

1. INTRODUCTION

1.1 Background

Pneumonia accounts for over 15% of all deaths of children under 5 years old internationally. In 2015, 920,000 children under the age of 5 died from the disease. While common, accurately diagnosing pneumonia is a tall order. It requires review of a chest radiograph (CXR) by highly trained specialists and confirmation through clinical history, vital signs and laboratory exams. To improve the efficiency and reach of diagnostic services, we designed a model that predict pneumonia by using chest x-ray images.

1.2 Overview of project

We are aiming to use Deep learning and Transfer learning in classifying a given greyscale Chest X-Ray image as pneumonia infected or not in medical application to significantly reduce the time required to diagnose a person with pneumonia. The training of the model to classify the Chest X-Ray images has a huge data set which requires a lot of processing power and time, to reduce the time required to train the model we are going to use Distributed Deep Learning with multiple nodes.

1.3 Motivation

India had the second-highest number of deaths of children under the age of five in 2018 due to pneumonia, a curable and preventable disease that claimed the life of one child every 39 seconds globally, according to a new report by the UN. The United Nations Children's Fund (UNICEF) said that globally, pneumonia claimed the lives of more than 800,000 children[5] under the age of five last year — or one child every 39 seconds. Most deaths occurred among children under the age of two, and almost 153,000 within the first month of life. Therefore, we intend to reduce the cost and time required to diagnose a person with pneumonia with our project to save lives. Also the existing deep learning techniques take a lot of time to train the model and the time increases as the data increases which would deter the purpose of staying up to date with the new data that is generated.

1.4 Scope and Objectives

Usually in normal diagnosis of pneumonia the specialist diagnose may not be that accurate and takes comparatively more time and there will be chance of wrong detection. The proposed system will overcome, as it will be implemented using deep learning. Since the detection process is computerized, speed of detecting is very fast.

Objectives:

1. To preform data pre-processing including data augmentation to balance the number of images in each class.
2. To implement VGG and ResNet models and select the best performing model for DDL based on the generalization result.
3. To redesign, implement, compare selected DL model for DDL.
4. To provide GUI interface for predictions.

1.5 Literature Survey

The previous techniques used in Pneumonia classification are CNN, deep convolutional neural network, SVM. Using the CNN network, the classification was being done. Where the images are reshaped into 100*100*3, 150*150*130, 200*200*3, 250*250*3, 300*300*3. Here the larger the size of the transformed images, the lesser the validation accuracy obtained [1].

Data size	Training accuracy	Validation accuracy
100	0.9375	0.9226
150	0.9422	0.9343
200	0.9531	0.9373

250	0.9513	0.9297
300	0.9566	0.9267
Average	0.94814	0.93012

Another model is Deep neural convolutional neural network using Resnet 50. A pretrained model is retrained with the use of transfer learning. The accuracy achieved is 96.76% [2].

IEEE paper studies the differences in the results when neural network and support vector machines are used in studying the gait of various age groups. The document shows the accuracies derived from using different neural network concepts and accuracies using different kernels of SVM. In this case, all the SVM kernels outperform the Neural Network algorithms by a significant margin. Therefore, this research paper shows that SVM has better system performance compared the neural network algorithms [3].

1.6 Problem Definition

Deep Learning can be used in medical application to train a model to classify Chest X-Ray images into pneumonia infected or not using a dataset of RSNA Chest X-Ray training images and then Distributed Deep learning can be used to reduce the time taken to train the model and also work with existing less powerful hardware by using multiple low performance nodes.

