Nile University

Core Requirement

Pneumonia Disease Detection using Machine Intelligence Techniques to Diagnose Acute Respiratory Failure

CSCI417/ECEN425: Machine Intelligence-FALL22-Report

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1. Introduction

- **Problem Statement:**
    - Pneumonia is an inflammatory condition of the lung is affected primarily the small air sacs known as alveoli. Symptoms typically include some combination of productive or dry cough, chest pain, fever and difficulty breathing. The severity of the condition is variable. Pneumonia is usually caused by infection with viruses or bacteria. As, Pneumonia worsens, making you more and more breathless.
    - Numerous variables may contribute to the Pneumonia disease. However, doctors are frequently unable to determine the exact cause of the issue.
    - Also, Pneumonia isn't just one disease. It is a family of more than 200 different lung diseases.

- **Signs and symptoms of Pneumonia may include:**
    - Cough
    - Fever, sweating and shaking chills
    - Shortness of breath
    - Rapid, shallow breathing
    - Sharp or stabbing chest pain that gets worse when you breathe deeply or cough
    - Loss of appetite, low energy, and fatigue
    - Nausea and vomiting, especially in small children.

- **Solution/Objective:**

  - Our main goal is earlier detection of Pneumonia by predicting a patient's severity of decline in lung function and based on Chest X-ray of their lungs.
  - Using image processing and machine intelligence techniques to help Pneumonia impacted patients and produce a prediction with the images of Pneumonia.

2. Related Work

- As the COVID epidemic worsened, more researchers concentrated on automated lung disease identification. To get the desired results, pre-processing, feature extraction, and classification were all necessary. Furthermore, enhancements were made at each stage of the operation. They performed CT image segmentation with an accuracy of 92% using a system based on U-NET and ResNet. Imperfect datasets are the fundamental barrier to overcoming the segmentation problem. As previously stated, medical picture segmentation datasets suffer from a scarcity of and poor-quality annotations. Furthermore, obtaining the data and annotations for the medical image might be exceedingly complex and costly. We suggested using a multi-level CNN-based preprocessor.

- Furthermore, our network is a universal platform that may be applied to a wide range of medical imaging techniques (e.g., chest X-ray, MRI, computed tomography) to reach a clinical diagnostic conclusion. We demonstrated this point by training our network on a dataset of pediatric pneumonia chest X-ray pictures. Because of the relatively high number of variable objects, particularly the imaged areas beyond the lungs that are irrelevant to the diagnosis of pneumonia, chest X-rays provide a tough categorization problem. The resulting high-accuracy model suggests that this AI system has the potential to effectively learn from increasingly complicated images with a high degree of generalization using a relatively small repository of data. This transfer learning framework presents a compelling system for further exploration and analysis in biomedical imaging and more generalized application to an automated community-based AI system for the diagnosis and triage of common human diseases by demonstrating efficacy with multiple imaging modalities and a wide range of pathology. We believe that by making our data and scripts publicly available, other biomedical researchers will be able to use our work as a resource to enhance the performance of future models and help move the field ahead. This might improve screening programmers and develop more efficient referral systems throughout medicine, particularly in distant or low-resource locations, with far-reaching clinical and public health implications.

- The primary objective for employing this preprocessor was to dynamically increase lung areas important in identifying pulmonary fibrosis. Experiments employing ReCoNet to differentiate between Pulmonary Fibrosis, Pneumonia, and Normal demonstrated an accuracy of more than 97%. The authors suggested a unique multimodal deep learning system that is hybrid and hybrid. The scientists were able to improve the contrast of X-ray pictures and minimize noise using Contrast-Limited Adaptive Histogram Equalization and a Butterworth bandpass filter, resulting in an accuracy of 99.93%. demonstrates how pre-processing may increase a system's accuracy. The visibility of the diaphragm on the chest X-ray was highlighted in this paper. It was discovered as a very light thing towards the bottom of the chest. Experiments with a convolutional neural network. However, experiments using a convolutional neural network (CNN) reported improved results when the diaphragm was removed from the sample.

- ResNet, which is a short form of Residual Network, was originally developed to two problems, such as the vanishing gradient and degradation problem. Residual learning tries to solve both these problems. ResNet has three different variants: ResNet18, ResNet50, and ResNet101 based on the number of layers in the residual network. ResNet was successfully used in biomedical image classification for transfer learning. We have used ResNet50 for the pneumonia detection. Typically, deep neural network layers learn low- or high-level features during training, while ResNet learns residuals instead of features.

Study characteristics for: *Pneumonia Disease Detection using Image Processing and Machine Learning Techniques to Diagnose Acute Respiratory Failure*

Study	Study purpose	Dataset	ML model(s)	Missing data handling	ML-Model Comparisons	Features	Event rate	Outcome
1) Nizar Rifat , Ali A. Hasan (2014)	To explore the demographic, clinical and physiological characteristics for Pneumonia in Upper	Dataset were obtained from Chest Departments at El-Minia and Assiut University Hospitals	FVC (forced vital capacity) and GERD.	The majority of patients enrolled in this study were elderly (the mean age at the time of enrollment	FVC was found to be negatively correlated with the duration of illness with the best results.	Clinical features for patients in Egypt had younger age of presentation while other demographic, clinical and	About 43% of patients developed disease before age of 50. Eighty-four (66.7%)	Pneumonia hypertension and cor - pulmonale were detected in one-third of our patients. Results coincide

