ds-classificationmulticlasswithvgg

March 31, 2024

[ ]:
```
import os
import xml.etree.ElementTree as ET
from natsort import natsorted
import pandas as pd
from PIL import Image
import numpy as np
import requests
from zipfile import ZipFile
from io import BytesIO
import cv2
import matplotlib.pyplot as plt
import tensorflow as tf
import math
import random
from six.moves import xrange
import collections
import string
```

[ ]:
```
def download_dataset(save_path):
    r = requests.get("http://cimalab.intec.co/applications/thyroid/thyroid.zip")
    print("Downloading...")
    z = ZipFile(BytesIO(r.content))
    z.extractall(save_path)
    print("Completed...")

# XML and Jpeg
def to_dataframe(path):
    dirs=natsorted(os.listdir(path))
    xml_list=[]
    img_list=[]
    for i in range(len(dirs)):
        if '.xml' in dirs[i]:
            xml_list.append(dirs[i])
        if not '.xml'  in dirs[i]:
            img_list.append(dirs[i])
    xml_list=natsorted(xml_list)
    img_list=natsorted(img_list)
```

```python
    tirads=[]
    for j in range(len(xml_list)):
        tree = ET.parse(path+'/'+xml_list[j])
        a=tree.findall("./tirads")
        if a[-1].text!=None:
            case=[xml_list[j],a[-1].text]
            tirads.append(case)
    data=[]
    for k in range(len(tirads)):
        xml=tirads[k][0][:-4]
        for z in range(len(img_list)):
            if xml+'_1.jpg'==img_list[z] or xml+'_2.jpg'==img_list[z] or␣
↪xml+'_3.jpg'==img_list[z]:
                m=[img_list[z],tirads[k][1]]
                data.append(m)

    df = pd.DataFrame(data,columns =['Jpeg_Name', 'Tirads'])
    return df

#Cropp Function
def croping(img,x, y, w, h):
    if abs(w)<abs(h):
        img2=np.zeros([h,h])
        img2[:,h-w:h]=img[y:y+h, x:x+w]
    if abs(h)<abs(w):
        img2=np.zeros([w,w])
        img2[w-h:w,:]=img[y:y+h, x:x+w]
    else:
        return img
    return img2

def convert_one_channel(img):
    #if some images have 3 channels , although they are grayscale image
    if len(img.shape)>2:
        img=img[:,:,0]
        return img
    else:
        return img

#Remove Fill area from Image and Resizeing
def crop_resize(path,resize_shape):
    img=plt.imread(path)
    img=convert_one_channel(np.asarray(img))
    kernel =( np.ones((5,5), dtype=np.float32))
    ret,thresh = cv2.threshold(img, 0, 255, cv2.THRESH_BINARY)
    thresh = thresh.astype(np.uint8)
    a1,b1=thresh.shape
```

```
    thresh=cv2.morphologyEx(thresh, cv2.MORPH_OPEN, kernel,iterations=3 )
    thresh=cv2.erode(thresh,kernel,iterations =5)
    contours, hierarchy = cv2.findContours(thresh.copy(), cv2.RETR_TREE, cv2.
 ↪CHAIN_APPROX_SIMPLE)
    c_area=np.zeros([len(contours)])
    for i in range(len(contours)):
        c_area[i]= cv2.contourArea(contours[i])
    cnts=contours[np.argmax(c_area)]
    x, y, w, h = cv2.boundingRect(cnts)
    roi = croping(img, x, y, w, h)
    roi=cv2.resize(roi,(resize_shape),interpolation=cv2.INTER_LANCZOS4)
    return roi


# TO Data Matrix
def to_imgmatrix(resize_shape,path,df):
    path=path+'/'
    images=crop_resize(path+df["Jpeg_Name"][0],resize_shape)
    for i in range (1,len(df["Jpeg_Name"])):
        img=crop_resize(path+df["Jpeg_Name"][i],resize_shape)
        images=np.concatenate((images,img))
    images=np.
 ↪reshape(images,(len(df["Jpeg_Name"]),resize_shape[0],resize_shape[1],1))
    return images

def prepare_data(path,resize_shape):
    df=to_dataframe(path)
    data=to_imgmatrix(resize_shape,path,df)
    return df,data


# We need numeric category
def to_categoricalmatrix(df):
    #There are little categories, so i handled manually
    Y=np.zeros([len(df["Tirads"])])
    for i in range(len(df["Tirads"])):
        if df["Tirads"][i]=="2":
          Y[i]=0
        if df["Tirads"][i]=="3":
          Y[i]=1
        if df["Tirads"][i]=="4a":
          Y[i]=2
        if df["Tirads"][i]=="4b":
          Y[i]=3
        if df["Tirads"][i]=="4c":
          Y[i]=4
        if df["Tirads"][i]=="5":
```

```
            Y[i]=5
    return Y
```

[ ]:
```
download_dataset("/content/Data")
```

```
Downloading…
Completed…
```

[ ]:
```
df,data=prepare_data("/content/Data",(256,256))
```

[ ]:
```
df.head()
```

[ ]:

	Jpeg_Name	Tirads
0	2_1.jpg	2
1	3_1.jpg	4a
2	4_1.jpg	4a
3	5_1.jpg	5
4	6_1.jpg	4b

[ ]:
```
# to integer
y=to_categoricalmatrix(df)
y=tf.keras.utils.to_categorical(y, dtype='float32')
```