2. PROPOSED SYSTEM

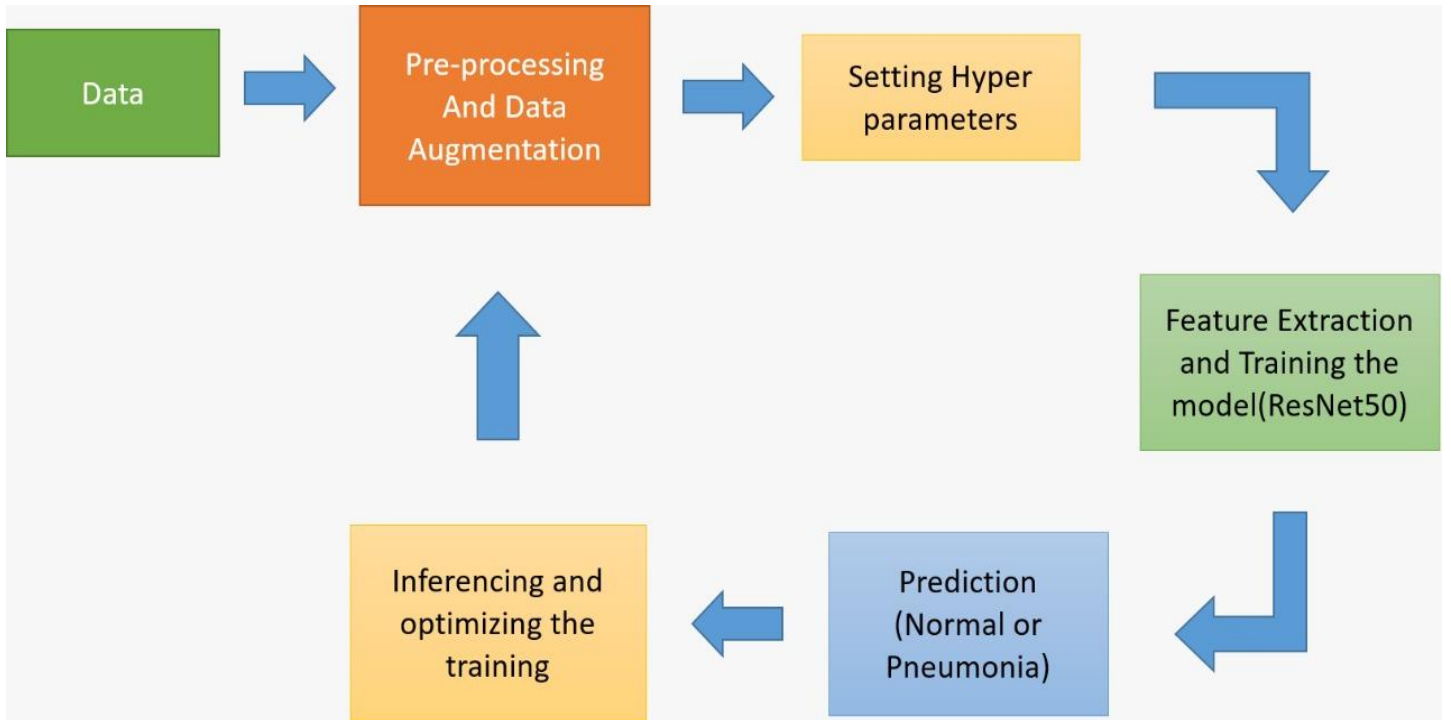


Figure 1. Block diagram of system

2.1 Description of Proposed System

The data is augmented to maintain balance in the number of images in each class to avoid bias towards one class, after which we set the hyperparameters for training the model on the dataset such as learning rate, optimizers, lossfunction. We are using ResNet50 model which is trained on the imageNet dataset and then retraining it to optimize the weughts for our dataset, we do this by retaining the values of the initial layers by freezing them i.e, not updating their weights but only the last 5 layers as the initial layers are optimised to extract the basic features. Training only the last 5 layers will reduce the computation time and increase efficiency. After training the model we infer and analyse the results and optimize the dataset and parameters accordingly to achieve a better result.

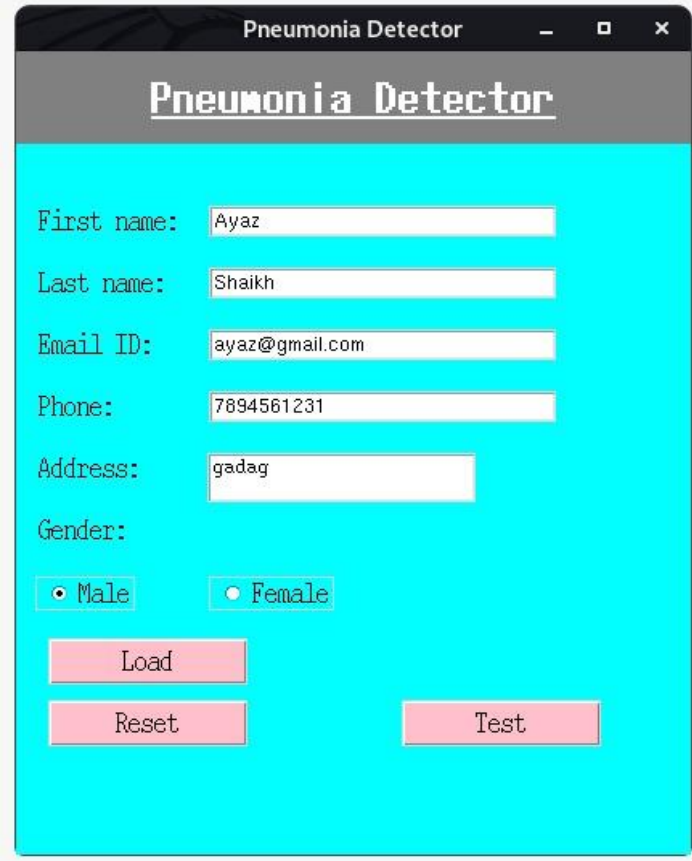
2.2 Description of target users

The target users are Medical Faculty, mainly Doctors (Lung specialists) who diagnose pneumonia in patients, however non-medical staff can also use the project after it is approved by the specialists of the accuracy and reliability.

