BACHELOR OF SCIENCE IN
COMPUTER SCIENCE AND ENGINEERING

Inspiring Excellence

Deep Learning Based Medical X-ray Image Recognition and Classification

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I would like to dedicate this thesis to my loving parents and loved one. . .

Declaration

It is hereby declared that, this thesis report or any part of it has not been submitted elsewhere for the award of any Degree or Diploma.

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Abstract

Analysis of radiology images are mostly being done by medical specialists, as it is a critical sector and people expect highest level of care and service regardless of cost. Though, it is quite limited due to its complexity and subjectivity of the images. Extensive variation exists across different interpreters and fatigue in terms of image interpretation by human experts. Our primary objective is to analyze medical X-ray images using deep learning and exploit images using Pandas, Keras, OpenCV, TensorFlow etc. to achieve classification of diseases like Atelectasis, Consolidation, Cardiomegaly, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pleural, Pneumonia, Pneumothorax, Thickening etc. We have used Convolutional Neural Networks (CNN) algorithm because CNN based deep learning classification approaches have ability to automatically extract the high level representations from big data using little pre-processing compared to other image classification algorithms. Ultimately, our simple and efficient model will lead clinicians towards better diagnostic decisions for patients to provide them solutions with good accuracy for medical imaging.

Keywords: Convolutional Neural Networks (CNN), X-ray, Deep Learning, Pandas, Keras, Radiography, TensorFlow, OpenCV and Artificial Intelligence.

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Chapter 1

Introduction

Thoracic diseases is a big issue for human health. Though, it affects millions of lives worldwide and causes significant morbidity and mortality all over the world, 90% of Chronic Obstructive Pulmonary Diseases (COPD) related deaths occur in low and 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, Atelectasis, Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pleural, Pneumonia, Pneumothorax etc. do suffer most. COPD has a mortality rate of 27.5 persons in per 1,00,000 people and costs lives of 1,035 people every year in Bangladesh [1]. In Bangladesh, the leading cause of death due to air pollution revolves around the fact, that access to proper diagnosis and subsequent treatments are limited. Though, advancements in medical technology have allowed physicians to better diagnose and treat their patients since the beginning of the professional practice of medicine. 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 inspection on a slice-by-slice basis [17]. 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 [21]. In this paper, we have 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.

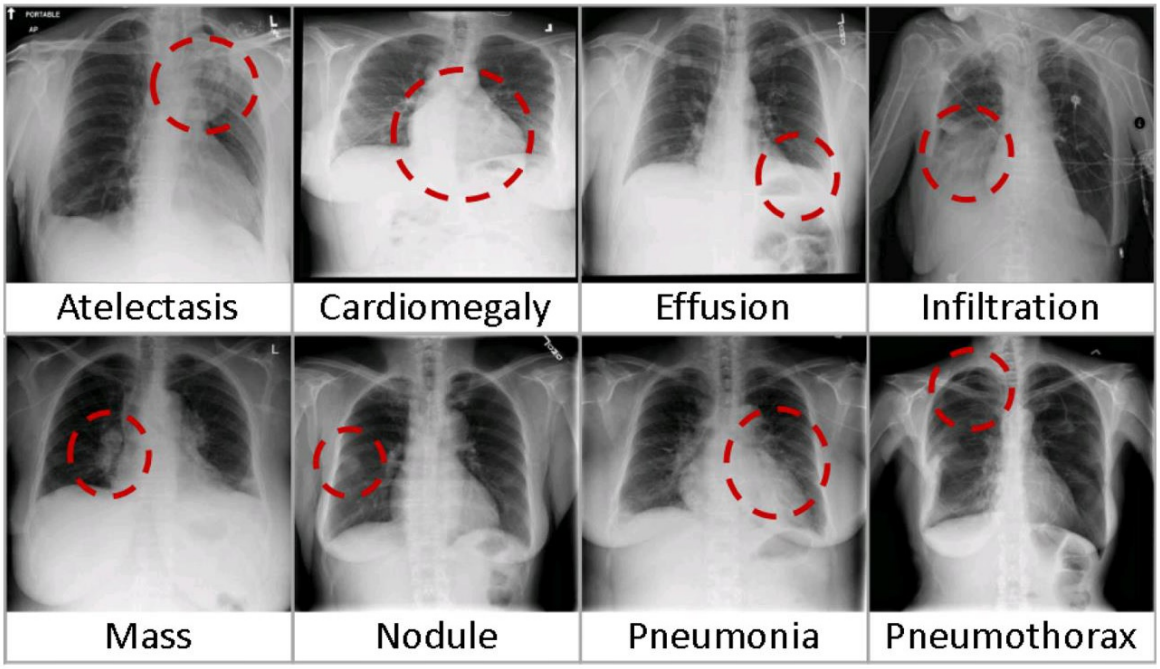

Fig. 1.1 Visual Examples of Common Thoracic Diseases

1.1 Objectives

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 the near future.