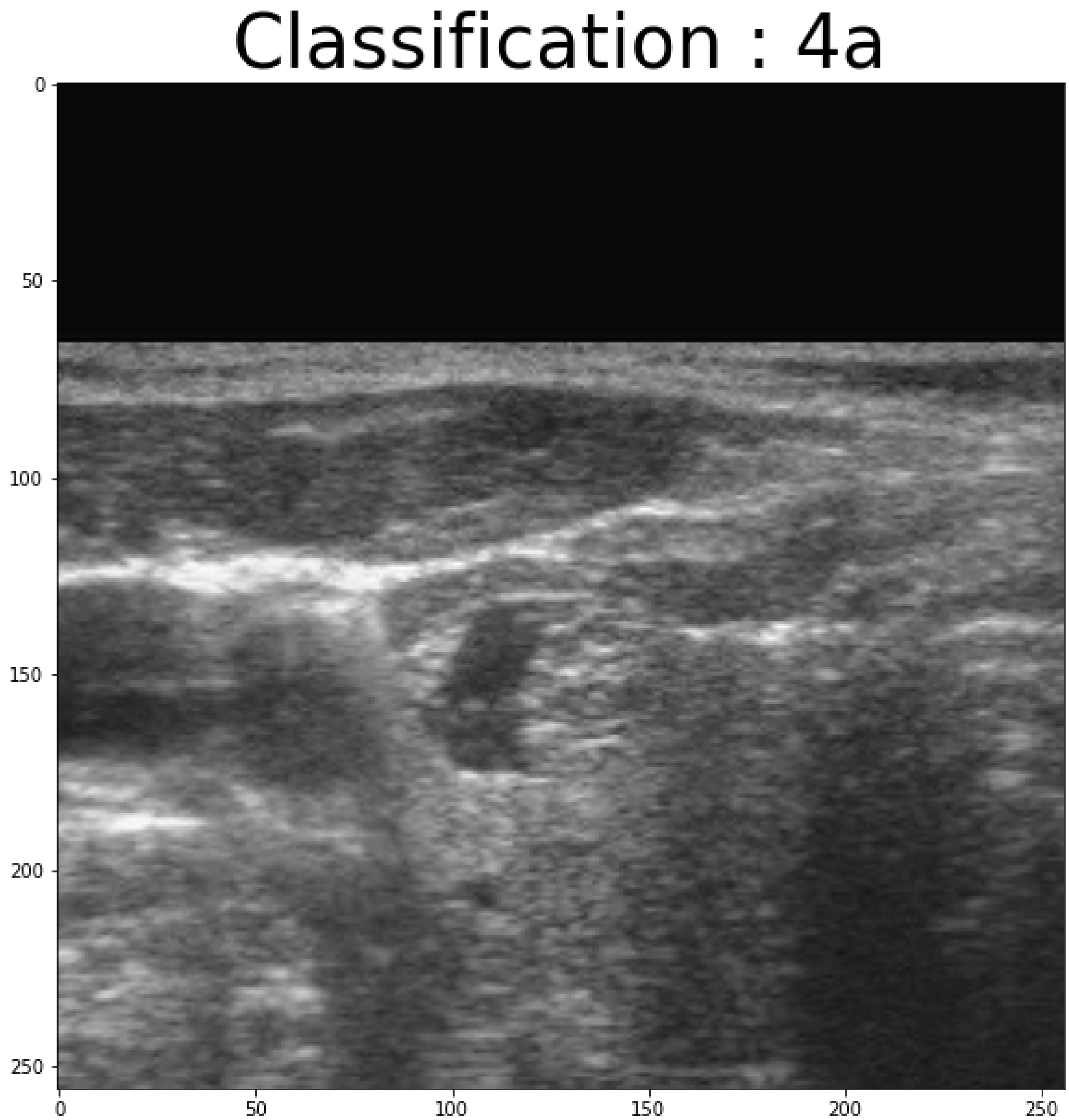
[ ]:
```
#normalize function
def normalize(data):
  for i in range(len(data)):
    data[i,:,:,:]=data[i,:,:,:]*(1/np.max(data[i,:,:,:]))
  return np.float32(data)

# we need noormalize to images
x=normalize(data)
```

[ ]:
```
random_number2=random. randint(0,len(df["Tirads"]))
plt.figure(figsize = (20,10))
tit2="Classification : "+np.str(df["Tirads"][random_number2])
plt.title(tit2,fontsize = 40)
plt.imshow(x[random_number2,:,:,0],cmap="gray")
```

[ ]:
```
<matplotlib.image.AxesImage at 0x7f2428131710>
```


```
[ ]: import random
     random_number=random. randint(0,len(df["Tirads"]))
     plt.figure(figsize = (20,10))
     tit="Classification : "+np.str(df["Tirads"][random_number])
     plt.title(tit,fontsize = 40)
     plt.imshow(x[random_number,:,:,0],cmap="gray")
```

```
[ ]: <matplotlib.image.AxesImage at 0x7f241a618fd0>
```




```
[ ]: #Splitting test and train
     x_train=np.copy(x[:300,:,:,:])
     x_test=np.copy(x[313:,:,:,:])
     x_valid=np.copy(x[300:313,:,:,:])

     y_train=np.copy(y[:300,:])
     y_valid=np.copy(y[300:313,:])
     y_test=np.copy(y[313:,:])
```

```
[ ]: from tensorflow.keras import layers
     #Data Augmention for to prevent Overfitting and to improve accuracy
```

```
data_augmentation1 = tf.keras.Sequential([
 layers.experimental.preprocessing.RandomFlip(
    "horizontal"),
layers.experimental.preprocessing.RandomZoom(height_factor=(-0.2, 0.
 ↪2),fill_mode="constant"),
layers.experimental.preprocessing.RandomRotation(factor=(-0.2, 0.
 ↪2),fill_mode="constant"),
tf.keras.layers.experimental.preprocessing.RandomContrast(0.1)])

x_train1=data_augmentation1(x_train)
y_train1=np.copy(y_train)
i=1

#22
while(i<22):
  x_aug=data_augmentation1(x)
  x_train1=np.concatenate((x_train1,x_aug),axis=0)
  y_aug=np.copy(y)
  y_train1=np.concatenate((y_train1,y_aug))

  #20
  if i == 20:
    break
  i += 1
```

