Chapter 1 INTRODUCTION

1.1 OVERVIEW

A respiratory illness called pneumonia causes inflammation in one or both of the lungs. Bacteria, fungi, viruses, and other microorganisms can all cause pneumonia. Basically Pneumonia affects the air sacs of the lungs. Symptoms like fever, including pain, coughing, and breathing difficulties can occur when the air sacs fill with fluid or pus. A lot of traditional methods that rely on radiologists' visual interpretation of chest X-ray images can be time-consuming and error-prone, even though they are still essential diagnostic tools. Using a sophisticated deep learning architecture and a multinet web interface with unique features, this study aims to overcome these limitations by automatically detecting pneumonia from chest X-ray images. This novel approach has the potential to revolutionize early diagnosis, boost accuracy and effectiveness, and ultimately save lives.

In this study we Proposed a method to automated pneumonia identification structure named “DeepPulmoMultinetWeb” architecture. In order to make the highest results we used multiple feature extraction model like MobileNet, NASNetMobile, VGG19, ResNet50, Vgg16, Xception and DenseNet201. Then to aggregate all of the features, we utilized a concatenation layer with the two best models (Xception, and DenseNet201). We achieve good classification performance in our proposed method.

1.2 PROBLEM STATEMENT

Pneumonia, a prevalent respiratory infection, poses a significant global health challenge, contributing to morbidity and mortality rates worldwide. The conventional methods of diagnosing pneumonia, particularly through chest X-rays, often rely on manual interpretation by medical professionals. However, this process is labor-intensive, subjective, and prone to interobserver variability, leading to potential delays in diagnosis and treatment.

Moreover, the high demand for healthcare services, especially in resource-constrained environments, has underscored the need for efficient and accurate diagnostic tools. Traditional approaches to pneumonia diagnosis may struggle to keep pace with the increasing number of cases, and there is a pressing demand for automated, technology-driven solutions that can augment and expedite the diagnostic process.

This project addresses the inherent challenges in pneumonia diagnosis by leveraging the power of deep learning techniques applied to chest X-ray images. The objective is to develop a robust and reliable model capable of accurately detecting pneumonia from medical imaging, with the potential to enhance diagnostic efficiency, reduce subjectivity, and facilitate timely interventions. The focus extends beyond merely automating the

diagnosis; it aims to contribute to improved patient outcomes by providing a tool that aids healthcare professionals in making more informed and faster decisions.

By identifying and addressing the limitations of current diagnostic methods, this project seeks to pave the way for a scalable and accessible solution that can make a meaningful impact on the early detection and management of pneumonia. Ultimately, the goal is to contribute to the advancement of medical technology, making pneumonia diagnosis more efficient, accurate, and widely accessible, especially in settings where prompt healthcare interventions are crucial.

1.3 MOTIVATION

The intersection of healthcare and technology has opened avenues for innovative solutions to address longstanding challenges in medical diagnostics. In this context, the integration of deep learning techniques into medical imaging has emerged as a promising approach. The motivation behind this project lies in leveraging the power of deep learning to enhance the detection of pneumonia from chest X-ray images. By automating and augmenting the diagnostic process, we aim to overcome the limitations of current methods and contribute to the development of a more efficient and reliable tool for pneumonia detection.

1.4 SCOPE AND OBJECTIVES

This project focuses on harnessing the capabilities of deep learning to analyze chest X-ray images and accurately identify signs of pneumonia. The scope extends to addressing the challenges associated with manual interpretation, enabling a more scalable and accessible solution. Our objectives include developing a robust deep learning model capable of distinguishing pneumonia-related abnormalities in X-ray images, optimizing diagnostic efficiency, and providing valuable support to healthcare professionals in making timely and informed decisions.

1.5 STRUCTURE OF THE PROJECT

The structure of this project encompasses various stages, including understanding the medical background of pneumonia, exploring deep learning concepts relevant to image analysis, collecting and preprocessing data, designing an effective model architecture, training the model, and evaluating its performance. We will also delve into the challenges and limitations associated with pneumonia detection, discuss future directions, and present real-world applications through case studies. The project concludes with a reflection on the contributions made and recommendations for future research and implementation.

1.6 MEDICAL BACKGROUND

The respiratory illness known as pneumonia is characterized by inflammation of the lung parenchyma, which affects the alveoli, or small air sacs. Viruses, fungi, bacteria, and, less frequently, parasites are the main infectious agents that cause it. Lung function is compromised as a result of the condition's buildup of fluid, mucus, and inflammatory cells in the alveoli, which hinders regular gas exchange.

1.6.1 Understanding Pneumonia

Pneumonia, a formidable respiratory infection, manifests as inflammation in the air sacs of the lungs, compromising their ability to function effectively. Typically caused by bacteria, viruses, or fungi, pneumonia leads to the accumulation of fluid and pus in the lungs, resulting in symptoms such as cough, fever, and difficulty breathing. Understanding the diverse etiologies, clinical presentations, and potential complications of pneumonia is crucial for effective diagnosis and management. Additionally, aspiration pneumonia results from the inhalation of foreign substances into the lungs, further highlighting the varied nature of this respiratory condition.

1.6.2 Importance of Early Detection

Early detection of pneumonia plays a pivotal role in improving patient outcomes and preventing the progression of the infection to severe complications. Timely diagnosis allows for prompt initiation of appropriate treatment, which may include antibiotic therapy or antiviral medications. Early intervention not only accelerates the recovery process but also reduces the risk of complications, such as respiratory failure or sepsis, associated with advanced stages of pneumonia.

Moreover, in a public health context, early detection is crucial for implementing effective containment measures, especially in cases of infectious agents causing pneumonia. Rapid identification and isolation of affected individuals contribute to preventing the spread of the infection within communities and healthcare settings.

The significance of early detection extends beyond individual patient care; it has broader implications for healthcare systems and resource allocation. Efficient and timely identification of pneumonia cases enables healthcare providers to allocate resources effectively, streamline patient care pathways, and minimize the burden on medical facilities.

1.6.3 Role of Chest X-rays in Diagnosis

Chest X-rays have long been integral to the diagnosis of pneumonia due to their ability to provide detailed images of the chest cavity. In pneumonia cases, chest X-rays reveal

characteristic patterns, such as opacities, consolidations, and infiltrates, indicative of lung inflammation. This imaging modality offers accessibility, speed, and cost-effectiveness, making it a widely utilized tool in pneumonia diagnosis.

1.7 DEEP LEARNING IN MEDICAL IMAGING

Deep learning, a subset of machine learning, has revolutionized the field of medical imaging by leveraging neural networks to automatically learn and extract complex patterns from vast datasets. At its core, deep learning involves the hierarchical representation of features, enabling the model to autonomously identify intricate structures within images. Convolutional Neural Networks (CNNs), a prevalent architecture in deep learning, have demonstrated remarkable success in tasks related to medical image analysis.

1.7.1 Applications in Medical Imaging

The applications of deep learning in medical imaging are extensive and transformative. In diagnostics, deep learning models excel at detecting abnormalities, localizing lesions, and classifying diseases from various imaging modalities such as X-rays, CT scans, and MRIs. Beyond diagnostics, deep learning contributes to image segmentation, aiding in the precise delineation of organs and structures for treatment planning. Furthermore, it facilitates image synthesis, enhancing the quality of medical images and generating realistic visualizations for educational purposes. The versatility of deep learning extends to pathology detection, risk stratification, and personalized treatment planning.

1.7.2 Advantages and Challenges

Advantages:

- Automation and Efficiency: Deep learning automates image analysis, reducing the dependence on manual interpretation and enhancing efficiency.
- Accurate Detection: Neural networks excel at recognizing intricate patterns, leading to high accuracy in detecting subtle abnormalities.
- Adaptability: Deep learning models can adapt to diverse imaging datasets, making them versatile across different medical imaging modalities.
- Continuous Learning: Models can continuously learn and improve performance with additional data, ensuring adaptability to evolving medical scenarios.

Challenges:

- Data Limitations: Deep learning models require large and diverse datasets for robust training, which may be challenging to obtain in certain medical domains.

- Interpretability: The "black-box" nature of deep learning models raises concerns about their interpretability, especially in critical medical decision-making scenarios.

- Overfitting: Models may overfit to specific datasets, potentially leading to poor generalization and performance on unseen data.

- Computational Resources: Training sophisticated deep learning models demands substantial computational resources, posing challenges for implementation in resource-limited environments.

1.8 PROJECT OUTLINE

In this chapter, summarize the overall structure and key components of the project and providing a roadmap. The rest of the book is organized as follows:

In Chapter 2, provides a structured approach to reviewing the literature, focusing on motif representation and algorithmic approaches relevant to your pneumonia detection project.

In Chapter 3, Chapter 3 offers an overview of the proposed methodology for pneumonia detection using a deep learning approach. The chapter also delves into data augmentation methods to enhance model robustness. The core of the methodology involves developing a multi-net feature learning model, incorporating Convolutional Neural Networks (CNN) such as MobileNet, NASNetMobile, VGG19, ResNet50, Vgg16, Xception and DenseNet201. A detailed section on the fine-tuning process is included. The chapter concludes with a summary of the algorithm utilized. The summary highlights the comprehensive methodology, integrating various deep learning architectures and fine-tuning processes for effective pneumonia detection.

In Chapter 4, the result and the comparison has been shown briefly and how we came up with our final model.

In Chapter 5, it has been describing comparison between some popular existing works and our works.

In Chapter 6, it has been describing evaluation, limitations and conclusions.

