Covid-19 induced Pneumonia Detection using Deep Learning

**Class** : ECSE 6420

**Project Participants** : Md Asaduzzaman Jabin

**Student ID(s)** : 811562873

**Date** : Jan 30, 2023

**NOTE: Delete the yellow highlighted regions and ADD YOUR TEXT**

# Introduction

Pneumonia is a severe and potentially fatal infection that affects the lungs and is often caused by the bacterium Streptococcus pneumoniae. According to the World Health Organization (WHO), one out of three deaths in India is due to pneumonia. Diagnosing pneumonia requires an expert radiologist to evaluate chest X-rays, making the development of an automated system to detect the disease beneficial, especially in remote areas. The use of Convolutional Neural Networks (CNNs) in medical image analysis, specifically in disease classification, has gained popularity due to the success of deep learning algorithms. By using pre-trained CNN models on large datasets, useful features can be learned for image classification tasks. This study evaluated the effectiveness of using pre-trained CNNs as feature extractors with various classifiers for distinguishing between normal and abnormal chest X-rays. The optimal CNN model for this purpose is determined, and the results show that using pre-trained CNNs with supervised classifiers can be highly effective in analyzing chest X-rays and detecting pneumonia.

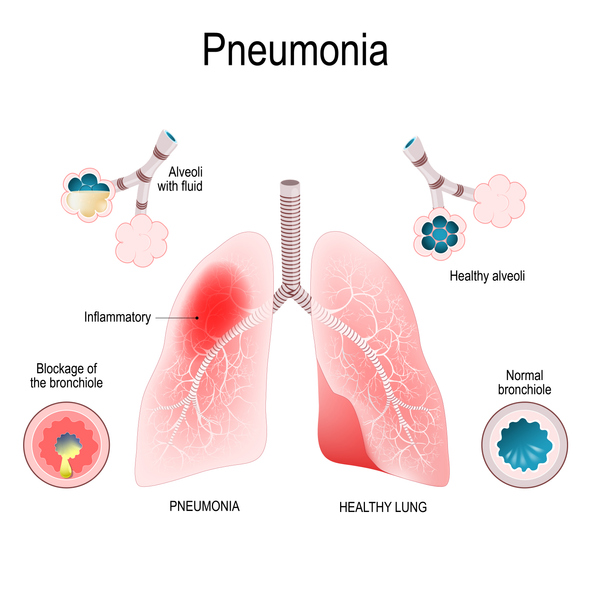


Fig. 1: The basic understanding of Pneumonia from X-ray samples (ref: kaggle.com)

This project sets itself apart by investigating various deep-learning algorithms such as VGG-16, ImageNet, ResNet50 and the transformer model for pneumonia detection, which has not been widely researched. The system will be evaluated using Kaggle datasets of x-ray images with blurred and noisy features to test its accuracy. To display masking, we need to use OpenCV tools and selective search algorithm to extract the feature from the image. The current highest accuracy reported in the literature for this task is around 80-90%, but the goal is to surpass this by striving for 95-98% accuracy using python TensorFlow. The aim is to achieve the highest accuracy possible in pneumonia classification by updating available open-source code from GitHub and Kaggle, which have been used for solving other image classification problems.

# Literature Review

Pneumonia is a life-threatening respiratory illness and remains a major cause of morbidity and mortality worldwide. It is important to diagnose pneumonia in a timely and accurate manner to ensure effective treatment. In recent years, deep learning-based methods have been proposed for pneumonia detection in chest radiographs. Among them, K. He eta al. [1] mentioned Mask Region-based Convolutional Neural Network (M-RCNN) has shown promising results. This literature review aims to provide an overview of the research studies that have used M-RCNN with COCO weights [2] for pneumonia detection.

M-RCNN is a state-of-the-art object detection framework that uses a two-stage pipeline to identify and classify objects in an image. The segmentation over a short period of time is always driven by a powerful base model like – ResNet [3], VGG-16 [3-4] with ImageNet weights or COCO weights [4]. The first stage generates object proposals using a Region Proposal Network (RPN), while the second stage uses a classifier to predict the class and refine the bounding box of each object. M-RCNN has been shown to achieve high accuracy in object detection tasks [5].

Lin et al. [6] described a COCO (Common Objects in Context) dataset is a large-scale object detection dataset that contains more than 330,000 images and 2.5 million object instances. COCO weights refer to pre-trained weights on this dataset, which can be used as a starting point for training deep learning models for various object detection tasks. Learning based on pre-trained model and pre-trained weights to solve a new problem by adding an extra layer next to the base layer is called transfer learning [7].