[ ]:
```
#Efficient Net Model based https://github.com/SerdarHelli/TensorflowWorks
CONV_KERNEL_INITIALIZER = {
    'class_name': 'VarianceScaling',
    'config': {
        'scale': 2.0,
        'mode': 'fan_out',
        'distribution': 'normal'
    }
}
BlockArgs = collections.namedtuple('BlockArgs', [
    'kernel_size', 'num_repeat', 'input_filters', 'output_filters',
    'expand_ratio', 'id_skip', 'strides', 'se_ratio'
])

BlockArgs.__new__.__defaults__ = (None,) * len(BlockArgs._fields)

DEFAULT_BLOCKS_ARGS = [
    BlockArgs(kernel_size=3, num_repeat=1, input_filters=32, output_filters=16,
              expand_ratio=1, id_skip=True, strides=[1, 1], se_ratio=0.25),
    BlockArgs(kernel_size=3, num_repeat=2, input_filters=16, output_filters=24,
              expand_ratio=6, id_skip=True, strides=[2, 2], se_ratio=0.25),
    BlockArgs(kernel_size=5, num_repeat=2, input_filters=24, output_filters=40,
```

```
            expand_ratio=6, id_skip=True, strides=[2, 2], se_ratio=0.25),
    BlockArgs(kernel_size=3, num_repeat=3, input_filters=40, output_filters=80,
            expand_ratio=6, id_skip=True, strides=[2, 2], se_ratio=0.25),
    BlockArgs(kernel_size=5, num_repeat=3, input_filters=80, output_filters=112,
            expand_ratio=6, id_skip=True, strides=[1, 1], se_ratio=0.25),
    BlockArgs(kernel_size=5, num_repeat=4, input_filters=112,␣
 ↪output_filters=192,
            expand_ratio=6, id_skip=True, strides=[2, 2], se_ratio=0.25),
    BlockArgs(kernel_size=3, num_repeat=1, input_filters=192,␣
 ↪output_filters=320,
            expand_ratio=6, id_skip=True, strides=[1, 1], se_ratio=0.25)
]

## Our MB_CONV_Block
def mb_conv_block(inputs,block_args,drop_rate):
  ##Mobile Inverted Residual block along with Squeeze  and Excitation block.
    kernel_size = block_args.kernel_size
    num_repeat= block_args.num_repeat
    input_filters= block_args.input_filters
    output_filters=block_args. output_filters
    expand_ratio= block_args.expand_ratio
    id_skip= block_args.id_skip
    strides= block_args.strides
    se_ratio= block_args.se_ratio
    # expansion phase
    expanded_filters = input_filters * expand_ratio
    x=tf.keras.layers.Conv2D(filters=expanded_filters, kernel_size=(1,1),␣
 ↪padding="same",use_bias=False,kernel_initializer=CONV_KERNEL_INITIALIZER,)(inputs)
    x=tf.keras.layers.BatchNormalization()(x)
    x=tf.keras.activations.swish(x)
    # Depthwise convolution phase
    x_depth=tf.keras.layers.DepthwiseConv2D(kernel_size=kernel_size,␣
 ↪padding="same",strides=strides,␣
 ↪use_bias=False,kernel_initializer=CONV_KERNEL_INITIALIZER,)(x)
    x=tf.keras.layers.BatchNormalization()(x_depth)
    x=tf.keras.activations.swish(x)
    #SE Block
    x =tf.keras.layers.GlobalAveragePooling2D()(x)
    x = tf.keras.layers.Reshape((1,1, expanded_filters ))(x)
    squeezed_filters = max (1, int(input_filters * se_ratio))
    x=tf.keras.layers.Conv2D(filters=squeezed_filters,␣
 ↪kernel_size=(1,1),padding="same",kernel_initializer=CONV_KERNEL_INITIALIZER,)(x)
    x=tf.keras.activations.swish(x)
    x=tf.keras.layers.Conv2D(filters=expanded_filters,␣
 ↪kernel_size=(1,1),padding="same",kernel_initializer=CONV_KERNEL_INITIALIZER,)(x)
    x=tf.keras.activations.sigmoid(x)
```

```
    x=tf.keras.layers.Multiply()([x_depth,x])
    #SE Block
    x=tf.keras.layers.Conv2D(filters=output_filters,␣
 ↪kernel_size=(1,1),padding="same",use_bias=False,kernel_initializer=CONV_KERNEL_INITIALIZER,
    x=tf.keras.layers.BatchNormalization()(x)
    x=tf.keras.layers.Dropout(drop_rate)(x)
    if id_skip and all( s == 1 for s in strides) and input_filters ==␣
 ↪output_filters:
      x=tf.keras.layers.Add()([inputs,x])
    return x

def round_filters(filters, width_coefficient, depth_divisor):
    """Round number of filters based on width multiplier."""
    filters *= width_coefficient
    new_filters = int(filters + depth_divisor / 2) // depth_divisor *␣
 ↪depth_divisor
    new_filters = max(depth_divisor, new_filters)
    # Make sure that round down does not go down by more than 10%.
    if new_filters < 0.9 * filters:
        new_filters += depth_divisor
    return int(new_filters)


def round_repeats(repeats, depth_coefficient):
    """Round number of repeats based on depth multiplier."""
    return int(math.ceil(depth_coefficient * repeats))

def EfficientNet(width_coefficient,
                 depth_coefficient,
                 default_resolution,
                 dropout_rate=0.2,
                 drop_connect_rate=0.2,
                 depth_divisor=8,
                 model_name='efficientnet',
                 weights='imagenet',
                 input_shape=None,
                 blocks_args=DEFAULT_BLOCKS_ARGS,
                 **kwargs):


  #### Stem
  inputs = tf.keras.layers.Input(shape=(input_shape))
  x = tf.keras.layers.Conv2D(round_filters(32, width_coefficient,␣
 ↪depth_divisor), 3,
                      strides=(2, 2),
                      padding='same',
                      use_bias=False,
```

```
                  ␣
↪name='stem_conv',kernel_initializer=CONV_KERNEL_INITIALIZER,)(inputs)
 x = tf.keras.layers.BatchNormalization( name='stem_bn')(x)
 x=tf.keras.activations.swish(x)
 num_blocks_total = sum(block_args.num_repeat for block_args in blocks_args)
 block_num = 0
 for idx, block_args in enumerate(blocks_args):
     assert block_args.num_repeat > 0
     # Update block input and output filters based on depth multiplier.
     block_args = block_args._replace(
         input_filters=round_filters(block_args.input_filters,
                                     width_coefficient, depth_divisor),
         output_filters=round_filters(block_args.output_filters,
                                      width_coefficient, depth_divisor),
         num_repeat=round_repeats(block_args.num_repeat, depth_coefficient))

     # The first block needs to take care of stride and filter size increase.
     drop_rate = drop_connect_rate * float(block_num) / num_blocks_total
     x = mb_conv_block(x, block_args,
                       drop_rate=drop_rate)
     block_num += 1
     if block_args.num_repeat > 1:
         # pylint: disable=protected-access
         block_args = block_args._replace(
             input_filters=block_args.output_filters, strides=(1, 1))
         # pylint: enable=protected-access
         for bidx in xrange(block_args.num_repeat - 1):
             drop_rate = drop_connect_rate * float(block_num) /␣
↪num_blocks_total
             block_prefix = 'block{}{}_'.format(
                 idx + 1,
                 string.ascii_lowercase[bidx + 1]
             )
             x = mb_conv_block(x, block_args,
                               drop_rate=drop_rate)
             block_num += 1
 x = tf.keras.layers.Conv2D(round_filters(1280, width_coefficient,␣
↪depth_divisor), 1,
                    padding='same',
                    use_bias=False,
                  ␣
↪name='top_conv',kernel_initializer=CONV_KERNEL_INITIALIZER,)(x)
 x = tf.keras.layers.BatchNormalization(name='top_bn')(x)
 x=tf.keras.activations.swish(x)
 return tf.keras.Model(inputs, x, name=model_name)
```

```
def EfficientNetB0(
        input_tensor=None,
        input_shape=None,
        **kwargs
):
    return EfficientNet(
        1.0, 1.0, 224, 0.2,
        model_name='efficientnet-b0',
        input_tensor=input_tensor, input_shape=input_shape,
        **kwargs
    )


def EfficientNetB1(
        input_tensor=None,
        input_shape=None,
        **kwargs
        ):
    return EfficientNet(
        1.0, 1.1, 240, 0.2,
        model_name='efficientnet-b1',
        input_tensor=input_tensor, input_shape=input_shape,
        **kwargs
    )


def EfficientNetB2(
                   input_tensor=None,
                   input_shape=None,
                   **kwargs
                   ):
    return EfficientNet(
        1.1, 1.2, 260, 0.3,
        model_name='efficientnet-b2',
        input_tensor=input_tensor, input_shape=input_shape,
        **kwargs
    )


def EfficientNetB3(
                   input_tensor=None,
                   input_shape=None,**kwargs
                   ):
    return EfficientNet(
        1.2, 1.4, 300, 0.3,
```

```
        model_name='efficientnet-b3',
        input_tensor=input_tensor, input_shape=input_shape,
        **kwargs
    )


def EfficientNetB4(
        input_tensor=None,
        input_shape=None,
        **kwargs
        ):
    return EfficientNet(
        1.4, 1.8, 380, 0.4,
        model_name='efficientnet-b4',
        input_tensor=input_tensor, input_shape=input_shape,
        **kwargs
    )


def EfficientNetB5(
        input_tensor=None,
        input_shape=None,
        **kwargs
        ):
    return EfficientNet(
        1.6, 2.2, 456, 0.4,
        model_name='efficient3dnet-b5',
        input_tensor=input_tensor, input_shape=input_shape,
        **kwargs
    )

def EfficientNetB6(
        input_tensor=None,
        input_shape=None,
        **kwargs
        ):
    return EfficientNet(
        1.8, 2.6, 528, 0.5,
        model_name='efficientnet-b6',
        input_tensor=input_tensor, input_shape=input_shape,

        **kwargs
    )


def EfficientNetB7(
        input_tensor=None,
```

```
        input_shape=None,
        **kwargs
        ):
    return EfficientNet(
        2.0, 3.1, 600, 0.5,
        model_name='efficientnet-b7',
        input_tensor=input_tensor, input_shape=input_shape,
        **kwargs
    )

def EfficientNetL2(
        input_tensor=None,
        input_shape=None,
        **kwargs
        ):
    return EfficientNet(
        4.3, 5.3, 800, 0.5,
        model_name='efficientnet-l2',
        input_tensor=input_tensor, input_shape=input_shape,
        **kwargs
    )
```

