In this Notebook the Phase-1 Evaluation of ML-4 Porject has been executed including EDA and Visualizing images

```
import os
from pathlib import Path
from tqdm import tqdm
import json
from tensorflow.keras.optimizers import Adam

import numpy as np # linear algebra
import pandas as pd

import math

import cv2
import json
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams["font.size"] = 10
plt.rcParams['figure.figsize'] = (15, 5)
import seaborn as sns
from PIL import Image

from collections import Counter
from collections import defaultdict

from keras.layers import *
from keras.models import Model
from keras.optimizers import *
from keras import backend as K
from keras.callbacks import ModelCheckpoint
```

```
DIRin1 = "D:/FSM Dataset/Dataset_2/"
print("DIRin1 =", os.listdir(DIRin1))
DIRtrain = os.path.join(DIRin1,"train_images")
DIRtest = os.path.join(DIRin1,"test_images")


print("Num of Train img\t:",len(os.listdir(DIRtrain)))
print("Num of Test img\t\t:",len(os.listdir(DIRtest)))
```

```
DIRin1 = ['sample_submission.csv', 'test_images', 'train.csv', 'train_images']
Num of Train img : 12568
Num of Test img       : 5506
```

```
train_df = pd.read_csv("train.csv")
train_df.head(10)
```

```
         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...
5  0025bde0c.jpg        3  8458 14 8707 35 8963 48 9219 71 9475 88 9731 8...
6  0025bde0c.jpg        4  315139 8 315395 15 315651 16 315906 17 316162 ...
7  002af848d.jpg        4  290800 6 291055 13 291311 15 291566 18 291822 ...
8  002fc4e19.jpg        1  146021 3 146275 10 146529 40 146783 46 147038 ...
9  002fc4e19.jpg        2  145658 7 145901 20 146144 33 146386 47 146629 ...
```

```
train_df.tail()
```

```
            ImageId  ClassId  \
7090  ffcf72ecf.jpg        3   
7091  fff02e9c5.jpg        3   
7092  fffe98443.jpg        3   
7093  ffff4eaa8.jpg        3   
7094  ffffd67df.jpg        3   

                                          EncodedPixels  
7090  121911 34 122167 101 122422 169 122678 203 122...  
7091  207523 3 207777 9 208030 15 208283 22 208537 2...  
7092  105929 5 106177 14 106424 24 106672 33 106923 ...  
7093  16899 7 17155 20 17411 34 17667 47 17923 60 18...  
7094  30931 43 31103 127 31275 211 31489 253 31745 2...  
```

```
train_df.shape
```

```
(7095, 3)
```

```
train_df.isnull().sum()
```

```
ImageId          0
ClassId          0
EncodedPixels    0
dtype: int64
```

Since there is no NULL/NAN/NA values in the given data set hence no data cleaning is required

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7095 entries, 0 to 7094
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   ImageId        7095 non-null   object
 1   ClassId        7095 non-null   int64 
 2   EncodedPixels  7095 non-null   object
dtypes: int64(1), object(2)
memory usage: 166.4+ KB
```

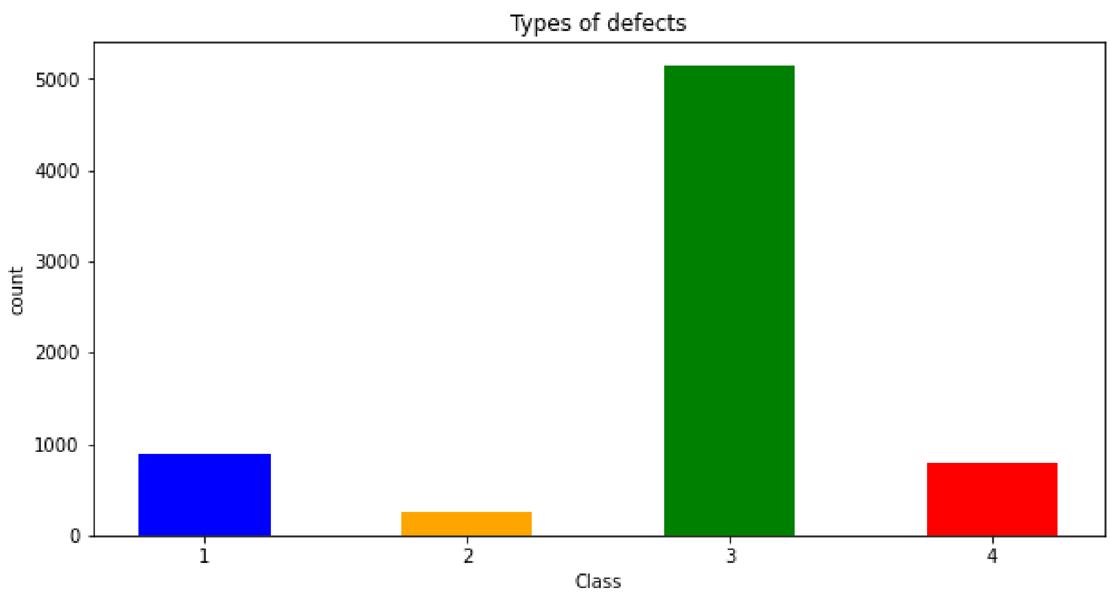
So, we can conclude that ImageId and EncodedPixel are of string/object type whereas ClassId is of integer type

Let's analyse number of labels for each defect type