	Egypt and early detection.	during the period from May 2013 to June 2014. A total of 126 patients were randomly recruited.		in the study was 53.4 years) and the disease was encountered more frequently above the age of 60 years (33.3%).		physiological features were more or less similar to those recorded worldwide.	patients were males. Dyspnea was present in 120 (95.2%) patients and the majority had grade 3 and 4 dyspnea.	with several others that have found that the prevalence of PH in patients with disease is between 32 and 85%, and PH seems to develop over time in most patients.
2) Hirotsugu Ohkuboa , , Hiroaki Nakagawab , Akio Niimia (2017)	Computer-based quantitative computed tomography image analysis in Pneumonia Disease	144 patients with PD	CNN and FEV1	Three-dimensional data of the bronchovesicular tree were advantageous over the two-dimensional x-rays data	Among these, CNN was the best validated and recommended indicator of disease progression in PD	The volumetric features including statistical features and histogram and fractal features can be successfully used in the pathology associated with lung diseases.	65 % percent predicted to have PD	Advanced x-rays imaging analysis will play essential roles in the future management of PD by using machine learning techniques
3) Sarah Jabbour, David Fouhey (2019)	Combining chest X-rays and electronic health record (EHR) data using machine learning to diagnose and solve problems related to acute respiratory failure	Models were trained using an internal cohort of patients who developed acute respiratory failure (ARF) during the hospitalization	Convolutional neural networks (CNNs), FIDDLE, FVC.net	Patients who were admitted with routine surgery or a surgical related problem were excluded.	Convolutional neural networks (CNNs) ML model helped with wide range in findings	Feature importance analysis was performed to understand how models used chest radiograph and EHR data to make predictions.	The internal cohort of 1,618 patients included 508 (31%) with pneumonia, 363 (22%) with heart failure, and 137 (8%) with COPD	Machine learning models combining chest radiographs and EHR data can accurately differentiate between common causes of acute respiratory failure.

3. Statistics for Pneumonia Disease Detection in Egypt

- Noncommunicable diseases (NCDs), including cardiovascular diseases, diabetes, cancer, and chronic respiratory diseases, are currently the leading national cause of death in Egypt. NCDs are estimated to account for **82% of all deaths in Egypt** and **67%** of premature deaths.

- Pneumonia is a form of acute respiratory infection that affects the lungs. It is caused by several infectious agents including viruses, bacteria, and fungi. Pneumonia can be spread in several ways. The viruses and bacteria that are commonly found in a child's nose or throat, can infect the lungs if they are inhaled. They may also spread via air-borne droplets from a cough or sneeze. In addition, pneumonia may spread through blood, especially during and shortly after birth.

- Pneumonia Disease is worse than most cancers after lung and Pancreatic cancer, it also affects around **14-43** people **per 100,000** population around the world. In addition, it primarily affects patients over **the age of 50**, and is more prevalent in males than females.

- Pneumonia Disease has an estimated prevalence **of 13 to 20 per 100,000** people worldwide. **About 100,000** people are affected in the United States, and **30,000 to 40,000** new cases are diagnosed each year.

- **<u>Pneumonia Disease issues statistics In Egypt:</u>**
  - Deaths **13,393** with **2.50 %** and Rate of **20.69** with a World Rank **100**
  - According to the latest WHO data published in 2020 Lung Disease Deaths in Egypt reached **13,393 or 2.50%** of total deaths. The age adjusted Death Rate is **20.69** per **100,000** of population ranks Egypt #100 in the world.

- **In addition to, Influenza and Pulmonary and lung diseases in Egypt**
  - Deaths **20,694** with **3.86 %** and Rate of **25.25** with a World Rank **99**
  - According to the latest WHO data published in 2020 Influenza and Pulmonary Deaths in Egypt reached **20,694** or **3.86%** of total deaths. The age adjusted Death Rate is **25.25** per **100,000** of population ranks Egypt **#99** in the world.

4. Methodology

4.1 Dataset:

In this work, a data set from Mendeley Data has been used, which is comprised of 5,856 chest X-ray images, 2 categories (Normal - Pneumonia). Out of these 5,856 X-ray images, 4273 are from different subjects affected by pneumonia and 1583 are normal subjects (Table 1).

Type	No. of X-ray images
Normal	1583
Pneumonia	4273

Table 1. complete dataset details.

Table 2. shows a number of train and test images for different evaluation experiments. In this work CNN Algorithm were trained using the training dataset and then evaluated on test dataset.

Types		Training Set	Testing Set	Validation Set
Normal & pneumonia	Normal	1082	234	267
	Pneumonia	3110	390	773

Table 2. Details of the training and test set.

In this study, Python was utilized to train, evaluate, and test CNN algorithm. Figure 4 illustrates the overview of the Model architecture of this study. Image sets undergo some Data Exploration, pre-processing steps, training using pre-trained Convolutional Neural Net model and then Testing.

4.2 Data loading

In this phase we need to:

- Decide validation percentage
- Provide path for training data
- Decide image size

4.3 Data Exploration

Our image dataset is stored as .jpg files in 2 different folders, with each folder holding the name of model of the images contained in the folder. We use a certain function to load the images and assign labels the images based on the name of the folder they're read from.

4.4 Data Preprocessing

we used data preprocessing here to prepare the raw data and making it suitable for a machine learning model. Also, helps generate accurate and reliable data while reducing the amount of time necessary to analyze raw data. So, this can improve the data reading and interpreting capabilities of our machine learning code.

4.5 Create and build Model

We use a pre-trained Convolutional Neural Net model and use transfer learning to learn weights of only the last layer of the network, because with transfer learning, you begin with an existing (trained) neural network used for image recognition. In figure 3 you will see a sample of the train loss, valid loss, accuracy, and time of this trained model.

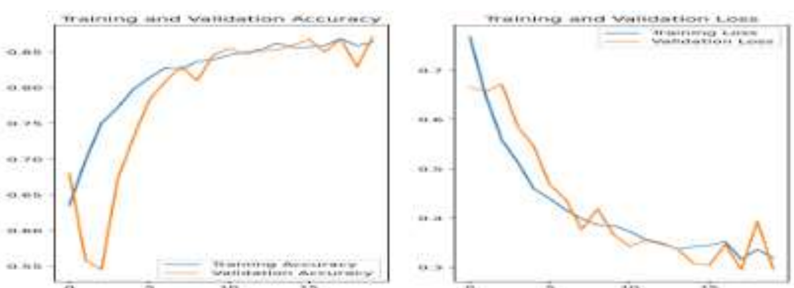

Figure 3. train and validate model results

4.6 Interpret the results and prediction

This is the final step to interpret the results and use the test data to predict weather the X-ray image of the patient indicates pneumonia or just a normal X-ray.