[ ]:
```
def VGG19(input_shape,filters):
    inputs=tf.keras.layers.Input(shape=input_shape)

    x = tf.keras.layers.Conv2D(filters//16,(3,3), activation = 'relu', padding␣
 ↪= 'same', kernel_initializer = 'he_normal')(inputs)
    x=tf.keras.layers.Dropout(0.1)(x)
    x = tf.keras.layers.Conv2D(filters//16,(3,3), activation = 'relu', padding␣
 ↪= 'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.BatchNormalization()(x)



    x = tf.keras.layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = tf.keras.layers.Conv2D(filters//8,(3,3), activation = 'relu', padding =␣
 ↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.Dropout(0.2)(x)
    x = tf.keras.layers.Conv2D(filters//8,(3,3), activation = 'relu', padding =␣
 ↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.BatchNormalization()(x)

    x = tf.keras.layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = tf.keras.layers.Conv2D(filters//4,(3,3), activation = 'relu', padding =␣
 ↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.Dropout(0.3)(x)
```

```
    x = tf.keras.layers.Conv2D(filters//4,(3,3), activation = 'relu', padding =␣
↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.BatchNormalization()(x)
    x = tf.keras.layers.Conv2D(filters//4,(3,3), activation = 'relu', padding =␣
↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.BatchNormalization()(x)

    x = tf.keras.layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = tf.keras.layers.Conv2D(filters//2,(3,3), activation = 'relu', padding =␣
↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.Dropout(0.4)(x)
    x = tf.keras.layers.Conv2D(filters//2,(3,3), activation = 'relu', padding =␣
↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.BatchNormalization()(x)
    x = tf.keras.layers.Conv2D(filters//2,(3,3), activation = 'relu', padding =␣
↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.BatchNormalization()(x)

    x = tf.keras.layers.MaxPooling2D(pool_size=(2, 2))(x)
    x = tf.keras.layers.Conv2D(filters,(3,3),activation = 'relu', padding =␣
↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.Dropout(0.5)(x)
    x = tf.keras.layers.Conv2D(filters,(3,3), activation = 'relu', padding =␣
↪'same', kernel_initializer = 'he_normal')(x)
    x=tf.keras.layers.BatchNormalization()(x)
    last = tf.keras.layers.Conv2D(filters,(3,3), activation = 'relu', padding =␣
↪'same', kernel_initializer = 'he_normal',name='top_conv')(x)

    model=tf.keras.Model(inputs,last,name="VGG19")
    return model
```

[ ]:

```
#Unbalanced Data
def check_balance(y):
  malign=0
  benign=0
  for i in range(len(y)):
    if y[i]<2:
      benign=benign+1
    else :
      malign=malign+1
  print("Maling Count :" , malign)
  print("Benign Count :" , benign)
  return malign,benign
```

Unbalanced Data

[ ]:
```
base_model=VGG19(input_shape=(256,256,1),filters=512)
x = base_model.output
f=tf.keras.layers.Flatten(name="flatten")(x)
#To prevent overfitting and unbalancing , used regularizer
d2=tf.keras.layers.Dense(1024,activation="relu",kernel_regularizer=tf.keras.
 ↪regularizers.l1_l2(0.00001))(f)
dp9=tf.keras.layers.Dropout(0.5)(d2)
d3=tf.keras.layers.Dense(1024,activation="relu")(f)
dp10=tf.keras.layers.Dropout(0.5)(d2)

final=tf.keras.layers.Dense(6,activation="softmax")(dp10)
model = tf.keras.Model( inputs =[ base_model.input], outputs = final)
```

