PNEUMONIA DISEASE DETECTION USING X RAYS

A Thesis Submitted
In Partial Fulfillment of
Requirements for the Degree of

MASTER OF SCIENCE

by

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CANDIDATE'S DECLARATION

I _Aastha rani__ hereby certify that the work which is being presented in the thesis entitled PNEUMONIA DISEASE DETECTION USING X RAYS in partial fulfillment of the requirements for the award of the Degree of Biotechnology, submitted in the Department of Biotechnology, Delhi Technological University is an authentic record of my own work carried out during the period from july 2019 to May 2021 under the supervision of Dr Yasha Hashija.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Candidate's Signature

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CERTIFICATE BY THE SUPERVISOR(s)

Certified that **Aastha Ran**i **(*2K19/MSCBIO/33*.)** has carried out their search work presented in this thesis entitled **"PNEUMONIA DISEASE DETECTION USING X RAYS."** for the award of **Master of Biotechnology** from Department of Information Technology, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the student himself/herself and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University/Institution.

PNEUMONIA DISEASE DETECTION USING X RAYS

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ABSTRACT

This project aims to develop a fully automated system for diagnosis of pneumonia diseases using chest x-rays. The platform will enable its users and professional diagnostic centres to upload their chest radiographs (x-rays) and get accurate predictions based on those. Chest radiography has important clinical value in the diagnosis of diseases. Thus the automatic detection of chest disease based on chest radiography has become a hot topic in medical imaging research.

This project has overall two parts :

1.Backend Server - The server will cater the request from the medical diagnosis labs and individual users who do not have access professional consultation for medical diagnosis. The server should be capable of generating report whenever a chest radiograph is uploaded and provide accurate results.

2. Mobile App - This mobile application will serve as a client to the backend server. It will be the primary target for interaction with the users. The user can install this application on their devices and use it to view reports.

All these components together will act as a Report Generation Tool from the chest radiographs that ensures accurate results.

Apart from the above said components, there will be a machine learning algorithm that will learn from the new x-rays being uploaded thus continuously improving its accuracy.

DECLARATION

We / I hereby certify that the work which is presented in the Major Project - 11 / Research Work entitled **PNEUMONIA DISEASE DETECTION USING X RAYS** in fulfilment of the requirement for the award of the Degree in **Master of Science** and submitted to the Department of Biotechnology in Delhi Technological University , Delhi is an authentic record of my / our own , carried out during a period from under the supervision of **Dr.Yasha Hasija**

The matter presented in this report / thesis has not been submitted by us / me for the awad of any other degree of this or any other Institute / University. The work has been published / accepted / c ommunicated in SCI / SCI expanded SSCI / Scopus indexed journal or peer reviewed Scopus inde xed conference with the following details :

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LIST OF ABBREVIATIONS

ML	Machine Learning
CNN	Convolutional Neural Network
SVM	Support Vector Machine
GPS	Global Positioning System
ABBR2	Abbreviation 2

CHAPTER 1 - INTRODUCTION

Pneumonia is linked to a huge range of illnesses that impact people all over the globe. Pulmonology research is important in public health studies because it focuses on infiltration, athelectasis, cardiomegaly, effusion, mass, nodule, pneumonia, and pneumothorax.

According to the World Health Organization (WHO), asthma affects 300 million people globally and is responsible for over 250 thousand deaths each year (Campos and Lemos, 2009). “In addition, the World Health Organization estimates that 210 million individuals suffer from Cardiomegaly." In 2005, the illness claimed the lives of almost 300,000 individuals (Gold Cardiomegaly, 2008). CARDIOMEGALY is seen in people between the ages of 20 and 45, despite the fact that it is thought to be a condition that affects people over the age of 50. According to WHO, by 2015, the number of fatalities attributable to CARDIOMEGALY would have increased by 30%, and by 2030, CARDIOMEGALY will be the third leading cause of death globally (World..., 2014).

Early and accurate identification of any lung illness is critical for prompt treatment and preventing future fatalities in the public health system. From a clinical aspect, diagnostic assistance tools and systems are critical for specialists and, as a result, for the general public's health.

X-ray pictures of pneumonias are slices of the ribcage that show a variety of structures such as blood vessels, arteries, respiratory vessels, pulmonary pleura, and parenchyma, each with its own set of data. As a result, segmenting pneumonia structures is required for pulmonary illness investigation and diagnosis. It's worth mentioning that segmentation, which delimits pneumonia structures in X RAY pictures, is an important stage in imaging systems for accurate pneumonia illness detection. If the pneumonia area is precisely determined, image processing methods may really aid computer diagnosis.

Following the segmentation, an automated approach is used to discover probable illnesses in pneumonia X RAY pictures, which helps the radiologist diagnose the patient.

Trindade (2009) used texture descriptors retrieved from the gray level concurrence matrix (GLCM) (Haralick et al., 1973) to describe three illness patterns (nodule, emphysema, and frosted glass) as well as a normal pattern to describe three disease patterns (nodule, emphysema, and frosted glass) and a normal pattern. GLCM texture descriptors are also used by Shimo et al. (2010) to identify if the pneumonias are healthy or unhealthy. Furthermore, several articles focus on the identification o f particular disorders, such as nodules (Ayres et al., 2010; Silva and Oliveira, 2010) and emphysem a (Silva and Oliveira, 2010). (Felix et al., 2007, 2011).

1.1 PROJECT OVERVIEW

1.1.1 TECHNICAL TERMINOLOGY

This project has overall two parts:

1. **Backend Server -** The server will cater the request from the medical diagnosis labs and individual users who do not have access professional consultation for medical diagnosis. The server should be capable of generating report whenever a chest radiograph is uploaded and provide accurate results.

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All these components together will act as a Report Generation Tool from the chest radiographs that ensures accurate results.

Apart from the above said components, there will be a machine learning algorithm that will learn from the new x-rays being uploaded thus continuously improving its accuracy.

1.1.2 PROBLEM STATEMENT

Lack of trained radiologists make it very difficult to provide accurate interpretation and get accurate predictions from chest x-rays.

1.1.3 GOAL

Accuracy in detection of disease in pneumonias.

1.1.4 SOLUTION

Pre prediction of the disease so that a proper treatment can take place. So design a fully automated system for diagnosis of pneumonia diseases using chest x-rays. The platform will enable its users and professionals to get accurate predictions based on chest x-rays.

1.2 NEED ANALYSIS

The need of our project is dire and can be defined and explained under the following headings:

1. Chest X-Rays have the advantages of being inexpensive and simple to use. Machines are fairly inexpensive even in poor regions. Chest radiographs are often used to identify and diagnose pulmonary infections, and they provide a wealth of information about a patient's health. However, appropriately evaluating the data is always a difficult task.
2. Overlapping of the tissue structure and lack of well-trained radiologists make it very difficult to provide accurate interpretations of the chest X-rays.
3. Contributing to the Director of the National Institutes of Health's global health effort by advancing the development and deployment of low-cost disease detection technologies in resource-constrained areas.
4. Developing technology for screening pneumonia illnesses, a serious global health concern listed by the WHO as the second biggest cause of infectious illness death. Co-infections with HIV and tuberculosis lead to treatment difficulties and disease transmission.
5. Improving image analysis technology to identify lung illnesses from digital CXR pictures automatically.
6. Instead of going to a medical professional for consultation from the report, the users can easily get accurate results even in areas where there is no professional help and based on those results they can get the required medical help.