```
defect1 = train_df[train_df['ClassId']==1].EncodedPixels.count()
defect2 = train_df[train_df['ClassId']==2].EncodedPixels.count()
defect3 = train_df[train_df['ClassId']==3].EncodedPixels.count()
defect4 = train_df[train_df['ClassId']==4].EncodedPixels.count()

print('There are {} defect1 images'.format(defect1))
print('There are {} defect2 images'.format(defect2))
print('There are {} defect3 images'.format(defect3))
print('There are {} defect4 images'.format(defect4))
```

```
There are 897 defect1 images
There are 247 defect2 images
There are 5150 defect3 images
There are 801 defect4 images
```

```
#Plotting bar graph based on the count of each labels
labels = '1','2','3','4'
sizes = [defect1,defect2,defect3,defect4]

fig = plt.figure(figsize=(10,5))

#creating the bar plot
plt.bar(labels,sizes,color=['blue','orange','green','red'],width = 
0.5)
plt.xlabel('Class')
plt.ylabel('count')
plt.title('Types of defects')
plt.show()
```

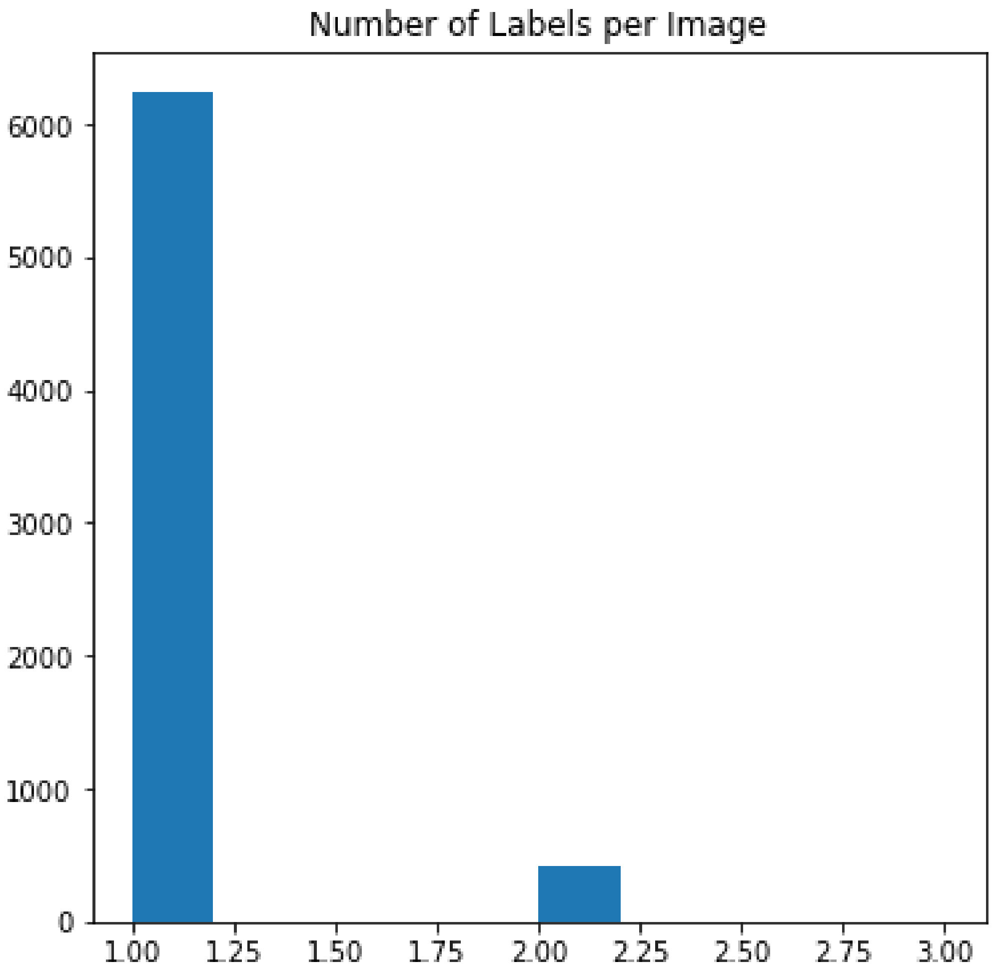


Here we can observe that defect type 3 is more dominant compared to any other defects and defect type 2 is least occuring defects. Hence there is a class imbalance.

Now let us check whether the single image has more than one defect simultaneously

