```
Downloading Keras_Applications-1.0.8-py3-none-any.whl (50 kB)
```

```
rle_1 rle_2
                                                      rle_3 rle_4 defect stratify defect_1 defect_2 defect_3 defect_4 total_defects
     image id
                29102 12 29346 24
0 0002cc93b.jpg 29602 24 29858 24
                30114 24 3...
1 00031f466.jpg
2 000418bfc.jpg
3 000789191.jpg
                                          18661 28 18863 82
                                          19091 110 19347
4 0007a71bf.jpg
                                          110 19603 11..
```

• Data is divided with respect to 4 defects because different segmentation model is trained for each 4 defects.

 The imgaug library provides a very useful feature called Augmentation pipeline. Such a pipeline is a sequence of steps that can be applied in a fixed or random order. This also gives the flexibility to apply certain transformations to a few images and https://www.kaggle.com/parulpandey/overview-of-popular-image-augmentation-packages

• Load UNET with pre-training on Imagenet data with backbone model as efficientnetb5.

stem activation (Activation)	(None.	None.	None, 4	0	stem bn[0][0]
 block1c se reshape (Reshape)					
	(None,				
block2a_se_reshape (Reshape)	(None,	1, 1,	144)	0	block2a_se_squeeze[0][0]

block2d_se_squeeze (GlobalAvera	(None, 240)	0	block2d_activation[0][0]

block2d_se_reshape (Reshape)	(None,	1, 1,	240)	0	block2d_se_squeeze[0][0]
block3b_se_squeeze (GlobalAvera	(None,	384)		0	block3b_activation[0][0]

block3b_se_reshape (Reshape)	(None,	1, 1,	384)	0	block3b_se_squeeze[0][0]

block3e_bn (BatchNormalization)	(None, None, None, 3 1536	block3e_dwconv[0][0]
block4c duceny (DepthyicaCopy2D	/None None 7 6912	blookin curred setimation[0][0]

DIOCK4C_dWCONV (DepthWiseconvzD	(None, None, None, / 8912	DIOCK4C_expand_activation[U][U]
hlock4f expand conv (Conv2D)	(None, None, None, 7 98304	block4e add[0][0]

DIOCKIT_CAPUNG_CONV (CONVED)	(Holic, Holic	, 110110, 7	J0J04	DIOCKIC_ddd[0][0]

block5b_expand_conv (Conv2D)	(None,	None,	None, 1	185856	block5a_project_bn[0][0]
block5d project bn (BatchNormal	(None,	None,	None, 1	704	block5d project conv[0][0]

/N	N	N 1	0	-1

block6c_se_excite (Multiply)	(None,	None,	None, 1	0	block6c_activation[0][0] block6c_se_expand[0][0]
	(None,	1824)		0	block6f_activation[0][0]

block6f_se_reshape (Reshape)	1, 1,	1824)	0	
block6f_project_bn (BatchNormal				
block6g_project_bn (BatchNormal				
block6h_expand_conv (Conv2D)  block6h_expand_bn (BatchNormali  block6h_expand_activation (Activation)  block6h_dwconv (DepthwiseConv2D)  block6h_bn (BatchNormalization)  block6h_se_squeeze (GlobalAverablock6h_se_reshape (Reshape)  block6h_se_reduce (Conv2D)  block6h_se_expand (Conv2D)  block6h_se_excite (Multiply)  block6h_project_conv (Conv2D)				
block6h_expand_conv (Conv2D)  block6h_expand_bn (BatchNormalist)  block6h_expand_activation (Activation)  block6h_dwconv (DepthwiseConv2D)  block6h_activation (Activation)  block6h_activation (Activation)  block6h_se_reshape (Reshape)  block6h_se_reshape (Conv2D)  block6h_se_expand (Conv2D)  block6h_se_excite (Multiply)  block6h_project_conv (Conv2D)  block6h_project_bn (BatchNormalist)				
block6h_expand_conv (Conv2D)  block6h_expand_bn (BatchNormaling block6h_expand_activation (Activation)  block6h_bn (BatchNormalization)  block6h_activation (Activation)  block6h_se_squeeze (GlobalAveration)  block6h_se_reshape (Reshape)  block6h_se_reduce (Conv2D)  block6h_se_expand (Conv2D)  block6h_se_expand (Conv2D)  block6h_project_conv (Conv2D)  block6h_project_bn (BatchNormaling block6h_drop (FixedDropout)  block6h_add (Add)				
block6h_expand_conv (Conv2D)  block6h_expand_bn (BatchNormali  block6h_expand_activation (Activation)  block6h_bn (BatchNormalization)  block6h_activation (Activation)  block6h_se_squeeze (GlobalAveration)  block6h_se_reshape (Reshape)  block6h_se_reduce (Conv2D)  block6h_se_expand (Conv2D)  block6h_se_excite (Multiply)  block6h_project_conv (Conv2D)  block6h_project_bn (BatchNormalick)  block6h_drop (FixedDropout)  block6h_add (Add)				