1.3 RESEARCH GAPS

Till now the research done on this topic is only limited to one specific disease but here we have done the detection with more than one disease on a single go in one model which will result in multiple detections with improved accuracy due to availability of huge dataset.

1.4 PROBLEM DEFINITION AND SCOPE

The major problem is expert doctors are not able to find the problem with the patient by just their x-ray as there is no clear visibility in them which may result in ignorance of the upcoming problem with patient. So the current scope of the project is to get that visibility by applying image processing techniques and then compare it with the available data set and generate the results which further can be verified by the experts this also saves time and chances of human errors.

1.5 ASSUMPTIONS AND CONSTRAINTS

S. No.	Assumptions
1	Availability : Clear chest radiographs should be available in digital form (eg. JPEG)
2	Good internet connection
3	Correct Labelling : The chest X-rays are correctly labelled.

1.6 APPROVED OBJECTIVES

This initiative takes advantage of the NLM's confluence of imaging research and system development with NIH policy goals in global health. The following are the project's goals:

1. Improve the state-of-the-art in CXR image analysis using automated software. Automatically identify the presence of pulmonary illnesses such as tuberculosis (TB) and other pertinent illnesses in digital CXRs, resulting in appropriate screening discrimination and a level of confidence in the finding.

2. Create deployable screening software to assist field clinical officers in making decisions at the point of treatment and to help radiologists organize their workload.

3. Given the severity of pulmonary infections and the scarcity of radiological services in western Kenya, AMPATH has created software that can be installed on a self-powered mobile X-ray vehicle that may be used in rural regions. Their team examines the population's chest x-rays and uses NLM-developed software to check for the presence of pneumonia and other infections.

1.7 METHODOLOGY USED

The system architecture is composed of a series of cascaded modules that allow for the implementation of alternative image analysis routes followed by late-stage decision fusion. Every picture is being analyzed for automated localization of the pneumonia location. Within the localised pneumonia border, image characteristics are retrieved, resulting in a 2-class normal/abnormal conclusion for the input CXR picture. We're also looking on other ways to identify anomalies in the CXR without having to pinpoint the precise pneumonia border. Edge detection is also used in the procedure to identify fictitious outlines that might be symptomatic of sickness. The approach seems to be quick and effective in diagnosing specific types of diseases, according to preliminary findings.

Pneumonia Region Localisation

The automated identification of pneumonia areas is a critical initial step in a computer-aided CXR screening system. For CXR images, we developed a unique automated pneumonia boundary identification system. There are three steps to it. Figure 1 depicts a high-level summary of the procedure.

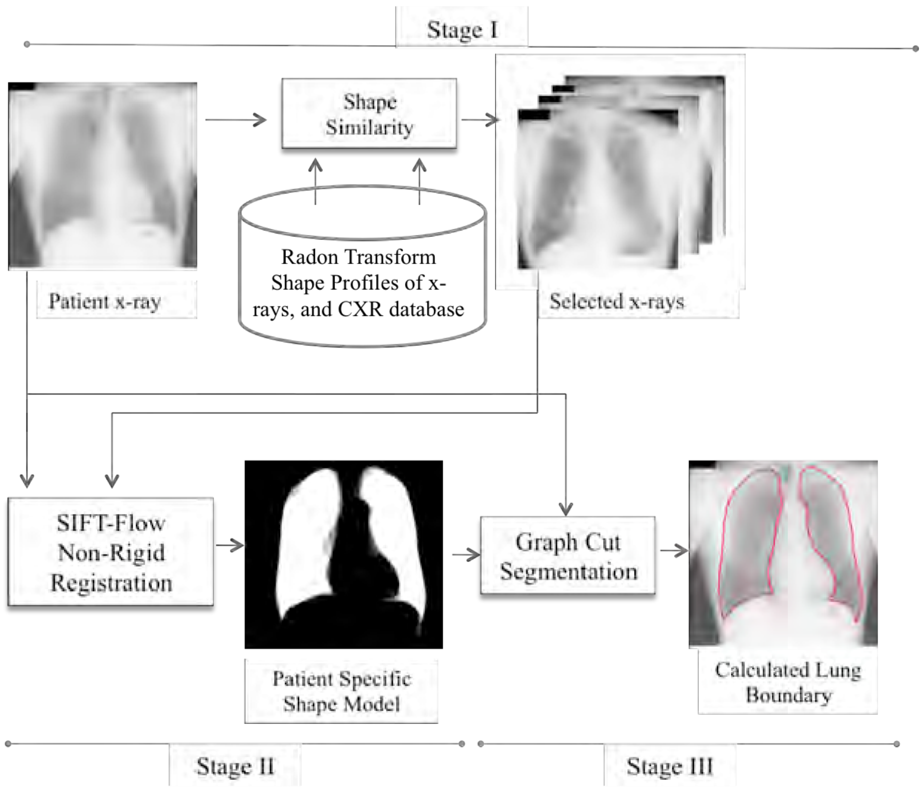

Figure 1. Our pneumonia segmentation technique is broken down into three stages: (Stage-I) locating comparable pneumonia CXRs from an atlas; (Stage-II) warping chosen pictures to patient CXR; and (Stage-III) detecting pneumonia boundaries using a graph-cuts optimization strategy.

Stage 1:

First, we employ a content-based image retrieval (CBIR) approach to choose a small group of CXR pictures with comparable appearances from an expert-annotated collection, which we'll refer to as the atlas set. All CXR pictures in the atlas set have their horizontal and vertical projection profiles calculated. The average Bhattacharyya coefficient is then used to assess the similarity of each projection profile between the atlas set and the patient chest X-ray.

Stage 2:

We record a group of CXR pictures that have a similar look but may have various pneumonia outlines in order to generate the pneumonia model. The SIFT-flow technique is used to map the transformations. Using scale invariant feature transformations, the technique initially models the observed image's local gradient information (SIFT). The SIFT-flow, the transformation mapping between each picked atlas picture and the patient picture, is then calculated using a minimization technique. The mapping is used to register and warp the atlas CXRs, ensuring that they are geometrically aligned with the patient picture. The mean of the warped pneumonia masks from the registered atlas pictures is then used to create the pneumonia model for the patient X-ray.

The model is a probabilistic shape prior in which each pixel value represents the likelihood that the pixel will be part of the pneumonia field in the patient picture.

Stage 3:

We execute picture segmentation using the graph cut technique as a refinement step, and we describe the segmentation process using an objective function. The max-flow/min-cut method finds a global minimum that corresponds to foreground (within-pneumonia) and background (outside-pneumonia) labeling of pixels by minimizing the objective function.

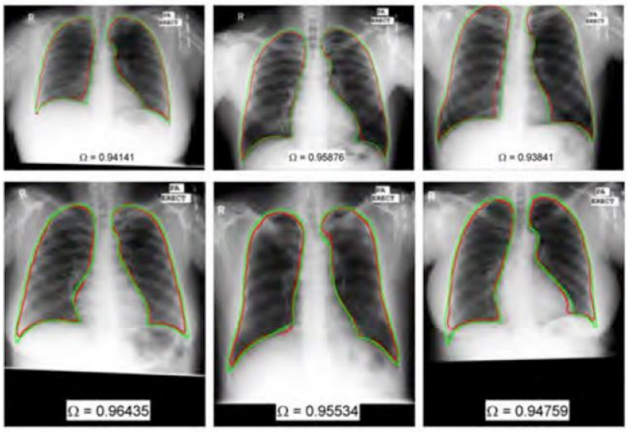

Figure 2. Sample segmentation results on Montgomery dataset.