Several studies have used M-RCNN with COCO weights for pneumonia detection [8] in chest radiographs. One such study by Wang et al. [9] used a pre-trained M-RCNN with COCO weights for pneumonia detection in a dataset of 6,000 chest radiographs. The study reported an overall accuracy of 94.7% and an area under the receiver operating characteristic curve (AUC-ROC) of 0.975, demonstrating the effectiveness of the approach for pneumonia detection.

Another study by Rajaraman et al. [10] used M-RCNN with COCO weights for pneumonia detection in a dataset of 5,232 chest radiographs. The study reported an AUC-ROC of 0.932 for detecting pneumonia, which outperformed the performance of radiologists in the same dataset.

A third study by Kermany et al. [11] used a pre-trained M-RCNN with COCO weights for pneumonia detection in a dataset of 5,856 chest radiographs. The study reported an AUC-ROC of 0.92, which was comparable to the performance of radiologists in the same dataset.

In summary, M-RCNN with COCO weights has shown promising results for pneumonia detection in chest radiographs. The pre-trained COCO weights provide a good starting point for training deep learning models, which can be fine-tuned for pneumonia detection. The studies reviewed in this literature review demonstrate the effectiveness of the approach for pneumonia detection, and further research is needed to validate and refine the approach for clinical use.

# Methodology

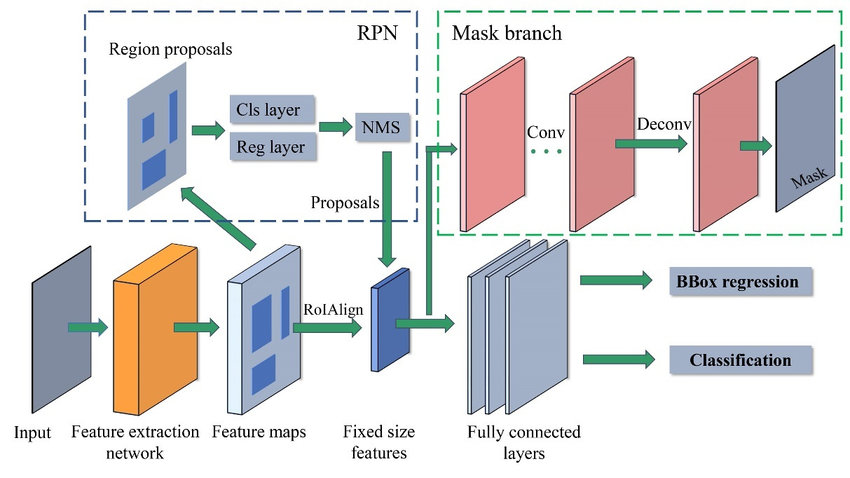
**3.1 Workflow**

The Mask R-CNN (M-RCNN) model is a popular deep learning-based approach for object detection that extends the Faster R-CNN model by adding a segmentation branch. The COCO weights refer to pre-trained weights that have been trained on the COCO dataset, which is a large-scale object detection, segmentation, and captioning dataset. We will use python packages including Keras, Tensorflow, OpenCV to implement M-RCNN and COCO weights.

Here's a general workflow for using M-RCNN with COCO weights:

1. Find out data set and data description
2. Prepare your dataset by annotating the images with object labels and segmentations.
3. Install the necessary dependencies, including TensorFlow, Keras, and the Mask R-CNN library.
4. Download the COCO pre-trained weights from the official Mask R-CNN repository.
5. Do data augmentation using any tools.
6. Preprocessing and Train/ Test split
7. Train the M-RCNN model using the COCO pre-trained weights as the starting point. First freeze the base model and train the data set by using extra added layers.
8. Fine-tune the model on your dataset to improve the accuracy of the detections and segmentations.
9. Evaluate the model on a separate validation set to measure its performance.

Use the model to detect objects in new images by running the inference pipeline, which involves passing an image through the network, generating proposals, refining them, and computing the final bounding boxes and masks.

