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DIAGNOSIS OF PNEUMONIA USING DEEP LEARNING

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ABSTRACT

Pneumonia is a high-mortality disease that claims the lives of 50,000 Americans each year. Pneumonia is a dangerous illness that affects children under the age of five and elderly people over the age of 65. Every year, the United States spends billions of dollars to combat pneumonia-related diseases. In the treatment of pneumonia-related illnesses, early detection and intervention are critical. We propose a deep learning approach based on convolutional neural networks to identify and classify pneumonia cases from chest x-ray pictures because it is one of the simplest and cheapest ways to diagnose pneumonia.

Keywords: Deep Convolutional Neural Networks, CNN Model, Flask Web-App.

I. INTRODUCTION

Pneumonia is a life-threatening respiratory infection caused by bacteria, fungi, or viruses that infect and fill the human lung air sacs with fluid or pus. Pneumonia is a leading cause of death in children and the elderly around the world. Chest X-rays are the most thorough method of detecting pneumonia, and the data must be examined by a physician. Due to erroneous diagnosis and treatment, a person died as a result of the inconvenient method of diagnosing pneumonia. It is now possible to construct an autonomous system for identifying pneumonia and treating the condition, especially if the patient is in a distant area with few medical services, thanks to advances in computer technology. As a result, this is the key motivation.

Deep Learning

Deep Learning is a data science approach that allows a computer to gain insight into patterns and existing data in order to forecast the outcomes. With a robust machine learning model, tasks like identifying Pneumonia disease may be automated, efficient, and accurate, as well as identify patterns and qualities in data that humans may forget. To train data input and apply statistical analysis to create specified output, a deep learning algorithm is used. Deep learning uses a variety of algorithms to predict disease. It's possible that humans will not notice. To train data input and apply statistical analysis to create specified output, a deep learning algorithm is used. Deep learning uses a variety of algorithms to anticipate outcomes.

II. RELATED WORKS

In the field of medical picture categorization, deep learning approaches are becoming increasingly popular. This is due in large part to the high success rate of these algorithms. Early machine learning models faced difficulties such as low accuracy, which was mostly dependent on the performance of feature extraction layers. Feature extraction techniques such as Scale Invariant Feature Transform (SIFT), Speeded Up Robust Features (SURF), and others are used in traditional machine learning techniques. Many of the most well-known and successful medical picture classification projects used deep learning algorithms like Convolutional Neural Networks (CNN). The results of a CT scan were used by Roth et al to identify and classify Lymph Node (LN) detection using CNN. They were able to achieve high classification accuracy when compared to previous approaches that used boosting-based feature selection, which resulted in a high number of false positives. For cell picture segmentation and tracking, CNN with the U-net technique was utilized, as demonstrated in. Olaf Ronneberger, Philipp Fischer, and Thomas Brox introduced U-net, a 23-layer CNN, in 2015. To correctly identify and categorize lung nodules, Lan et al used deep CNN with the U-Net algorithm and the addition of a Residual network. In 2015, the residual network was introduced.

Another significant aspect of medical image analysis is organ segmentation. The pancreas, liver, kidneys, and heart are just a few of the organs in our body that have a lot of structural variation. As a result, medical picture analysis becomes a considerably more difficult task. Deep CNN was employed for pancreatic segmentation using Computerized Tomography (CT) findings, as previously stated. Organ segmentation is a critical step in

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detecting aberrant growth or malignancy in organs with a lot of anatomical variation. Bier et al. present a new method for recognizing anatomical landmarks in X-ray pictures that is independent of viewing direction. They were able to identify 23 anatomical landmarks of the pelvis from a single x-ray using the CNN model. presented a bottom-up strategy including intensive tagging of picture patches to cover the entire organ. When compared to prior organ segmentation methods that used random forests, this method has a high level of accuracy. This is a difficult assignment since scans of the lung field tend to involve rib cages with variable bone densities, the presence of clavicles, and, in some circumstances, the existence of different lung irregularities can change the lung field. The thoracic cage boundary was produced using this method from several manually built boundaries. However, this approach has been only tested on a small dataset, so I'm not sure how the model performs on a wider scale. Furthermore, when various pulmonary abnormalities are present, like those in cases of pneumonectomy, this methodology tends to fail.

