PNEUMONIA DETECTION CHALLENGE

AIML Capstone Project Group 10

Table of Contents

Project Details 3
- 1.1 Need of Pneumonia detection 3
- 1.2 Current challenges in Pneumonia treatment: 4

Overview 6
- Data Pre-Processing 6
- Data Distribution 7
- Salient features of the data 8
- Salient features of the model used 9

Deep Learning Model 9
- ResNet Model Architecture 9
- DenseNet model Architecture 10
- U-Net model Architecture 11
- Sigmoid Activation 12
- IoU Accuracy 13

Model evaluation 14

Comparison to benchmark 14

Visualization 14
- Data Visualization 14
- Images visualization 16
- Model performance graph 17
  - ResNet 17
  - DenseNet 18
  - U-Net 18
- Model prediction visualization 18

Implications 18

Approach to improve model performance and Comparison: 20

Constraints 21

Conclusion 21

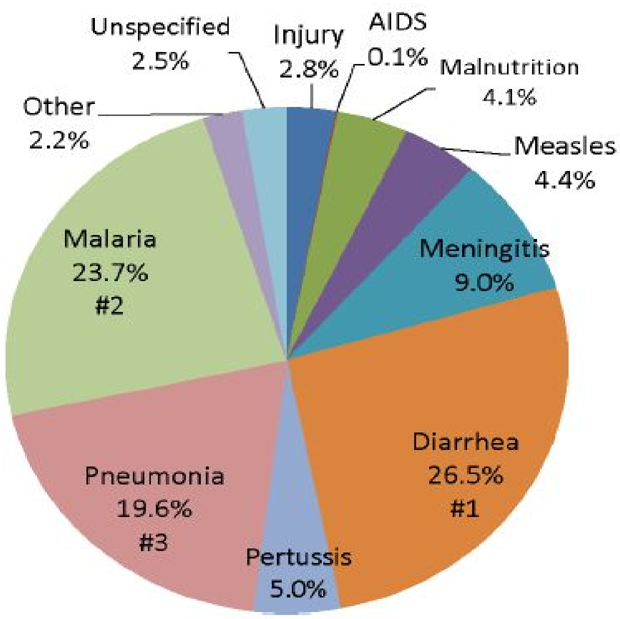
References 21

1. Project Details

This project is for Pneumonia detection that is present in patient's lungs which the below explained model will learn through 26684 scan images which are actually dicom files. The images are classified into 2 categories 0 i.e., normal and 1 i.e, a person is having infection. Also the model will detect the location of infected areas into the scanned images of the patient's lungs. This model was required for below reasons.

1.1 Need of Pneumonia detection

The risk of pneumonia is immense for many, especially in developing nations where billions face energy poverty and rely on polluting forms of energy. The WHO estimates that over 4 million premature deaths occur annually from household air pollution-related diseases including pneumonia.



It is the most spread disease after malaria and diarrhea. Over 150 million people get infected with pneumonia on an annual basis especially children under 5 years old. In such regions, the problem can be further aggravated due to the dearth of medical resources and personnel. For example, in Africa's 57 nations, a gap of 2.3 million doctors and nurses exists. For these populations, **accurate and fast diagnosis** means everything. It can guarantee timely access to treatment and save much needed time and money for those already experiencing poverty.

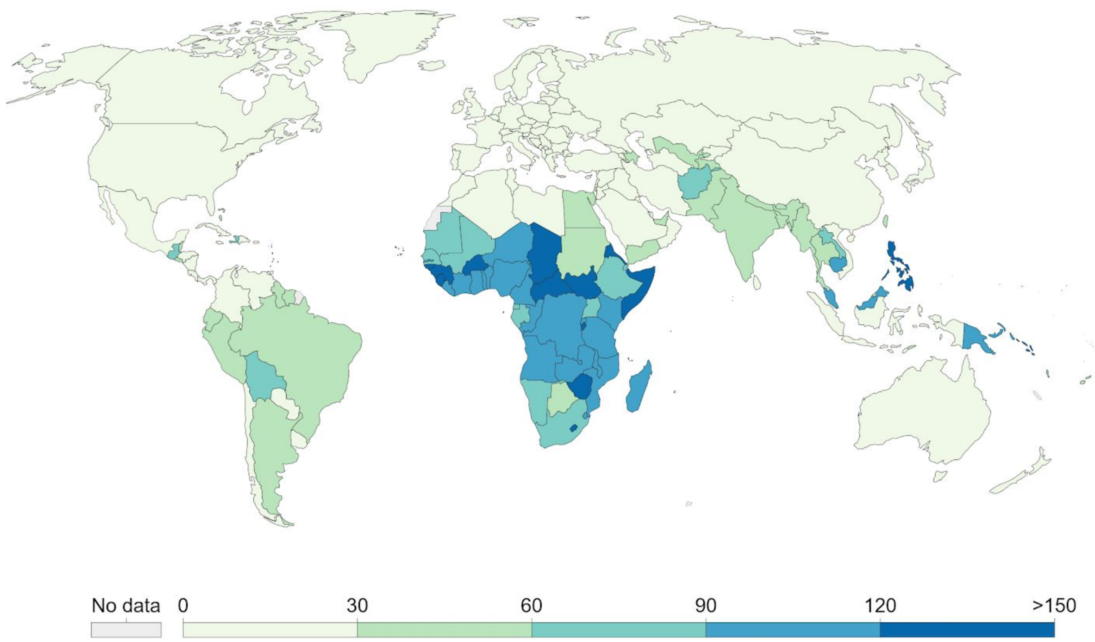
1.2 Current challenges in Pneumonia treatment:

There are many developing countries where people die due to pneumonia because the diagnosys starts when it's already late. Any approach like what we have adopted in this model, will detect the pneumonia within seconds and patients can be diagnosed at the early stages of infection. The regions of the world where such an approach is required are in the below image.

Death rate from pneumonia, 2017

The annual number of deaths from pneumonia per 100,000 people.

Our World in Data



Source: Global Burden of Disease Study, IHME (2018)

Note: To allow comparisons between countries and over time this metric is age-standardized. Deaths from 'clinical pneumonia', which refers to a diagnosis based on disease symptoms such as coughing and difficulty breathing and may include other lower respiratory diseases.

2. Overview

In EDA we have done analysis of 4 files. Two CSV files & two zip files which contain images. Total 30227 records are there in the CSV file.

2.1. Data Pre-Processing

For the data provided there are no missing values or NULL values so as per the data and the values there is no need for pre-processing to be done. Also we can observe that without pre-processing the output of the data is looking good and there is no gap present.

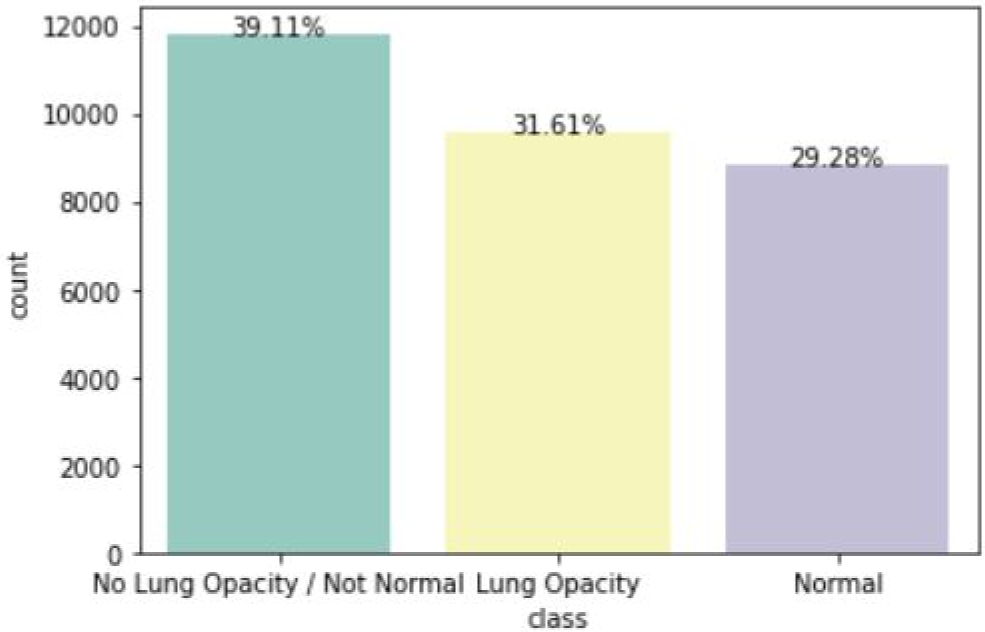
We have prepared balanced data with 1.5K records for pneumonia positive type & 1.5K images for normal images.