Evaluation:

For the atlas chest X-ray pictures, a radiologist manually created gold standard segmentations. An interactive border marking tool [39], created in previous NLM research and submitted to the Board, assisted the process. The radiologist then used FireFly [40], a web-based labeling tool created at the University of Missouri, to rectify these outlines. Three datasets (JSRT, Montgomery, and India) were used to test the approach, as mentioned in Section 3 above. We also compared the performance of the system to that of other systems in the literature. On the public JSRT database, the Jaccard Index3 (which quantifies overlap agreement) yielded an average accuracy of 95.4 percent, outperforming all previous reported findings. Its tolerance to picture diversity is shown by its accuracy of 94.1 percent and 91.7 percent on the Montgomery and India datasets, respectively.

1.8 PROJECT OUTCOMES AND DELIVERABLES

The outcomes of the project are:

! A well trained accurate model for prediction of pneumonia diseases using chest X-rays.

! Aid the professionals in early and speedy classification of X-rays.

! Providing accurate results where trained medical professionals are not available.

Mobile App - This mobile application will be the primary target for interaction with the users. The user can install this application on their devices and use it to view reports.

1.9 NOVELTY OF WORK

The model we are designing will be generating results for Infiltration, Atelectasis, Cardiomegaly, Effusion, Mass, Nodule, Pneumonia, Pneumothorax with a good accuracy. On the other hand existing model focuses only on one of the above mentioned diseases. While the app will be generating report that is directly available to the fellow person. So no long waiting queues.

CHAPTER 2: REQUIREMENT ANALYSIS

2.1 LITERATURE SURVEY:

2.1.1 Theory Associated with Problem area :

Images of your heart, pneumonias, blood vessels, airways, and the bones of your chest and spine are produced by chest X-rays. Fluid in or around your pneumonias, as well as air around a pneumonia, may be shown by chest X-rays.

Chest radiography, being the most prevalent examination method in medical practice, provid es significant clinical utility in illness diagnosis. As a result, one of the hottest issues in medi cal imaging research is the automated identification of chest illness using chest radiography. Our research focuses on the application of computer-

aided detection (CAD) systems in chest radiography. The study offers many popular chest X -ray datasets and briefly discusses typical image preprocessing strategies used in chest radiography, such as contrast enhancement and segmentation, as well as bone suppression approaches. A chest X-ray is usually ordered if you see your doctor or go to the emergency department with chest discomfort, a chest injury, or shortness of breath. The picture aids your doctor in determining if you have heart difficulties, pneumonia, fractured ribs, emphysema, cancer, or any of a number of other illnesses.

A chest X-ray is a popular method of illness diagnosis. However, it may also be used to determine if a therapy is effective. Some patients have a series of chest X-rays over time to see whether a health condition is improving or worsening.

2.1.2 Existing Systems and solutions:

Chest X-ray AI Algorithm detection by Dubai Health Authority:

The early findings of a chest Xray artificial intelligence (AI) algorithm implemented throughout DHA medical fitness clinics were revealed by the Dubai Health Authority (DHA) on April 17, 2018. (MFCs). The partnership marks the first time Agfa Healthcare's Augmented Intelligence (AI) has been validated in the United Arab Emirates (UAE). More than two years ago, the partners started discussing the application of artificial intelligence-enabled processes in radiology with Agfa. Early in January 2018, the algorithm was able to properly detect pneumonia infections in chest X-rays roughly 90% of the time after completing phase one of onsite validation and analyzing preliminary data. In March 2018, phase two data revealed that sensitivity had increased to 95%.

Computer-aided detection in chest radiography based on artificial intelligence by US National Libraryof Medicine:

The paper presents several common chest X-ray datasets and briefly introduces general image preprocessing procedures, such as contrast enhancement and segmentation, and bone suppres sion techniques that are applied to chest radiography. The CAD system is then presented in t erms of its usage in detecting particular illnesses (pulmonary nodules, TB, and interstitial pn eumonia illnesses) as well as many illnesses, with an emphasis on the algorithm's fundament al principles, the data utilized in the research, the assessment measures, and the outcomes. Fi nally, the study reviews the artificial intelligence-based CAD system in chest radiography and addresses current issues and developments.

Detecting Diseases in Chest X-ray Using Deep Learning by ParallelDots:

They test a variety of deep learning approaches for multi-
label classification on the ChestXray14 dataset and get results that are similar to the best in t he field. For the job of multi label classification of the dataset, they present comparative find ings for cross entropy and pairwise error loss. In addition, they use a cascade network to incr

ease the performance of deep learning models while also modeling label relationships. In con clusion, the current study yields encouraging findings for the automated identification of thor acic illnesses. Future study on illness localization and classification performance, on the other hand, is now underway.

Uses of Deep Learning In Chest Abnormality Detection by Stanford AI Healthcare:

They addressed a variety of cutting-edge models and creative ways for detecting, classifying, and analyzing different chest anomalies. The absence of huge, high-quality datasets seems to be the most significant hurdle to obtaining superhuman level performance. However, the future is bright: with bigger, better-annotated datasets and creative models tailored to dealing with medical pictures, deep learning is likely to increase the efficiency of radiologists' workflow and the quality of radiological diagnoses globally.

2.1.4 The Problem That Has Been Identified

A CAD system usually has four steps: algorithm preprocessing, ROI area extraction, ROI feature extraction, and disease classification based on the features. Enhancement and segmentation methods are critical in the preparation of algorithms and the extraction of ROI. There are a variety of methods for highlighting lesions and suppressing noise. The deformable model and deep learning approach are the best for segmentation, but rule-based approaches perform poorly and are often combined with other approaches to increase segmentation performance. Bone suppression strategies are less often employed in the literature, however eliminating the rib and clavicle that impede pneumonia anomalies may increase system functioning. Geometric features, texture features, and form features are among the features retrieved by classic machine learning methods, which are frequently treated to minimize dimensionality owing to feature redundancy. Hand-crafted features, on the other hand, may include flaws that influence classification results, and deep learning approaches are rapidly replacing them. Although the performance of support vector machine and random forest in classical algorithms may be superior in terms of classifier selection, deep learning approaches have increasingly reached the mainstream due to their superior performance in image classification.

2.1.5 Survey of Tools and Technologies Used

Following are the tools that have been surveyed for both software and hardware components:

Hardware:

1.Servers to host the application.

Software:

1.Python

2.Tensorflow/Keras

3.Google Colab

4.Kaggle

5.Flask

2.3 SOFTWARE REQUIREMENTS SPECIFICATION

2.3.1 Introduction

2.3.1.1 Purpose:

There are 126 radiologists at one Boston hospital. Liberia has two of them. Even if these two radiologists had the speed of light, the mental powers of Einstein, and no need for sleep or social interaction, the load of chest ailments would be too great to bear. In the United States alone, 18 people die from pulmonary cancer every hour, and the figure would be far higher if patients were not routinely screened and nodules were detected early. Deep learning may be able to automatically detect chest ailments at the expert level, giving the two Liberian radiologists some relief while possibly saving countless lives throughout the globe.

2.3.1.2 Intended Audience and Reading Suggestions

The intended audience for this product is doctors as it will aid and assist them in classifying XRays, sorting and pre-processing so they are able to focus on the cases which require their attention and screening out the normal ones. Once we get a stable and accurate model that can correctly predict the results independently without requiring any human intervention they can be used to screen the X-Rays autonomously and generate automated templates giving much faster results and reports.

