A Synopsis Report on

"Detection of Thoracic Diseases using Deep Learning"

Submitted in partial fulfillment of the requirement for Degree in Bachelor of Engineering (Computer Engineering)

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2019-2020

APPROVAL SHEET

This is to certify that the project entitled

"Detection of Thoracic Diseases using Deep Learning"

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In partial fulfillment of degree of **B.E.** in **Computer Engineering** for term work of the project is approved.

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Head of Department : _____

Date :

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Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited them and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause of disciplinary action by the Institute and can also evoke penal action from the sources which have not been properly cited or from whom proper permission has not been taken when needed.

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Acknowledgment

Success of a project like this involving high technical expertise, patience and massive support of guides, is possible when team members work together. We take this opportunity to express our gratitude to those who have been instrumental in the successful completion of this project. We deem it a pleasure to acknowledge our sense of gratitude and appreciation to our project guide **Ms. M. Kiruthika** for her tremendous support and help, without which this project would have reached nowhere. Her incisive and objective guidance and timely advice encouraged us with constant flow of energy to continue the work. A big thanks to our **HOD Dr. Lata Ragha** for all the encouragement given to our team. We shall remain grateful to computer department, for providing us a strong academic atmosphere by enforcing strict discipline to do the project work with utmost concentration and dedication. Finally, we must say that no height is ever achieved without some sacrifices made at some end and it is here where we owe our special debt to our parents and our friends for showing their generous love and care throughout.

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Abstract

Chest X-rays are currently the most common and globally used radiology practices for detecting thoracic diseases. Patients suffering from thoracic diseases need to take Chest X-Rays which are read by radiologists and a report is generated by them. However, today with the increase in number of thoracic patients, a quick method to classify the disease and generate the report has become necessary. Also, patient history has to be considered for diagnosis. Hence, using a Text-Image Embedding network to classify the Chest X-rays of 14 different thoracic diseases and predict the disease of the new sample provided by the patient and generate a report for the same is proposed. This project seeks to use Deep Convolutional Neural networks (D-CNN) which are capable of efficiently processing the Chest X-rays and locating the patterns of the diseases.

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Chapter 1

Introduction

1.1 Background

The thorax also called chest, is the upper part of the trunk located between the neck and the abdomen. It is mostly protected and supported by the rib cage, spine, and shoulder girdle. It is the region of the body formed by the sternum, the thoracic vertebrae, and the ribs. It extends from the neck to the diaphragm, and does not include the upper limbs. The heart and the lungs reside in the thoracic cavity, as well as many blood vessels which play a vital role in feeding (oesophagus), breathing, and pumping the blood to all parts of the body. Chest pain is the most frequent reason for consultation and emergency room visits. Chest radiography is the most common imaging examination globally, critical for screening, diagnosis, and management of many life-threatening thoracic diseases. Currently reading CXRs mainly relies on professional knowledge and careful manual observation. Due to complex pathologies and subtle changes of different lung lesions in images, radiologists could miss upon some minute details even when they have long term experience. Also, there is lack of trained and expertise radiologists. Hence, in this report , we propose a system that will be able to automatically detect thoracic diseases from chest X-rays as well as generate reports.

1.2 Motivation

Presently, Chest X-rays are the best method to predict thoracic diseases like pneumonia, hernia etc. To interpret these X-rays, radiologists are required. They read the X-ray images and produce reports manually based on their observations. However, according to the WHO, two-thirds of the world population lacks insufficient access to trained radiologists. Also, according to a study conducted by ICMR, India bears 32 percent global burden of respiratory diseases. This is a major health concern for our society. Hence, we aim to develop an algorithm to interpret chest X-ray images.

1.3 Aim and Objective

Our proposed system aims to automatically detect and classify thoracic diseases from chest X-rays and generate reports at a level exceeding practicing radiologists. The objective of our system is:

- To develop a deep learning model which can detect abnormalities in Chest X-rays and produce the correct lung disease as output.

1.4 Problem Statement

Today, lung diseases pose a serious, prevailing threat to the health of the global population. Hence, timely diagnosis is critical. This system will take chest X-Rays as input and process them using a deep learning trained model to detect thoracic disease. The model

is capable of detecting any one from a range of 14 different lung diseases at a time. The model will be based on a D-CNN (Deep Convolutional Neural Network). It will employ various techniques like image enhancement, segmentation, feature extraction to detect thoracic disease. Critical techniques are: Lung Area Segmentation, Data Processing, Feature Extraction and finally classification via the trained classifier. The model will be trained and tested on two different datasets, with different parameters. The results will be compared and reported.

1.5 Scope

The project envisages a system that will detect the type of thoracic disease as well as generate reports. This system can be generalized and further extended to detect any other type of thoracic diseases. Detection is achieved using Image Processing and Deep Learning techniques.

Chapter 2

Study of Detection of Thoracic Diseases using Deep Learning

2.1 Classification of Thoracic Diseases

2.1.1 Atelectasis

When alveoli (air sacs) within the lung deflate or are filled with alveolar fluid, then the lung or lobe of the lung collapses partially or completely. This is called atelectasis. It can happen due to complications after surgery, cystic fibrosis, lung tumors, chest injuries, fluid in the lung, inhalation of foreign objects and respiratory weakness. The symptoms of atelectasis include:

- Shortness of breath or difficulty in breathing
- Rapid, shallow breathing
- Wheezing
- Cough

On a chest x-ray, it is normally associated with increased linear density and loss of volume of the gas in the affected lung or the lobe.

2.1.2 Mass and Nodule

When the lung cells multiply too fast or do not die off normally as they should, an abnormal growth of tissue called a tumour is formed.
If this growth is less than or equal to 3 centimetre in diameter, it is called a nodule (more specifically pulmonary nodule as it is formed in the lungs).
If the growth is more than 3 centimetre in diameter, it is called a mass.
The patient does not present any symptoms for tumours, however, if symptoms do appear, they may include the following:

- Persistent coughing or wheezing
- Shortness of breath or difficulty in breathing
- Coughing up blood

- Rattling sounds in the lungs
- Higher likelihood of pneumonia
- Lung tissue collapse

These appear in X-rays as a coin-like round growth, and may look like fuffy wool or popcorn.

2.1.3 Cardiomegaly

It means an enlarged heart and is usually a sign of another condition such as a heart valve or heart disease, a signal prior to heart attack, bodily stress caused by certain infection or pregnancy.
Its symptoms include:

- Shortness of breath
- Edema (Swelling)
- Fatigue
- Palpitations

It can be detected on an X-ray with the use of cardiothoracic ratio. If the ratio is greater than 0.50 (especially ¿0.60), then it indicates cardiomegaly.

2.1.4 Effusion

The medical condition in which there is an unusual amount of fluid around the lung. It can be caused due to many medical conditions like leakage from other organs (liver or kidney diseases), cancer, infections, autoimmune conditions and pulmonary embolism. The effusion needs to be drained. If symptoms do occur, they may include:

- Shortness of breath
- Chest pain (especially when breathing deeply)
- Fever
- Cough

On an X-ray, effusions appear white, while air space looks black. Lateral X-rays are useful in detection of effusion as these can show if the fluid flows freely within the pleural space.

2.1.5 Infiltration

This occurs when a substance denser than air like pus, edema, blood, protein or cells lingers within the lungs. This can be caused due to pneumonia.

- Shortness of breath
- Chest pain
- Cough

They appear as white spots on X-ray.

2.1.6 Pneumonia

It is an infection that causes inflammation in one or both the lungs. It can be caused by a virus, bacteria, a fungi or other parasites. The symptoms associated with pneumonia are:

- Cough producing phlegm or blood
- Shortness of breath or difficulty in breathing
- Fever
- Chills or shaking
- Sweating
- Chest or muscle pain

While interpreting the X-ray, a radiologist will look for white spots to identify infection, and abscesses or effusions.

2.1.7 Pneumothorax

Air leaks into the space between the lungs and the chest wall causing the lung to collapse. This condition can be caused due to a blunt or penetrating chest injury, certain medical procedures or lung disease. Its symptoms include:

- Shortness of breath
- Pain in chest
- Fast or shallow breathing
- Chest pressure
- Coughing
- High heart rate
- Low oxygen in the body

It can be diagnosed in an X ray by demonstrating the outer margin of the lung is separated from the chest wall by a lucent gas space devoid of pulmonary vessels.

2.1.8 Emphysema

It is a type of a chronic obstructive pulmonary disease that damages the alveoli (air sacs) in the lungs. This results in low oxygen to the body that causes shortness of breath. Its symptoms include:

- Difficult to catch breath
- Chronic cough
- Trouble breathing even for simple exercises like climbing the stairs
- Lips or fingernails turning blue or grey
- Not alert mentally

In an X-ray, the lungs appear to be much larger than they should be.