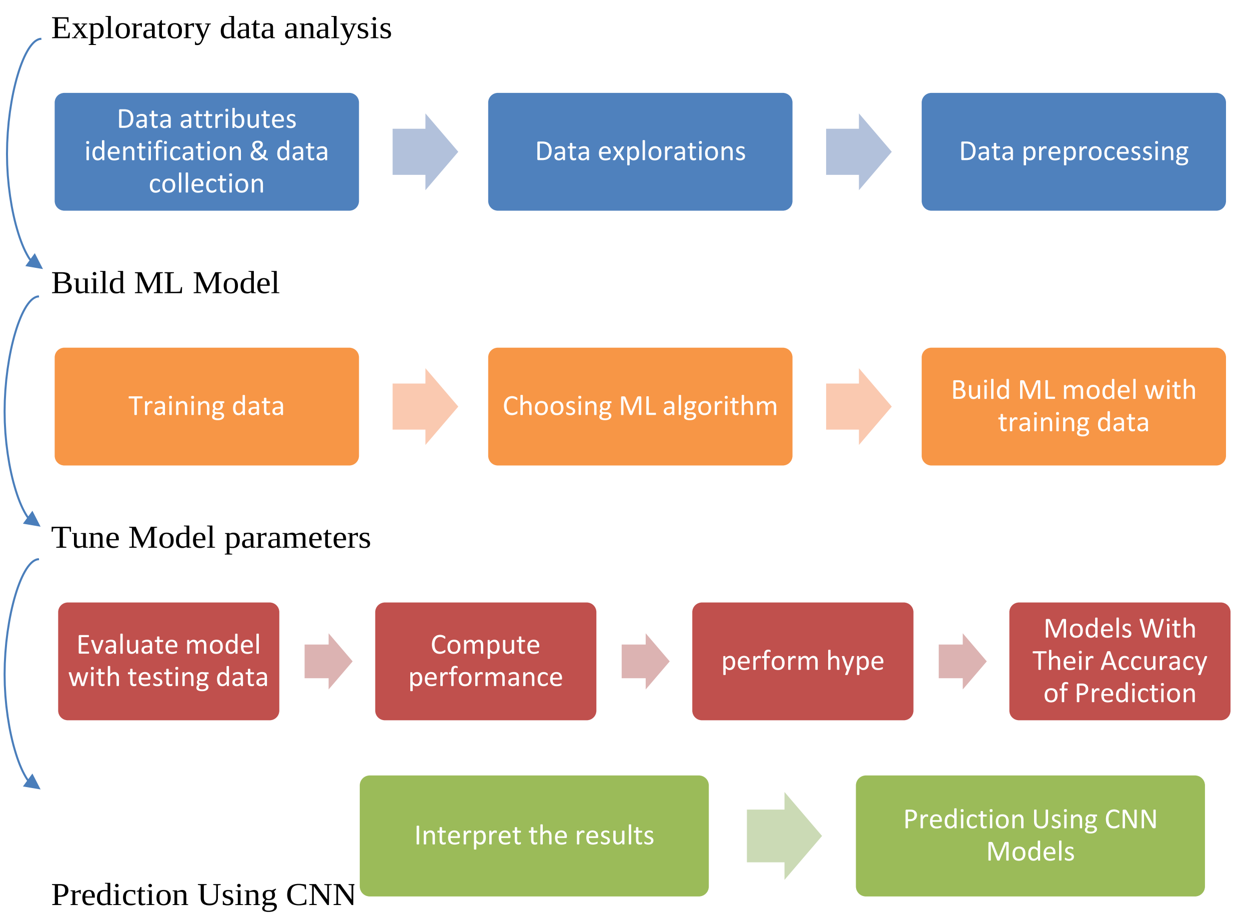

Figure 4. the Model architecture of this study

4.7 survey

A survey was done to evaluate people's knowledge about this disease and to know the symptoms they had if they ever had pneumonia and what are the causes of this disease. We also asked about other things like smoking status and more will be explained in the results part.

5. Evaluation Results

5.1. Survey results

This section presents the results of the questionnaire using charts and tables to highlight the quantitative and qualitative results.

Description of Participants

These questions determined whether the responder would continue to the next sections of the questionnaire. The questions were "Your age?", "Gender?", "Smoked before?", "symptoms have you experienced before?".

Table 1.

Summary of general questions

Country	Age	Average of having pneumonia symptoms	Count
Egypt	10 to 20 20 to 30 30 to 55 55 or above	Males	21
		Females	17

As mentioned before in the previous chapters, the target for the questionnaire were Egyptian adolescents and adults that are between the age of 10 to 55 or above if they faced symptoms of pneumonia. Thus, the 38 participants do belong to the population.