III. PROPOSED METHOD

We will be using Deep Learning Algorithms to detect Pneumonia in this project. There are different methods to diagnose Pneumonia using Chest X-Ray images, but we'll examine different algorithms, test overall accuracy, and select the best algorithm for detecting Pneumonia. We'll use Flask and HTML to create a Web app to view the results after choosing the best algorithm from the pre-trained ones. The dataset we used for this research is from Kaggle, which is a free source. The dataset is split into 3 folders (train, test, and val) with subfolders for each image type (Pneumonia/Normal). There are 5,863 X-Ray pictures (JPEG) in total, divided into two categories (Pneumonia/Normal). Anterior-posterior chest X-ray images were selected from retrospective cohorts of children patients aged one to five years old at Guangzhou Women and Children's Medical Center in Guangzhou. Various deep learning techniques are used in this project to generate the prediction of Pneumonia using various steps. Dataset extraction, image preprocessing, data augmentation, model selection, training, and detection are all improvements that can be made with data.

Block Diagram of the System

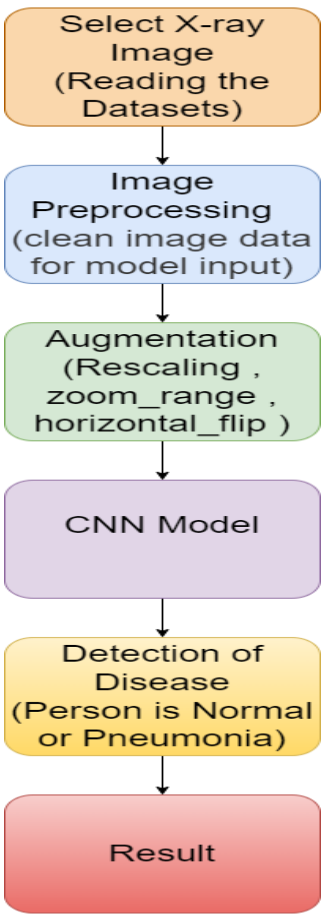

Fig 1: Block Diagram of the System

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Use case of the System

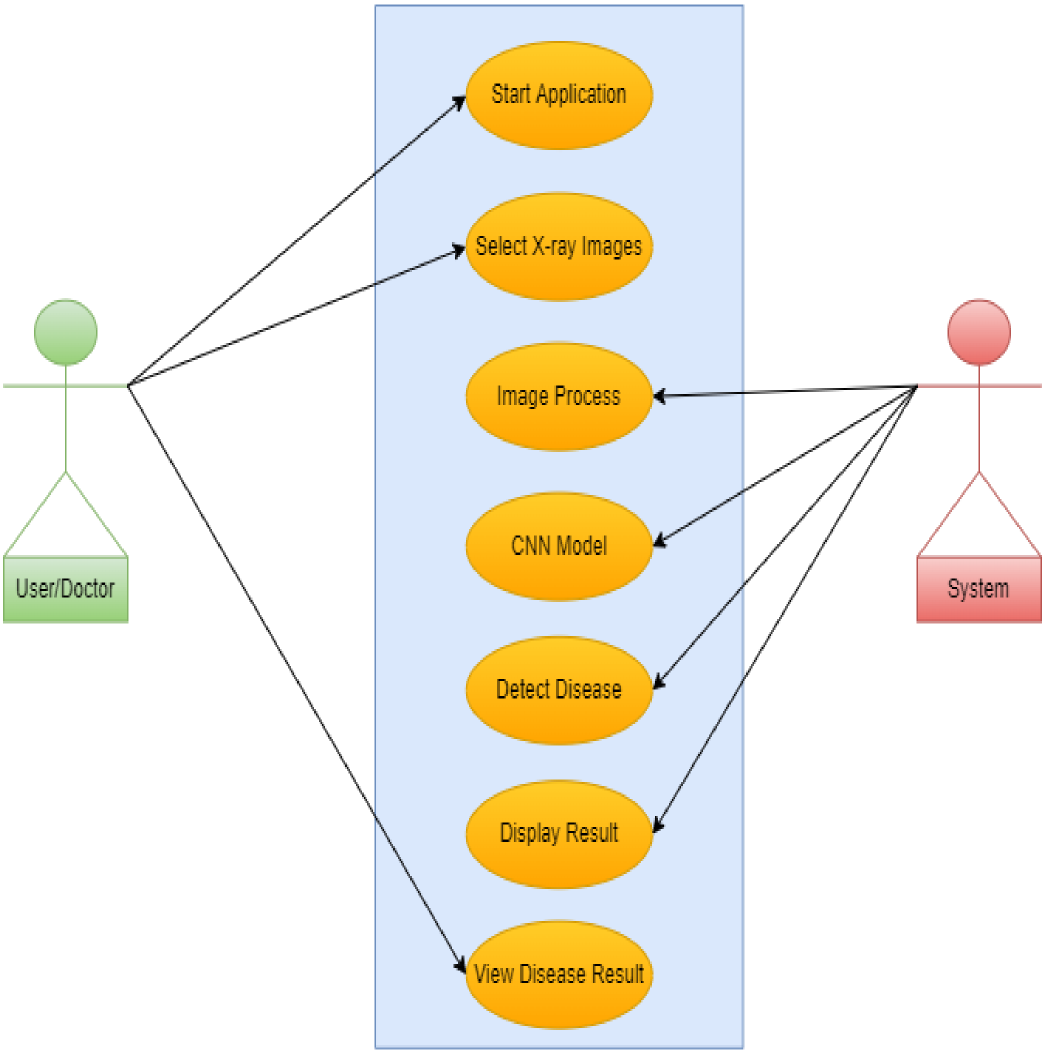

Fig 2: Use case of the System

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Flowchart of the System

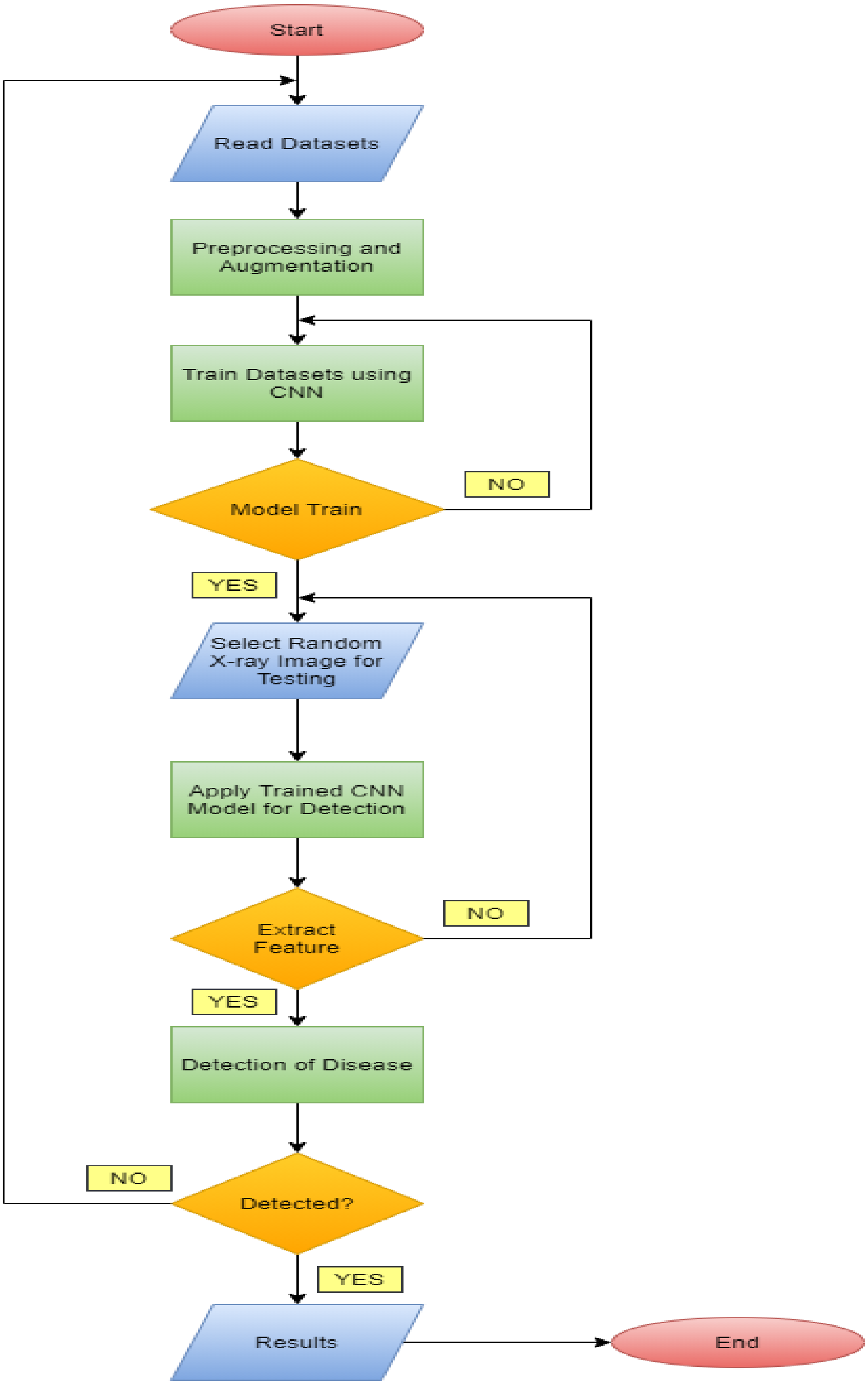

Fig 3: Flowchart of the System

IV. DATASET DESCRIPTION

The dataset utilized in the proposed study was discussed and evaluated in the context of deep learning-based disease categorization and referral for treatable human diseases. There are a total of 5856 Chest X-Ray images in this collection. These photos are then divided into two categories: 1583 for normal chest X-ray scans and 4273 for Pneumonia X-Ray scans. Each image was almost 1000x1000 pixels in size. These photos were resized to 175x175 pixels before being submitted to CNN algorithms.

