Face Mask Prediction using U-Net

Mounting Google drive for using google colab

In [ ]:

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

```
Drive already mounted at /content/drive/; to attempt to forcibly remount, call
drive.mount("/content/drive/", force_remount=True).
```

Loading "images.npy" file

In [ ]:

```
import numpy as np
import cv2
from tensorflow.keras.applications.mobilenet import preprocess_input
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from tensorflow.keras.applications.mobilenet import MobileNet
from tensorflow.keras.layers import Reshape, UpSampling2D, Concatenate, Conv2D,Activation, BatchNor
malization, SpatialDropout2D
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import binary_crossentropy
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping, ReduceLROnPlateau
from tensorflow.keras.backend import log, epsilon
import tensorflow as tf
```

In [ ]:

```
data =np.load('/content/drive/My Drive/Colab Notebooks/images.npy',allow_pickle=True)
```

Checking one sample from the loaded "images.npy" file

In [ ]:

```
print(data[10][1])
```

```
[{'label': ['Face'], 'notes': '', 'points': [{'x': 0.48, 'y': 0.10385756676557864}, {'x':
0.7716666666666666, 'y': 0.6795252225519288}], 'imageWidth': 600, 'imageHeight': 337}]
```

Setting image dimensions

- Initializing image height, image width with value: 224

In [ ]:

```
ALPHA = 1
IMAGE_HEIGHT = 224
IMAGE_WIDTH = 224
IMAGE_SIZE = 224
HEIGHT_CELLS = 28
WIDTH_CELLS = 28
```

Create features and labels

In [ ]:

```
masks = np.zeros((int(data.shape[0]), IMAGE_HEIGHT, IMAGE_WIDTH))
X = np.zeros((int(data.shape[0]), IMAGE_HEIGHT, IMAGE_WIDTH, 3))
for index in range(data.shape[0]):
    img = data[index][0]
    img = cv2.resize(img, dsize=(IMAGE_HEIGHT, IMAGE_WIDTH), interpolation=cv2.INTER_CUBIC)
    try:
      img = img[:, :, :3]
    except:
      continue
    X[index] = preprocess_input(np.array(img, dtype=np.float32))
    for i in data[index][1]:
        x1 = int(i["points"][0]['x'] * IMAGE_WIDTH)
        x2 = int(i["points"][1]['x'] * IMAGE_WIDTH)
        y1 = int(i["points"][0]['y'] * IMAGE_HEIGHT)
        y2 = int(i["points"][1]['y'] * IMAGE_HEIGHT)
        masks[index][y1:y2, x1:x2] = 1
```

Splitting the data into training and testing

- 400 images in training
- 9 images in testing data

In [ ]:

```
X_train, X_test, y_train, y_test = train_test_split(X,masks, test_size=0.02, random_state=0)
```

Shape of training and testing data

In [ ]:

```
X_train.shape
```

Out[ ]:

```
(400, 224, 224, 3)
```

In [ ]:

```
y_train.shape
```

Out[ ]:

```
(400, 224, 224)
```

In [ ]:

```
y_test.shape
```

Out[ ]:

```
(9, 224, 224)
```

In [ ]:

```
X_test.shape
```

Out[ ]:

```
(9, 224, 224, 3)
```

Print a sample training image, image array and its mask

Print the image and image array

Print the image and image array

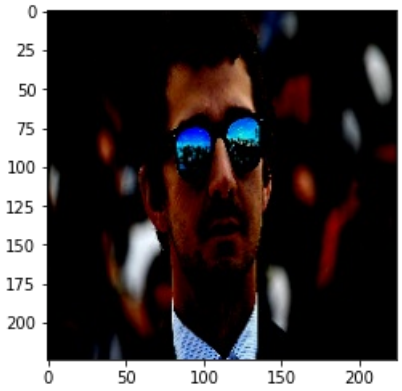
In [ ]:

```
plt.imshow(X_train[1])
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

Out[ ]:

```
<matplotlib.image.AxesImage at 0x7f86167071d0>
```



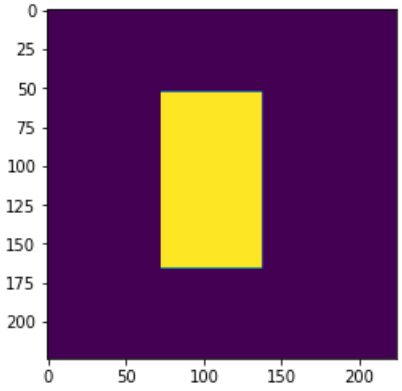
Print the mask

In [ ]:

```
plt.imshow(y_train[1])
```

Out[ ]:

```
<matplotlib.image.AxesImage at 0x7f861676a160>
```



Creating the model

- Adding MobileNet as model with below parameter values
  - input_shape: IMAGE_HEIGHT, IMAGE_WIDTH, 3
  - include_top: False
  - alpha: 1.0
  - weights: "imagenet"
- Adding UNET architecture layers

In [ ]:

```
def conv_block_simple(prevlayer, filters, prefix, strides=(1, 1)):
    conv = Conv2D(filters, (3, 3), padding = 'same', kernel_initializer = 'he_normal', strides = st
rides, name = prefix + '_conv')(prevlayer)
    conv = BatchNormalization(name = prefix + 'BatchNormalization')(conv)
```

```
    conv = Activation('relu', name = prefix + 'ActivationLayer')(conv)
    return conv

def create_model(trainable = True):
    model = MobileNet(input_shape = (IMAGE_HEIGHT, IMAGE_WIDTH, 3), include_top = False, alpha = AL
PHA, weights = 'imagenet')
    for layer in model.layers:
        layer.trainable = trainable

    block1 = model.get_layer('conv_pw_13_relu').output
    block2 = model.get_layer('conv_pw_11_relu').output
    block3 = model.get_layer('conv_pw_5_relu').output
    block4 = model.get_layer('conv_pw_3_relu').output
    block5 = model.get_layer('conv_pw_1_relu').output

    up1 = Concatenate()([UpSampling2D()(block1), block2])
    conv6 = conv_block_simple(up1, 256, 'Conv_6_1')
    conv6 = conv_block_simple(conv6, 256, 'Conv_6_2')

    up2 = Concatenate()([UpSampling2D()(conv6), block3])
    conv7 = conv_block_simple(up2, 256, 'Conv_7_1')
    conv7 = conv_block_simple(conv7, 256, 'Conv_7_2')

    up3 = Concatenate()([UpSampling2D()(conv7), block4])
    conv8 = conv_block_simple(up3, 192, 'Conv_8_1')
    conv8 = conv_block_simple(conv8, 128, 'Conv_8_2')

    up4 = Concatenate()([UpSampling2D()(conv8), block5])
    conv9 = conv_block_simple(up4, 96, 'Conv_9_1')
    conv9 = conv_block_simple(conv9, 64, 'Conv_9_2')

    up5 = Concatenate()([UpSampling2D()(conv9), model.input])
    conv10 = conv_block_simple(up5, 48, 'Conv_10_1')
    conv10 = conv_block_simple(conv10, 32, 'Conv_10_2')
    conv10 = SpatialDropout2D(0.2)(conv10)

    x = Conv2D(1, (1, 1), activation = 'sigmoid')(conv10)
    x = Reshape((IMAGE_SIZE, IMAGE_SIZE))(x)
    return Model(inputs = model.input, outputs = x)
```

Calling the create_model function

- Giving trainable=False as argument

In [ ]:

```
model = create_model(False)
```

Model summary

In [ ]:

```
model.summary()
```

```
Model: "functional_9"
_________________________________________________________________________________________________
Layer (type)                 Output Shape              Param #     Connected to
=================================================================================================
input_5 (InputLayer)         [(None, 224, 224, 3)      0
_________________________________________________________________________________________________
conv1_pad (ZeroPadding2D)    (None, 225, 225, 3)       0           input_5[0][0]
_________________________________________________________________________________________________
conv1 (Conv2D)               (None, 112, 112, 32)      864         conv1_pad[0][0]
_________________________________________________________________________________________________
conv1_bn (BatchNormalization)  (None, 112, 112, 32)    128         conv1[0][0]
_________________________________________________________________________________________________
conv1_relu (ReLU)            (None, 112, 112, 32)      0           conv1_bn[0][0]
_________________________________________________________________________________________________
conv_dw_1 (DepthwiseConv2D)  (None, 112, 112, 32)      288         conv1_relu[0][0]
_________________________________________________________________________________________________
conv_dw_1_bn (BatchNormalizatio (None, 112, 112, 32)   128         conv_dw_1[0][0]
```

conv_dw_1_relu (ReLU)	(None, 112, 112, 32)	0	conv_dw_1_bn[0][0]
conv_pw_1 (Conv2D)	(None, 112, 112, 64)	2048	conv_dw_1_relu[0][0]
conv_pw_1_bn (BatchNormalizatio	(None, 112, 112, 64)	256	conv_pw_1[0][0]
conv_pw_1_relu (ReLU)	(None, 112, 112, 64)	0	conv_pw_1_bn[0][0]
conv_pad_2 (ZeroPadding2D)	(None, 113, 113, 64)	0	conv_pw_1_relu[0][0]
conv_dw_2 (DepthwiseConv2D)	(None, 56, 56, 64)	576	conv_pad_2[0][0]
conv_dw_2_bn (BatchNormalizatio	(None, 56, 56, 64)	256	conv_dw_2[0][0]
conv_dw_2_relu (ReLU)	(None, 56, 56, 64)	0	conv_dw_2_bn[0][0]
conv_pw_2 (Conv2D)	(None, 56, 56, 128)	8192	conv_dw_2_relu[0][0]
conv_pw_2_bn (BatchNormalizatio	(None, 56, 56, 128)	512	conv_pw_2[0][0]
conv_pw_2_relu (ReLU)	(None, 56, 56, 128)	0	conv_pw_2_bn[0][0]
conv_dw_3 (DepthwiseConv2D)	(None, 56, 56, 128)	1152	conv_pw_2_relu[0][0]
conv_dw_3_bn (BatchNormalizatio	(None, 56, 56, 128)	512	conv_dw_3[0][0]
conv_dw_3_relu (ReLU)	(None, 56, 56, 128)	0	conv_dw_3_bn[0][0]
conv_pw_3 (Conv2D)	(None, 56, 56, 128)	16384	conv_dw_3_relu[0][0]
conv_pw_3_bn (BatchNormalizatio	(None, 56, 56, 128)	512	conv_pw_3[0][0]
conv_pw_3_relu (ReLU)	(None, 56, 56, 128)	0	conv_pw_3_bn[0][0]
conv_pad_4 (ZeroPadding2D)	(None, 57, 57, 128)	0	conv_pw_3_relu[0][0]
conv_dw_4 (DepthwiseConv2D)	(None, 28, 28, 128)	1152	conv_pad_4[0][0]
conv_dw_4_bn (BatchNormalizatio	(None, 28, 28, 128)	512	conv_dw_4[0][0]
conv_dw_4_relu (ReLU)	(None, 28, 28, 128)	0	conv_dw_4_bn[0][0]
conv_pw_4 (Conv2D)	(None, 28, 28, 256)	32768	conv_dw_4_relu[0][0]
conv_pw_4_bn (BatchNormalizatio	(None, 28, 28, 256)	1024	conv_pw_4[0][0]
conv_pw_4_relu (ReLU)	(None, 28, 28, 256)	0	conv_pw_4_bn[0][0]
conv_dw_5 (DepthwiseConv2D)	(None, 28, 28, 256)	2304	conv_pw_4_relu[0][0]
conv_dw_5_bn (BatchNormalizatio	(None, 28, 28, 256)	1024	conv_dw_5[0][0]
conv_dw_5_relu (ReLU)	(None, 28, 28, 256)	0	conv_dw_5_bn[0][0]
conv_pw_5 (Conv2D)	(None, 28, 28, 256)	65536	conv_dw_5_relu[0][0]
conv_pw_5_bn (BatchNormalizatio	(None, 28, 28, 256)	1024	conv_pw_5[0][0]
conv_pw_5_relu (ReLU)	(None, 28, 28, 256)	0	conv_pw_5_bn[0][0]
conv_pad_6 (ZeroPadding2D)	(None, 29, 29, 256)	0	conv_pw_5_relu[0][0]
conv_dw_6 (DepthwiseConv2D)	(None, 14, 14, 256)	2304	conv_pad_6[0][0]
conv_dw_6_bn (BatchNormalizatio	(None, 14, 14, 256)	1024	conv_dw_6[0][0]
conv_dw_6_relu (ReLU)	(None, 14, 14, 256)	0	conv_dw_6_bn[0][0]
conv_pw_6 (Conv2D)	(None, 14, 14, 512)	131072	conv_dw_6_relu[0][0]
conv_pw_6_bn (BatchNormalizatio	(None, 14, 14, 512)	2048	conv_pw_6[0][0]
conv_pw_6_relu (ReLU)	(None, 14, 14, 512)	0	conv_pw_6_bn[0][0]
conv_dw_7 (DepthwiseConv2D)	(None, 14, 14, 512)	4608	conv_pw_6_relu[0][0]

conv_dw_7_bn (BatchNormalizatio	(None, 14, 14, 512)	2048	conv_dw_7[0][0]
conv_dw_7_relu (ReLU)	(None, 14, 14, 512)	0	conv_dw_7_bn[0][0]
conv_pw_7 (Conv2D)	(None, 14, 14, 512)	262144	conv_dw_7_relu[0][0]
conv_pw_7_bn (BatchNormalizatio	(None, 14, 14, 512)	2048	conv_pw_7[0][0]
conv_pw_7_relu (ReLU)	(None, 14, 14, 512)	0	conv_pw_7_bn[0][0]
conv_dw_8 (DepthwiseConv2D)	(None, 14, 14, 512)	4608	conv_pw_7_relu[0][0]
conv_dw_8_bn (BatchNormalizatio	(None, 14, 14, 512)	2048	conv_dw_8[0][0]
conv_dw_8_relu (ReLU)	(None, 14, 14, 512)	0	conv_dw_8_bn[0][0]
conv_pw_8 (Conv2D)	(None, 14, 14, 512)	262144	conv_dw_8_relu[0][0]
conv_pw_8_bn (BatchNormalizatio	(None, 14, 14, 512)	2048	conv_pw_8[0][0]
conv_pw_8_relu (ReLU)	(None, 14, 14, 512)	0	conv_pw_8_bn[0][0]
conv_dw_9 (DepthwiseConv2D)	(None, 14, 14, 512)	4608	conv_pw_8_relu[0][0]
