Deep Learning Based Thoracic X-ray Image Classification

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APPROVAL

This Project/Thesis titled **"Deep Learning Based Thoracic X-ray Image Classification"**, submitted by Fatema Tuz Zohora, ID No: 182-25-679 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 06-12-2019.

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DECLARATION

I hereby declare that, this thesis has been done by me under the supervision of Md. Zahid Hasan, Assistant Professor Department of CSE Daffodil International University. I also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

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I feel grateful to my profound indebtedness to **Md. Zahid Hasan, Assistant Professor** Department of CSE, Deep knowledge & keen interest of my supervisor in the field of image processing and deep learning based application influenced me to carry out this thesis. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior draft and correcting them at all stage have made it possible to complete this thesis.

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Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

Radiology Image Analysis is a critical sector and this job mostly being done by medical specialists and people expect highest level of care and service regardless of cost. Due to complexity and subjectivity of images it is limited. Widespread variation exits across different interpreters and labour in terms of image interpretation by human experts. My objective is to analyze medical X-ray images using deep learning and utilize images using Pandas, Keras, OpenCV, Tensorflow etc to obtain classification of images like Atelectasis, Consolidation, Cardiomegaly, Edema, Effusion, Emphysema, Fibrosis, Her-nia, Infiltration, Mass, Nodule, Pleural, Pneumonia, Pneumothorax, Thickening etc. I have used Convolution Neural Networks(CNN) algorithm because compared to other image classification algorithms CNN have ability to automatically extract the high level representations from big data using little pre- processing. Ultimately, a simple and efficient model will lead clinicians towards better diagnostic decision for patients to provide them solutions with good accuracy.

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CHAPTER 1

Introduction

1.1Introduction

Thoracic diseases is a big issue for human health. Though, it affects millions of lives world-wide and causes significant symptoms and mortality all over the world, 90% of Chronic Obstructive Pulmonary Diseases related deaths occur in low middle income countries such as Bangladesh. People those are badly affected for an extended period of time by Chronic Obstructive Pulmonary Diseases (COPD) such as Tuberculosis, Edema, Effusion, Emphysema, Fibrosis, Nodule, Pleural, Pneumonia, Pneumothorax etc. do suffer most. COPD has a mortality rate pf 27.5 persons in per 1,00,000 people and costs lives of 1,035 people every year in Bangladesh. In Bangladesh, the main cause of death due to air pollution revolves around the fact that access to proper diagnosis and subsequent treatments are limited. In developing countries like Bangladesh medical treatment is really costly, because here medical equipment, doctors and experts are low in number. Also, an incredible number of individuals in our general population are not aware of COPD and sometime human error may also occur through the treatments.

Enormous number of chest radiography produced globally are currently being analyzed almost entirely through visual in section on a slice-by-slice basis [1]. This re- quires a high degree of skill and concentration. Additionally, this process is time consuming, expensive, prone to human error and unable to exploit the invaluable informatics contained in such large scale of data [2]

In this paper, I proposed a deep learning based neural network model, which will allow doctors to give their attention immediately on higher risk cases before the cases gone worst. Additionally, it would help radiologists to get more information to correct themselves from potential misdiagnoses. Moreover, it would allow doctors to monitor the patients weekly basis at low cost. Finally, it would provide the doctors immediate information about patient's condition and risk level to suggest more diagnostic tests without delay.