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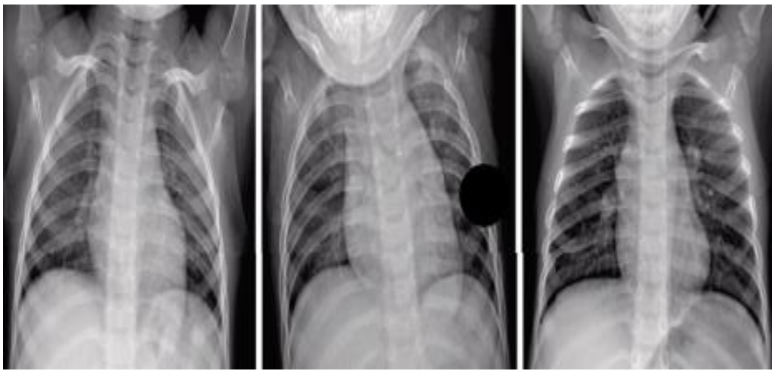

Fig 4: Chest X-ray Images of non-pneumonia patients

Fig 5: Chest X-ray Images of pneumonia patients

Images from the normal and pneumonia classes are depicted in Figures 4 and 5. The pneumonia class's first two X-Ray images (Figure 5) are noticeably blurrier than the normal class's images, making them immediately distinguishable. However, without the requisite domain knowledge in medical science concerning pneumonia, the third image from the pneumonia class cannot be separated from photographs from the normal class (Figure 4). In the following section, we propose various deep learning models for pneumonia classification by providing entire X-Ray images to extract and learn the unique features of X-Ray images from both normal and pneumonia classes in the dataset.

