# **Pneumonia Detection**

#### Mini Project

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```
In [0]: ## disable future warnings
        import warnings
        warnings.filterwarnings('ignore')
        import numpy as npNortheastern
        import matplotlib.pyplot as plt
        import pydicom
        import pandas as pd
        from glob import glob
        import pylab
        import os
        import seaborn as sns
        from matplotlib.patches import Rectangle
        import csv
        import random
        from skimage import measure
        from skimage.transform import resize
        import tensorflow as tf
        from tensorflow import keras
        from matplotlib import pyplot as plt
        import gc
        from skimage.transform import resize
        from keras.models import Sequential
        from keras.layers import Dense
        from keras.utils.vis_utils import plot_model
        ## input dir
        data dir = os.path.join(os.getcwd() + '/rsna')
        ###Exploratory Data Analysis: EDA
In [4]: ## list all the files in the input folder
        print("\n".join(os.listdir(data_dir)))
        stage_2_train_labels.csv
        stage_2_sample_submission.csv
        stage_2_test_images
        stage_2 train images
        stage_2_detailed_class_info.csv
```

```
GCP Credits Request Link - RSNA.txt

In [0]: ## load and set file/folder variables
    details_class_info_csv = os.path.join(data_dir, 'stage_2_detailed_class_info.csv')
    labeled_boxes_csv = os.path.join(data_dir, 'stage_2_train_labels.csv')
    train_images_folder = os.path.join(data_dir, 'stage_2_train_images')
    test_images = os.path.join(data_dir, 'stage_2_test_images')
```

```
In [7]: ## load the csv's as dataframe
labled_df = pd.read_csv(labeled_boxes_csv)
print("Content of the stage_2_train_labels.csv: \n")
labled_df.head()
```

Content of the stage\_2\_train\_labels.csv:

# Out[7]:

	patientId	Х	У	width	height	Target
0	0004cfab-14fd-4e49-80ba-63a80b6bddd6	NaN	NaN	NaN	NaN	0
1	00313ee0-9eaa-42f4-b0ab-c148ed3241cd	NaN	NaN	NaN	NaN	0
2	00322d4d-1c29-4943-afc9-b6754be640eb	NaN	NaN	NaN	NaN	0
3	003d8fa0-6bf1-40ed-b54c-ac657f8495c5	NaN	NaN	NaN	NaN	0
4	00436515-870c-4b36-a041-de91049b9ab4	264.0	152.0	213.0	379.0	1

```
In [8]:
    class_info_df = pd.read_csv(details_class_info_csv)
    print("\n\n\content of the stage_2_detailed_class_info.csv:\n")
    class_info_df.head()
```

Content of the stage\_2\_detailed\_class\_info.csv:

```
        Out[8]:
        patientId
        class

        0
        0004cfab-14fd-4e49-80ba-63a80b6bddd6
        No Lung Opacity / Not Normal

        1
        00313ee0-9eaa-42f4-b0ab-c148ed3241cd
        No Lung Opacity / Not Normal

        2
        00322d4d-1c29-4943-afc9-b6754be640eb
        No Lung Opacity / Not Normal

        3
        003d8fa0-6bf1-40ed-b54c-ac657f8495c5
        Normal

        4
        00436515-870c-4b36-a041-de91049b9ab4
        Lung Opacity
```

#### **Description of the files:**

```
stage_2_train_labels.csv : training set with patientId and labels
stage_2_sample_submission.csv
stage_2_test_images : folder containing test images
stage_2_train_images : folder containing training images
stage 2 detailed class info.csv : contains more details about the patient and lung opacities
```

```
In [0]: def get_dcm_image(patientId, data_type="train"):
    '''returns the path to the corresponding patientId
    image file path
    '''
    filepath = ''
    if data_type == 'train':
        filepath = os.path.join(data_dir, 'stage_2_train_images/%s.dcm' % patientId)
    else:
        filepath = os.path.join(data_dir, 'stage_2_test_images/%s.dcm' % patientId)
    return filepath
```

View files types, content and format

```
In [10]: | ## viewing the individual image sample given patientId
         def view_individual_patient_image(patientId,
                                            cmap_value=pylab.cm.gist_gray):
            '''Views the individuals patients image
           patientId : patient's id
           dcm_file = get_dcm_image(patientId)
           dcm data = pydicom.read file(dcm file)
           sample img = dcm data.pixel array
           pylab.imshow(sample_img, cmap=cmap_value)
           pylab.axis('off')
         ## view the content of the dcm file
         pid = labled_df['patientId'][4]
         dcm_file = get_dcm_image(pid)
         dcm data = pydicom.read file(dcm file)
         print("dcm_file format for patientId=4\n")
         print(dcm data)
```

#### dcm\_file format for patientId=4

```
(0008, 0005) Specific Character Set
                                                  CS: 'ISO IR 100'
(0008, 0016) SOP Class UID
                                                  UI: Secondary Capture Image Storage
(0008, 0018) SOP Instance UID
                                                  UI: 1.2.276.0.7230010.3.1.4.8323329.6379.1517874325.469569
(0008, 0020) Study Date
                                                 DA: '19010101'
(0008, 0030) Study Time
                                                  TM: '000000.00'
                                                  SH: ''
(0008, 0050) Accession Number
                                                  CS: 'CR'
(0008, 0060) Modality
(0008, 0064) Conversion Type
                                                  CS: 'WSD'
                                                  PN: ''
(0008, 0090) Referring Physician's Name
(0008, 103e) Series Description
                                                  LO: 'view: AP'
(0010, 0010) Patient's Name
                                                  PN: '00436515-870c-4b36-a041-de91049b9ab4'
(0010, 0020) Patient ID
                                                  L0: '00436515-870c-4b36-a041-de91049b9ab4'
                                                 DA: ''
(0010, 0030) Patient's Birth Date
(0010, 0040) Patient's Sex
                                                  CS: 'F'
                                                  AS: '32'
(0010, 1010) Patient's Age
                                                  CS: 'CHEST'
(0018, 0015) Body Part Examined
                                                  CS: 'AP'
(0018, 5101) View Position
(0020, 000d) Study Instance UID
                                                  UI: 1.2.276.0.7230010.3.1.2.8323329.6379.1517874325.469568
(0020, 000e) Series Instance UID
                                                 UI: 1.2.276.0.7230010.3.1.3.8323329.6379.1517874325.469567
(0020, 0010) Study ID
                                                  SH: ''
                                                  IS: "1"
(0020, 0011) Series Number
                                                 IS: "1"
(0020, 0013) Instance Number
                                                 CS: ''
(0020, 0020) Patient Orientation
(0028, 0002) Samples per Pixel
                                                 US: 1
(0028, 0004) Photometric Interpretation
                                                  CS: 'MONOCHROME2'
(0028, 0010) Rows
                                                 US: 1024
                                                 US: 1024
(0028, 0011) Columns
(0028, 0030) Pixel Spacing
                                                 DS: [0.139, 0.139]
(0028, 0100) Bits Allocated
                                                  US: 8
(0028, 0101) Bits Stored
                                                  US: 8
(0028, 0102) High Bit
                                                  US: 7
(0028, 0103) Pixel Representation
                                                  US: 0
(0028, 2110) Lossy Image Compression
                                                  CS: '01'
(0028, 2114) Lossy Image Compression Method
                                                  CS: 'ISO_10918_1'
(7fe0, 0010) Pixel Data
                                                  OB: Array of 119382 elements
```

# View different classes of patient images

It will help us manually guess the what we are trying to classify and what approach we can take.

```
In [27]:
## view image
print("\n\nimage of patientId=4 with class 'Lung Opacity'")
view_individual_patient_image(pid)
```

image of patientId=4 with class 'Lung Opacity'



```
In [319]: print("\n\nimage of patientId=1 with class 'No Lung Opacity / Not Normal'")
  view_individual_patient_image(labled_df['patientId'][1])
```

image of patientId=1 with class 'No Lung Opacity / Not Normal'



```
In [166]: print("\n\nimage of patientId=3 with class 'Normal'")
   view_individual_patient_image(labled_df['patientId'][3])
```

image of patientId=3 with class 'Normal'



In [167]: print("\n\nimage of patientId=2 with class 'No Lung Opacity / Not Normal'")
 view\_individual\_patient\_image(labled\_df['patientId'][2])

image of patientId=2 with class 'No Lung Opacity / Not Normal'



```
In [214]: print("patient with heart condition")
    print("\n\nimage of patientId=38 with class 'No Lung Opacity / Not Normal'")
    view_individual_patient_image(labled_df['patientId'][38])
```

image of patientId=38 with class 'No Lung Opacity / Not Normal'



```
In [222]: ## missing half lung
pid_missing = box_df.loc[box_df['patientId'] == "924f4f8b-fc27-4dfd-b5ae-59c40715e150"]
print(pid_missing)
view_individual_patient_image(labled_df['patientId'][14879])
```

```
patientId x y width height \
14879 924f4f8b-fc27-4dfd-b5ae-59c40715e150 85.0 215.0 378.0 681.0

Target
14879 1
```



#### **Check missing values**

```
In [241]: def missing_data(data):
    '''
    total = data.isnull().sum().sort_values(ascending = False)
    percent = (data.isnull().sum()/data.isnull().count()*100).sort_values(ascending = False)
    return np.transpose(pd.concat([total, percent], axis=1, keys=['Total', 'Percent']))

## check for missing data 'stage_2_train_labels'
missing_data(labled_df)
```

# Out[241]: height width y x Target patientId Total 20672.000000 20672.000000 20672.000000 20672.000000 0.0 0.0 Percent 68.389188 68.389188 68.389188 68.389188 0.0 0.0

