



# A Mobile Application for Early Diagnosis of Pneumonia

<sup>1</sup>Aniket Fulzele, <sup>2</sup>Prof.Pramod Patil, <sup>3</sup>Abhishek Thakre <sup>4</sup>Ameya Mahale, <sup>5</sup>Shubham Shelke

<sup>1,3,4,5</sup>Student, <sup>2</sup>Professor, <sup>1,2,3,4,5</sup>Computer Engineering

<sup>1,2,3,4,5</sup>Sandip Institute of Technology and Research Centre, Nashik, Maharashtra, India

**Abstract:** Pneumonia is a life-threatening infectious disease affecting one or both lungs in humans commonly caused by bacteria called Streptococcus pneumoniae. The COVID-19 can cause severe pneumonia and is estimated to have a high impact on the healthcare system. Early diagnosis is crucial for correct treatment in order to possibly reduce the stress in the healthcare system. Pneumonia has caused significant deaths worldwide, and it is a challenging task to detect many lung diseases such as like atelectasis, cardiomegaly, lung cancer, etc., often due to limited professional radiologists in hospital settings. The standard image diagnosis tests for pneumonia are chest X-ray (CXR) and computed tomography (CT) scan. Although CT scan is the gold standard, CXR are still useful because it is cheaper, faster and more widespread. Chest X-Rays which are used to diagnose pneumonia need expert radiotherapists for evaluation. Thus, developing an automatic system for detecting pneumonia would be beneficial and it can save lots of peoples life and help stopping and curing and control for treating the disease without any delay particularly in remote areas. Due to the success of deep learning algorithms in analyzing medical images, Convolutional Neural Networks (CNNs) have gained much attention for disease classification. In addition, features learned by pre-trained CNN models on large- scale datasets are much useful in image classification tasks. In this work, we appraise the functionality of pre-trained CNN models utilized as feature-extractors followed by different classifiers for the classification of abnormal and normal chest X-Rays. We analytically determine the optimal CNN model for the purpose. Statistical results obtained demonstrates that pretrained CNN models employed along with supervised classifier algorithms can be very beneficial in analyzing chest X-ray images, specifically to detect Pneumonia. This study aims to identify pneumonia caused from other types and also healthy lungs using only X-Ray images. The model's performance in pneumonia detection shows that the proposed model could effectively classify normal and abnormal X-rays in practice, hence reducing the burden of radiologists

**Index Terms – X-Ray, CXR, COVID-19, Chest X-ray images, pneumonia detection; convolutional network (CNN), image enhance.**

## I. INTRODUCTION

(a) Pneumonia is an infectious and deadly illness in respiratory that is caused by bacteria, fungi, or a virus that infects the human lung with the load full of fluid or pus. Chest X-rays are the common method used to diagnose pneumonia and it needs a medical expert to evaluate the result of X-ray. The troublesome method of detecting the pneumonia cause a life loss due to improper diagnosis and treatment. And the diagnosis of this diseases can take time to do that and hospital must have good radiologist but in our country we can't afford it. So we must go to the automated system. With the emerging computer technology, development on an automatic system to detect pneumonia and treating the disease is now possible especially if the patient is in a distant area and medical services is limited. Pneumonia is a lung parenchyma

inflammation often caused by pathogenic microorganisms, factors of physical and chemical, immunologic injury and other pharmaceuticals. There are several popular pneumonia classification methods:

(1) pneumonia is classified as infectious and non-infectious based on different pathogeneses in which infectious pneumonia is then classified to bacteria, virus, mycoplasmas, chlamydial pneumonia, and others, while non-infectious pneumonia is classified as immune-associated pneumonia, aspiration pneumonia caused by physical and chemical factors, and radiation pneumonia.

(2) Pneumonia is classified as CAP (community-acquired pneumonia), HAP (hospital-acquired pneumonia) and VAP (ventilator-associated pneumonia) based on different infections, among which CAP accounts for a larger part. Because of the different range of pathogens, HAP is easier to develop resistance to various antibiotics, making treatment more difficult. Pneumonia kills more than 800,000 children under five per year, with around 2200 deaths every day. There are more than 1400 children infected with pneumonia per 100,000 children. The Global Burden of Disease Study reported that lower respiratory tract infections, including pneumonia, were the second largest cause of death in 2013. In Europe, nearly 35% of patients in hospital are infected with pneumococcal disease and worldwide, the percentage is 27.3%. In India, the latest report of John Hopkins Bloomberg School of Public Health has said that India suffers the most pneumonia deaths and in 2015, there were about

2.97 lakh pneumonia and diarrhea deaths in children aged less than five years old. The COVID-19 can cause illness to the respiratory system, fever and cough and in some extreme cases can lead to severe pneumonia. Pneumonia is an infection that causes inflammation primarily in the lungs' air sacs responsible for the oxygen exchange. Pneumonia can be caused by other pathogens besides SARS-