SUMMARY

The first chapter of the project book provides a comprehensive overview of the research, addressing key elements such as the project's background, problem statement, and motivation. The scope and objectives of the project are clearly defined, setting the stage for a detailed exploration of the subject matter. The structure of the project is outlined to guide readers through the subsequent chapters. Additionally, the chapter delves into the medical background, focusing on understanding pneumonia and emphasizing the importance of early detection. The role of chest X-rays in the diagnosis process is highlighted to underscore their significance in the medical field. The section on deep learning in medical imaging explores its applications, advantages, and challenges, setting the context for the project's focus on leveraging deep learning techniques for pneumonia detection through chest X-rays. The chapter concludes with an outline of the project, providing a roadmap for readers to follow as they navigate through the subsequent chapters.

Chapter 2 LITERATURE REVIEW

2.1 HISTORICAL PERSPECTIVE

Pneumonia, a severe respiratory infection affecting the lungs, has long been a focus of medical research. In the past, radiologist had to manually evaluate chest x-ray picture in order to diagnose pneumonia. Automated solutions have been explored dure to the subjectively of visual assessment and the differently of spotting tiny patterns.

Early efforts in pneumonia detection centered around manual image analysis and rudimentary image processing techniques. Radiologists utilized basic visual cues, such as the presence of opacities or infiltrates, to identity potentials cases. However, these methods lacked the precision required for accurate and consistent diagnosis.

The history of pneumonia detentions has been significantly shaped by the advancement of imaging technology. Better image quality and easier algorithm development were made possible by the switch from analog to digital X-rays.

Even with these early success, historical methods were limited by the variety of pneumonia types, the complexity of imaging characteristics and the requirement for large training datasets. The shortcomings of earlier techniques highlighted the need for more complex, data-driven solutions which paved the way for the AI based techniques used today.

2.2 CURRENT-STATE-OF-ART

Advances in deep learning techniques have led to a transformation shift in pneumonia detection in recent years. Accuracy and efficiency improvements in chest x-ray analysis have resulted from the use of neural networks. There are several models and methodologies that have propelled pneumonia detection into a new era:

Convolutional Neural Networks (CNN) the widespread adoption of CNNs has been a cornerstone in the current landscape of pneumonia detection. Modes like MobileNet, NASNetMobile, VGG19, ResNet50, Vgg16, Xception and DenseNet201 have demonstrated exceptional capabilities in feature extraction and hierarchical representation learning, contributing to superior diagnostic accuracy.

Attention Mechanism recent innovation includes the integration of attention mechanisms within neural networks, allowing models to focus on relevant image regions. Attention-based models, such as those utilizing spatial and channel wise attention, have show promise in improving localization and interpretability.

Transfer learning the utilization of pre-trained models on large datasets has become a prevailing strategy in pneumonia detection. Transfer learning leveraging knowledge gained from tasks like image classification, has facilitated the training of effective models even with limited labeled medical imaging data.

The translation of deep learning models from research to clinical practice is underway. On order to improve patient outcomes, computer scientists, radiologists and other healthcare professionals are working together to develop automated methods for pneumonia identification that can be smoothly integrated into standard diagnostic procedures.

2.3 KEY RESEARCH AND DEVELOPMENT

Deep learning approach has been greatly influenced in the healthcare and biological field in recent years. Artificial Intelligence and deep learning are being used in prediction system widely. Many academics has proposed different methodology on pneumonia detection in recent years, using the x-ray images of chest.

Mobarouk A. suggested ensemble learning approach where at first stage three pretrained DL models used MobileNetV2, DenseNet169 and Vision Transformer for dimensionality reduction then for pooling operation and then the output is flattened and concatenated to generate a single feature vector for input image then the final output is ensemble method is generated using a connected layers of neural network for classification result [1]. At Jain, R. the dataset divided into train and test consisted of 5216 and 624 images and total six models were used where the first two model are made of three convolutional layers and these two got the highest accuracy 92% [2]. Chouhan, V. proposed a method where the augmented data is pass through transfer learning using AlexNet, DenseNet121, InceptionV3, restNet18 and GoogleNet neural networks and combined the results of the five models and got accuracy of about 96.39% [3]. D. Varshni used the DenseNet for feature extraction and the SVM for classification and obtained the AUC of 0.8002 [4]. Yi, R. proposed a Deep CNN with 52 convolution layers and two dense layers for the identification of pneumonia using a chest x-ray [5]. Rachna Jain used six models using the VGG16, VGG19, ResNet50 and Inception-v3 where the accuracy is 87.28%, 88.46%, 77,56% and 70.99% respectively [6]. At Nalluri, S. The finest qualities from these returned attributes were chosen using the suggested AHGOA (Archimedes-assisted Henry Gas Optimization Algorithm) model. The easiest way to escape the curse of dimensionality is to choose this. With Chest X-ray pictures, the chosen EC + AHGOA approach achieves good accuracy (~0.95) for tuning percentage 70 in pneumonia diagnosis [7].

Table 2.1: Comparative analysis of existing research.

Reference	Dataset	Method	Accuracy
Mabrouk, A. (2022) [1]	5856 chest x-ray images	Deep CNN & ensemble learning	94%
Jain, R. (2020) [2]	Chest x-ray image from kaggle	VGG16, VGG19, RestNet50, Inception-v3	92%
Chouhan, V. (2020) [3]	Chest x-ray images	Ensemble model	96%
D. Varshni, K. (2019) [4]	112,120 chest x-ray images	Dens3Net(Feature Extraction)+SVMas(classifier)	92%
Yi, R. (2023) [5]		Deep CNN	96%
Rechna Jain. [6]	5856 chest x-ray images	VGG19, RegNetY008 and DenseNet121	87.28%
Nalluri, S. (2024) [7]	Chest x-ray images	EC+AHGOA	95%

The above **Table 2.1** showing a little description of other related work that has similarities with our project and their method they have approached.

SUMMARY

The literature review traces the trajectory of pneumonia detection methods, showcasing the evolution from manual interpretation to the contemporary era dominated by deep learning techniques. Historical milestones underscore the persistent challenges, while the current state-of-the-art highlights the transformative impact of models like CNNs, attention mechanisms, and transfer learning. As the field continues to progress, ongoing research endeavors are steering towards addressing challenges and defining the future directions for pneumonia detection using advanced computational methodologies.

Chapter 3 PROPOSED METHODOLOGY

3.1 OVERVIEW

In this section, we outline the experiments conducted to evaluate the efficiency and effectiveness of our proposed "DeepPulmoMultinetWeb" architecture for pneumonia identification using chest X-ray images. The study employs several multi-scale transfer learning models to enhance the accuracy of pneumonia detection. The schematic representation of the suggested architecture is illustrated in **Figure 3.2**. The experimental process involves various preprocessing techniques applied before the dataset is partitioned into training, testing, and validation classes.

3.2 DATASET

In this work, the kaggle chest X-ray pneumonia database was used, which is comprised of 5856 chest X-ray images [8]. Out of 5856 chest X-ray images, 4273 images are affected by pneumonia and 1583 images are from normal subjects. There are two labels being used to split all the folders: pneumonia and normal, which were applied to all the other pneumonia X-ray images.

In this **Figure 3.1** below shows that 5856 chest X-ray images divided into two categories (Normal and Pneumonia).

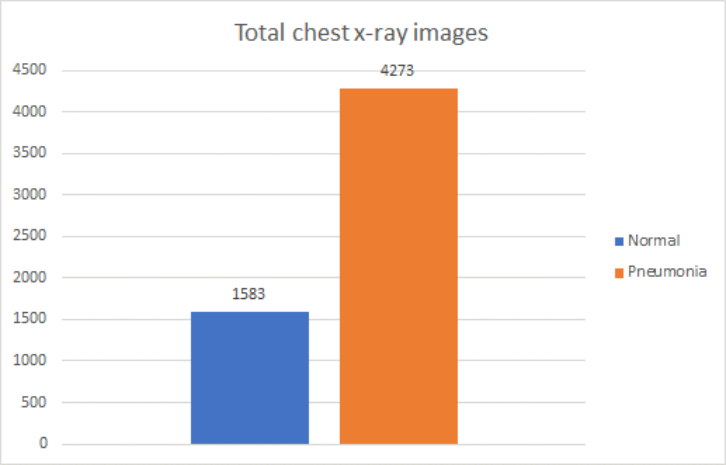


Figure 3.1: Quantity of normal and pneumonia images

3.3 PREPROCESSING

As shown in **Figure 3.2**, a variety of preprocessing methods were used before the pictures were input into the optimized variational deep learning methodology. All of the chest X-ray data is in jpeg format, with each channel having an 8-bit resolution and one grayscale channel. Using machine learning methods, we reduced the size of a large number of high-resolution photos to 224 × 224 pixels. The proposed technique reduces storage requirements and speeds up model training by transforming collected photos into

Numpy arrays. We create labels in the dataset, merge normal and pneumonia data, and shuffle train data. The entire image dataset was reorganized into 80% for training purposes, and 20% for testing. Hence, the measure of information is assigned to the complete dataset. A number of 4684 X-ray images were allocated to the training, and 1172 X-ray images to the testing data to test the system. The dataset is a publicly accessible dataset: containing JPEG images only. The Chest X-Ray Images (Pneumonia) data set is categorized as follows: normal and pneumonia.

3.4 DATA AUGMENTATION TECHNIQUES

To strengthen the model, the overfitting issue is resolved, and several data augmentation techniques are also applied. The size of this dataset increased from 5,856 to 33,965 after employing the data preparation technique. we apply some features to create a diverse set of augmented images, ensuring that the model is exposed to a wide range of variations in the training data. This is especially useful for improving the model's robustness and generalization to different conditions.

```
rotation_range=90,
width_shift_range=0.2,
height_shift_range=0.2,
shear_range=0.2,
zoom_range=0.2,
horizontal_flip=True,
fill_mode='nearest'
```

Table 3.1 and **Table 3.2** shows the differences in chest X-ray data before and after the augmentation process.

Table 3.1: Dataset before data augmentation.