1.2 Methodology

Utilizing the NIH Chest X-rays Dataset, which contains over 112,000 frontal-view Chest X-ray images from more than 30,000 unique patients released by NIH (National Institutes of Health, USA), we have build our model using automatic extraction methods on radiology reports. Every image have been annotated with 14 different thoracic pathology labels [22]. We will label images that is disease affected as one of the annotated pathology as positive examples and label all other images as negative examples. As, their is too many categories, we have drop categories those have less then 5000 cases. For the detection task, we have randomly split the dataset into training, validation and test. We have used 80% (32000 images) for training and 20% (8000 images) for testing.

1.3 Contribution Summary

The summary of the main contribution is as follows:

- Dataset initialization using Pandas.
- Image pre-processing labeling using Multi-label Classification Loss Function, Transition Layer and Multi-label Classification Loss Layer.
- We have trained the dataset using Keras on the top of TensorFlow.
- We have recognized chest X-ray images using CNN with an accuracy rate of 86.15%.

1.4 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 we have built this model and distribution of training and testing dataset. Also, contribution summary is provided here.

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

Chapter 3: Provides idea about our proposed model, workflow diagram, dataset, meta data and bounding box for the images.

Chapter 4: Shows the steps of experimental setup, discusses results and challenges we have faced during this research work.

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

Chapter 2

Literature Review

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 [17].

2.1 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 [2]. They translate tactile information through a sort of machine discernment, naming or grouping crude info. Preceptron is one of the earliest neural network that was based on human brain system. It consists of input layer that is directly connect to output layer and was good to classify linearly separable patterns. To solve more complex pattern, neural network was introduced, that has a layered architecture i.e., input layer, output layer and one or more hidden layers [19]. 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 deep learning system prepared on named information would then be able to be connected to unstructured information, giving it access to substantially more contribution than machine learning nets [18]. Deep learning's capacity to process and gain from colossal amounts of unlabeled information give it a particular preferred standpoint over past calculations.

The node or artificial neuron multiplies each inputs by a weight. Then it adds the multiplications and passes the sum to an activation function. Some neural networks do not use an activation function when their principle is different. The following equation summarizes the calculated output:

$$f(x,w) = \phi(x.w) = \phi(\sum_{i=1}^{p}(x_i.w_i)) \tag{2.1}$$

Here,

x = input vector

w = weight vector

p = inputs into the neuron

$\phi = activation\ function$

Using bias, the perception rule can be written as:

$$output = \begin{cases} 1, if\ w.x+b \leq 0 \\ 0, if\ w.x+b > 0 \end{cases} \tag{2.2}$$

Here,

b = bias

2.2 Algorithm Used: Convolutional Neural Network (CNN)

Convolutional 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 [13]. CNN use weight sharing network structure and has ability to reduce the number of weights and complexity of the network [14]. It has shown an essential ability to extract the mid-level and high-level abstractions obtained from raw data [15]. 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 fully connected layers [20].

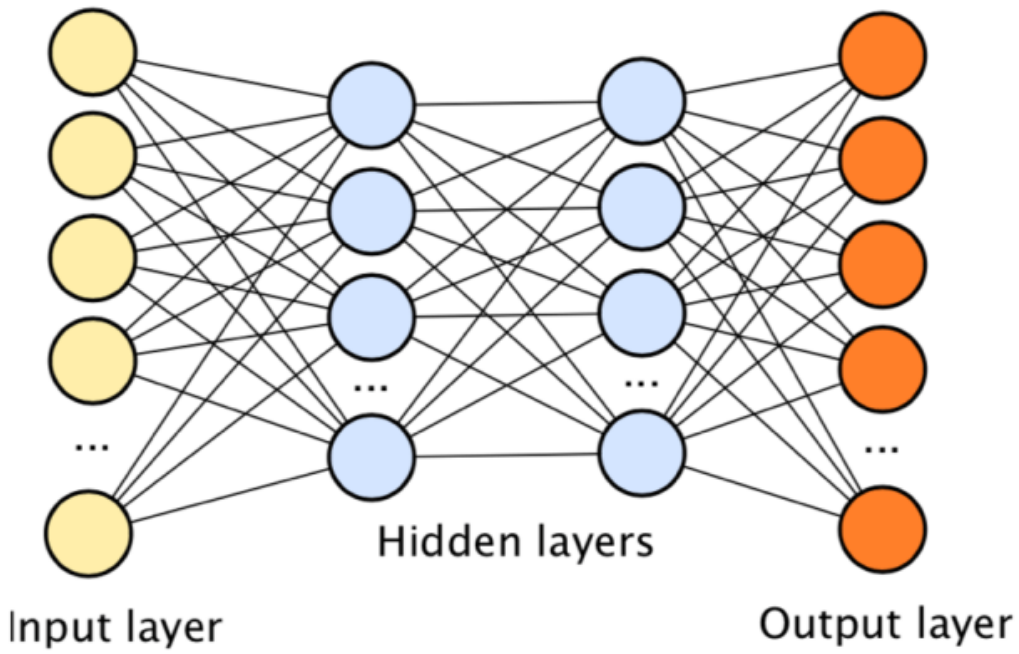

Fig. 2.1 Convolutional Neural Networks (CNN) Layers

It establishes a feed-forward group of deep networks, where neuron receives an input (a single vector) for transforming it through a series of hidden layers. Every hidden layer is fully connected to all neurons of the previous layer and where neurons in a single layer

function completely independently without sharing any connection. The last layer is called the output layer and it represents the class scores in classification settings. The hidden layers to build a CNN architectures are convolutional layers, pooling layers, fully connected layers and normalization layers[9]. Each Layer accepts an input 3D volume for transforming it to an output 3D volume through a differentiable function.