Below we can see column description and the Null values count

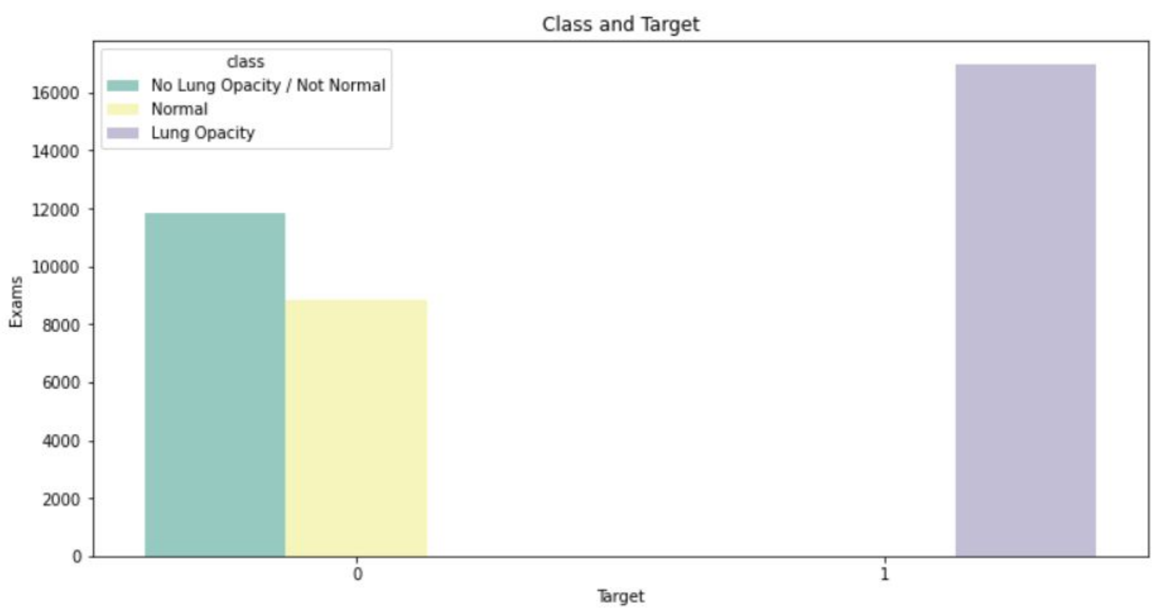
S No	Column	Description	Null Values
1	patientId	A patientId. Each patientId corresponds to a unique image.	0
2	x	the upper-left x coordinate of the bounding box.	20,672
3	y	the upper-left y coordinate of the bounding box.	20,672
4	width	the width of the bounding box.	20,672
5	height	the height of the bounding box.	20,672
6	Target	the binary Target, indicating whether this sample has evidence of pneumonia.	0
7	Class	Normal, No Lung Opacity / Not Normal, Lung Opacity	0

Our observation is Null values are only present in columns (x,y,width,height) where target is 0 (No opacity/Normal).

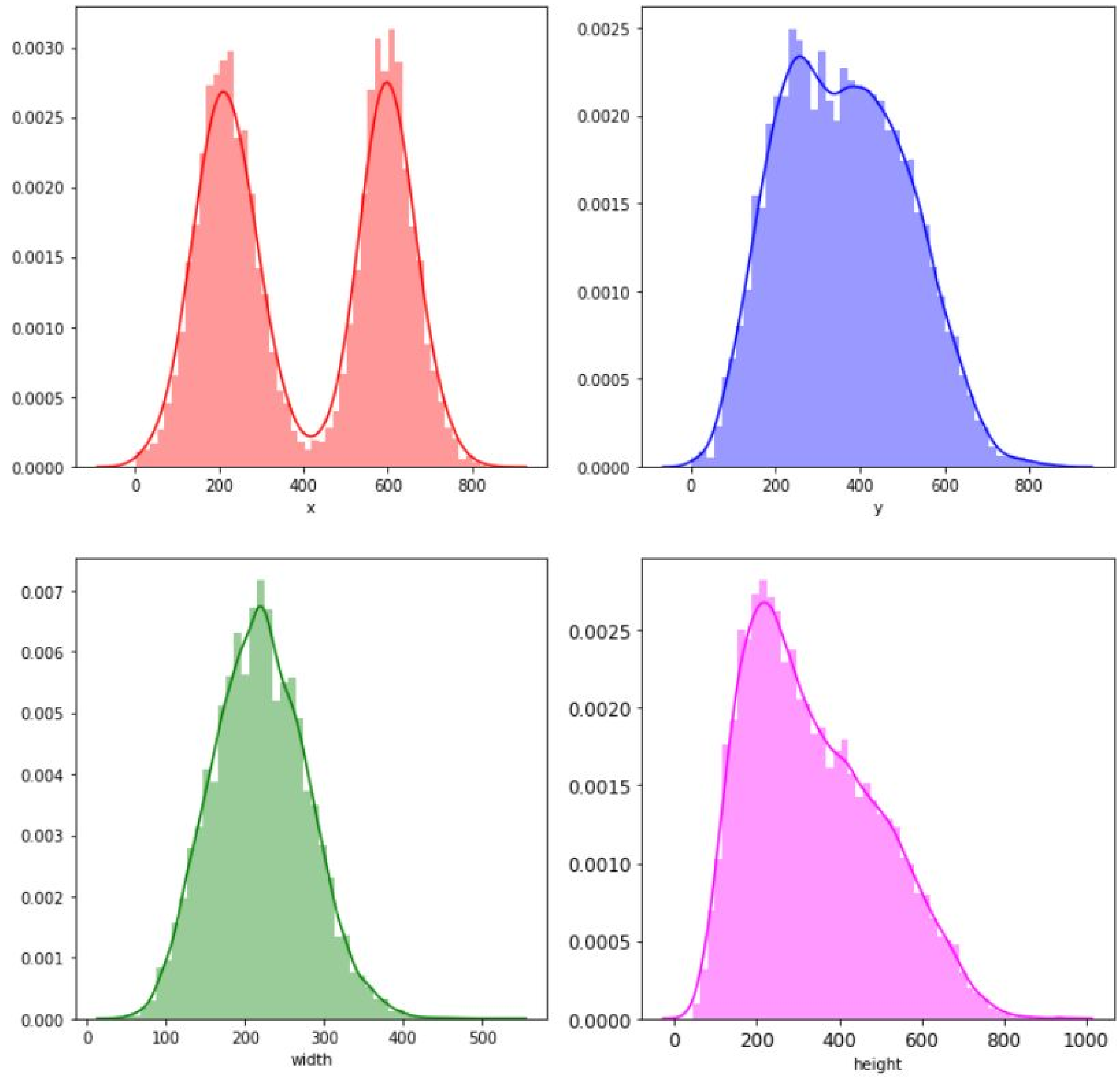
2.2. Data Distribution



In above graph we can see distribution of data against 3 classes (Lung Opacity, Normal & Not normal)



From above graph we can see that Target = 1 is associated with class: Lung Opacity & Target = 0 are either of class: Normal or class: No Lung Opacity / Normal



Above graph is distribution of x,y,width & height columns.