Total Chest X-ray Images	Train	Test
5856	4684	1172

Table 3.2: Dataset after data augmentation.

Total Chest X-ray Images	Train	Test
33965	32788	1172

3.5 CONSTRUCTING MULTI-NET FEATURE LEARNING MODEL

This section shows how to use several multi-scale transfer learning models to identify pneumonia images. In this work, we proposed a novel multi-net neural adaptation system by combining Xception and DensNet201. Low-level attributes are captured by the hybrid

model, which then builds a multiple-net feature learning process to assess these features at different scales. The proposed "DeepPulmoMultinetWeb" architecture has 39,708,138 parameters after combining all of the features. The next subsections address the structure and contents of every recognized CNN pre-trained system in addition to the methods for fine-tuning.

The suggested "DeepPulmoMultinetWeb" structure employed in this identification is depicted in **Figure 3.2**.

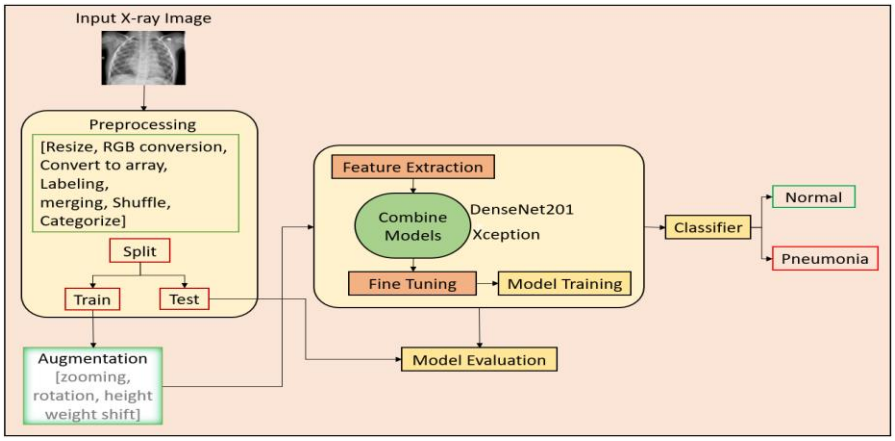


Figure 3.2: Basic diagram of proposed pneumonia detection system.

This **Figure 3.3** shows a selected group of images derived from chest X-ray datasets.

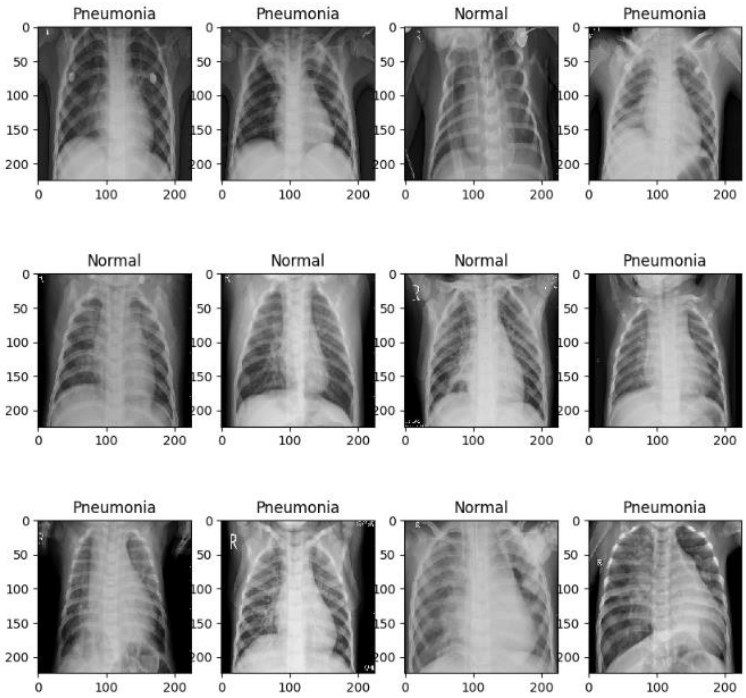


Figure 3.3: Derived sample images from chest X-ray datasets.

By merging DensNet201 with Xception, we suggested a unique multi-scale neural adapting system in this study. The hybrid model captures low-level properties before constructing a multiple-scale feature learning process to evaluate these features at various scales. Propose "DeepPulmoMultinetWeb" fine tuning process is illustrated in **Figure 3.4**.

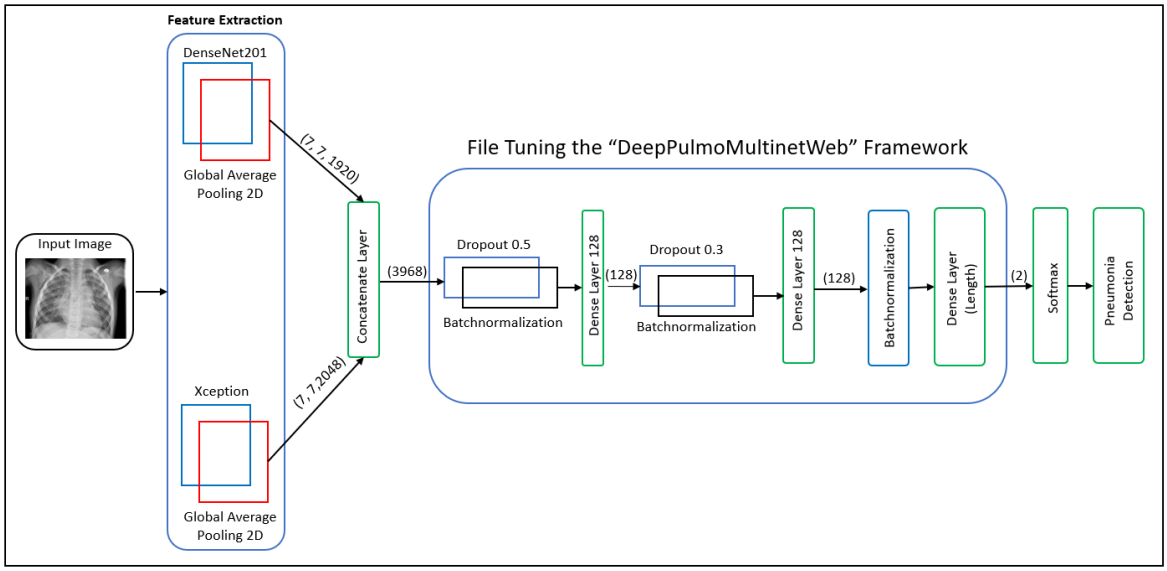


Figure 3.4: Fine Tuning Process of "DeepPulmoMultinetWeb" framwork.

3.5.1.1 MobileNet

The MobileNet architecture was designed by Howard et al.[9]. MobileNet works on multuple distinguish layers: (a) Depth-wise convolution-- where there is a single filter applied to each input channel and produce output (b) Point-wise convolution-- It takes all the output from the previous phrase as input a produce a output using a single line filter as 1×1×C×K where C is the number of output channels from the Depth-wise Convolution. After Convolution process MobileNet usually applied batch normalization and activation methods like ReLU. This model is widely used in object detection, Face recognition etc.

3.5.1.2 DenseNet

The DenseNet was suggested by Huang et al. [10]. It is a one of the kind of Convulation Nerual Network(CNN) used in deep learning is called DenseNet. Creating dense connections between layers is the main concept of DenseNet. DenseNet connections enable each layer to get input from every previous layer, in contrast to typical designs where each layer only receives data from the one before it. Using a DenseNet structure optimizes its capacity by minimizing the need for a deep or broad design through feature recycling, which is one of the main advantages of doing so.

DenseNet does not train redundant features, in contrast to conventional CNNs. It therefore needs fewer parameters. Furthermore, only a small number of new feature maps are added by the structure because of its very shallow layering. Additionally, throughout

the training phase, the structure depends on each layer having instant access to the gradients from the input image and the loss function.

3.5.1.3 RestNet50

RestNet50 was first introduced by He, K. [11]. To make training deeper networks easier, the ResNet model includes a residual learning architecture. Network layers are reformulated as learning residual functions with regard to the layer inputs, which forms the basis of the architecture. The depth of the residual network is eight times deeper than VGG nets [12] and its complexity is less.

3.5.1.4 Xception

Xception was first introduced by F Chollet [13]. The foundation of the Xception architenture is depthwise separable convolutions. It consists of two layers: (a) Depthwise Convolution- where all the input channels get separate applications of the depthwise convolution with a 3×3 kernel (b) Pointwise Convolution- This combines the depthwise convolution's output channels using a 1×1 kernel. Xception is also referes to Extreme Inception which is an expansion of the Inception architecture.

3.5.1.5 NASNet-Mobile

It was first mentioned in a publication by Zoph, B. [14]. Like other neural network designs, NASNet-Mobile was created with specific applications in computer vision in mind, most notably image recognition tasks. NASNet-Mobile was developed with certain computer vision applications in mind, most notably image recognition tasks, similar to other neural network architectures. For jobs on devices with limited resources, NASNet-Mobile is a good fit.

3.5.1.6 VGG

Visual Geometry Group (VGG) of the university of Oxford has introduced many vgg model variants in the field of deep learning such as vgg19, vgg16. These models are most used for feature extraction, large scale of visual Recognition challenge and strong image classification. The convolutional layers that remain can then be used to extract feature representations from the input pictures. Then, additional activities like picture categorization, object identification, or image synthesis can use these extracted characteristics as input.