Participants' Gender & Age

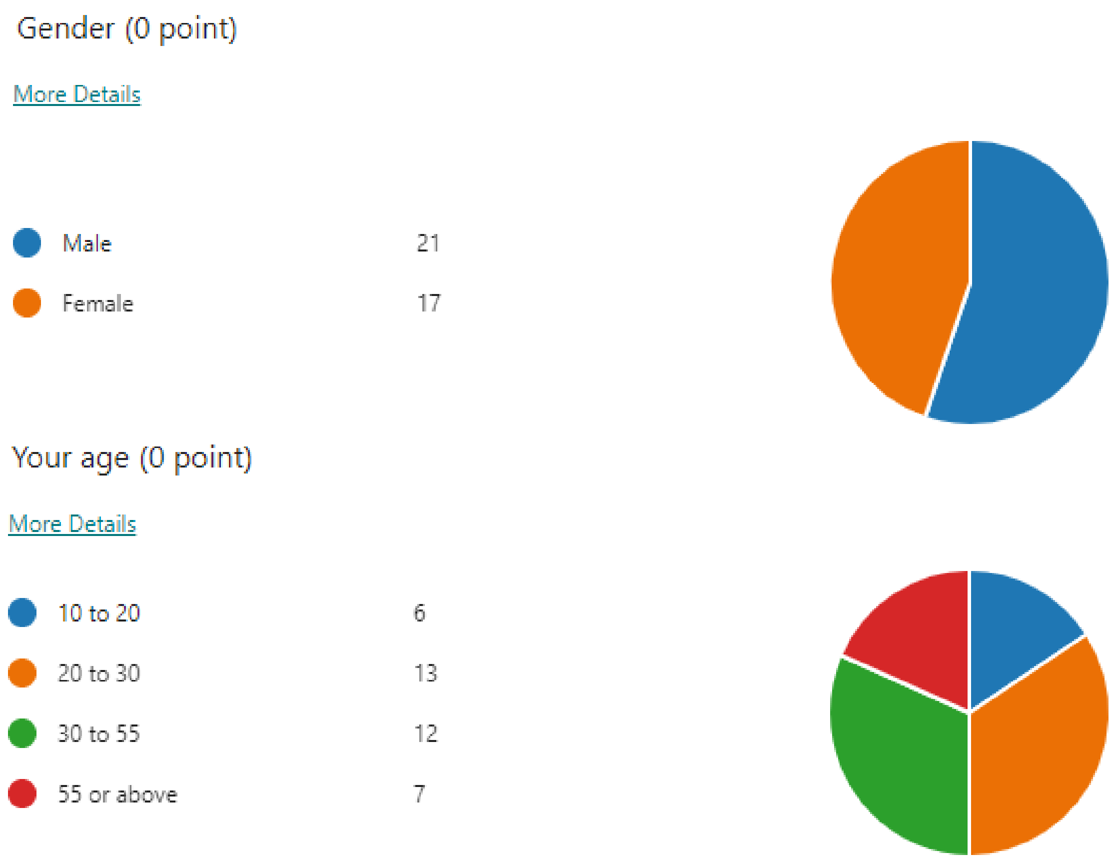

Figure 1: Gender & Age

We have here demographic questions which asked for the participant's gender and age. 21 of the participants were Males and 17 were Females (see Figure 1).

Smoking status

Figure 2: Categorizing of smoking people

The third question asked about smoking status “Ex-smoker”, “Still smoking”, “Never smoked”. As shown in figure 11 are ex-smoker and 14 are still smoking and 13 never smoked. This part is important as Pneumococcal pneumonia is significantly increased by cigarette smoking, especially in people with chronic obstructive pulmonary disease.

Symptoms & Participants with pneumonia

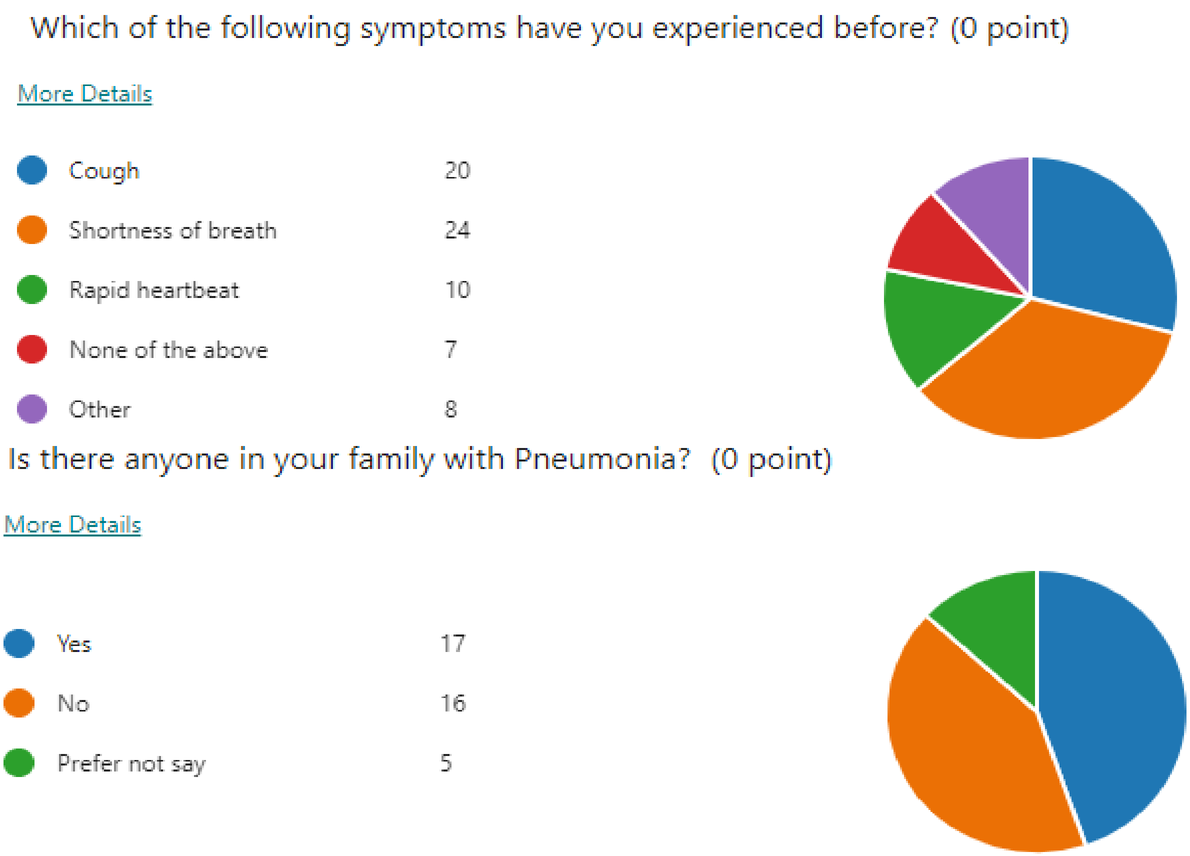

Figure 3

The fourth and fifth questions asked if participants had pneumonia symptoms or if anyone in their family had the illness, which helped us discover a link between pneumonia and genetic factors that may make it more likely. Most frequently, genetic polymorphisms, but in a few rare instances, monogenic abnormalities, are what cause susceptibility to repeated infections.

If yes, how is he or she dealing with the treatment? If you don't know state NA

The sixth question was a qualitative optional question that was a follow-up on the fifth question that asked the participants to state **Is there anyone in your family with Pneumonia?** This will allow us to see how treatment is progressing and whether or not most symptoms have resolved.