2.1.9 Consolidation

It is a region in lung that is filled with liquid instead of air. It can happen due to infiltrates in the lungs like pus, inhaled water or blood (from a hemorrhage). Its symptoms include:

- Coughing up thick green or bloody sputum
- Dry cough
- Breathing sound is funny or noisy
- Chest pain or pressure
- Rapid breathing
- Fever
- Fatigue

In an X-ray, it is seen as an area of white lung

2.1.10 Edema

It is a condition caused due to excess fluid in the lungs that collects itself in the alveoli of the lungs making it difficult to breath. Its symptoms are:

- Extreme shortness of breath
- Suffocation (especially when lying down)
- Wheezing
- Anxiety, restlessness
- Blue-tinged lips
- Cough producing frothy sputum
- Palpitations

In an X-ray, 'bat wing' like patterns can be seen, patchy shadowing with air bronchograms, increased cardiac size.

2.1.11 Fibrosis

This is a lung disease that occurs when the lung tissue becomes damaged and scarred which makes the tissue stiff and the lungs cannot work properly. The lung damage cannot be repaired.
Symptoms are:

- Shortness of breath
- Dry cough
- Fatigue
- Unexplained weight loss
- Aching muscles and joints
- Widening and rounding of the tips of fingers or toes.

The X-ray shows the scar tissue typical of pulmonary fibrosis.

2.1.12 Pleural Thickening

Extensive scarring of lungs thickens the pleura (lining of the lungs) and causes chest pain and difficulty in breathing. It is commonly diagnosed sign of asbestos exposure. Its symptoms are:
Symptoms are:

- Breathlessness
- Difficulty in breathing
- Shortness of breath
- Chest pain while breathing
- Pain with coughing
- Dull chronic chest pain
- Reduced pulmonary function

In X-ray, it appears as an irregular shadow on the pleura and extends over at least 25 percent of the chest wall.

2.1.13 Hernia

It refers to a part of lung pushing through a tear, bulging through a weak spot in the chest wall, neck, passageway or diaphragm. Symptoms of hernia:
Symptoms are:

- Sharp pain when inhaling, coughing or sneezing
- Difficulty in breathing
- General soreness in a particular area of the chest
- Fever

They are fairly easy to locate and diagnose. The affected area can be plainly observed in in chest X-ray.

2.2 Deep Learning

Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, semi-supervised or unsupervised. Deep learning architectures such as deep neural networks, deep belief networks and recurrent neural networks have been applied to fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bio-informatics, drug design and board game programs, where they have produced results comparable to and in some cases superior to human experts.

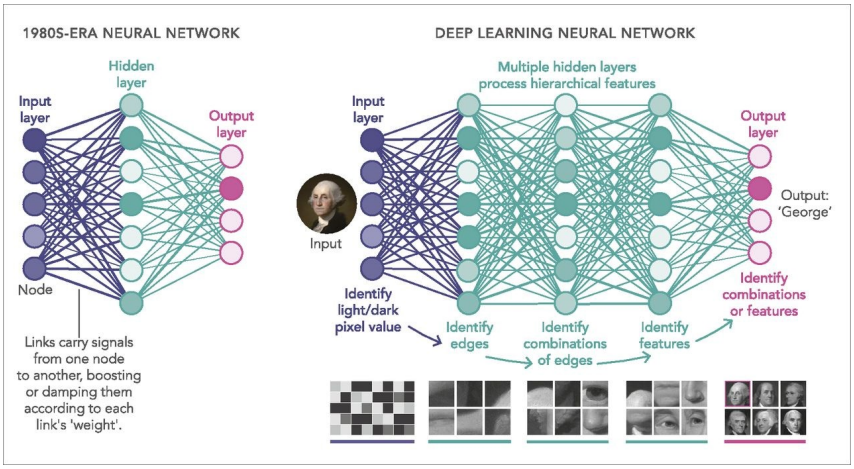

Figure 2.1: Deep Learning Neural Network

Deep learning models are vaguely inspired by information processing and communication patterns in biological nervous systems yet have various differences from the structural and functional properties of biological brains (especially human brain), which make them incompatible with neuroscience evidences.
Deep learning networks are distinguished from the more commonplace single-hidden-layer neural networks by their depth; that is, the number of node layers through which data passes in a multistep process of pattern recognition. Earlier versions of neural networks such as the first perceptrons were shallow, composed of one input and one output layer, and at most one hidden layer in between. More than three layers (including input and output) qualifies as “deep” learning. So deep is a strictly defined, technical term that means more than one hidden layer. In deep-learning networks, each layer of nodes trains on a distinct set of features based on the previous layer’s output. The further you advance into the neural net, the more complex the features your nodes can recognize, since they aggregate and recombine features from the previous layer.

2.2.1 Deep Neural Networks

Artificial neural networks (ANN) or connectionist systems are computing systems that are inspired by, but not identical to, biological neural networks that constitute animal brains. Such systems ”learn” to perform tasks by considering examples, generally without being programmed with task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analysing example images that have been manually labelled as ”cat” or ”no cat” and using the results to identify cats in other images.
An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron that receives a signal then processes it and can signal neurons connected to it.
In ANN implementations, the ”signal” at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called edges. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.

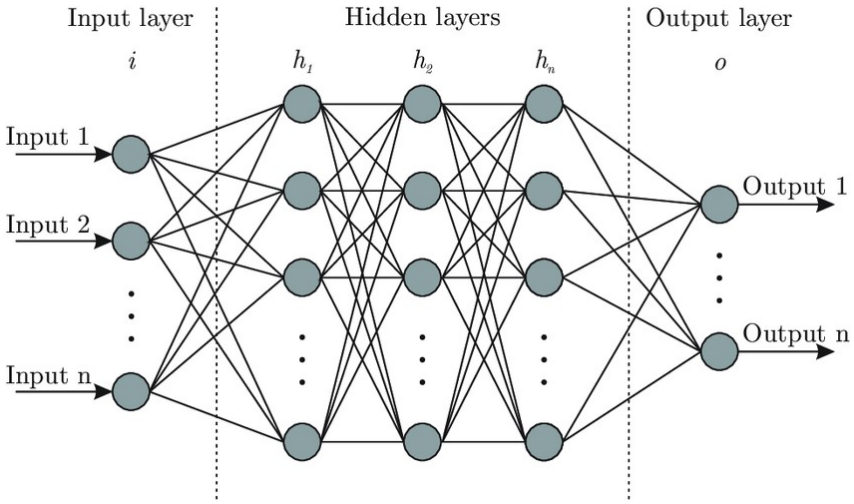

Figure 2.2: Artificial Neural Network

2.2.2 Convolutional Neural Networks

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analysing visual imagery.

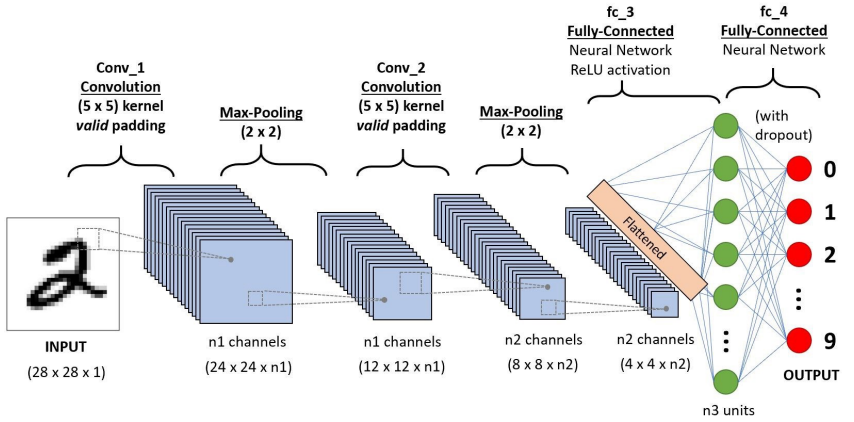

Figure 2.3: Convolutional Neural Network

CNNs are regularized versions of multilayer perceptrons. Multilayer perceptrons usually mean fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks makes them prone to overfitting data. Typical ways of regularization include adding some form of magnitude measurement of weights to the loss function. However, CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Therefore, on the scale of connectedness and complexity, CNNs are on the lower extreme. A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of a series of convolutional layers that convolve with a multiplication or other dot product. The activation function is commonly a RELU layer, and is subsequently followed by additional convolutions such as pooling layers, fully connected layers and normalization layers, referred to as hidden layers because their inputs and outputs are masked by the activation function and final convolution. The final convolution, in turn, often involves backpropagation in order to more accurately weight the end product.

2.2.3 Recurrent Neural Networks

A recurrent neural network (RNN) is a type of artificial neural network commonly used in speech recognition and natural language processing (NLP). RNNs are designed to recognize a data's sequential characteristics and use patterns to predict the next likely scenario.