```
In [242]: ## check for missing data in stage_2_detailed_class_info
missing_data(class_info_df)
```

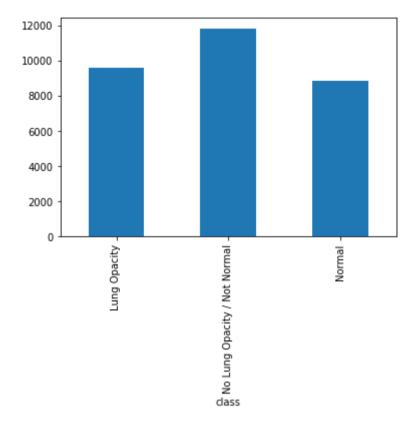
Out[242]:		class	patientId
	Total	0.0	0.0
	Percent	0.0	0.0

#### Shape of the data

```
In [12]: ## view the dimensions, counts
print("Shape of stage_2_detailed_class_info.csv : {0}".format(class_info_df.shape))
print("Unique values : {0}\n\n".format(class_info_df['patientId'].value_counts().shape[0]))
## plot the distribution of classes
class_info_df.groupby('class').size().plot.bar()
```

Shape of stage\_2\_detailed\_class\_info.csv : (30227, 2) Unique values : 26684

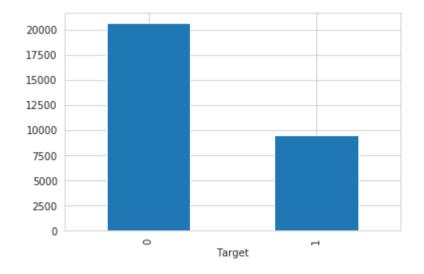
#### Out[12]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f3002be0190>



```
In [252]:
    print("Shape of stage_2_train_labels.csv : {0}".format(labled_df.shape))
    print("Unique values : {0}\n\n".format(labled_df['patientId'].value_counts().shape[0]))
    ## plot the distribution of classes
    labled_df.groupby('Target').size().plot.bar()
```

Shape of stage\_2\_train\_labels.csv.csv : (30227, 6) Unique values : 26684

Out[252]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7fe58bff4410>



```
In [54]: ## train
print("Total image files in 'stage_2_train_images' : {0}".format(len(os.listdir(train_images_folder))))
```

Total image files in 'stage\_2\_train\_images' : 26684

Total no. of image files in 'stage\_2\_train\_images': 26684

Total no. of records in 'stage\_2\_train\_labels.csv': 26684

Total no. of unique records in 'stage\_2\_detailed\_class\_info': 26684

#### View the distribution of 3 different types of classes

```
In [14]: merged_df = labled_df.merge(class_info_df, left_on='patientId', right_on='patientId', how='inner')
    print(merged_df.shape)
    print("unique values in merged dataframe : {0}".format(len(merged_df['patientId'].unique())))
    merged_df.sample(5)
```

(37629, 7) unique values in merged dataframe : 26684

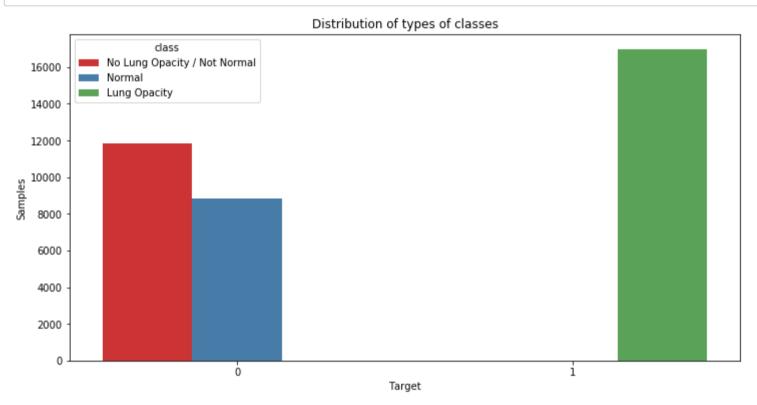
class	Target	height	width	у	x	patientId		Out[14]:
No Lung Opacity / Not Normal	0	NaN	NaN	NaN	NaN	49467153-bfcf-4d73-be8c-54dd133771c0	7855	
Lung Opacity	1	411.0	202.0	360.0	355.0	6fd0d3d2-a990-41a8-b843-94d2356afe42	13192	
Normal	0	NaN	NaN	NaN	NaN	27aa5880-422d-4084-b907-409754c89713	37125	
Normal	0	NaN	NaN	NaN	NaN	a1dc7fe9-1e55-4956-9f04-f99f624faefb	20785	

fbbd1c86-6545-4cf7-8273-0c77161c847c NaN NaN NaN

```
In [15]: fig, ax = plt.subplots(nrows=1,figsize=(12,6))
    tmp = merged_df.groupby('Target')['class'].value_counts()
    df = pd.DataFrame(data={'Samples': tmp.values}, index=tmp.index).reset_index()
    sns.barplot(ax=ax,x = 'Target', y='Samples',hue='class',data=df, palette='Set1')
    plt.title("Distribution of types of classes")
    plt.show()
```

NaN

Normal



#### Combine both the csv

35254

```
In [11]: combined_df = pd.merge(labled_df, class_info_df, how='inner', on='patientId')
print(combined_df.shape[0], 'combined cases')
```

37629 combined cases

#### Find lungs opacity intervals

We will filter out all the records with box values so that we can plot the ranges of the box. This will give us an vague idea of the localization of the target boxes for opacity.

```
In [13]: final = combined_df.dropna() ## this will filter all the records only with boxes
print(final.shape[0], 'combined cases')
final.sample(5)
```

16957 combined cases

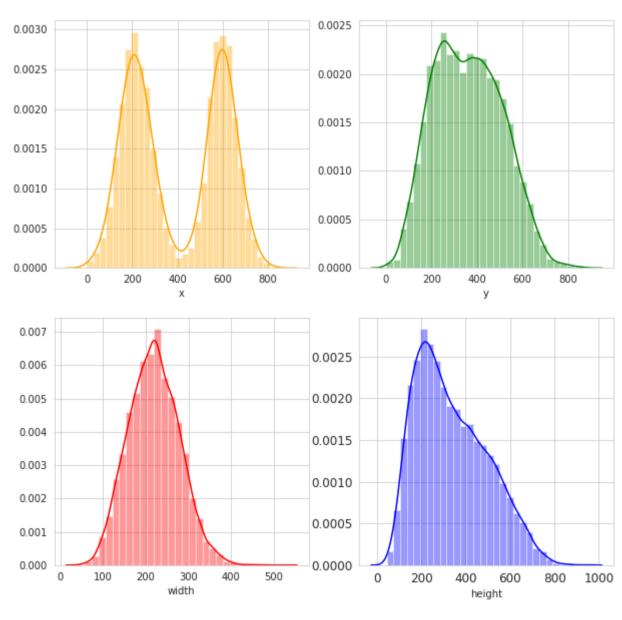
#### Out[13]:

	patientId	X	у	width	height	Target	class
27024	c10053b8-7bc8-4d8f-99f0-92d86a97ee2e	680.0	372.0	179.0	319.0	1	Lung Opacity
6822	41abed8d-8781-4564-b0cc-9d4abbfcad5f	231.0	538.0	161.0	204.0	1	Lung Opacity
22801	ad89c871-f23f-40a2-a39e-53db93884b59	220.0	301.0	201.0	397.0	1	Lung Opacity
4875	3874e3f6-0c79-4fc1-a874-1d761e475e53	336.0	413.0	171.0	368.0	1	Lung Opacity
3006	2d09d0bb-a4fb-4a50-99c4-496ad756533e	199.0	663.0	188.0	70.0	1	Lung Opacity

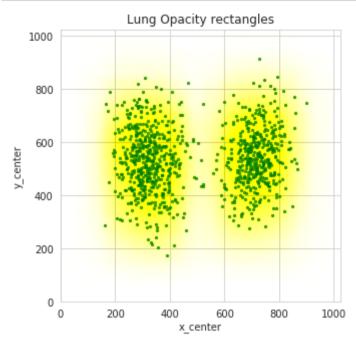
```
In [19]: sns.set_style('whitegrid')
    plt.figure()
    fig, ax = plt.subplots(2,2,figsize=(10,10))
    sns.distplot(final['x'],kde=True,bins=30, color="orange", ax=ax[0,0])
    sns.distplot(final['y'],kde=True,bins=30, color="green", ax=ax[0,1])
    sns.distplot(final['width'],kde=True,bins=30, color="red", ax=ax[1,0])
    sns.distplot(final['height'],kde=True,bins=30, color="blue", ax=ax[1,1])

locs, labels = plt.xticks()
    plt.tick_params(axis='both', which='major', labelsize=12)
    plt.show()
```

<Figure size 432x288 with 0 Axes>



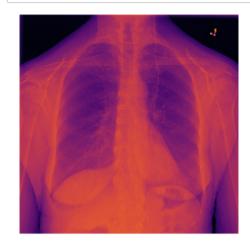
In [0]: ## Centers of rectangle



```
In [0]: final.groupby(['class', 'Target']).size().reset_index(name='Patient Count')
Out[46]:
                  class Target Patient Count
           0 Lung Opacity
                                    9555
In [368]: box_df = combined_df.groupby('patientId').size().reset_index(name='boxes')
          combined df = pd.merge(combined df, box_df, on='patientId')
          box_df.groupby('boxes').size().reset_index(name='patients')
Out[368]:
             boxes patients
           0
                     23286
                 1
                      3266
           2
                 9
                       119
                16
                        13
In [369]: box1_df = final.groupby('patientId').size().reset_index(name='boxes1')
          final = pd.merge(final, box1_df, on='patientId')
          box1_df.groupby('boxes1').size().reset_index(name='patients')
Out[369]:
             boxes1 patients
           0
                  1
                       2614
```

#### View the individual images with different color maps