3.5.2 Fine Tuning Process

To incorporate several transfer learning algorithms for pneumonia classifications, Figure 3 shows how to employ unique, completely connected tiers. As they extract each feature one at a time, all of the pre-trained models use GlobalAveragePooling2D to calculate the average value for every input channel, flattening all of the layers into a vector. All the

separate vectors are combined into one vector using the concatenate layer. Then, six layers and a SoftMax activation function are used to refine the combined features for our classification task. In the context of deep learning models, overfitting is a serious issue that arises when the system over-trains on training instances, leading to subpar test outcomes. To solve the overfitting issue, we use two dropout layers. While the next dropout stage will remove fewer samples than the preceding tier, the initial dropping tier will abandon the majority of the sample during model training. Additionally, this kind of approach greatly speeds up the training period. Moreover, our classification model has two batch normalization layers, which is crucial. All of the data will be swiftly normalized by the batch normalization layer through reorganization. The rearranged data will lessen startup-related vulnerabilities and help to speed up the training process. With the majority of neurons from both the previous and current levels, a density tier is a fully connected layer. These levels handle the incoming data and generate an output. The probability will be determined by this last layer using the anticipated class length as a basis. The SoftMax activation function determines which traits are most closely related to the particular predicted class by analyzing the likelihood of each result. When the output value in the SoftMax algorithm falls between 0 and 1, the neuron fires. The SoftMax function is defined by the above equation:

$$\text{softmax}(z)_j = \frac{\exp(z_j)}{\sum_{k=1}^{l} \exp(x_k)} \quad \text{.....(1)}$$

Here's step by step explanation of the softmax function for the j-th element:

- z_j is the j-th element of the input vector z.
- $\exp(z_j)$ is the exponential function applied to z_j.
- $\sum_{k=1}^{l} \exp(x_k)$ is the sum of the exponential values of all elements in the vector z (from k=1 to l).

The softmax value for the j-th element $(softmax(z)_j)$ is obtained br dividing the exponential of the j-th element by the sum of exponentials of all elements in the vector z.
The results of combining diverse deep learning methods and ultimately linked tiers are shown in **Table 3.3.** The statistic was generated during working on the boolean segmentation technique. As a result, there are two units in the ultimate entirely linked tier.

Table 3.3: The details of the proposed "DeepPulmoMultinetWeb" framework.

Layer (type)	Parameters	Result Formation
Input_1 (InputLayer)	0	[(None, 224, 224, 3)]
Mobilenet_1.00_224 (Functional)	3228864	(None, 7, 7, 1024)
Global_average_pooling2d (GlobalAveragePooling2D)	0	(None, 1024)
dropout (Dropout)	0	(None, 1024)
batch_normalization (Batch Normalization)	4096	(None, 1024)
dense (Dense)	131200	(None, 128)
dropout_1 (Dropout)	0	(None, 128)
batch_normalization_1 (BatchNormalization)	512	(None, 128)
dense_1 (Dense)	258	(None, 2)
Total params : 3364930		
Trainable params : 3340738		
Non-trainable params : 24192		

3.6 ALGORITHM

Algorithm 1 presents the suggested "DeepPulmoMultinetWeb" architecture for pneumonia detection.

Input: chest X-ray images Training set δ1, Validation set δ2, and Testing set δ3.
a ← Learning rate.
b ← Epochs.
c ← Batch size.
n ← The number of images covered in one batch size.
Output: w← "chest X-ray" framework weight.
begin:
1. Convert each chest X-ray image in training set into 224 × 224.
2. Perform data augmentation strategy for increasing the dataset size.

3. Extract the features from the chest X-ray images using Desnet201 and Xception CNN pre-trained models.
4. Combine the extracted features using the concatenate layer.
5. Set the fine-tuned layers $CNN_{dense,}$ $CNN_{batchnormalization,}$ $CNN_{dropout,}$ and $CNN_{softmax.}$.
6. Initialize the CNN pre-trained model parameters: a, b, c, n.
7. Train the "DeepPulmoMultinetWeb" framework and determine the initial weights.
8. for b = 1 to b do.
9. Select a mini batch size (size: n) for training set δ1.
10. Forward propagation and determine the loss function.
11. Backpropagation and update the weight w.
12. end for.

SUMMARY

DeepPulmoMultinetWeb is a comprehensive deep learning framework designed for the automated detection of pneumonia from chest X-ray images. We sourced chest X-ray images from Kaggle and performed many preprocessing steps, including resizing and conversion into numpy arrays. Overfitting concerns were addressed, and various data augmentation techniques were applied. The dataset was then split into 80% for training and 20% for testing. Our approach leverages Convolutional Neural Network (CNN) models, specifically MobileNet, NASNetMobile, VGG19, ResNet50, Vgg16, Xception and DenseNet201. Feature extraction from chest X-ray images was conducted using these CNNs, which were trained, validated, and tested on a dataset comprising 5856 high-resolution frontal view chest X-ray images. The top-performing models, DenseNet201 and Xception, were identified, and their extracted features were combined to provide the final results.

Chapter 4 IMPLEMENTATOIN AND RESULT COMPUTATION

4. 1 OVERVIEW

The discovered architecture, hyper-parameters utilized in the research, and findings obtained from the chest X-ray images datasets using the “DeepPulmoMultinetWeb” architecture are shown in this section.

4.2 HARDWARE & SOFTWARE USED

The "DeepPulmoMultinetWeb" architecture that has been proposed was constructed with the aid of Keras, an open-source software that links neural networks with Python. We use Jypter Notebook (PC) to train and assess the model on a 64-bit Windows 11 computer. The PC has an Intel 11th Generation Core i7 CPU running at 2.80 GHz with 8 GB of RAM.

4.3 PERFORMANCE MATRIX

The effectiveness of the suggested framework is assessed using a number of quantitative metrics, including Precision, Recall, False-positive rate, True negative rate (TNR) and F1-Score. The confusion matrix's conclusion determines parameters like True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). "TP" stands for a result where the recommended "DeepPulmoMultinetWeb" framework correctly identified the type of positive pneumonia. The result for which the proposed system correctly recognized the pneumonia that is negative is denoted by the word "TN." The word "FP" refers to a scenario where normal was incorrectly detected by the suggested framework. When a negative tumor type is incorrectly recognized by the suggested framework, it is referred to as "FN". Each assessment metric has the following name:

$$softmax(z)_j = \frac{exp(z_j)}{\sum_{k=1}^{l} exp(x_k)} \quad \text{.....(2)}$$

$$Accuracy = \frac{TP + TN}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad \text{.....(3)}$$

$$Sensitivity = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \quad \text{.....(4)}$$

$$Specificity = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \quad \text{.....(5)}$$

$$Precision = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \quad \text{.....(6)}$$

$$F1 - score = 2 * \frac{\mathrm{Pr} * \mathrm{Re}}{\mathrm{Pr} + \mathrm{Re}} \quad \text{.....(7)}$$

4.4 TRAINING AND PARAMETERS OPTIMIZATION

Figure 4.1 depicts the simulation outcome for the dataset while training the proposed "DeepPulmoMultinetWeb" architecture. The error unit of slope descent and the optimization equation are two important hyperparameters to consider while training a model. We chose adam variable employed as the optimization equation because it connects important values of various optimizers capable of handling sparse gradients on big datasets. Because our dataset has binary features, we used binary cross-entropy as a loss function. We require an ideal learning rate value to reduce the loss function. We chose a learning rate of 0.0001 in this experiment. Furthermore, a modest batch size of 32 was utilized, demonstrating appropriate generalization of the system. The suggested approach was acquainted on the 25th epoch. However, after just the 19th epoch of training, the model achieved more than 99% training accuracy and 98% validation accuracy. The overfitting problem is also absent during the training phase.

As seen in **Figure 4.1(a)**, **Figure 4.1 (b)** below shows how the arc drastically reduces the loss percentage.

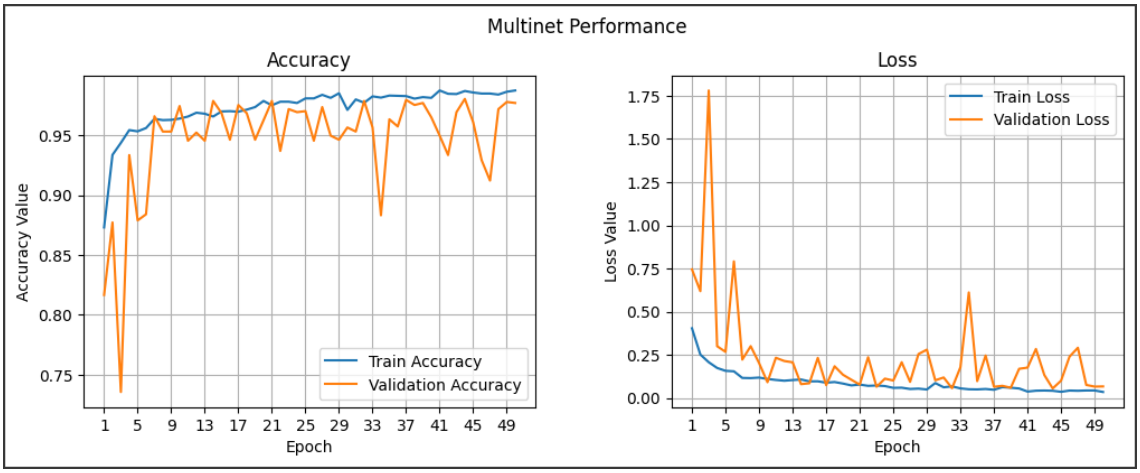


Figure 4.1: Data during training and validation (a) Epoch vs Accuracy value. (b) Epoch vs Loss Value.

4.5 RESUTL DISCUSSION

The confusion table and ROC graph for the dataset utilizing the "DeepPulmoMultinetWeb" architecture are shown in **Figure 4.2**. The suggested system merged two well-known transfer learning approaches, DenseNet201 and Xception, and then used the fusion characteristics to determine whether the x-ray shows pneumonia or normal lungs. **Figure 4.2(a)** indicates that most of the images are correctly labeled as

normal and pneumonia, with only eight misclassifications. Simultaneously, the suggested approach misclassifies just nineteen pneumonia x-ray images. The region score for this design is 0.977, suggesting that the model is consistent and reliable. In addition, various deep learning techniques are tested independently on the data better to understand the usefulness of the "DeepPulmoMultinetWeb" architecture.