block6i_bn (BatchNormalization)	) (None, None, None, 1 7296	block6i_dwconv[0][0]
blook7a dugany (Donthy) accomy?D	D (Napa Napa 2 27649	blook7g grand activation[0][0]

plock/c_awconv (pepinwiseconvzp	(None, None,	None, 3 2/040	plock/c_expand_activation[0][0]
decoder_stage3a_conv (Conv2D)	(None, None,	None, 3 59904	decoder_stage3_concat[0][0]

```
decoder_stage3a_relu (Activatio (None, None, None, 3 0 decoder_stage3a_bn[0][0]

decoder_stage3b_conv (Conv2D) (None, None, None, 3 9216 decoder_stage3a_relu[0][0]

decoder_stage3b_bn (BatchNormal (None, None, None, 3 128 decoder_stage3b_conv[0][0]

decoder_stage3b_relu (Activatio (None, None, None, 3 0 decoder_stage3b_bn[0][0]

decoder_stage4_upsampling (UpSa (None, None, None, 3 0 decoder_stage3b_relu[0][0]

decoder_stage4a_conv (Conv2D) (None, None, None, 1 4608 decoder_stage4_upsampling[0][0]

decoder_stage4a_bn (BatchNormal (None, None, None, 1 64 decoder_stage4a_conv[0][0]

decoder_stage4a_relu (Activatio (None, None, None, 1 0 decoder_stage4a_bn[0][0]

decoder_stage4b_conv (Conv2D) (None, None, None, 1 2304 decoder_stage4a_relu[0][0]

decoder_stage4b_bn (BatchNormal (None, None, 1 64 decoder_stage4b_conv[0][0]

decoder_stage4b_relu (Activatio (None, None, 1 145 decoder_stage4b_bn[0][0]

final_conv (Conv2D) (None, None, None, 1 0 final_conv[0][0]

sigmoid (Activation) (None, None, None, 1 0 final_conv[0][0]

Total params: 37,468,673

Trainable params: 174,720
```

```
Defect_1
valid batch=test DataGenerator(val 1,preprocess=preprocess)
```

• For validation, test datasets loss increases and metrics decreases as compared with train data thus better to train model for more epochs (e.g. epoch =100) which might help to reduce loss and increase dice coefficient on unseen data.

```
In []:
model=load_model('/content/drive//My Drive/Steel_Detection /segmentation_defect_l.h5',custom_
objects={'bbe_dice_loss':bbe_dice_loss,'dice_coef':dice_coef})

In []:

def plot_mask(rle_defect,k,pred):
    train_folder_path='/content/drive//My Drive/Steel_Detection /train_images/'
    # Create figure and axes
    fig,ax=plt.subplots(4,3,figsize=(14,9))
    fig.suptitle('Defect_'+ \cdots(k)+'_Images',fontsize=20,fontweight='bold')
    for i in record(4):
        image_id=rle_defect[i][0]
        rle=rle_defect[i][1]
        im=Image.open(train_folder_path+ \cdots(image_id))
        ax[i,0].set_title(image_id)
        mask=rle2mask(rle)
        ax[i,1].imshow(mask)
        ax[i,1].set_title("Actual Mask for "++++ (image_id))
        cl=Image.fromarray(pred[i][:::,0])
        ax[i,2].set_title("Predicted Mask for "++++ (image_id))
        fig.set_facecolor("tsn")
        plt.show()
```