2.3. Salient features of the data

- We have a total of 26,684 images in the training data set & 3000 images in testing dataset.
- Target = 1 is associated with class: Lung Opacity.
- Target = 0 are either of class: Normal or class: No Lung Opacity
- There is no x,y,width & height value for records with Target 0.
- There are two gaussians for the x point distribution graph. This represents Lung opacity in both left & right lungs in the given dataset.
- There is x,y,width & height value for records with Target 1. We are going to use this for model training.

2.4. Salient features of the model used

The proposed pneumonia detection system is using “U-Net Model Architecture” with this model we achieved an accuracy of 96% . Also we checked with the models like DenseNet and ResNet but it looks that better accuracy is achieved using the U-Net Model.

3. Deep Learning Model

Build an algorithm to automatically identify whether a patient is suffering from pneumonia or not by looking at chest X-ray images. The algorithm had to be extremely accurate because lives of people are at stake.

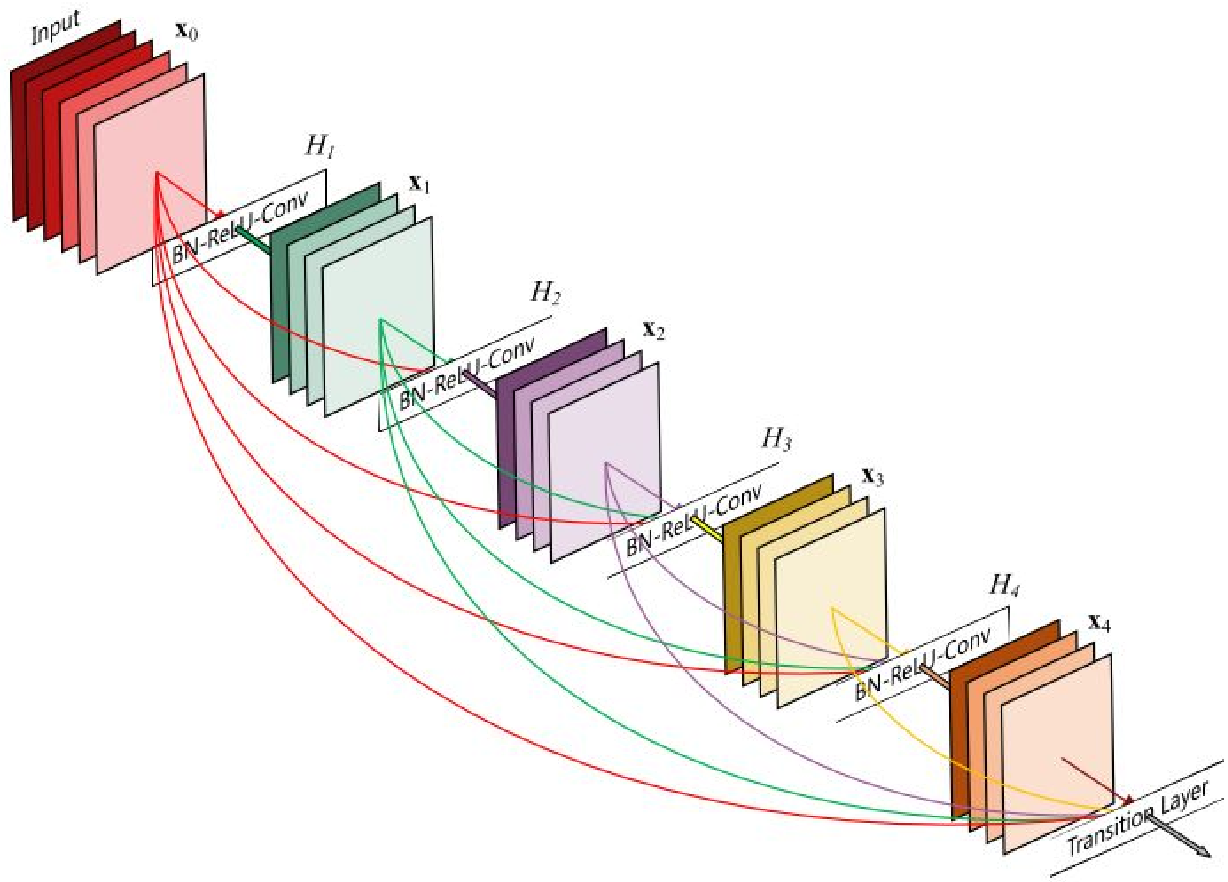
In recent times, CNN-motivated deep learning algorithms have become the standard choice for medical image classifications although the state-of-the-art CNN-based classification techniques pose similar fixated network architectures of the trial-and-error system which have been their designing principle. ResNet, U-Net, DenseNet, SegNet and CardiacNet are some of the prominent architectures for medical image examination. To design these models, specialists often have a large number of choices to make design decisions, and intuition significantly guides manual search processes. Models like evolutionary-based algorithms and reinforcement learning (RL) have been introduced to locate optimum network hyperparameters during training.

We are going to propose a U-Net model for Pneumonia detection. Unet architecture is outperformed on bio-medical images and image segmentation.The U-Net combines the location information from the downsampling path with the contextual information in the upsampling path to finally obtain a general information combining localisation and context, which is necessary to predict a good segmentation map.As a general convolutional neural network focuses its task on image classification, where input is an image and output is one label, but in biomedical cases, it requires us not only to distinguish whether there is a disease, but also to localise the area of abnormality.The another main advantage is , U-Net doesn't have any dense layer, so we can use different sizes of images as input.

Here we are using a Sigmoid as output function hence its a binary cross entropy. It is also having a classifier called as Sigmoid Activation Function.The output of each layer is being forwarded in the next proceeding layer as its input in all the feature extraction layers.

ResNet Model Architecture

The proposed CNN architecture is having combination of several layers like Convolution layers, max pooling and various classification layers. The layers for feature extractors consist of conv3×3,64, conv3×3, 128, conv3×3,256,conv3×3,32,conv3×3,16,conv3×3,64 and LeakyRELU activators in between them. Then, the output obtained from the convolutional layers and max pooling layers are being converted into 2D planes which are called as feature maps and further we get the feature maps, respectively for the convolution operations and pooling operations. The size of the input image is 256×256×1. Moreover, the plane of each layer was obtained by merging more planes occurred in the previous layers.In this model, Sigmoid Activation Function is used as the classifier which is kept at the far end of the model. It has a lot of dense layers so it is also called an ANN model. This function is sometimes also called the squashing function. They limit the output range in between 0 and 1, which helps in the possible prediction of probabilities.



Source: Wikipedia

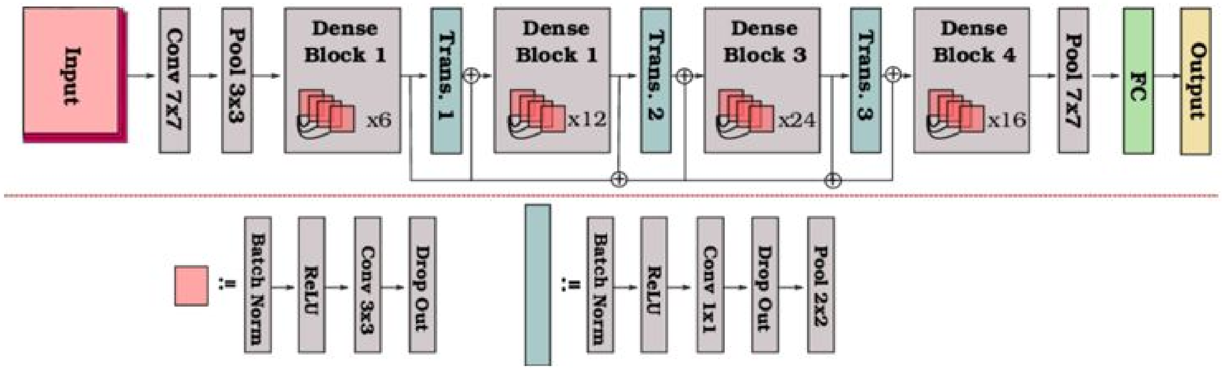
DenseNet model Architecture

DenseNet falls in the category of classic networks. DenseNet is quite similar to ResNet with some fundamental differences. ResNet uses an additive method (+) that merges the previous layer (identity) with the future layer, whereas DenseNet concatenates (.) the output of the previous layer with the future layer.