CoV-2, such as bacteria, fungi and other viruses. Several characteristics can influence its severity: weak or impaired immune system, chronic diseases like asthma or bronchitis, elderly people and smoking. The treatment depends on the organism responsible for the infection, but usually requires antibiotics, cough medicine, fever reducer and painreliever

## (b) Motivation:

Pneumonia affects a large number of individuals, especially children, mostly in developing and underdeveloped countries characterized by risk factors such as overcrowding, poor hygienic conditions, and malnutrition, coupled with the unavailability of appropriate medical facilities. Early diagnosis of pneumonia is crucial to cure the disease completely. Examination of X-ray scans is the most common means of diagnosis, but it depends on the interpretative ability of the radiologist and frequently is not agreed upon by the radiologists. Thus, an automatic CAD system with generalizing capability is required to diagnose the disease. To the best of our knowledge, most previous methods in the literature focused on developing a single CNN model for the classification of pneumonia cases, and the use of the ensemble learning paradigm in this classification task has not been explored. However, the ensemble learning model incorporates the discriminative information from all the constituent base learners, allowing it to make superior predictions, and thus was implemented in this study. To handle the low amount of available biomedical data, transfer learning models were used as base learners, the decision scores of which were ensemble

## II. LITERATURE REVIEW

In 2016, Redmon et al. proposed YOLO, which does not require a separate region proposal network, so its detection speed is extremely fast and can reach 45FPS. In the same year, Liu et al. [11] proposed the SSD algorithm. Both SSD and YOLO win in detection speed, but SSD uses a multiscale feature map to detect independently, the spatial resolution of images in deep networks has been significantly reduced, and it may not be possible to locate small targets that are difficult to detect in low resolution, reducing the accuracy of detection. YOLO does not use multiscale feature maps for independent detection. It smoothes the feature map and splices it with another lower-resolution feature map, but it treats the detection only as a regression problem and the detection accuracy is low. In 2014, Girshick et al. proposed R-CNN, which greatly improved the speed of training. On the PASCAL VOC 2010 dataset, the mAP improved from 35.1% to 53.7%

[1]In 2018, Lee et al. proposed DetNet, which was designed specifically for target detection and achieved better detection results with fewer layers. To avoid the large computational complexity and memory consumption caused by the high-resolution feature map, the network adopts a low-complexity dilated bottleneck structure; a higher resolution of the feature map is ensured while obtaining a higher subtractive field. This paper draws on the idea of DetNet and the framework of Faster R-CNN to study the detection of pneumonia

In recent years, many scholars have made efforts to detect pneumonia. Abiyev and Ma'aitah apply a convolutional neural network (CNN) for the diagnosis of chest X-ray diseases. Compared to BPNN and RNN, CNN gets higher precision but longer training time. Vijendran and Dubey combine multilayer extreme learning machine (MLELM) and online sequential extreme learning machines (OSELM) to detect pneumonia on the chest X-ray image. Abiyev and Ma'aitah explore the features extracted from layers of the CNN along with a set of classical features, including GIST and bag of words on a dataset of more than 600 radiographs

Chowdhury et al. worked with chest X-ray images to develop a novel framework named PDCOVIDNet based on parallel-dilated CNN. In the proposed method, the authors used a dilated convolution in the parallel stack that could capture and stretch necessary features for obtaining a detection accuracy of 96.58%.

Abbas et al. proposed and validated a deep convolutional neural network called decompose, transfer, and compose (DeTraC) to detect COVID-19 patients from their chest X-ray images. They proposed a decomposition mechanism to check irregularities from the dataset by investigating class boundaries for obtaining a high accuracy (93.1%) and sensitivity(100%).

## PROBLEM STATEMENT

To make an efficient use of Machine Learning techniques. Provide solution with least hardware requirement. To develop an application that is cost efficient. Minimize the use of Treatment as Normal People can't afford costly equipment. Easy to use and accurate so that medical can adopt the application quickly. To Implement application to Detect Pneumonia in early stage by using Deep Learning Classification algorithm are executed using Convocational Neural Network (CNN)