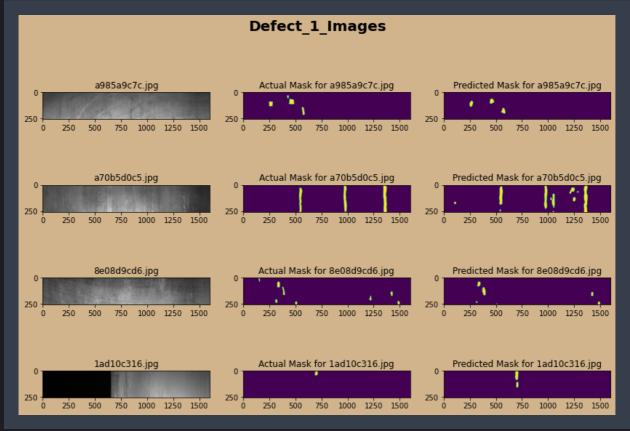
### **Train Dataset**

In [ ]:

train\_preds=model.predict\_generator(test\_DataGenerator(train\_1[10:14],preprocess=preprocess),
verbose=1)

In [ ]:

plot\_mask(train\_1[10:14].values,1,train\_preds)



# **Validation Dataset**

```
val_preds=model.predict_generator(test_DataGenerator(val_1[10:14],preprocess=preprocess),verb
ose=1)
```

#### In [ ]:

plot mask(val 1[10:14] values,1,val preds)



### Test Dataset

#### In [ ]:

 $test\_preds=model.predict\_generator(test\_DataGenerator(test\_1[10:14],preprocess=preprocess), version set in the predict\_generator(test\_DataGenerator(test\_1[10:14],preprocess=preprocess)), version set in the predict\_generator(test\_DataGenera$ 

4/4 [======] - 2s 561ms/step

#### In [ ]:

plot mask(test 1[10:14] values,1, test preds)

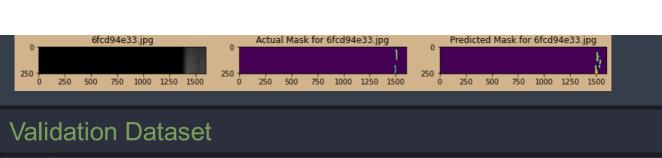


# Defect 2

• One can observe the value of loss and metrics are similar for train, validation and test datasets thus the model is not over-fitting. On unseen data (test) dice coefficient increases and loss decreases as compared to train, validation datasets thus, model is performing really good.

# Training Dataset





In [ ]:

 $val\_preds=model.predict\_generator(test\_DataGenerator(val\_2[10:14],preprocess=preprocess),verbose=1)$ 

4/4 [=======] - Os 122ms/step

In [ ]:

plot mask(val 2[10:14].values,2,val preds)



# **Test Datset**

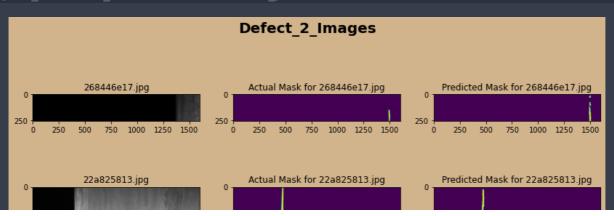
In [ ]:

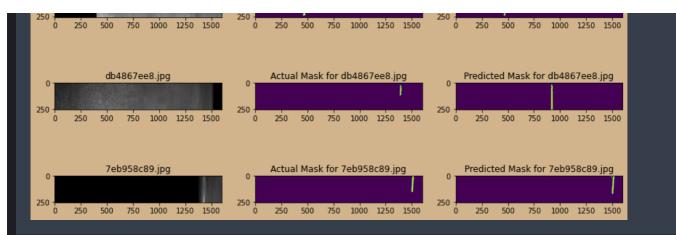
test\_preds=model.predict\_generator(test\_DataGenerator(test\_2[10:14],preprocess=preprocess),verbose=1)

4/4 [======] - 2s 510ms/step

In [ ]:

olot mask(test 2[10:14].values,2,test preds)





## Defect 3

One can observe the value of loss and metrics are similar for train, validation and test datasets thus the model is not overfitting. On unseen data (test) dice coefficient slightly increases and loss decreases as compared to train, validation
datasets thus, model is performing really good.