DenseNet architecture is new, it is a logical extension of ResNet.

DenseNet was developed specifically to improve the declined accuracy caused by the vanishing gradient in high-level neural networks. In simpler terms, due to the longer path between the input layer and the output layer, the information vanishes before reaching its destination.

This image shows a 4-layer dense block. see what's inside the DenseBlock and transition layer.



The DenseNet has different versions, like DenseNet-121, DenseNet-160, DenseNet-201, etc. The numbers denote the number of layers in the neural network.

U-Net model Architecture

The UNET architecture contains two paths. First path is the contraction path (also called the encoder) which is used to capture the context in the image. The encoder is just a traditional stack of convolutional and max pooling layers.

2

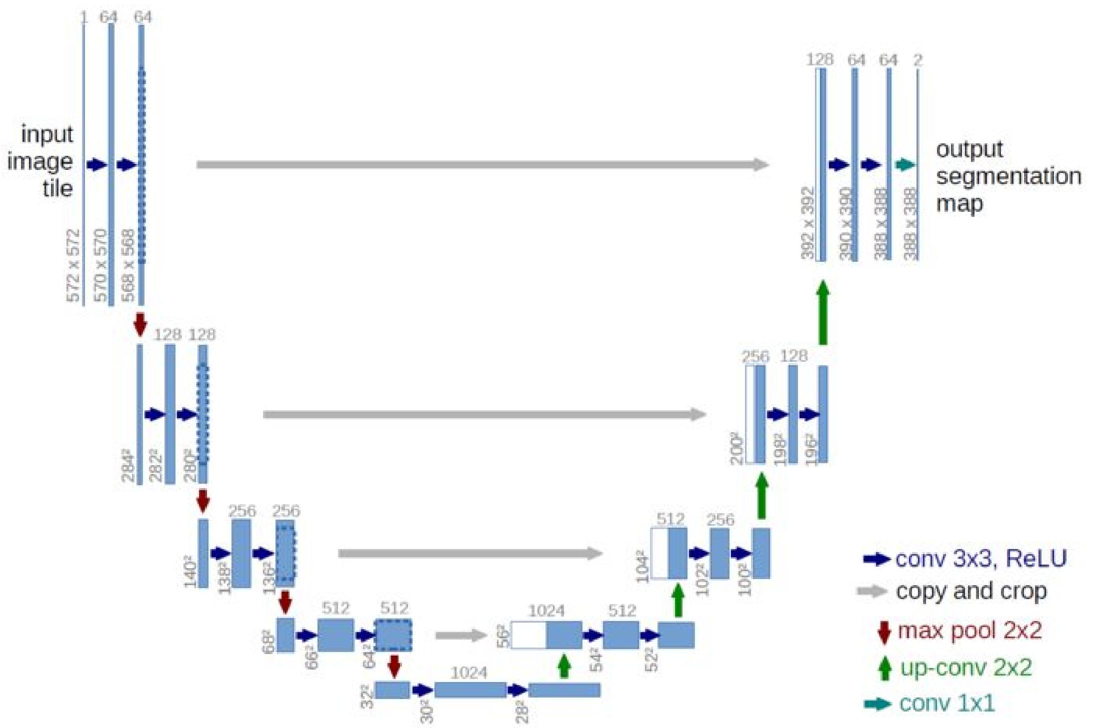


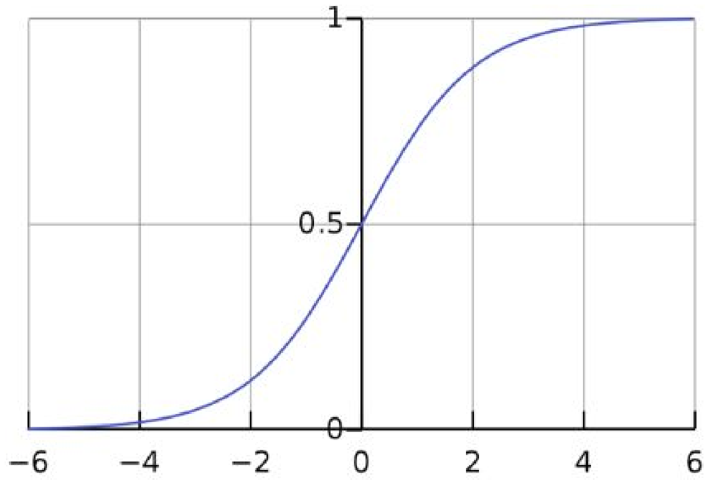
Fig. 1. U-net architecture (example for 32x32 pixels in the lowest resolution). Each blue box corresponds to a multi-channel feature map. The number of channels is denoted on top of the box. The x-y-size is provided at the lower left edge of the box. White boxes represent copied feature maps. The arrows denote the different operations.

Image Source:pinterest

The second path is the symmetric expanding path (also called the decoder) which is used to enable precise localization using transposed convolutions. Thus it is an end-to-end fully convolutional network (FCN), i.e. it only contains Convolutional layers and does not contain any Dense layer because of which it can accept images of any size.

Sigmoid Activation

The sigmoid activation function, also called the logistic function, is traditionally a very popular activation function for neural networks. The reason why we use sigmoid function is because it squashes the input between (0 to 1). Therefore, it is especially used for models where we have to predict the probability as an output. Since probability of anything exists only between the range of 0 and 1, sigmoid is the way to go.



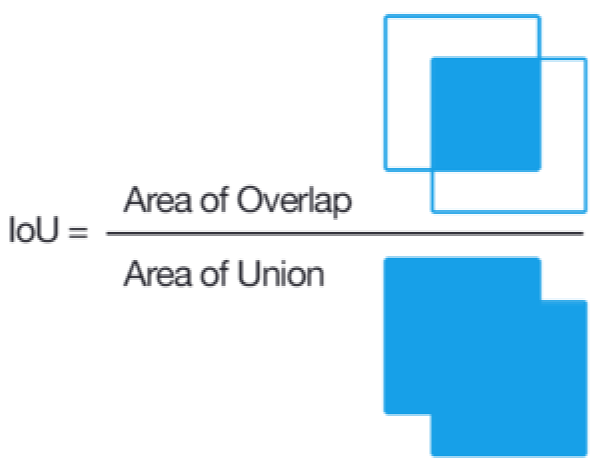
$$S(x) = \frac{1}{1+e^{-x}} = \frac{e^x}{e^x+1}.$$

Sigmoid Activation Function. Source: Wikipedia

IoU Accuracy

The Intersection-Over-Union (IoU), also known as the Jaccard Index, is one of the most commonly used metrics in semantic segmentation. To identify the mask area using this function is like a straightforward technique.

IoU is the area of overlap between the predicted segmentation and the ground truth divided by the area of union between the predicted segmentation and the ground truth.This metric ranges from 0–1 (0–100%) with 0 signifying no overlap and 1 signifying perfectly overlapping segmentation.