```
labels_per_image = train_df.groupby('ImageId')
['EncodedPixels'].count()
fig,ax = plt.subplots(figsize=(6,6))
ax.hist(labels_per_image)
ax.set_title('Number of Labels per Image')
```

```
Text(0.5, 1.0, 'Number of Labels per Image')
```




```
print('There are {} images with 1 label'.format(labels_per_image[labels_per_image==1].count()))
print('There are {} images with 2 label'.format(labels_per_image[labels_per_image==2].count()))
print('There are {} images with 3 label'.format(labels_per_image[labels_per_image==3].count()))
print('There are {} images with 4 label'.format(labels_per_image[labels_per_image==3].count()))
```

```
There are 6239 images with 1 label
There are 425 images with 2 label
There are 2 images with 3 label
There are 2 images with 4 label
```

Conclusion:

1. Most of images with defects contain the defects of only one type
2. In rare cases an image contains the defects of two different types simulataneously

It would be quiet convenient to Transform class to column

```
try:
    train_df['fname'], train_df['cls'] =
zip(*train_df['ImageId_ClassId'].str.split('_'))
except:
    train_df['fname'], train_df['cls'] = train_df['ImageId'],
train_df['ClassId']
train_df['cls'] = train_df['cls'].astype(int)
train_df =
train_df.pivot(index='fname',columns='cls',values='EncodedPixels')
train_df['defects'] = train_df.count(axis=1)
#train_df.reset_index()
train_df.head()
```

```
cls                                                             1    2  \
fname

0002cc93b.jpg  29102 12 29346 24 29602 24 29858 24 30114 24 3...  NaN

0007a71bf.jpg                                                 NaN  NaN

000a4bcdd.jpg  37607 3 37858 8 38108 14 38359 20 38610 25 388...  NaN

000f6bf48.jpg                                                 NaN  NaN

0014fce06.jpg                                                 NaN  NaN


cls                                                             3  \
fname
0002cc93b.jpg                                                 NaN
0007a71bf.jpg  18661 28 18863 82 19091 110 19347 110 19603 11...
000a4bcdd.jpg                                                 NaN
000f6bf48.jpg                                                 NaN
0014fce06.jpg  229501 11 229741 33 229981 55 230221 77 230468...

cls                                                             4
defects
fname

0002cc93b.jpg                                                 NaN
1
0007a71bf.jpg                                                 NaN
1
000a4bcdd.jpg                                                 NaN
1
000f6bf48.jpg  131973 1 132228 4 132483 6 132738 8 132993 11 ...
1
```

```
0014fce06.jpg                                               NaN
1
```

```python
# Presence of defects in each images
no_defects_num = np.sum(train_df['defects'] == 0)
defects_num = len(train_df) - no_defects_num
print("no defect imgs \t:", no_defects_num)
print("defects imgs \t:", defects_num)
```

```
no defect imgs   : 0
defects imgs     : 6666
```

```python
# Number of defects for each class
class_defects = len(train_df) - train_df.isnull().sum()
class_defects[:4]
```

```
cls
1     897
2     247
3    5150
4     801
dtype: int64
```

```python
# check images size
train_size = defaultdict(int)
test_size = defaultdict(int)

for fPath in tqdm(Path(DIRtrain).iterdir(),
total=len(os.listdir(DIRtrain))):
    img = Image.open(fPath)
    train_size[img.size] += 1
for fPath in tqdm(Path(DIRtest).iterdir(),
total=len(os.listdir(DIRtest))):
    img = Image.open(fPath)
    test_size[img.size] += 1

print("train_img_size :",train_size)
print("test_img_size  :",test_size)
```

```
100%|██████████| 12568/12568 [00:04<00:00, 2628.62it/s]
100%|██████████| 5506/5506 [00:02<00:00, 2737.74it/s]
```