2.3 Application of proposed system

- Requires less data and time to train the model.
- Better performance of Neural Networks (in most cases).
- Can be used with existing hardware.
- Can handle large data efficiently.

2.4 GUI Snapshots



The screenshot displays a web application window titled "Pneumonia Detector". The interface has a dark blue header with the title "Pneumonia Detector" in white. Below the header, the form is set against a light blue background. It contains several input fields: "First name:" with the value "Ayaz", "Last name:" with "Shaikh", "Email ID:" with "ayaz@gmail.com", "Phone:" with "7894561231", and "Address:" with "gadag". There is also a "Gender:" section with two radio buttons, "Male" (selected) and "Female". At the bottom of the form, there are three buttons: "Load", "Reset", and "Test".

Figure 2: Patient Details and Loading Input X-ray Image

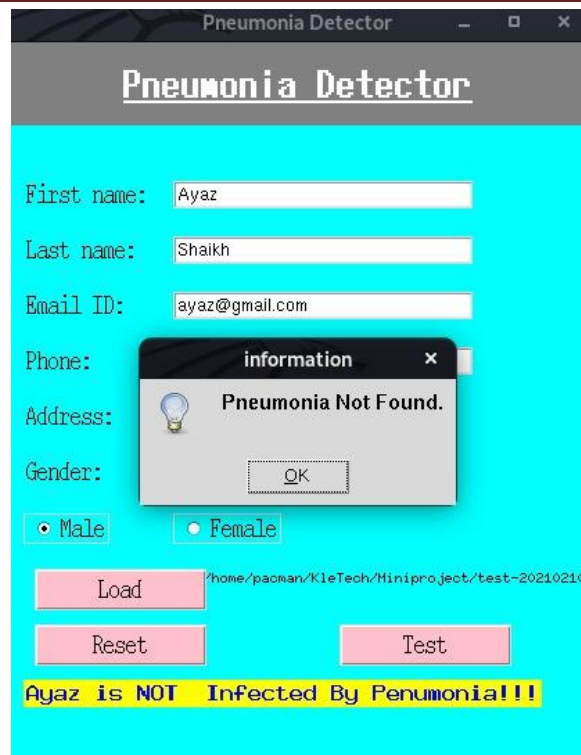


Figure 3: A person without Pneumonia



Figure 4: A person with Pneumonia

3. Software Requirement Specifications

3.1 Overview of SRS

A software requirements specification is the basis for your entire project. It lays the framework that every team involved in development will follow. It's used to provide critical information to multiple teams-development, quality Assurance, operations, and maintenance. This keeps everyone on the same page Using SRS helps to ensure requirements are fulfilled.

3.2 Requirement Specification

3.2.1 Functional Requirement

User

- User should input the greyscale image.

Administrator

- Administrator should update the training data.
- Administrator should initiate the training
- Administrator should view the training and validation results

System

- System should classify the x-ray images into Pneumonia infected or not.

3.2.2 Use Case Diagram

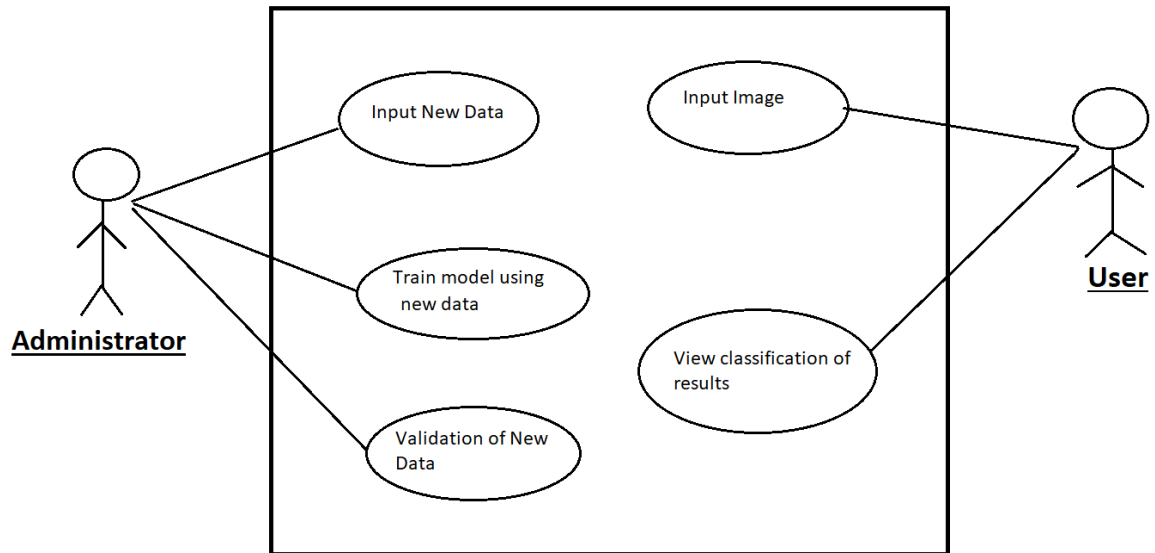


Figure 1. Use Case Diagram

3.2.3 Use case description

Use case 1: Input data (image).

