
t-train_df.shape[0]))
```

Number of images in the train folder which do not have defects are: 5473

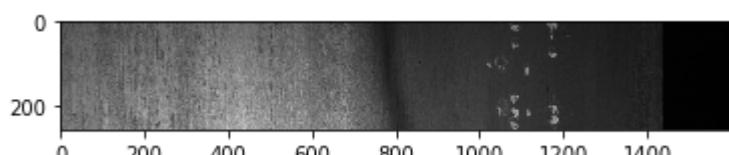
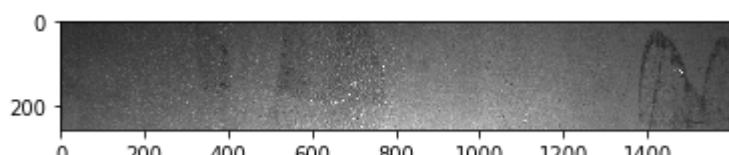
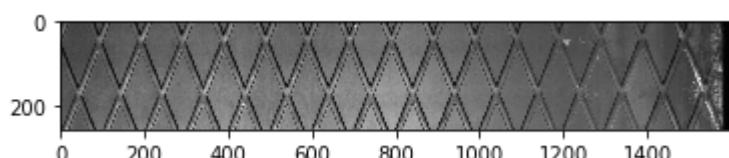
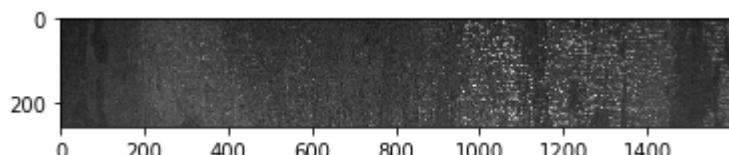
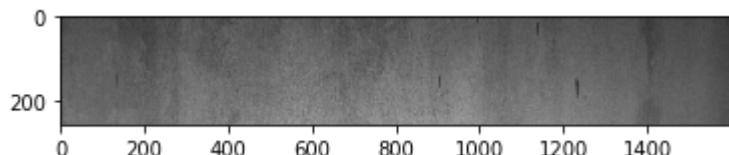
3.3.2 Printing few sample images containing no defects

In [0]:

```
# Load all images in a directory
#from os import listdir
from matplotlib import image
# Load all images in a directory
loaded_images = list()
defects= list(train_df.ImageId.values)
for filename in listdir('train_images'):
    if str(filename) not in defects:
# Load image
        img_data = image.imread('train_images/' + filename)
# store Loaded image
        loaded_images.append(img_data)
```

In [0]:

```
from matplotlib import pyplot
for i in range(5):
    disp= loaded_images[i]
    pyplot.imshow(disp)
    pyplot.show()
```



3.3.3 Basic properties of an image

In [0]:

```
from PIL import Image
# Load the image
image = Image.open('0a5a82b86.jpg')
# summarize some details about the image
print(image.format)
print(image.mode)
print(image.size)
# show the image
image.show()
```

JPEG

RGB

(1600, 256)

3.3.4 Check if all images in train and test are of the same size

Train images

In [0]:

```
from PIL import Image
image_size=[]
for image_id in listdir('train_images'):
    img=Image.open("train_images/"+image_id)
    width,height=img.size
    image_size.append((width,height))
```

In [0]:

```
train_image_size_df=pd.DataFrame(image_size,columns=["width","height"])
train_image_size_df.head()
```

Out[0]:

	width	height
0	1600	256
1	1600	256
2	1600	256
3	1600	256
4	1600	256

In [0]:

```
print(train_image_size_df.width.unique())
print(train_image_size_df.height.unique())
```

[1600]

[256]

Test images

In [0]:

```
from PIL import Image
image_size=[]
for image_id in listdir('test_images'):
    img=Image.open("test_images/"+image_id)
    width,height=img.size
    image_size.append((width,height))
```

In [0]:

```
test_image_size_df=pd.DataFrame(image_size,columns=["width","height"])
test_image_size_df.head()
```

Out[0]:

	width	height
0	1600	256
1	1600	256
2	1600	256
3	1600	256
4	1600	256

In [0]:

```
print(test_image_size_df.width.unique())
print(test_image_size_df.height.unique())
```

[1600]
[256]

Therefore all images in train and test folders have the same size of (1600,256)

3.4 Analysis of response label: ClassId

3.4.1 Checking for class count

In [0]:

```
counts= train_df.ClassId.value_counts()
counts
```

Out[0]:

```
3      5150
1      897
4      801
2      247
Name: ClassId, dtype: int64
```

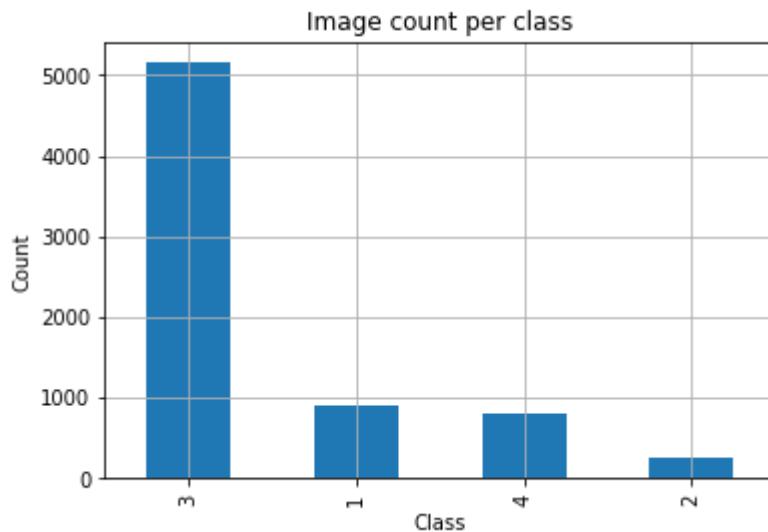
In [0]:

```

my_colors = 'rgbkymc'
counts.plot(kind='bar')
plt.xlabel('Class')
plt.ylabel('Count')
plt.title('Image count per class')
plt.grid()
plt.show()

# ref: argsort https://docs.scipy.org/doc/numpy/reference/generated/numpy.argsort.html
# -(train_class_distribution.values): the minus sign will give us in decreasing order
sorted_counts = np.argsort(-counts.values)
for i in sorted_counts:
    k=[3,1,4,2]
    print('Number of images in class', k[i], ':',counts.values[i], '(', np.round((counts.values[i]/train_df.shape[0])*100), 3), '%')

```



Number of images in class 3 : 5150 (72.586 %)
 Number of images in class 1 : 897 (12.643 %)
 Number of images in class 4 : 801 (11.29 %)
 Number of images in class 2 : 247 (3.481 %)

Observations:

- Number of images with class 3 defect is found to be maximum compared to other defect classes
- Images with class 2 defects are least found
- Therefore the dataset is imbalanced with dominance of Class 3 defects**

3.4.1.1 Finding class weights

In [0]:

```
#https://scikit-learn.org/stable/modules/generated/sklearn.utils.class_weight.compute_class_weight.html
from sklearn.utils import class_weight
class_wts = class_weight.compute_class_weight('balanced', np.unique(train_df.ClassId.values),train_df.ClassId)
print(class_wts)
for i in range(len(class_wts)):
    print("Weight for class {}: {}".format(i+1, class_wts[i]))
```

[1.97742475 7.18117409 0.34441748 2.21441948]

Weight for class 1: 1.9774247491638797

Weight for class 2: 7.181174089068826

Weight for class 3: 0.34441747572815534

Weight for class 4: 2.2144194756554305

Will be using these weights during training in the fit_generator function.

3.4.2 Checking number of labels tagged to each image

In [0]:

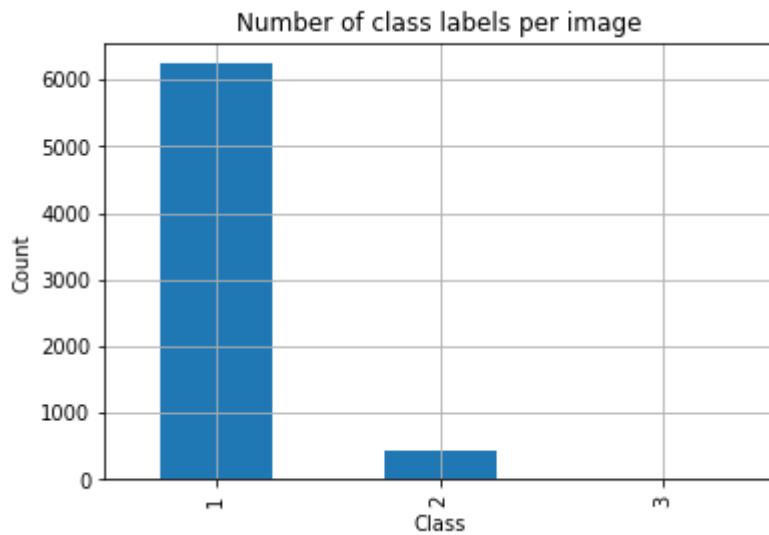
```
labels_per_image = train_df.groupby('ImageId')['ClassId'].count()
labels_per_image.value_counts()
```

Out[0]:

```
1    6239
2     425
3      2
Name: ClassId, dtype: int64
```

In [0]:

```
my_colors = 'rgbkymc'  
labels_per_image.value_counts().plot(kind='bar')  
plt.xlabel('Class')  
plt.ylabel('Count')  
plt.title('Number of class labels per image')  
plt.grid()  
plt.show()
```



Observations:

- There are 6239 steel sheet images possessing only one class of defect i.e. either 1,2,3 or 4
- There are 425 steel sheet images possessing a combination of 2 classes defects
- There are 2 steel sheet images possessing a combination of 3 classes defects
- There are no steel sheet images possessing a combination of 4 classes defects

3.4.3 Displaying few sample images belonging to each of the 4 classes

In [0]:

```
d1= train_df[train_df.ClassId==1]
d2= train_df[train_df.ClassId==2]
d3= train_df[train_df.ClassId==3]
d4= train_df[train_df.ClassId==4]
```

In [0]:

```
d1.head()
```

Out[0]:

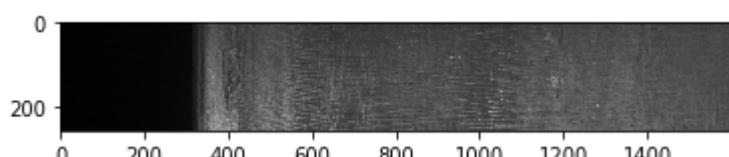
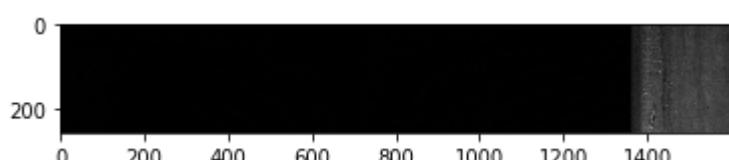
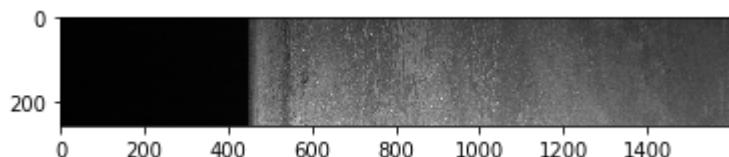
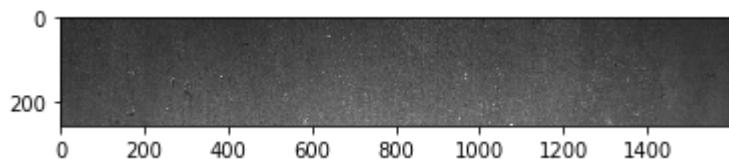
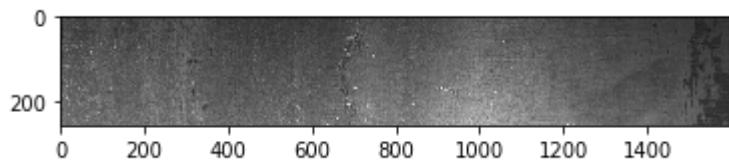
	ImageId	ClassId	EncodedPixels
0	0002cc93b.jpg	1	29102 12 29346 24 29602 24 29858 24 30114 24 3...
2	000a4bcdd.jpg	1	37607 3 37858 8 38108 14 38359 20 38610 25 388...
8	002fc4e19.jpg	1	146021 3 146275 10 146529 40 146783 46 147038 ...
18	008ef3d74.jpg	1	356336 4 356587 11 356838 18 357089 25 357340 ...
21	00ac8372f.jpg	1	101742 3 101998 12 102253 19 102301 22 102509 ...

Class-1

In [0]:

```
# Load all images in a directory
from matplotlib import image
loaded_images = list()
img_names= list(d1.ImageId.values)
for filename in listdir('train_images'):
    if str(filename) in img_names:
# Load image
        img_data = image.imread('train_images/' + filename)
# store loaded image
        loaded_images.append(img_data)

#displaying images
from matplotlib import pyplot
for i in range(5):
    disp= loaded_images[i]
    pyplot.imshow(disp)
    pyplot.show()
```

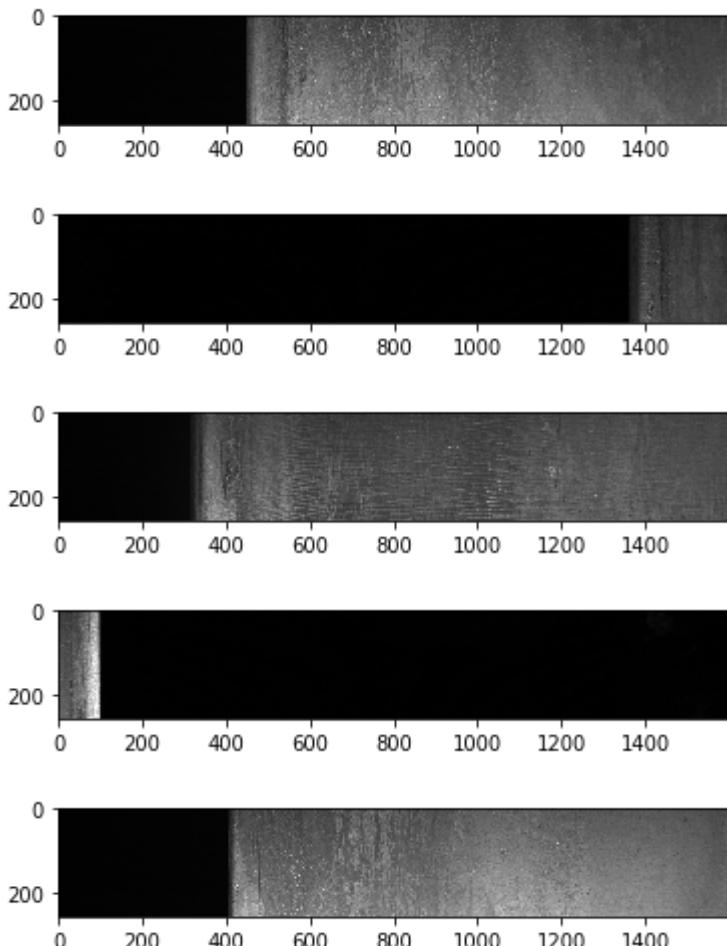


Class-2

In [0]:

```
# Load all images in a directory
loaded_images = list()
img_names= list(d2.ImageId.values)
for filename in listdir('train_images'):
    if str(filename) in img_names:
# Load image
        img_data = image.imread('train_images/' + filename)
# store loaded image
        loaded_images.append(img_data)

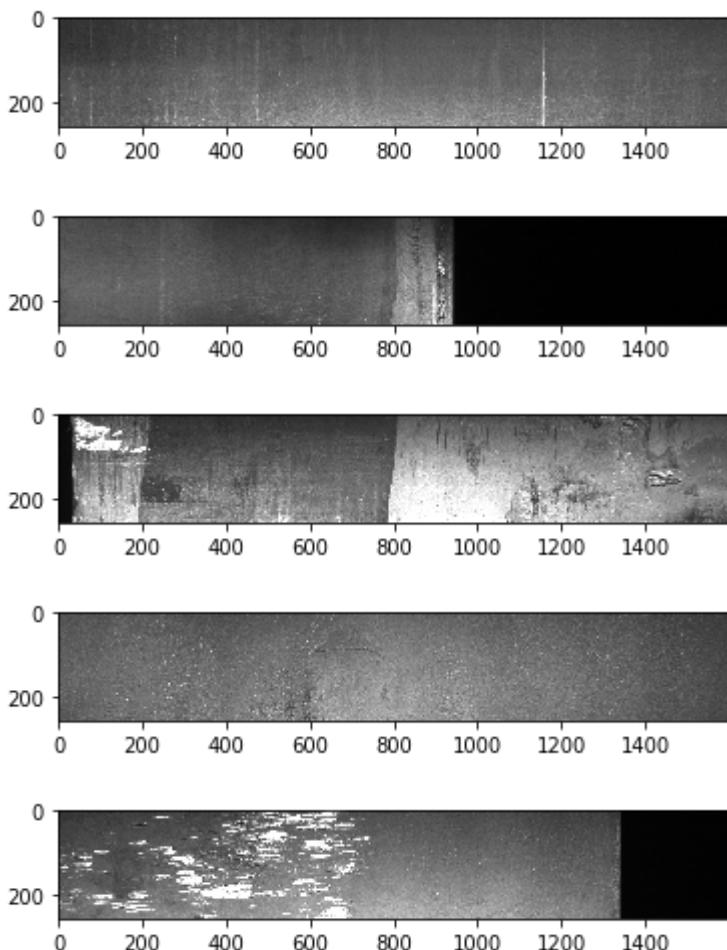
#displaying images
from matplotlib import pyplot
for i in range(5):
    disp= loaded_images[i]
    pyplot.imshow(disp)
    pyplot.show()
```

**Class-3**

In [0]:

```
# Load all images in a directory
loaded_images = list()
img_names= list(d3.ImageId.values)
for filename in listdir('train_images'):
    if str(filename) in img_names:
# Load image
        img_data = image.imread('train_images/' + filename)
# store loaded image
        loaded_images.append(img_data)

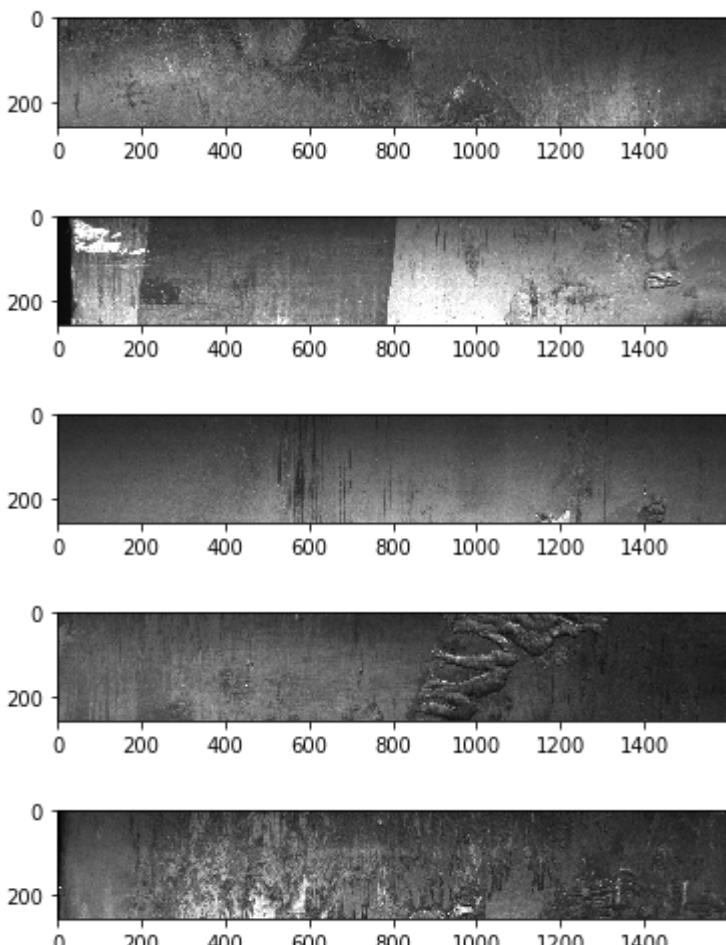
#displaying images
from matplotlib import pyplot
for i in range(5):
    disp= loaded_images[i]
    pyplot.imshow(disp)
    pyplot.show()
```

**Class-4**

In [0]:

```
# Load all images in a directory
loaded_images = list()
img_names= list(d4.ImageId.values)
for filename in listdir('train_images'):
    if str(filename) in img_names:
# Load image
        img_data = image.imread('train_images/' + filename)
# store loaded image
        loaded_images.append(img_data)

#displaying images
from matplotlib import pyplot
for i in range(5):
    disp= loaded_images[i]
    pyplot.imshow(disp)
    pyplot.show()
```



4.0 Data preparation

4.1 Preparing defect data for each image

In [0]:

```
# preparing a dataframe with each image ID being represented with 4 classes
images= []
class_id= []
for img in.listdir('train_images'):
    images.append(img)
    class_id.append(1)
    images.append(img)
    class_id.append(2)
    images.append(img)
    class_id.append(3)
    images.append(img)
    class_id.append(4)
train_images= pd.DataFrame(images,columns=['ImageId'])
train_images['ClassId'] = class_id
train_images.head()
```

Out[0]:

	ImageId	ClassId
0	0002cc93b.jpg	1
1	0002cc93b.jpg	2
2	0002cc93b.jpg	3
3	0002cc93b.jpg	4
4	00031f466.jpg	1

In [0]:

train_images.shape

Out[0]:

(50272, 2)

In [0]:

```
# Dataframe containing RLE(run Length encoded pixels) representing defects
train_df.head()
```

Out[0]:

	ImageId	ClassId	EncodedPixels
0	0002cc93b.jpg	1	29102 12 29346 24 29602 24 29858 24 30114 24 3...
1	0007a71bf.jpg	3	18661 28 18863 82 19091 110 19347 110 19603 11...
2	000a4bcdd.jpg	1	37607 3 37858 8 38108 14 38359 20 38610 25 388...
3	000f6bf48.jpg	4	131973 1 132228 4 132483 6 132738 8 132993 11 ...
4	0014fce06.jpg	3	229501 11 229741 33 229981 55 230221 77 230468...

In [0]:

```
# merging defect & non-defect data
temp_df = pd.merge(train_images, train_df, how='outer', on=['ImageId', 'ClassId'])
temp_df = temp_df.fillna('')
print(temp_df.shape)
temp_df.head()
```

(50272, 3)

Out[0]:

	ImageId	ClassId	EncodedPixels
0	0002cc93b.jpg	1	29102 12 29346 24 29602 24 29858 24 30114 24 3...
1	0002cc93b.jpg	2	
2	0002cc93b.jpg	3	
3	0002cc93b.jpg	4	
4	00031f466.jpg	1	

In [0]:

```
# Grouping the data according to ImageID with each row representing images with single
or multiple defects
#https://www.geeksforgeeks.org/python-pandas-pivot_table/

defect_data = pd.pivot_table(temp_df, values='EncodedPixels', index='ImageId', columns='ClassId', aggfunc=np.sum).astype(str)
defect_data = defect_data.reset_index()
defect_data.columns = ['ImageId', 'Defect_1', 'Defect_2', 'Defect_3', 'Defect_4']
defect_data.head()
```

Out[0]:

	ImageId	Defect_1	Defect_2	Defect_3	Defect_4
0	0002cc93b.jpg	29102 12 29346 24 29602 24 29858 24 30114 24 3...			
1	00031f466.jpg				
2	000418bfc.jpg				
3	000789191.jpg				
4	0007a71bf.jpg			18661 28 18863 82 19091 110 19347 110 19603 11...	

In [0]:

```
defect_data.shape
```

Out[0]:

```
(12568, 5)
```

4.2 Splitting the data into train & CV

In [0]:

```
from sklearn.model_selection import train_test_split
data= defect_data
train_data, cv_data = train_test_split(data, test_size=0.15)
print(train_data.shape)
print(cv_data.shape)
```

```
(10682, 5)
(1886, 5)
```

5.0 Utility functions

5.1 Mask encoding and decoding

In [0]:

```
# to convert masks to run length encoded values
#https://www.kaggle.com/aleksandradeis/steel-defect-detection-eda

def mask2rle(img):
    """
    img: numpy array, 1 - mask, 0 - background
    Returns run Length as string formated
    """
    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 [0]:

```
# to convert run length encoded pixels to masks
#https://www.kaggle.com/aleksandradeis/steel-defect-detection-eda
def rle2mask(rle):
    """
    Returns mask array by converting run length encoded pixels
    """

    # If rle is empty or null
    if(len(rle)<1):
        return np.zeros((128,800) ,dtype=np.uint8)

    height = 256
    width = 1600
    # Defining the Length of mask. This will be a 1d array which will be reshaped to 2d
    # Later.
    mask = np.zeros(height*width ).astype(np.uint8)
    array = np.asarray([int(x) for x in rle.split()]) # array containing rle
    start = array[0::2]-1 # this will contain the start of run length
    length = array[1::2] # this will contain the length of each rle.
    for i,start in enumerate(start):
        mask[int(start):int(start+length[i])] = 1
    return mask.reshape( (height,width), order='F' )[:2,:,:2]
```

5.2 Custom metric and loss function

In [0]:

```
from keras import backend as K
from keras.losses import binary_crossentropy
#https://lars76.github.io/neural-networks/object-detection/Losses-for-segmentation/
#https://www.kaggle.com/wh1tezzz/correct-dice-metrics-for-this-competition
#https://forums.fast.ai/t/understanding-the-dice-coefficient/5838

def dice_coef(y_true, y_pred, smooth=1):
    """
    Function that returns dice coefficient by taking input masks and predicted mask
    """
    y_true_f = K.flatten(y_true)
    y_pred_f = K.flatten(y_pred)
    intersection = K.sum(y_true_f * y_pred_f)
    return (2. * intersection + smooth) / (K.sum(y_true_f) + K.sum(y_pred_f) + smooth)

def bce_dice_loss(y_true, y_predict): #combination of dice loss and binary cross entropy for all pixels
    return binary_crossentropy(y_true, y_predict) + (1-dice_coef(y_true, y_predict))
```

5.3 Training Plots

In [0]:

```
from matplotlib import pyplot
def plot(history):
    '''function to plot epoch vs bce_dice_loss & epoch vs dice_coeff '''
    # plot bce_dice_loss
    pyplot.subplot(121)
    pyplot.title('bce_dice_loss')
    pyplot.xlabel('Epoch')
    pyplot.plot(history.history['loss'], color='blue', label='train')
    pyplot.plot(history.history['val_loss'], color='orange', label='CV')
    # plot dice_coeff
    pyplot.subplot(122)
    pyplot.title('Dice_coef')
    pyplot.xlabel('Epoch')
    pyplot.plot(history.history['dice_coef'], color='blue', label='train')
    pyplot.plot(history.history['val_dice_coef'], color='orange', label='CV')
```

5.4 Visualizing defects on train & validation images

In [0]:

```
def visualize_defects(data,model):
    ''' Function that takes data containing imageID's ,model and outputs 4 masks for each image '''

    import random
    image_id= list(data.ImageId.values)
    for i in random.sample(image_id, 5):
        df= data[data.ImageId==i]
        X = np.empty((1,128,800,3),dtype=np.float32)
        img = cv2.imread('/content/' +'train_images/' + i)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
        img = cv2.resize(img, (800,128))
        X[0,] = img
        mask_pred = model.predict(X)
        fig, axs = plt.subplots(4,3,figsize=(18, 7))
        axs[0,0].imshow(img)
        axs[0,0].set_title(i)
        for j in range(4):

            if j<3:
                axs[j+1,0].axis('off')
            k=0
            gt= rle2mask(df.iloc[0][j+1])
            m = mask_pred[0,:,:,:j].round().astype(int)
            axs[j,k+1].imshow(gt)
            axs[j,k+1].set_title('Ground truth mask: Class_'+str(j+1))
            axs[j,k+2].imshow(m)
            axs[j,k+2].set_title('Predicted mask: Class_'+str(j+1))
        plt.show()
        print('-'*100)
```

5.5 Visualizing defects on raw test images

In [0]:

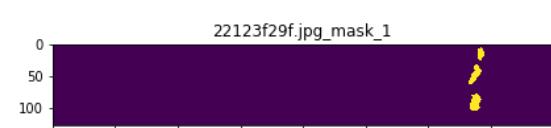
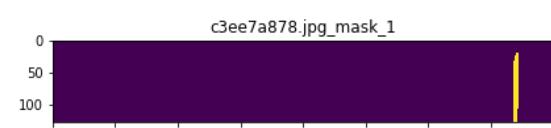
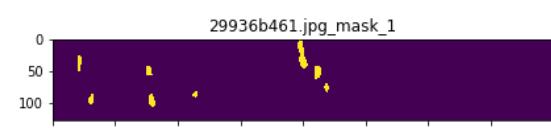
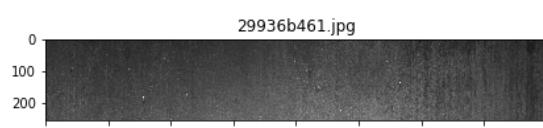
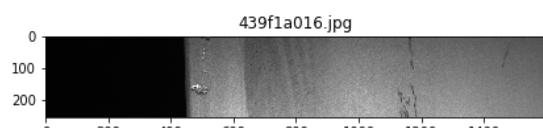
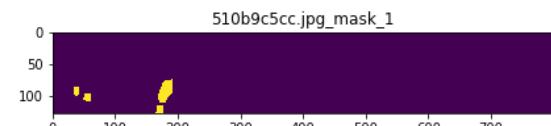
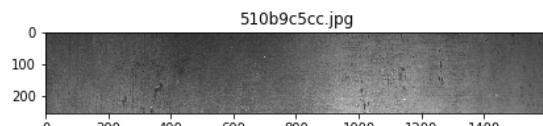
```
def visualize_defects_test(data,n):  
  
    ''' Function that takes test ImageID's and the number of images to display as input  
and therefore outputs  
mask with class ID'''  
  
    data= data[data['EncodedPixels']!='']  
    for i in random.sample(list(data['ImageId_ClassId'].values), n):  
        df= data[data.ImageId_ClassId==i]  
        img = Image.open('/content/' + 'test_images/' + i.split('_')[0])  
        pixels= df.iloc[0][1]  
        mask= rle2mask(pixels)  
        fig, (ax1,ax2) = plt.subplots(1,2,figsize=(15, 7))  
        ax1.imshow(img)  
        ax1.set_title(i.split('_')[0])  
        ax2.imshow(mask)  
        ax2.set_title('Predicted mask with Class-' +i.split('_')[1]+ ' defect.')  
        plt.show()  
        print('-'*150)
```

6.0 Check rle2mask function and visualize few masks & images

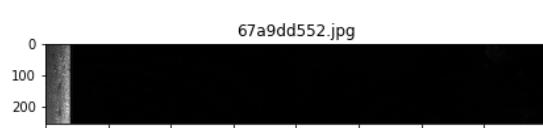
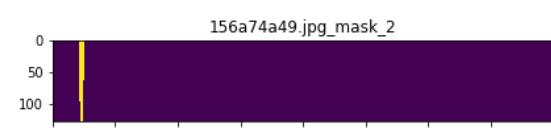
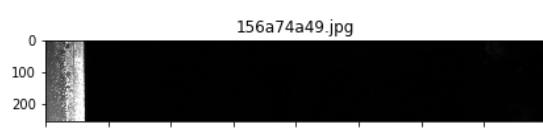
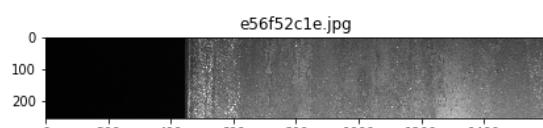
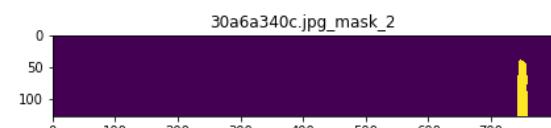
In [0]:

```
for k in [1,2,3,4]: #classes
    tmp = []
    cnt=0
    print("Sample images with Class {} defect:".format(k))
    for i in train_data[train_data[f'Defect_{k}']!=''][['ImageId',f'Defect_{k}']].value
s:
    if cnt<5:
        fig, (ax1,ax2) = plt.subplots(nrows = 1,ncols = 2,figsize=(15, 7))
        img = Image.open('train_images/' + str(i[0]))
        ax1.imshow(img)
        ax1.set_title(i[0])
        cnt+=1
        ax2.imshow(rle2mask(i[1]))
        ax2.set_title(i[0]+'_mask_'+str(k))
        plt.show()
print('-'*100)
```

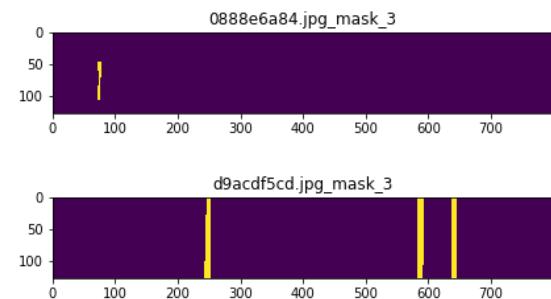
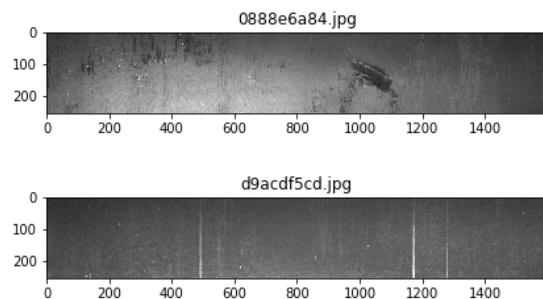
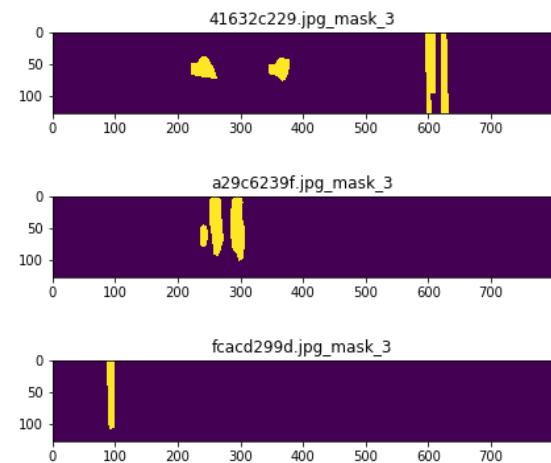
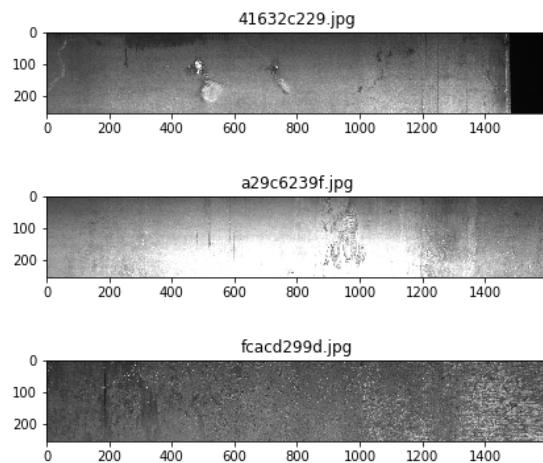
Sample images with Class 1 defect:



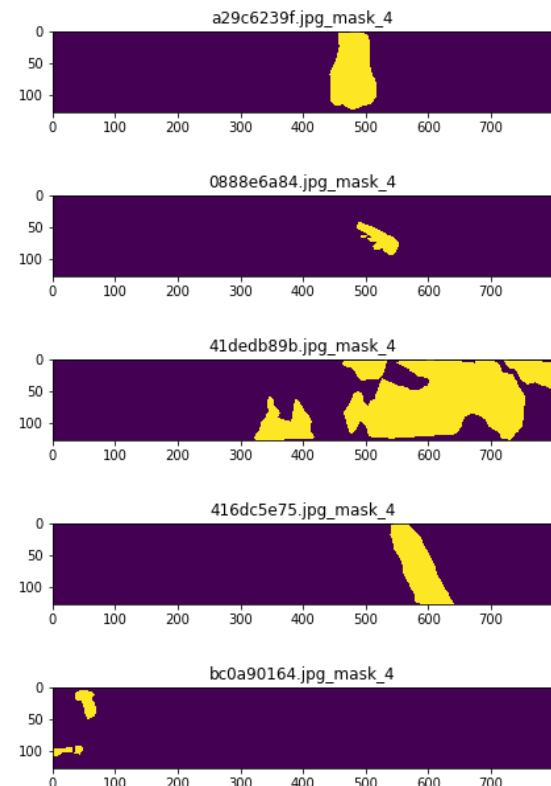
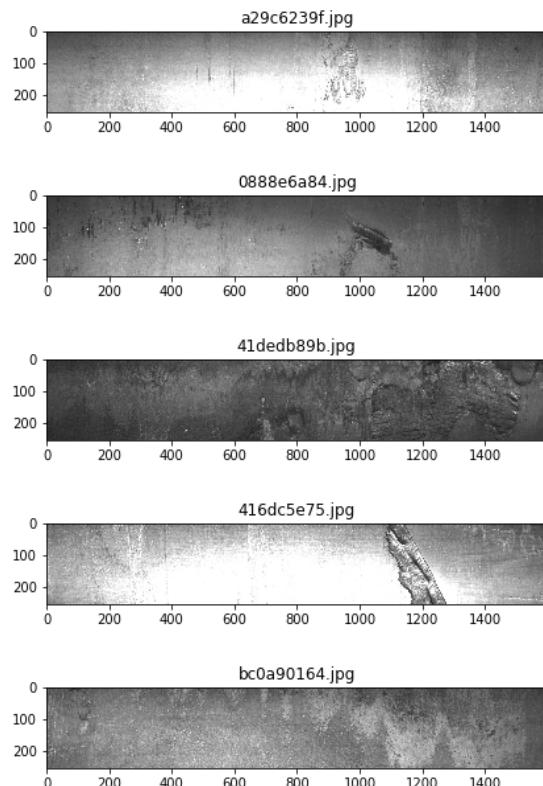
Sample images with Class 2 defect:



Sample images with Class 3 defect:



Sample images with Class 4 defect:



7.0 Generating data for Keras model

7.1 Train generator

In [0]:

```
# https://stanford.edu/~shervine/blog/keras-how-to-generate-data-on-the-fly
# https://keras.io/preprocessing/image/

import keras
from keras.preprocessing.image import ImageDataGenerator
class Train_DataGenerator(keras.utils.Sequence):
    def __init__(self, df, batch_size = 16,shuffle=False,
                 preprocess=None, info={}):
        super().__init__()
        self.df = df
        self.shuffle = shuffle
        self.batch_size = batch_size
        self.preprocess = preprocess
        self.info = info
        self.data_path = '/content/' + 'train_images/'
        self.on_epoch_end()

    def __len__(self):
        return int(np.floor(len(self.df) / self.batch_size))

    def on_epoch_end(self):
        self.indexes = np.arange(len(self.df))
        if self.shuffle == True:
            np.random.shuffle(self.indexes)

    def __getitem__(self, index):
        train_datagen = ImageDataGenerator()
        param = {'flip_horizontal':True, 'flip_vertical' : True}
        """
        Performing data augmentation on images and the masks generated which includes H
        orizontal flip & Vertical flip
        """

        X = np.empty((self.batch_size,128,800,3),dtype=np.float32) #images
        y = np.empty((self.batch_size,128,800,4),dtype=np.int8)      #masks
        indexes = self.indexes[index*self.batch_size:(index+1)*self.batch_size]
        for i,f in enumerate(self.df['ImageId'].iloc[indexes]):
            self.info[index*self.batch_size+i]=f
            img = Image.open(self.data_path + f).resize((800,128))
            X[i,] = train_datagen.apply_transform(x = img, transform_parameters = param)
        """
        #run-Length encoding on the pixel values
        for j in range(4):
            mask= rle2mask(self.df['Defect_ '+str(j+1)].iloc[indexes[i]])
            y[i,:,:,:j] = train_datagen.apply_transform(x = mask, transform_parameters = param)
        """
        if self.preprocess!=None: X = self.preprocess(X)
        return X, y
```

7.2 Validation generator(Without Augmentation)

In [0]:

```
# https://stanford.edu/~shervine/blog/keras-how-to-generate-data-on-the-fly

import keras
from keras.preprocessing.image import ImageDataGenerator
class Val_DataGenerator(keras.utils.Sequence):
    def __init__(self, df, batch_size = 16,shuffle=False,
                 preprocess=None, info={}):
        super().__init__()
        self.df = df
        self.shuffle = shuffle
        self.batch_size = batch_size
        self.preprocess = preprocess
        self.info = info
        self.data_path = '/content/' + 'train_images/'
        self.on_epoch_end()

    def __len__(self):
        return int(np.floor(len(self.df) / self.batch_size))

    def on_epoch_end(self):
        self.indexes = np.arange(len(self.df))
        if self.shuffle == True:
            np.random.shuffle(self.indexes)

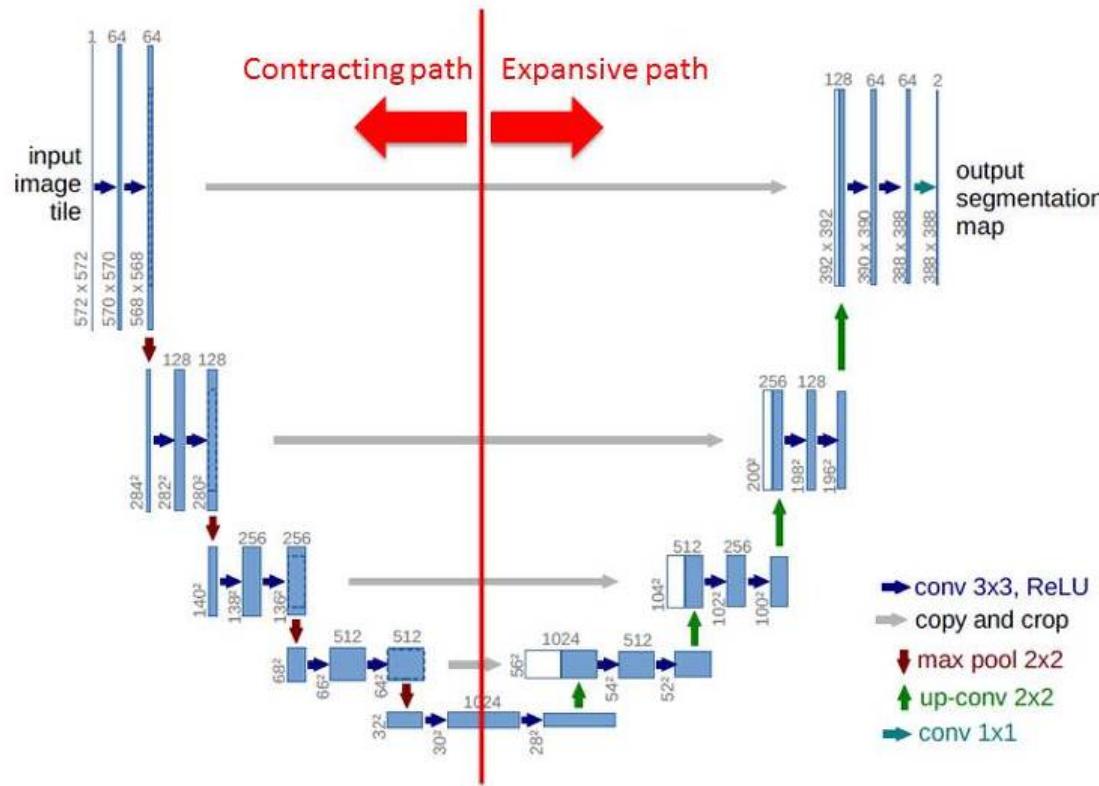
    def __getitem__(self, index):

        X = np.empty((self.batch_size,128,800,3),dtype=np.float32) #images
        y = np.empty((self.batch_size,128,800,4),dtype=np.int8)      #masks
        indexes = self.indexes[index*self.batch_size:(index+1)*self.batch_size]
        for i,f in enumerate(self.df['ImageId'].iloc[indexes]):
            self.info[index*self.batch_size+i]=f
            X[i,] = Image.open(self.data_path + f).resize((800,128))
            #run-Length encoding on the pixel values
            for j in range(4):
                y[i,:,:,:,j] = rle2mask(self.df['Defect_'+str(j+1)].iloc[indexes[i]])
        if self.preprocess!=None: X = self.preprocess(X)
        return X, y
```

Implementing Segmentation Architectures

1.0 Basic U-NET (First-cut approach)

Network Architecture



References-

- <https://towardsdatascience.com/understanding-semantic-segmentation-with-unet-6be4f42d4b47>
(<https://towardsdatascience.com/understanding-semantic-segmentation-with-unet-6be4f42d4b47>)

In [0]:

```
def conv2d_block(input_tensor, n_filters, kernel_size = 3, batchnorm = True):
    """Function to add 2 convolutional layers with the parameters passed to it"""
    # first layer
    x = Conv2D(filters = n_filters, kernel_size = (kernel_size, kernel_size), \
               kernel_initializer = 'he_normal', padding = 'same')(input_tensor)
    if batchnorm:
        x = BatchNormalization()(x)
    x = Activation('relu')(x)

    # second layer
    x = Conv2D(filters = n_filters, kernel_size = (kernel_size, kernel_size), \
               kernel_initializer = 'he_normal', padding = 'same')(x)
    if batchnorm:
        x = BatchNormalization()(x)
    x = Activation('relu')(x)

    return x
```

In [0]:

```
def get_unet(input_img, n_filters, dropout, batchnorm):  
    """Function to define the UNET architecture"""\n  
    # Contracting Path  
    c1 = conv2d_block(input_img, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)  
    p1 = MaxPooling2D((2, 2))(c1)  
    p1 = Dropout(dropout)(p1)  
  
    c2 = conv2d_block(p1, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)  
    p2 = MaxPooling2D((2, 2))(c2)  
    p2 = Dropout(dropout)(p2)  
  
    c3 = conv2d_block(p2, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)  
    p3 = MaxPooling2D((2, 2))(c3)  
    p3 = Dropout(dropout)(p3)  
  
    c4 = conv2d_block(p3, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)  
    p4 = MaxPooling2D((2, 2))(c4)  
    p4 = Dropout(dropout)(p4)  
  
    c5 = conv2d_block(p4, n_filters = n_filters * 16, kernel_size = 3, batchnorm = batchnorm)  
  
    # Expansive Path  
    u6 = Conv2DTranspose(n_filters * 8, (3, 3), strides = (2, 2), padding = 'same')(c5)  
    u6 = concatenate([u6, c4])  
    u6 = Dropout(dropout)(u6)  
    c6 = conv2d_block(u6, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)  
  
    u7 = Conv2DTranspose(n_filters * 4, (3, 3), strides = (2, 2), padding = 'same')(c6)  
    u7 = concatenate([u7, c3])  
    u7 = Dropout(dropout)(u7)  
    c7 = conv2d_block(u7, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)  
  
    u8 = Conv2DTranspose(n_filters * 2, (3, 3), strides = (2, 2), padding = 'same')(c7)  
    u8 = concatenate([u8, c2])  
    u8 = Dropout(dropout)(u8)  
    c8 = conv2d_block(u8, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)  
  
    u9 = Conv2DTranspose(n_filters * 1, (3, 3), strides = (2, 2), padding = 'same')(c8)  
    u9 = concatenate([u9, c1])  
    u9 = Dropout(dropout)(u9)  
    c9 = conv2d_block(u9, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)  
  
    outputs = Conv2D(4, (1, 1), activation='sigmoid')(c9)  
    model = Model(inputs=[input_img], outputs=[outputs])  
    return model
```

In [0]:

```
input_img = Input((128, 800, 3), name='img')
model = get_unet(input_img, n_filters=8, dropout=0.2, batchnorm=True)
model.compile(optimizer=Adam(), loss=bce_dice_loss, metrics=[dice_coef])
model.summary()
```

Model: "model_2"

Layer (type)	Output Shape	Param #	Connected to
img (InputLayer)	(None, 128, 800, 3)	0	
conv2d_20 (Conv2D)	(None, 128, 800, 8)	224	img[0][0]
batch_normalization_19 (BatchNo)	(None, 128, 800, 8)	32	conv2d_20[0][0]
activation_19 (Activation)	(None, 128, 800, 8)	0	batch_normalization_19[0][0]
conv2d_21 (Conv2D)	(None, 128, 800, 8)	584	activation_19[0][0]
batch_normalization_20 (BatchNo)	(None, 128, 800, 8)	32	conv2d_21[0][0]
activation_20 (Activation)	(None, 128, 800, 8)	0	batch_normalization_20[0][0]
max_pooling2d_5 (MaxPooling2D)	(None, 64, 400, 8)	0	activation_20[0][0]
dropout_9 (Dropout)	(None, 64, 400, 8)	0	max_pooling2d_5[0][0]
conv2d_22 (Conv2D)	(None, 64, 400, 16)	1168	dropout_9[0][0]
batch_normalization_21 (BatchNo)	(None, 64, 400, 16)	64	conv2d_22[0][0]
activation_21 (Activation)	(None, 64, 400, 16)	0	batch_normalization_21[0][0]
conv2d_23 (Conv2D)	(None, 64, 400, 16)	2320	activation_21[0][0]
batch_normalization_22 (BatchNo)	(None, 64, 400, 16)	64	conv2d_23[0][0]

activation_22 (Activation) (None, 64, 400, 16) 0 batch_norm22[0][0]

max_pooling2d_6 (MaxPooling2D) (None, 32, 200, 16) 0 activation_22[0][0]

dropout_10 (Dropout) (None, 32, 200, 16) 0 max_pooling2d_6[0][0]

conv2d_24 (Conv2D) (None, 32, 200, 32) 4640 dropout_10[0][0]

batch_normalization_23 (BatchNormalizat (None, 32, 200, 32) 128 conv2d_24[0][0]

activation_23 (Activation) (None, 32, 200, 32) 0 batch_normalization_23[0][0]

conv2d_25 (Conv2D) (None, 32, 200, 32) 9248 activation_23[0][0]

batch_normalization_24 (BatchNormalizat (None, 32, 200, 32) 128 conv2d_25[0][0]

activation_24 (Activation) (None, 32, 200, 32) 0 batch_normalization_24[0][0]

max_pooling2d_7 (MaxPooling2D) (None, 16, 100, 32) 0 activation_24[0][0]

dropout_11 (Dropout) (None, 16, 100, 32) 0 max_pooling2d_7[0][0]

conv2d_26 (Conv2D) (None, 16, 100, 64) 18496 dropout_11[0][0]

batch_normalization_25 (BatchNormalizat (None, 16, 100, 64) 256 conv2d_26[0][0]

activation_25 (Activation) (None, 16, 100, 64) 0 batch_normalization_25[0][0]

conv2d_27 (Conv2D) (None, 16, 100, 64) 36928 activation_25[0][0]

batch_normalization_26 (BatchNormalizat (None, 16, 100, 64) 256 conv2d_27

[0][0]

activation_26 (Activation) normalization_26[0][0]	(None, 16, 100, 64) 0	batch_norm
max_pooling2d_8 (MaxPooling2D) n_26[0][0]	(None, 8, 50, 64) 0	activation
dropout_12 (Dropout) ng2d_8[0][0]	(None, 8, 50, 64) 0	max_pooli
conv2d_28 (Conv2D) 2[0][0]	(None, 8, 50, 128) 73856	dropout_1
batch_normalization_27 (BatchNo [0][0]	(None, 8, 50, 128) 512	conv2d_28
activation_27 (Activation) malization_27[0][0]	(None, 8, 50, 128) 0	batch_nor
conv2d_29 (Conv2D) n_27[0][0]	(None, 8, 50, 128) 147584	activatio
batch_normalization_28 (BatchNo [0][0]	(None, 8, 50, 128) 512	conv2d_29
activation_28 (Activation) malization_28[0][0]	(None, 8, 50, 128) 0	batch_nor
conv2d_transpose_5 (Conv2DTrans n_28[0][0]	(None, 16, 100, 64) 73792	activatio
concatenate_5 (Concatenate) anspose_5[0][0]	(None, 16, 100, 128) 0	conv2d_tr
activation_26[0][0]		activatio
dropout_13 (Dropout) te_5[0][0]	(None, 16, 100, 128) 0	concatena
conv2d_30 (Conv2D) 3[0][0]	(None, 16, 100, 64) 73792	dropout_1
batch_normalization_29 (BatchNo [0][0]	(None, 16, 100, 64) 256	conv2d_30

activation_29 (Activation) (None, 16, 100, 64) 0 batch_norm
alization_29[0][0]

conv2d_31 (Conv2D) (None, 16, 100, 64) 36928 activation
n_29[0][0]

batch_normalization_30 (BatchNorm (None, 16, 100, 64) 256 conv2d_31
[0][0]

activation_30 (Activation) (None, 16, 100, 64) 0 batch_norm
alization_30[0][0]

conv2d_transpose_6 (Conv2DTrans (None, 32, 200, 32) 18464 activation
n_30[0][0]

concatenate_6 (Concatenate) (None, 32, 200, 64) 0 conv2d_tr
anspose_6[0][0] activation
n_24[0][0]

dropout_14 (Dropout) (None, 32, 200, 64) 0 concatenation
te_6[0][0]

conv2d_32 (Conv2D) (None, 32, 200, 32) 18464 dropout_1
4[0][0]

batch_normalization_31 (BatchNorm (None, 32, 200, 32) 128 conv2d_32
[0][0]

activation_31 (Activation) (None, 32, 200, 32) 0 batch_norm
alization_31[0][0]

conv2d_33 (Conv2D) (None, 32, 200, 32) 9248 activation
n_31[0][0]

batch_normalization_32 (BatchNorm (None, 32, 200, 32) 128 conv2d_33
[0][0]

activation_32 (Activation) (None, 32, 200, 32) 0 batch_norm
alization_32[0][0]

conv2d_transpose_7 (Conv2DTrans (None, 64, 400, 16) 4624 activation
n_32[0][0]

concatenate_7 (Concatenate) (None, 64, 400, 32) 0 conv2d_tr
anspose_7[0][0] activation

n_22[0][0]

dropout_15 (Dropout) (None, 64, 400, 32) 0 concatena
te_7[0][0]

conv2d_34 (Conv2D) (None, 64, 400, 16) 4624 dropout_1
5[0][0]

batch_normalization_33 (BatchNo (None, 64, 400, 16) 64 conv2d_34
[0][0]

activation_33 (Activation) (None, 64, 400, 16) 0 batch_nor
malization_33[0][0]

conv2d_35 (Conv2D) (None, 64, 400, 16) 2320 activation
n_33[0][0]

batch_normalization_34 (BatchNo (None, 64, 400, 16) 64 conv2d_35
[0][0]

activation_34 (Activation) (None, 64, 400, 16) 0 batch_nor
malization_34[0][0]

conv2d_transpose_8 (Conv2DTrans (None, 128, 800, 8) 1160 activation
n_34[0][0]

concatenate_8 (Concatenate) (None, 128, 800, 16) 0 conv2d_tr
anspose_8[0][0] activation
n_20[0][0]

dropout_16 (Dropout) (None, 128, 800, 16) 0 concatena
te_8[0][0]

conv2d_36 (Conv2D) (None, 128, 800, 8) 1160 dropout_1
6[0][0]

batch_normalization_35 (BatchNo (None, 128, 800, 8) 32 conv2d_36
[0][0]

activation_35 (Activation) (None, 128, 800, 8) 0 batch_nor
malization_35[0][0]

conv2d_37 (Conv2D) (None, 128, 800, 8) 584 activation
n_35[0][0]

```
batch_normalization_36 (BatchNo (None, 128, 800, 8) 32          conv2d_37
[0][0]

activation_36 (Activation)      (None, 128, 800, 8)  0          batch_nor
malization_36[0][0]

conv2d_38 (Conv2D)            (None, 128, 800, 4)  36          activatio
n_36[0][0]
=====
=====
Total params: 543,188
Trainable params: 541,716
Non-trainable params: 1,472
```


1.1 Checkpointing the model and creating the callback list

In [0]:

```
from keras.callbacks import ModelCheckpoint
from keras.callbacks import CSVLogger
import matplotlib.pyplot as plt
from tensorflow.python.keras.callbacks import TensorBoard
from keras.callbacks import TensorBoard
import tensorflow as tf
import datetime
import keras
from tensorboardcolab import *
from keras.callbacks import ReduceLROnPlateau

#https://github.com/taomanwai/tensorboardcolab/
tbc=TensorBoardColab()
#https://machinelearningmastery.com/check-point-deep-Learning-models-keras/
mc = ModelCheckpoint('best_model_unet.h5', monitor='val_dice_coef', verbose=1, save_bes
t_only=True, mode='max')
callbacks_list = [mc, TensorBoardColabCallback(tbc)]
```

Wait for 8 seconds...

TensorBoard link:

<https://bde24643.ngrok.io>

1.2 Fitting the train data and validation

In [0]:

```
train_batches = Train_DataGenerator(train_data,shuffle=True)
valid_batches = Val_DataGenerator(cv_data)
history = model.fit_generator(train_batches, validation_data = valid_batches, epochs =
50, verbose=1,
                                class_weight= class_wts,callbacks= callbacks_list) #class
_wts as calculated in EDA
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please use tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is deprecated. Please use tf.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorboard_colab/core.py:49: The name tf.summary.FileWriter is deprecated. Please use tf.compat.v1.summary.FileWriter instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1122: The name tf.summary.merge_all is deprecated. Please use tf.compat.v1.summary.merge_all instead.

Epoch 1/50

667/667 [=====] - 235s 352ms/step - loss: 1.2888
- dice_coef: 0.0286 - val_loss: 0.9921 - val_dice_coef: 0.0688

Epoch 00001: val_dice_coef improved from -inf to 0.06879, saving model to /content/weights.best.hdf5

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorboard_colab/callbacks.py:51: The name tf.Summary is deprecated. Please use tf.compat.v1.Summary instead.

Epoch 2/50

667/667 [=====] - 221s 332ms/step - loss: 0.7664
- dice_coef: 0.2798 - val_loss: 0.6661 - val_dice_coef: 0.3743

Epoch 00002: val_dice_coef improved from 0.06879 to 0.37426, saving model to /content/weights.best.hdf5

Epoch 3/50

667/667 [=====] - 218s 327ms/step - loss: 0.6021
- dice_coef: 0.4394 - val_loss: 0.6355 - val_dice_coef: 0.4068

Epoch 00003: val_dice_coef improved from 0.37426 to 0.40684, saving model to /content/weights.best.hdf5

Epoch 4/50

667/667 [=====] - 218s 327ms/step - loss: 0.5688
- dice_coef: 0.4727 - val_loss: 0.5948 - val_dice_coef: 0.4483

Epoch 00004: val_dice_coef improved from 0.40684 to 0.44832, saving model to /content/weights.best.hdf5

Epoch 5/50

667/667 [=====] - 218s 327ms/step - loss: 0.5578
- dice_coef: 0.4831 - val_loss: 0.5886 - val_dice_coef: 0.4532

Epoch 00005: val_dice_coef improved from 0.44832 to 0.45317, saving model to /content/weights.best.hdf5

Epoch 6/50

667/667 [=====] - 218s 327ms/step - loss: 0.5479
- dice_coef: 0.4926 - val_loss: 0.6220 - val_dice_coef: 0.4202

Epoch 00006: val_dice_coef did not improve from 0.45317

Epoch 7/50

667/667 [=====] - 219s 328ms/step - loss: 0.5365
- dice_coef: 0.5031 - val_loss: 0.5678 - val_dice_coef: 0.4741

Epoch 00007: val_dice_coef improved from 0.45317 to 0.47414, saving model to /content/weights.best.hdf5

Epoch 8/50
667/667 [=====] - 218s 327ms/step - loss: 0.5266
- dice_coef: 0.5121 - val_loss: 0.5805 - val_dice_coef: 0.4598

Epoch 00008: val_dice_coef did not improve from 0.47414

Epoch 9/50
667/667 [=====] - 218s 327ms/step - loss: 0.5284
- dice_coef: 0.5105 - val_loss: 0.6018 - val_dice_coef: 0.4460

Epoch 00009: val_dice_coef did not improve from 0.47414

Epoch 10/50
667/667 [=====] - 218s 327ms/step - loss: 0.5184
- dice_coef: 0.5197 - val_loss: 0.6106 - val_dice_coef: 0.4335

Epoch 00010: val_dice_coef did not improve from 0.47414

Epoch 11/50
667/667 [=====] - 218s 327ms/step - loss: 0.5083
- dice_coef: 0.5291 - val_loss: 0.5716 - val_dice_coef: 0.4732

Epoch 00011: val_dice_coef did not improve from 0.47414

Epoch 12/50
667/667 [=====] - 218s 327ms/step - loss: 0.5064
- dice_coef: 0.5309 - val_loss: 0.5848 - val_dice_coef: 0.4641

Epoch 00012: val_dice_coef did not improve from 0.47414

Epoch 13/50
667/667 [=====] - 218s 328ms/step - loss: 0.5143
- dice_coef: 0.5233 - val_loss: 0.5851 - val_dice_coef: 0.4597

Epoch 00013: val_dice_coef did not improve from 0.47414

Epoch 14/50
667/667 [=====] - 218s 327ms/step - loss: 0.5044
- dice_coef: 0.5327 - val_loss: 0.5585 - val_dice_coef: 0.4843

Epoch 00014: val_dice_coef improved from 0.47414 to 0.48428, saving model to /content/weights.best.hdf5

Epoch 15/50
667/667 [=====] - 219s 329ms/step - loss: 0.4969
- dice_coef: 0.5393 - val_loss: 0.5834 - val_dice_coef: 0.4602

Epoch 00015: val_dice_coef did not improve from 0.48428

Epoch 16/50
667/667 [=====] - 220s 330ms/step - loss: 0.4981
- dice_coef: 0.5378 - val_loss: 0.5541 - val_dice_coef: 0.4882

Epoch 00016: val_dice_coef improved from 0.48428 to 0.48824, saving model to /content/weights.best.hdf5

Epoch 17/50
667/667 [=====] - 220s 329ms/step - loss: 0.4986
- dice_coef: 0.5371 - val_loss: 0.5414 - val_dice_coef: 0.4994

Epoch 00017: val_dice_coef improved from 0.48824 to 0.49937, saving model to /content/weights.best.hdf5

Epoch 18/50
667/667 [=====] - 220s 330ms/step - loss: 0.4927
- dice_coef: 0.5427 - val_loss: 0.5506 - val_dice_coef: 0.4906

Epoch 00018: val_dice_coef did not improve from 0.49937

Epoch 19/50
667/667 [=====] - 220s 329ms/step - loss: 0.4946
- dice_coef: 0.5407 - val_loss: 0.5521 - val_dice_coef: 0.4894

```
Epoch 00019: val_dice_coef did not improve from 0.49937
Epoch 20/50
667/667 [=====] - 220s 330ms/step - loss: 0.4869
- dice_coef: 0.5477 - val_loss: 0.5352 - val_dice_coef: 0.5063

Epoch 00020: val_dice_coef improved from 0.49937 to 0.50629, saving model
to /content/weights.best.hdf5
Epoch 21/50
667/667 [=====] - 220s 330ms/step - loss: 0.4799
- dice_coef: 0.5545 - val_loss: 0.5675 - val_dice_coef: 0.4741

Epoch 00021: val_dice_coef did not improve from 0.50629
Epoch 22/50
667/667 [=====] - 220s 330ms/step - loss: 0.4698
- dice_coef: 0.5637 - val_loss: 0.5634 - val_dice_coef: 0.4798

Epoch 00022: val_dice_coef did not improve from 0.50629
Epoch 23/50
667/667 [=====] - 219s 328ms/step - loss: 0.4649
- dice_coef: 0.5683 - val_loss: 0.5331 - val_dice_coef: 0.5066

Epoch 00023: val_dice_coef improved from 0.50629 to 0.50659, saving model
to /content/weights.best.hdf5
Epoch 24/50
667/667 [=====] - 221s 331ms/step - loss: 0.4522
- dice_coef: 0.5803 - val_loss: 0.5130 - val_dice_coef: 0.5247

Epoch 00024: val_dice_coef improved from 0.50659 to 0.52471, saving model
to /content/weights.best.hdf5
Epoch 25/50
667/667 [=====] - 220s 329ms/step - loss: 0.4521
- dice_coef: 0.5806 - val_loss: 0.4926 - val_dice_coef: 0.5441

Epoch 00025: val_dice_coef improved from 0.52471 to 0.54411, saving model
to /content/weights.best.hdf5
Epoch 26/50
667/667 [=====] - 222s 332ms/step - loss: 0.4461
- dice_coef: 0.5862 - val_loss: 0.4957 - val_dice_coef: 0.5411

Epoch 00026: val_dice_coef did not improve from 0.54411
Epoch 27/50
667/667 [=====] - 224s 335ms/step - loss: 0.4415
- dice_coef: 0.5903 - val_loss: 0.5474 - val_dice_coef: 0.4974

Epoch 00027: val_dice_coef did not improve from 0.54411
Epoch 28/50
667/667 [=====] - 221s 331ms/step - loss: 0.4380
- dice_coef: 0.5938 - val_loss: 0.5168 - val_dice_coef: 0.5255

Epoch 00028: val_dice_coef did not improve from 0.54411
Epoch 29/50
667/667 [=====] - 221s 331ms/step - loss: 0.4381
- dice_coef: 0.5933 - val_loss: 0.4751 - val_dice_coef: 0.5607

Epoch 00029: val_dice_coef improved from 0.54411 to 0.56069, saving model
to /content/weights.best.hdf5
Epoch 30/50
667/667 [=====] - 220s 330ms/step - loss: 0.4303
- dice_coef: 0.6009 - val_loss: 0.4815 - val_dice_coef: 0.5556
```

```
Epoch 00030: val_dice_coef did not improve from 0.56069
Epoch 31/50
667/667 [=====] - 221s 332ms/step - loss: 0.4316
- dice_coef: 0.5998 - val_loss: 0.4972 - val_dice_coef: 0.5385

Epoch 00031: val_dice_coef did not improve from 0.56069
Epoch 32/50
667/667 [=====] - 220s 330ms/step - loss: 0.4255
- dice_coef: 0.6053 - val_loss: 0.4764 - val_dice_coef: 0.5602

Epoch 00032: val_dice_coef did not improve from 0.56069
Epoch 33/50
667/667 [=====] - 222s 332ms/step - loss: 0.4228
- dice_coef: 0.6079 - val_loss: 0.4917 - val_dice_coef: 0.5472

Epoch 00033: val_dice_coef did not improve from 0.56069
Epoch 34/50
667/667 [=====] - 221s 331ms/step - loss: 0.4186
- dice_coef: 0.6119 - val_loss: 0.4691 - val_dice_coef: 0.5668

Epoch 00034: val_dice_coef improved from 0.56069 to 0.56676, saving model
to /content/weights.best.hdf5
Epoch 35/50
667/667 [=====] - 223s 334ms/step - loss: 0.4233
- dice_coef: 0.6072 - val_loss: 0.4857 - val_dice_coef: 0.5514

Epoch 00035: val_dice_coef did not improve from 0.56676
Epoch 36/50
667/667 [=====] - 223s 335ms/step - loss: 0.4080
- dice_coef: 0.6219 - val_loss: 0.4777 - val_dice_coef: 0.5587

Epoch 00036: val_dice_coef did not improve from 0.56676
Epoch 37/50
667/667 [=====] - 221s 332ms/step - loss: 0.4142
- dice_coef: 0.6159 - val_loss: 0.4701 - val_dice_coef: 0.5660

Epoch 00037: val_dice_coef did not improve from 0.56676
Epoch 38/50
667/667 [=====] - 221s 332ms/step - loss: 0.4136
- dice_coef: 0.6163 - val_loss: 0.4693 - val_dice_coef: 0.5670

Epoch 00038: val_dice_coef improved from 0.56676 to 0.56701, saving model
to /content/weights.best.hdf5
Epoch 39/50
667/667 [=====] - 221s 332ms/step - loss: 0.4096
- dice_coef: 0.6203 - val_loss: 0.4714 - val_dice_coef: 0.5647

Epoch 00039: val_dice_coef did not improve from 0.56701
Epoch 40/50
667/667 [=====] - 221s 331ms/step - loss: 0.4091
- dice_coef: 0.6204 - val_loss: 0.4560 - val_dice_coef: 0.5791

Epoch 00040: val_dice_coef improved from 0.56701 to 0.57912, saving model
to /content/weights.best.hdf5
Epoch 41/50
667/667 [=====] - 219s 329ms/step - loss: 0.3994
- dice_coef: 0.6299 - val_loss: 0.4466 - val_dice_coef: 0.5882

Epoch 00041: val_dice_coef improved from 0.57912 to 0.58820, saving model
to /content/weights.best.hdf5
Epoch 42/50
```

```
667/667 [=====] - 221s 331ms/step - loss: 0.3987
- dice_coef: 0.6305 - val_loss: 0.5524 - val_dice_coef: 0.4881

Epoch 00042: val_dice_coef did not improve from 0.58820
Epoch 43/50
667/667 [=====] - 221s 332ms/step - loss: 0.4020
- dice_coef: 0.6272 - val_loss: 0.4623 - val_dice_coef: 0.5736

Epoch 00043: val_dice_coef did not improve from 0.58820
Epoch 44/50
667/667 [=====] - 223s 335ms/step - loss: 0.4019
- dice_coef: 0.6273 - val_loss: 0.4785 - val_dice_coef: 0.5597

Epoch 00044: val_dice_coef did not improve from 0.58820
Epoch 45/50
667/667 [=====] - 221s 331ms/step - loss: 0.4001
- dice_coef: 0.6291 - val_loss: 0.4919 - val_dice_coef: 0.5482

Epoch 00045: val_dice_coef did not improve from 0.58820
Epoch 46/50
667/667 [=====] - 220s 330ms/step - loss: 0.3934
- dice_coef: 0.6351 - val_loss: 0.4582 - val_dice_coef: 0.5753

Epoch 00046: val_dice_coef did not improve from 0.58820
Epoch 47/50
667/667 [=====] - 220s 329ms/step - loss: 0.3943
- dice_coef: 0.6344 - val_loss: 0.4543 - val_dice_coef: 0.5809

Epoch 00047: val_dice_coef did not improve from 0.58820
Epoch 48/50
667/667 [=====] - 220s 329ms/step - loss: 0.3905
- dice_coef: 0.6381 - val_loss: 0.4447 - val_dice_coef: 0.5897

Epoch 00048: val_dice_coef improved from 0.58820 to 0.58972, saving model
to /content/weights.best.hdf5
Epoch 49/50
667/667 [=====] - 220s 329ms/step - loss: 0.3942
- dice_coef: 0.6345 - val_loss: 0.4480 - val_dice_coef: 0.5867

Epoch 00049: val_dice_coef did not improve from 0.58972
Epoch 50/50
667/667 [=====] - 219s 329ms/step - loss: 0.3922
- dice_coef: 0.6364 - val_loss: 0.4546 - val_dice_coef: 0.5802

Epoch 00050: val_dice_coef did not improve from 0.58972
```

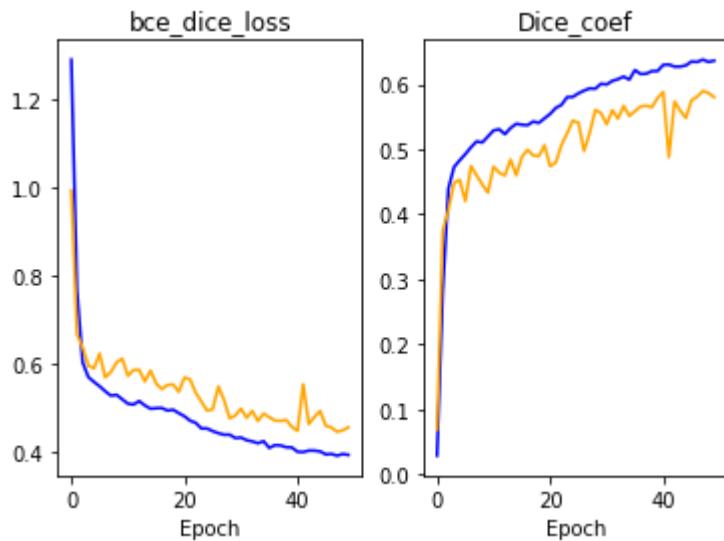
1.3 Plots on training & validation results

Loss function & metric plots

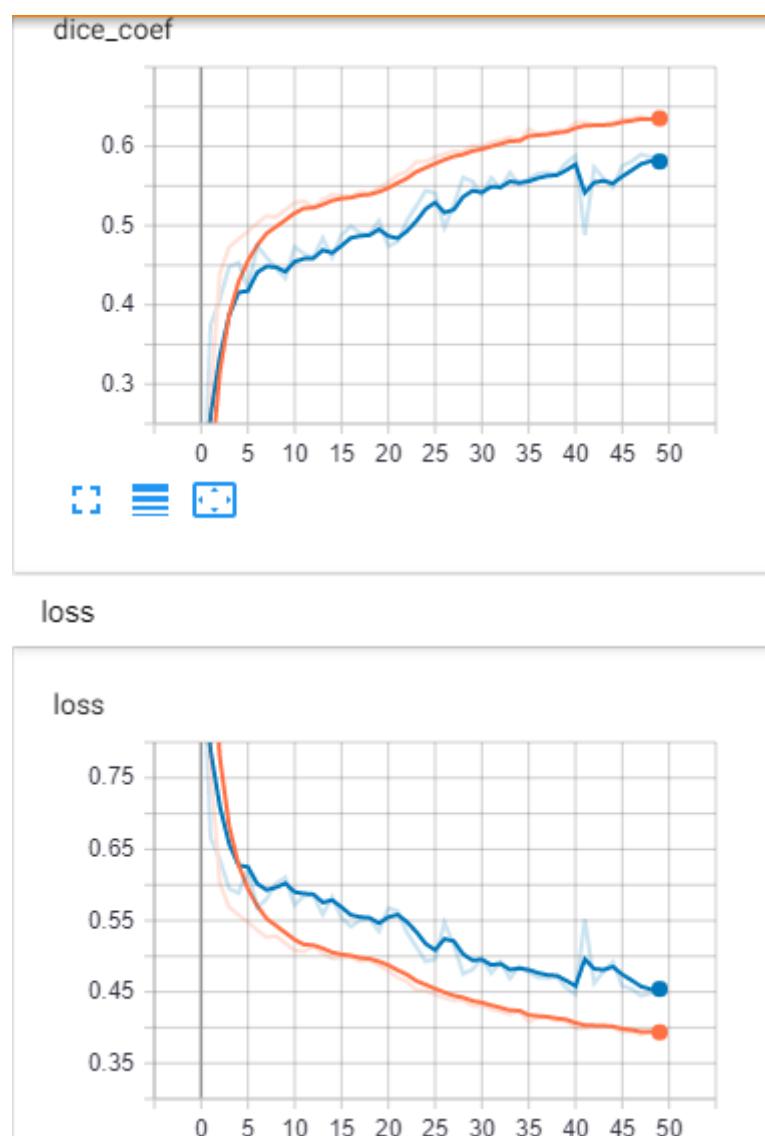
Please refer to Training Plots in utility functions section.

In [0]:

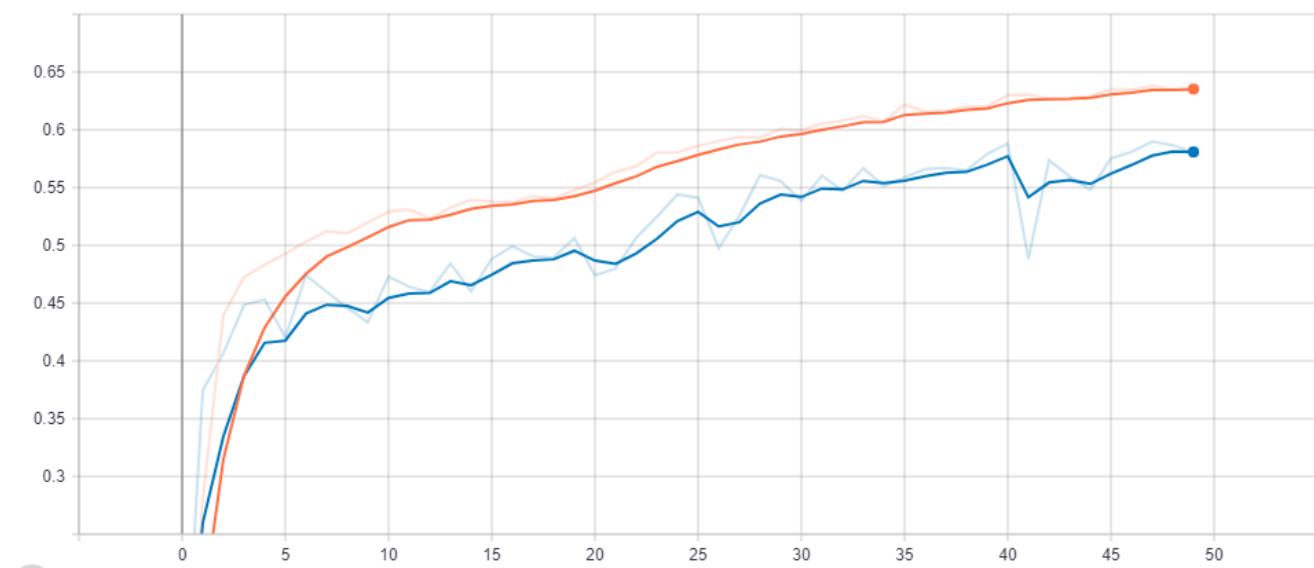
plot(history)



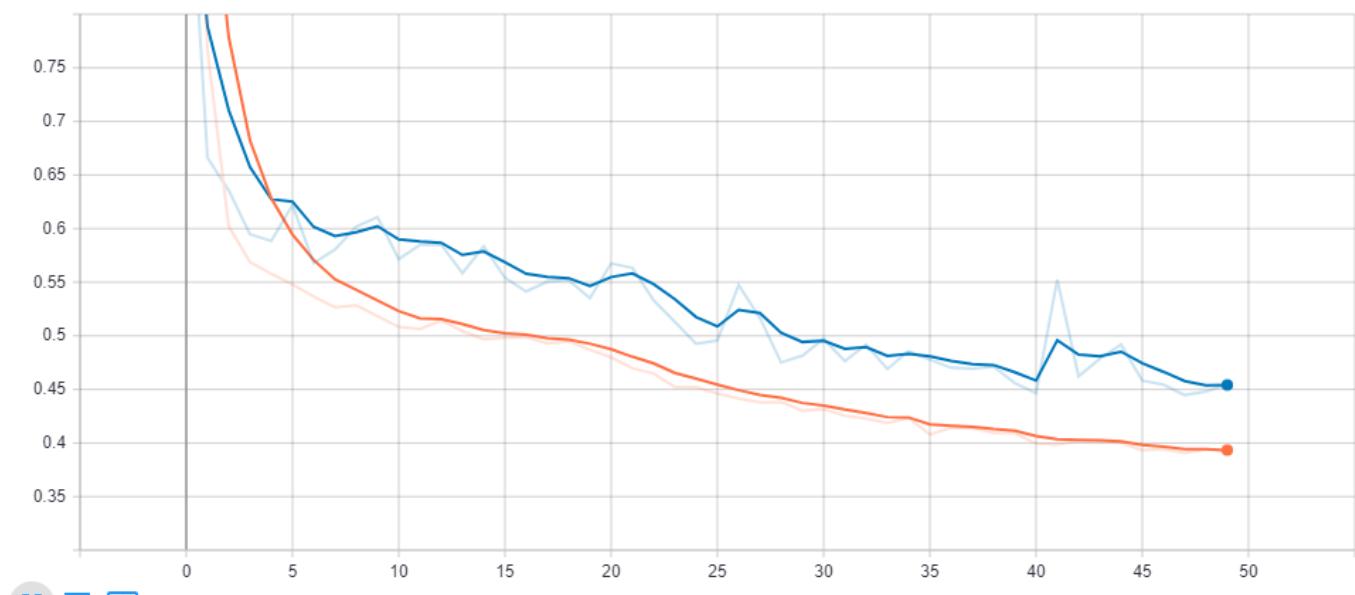
Tensorboard images



dice_coef



loss



1.4 Model Testing

Loading the best model for evaluation

In [0]:

```
from keras.models import load_model
dependencies = {'bce_dice_loss':bce_dice_loss,'dice_coef':dice_coef,}
model_best = load_model('/content/best_model_unet.h5',custom_objects=dependencies)
```

Evaluating on validation images

In [0]:

```
evals= model_best.evaluate(valid_batches,verbose=1)

117/117 [=====] - 36s 306ms/step
```

In [0]:

```
print('Validation set evaluation score:')
print('bce_dice loss:',evals[0])
print('dice_coeff:',evals[1])
```

```
Validation set evaluation score:
bce_dice loss: 0.4407530933873266
dice_coeff: 0.5941144448314977
```

1.5 Defects visualization

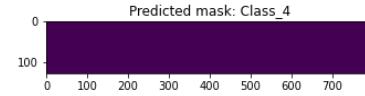
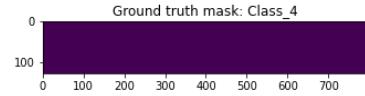
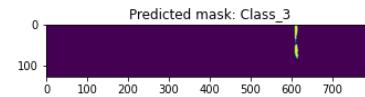
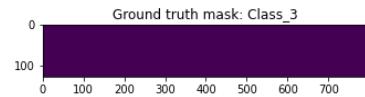
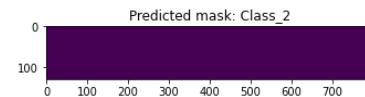
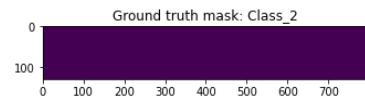
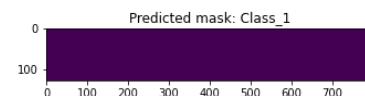
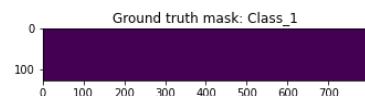
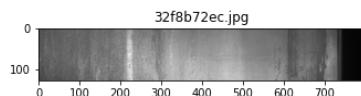
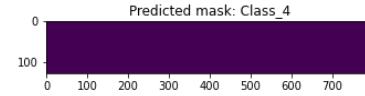
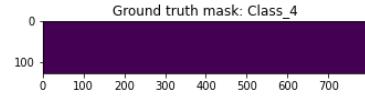
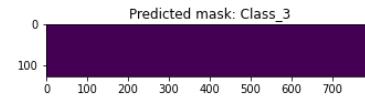
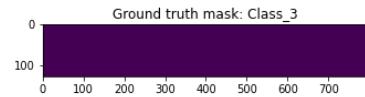
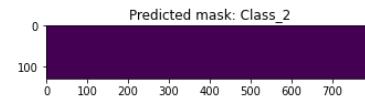
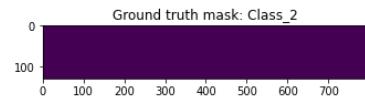
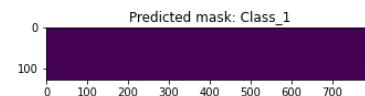
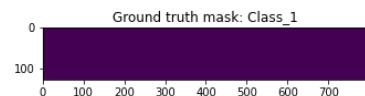
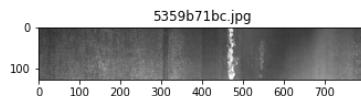
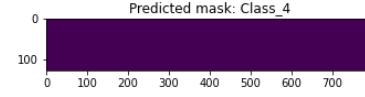
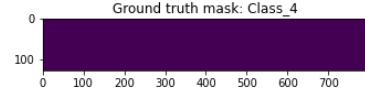
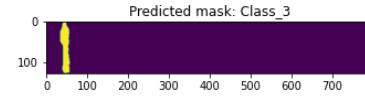
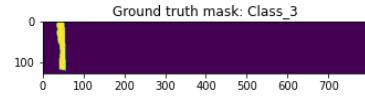
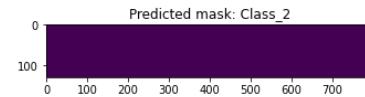
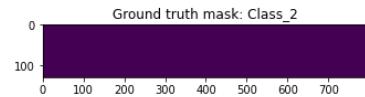
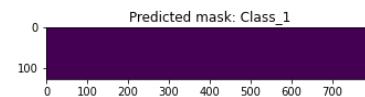
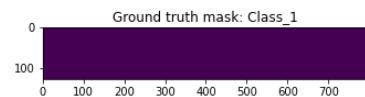
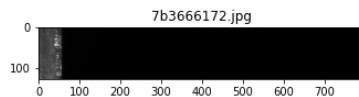
Please refer to the "visualize_defects" function in Utility functions section.

Training set

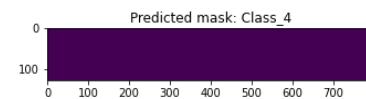
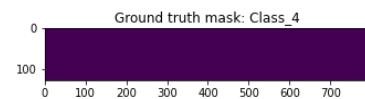
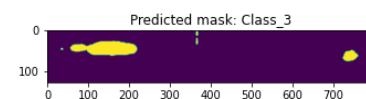
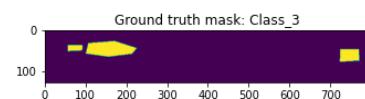
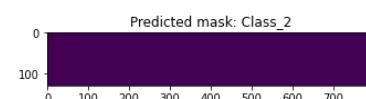
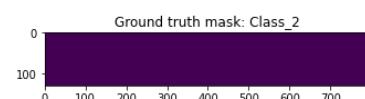
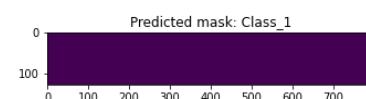
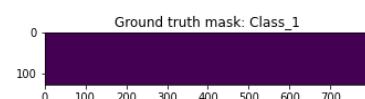
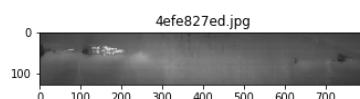
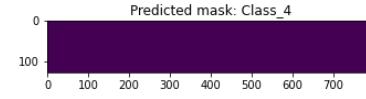
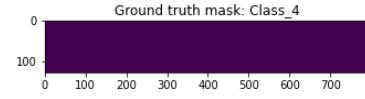
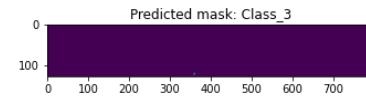
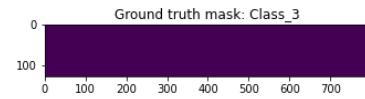
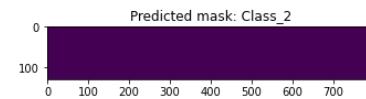
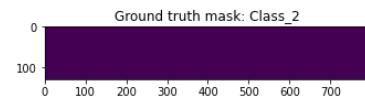
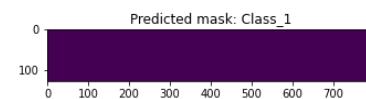
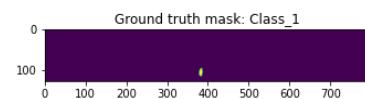
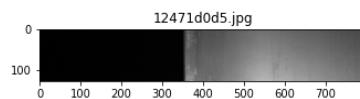
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visualize_defects(train_data,model_best)
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Severstal Steel Defect Detection



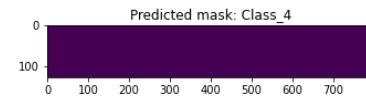
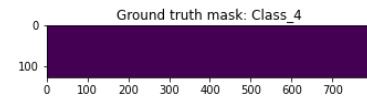
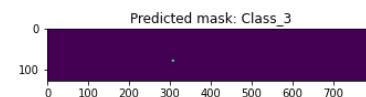
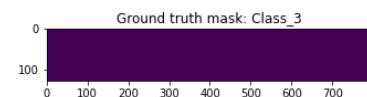
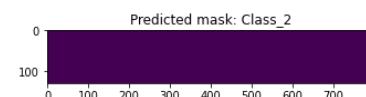
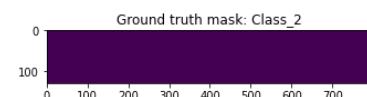
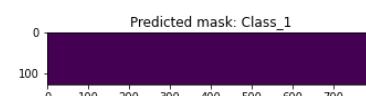
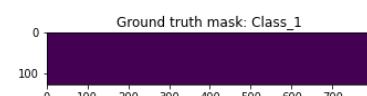
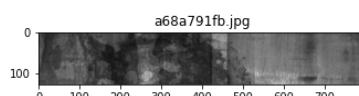
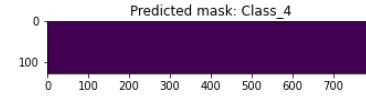
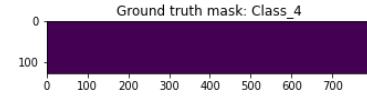
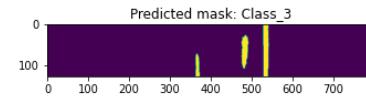
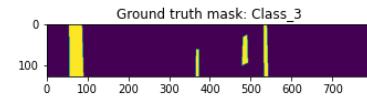
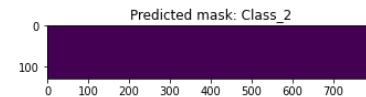
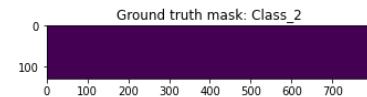
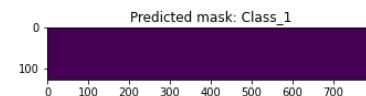
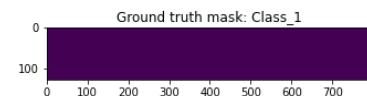
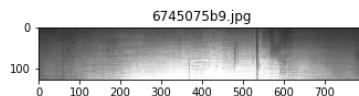
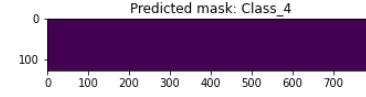
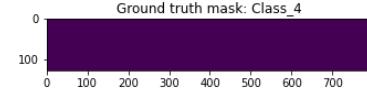
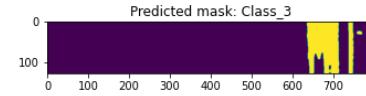
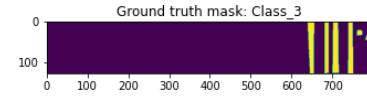
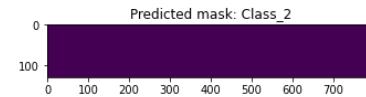
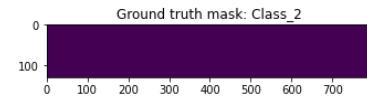
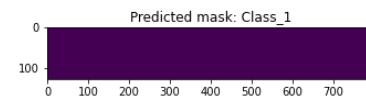
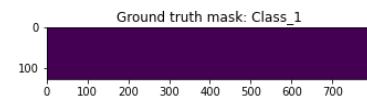
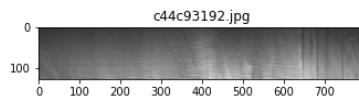
Severstal Steel Defect Detection



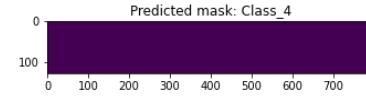
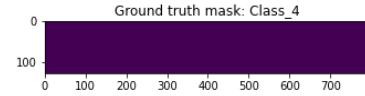
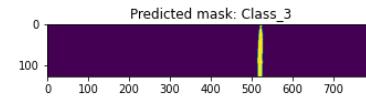
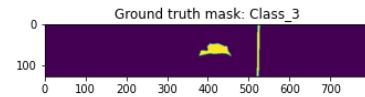
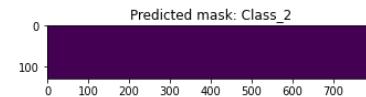
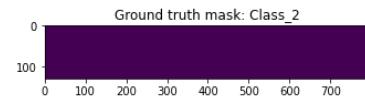
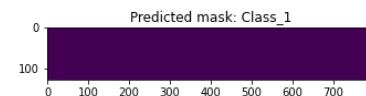
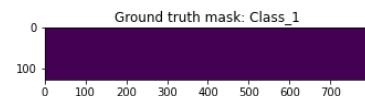
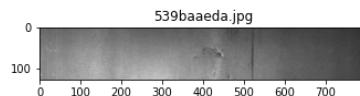
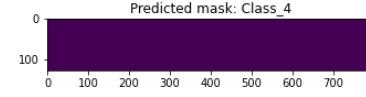
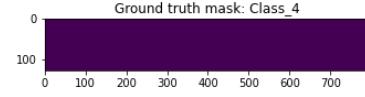
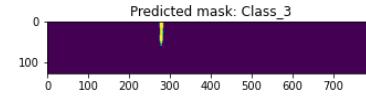
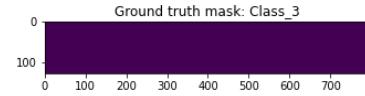
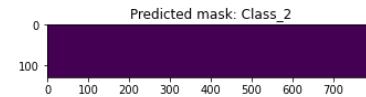
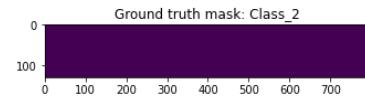
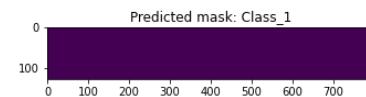
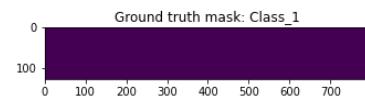
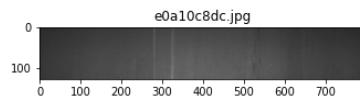
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visualize_defects(train_data,model_best)
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Severstal Steel Defect Detection



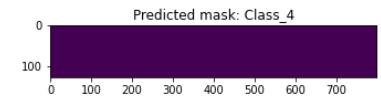
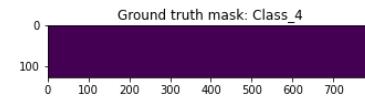
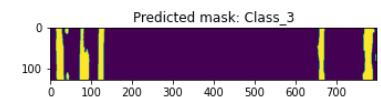
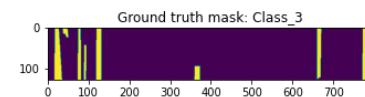
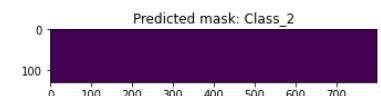
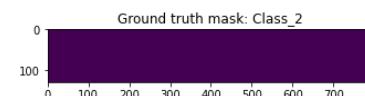
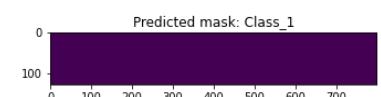
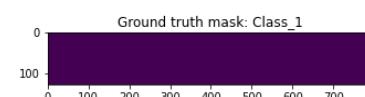
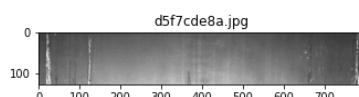
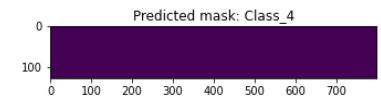
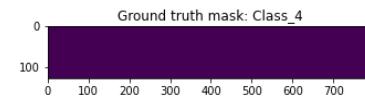
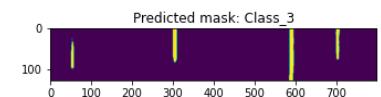
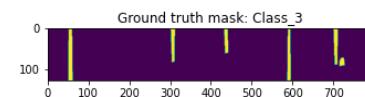
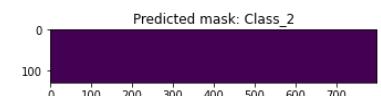
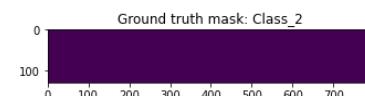
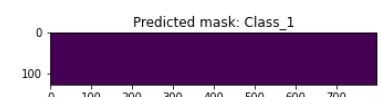
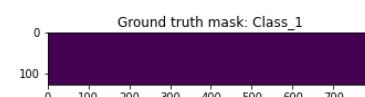
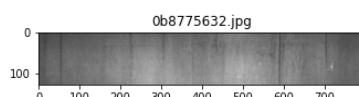
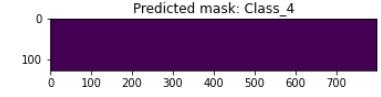
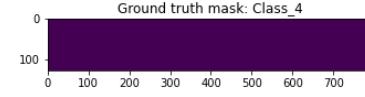
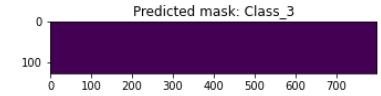
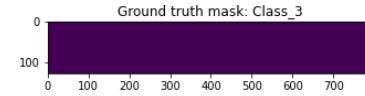
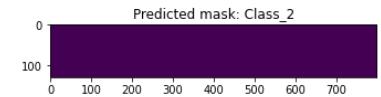
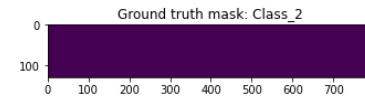
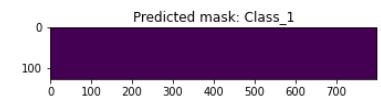
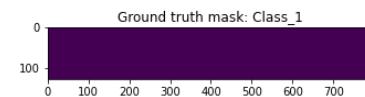
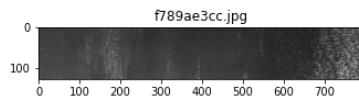
Severstal Steel Defect Detection

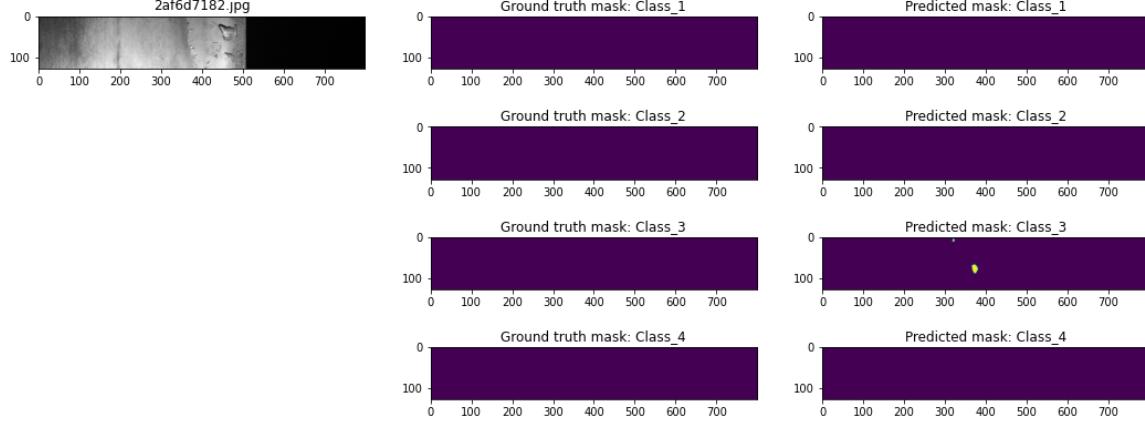
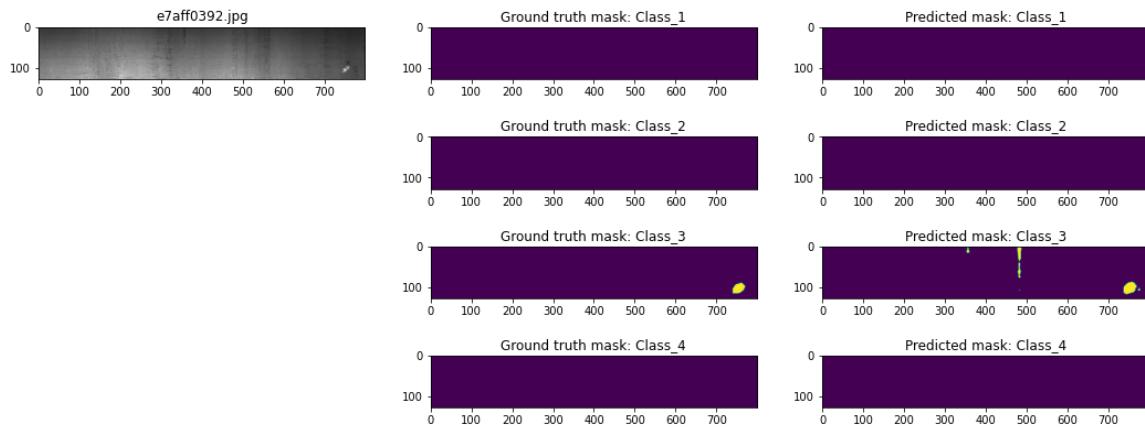


In [0]:

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visualize_defects(train_data,model_best)
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Severstal Steel Defect Detection

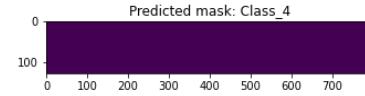
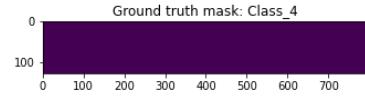
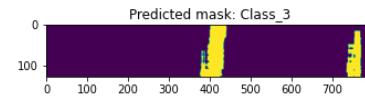
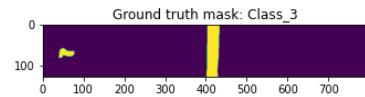
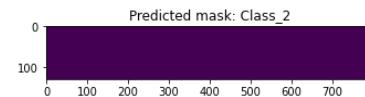
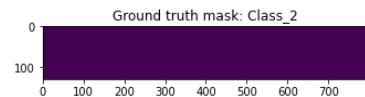
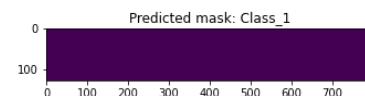
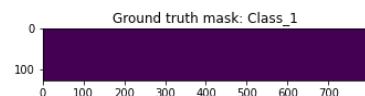
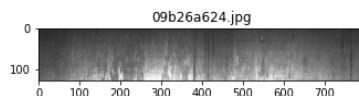
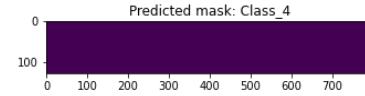
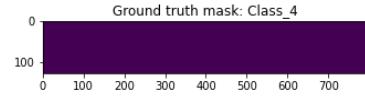
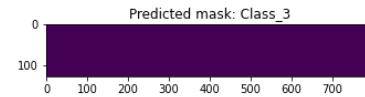
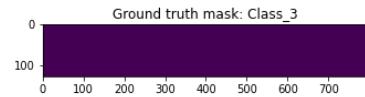
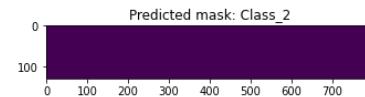
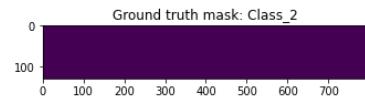
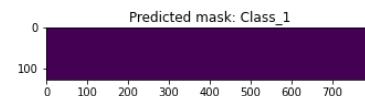
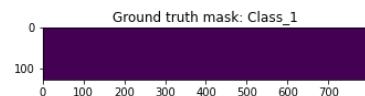
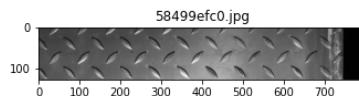
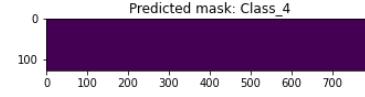
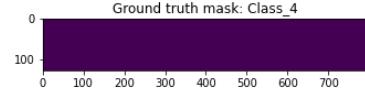
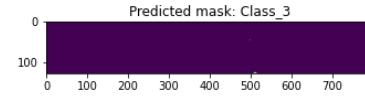
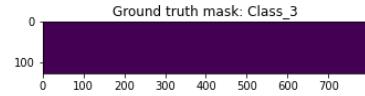
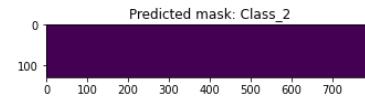
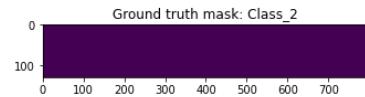
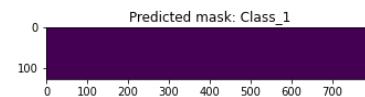
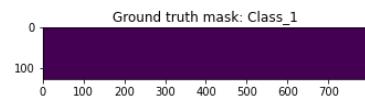
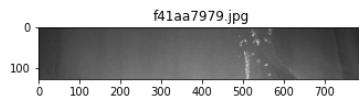




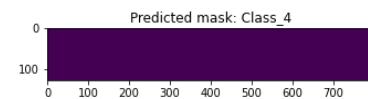
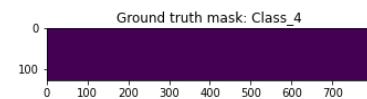
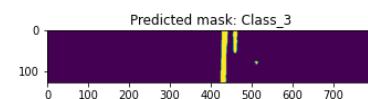
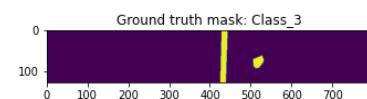
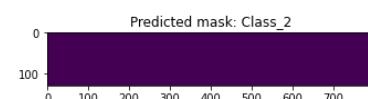
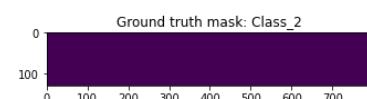
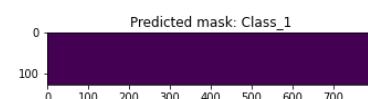
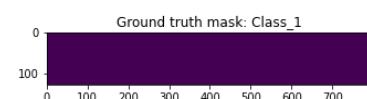
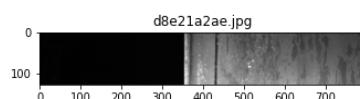
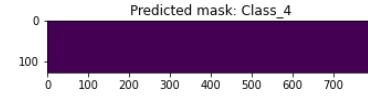
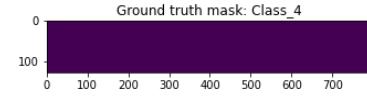
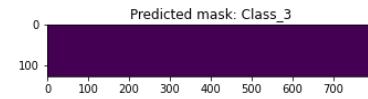
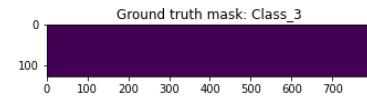
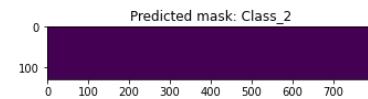
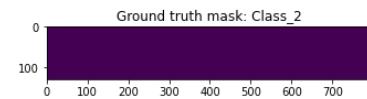
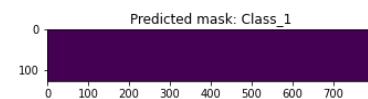
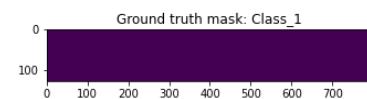
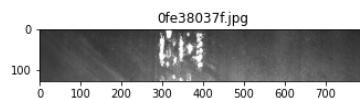
Validation set

In [0]:

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visualize_defects(cv_data,model_best)
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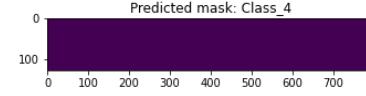
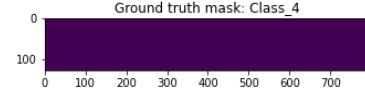
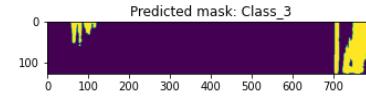
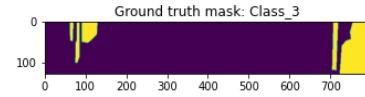
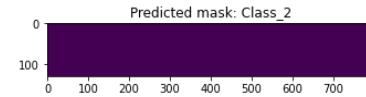
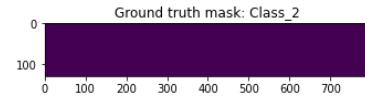
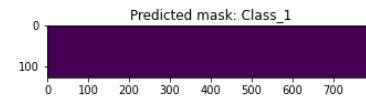
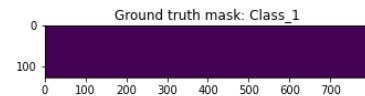
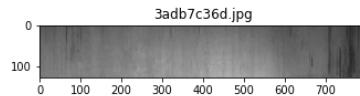
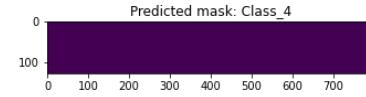
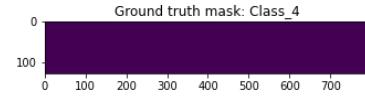
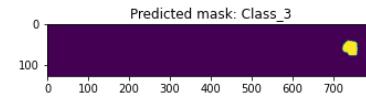
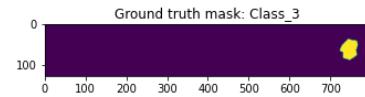
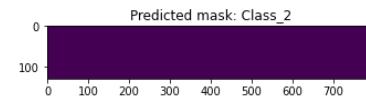
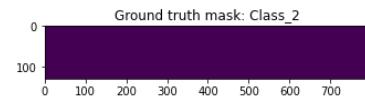
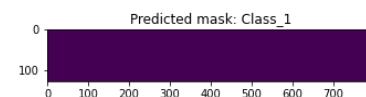
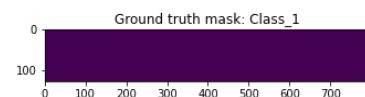
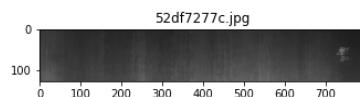
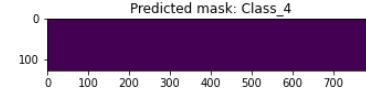
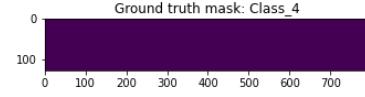
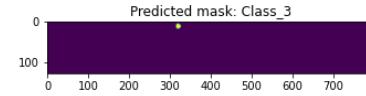
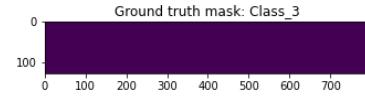
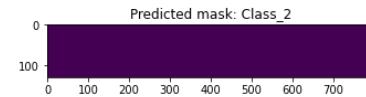
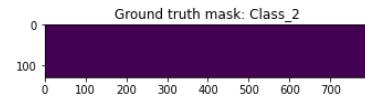
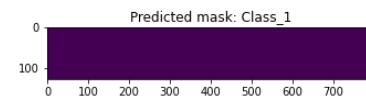
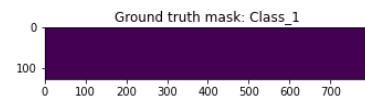
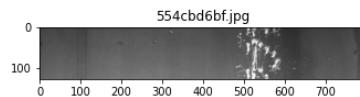
Severstal Steel Defect Detection



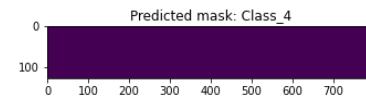
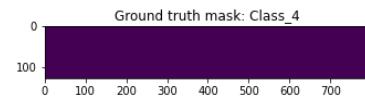
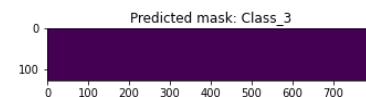
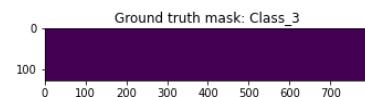
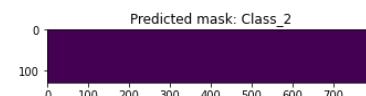
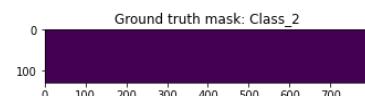
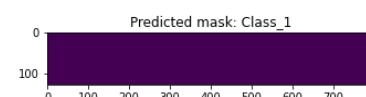
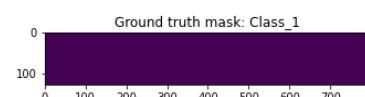
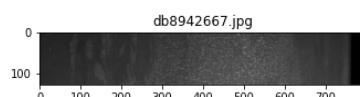
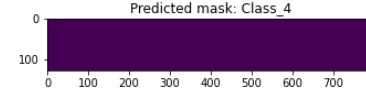
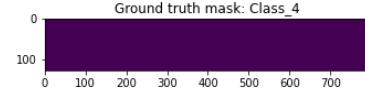
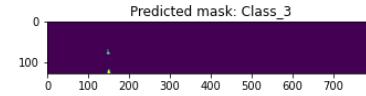
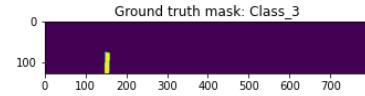
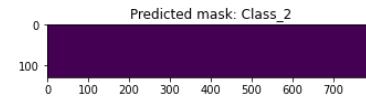
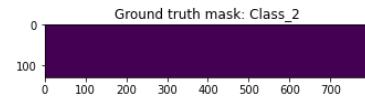
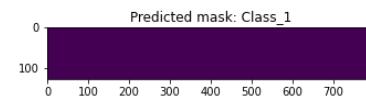
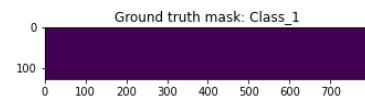
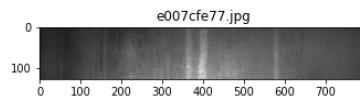
In [0]:

```
visualize_defects(cv_data,model_best)
```

Severstal Steel Defect Detection



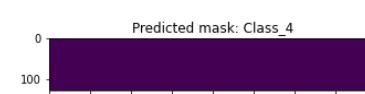
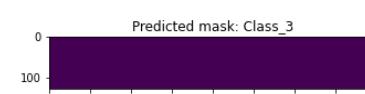
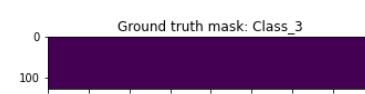
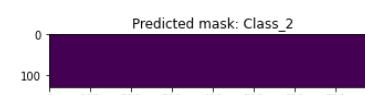
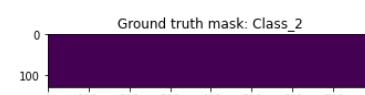
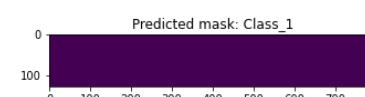
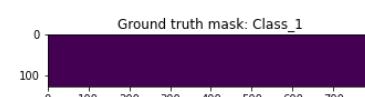
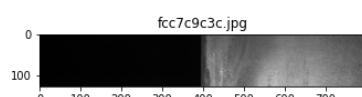
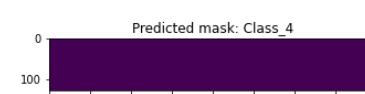
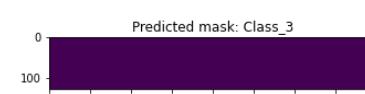
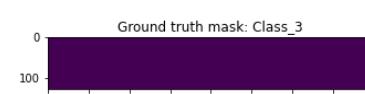
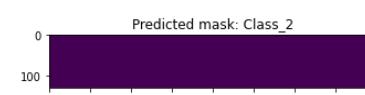
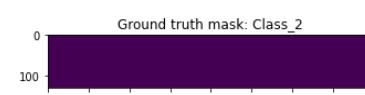
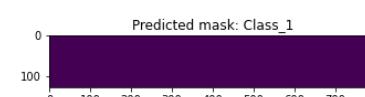
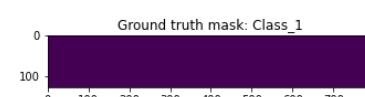
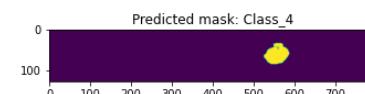
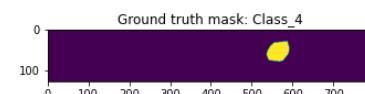
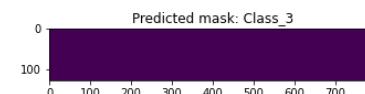
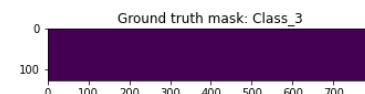
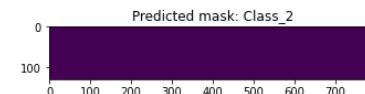
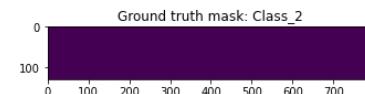
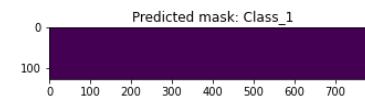
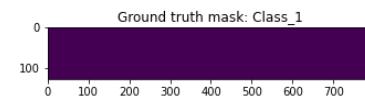
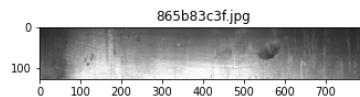
Severstal Steel Defect Detection

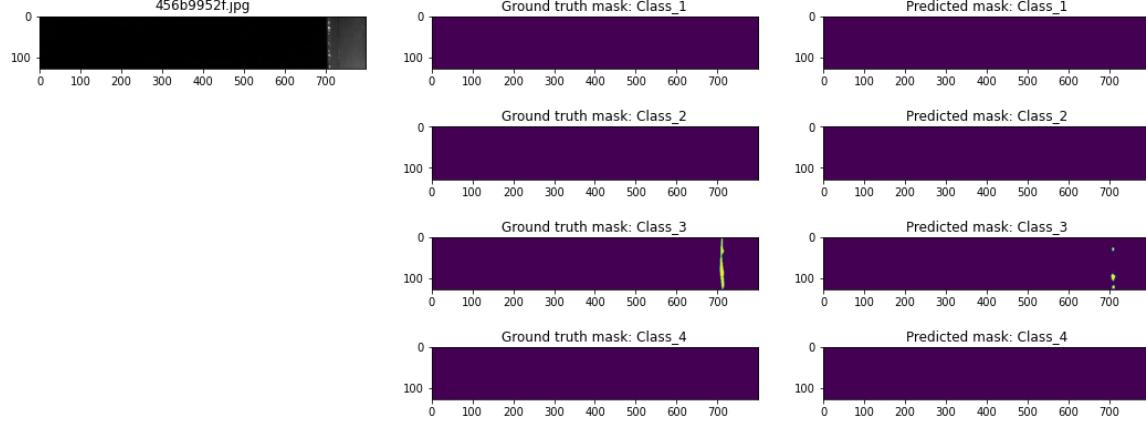
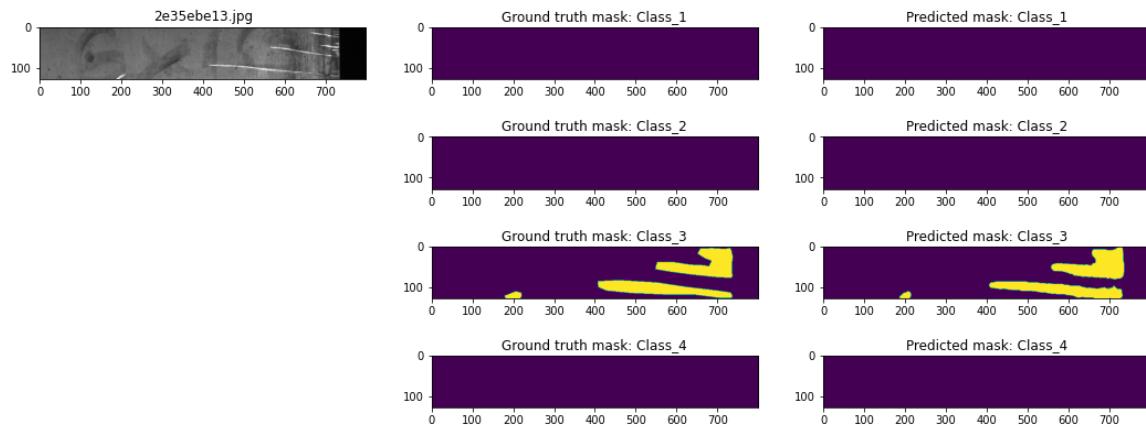


In [0]:

```
visualize_defects(cv_data,model_best)
```

Severstal Steel Defect Detection





1.6 Predicting defects on raw test images

Predicting on raw test images by resizing images to 128x800 dimensions in order to apply the model

In [0]:

```
# Predicting on test images
from tqdm import tqdm
import cv2
data_path = '/content/' + 'test_images/'
files = list(os.listdir(data_path))
rle_lst = [] #list to store defect in run length encoding format
img_classId= [] #list to store Image ID + classId
for f in tqdm(files):
    X = np.empty((1,128,800,3),dtype=np.float32)
    img = cv2.imread(data_path + f)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (800,128))
    X[0,] = img
    mask = model_best.predict(X)
    rle_m = np.empty((128,800),dtype=np.uint8)
    for i in range(4):
        rle_m = mask[0,:,:,:,i].round().astype(int)
        rle = mask2rle(rle_m)
        rle_lst.append(rle)
        img_classId.append(f+'_'+str(i+1))
```

100%|██████████| 5506/5506 [01:29<00:00, 61.81it/s]

In [0]:

```
output = {'ImageId_ClassId':img_classId, 'EncodedPixels' : rle_lst}
import pandas as pd
output_df = pd.DataFrame(output)
output_df.to_csv('submission_unet_128X800.csv', index=False)
```

With this submission in kaggle, I got a private dice coefficient score of 0.79814 & a public score of 0.78045.

Redefining the unet architecture for original image size of 256x1600

In [0]:

```
input_img = Input((256,1600,3), name='img')
model = get_unet(input_img, n_filters=8, dropout=0.2, batchnorm=True)
model.compile(optimizer=Adam(), loss=bce_dice_loss, metrics=[dice_coef])
model.summary()
```

Model: "model_3"

Layer (type)	Output Shape	Param #	Connected to
img (InputLayer)	(None, 256, 1600, 3)	0	
conv2d_39 (Conv2D)	(None, 256, 1600, 8)	224	img[0][0]
batch_normalization_37 (BatchNo)	(None, 256, 1600, 8)	32	conv2d_39[0][0]
activation_37 (Activation)	(None, 256, 1600, 8)	0	batch_normalization_37[0][0]
conv2d_40 (Conv2D)	(None, 256, 1600, 8)	584	activation_37[0][0]
batch_normalization_38 (BatchNo)	(None, 256, 1600, 8)	32	conv2d_40[0][0]
activation_38 (Activation)	(None, 256, 1600, 8)	0	batch_normalization_38[0][0]
max_pooling2d_9 (MaxPooling2D)	(None, 128, 800, 8)	0	activation_38[0][0]
dropout_17 (Dropout)	(None, 128, 800, 8)	0	max_pooling2d_9[0][0]
conv2d_41 (Conv2D)	(None, 128, 800, 16)	1168	dropout_17[0][0]
batch_normalization_39 (BatchNo)	(None, 128, 800, 16)	64	conv2d_41[0][0]
activation_39 (Activation)	(None, 128, 800, 16)	0	batch_normalization_39[0][0]
conv2d_42 (Conv2D)	(None, 128, 800, 16)	2320	activation_39[0][0]
batch_normalization_40 (BatchNo)	(None, 128, 800, 16)	64	conv2d_42[0][0]

activation_40 (Activation) (None, 128, 800, 16) 0 batch_norm
alization_40[0][0]

max_pooling2d_10 (MaxPooling2D) (None, 64, 400, 16) 0 activation
_40[0][0]

dropout_18 (Dropout) (None, 64, 400, 16) 0 max_pooli
ng2d_10[0][0]

conv2d_43 (Conv2D) (None, 64, 400, 32) 4640 dropout_1
8[0][0]

batch_normalization_41 (BatchNo (None, 64, 400, 32) 128 conv2d_43
[0][0]

activation_41 (Activation) (None, 64, 400, 32) 0 batch_norm
alization_41[0][0]

conv2d_44 (Conv2D) (None, 64, 400, 32) 9248 activation
_41[0][0]

batch_normalization_42 (BatchNo (None, 64, 400, 32) 128 conv2d_44
[0][0]

activation_42 (Activation) (None, 64, 400, 32) 0 batch_norm
alization_42[0][0]

max_pooling2d_11 (MaxPooling2D) (None, 32, 200, 32) 0 activation
_42[0][0]

dropout_19 (Dropout) (None, 32, 200, 32) 0 max_pooli
ng2d_11[0][0]

conv2d_45 (Conv2D) (None, 32, 200, 64) 18496 dropout_1
9[0][0]

batch_normalization_43 (BatchNo (None, 32, 200, 64) 256 conv2d_45
[0][0]

activation_43 (Activation) (None, 32, 200, 64) 0 batch_norm
alization_43[0][0]

conv2d_46 (Conv2D) (None, 32, 200, 64) 36928 activation
_43[0][0]

batch_normalization_44 (BatchNo (None, 32, 200, 64) 256 conv2d_46

[0][0]

activation_44 (Activation) normalization_44[0][0]	(None, 32, 200, 64) 0	batch_norm
max_pooling2d_12 (MaxPooling2D) n_44[0][0]	(None, 16, 100, 64) 0	activation
dropout_20 (Dropout) ng2d_12[0][0]	(None, 16, 100, 64) 0	max_pooli
conv2d_47 (Conv2D) 0[0][0]	(None, 16, 100, 128) 73856	dropout_2
batch_normalization_45 (BatchNo [0][0]	(None, 16, 100, 128) 512	conv2d_47
activation_45 (Activation) malization_45[0][0]	(None, 16, 100, 128) 0	batch_nor
conv2d_48 (Conv2D) n_45[0][0]	(None, 16, 100, 128) 147584	activatio
batch_normalization_46 (BatchNo [0][0]	(None, 16, 100, 128) 512	conv2d_48
activation_46 (Activation) malization_46[0][0]	(None, 16, 100, 128) 0	batch_nor
conv2d_transpose_9 (Conv2DTrans n_46[0][0]	(None, 32, 200, 64) 73792	activatio
concatenate_9 (Concatenate) anspose_9[0][0]	(None, 32, 200, 128) 0	conv2d_tr
dropout_21 (Dropout) te_9[0][0]	(None, 32, 200, 128) 0	activatio
concatena		
conv2d_49 (Conv2D) 1[0][0]	(None, 32, 200, 64) 73792	dropout_2
batch_normalization_47 (BatchNo [0][0]	(None, 32, 200, 64) 256	conv2d_49

activation_47 (Activation) (None, 32, 200, 64) 0 batch_norm
alization_47[0][0]

conv2d_50 (Conv2D) (None, 32, 200, 64) 36928 activation
n_47[0][0]

batch_normalization_48 (BatchNorm (None, 32, 200, 64) 256 conv2d_50
[0][0]

activation_48 (Activation) (None, 32, 200, 64) 0 batch_norm
alization_48[0][0]

conv2d_transpose_10 (Conv2DTran (None, 64, 400, 32) 18464 activation
n_48[0][0]

concatenate_10 (Concatenate) (None, 64, 400, 64) 0 conv2d_tr
anspose_10[0][0] activation
n_42[0][0]

dropout_22 (Dropout) (None, 64, 400, 64) 0 concatenate
te_10[0][0]

conv2d_51 (Conv2D) (None, 64, 400, 32) 18464 dropout_2
2[0][0]

batch_normalization_49 (BatchNorm (None, 64, 400, 32) 128 conv2d_51
[0][0]

activation_49 (Activation) (None, 64, 400, 32) 0 batch_norm
alization_49[0][0]

conv2d_52 (Conv2D) (None, 64, 400, 32) 9248 activation
n_49[0][0]

batch_normalization_50 (BatchNorm (None, 64, 400, 32) 128 conv2d_52
[0][0]

activation_50 (Activation) (None, 64, 400, 32) 0 batch_norm
alization_50[0][0]

conv2d_transpose_11 (Conv2DTran (None, 128, 800, 16) 4624 activation
n_50[0][0]

concatenate_11 (Concatenate) (None, 128, 800, 32) 0 conv2d_tr
anspose_11[0][0] activation

n_40[0][0]

dropout_23 (Dropout) (None, 128, 800, 32) 0 concatena
te_11[0][0]

conv2d_53 (Conv2D) (None, 128, 800, 16) 4624 dropout_2
3[0][0]

batch_normalization_51 (BatchNo (None, 128, 800, 16) 64 conv2d_53
[0][0]

activation_51 (Activation) (None, 128, 800, 16) 0 batch_nor
malization_51[0][0]

conv2d_54 (Conv2D) (None, 128, 800, 16) 2320 activation
n_51[0][0]

batch_normalization_52 (BatchNo (None, 128, 800, 16) 64 conv2d_54
[0][0]

activation_52 (Activation) (None, 128, 800, 16) 0 batch_nor
malization_52[0][0]

conv2d_transpose_12 (Conv2DTran (None, 256, 1600, 8) 1160 activation
n_52[0][0]

concatenate_12 (Concatenate) (None, 256, 1600, 16 0 conv2d_tr
anspose_12[0][0] activation
n_38[0][0]

dropout_24 (Dropout) (None, 256, 1600, 16 0 concatena
te_12[0][0]

conv2d_55 (Conv2D) (None, 256, 1600, 8) 1160 dropout_2
4[0][0]

batch_normalization_53 (BatchNo (None, 256, 1600, 8) 32 conv2d_55
[0][0]

activation_53 (Activation) (None, 256, 1600, 8) 0 batch_nor
malization_53[0][0]

conv2d_56 (Conv2D) (None, 256, 1600, 8) 584 activation
n_53[0][0]

```

batch_normalization_54 (BatchNo (None, 256, 1600, 8) 32           conv2d_56
[0][0]

activation_54 (Activation)          (None, 256, 1600, 8) 0           batch_nor
malization_54[0][0]

conv2d_57 (Conv2D)                 (None, 256, 1600, 4) 36           activatio
n_54[0][0]
=====
=====

Total params: 543,188
Trainable params: 541,716
Non-trainable params: 1,472

```



In [0]:

```
model.set_weights(model_best.get_weights()) #transferring the weights of 128x800 model
```

Predicting on full 256x1600 raw test images

In [0]:

```

# Predicting on test images
from tqdm import tqdm
import cv2
data_path = '/content/' + 'test_images/'
files = list(os.listdir(data_path))
rle_lst = [] #list to store defect in run length encoding format
img_classId= [] #list to store Image ID + classId

for f in tqdm(files):
    X = np.empty((1,256,1600,3),dtype=np.float32)
    img = cv2.imread(data_path + f)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    X[0,] = img
    mask = model.predict(X)
    rle_m = np.empty((256,1600),dtype=np.uint8)
    for i in range(4):
        rle_m = mask[0,:,:,:i].round().astype(int)
        rle = mask2rle(rle_m)
        rle_lst.append(rle)
        img_classId.append(f+'_'+str(i+1))

```

100%|██████████| 5506/5506 [04:12<00:00, 21.80it/s]

In [0]:

```

output = {'ImageId_ClassId':img_classId, 'EncodedPixels' : rle_lst}
import pandas as pd
output_df = pd.DataFrame(output)
output_df.to_csv('submission_unet_256_1600.csv', index=False)

```

With this submission, I got a private dice coefficient score of 0.81171 & a public score of 0.80041.

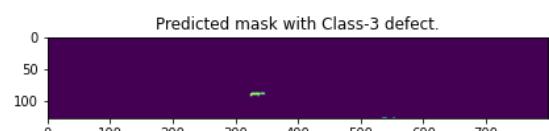
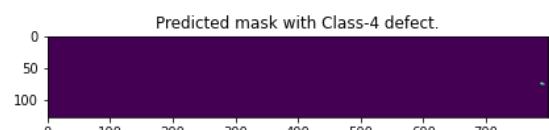
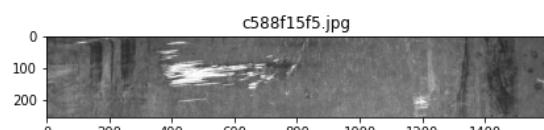
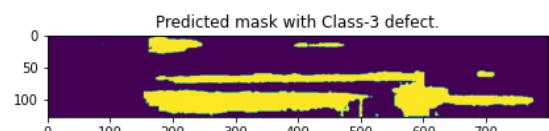
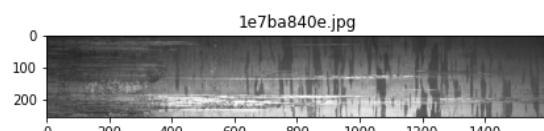
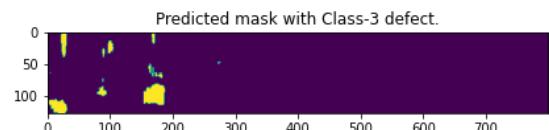
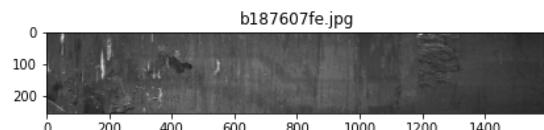
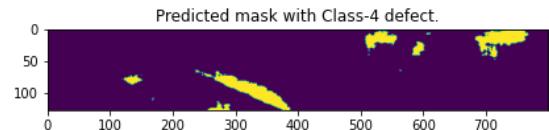
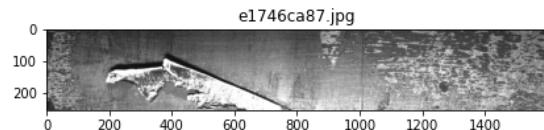
- This task of predicting on full images was inspired from this kernel:
<https://www.kaggle.com/c/severstal-steel-defect-detection/discussion/114321>
(<https://www.kaggle.com/c/severstal-steel-defect-detection/discussion/114321>)
- The author of the kernel had proof of better scores when defects were predicted on 256x1600 instead of 128x800
- This strategy worked out for me as I got a higher score when predicted on full images compared to half images
- **Henceforth, for other architectures, I will be predicting on 256x1800 images instead of 128x800**

1.7 Visualizing defects of raw test images(256x1600)

Please refer to the "visualize_defects_test" function in Utility functions section.

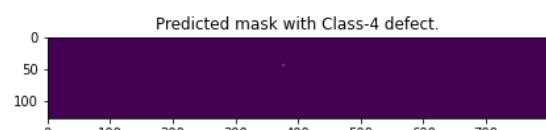
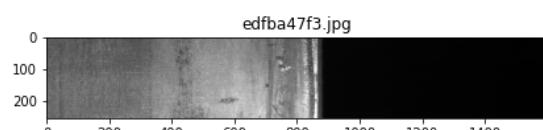
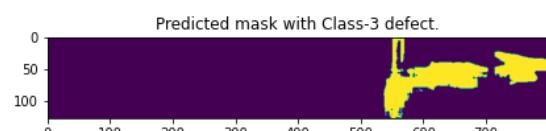
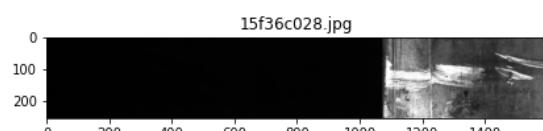
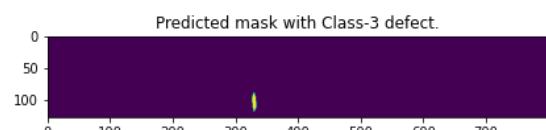
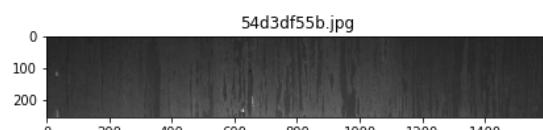
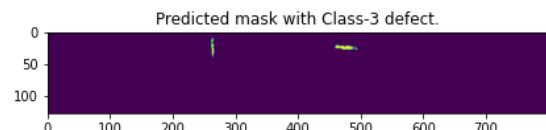
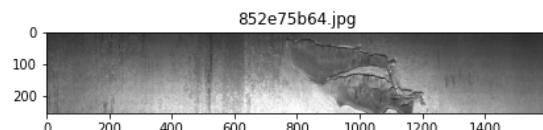
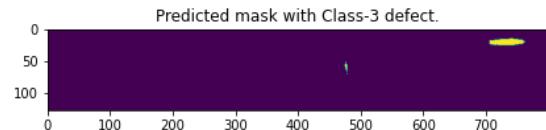
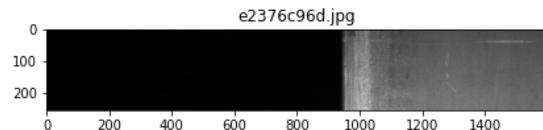
In [0]:

visualize_defects_test(output_df,5)



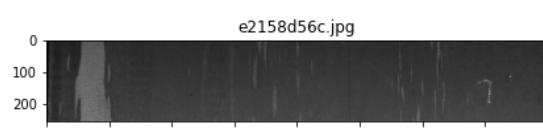
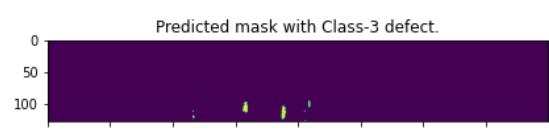
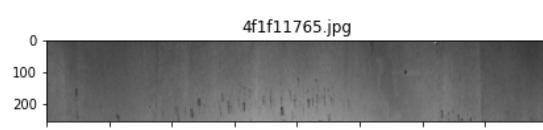
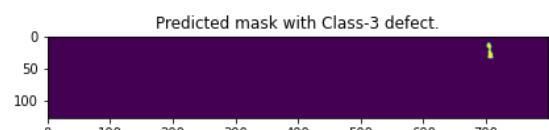
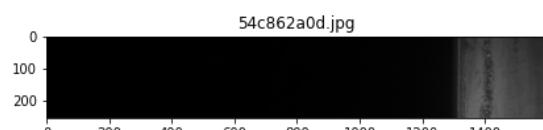
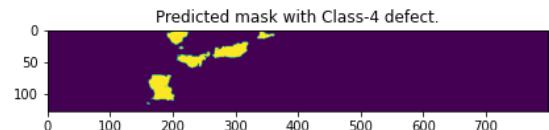
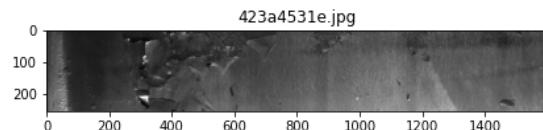
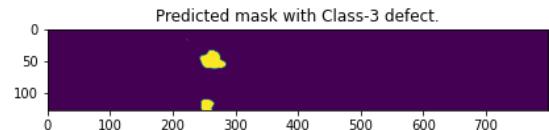
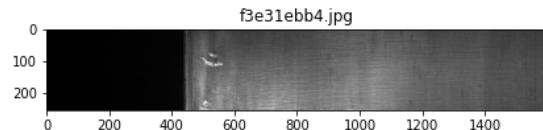
In [0]:

visualize_defects_test(output_df,5)

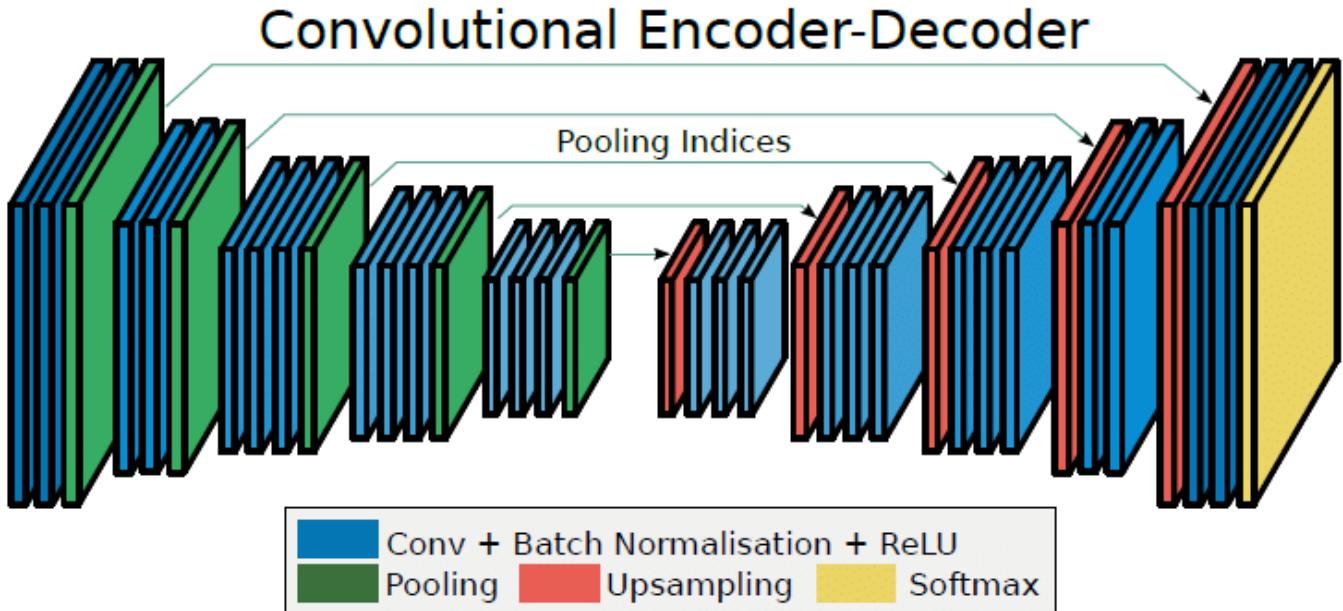


In [0]:

visualize_defects_test(output_df,5)



2.0 Segmentation Net(Segnet)



References-

- <https://github.com/imlab-uiip/keras-segnet> (<https://github.com/imlab-uiip/keras-segnet>)
- <https://arxiv.org/pdf/1505.04366.pdf> (<https://arxiv.org/pdf/1505.04366.pdf>)

In [0]:

```
def two_conv2d_blocks(input_tensor, n_filters, kernel_size = 3, batchnorm = True):
    """Function containing 2 convolutional layers with the parameters passed to it"""
    # first layer
    x = Conv2D(filters = n_filters, kernel_size = (kernel_size, kernel_size), \
               kernel_initializer = 'he_normal', padding = 'same')(input_tensor)
    if batchnorm:
        x = BatchNormalization()(x)
    x = Activation('relu')(x)

    # second layer
    x = Conv2D(filters = n_filters, kernel_size = (kernel_size, kernel_size), \
               kernel_initializer = 'he_normal', padding = 'same')(x)
    if batchnorm:
        x = BatchNormalization()(x)
    x = Activation('relu')(x)

    return x
```

In [0]:

```
def single_conv2d_block(input_tensor, n_filters, kernel_size = 3, batchnorm = True):
    """Function containing 1 convolutional layer with the parameters passed to it"""
    # first layer
    x = Conv2D(filters = n_filters, kernel_size = (kernel_size, kernel_size), \
               kernel_initializer = 'he_normal', padding = 'same')(input_tensor)
    if batchnorm:
        x = BatchNormalization()(x)
    x = Activation('relu')(x)

    return x
```

In [0]:

```
def get_segnet(input_img, n_filters, dropout, batchnorm):  
    """Function to define the Segnet architecture"""  
  
    # Encoder Path  
    c1 = two_conv2d_blocks(input_img, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)  
    p1 = MaxPooling2D((2, 2))(c1)  
    p1 = Dropout(dropout)(p1)  
  
    c2 = two_conv2d_blocks(p1, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)  
    p2 = MaxPooling2D((2, 2))(c2)  
    p2 = Dropout(dropout)(p2)  
  
    c3 = two_conv2d_blocks(p2, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)  
    c3_1 = single_conv2d_block(c3, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)  
    p3 = MaxPooling2D((2, 2))(c3_1)  
    p3 = Dropout(dropout)(p3)  
  
    c4 = two_conv2d_blocks(p3, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)  
    c4_1 = single_conv2d_block(c4, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)  
    p4 = MaxPooling2D((2, 2))(c4_1)  
    p4 = Dropout(dropout)(p4)  
  
    c5 = two_conv2d_blocks(p4, n_filters = n_filters * 8, kernel_size = 3, batchnorm = batchnorm)  
    c5_1 = single_conv2d_block(c5, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)  
    p5 = MaxPooling2D((2, 2))(c5_1)  
    p5 = Dropout(dropout)(p5)  
  
    # Decoder Path  
    u6 = UpSampling2D()(p5)  
    c6 = two_conv2d_blocks(u6, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)  
    c6 = single_conv2d_block(c6, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)  
    c6 = Dropout(dropout)(c6)  
  
    u7 = UpSampling2D()(c6)  
    c7 = two_conv2d_blocks(u7, n_filters * 8, kernel_size = 3, batchnorm = batchnorm)  
    c7 = single_conv2d_block(c7, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)  
    c7 = Dropout(dropout)(c7)  
  
    u8 = UpSampling2D()(c7)  
    c8 = two_conv2d_blocks(u8, n_filters * 4, kernel_size = 3, batchnorm = batchnorm)  
    c8 = single_conv2d_block(c8, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)  
    c8 = Dropout(dropout)(c8)  
  
    u9 = UpSampling2D()(c8)  
    c9 = single_conv2d_block(u9, n_filters * 2, kernel_size = 3, batchnorm = batchnorm)  
    c9 = single_conv2d_block(c9, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)  
    c9 = Dropout(dropout)(c9)  
  
    u10 = UpSampling2D()(c9)  
    c10 = single_conv2d_block(u10, n_filters * 1, kernel_size = 3, batchnorm = batchnorm)  
    c10 = Dropout(dropout)(c10)
```

```
outputs = Conv2D(4, (1, 1), activation='sigmoid')(c10)
model = Model(inputs=[input_img], outputs=[outputs])
return model
```

In [0]:

```
input_img = Input((128,800,3),name='img')
model = get_segnet(input_img, n_filters=16, dropout=0.5, batchnorm=True)
model.compile(optimizer=Adam(), loss=bce_dice_loss, metrics=[dice_coef])
model.summary()
```

Model: "model_4"

Layer (type)	Output Shape	Param #
img (InputLayer)	(None, 128, 800, 3)	0
conv2d_79 (Conv2D)	(None, 128, 800, 16)	448
batch_normalization_76 (BatchNormalization)	(None, 128, 800, 16)	64
activation_76 (Activation)	(None, 128, 800, 16)	0
conv2d_80 (Conv2D)	(None, 128, 800, 16)	2320
batch_normalization_77 (BatchNormalization)	(None, 128, 800, 16)	64
activation_77 (Activation)	(None, 128, 800, 16)	0
max_pooling2d_16 (MaxPooling)	(None, 64, 400, 16)	0
dropout_31 (Dropout)	(None, 64, 400, 16)	0
conv2d_81 (Conv2D)	(None, 64, 400, 32)	4640
batch_normalization_78 (BatchNormalization)	(None, 64, 400, 32)	128
activation_78 (Activation)	(None, 64, 400, 32)	0
conv2d_82 (Conv2D)	(None, 64, 400, 32)	9248
batch_normalization_79 (BatchNormalization)	(None, 64, 400, 32)	128
activation_79 (Activation)	(None, 64, 400, 32)	0
max_pooling2d_17 (MaxPooling)	(None, 32, 200, 32)	0
dropout_32 (Dropout)	(None, 32, 200, 32)	0
conv2d_83 (Conv2D)	(None, 32, 200, 64)	18496
batch_normalization_80 (BatchNormalization)	(None, 32, 200, 64)	256
activation_80 (Activation)	(None, 32, 200, 64)	0
conv2d_84 (Conv2D)	(None, 32, 200, 64)	36928
batch_normalization_81 (BatchNormalization)	(None, 32, 200, 64)	256
activation_81 (Activation)	(None, 32, 200, 64)	0
conv2d_85 (Conv2D)	(None, 32, 200, 64)	36928
batch_normalization_82 (BatchNormalization)	(None, 32, 200, 64)	256
activation_82 (Activation)	(None, 32, 200, 64)	0
max_pooling2d_18 (MaxPooling)	(None, 16, 100, 64)	0
dropout_33 (Dropout)	(None, 16, 100, 64)	0
conv2d_86 (Conv2D)	(None, 16, 100, 128)	73856

batch_normalization_83 (Batch Normalization)	(None, 16, 100, 128)	512
activation_83 (Activation)	(None, 16, 100, 128)	0
conv2d_87 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_84 (Batch Normalization)	(None, 16, 100, 128)	512
activation_84 (Activation)	(None, 16, 100, 128)	0
conv2d_88 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_85 (Batch Normalization)	(None, 16, 100, 128)	512
activation_85 (Activation)	(None, 16, 100, 128)	0
max_pooling2d_19 (MaxPooling)	(None, 8, 50, 128)	0
dropout_34 (Dropout)	(None, 8, 50, 128)	0
conv2d_89 (Conv2D)	(None, 8, 50, 128)	147584
batch_normalization_86 (Batch Normalization)	(None, 8, 50, 128)	512
activation_86 (Activation)	(None, 8, 50, 128)	0
conv2d_90 (Conv2D)	(None, 8, 50, 128)	147584
batch_normalization_87 (Batch Normalization)	(None, 8, 50, 128)	512
activation_87 (Activation)	(None, 8, 50, 128)	0
conv2d_91 (Conv2D)	(None, 8, 50, 128)	147584
batch_normalization_88 (Batch Normalization)	(None, 8, 50, 128)	512
activation_88 (Activation)	(None, 8, 50, 128)	0
max_pooling2d_20 (MaxPooling)	(None, 4, 25, 128)	0
dropout_35 (Dropout)	(None, 4, 25, 128)	0
up_sampling2d_16 (UpSampling)	(None, 8, 50, 128)	0
conv2d_92 (Conv2D)	(None, 8, 50, 128)	147584
batch_normalization_89 (Batch Normalization)	(None, 8, 50, 128)	512
activation_89 (Activation)	(None, 8, 50, 128)	0
conv2d_93 (Conv2D)	(None, 8, 50, 128)	147584
batch_normalization_90 (Batch Normalization)	(None, 8, 50, 128)	512
activation_90 (Activation)	(None, 8, 50, 128)	0
conv2d_94 (Conv2D)	(None, 8, 50, 128)	147584
batch_normalization_91 (Batch Normalization)	(None, 8, 50, 128)	512

activation_91 (Activation)	(None, 8, 50, 128)	0
dropout_36 (Dropout)	(None, 8, 50, 128)	0
up_sampling2d_17 (UpSampling)	(None, 16, 100, 128)	0
conv2d_95 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_92 (Batch Normalization)	(None, 16, 100, 128)	512
activation_92 (Activation)	(None, 16, 100, 128)	0
conv2d_96 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_93 (Batch Normalization)	(None, 16, 100, 128)	512
activation_93 (Activation)	(None, 16, 100, 128)	0
conv2d_97 (Conv2D)	(None, 16, 100, 64)	73792
batch_normalization_94 (Batch Normalization)	(None, 16, 100, 64)	256
activation_94 (Activation)	(None, 16, 100, 64)	0
dropout_37 (Dropout)	(None, 16, 100, 64)	0
up_sampling2d_18 (UpSampling)	(None, 32, 200, 64)	0
conv2d_98 (Conv2D)	(None, 32, 200, 64)	36928
batch_normalization_95 (Batch Normalization)	(None, 32, 200, 64)	256
activation_95 (Activation)	(None, 32, 200, 64)	0
conv2d_99 (Conv2D)	(None, 32, 200, 64)	36928
batch_normalization_96 (Batch Normalization)	(None, 32, 200, 64)	256
activation_96 (Activation)	(None, 32, 200, 64)	0
conv2d_100 (Conv2D)	(None, 32, 200, 32)	18464
batch_normalization_97 (Batch Normalization)	(None, 32, 200, 32)	128
activation_97 (Activation)	(None, 32, 200, 32)	0
dropout_38 (Dropout)	(None, 32, 200, 32)	0
up_sampling2d_19 (UpSampling)	(None, 64, 400, 32)	0
conv2d_101 (Conv2D)	(None, 64, 400, 32)	9248
batch_normalization_98 (Batch Normalization)	(None, 64, 400, 32)	128
activation_98 (Activation)	(None, 64, 400, 32)	0
conv2d_102 (Conv2D)	(None, 64, 400, 16)	4624
batch_normalization_99 (Batch Normalization)	(None, 64, 400, 16)	64
activation_99 (Activation)	(None, 64, 400, 16)	0

dropout_39 (Dropout)	(None, 64, 400, 16)	0
up_sampling2d_20 (UpSampling	(None, 128, 800, 16)	0
conv2d_103 (Conv2D)	(None, 128, 800, 16)	2320
batch_normalization_100 (Batch Normalization)	(None, 128, 800, 16)	64
activation_100 (Activation)	(None, 128, 800, 16)	0
dropout_40 (Dropout)	(None, 128, 800, 16)	0
conv2d_104 (Conv2D)	(None, 128, 800, 4)	68
<hr/>		
Total params: 1,849,012		
Trainable params: 1,845,044		
Non-trainable params: 3,968		

2.1 Checkpointing the model and creating the callback list

In [0]:

```
tbc=TensorBoardColab()
mc = ModelCheckpoint('best_model_segnet.h5', monitor='val_dice_coef', verbose=1, save_best_only=True, mode='max')
callbacks_list = [mc, TensorBoardColabCallback(tbc)]
```

Wait for 8 seconds...

TensorBoard link:

<http://513dcfc3.ngrok.io>

2.2 Fitting the train data and validation

In [0]:

```
train_batches = Train_DataGenerator(train_data,shuffle=True)
valid_batches = Val_DataGenerator(cv_data)
history = model.fit_generator(train_batches, validation_data = valid_batches, epochs =
30, verbose=1,
                                class_weight=class_wts, callbacks = callbacks_list)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please use tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is deprecated. Please use tf.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorboard_colab/core.py:49: The name tf.summary.FileWriter is deprecated. Please use tf.compat.v1.summary.FileWriter instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1122: The name tf.summary.merge_all is deprecated. Please use tf.compat.v1.summary.merge_all instead.