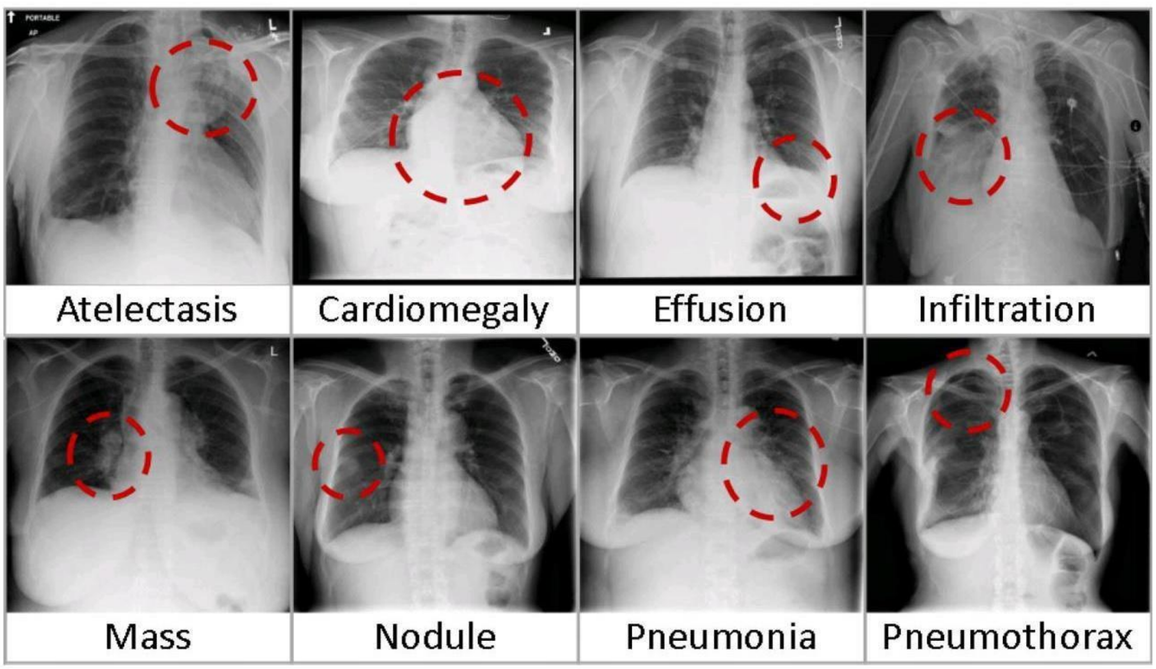

Fig. 1.1 Visual Examples of Common Thoracic Diseases

1.2 Objective

The primary objective of this research is to provide radiologists and medical experts a low cost tool to cross check their interpretations and identify other potential findings that may have been missed otherwise. Other objectives are,

1. Helping radiologists and medical experts to identify the slit and slow changes among multiple X-rays, that otherwise could be overlooked.
2. Many people in developing country do not have access to radiologist due to high cost. This tool could help them to read their X-ray images.
3. Create a basis for a model to read more complex data like CT and MRI images in near future.

1.3 Methodology

Utilizing the NIDCH, Chest X-rays Dataset, which contains over 112,000 frontal-view Chest X-ray images from more than 30,000 unique patients released by NIDCH(National Insti-tute of Diseases of the Chest and Hospital), I have build o model using automatic extraction methods on radiology reports. Every image have been annotated with 14 different thoracic patholo-ogy labels [3]. I will label images that is disease affected as one of the annoted pathology. As, there is too many categories, I have drop categories those have less then 6000 cases. For this task, I have randomly divide the dataset training, validation and test. I have used 80% image for training and 20% image for testing**.**

1.4 Contribution Summary

The summary of the main contribution is as follows:

- Dataset initialization using Pandas.
- I have trained the dataset using Keras on the top of TensorFlow.
- I have recognized chest X-ray images using CNN and accuracyrate of different disease.

1.5 Thesis Outline

This research paper is partitioned into five chapters. The layout of every chapter is given beneath:

Chapter 1: Contains an introduction to the research work and it's features. Additionally, objectives and methodology of this research, which describes how I have built this model and distribution of training and testing dataset. Also, contribution summary is proved here.

Chapter 2: Presents the literature review of Neural Network and Deep Learning. Also, briefly describes about the algorithm I have used. Moreover, discusses about the related works that I have studied extensively to understand the current development in this area.

Chapter 3: Provides idea about my proposed model, dataset, meta data , sample images and challenges I have faced during the research work.

Chapter 4: Shows the steps of experimental setup, discusses results and accuracy measurement.

Chapter 5: Contains the conclusion and future working plan. Here I abbreviate my idea and give the degree to improvement later on.

CHAPTER 2

Literature review

2.1 Introduction

Accurate image analysis and image interpretation is very crucial for better diagnoses. Though, image interpretation by conventional machine learning algorithms depends mostly on expert crafted features, computer vision is the best machine learning application. Now-a-days in every field, specially in medical image analysis deep learning has got a great pace.[4]

2.2 Related works

Through extensive study about related sort of research works, I have discovered that, there has been a generous amount of recognition and classification systems has been built with respect to different regions and subjects. Here, I will bring up a portion of those works and methods that have been utilized.

Deep learning suggests a category of machine learning method, where various layers of data handling stages in progressive models are abused for example grouping and highlight learning. By using deep learning many people already have achieved promising outcomes in image classification. For digit recognition LeCun [5] received the the deep supervised back propagation Convolutional Neural Network(CNN). From that point forward, deep supervised Convolutional Neural Networks (CNN) proposed in ended up being a leap forward, thst was announced first in the image classification undertaking of ILSVRC-2012[10]. After that, more work has been finished by enhancing models to enhance the image classification results.