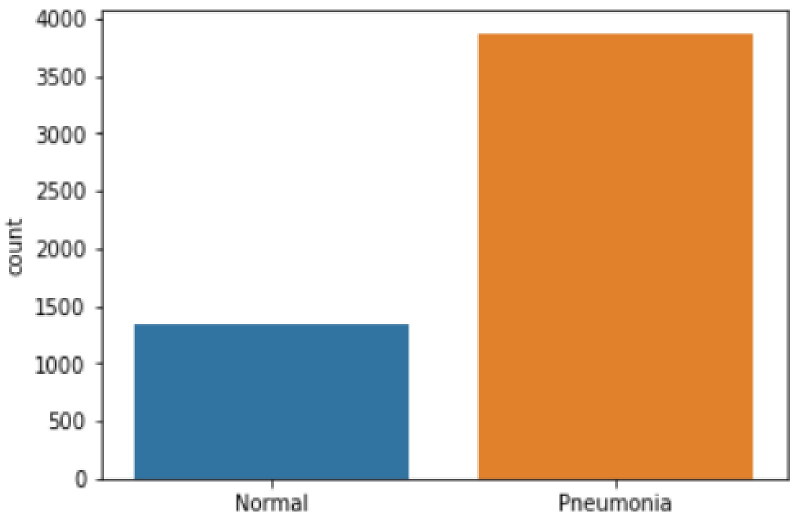

Fig 6: Representational Datasets (Normal or Pneumonia)

V. DIFFERENT METHODS AND RESULTS

The Different Deep Learning Models used in comparing and detecting Pnemounia are CNN_1, CNN_2, DenseNet121, VGG16, ResNet50, InceptionV3

A) Different models :

Here is a small comparison of all the models:

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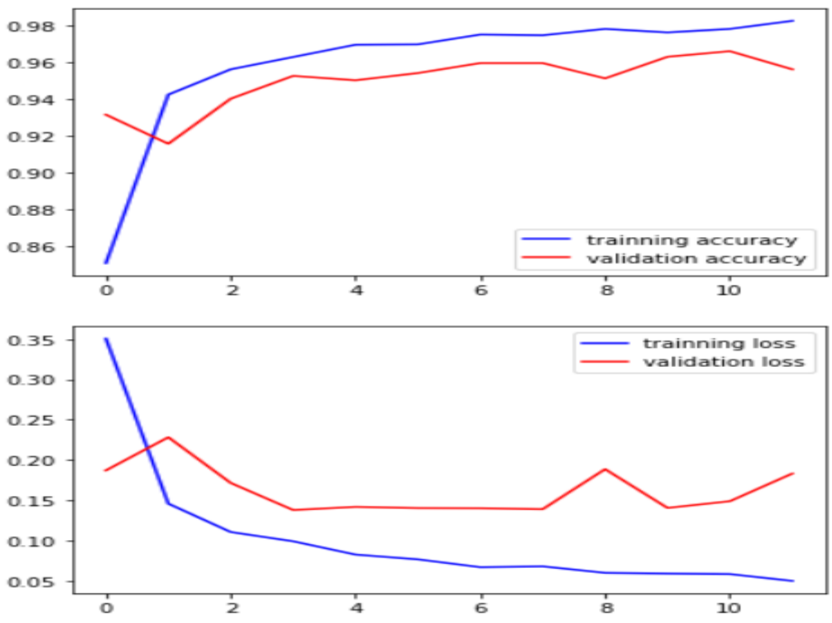
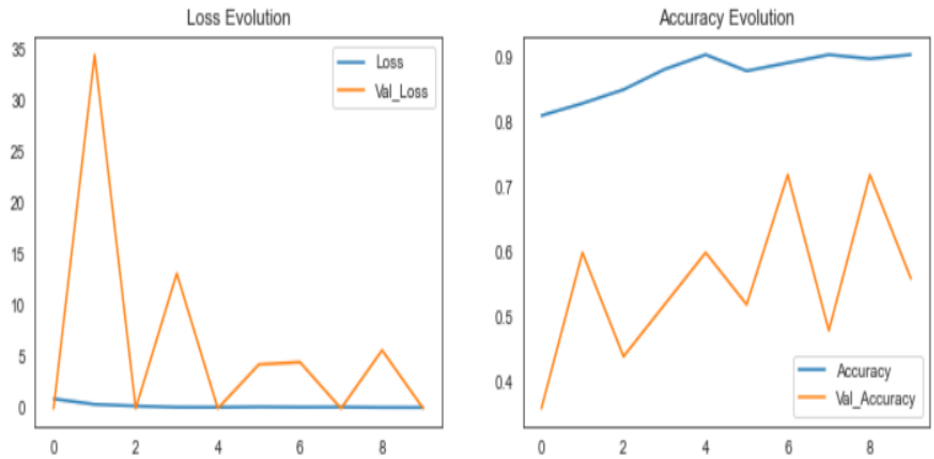
1) CNN-2 :