2.3.1.3 Project Scope:

! Workflow automation f0r radiologists - Ability t0 focus on suspected chest X-rays faster instead 0f manual searching.

! Automated report templates.

! Improved turn-around times - Expand the scope of chest X-ray screening program t0 add more volume and capacity

! Improved patient satisfaction by providing fast results and reports.

2.3.2 Overall Description

2.3.2.1 Product Perspective

The device has a broad range of uses in identifying different ailments, and it serves as a valuable second opinion for medical professionals. Furthermore, by swiftly analyzing a large number of CXRs, CAD algorithms lessen the burden of medical personnel.

2.3.2.2 Product Features

The major features of the product is:

! Assistance to Radiologists for screening X-rays.

! Generating report template.

! Improved results by faster screening and results and ability to hande large volumes.

2.3.3 External Interface Requirements

This section describes the way user interact with the system.

2.3.3.1 User Interfaces

Front End Software- Colab for Web App

Back End- Python+Terminal

2.3.3.2 Hardware Interfaces

Can run on any desktop with web browser and internet connection.

2.3.3.3 Software Interfaces

Some important software interfaces are:

1.The ability of web browser to open the web-app.

2.The database is made on Kaggle which requires a Kaggle account.

2.3.4 Other Non-functional Requirements

This section will deal with some non-functional requirements of our project.

2.3.4.1 Performance Requirements

Availability

Our product should be up and running and available at all times.

Response Time

The product should be able to reply to the query in a given amount of time

Processing speed

Processing speed of the app should be fast as it needs to process large volume data for optimal functionality.

2.3.4.2 Safety Requirements

Data should be encrypted to prevent any leak of personal data.

Users will have unique id and password which they can use to login the app.

User's personal data will not be shared with any other company/person.

2.4 COST ANALYSIS

Item	**Price**
1.Hosting the WebApp on Cloud	Rs.3000
Total Cost	**Rs.3000**

2.5 RISK ANALYSIS

Project Risk

If any member gets sick or is not able to do his part of work for some reason, project deadline can be delayed or the workload of other members will increase.

Product Risk

If the model does not give accurate results, it may diagnose incorrectly which can have fatal results.

CHAPTER 3 – METHODOLOGY ADOPTED

3.1 INVESTIGATIVE TECHNIQUES

The investigation project technique is of experiment type. There are many similar models that are detecting pneumonia diseases available but their number of diseases is limited to just one. We are trying to get an accuracy above 90% for more than 5 pneumonia diseases.

3.2 PROPOSED SOLUTION

We will ask user to upload digital Jpeg format images of X rays . The uploaded image will be pre-processed i.e its contrast will be increased , ribs will be removed and images will be highlighted. After that inference will be performed which , with the help of depth-wise convolution will detect the diseases. The detected disease will be displayed on the website with its %.

3.3 WORK BREAKDOWN STRUCTURE

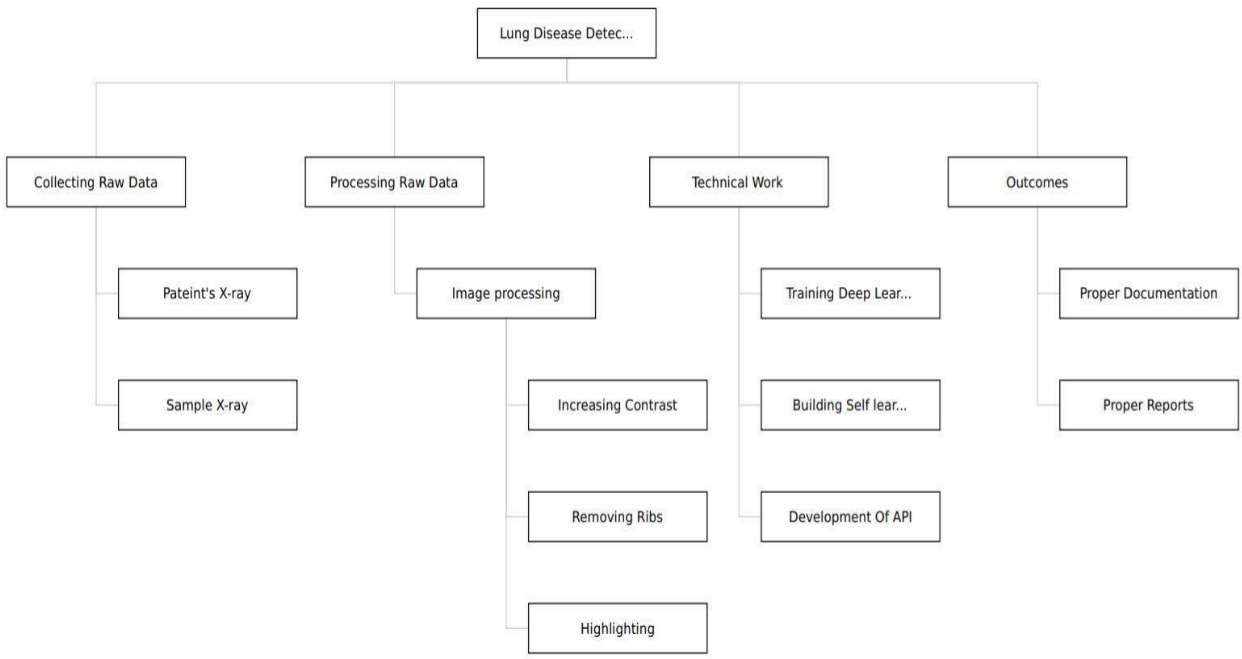

Figure 3 - WORK BREAKDOWN STRUCTURE

3.4 TOOLS AND TECHNOLOGIES USED

Image Processing (Segmentation)