```
train_img_size : defaultdict(<class 'int'>, {(1600, 256): 12568})
test_img_size  : defaultdict(<class 'int'>, {(1600, 256): 5506})
```

Therefore, And all the images is of size 256X1600

```python
palet = [(250, 230, 20), (30, 200, 241), (200, 30, 250), (250,60,20)]

fig, ax = plt.subplots(1, 4, figsize=(6, 2))
```

```python
for i in range(4):
    ax[i].axis('off')
    ax[i].imshow(np.ones((10, 40, 3), dtype=np.uint8) * palet[i])
    ax[i].set_title(f"class{i+1}")

plt.show()
```

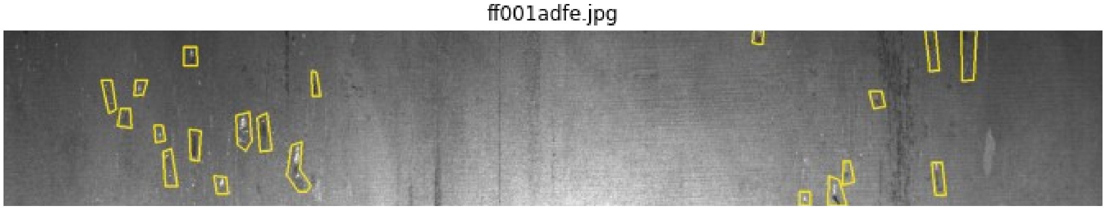
For simplicity Class 1 defect is identifies by Yellow Colour, class 2 as Blue, class as purple and class 4 as red

```python
def mask2rgba(mask):
    rgba_list = []
    for idx in range(4):    # idx: class id
        rgba = cv2.cvtColor(mask[:, :, idx], cv2.COLOR_GRAY2RGBA)
        rgba[:, :, :3] = rgba[:, :, :3] /255 * palet[idx]
        rgba_list.append(rgba)
    return rgba_list

def make_mask(row_id):
    fname = train_df.iloc[row_id].name

    labels = train_df.iloc[row_id][:4]
    masks = np.zeros((256, 1600, 4), dtype=np.uint8)    # 4:class 1～4 (ch:0～3)

    for idx, label in enumerate(labels.values):
        if label is not np.nan:
            label = label.split(" ")
            positions = map(int, label[0::2])
            length = map(int, label[1::2])
            mask = np.zeros(256 * 1600, dtype=np.uint8)
            for pos, le in zip(positions, length):
                mask[pos:(pos + le)] = 255
            masks[:, :, idx] = mask.reshape(256, 1600, order='F')
    return fname, masks

def show_mask_image(row_id, contour = True):
    name, mask = make_mask(row_id)
    img = cv2.imread(os.path.join(DIRtrain, name))

    if contour:
        for ch in range(4):
            contours, _ = cv2.findContours(mask[:, :, ch],
                                    cv2.RETR_LIST, cv2.CHAIN_APPROX_NONE)
            for i in range(0, len(contours)):
                cv2.polylines(img, contours[i], True, palet[ch], 2)
```

```
    else:
        for ch in range(4):
            img[mask[:,:,ch]==255] = palet[ch]

    fig, ax = plt.subplots(figsize=(12,12))
    ax.set_title(name)
    ax.imshow(img)
    ax.axis('off')
    plt.show()

# classify defects
idx_class_1 = list(filter(lambda r:not pd.isna(train_df.iloc[r,0]),
range(len(train_df))))
idx_class_2 = list(filter(lambda r:not pd.isna(train_df.iloc[r,1]),
range(len(train_df))))
idx_class_3 = list(filter(lambda r:not pd.isna(train_df.iloc[r,2]),
range(len(train_df))))
idx_class_4 = list(filter(lambda r:not pd.isna(train_df.iloc[r,3]),
range(len(train_df))))
# Number of defects class
idx_no_defect = list(filter(lambda r:train_df.iloc[r,4] == 0,
range(len(train_df))))
idx_1_defect = list(filter(lambda r:train_df.iloc[r,4] == 1,
range(len(train_df))))
idx_class_multi = list(filter(lambda r:train_df.iloc[r,4] >= 2,
range(len(train_df))))