Actor: Radiologist.

Pre-condition: The Image is a Chest X-ray image.

Success Case Scenario:

- Step 1: User uploads an image.
- Step 2: System reads the image.
- Step 3: Details of images will be displayed.

Exception Case Scenario:

- The image given is not of chest X-ray

System tells the Radiologist this situation

Use case2: Updating the data

Actor: Administrator

Pre-condition: The images must be Chest X-rays.

Success Case Scenario:

- Step 1: User uploads the data (images).
- Step 2: Training Data is updated.

Exception Case Scenario:

- The image given is not of chest X-ray

System tells the Radiologist this situation

Use case 3: Initiate training

Actor: Administrator

Pre-condition: Training data is available.

Success Case Scenario:

- Step 1: Data pre-processing is done.(Data augmentation)
- Step 2: Select the type of neural network, for example CNN.
- Step 3: Input the pre-processed data and train the model.

Exception Case Scenario:

- Step 1: System will be overfitting or under fitting the model.

System tells the Radiologist this situation

Use case 4: view the training and validation results

Actor: Administrator

Pre-condition: Training must be done properly.

Success Case Scenario:

- Step 1: We can see the result with high accuracy.

Exception Case Scenario:

- Step 1: We can visualize the result but the model is over or under fitted.

Use case 5: Classification of x-ray images

Actor: User

Pre-condition: Model must already be trained

Success Case Scenario:

- Step 1: System reads an image
- Step 2: System classifies the image into Pneumonia infected or not.

Exception Case Scenario:

- Improper classification of images by the model.

3.2.4 Non-Functional Requirements

3.2.4.1. Performance Requirements

- The system should have an accuracy of at least 85%.

3.2.4.2. Usability

- Once the user input the x ray image the system should detect within 3sec.

3.2.4.3. Any Other

- Input of the image is independent of size.