**Fig. 2 The schematic architecture of M-RCNN**

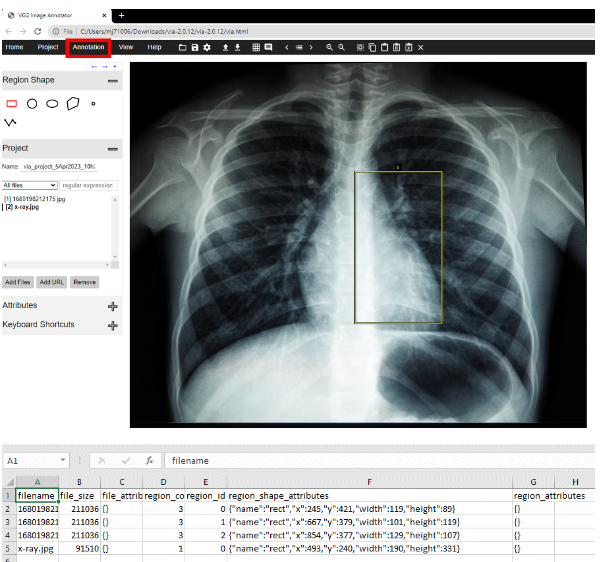
1. **Data Set:**

**Source:** RSNA Pneumonia Detection Challenge with transfer learning (<https://www.kaggle.com/competitions/rsna-pneumonia-detection-challenge/data>)

**Data fields:**

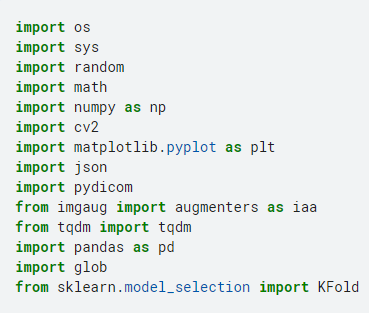
1. patientId \_- A patientId. Each patientId corresponds to a unique image.
2. x - the upper-left x coordinate of the bounding box.
3. y - the upper-left y coordinate of the bounding box.
4. width - the width of the bounding box.
5. height - the height of the bounding box.
6. Target - the binary Target, indicating whether this sample has evidence of pneumonia
7. **Data Annotation:**

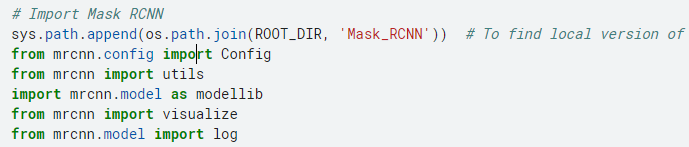
Data Annotation via VGG Image Annotator (<https://www.robots.ox.ac.uk/~vgg/software/via/>)



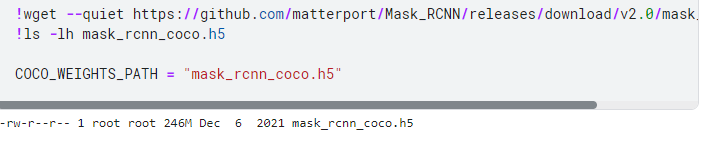
**Fig 3: Image Annotation using VGG Image Annotator**