Mechanized understanding from chest radiographs has set up total consideration with calculations for Pulmonary Tuberculosis Classfication and Lung Nodule detection [6] Islam et al. [7] contemplated the execution of different convolutional designs on assorted anomalies utilizing the freely accessible OpenI dataset [8].

Wang et al. [9] released a bigger dataset called ChestX-ray-14, bigger than earlier datasets and furthermore benchmarked on ImageNet divergent Convolutional Neural Network models. Additionally, the Japanese Society of Radio;ogical Technology (JSRT)

2.3 Overview of Neural network and Deep Learning

Neural Networks are a specific set of algorithms that has reformed the field of Machine learning. Counterfeit, neural systems basically and adroitly roused by human natural sensory system to perceive designs [5]. The examples they perceive are numerical, contained in vectors, into which all genuine information, be it pictures, sounds, content or time arrangement, must be deciphered [6]. They translate tactile information through a sort of machine discernment, naming or grouping crude info. Perception layer, output layer and one. Neural Networks are themselves general capacity approximations, that is the reason they can be connected to truly any machine learning issue, where the issue is tied in with taking in an intricate mapping from the contribution to the yield space.

Any names that people can create, any results you care about and which associate to information, can be utilized to prepare a neural system. A access to substantially more [8]. Deep learning capacity to process and gain from colossal amounts of unlabeled information give it a particular preferred standpoint over past calculations.

$$f(x, w) = \varphi(x.w) = \varphi(\sum(xi.wi)) \quad (2.1)$$

Here,

x = input vector

w = weight vector

p = inputs into the neuron

φ = activation f unction

Using bias, the perception rule can be written as:

$$\text{output} = \begin{cases} n1, \text{ i f } w.x+b \leq 0 \\ 0, \text{ i f } w.x+b > 0 \end{cases} \quad (2.2)$$

Here,

b = bias

2.4 Scope of problem

1. Deep learning based neural network model, which will allow doctors to give their attention immediately on higher risk cases before the cases gone worst. .
2. It would help radiologists to get more information to correct themselves from potential misdiagnoses.
3. It would allow doctors to monitor the patients weekly basis at low cost.
4. It would provide the doctors immediate information about patient’s condition and risk level to suggest more diagnostic tests without delay.

2.5 Challenges

During this research work, I have faced some specific challenges associated with this dataset. Those are,

1. Challenges associated with labeling,
    a) Accuracy of the labels were not perfect.
    b) Medical meaning of the labels was unknown to me.
2. Other non-image clinical problems are,
    a) Fibrosis diseases like Pneumonia, Edema are diagnosed clinically, not on imaging.
    b) Report mined nodule labels' value is questionable, as on x-rays upto 50% of nodules are missed.
    c) There are some thoracic diseases that no one really cares about like Hiatus Hernias. So they are merely reported.
3. The dataset was very large (6000 image). So, it required a lots of processing power.

CHAPTER 3
Methodology

3.1 Convolution Neural Network

Convolution Neural Network (CNN) is a particular implementation of a neural network used in machine learning that exclusively processes array data such as images, frequently used in machine learning applications targeted at medical images [9]. essential ability to extract the mid-level and high- level abstractions obtained from raw data [10]. CNN can capture highly nonlinear mapping between inputs and outputs, as it is multi-layered and fully trainable [8]. CNN consists of input, output and multiple hidden layers. This hidden layers are consist of convolutional layers, pooling layers and full- connected layers

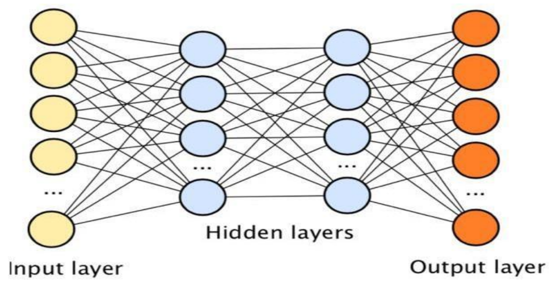

Fig 3.1 Convolutional Neural network(CNN)

The last layer is called the output layer and it represents the class scores in classification setting. The hidden layers to build a CNN architectures are convolution layers, pooling layers, full-connected layers and normalization layers . Each layer accepts an input 3D volume for transforming into an output 3D through a differentiable function.

3.2 Image Classification using CNN Architecture.

Building Blocks of CNN are:

1. Convolution Layer
2. Activation Function
3. Pooling Layer
4. Full-Connected Layer

3.2.1 Convolution Layer

The Convolution Layer is the core building block of a Convolutional Neural Network. Conv layer applies a series of different image filters also known as convolutional kernels to an input images. The resulting filtered images have different appearance. The filters may have extracted features like the edges object or the color that distinguish different class of images.