[ ]:
```
model.summary()
```

```
Model: "model"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 256, 256, 1)]     0
_________________________________________________________________
conv2d (Conv2D)              (None, 256, 256, 32)      320
_________________________________________________________________
dropout (Dropout)            (None, 256, 256, 32)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 256, 256, 32)      9248
_________________________________________________________________
batch_normalization (BatchNo (None, 256, 256, 32)      128
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 128, 128, 32)      0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 128, 128, 64)      18496
_________________________________________________________________
dropout_1 (Dropout)          (None, 128, 128, 64)      0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 128, 128, 64)      36928
_________________________________________________________________
batch_normalization_1 (Batch (None, 128, 128, 64)      256
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 64, 64, 64)        0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 64, 64, 128)       73856
_________________________________________________________________
dropout_2 (Dropout)          (None, 64, 64, 128)       0
_________________________________________________________________
conv2d_5 (Conv2D)            (None, 64, 64, 128)       147584
_________________________________________________________________
```

```
batch_normalization_2 (Batch (None, 64, 64, 128)       512
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 64, 64, 128)       147584
_________________________________________________________________
batch_normalization_3 (Batch (None, 64, 64, 128)       512
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 32, 32, 128)       0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 32, 32, 256)       295168
_________________________________________________________________
dropout_3 (Dropout)          (None, 32, 32, 256)       0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 32, 32, 256)       590080
_________________________________________________________________
batch_normalization_4 (Batch (None, 32, 32, 256)       1024
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 32, 32, 256)       590080
_________________________________________________________________
batch_normalization_5 (Batch (None, 32, 32, 256)       1024
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 16, 16, 256)       0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 16, 16, 512)       1180160
_________________________________________________________________
dropout_4 (Dropout)          (None, 16, 16, 512)       0
_________________________________________________________________
conv2d_11 (Conv2D)           (None, 16, 16, 512)       2359808
_________________________________________________________________
batch_normalization_6 (Batch (None, 16, 16, 512)       2048
_________________________________________________________________
top_conv (Conv2D)            (None, 16, 16, 512)       2359808
_________________________________________________________________
flatten (Flatten)            (None, 131072)            0
_________________________________________________________________
dense (Dense)                (None, 1024)              134218752
_________________________________________________________________
dropout_6 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_2 (Dense)              (None, 6)                 6150
=================================================================
Total params: 142,039,526
Trainable params: 142,036,774
Non-trainable params: 2,752
_________________________________________________________________
```

[ ]:
```
metrics=tf.keras.metrics.AUC(
    num_thresholds=200, curve='ROC',
```

```
    summation_method='interpolation'
)
#categorical_crossentropy
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=0.0001),␣
 ↪loss="categorical_crossentropy",metrics=metrics)


def lr_scheduler(epoch, lr):
    decay_rate = 0.1
    decay_step = 15
    if epoch % decay_step == 0 and epoch:
        return lr * decay_rate
    return lr

#after each 15 epochs , we want to decrease learning rate for converge to model
lr_call = tf.keras.callbacks.LearningRateScheduler(lr_scheduler)
epochs=35
history=model.
 ↪fit(x=[x_train1],y=[y_train1],batch_size=16,epochs=epochs,callbacks=[lr_call],validation_da
```

```
Epoch 1/35
453/453 [==============================] - 56s 114ms/step - loss: 15.5637 - auc:
0.5971 - val_loss: 9.2236 - val_auc: 0.3775
Epoch 2/35
453/453 [==============================] - 50s 111ms/step - loss: 6.3037 - auc:
0.6218 - val_loss: 4.8171 - val_auc: 0.3923
Epoch 3/35
453/453 [==============================] - 50s 111ms/step - loss: 3.7635 - auc:
0.6219 - val_loss: 3.4027 - val_auc: 0.3917
Epoch 4/35
453/453 [==============================] - 50s 111ms/step - loss: 2.8409 - auc:
0.6193 - val_loss: 2.7490 - val_auc: 0.3840
Epoch 5/35
453/453 [==============================] - 50s 111ms/step - loss: 2.3876 - auc:
0.6234 - val_loss: 2.4099 - val_auc: 0.4538
Epoch 6/35
453/453 [==============================] - 50s 111ms/step - loss: 2.0809 - auc:
0.6375 - val_loss: 2.1043 - val_auc: 0.4379
Epoch 7/35
453/453 [==============================] - 50s 110ms/step - loss: 1.8727 - auc:
0.6501 - val_loss: 2.0398 - val_auc: 0.4444
Epoch 8/35
453/453 [==============================] - 50s 110ms/step - loss: 1.8115 - auc:
0.6595 - val_loss: 2.0547 - val_auc: 0.3763
Epoch 9/35
453/453 [==============================] - 50s 111ms/step - loss: 1.7994 - auc:
0.6675 - val_loss: 2.0574 - val_auc: 0.3870
```