4. SYSTEM DESIGN

4.1 Architecture of the system

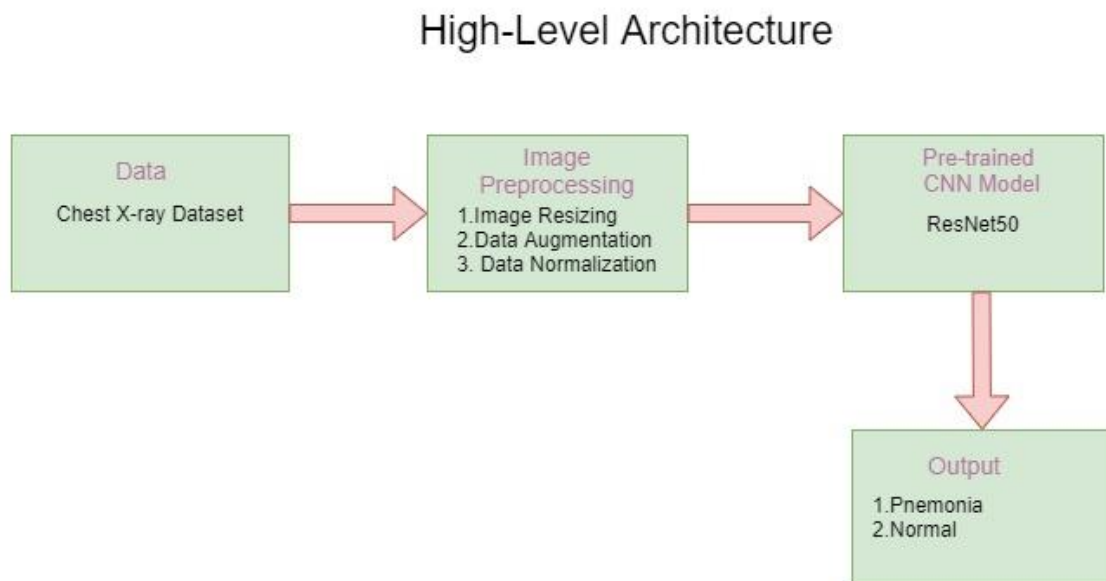


Figure 1. Architecture of the system

4.1 Class Diagram

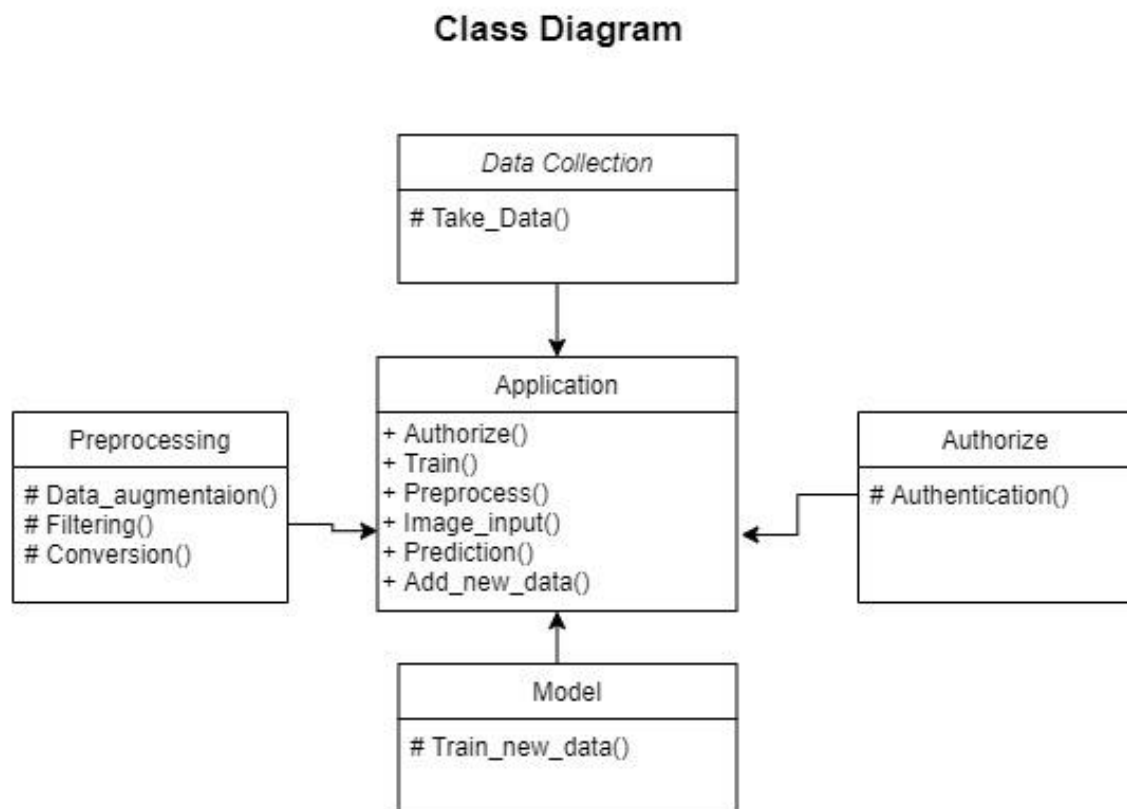


Figure 2. Class diagram

5 IMPLEMENTATION

5.1 Proposed Methodology

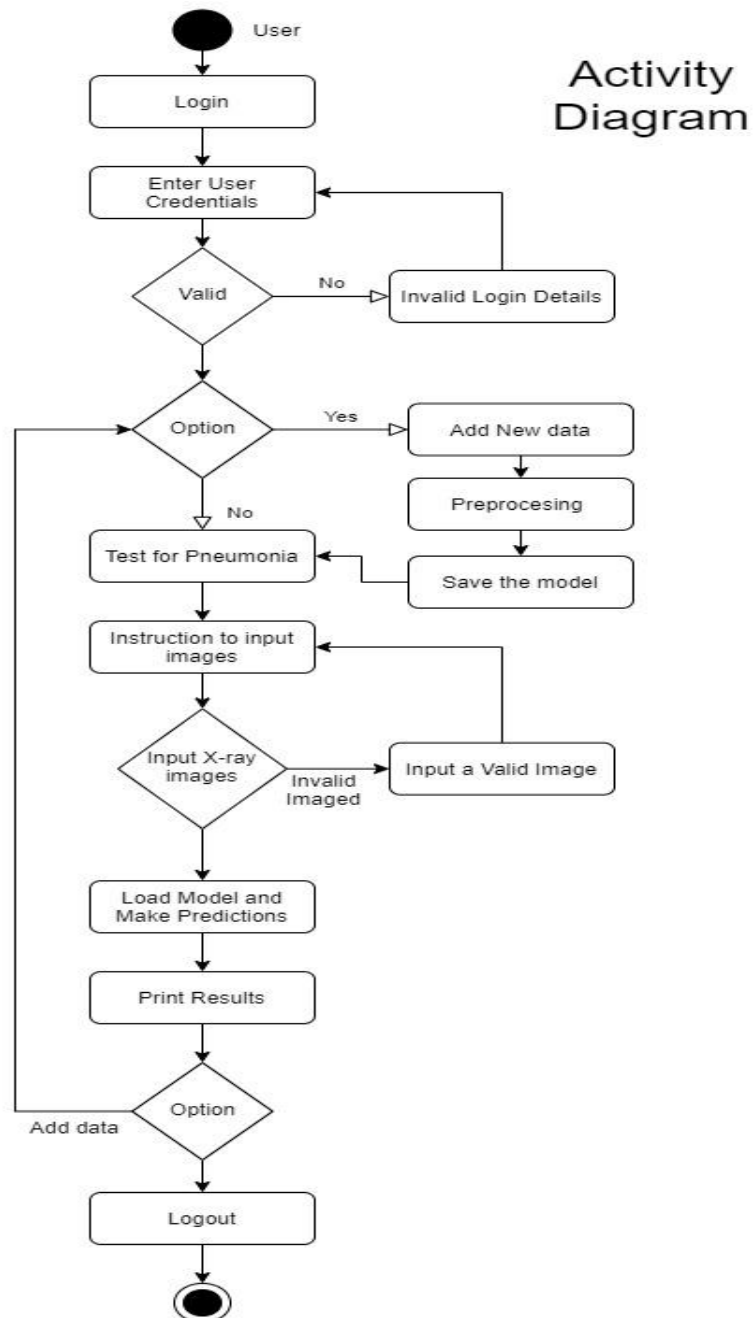


Figure 3. Flow chart

6. TESTING

6.1 Acceptance Testing

Table 1: Acceptance test plan

Test id	Input Description	Expected output	Actual output
1.	Loads the image of class normal.	Loads the image from class normal.	Loads the image from class normal.
2.	Loads the image of class pneumonia.	Loads the image from class pneumonia.	Loads the image from class pneumonia.
2.	Trained the model using resnet 50 with batch size 10.	Accuracy above 90.	Accuracy of 94.
3.	Given chest Xray image	Predict the appropriate class.	Predict the appropriate class.

6.2 Unit Testing

Table 2: Unit test plan for module search ()

Test id	Input Description	Expected output	Actual output