```
In [325]: pid_45 = box_df['patientId'][45]
view_individual_patient_image(pid_45, cmap_value=pylab.cm.inferno)
```

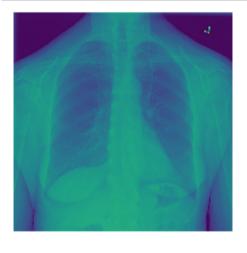


In [324]: view\_individual\_patient\_image(pid\_45, cmap\_value=pylab.cm.bone)



```
In [0]:
```

In [327]: | view\_individual\_patient\_image(pid\_45, cmap\_value=pylab.cm.viridis)



```
print(len(parsed.keys()))
26684

In [0]:
# print(parsed['003d8fa0-6bf1-40ed-b54c-ac657f8495c5']) ## normal
# print(parsed['00704310-78a8-4b38-8475-49f4573b2dbb']) ## opaque
```

#### Visualize the boxes

In [363]: parsed = parse\_data\_dict(labled\_df)

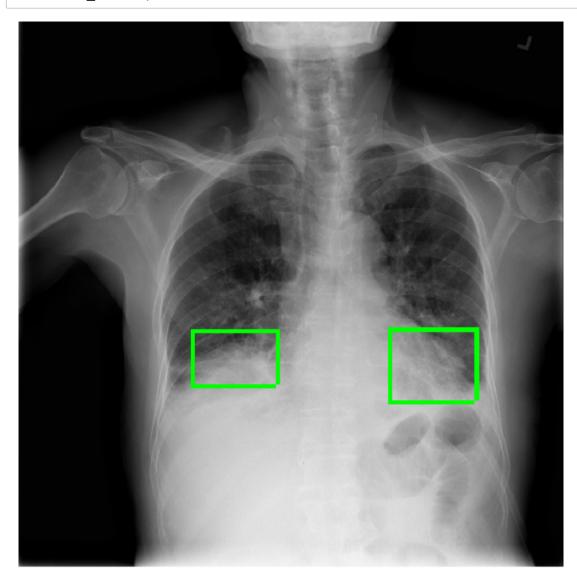
```
In [0]: def overlay box(pixels, box, rgb, stroke=8):
            #get integers coordinates
            box = [int(b) for b in box]
            #get x,y coordinates
            y1, x1, height, width = box
            y2 = y1 + height
            x2 = x1 + width
            pixels[y1:y1 + stroke, x1:x2] = rgb
            pixels[y2:y2 + stroke, x1:x2] = rgb
            pixels[y1:y2, x1:x1 + stroke] = rgb
            pixels[y1:y2, x2:x2 + stroke] = rgb
            return pixels
        def construct_boxes(image, size=(20,10)):
            '''Create boxes using the lables information of
            boxes given in stage_2_train_labels.csv
            fig=plt.figure(figsize=size)
            d = pydicom.read_file(image['dicom'])
            pixels = d.pixel_array
            #Convert from 3d for rgb pixels
            pixels = np.stack([pixels] * 3, axis=2)
            for box in image['boxes']:
                rgb = [0,255,0]
                pixels = overlay_box(pixels=pixels, box=box, rgb=rgb, stroke=8)
            pylab.imshow(pixels, cmap=pylab.cm.viridis)
            pylab.axis('off')
            plt.show()
```

In [316]: construct\_boxes(parsed['01aad2a6-3b93-45e3-bf37-2d73348cb6fc'])

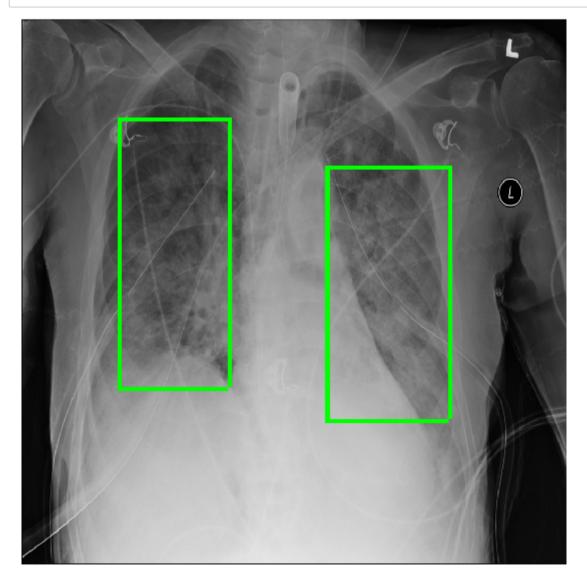


In [317]:

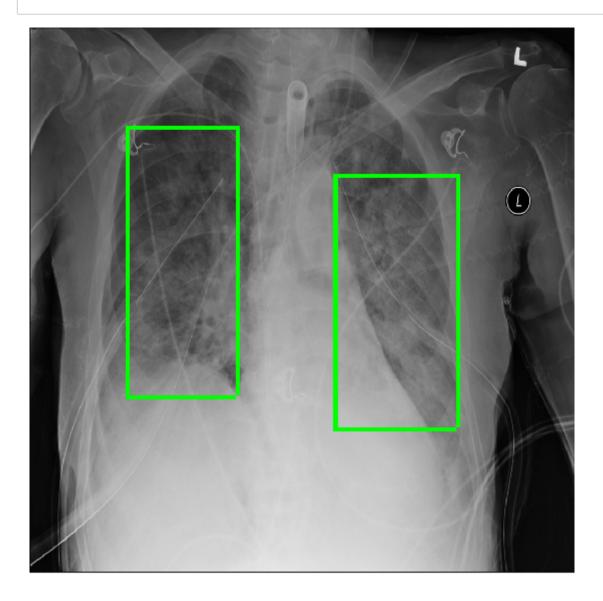
construct\_boxes(parsed['00704310-78a8-4b38-8475-49f4573b2dbb'])



In [307]: construct\_boxes(parsed['00f08del-517e-4652-a04f-dldc9ee48593'])



In [308]: construct\_boxes(parsed['00f08de1-517e-4652-a04f-d1dc9ee48593'])



```
In [20]: pneumonia_locations = {}
         # load table
         with open(labeled_boxes_csv, mode='r') as infile:
             # open reader
             reader = csv.reader(infile)
             # skip header
             next(reader, None)
             # loop through rows
             for rows in reader:
                 # retrieve information
                 filename = rows[0]
                 location = rows[1:5]
                 pneumonia = rows[5]
                 # if row contains pneumonia add label to dictionary
                 # which contains a list of pneumonia locations per filename
                 if pneumonia == '1':
                     # convert string to float to int
                     location = [int(float(i)) for i in location]
                     # save pneumonia location in dictionary
                     if filename in pneumonia_locations:
                         pneumonia_locations[filename].append(location)
                     else:
                         pneumonia_locations[filename] = [location]
         print(len(pneumonia_locations))
```

6012

Split the dataset into train and test

```
In [14]: ## train
    filenames = os.listdir(train_images_folder)
    print("Total image files in 'stage_2_train_images' : {0}".format(len(filenames)))

## test
    filenames_test = os.listdir(test_images)
    print("Total image files in 'stage_2_train_images' : {0}".format(len(filenames_test)))

# split into train and test filenames by 80/20
    test = int(len(filenames) * 0.2)
    train = filenames[test:]
    test = filenames[test:]
    print('Train :', len(train))
    print('Trast :', len(train))
    print('Test :', len(test))