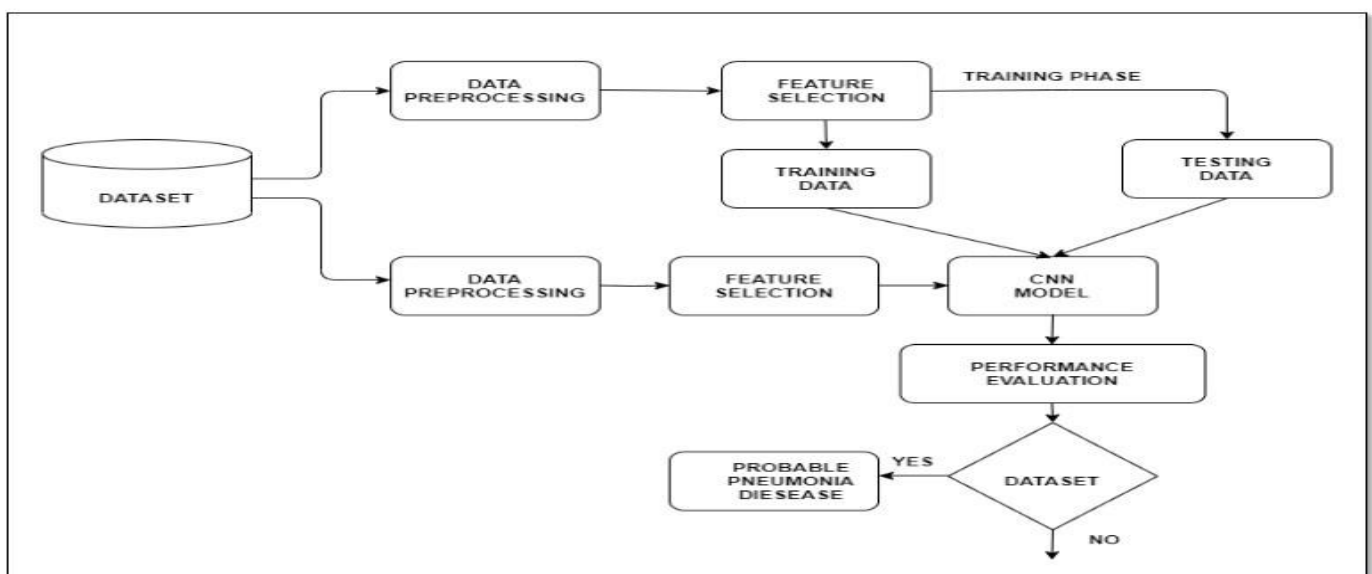
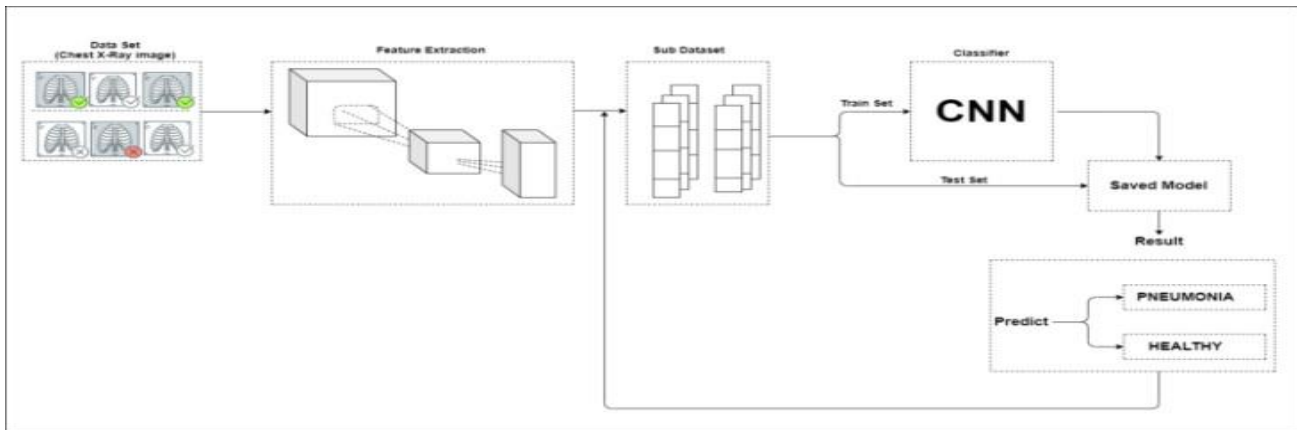
## III. OBJECTIVE

The objectives are as follows:

- 1) Different models of deep learning and transfer learning are analyzed in this work for the image classification application. Using Deep Learning features are extracted from the images and are used for classification of x-rays having pneumonia.
- 2) A convolutional neural network architecture is made and it is trained with the images of x-rays with pneumonia and normal x-rays which will be used for further classification. CNN models have been created from scratch and trained on Chest X-Ray Images (Pneumonia) dataset on Kaggle. To discover this disease as early as possible.
- 3) .If we discover this disease earlier, then the treatments are more likely to improve the quality life of the patients and their families.
- 4) Develop predictive models to differentiate between healthy people and people with Pneumonia Disease. Study and analyse different learning models, including CNN

#### IV. PROPOSED SYSTEM

Our proposed system give all the features provided by the traditional existing systems, but instead of working only with no spatial database, the system also works with spatial data



#### V. APPLICATIONS

1.Used to detect Pneumonia at early stage. 2.Medical System

#### VI. HARDWARE INTERFACE

-PROCESSOR – I3

-HARD DISK – 5 GB

- MEMORY – 1GB RAM

#### VII. SOFTWARE INTERFACE

-OPERATING SYSTEM: WINDOWS XP AND LATER VERSIONS.