# class_1 defect sample (Yellow)
for idx in idx_class_1[-3:]:
    show_mask_image(idx, contour=True)
```

fed07ccf3.jpg

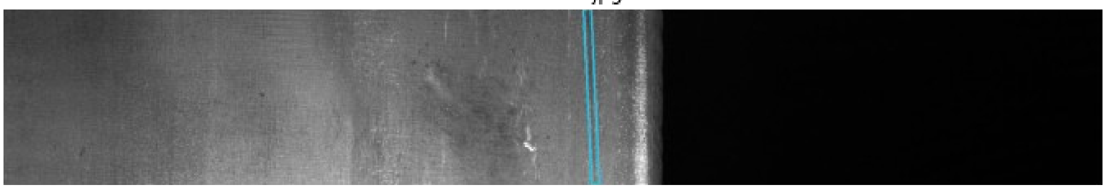
ff001adfe.jpg



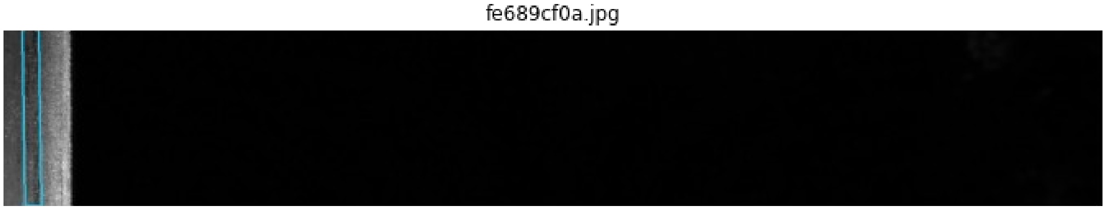
ff6e35e0a.jpg

```
# class_2 defect sample (lightblue)
for idx in idx_class_2[-3:]:
    show_mask_image(idx, contour=True)
```

fcd374576.jpg



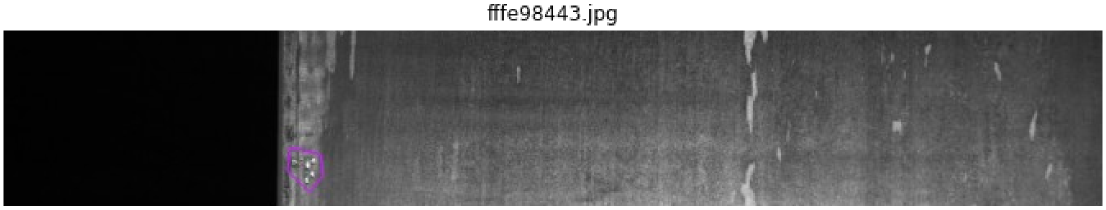
fe689cf0a.jpg



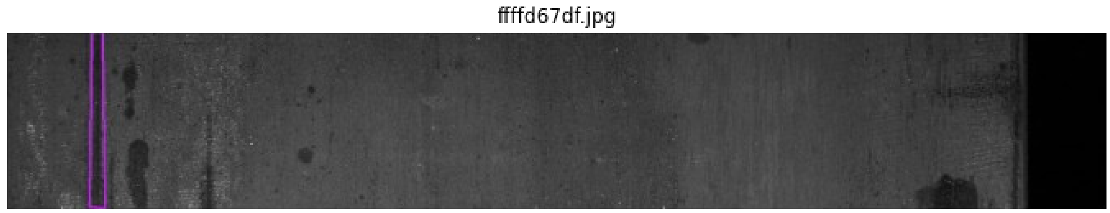
ff6e35e0a.jpg

```
# class_3 defect sample (purple)
for idx in idx_class_3[-3:]:
    show_mask_image(idx, contour=True)
```

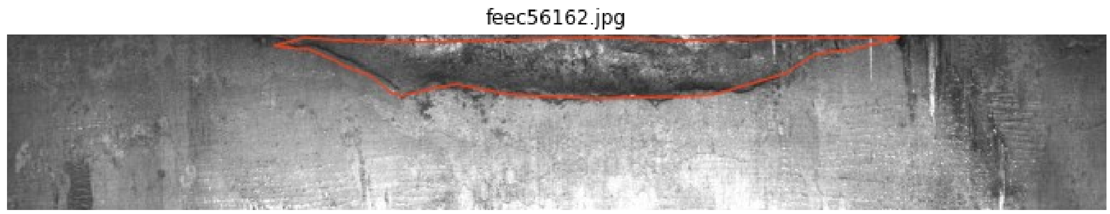
fffe98443.jpg



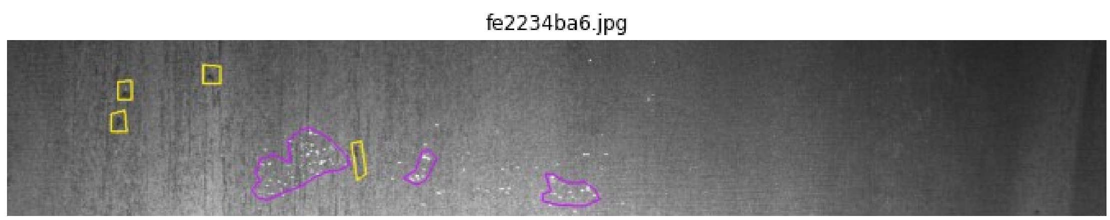
ffff4eaa8.jpg

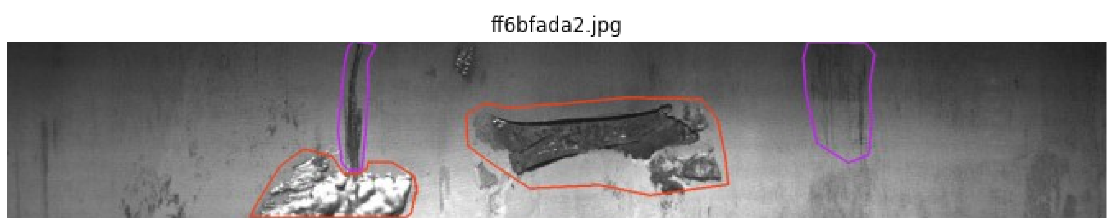