Machine Learning

Deep Learning

Web development

Powerful Computer with GPU

Google Colab

Kaggle

Python

Keras/Tensorflow

Terminal

CHAPTER 4 - DESIGN SPECIFICATION

4.1 SYSTEM ARCHITECTURE

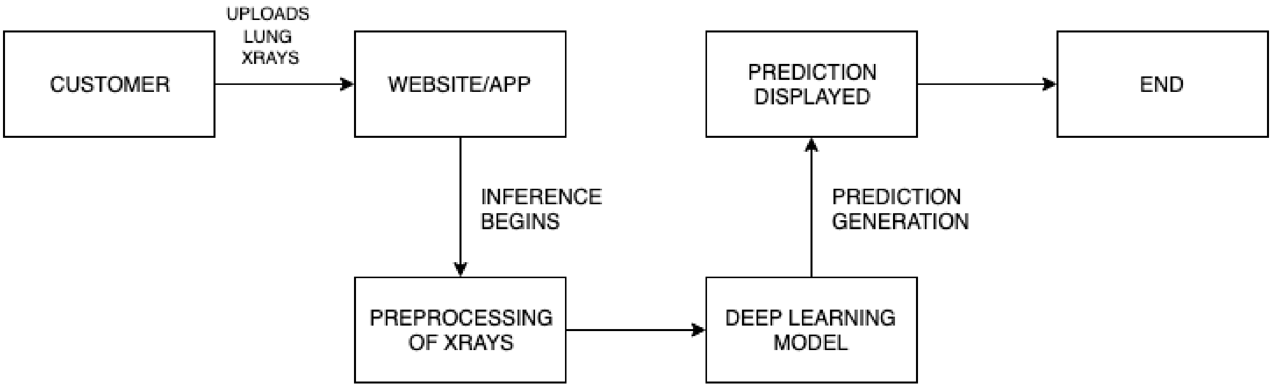

Figure 4 - Block Diagram Of The Project

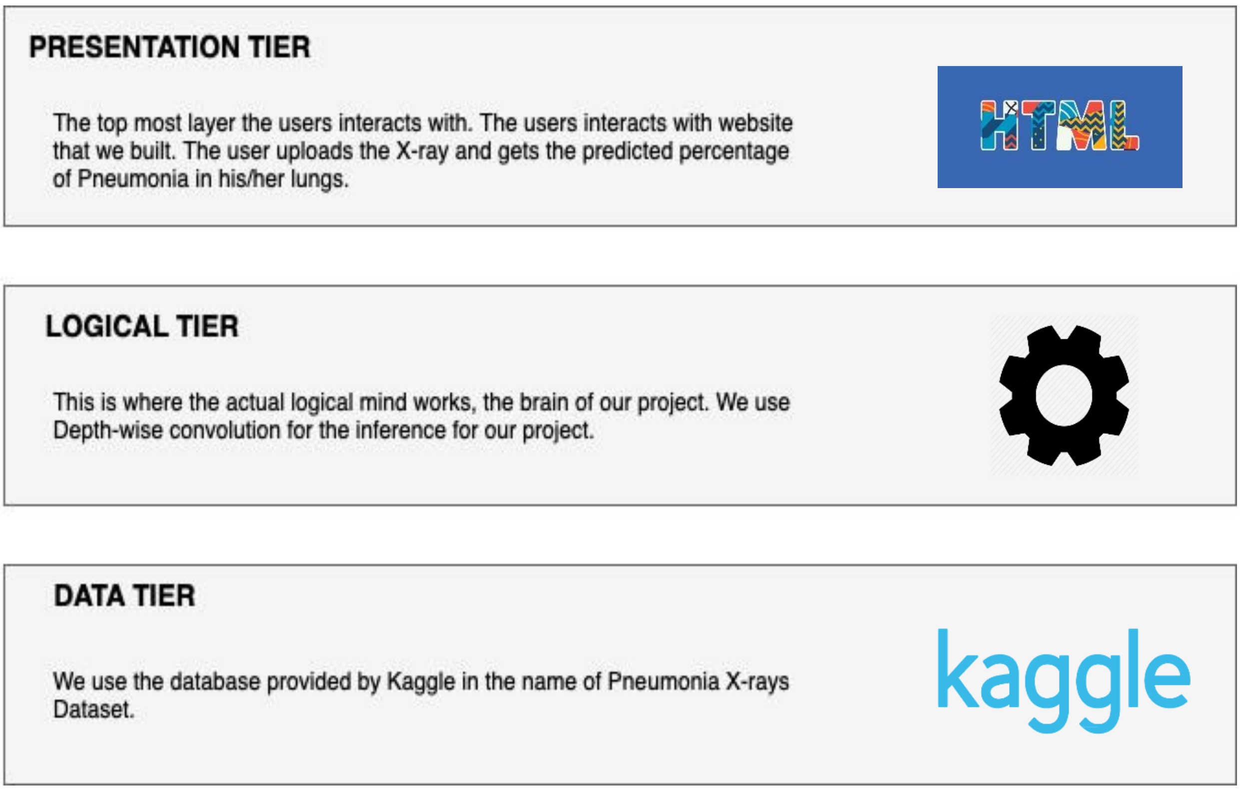

Figure 5 - Three Tier Architecture

4.2 DESIGN LEVEL DIAGRAMS

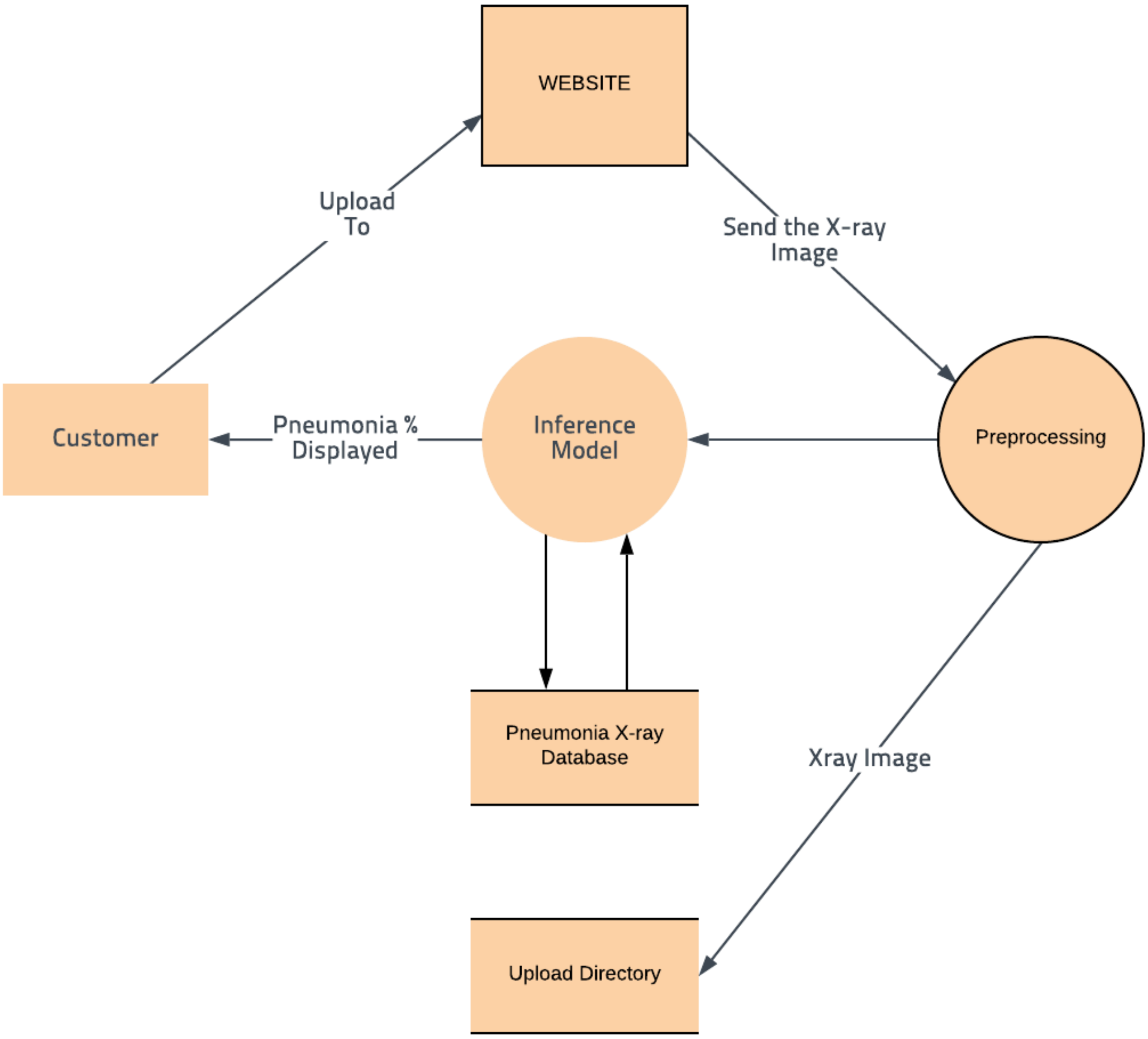

Figure 6 - DFD Level 0

USE CASE DIAGRAM

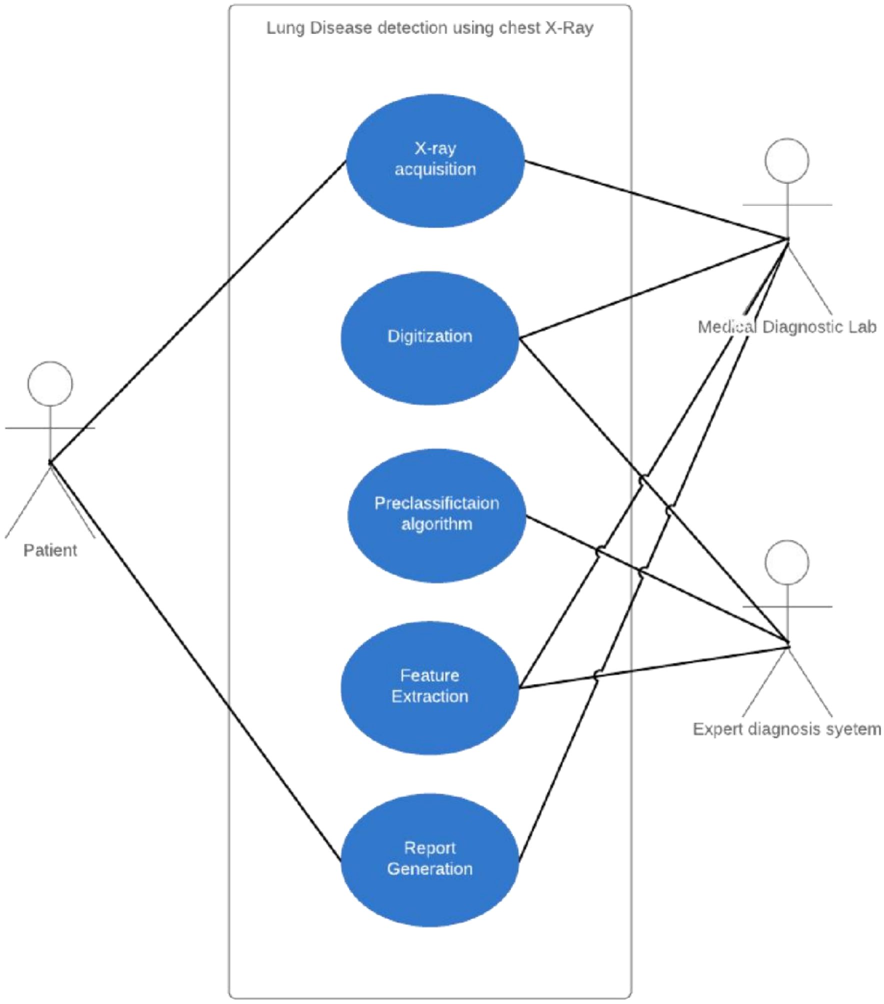

Figure 7 - Use Case Diagram

Use Case Id:	UC-4
Use Case Name:	Pneumonia Disease detection using Chest X-Rays
Use Case Purpose:	
Use case description:	Patient gets the X-Ray done. The file gets digitized and uploaded to the app. The file will get pre-processed and then the necessary features will be extracted. The report will be generated based on the conclusions.
Assumptions:	We will make conclusions based on the uploaded file.
Variations:	Different machine learning algorithms can be used.
Trigger:	Uploading the Chest X-ray.

Actor:	User, Medical Diagnostic Lab
Preconditions:	User wants a report based on their Chest X-ray
Postconditions:	● Success end Condition 1. Report will be generated based on the file uploaded. 2. User will be alerted in case of abnormalities. ● Failure end Condition 1. Report Not Generated 2. Inaccurate Report Generated.
Normal Scenario:	1. User will log into the application. 2. User will upload the file. 3. Pre-processed Image will be fed to the neural network. 4. The neural network makes predictions and a report is generated based on the predictions

Alternative Flow:	● First 1. System determines user is logged on. 2. Return to normal scenario step 2. ● Second 1. User logs out. 2. Return to normal scenario step 1. ● Third 1. User does not have an account. 2. User creates an account. 3. System confirms account creation. 4. Return to normal scenario step 1.
Extensions:	If there is abnormality in the report then the user will get a recommendation of doctors.
Special Requirements:	● Performance 1. The device shall display report within 5 minutes. ● User Interface 1. The application shall display all outputs in english language. 2. User-friendly interface.

FUTURE PRPOSED MODEL

As we can prposed this model for implementation for future proceeding.