Test Accuracy: 95.70%

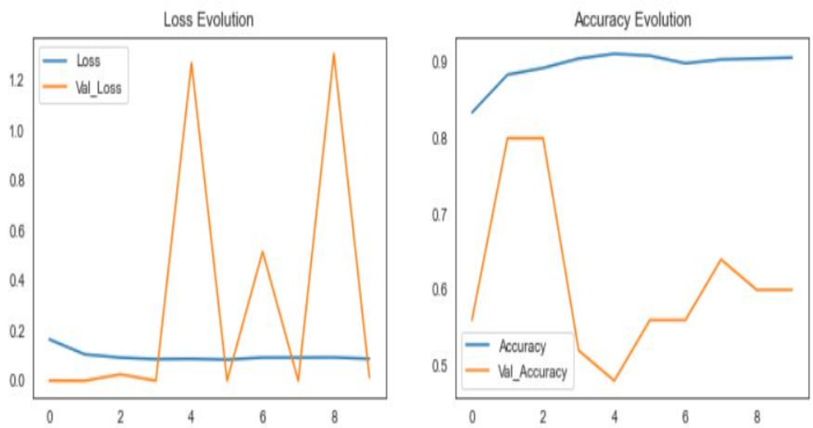
Train Accuracy: 96.88%

2) CNN-1:



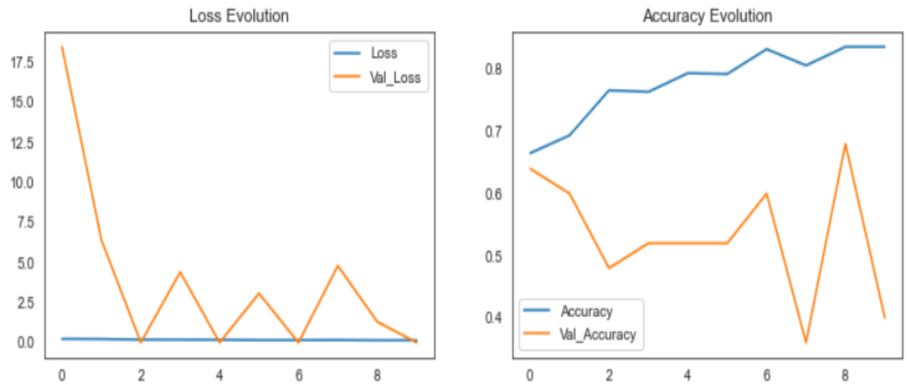
Test Accuracy: 80.77% Train Accuracy: 92.87%

3) DenseNet121:



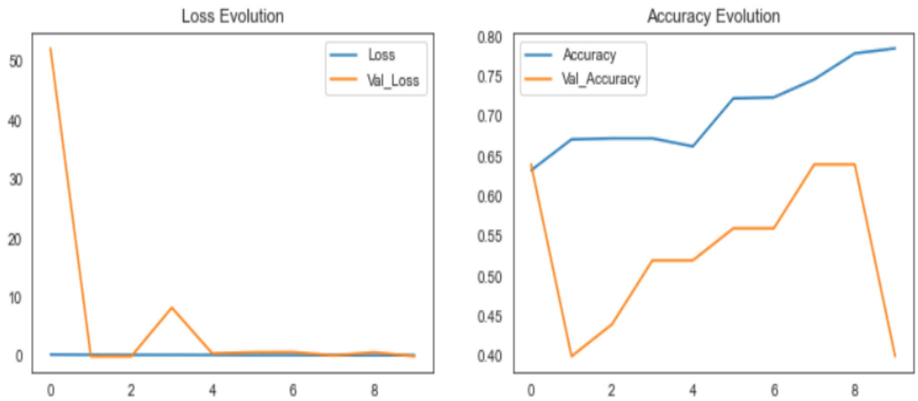
Test Accuracy: 87.66% Train Accuracy: 93.00%