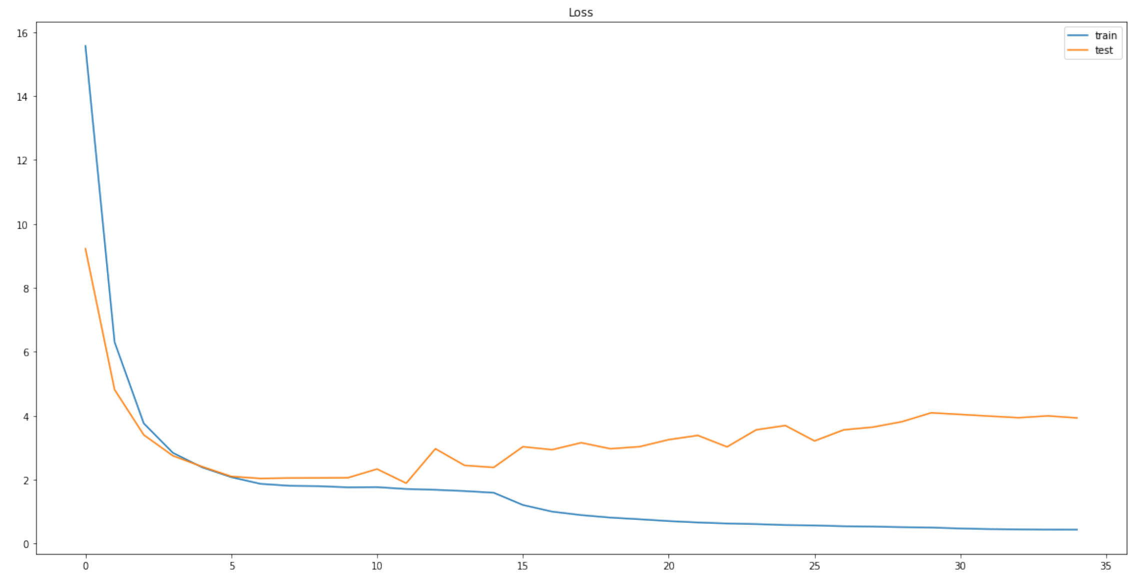
```
Epoch 10/35
453/453 [==============================] - 50s 110ms/step - loss: 1.7626 - auc:
0.6806 - val_loss: 2.0618 - val_auc: 0.4272
Epoch 11/35
453/453 [==============================] - 50s 111ms/step - loss: 1.7688 - auc:
0.7088 - val_loss: 2.3343 - val_auc: 0.4686
Epoch 12/35
453/453 [==============================] - 50s 110ms/step - loss: 1.7108 - auc:
0.7526 - val_loss: 1.8921 - val_auc: 0.6692
Epoch 13/35
453/453 [==============================] - 50s 110ms/step - loss: 1.6859 - auc:
0.8031 - val_loss: 2.9689 - val_auc: 0.5799
Epoch 14/35
453/453 [==============================] - 50s 110ms/step - loss: 1.6464 - auc:
0.8514 - val_loss: 2.4487 - val_auc: 0.7047
Epoch 15/35
453/453 [==============================] - 50s 110ms/step - loss: 1.5935 - auc:
0.8992 - val_loss: 2.3850 - val_auc: 0.8036
Epoch 16/35
453/453 [==============================] - 50s 110ms/step - loss: 1.2110 - auc:
0.9584 - val_loss: 3.0322 - val_auc: 0.7237
Epoch 17/35
453/453 [==============================] - 50s 110ms/step - loss: 1.0035 - auc:
0.9751 - val_loss: 2.9390 - val_auc: 0.7243
Epoch 18/35
453/453 [==============================] - 50s 110ms/step - loss: 0.8945 - auc:
0.9838 - val_loss: 3.1573 - val_auc: 0.7438
Epoch 19/35
453/453 [==============================] - 50s 110ms/step - loss: 0.8167 - auc:
0.9892 - val_loss: 2.9691 - val_auc: 0.7272
Epoch 20/35
453/453 [==============================] - 50s 110ms/step - loss: 0.7648 - auc:
0.9922 - val_loss: 3.0337 - val_auc: 0.7219
Epoch 21/35
453/453 [==============================] - 50s 110ms/step - loss: 0.7081 - auc:
0.9950 - val_loss: 3.2531 - val_auc: 0.7355
Epoch 22/35
453/453 [==============================] - 50s 110ms/step - loss: 0.6644 - auc:
0.9963 - val_loss: 3.3856 - val_auc: 0.7467
Epoch 23/35
453/453 [==============================] - 50s 110ms/step - loss: 0.6329 - auc:
0.9973 - val_loss: 3.0278 - val_auc: 0.7373
Epoch 24/35
453/453 [==============================] - 50s 110ms/step - loss: 0.6136 - auc:
0.9976 - val_loss: 3.5608 - val_auc: 0.7266
Epoch 25/35
453/453 [==============================] - 50s 110ms/step - loss: 0.5840 - auc:
0.9983 - val_loss: 3.6944 - val_auc: 0.7414
```

```
Epoch 26/35
453/453 [==============================] - 50s 110ms/step - loss: 0.5715 - auc:
0.9984 - val_loss: 3.2131 - val_auc: 0.7467
Epoch 27/35
453/453 [==============================] - 50s 110ms/step - loss: 0.5467 - auc:
0.9988 - val_loss: 3.5597 - val_auc: 0.7237
Epoch 28/35
453/453 [==============================] - 50s 110ms/step - loss: 0.5358 - auc:
0.9987 - val_loss: 3.6446 - val_auc: 0.7213
Epoch 29/35
453/453 [==============================] - 50s 110ms/step - loss: 0.5179 - auc:
0.9991 - val_loss: 3.8151 - val_auc: 0.7320
Epoch 30/35
453/453 [==============================] - 50s 110ms/step - loss: 0.5055 - auc:
0.9991 - val_loss: 4.0924 - val_auc: 0.7391
Epoch 31/35
453/453 [==============================] - 50s 110ms/step - loss: 0.4763 - auc:
0.9996 - val_loss: 4.0410 - val_auc: 0.7349
Epoch 32/35
453/453 [==============================] - 50s 110ms/step - loss: 0.4569 - auc:
0.9997 - val_loss: 3.9889 - val_auc: 0.7325
Epoch 33/35
453/453 [==============================] - 50s 110ms/step - loss: 0.4479 - auc:
0.9997 - val_loss: 3.9388 - val_auc: 0.7349
Epoch 34/35
453/453 [==============================] - 50s 110ms/step - loss: 0.4414 - auc:
0.9998 - val_loss: 3.9967 - val_auc: 0.7361
Epoch 35/35
453/453 [==============================] - 50s 110ms/step - loss: 0.4404 - auc:
0.9996 - val_loss: 3.9325 - val_auc: 0.7337
```

[ ]:
```python
from sklearn.metrics import confusion_matrix
predict=model.predict(x_test)
```

[ ]:
```python
plt.figure(figsize = (20,10))
plt.title('Loss')
plt.plot(history.history['loss'], label='train')
plt.plot(history.history['val_loss'], label='test')
plt.legend()
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f23cc2993d0>
```



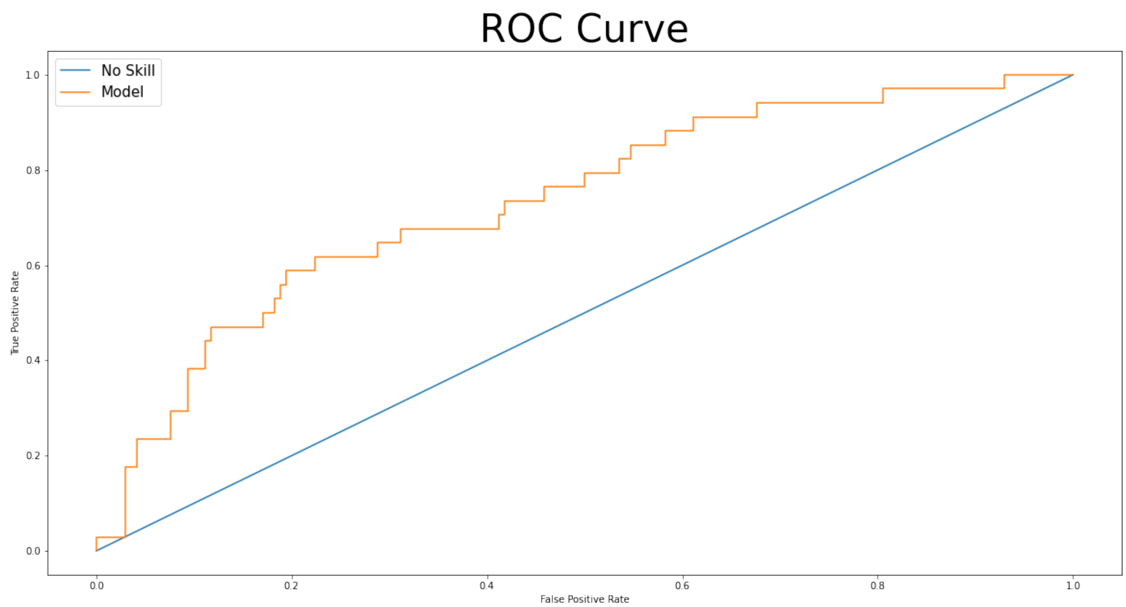

```
[ ]: import sklearn
     from sklearn.metrics import accuracy_score

     auc = sklearn.metrics.roc_auc_score(y_test, predict)
```

```
[ ]: y_test=np.reshape(y_test,(34*6))
     predict=np.reshape(predict,(34*6))
```

```
[ ]: #Actually , the best is cross validation but we have no time
     from sklearn.metrics import roc_curve
     from sklearn.metrics import roc_auc_score

     # keep probabilities for the positive outcome only
     ns_probs = [0 for _ in range(len(y_test))]
     # calculate scores
     ns_auc = roc_auc_score(y_test, ns_probs)
     lr_auc = roc_auc_score(y_test, predict)
     # summarize scores
     print('No Skill: ROC AUC=%.3f' % (ns_auc))
     print('Model: ROC AUC=%.3f' % (lr_auc))
     # calculate roc curves
     ns_fpr, ns_tpr, _ = roc_curve(y_test, ns_probs)
     lr_fpr, lr_tpr, _ = roc_curve(y_test, predict)
     # plot the roc curve for the model
     plt.figure(figsize = (20,10))
     plt.title("ROC Curve",fontsize = 40)
     plt.plot(ns_fpr, ns_tpr,label='No Skill')
     plt.plot(lr_fpr, lr_tpr, label='Model')
```

```
# axis labels
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.rcParams["font.size"] = "15"

# show the legend
plt.legend()
# show the plot
plt.show()
```

```
No Skill: ROC AUC=0.500
Model: ROC AUC=0.734
```