IoU calculation visualized. Source: Wikipedia

For multi-class segmentation, the mean IoU of the image is calculated by taking the IoU of each class and averaging them.
Mean IoU = ((Area of Overlap/Area of Union) + Area of Overlap/Area of Union)/2

4. Model evaluation

In this project , implemented three different models (ResNet,U-Net and Dense Net) to identify the pneumonia in lungs.These all three models evaluated with different hyper parameters and different sets of images. Initially we started the evaluation with below 1000 images and kept on increasing the images and captured the Model Accuracy and validation accuracy.For model evaluation ,we have used Jaccord index and Mean IOU technique.In Initial stage , we have achieved the accuracy of 92%,90% and 92% using Resnet,Dense and Unet respectively.
To further improve the performance of models, we performed parameter tuning like modifying learning rate, batch size , dropout and batch normalization techniques also increased the network size and optimizer as adam. After Parameter tuning , we have achieved the accuracy of 94%,90% and 96% using Resnet,Dense and Unet respectively. All three models are performing well , compared to others Unet models have outperformed.

5. Comparison to benchmark

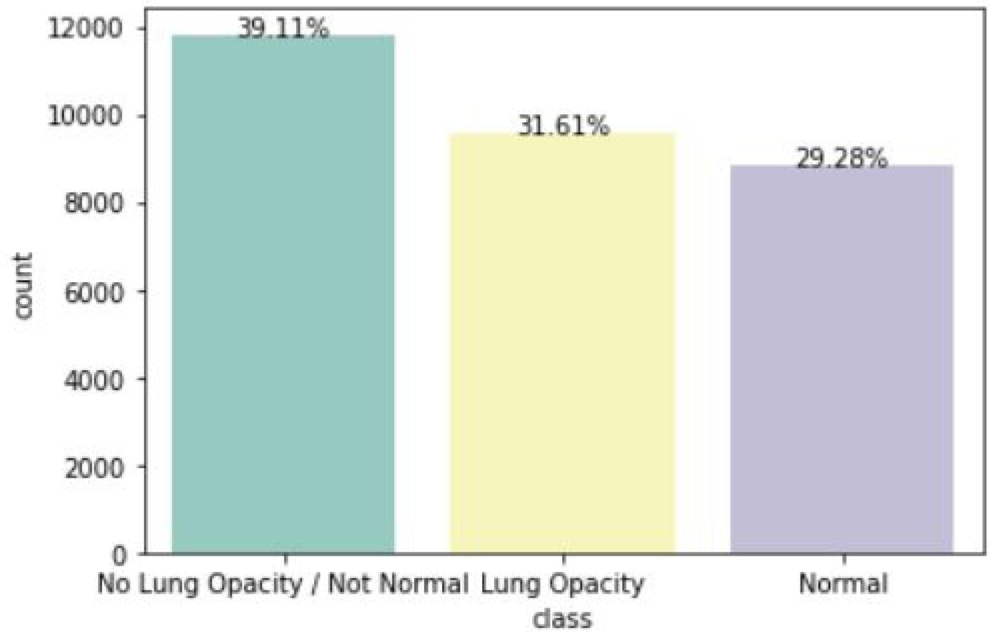
Following 3 models were tried and compared for the requirement. After comparison it can be concluded that ResNet is having maximum accuracy and can be opted for the project.

ResNet			
Accuracy	***Val accuracy***	***Loss***	***Parameters generated***
94%	93%	35%	12,718,305
DenseNet			
Accuracy	***Val accuracy***	***Loss***	***Parameters generated***
92%	91%	47%	7,032,257
UNet			
Accuracy	***Val accuracy***	***Loss***	***Parameters generated***
96%	95%	28%	7,929,673

We have tried to improve model accuracy using different parameters & different sets of data. In milestone 1 we had achieved accuracy around 92%. Later we tried DenseNet & U-Net & achieved around 96% accuracy with U-Net. We were trying to use maximum data for model training but due to hardware constraint we were not able to use & train mode using all images.

6. Visualization

6.1. Data Visualization



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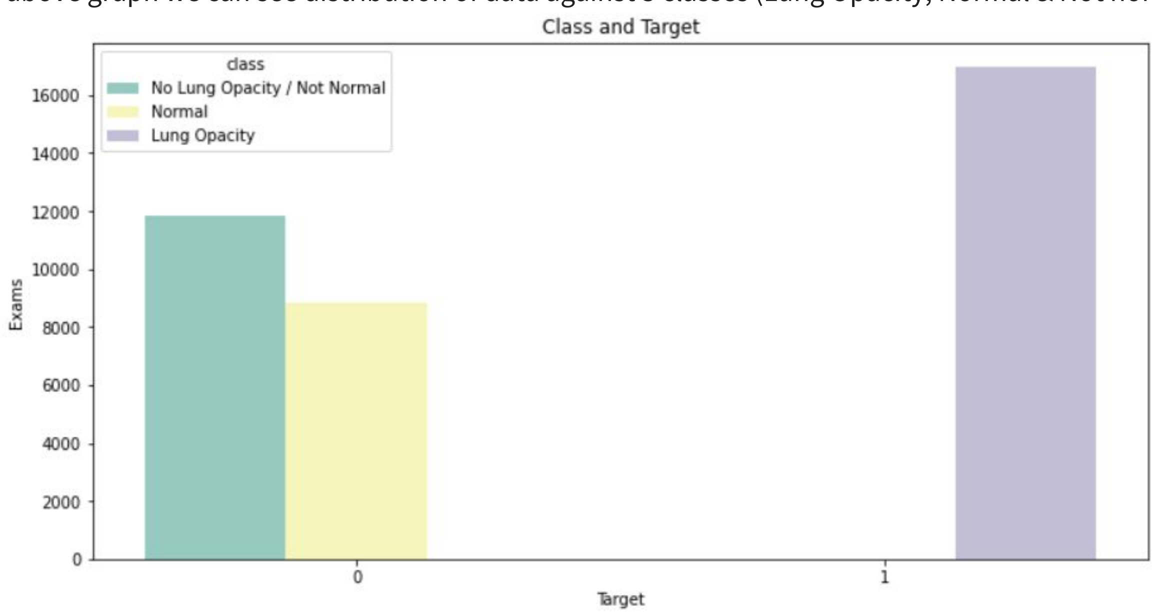