ACTIVITY DIAGRAM

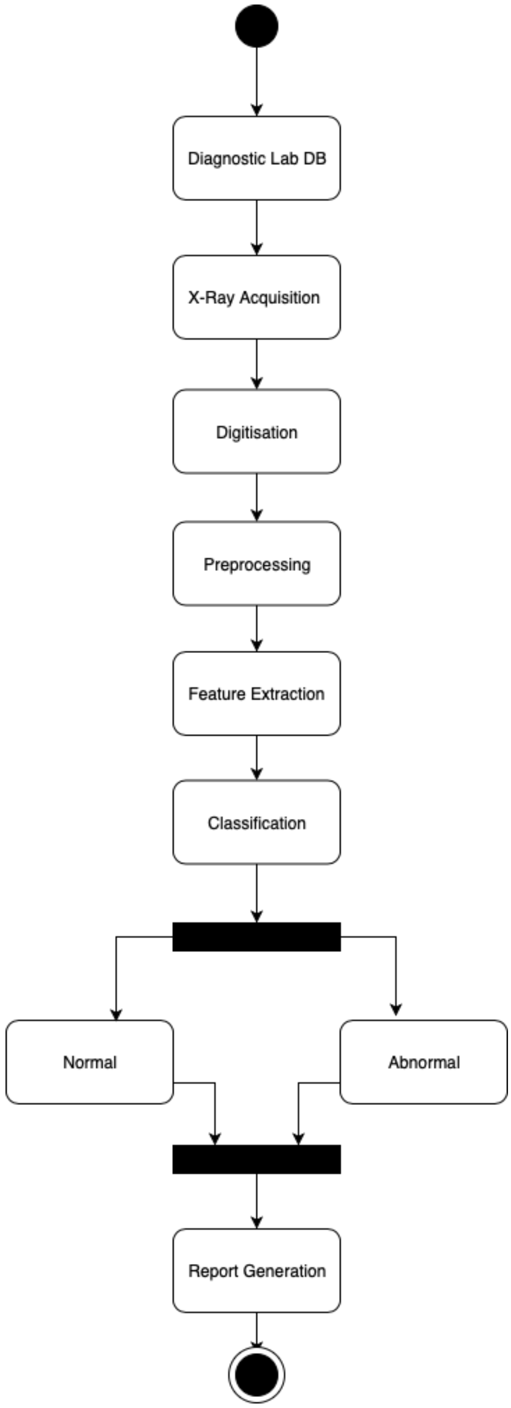

Figure 8 - Activity Diagram

Class Diagram

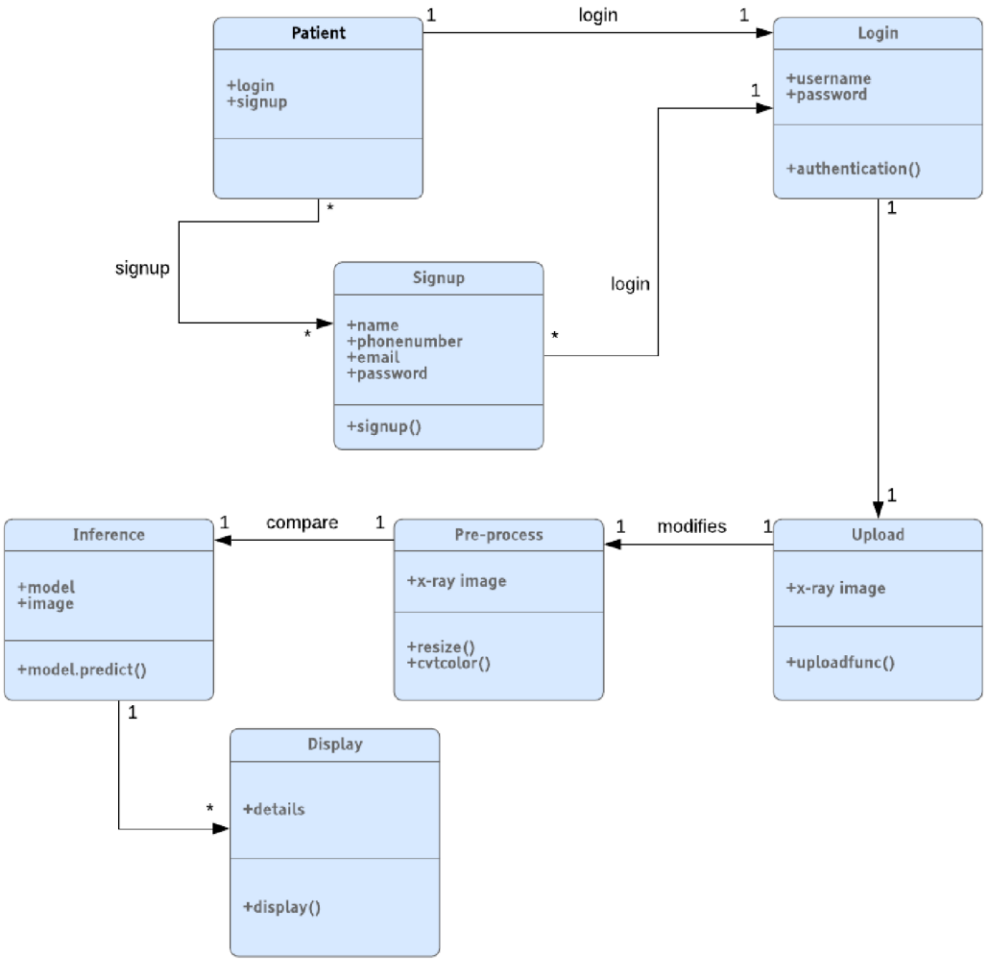

Figure 9 - Class Diagram

4.3 USER INTERFACE DIAGRAMS

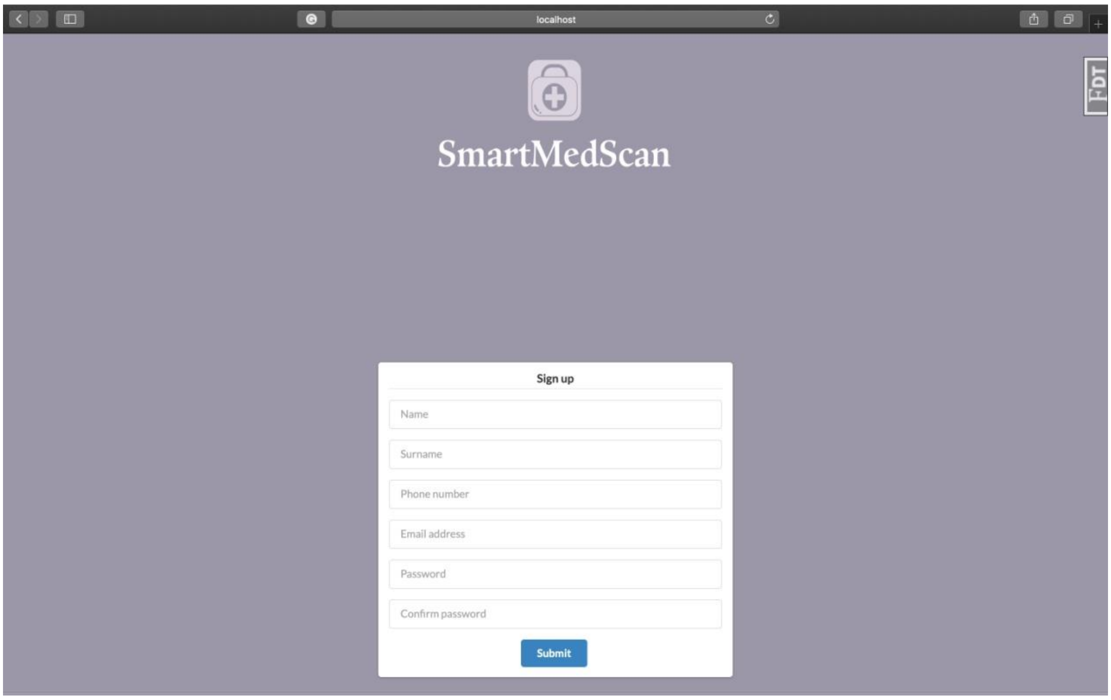

Figure 10

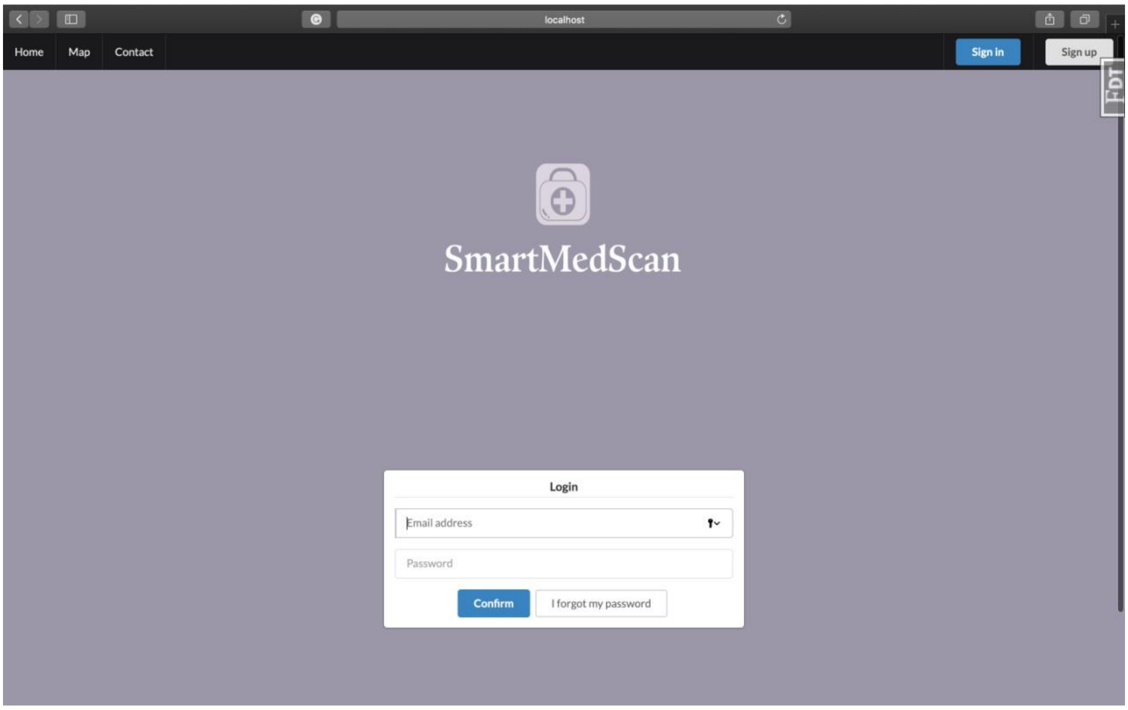

Figure 10

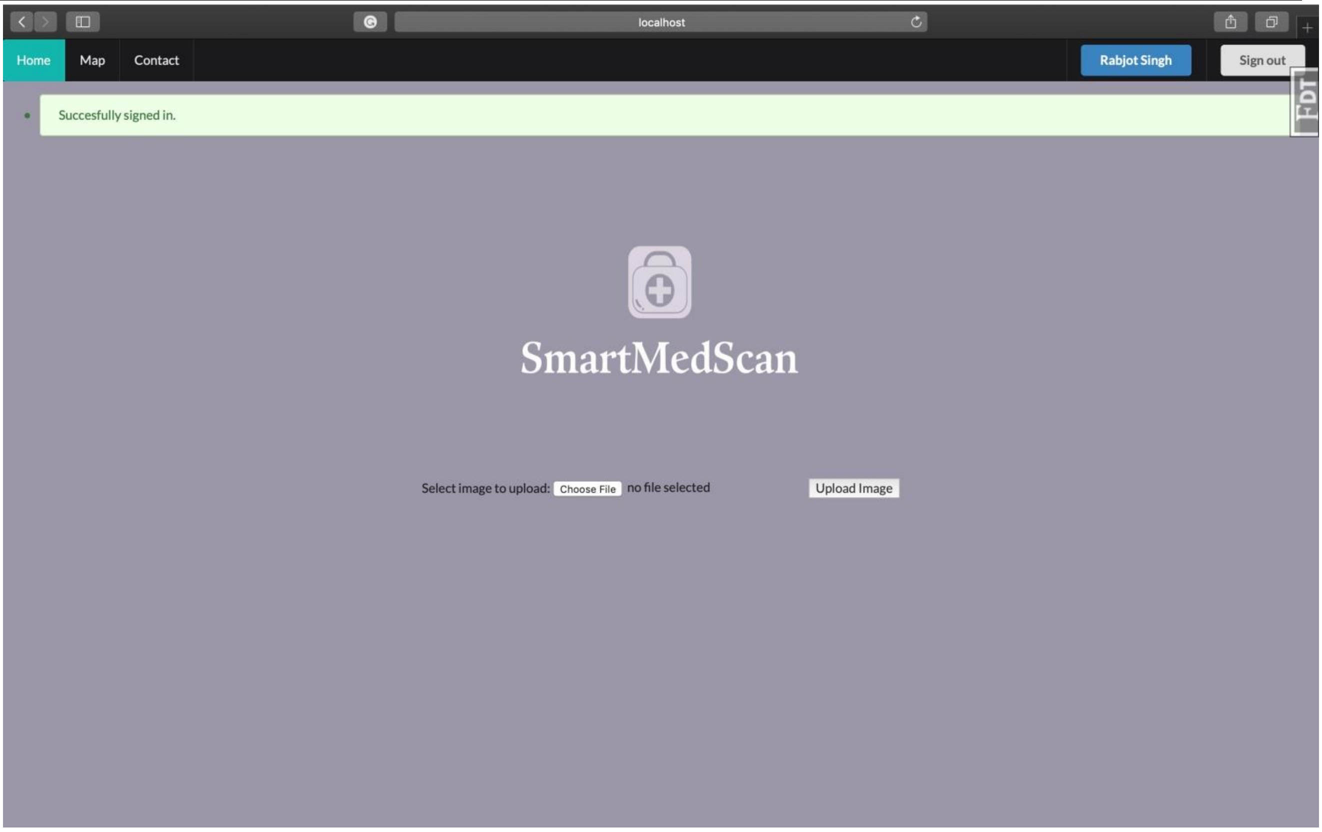
localhost
Home
Map
Contact
Rabjot Singh
Sign out
Succesfully signed in.
SmartMedScan
Select image to upload:
Choose File
no file selected
Upload Image

Figure 11

4.4 SNAPSHOTS OF WORKING PROTOTYPE MODEL

Layer (type)	Output Shape	Param #
ImageInput (InputLayer)	(None, 224, 224, 3)	0
Conv1_1 (Conv2D)	(None, 224, 224, 64)	1792
Conv1_2 (Conv2D)	(None, 224, 224, 64)	36928
pool1 (MaxPooling2D)	(None, 112, 112, 64)	0
Conv2_1 (SeparableConv2D)	(None, 112, 112, 128)	8896
Conv2_2 (SeparableConv2D)	(None, 112, 112, 128)	17664
pool2 (MaxPooling2D)	(None, 56, 56, 128)	0
Conv3_1 (SeparableConv2D)	(None, 56, 56, 256)	34176
bn1 (BatchNormalization)	(None, 56, 56, 256)	1024
Conv3_2 (SeparableConv2D)	(None, 56, 56, 256)	68096
bn2 (BatchNormalization)	(None, 56, 56, 256)	1024
Conv3_3 (SeparableConv2D)	(None, 56, 56, 256)	68096
pool3 (MaxPooling2D)	(None, 28, 28, 256)	0
Conv4_1 (SeparableConv2D)	(None, 28, 28, 512)	133888
bn3 (BatchNormalization)	(None, 28, 28, 512)	2048
Conv4_2 (SeparableConv2D)	(None, 28, 28, 512)	267264
bn4 (BatchNormalization)	(None, 28, 28, 512)	2048
Conv4_3 (SeparableConv2D)	(None, 28, 28, 512)	267264
pool4 (MaxPooling2D)	(None, 14, 14, 512)	0
flatten (Flatten)	(None, 100352)	0
fc1 (Dense)	(None, 1024)	102761472
dropout1 (Dropout)	(None, 1024)	0
fc2 (Dense)	(None, 512)	524800