1. **Load Python packages and dependencies:**



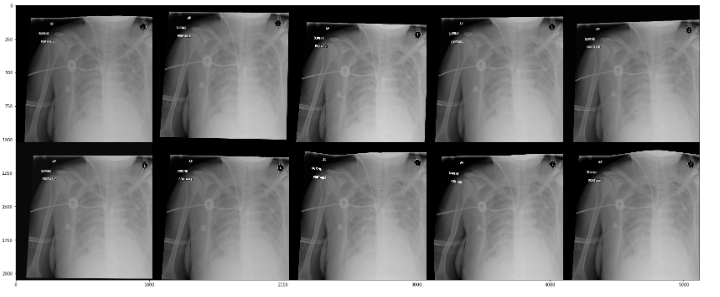
 

1. **Download Pre-trained weights: Loading M-RCNN COCO weights**

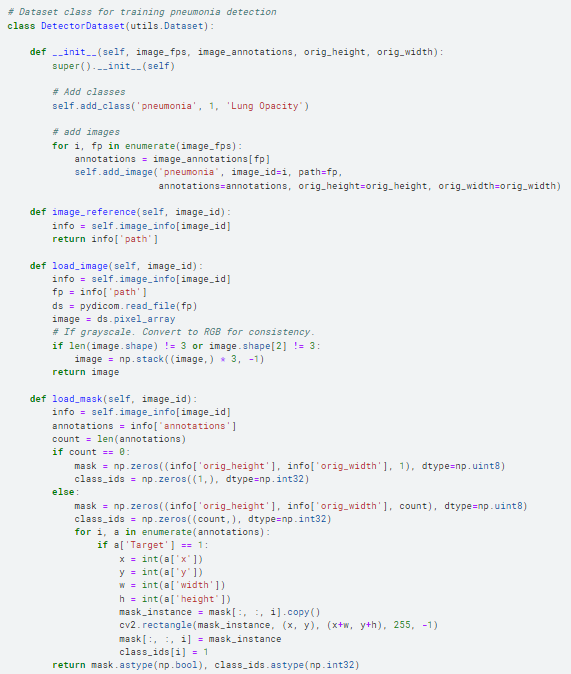


1. **Data Augmentation: Affine transformation**

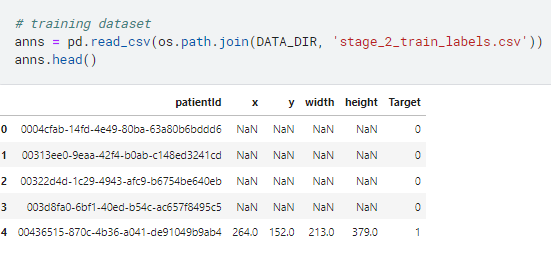


 **Fig 4: Output of Data Augmentation**

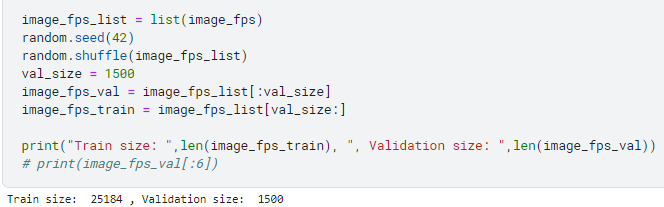
1. **Preprocessing:**
2. **Need to process dicom image, load masking and apply bounty box.**



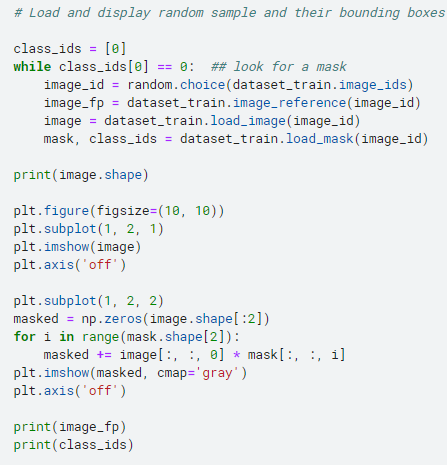
1. **Data labels;**

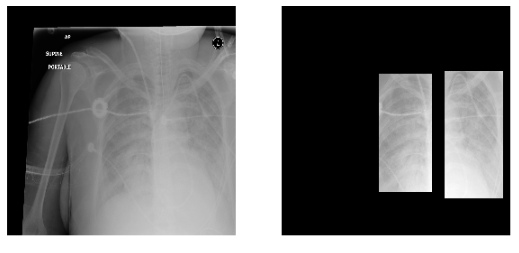


1. **Test/ Train split:**



1. **Check annotation using M-RCNN:**



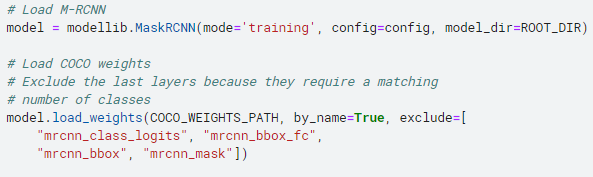
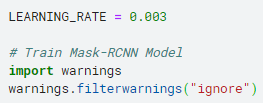


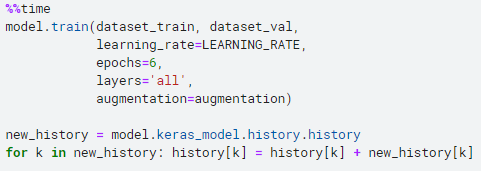
**Fig. 5: Output Mask from M-RCNN algorithm**