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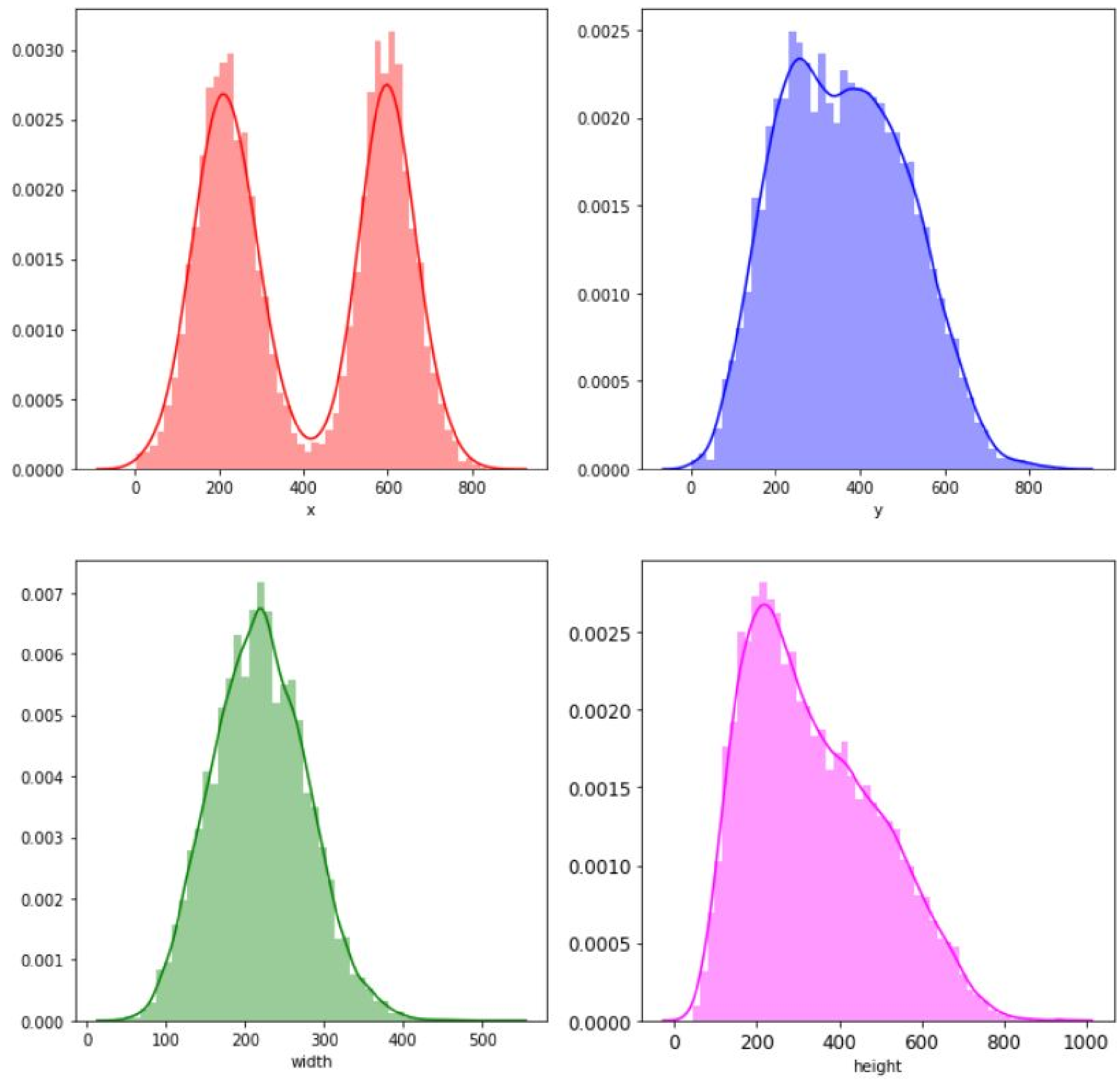
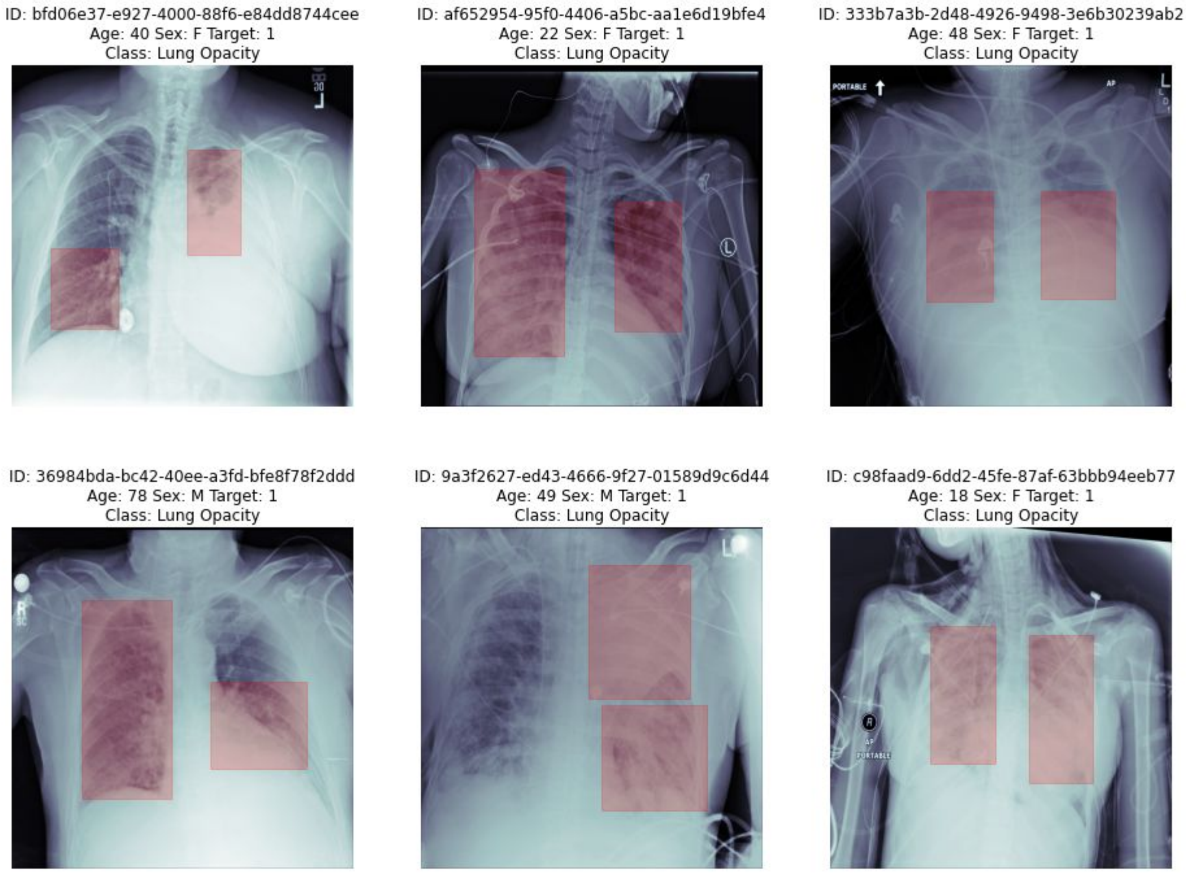


Above graph is distribution of x,y,width & height columns.

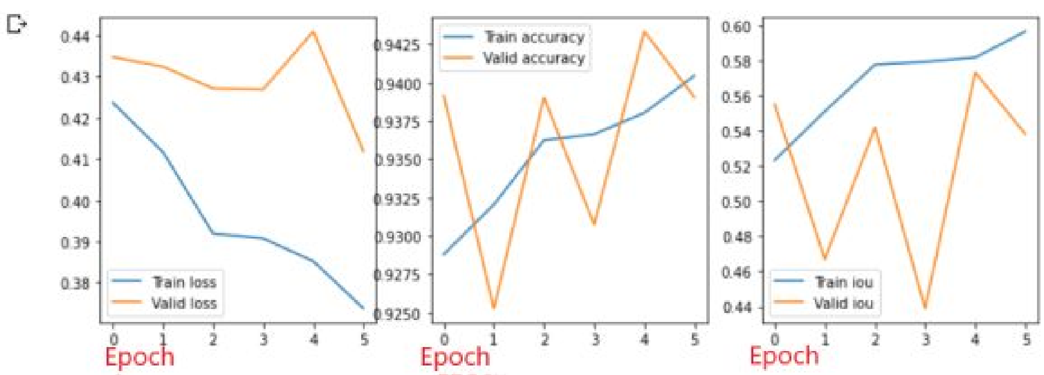
6.2. Images visualization

We have read dicom images using pydicom lib. Our data contains image & boxes for infection detected in the image. We have plotted image with box (pneumonia location) on image given below :