```
# class_4 defect sample (red)
for idx in idx_class_4[-3:]:
    show_mask_image(idx, contour=True)
```




```
# contain multi class defects
for idx in idx_class_multi[-3:]:
    show_mask_image(idx, contour=True)
```





ff6e35e0a.jpg

```
input_shape = (256, 1600, 1)
inputs = Input(input_shape)

c1 = Conv2D(8, (3, 3), activation='relu', padding='same') (inputs)
c1 = Conv2D(8, (3, 3), activation='relu', padding='same') (c1)
p1 = MaxPooling2D((2, 2)) (c1)

c2 = Conv2D(16, (3, 3), activation='relu', padding='same') (p1)
c2 = Conv2D(16, (3, 3), activation='relu', padding='same') (c2)
p2 = MaxPooling2D((2, 2)) (c2)

c3 = Conv2D(32, (3, 3), activation='relu', padding='same') (p2)
c3 = Conv2D(32, (3, 3), activation='relu', padding='same') (c3)
p3 = MaxPooling2D((2, 2)) (c3)

c4 = Conv2D(64, (3, 3), activation='relu', padding='same') (p3)
c4 = Conv2D(64, (3, 3), activation='relu', padding='same') (c4)
p4 = MaxPooling2D(pool_size=(2, 2)) (c4)

c5 = Conv2D(64, (3, 3), activation='relu', padding='same') (p4)
c5 = Conv2D(64, (3, 3), activation='relu', padding='same') (c5)
p5 = MaxPooling2D(pool_size=(2, 2)) (c5)

c55 = Conv2D(128, (3, 3), activation='relu', padding='same') (p5)
c55 = Conv2D(128, (3, 3), activation='relu', padding='same') (c55)

u6 = Conv2DTranspose(64, (2, 2), strides=(2, 2), padding='same') (c55)
u6 = concatenate([u6, c5])
c6 = Conv2D(64, (3, 3), activation='relu', padding='same') (u6)
c6 = Conv2D(64, (3, 3), activation='relu', padding='same') (c6)

u71 = Conv2DTranspose(32, (2, 2), strides=(2, 2), padding='same') (c6)
u71 = concatenate([u71, c4])
c71 = Conv2D(32, (3, 3), activation='relu', padding='same') (u71)
c61 = Conv2D(32, (3, 3), activation='relu', padding='same') (c71)

u7 = Conv2DTranspose(32, (2, 2), strides=(2, 2), padding='same') (c61)
u7 = concatenate([u7, c3])
c7 = Conv2D(32, (3, 3), activation='relu', padding='same') (u7)
c7 = Conv2D(32, (3, 3), activation='relu', padding='same') (c7)

u8 = Conv2DTranspose(16, (2, 2), strides=(2, 2), padding='same') (c7)
```

```
u8 = concatenate([u8, c2])
c8 = Conv2D(16, (3, 3), activation='relu', padding='same') (u8)
c8 = Conv2D(16, (3, 3), activation='relu', padding='same') (c8)

u9 = Conv2DTranspose(8, (2, 2), strides=(2, 2), padding='same') (c8)
u9 = concatenate([u9, c1], axis=3)
c9 = Conv2D(8, (3, 3), activation='relu', padding='same') (u9)
c9 = Conv2D(8, (3, 3), activation='relu', padding='same') (c9)

outputs = Conv2D(4, (1, 1), activation='sigmoid') (c9)

model = Model(inputs=[inputs], outputs=[outputs])
```

```
model.summary()
```

```
Model: "model_2"
______________________________________________________________________
____________________________
Layer (type)                    Output Shape         Param #
Connected to
======================================================================
============================
input_3 (InputLayer)            [(None, 256, 1600, 1 0