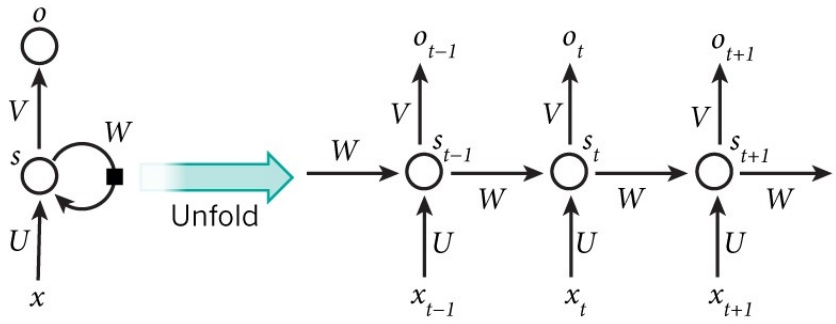

Figure 2.4: Recurrent Neural Network

RNNs are used in deep learning and in the development of models that simulate the activity of neurons in the human brain. They are especially powerful in use cases in which context is critical to predicting an outcome and are distinct from other types of artificial neural networks because they use feedback loops to process a sequence of data that informs the final output, which can also be a sequence of data . These feedback loops allow information to persist; the effect is often described as memory. RNN use cases tend to be connected to language models in which knowing the next letter in a word or the next word in a sentence is predicated on the data that comes before it. A compelling experiment involves an RNN trained with the works of Shakespeare to produce Shakespeare like prose – successfully. Writing by RNNs is a form of computational creativity. This simulation of human creativity is made possible by the AI's understanding of grammar and semantics learned from its training set.

2.3 Activation Functions

Activation function f(x) is used to make the network more powerful and add ability to it to learn something complex and complicated form data and represent non-linear complex arbitrary functional mappings between inputs and outputs. Hence using a non-linear Activation we are able to generate non-linear mappings from inputs to outputs. Another important feature of activation functions is that they should be differentiable. Most popular types of Activation functions:

1. Sigmoid or Logistic
2. Tanh—Hyperbolic tangent
3. ReLu -Rectified linear units

2.3.1 Sigmoid Activation Function

It is a activation function of form f(x) = 1 / 1 + exp(-x) .
Its Range is between 0 and 1. It is a S—shaped curve.

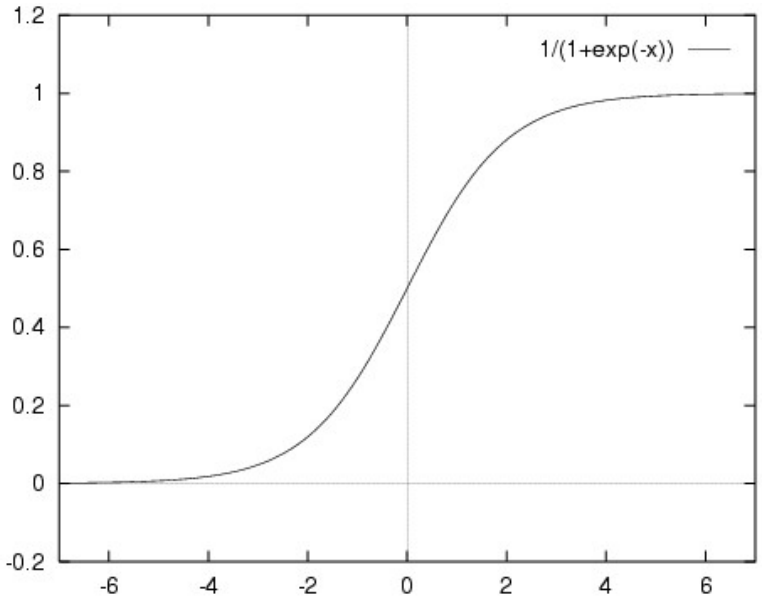

Figure 2.5: Sigmoid Activation Function

It is easy to understand and apply but it has major reasons which have made it fall out of popularity.
-Vanishing gradient problem Secondly, its output isn't zero centered. It makes the gradient updates go too far in different directions. 0 ¡ output ¡ 1, and it makes optimization harder. Sigmoids saturate and kill gradients. Sigmoids have slow convergence. Now how do we solve the above problems?

2.3.2 Hyperbolic Tangent Function

Its mathematical formula is f(x) = 1 — exp(-2x) / 1 + exp(-2x). Now it's output is zero centred because its range in between -1 to 1 i.e. -1 ¡ output ¡ 1.

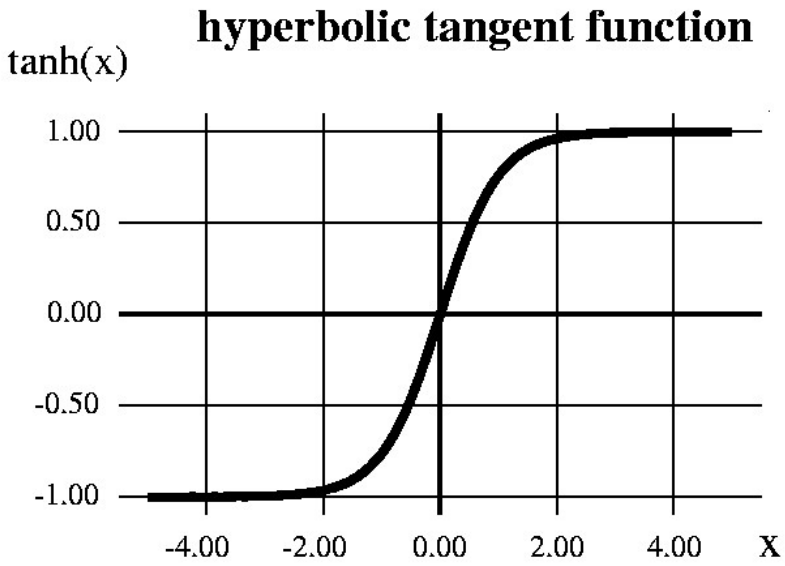

Figure 2.6: Hyperbolic Tangent Function

Hence optimization is easier in this method hence in practice it is always preferred over Sigmoid function. But still it suffers from Vanishing gradient problem.

Then how do we deal and rectify the vanishing gradient problem?

2.3.3 ReLu - Rectified Linear Units Function

It has become very popular in the past couple of years. It was recently proved that it had 6 times improvement in convergence from Tanh function. It's just R(x) = max(0,x) i.e. if x ¡ 0 , R(x) =0 and if x ¿= 0 , R(x) = x. Hence as seeing the mathematical form of this function we can see that it is very simple and efficient. A lot of times in Machine learning and computer science we notice that most simple and consistent techniques and methods are only preferred and are best. Hence it avoids and rectifies vanishing gradient problem. Almost all deep learning models use ReLu nowadays. But its limitation is that it should only be used within Hidden layers of a Neural Network Model.
Hence for output layers we should use a SoftMax function for a Classification problem to compute the probabilities for the classes, and for a regression problem it should simply use a linear function.

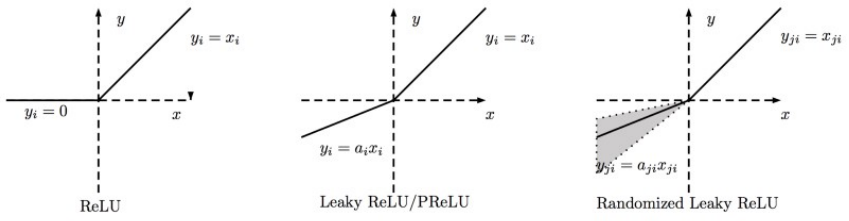

Figure 2.7: ReLu - Rectified Linear Unit Function

Another problem with ReLu is that some gradients can be fragile during training and can die. It can cause a weight update which will makes it never activate on any data point again. Simply saying that ReLu could result in Dead Neurons. To fix this problem another modification was introduced called Leaky ReLu to fix the problem of dying neurons. It introduces a small slope to keep the updates alive. We then have another variant made from both ReLu and Leaky ReLu called Maxout function.