Table 4.1 shows a comparison of the "DeepPulmoMultinetWeb" architecture and the other seven transfer learning models. The "DeepPulmoMultinetWeb" architecture exceeds all existing state-of-the-art models with an average accuracy of 98%, recall of 98% and f1-score of 97%. The FPR is 0.0096, and the TNR is close to one, showing that the model is effective. The DenseNet201 performed well, with a f1-score and TNR value of 95% and 0.957, respectively. And the Xception also showed very promising result with a f1=score and TNR value of 95% and 0.991 respectively.

As in the **Figure 4.2** below shows the Confusion matrix and the Roc curve of the dataset after applying the multinet.

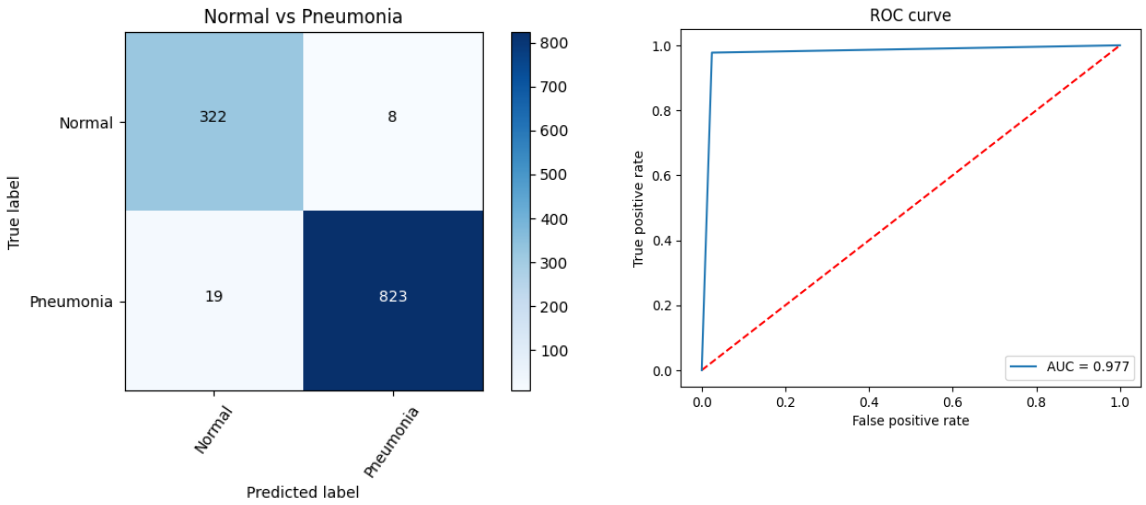


Figure 4.2: (a) Confusion Matrix. (b) ROC Curve.

Here in this confusion matrix The Value of True Positive and True Negative is 322 and 823 respectively and False Positive and False Negative are 8 and 19. And in the ROC curve is showing promising result with AUC value of 0.977. This is a very good result that shows that this combined model is capable of giving us result with higher TP value while maintaining the FP rate at its lowest.

Table 4.1: Comparison of five learning models and multinet.

Model	Category	Precision	Recall	f1-score	Accuracy	TP	TN	FP	FN	FPR	TNR
MobileNet	Normal	88%	98%	93%	95%	335	783	7	47	0.0089	0.99
	Pneumonia	99%	94%	97%							
VGG16	Normal	99%	57%	72%	88%	186	844	140	2	0.1423	0.86
	Pneumonia	86%	100%	92%							
VGG19	Normal	51%	100%	67%	75%	307	570	1	296	0.0018	1.00
	Pneumonia	100%	66%	79%							
Xception	Normal	90%	98%	94%	96%	330	800	7	35	0.0087	0.99
	Pneumonia	99%	96%	97%							
DenseNet201	Normal	99%	87%	92%	96%	265	864	39	4	0.0432	0.96
	Pneumonia	96%	100%	98%							
RestNet50	Normal	71%	100%	83%	88%	333	701	1	139	0.0014	1.00
	Pneumonia	100%	83%	91%							
NASNetMobile	Normal	66%	99%	79%	86%	317	689	4	162	0.0058	0.99
	Pneumonia	99%	81%	89%							
Proposed method	Normal	94%	98%	96%	98%	322	823	8	19	0.0096	0.99
	Pneumonia	99%	98%	98%							

This above **Table 4.1** shows the comparison of the multinet with the other seven models that has been evaluated on the dataset.

The **Figure 4.3** below shows a bar chart of accuracy of the all seven models and the Proposed method that we have shown in this project.

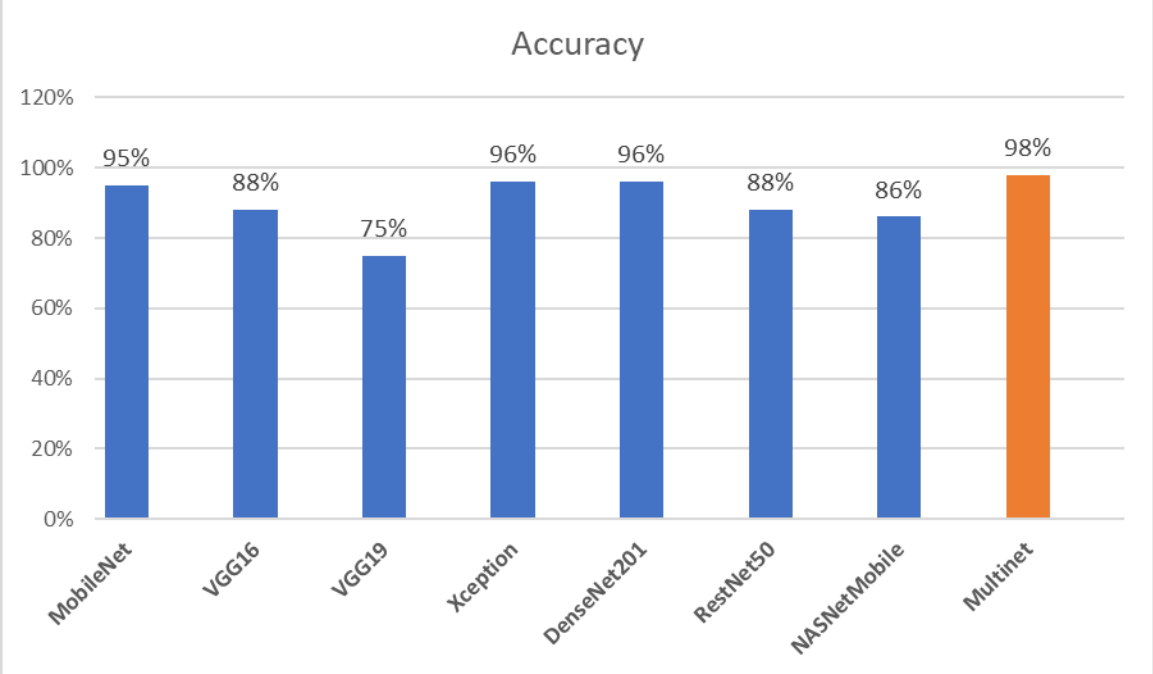
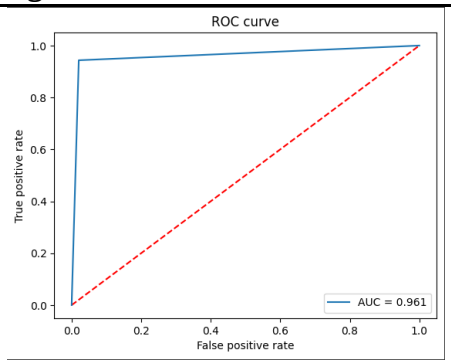
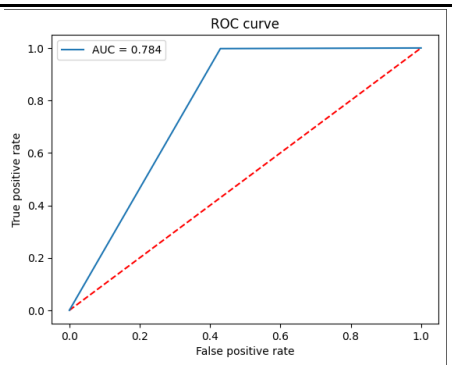


Figure 4.3: Accuracy Bar chart.

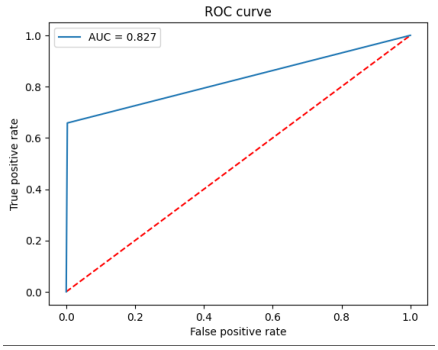
The **Figure 4.4** below shows the ROC curves of all the seven models that we have used.