[ ]:
```
#The GradCam observes the results
def make_gradcam_heatmap(img_array, model, last_conv_layer_name,␣
↪classifier_layer_names ):
    # First, we create a model that maps the input image to the activations
    # of the last conv layer
    last_conv_layer = model.get_layer(last_conv_layer_name)
    last_conv_layer_model = keras.Model(model.inputs, last_conv_layer.output)
    # Second, we create a model that maps the activations of the last conv
    # layer to the final class predictions
    classifier_input = keras.Input(shape=last_conv_layer.output.shape[1:])
    x = classifier_input
    for layer_name in classifier_layer_names:
        x = model.get_layer(layer_name)(x)
    classifier_model = keras.Model(classifier_input, x)
```

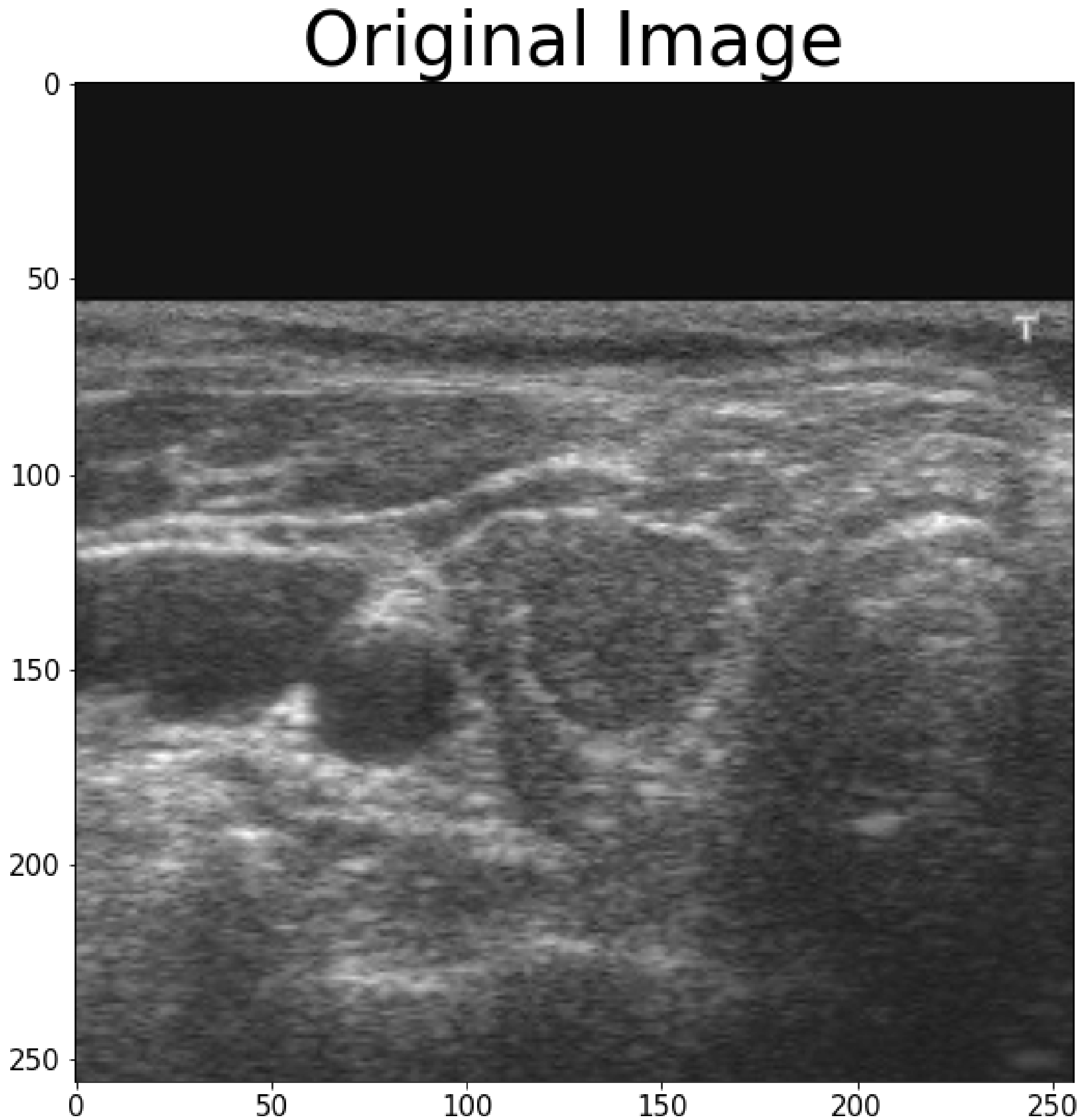
```
    # Then, we compute the gradient of the top predicted class for our input␣
↪image
    # with respect to the activations of the last conv layer
    with tf.GradientTape() as tape:
        # Compute activations of the last conv layer and make the tape watch it
        last_conv_layer_output = last_conv_layer_model(img_array)
        tape.watch(last_conv_layer_output)
        # Compute class predictions
        preds = classifier_model(last_conv_layer_output)
        top_pred_index = tf.argmax(preds[0])
        top_class_channel = preds[:, top_pred_index]
    # This is the gradient of the top predicted class with regard to
    # the output feature map of the last conv layer
    grads = tape.gradient(top_class_channel, last_conv_layer_output)

    # This is a vector where each entry is the mean intensity of the gradient
    # over a specific feature map channel
    pooled_grads = tf.reduce_mean(grads, axis=(0, 1, 2))

    # We multiply each channel in the feature map array
    # by "how important this channel is" with regard to the top predicted class
    last_conv_layer_output = last_conv_layer_output.numpy()[0]
    pooled_grads = pooled_grads.numpy()
    for i in range(pooled_grads.shape[-1]):
        last_conv_layer_output[:, :, i] *= pooled_grads[i]

    # The channel-wise mean of the resulting feature map
    # is our heatmap of class activation
    heatmap = np.mean(last_conv_layer_output, axis=-1)

    # For visualization purpose, we will also normalize the heatmap between 0 &␣
↪1
    heatmap = np.maximum(heatmap, 0) / np.max(heatmap)
    return heatmap
```