Total image files in 'stage_2_train_images' : 26684
    Total image files in 'stage_2_train_images' : 3000
    Train : 21348
    Test : 5336
```

# **Convolutional Neural Network**

#### **Data augmentations**

Images can vary in dimensions and rotation, we need to to take care of the image augmentations while training. These augmentation includes the

- Resizing
- Rotation
- Horizontal flips

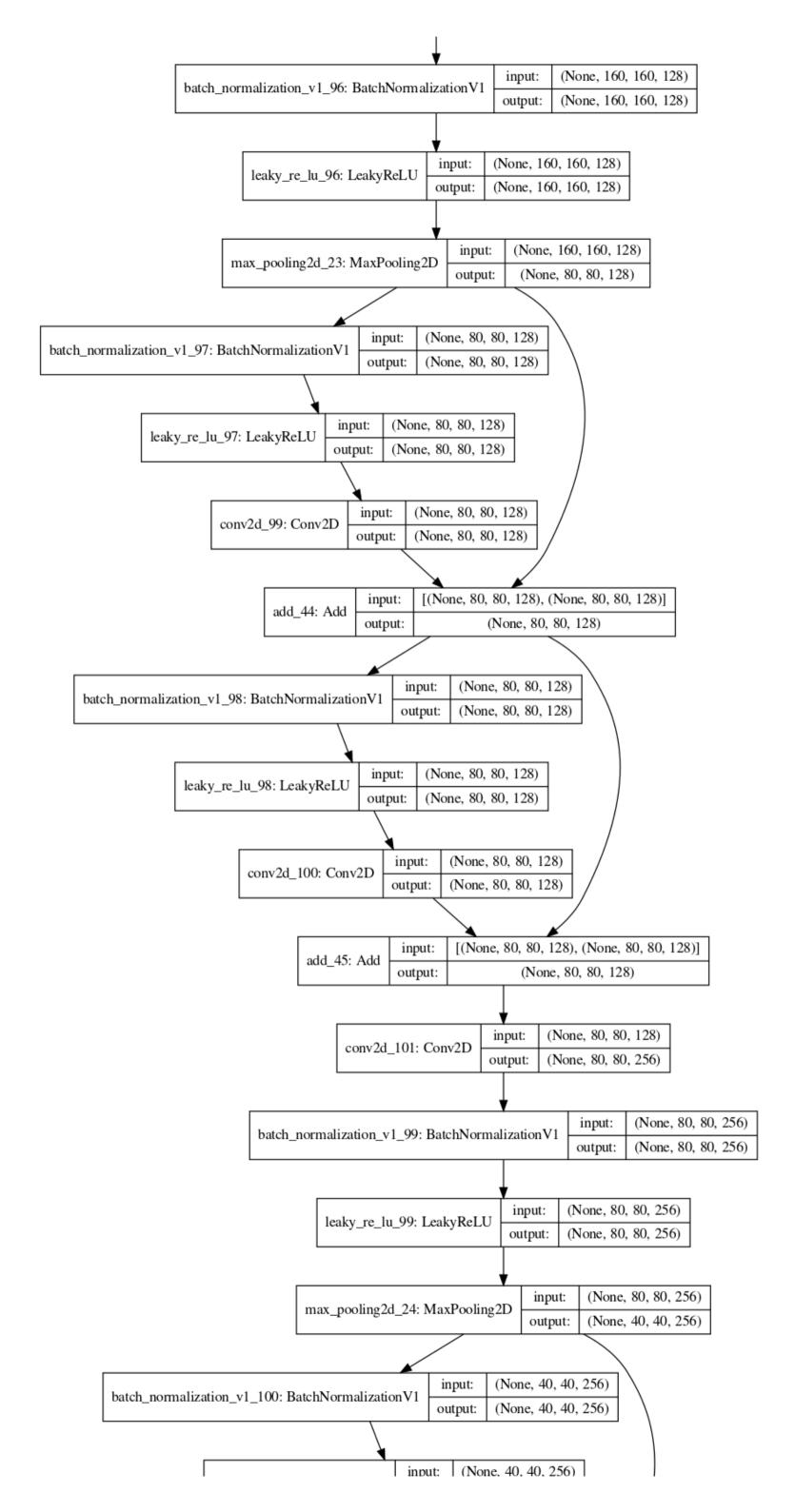
We will be using the keras.utils.Sequence and implement it to generate the data efficiently.

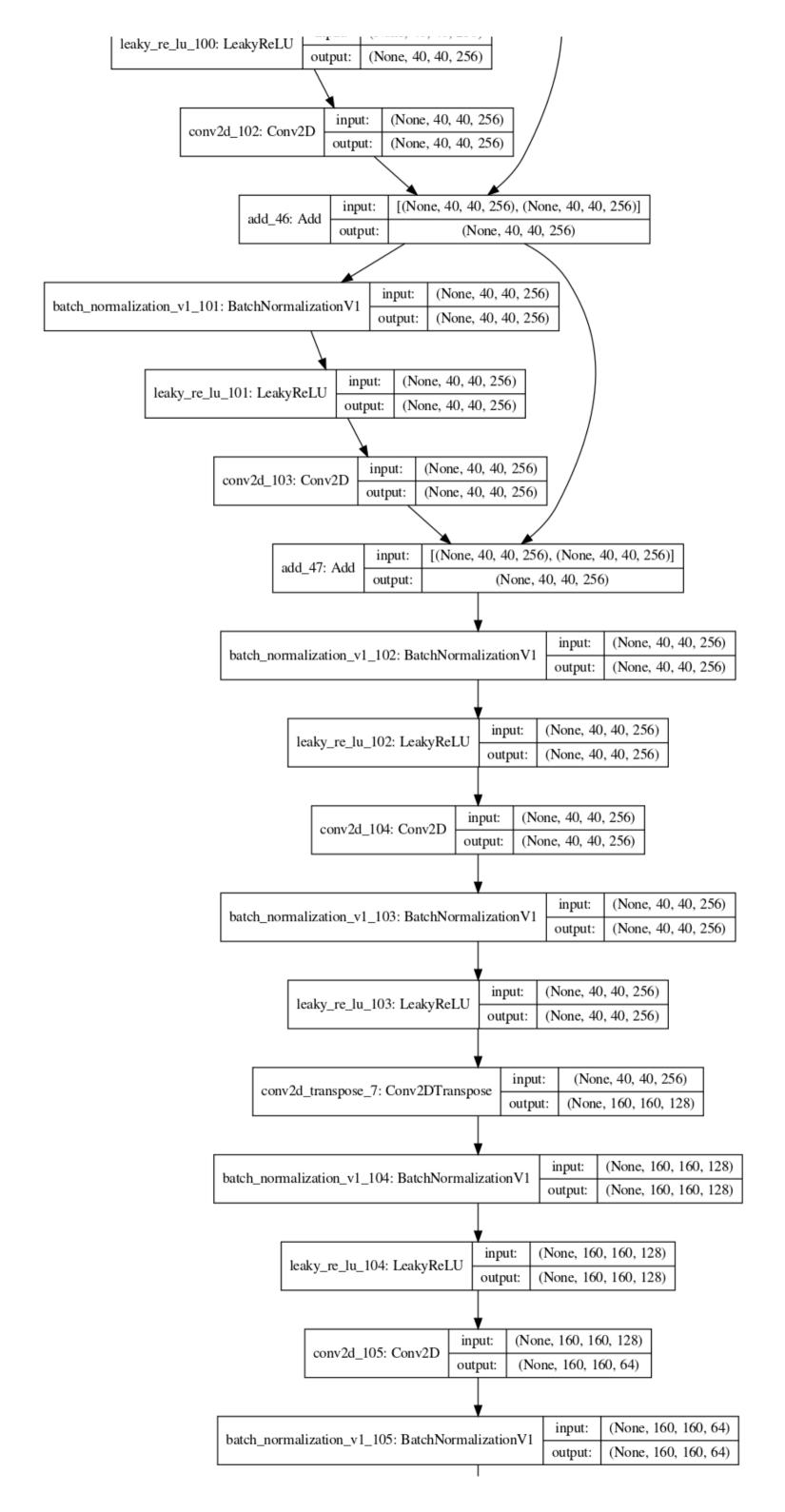
```
In [0]: '''Generic class to augment the image data
        Referenced from official documentations
        with batch mode
        class Generator(keras.utils.Sequence):
            def init (self, folder,
                         filenames,
                         pneumonia_locations=None,
                         batch size=32,
                         image_size=320,
                         shuffle=True,
                         augment=False,
                         predict=False):
                self.folder = train images folder
                self.augment = augment
                self.filenames = filenames
                self.pneumonia_locations = pneumonia_locations
                self.batch_size = batch_size
                self.image_size = image_size
                self.shuffle = shuffle
                self.predict = predict
                self.on_epoch_end()
            def __load__(self, filename):
                # diacom as array
                img = pydicom.dcmread(os.path.join(self.folder, filename)).pixel array
                msk = np.zeros(img.shape)
                ## discard file extension
                filename = filename.split('.')[0]
                ### if image has pnemonia target then extract the box
                if filename in pneumonia_locations:
                    for location in pneumonia locations[filename]:
                        ## set '1' if it has pneumonia
                        x, y, w, h = location
                        msk[y:y+h, x:x+w] = 1
                ## horizontal flip
                if self.augment and random.random() > 0.5:
                    img = np.fliplr(img)
                    msk = np.fliplr(msk)
                ## resize
                img = resize(img, (self.image_size, self.image_size), mode='reflect')
                msk = resize(msk, (self.image_size, self.image_size), mode='reflect') > 0.5
                img = np.expand_dims(img, -1)
                msk = np.expand_dims(msk, -1)
                return img, msk
            def __loadpredict__(self, filename):
                ## diacom as array
                img = pydicom.dcmread(os.path.join(self.folder, filename)).pixel_array
                # resize image
                img = resize(img, (self.image_size, self.image_size), mode='reflect')
                # add trailing channel dimension
                img = np.expand_dims(img, -1)
                return img
            def __getitem__(self, idx):
                # set batch size
                filenames = self.filenames[idx*self.batch_size:(idx+1)*self.batch_size]
                # predict mode: return images and filenames
                if self.predict:
                    # load files
                    imgs = [self.__loadpredict__(filename) for filename in filenames]
                    # create numpy batch
                    imgs = np.array(imgs)
                    return imgs, filenames
                ## return images and masks
                else:
                    items = [self. load (filename) for filename in filenames]
                    imgs, msks = zip(*items)
                    # create numpy batch
                    imgs = np.array(imgs)
                    msks = np.array(msks)
                    return imgs, msks
            def on epoch end(self):
                if self.shuffle:
                    random.shuffle(self.filenames)
                <u>len</u>(self):
                if self.predict:
                    # return everything
                    return int(np.ceil(len(self.filenames) / self.batch_size))
                    # return full batches only
```

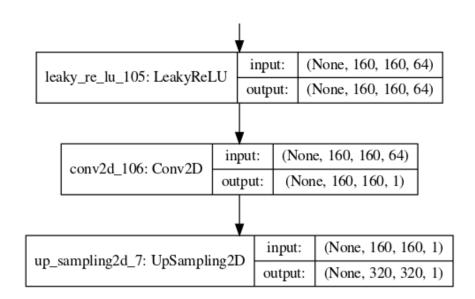
return model