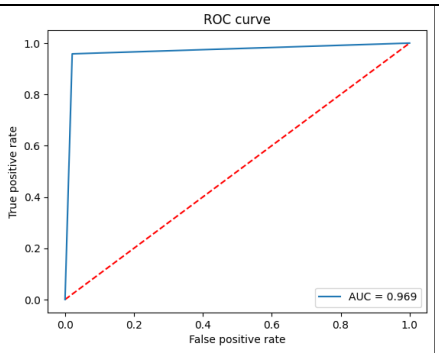
MobileNet



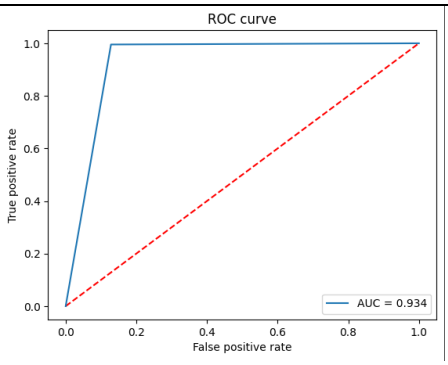
VGG16



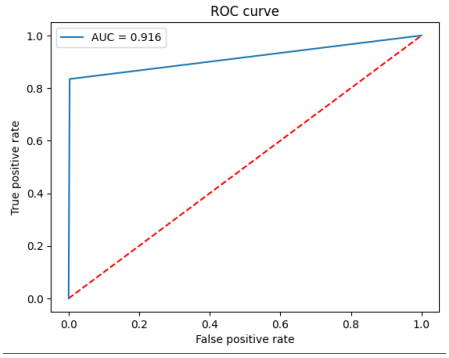
VGG19



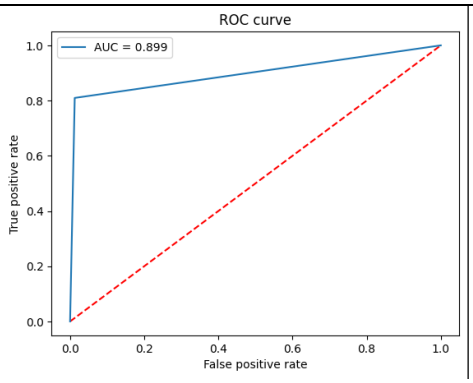
Xception



DenseNet201



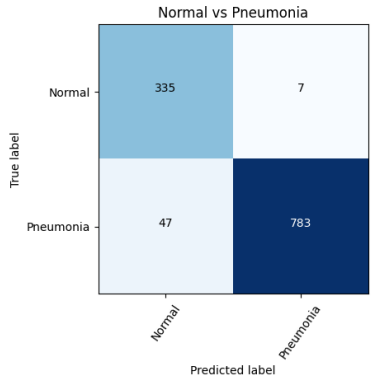
RestNet50



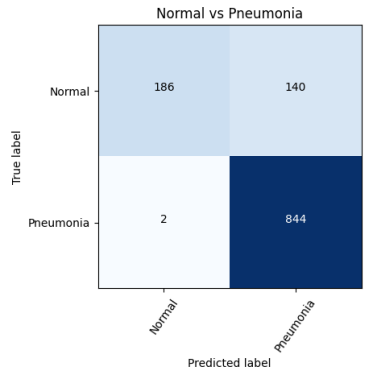
NasNetMobile

Figure 4.4: ROC Curve of the individual models.

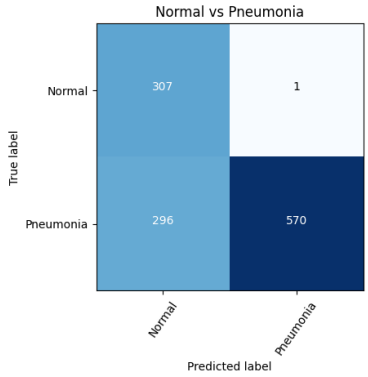
The **Figure 4.5** shows the confusion matrix for the seven individuals used on dataset.



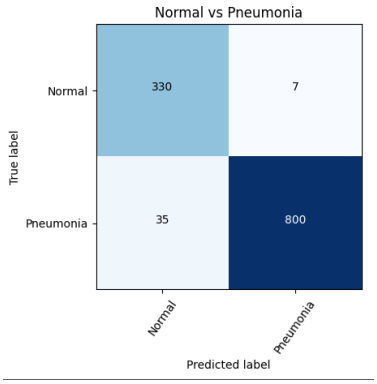
MobileNet



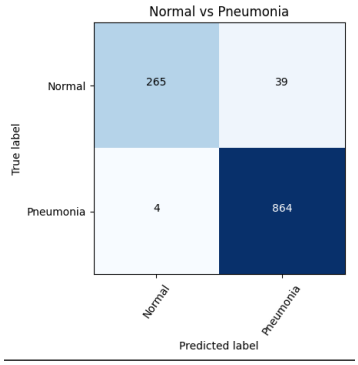
VGG16



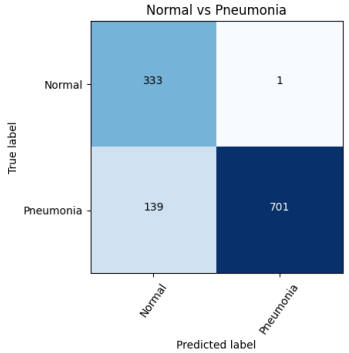
VGG19



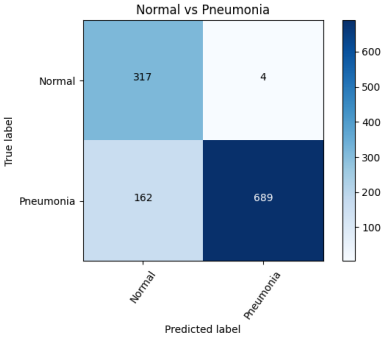
Xception



DenseNet201



RestNet50



NasNetMobile

Figure 4.5: Confusion Matrix of the individual models.

The **Figure 4.6** below showing the performance result of epochs of those seven models.

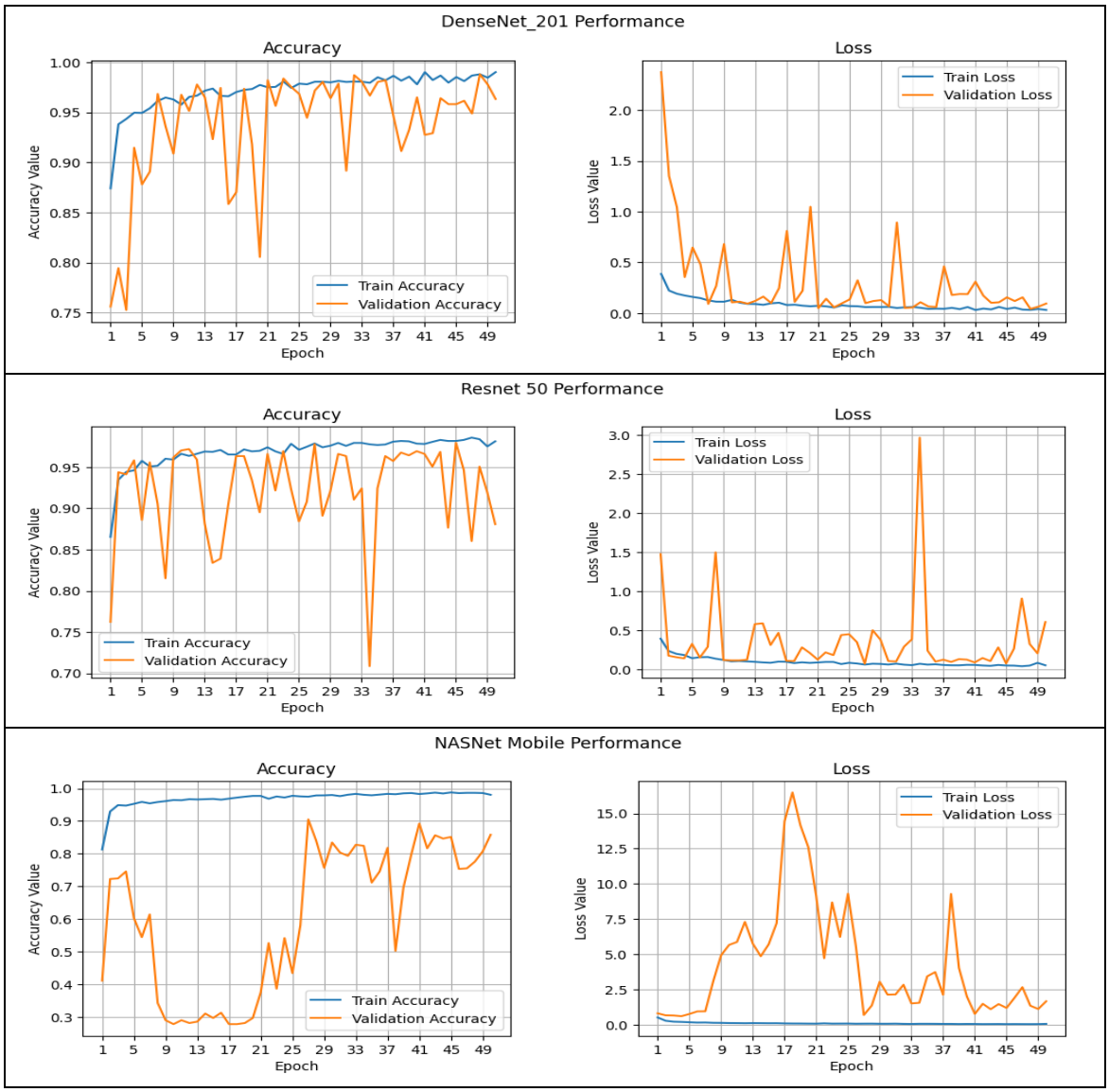


Figure 4.6: The Performance of accuracy and loss compare to epochs.

4.5 WEB INTERFACE

we have implemented our final Hybrid model into a web interface. We used the Django framework to implement the deep learning code into our webpage and used the HTML, CSS and JavaScript for frontend.