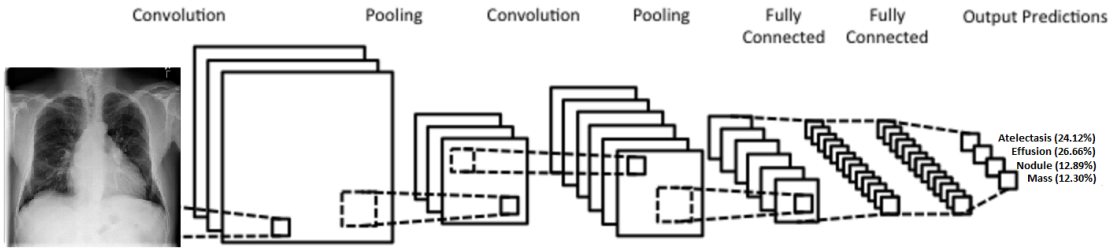

Fig. 2.2 CNN Architecture

2.3 Related Works

Through extensive study about related sort of research works, we 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, we 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 [12] received the deep supervised back-propagation Convolution Neural Network (CNN). From that point forward, deep supervised Convolutional Neural Networks (CNN) proposed in ended up being a leap forward, that was announced first in the image classification undertaking of ILSVRC-2012 [10]. After that, more work has been finished by enhancing CNN models to enhance the image classification

results [16]. Mechanized understanding from chest radiographs has set up total consideration with calculations for Pulmonary Tuberculosis Classification [11] 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 [3]. Wang et al. [22] 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 Radiological Technology (JSRT) dataset is a small frontal CXR dataset that contains normal images, as well as radiographs exhibiting malignant and benign lung nodules. Gordienko et al. train small convolutional neural networks both with and without lung segmentation for the task of classifying whether lung nodules are present within a CXR image or not. They apply their method on the JSRT dataset and also on a version of the JSRT dataset where bone shadows have been eliminated. As the size of the JSRT dataset (247 images) is so limited, the training/validation set results presented, exhibit significant over thing [4]. However, the authors showed better performance while using the BSE-JSRT dataset after removing bone shadows.

Chapter 3

Proposed Model

In this research, we have recognized and classified medical X-ray images using NIH Chest X-rays Dataset consisted around 112,120 images. Step by step process is shown bellow,

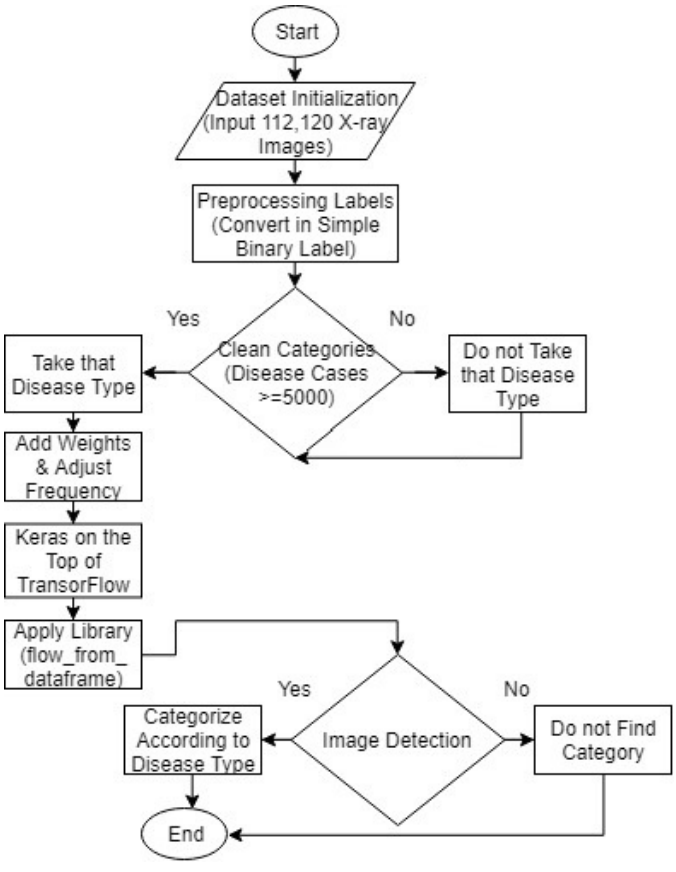

Fig. 3.1 Workflow Diagram

3.1 Meta Data and Bounding Box for Images

3.1.1 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.