[ ]:
```
from tensorflow import keras
img_array=x_test[0,:,:,:]

img_array=np.reshape(img_array,(1,256,256,1))
preds = model.predict(img_array)
last_conv_layer_name = "top_conv"
classifier_layer_names = ["flatten"]

# Generate class activation heatmap
heatmap = make_gradcam_heatmap(
    img_array, model, last_conv_layer_name, classifier_layer_names
)
```

```python
img = keras.preprocessing.image.img_to_array(x_test[0,:,:,:])
import matplotlib.cm as cm
# We rescale heatmap to a range 0-255
heatmap = np.uint8(255 * heatmap)
# We use jet colormap to colorize heatmap
jet = cm.get_cmap("jet")
# We use RGB values of the colormap
jet_colors = jet(np.arange(256))[:, :3]
jet_heatmap = jet_colors[heatmap]
# We create an image with RGB colorized heatmap
jet_heatmap = keras.preprocessing.image.array_to_img(jet_heatmap)
jet_heatmap = jet_heatmap.resize((img.shape[1], img.shape[0]))
jet_heatmap = keras.preprocessing.image.img_to_array(jet_heatmap)
# Superimpose the heatmap on original image
img2=np.zeros([256,256,3])
img2[:,:,0]=img[:,:,0]
superimposed_img = jet_heatmap * 0.0025 + img2
superimposed_img = keras.preprocessing.image.array_to_img(superimposed_img)
superimposed_img=np.uint8(superimposed_img)
```

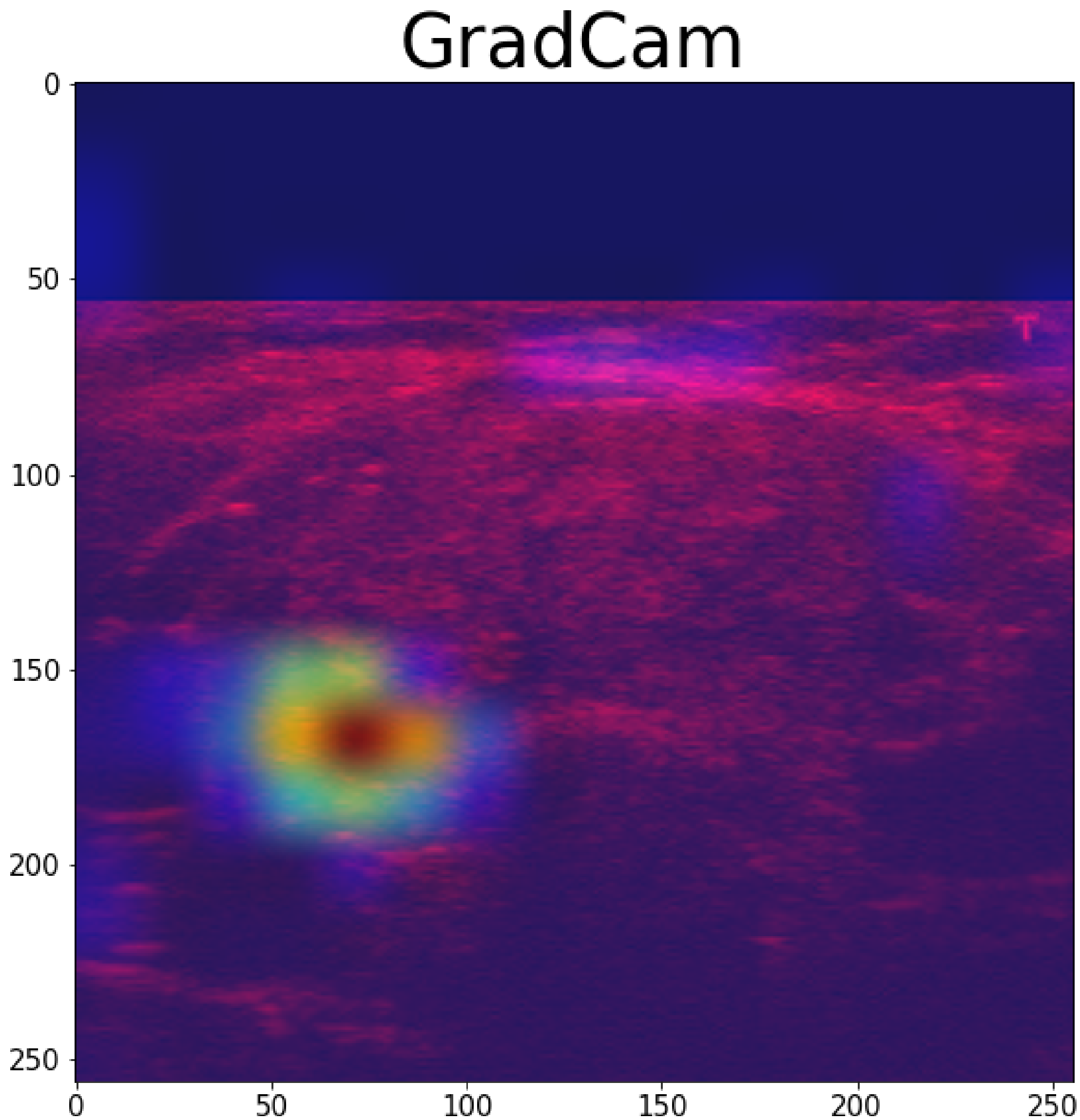
[ ]:
```python
plt.figure(figsize = (20,10))
plt.title("Original Image",fontsize = 40)
plt.imshow(img_array[0,:,:,0],cmap="gray")
```

[ ]: <matplotlib.image.AxesImage at 0x7f214fc354d0>



[ ]:
```
plt.figure(figsize = (20,10))
plt.title("GradCam",fontsize = 40)
plt.imshow(superimposed_img)
```

[ ]: <matplotlib.image.AxesImage at 0x7f214fd54250>


GradCam
0
50
100
150
200
250
0
50
100
150
200
250