4) VGG16 :



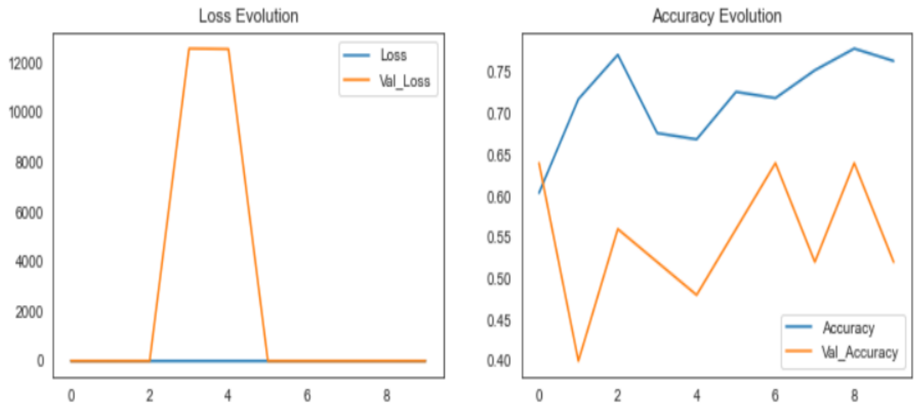
Test Accuracy: 62.50% Train Accuracy: 74.31%

5) Resnet50 :



Test Accuracy: 62.50% Train Accuracy: 74.19%

6) InceptionNetV3 :



Test Accuracy: 71.47% Train Accuracy: 88.40%

Table of Accuracy Content

Models	Test Accuracy
CNN-2	95.70 %
CNN-1	80.77 %
DenseNet121	87.66 %
VGG16	62.50 %

ResNet50	62.50 %
InceptionNetV3	71.47 %

B) Results:

1) Visualizing result:

Some correct visualization

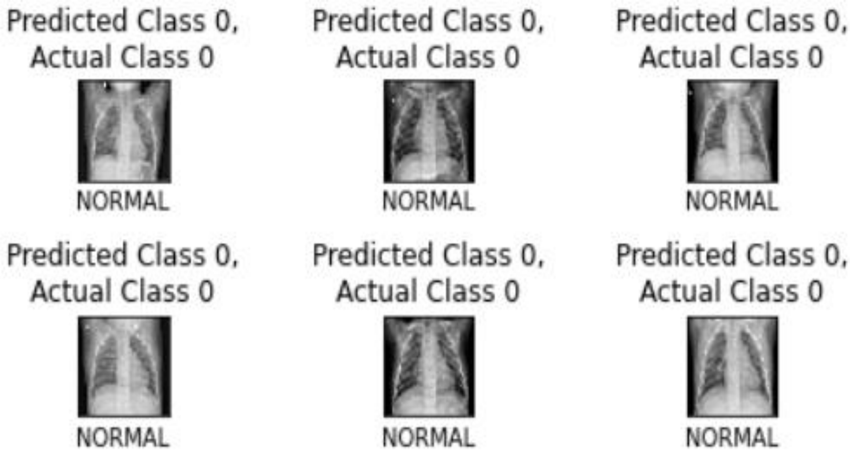


Fig 7: Using the proposed model, the results of six random chest radiographs were obtained from the Normal test dataset