3.2.2 Activation Function

After convolutional layer in CNN, we apply nonlinear activation function such as ReLU. ReLU is $f(x) = \max(0,x)$ It effectively removes negative values from an activation map by setting them to zero. It increases the nonlinear properties of the decision and of the overall network without affecting the receptive fields of the convolution layer.

3.2.3 Pooling Layers

Pooling layers provide an approach to down sampling feature maps by summarizing the presence of features in patches of the feature map. Two common pooling methods are average pooling and max pooling that summarize the average presence of a feature and the most activated presence of a feature respectively.

3.2.4 Full- connected layer

It takes as inputs the output from the last convolution layer and does the computations in its hidden layers and produces class probability outputs in its output layer. They take in the flattened output of the last convolution layer. This output must be flattened because as we have seen the convolution operation takes an input image with (H, W, D) dimension where ‘H’ and ‘W’ are height and width and ‘D’ is the depth representation.

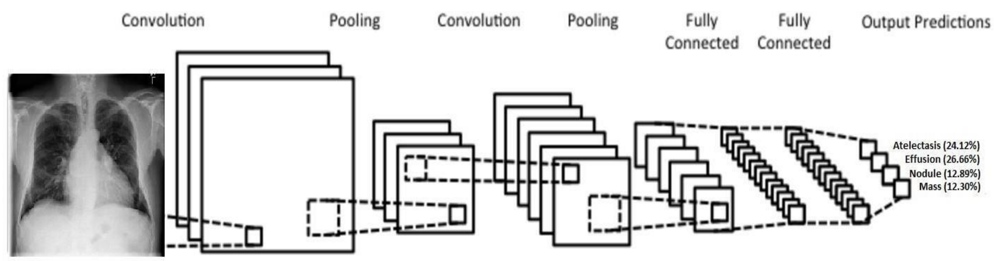

Fig 3.2 Image classification using CNN Architecture

CHAPTER 4

Experimental Result and Analysis

4.1 Meta Data for Images

Meta data for images includes Image Index, Finding Labels, Follow-up #, Patient ID, Patient Age, Patient Gender, View Position, Original Image Size and Original Image Pixel Spacing.

<table>
<tr><th>Image Index</th><th>Finding Labels</th><th>Follow-up #</th><th>Patient ID</th><th>Patient Age</th><th>Patient Gender</th><th>View Position</th><th>OriginalImage[Width</th><th>Height]</th><th>OriginalImagePixelSpacing[x</th><th>y]</th></tr>
<tr><td>00000001_000.png</td><td>Cardiomegaly</td><td>0</td><td>1</td><td>58</td><td>M</td><td>PA</td><td>2682</td><td>2749</td><td>0.143</td><td>0.143</td></tr>
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<tr><td>00000003_004.png</td><td>Hernia</td><td>4</td><td>3</td><td>77</td><td>F</td><td>PA</td><td>2500</td><td>2048</td><td>0.168</td><td>0.168</td></tr>
<tr><td>00000003_005.png</td><td>Hernia</td><td>5</td><td>3</td><td>78</td><td>F</td><td>PA</td><td>2686</td><td>2991</td><td>0.143</td><td>0.143</td></tr>
<tr><td>00000003_006.png</td><td>Hernia</td><td>6</td><td>3</td><td>79</td><td>F</td><td>PA</td><td>2992</td><td>2991</td><td>0.143</td><td>0.143</td></tr>
<tr><td>00000003_007.png</td><td>Hernia</td><td>7</td><td>3</td><td>80</td><td>F</td><td>PA</td><td>2582</td><td>2905</td><td>0.143</td><td>0.143</td></tr>
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<tr><td>00000007_000.png</td><td>No Finding</td><td>0</td><td>7</td><td>82</td><td>M</td><td>PA</td><td>2500</td><td>2048</td><td>0.168</td><td>0.168</td></tr>
<tr><td>00000008_000.png</td><td>Cardiomegaly</td><td>0</td><td>8</td><td>69</td><td>F</td><td>PA</td><td>2048</td><td>2500</td><td>0.171</td><td>0.171</td></tr>
<tr><td>00000008_001.png</td><td>No Finding</td><td>1</td><td>8</td><td>70</td><td>F</td><td>PA</td><td>2048</td><td>2500</td><td>0.171</td><td>0.171</td></tr>
<tr><td>00000008_002.png</td><td>Nodule</td><td>2</td><td>8</td><td>73</td><td>F</td><td>PA</td><td>2048</td><td>2500</td><td>0.168</td><td>0.168</td></tr>
</table>

Table 4.1 Sample of Meta Data for Images

4.2 Dataset Initialization

At first, to begin the X-ray image recognition process I have taken selected dataset and setup the initial training and testing data using "Pandas". Here, I have taken 6000 sample images to use later on for classification of different thoracic diseases.