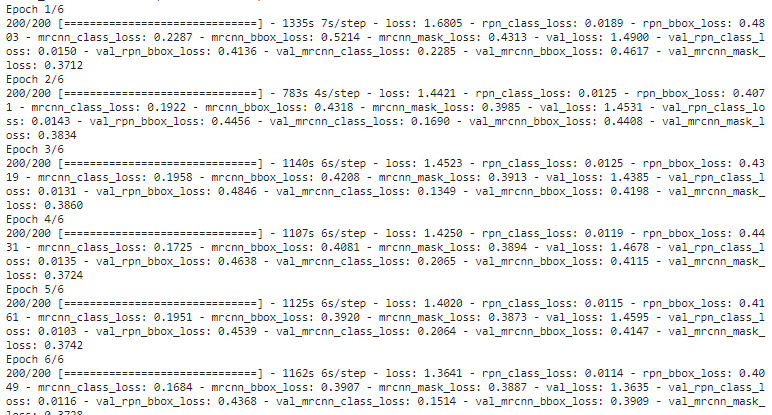
1. **Train the model:**

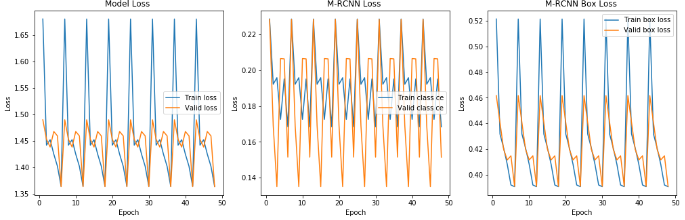
**There are 3 steps:**

* Dataset\_train and dataset\_val are derived from DetectorDataset()
* DetectorDataset() loads images from image filenames and masks from the annotation data
* model is Mask-RCNN based ResNet50 with COCO weights