______________________________________________________________________
____________________________
conv2d_46 (Conv2D)              (None, 256, 1600, 8) 80
input_3[0][0]
______________________________________________________________________
____________________________
conv2d_47 (Conv2D)              (None, 256, 1600, 8) 584
conv2d_46[0][0]
______________________________________________________________________
____________________________
max_pooling2d_10 (MaxPooling2D) (None, 128, 800, 8)  0
conv2d_47[0][0]
______________________________________________________________________
____________________________
conv2d_48 (Conv2D)              (None, 128, 800, 16) 1168
max_pooling2d_10[0][0]
______________________________________________________________________
____________________________
conv2d_49 (Conv2D)              (None, 128, 800, 16) 2320
conv2d_48[0][0]
______________________________________________________________________
____________________________
max_pooling2d_11 (MaxPooling2D) (None, 64, 400, 16)  0
conv2d_49[0][0]
```

```
conv2d_50 (Conv2D)              (None, 64, 400, 32)  4640
max_pooling2d_11[0][0]

conv2d_51 (Conv2D)              (None, 64, 400, 32)  9248
conv2d_50[0][0]

max_pooling2d_12 (MaxPooling2D) (None, 32, 200, 32)  0
conv2d_51[0][0]

conv2d_52 (Conv2D)              (None, 32, 200, 64)  18496
max_pooling2d_12[0][0]

conv2d_53 (Conv2D)              (None, 32, 200, 64)  36928
conv2d_52[0][0]

max_pooling2d_13 (MaxPooling2D) (None, 16, 100, 64)  0
conv2d_53[0][0]

conv2d_54 (Conv2D)              (None, 16, 100, 64)  36928
max_pooling2d_13[0][0]

conv2d_55 (Conv2D)              (None, 16, 100, 64)  36928
conv2d_54[0][0]

max_pooling2d_14 (MaxPooling2D) (None, 8, 50, 64)    0
conv2d_55[0][0]

conv2d_56 (Conv2D)              (None, 8, 50, 128)   73856
max_pooling2d_14[0][0]

conv2d_57 (Conv2D)              (None, 8, 50, 128)   147584
conv2d_56[0][0]

conv2d_transpose_10 (Conv2DTran (None, 16, 100, 64)  32832
conv2d_57[0][0]
```

```
concatenate_10 (Concatenate)    (None, 16, 100, 128) 0
conv2d_transpose_10[0][0]

conv2d_55[0][0]
__________________________________________________________________________________________________
conv2d_58 (Conv2D)              (None, 16, 100, 64)  73792
concatenate_10[0][0]
__________________________________________________________________________________________________
conv2d_59 (Conv2D)              (None, 16, 100, 64)  36928
conv2d_58[0][0]
__________________________________________________________________________________________________
conv2d_transpose_11 (Conv2DTran (None, 32, 200, 32)  8224
conv2d_59[0][0]
__________________________________________________________________________________________________
concatenate_11 (Concatenate)    (None, 32, 200, 96)  0
conv2d_transpose_11[0][0]

conv2d_53[0][0]
__________________________________________________________________________________________________
conv2d_60 (Conv2D)              (None, 32, 200, 32)  27680
concatenate_11[0][0]
__________________________________________________________________________________________________
conv2d_61 (Conv2D)              (None, 32, 200, 32)  9248
conv2d_60[0][0]
__________________________________________________________________________________________________
conv2d_transpose_12 (Conv2DTran (None, 64, 400, 32)  4128
conv2d_61[0][0]
__________________________________________________________________________________________________
concatenate_12 (Concatenate)    (None, 64, 400, 64)  0
conv2d_transpose_12[0][0]