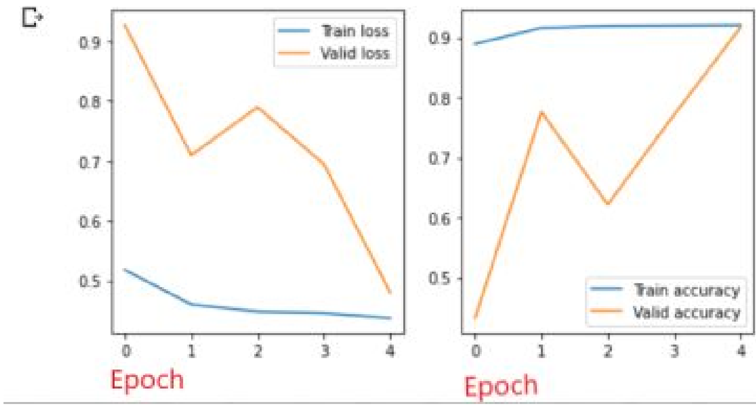


6.3. Model performance graph

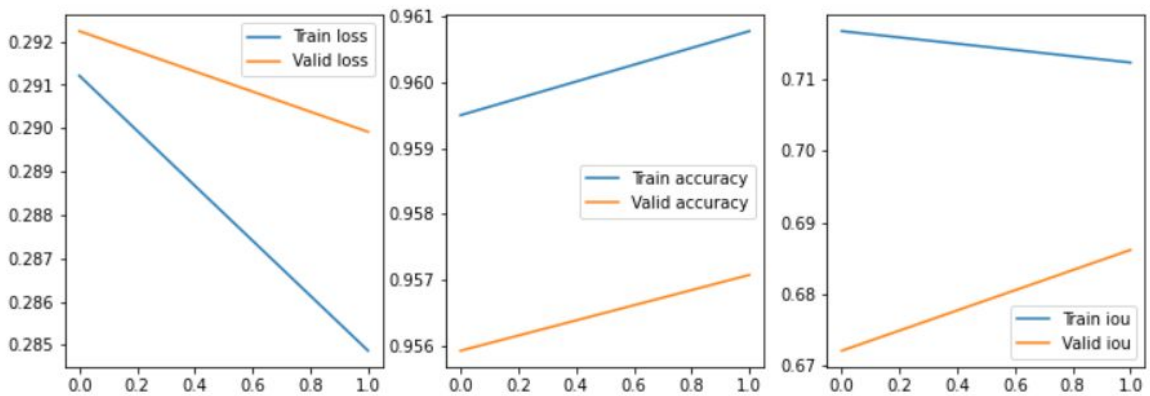
6.3.1. ResNet



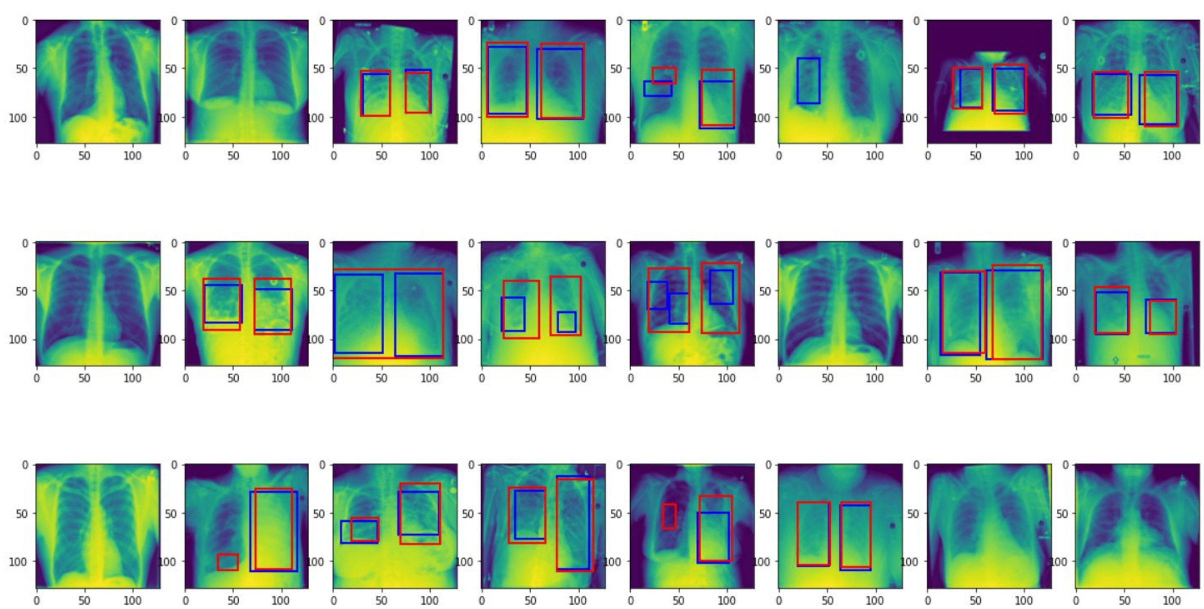
6.3.2. DenseNet



6.3.3. U-Net



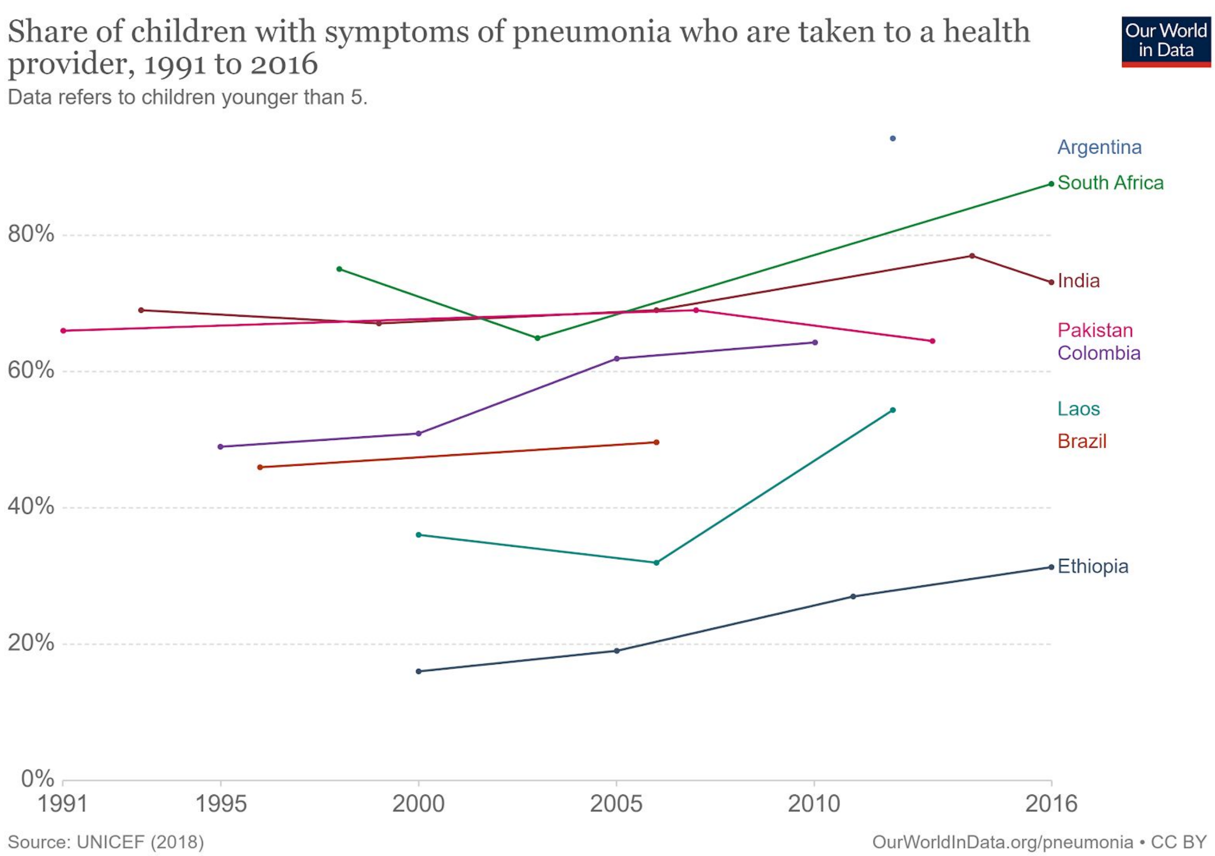
6.4. Model prediction visualization



In the above image the red box is the prediction of pneumonia location & blue boxes are the actual location of Pneumonia. We have plotted the above boxes using the U-Net model.