Scale question

The seventh question is a scale question from 1 to 10 to identify how severe the symptoms were it depends on the fourth question. We can see the scale 8 is highest percentage of severity.

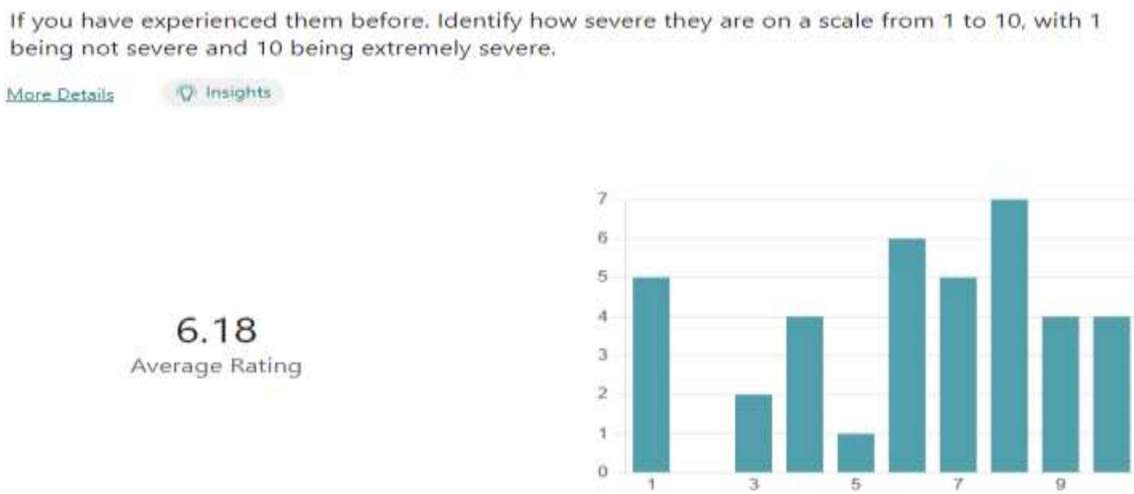

Figure 4

Changes of ability daily activities

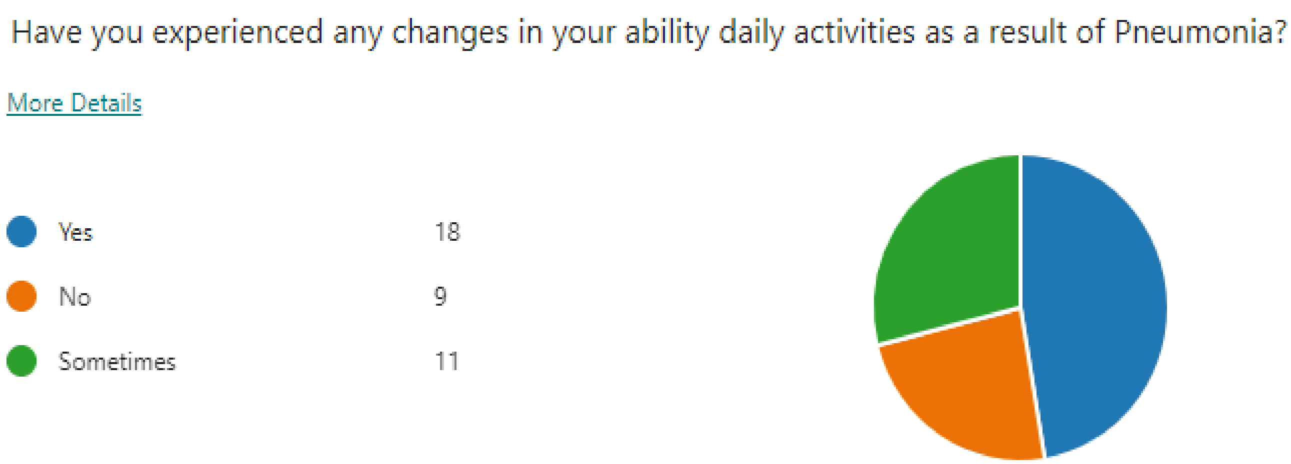

Figure 5

The eighth question was asking about whether you experienced any changes in your ability daily activities as a result of Pneumonia? From the figure, 47% of the participants said “Yes” while only 24% said “No” and the rest “Sometimes”.

Avoiding this disease

The ninth question was a qualitative question asking about your advice for avoiding this disease. This will help us to be more cautious and how to prepare for this disease.

5.2. Simulation results

Our dataset is kept in two separate folders as.jpg files, and each folder has a name that corresponds to the Directory Setup of the photos it holds. The photos are loaded, and labels are assigned to the images depending on the folder name from which they were read. **So, our results were as following:**