2.3.4 Softmax Activation Function

A Softmax function is a type of squashing function. Squashing functions limit the output of the function into the range 0 to 1. This allows the output to be interpreted directly as a probability. Similarly, softmax functions are multi-class sigmoids, meaning they are used in determining probability of multiple classes at once. Since the outputs of a softmax function can be interpreted as a probability (i.e. They must sum to 1), a softmax layer is typically the final layer used in neural network functions. It is important to note that a softmax layer must have the same number of nodes as the output later.

$$\phi(z) = \frac{e^i}{\sum_{j=0}^{k} e^j} \quad \text{where i=0,1,....k}$$

Figure 2.8: Softmax Activation Function

2.4 Loss Functions

Loss function is an important part in artificial neural networks, which is used to measure the inconsistency between predicted value (ŷ) and actual label (y). It is a non-negative value, where the robustness of model increases along with the decrease of the value of loss function. Loss function is the hard core of empirical risk function as well as a significant component of structural risk function. Generally, the structural risk function of a model is consisting of empirical risk term and regularization term, which can be represented as

$$\begin{aligned}\boldsymbol{\theta}^* &= \arg\min_{\boldsymbol{\theta}} \boldsymbol{\mathcal{L}}(\boldsymbol{\theta}) + \lambda \cdot \Phi(\boldsymbol{\theta}) \\ &= \arg\min_{\boldsymbol{\theta}} \frac{1}{n} \sum_{i=1}^{n} L\left(y^{(i)}, \hat{y}^{(i)}\right) + \lambda \cdot \Phi(\boldsymbol{\theta}) \\ &= \arg\min_{\boldsymbol{\theta}} \frac{1}{n} \sum_{i=1}^{n} L\left(y^{(i)}, f(\mathbf{x}^{(i)}, \boldsymbol{\theta})\right) + \lambda \cdot \Phi(\boldsymbol{\theta})\end{aligned}$$

Figure 2.9: Structural Risk Function

where is the regularization term or penalty term, is the parameters of model to be learned, f() represents the activation function and x(i)=x(i)1,x(i)2,. . . ,x(i)mRm denotes the training sample. Here we only concentrate on the empirical risk term (loss function).

$$\boldsymbol{\mathcal{L}}(\boldsymbol{\theta}) = \frac{1}{n} \sum_{i=1}^{n} L\left(y^{(i)}, f(\mathbf{x}^{(i)}, \boldsymbol{\theta})\right)$$

Figure 2.10: Loss Function

2.4.1 Mean Squared Error (MSE)

Mean Squared Error (MSE), or quadratic, loss function is widely used in linear regression as the performance measure, and the method of minimizing MSE is called Ordinary Least Squares (OSL), the basic principle of OSL is that the optimized fitting line should be a line which minimizes the sum of distance of each point to the regression line, i.e., minimizes the quadratic sum. The standard form of MSE loss function is defined as

$$\boldsymbol{\mathcal{L}}(\boldsymbol{\theta}) = \frac{1}{n} \sum_{i=1}^{n} L\left(y^{(i)}, f(\mathbf{x}^{(i)}, \boldsymbol{\theta})\right)$$

Figure 2.11: MSE Loss Function

2.4.2 Mean Absolute Error

Mean Absolute Error (MAE) is a quantity used to measure how close forecasts or predictions are to the eventual outcomes, which is computed by

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^{n} \left| y^{(i)} - \hat{y}^{(i)} \right|$$

Figure 2.12: MAE Loss Function

where ———— denotes the absolute value. Albeit, both MSE and MAE are used in predictive modelling, there are several differences between them. MSE has nice mathematical properties which makes it easier to compute the gradient. However, MAE requires more complicated tools such as linear programming to compute the gradient. Because of the square, large errors have relatively greater influence on MSE than do the smaller error. Therefore, MAE is more robust to outliers since it does not make use of square. On the other hand, MSE is more useful if concerning about large errors whose consequences are much bigger than equivalent smaller ones. MSE also corresponds to maximizing the likelihood of Gaussian random variables.

2.4.3 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is a variant of MAE, it is computed by

$$\mathcal{L} = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y^{(i)} - \hat{y}^{(i)}}{y^{(i)}} \right| \cdot 100$$

Figure 2.13: MAPE Loss Function

Figure 2.13. MAPE Loss Function
Although the concept of MAPE sounds very simple and convincing, it has major drawbacks in practical application:

1. It cannot be used if there are zero values (which sometimes happens for example in demand data) because there would be a division by zero.
2. For forecasts which are too low the percentage error cannot exceed 100100, but for forecasts which are too high there is no upper limit to the percentage error.
3. When MAPE is used to compare the accuracy of prediction methods it is biased in that it will systematically select a method whose forecasts are too low. This little-known but serious issue can be overcome by using an accuracy measure based on the ratio of the predicted to actual value (called the Accuracy Ratio), this approach leads to superior statistical properties and leads to predictions which can be interpreted in terms of the geometric mean.

2.4.4 L1

L1 loss function is sum of absolute errors of the difference between actual value and predicted value. Similar to the relation between MSE and L2, L1 is mathematically similar to MAE, only do not have division by n, and it is defined as

$$\mathcal{L} = \sum_{i=1}^{n} \left| y^{(i)} - \hat{y}^{(i)} \right|$$

Figure 2.14: L1 Loss Function

2.4.5 Cross Entropy

Cross Entropy is commonly-used in binary classification (labels are assumed to take values 0 or 1) as a loss function (For multi-classification, use Multi-class Cross Entropy), which is computed by

$$\mathcal{L} = -\frac{1}{n} \sum_{i=1}^{n} \left[y^{(i)} \log(\hat{y}^{(i)}) + (1 - y^{(i)}) \log(1 - \hat{y}^{(i)}) \right]$$

Figure 2.15: Cross Entropy

Cross entropy measures the divergence between two probability distribution, if t he cross entropy is large, which means that the difference between two distribution is large, while if the cross entropy is small, which means that two distribution is similar to each other. As we have mentioned in MSE that it suffers slow divergence when using Sigmoid as activation function, here the cross entropy does not have such problem.

2.5 Related Work

Pranav Rajpurkar* et. al., this paper proposed the development of a deep learning algorithm called CheXNet, a 121 layer convolutional neural network trained on Chest Xray14, currently the largest publicly available dataset. The model CheXNet inputs a chest X-Ray image and outputs the probability of pneumonia along with a heatmap localizing the areas of the image most indicative of pneumonia. Simple modifications to CheXNet were made to detect all 14 diseases in Chest Xray14, it was found that CheXNet outperforms results on all 14 diseases[1]. Pulkit Kumar et. al., The authors experimented with a set of deep learning models and presented a cascaded deep neural network that can diagnose all 14 pathologies better its baseline and other models[2].
Xiaosong Wang et. al., This paper proposed a novel Text Image Embedding Network (TieNet) for extracting the distinctive image and text representations. TieNet is used to classify the chest X - Rays by using both image features and text embeddings extracted from associated reports[3]. Qingji Guan et. al., A 3 branch guided CNN (AG - CNN), is proposed which learns from disease - specific regions to avoid noise and improve alignment. It combines the global and the local information[4]. Imane Allaouzi et. al., Extraction of relevant features from CXRs using pre-trained CNN and then classifying the extracted features with multi label problem transformation methods that transform the multi label problem to single-label classification[5].
Mohammad Tariqul Islam et. al., To detect abnormalities in chest X-rays and localize using deep convolutional neural networks to use in different datasets. As a measure of localization in the CXRs (Chest X-rays), heat maps are used. Localization experiments using the trained classifiers show that for spatially spread out abnormalities like cardiomegaly and pulmonary edema, the network can localize the abnormalities successfully most of the time.[6] Xiaosong Wang et. al., This paper presents the chest X - Ray dataset, which comprises of 108,948 frontal X - Ray images. Importantly it demonstrates the detection and localization of the commonly occurring thorax diseases.[7] Jeremy Irvin et. al., To present CheXpert, a large dataset that contains 224,316 chest radiographs of 65,240 patients. Labeler is designed to automatically detect the presence of 14 observations in radiology reports, capturing uncertainties inherent in radiograph interpretation.[8] Juan Manuel et. Al, The objective of this paper is to perform an automatic normality/pathology classification of posteroanterior (PA) digital chest radiographs. The proposed method is not specialized in a given set of types of lesions or diseases but is able to detect anything that differs from normality.[9] Paras Lakhani et. al., Recognizing the potential displayed by DCNN, a practical, result-based, statistical study was performed to determine DCNN efficiency by applying GoogLeNet and AlexNet DCNNs in the classification of images as displaying pulmonary TB or healthy.[10]

Chapter 3

Design of the System

3.1 Proposed System

The proposed system is designed with the aim of automating the process of detection, classification and report generation of thoracic diseases with the help of deep learning techniques.
The proposed system will involve use of deep convolutional neural networks for building a classifier that will learn the features of the chest X-ray images as well as their corresponding reports. Once the model is trained, it would be capable to detect, classify the thoracic diseases as well generate reports for the same.
The system can be further extended to detect any type of thoracic disease.