Image Index	Finding Labels	Follow-up #	Patient ID	Patient Age	Patient Gender	View Position	OriginalImage[Width	Height]	OriginalImagePixelSpacing[x	y]
00000001_000.png	Cardiomegaly	0	1	58	M	PA	2682	2749	0.143	0.143
00000001_001.png	Cardiomegaly|Emphysema	1	1	58	M	PA	2894	2729	0.143	0.143
00000001_002.png	Cardiomegaly|Effusion	2	1	58	M	PA	2500	2048	0.168	0.168
00000002_000.png	No Finding	0	2	81	M	PA	2500	2048	0.171	0.171
00000003_000.png	Hernia	0	3	81	F	PA	2582	2991	0.143	0.143
00000003_001.png	Hernia	1	3	74	F	PA	2500	2048	0.168	0.168
00000003_002.png	Hernia	2	3	75	F	PA	2048	2500	0.168	0.168
00000003_003.png	Hernia|Infiltration	3	3	76	F	PA	2698	2991	0.143	0.143
00000003_004.png	Hernia	4	3	77	F	PA	2500	2048	0.168	0.168
00000003_005.png	Hernia	5	3	78	F	PA	2686	2991	0.143	0.143
00000003_006.png	Hernia	6	3	79	F	PA	2992	2991	0.143	0.143
00000003_007.png	Hernia	7	3	80	F	PA	2582	2905	0.143	0.143
00000004_000.png	Mass|Nodule	0	4	82	M	AP	2500	2048	0.168	0.168
00000005_000.png	No Finding	0	5	69	F	PA	2048	2500	0.168	0.168
00000005_001.png	No Finding	1	5	69	F	AP	2500	2048	0.168	0.168
00000005_002.png	No Finding	2	5	69	F	AP	2500	2048	0.168	0.168
00000005_003.png	No Finding	3	5	69	F	PA	2992	2991	0.143	0.143
00000005_004.png	No Finding	4	5	70	F	PA	2986	2991	0.143	0.143
00000005_005.png	No Finding	5	5	70	F	PA	2514	2991	0.143	0.143
00000005_006.png	Infiltration	6	5	70	F	PA	2992	2991	0.143	0.143
00000005_007.png	Effusion|Infiltration	7	5	70	F	PA	2566	2681	0.143	0.143
00000006_000.png	No Finding	0	6	81	M	PA	2500	2048	0.168	0.168
00000007_000.png	No Finding	0	7	82	M	PA	2500	2048	0.168	0.168
00000008_000.png	Cardiomegaly	0	8	69	F	PA	2048	2500	0.171	0.171
00000008_001.png	No Finding	1	8	70	F	PA	2048	2500	0.171	0.171
00000008_002.png	Nodule	2	8	73	F	PA	2048	2500	0.168	0.168

Fig. 3.2 Sample of Meta Data for Images

3.1.2 Bounding Boxes

As a part of the chest X-ray database, around 1000 images with pathology are given with hand labeled bounding boxes. We have used this as the reference to evaluate the disease localization performance. Bounding boxes for around 1000 images includes Image Index, Finding Label and Bbox[x, y, w, h]. [x y] are coordinates of each box's top left corner. [w h] represent the width and height of each box.

Image Index	Finding Label	Bbox [x	y	w	h]
00013118_008.png	Atelectasis	225.0847	547.0192	86.77966	79.18644
00014716_007.png	Atelectasis	686.1017	131.5435	185.4915	313.4915
00029817_009.png	Atelectasis	221.8305	317.0531	155.1186	216.9492
00014687_001.png	Atelectasis	726.2373	494.9514	141.0169	55.32203
00017877_001.png	Atelectasis	660.0678	569.7808	200.678	78.10169
00003148_004.png	Atelectasis	596.0678	505.7808	56.40678	180.0678
00012515_002.png	Atelectasis	289.0847	638.1379	83.52542	56.40678
00022098_006.png	Atelectasis	494.1017	577.3921	271.1864	154.0339
00014198_000.png	Atelectasis	676.339	512.3074	98.71186	193.0847
00021007_000.png	Atelectasis	344.4068	468.9175	105.2203	101.9661
00030674_000.png	Atelectasis	632.9492	251.9684	227.7966	210.4407
00003945_004.png	Atelectasis	68.88136	471.087	305.8983	168.1356
00000808_002.png	Atelectasis	558.1017	384.3074	227.7966	167.0508
00006621_004.png	Atelectasis	307.5254	401.6633	214.7797	214.7797
00000865_006.png	Atelectasis	839.0508	624.0362	78.10169	40.13559
00028452_001.png	Atelectasis	629.6949	410.3413	256	148.6102
00007557_026.png	Atelectasis	131.7966	706.4768	221.2881	123.661
00000181_061.png	Atelectasis	209.8983	568.7141	213.6949	254.9153
00009669_003.png	Atelectasis	157.8305	648.9853	261.4237	220.2034
00025368_014.png	Atelectasis	294.5085	684.7638	117.1525	84.61017
00000468_033.png	Atelectasis	204.4746	502.5446	116.0678	53.15254
00010770_000.png	Atelectasis	244.6102	371.2904	206.1017	68.33898
00016972_019.png	Atelectasis	514.7119	634.8836	298.3051	228.8814
00030635_001.png	Atelectasis	576.5424	490.6124	240.8136	222.3729
00021481_014.png	Atelectasis	594.9831	400.5785	100.8814	159.4576
00019124_045.png	Atelectasis	332.4746	520.9853	125.8305	68.33898