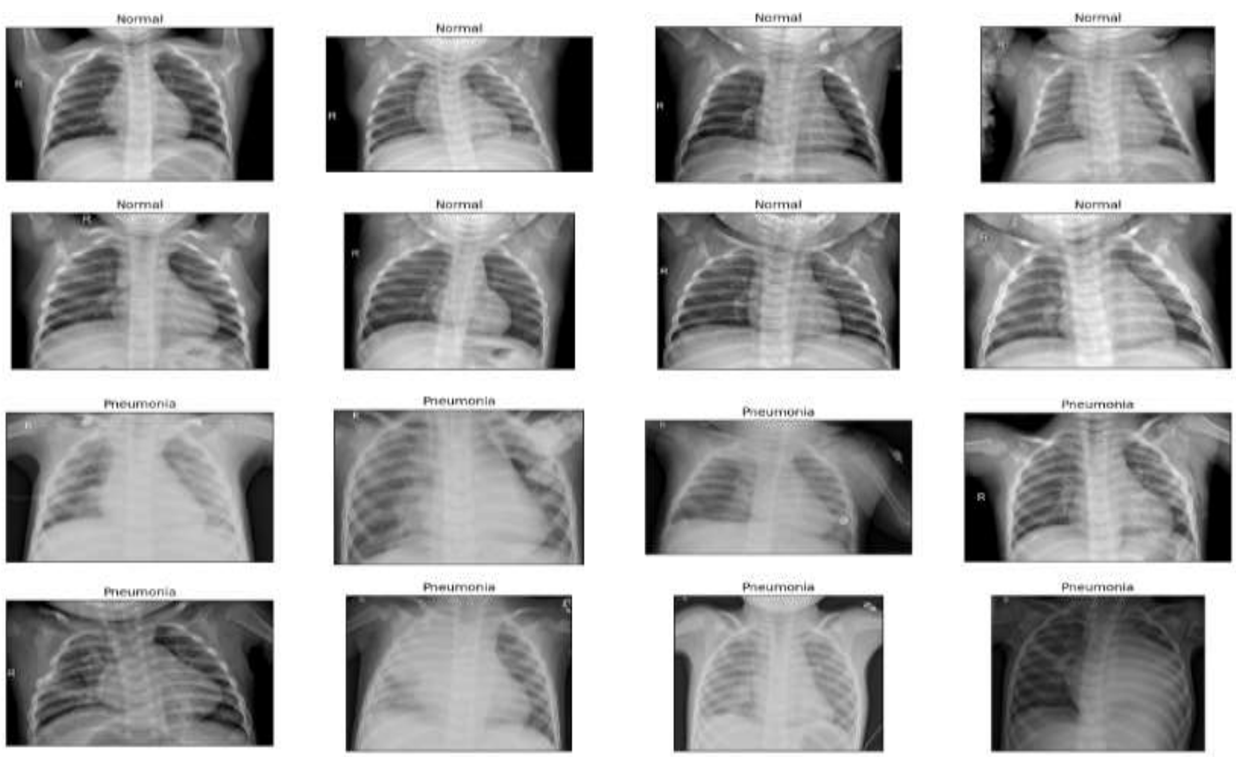

Figure 6: Shows visualization of train data for 16 random images (8 normal and 8 with Pneumonia)

Here we are training our CNN models as in our situation, we had a training set of over 4000 photos, so we can only speculate as to whether that would have been sufficient to train a neural network from start.

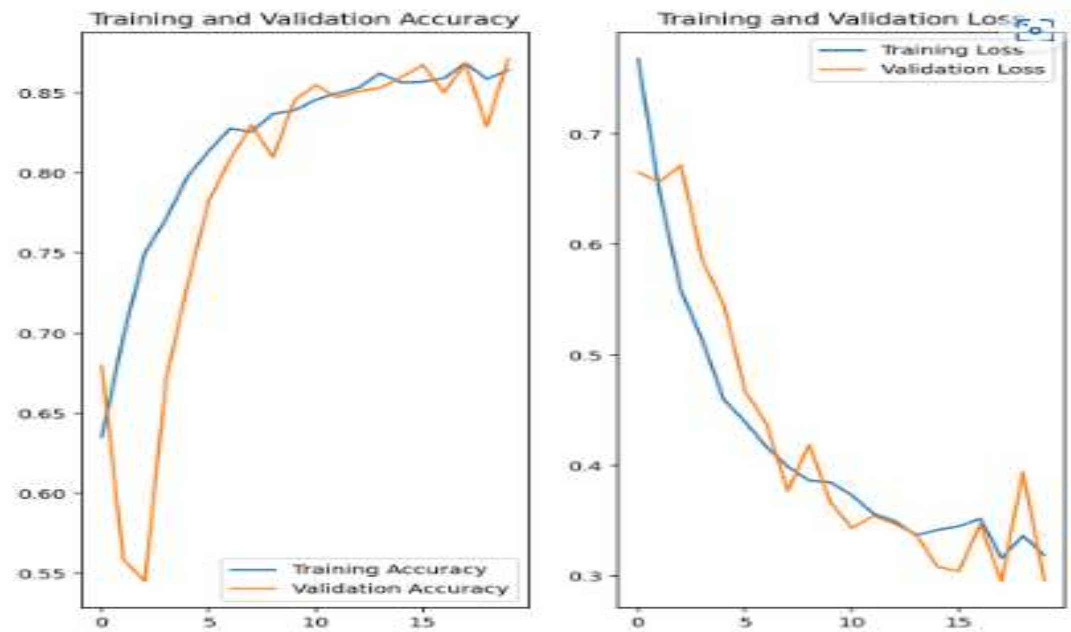

Figure 7: Shows visualization of training and validation accuracy for first model ***VGG16***

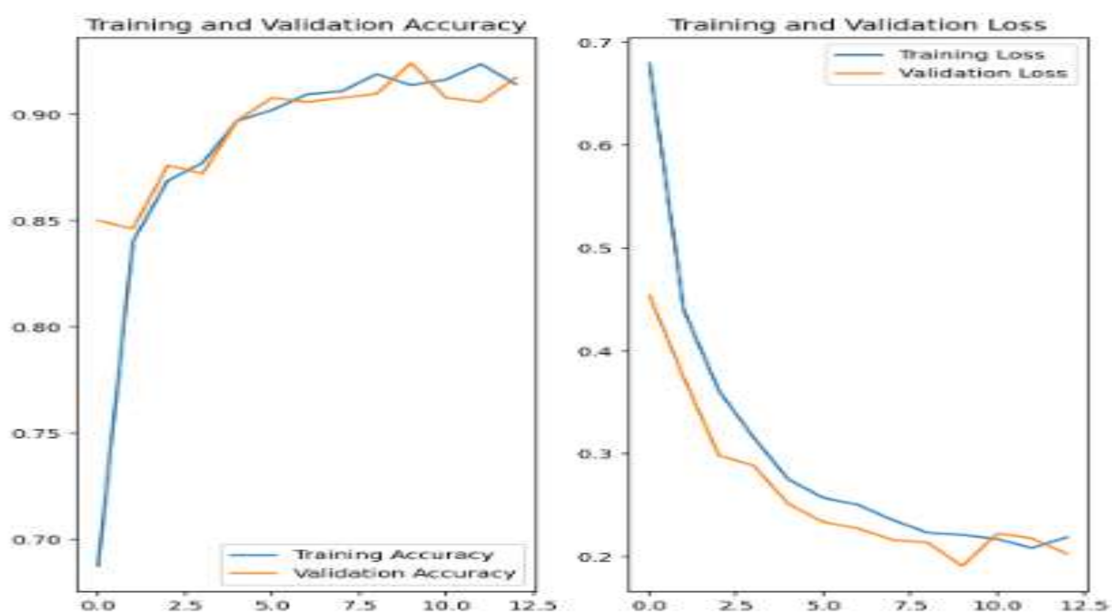

Figure 8: Shows visualization of training and validation accuracy for second model ***MobileNetV2***