3.2 Block Diagram

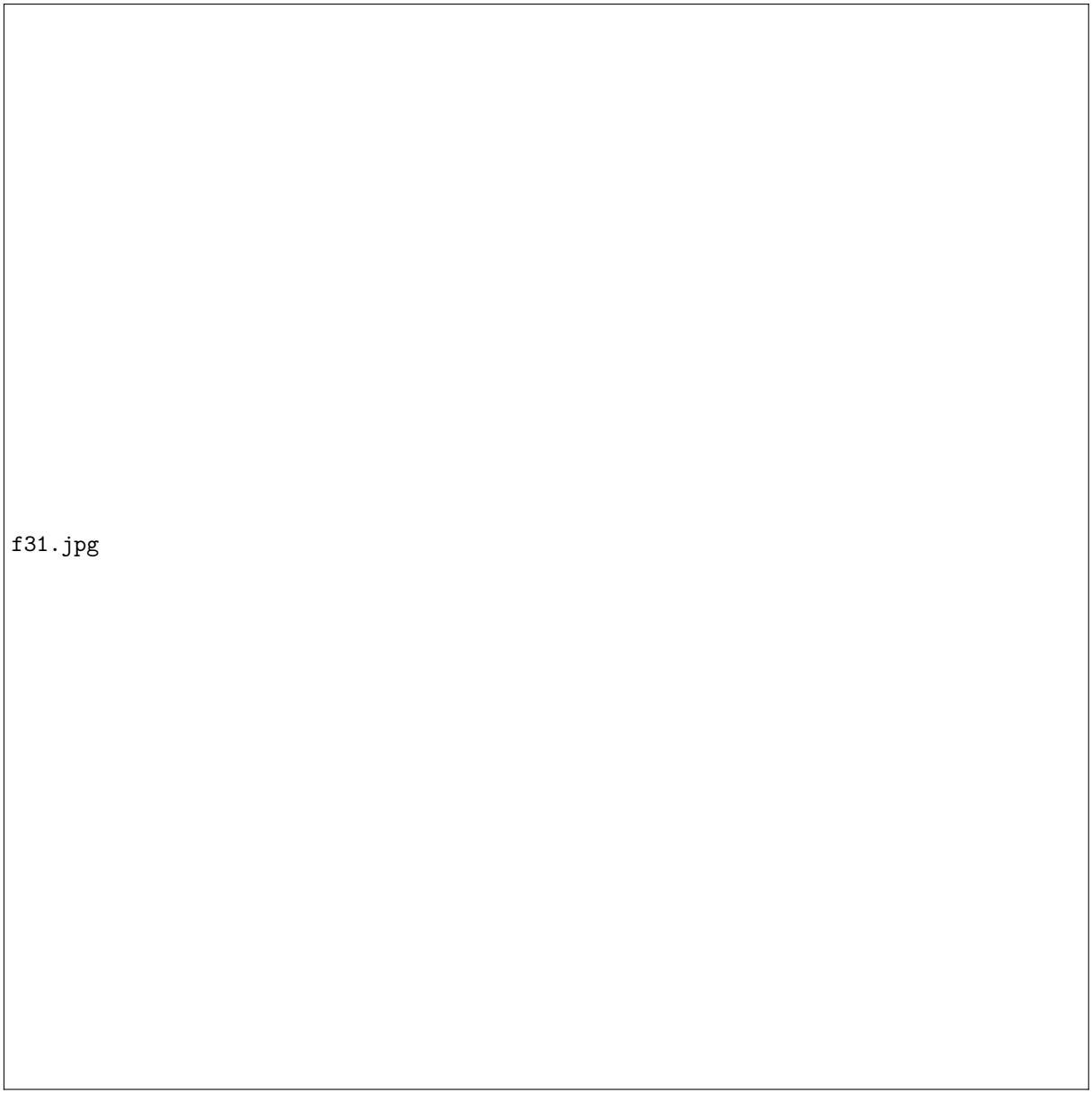

Figure 3.1: Block Diagram of the system

3.2.1 Components of Block diagram

1. Input
   The input of the system are chest x-ray images with their corresponding thoracic disease as label.

2. Pre-processing
   The chest x-ray images will be preprocessed using various image processing techniques.

3. Feature Extraction
   The features of the images will be extracted through the deep convolutional neural network.

4. Output
   The output that will be detected thoracic disease and a generated report

3.3 Activity Diagram

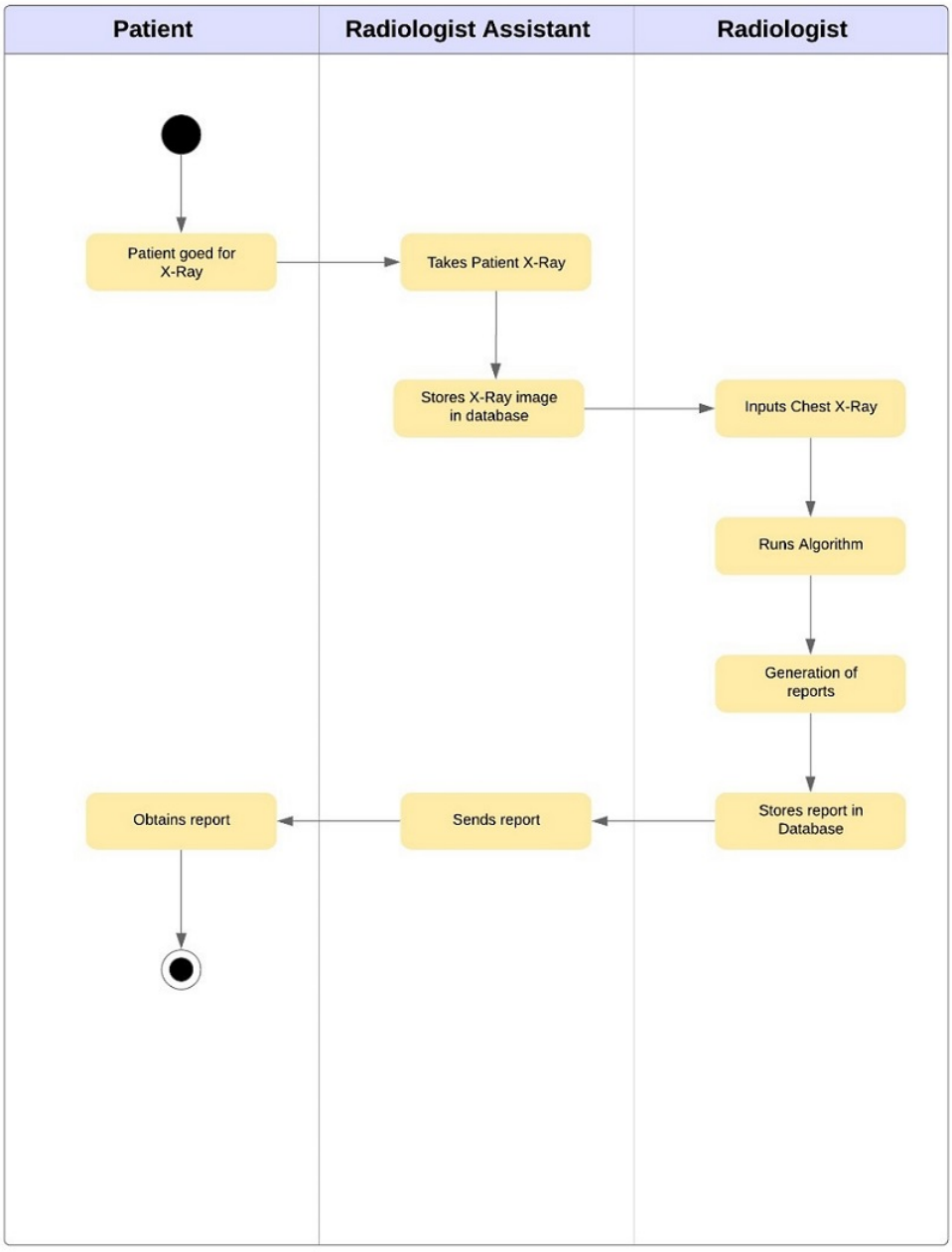

Figure 3.2: Activity Diagram of the system

3.4 System Requirements

3.4.1 Hardware Requirements

- Operating System : Windows or Linux
- Hard disk : 1 TB minimum
- RAM : 8 GB minimum
- Processor : Quad Core Intel Core i5 minimum

3.4.2 3.4.2 Software Requirements

- Python version 3 (and above)
- Pytorch
- Google Cloud Platform (GCP)
- Colab Notebooks

Chapter 4

Results and Discussions

4.1 Implementation Details

4.1.1 Dataset

There are number of publicly available datasets consisting of Chest X-rays and reports provided by the NIH (National Institute of Health) and by various universities. Two datasets have been described below.

4.1.1.1 ChestXray14 Dataset

NIH(National Institute of Health) Clinical Centre has provided one of the largest publicly available chest x-ray datasets.

f41.jpg

Figure 4.1: Chest X-Ray14 dataset Images

The dataset of scans is from more than 30,000 patients, including many with advanced lung disease. It contains about 1,12,121 chest x-ray images. The dataset comprises of 14 different thoracic diseases namely Atelectasis, Cardiomegaly, Fibrosis, Emphysema. Pneumonia, etc.