conv_dw_9_bn (BatchNormalizatio	(None, 14, 14, 512)	2048	conv_dw_9[0][0]
conv_dw_9_relu (ReLU)	(None, 14, 14, 512)	0	conv_dw_9_bn[0][0]
conv_pw_9 (Conv2D)	(None, 14, 14, 512)	262144	conv_dw_9_relu[0][0]
conv_pw_9_bn (BatchNormalizatio	(None, 14, 14, 512)	2048	conv_pw_9[0][0]
conv_pw_9_relu (ReLU)	(None, 14, 14, 512)	0	conv_pw_9_bn[0][0]
conv_dw_10 (DepthwiseConv2D)	(None, 14, 14, 512)	4608	conv_pw_9_relu[0][0]
conv_dw_10_bn (BatchNormalizati	(None, 14, 14, 512)	2048	conv_dw_10[0][0]
conv_dw_10_relu (ReLU)	(None, 14, 14, 512)	0	conv_dw_10_bn[0][0]
conv_pw_10 (Conv2D)	(None, 14, 14, 512)	262144	conv_dw_10_relu[0][0]
conv_pw_10_bn (BatchNormalizati	(None, 14, 14, 512)	2048	conv_pw_10[0][0]
conv_pw_10_relu (ReLU)	(None, 14, 14, 512)	0	conv_pw_10_bn[0][0]
conv_dw_11 (DepthwiseConv2D)	(None, 14, 14, 512)	4608	conv_pw_10_relu[0][0]
conv_dw_11_bn (BatchNormalizati	(None, 14, 14, 512)	2048	conv_dw_11[0][0]
conv_dw_11_relu (ReLU)	(None, 14, 14, 512)	0	conv_dw_11_bn[0][0]
conv_pw_11 (Conv2D)	(None, 14, 14, 512)	262144	conv_dw_11_relu[0][0]
conv_pw_11_bn (BatchNormalizati	(None, 14, 14, 512)	2048	conv_pw_11[0][0]
conv_pw_11_relu (ReLU)	(None, 14, 14, 512)	0	conv_pw_11_bn[0][0]
conv_pad_12 (ZeroPadding2D)	(None, 15, 15, 512)	0	conv_pw_11_relu[0][0]
conv_dw_12 (DepthwiseConv2D)	(None, 7, 7, 512)	4608	conv_pad_12[0][0]
conv_dw_12_bn (BatchNormalizati	(None, 7, 7, 512)	2048	conv_dw_12[0][0]
conv_dw_12_relu (ReLU)	(None, 7, 7, 512)	0	conv_dw_12_bn[0][0]
conv_pw_12 (Conv2D)	(None, 7, 7, 1024)	524288	conv_dw_12_relu[0][0]
conv_pw_12_bn (BatchNormalizati	(None, 7, 7, 1024)	4096	conv_pw_12[0][0]
conv_pw_12_relu (ReLU)	(None, 7, 7, 1024)	0	conv_pw_12_bn[0][0]
conv_dw_13 (DepthwiseConv2D)	(None, 7, 7, 1024)	9216	conv_pw_12_relu[0][0]
conv_dw_13_bn (BatchNormalizati	(None, 7, 7, 1024)	4096	conv_dw_13[0][0]
conv_dw_13_relu (ReLU)	(None, 7, 7, 1024)	0	conv_dw_13_bn[0][0]

conv_dw_13_relu (ReLU)	(None, 7, 7, 1024)	0	conv_dw_13_bn[0][0]
conv_pw_13 (Conv2D)	(None, 7, 7, 1024)	1048576	conv_dw_13_relu[0][0]
conv_pw_13_bn (BatchNormalizati	(None, 7, 7, 1024)	4096	conv_pw_13[0][0]
conv_pw_13_relu (ReLU)	(None, 7, 7, 1024)	0	conv_pw_13_bn[0][0]
up_sampling2d_20 (UpSampling2D)	(None, 14, 14, 1024)	0	conv_pw_13_relu[0][0]
concatenate_20 (Concatenate)	(None, 14, 14, 1536)	0	up_sampling2d_20[0][0] conv_pw_11_relu[0][0]
Conv_6_1_conv (Conv2D)	(None, 14, 14, 256)	3539200	concatenate_20[0][0]
Conv_6_1BatchNormalization (Bat	(None, 14, 14, 256)	1024	Conv_6_1_conv[0][0]
Conv_6_1ActivationLayer (Activa	(None, 14, 14, 256)	0	Conv_6_1BatchNormalization[0][0]
Conv_6_2_conv (Conv2D)	(None, 14, 14, 256)	590080	Conv_6_1ActivationLayer[0][0]
Conv_6_2BatchNormalization (Bat	(None, 14, 14, 256)	1024	Conv_6_2_conv[0][0]
Conv_6_2ActivationLayer (Activa	(None, 14, 14, 256)	0	Conv_6_2BatchNormalization[0][0]
up_sampling2d_21 (UpSampling2D)	(None, 28, 28, 256)	0	Conv_6_2ActivationLayer[0][0]
concatenate_21 (Concatenate)	(None, 28, 28, 512)	0	up_sampling2d_21[0][0] conv_pw_5_relu[0][0]
Conv_7_1_conv (Conv2D)	(None, 28, 28, 256)	1179904	concatenate_21[0][0]
Conv_7_1BatchNormalization (Bat	(None, 28, 28, 256)	1024	Conv_7_1_conv[0][0]
Conv_7_1ActivationLayer (Activa	(None, 28, 28, 256)	0	Conv_7_1BatchNormalization[0][0]
Conv_7_2_conv (Conv2D)	(None, 28, 28, 256)	590080	Conv_7_1ActivationLayer[0][0]
Conv_7_2BatchNormalization (Bat	(None, 28, 28, 256)	1024	Conv_7_2_conv[0][0]
Conv_7_2ActivationLayer (Activa	(None, 28, 28, 256)	0	Conv_7_2BatchNormalization[0][0]
up_sampling2d_22 (UpSampling2D)	(None, 56, 56, 256)	0	Conv_7_2ActivationLayer[0][0]
concatenate_22 (Concatenate)	(None, 56, 56, 384)	0	up_sampling2d_22[0][0] conv_pw_3_relu[0][0]
Conv_8_1_conv (Conv2D)	(None, 56, 56, 192)	663744	concatenate_22[0][0]
Conv_8_1BatchNormalization (Bat	(None, 56, 56, 192)	768	Conv_8_1_conv[0][0]
Conv_8_1ActivationLayer (Activa	(None, 56, 56, 192)	0	Conv_8_1BatchNormalization[0][0]
Conv_8_2_conv (Conv2D)	(None, 56, 56, 128)	221312	Conv_8_1ActivationLayer[0][0]
Conv_8_2BatchNormalization (Bat	(None, 56, 56, 128)	512	Conv_8_2_conv[0][0]
Conv_8_2ActivationLayer (Activa	(None, 56, 56, 128)	0	Conv_8_2BatchNormalization[0][0]
up_sampling2d_23 (UpSampling2D)	(None, 112, 112, 128	0	Conv_8_2ActivationLayer[0][0]
concatenate_23 (Concatenate)	(None, 112, 112, 192	0	up_sampling2d_23[0][0] conv_pw_1_relu[0][0]
Conv_9_1_conv (Conv2D)	(None, 112, 112, 96)	165984	concatenate_23[0][0]
Conv_9_1BatchNormalization (Bat	(None, 112, 112, 96)	384	Conv_9_1_conv[0][0]
Conv_9_1ActivationLayer (Activa	(None, 112, 112, 96)	0	Conv_9_1BatchNormalization[0][0]
Conv_9_2_conv (Conv2D)	(None, 112, 112, 64)	55360	Conv_9_1ActivationLayer[0][0]
Conv_9_2BatchNormalization (Bat	(None, 112, 112, 64)	256	Conv_9_2_conv[0][0]
Conv_9_2ActivationLayer (Activa	(None, 112, 112, 64)	0	Conv_9_2BatchNormalization[0][0]
up_sampling2d_24 (UpSampling2D)	(None, 224, 224, 64)	0	Conv_9_2ActivationLayer[0][0]