Epoch 1/30

667/667 [=====] - 263s 395ms/step - loss: 1.0959
- dice_coef: 0.0619 - val_loss: 1.1521 - val_dice_coef: 0.1376

Epoch 00001: val_dice_coef improved from -inf to 0.13762, saving model to best_model.h5

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorboard_colab/callbacks.py:51: The name tf.Summary is deprecated. Please use tf.compat.v1.Summary instead.

Epoch 2/30

667/667 [=====] - 236s 353ms/step - loss: 0.7808
- dice_coef: 0.2758 - val_loss: 0.7062 - val_dice_coef: 0.3639

Epoch 00002: val_dice_coef improved from 0.13762 to 0.36390, saving model to best_model.h5

Epoch 3/30

667/667 [=====] - 238s 357ms/step - loss: 0.6896
- dice_coef: 0.3686 - val_loss: 0.6413 - val_dice_coef: 0.4156

Epoch 00003: val_dice_coef improved from 0.36390 to 0.41558, saving model to best_model.h5

Epoch 4/30

667/667 [=====] - 237s 356ms/step - loss: 0.6508
- dice_coef: 0.4057 - val_loss: 0.6436 - val_dice_coef: 0.4211

Epoch 00004: val_dice_coef improved from 0.41558 to 0.42105, saving model to best_model.h5

Epoch 5/30

667/667 [=====] - 238s 357ms/step - loss: 0.6210
- dice_coef: 0.4337 - val_loss: 0.6254 - val_dice_coef: 0.4399

Epoch 00005: val_dice_coef improved from 0.42105 to 0.43994, saving model to best_model.h5

Epoch 6/30

667/667 [=====] - 239s 358ms/step - loss: 0.6091
- dice_coef: 0.4445 - val_loss: 0.6371 - val_dice_coef: 0.4211

Epoch 00006: val_dice_coef did not improve from 0.43994

Epoch 7/30

667/667 [=====] - 244s 366ms/step - loss: 0.5947
- dice_coef: 0.4569 - val_loss: 0.6352 - val_dice_coef: 0.4325

Epoch 00007: val_dice_coef did not improve from 0.43994

Epoch 8/30

667/667 [=====] - 240s 360ms/step - loss: 0.5845
- dice_coef: 0.4672 - val_loss: 0.6019 - val_dice_coef: 0.4513

Epoch 00008: val_dice_coef improved from 0.43994 to 0.45134, saving model to best_model.h5

Epoch 9/30

667/667 [=====] - 239s 359ms/step - loss: 0.5736
- dice_coef: 0.4768 - val_loss: 0.5895 - val_dice_coef: 0.4672

Epoch 00009: val_dice_coef improved from 0.45134 to 0.46723, saving model to best_model.h5

Epoch 10/30

667/667 [=====] - 240s 360ms/step - loss: 0.5593
- dice_coef: 0.4895 - val_loss: 0.6522 - val_dice_coef: 0.4122

Epoch 00010: val_dice_coef did not improve from 0.46723

Epoch 11/30

667/667 [=====] - 239s 358ms/step - loss: 0.5594
- dice_coef: 0.4894 - val_loss: 0.5801 - val_dice_coef: 0.4741

Epoch 00011: val_dice_coef improved from 0.46723 to 0.47410, saving model to best_model.h5

Epoch 12/30

667/667 [=====] - 240s 360ms/step - loss: 0.5619
- dice_coef: 0.4867 - val_loss: 0.6055 - val_dice_coef: 0.4546

Epoch 00012: val_dice_coef did not improve from 0.47410

Epoch 13/30

667/667 [=====] - 241s 361ms/step - loss: 0.5493
- dice_coef: 0.4989 - val_loss: 0.5845 - val_dice_coef: 0.4650

Epoch 00013: val_dice_coef did not improve from 0.47410

Epoch 14/30

667/667 [=====] - 240s 359ms/step - loss: 0.5404
- dice_coef: 0.5069 - val_loss: 0.5687 - val_dice_coef: 0.4856

Epoch 00014: val_dice_coef improved from 0.47410 to 0.48559, saving model to best_model.h5

Epoch 15/30

667/667 [=====] - 240s 359ms/step - loss: 0.5381
- dice_coef: 0.5094 - val_loss: 0.7156 - val_dice_coef: 0.3725

Epoch 00015: val_dice_coef did not improve from 0.48559

Epoch 16/30

667/667 [=====] - 239s 359ms/step - loss: 0.5410
- dice_coef: 0.5058 - val_loss: 0.5595 - val_dice_coef: 0.4894

Epoch 00016: val_dice_coef improved from 0.48559 to 0.48944, saving model to best_model.h5

Epoch 17/30

667/667 [=====] - 240s 359ms/step - loss: 0.5360
- dice_coef: 0.5105 - val_loss: 0.5967 - val_dice_coef: 0.4563

Epoch 00017: val_dice_coef did not improve from 0.48944

Epoch 18/30

667/667 [=====] - 239s 358ms/step - loss: 0.5295
- dice_coef: 0.5164 - val_loss: 0.5505 - val_dice_coef: 0.4981

Epoch 00018: val_dice_coef improved from 0.48944 to 0.49810, saving model to best_model.h5

Epoch 19/30

667/667 [=====] - 240s 359ms/step - loss: 0.5234
- dice_coef: 0.5230 - val_loss: 0.5758 - val_dice_coef: 0.4763

Epoch 00019: val_dice_coef did not improve from 0.49810

Epoch 20/30

667/667 [=====] - 241s 361ms/step - loss: 0.5167
- dice_coef: 0.5284 - val_loss: 0.5626 - val_dice_coef: 0.4922

Epoch 00020: val_dice_coef did not improve from 0.49810

Epoch 21/30

667/667 [=====] - 242s 363ms/step - loss: 0.5274
- dice_coef: 0.5178 - val_loss: 0.6572 - val_dice_coef: 0.4105

Epoch 00021: val_dice_coef did not improve from 0.49810

Epoch 22/30

667/667 [=====] - 246s 368ms/step - loss: 0.5064
- dice_coef: 0.5377 - val_loss: 0.5872 - val_dice_coef: 0.4704

Epoch 00022: val_dice_coef did not improve from 0.49810

Epoch 23/30

667/667 [=====] - 241s 361ms/step - loss: 0.5090
- dice_coef: 0.5348 - val_loss: 0.5943 - val_dice_coef: 0.4617

Epoch 00023: val_dice_coef did not improve from 0.49810

Epoch 24/30

667/667 [=====] - 241s 361ms/step - loss: 0.5079
- dice_coef: 0.5363 - val_loss: 0.5492 - val_dice_coef: 0.5000

Epoch 00024: val_dice_coef improved from 0.49810 to 0.49997, saving model to best_model.h5

Epoch 25/30

667/667 [=====] - 240s 360ms/step - loss: 0.5093
- dice_coef: 0.5347 - val_loss: 0.6005 - val_dice_coef: 0.4578

Epoch 00025: val_dice_coef did not improve from 0.49997

Epoch 26/30

667/667 [=====] - 239s 358ms/step - loss: 0.5058
- dice_coef: 0.5381 - val_loss: 0.5470 - val_dice_coef: 0.5024

Epoch 00026: val_dice_coef improved from 0.49997 to 0.50239, saving model to best_model.h5

Epoch 27/30

667/667 [=====] - 239s 358ms/step - loss: 0.5077
- dice_coef: 0.5356 - val_loss: 0.5569 - val_dice_coef: 0.4951

Epoch 00027: val_dice_coef did not improve from 0.50239

Epoch 28/30

667/667 [=====] - 238s 356ms/step - loss: 0.4997
- dice_coef: 0.5436 - val_loss: 0.5490 - val_dice_coef: 0.4992

Epoch 00028: val_dice_coef did not improve from 0.50239

Epoch 29/30

667/667 [=====] - 238s 356ms/step - loss: 0.4985
- dice_coef: 0.5445 - val_loss: 0.5404 - val_dice_coef: 0.5100

Epoch 00029: val_dice_coef improved from 0.50239 to 0.51004, saving model to best_model.h5

Epoch 30/30

667/667 [=====] - 236s 354ms/step - loss: 0.4886
- dice_coef: 0.5541 - val_loss: 0.5641 - val_dice_coef: 0.4931

```
Epoch 00030: val_dice_coef did not improve from 0.51004
```

Continued for another 20 epochs to see if the score improves

In [0]:

```
train_batches = Train_DataGenerator(train_data,shuffle=True)
valid_batches = Val_DataGenerator(cv_data)
history = model.fit_generator(train_batches, validation_data = valid_batches, epochs =
20, verbose=1,
                                class_weight=class_wts, callbacks = callbacks_list)
```

Epoch 1/20
667/667 [=====] - 246s 369ms/step - loss: 0.4945
- dice_coef: 0.5485 - val_loss: 0.5506 - val_dice_coef: 0.5031

Epoch 00001: val_dice_coef improved from -inf to 0.50306, saving model to best_model.h5

Epoch 2/20
667/667 [=====] - 240s 359ms/step - loss: 0.4942
- dice_coef: 0.5486 - val_loss: 0.5610 - val_dice_coef: 0.4920

Epoch 00002: val_dice_coef did not improve from 0.50306

Epoch 3/20
667/667 [=====] - 240s 360ms/step - loss: 0.4987
- dice_coef: 0.5444 - val_loss: 0.6268 - val_dice_coef: 0.4365

Epoch 00003: val_dice_coef did not improve from 0.50306

Epoch 4/20
667/667 [=====] - 240s 360ms/step - loss: 0.4955
- dice_coef: 0.5482 - val_loss: 0.5665 - val_dice_coef: 0.4886

Epoch 00004: val_dice_coef did not improve from 0.50306

Epoch 5/20
667/667 [=====] - 240s 361ms/step - loss: 0.4876
- dice_coef: 0.5549 - val_loss: 0.5313 - val_dice_coef: 0.5168

Epoch 00005: val_dice_coef improved from 0.50306 to 0.51678, saving model to best_model.h5

Epoch 6/20
667/667 [=====] - 244s 365ms/step - loss: 0.4836
- dice_coef: 0.5584 - val_loss: 0.5563 - val_dice_coef: 0.4974

Epoch 00006: val_dice_coef did not improve from 0.51678

Epoch 7/20
667/667 [=====] - 244s 365ms/step - loss: 0.4840
- dice_coef: 0.5582 - val_loss: 0.5821 - val_dice_coef: 0.4724

Epoch 00007: val_dice_coef did not improve from 0.51678

Epoch 8/20
667/667 [=====] - 244s 365ms/step - loss: 0.4810
- dice_coef: 0.5614 - val_loss: 0.5663 - val_dice_coef: 0.4886

Epoch 00008: val_dice_coef did not improve from 0.51678

Epoch 9/20
667/667 [=====] - 243s 364ms/step - loss: 0.4818
- dice_coef: 0.5605 - val_loss: 0.5494 - val_dice_coef: 0.5044

Epoch 00009: val_dice_coef did not improve from 0.51678

Epoch 10/20
667/667 [=====] - 250s 374ms/step - loss: 0.4814
- dice_coef: 0.5605 - val_loss: 0.5572 - val_dice_coef: 0.4952

Epoch 00010: val_dice_coef did not improve from 0.51678

Epoch 11/20
667/667 [=====] - 242s 363ms/step - loss: 0.4744
- dice_coef: 0.5668 - val_loss: 0.5548 - val_dice_coef: 0.4967

Epoch 00011: val_dice_coef did not improve from 0.51678

Epoch 12/20
667/667 [=====] - 238s 357ms/step - loss: 0.4716
- dice_coef: 0.5698 - val_loss: 0.5408 - val_dice_coef: 0.5097

```
Epoch 00012: val_dice_coef did not improve from 0.51678
Epoch 13/20
667/667 [=====] - 239s 358ms/step - loss: 0.4791
- dice_coef: 0.5629 - val_loss: 0.5572 - val_dice_coef: 0.4991

Epoch 00013: val_dice_coef did not improve from 0.51678
Epoch 14/20
667/667 [=====] - 238s 357ms/step - loss: 0.4750
- dice_coef: 0.5665 - val_loss: 0.5366 - val_dice_coef: 0.5147

Epoch 00014: val_dice_coef did not improve from 0.51678
Epoch 15/20
667/667 [=====] - 241s 361ms/step - loss: 0.4744
- dice_coef: 0.5667 - val_loss: 0.5767 - val_dice_coef: 0.4793

Epoch 00015: val_dice_coef did not improve from 0.51678
Epoch 16/20
667/667 [=====] - 241s 361ms/step - loss: 0.4688
- dice_coef: 0.5727 - val_loss: 0.5620 - val_dice_coef: 0.4903

Epoch 00016: val_dice_coef did not improve from 0.51678
Epoch 17/20
667/667 [=====] - 239s 358ms/step - loss: 0.4686
- dice_coef: 0.5734 - val_loss: 0.5236 - val_dice_coef: 0.5249

Epoch 00017: val_dice_coef improved from 0.51678 to 0.52488, saving model
to best_model.h5
Epoch 18/20
667/667 [=====] - 238s 358ms/step - loss: 0.4636
- dice_coef: 0.5777 - val_loss: 0.5377 - val_dice_coef: 0.5160

Epoch 00018: val_dice_coef did not improve from 0.52488
Epoch 19/20
667/667 [=====] - 240s 360ms/step - loss: 0.4617
- dice_coef: 0.5794 - val_loss: 0.6208 - val_dice_coef: 0.4395

Epoch 00019: val_dice_coef did not improve from 0.52488
Epoch 20/20
667/667 [=====] - 240s 360ms/step - loss: 0.4670
- dice_coef: 0.5737 - val_loss: 0.5473 - val_dice_coef: 0.5049

Epoch 00020: val_dice_coef did not improve from 0.52488
```

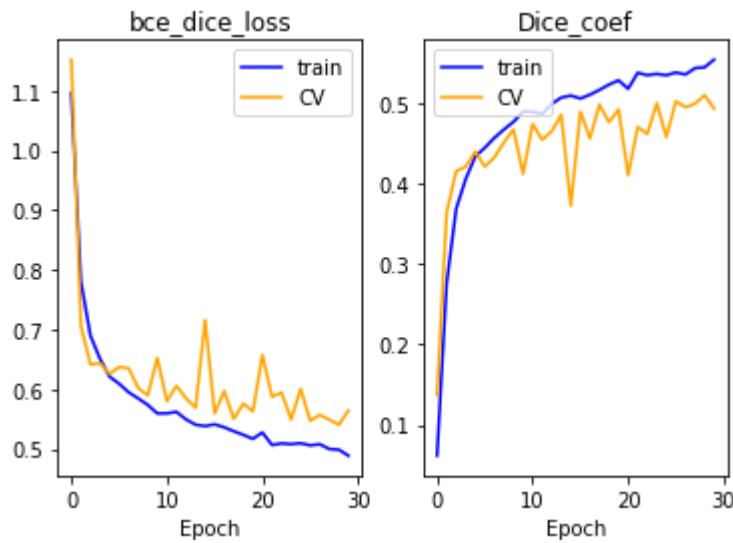
2.3 Plots on training & validation results

Loss function & metric plots

Please refer to Training Plots in utility functions section.

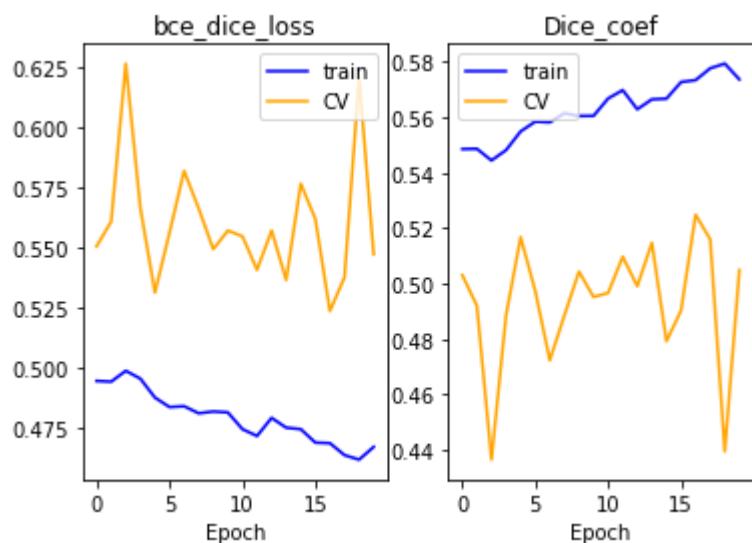
In [0]:

```
#first 30 epochs
plot(history)
```



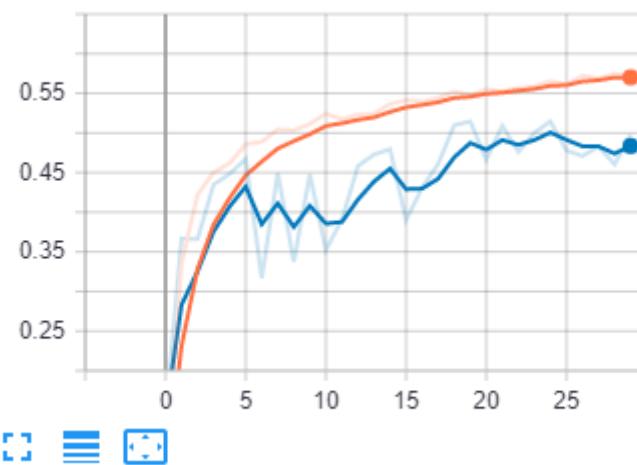
In [0]:

```
#next 20 epochs
plot(history)
```



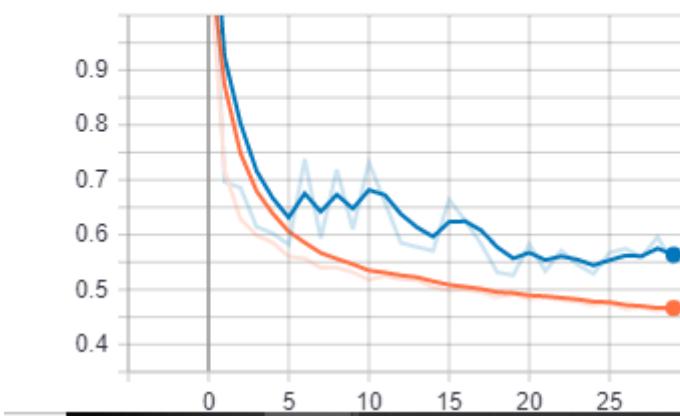
Tensorboard images

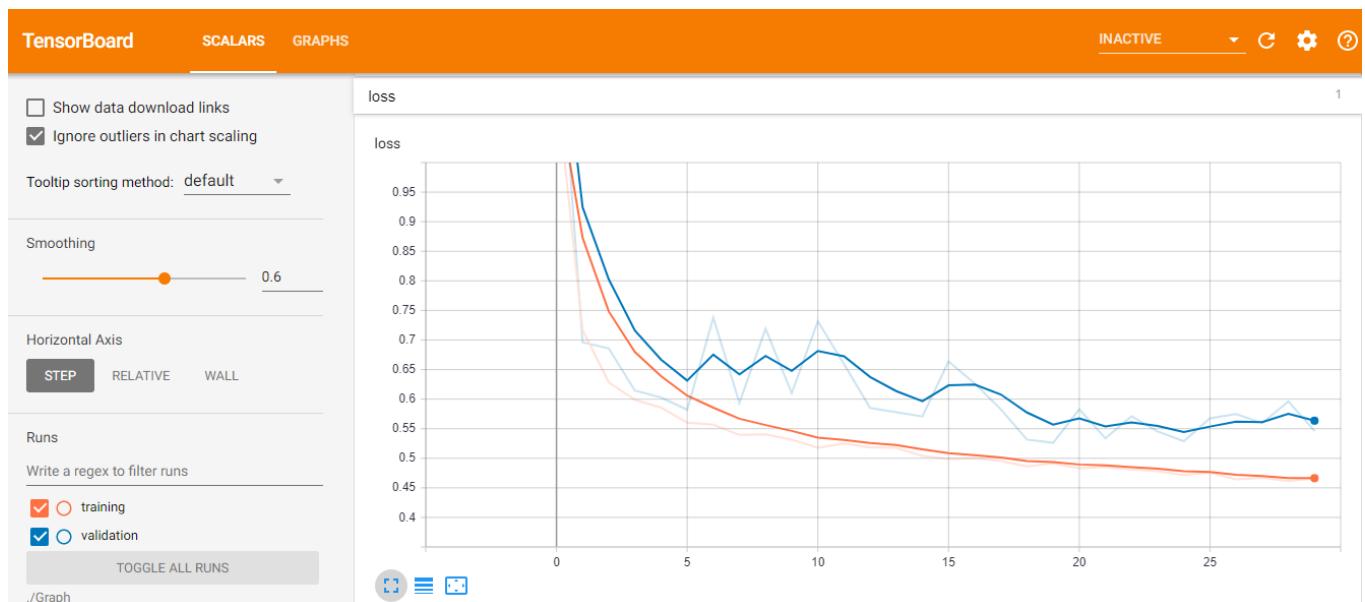
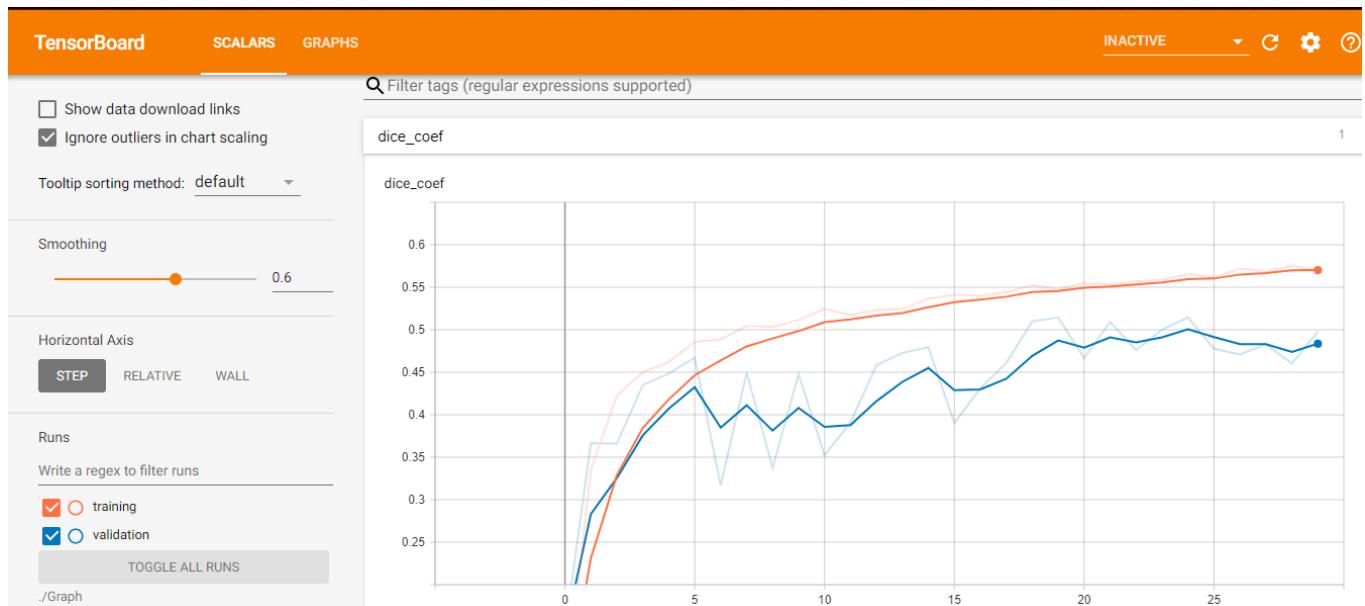
dice_coef



loss

loss





2.4 Model Testing

Loading the best model for evaluation

Considering the best model which was trained on 30 epochs as the model in the next 20 epochs experienced the problem of overfitting.

In [0]:

```
from keras.models import load_model
dependencies = {'bce_dice_loss':bce_dice_loss,'dice_coef':dice_coef,}
model_best = load_model('/content/best_model_segnet.h5',custom_objects=dependencies)
```

Evaluating on validation images

In [0]:

```
evals= model_best.evaluate(valid_batches,verbose=1)
117/117 [=====] - 31s 261ms/step
```

In [0]:

```
print('Validation set evaluation score: ')
print('bce_dice loss:',evals[0])
print('dice_coeff:',evals[1])
```

```
Validation set evaluation score:
bce_dice loss: 0.5403748965925641
dice_coeff: 0.5100375587515171
```

2.5 Defects visualization

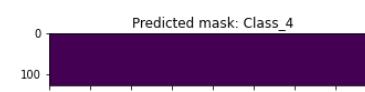
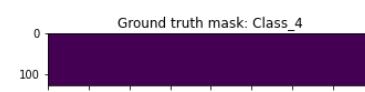
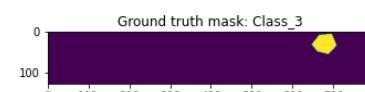
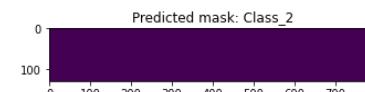
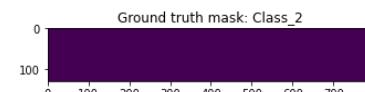
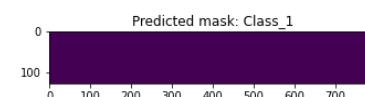
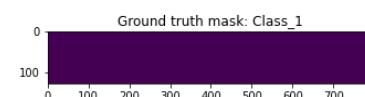
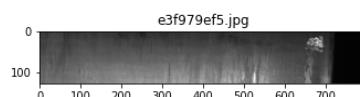
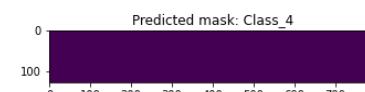
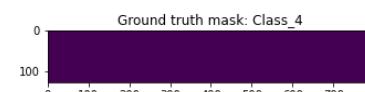
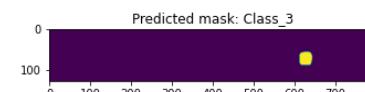
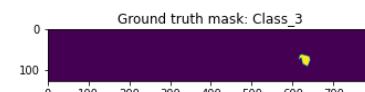
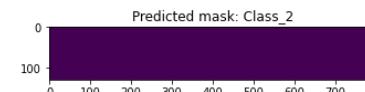
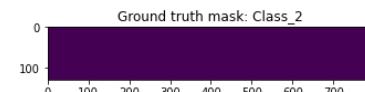
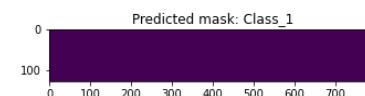
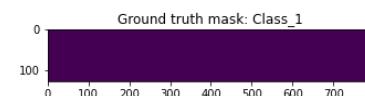
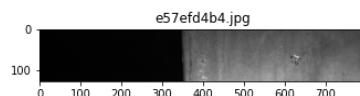
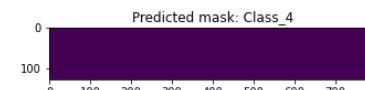
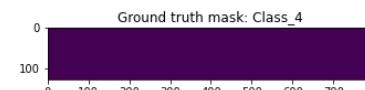
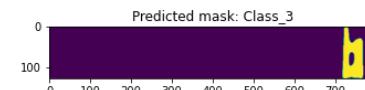
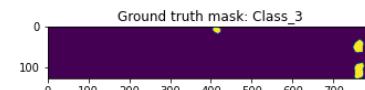
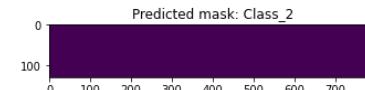
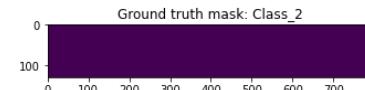
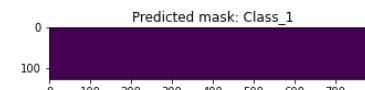
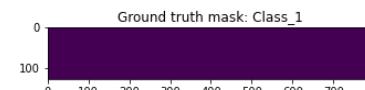
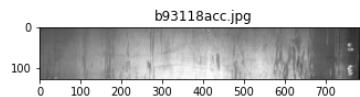
Please refer to the "visualize_defects" function in Utility functions section.

Training set

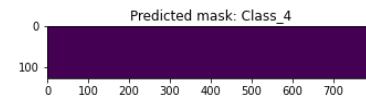
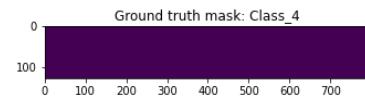
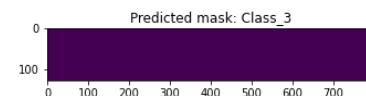
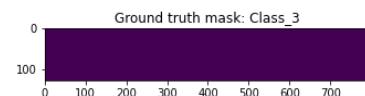
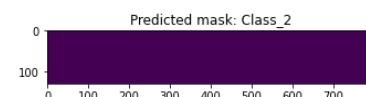
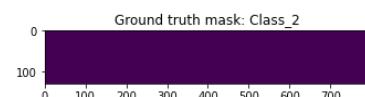
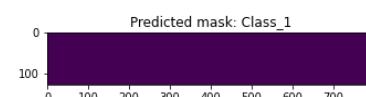
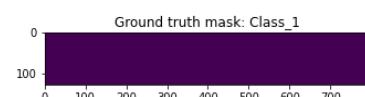
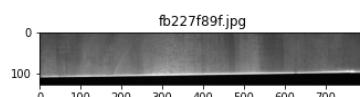
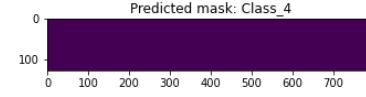
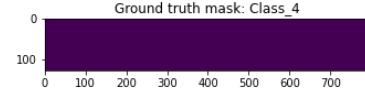
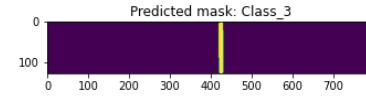
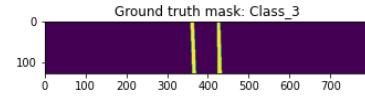
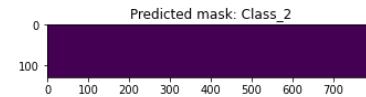
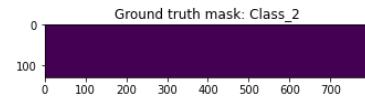
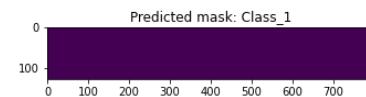
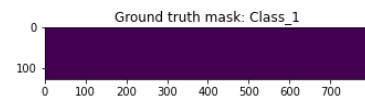
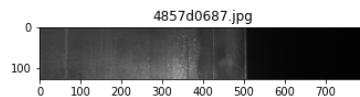
In [0]:

```
visualize_defects(train_data,model_best)
```

Severstal Steel Defect Detection

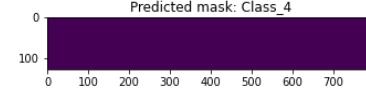
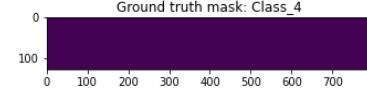
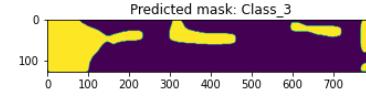
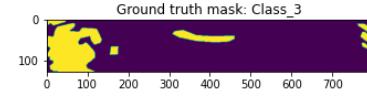
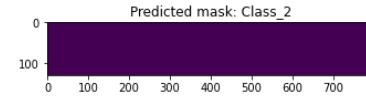
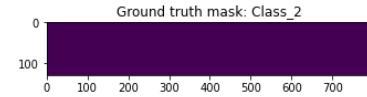
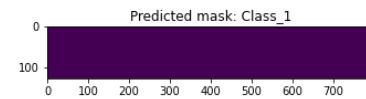
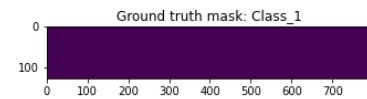
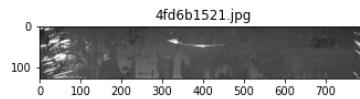
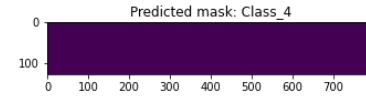
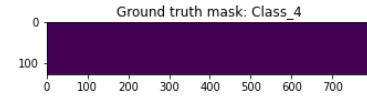
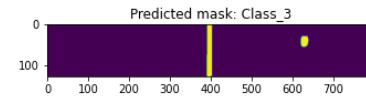
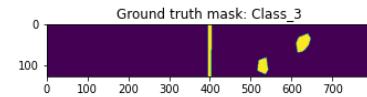
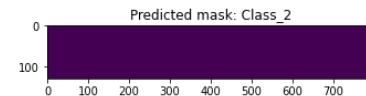
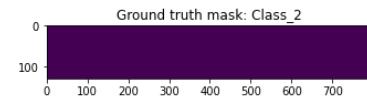
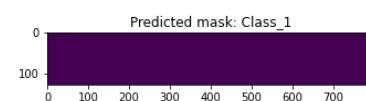
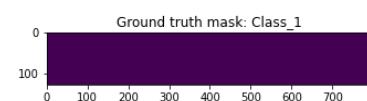
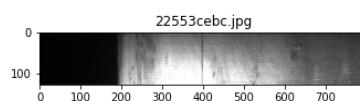
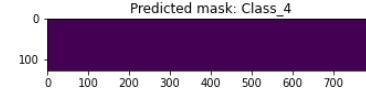
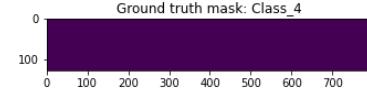
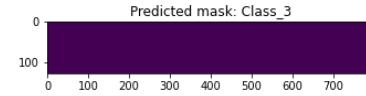
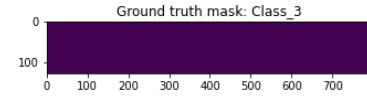
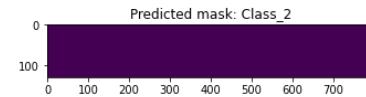
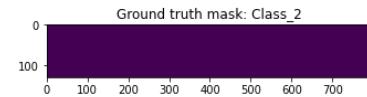
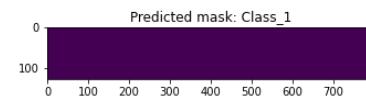
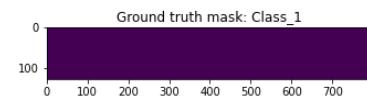
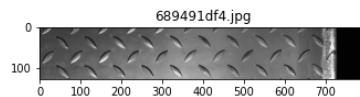


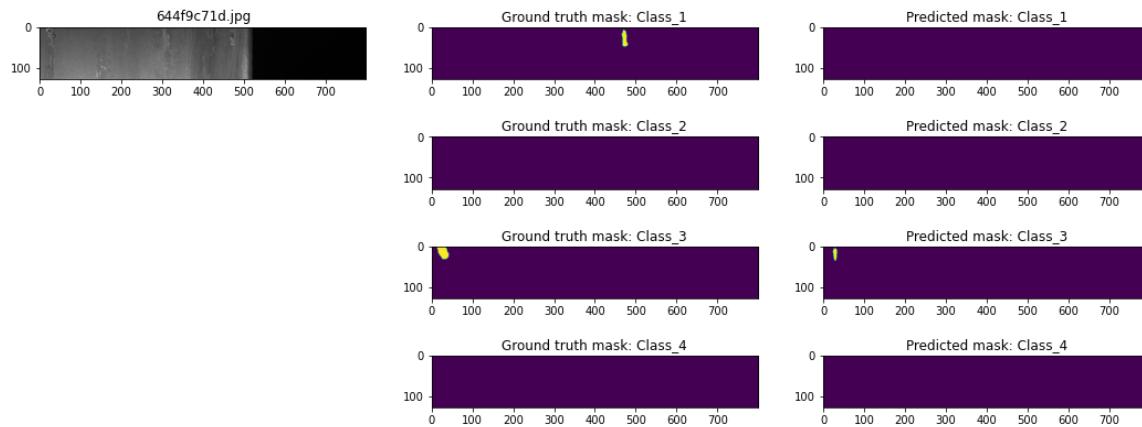
Severstal Steel Defect Detection



In [0]:

```
visualize_defects(train_data,model_best)
```



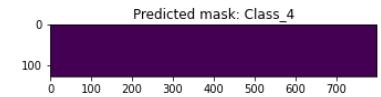
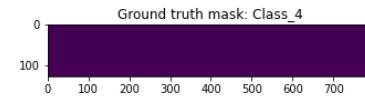
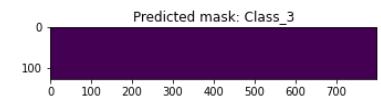
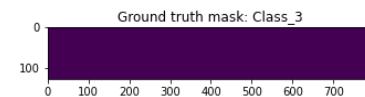
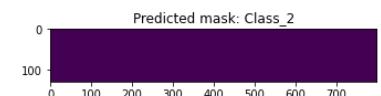
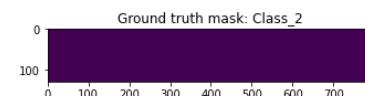
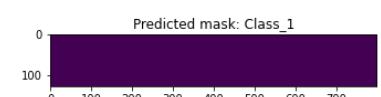
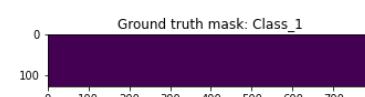
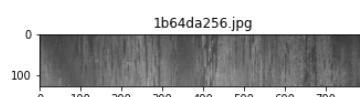
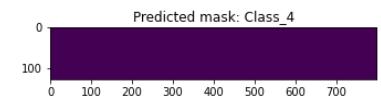
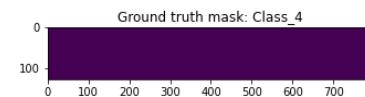
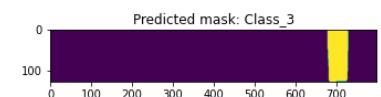
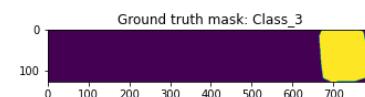
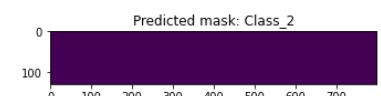
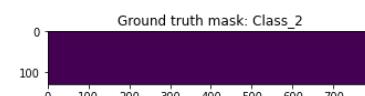
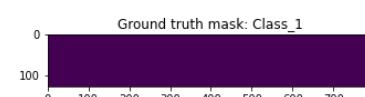
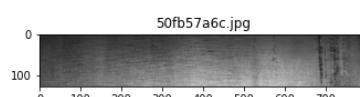
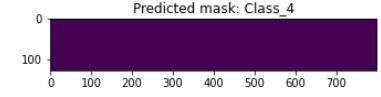
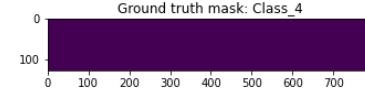
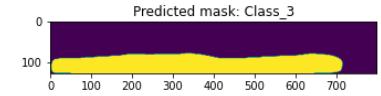
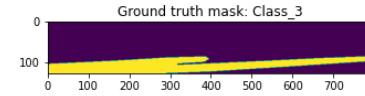
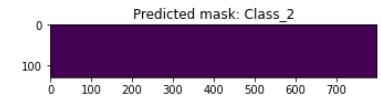
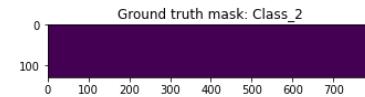
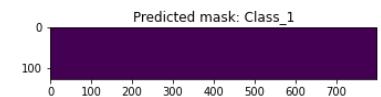
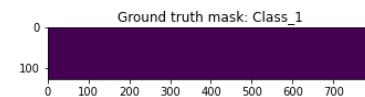
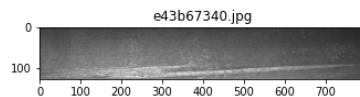