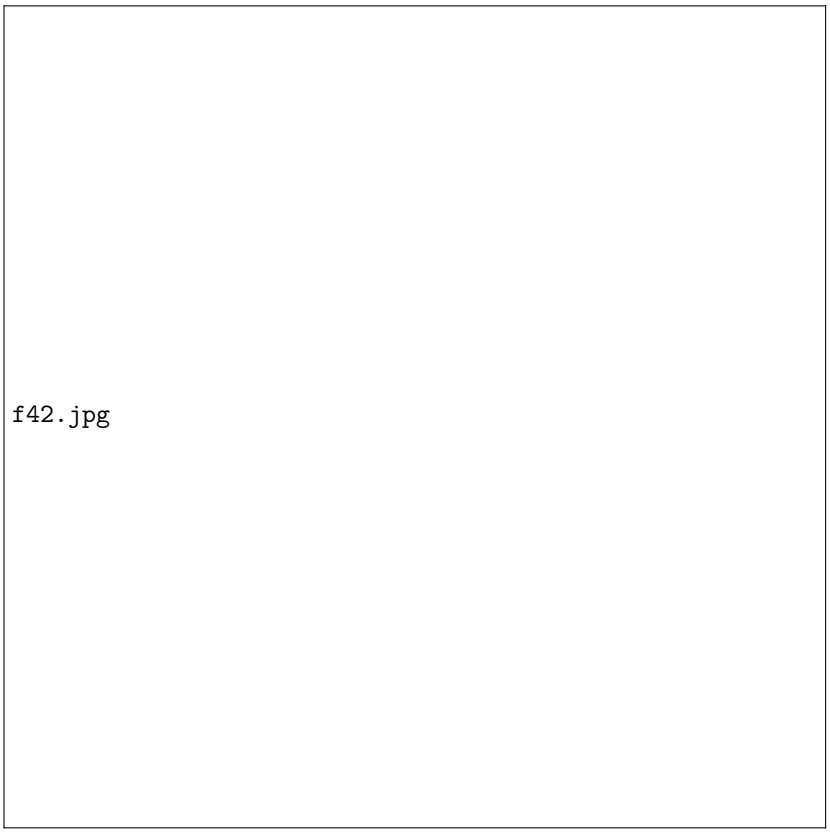

Figure 4.2: Metadata for Chest X-ray images

4.1.1.2 OpenI Dataset

OpenI is a publicly available radiography dataset collected from multiple institutes by Indiana University. It contains 7,471 frontal and lateral chest X-ray images and also contains 3,955 reports for the same.

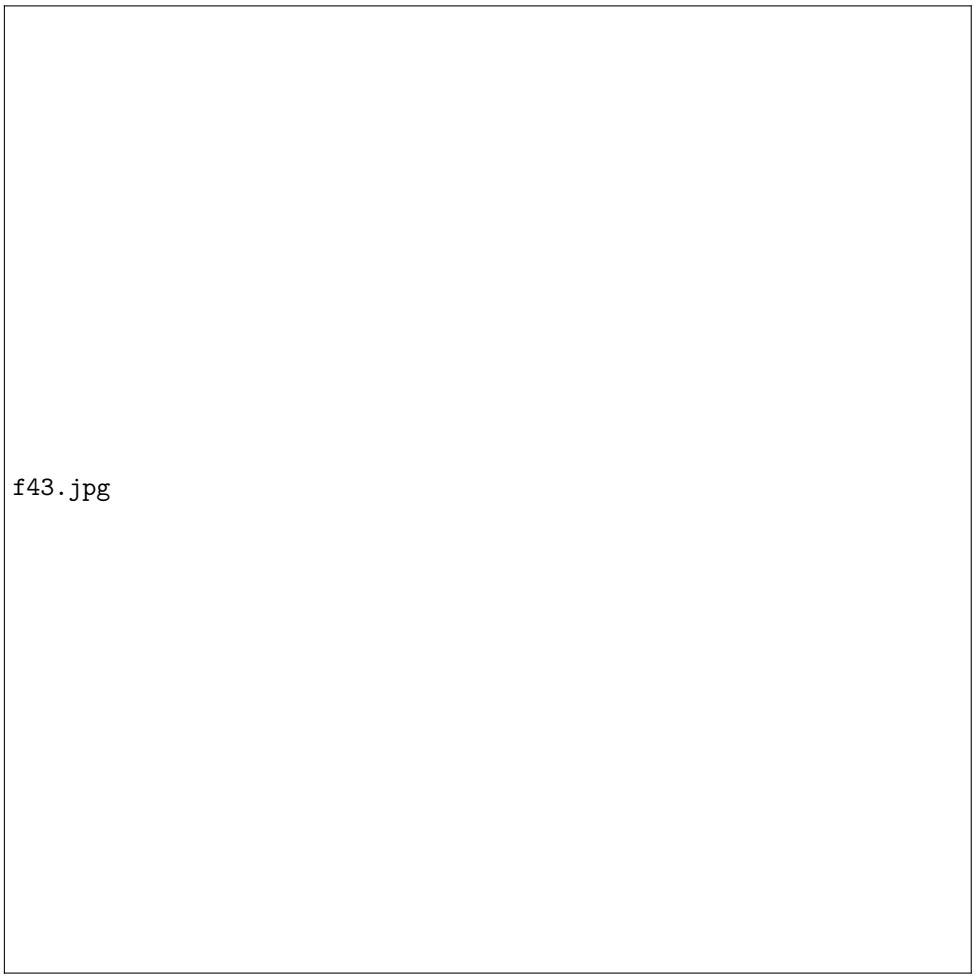

Figure 4.3: OpenI dataset Sample Report

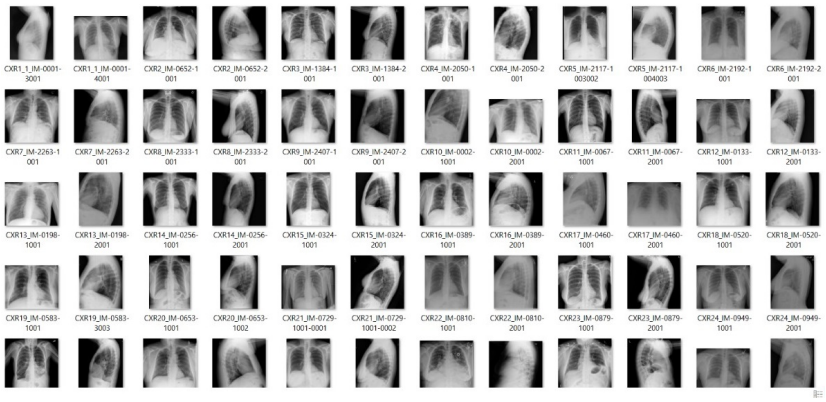

Figure 4.4: OpenI dataset Chest X-rays (frontal and lateral)

4.1.2 Dataset Analysis – ChestXray14

In order to understand the characteristics of data such as size, format and distribution of data, the dataset has been analysed using Python. The two bar plots are shown below:

1. Indicates the number of CXRS per pathology label.
2. the number of CXRs having multiple labels.

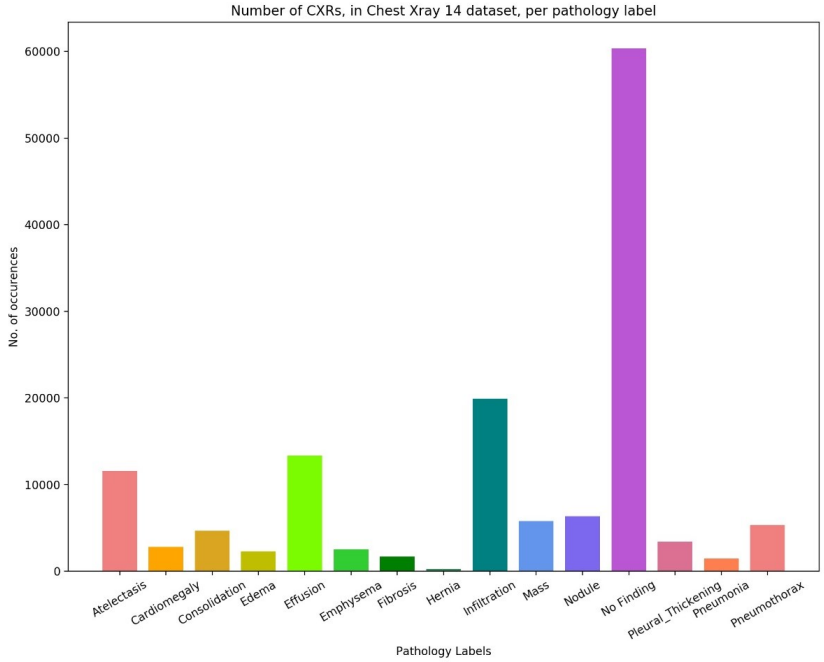

Figure 4.5: Bar Plot 1

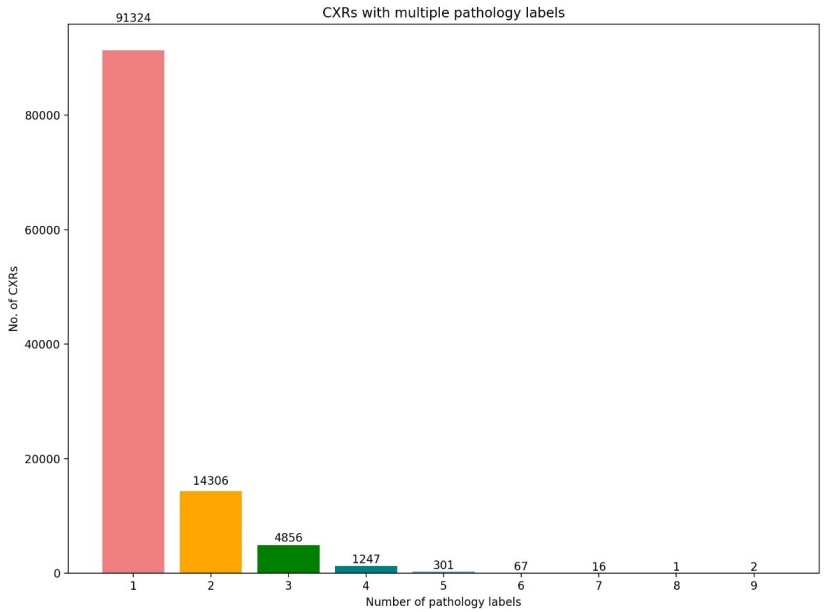

Figure 4.6: Bar Plot 2

4.1.3 Sample Code (Implementation)

4.1.3.1 Creation of bar plots

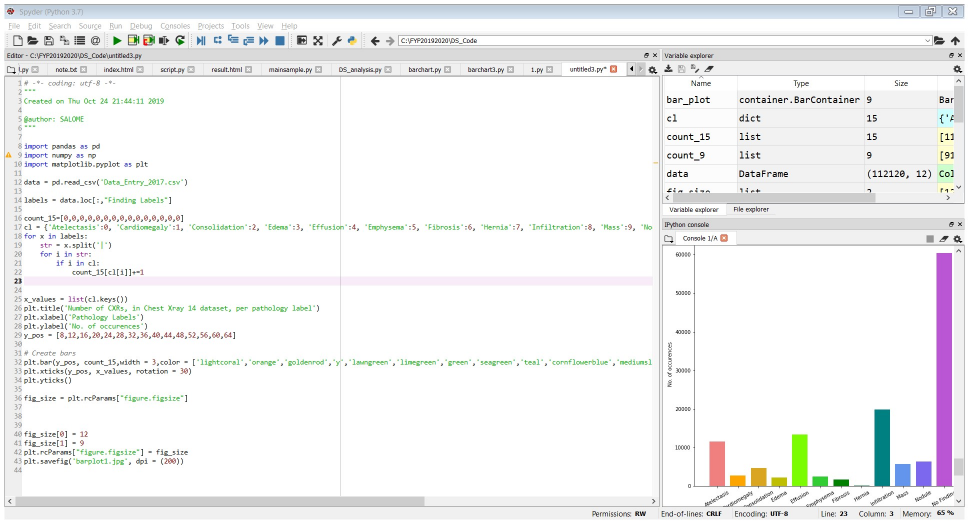

Figure 4.7: Bar plot 1 implementation code

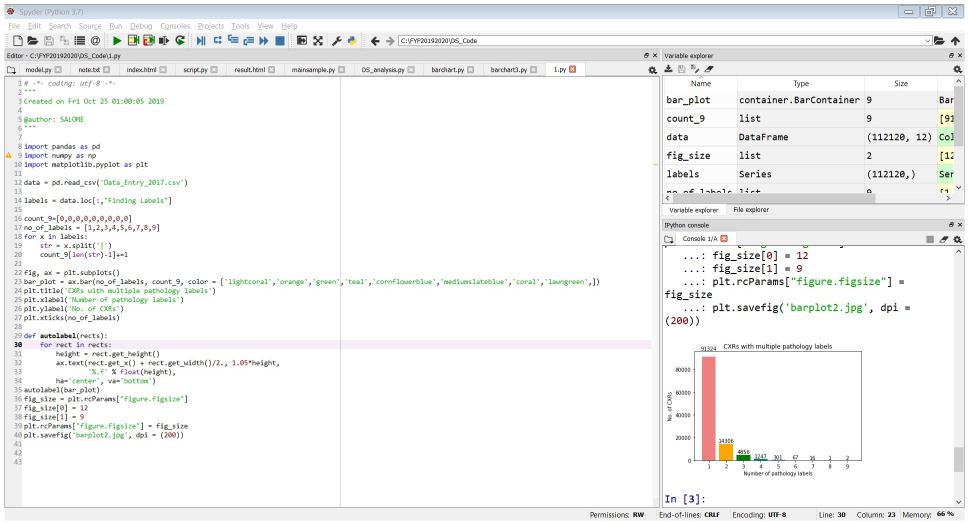

Figure 4.8: Bar plot 2 implementation code

4.1.3.2 Data Pre-processing

The NIH Chest X-ray14 Dataset consisted of images stored in an unsorted manner. Hence inorder, to prepare input data for training, the images were sorted in their respective disease label named folders using Python.