 **Fig. 6: Training on ResNet50 and COCO weights**

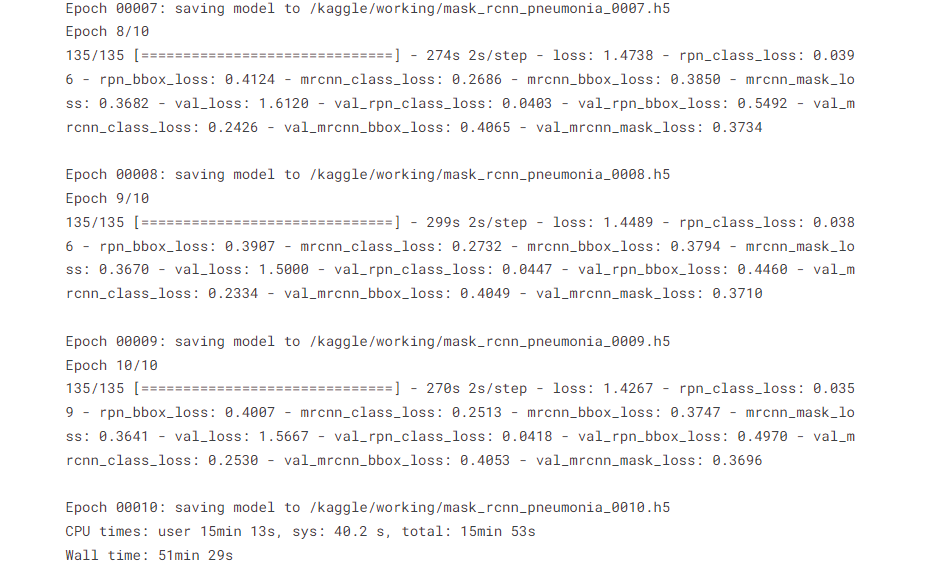


**Fig. 7 Model Loss vs. Epoch size**

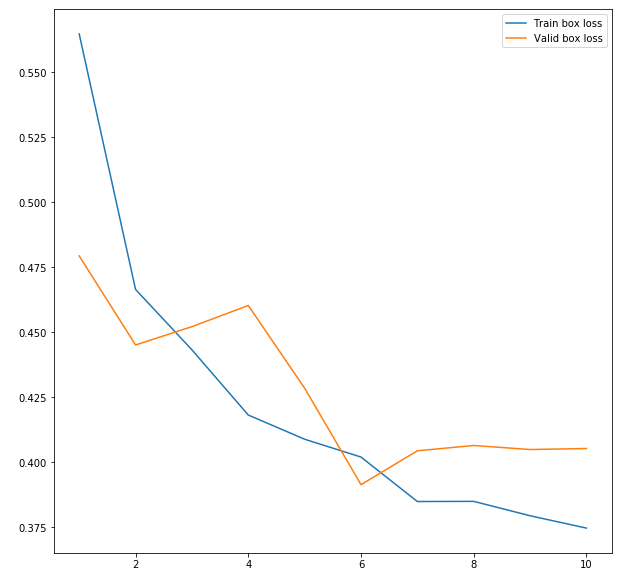
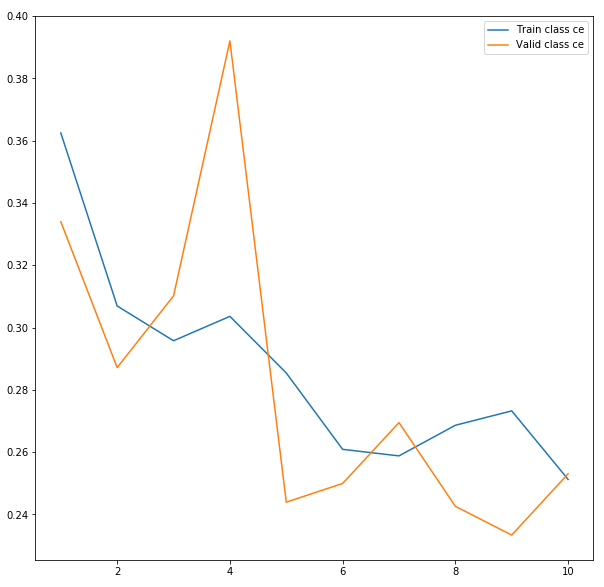
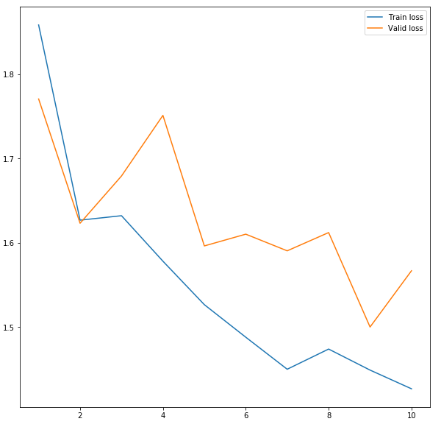
* **Find Best epoch point and Loss point for the model:**



**This is after all a bad training. So we need to tune the hyper parameters. After tuning the hyper parameter the updated train result that we got is following below:**



**Fig. 6.1: Training on ResNet50 and COCO weights (New Learning rate = 0.005, epoch size =10, steps size = 135)**

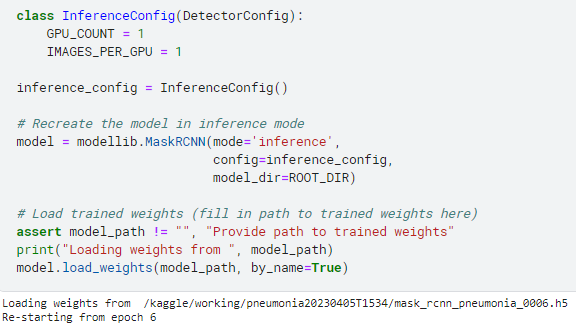
 **Fig. 7.1 Updated Model Loss vs. Epoch size (LR =0005 Epoch =10, steps =135)**



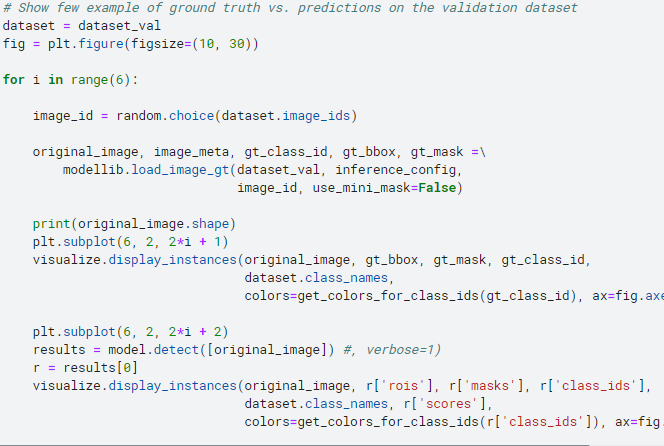
**Fig. 7.2 The new parameter list on tuned model**