```
In [0]: BATCH_SIZE = 16
        IMAGE\_SIZE = 320
In [0]: def downSample(channels, inputs):
            x = keras.layers.Conv2D(channels, 1, padding='same', use bias=False)(inputs)
            x = keras.layers.BatchNormalization(momentum=0.9)(x)
            x = keras.layers.LeakyReLU(0)(x)
            x = keras.layers.MaxPool2D(2)(x)
            return x
        def resNet(channels, inputs):
            x = keras.layers.BatchNormalization(momentum=0.9)(inputs)
            x = keras.layers.LeakyReLU(0)(x)
            x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(x)
            return keras.layers.add([x, inputs])
        def myRESNET(input size, channels, blocks=2, depth=3):
            #Input layer
            inputs = keras.Input(shape=(input_size, input_size, 1))
            x = keras.layers.Conv2D(channels, 3, padding='same', use_bias=False)(inputs)
            #Residual layer
            for d in range(depth):
                channels = channels * 2
                x = downSample(channels, x)
                for b in range(blocks):
                    x = resNet(channels, x)
            # output
            x = keras.layers.BatchNormalization(momentum=0.9)(x)
            x = keras.layers.LeakyReLU(0)(x)
            x = keras.layers.Conv2D(256, 1, activation=None)(x)
            x = keras.layers.BatchNormalization(momentum=0.9)(x)
            x = keras.layers.LeakyReLU(0)(x)
            x = keras.layers.Conv2DTranspose(128, (8,8), (4,4), padding="same", activation=None)(x)
            x = keras.layers.BatchNormalization(momentum=0.9)(x)
            x = keras.layers.LeakyReLU(0)(x)
            x = keras.layers.Conv2D(64,1, padding="same", activation=None)(x)
            x = keras.layers.BatchNormalization(momentum=0.9)(x)
            x = keras.layers.LeakyReLU(0)(x)
            x = keras.layers.Conv2D(1, 1, activation='sigmoid')(x)
            outputs = keras.layers.AveragePooling2D(pool_size=(2, 2), strides=None, padding='valid', data_format=Non
            outputs = keras.layers.UpSampling2D(2**(depth-2))(x)
            model = keras.Model(inputs=inputs, outputs=outputs)
```

```
In [14]: |## plot the model
           from keras.models import Sequential
           from keras.layers import Dense
           from keras.utils.vis_utils import plot_model
           model = myRESNET(input_size=320, channels=32, blocks=2, depth=3)
           plot_model(model, to_file='cnn_model.png', show_shapes=True, show_layer_names=True, dpi=90)
Out[14]:
                                                                                (None, 320, 320, 1)
                                                                        input:
                                                   input_9: InputLayer
                                                                                (None, 320, 320, 1)
                                                                       output:
                                                                                 (None, 320, 320, 1)
                                                                        input:
                                                  conv2d_94: Conv2D
                                                                                (None, 320, 320, 32)
                                                                       output:
                                                                        input:
                                                                                (None, 320, 320, 32)
                                                  conv2d_95: Conv2D
                                                                       output:
                                                                                (None, 320, 320, 64)
                                                                                              (None, 320, 320, 64)
                                                                                      input:
                                    batch_normalization_v1_93: BatchNormalizationV1
                                                                                              (None, 320, 320, 64)
                                                                                     output:
                                                                           input:
                                                                                    (None, 320, 320, 64)
                                              leaky_re_lu_93: LeakyReLU
                                                                                    (None, 320, 320, 64)
                                                                           output:
                                                                                       (None, 320, 320, 64)
                                                                               input:
                                           max_pooling2d_22: MaxPooling2D
                                                                                       (None, 160, 160, 64)
                                                                              output:
                                                                        (None, 160, 160, 64)
                                                               input:
             batch_normalization_v1_94: BatchNormalizationV1
                                                                        (None, 160, 160, 64)
                                                               output:
                                                                   (None, 160, 160, 64)
                                                          input:
                             leaky_re_lu_94: LeakyReLU
                                                          output:
                                                                   (None, 160, 160, 64)
                                                           input:
                                                                    (None, 160, 160, 64)
                                     conv2d_96: Conv2D
                                                                    (None, 160, 160, 64)
                                                           output:
                                                                     [(None, 160, 160, 64), (None, 160, 160, 64)]
                                                            input:
                                             add_42: Add
                                                                                (None, 160, 160, 64)
                                                            output:
                                                                           (None, 160, 160, 64)
                                                                  input:
                batch_normalization_v1_95: BatchNormalizationV1
                                                                           (None, 160, 160, 64)
                                                                  output:
                                                                      (None, 160, 160, 64)
                                                             input:
                                leaky_re_lu_95: LeakyReLU
                                                                      (None, 160, 160, 64)
                                                             output:
                                                                         (None, 160, 160, 64)
                                                                 input:
                                           conv2d_97: Conv2D
                                                                         (None, 160, 160, 64)
                                                                output:
                                                                          [(None, 160, 160, 64), (None, 160, 160, 64)]
                                                                 input:
                                                   add_43: Add
                                                                                     (None, 160, 160, 64)
                                                                 output:
                                                                                        (None, 160, 160, 64)
                                                                               input:
                                                          conv2d_98: Conv2D
                                                                                        (None, 160, 160, 128)
                                                                               output:
```







Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	(None, 320, 320, 1)	0	
conv2d_13 (Conv2D)	(None, 320, 320, 32)	288	input_2[0][0]
conv2d_14 (Conv2D)	(None, 320, 320, 64)	2048	conv2d_13[0][0]
batch_normalization_v1_13 (Batc	(None, 320, 320, 64)	256	conv2d_14[0][0]
leaky_re_lu_13 (LeakyReLU)	(None, 320, 320, 64)	0	batch_normalization_v1_13[0][0]
max_pooling2d_3 (MaxPooling2D)	(None, 160, 160, 64)	0	leaky_re_lu_13[0][0]
batch_normalization_v1_14 (Batc	(None, 160, 160, 64)	256	max_pooling2d_3[0][0]
leaky_re_lu_14 (LeakyReLU)	(None, 160, 160, 64)	0	batch_normalization_v1_14[0][0]
conv2d_15 (Conv2D)	(None, 160, 160, 64)	36864	leaky_re_lu_14[0][0]
add_6 (Add)	(None, 160, 160, 64)	0	conv2d_15[0][0] max_pooling2d_3[0][0]
batch_normalization_v1_15 (Batc	(None, 160, 160, 64)	256	add_6[0][0]
leaky_re_lu_15 (LeakyReLU)	(None, 160, 160, 64)	0	batch_normalization_v1_15[0][0]
conv2d_16 (Conv2D)	(None, 160, 160, 64)	36864	leaky_re_lu_15[0][0]
add_7 (Add)	(None, 160, 160, 64)	0	conv2d_16[0][0] add_6[0][0]
conv2d_17 (Conv2D)	(None, 160, 160, 128	8 8192	add_7[0][0]
batch_normalization_v1_16 (Batc	(None, 160, 160, 128	3 512	conv2d_17[0][0]
leaky_re_lu_16 (LeakyReLU)	(None, 160, 160, 128	3 0	batch_normalization_v1_16[0][0]
max_pooling2d_4 (MaxPooling2D)	(None, 80, 80, 128)	0	leaky_re_lu_16[0][0]
batch_normalization_v1_17 (Batc	(None, 80, 80, 128)	512	max_pooling2d_4[0][0]
leaky_re_lu_17 (LeakyReLU)	(None, 80, 80, 128)	0	batch_normalization_v1_17[0][0]
conv2d_18 (Conv2D)	(None, 80, 80, 128)	147456	leaky_re_lu_17[0][0]
add_8 (Add)	(None, 80, 80, 128)	0	conv2d_18[0][0] max_pooling2d_4[0][0]
batch_normalization_v1_18 (Batc	(None, 80, 80, 128)	512	add_8[0][0]
leaky_re_lu_18 (LeakyReLU)	(None, 80, 80, 128)	0	batch_normalization_v1_18[0][0]
conv2d_19 (Conv2D)	(None, 80, 80, 128)	147456	leaky_re_lu_18[0][0]
add_9 (Add)	(None, 80, 80, 128)	0	conv2d_19[0][0] add_8[0][0]
conv2d_20 (Conv2D)	(None, 80, 80, 256)	32768	add_9[0][0]
batch_normalization_v1_19 (Batc	(None, 80, 80, 256)	1024	conv2d_20[0][0]
leaky_re_lu_19 (LeakyReLU)	(None, 80, 80, 256)	0	batch_normalization_v1_19[0][0]
max_pooling2d_5 (MaxPooling2D)	(None, 40, 40, 256)	0	leaky_re_lu_19[0][0]
batch_normalization_v1_20 (Batc	(None, 40, 40, 256)	1024	max_pooling2d_5[0][0]

```
conv2d_21 (Conv2D)
                                         (None, 40, 40, 256)
                                                                           leaky_re_lu_20[0][0]
                                                              589824
                                                                           conv2d 21[0][0]
        add 10 (Add)
                                         (None, 40, 40, 256)
                                                                           max pooling2d 5[0][0]
        batch normalization v1 21 (Batc (None, 40, 40, 256)
                                                              1024
                                                                           add 10[0][0]
        leaky_re_lu_21 (LeakyReLU)
                                         (None, 40, 40, 256)
                                                                           batch_normalization_v1_21[0][0]
        conv2d 22 (Conv2D)
                                         (None, 40, 40, 256)
                                                              589824
                                                                           leaky_re_lu_21[0][0]
        add_11 (Add)
                                         (None, 40, 40, 256)
                                                                           conv2d 22[0][0]
                                                                           add 10[0][0]
        batch normalization v1 22 (Batc (None, 40, 40, 256)
                                                              1024
                                                                           add_11[0][0]
        leaky_re_lu_22 (LeakyReLU)
                                         (None, 40, 40, 256)
                                                                           batch_normalization_v1_22[0][0]
        conv2d 23 (Conv2D)
                                         (None, 40, 40, 256)
                                                              65792
                                                                           leaky_re_lu_22[0][0]
        batch_normalization_v1_23 (Batc (None, 40, 40, 256)
                                                              1024
                                                                           conv2d_23[0][0]
        leaky_re_lu_23 (LeakyReLU)
                                         (None, 40, 40, 256)
                                                                           batch_normalization_v1_23[0][0]
        conv2d_transpose_1 (Conv2DTrans (None, 160, 160, 128 2097280
                                                                           leaky_re_lu_23[0][0]
        batch normalization v1 24 (Batc (None, 160, 160, 128 512
                                                                           conv2d transpose 1[0][0]
        leaky_re_lu_24 (LeakyReLU)
                                         (None, 160, 160, 128 0
                                                                           batch_normalization_v1_24[0][0]
                                         (None, 160, 160, 64) 8256
        conv2d_24 (Conv2D)
                                                                           leaky_re_lu_24[0][0]
        batch_normalization_v1_25 (Batc (None, 160, 160, 64) 256
                                                                           conv2d_24[0][0]
        leaky re lu 25 (LeakyReLU)
                                         (None, 160, 160, 64) 0
                                                                           batch_normalization_v1_25[0][0]
        conv2d_25 (Conv2D)
                                         (None, 160, 160, 1)
                                                                           leaky_re_lu_25[0][0]
                                                                           conv2d 25[0][0]
        up_sampling2d_1 (UpSampling2D) (None, 320, 320, 1) 0
        Total params: 3,771,169
        Trainable params: 3,767,073
        Non-trainable params: 4,096
        None
In [0]:
In [0]: myRESNET = model.fit_generator(train_gen, validation_data=test_gen,
                                        callbacks=[learning_rate],
                                        epochs=1,
                                        shuffle=True)
In [0]: | duplicate_RESNET = myRESNET
In [0]: print(myRESNET.history.keys())
        dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy', 'lr'])
In [0]: |print(myRESNET.history['accuracy'])
        print(myRESNET.history['val_accuracy'])
```

(None, 40, 40, 256)

batch\_normalization\_v1\_20[0][0]

# **Support vector machine**

[0.97607964] [0.96008945]

leaky\_re\_lu\_20 (LeakyReLU)