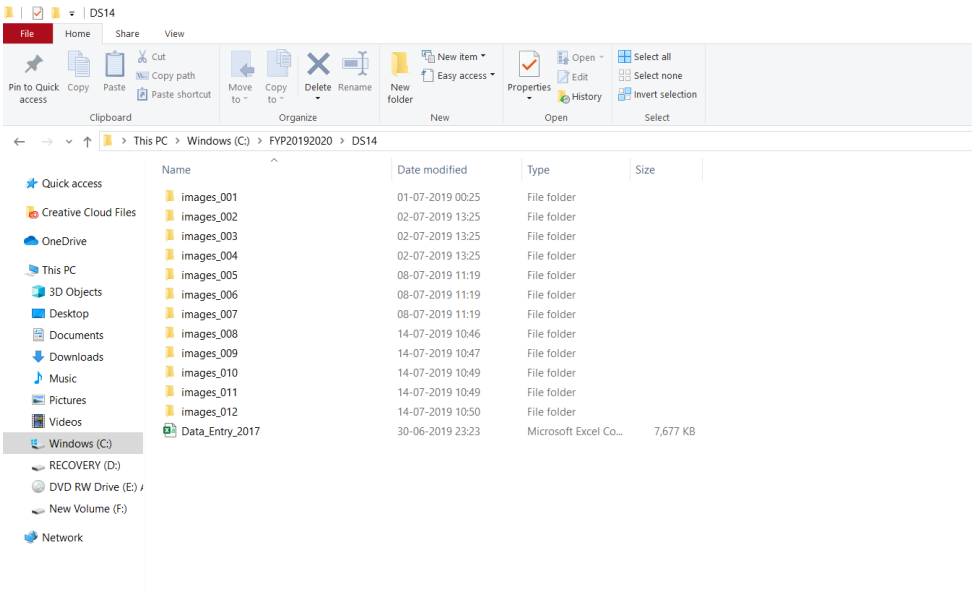

Figure 4.9: Unsorted Data

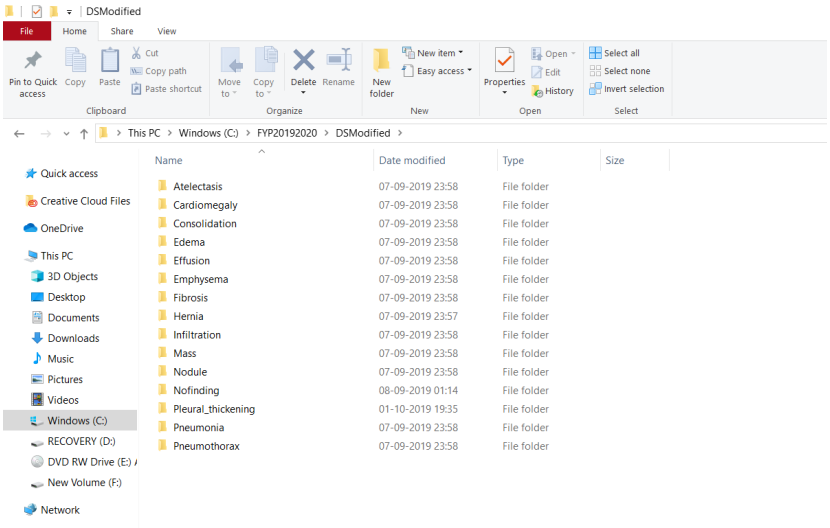

Figure 4.10: Data sorted into folders based on disease labels

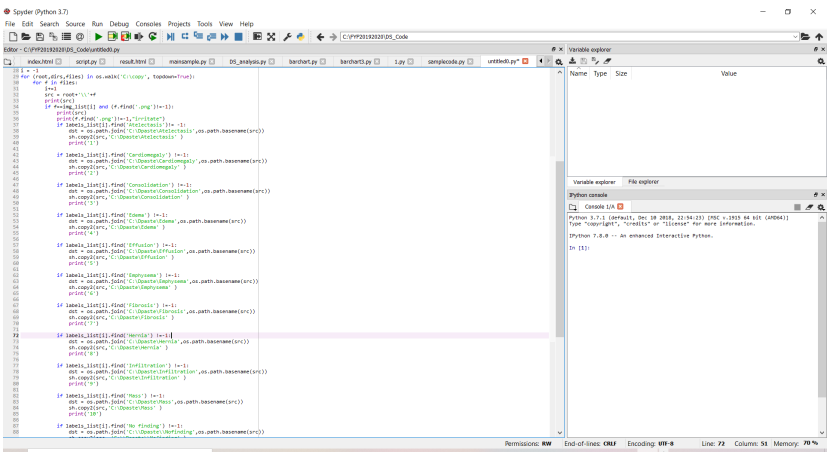

Figure 4.11: Main logic for sorting data

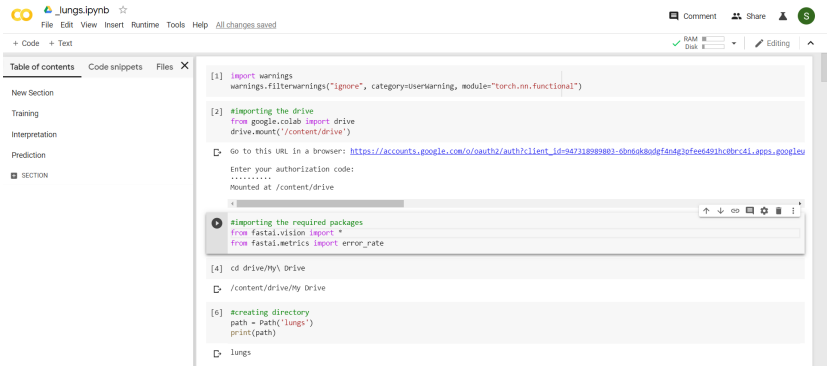

Figure 4.12: Loading Data

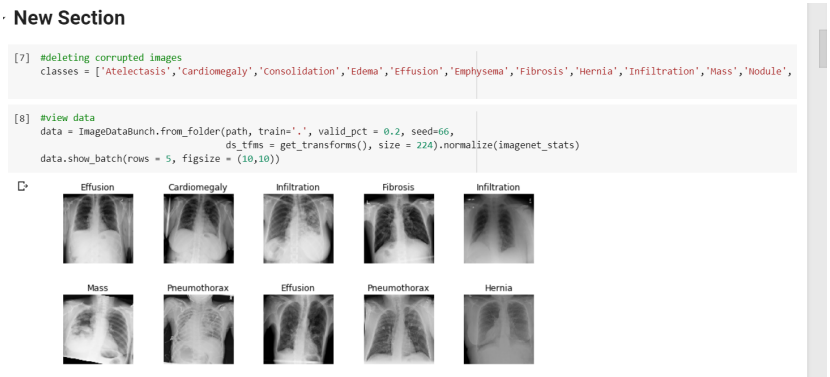

Figure 4.13: Summary of Data

Figure 4.14: Classes

Chapter 5

Conclusion

5.1 Work Done

Literature survey on Deep Neural Networks gave us the insight of the concept and helped us in understanding the basics. From the literature survey conducted we have inferred that the system can be developed using a combination of Computer Vision and Deep Learning to detect the diseases which will make it an accurate system. Hence, in implementation, the NIH Chest X-ray14 dataset has been pre-processed. The dataset contained chest X-ray images arranged in a random fashion. These images were arranged and seggregated as per their disease labels into 14 different folders by using python. 300 images of each label were taken. This dataset will now be used for training and testing.

5.2 Work to be done

The model is yet to be trained on the preprocessed data. The data that has been processed will now be used to train the model. The Chest X-Rays will be fed to the Neural Network. The images have been segregated into different folders based on the disease(s) will serve as an input to a deep convolutional neural network.
Various image processing techniques will be used as feature extractors and Deep Neural Networks as classifier. The trained model will be tested for its accuracy on new Chest X-Ray data.

References

[1] Xiaosong Wang et.al. ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly Supervised Classification and Localization of Common Thorax Diseases. arXiv:1705.02315v5, 2017.

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[11][online] Available : https://towardsdatascience.com/activation-functions-and-its-types-which-is-better-a9a5310cc8f

[12][online] Available : https://en.wikipedia.org/wiki/Convolutional$_n eural_n etwork$

[13][$online$]$Available$: $https$: $//skymind.ai/wiki/neural-network$

[14][$online$]$Available$: $https$: $//en.wikipedia.org/wiki/Artificial_n eural_n etwork$

[15][$online$]$Available$: $https$: $//www.nih.gov/news-events/news-releases/nih-clinical-center-provides-one-largest-publicly-available-chest-x-ray-datasets-scientific-community$

[16][$online$]$Available$: $https$: $//www.nhlbi.nih.gov/health-topics$

Appendix

Appendix A : Timeline Chart

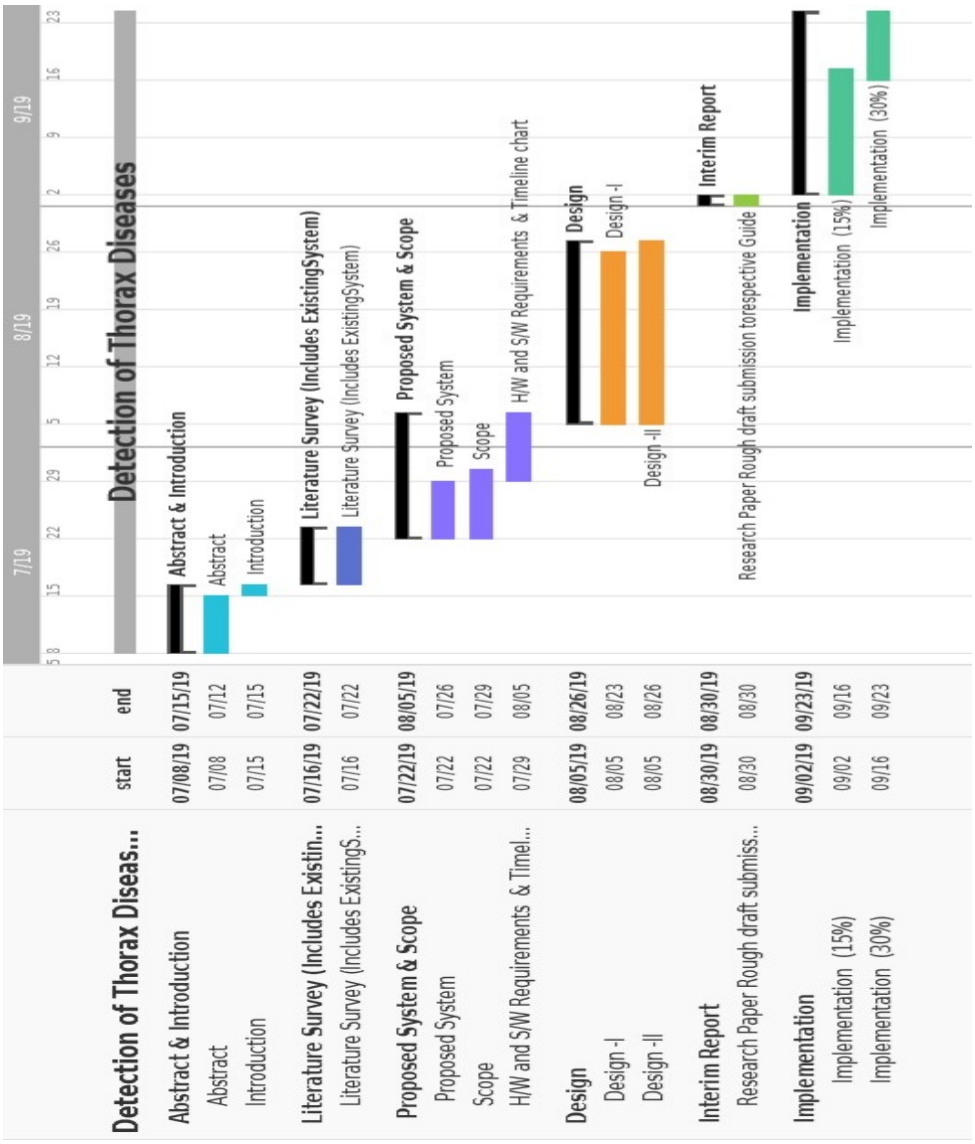

Figure 5.1: Timeline chart for project (sem 7)

Appendix

Appendix B : Publication Details

Salome Palani, Arya Kulkarni, Abishai Kochara, M. Kiruthika have published a paper, titled "Detection of Thoracic Diseases using Deep Learning" in ITM Web of Conferences at ICACC 2020 International Conference.