```
__________________________________________________________________________________________________
concatenate_24 (Concatenate)    (None, 224, 224, 67) 0           up_sampling2d_24[0][0]
                                                                 input_5[0][0]
__________________________________________________________________________________________________
Conv_10_1_conv (Conv2D)         (None, 224, 224, 48) 28992       concatenate_24[0][0]
__________________________________________________________________________________________________
Conv_10_1BatchNormalization (Ba (None, 224, 224, 48) 192         Conv_10_1_conv[0][0]
__________________________________________________________________________________________________
Conv_10_1ActivationLayer (Activ (None, 224, 224, 48) 0           Conv_10_1BatchNormalization[0][0]
__________________________________________________________________________________________________
Conv_10_2_conv (Conv2D)         (None, 224, 224, 32) 13856       Conv_10_1ActivationLayer[0][0]
__________________________________________________________________________________________________
Conv_10_2BatchNormalization (Ba (None, 224, 224, 32) 128         Conv_10_2_conv[0][0]
__________________________________________________________________________________________________
Conv_10_2ActivationLayer (Activ (None, 224, 224, 32) 0           Conv_10_2BatchNormalization[0][0]
__________________________________________________________________________________________________
spatial_dropout2d_4 (SpatialDro (None, 224, 224, 32) 0           Conv_10_2ActivationLayer[0][0]
__________________________________________________________________________________________________
conv2d_4 (Conv2D)               (None, 224, 224, 1)  33          spatial_dropout2d_4[0][0]
__________________________________________________________________________________________________
reshape_4 (Reshape)             (None, 224, 224)     0           conv2d_4[0][0]
==================================================================================================
Total params: 10,283,745
Trainable params: 7,051,713
Non-trainable params: 3,232,032
__________________________________________________________________________________________________
```

Defining dice coefficient function

In [ ]:

```
def dice_coefficient(y_true, y_pred):
    numerator = 2 * tf.reduce_sum(y_true * y_pred)
    denominator = tf.reduce_sum(y_true + y_pred)

    return numerator / (denominator + epsilon())
```

Defining loss function

In [ ]:

```
def loss(y_true, y_pred):
    return binary_crossentropy(y_true, y_pred) - log(dice_coefficient(y_true, y_pred) + epsilon())
```

Compiling the model

- Compliing the model using below parameters
  - loss: using the loss function defined above
  - optimizers: using Adam optimizer
  - metrics: using dice_coefficient function defined above

In [ ]:

```
optimizer = Adam(lr=1e-4, beta_1=0.9, beta_2=0.999, epsilon=None, decay=0.0, amsgrad=False)
model.compile(loss=loss, optimizer=optimizer, metrics=[dice_coefficient])
```

Defining callbacks

- Using ModelCheckpoint
- Using EarlyStopping
- Using ReduceLROnPlateau

In [ ]:

```
checkpoint = ModelCheckpoint("model-{val_loss:.2f}.h5", monitor="val_loss", verbose=1,
save_best_only=True, save_weights_only=True)
```

```
stop = EarlyStopping(monitor="val_loss", patience=5)

reduce_lr = ReduceLROnPlateau(monitor="val_loss", factor=0.2, patience=5, min_lr=1e-6, verbose=1)
```

Fitting the model

- Fitting the model using below parameters
  - epochs: 10
  - batch_size: 1
  - callbacks: using the callbacks defined above

In [ ]:

```
model.fit(X_train, y_train, epochs = 10, batch_size = 1, callbacks = [checkpoint, reduce_lr, stop],
validation_data = (X_test,y_test))
```

```
Epoch 1/10
  2/400 [..............................] - ETA: 17s - loss: 2.7443 - dice_coefficient:
0.1412WARNING:tensorflow:Callbacks method `on_train_batch_end` is slow compared to the batch time
(batch time: 0.0148s vs `on_train_batch_end` time: 0.0724s). Check your callbacks.
400/400 [==============================] - ETA: 0s - loss: 1.3733 - dice_coefficient:
0.4295WARNING:tensorflow:Callbacks method `on_test_batch_end` is slow compared to the batch time (
batch time: 0.0054s vs `on_test_batch_end` time: 0.0158s). Check your callbacks.

Epoch 00001: val_loss improved from inf to 0.93462, saving model to model-0.93.h5
400/400 [==============================] - 26s 65ms/step - loss: 1.3733 - dice_coefficient: 0.4295
- val_loss: 0.9346 - val_dice_coefficient: 0.5940
Epoch 2/10
400/400 [==============================] - ETA: 0s - loss: 0.9414 - dice_coefficient: 0.5445
Epoch 00002: val_loss improved from 0.93462 to 0.88956, saving model to model-0.89.h5
400/400 [==============================] - 26s 64ms/step - loss: 0.9414 - dice_coefficient: 0.5445
- val_loss: 0.8896 - val_dice_coefficient: 0.5494
Epoch 3/10
400/400 [==============================] - ETA: 0s - loss: 0.7281 - dice_coefficient: 0.6218
Epoch 00003: val_loss improved from 0.88956 to 0.75400, saving model to model-0.75.h5
400/400 [==============================] - 25s 63ms/step - loss: 0.7281 - dice_coefficient: 0.6218
- val_loss: 0.7540 - val_dice_coefficient: 0.6224
Epoch 4/10
400/400 [==============================] - ETA: 0s - loss: 0.5409 - dice_coefficient: 0.7009
Epoch 00004: val_loss did not improve from 0.75400
400/400 [==============================] - 25s 63ms/step - loss: 0.5409 - dice_coefficient: 0.7009
- val_loss: 0.7885 - val_dice_coefficient: 0.6292
Epoch 5/10
400/400 [==============================] - ETA: 0s - loss: 0.4265 - dice_coefficient: 0.7573
Epoch 00005: val_loss improved from 0.75400 to 0.73409, saving model to model-0.73.h5
400/400 [==============================] - 25s 63ms/step - loss: 0.4265 - dice_coefficient: 0.7573
- val_loss: 0.7341 - val_dice_coefficient: 0.6447
Epoch 6/10
400/400 [==============================] - ETA: 0s - loss: 0.3414 - dice_coefficient: 0.8043
Epoch 00006: val_loss did not improve from 0.73409
400/400 [==============================] - 25s 63ms/step - loss: 0.3414 - dice_coefficient: 0.8043
- val_loss: 0.9186 - val_dice_coefficient: 0.5871
Epoch 7/10
400/400 [==============================] - ETA: 0s - loss: 0.2959 - dice_coefficient: 0.8304
Epoch 00007: val_loss did not improve from 0.73409
400/400 [==============================] - 25s 63ms/step - loss: 0.2959 - dice_coefficient: 0.8304
- val_loss: 0.7356 - val_dice_coefficient: 0.6740
Epoch 8/10
400/400 [==============================] - ETA: 0s - loss: 0.2594 - dice_coefficient: 0.8520
Epoch 00008: val_loss did not improve from 0.73409
400/400 [==============================] - 25s 63ms/step - loss: 0.2594 - dice_coefficient: 0.8520
- val_loss: 0.8430 - val_dice_coefficient: 0.6313
Epoch 9/10
400/400 [==============================] - ETA: 0s - loss: 0.2284 - dice_coefficient: 0.8708
Epoch 00009: val_loss did not improve from 0.73409
400/400 [==============================] - 25s 63ms/step - loss: 0.2284 - dice_coefficient: 0.8708
- val_loss: 0.9912 - val_dice_coefficient: 0.5912
Epoch 10/10
400/400 [==============================] - ETA: 0s - loss: 0.1990 - dice_coefficient: 0.8905
Epoch 00010: val_loss did not improve from 0.73409