```
In [0]: ## from sklearn.model_selection import train_test_split
    from sklearn.model_selection import StratifiedKFold
    from sklearn import datasets
    from sklearn.metrics import auc
    from sklearn.metrics import plot_roc_curve
    import numpy as np
    import pandas as pd
    from numpy import interp
    from sklearn.model_selection import train_test_split
    import matplotlib.pyplot as plt
```

```
In [16]: | combined_svm_df.shape
          combined_svm_df.sample(20)
          forSVMFinal_df = combined_svm_df.drop('class', axis = 1).copy()
          forSVMFinal_df.sample(5)
Out[16]:
                                         patientId
                                                     Х
                                                             width height Target
           24911 b71bca51-9eed-4780-9835-12f3245834e6
                                                   NaN
                                                         NaN
                                                               NaN
                                                                     NaN
                                                                              0
           12251
                  69702abd-0555-4e3c-bb6a-f73a1d47adfd
                                                              196.0
                                                                    149.0
                                                  656.0
                                                        541.0
                                                                              1
           27008
                  c04866bb-85d2-4186-8c48-3ce46dcfa80c
                                                                              0
                                                   NaN
                                                         NaN
                                                               NaN
                                                                     NaN
                  3b039064-dc2b-43dc-a9d3-0edf181f523a
                                                   NaN
                                                         NaN
                                                               NaN
                                                                     NaN
           17466
                  8b60f253-6ae0-4b16-89bc-f3e3163dbbae 314.0 270.0
                                                                    223.0
                                                               96.0
                                                                              1
 In [0]: ## fresh load file again and resets the variables
          ## load and set file/folder variables
          details_class_info_csv = os.path.join(data_dir, 'stage_2_detailed_class_info.csv')
          labeled_boxes_csv = os.path.join(data_dir, 'stage_2_train_labels.csv')
          train_images_folder = os.path.join(data_dir, 'stage_2_train_images')
          test_images = os.path.join(data_dir, 'stage_2_test_images')
In [18]: | ## load the csv's as dataframe
          labled_df_tmp = pd.read_csv(labeled_boxes_csv)
          print("Content of the stage_2_train_labels.csv: \n")
          labled_df_tmp.head()
          Content of the stage_2_train_labels.csv:
Out[18]:
                                      patientId
                                                  X
                                                          width
                                                                height Target
              0004cfab-14fd-4e49-80ba-63a80b6bddd6
                                                     NaN
                                               NaN
                                                           NaN
                                                                  NaN
                                                                           0
           1 00313ee0-9eaa-42f4-b0ab-c148ed3241cd
                                               NaN
                                                     NaN
                                                           NaN
                                                                  NaN
                                                                           0
              00322d4d-1c29-4943-afc9-b6754be640eb
                                               NaN
                                                     NaN
                                                           NaN
                                                                  NaN
                                                                           0
               003d8fa0-6bf1-40ed-b54c-ac657f8495c5
                                                                  NaN
                                                                           0
                                               NaN
                                                     NaN
                                                           NaN
           4 00436515-870c-4b36-a041-de91049b9ab4 264.0 152.0
                                                                 379.0
                                                          213.0
                                                                           1
In [19]: | ## second csv
          class_info_df_tmp = pd.read_csv(details_class_info_csv)
          print("\n\nContent of the stage_2_detailed_class_info.csv:\n")
          class_info_df_tmp.head()
          Content of the stage_2_detailed_class_info.csv:
Out[19]:
                                      patientId
                                                                 class
              0004cfab-14fd-4e49-80ba-63a80b6bddd6 No Lung Opacity / Not Normal
           1 00313ee0-9eaa-42f4-b0ab-c148ed3241cd No Lung Opacity / Not Normal
              00322d4d-1c29-4943-afc9-b6754be640eb No Lung Opacity / Not Normal
               003d8fa0-6bf1-40ed-b54c-ac657f8495c5
           3
                                                               Normal
```

**Lung Opacity** 

4 00436515-870c-4b36-a041-de91049b9ab4

```
In [20]: df = pd.merge(left = class_info_df_tmp, right = labled_df_tmp, how = 'left', on = 'patientId')

del class_info_df_tmp, labled_df_tmp
gc.collect()

df = df.drop_duplicates()
df_meta = df.drop('class', axis = 1).copy()
df_meta.sample(20)
```

#### Out[20]:

	patientId	x	у	width	height	Target
31807	e3dca188-6311-4214-9d15-c1d4ba4dea55	694.0	488.0	99.0	342.0	1
10036	58cbbc5a-4d66-4c43-8def-b407ec2ce8a9	NaN	NaN	NaN	NaN	0
3484	32696785-8a96-4e01-977e-03559d1afd71	NaN	NaN	NaN	NaN	0
23673	b1827a4d-c98c-4719-8296-1659617870a7	NaN	NaN	NaN	NaN	0
51	019ca122-9cdf-4704-b7a9-449c8a1c263e	NaN	NaN	NaN	NaN	0
29605	d2dd6b61-572f-4d66-9a5b-05a026fa40c9	NaN	NaN	NaN	NaN	0
34251	f4fffaa6-a5b8-494e-911b-1560d1937422	212.0	350.0	197.0	339.0	1
12588	6bd01448-46f5-4ff9-aa10-ed934881427f	NaN	NaN	NaN	NaN	0
23741	b1d545f0-8658-4533-959f-dc32955904ca	NaN	NaN	NaN	NaN	0
35470	fd43dbd5-4dcb-4b62-ae2a-e991a703b48d	152.0	276.0	212.0	382.0	1
9309	537cd661-6eba-499a-a4bb-2f442897db12	498.0	410.0	362.0	282.0	1
30871	dcdbbcdb-fb5f-4984-84e4-43e0798fb4a2	NaN	NaN	NaN	NaN	0
27929	c6c3c02d-5820-4209-8c5a-6c2b50951f8f	NaN	NaN	NaN	NaN	0
26169	bc91bcb0-a7b6-4dd0-8098-ffd354264ea0	NaN	NaN	NaN	NaN	0
17550	8bcbe2a3-800a-47b0-8a2c-279c56eaf372	NaN	NaN	NaN	NaN	0
31338	e0500fbd-7565-40a4-94ba-5bbed47f90a7	NaN	NaN	NaN	NaN	0
25706	ba7af3a4-033a-44cd-879d-13130fad6d60	NaN	NaN	NaN	NaN	0
4906	38943e84-044b-4faf-b4dd-cf4a0215cc8b	NaN	NaN	NaN	NaN	0
19042	954d091a-3c7f-4d02-83cc-9e7b6a8d74de	NaN	NaN	NaN	NaN	0
8384	4d088744-58b9-41bf-879a-9fe39e9efdca	NaN	NaN	NaN	NaN	0