4.3 Create Categories

As, I have too many categories (8 categories) and some of those pathologies have vary few cases, I have drop categories those have less then 500 cases in favour of getting more accuracy. I have only taken the 4 thoracic diseases (Edema, Pneumonia, Mass, Nodule) on the training and testing set.

Thoracic disease	**No of cases**
Edema	1500
Pneumonia	1000
Mass	1200
Nodule	2000

Table 4.2 Creating Categories

4.4 Prepareing Training Data

I have randomly divided the entire dataset into three group, i.e. training, validation and testing. Here I have divided the data into training and validation sets into 80% to 20% ratio

Thoracic disease	Total data	Training data (80% ratio)	Testing data (20% ratio)
Edema	1500	1200	300
Pneumonia	1000	800	200
Mass	1200	960	240
Nodule	2000	1600	400

Table 4.3 Tranning data

4.5 CNN Setting

CNN architecture is implemented using "flow_from_dataframe" framework. Due to huge image number and size and the limitation of processing power, I have reduce the image batch size and set the steps per epoch at 100.

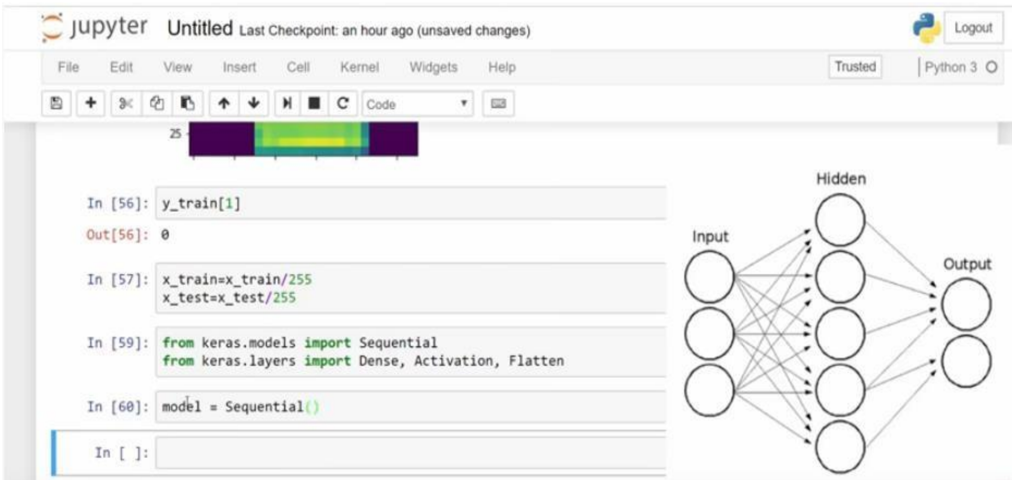

Fig 4.1 CNN setting

4.6 Compilation and Training of Model

I compile and train the data using python library. Before training our neural network we have to normalize our dataset. After that I have to build neural network using CNN. In neural network I have created 3 layer that is input layer, activation layer and output layer.