conv2d_51[0][0]
__________________________________________________________________________________________________
conv2d_62 (Conv2D)              (None, 64, 400, 32)  18464
concatenate_12[0][0]
__________________________________________________________________________________________________
conv2d_63 (Conv2D)              (None, 64, 400, 32)  9248
conv2d_62[0][0]
__________________________________________________________________________________________________
```

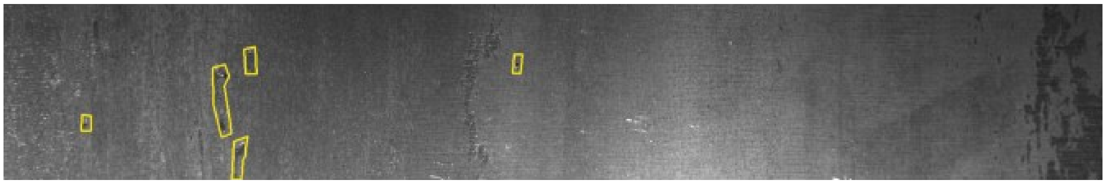
```
conv2d_transpose_13 (Conv2DTran (None, 128, 800, 16) 2064
conv2d_63[0][0]
__________________________________________________________________________________________________
concatenate_13 (Concatenate)    (None, 128, 800, 32) 0
conv2d_transpose_13[0][0]

conv2d_49[0][0]
__________________________________________________________________________________________________
conv2d_64 (Conv2D)              (None, 128, 800, 16) 4624
concatenate_13[0][0]
__________________________________________________________________________________________________
conv2d_65 (Conv2D)              (None, 128, 800, 16) 2320
conv2d_64[0][0]
__________________________________________________________________________________________________
conv2d_transpose_14 (Conv2DTran (None, 256, 1600, 8) 520
conv2d_65[0][0]
__________________________________________________________________________________________________
concatenate_14 (Concatenate)    (None, 256, 1600, 16 0
conv2d_transpose_14[0][0]

conv2d_47[0][0]
__________________________________________________________________________________________________
conv2d_66 (Conv2D)              (None, 256, 1600, 8) 1160
concatenate_14[0][0]
__________________________________________________________________________________________________
conv2d_67 (Conv2D)              (None, 256, 1600, 8) 584
conv2d_66[0][0]
__________________________________________________________________________________________________
conv2d_68 (Conv2D)              (None, 256, 1600, 4) 36
conv2d_67[0][0]
==================================================================================================
Total params: 600,612
Trainable params: 600,612
Non-trainable params: 0
__________________________________________________________________________________________________
```

```python
def dice_coef(y_true, y_pred, smooth=1):
    y_true_f = K.flatten(y_true)
    y_pred_f = K.flatten(y_pred)
    intersection = K.sum(y_true_f * y_pred_f)
```

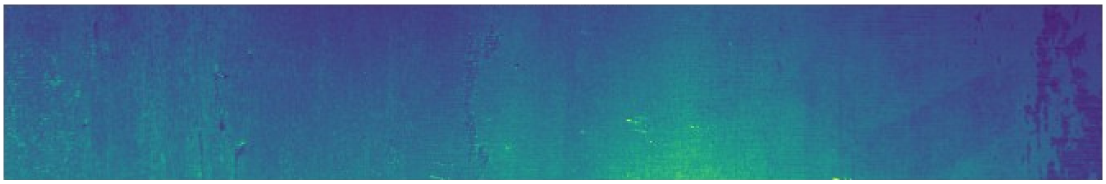
```
    return (2. * intersection + smooth) \
            / (K.sum(y_true_f) + K.sum(y_pred_f) + smooth)

optimizer = Adam()
model.compile(optimizer, 'binary_crossentropy', metrics=[dice_coef])

# Train Data Generator
def Xy_generator(ids, batch_size):
    Xs = []; ys = []
    while True:
        for i in ids:
            name, mask = make_mask(i)
            img = cv2.imread(os.path.join(DIRtrain, name),
                             cv2.IMREAD_GRAYSCALE)
            img = img[..., np.newaxis]    # Add channel axis
            img = img / 255.           # 0～1
            mask = mask / 255.         # 0～1
            Xs.append(img); ys.append(mask)
            if len(Xs) == batch_size:
                X = np.array(Xs); y = np.array(ys)
                Xs = []; ys = []
                yield [X, y]

# generator test
for X, y in Xy_generator(range(len(train_df)), 4):
    break

print('X.shape:',X.shape, '\ny.shape:',y.shape)

row = 0
# from train_df
show_mask_image(row, contour=True)
# from generator
fig, axs = plt.subplots(5, figsize=(12,12))
axs[0].imshow(X[row,:,:,0])
axs[0].axis('off')
axs[0].set_title(train_df.iloc[row].name)
for i in range(4):
    axs[i+1].imshow(y[row,:,:,i])
    axs[i+1].set_title(f"defect {i+1}")
    axs[i+1].axis('off')
```

```
X.shape: (4, 256, 1600, 1)
y.shape: (4, 256, 1600, 4)
```

0002cc93b.jpg



0002cc93b.jpg



defect 1

defect 2

defect 3

defect 4