Some incorrect visualization

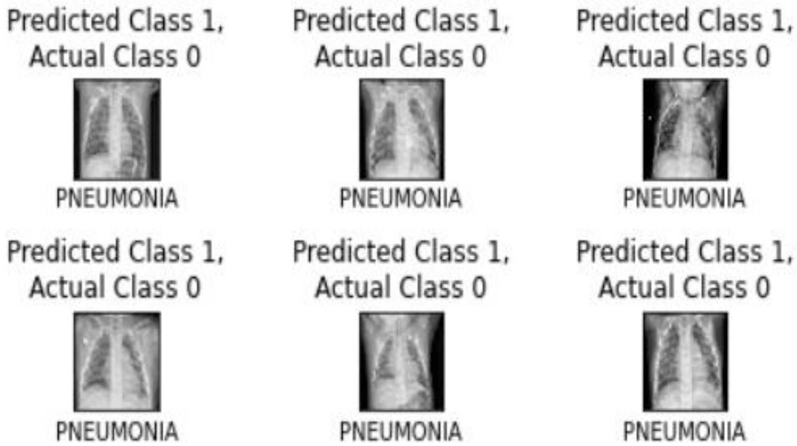


Fig 8: Using the proposed model, the results of six random chest radiographs were obtained from Pneumonia test dataset

2) Grad-CAM Results(Model visualization) :

Gradient-weighted Class Activation Mapping (Grad-CAM), uses the gradients of any target concept (such as 'chest x-ray' in a classification network or a sequence of words in the captioning network) flowing into the final convolutional layer to produce a coarse localization map highlighting the important regions in the image for predicting the output. We can use the Grad-CAM heat maps to give us clues into why the model had trouble making the correct classification.

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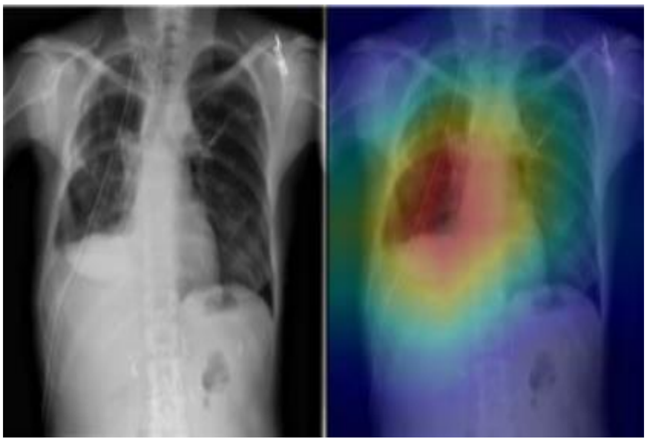

Fig 9: Disease detection from left Portion of Chest X-ray

Fig 10: Disease detection from Right Portion of Chest X-ray

In this case, we employed the CNN-2 model, which provides more accurate results. This model will diagnose pneumonia with 95% accuracy, after which visualization will be used to depict the affected section area using the grad-Cam algorithm to determine which side of the lungs is affected.

3) Flask Web-app:

Flask is a simple and lightweight Python web framework that provides essential tools and capabilities for developing online applications in Python. We present a platform that makes it easier to detect pneumonia sickness by utilizing a graphical user interface (GUI), which is a web application that allows users to interact with the web app in order to reduce the time it takes to announce a result.

Fig 11: Result Pneumonia with Basic Uploaded Image

Fig 12: Pneumonia Result with Grad-Cam Image (Highlighted means Infected)

VI. CONCLUSION

Pneumonia is a contagious illness that has plagued mankind for millennia. Despite substantial technological advancements, pneumonia remains one of the top ten causes of mortality worldwide. In order to treat pneumonia, it is vital to act quickly and accurately. One of the cheapest and most regularly used diagnostic tools for detecting pneumonia and other lung problems is a chest x-ray. We have proposed a novel tool that can assist enhance diagnosis accuracy of pulmonary problems from chest radiographs, thanks to startling breakthroughs in modern deep learning algorithms. We used the most prevalent deep learning method known as a convolutional neural network to implement computer-aided diagnostics of pneumonia throughout this study (CNN).

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