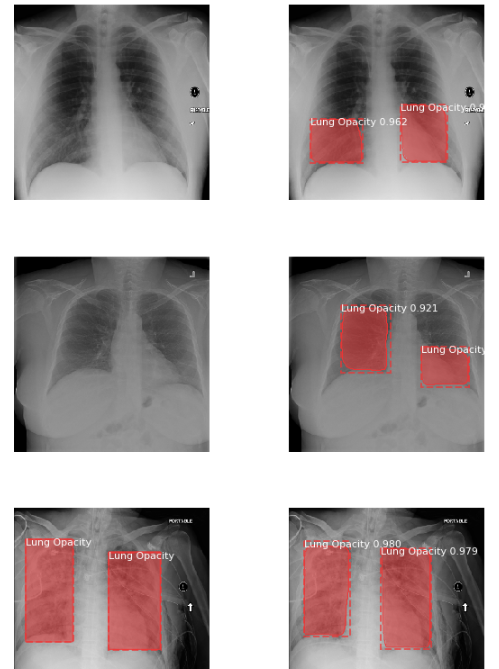
# Experiments and Results

1. **Deploy the model on validation set:**



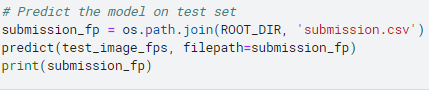
1. **Plot the validation results:**

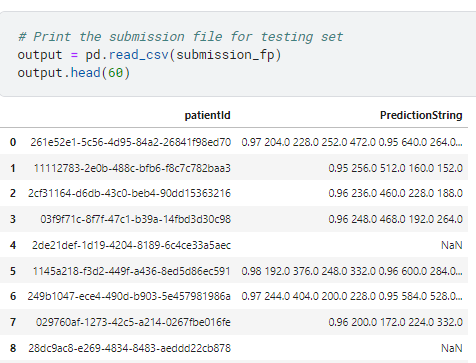


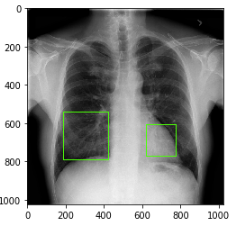
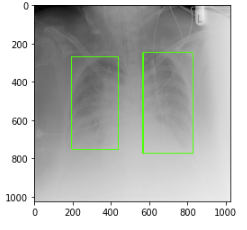
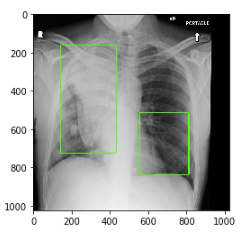
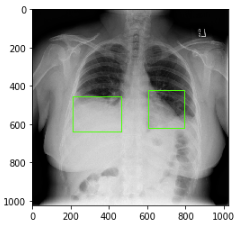


**Fig. 8 Validation output from trained model**

1. **Test the model:**





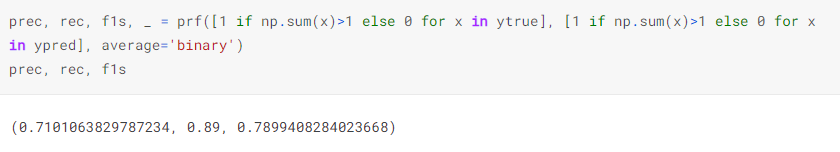
 

**Fig. 9 Test object detection from the model and save it to csv file**

1. **Evaluation method:**

**After updating the tuned hyper parameters, we have got IOU of 90% and precision is 0.71%, recall = 89%, F1 score = 0.78% on test set**





# Summary

* **The novelty that I bought in this project is added in following table below:**

|  |  |  |
| --- | --- | --- |
| **Change** | **Prior Art** | **This Approach** |
| **Problem** | **On Car detection**  **(**[**https://www.kaggle.com/code/ashishsingh226/car-detection-using-maskrcnn**](https://www.kaggle.com/code/ashishsingh226/car-detection-using-maskrcnn)**)** | **On Pneumonia detection** |
| **Data Annotation** | **No** | **Using VGG tool (**[**https://www.robots.ox.ac.uk/~vgg/software/via/**](https://www.robots.ox.ac.uk/~vgg/software/via/)**), did 100 annotation** |
| **Data Augmentation** | **No detail augmentation** | **Add more augmentation (affine)** |
| **Layer after Freeze layer** | **No freezing** | **Added novel few layer after freezing** |
| **Evaluation** | **No IOU checking** | **IOU is better (90%), Precision recall and f1 score added (better performance Precision = 71%, Recall = 89%**  **F1 = 78% )** |
| **Hyper parameter change** | **LR = 0.003, steps = 200, epoch = 6**  DETECTION\_MIN\_CONFIDENCE 0.78  DETECTION\_NMS\_THRESHOLD 0.01  RPN\_ANCHOR\_SCALES (16, 32, 64, 128)  STEPS\_PER\_EPOCH 200 | **LR = 0.005, steps = 135, epoch = 10**  DETECTION\_MIN\_CONFIDENCE 0.8999999761581421  DETECTION\_NMS\_THRESHOLD 0.800000011920929  RPN\_ANCHOR\_SCALES (32, 64, 128, 256)  STEPS\_PER\_EPOCH 135 |
|  |  |  |