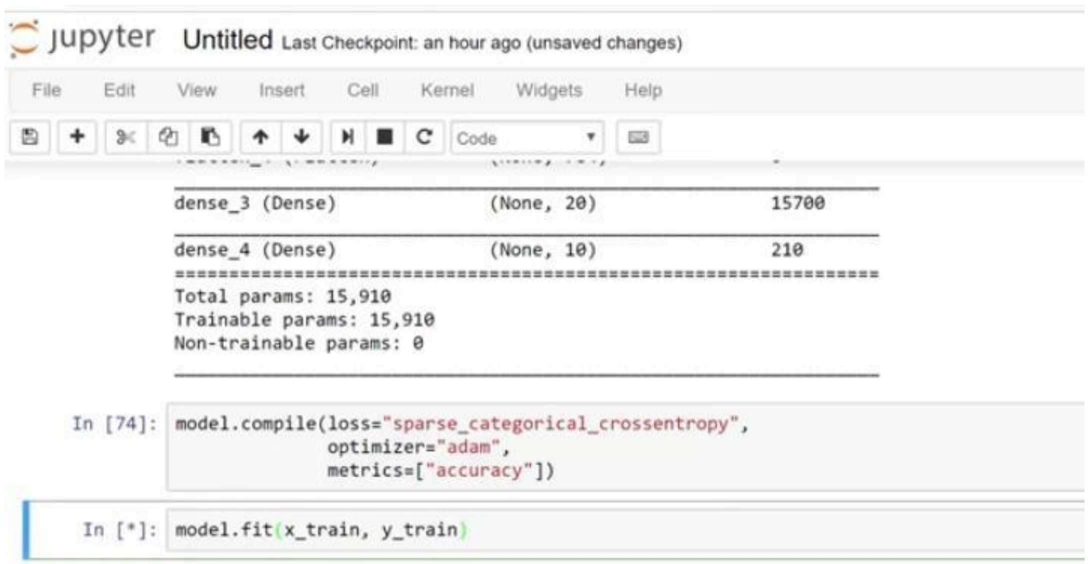

Fig 4.2 Tranning of model

4.7 Experimental Results According to Classification of Disease

My proposed model is designed to classify medical chest X-ray images. This model is built on the base of CNN. Accuracy rate depends on the threshold values. During each epoch data is trained over and over again to get accuracy of the model **.**

Disease name	Testing data	Accuracy rate
Edema	300	84%
Pneumonia	200	80%
Mass	240	83%
Nodule	400	92%

Table 4.4 Accuracy according to classification

4.8 Evaluting confusion matrix according to disease classification

Confusion matrix is used to measure the performance accuracy of an machine learning algorithm usually a supervised learning. Each row of the confusion matrix represents the instances of an actual class and each column represents the instances of an predicted one.

4.8.1. Confuson matrix for Edema

To evaluate confusion matrix for Edema I have taken 300 test data. After evolution I have found the model accuracy is 80% error rate is 16% precision 87% and recall 90%

n= 300		Actual	
		yes	No
Predicted	Yes	TP 200	FP 28
	No	FN 20	TN 52

Accuracy	=TP+TN / Total = 252/300 = 84%
Error rate	= FP+FN / Total = 48/300 = 16%
Precision	=TP/TP+FP =200/228=87%
Recall	=TP/TP+FN =200/220=90%

Table -Confusion matrix for Edema

4.8.2 Confuson matrix for Pneumonia

To evaluate confusion matrix for Pneumonia I have taken 200 test data. After evolution I have found the model accuracy is 80% and error rate is 20% precision 86% and recall 90%

n= 200		Actual	
		yes	No
Predicted	Yes	TP 100	FP 15
	No	FN 25	TN 60

Accuracy =TP+TN / Total
= 160/200 = 80%
Error rate = FP+FN / Total
= 40/200 = 20%
Precision =TP/TP+FP
=100/115=86%
Recall =TP/TP+FN
=100/125=80%

Table -Confusion matrix for Pneumonia

4.8.3 Confuson matrix for Mass

To evaluate confusion matrix for Mass I have taken 240 test data. After evolution I have found the model accuracy is 83% and error rate is 16% precision 94% and recall 84%

n= 240		Actual	
		yes	No
Predicted	Yes	TP 160	FP 10
	No	FN 30	TN 40

Accuracy =TP+TN / Total
= 200/240 = 83%
Error rate = FP+FN / Total
= 40/240= 16%
Precision =TP/TP+FP
=160/170=94%
Recall =TP/TP+FN
=160/190=84%

Table -Confusion matrix for Mass

4.8.4 Confuson matrix for Nodule

4.8.5 To evaluate confusion matrix for Nodule I have taken 400 test data. I have found the model accuracy is 92% and error rate is 7% precision and recall 96%

n=400		Actual	
		yes	No
Predicted	Yes	TP 290	FP 20
	No	FN 10	TN 80

Accuracy =TP+TN / Total
= 370/400 = 92%

Error rate = FP+FN / Total
= 30/400= 7%

Precision =TP/TP+FP
=290/310=93%

Recall =TP/TP+FN
=290/300=96%

Table -Confusion matrix for Nodule

4.9 Graphical Representation

4.9.1 Graphical Representation of different disease accuracy

In the graph I found among 4 different disease(Edema, Pneumonia, Mass Nodule) the accuracy of Nodule is the highest. That is 92%