1	Load button in GUI	Loads the input image from the local disk	Loads the input image from the local disk
2	Reset button in GUI	Removes all the text inputs for fresh entry.	Removes all the text inputs for fresh entry.
3	Test button in GUI	Predicts the given image in two class i.e normal or pneumonia.	Predicts the given image in two class i.e normal or pneumonia.
4	Takes input of only greyscale image	Loads only grey scale image.	Loads only grey scale image.

7. RESULTS AND DISCUSSIONS

By training the model on a single GPU and two GPUs (DDL) for 50 epochs on the dataset, we get the following result.

	Single GPU	DDL using 2 GPUs
Accuracy (%)	95.3	95.4
Training Time (50 epochs)	1.8 hours	1 hours
Best validation accuracy (%)	96.4	96.4

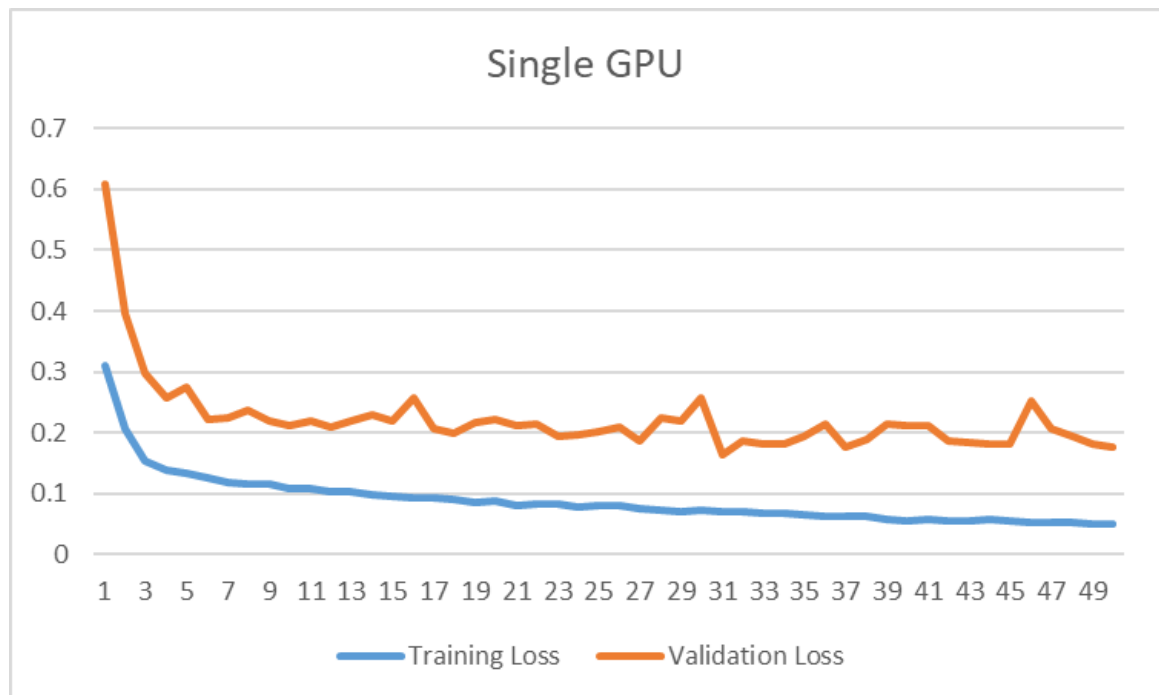


Figure 4. Loss vs Epoch Graph for Single GPU training

The training loss in Fig 4 is decreasing steadily as the cost function updates the weights to reduce the training loss and the validation loss varies but over time it is decreasing indicating the model is generalizing.