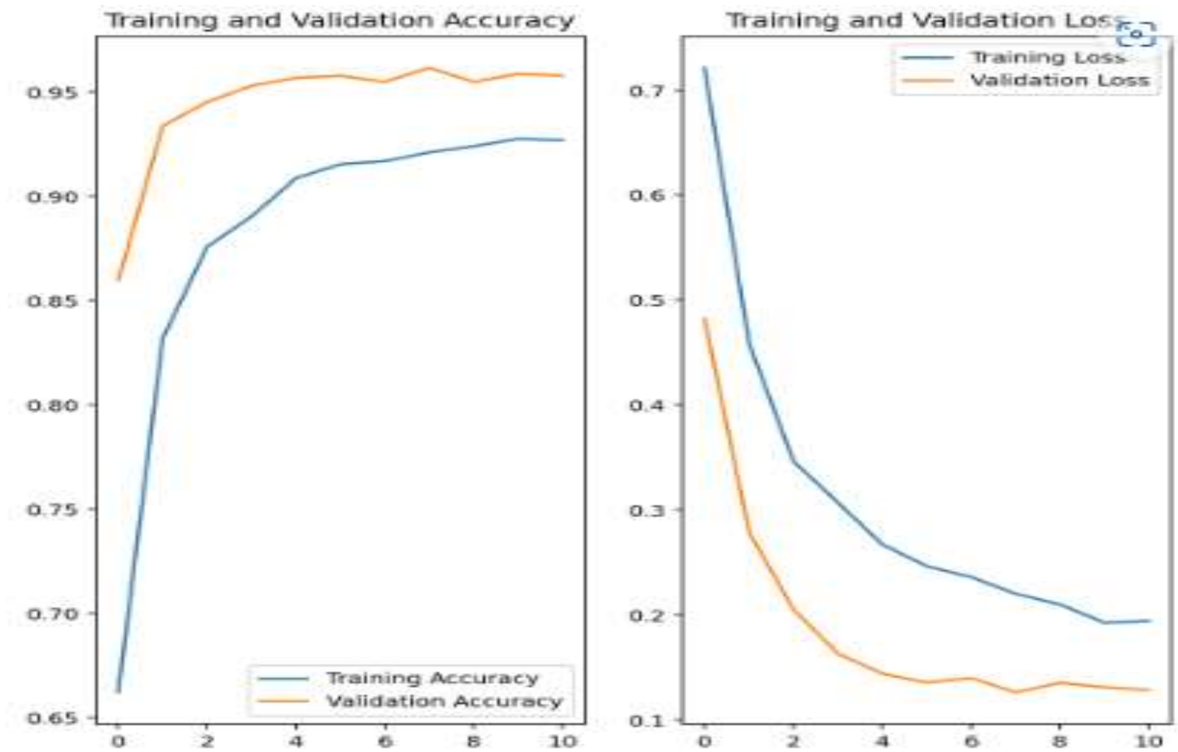

Figure 9: Shows visualization of training and validation accuracy for third model ***DenseNet169***

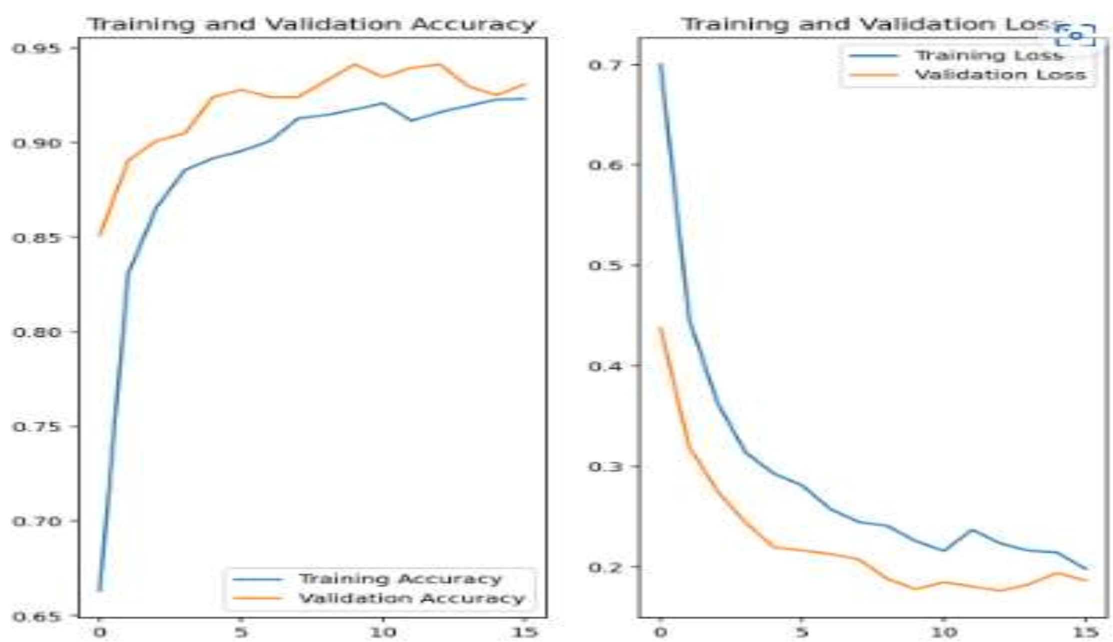

Figure 10: Shows visualization of training and validation accuracy for fourth model ***InceptionV3***