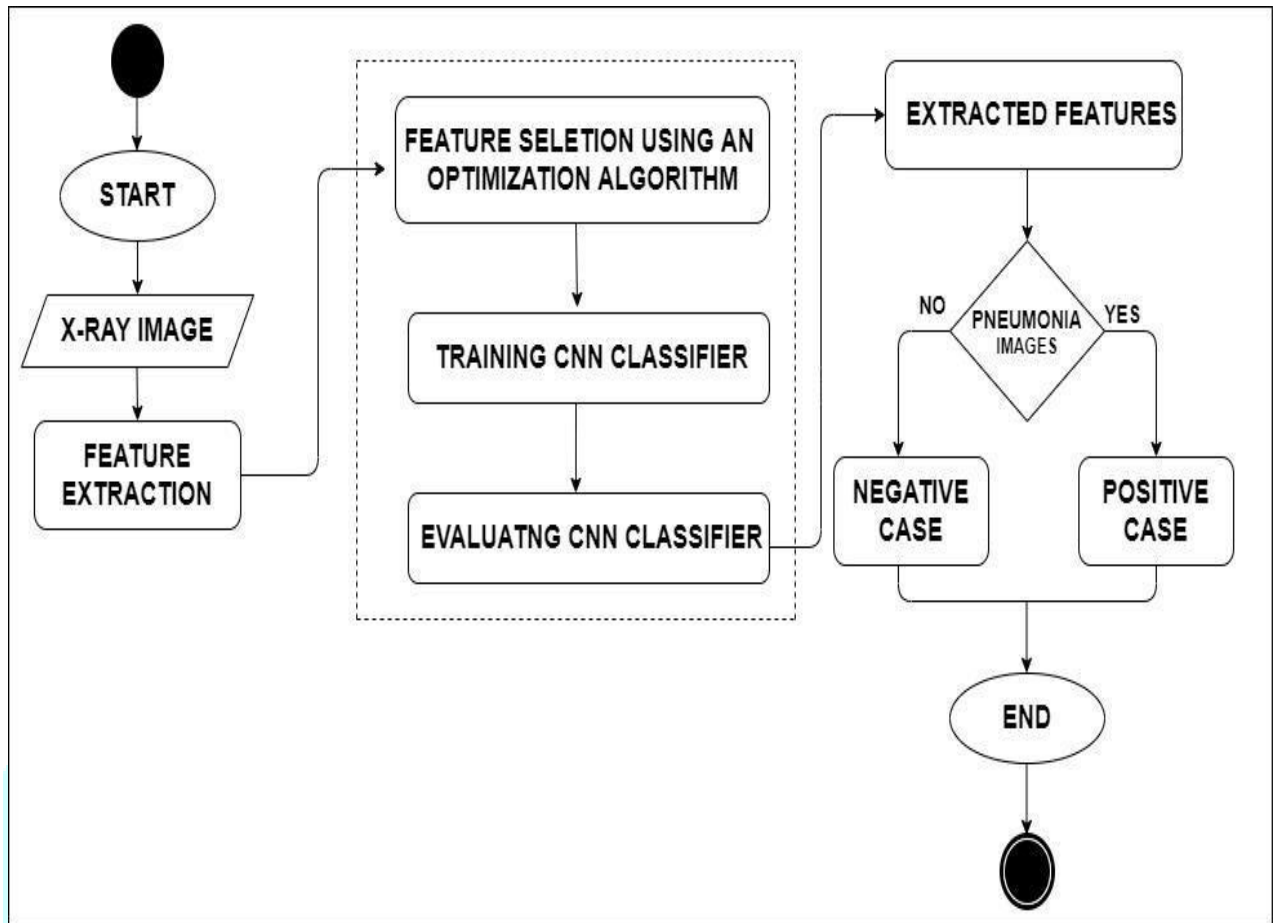
-FRONT END: HTML,CSS

-PROGRAMMING LANGUAGE: PYTHON

-.DATABASE: MYSQL

- ALGORITHM: CNN

## VIII. ALGORITHM FLOW CHART



## IX. CONCLUSION

In this paper, study describes a CNN-based model aiming to diagnose pneumonia on a chest X-ray image set. This will help our early detection of pneumonia quickly. Our project successfully provides with a CNN based approach for detection of pneumonia automatically.

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