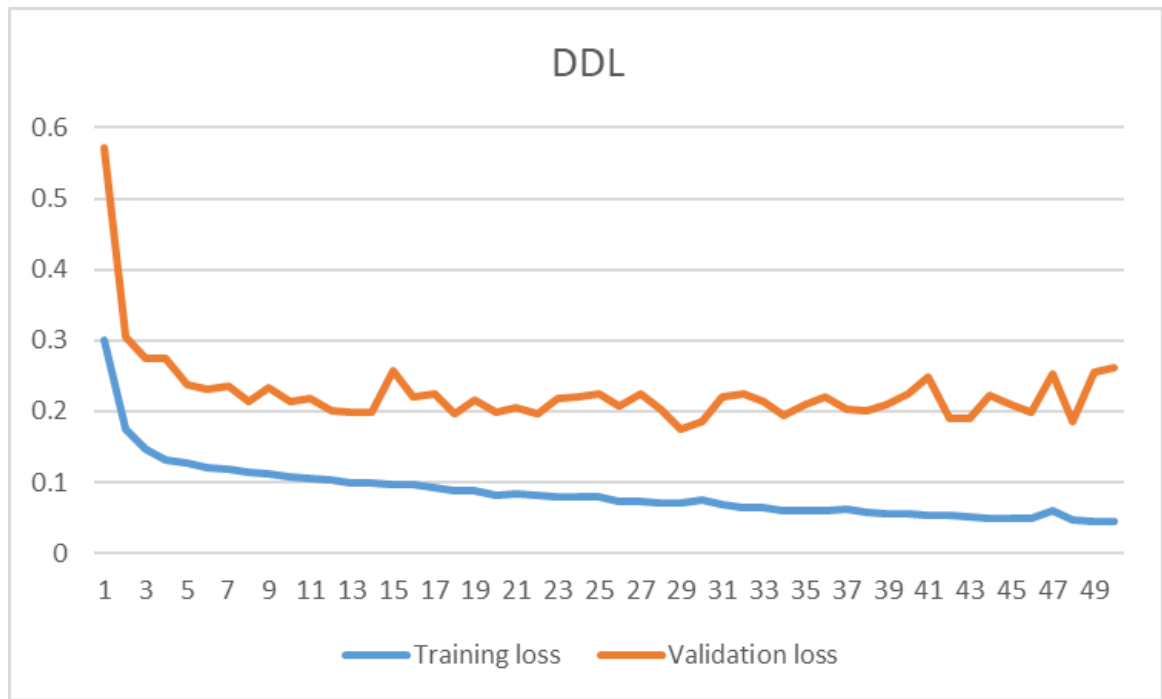


Figure 5. Loss vs Epoch Graph for 2 GPUs training

The training loss in Fig 5 is decreasing steadily as the cost function updates the weights to reduce the training loss and the validation loss varies but over time it is decreasing indicating the model is generalizing.