In this system, the user mut first create a user account. If he/she already have one then the login page would appear or the registration page will be shown to our user just like the **Figure 4.7**. Then after login the input page would load where users will see a upload button along with a box. By clicking the upload button user can upload the desire image. The image should be a chest x-ray image and the image should cover both of the lungs and clear image not blurry. After final uploading the backend program will test the image and predict the positivity of the pneumonia. If the model finds it pneumonia

positive then there would be a text telling You Have Pneumonia and if it predicts normal then it would say You Don't Have Pneumonia just like shown in the **Figure 4.8**.
The below figure 4.7 is the snapshot of the user interface for registration and login page.

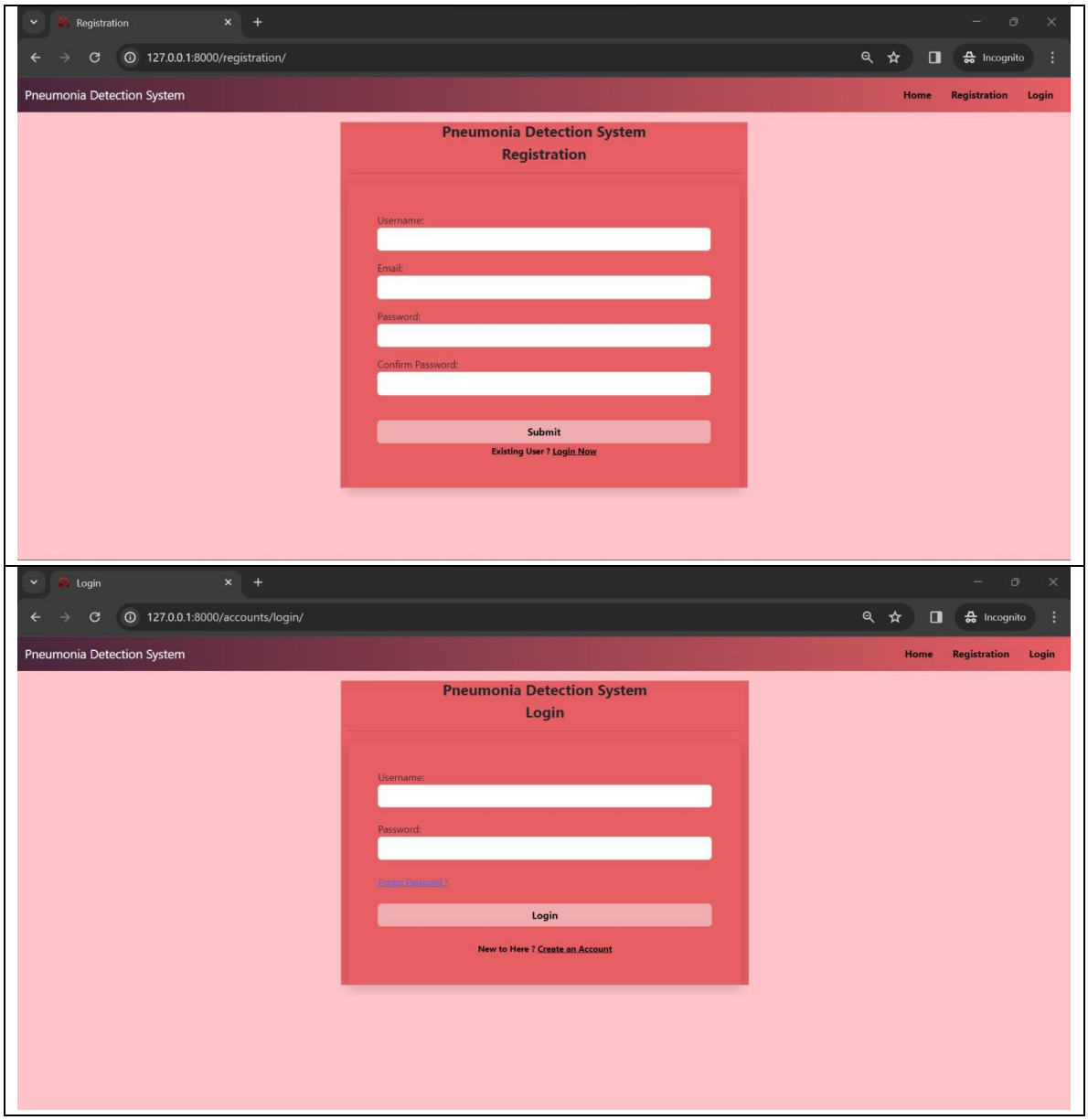


Figure 4.7: Registration and login page.

The **Figure 4.8** shown in the next page is the snapshot of the use interface and outcome page. Here in the first page the user would upload their chest x-ray image and the result will appear as in the second image.

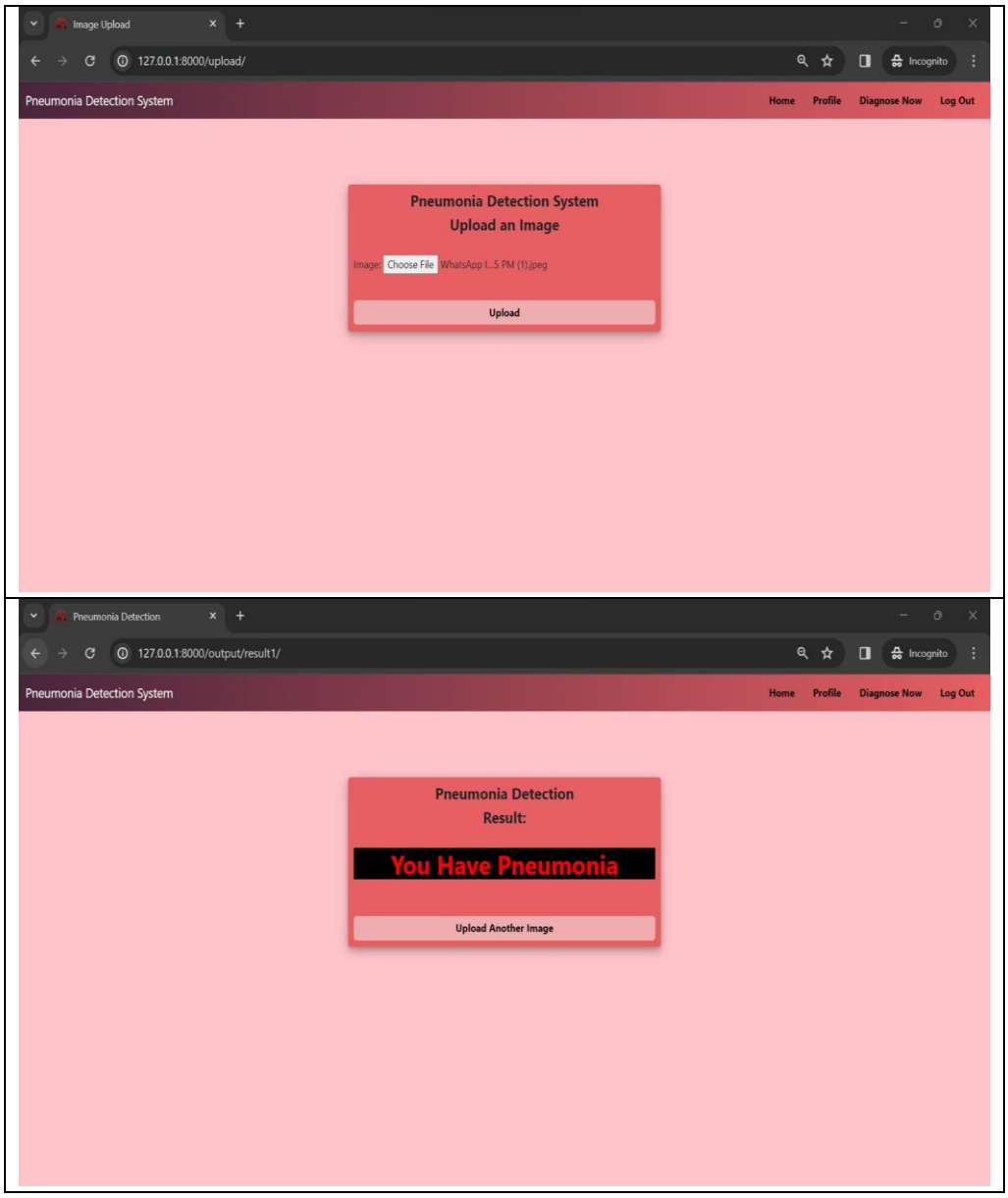


Figure 4.8: User input and result page.

SUMMARY

After applying all the seven models on our dataset, we analyzed the results using the confusion matrix and the ROC curve and decided to combine the DenseNet201 and Xceptoin model to create a hybrid model. The Hybrid model fulfilled most of our expectations and given us a promising result with a decent confusion matrix and well AUC value of 0.977. And also, it achieved an accuracy score about 98% which surpass all the accuracy we got from the individual models. By analyzing all the measures and parameters we can see that the new method is performing well and we can hope it will also give good result in real life use.

Chapter 5 RESULT ANALYSIS

5.1 OVERVIEW

For a very long period many researchers have been working in such project where they are trying to create a method using deep learning that can predict any medical disease from any diagnosis result. Pneumonia detections is one of among many. In this chapter we will show how these researches has developed day by day and also show a comparison how we have proposed a efficient method regarding to this problem.

5.2 COMPARISON

Table 5.1: Comparison between related works.

Reference	Classification Class	Method	Accuracy
Mabrouk, A. (2022) [1]	Multiclass	Deep CNN & ensemble learning	94%
Jain, R. [2]	Multiclass	VGG16, VGG19, RestNet50, Inception-v3	92%
Chouhan, V. [3]	Binary Class	Ensemble model	96%
D. Varshni, K. [4]	Multiclass	Dens3Net(Feature Extraction)+SVM(classifier)	AUC 0.8002
Yi, R. [5]	Binary Class	Deep CNN	96%
Rachna Jain [6]	Multiclass	VGG19, RegNetY008 and DenseNet121	87.28%
Nalluri, S. [7]	Multiclass	EC+AHGOA	95%
Proposed method	Binary class	DenseNet201+Xception Multinet	98%

Here in the **Table: 5.1** shows a comparison between other popular works and our proposed method.