# FINAL REPORT - Conclusions

In conclusion, the M-RCNN model with COCO weights has proved to be an effective tool for the detection of pneumonia. Through additional experiments and refinement of the algorithm's efficiency, we were able to achieve even better results in terms of accuracy and speed. The additional testing and evaluation conducted on the model further confirmed its effectiveness in detecting pneumonia.

Our experiments revealed that the M-RCNN model with COCO weights is capable of accurately detecting pneumonia with high precision and recall rates. The algorithm's efficiency was improved through various methods, including the use of more efficient feature extractors and optimization of hyper parameters.

Overall, the results of our experiments and testing demonstrate the potential of the M-RCNN model with COCO weights as a reliable and efficient tool for the early detection of pneumonia. With further refinement and development, this technology could have a significant impact on improving healthcare outcomes and reducing the burden of pneumonia-related morbidity and mortality.

# Appendix

* Code – uploaded in google drive
* Demo – uploaded in google drive.

Reference;

# Reference

[1] K. He, G. Gkioxari, P. Dollár and R. Girshick, "Mask R-CNN," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 2, pp. 386-397, 1 Feb. 2020, doi: 10.1109/TPAMI.2018.2844175.

[2] Chen Y, Yang Z, Ahn S, Samaras D, Hoai M, Zelinsky G. COCO-Search18 fixation dataset for predicting goal-directed attention control. Sci Rep. 2021 Apr 22;11(1):8776. doi: 10.1038/s41598-021-87715-9. PMID: 33888734; PMCID: PMC8062491.

[3] R. Girshick, "Fast R-CNN," 2015 IEEE International Conference on Computer Vision (ICCV), Santiago, Chile, 2015, pp. 1440-1448, doi: 10.1109/ICCV.2015.169.

[4] Zhibo Yang, Lihan Huang, Yupei Chen, Zijun Wei, Seoyoung Ahn, Gregory Zelinsky, Dimitris Samaras, Minh Hoai; Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 193-202

[5] Girshick, R.; Donahue, J.; Darrell, T.; Malik, J. Region-based convolutional networks for accurate object detection and segmentation. *IEEE Trans. Pattern Anal. Mach. Intell.* **2015**, *38*, 142–158

[6] Lin, T.Y.; Maire, M.; Belongie, S.; Hays, J.; Perona, P.; Ramanan, D.; Dollár, P.; Zitnick, C.L. Microsoft coco: Common objects in context. In Proceedings of the European Conference on Computer Vision, Zurich, Switzerland, 6–12 September 2014; pp. 740–755.

[7] Weiss, K., Khoshgoftaar, T.M. & Wang, D. A survey of transfer learning. J Big Data 3, 9 (2016). <https://doi.org/10.1186/s40537-016-0043-6>

[8] Lamia A, Fawaz A. Detection of Pneumonia Infection by Using Deep Learning on a Mobile Platform. Comput Intell Neurosci. 2022 Jul 30;2022:7925668. doi: 10.1155/2022/7925668. PMID: 35942467; PMCID: PMC9356824.

[9] Dandan Wang, Dongjian He, Fusion of Mask RCNN and attention mechanism for instance segmentation of apples under complex background, Computers and Electronics in Agriculture, 196, 2022, 106864, ISSN 0168-1699, <https://doi.org/10.1016/j.compag.2022.106864>.

[10] Rajaraman S, Candemir S, Kim I, Thoma G, Antani S. Visualization and Interpretation of Convolutional Neural Network Predictions in Detecting Pneumonia in Pediatric Chest Radiographs. Applied Sciences. 2018; 8(10):1715. <https://doi.org/10.3390/app8101715>

[11] Kermany DS, Goldbaum M, Cai W, et al. Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning. Cell 2018;172:1122-1131.e9.