Fig. 3.3 Sample of Bounding Boxes

Chapter 4

Experimental Setup and Analysis

4.1 Dataset Initialization

At first, to begin the X-ray image recognition process we have taken our selected dataset and setup the initial training and testing data using "Pandas". Here, we have taken 112,120 sample images to use later on for recognition and classification of different thoracic diseases.

4.2 Preprocessing Labels

4.2.1 Multi-level Setup

For image label representation there are several options and choices of multi-label classification loss functions. Here, have we defined a 8 dimensional label vector,

$$y = [y_1, ..., y_c, ..., y_C], \quad y_c \in \{0, 1\}, \quad C = 8 \tag{4.1}$$

Here,

y_c = *presence with respect to according pathology*

All zero vector [0, 0, 0, 0, 0, 0, 0, 0] represents no pathology is found. This transits the multi-label classification into a regression like loss setting.

4.2.2 Transition Layer

Transition layer has been used to transform the activation from previous layers into a uniform dimension of output,

$$S * S * D, \quad S \in \{8, 16, 32\} \tag{4.2}$$

Here,

D = dimension of features at spatial location (i, j), i, j $\in \{1, ..., S\}$

Which varied in different model. For our model, D = 1024. The transition layer pass down the weights from pre-trained DCNN models in a standard form.

4.2.3 Multi-label Classification Loss Layer

First, for multi-class classification we have run 3 standard loss functions i.e., Euclidean Loss (EL), Cross Entropy Loss (CEL) and Hinge Loss (HL) for the regression task instead of softmax loss. From this, we observed that, this model has difficulties in learning images with pathology. As, there are highly more '0's than '1's.

4.2.4 Converting into Simple Binary Labels

Here, we have taken the labels and make them into a more clear format by see the distribution of findings and converting them to simple binary labels.

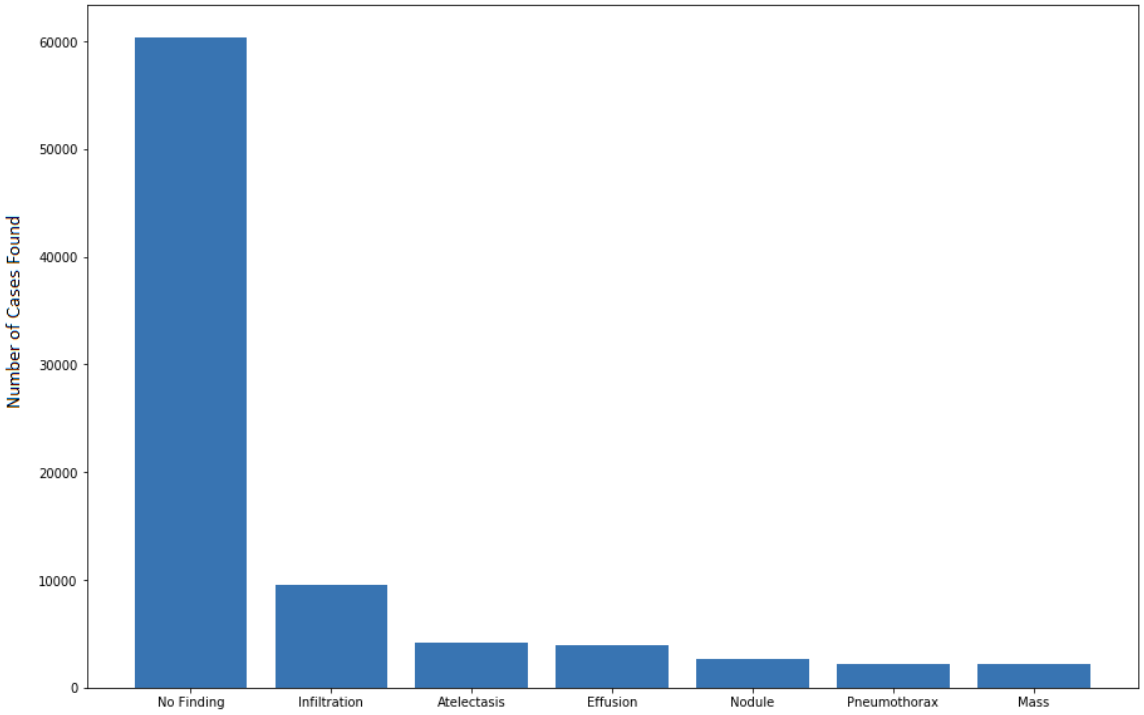

Fig. 4.1 Simple Binary Labels

4.2.5 Data

We have evaluate that, among total 112,120 frontal-view X-ray images there are 24,636 images contain one or more diseases and remaining 87,484 images are normal cases.