dropout2 (Dropout)	(None, 512)	0
fc3 (Dense)	(None, 2)	1026

Total params: 104,197,506
Trainable params: 104,194,434
Non-trainable params: 3,072

Figure 12

CHAPTER 5: CONCLUSIONS AND FUTURE DIRECTIONS

5.1 WORK ACCOMPLISHED

S No.	Work Done
1	Dataset is taken from the online servers of ‘Kaggle’.
2	Website has been hosted locally.
3	ML Model is being trained on the dataset for Pneumonia Detection.
4	Upload functionality has been implemented.

5.2 CONCLUSION

In a developing nation like India, it is difficult for the government to keep track on road conditions on a regular basis, and as a consequence, little potholes may cause huge accidents, sometimes resulting in fatalities. That’s where our project comes in, with this we can not only mark the potholes present on the road but also the road conditions preventing the user from any major accidents and also alerting the government about these potholes. ‘‘With this quick actions can be taken by the government to repair the potholes.” We look forward to further improve and expand our project with the coming period of time.

5.3 ENVIRONMENTAL BENEFITS

- Our project can help people to prevent any major accident.
- It will also assist government to repair potholes more effectively and efficiently.
- People can also prevent their vehicle from getting damaged by these potholes.

5.4 Future Work Plan

S.No.	Work Plan

1	Better training of the ML model for more accuracy.
2	Integration of the inference model with the website.
3	Display of the percentage of the disease.
5	Completing the website.
7	Testing for the working of out project.

APPENDIX A: REFERENCES

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