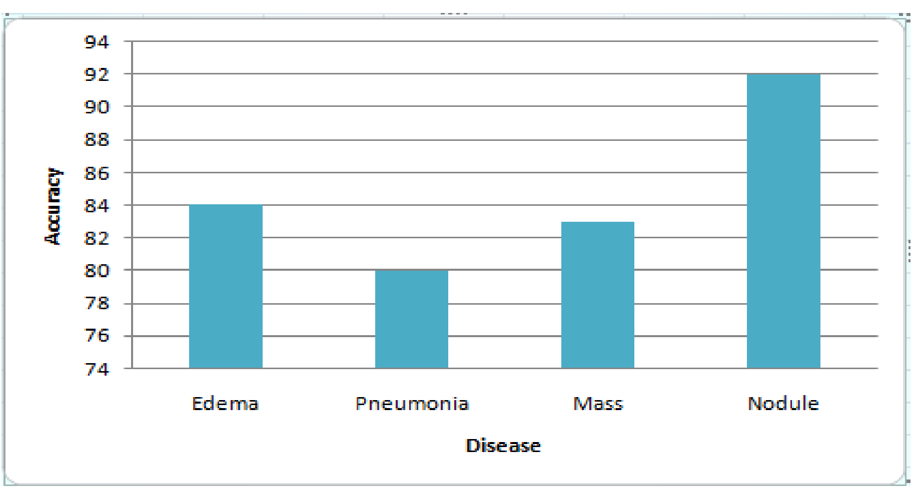

Fig 4.4 Graphical Representation of different disease accuracy

4.9.2 Graphical Representation of different disease error rate

4.9.3 In the graph I found among 4 different disease(Edema, Pneumonia, Mass Nodule) the error rate of Pneumonia is the highest. That is 20%.

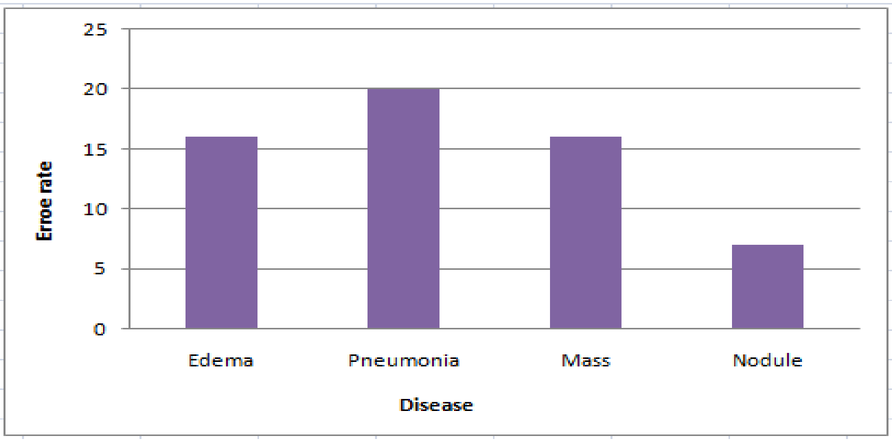

Fig4.3 Graphical Representation of different disease error rate

4.9.4 Graphical Representation of different disease precision

In the graph I found among 4 different disease(Edema, Pneumonia, Mass Nodule) the precision of Mass is the highest. That is 94%

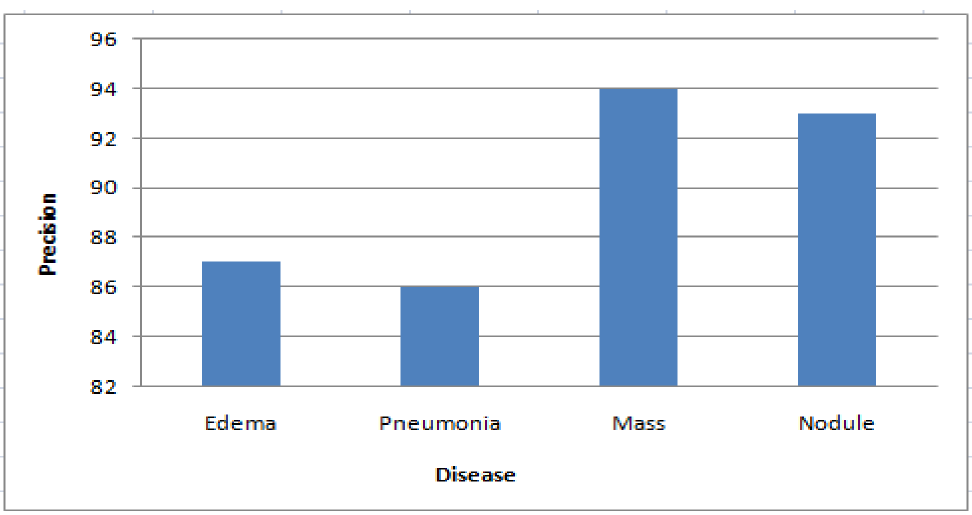

Fig4.5 Graphical Representation of different disease precision

4.9.5 Graphical Representation of different disease recall rate

4.9.6 In the graph I found among 4 different disease(Edema, Pneumonia, Mass Nodule) the recall rate of Nodule is the highest. That is 96%