4.3 Finding all Unique Labels

Then we have ignored images with no labels and find out all 14 unique labels. All 14 unique labels: Atelectasis, Cardiomegaly, Consolidation, Edema, Effusion, Emphysema, Fibrosis, Hernia, Infiltration, Mass, Nodule, Pleural Thickening, Pneumonia and Pneumothorax.

	Image Index	Finding Labels	Follow-up #	Patient ID	Patient Age	Patient Gender	View Position	OriginalImage[Width	Height]	Or
110462	00030079_054.png	Infiltration	54	30079	16	M	AP	3056	2544	0.
42117	00010828_060.png	Atelectasis|Effusion|Infiltration	60	10828	45	M	AP	2500	2048	0.
31705	00008291_018.png	Emphysema	18	8291	34	F	AP	2500	2048	0.

Fig. 4.2 Finding all Unique Labels

4.4 Clean Categories

As, we have too many categories (14 categories) and some of those pathologies have vary few cases, we have drop categories those have less then 5000 cases in favour of getting more accuracy. We have only taken the 6 thoracic diseases (Atelectasis, Effusion, Infiltration, Mass, Nodule and Pneumothorax) on the training and testing set.

Table 4.1 Cleaned Categories

Thoracic Diseases	No. of Cases
Atelectasis	11559
Effusion	13317
Infiltration	19894
Mass	5782
Nodule	6331
Pneumothorax	5302

4.5 Adjusted Frequency and Adding Weight

As the dataset is very unbiased, we have re-sample it to be a more reasonable collection by adding weight. After that, we have adjusted frequency of diseases in patient group.

$$weight = 0.1 + number\ of\ findings \tag{4.3}$$

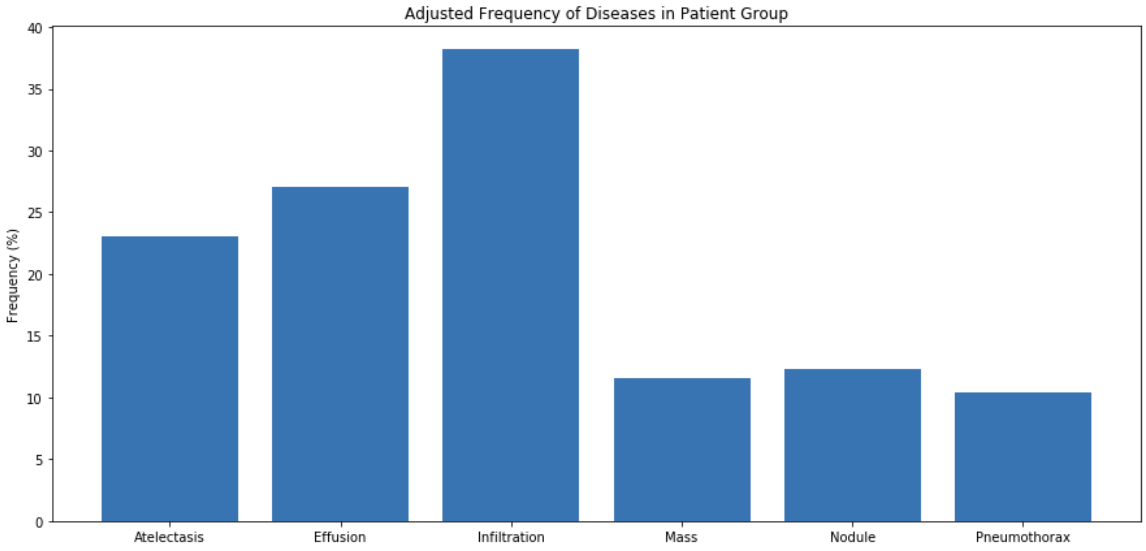

Fig. 4.3 Adjusted Frequency of Diseases in Patient Group

4.6 Prepare Training Data

We have randomly divided the entire dataset into three group, i.e. training, validation and testing. Here we have divided the data into training and validation sets into 80% to 20% ratio and made a single vector (disease_vec) with the 0/1 outputs for the disease status.