Here we are interpreting the results. Besides, giving a clearer picture whether the classification model is accurate and what kinds of mistakes it makes, as follows:

	precision	recall	f1-score	support
0	0.77	0.89	0.83	234
1	0.93	0.84	0.88	390
accuracy			0.86	624
macro avg	0.85	0.87	0.86	624
weighted avg	0.87	0.86	0.86	624

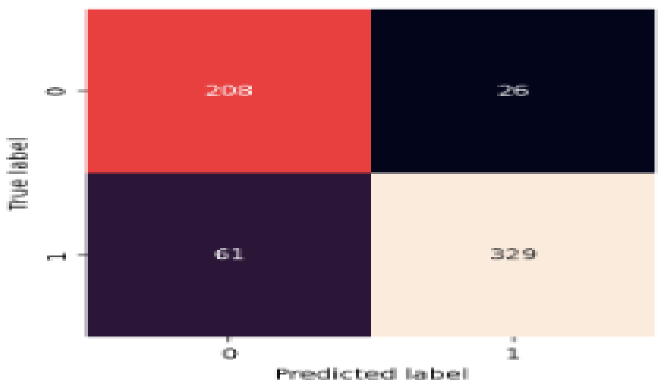

Figure 11: Shows accuracy for first model ***VGG16***

	precision	recall	f1-score	support
0	0.88	0.85	0.86	234
1	0.91	0.93	0.92	390
accuracy			0.90	624
macro avg	0.89	0.89	0.89	624
weighted avg	0.90	0.90	0.90	624

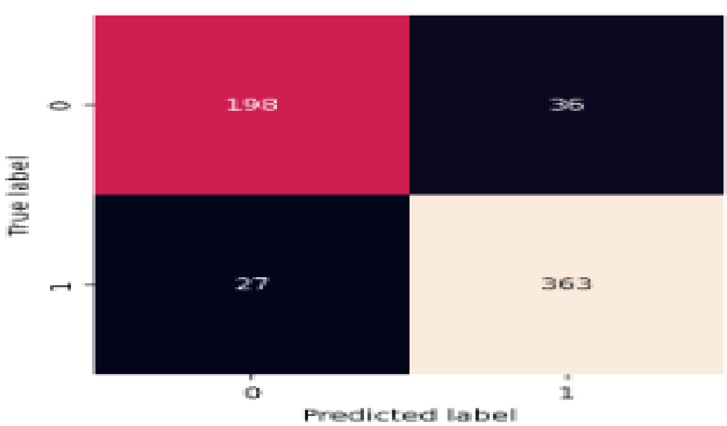

Figure 12: Shows accuracy for second model ***MobileNetV2***

	precision	recall	f1-score	support
0	0.91	0.82	0.86	234
1	0.90	0.95	0.92	390
accuracy			0.90	624
macro avg	0.90	0.88	0.89	624
weighted avg	0.90	0.90	0.90	624

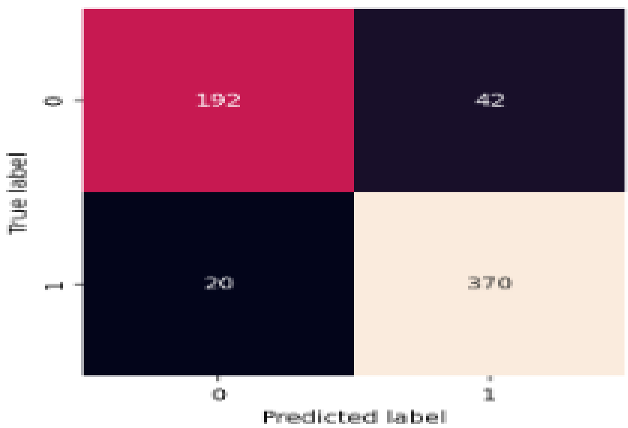

Figure 13: Shows accuracy for third model ***DenseNet169***

	precision	recall	f1-score	support
0	0.90	0.64	0.75	234
1	0.81	0.96	0.88	390
accuracy			0.84	624
macro avg	0.86	0.80	0.81	624
weighted avg	0.85	0.84	0.83	624

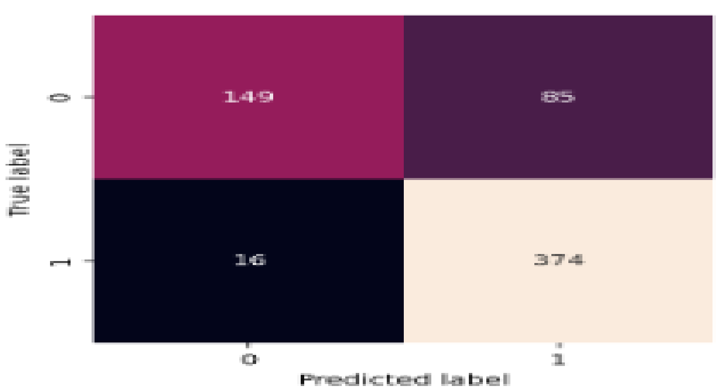

Figure 14: Shows accuracy for fourth model ***InceptionV3***

6. Discussion and Conclusion

CNN and Transfer Learning algorithms like VGG-16, MobileNetV2, DenseNet169 and InceptionV3 has been used for this experiment

Models With Their Accuracy of Prediction

CNN Model	Accuracy	Loss
VGG-16	86%	0.29
MobileNetV2	92%	0.19
DenseNet169	96%	0.12
InceptionV3	94%	0.17

To sum up, the model's presentation could be an extraordinary aid for exact assurance of the decay rate in the help of Pneumonia impacted patients. The proposed method further states that high resolution X-rays, evaluated by the proposed deep learning algorithm, provides a low-cost, fast, and accurate way to find the decline in the lung function of a patient suffering from Pneumonia disease.

7. Future Work and Suggestions

In our future work, a convolutional Neural Network (CNN) algorithm will be more developed, and we can apply our code on real world environment so it can be used on a larger scale as it's very effective compared to other deep learning algorithms. Also, the model's presentation could be an extraordinary aid for exact assurance of the decay rate in for COVID-19 impacted patients.

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