Epoch 00010: ReduceLROnPlateau reducing learning rate to 1.9999999494757503e-05.
```

```
400/400 [==============================] - 25s 63ms/step - loss: 0.1990 - dice_coefficient: 0.8905
- val_loss: 0.7871 - val_dice_coefficient: 0.6678
```

Out[ ]:

```
<tensorflow.python.keras.callbacks.History at 0x7f85b835db70>
```

In [ ]:

```
model.evaluate(X_test, y_test, verbose = 1)
```

```
1/1 [==============================] - 0s 2ms/step - loss: 0.7727 - dice_coefficient: 0.6681
```

Out[ ]:

```
[0.7726632356643677, 0.6680853962898254]
```

Getting the predicted mask for a test image

In [ ]:

```
WEIGHTS_FILE = "model-0.73.h5"
learned_model = create_model()
learned_model.load_weights(WEIGHTS_FILE)
y_pred = learned_model.predict(X_test, verbose = 1)
```

```
1/1 [==============================] - 0s 164ms/step
```

In [ ]:

```
n = 5
image = cv2.resize(X_test[n], dsize = (IMAGE_HEIGHT, IMAGE_WIDTH), interpolation = cv2.INTER_CUBIC)
pred_mask = cv2.resize(1.0*(y_pred[n] > 0.1), (IMAGE_WIDTH, IMAGE_HEIGHT))

image2 = image
image2[:,:,0] = pred_mask*image[:,:,0]
image2[:,:,1] = pred_mask*image[:,:,1]
image2[:,:,2] = pred_mask*image[:,:,2]
out_image = image2

fig = plt.figure(figsize = (15, 7.2))
ax = fig.add_subplot(1, 1, 1)
plt.axis('off')
plt.imshow(out_image)
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for
integers).
```

Out[ ]:

```
<matplotlib.image.AxesImage at 0x7f85b33f9978>
```

In [ ]:

```
fig = plt.figure(figsize = (15, 7.2))
ax = fig.add_subplot(1, 1, 1)
plt.axis('off')
plt.imshow(pred_mask, alpha = 1)
```

Out[ ]:

```
<matplotlib.image.AxesImage at 0x7f85b33f1320>
```

In [ ]:

```
fig = plt.figure(figsize = (10, 7))
ax = fig.add_subplot(1, 1, 1)
plt.axis('off')
plt.imshow(X_test[n])
plt.savefig('image1.jpg', bbox_inches = 'tight', pad_inches = 0)
```

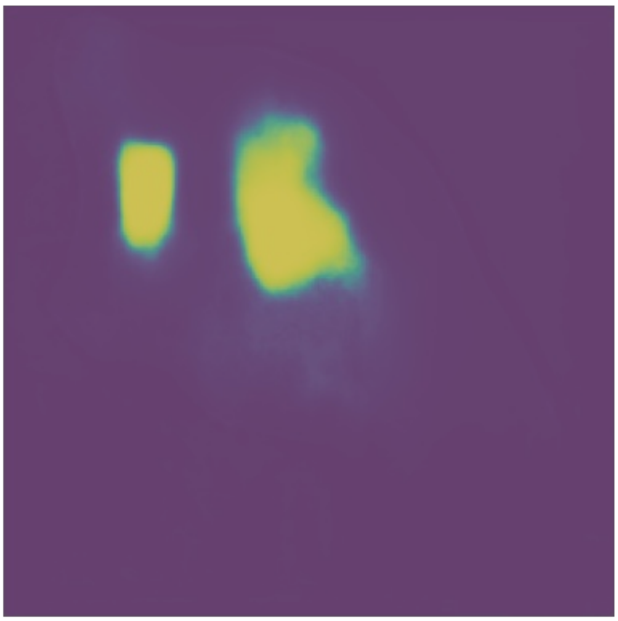
```
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for
integers).
```

Imposing the mask on the test image

- In imshow using the alpha parameter and setting it to greater than 0.5

In [ ]:

```
fig = plt.figure(figsize = (10, 7))
ax = fig.add_subplot(1, 1, 1)
plt.axis('off')
plt.imshow(y_pred[n], alpha = 0.75)
plt.savefig('mask1.jpg', bbox_inches = 'tight', pad_inches = 0)
```



In [ ]:

```
from google.colab.patches import cv2_imshow
img = cv2.imread('image1.jpg', 1)
mask = cv2.imread('mask1.jpg', 1)
img = cv2.add(img, mask)
cv2_imshow(img)
```