4.6.1 CNN Setting

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

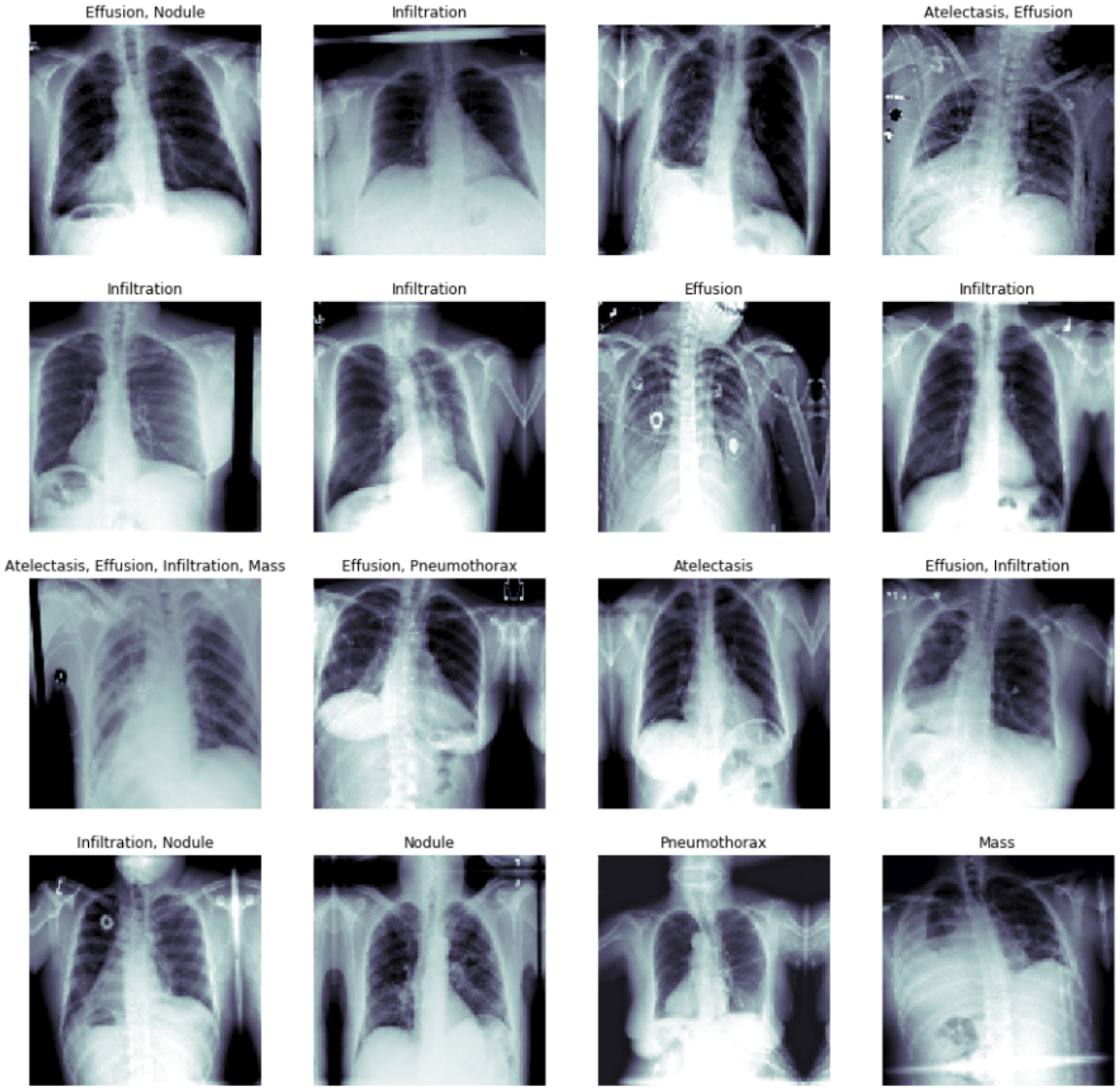

Fig. 4.4 X-ray Image Recognition and Classification

4.6.2 ROC Curves

Multi-label classification ROC curves on 6 pathologies is demonstrated bellow. The quantitative performance varies greatly. Atelectasis (AUC=0.54) and Effusion (AUC=0.53) classes are well recognized compared to other diseases. While the detection rate is lower for Nodule (AUC=0.49) and Pneumothorax (AUC=0.50) pathologies which contain small objects. Due to it's huge within class appearance variation Mass is also difficult to detect.