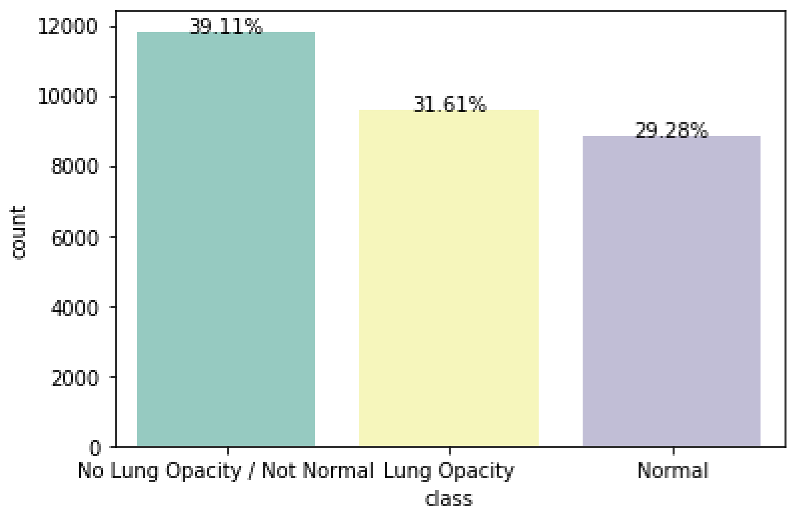
7. Implications

The risk of pneumonia is immense for many, especially in developing nations where billions face energy poverty and rely on polluting forms of energy. The WHO estimates that over 4 million premature deaths occur annually from household air pollution-related diseases including pneumonia. Over 150 million people get infected with pneumonia on an annual basis especially children under 5 years old. In such regions, the problem can be further aggravated due to the dearth of medical resources and personnel. For example, in Africa's 57 nations, a gap of 2.3 million doctors and nurses exists. For these populations, accurate and fast diagnosis means everything. It can guarantee timely access to treatment and save much needed time and money for those already experiencing poverty.

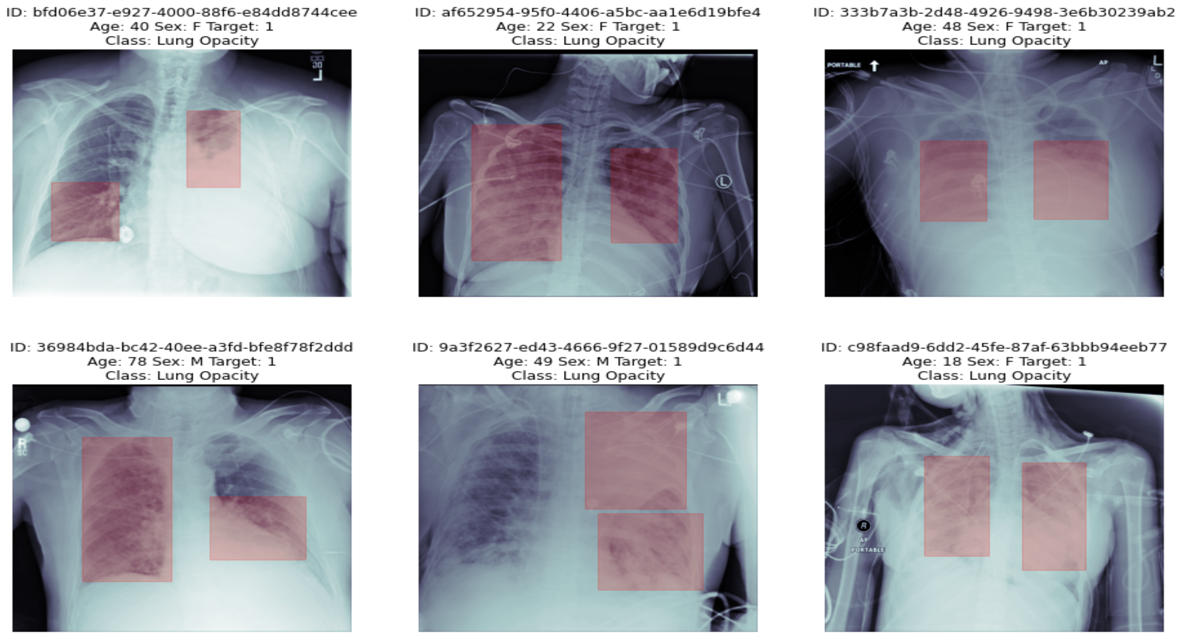


In the world of healthcare, one of the major issues that medical professionals face is the correct diagnosis of conditions and diseases of patients. Not being able to correctly diagnose a condition is a problem for both the patient and the doctor. The doctor is not benefiting the patient in the appropriate way if the doctor misdiagnoses the patient. This could lead to malpractice lawsuits and overall hurt the doctor's business. The patient suffers by not receiving the proper treatment and

risking greater harm to health by the condition that goes undetected; further, the patient undergoes unnecessary treatment and takes unnecessary medications, costing the patient time and money.
If we can correctly diagnose a patient's condition, we have the potential to solve the above-mentioned problems. If we can produce deep learning models that can classify whether a patient has a condition or not, that can determine which particular condition the patient has, and that can determine the severity of the condition, then medical professionals will be able to use these models to better diagnose their patients. Accurate diagnosis can also be useful by allowing for timely treatment of a patient; being misdiagnosed can cause a delay in receiving the proper treatment. There were basically 3 categories in the data set, with the following distribution in the data set which was extracted as part of EDA.



In this project, we will perform deep learning to a dataset representing the chest x-rays of patients and
will apply a convolutional neural network (CNN) and try to highlight the area of the infection in the lungs that is present in X-ray images. The model could identify the infected area with **85% confidence**. Here is a sample of how the highlighted area looks like:



8. Approach to improve model performance and Comparison

When we observed U-Net is giving better accuracy of 96% when compared with DenseNet & ResNet. For the same data when Model evaluation is done with ResNet we got an accuracy of 94% & 92% with DenseNet121.

To Improve Model Performance below points to be considered

1. Try with different hyperparameter
2. Current model is trained with 3000 images. We can train models with more data to improve accuracy. (Due to hardware limitation we have used only 3K images)
3. We can try with different image sizes to check the accuracy. Right now using 128*128 for U-Net & 256*256 for DenseNet & ResNet.

9. Constraints

Although the results were overwhelming, there were still some limitations in our model which we believe are vital to keep in consideration. The first biggest limitation is that there is no history of the associated patient considered in our evaluation model. Secondly, only frontal chest X-rays were used but it has been shown that lateral view chest X-rays are also helpful in diagnosis.. Thirdly, we have done model training for 3000 images using U-Net. It took almost 10 hours to complete.

10. Conclusion

The report primarily aims to improve the medical adeptness in areas where the availability of radiotherapists is still limited. The study facilitates the early diagnosis of Pneumonia to prevent adverse consequences (including death) in such remote areas.The aim of our report is to provide the dominating pre-trained U-Net model and classifier for the future work in the similar research domain. The report will likely lead to the development of better algorithms for detecting Pneumonia in the foreseeable future.

11. References

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[4] *Benjamin Antin, Joshua Kravitz, and Emil Martayan. 2017. Detecting Pneumonia in Chest X-Rays with Supervised Learning. (2017).*