Validation set

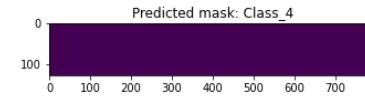
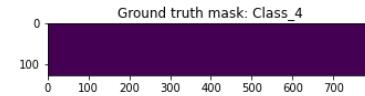
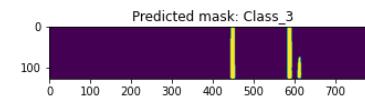
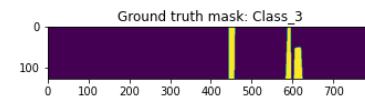
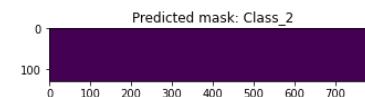
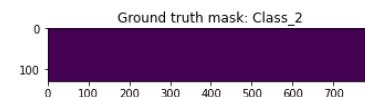
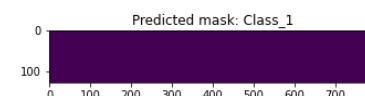
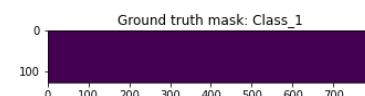
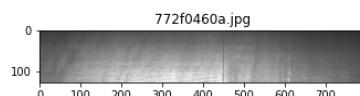
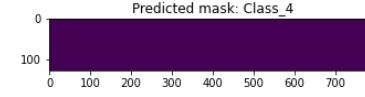
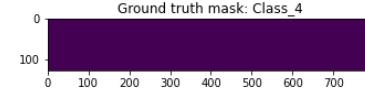
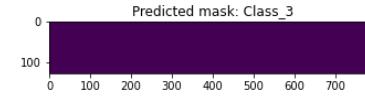
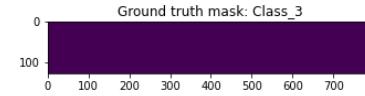
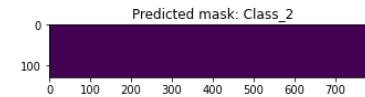
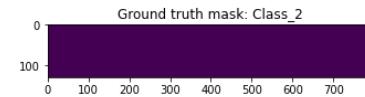
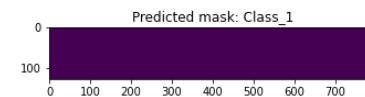
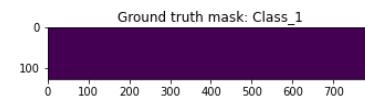
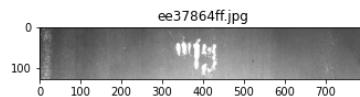
In [0]:

```
visualize_defects(cv_data,model_best)
```

Severstal Steel Defect Detection



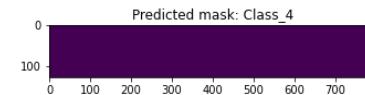
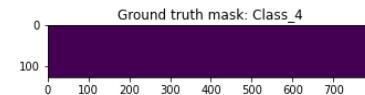
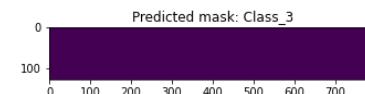
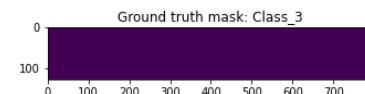
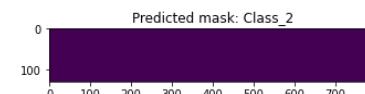
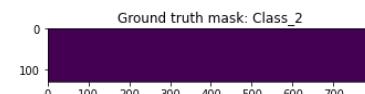
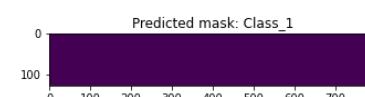
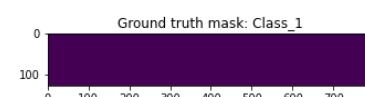
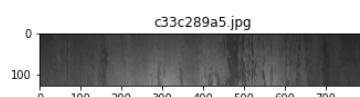
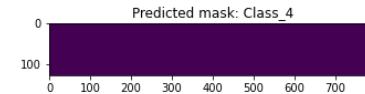
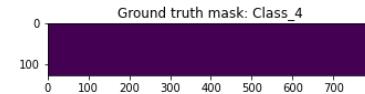
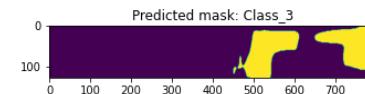
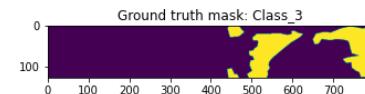
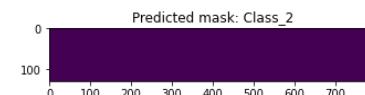
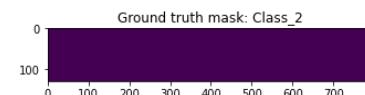
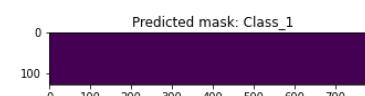
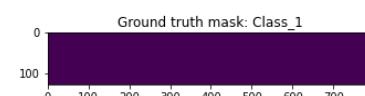
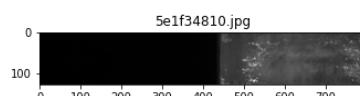
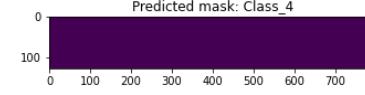
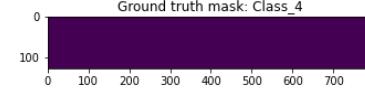
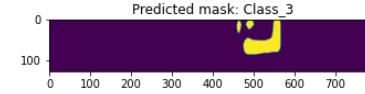
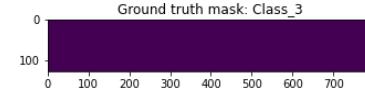
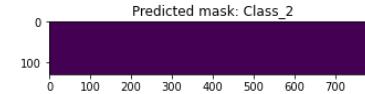
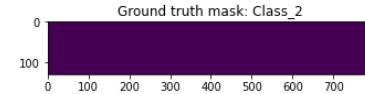
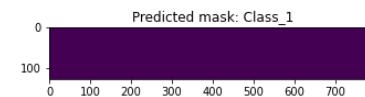
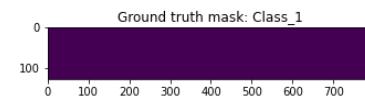
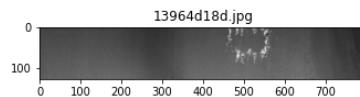
Severstal Steel Defect Detection

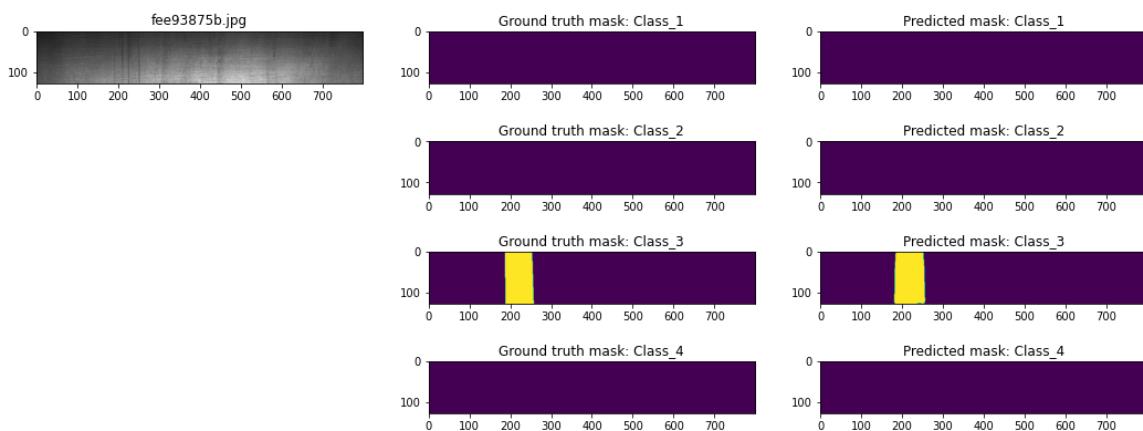
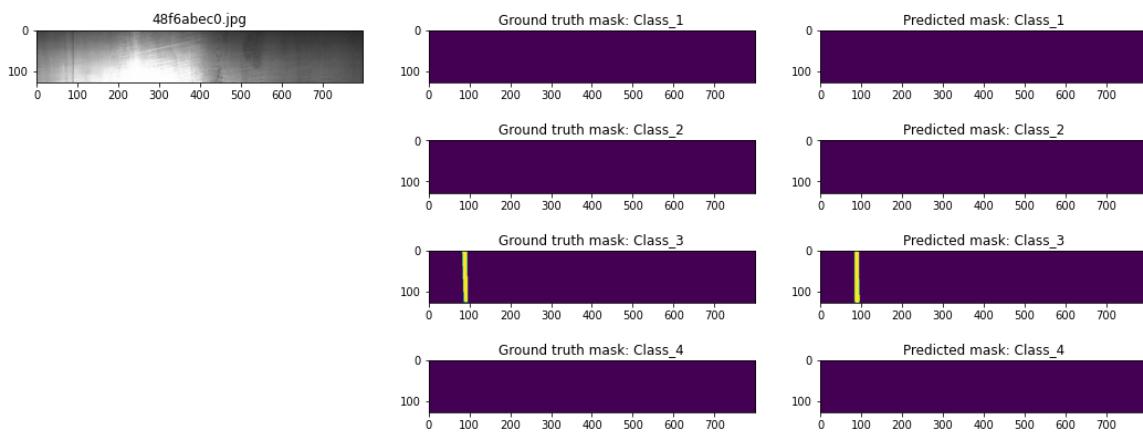


In [0]:

```
visualize_defects(cv_data,model_best)
```

Severstal Steel Defect Detection





2.6 Predicting defects on raw test images

Redefining the segnet architecture for original image size of 256x1600

In [0]:

```
input_img = Input((256,1600,3),name='img')
model1 = get_segnet(input_img, n_filters=16, dropout=0.5, batchnorm=True)
model1.compile(optimizer=Adam(), loss=bce_dice_loss, metrics=[dice_coef])
model1.summary()
```

Model: "model_5"

Layer (type)	Output Shape	Param #
img (InputLayer)	(None, 256, 1600, 3)	0
conv2d_105 (Conv2D)	(None, 256, 1600, 16)	448
batch_normalization_101 (Batch Normalization)	(None, 256, 1600, 16)	64
activation_101 (Activation)	(None, 256, 1600, 16)	0
conv2d_106 (Conv2D)	(None, 256, 1600, 16)	2320
batch_normalization_102 (Batch Normalization)	(None, 256, 1600, 16)	64
activation_102 (Activation)	(None, 256, 1600, 16)	0
max_pooling2d_21 (MaxPooling)	(None, 128, 800, 16)	0
dropout_41 (Dropout)	(None, 128, 800, 16)	0
conv2d_107 (Conv2D)	(None, 128, 800, 32)	4640
batch_normalization_103 (Batch Normalization)	(None, 128, 800, 32)	128
activation_103 (Activation)	(None, 128, 800, 32)	0
conv2d_108 (Conv2D)	(None, 128, 800, 32)	9248
batch_normalization_104 (Batch Normalization)	(None, 128, 800, 32)	128
activation_104 (Activation)	(None, 128, 800, 32)	0
max_pooling2d_22 (MaxPooling)	(None, 64, 400, 32)	0
dropout_42 (Dropout)	(None, 64, 400, 32)	0
conv2d_109 (Conv2D)	(None, 64, 400, 64)	18496
batch_normalization_105 (Batch Normalization)	(None, 64, 400, 64)	256
activation_105 (Activation)	(None, 64, 400, 64)	0
conv2d_110 (Conv2D)	(None, 64, 400, 64)	36928
batch_normalization_106 (Batch Normalization)	(None, 64, 400, 64)	256
activation_106 (Activation)	(None, 64, 400, 64)	0
conv2d_111 (Conv2D)	(None, 64, 400, 64)	36928
batch_normalization_107 (Batch Normalization)	(None, 64, 400, 64)	256
activation_107 (Activation)	(None, 64, 400, 64)	0
max_pooling2d_23 (MaxPooling)	(None, 32, 200, 64)	0
dropout_43 (Dropout)	(None, 32, 200, 64)	0
conv2d_112 (Conv2D)	(None, 32, 200, 128)	73856

batch_normalization_108 (Batch Normalization)	(None, 32, 200, 128)	512
activation_108 (Activation)	(None, 32, 200, 128)	0
conv2d_113 (Conv2D)	(None, 32, 200, 128)	147584
batch_normalization_109 (Batch Normalization)	(None, 32, 200, 128)	512
activation_109 (Activation)	(None, 32, 200, 128)	0
conv2d_114 (Conv2D)	(None, 32, 200, 128)	147584
batch_normalization_110 (Batch Normalization)	(None, 32, 200, 128)	512
activation_110 (Activation)	(None, 32, 200, 128)	0
max_pooling2d_24 (MaxPooling)	(None, 16, 100, 128)	0
dropout_44 (Dropout)	(None, 16, 100, 128)	0
conv2d_115 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_111 (Batch Normalization)	(None, 16, 100, 128)	512
activation_111 (Activation)	(None, 16, 100, 128)	0
conv2d_116 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_112 (Batch Normalization)	(None, 16, 100, 128)	512
activation_112 (Activation)	(None, 16, 100, 128)	0
conv2d_117 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_113 (Batch Normalization)	(None, 16, 100, 128)	512
activation_113 (Activation)	(None, 16, 100, 128)	0
max_pooling2d_25 (MaxPooling)	(None, 8, 50, 128)	0
dropout_45 (Dropout)	(None, 8, 50, 128)	0
up_sampling2d_21 (UpSampling)	(None, 16, 100, 128)	0
conv2d_118 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_114 (Batch Normalization)	(None, 16, 100, 128)	512
activation_114 (Activation)	(None, 16, 100, 128)	0
conv2d_119 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_115 (Batch Normalization)	(None, 16, 100, 128)	512
activation_115 (Activation)	(None, 16, 100, 128)	0
conv2d_120 (Conv2D)	(None, 16, 100, 128)	147584
batch_normalization_116 (Batch Normalization)	(None, 16, 100, 128)	512

activation_116 (Activation)	(None, 16, 100, 128)	0
dropout_46 (Dropout)	(None, 16, 100, 128)	0
up_sampling2d_22 (UpSampling)	(None, 32, 200, 128)	0
conv2d_121 (Conv2D)	(None, 32, 200, 128)	147584
batch_normalization_117 (Batch Normalization)	(None, 32, 200, 128)	512
activation_117 (Activation)	(None, 32, 200, 128)	0
conv2d_122 (Conv2D)	(None, 32, 200, 128)	147584
batch_normalization_118 (Batch Normalization)	(None, 32, 200, 128)	512
activation_118 (Activation)	(None, 32, 200, 128)	0
conv2d_123 (Conv2D)	(None, 32, 200, 64)	73792
batch_normalization_119 (Batch Normalization)	(None, 32, 200, 64)	256
activation_119 (Activation)	(None, 32, 200, 64)	0
dropout_47 (Dropout)	(None, 32, 200, 64)	0
up_sampling2d_23 (UpSampling)	(None, 64, 400, 64)	0
conv2d_124 (Conv2D)	(None, 64, 400, 64)	36928
batch_normalization_120 (Batch Normalization)	(None, 64, 400, 64)	256
activation_120 (Activation)	(None, 64, 400, 64)	0
conv2d_125 (Conv2D)	(None, 64, 400, 64)	36928
batch_normalization_121 (Batch Normalization)	(None, 64, 400, 64)	256
activation_121 (Activation)	(None, 64, 400, 64)	0
conv2d_126 (Conv2D)	(None, 64, 400, 32)	18464
batch_normalization_122 (Batch Normalization)	(None, 64, 400, 32)	128
activation_122 (Activation)	(None, 64, 400, 32)	0
dropout_48 (Dropout)	(None, 64, 400, 32)	0
up_sampling2d_24 (UpSampling)	(None, 128, 800, 32)	0
conv2d_127 (Conv2D)	(None, 128, 800, 32)	9248
batch_normalization_123 (Batch Normalization)	(None, 128, 800, 32)	128
activation_123 (Activation)	(None, 128, 800, 32)	0
conv2d_128 (Conv2D)	(None, 128, 800, 16)	4624
batch_normalization_124 (Batch Normalization)	(None, 128, 800, 16)	64
activation_124 (Activation)	(None, 128, 800, 16)	0

dropout_49 (Dropout)	(None, 128, 800, 16)	0
up_sampling2d_25 (UpSampling)	(None, 256, 1600, 16)	0
conv2d_129 (Conv2D)	(None, 256, 1600, 16)	2320
batch_normalization_125 (Batch Normalization)	(None, 256, 1600, 16)	64
activation_125 (Activation)	(None, 256, 1600, 16)	0
dropout_50 (Dropout)	(None, 256, 1600, 16)	0
conv2d_130 (Conv2D)	(None, 256, 1600, 4)	68
<hr/>		
Total params: 1,849,012		
Trainable params: 1,845,044		
Non-trainable params: 3,968		

In [0]:

```
model1.set_weights(model_best.get_weights())
```

Predicting on full 256x1600 raw test images

In [0]:

```
# Predicting on test images
from tqdm import tqdm
import cv2
data_path = '/content/' + 'test_images/'
files = list(os.listdir(data_path))
rle_lst = [] #list to store defect in run length encoding format
img_classId= [] #list to store Image ID + classId

for f in tqdm(files):
    X = np.empty((1,256,1600,3),dtype=np.float32)
    img = cv2.imread(data_path + f)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    X[0,] = img
    mask = model1.predict(X)
    rle_m = np.empty((256,1600),dtype=np.uint8)
    for i in range(4):
        rle_m = mask[0,:,:,:,i].round().astype(int)
        rle = mask2rle(rle_m)
        rle_lst.append(rle)
        img_classId.append(f+'_'+str(i+1))
```

100%|██████████| 5506/5506 [05:19<00:00, 17.21it/s]

In [0]:

```
output = {'ImageId_ClassId':img_classId, 'EncodedPixels' : rle_lst}
output_df = pd.DataFrame(output)
output_df.to_csv('submission_segnet_256x1600.csv', index=False)
```

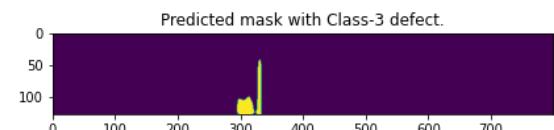
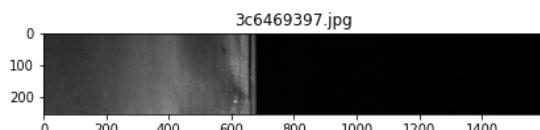
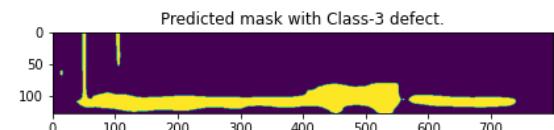
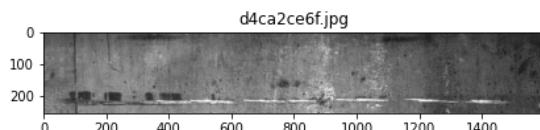
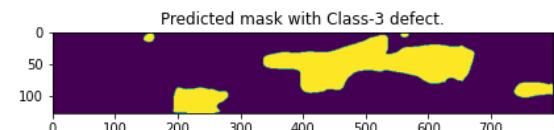
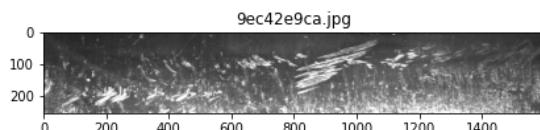
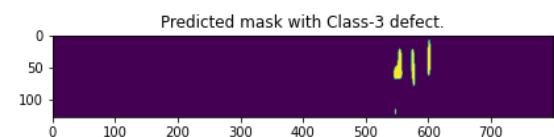
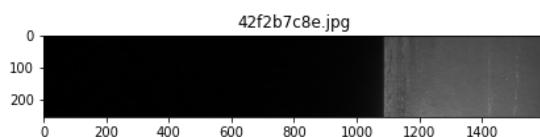
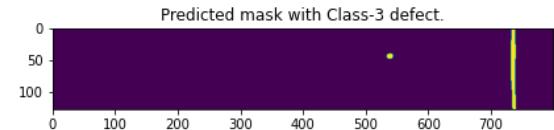
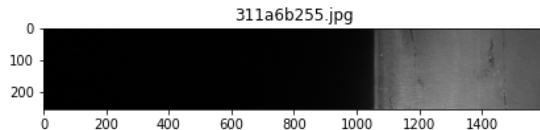
With this submission, I got a private dice coefficient score of 0.83437 & a public score of 0.84740.

2.7 Visualizing defects of raw test images(256x1600)

Please refer to the "visualize_defects_test" function in Utility functions section.

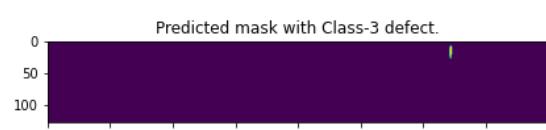
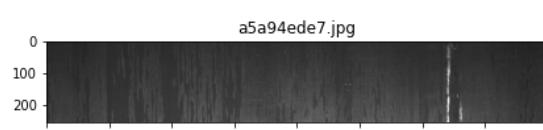
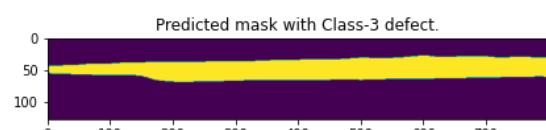
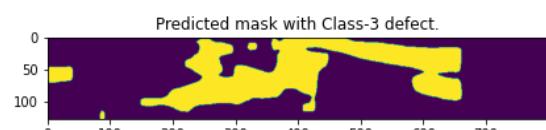
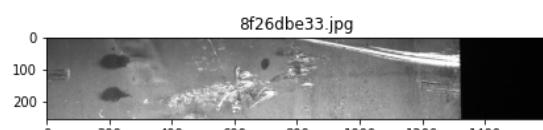
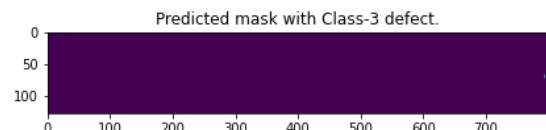
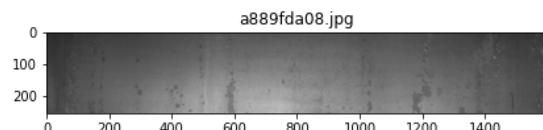
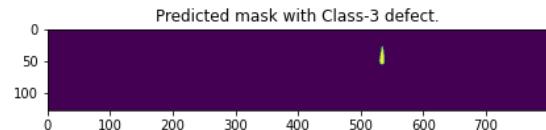
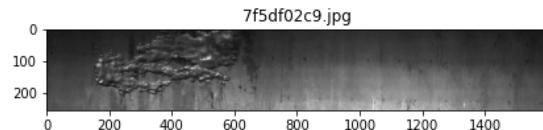
In [0]:

```
visualize_defects(output_df,5)
```



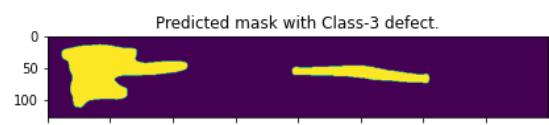
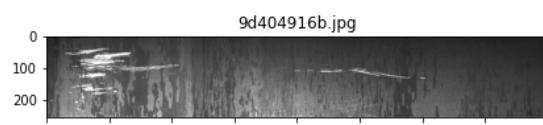
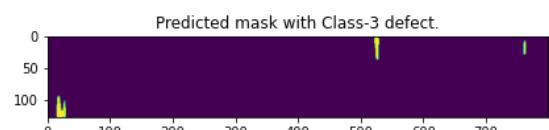
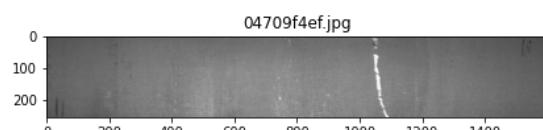
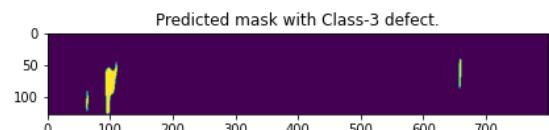
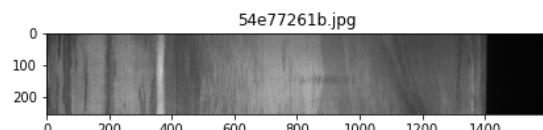
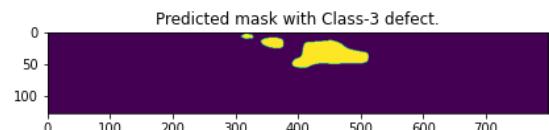
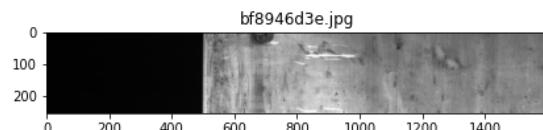
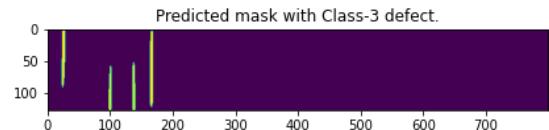
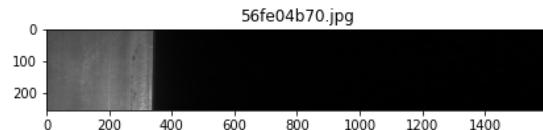
In [0]:

visualize_defects(output_df,5)



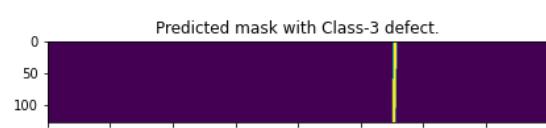
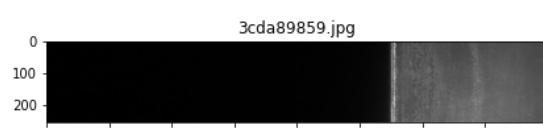
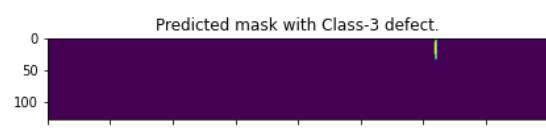
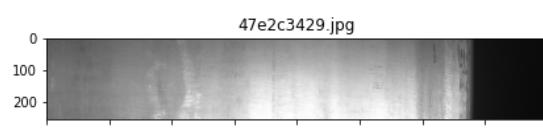
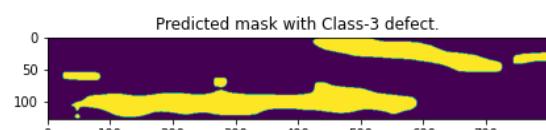
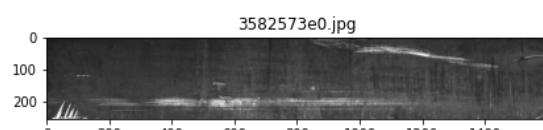
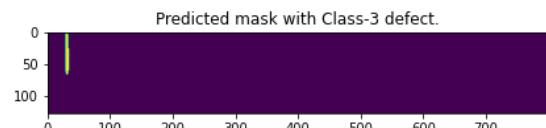
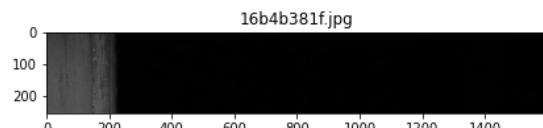
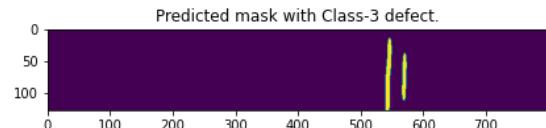
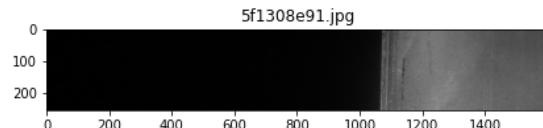
In [0]:

visualize_defects(output_df,5)



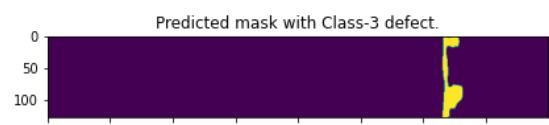
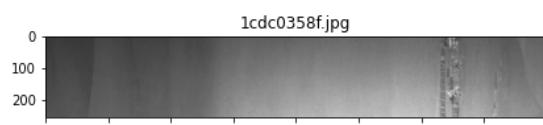
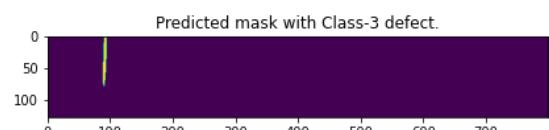
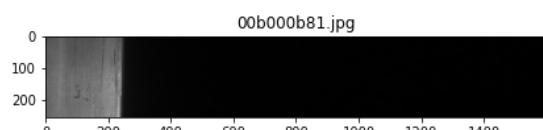
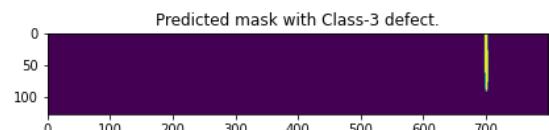
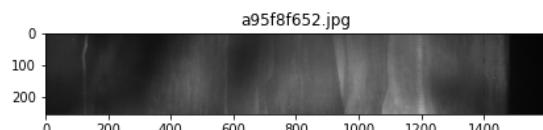
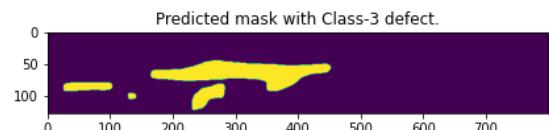
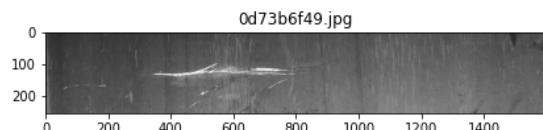
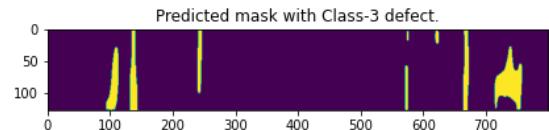
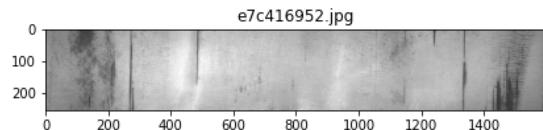
In [0]:

visualize_defects(output_df,5)

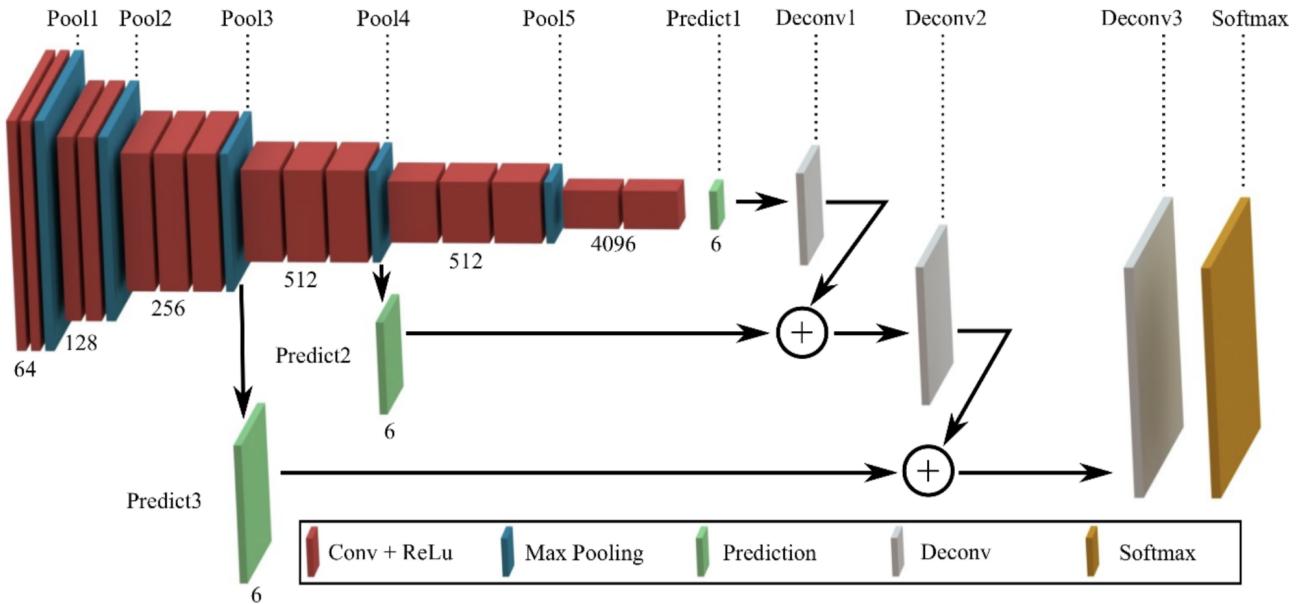


In [0]:

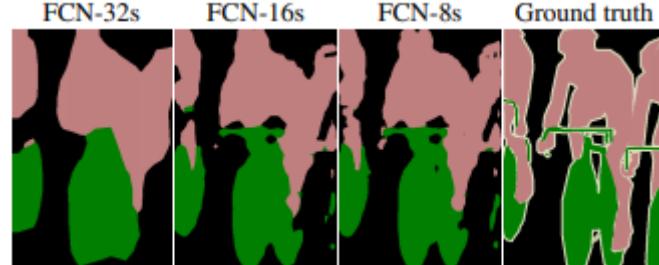
visualize_defects(output_df,5)



3.0 Implementing FCN-8 architecture



Original Skip Layer Architecture



References-

- <https://github.com/seyh814/Semantic-Shapes> (<https://github.com/seyh814/Semantic-Shapes>)
- <https://fairyonice.github.io/Learn-about-Fully-Convolutional-Networks-for-semantic-segmentation.html> (<https://fairyonice.github.io/Learn-about-Fully-Convolutional-Networks-for-semantic-segmentation.html>)
- <https://www.youtube.com/watch?v=-3yIPH3BCWY> (<https://www.youtube.com/watch?v=-3yIPH3BCWY>)

In [0]:

```

def fcn_8(img_shape, base, dropout, n_classes):
    i = Input(shape=img_shape)
    b = base

    ## Block 1
    x = Conv2D(2**b, (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block1_conv1')(i)
    x = BatchNormalization()(x)
    x = Conv2D(2**b, (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block1_conv2')(x)
    x = BatchNormalization()(x)
    x = MaxPooling2D((2, 2), strides=(2, 2), name='block1_pool')(x)
    x = Dropout(dropout)(x)

    # Block 2
    x = Conv2D(2***(b+1), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block2_conv1')(x)
    x = BatchNormalization()(x)
    x = Conv2D(2***(b+1), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block2_conv2')(x)
    x = BatchNormalization()(x)
    x = MaxPooling2D((2, 2), strides=(2, 2), name='block2_pool')(x)
    x = Dropout(dropout)(x)

    # Block 3
    x = Conv2D(2***(b+2), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block3_conv1')(x)
    x = BatchNormalization()(x)
    x = Conv2D(2***(b+2), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block3_conv2')(x)
    x = BatchNormalization()(x)
    x = Conv2D(2***(b+2), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block3_conv3')(x)
    x = BatchNormalization()(x)
    x = MaxPooling2D((2, 2), strides=(2, 2), name='block3_pool')(x)
    x = Dropout(dropout)(x)
    pool3 = x

    # Block 4
    x = Conv2D(2***(b+3), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block4_conv1')(x)
    x = BatchNormalization()(x)
    x = Conv2D(2***(b+3), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block4_conv2')(x)
    x = BatchNormalization()(x)
    x = Conv2D(2***(b+3), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block4_conv3')(x)
    x = BatchNormalization()(x)
    pool4 = MaxPooling2D((2, 2), strides=(2, 2), name='block4_pool')(x)
    pool4 = Dropout(dropout)(pool4)

    # Block 5
    x = Conv2D(2***(b+3), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block5_conv1')(pool4)
    x = BatchNormalization()(x)
    x = Conv2D(2***(b+3), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block5_conv2')(x)
    x = BatchNormalization()(x)
    x = Conv2D(2***(b+3), (3, 3), activation='relu', kernel_initializer = 'he_normal', padding='same', name='block5_conv3')(x)
    x = BatchNormalization()(x)