```
In [38]: | ## if df_meta.pkl pickle is not available then run the following.
          ## it takes couple of hrs to parse through each file
          dcm_columns = None
          for n, pid in enumerate(df_meta['patientId'].unique()):
              dcm file = get dcm image(pid)
              dcm_data = pydicom.read_file(dcm_file)
              if not dcm columns:
                  dcm_columns = dcm_data.dir()
                  dcm_columns.remove('PixelSpacing')
                  dcm_columns.remove('PixelData')
              for col in dcm_columns:
                  if not (col in df_meta.columns):
                       df_meta[col] = np.nan
                  index = df meta[df meta['patientId'] == pid].index
                  df_meta.loc[index, col] = dcm_data.data_element(col).value
              del dcm_data
          gc.collect()
          df_meta.head()
Out[38]:
                                  y width height Target AccessionNumber BitsAllocated BitsStored BodyPartExamined ... SamplesPerPixel Serie
                 patientId
             0004cfab-14fd-
                4e49-80ba-
                                                                                                    CHEST ...
                          NaN
                               NaN
                                            NaN
                                                    0
                                                                             8.0
                                                                                       8.0
                                                                                                                        1.0
                                     NaN
             63a80b6bddd6
                00313ee0-
                9eaa-42f4-
                                                                             8.0
                                                                                                    CHEST ...
                          NaN
                               NaN
                                     NaN
                                            NaN
                                                                                       8.0
                                                                                                                        1.0
                   b0ab-
             c148ed3241cd
                00322d4d-
                1c29-4943-
                                                                                                    CHEST ...
                          NaN
                               NaN
                                     NaN
                                            NaN
                                                    0
                                                                             8.0
                                                                                       8.0
                                                                                                                        1.0
                    afc9-
             b6754be640eb
                003d8fa0-
                6bf1-40ed-
                                            NaN
                                                                              8.0
                                                                                       8.0
                                                                                                    CHEST ...
                                                                                                                        1.0
                          NaN
                               NaN
                                     NaN
                    b54c-
              ac657f8495c5
                00436515-
                870c-4b36-
                         264.0 152.0 213.0
                                           379.0
                                                                              8.0
                                                                                       8.0
                                                                                                    CHEST ...
                                                                                                                        1.0
                   a041-
             de91049b9ab4
          5 rows × 39 columns
 In [0]: | ## save to pickle so that we dont have to parse the images again
          ## which takes more than 2hrs
          df_meta.to_pickle("./df_meta.pkl")
 In [0]: |## read from pickle
          df_meta = pd.read_pickle("./df_meta.pkl")
In [23]: |print(df_meta.head())
                                                                      width
                                                                             height Target
                                           patientId
                                                           X
                                                         NaN
             0004cfab-14fd-4e49-80ba-63a80b6bddd6
                                                                        NaN
                                                                                 NaN
                                                                                            0
                                                                 NaN
          1
             00313ee0-9eaa-42f4-b0ab-c148ed3241cd
                                                         NaN
                                                                 NaN
                                                                        NaN
                                                                                 NaN
                                                                                            0
          2
                                                                                            0
             00322d4d-1c29-4943-afc9-b6754be640eb
                                                         NaN
                                                                 NaN
                                                                        NaN
                                                                                 NaN
          3 003d8fa0-6bf1-40ed-b54c-ac657f8495c5
                                                        NaN
                                                                                            0
                                                                NaN
                                                                        NaN
                                                                                 NaN
          4 00436515-870c-4b36-a041-de91049b9ab4 264.0 152.0 213.0
                                                                              379.0
 In [0]: def get meta data(pid, columns):
              dicom = pydicom.read file(get dcm image(pid))
              wantedColumn = getattr(dicom, columns)
              return wantedColumn
```

### Adding few important columns from the image metadata.

```
In [0]: ## important columns - should have some variance and distribution
    columns = ['PatientSex', 'PatientAge', 'ViewPosition']
    for i in columns:
        forSVMFinal_df[i] = forSVMFinal_df['patientId'].apply(lambda l: get_meta_data(l, i))
    forSVMFinal_df['PatientAge'] = forSVMFinal_df['PatientAge'].apply(pd.to_numeric, errors='coerce')
    forSVMFinal_df['PatientAge'] = forSVMFinal_df['PatientAge'].apply(lambda l: l if l<120 else np.nan)</pre>
```

```
In [26]: |forSVMFinal_df.head()
Out[26]:
                                           patientId
                                                                 width
                                                                        height Target PatientSex PatientAge ViewPosition
                                                        Х
                0004cfab-14fd-4e49-80ba-63a80b6bddd6
                                                      NaN
                                                            NaN
                                                                   NaN
                                                                          NaN
                                                                                     0
                                                                                                         51.0
                                                                                                                       PA
                00313ee0-9eaa-42f4-b0ab-c148ed3241cd
                                                                          NaN
                                                                                    0
                                                                                                F
                                                                                                         48.0
                                                                                                                       PA
             1
                                                      NaN
                                                            NaN
                                                                   NaN
             2
                00322d4d-1c29-4943-afc9-b6754be640eb
                                                      NaN
                                                            NaN
                                                                   NaN
                                                                          NaN
                                                                                    0
                                                                                                Μ
                                                                                                         19.0
                                                                                                                       ΑP
             3
                 003d8fa0-6bf1-40ed-b54c-ac657f8495c5
                                                                                    0
                                                                                               Μ
                                                                                                         28.0
                                                                                                                       PA
                                                      NaN
                                                            NaN
                                                                   NaN
                                                                          NaN
                                                                                                F
             4 00436515-870c-4b36-a041-de91049b9ab4
                                                    264.0
                                                           152.0
                                                                  213.0
                                                                         379.0
                                                                                    1
                                                                                                         32.0
                                                                                                                       AΡ
           svmDuplicate_df = forSVMFinal_df
 In [0]:
In [28]:
           svmDuplicate_df.sample(20)
Out[28]:
                                                                      width
                                                                                    Target
                                                                                           PatientSex
                                                                                                      PatientAge ViewPosition
                                               patientId
                                                            Х
                                                                            height
                     5fe48afd-ee8e-4b82-9ca9-a766a0fb0924
             10971
                                                          NaN
                                                                NaN
                                                                       NaN
                                                                               NaN
                                                                                         0
                                                                                                    F
                                                                                                             52.0
                                                                                                                           PΑ
             23669
                                                               596.0
                                                                      131.0
                                                                              132.0
                                                                                                    F
                                                                                                             55.0
                                                                                                                           AP
                    b181eb13-a6b0-4576-afcd-0e23c90723ba
                                                         367.0
                                                                                         1
              2616
                     1d5fdb0a-0f8d-4972-9630-f36eb12c694b
                                                          NaN
                                                                NaN
                                                                       NaN
                                                                               NaN
                                                                                         0
                                                                                                    Μ
                                                                                                             62.0
                                                                                                                           PΑ
             29742
                    d4160dce-b9e6-4a58-b12d-7dc4455dee1c
                                                                                         0
                                                                                                    Μ
                                                                                                              8.0
                                                                                                                           PA
                                                         NaN
                                                                NaN
                                                                       NaN
                                                                               NaN
             13435
                    717e8c41-2b54-4f7a-b7a8-d51b53108d82
                                                          NaN
                                                                NaN
                                                                       NaN
                                                                               NaN
                                                                                         0
                                                                                                    F
                                                                                                             37.0
                                                                                                                           PΑ
              7306
                      457e1b0b-89f5-4f7f-b752-fd8420414b97
                                                         199.0
                                                               178.0
                                                                      186.0
                                                                              143.0
                                                                                                    Μ
                                                                                                             18.0
                                                                                                                           PA
                                                                                                    F
              3690
                     335d17b1-bdfb-4939-9dc9-fa93f09648eb
                                                         604.0
                                                               323.0
                                                                      264.0
                                                                              270.0
                                                                                         1
                                                                                                              9.0
                                                                                                                           AP
             24498
                      b51c3c24-f9aa-4039-9fc1-527a5567dff6
                                                         187.0
                                                               430.0
                                                                      112.0
                                                                              142.0
                                                                                         1
                                                                                                    Μ
                                                                                                             40.0
                                                                                                                           AP
             13772
                     73557193-9f08-4353-adb9-a9e0f54bbd8c
                                                          NaN
                                                                NaN
                                                                       NaN
                                                                               NaN
                                                                                         0
                                                                                                    Μ
                                                                                                             33.0
                                                                                                                           PΑ
              2706
                                                         709.0
                                                               479.0
                                                                      177.0
                                                                              303.0
                                                                                                    Μ
                                                                                                             31.0
                                                                                                                           AP
                     21eca20b-515e-4f51-95e3-c5721e1fd6a1
                                                                                         1
                     f42223b1-1a5b-45c2-a1d2-25c6df776484
             34145
                                                         294.0
                                                                73.0
                                                                      211.0
                                                                              275.0
                                                                                         1
                                                                                                    Μ
                                                                                                             56.0
                                                                                                                           AP
             34709
                     f7e14331-ae8f-4367-8ca3-93699785e0e2
                                                                                         0
                                                                                                    F
                                                          NaN
                                                                NaN
                                                                       NaN
                                                                               NaN
                                                                                                             64.0
                                                                                                                           PA
              2157
                    174a9cbb-cf69-4122-b0b4-e4dd980b4b42
                                                          NaN
                                                                NaN
                                                                       NaN
                                                                               NaN
                                                                                         0
                                                                                                    Μ
                                                                                                             54.0
                                                                                                                           AP
             11792
                                                                                                    M
                                                                                                             60.0
                                                                                                                           AP
                     66019687-92c9-4137-93dd-dcc82a1f1c7a
                                                                               NaN
                                                                                         0
                                                         NaN
                                                                NaN
                                                                       NaN
             12178
                      68feb3b4-fbfc-47dd-808a-d58bf9a65764
                                                          NaN
                                                                               NaN
                                                                                                    F
                                                                                                             71.0
                                                                                                                           AP
                                                                NaN
                                                                       NaN
                                                                                                    F
             14392
                                                                      296.0
                                                                                                             23.0
                    77633bed-c31b-466a-946d-6624b97231a8
                                                          73.0
                                                               427.0
                                                                              208.0
                                                                                                                           AP
             21646
                     a73a46b2-fcef-41ad-a292-60df60ebba72
                                                         544.0
                                                               427.0
                                                                      209.0
                                                                              271.0
                                                                                                             59.0
                                                                                                                           AP
             30977
                                                                                         0
                                                                                                    Μ
                                                                                                                           PA
                     dd9d6811-a4f2-497f-aced-d7b532eaedda
                                                          NaN
                                                                NaN
                                                                       NaN
                                                                               NaN
                                                                                                             51.0
             23482
                     b0c6e2ba-ceaa-4eb9-b241-7c387f8df4ef
                                                         248.0
                                                               200.0
                                                                      240.0
                                                                              525.0
                                                                                                    Μ
                                                                                                             78.0
                                                                                                                           ΑP
             10378
                                                                                                    F
                     5b87ecdd-73ea-4dea-887c-85a52c6d2f9f
                                                        271.0
                                                               452.0
                                                                      169.0
                                                                              137.0
                                                                                                             33.0
                                                                                                                           AP
 In [0]:
           ## mapping the categorical values to the numeric
            svmDuplicate_df['PatientSex'] = svmDuplicate_df['PatientSex'].map({'F': 0, 'M': 1})
            svmDuplicate_df['ViewPosition'] = svmDuplicate_df['ViewPosition'].map({'PA': 0, 'AP': 1})
In [38]:
           forSVMFinal_df.head()
Out[38]:
                                           patientId
                                                                  width
                                                                         height Target PatientSex PatientAge ViewPosition
                                                        X
                                                               У
                                                                                                0
                                                                                                                         0
                0004cfab-14fd-4e49-80ba-63a80b6bddd6
                                                      NaN
                                                            NaN
                                                                   NaN
                                                                          NaN
                                                                                    0
                                                                                                         51.0
                00313ee0-9eaa-42f4-b0ab-c148ed3241cd
                                                      NaN
                                                                   NaN
                                                                          NaN
                                                                                    0
                                                                                                0
                                                                                                         48.0
                                                                                                                         0
                                                            NaN
             2
                00322d4d-1c29-4943-afc9-b6754be640eb
                                                      NaN
                                                            NaN
                                                                   NaN
                                                                          NaN
                                                                                    0
                                                                                                1
                                                                                                         19.0
                                                                                                                         1
                 003d8fa0-6bf1-40ed-b54c-ac657f8495c5
                                                                                    0
                                                                                                1
                                                                                                         28.0
                                                                                                                         0
                                                      NaN
                                                            NaN
                                                                   NaN
                                                                          NaN
               00436515-870c-4b36-a041-de91049b9ab4
                                                                                                0
                                                    264.0
                                                           152.0
                                                                  213.0
                                                                         379.0
                                                                                                         32.0
                                                                                                                         1
 In [0]: svm_df = forSVMFinal_df[['PatientSex', 'PatientAge', 'ViewPosition', 'Target']]
```

In [40]: svm\_df.sample(20)

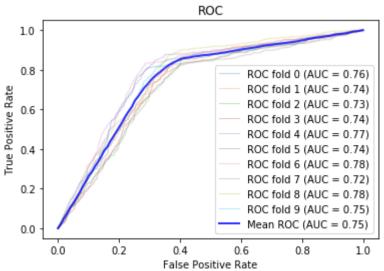
_			г 4	A 1	
(1)	ш	Τ.	1 /1	(-)	
v	u		. —	v	

	PatientSex	PatientAge	ViewPosition	Target
22947	1	65.0	0	0
36037	0	25.0	0	1
5421	0	40.0	1	1
27267	0	33.0	0	0
18505	1	77.0	1	1
26065	1	21.0	1	1
9921	1	28.0	1	1
33017	1	55.0	0	0
193	0	49.0	1	1
3463	1	24.0	1	1
16996	0	39.0	1	1
9468	1	27.0	1	1
15306	0	52.0	1	1
23176	1	40.0	0	0
12212	1	26.0	0	0
3467	1	24.0	1	1
9536	0	43.0	0	0
11994	1	34.0	1	0
37204	0	65.0	1	0
898	0	65.0	1	1