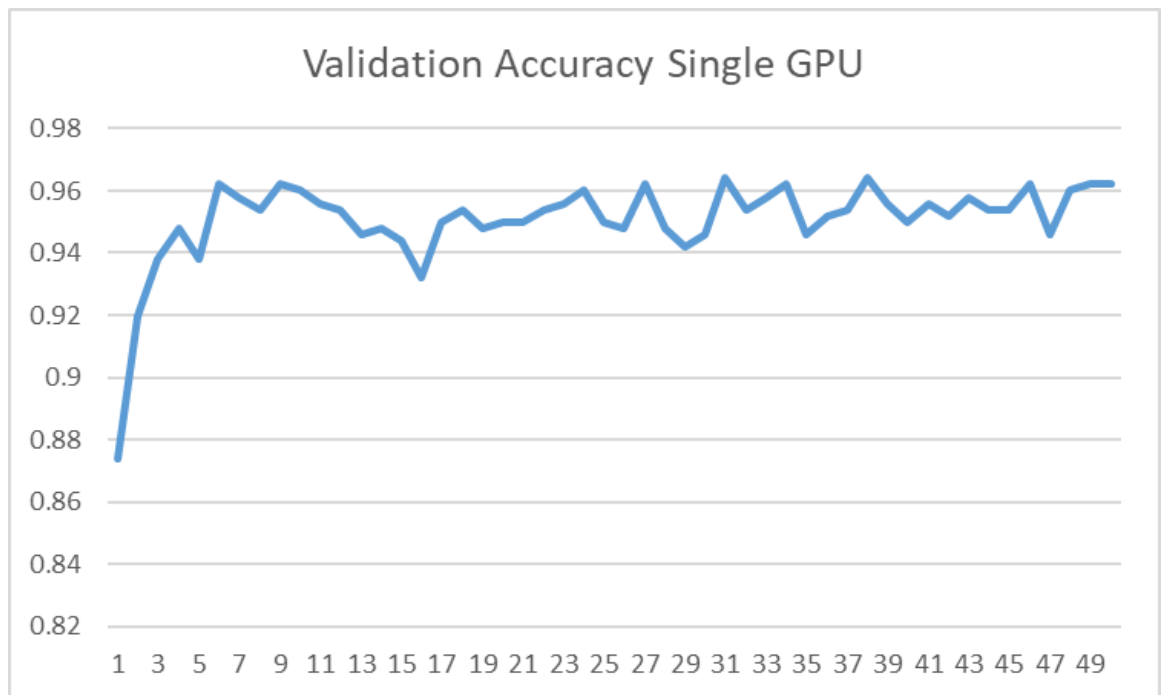


Figure 6. Validation Accuracy vs Epoch Graph for Single GPU training

In Fig 6 the validation accuracy is increasing with the epochs in general

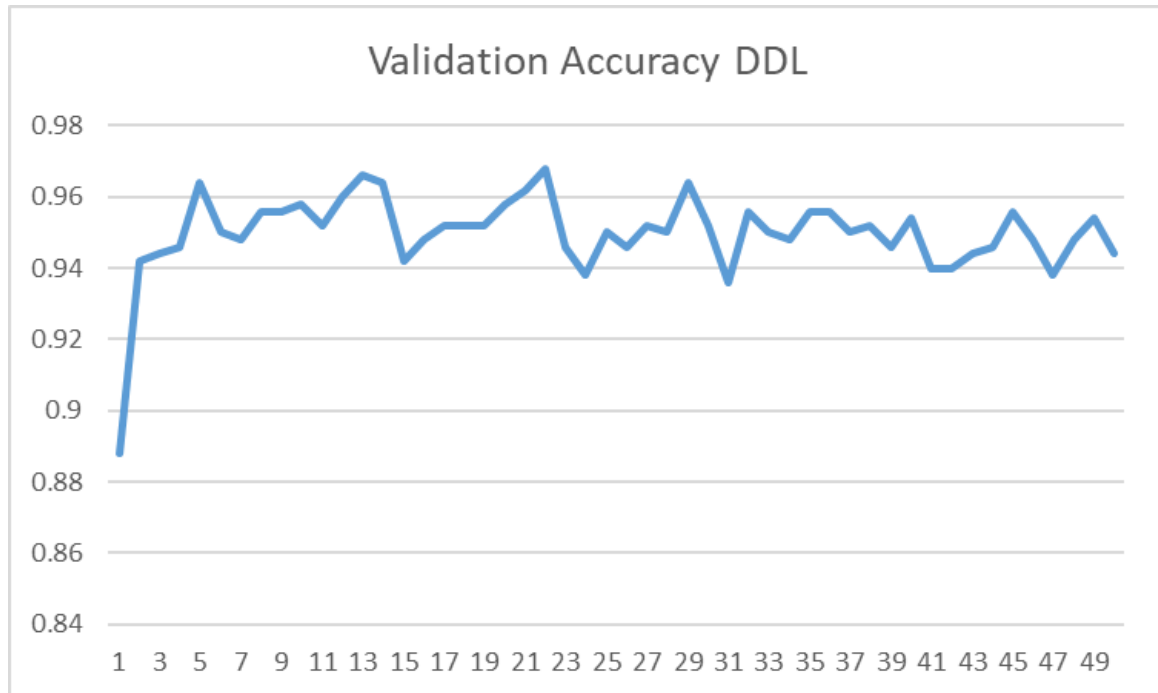


Figure 7. Validation Accuracy vs Epoch Graph for 2 GPUs training

In Fig 7 the validation accuracy is increasing with the epochs in general

8. Conclusion

We used ResNet50 Model trained on the ImageNet Dataset and retrained it to classify a given greyscale Chest X-ray image into Normal or Pneumonia. We reduced the training time by using Distributed Deep Learning. Based on the results we can see that using the Distributed Deep learning approach we can achieve faster results and work with existing hardware to train and evaluate complex models. With this, we can deploy the model to significantly reduce the time taken to diagnose a person suffering from pneumonia from a simple chest X-ray image.

9. BIBLIOGRAPHY

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10. APPENDIX

10.1 Gantt Chart