```

```
adding='same', name='block5_conv3')(x)
x = BatchNormalization()(x)
pool5 = MaxPooling2D((2, 2), strides=(2, 2), name='block5_pool')(x)
pool5 = Dropout(dropout)(pool5)

conv6 = Conv2D(2** (b+3)*8 , (7, 7) , activation='relu', kernel_initializer = 'he_normal' , padding='same', name="conv6")(pool5)
conv6 = BatchNormalization()(conv6)
conv6 = Dropout(0.5)(conv6)
conv7 = Conv2D(2** (b+3)*8 , (1, 1) , activation='relu', kernel_initializer = 'he_normal' , padding='same', name="conv7")(conv6)
conv7 = BatchNormalization()(conv7)
conv7 = Dropout(0.5)(conv7)

pool4_n = Conv2D(n_classes, (1, 1), activation='relu', kernel_initializer = 'he_normal', padding='same')(pool4)
u2 = Conv2DTranspose(n_classes, kernel_size=(2, 2), strides=(2, 2), padding='same')(conv7)
u2_skip = Add()([pool4_n, u2])

pool3_n = Conv2D(n_classes, (1, 1), activation='relu', padding='same')(pool3)
u4 = Conv2DTranspose(n_classes, kernel_size=(2, 2), strides=(2, 2), padding='same')(u2_skip)
u4_skip = Add()([pool3_n, u4])

output = Conv2DTranspose(n_classes, kernel_size=(8, 8), strides=(8, 8), padding='same',activation='sigmoid')(u4_skip)

model = Model(inputs=[i], outputs=[output])

return model
```

In [0]:

```
#https://keras.io/models/model/#fit_generator
model= fcn_8(img_shape= (128,800,3), base= 4, dropout= 0.3, n_classes= 4)
model.compile(optimizer=Adam(), loss=bce_dice_loss, metrics=[dice_coef])
model.summary()
```

Model: "model_2"

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	(None, 128, 800, 3)	0	
block1_conv1 (Conv2D)	(None, 128, 800, 16)	448	input_2[0][0]
batch_normalization_16 (BatchNo)	(None, 128, 800, 16)	64	block1_conv1[0][0]
block1_conv2 (Conv2D)	(None, 128, 800, 16)	2320	batch_normalization_16[0][0]
batch_normalization_17 (BatchNo)	(None, 128, 800, 16)	64	block1_conv2[0][0]
block1_pool (MaxPooling2D)	(None, 64, 400, 16)	0	batch_normalization_17[0][0]
dropout_8 (Dropout)	(None, 64, 400, 16)	0	block1_pool[0][0]
block2_conv1 (Conv2D)	(None, 64, 400, 32)	4640	dropout_8[0][0]
batch_normalization_18 (BatchNo)	(None, 64, 400, 32)	128	block2_conv1[0][0]
block2_conv2 (Conv2D)	(None, 64, 400, 32)	9248	batch_normalization_18[0][0]
batch_normalization_19 (BatchNo)	(None, 64, 400, 32)	128	block2_conv2[0][0]
block2_pool (MaxPooling2D)	(None, 32, 200, 32)	0	batch_normalization_19[0][0]
dropout_9 (Dropout)	(None, 32, 200, 32)	0	block2_pool[0][0]
block3_conv1 (Conv2D)	(None, 32, 200, 64)	18496	dropout_9[0][0]

batch_normalization_20 (BatchNo (None, 32, 200, 64) 256 nv1[0][0]		block3_co
block3_conv2 (Conv2D) (None, 32, 200, 64) 36928 normalization_20[0][0]		batch_nor malization_20[0][0]
batch_normalization_21 (BatchNo (None, 32, 200, 64) 256 nv2[0][0]		block3_co nv2[0][0]
block3_conv3 (Conv2D) (None, 32, 200, 64) 36928 normalization_21[0][0]		batch_nor malization_21[0][0]
batch_normalization_22 (BatchNo (None, 32, 200, 64) 256 nv3[0][0]		block3_co nv3[0][0]
block3_pool (MaxPooling2D) (None, 16, 100, 64) 0 normalization_22[0][0]		batch_nor malization_22[0][0]
dropout_10 (Dropout) (None, 16, 100, 64) 0 ol[0][0]		block3_po ol[0][0]
block4_conv1 (Conv2D) (None, 16, 100, 128) 73856 0[0][0]		dropout_1 0[0][0]
batch_normalization_23 (BatchNo (None, 16, 100, 128) 512 nv1[0][0]		block4_co nv1[0][0]
block4_conv2 (Conv2D) (None, 16, 100, 128) 147584 normalization_23[0][0]		batch_nor malization_23[0][0]
batch_normalization_24 (BatchNo (None, 16, 100, 128) 512 nv2[0][0]		block4_co nv2[0][0]
block4_conv3 (Conv2D) (None, 16, 100, 128) 147584 normalization_24[0][0]		batch_nor malization_24[0][0]
batch_normalization_25 (BatchNo (None, 16, 100, 128) 512 nv3[0][0]		block4_co nv3[0][0]
block4_pool (MaxPooling2D) (None, 8, 50, 128) 0 normalization_25[0][0]		batch_nor malization_25[0][0]
dropout_11 (Dropout) (None, 8, 50, 128) 0 ol[0][0]		block4_po ol[0][0]

block5_conv1 (Conv2D) 1[0][0]	(None, 8, 50, 128)	147584	dropout_1
batch_normalization_26 (BatchNo nv1[0][0]	(None, 8, 50, 128)	512	block5_co
block5_conv2 (Conv2D) malization_26[0][0]	(None, 8, 50, 128)	147584	batch_nor
batch_normalization_27 (BatchNo nv2[0][0]	(None, 8, 50, 128)	512	block5_co
block5_conv3 (Conv2D) malization_27[0][0]	(None, 8, 50, 128)	147584	batch_nor
batch_normalization_28 (BatchNo nv3[0][0]	(None, 8, 50, 128)	512	block5_co
block5_pool (MaxPooling2D) malization_28[0][0]	(None, 4, 25, 128)	0	batch_nor
dropout_12 (Dropout) ol[0][0]	(None, 4, 25, 128)	0	block5_po
conv6 (Conv2D) 2[0][0]	(None, 4, 25, 1024)	6423552	dropout_1
batch_normalization_29 (BatchNo [0]	(None, 4, 25, 1024)	4096	conv6[0]
dropout_13 (Dropout) malization_29[0][0]	(None, 4, 25, 1024)	0	batch_nor
conv7 (Conv2D) 3[0][0]	(None, 4, 25, 1024)	1049600	dropout_1
batch_normalization_30 (BatchNo [0]	(None, 4, 25, 1024)	4096	conv7[0]
dropout_14 (Dropout) malization_30[0][0]	(None, 4, 25, 1024)	0	batch_nor
conv2d_3 (Conv2D) 1[0][0]	(None, 8, 50, 4)	516	dropout_1
conv2d_transpose_4 (Conv2DTrans conv2d_transpose_4[0][0]	(None, 8, 50, 4)	16388	dropout_1

4[0][0]

add_3 (Add) [0][0]	(None, 8, 50, 4)	0	conv2d_3
anspose_4[0][0]			conv2d_tr
conv2d_4 (Conv2D) 0[0][0]	(None, 16, 100, 4)	260	dropout_1
conv2d_transpose_5 (Conv2DTrans) [0]	(None, 16, 100, 4)	68	add_3[0]
add_4 (Add) [0][0]	(None, 16, 100, 4)	0	conv2d_4
anspose_5[0][0]			conv2d_tr
conv2d_transpose_6 (Conv2DTrans) [0]	(None, 128, 800, 4)	1028	add_4[0]
<hr/>			
<hr/>			
Total params: 8,424,612			
Trainable params: 8,418,404			
Non-trainable params: 6,208			



3.1 Checkpointing the model and creating the callback list

In [0]:

```
tbc=TensorBoardColab()
mc = ModelCheckpoint('best_model_fcn8.h5', monitor='val_dice_coef', verbose=1, save_bes
t_only=True, mode='max')
callbacks_list = [mc, TensorBoardColabCallback(tbc)]
```

Wait for 8 seconds...

TensorBoard link:

<https://358ac569.ngrok.io>

3.2 Fitting the train data and validation

In [0]:

```
train_batches = Train_DataGenerator(train_data,shuffle=True)
valid_batches = Val_DataGenerator(cv_data)
history = model.fit_generator(train_batches, validation_data = valid_batches, epochs =
30, verbose=1,
                                class_weight=class_wts, callbacks = callbacks_list)
```

ERROR! Session/line number was not unique in database. History logging moved to new session 60

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please use tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is deprecated. Please use tf.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorboard_colab/core.py:49: The name tf.summary.FileWriter is deprecated. Please use tf.compat.v1.summary.FileWriter instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1122: The name tf.summary.merge_all is deprecated. Please use tf.compat.v1.summary.merge_all instead.

Epoch 1/30

667/667 [=====] - 262s 392ms/step - loss: 0.8073
- dice_coef: 0.2814 - val_loss: 0.7385 - val_dice_coef: 0.3199

Epoch 00001: val_dice_coef improved from -inf to 0.31990, saving model to best_model.h5

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorboard_colab/callbacks.py:51: The name tf.Summary is deprecated. Please use tf.compat.v1.Summary instead.

Epoch 2/30

667/667 [=====] - 236s 354ms/step - loss: 0.6018
- dice_coef: 0.4443 - val_loss: 0.7356 - val_dice_coef: 0.3235

Epoch 00002: val_dice_coef improved from 0.31990 to 0.32351, saving model to best_model.h5

Epoch 3/30

667/667 [=====] - 238s 357ms/step - loss: 0.5655
- dice_coef: 0.4768 - val_loss: 0.6561 - val_dice_coef: 0.3929

Epoch 00003: val_dice_coef improved from 0.32351 to 0.39290, saving model to best_model.h5

Epoch 4/30

667/667 [=====] - 239s 358ms/step - loss: 0.5419
- dice_coef: 0.4991 - val_loss: 0.5570 - val_dice_coef: 0.4868

Epoch 00004: val_dice_coef improved from 0.39290 to 0.48675, saving model to best_model.h5

Epoch 5/30

667/667 [=====] - 237s 355ms/step - loss: 0.5287
- dice_coef: 0.5118 - val_loss: 0.8987 - val_dice_coef: 0.1731

Epoch 00005: val_dice_coef did not improve from 0.48675

Epoch 6/30

667/667 [=====] - 236s 354ms/step - loss: 0.5213
- dice_coef: 0.5176 - val_loss: 0.5272 - val_dice_coef: 0.5125

Epoch 00006: val_dice_coef improved from 0.48675 to 0.51246, saving model to best_model.h5

Epoch 7/30

667/667 [=====] - 237s 355ms/step - loss: 0.5106
- dice_coef: 0.5279 - val_loss: 0.5975 - val_dice_coef: 0.4473

```
Epoch 00007: val_dice_coef did not improve from 0.51246
Epoch 8/30
667/667 [=====] - 237s 356ms/step - loss: 0.5019
- dice_coef: 0.5359 - val_loss: 0.5189 - val_dice_coef: 0.5206

Epoch 00008: val_dice_coef improved from 0.51246 to 0.52060, saving model
to best_model.h5
Epoch 9/30
667/667 [=====] - 239s 358ms/step - loss: 0.4876
- dice_coef: 0.5491 - val_loss: 0.6301 - val_dice_coef: 0.4224

Epoch 00009: val_dice_coef did not improve from 0.52060
Epoch 10/30
667/667 [=====] - 239s 358ms/step - loss: 0.4790
- dice_coef: 0.5578 - val_loss: 0.5311 - val_dice_coef: 0.5095

Epoch 00010: val_dice_coef did not improve from 0.52060
Epoch 11/30
667/667 [=====] - 238s 357ms/step - loss: 0.4614
- dice_coef: 0.5740 - val_loss: 0.5877 - val_dice_coef: 0.4614

Epoch 00011: val_dice_coef did not improve from 0.52060
Epoch 12/30
667/667 [=====] - 238s 357ms/step - loss: 0.4479
- dice_coef: 0.5862 - val_loss: 1.0221 - val_dice_coef: 0.0805

Epoch 00012: val_dice_coef did not improve from 0.52060
Epoch 13/30
667/667 [=====] - 238s 357ms/step - loss: 0.4405
- dice_coef: 0.5940 - val_loss: 0.5188 - val_dice_coef: 0.5230

Epoch 00013: val_dice_coef improved from 0.52060 to 0.52296, saving model
to best_model.h5
Epoch 14/30
667/667 [=====] - 238s 357ms/step - loss: 0.4296
- dice_coef: 0.6049 - val_loss: 0.6698 - val_dice_coef: 0.3900

Epoch 00014: val_dice_coef did not improve from 0.52296
Epoch 15/30
667/667 [=====] - 239s 358ms/step - loss: 0.4174
- dice_coef: 0.6153 - val_loss: 0.5601 - val_dice_coef: 0.4845

Epoch 00015: val_dice_coef did not improve from 0.52296
Epoch 16/30
667/667 [=====] - 238s 357ms/step - loss: 0.4189
- dice_coef: 0.6137 - val_loss: 0.5328 - val_dice_coef: 0.5116

Epoch 00016: val_dice_coef did not improve from 0.52296
Epoch 17/30
667/667 [=====] - 239s 359ms/step - loss: 0.4013
- dice_coef: 0.6302 - val_loss: 0.5416 - val_dice_coef: 0.5084

Epoch 00017: val_dice_coef did not improve from 0.52296
Epoch 18/30
667/667 [=====] - 239s 358ms/step - loss: 0.4004
- dice_coef: 0.6315 - val_loss: 0.5761 - val_dice_coef: 0.4751

Epoch 00018: val_dice_coef did not improve from 0.52296
Epoch 19/30
667/667 [=====] - 240s 361ms/step - loss: 0.3974
- dice_coef: 0.6340 - val_loss: 0.8097 - val_dice_coef: 0.2653
```

```
Epoch 00019: val_dice_coef did not improve from 0.52296
Epoch 20/30
667/667 [=====] - 239s 359ms/step - loss: 0.3906
- dice_coef: 0.6410 - val_loss: 0.5715 - val_dice_coef: 0.4794

Epoch 00020: val_dice_coef did not improve from 0.52296
Epoch 21/30
667/667 [=====] - 241s 361ms/step - loss: 0.3869
- dice_coef: 0.6440 - val_loss: 0.5087 - val_dice_coef: 0.5357

Epoch 00021: val_dice_coef improved from 0.52296 to 0.53567, saving model
to best_model.h5
Epoch 22/30
667/667 [=====] - 240s 360ms/step - loss: 0.3887
- dice_coef: 0.6425 - val_loss: 0.6491 - val_dice_coef: 0.4090

Epoch 00022: val_dice_coef did not improve from 0.53567
Epoch 23/30
667/667 [=====] - 241s 362ms/step - loss: 0.3774
- dice_coef: 0.6527 - val_loss: 0.5835 - val_dice_coef: 0.4682

Epoch 00023: val_dice_coef did not improve from 0.53567
Epoch 24/30
667/667 [=====] - 240s 360ms/step - loss: 0.3769
- dice_coef: 0.6533 - val_loss: 0.5461 - val_dice_coef: 0.5020

Epoch 00024: val_dice_coef did not improve from 0.53567
Epoch 25/30
667/667 [=====] - 242s 363ms/step - loss: 0.3630
- dice_coef: 0.6658 - val_loss: 0.5320 - val_dice_coef: 0.5144

Epoch 00025: val_dice_coef did not improve from 0.53567
Epoch 26/30
667/667 [=====] - 245s 367ms/step - loss: 0.3636
- dice_coef: 0.6660 - val_loss: 0.5159 - val_dice_coef: 0.5279

Epoch 00026: val_dice_coef did not improve from 0.53567
Epoch 27/30
667/667 [=====] - 246s 369ms/step - loss: 0.3597
- dice_coef: 0.6687 - val_loss: 0.7179 - val_dice_coef: 0.3530

Epoch 00027: val_dice_coef did not improve from 0.53567
Epoch 28/30
667/667 [=====] - 242s 363ms/step - loss: 0.3620
- dice_coef: 0.6665 - val_loss: 0.5897 - val_dice_coef: 0.4616

Epoch 00028: val_dice_coef did not improve from 0.53567
Epoch 29/30
667/667 [=====] - 242s 363ms/step - loss: 0.3553
- dice_coef: 0.6726 - val_loss: 0.5552 - val_dice_coef: 0.4953

Epoch 00029: val_dice_coef did not improve from 0.53567
Epoch 30/30
667/667 [=====] - 240s 360ms/step - loss: 0.3535
- dice_coef: 0.6746 - val_loss: 0.5141 - val_dice_coef: 0.5302

Epoch 00030: val_dice_coef did not improve from 0.53567
```

In [0]:

```
#round 2 for 20 epochs
model= model_best
train_batches = Train_DataGenerator(train_data,shuffle=True)
valid_batches = Val_DataGenerator(cv_data)
class_wts= [1.98,7.18,0.34,2.21]
history = model.fit_generator(train_batches, validation_data = valid_batches, epochs =
20, verbose=1,
                                class_weight=class_wts, callbacks = callbacks_list)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorboard/colab/core.py:49: The name tf.summary.FileWriter is deprecated. Please use tf.compat.v1.summary.FileWriter instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/callbacks.py:1122: The name tf.summary.merge_all is deprecated. Please use tf.compat.v1.summary.merge_all instead.

Epoch 1/20

667/667 [=====] - 260s 389ms/step - loss: 0.5078
- dice_coef: 0.5295 - val_loss: 0.5507 - val_dice_coef: 0.5024

Epoch 00001: val_dice_coef improved from -inf to 0.50236, saving model to best_model.h5

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorboard/colab/callbacks.py:51: The name tf.Summary is deprecated. Please use tf.compat.v1.Summary instead.

Epoch 2/20

667/667 [=====] - 244s 366ms/step - loss: 0.5027
- dice_coef: 0.5344 - val_loss: 0.5386 - val_dice_coef: 0.5093

Epoch 00002: val_dice_coef improved from 0.50236 to 0.50929, saving model to best_model.h5

Epoch 3/20

667/667 [=====] - 251s 376ms/step - loss: 0.4952
- dice_coef: 0.5414 - val_loss: 0.5888 - val_dice_coef: 0.4639

Epoch 00003: val_dice_coef did not improve from 0.50929

Epoch 4/20

667/667 [=====] - 249s 374ms/step - loss: 0.4775
- dice_coef: 0.5588 - val_loss: 0.5142 - val_dice_coef: 0.5323

Epoch 00004: val_dice_coef improved from 0.50929 to 0.53226, saving model to best_model.h5

Epoch 5/20

667/667 [=====] - 241s 362ms/step - loss: 0.4601
- dice_coef: 0.5747 - val_loss: 0.6080 - val_dice_coef: 0.4484

Epoch 00005: val_dice_coef did not improve from 0.53226

Epoch 6/20

667/667 [=====] - 241s 362ms/step - loss: 0.4497
- dice_coef: 0.5850 - val_loss: 0.7672 - val_dice_coef: 0.3144

Epoch 00006: val_dice_coef did not improve from 0.53226

Epoch 7/20

667/667 [=====] - 240s 360ms/step - loss: 0.4421
- dice_coef: 0.5913 - val_loss: 0.5534 - val_dice_coef: 0.5002

Epoch 00007: val_dice_coef did not improve from 0.53226

Epoch 8/20

667/667 [=====] - 240s 360ms/step - loss: 0.4405
- dice_coef: 0.5932 - val_loss: 0.6820 - val_dice_coef: 0.3835

Epoch 00008: val_dice_coef did not improve from 0.53226

Epoch 9/20

667/667 [=====] - 239s 359ms/step - loss: 0.4238
- dice_coef: 0.6085 - val_loss: 0.6206 - val_dice_coef: 0.4392

Epoch 00009: val_dice_coef did not improve from 0.53226

Epoch 10/20

```
667/667 [=====] - 242s 363ms/step - loss: 0.4134
- dice_coef: 0.6189 - val_loss: 0.5577 - val_dice_coef: 0.4948

Epoch 00010: val_dice_coef did not improve from 0.53226
Epoch 11/20
667/667 [=====] - 241s 362ms/step - loss: 0.4039
- dice_coef: 0.6272 - val_loss: 0.6911 - val_dice_coef: 0.3801

Epoch 00011: val_dice_coef did not improve from 0.53226
Epoch 12/20
667/667 [=====] - 244s 366ms/step - loss: 0.4045
- dice_coef: 0.6274 - val_loss: 0.5428 - val_dice_coef: 0.5117

Epoch 00012: val_dice_coef did not improve from 0.53226
Epoch 13/20
667/667 [=====] - 246s 369ms/step - loss: 0.4046
- dice_coef: 0.6270 - val_loss: 0.5021 - val_dice_coef: 0.5462

Epoch 00013: val_dice_coef improved from 0.53226 to 0.54618, saving model
to best_model.h5
Epoch 14/20
667/667 [=====] - 250s 375ms/step - loss: 0.3877
- dice_coef: 0.6427 - val_loss: 0.4743 - val_dice_coef: 0.5711

Epoch 00014: val_dice_coef improved from 0.54618 to 0.57108, saving model
to best_model.h5
Epoch 15/20
667/667 [=====] - 241s 361ms/step - loss: 0.3896
- dice_coef: 0.6407 - val_loss: 0.9046 - val_dice_coef: 0.2007

Epoch 00015: val_dice_coef did not improve from 0.57108
Epoch 16/20
667/667 [=====] - 246s 368ms/step - loss: 0.3856
- dice_coef: 0.6449 - val_loss: 0.4810 - val_dice_coef: 0.5668

Epoch 00016: val_dice_coef did not improve from 0.57108
Epoch 17/20
667/667 [=====] - 247s 371ms/step - loss: 0.3815
- dice_coef: 0.6487 - val_loss: 0.6442 - val_dice_coef: 0.4214

Epoch 00017: val_dice_coef did not improve from 0.57108
Epoch 18/20
667/667 [=====] - 249s 373ms/step - loss: 0.3723
- dice_coef: 0.6573 - val_loss: 0.6303 - val_dice_coef: 0.4345

Epoch 00018: val_dice_coef did not improve from 0.57108
Epoch 19/20
667/667 [=====] - 249s 373ms/step - loss: 0.3709
- dice_coef: 0.6579 - val_loss: 0.5422 - val_dice_coef: 0.5118

Epoch 00019: val_dice_coef did not improve from 0.57108
Epoch 20/20
667/667 [=====] - 251s 376ms/step - loss: 0.3637
- dice_coef: 0.6647 - val_loss: 0.6284 - val_dice_coef: 0.4359

Epoch 00020: val_dice_coef did not improve from 0.57108
```

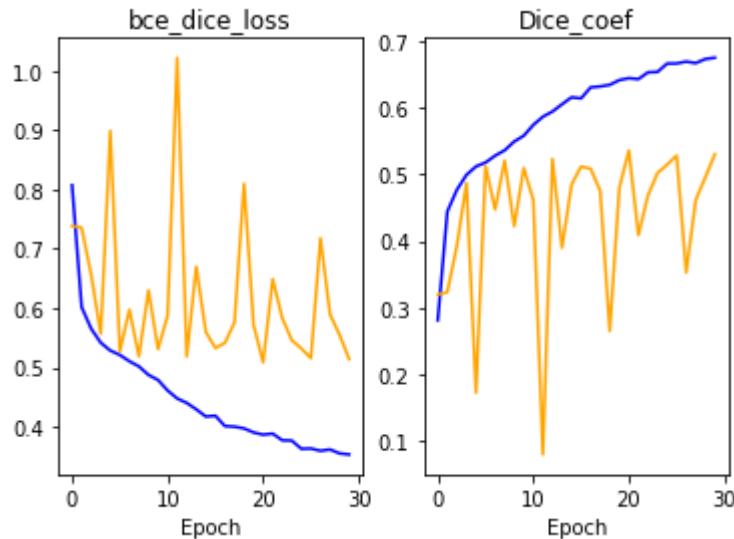
3.3 Plots on training & validation results

Loss function & metric plots

Please refer to Training Plots in utility functions section.

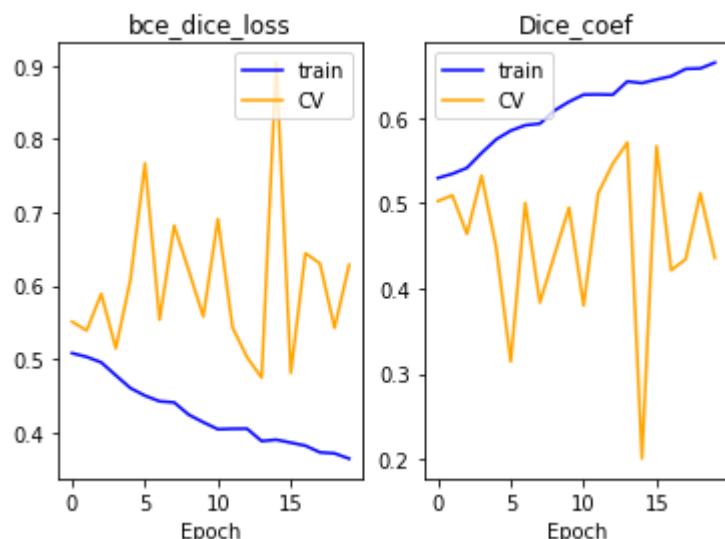
In [0]:

```
#first 30 epochs
plot(history)
```



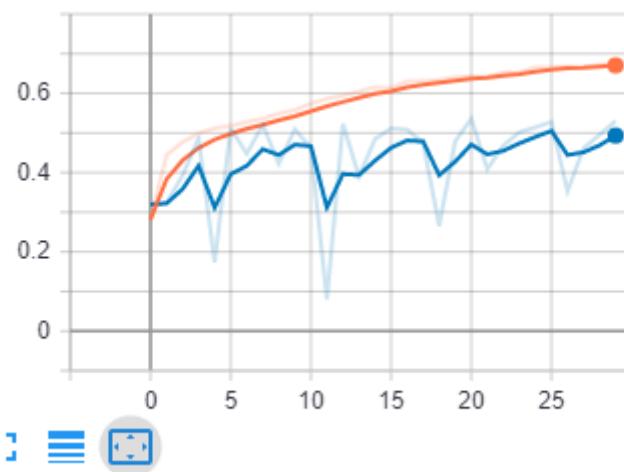
In [0]:

```
#next 20 epochs
plot(history)
```



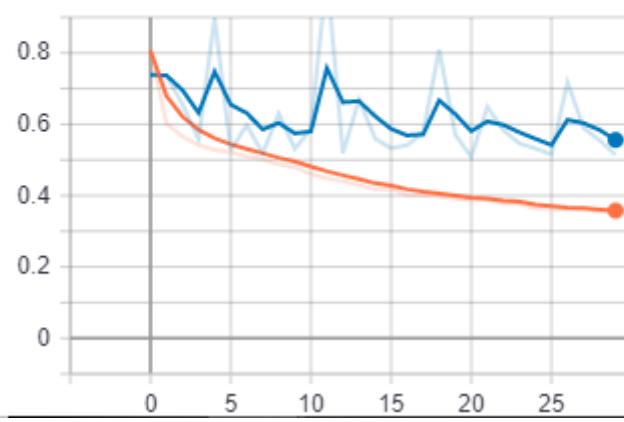
Tensorboard images

dice_coef



loss

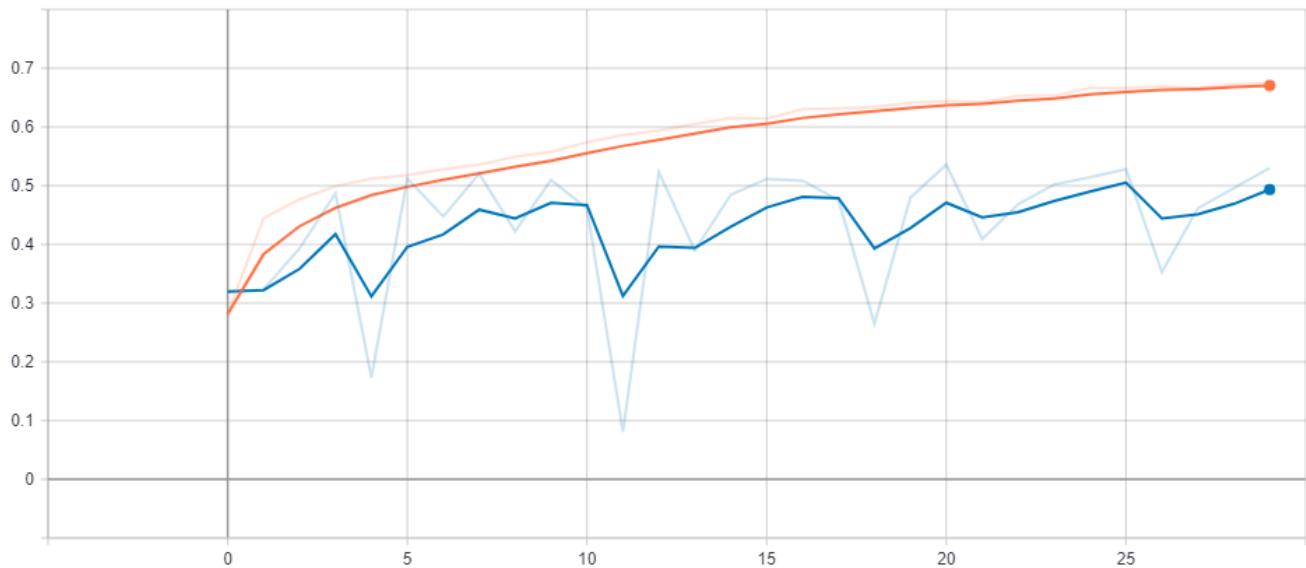
loss



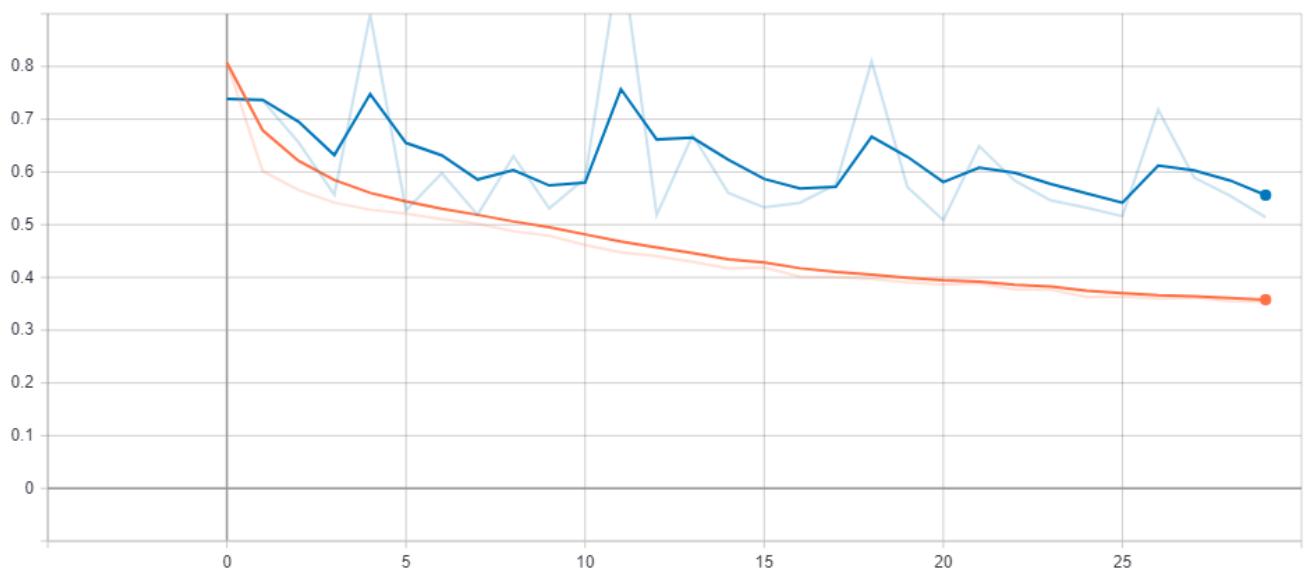
dice_coef

1

dice_coef



loss



3.4 Model Testing

Loading the best model for evaluation

Considering the best model which was trained on 30 epochs as the model in the next 20 epochs experienced the problem of overfitting.

In [0]:

```
from keras.models import load_model
dependencies = {'bce_dice_loss':bce_dice_loss,'dice_coef':dice_coef,}
model_best = load_model('/content/best_model_fcn8.h5',custom_objects=dependencies)
```

Evaluating on validation images

In [0]:

```
evals1= model_best.evaluate(valid_batches,verbose=1)
```

```
117/117 [=====] - 33s 282ms/step
```

In [0]:

```
print('Validation set evaluation score: ')
print('bce_dice loss:',evals1[0])
print('dice_coeff:',evals1[1])
```

```
Validation set evaluation score:
bce_dice loss: 0.5122087106236026
dice_coeff: 0.531455701447896
```

3.5 Defects visualization

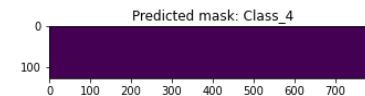
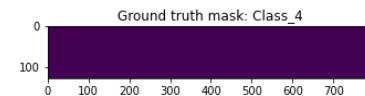
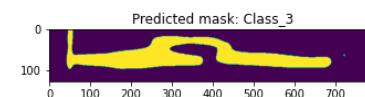
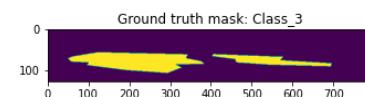
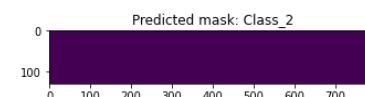
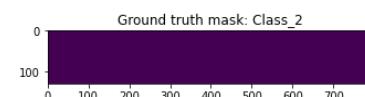
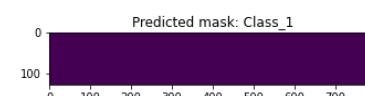
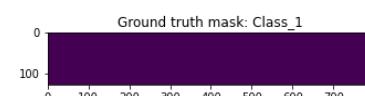
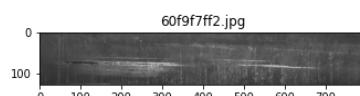
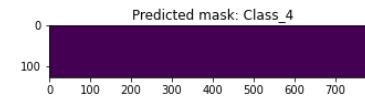
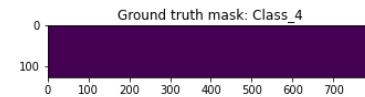
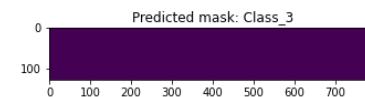
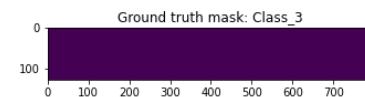
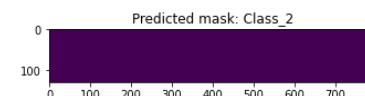
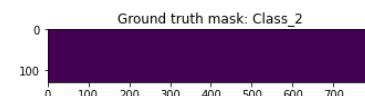
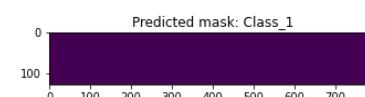
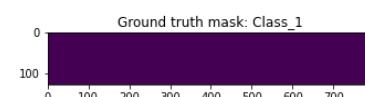
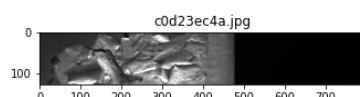
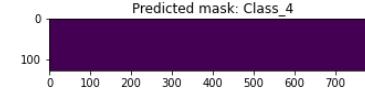
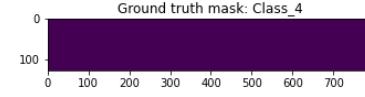
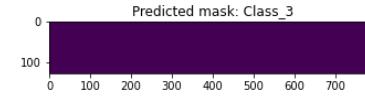
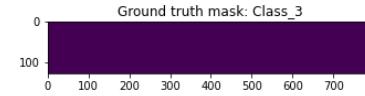
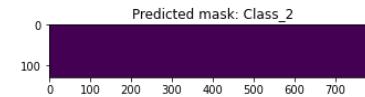
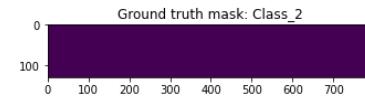
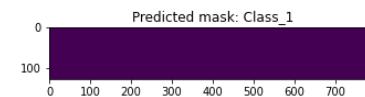
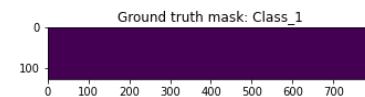
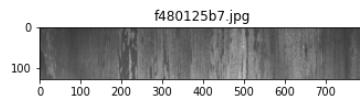
Please refer to the "visualize_defects" function in Utility functions section.

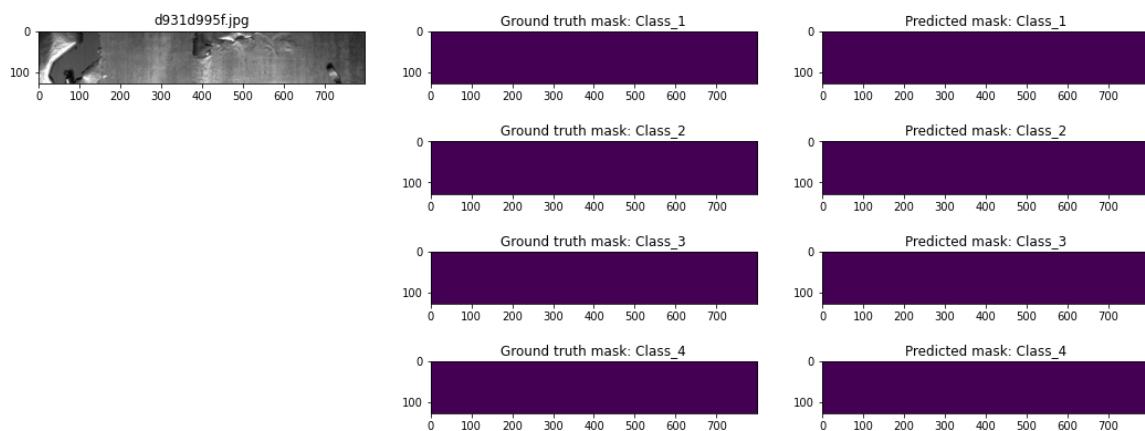
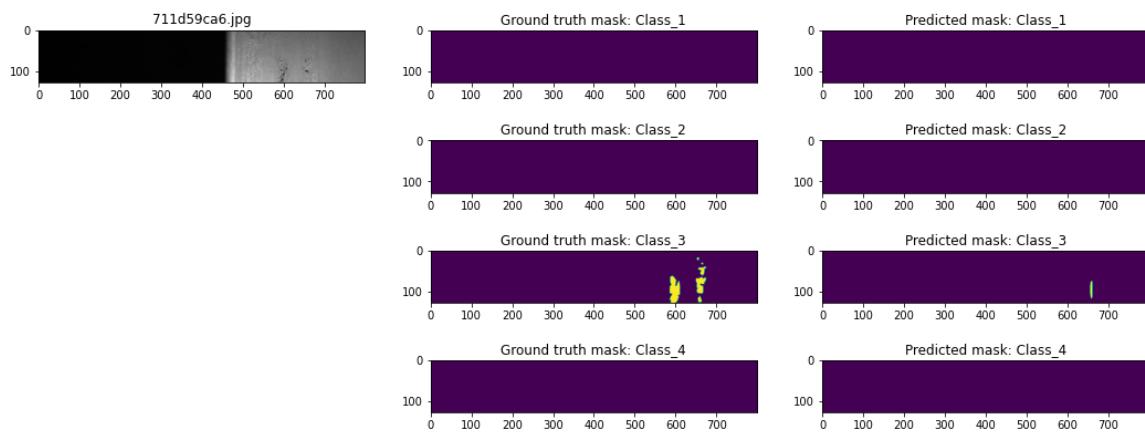
Training set

In [0]:

```
visualize_defects(train_data,model_best)
```

Severstal Steel Defect Detection

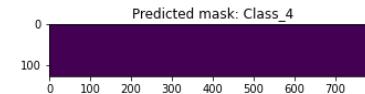
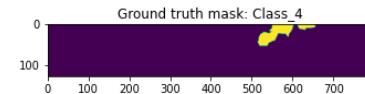
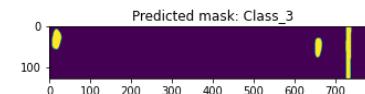
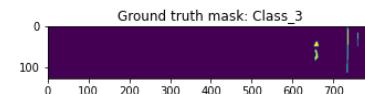
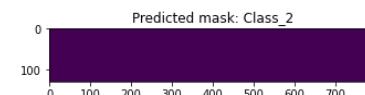
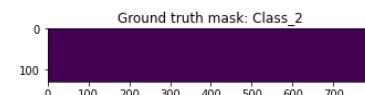
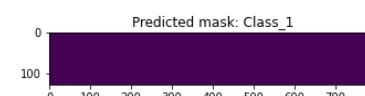
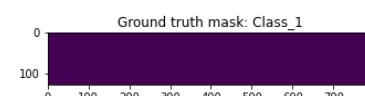
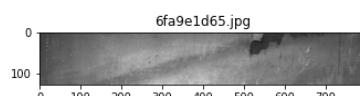
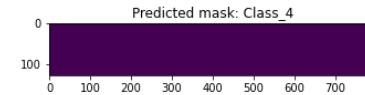
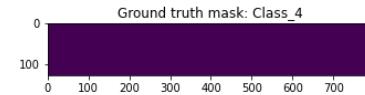
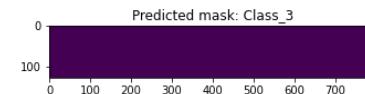
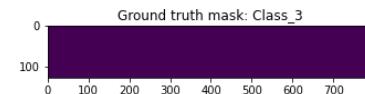
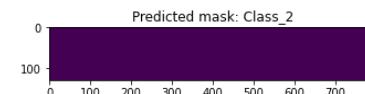
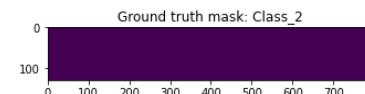
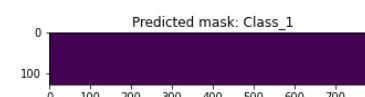
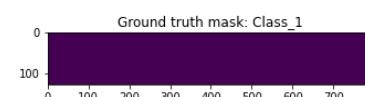
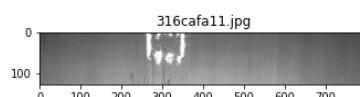
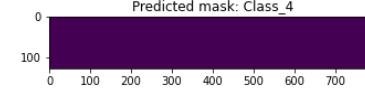
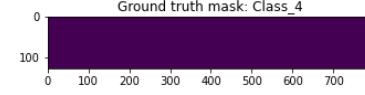
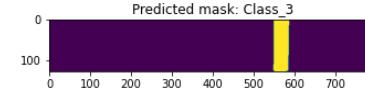
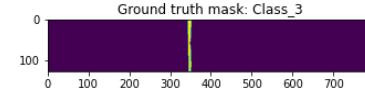
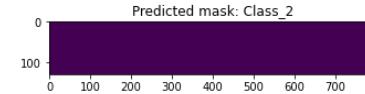
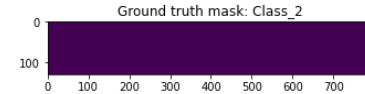
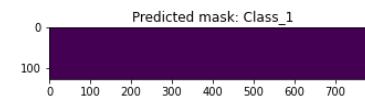
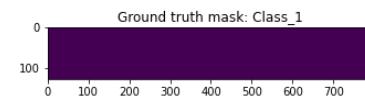
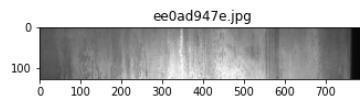


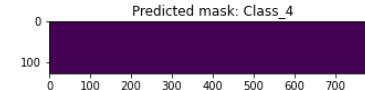
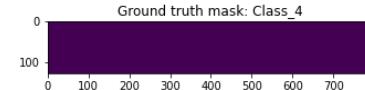
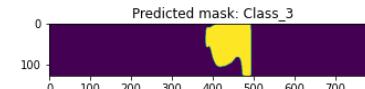
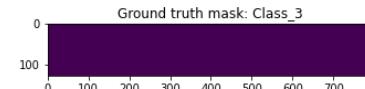
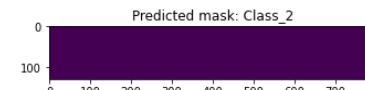
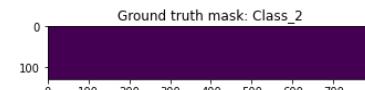
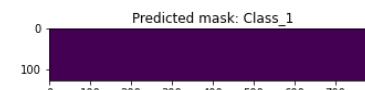
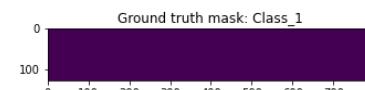
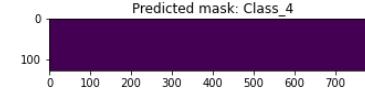
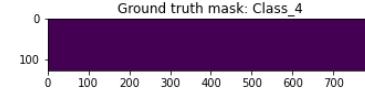
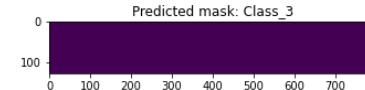
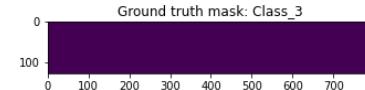
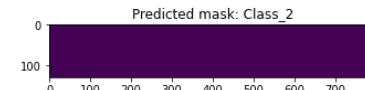
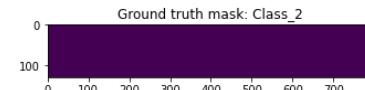
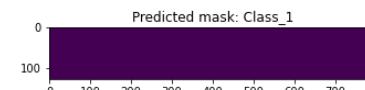
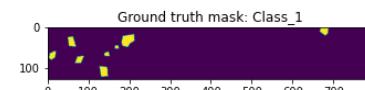
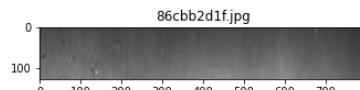


In [0]:

```
visualize_defects(train_data,model_best)
```

Severstal Steel Defect Detection



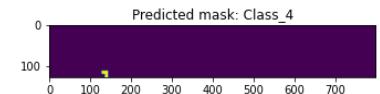
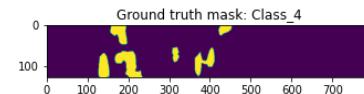
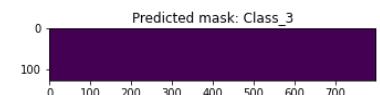
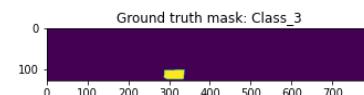
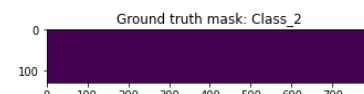
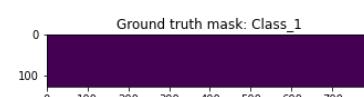
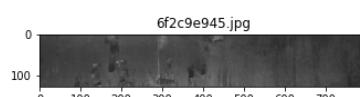
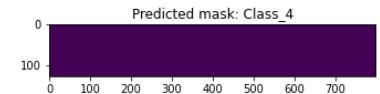
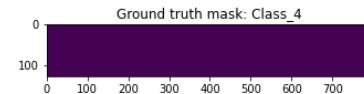
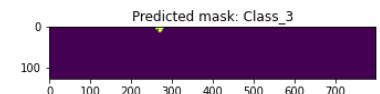
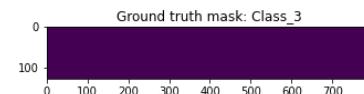
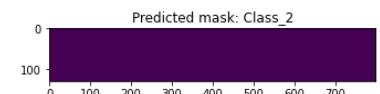
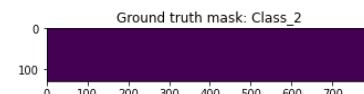
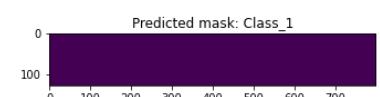
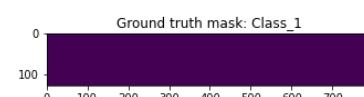
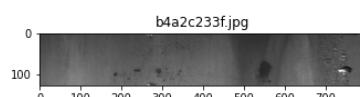
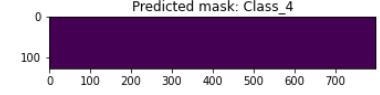
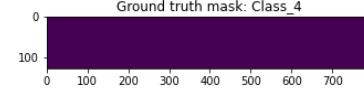
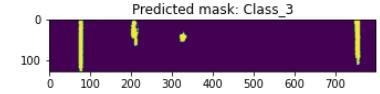
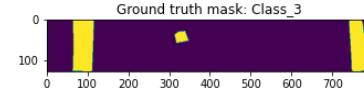
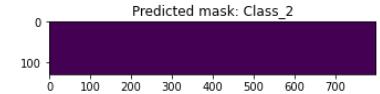
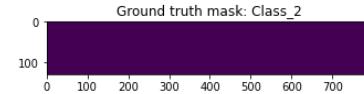
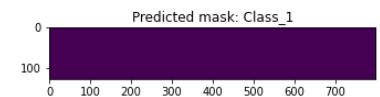
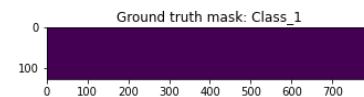
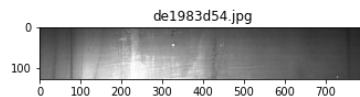


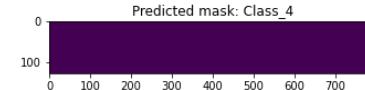
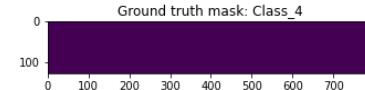
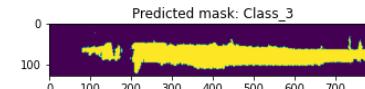
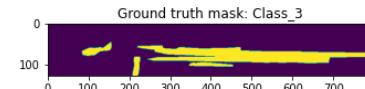
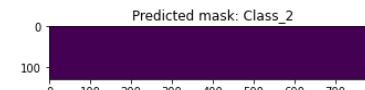
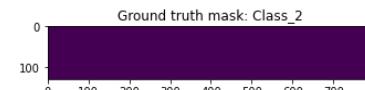
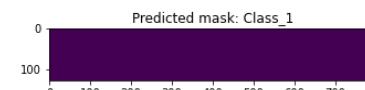
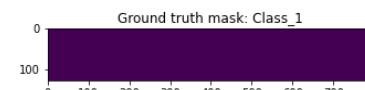
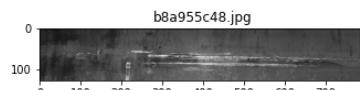
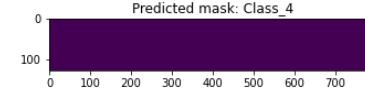
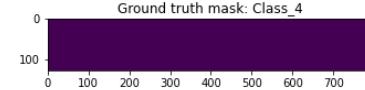
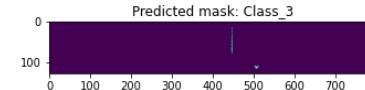
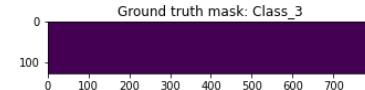
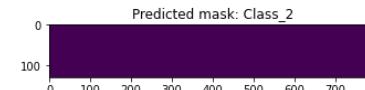
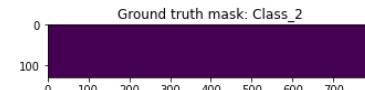
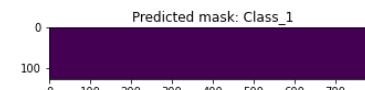
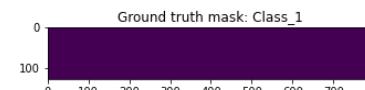
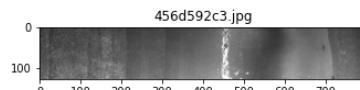
Validation set

In [0]:

```
visualize_defects(cv_data,model_best)
```

Severstal Steel Defect Detection

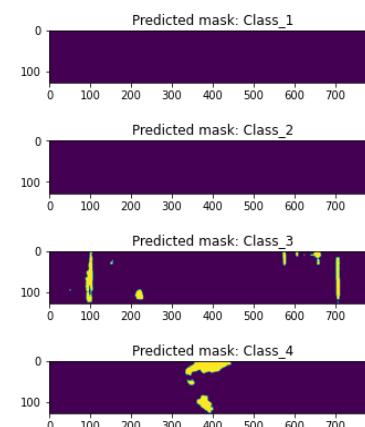
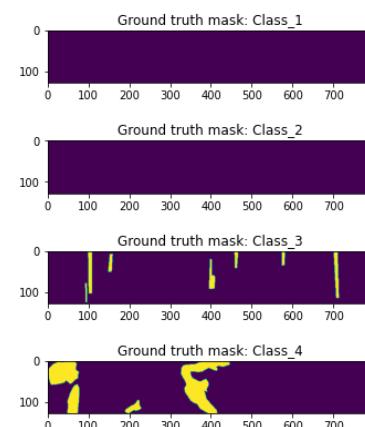
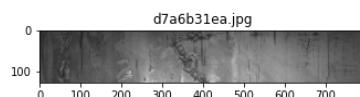
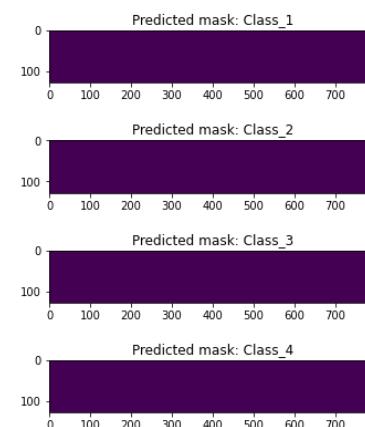
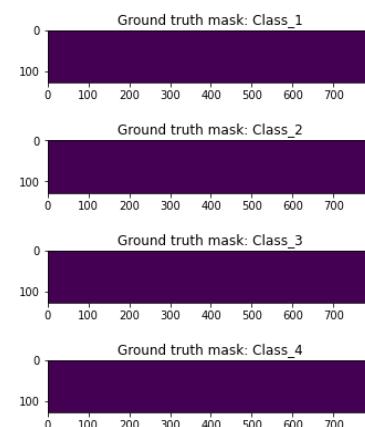
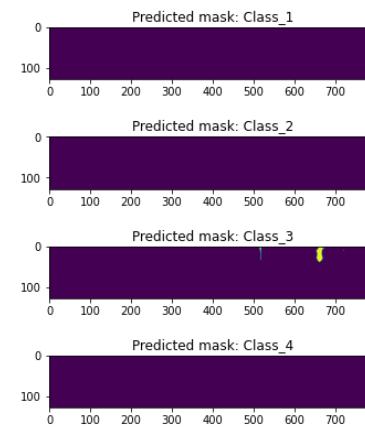
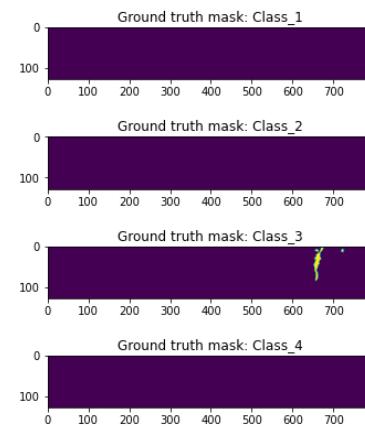
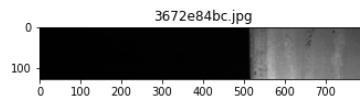


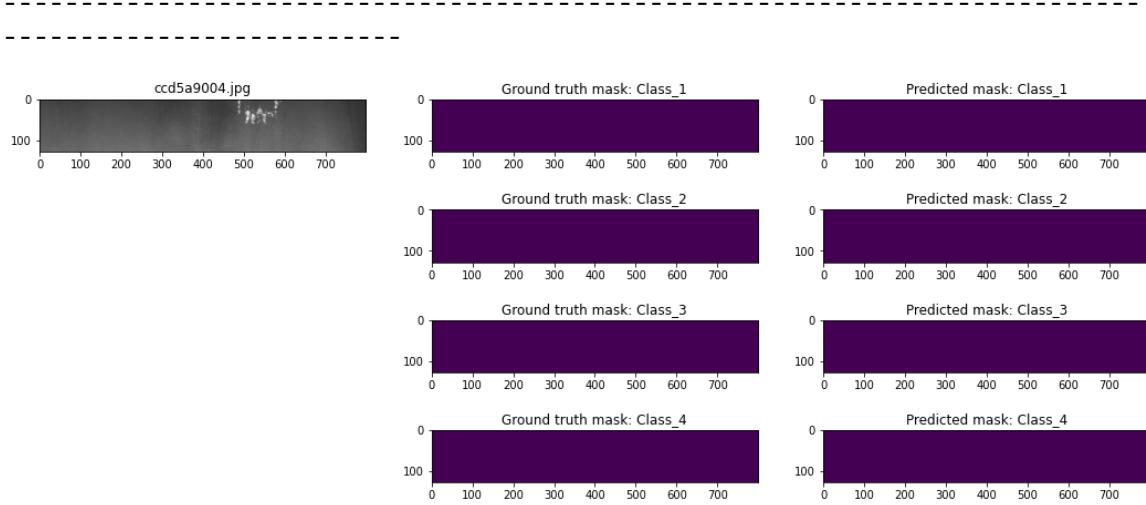
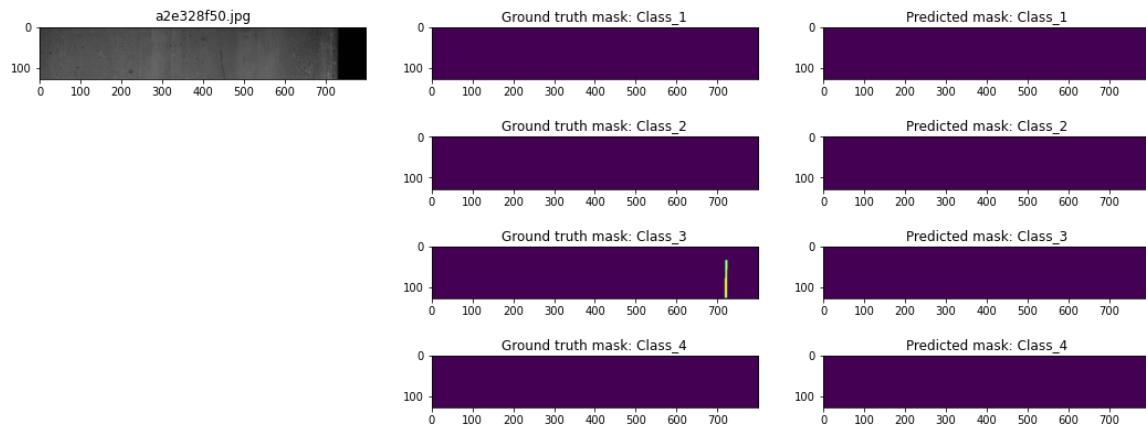


In [0]:

```
visualize_defects(cv_data,model_best)
```

Severstal Steel Defect Detection





3.6 Predicting defects on raw test images

Redefining the FCN8 architecture for original image size of 256x1600

In [0]:

```
#https://keras.io/models/model/#fit_generator
model= fcn_8(img_shape= (256,1600,3), base= 4, dropout= 0.3, n_classes= 4)
model.compile(optimizer=Adam(), loss=bce_dice_loss, metrics=[dice_coef])
model.summary()
```

Model: "model_5"

Layer (type)	Output Shape	Param #	Connected to
input_5 (InputLayer)	(None, 256, 1600, 3)	0	
block1_conv1 (Conv2D)	(None, 256, 1600, 16)	448	input_5[0][0]
batch_normalization_61 (BatchNo)	(None, 256, 1600, 16)	64	block1_conv1[0][0]
block1_conv2 (Conv2D)	(None, 256, 1600, 16)	2320	batch_normalization_61[0][0]
batch_normalization_62 (BatchNo)	(None, 256, 1600, 16)	64	block1_conv2[0][0]
block1_pool (MaxPooling2D)	(None, 128, 800, 16)	0	batch_normalization_62[0][0]
dropout_29 (Dropout)	(None, 128, 800, 16)	0	block1_pool[0][0]
block2_conv1 (Conv2D)	(None, 128, 800, 32)	4640	dropout_29[0][0]
batch_normalization_63 (BatchNo)	(None, 128, 800, 32)	128	block2_conv1[0][0]
block2_conv2 (Conv2D)	(None, 128, 800, 32)	9248	batch_normalization_63[0][0]
batch_normalization_64 (BatchNo)	(None, 128, 800, 32)	128	block2_conv2[0][0]
block2_pool (MaxPooling2D)	(None, 64, 400, 32)	0	batch_normalization_64[0][0]
dropout_30 (Dropout)	(None, 64, 400, 32)	0	block2_pool[0][0]
block3_conv1 (Conv2D)	(None, 64, 400, 64)	18496	dropout_30[0][0]

batch_normalization_65 (BatchNo nv1[0][0]	(None, 64, 400, 64)	256	block3_c
block3_conv2 (Conv2D) malization_65[0][0]	(None, 64, 400, 64)	36928	batch_nor
batch_normalization_66 (BatchNo nv2[0][0]	(None, 64, 400, 64)	256	block3_c
block3_conv3 (Conv2D) malization_66[0][0]	(None, 64, 400, 64)	36928	batch_nor
batch_normalization_67 (BatchNo nv3[0][0]	(None, 64, 400, 64)	256	block3_c
block3_pool (MaxPooling2D) malization_67[0][0]	(None, 32, 200, 64)	0	batch_nor
dropout_31 (Dropout) ol[0][0]	(None, 32, 200, 64)	0	block3_po
block4_conv1 (Conv2D) 1[0][0]	(None, 32, 200, 128)	73856	dropout_3
batch_normalization_68 (BatchNo nv1[0][0]	(None, 32, 200, 128)	512	block4_c
block4_conv2 (Conv2D) malization_68[0][0]	(None, 32, 200, 128)	147584	batch_nor
batch_normalization_69 (BatchNo nv2[0][0]	(None, 32, 200, 128)	512	block4_c
block4_conv3 (Conv2D) malization_69[0][0]	(None, 32, 200, 128)	147584	batch_nor
batch_normalization_70 (BatchNo nv3[0][0]	(None, 32, 200, 128)	512	block4_c
block4_pool (MaxPooling2D) malization_70[0][0]	(None, 16, 100, 128)	0	batch_nor
dropout_32 (Dropout) ol[0][0]	(None, 16, 100, 128)	0	block4_po

block5_conv1 (Conv2D) 2[0][0]	(None, 16, 100, 128) 147584	dropout_3
batch_normalization_71 (BatchNo nv1[0][0]	(None, 16, 100, 128) 512	block5_co
block5_conv2 (Conv2D) normalization_71[0][0]	(None, 16, 100, 128) 147584	batch_nor
batch_normalization_72 (BatchNo nv2[0][0]	(None, 16, 100, 128) 512	block5_co
block5_conv3 (Conv2D) malization_72[0][0]	(None, 16, 100, 128) 147584	batch_nor
batch_normalization_73 (BatchNo nv3[0][0]	(None, 16, 100, 128) 512	block5_co
block5_pool (MaxPooling2D) malization_73[0][0]	(None, 8, 50, 128) 0	batch_nor
dropout_33 (Dropout) ol[0][0]	(None, 8, 50, 128) 0	block5_po
conv6 (Conv2D) 3[0][0]	(None, 8, 50, 1024) 6423552	dropout_3
batch_normalization_74 (BatchNo [0]	(None, 8, 50, 1024) 4096	conv6[0]
dropout_34 (Dropout) malization_74[0][0]	(None, 8, 50, 1024) 0	batch_nor
conv7 (Conv2D) 4[0][0]	(None, 8, 50, 1024) 1049600	dropout_3
batch_normalization_75 (BatchNo [0]	(None, 8, 50, 1024) 4096	conv7[0]
dropout_35 (Dropout) malization_75[0][0]	(None, 8, 50, 1024) 0	batch_nor
conv2d_9 (Conv2D) 2[0][0]	(None, 16, 100, 4) 516	dropout_3
conv2d_transpose_13 (Conv2DTran	(None, 16, 100, 4) 16388	dropout_3

5[0][0]

add_9 (Add) [0][0]	(None, 16, 100, 4)	0	conv2d_9
anspose_13[0][0]			conv2d_tr

conv2d_10 (Conv2D) 1[0][0]	(None, 32, 200, 4)	260	dropout_3
-------------------------------	--------------------	-----	-----------

conv2d_transpose_14 (Conv2DTran) [0]	(None, 32, 200, 4)	68	add_9[0]
---	--------------------	----	----------

add_10 (Add) [0][0]	(None, 32, 200, 4)	0	conv2d_10
anspose_14[0][0]			conv2d_tr

conv2d_transpose_15 (Conv2DTran) [0]	(None, 256, 1600, 4)	1028	add_10[0]
---	----------------------	------	-----------

Total params: 8,424,612
Trainable params: 8,418,404
Non-trainable params: 6,208

In [0]:

```
model.set_weights(model_best.get_weights())
```

Predicting on full 256x1600 raw test images

In [0]:

```
# Predicting on test images
from tqdm import tqdm
import cv2
data_path = '/content/' + 'test_images/'
files = list(os.listdir(data_path))
rle_lst = [] #list to store defect in run length encoding format
img_classId= [] #list to store Image ID + classId

for f in tqdm(files):
    X = np.empty((1,256,1600,3),dtype=np.float32)
    img = cv2.imread(data_path + f)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    X[0,] = img
    mask = model.predict(X)
    rle_m = np.empty((256,1600),dtype=np.uint8)
    for i in range(4):
        rle_m = mask[0,:,:,:,i].round().astype(int)
        rle = mask2rle(rle_m)
        rle_lst.append(rle)
        img_classId.append(f+'_'+str(i+1))
```

100%|██████████| 5506/5506 [05:48<00:00, 15.82it/s]

In [0]:

```
output = {'ImageId_ClassId':img_classId, 'EncodedPixels' : rle_lst}
import pandas as pd
output_df = pd.DataFrame(output)
output_df.to_csv('submission_fcn8_256x1600.csv', index=False)
```

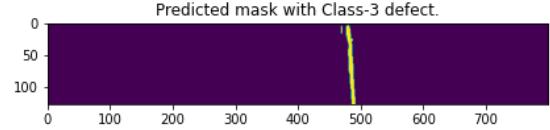
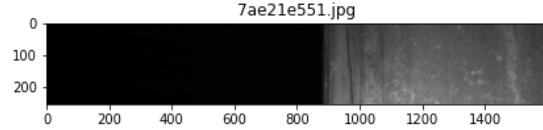
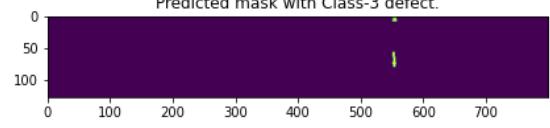
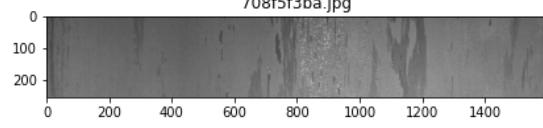
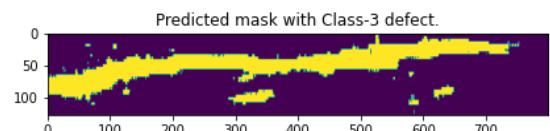
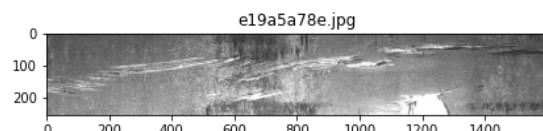
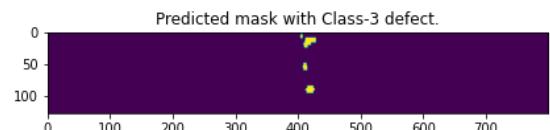
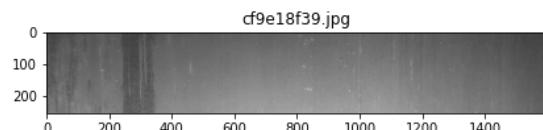
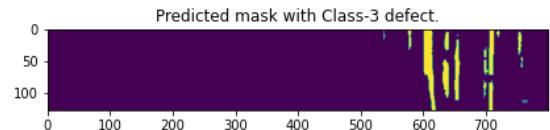
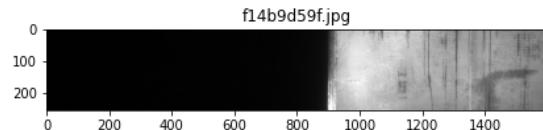
With this submission, I got a private dice coefficient score of 0.82818 & a public score of 0.84935.

3.7 Visualizing defects of raw test images(256x1600)

Please refer to the "visualize_defects_test" function in Utility functions section.

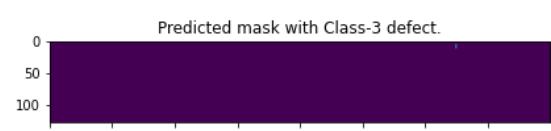
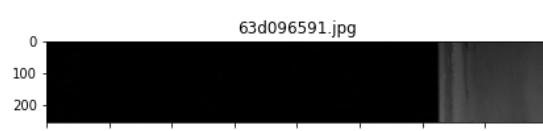
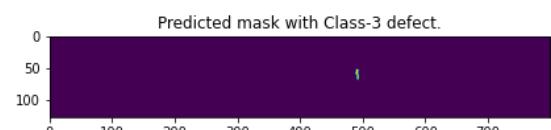
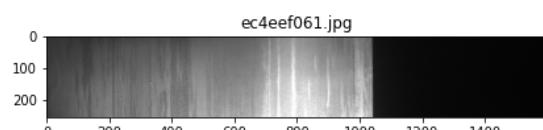
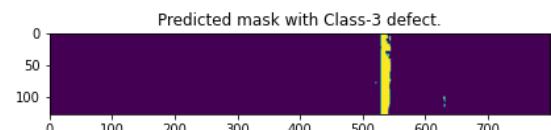
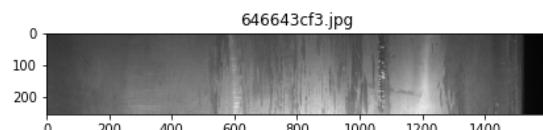
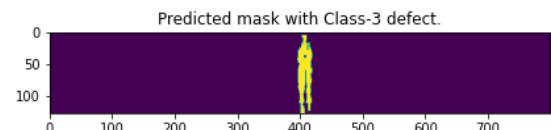
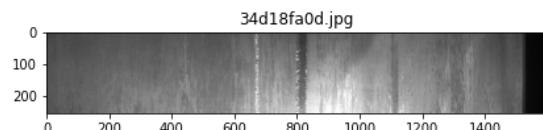
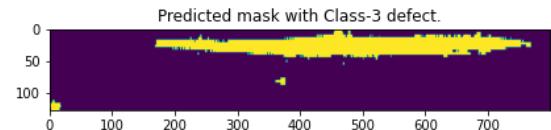
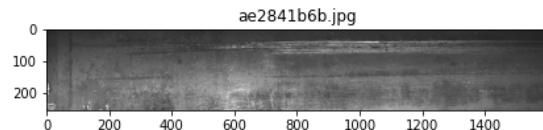
In [0]:

visualize_defects_test(output_df,5)



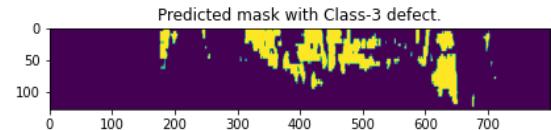
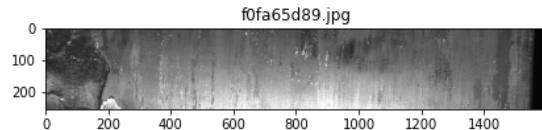
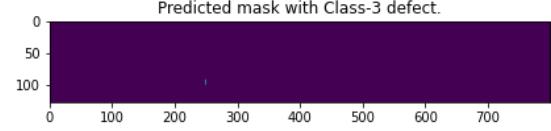
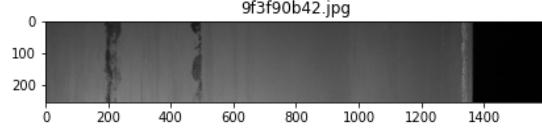
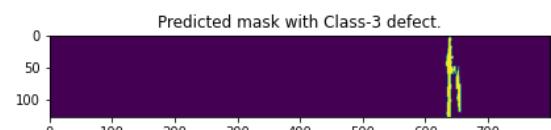
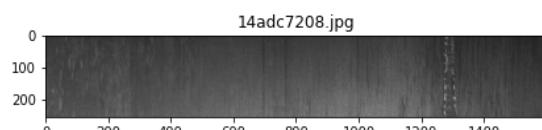
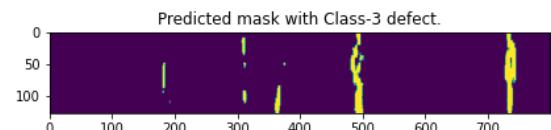
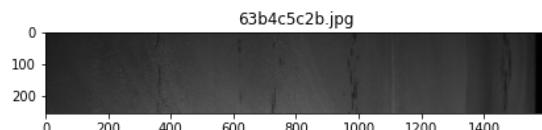
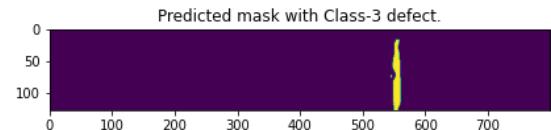
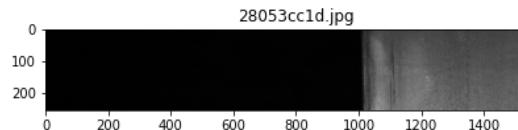
In [0]:

visualize_defects_test(output_df,5)



In [0]:

visualize_defects_test(output_df,5)



Results Summary

In [2]:

```
#Ref: http://zetcode.com/python/prettytable/
from prettytable import PrettyTable

x = PrettyTable()
x.field_names = ["Architecture", "Test Dice_coeff-Private", "Test Dice_coeff-Public"]
x.add_row(["UNET", 0.81171, 0.80041])
x.add_row(["SEGNET", 0.83437, 0.84741])
x.add_row(["FCN-8", 0.82818, 0.84935])
print(x)
```

Architecture	Test Dice_coeff-Private	Test Dice_coeff-Public
UNET	0.81171	0.80041
SEGNET	0.83437	0.84741
FCN-8	0.82818	0.84935

Conclusion

- Countered the issue of class imbalance by assigning class weights (calculated using SKLearn) during the training stage
- Model training for all architectures was done on resized 128x800 images considering efficiency and computational power
- Model prediction on full sized raw test images (256x1600) gave better scores compared to prediction on half images (128x800)
- Highest score of 0.83437 on private leaderboard & 0.84935 on public leaderboard was obtained with SEGNET & FCN-8 architecture respectively. These scores were better compared to the basic U-NET architecture which was the first cut aproach.

Steps followed to solve this case study(in brief):

1. The first basic step was to carry out EDA on the defect data. This included analysing images in train & test folder to get a gist of defective & non-defective images, knowing the basic properties of the given images, analysing response label, determining class weights, checking number of labels tagged to each image & observing images with defects belonging to each class.
2. EDA was then followed by Data preparation stage where a master csv file was prepared in which each row represented a image with all possible defects that image possessed.
3. The final data was split into train & CV data in the ratio 85:15 and basic utility functions were defined.
4. Next was the data generator phase where train & validation data was generated in order to feed the keras models with augmented images (in case of train) and ground truth masks.
5. Once the flow of input was set, it was time to implement various segmentation architectures, This included UNET, SEGNET & FCN-8.
6. For each architecture, the performance was checked on the validation image data and few predicted masks were observed.
7. Predictions were made on full sized (i.e 256x1600) raw test images and the predicted masks were observed.
8. Predictions on test images were uploaded on kaggle to get the dice coefficient score