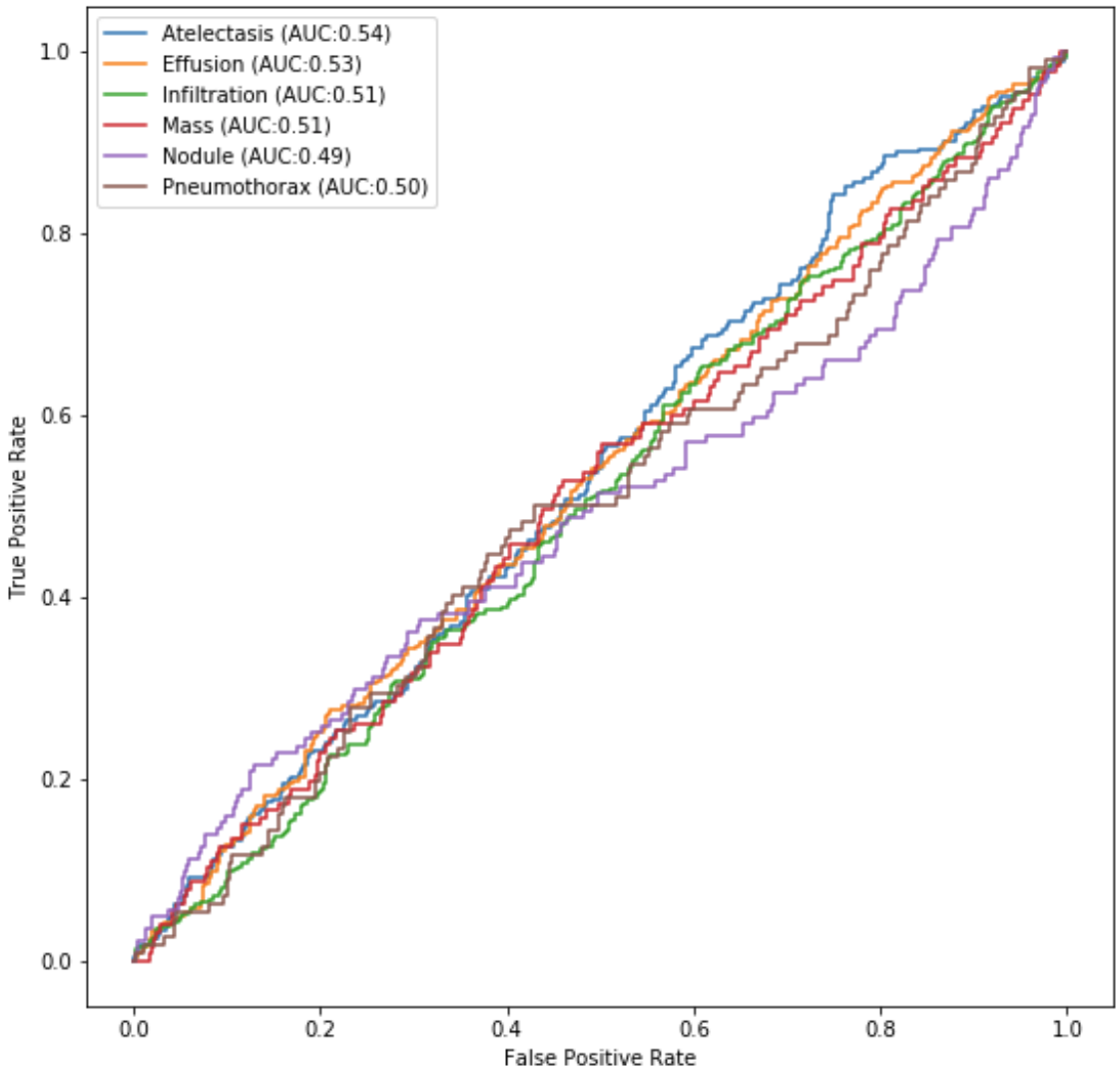

Fig. 4.5 ROC Curves

4.7 Experimental Results

Our proposed model is designed to recognize and classify medical chest X-ray images. It contains both image processing and convolutional neural network. Accuracy rate depends on the threshold values. During each epoch data is trained over and over again to learn the feature of data.

Table 4.2 Loss and Accuracy Rate for Training and Validation

Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
0.4865	0.7922	0.5059	0.7775
0.4818	0.7933	0.4840	0.7843
0.4692	0.8204	0.5457	0.8266
0.4572	0.8327	0.6458	0.8416
0.4496	0.8615	0.7959	0.8619

Table 4.3 Output

Thoracic Diseases	Pecentage
Atelectasis	24.12%
Effusion	26.66%
Infiltration	36.04%
Mass	12.30%
Nodule	12.89%
Pneumothorax	11.23%

Accuracy rate we have gotten using CNN is 86.15%

4.8 Challenges

During this research work, we 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, Emphysema are diagnosed clinically, not on imaging.

(b) Report mined nodule labels' value is questionable, as on x-rays up to 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 (around 112,120 images). So, it required a lots of processing power.

Chapter 5

Conclusion

5.1 Conclusion

In this paper, we offered a model for medical application of chest pathology detection in chest radiography using Convolutional Neural Networks (CNN) and thus propose the model to address 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 attention branch exploits the correlation between class labels and the areas of pathological irregularities and enables the model to focus adapting on the pathologically abnormal regions. The result of our model indicate that our model out performs other methods, which use no extra training data, in diagnosing 6 thorax diseases on chest radiography 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 pictures 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

We have successfully recognized and classified 6 thoracic diseases (Atelectasis, Effusion, Infiltration, Mass, Nodule and Pneumothorax) using chest X-rays dataset provided by NIH. Which is basically data collected from USA. In near future, we will collect X-ray images from local hospitals to train and test the system to predict better results. Also, we have plan to work with more complex medical data like CT and MRI images.

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