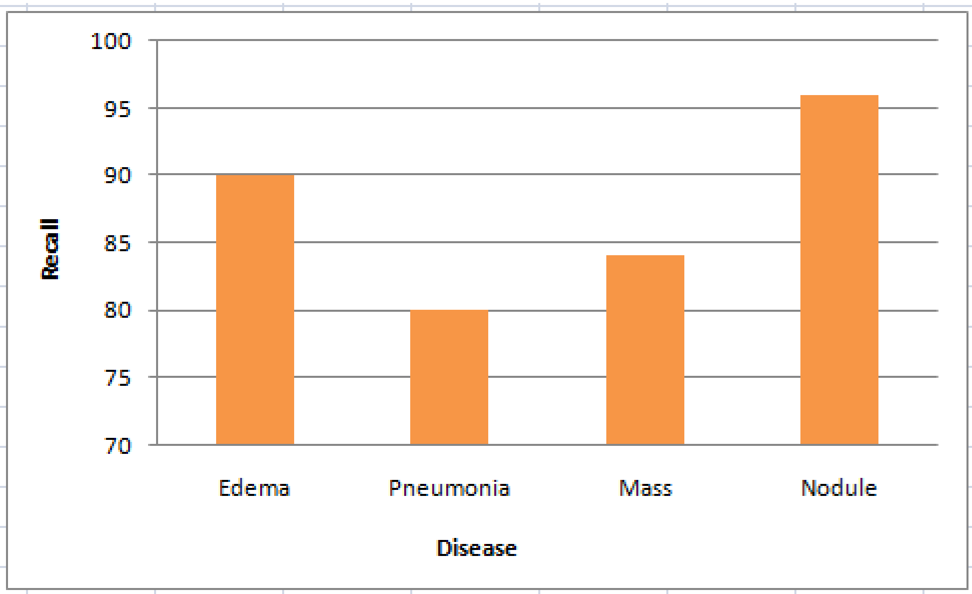

Fig4.6Graphical Representation of different disease recall rate

CHAPTER 5
Conclusion

5.1 Conclusion

In this paper, I have offered a model for medical application of chest pathology detection in chest radiography using Convolutional Neural Networks (CNN) propose the model to for effective diagnosis of thoracic diseases on chest radiography by doing the recognition and classification of pathological structures from classified anatomies which will help doctors fasten the detection process for multiple diseases. Hence, providing them additional valuable time to focus more on the curing the diseases. This model consists of a classification branch and an attention branch. Classification branch performs as a uniform feature extraction classification network and of pathological irregularities and enables the model to focus adapting on the pathologically abnormal regions. The result of the model indicate that model out performs and shows that image training may be sufficient for general medical image recognition tasks. Despite the fact that this model is not prepared for clinical selection, it guarantees a future useful arrangement organize that can order typical versus anomalous chest x-beam picture and furnish essential consideration doctors and radiologists with important data to fundamentally diminish time to finding and incredibly improve the current situation of the medical sector.

5.2 Future Work

I have successfully classified 4 thoracic diseases (Edema, Pneumonia, Mass, Nodule) using chest X-rays dataset provided by NICDH. Which is basically data collected from Bangladesh. In near future, I will collect X-ray images from local hospitals to train and test the system to predict better results. Also, I have plan to work with more complex medical data like CT and MRI images.

References

[1] Akif, M., Khan, B., Shoumik, N. F., Mithila, R. R., Rahman, N., and Shafa, S. (2018). Respiratory diseases skyrocketing in bangladesh | the daily star. Accessed: 20 November, 2018.

[2] Bose, N. K. and Liang, P. (1996). Neural network fundamentals with graphs, algorithms, and applications (mcgraw-hill series in electrical computer engineering).

[3] Demner-Fushman, D., Kohli, M. D., Rosenman, M. B., Shooshan, S. E., Rodriguez, L., Antani, S., Thoma, G. R., and McDonald, C. J. (2015). Preparing a collection of radiology examinations for distribution and retrieval. Journal of the American Medical Informatics Association, 23(2):304–310.

[4] Gordienko, Y., Gang, P., Hui, J., Zeng, W., Kochura, Y., Alienin, O., Rokovyi, O., and Stirenko, S. (2018). Deep learning with lung segmentation and bone shadow exclusion techniques for chest x-ray analysis of lung cancer. In International Conference on Theory and Applications of Fuzzy Systems and Soft Computing, pages 638–647. Springer.

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