```
In [33]: ## save the metadata information in csv
METADATA_FILE = "svm_metadat_df.csv"
svm_df = svm_df.dropna()
svm_df.to_csv(METADATA_FILE, index = False)
print(svm_df.shape)
```

(37624, 4)

```
In [41]: | ## finally traning the SVM
         image_metadata_df = pd.read_csv(METADATA_FILE);
         array = image_metadata_df.values
         X = array[:,0:3]
         y = array[:,3]
         cv = StratifiedKFold(n splits=10)
         svm_model = SVC(kernel='rbf', gamma=0.05, C=1.0)
         aucs = []
         tprs = []
         mean fpr = np.linspace(0, 1, 100)
         fig, ax = plt.subplots()
         for i, (train, test) in enumerate(cv.split(X, y)):
             svm_model.fit(X[train], y[train])
             figure = plot_roc_curve(svm_model, X[test], y[test],
                                      name='ROC fold {}'.format(i),
                                      alpha=0.3,
                                      lw=1,
                                      ax=ax)
             interp_tpr = interp(mean_fpr, figure.fpr, figure.tpr)
             interp_tpr[0] = 0.0
             tprs.append(interp_tpr)
             aucs.append(figure.roc_auc)
             print('AUC = ', end =""),
             print(float(figure.roc_auc))
         mean_tpr = np.mean(tprs, axis=0)
         mean tpr[-1] = 1.0
         mean_auc = auc(mean_fpr, mean_tpr)
         print('Mean AUC = ', end ="")
         print(mean_auc)
         ax.plot(mean_fpr, mean_tpr, color='b',
                 label=r'Mean ROC (AUC = %0.2f)' % (mean_auc),
                 lw=2, alpha=.8)
         std_tpr = np.std(tprs, axis=0)
         tprs_upper = np.minimum(mean_tpr + std_tpr, 1)
         tprs_lower = np.maximum(mean_tpr - std_tpr, 0)
         ax.set(xlim=[-0.05, 1.05], ylim=[-0.05, 1.05],
                title="ROC")
         ax.legend(loc="lower right")
         plt.show()
         x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.20, shuffle=True, random_state=0)
         svm_model = SVC(kernel='rbf', gamma=0.1, C=1.0)
         svm_model.fit(x_train, y_train)
         predictions = svm_model.predict(x_test)
         score = svm_model.score(x_test, y_test)
         print('Accuracy =',score)
         AUC = 0.7603543383903387
         AUC = 0.7352565814095717
         AUC = 0.7318865756588255
         AUC = 0.739970282106051
         AUC = 0.7748791587996797
         AUC = 0.7414709017814711
         AUC = 0.7813776824463083
         AUC = 0.7150638596138742
         AUC = 0.7753649039251859
         AUC = 0.751559674605929
         Mean AUC = 0.750701584668296
                                  ROC
            1.0
            0.8
                                        ROC fold 0 (AUC = 0.76)
```



Accuracy = 0.7326245847176079

# **Logistic Regression**

```
In [0]: ## imports
    from sklearn.model_selection import StratifiedKFold
    from sklearn.linear_model import LogisticRegression
    from sklearn import datasets
    from sklearn.metrics import auc
    from sklearn.metrics import roc_curve
    from sklearn.metrics import plot_roc_curve
    import numpy as np
    import pandas as pd
    from numpy import interp
    from sklearn.model_selection import train_test_split
    import matplotlib.pyplot as plt
```

```
In [43]:
          image_data = pd.read_csv(METADATA_FILE);
          array = image_data.values
          X = array[:,0:3]
          y = array[:,3]
          n_samples, n_features = X.shape
          # 10 fold cross-validation and plot ROC curves
          cv = StratifiedKFold(n_splits=10)
          classifier = LogisticRegression(max_iter=1000)
          aucs = []
          tprs = []
          mean\_fpr = np.linspace(0, 1, 100)
          fig, ax = plt.subplots()
          for i, (train, test) in enumerate(cv.split(X, y)):
               classifier.fit(X[train], y[train])
               figure = plot_roc_curve(classifier, X[test], y[test],
                                      name='ROC fold {}'.format(i),
                                      alpha=0.3, lw=1, ax=ax)
              interp_tpr = interp(mean_fpr, figure.fpr, figure.tpr)
              interp_tpr[0] = 0.0
              tprs.append(interp_tpr)
              aucs.append(figure.roc_auc)
              print('AUC = ', end =""),
              print(float(figure.roc auc))
          mean tpr = np.mean(tprs, axis=0)
          mean\_tpr[-1] = 1.0
          mean_auc = auc(mean_fpr, mean_tpr)
          print('Mean AUC = ', end ="")
          print(mean_auc)
          ax.plot(mean_fpr, mean_tpr, color='b',
                   label=r'Mean ROC (AUC = %0.2f)' % (mean auc),
                   lw=2, alpha=.8)
          std_tpr = np.std(tprs, axis=0)
          tprs_upper = np.minimum(mean_tpr + std_tpr, 1)
          tprs_lower = np.maximum(mean_tpr - std_tpr, 0)
          ax.set(xlim=[-0.05, 1.05], ylim=[-0.05, 1.05],
                  title="ROC")
          ax.legend(loc="lower right")
          plt.show()
          x_{train}, x_{test}, y_{train}, y_{test} = train_{test}, y_{test}, y_{test}
          classifier.fit(x_train, y_train)
          predictions = classifier.predict(x_test)
          score = classifier.score(x_test, y_test)
          print('Accuracy =',score)
          AUC = 0.7607636797016915
          AUC = 0.7187631217423848
          AUC = 0.7404661983916168
          AUC = 0.7381497829777912
          AUC = 0.7860680478312805
          AUC = 0.7341965968948769
          AUC = 0.7650417503314481
          AUC = 0.7164905409231219
          AUC = 0.7878211816654186
          AUC = 0.7484251995470237
          Mean AUC = 0.7495639166290029
             1.0
             0.8
                                           ROC fold 0 (AUC = 0.76)
                                           ROC fold 1 (AUC = 0.72)
           True Positive Rate
                                           ROC fold 2 (AUC = 0.74)
             0.6
                                           ROC fold 3 (AUC = 0.74)
                                           ROC fold 4 (AUC = 0.79)
                                           ROC fold 5 (AUC = 0.73)
             0.4
                                           ROC fold 6 (AUC = 0.77)
                                           ROC fold 7 (AUC = 0.72)
             0.2
                                           ROC fold 8 (AUC = 0.79)
                                           ROC fold 9 (AUC = 0.75)
```

Accuracy = 0.7327574750830564

0.2

0.4

False Positive Rate

0.6

Mean ROC (AUC = 0.75)

0.8

1.0

0.0

0.0