Here shows Mobarouk A. proposed an ensemble learning approach using pretrained DL models MobileNetV2, DenseNet169, and Vision Transformer for dimensionality reduction. These models were concatenated to form a single feature vector, which was then passed through connected layers of a neural network for classification, achieving a performance of 94% [1]. Jain, R. utilized six models, including those with three convolutional layers, achieving a notable accuracy of 92% on a dataset divided into train and test sets [2]. Chouhan, V. employed transfer learning using various neural networks like AlexNet, DenseNet121, InceptionV3, ResNet18, and GoogleNet, combining their results to achieve an impressive accuracy of 96.39% [3]. D. Varshni utilized DenseNet for feature extraction and SVM for classification, achieving an AUC of 0.8002 [4]. Yi, R. proposed a Deep CNN with 52 convolution layers and two dense layers for pneumonia identification from chest x-rays [5]. Rachna Jain employed six models including VGG16, VGG19, ResNet50, and Inception-v3, achieving accuracies ranging from 70.99% to 88.46% [6]. Nalluri, S. employed the AHGOA model for feature selection from chest x-ray images, achieving an accuracy of approximately 95% [7].

In our project, we leveraged deep learning techniques to detect pneumonia from X-ray images with remarkable accuracy. Our approach involved the utilization of a sophisticated combined model, merging the capabilities of DenseNet201 and Xception architectures. By synergizing the strengths of these two models, we achieved an outstanding accuracy rate of approximately 98%. This significant milestone underscores the effectiveness of our methodology in accurately diagnosing pneumonia from X-ray images, showcasing the potential of deep learning in medical image analysis.

Here the **Figure 5.1** below shows the accuracy comparison bar chart between the works that have been discussed in this chapter.

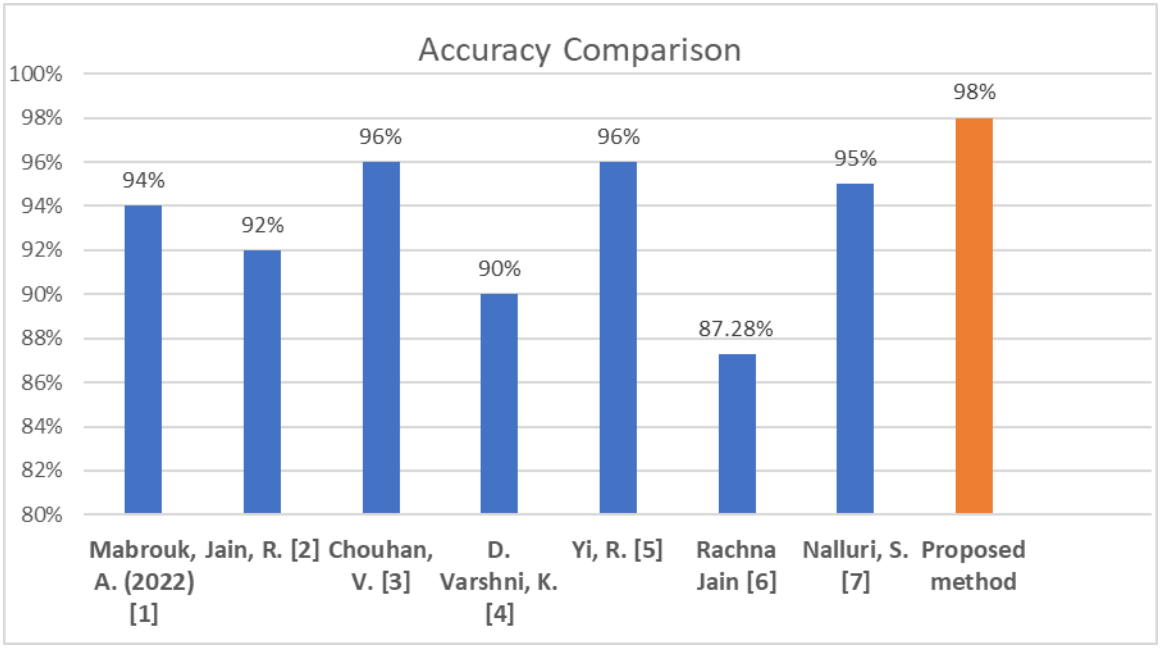


Figure 5.1: accuracy comparison of related works.

SUMMARY

The table presents a comparative analysis of various deep learning methodologies employed in classifying medical images for pneumonia detection. Each entry outlines the author, classification class, methodology utilized, and corresponding accuracy or performance metric. Notably, while previous studies employed a range of deep learning architectures such as Deep CNN, VGG16, VGG19, ResNet50, and Inception-v3, your proposed method stands out by combining DenseNet201 and Xception architectures. This innovative approach yielded a remarkable accuracy of 98%, surpassing the accuracies reported by other works, which range from 87.28% to 96%. These findings underscore the efficacy of your method in achieving superior classification performance, signaling its potential for advancing the field of medical image analysis.

Chapter 6 CONCLUSION AND FUTUERE WORK

6.1 LIMITATION

Data Imbalance If the dataset used for training is imbalanced, where one class (pneumonia or normal) significantly outnumbers the other, the model may develop a bias towards the majority class, affecting its generalization to real-world scenarios.

Generalization: The model's high accuracy on the training dataset does not guarantee its performance on new, unseen data. Overfitting may occur, especially if the model has memorized patterns specific to the training set that do not generalize well.

Interpretable Features: Deep learning models, particularly complex ones like Densenet201 and EfficientNet, often act as black boxes, making it challenging to interpret the features they rely on for making predictions. Understanding the decision-making process is crucial for gaining trust in the model.

False Positives and Negatives: The model might misclassify some cases, leading to false positives (predicting pneumonia when it's not present) or false negatives (failing to detect pneumonia when it is present). These errors could have severe consequences in a clinical setting.

6.2 FUTURE SCOPE

Continuous Monitoring and Model Updating: Implement a system for continuous monitoring of model performance over time.
Integrate mechanisms for automated model retraining as new data becomes available.
Explore online learning techniques to adapt the model to evolving patterns in the data.

Explainability Techniques: Integrate explainability techniques like SHAP values or Grad-CAM to interpret and visualize the regions of input images that contribute most to the model's decision, aiding clinicians in understanding the model's reasoning.

Real-world Deployment: Test the model in real-world clinical settings and gather feedback from healthcare professionals to ensure its practical utility and address any issues that may arise.

Real-time Diagnosis and Telemedicine: Explore the feasibility of real-time pneumonia diagnosis for timely intervention._Adapt the system for telemedicine applications, enabling remote diagnosis and consultation.

User Interface Refinement: Gather feedback from end-users, including clinicians and radiologists, to refine and improve the user interface for better usability and user

experience. Consider additional features or tools that could assist healthcare professionals in their decision-making process.

Cross-Dataset Generalization: Evaluate the model's performance on datasets from different sources and healthcare institutions to ensure generalizability across diverse patient populations. Consider domain adaptation techniques to improve performance when the training and deployment environments differ.

6.3 CONCLUSION

In conclusion, the developed pneumonia detection system shows promising accuracy in the initial stages. However, it is important to address the mentioned limitations to ensure the model's reliability and applicability in a clinical environment. Future work should focus on continuous model improvement, interpretability, and validation in real-world scenarios to enhance its effectiveness as a diagnostic tool. The integration of user feedback and collaboration with medical professionals will be crucial in refining and optimizing the system for practical use.

REFERENCES

[1] Mabrouk, A., Díaz Redondo, R.P., Dahou, A., Abd Elaziz, M. and Kayed, M., 2022. Pneumonia detection on chest X-ray images using ensemble of deep convolutional neural networks. *Applied Sciences*, *12*(13), p.6448.

[2] Jain, R., Nagrath, P., Kataria, G., Kaushik, V.S. and Hemanth, D.J., 2020. Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning. *Measurement*, *165*, p.108046.

[3] Chouhan, V., Singh, S.K., Khamparia, A., Gupta, D., Tiwari, P., Moreira, C., Damaševičius, R. and De Albuquerque, V.H.C., 2020. A novel transfer learning based approach for pneumonia detection in chest X-ray images. *Applied Sciences*, *10*(2), p.559.

[4] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan and A. Mittal, "Pneumonia Detection Using CNN based Feature Extraction," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp. 1-7, doi: 10.1109/ICECCT.2019.8869364.

[5] Yi, R., Tang, L., Tian, Y. *et al.* Identification and classification of pneumonia disease using a deep learning-based intelligent computational framework. *Neural Comput & Applic* **35**, 14473–14486 (2023). https://doi.org/10.1007/s00521-021-06102-7

[6] Rachna Jain, Preeti Nagrath, Gaurav Kataria, V. Sirish Kaushik, D. Jude Hemanth, Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning, https://doi.org/10.1016/j.measurement.2020.108046

[7] Nalluri, S. and Sasikala, R., 2024. Pneumonia screening on chest X-rays with optimized ensemble model. *Expert Systems with Applications*, *242*, p.122705.

[8] https://www.kaggle.com/datasets/paultimothymooney/chest-xray-pneumonia

[9] Howard, A.G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M. and Adam, H., 2017. Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.

[10] Huang, G., Liu, Z., Van Der Maaten, L. and Weinberger, K.Q., 2017. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).

[11] He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[12] Simonyan, K. and Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

[13] Chollet, F., 2017. Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1251-1258).

[14] Zoph, B., Vasudevan, V., Shlens, J. and Le, Q.V., 2018. Learning transferable architectures for scalable image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 8697-8710).