# Training Dataset

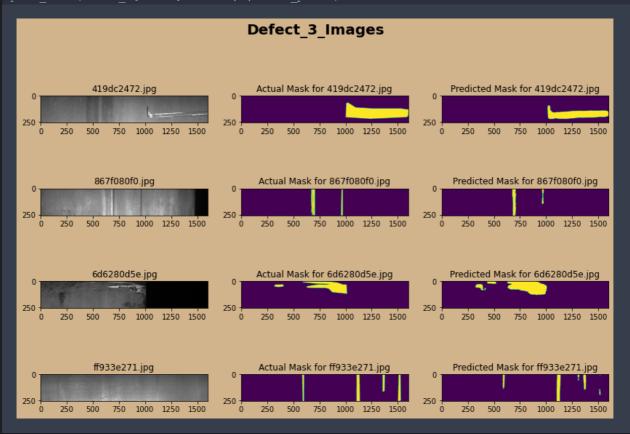
```
In [ ]:
```

train\_preds=model.predict\_generator(test\_DataGenerator(train\_3[12:16],preprocess=preprocess),
verbose=1)

4/4 [=======] - 1s 157ms/step

#### In [ ]:

plot mask(train 3[12:16].values,3,train preds)

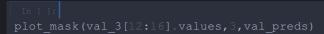


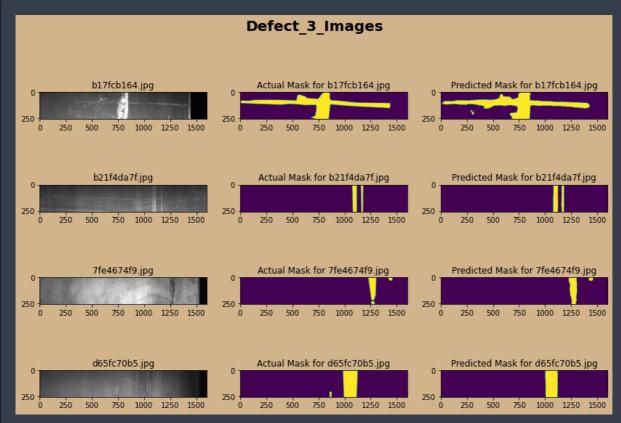
# Validation Dataset

In [ ]:

val\_preds=model.predict\_generator(test\_DataGenerator(val\_3[12:16],preprocess=preprocess),verb
ose=1)

4/4 [======] - 1s 305ms/step





## **Test Dataset**

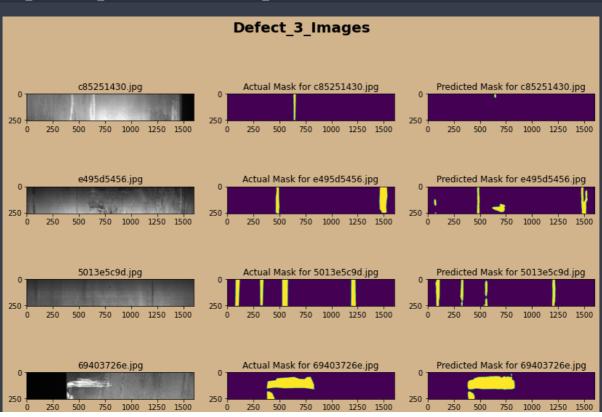
In [ ]:

test\_preds=model.predict\_generator(test\_DataGenerator(test\_3[12:16],preprocess=preprocess),verbose=1)

4/4 [======] - 1s 269ms/step

In [ ]:

plot mask(test 3[12:16].values, 3, test preds)



# Defect 4

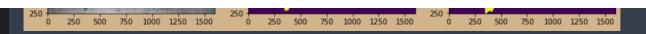
```
    For validation, test datasets loss slightly increases and metrics slightly decreases as compared with train data but overall

  values are similar thus model is not over-fitting. For better results on unseen data train model for more epochs (e.g. epoch
```

=100) based on the available resources (memory).

# **Training Dataset**





# Validation Dataset

In [ ]:

val\_preds=model.predict\_generator(test\_DataGenerator(val\_4[14:18],preprocess=preprocess),verb
ose=1)

In [ ]:

plot mask(val 4[14:18].values, 4, val preds)



## **Test Dataset**

In [ ]:

test\_preds=model.predict\_generator(test\_DataGenerator(test\_4[14:18],preprocess=preprocess),verbose=1)

4/4 [=======] - 6s 1s/step

In [ ]·

plot mask(test 4[14:18] values, 4, test preds)

