

# **Department of Computer Science and Engineering**

*A Deep Learning Report on*

*on*

## **Comparative Analysis of AlexNet and DenseNet for Pneumonia Detection using Chest X-ray Images**

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# Chapter 1

## Introduction

The realm of medical diagnostics and image analysis has been significantly revolutionized by the advent of deep learning techniques. In particular, convolutional neural networks (CNNs) have proven to be invaluable tools in the automated interpretation of medical images, aiding healthcare professionals in the timely and accurate diagnosis of various conditions. One critical application of deep learning in this domain is the detection of pneumonia through the analysis of chest X-ray images.

Pneumonia, an inflammatory condition of the lung, is a leading cause of morbidity and mortality worldwide. Early and accurate detection of pneumonia is essential for prompt medical intervention and improved patient outcomes. Medical imaging, especially chest X-ray images, plays a pivotal role in the diagnosis of pneumonia, as it offers detailed insights into the pulmonary health of patients. The ability to rapidly and accurately identify pneumonia in X-ray images is paramount, as it can expedite the treatment process, reduce healthcare costs, and ultimately save lives.

Two prominent deep learning architectures, AlexNet and DenseNet, have garnered significant attention for their outstanding performance in image classification tasks. AlexNet, developed by Krizhevsky et al. in 2012, is often credited with popularizing deep learning in the computer vision community. On the other hand, DenseNet, introduced by Huang et al. in 2017, has gained recognition for its unique architecture that facilitates feature reuse, mitigates vanishing gradient problems, and enhances training efficiency.

The primary objective of this project is to undertake a comprehensive comparative analysis of these two deep learning models, AlexNet and DenseNet, in the context of pneumonia detection from chest X-ray images. This investigation aims to shed light on their respective strengths and weaknesses, assess their performance, and offer insights into which model might be better suited for this specific medical imaging task.

Furthermore, our study extends to consider the generalizability of these models across diverse patient populations. We recognize that medical datasets can exhibit variations in image quality, patient demographics, and disease severity. Investigating the robustness of AlexNet and DenseNet to these variations is essential in determining their suitability for pneumonia detection in real-world healthcare settings. Additionally, we aim to explore the potential for fine-tuning these models to adapt to the specific nuances of pneumonia detection, thus contributing to the ongoing efforts to improve medical diagnostics through deep learning.

## Chapter 2

### Literature Review

Tawsifur Rahman et al.,[1] presents a study focused on the development of an automated system for pneumonia detection using deep learning techniques, specifically Convolutional Neural Networks (CNNs). The researchers employ four pre-trained CNN models, including AlexNet, ResNet18, DenseNet201, and SqueezeNet, and implement transfer learning to facilitate the detection of pneumonia and its differentiation into bacterial and viral pneumonia. The study outlines the methodology, which involves dataset preparation and preprocessing steps, and assesses the performance of the CNN models in various classification schemes. Among the models, DenseNet201 proves to be the most effective, achieving high accuracy and demonstrating superior performance metrics. The research's potential impact lies in its ability to enhance computer-aided pneumonia diagnosis, especially in resource-limited settings, offering the potential to expedite accurate disease detection and save lives.

Alisha Imran et al.,[2] addresses the critical issue of pneumonia diagnosis by developing a Convolutional Neural Network (CNN) capable of automatically detecting pneumonia, both bacterial and viral, from chest X-ray images. By utilizing a dataset of 5,863 X-ray images, categorized into normal and pneumonia cases, the problem is framed as a binary classification task. The author employs transfer learning, utilizing the pre-trained VGG19 model, and explains the model training process, where the CNN's parameters are iteratively adjusted to improve prediction accuracy. The trained model achieves an impressive 88% accuracy, showcasing the potential of CNNs to significantly enhance the efficiency and accuracy of pneumonia diagnosis, ultimately benefiting patients and healthcare professionals alike.

Vikash chouhan et al.,[3] introduces an innovative deep learning framework for pneumonia detection in chest X-ray images, addressing the critical global health issue of pneumonia caused by viruses, bacteria, and fungi. Leveraging transfer learning and ensemble modeling, the study utilizes pre-trained neural networks (AlexNet, DenseNet121, ResNet18, InceptionV3, and GoogLeNet) and employs data augmentation techniques to enhance model generalization. The ensemble model, combining predictions from these networks, achieves a remarkable accuracy of 96.4% and an outstanding recall of 99.62%, surpassing individual models and previous studies. This approach significantly contributes to the field of medical image analysis, offering a robust solution for accurate pneumonia diagnosis, with potential implications for global healthcare.

A. Saraiva et al.,[4] presents a comparative study of two neural network models, Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN), for detecting and classifying pneumonia in X-ray images. The study uses a dataset of 5840 chest X-ray images with two classes: normal and pneumonia. Cross-validation with k-fold is employed for model validation. The results indicate that both models are efficient, with an average accuracy of 92.16% for MLP and 94.40% for CNN. The paper aims to address the challenge of pneumonia diagnosis, which remains difficult in clinical settings due to the lack of specific signs. It explores the potential of deep learning models to automate and expedite the diagnosis of pneumonia using chest X-ray images.

Rachna Jain et al.,[5] presents a study focused on the development and evaluation of neural network models for the detection of pneumonia in X-ray images, with the aim of aiding in the early diagnosis and treatment of this potentially life-threatening condition. The research introduces high-performing Convolutional Neural Network (CNN) models, along with four transfer learning models (VGG16, VGG19, ResNet50, and Inception-v3). VGG19 is highlighted as one of the most accurate models, achieving significant recall and F1 scores. The research emphasizes the importance of recall in medical imaging, given its role in minimizing false negatives. The proposed models have the potential to provide fast and accurate diagnostic results, contributing to more efficient patient care services and reduced mortality rates. Future work includes fine-tuning parameters, extending the models to classify other diseases, and improving their overall performance with larger datasets.

Patrik Szepesi et al.,[6] introduces an innovative Convolutional Neural Network (CNN) model designed for the efficient and accurate detection of pneumonia in X-ray images. Distinguished by the strategic placement of a dropout layer within the convolutional layers, a departure from conventional practices, the model is notably constructed from scratch, avoiding reliance on pre-trained networks through transfer learning. The experimental results are compelling, with the proposed model consistently achieving recall and precision rates exceeding 97%. Furthermore, it demonstrates exceptional efficiency by providing rapid predictions within a mere 122 milliseconds. These findings represent a significant advancement in computer-aided medical image analysis, promising enhanced speed and precision in pneumonia diagnosis.

## **Chapter 3**

### **Existing system and Drawbacks**

#### **3.1 Introduction**

Pneumonia, a potentially life-threatening lung infection, demands early detection for effective treatment and improved patient outcomes. The conventional approach to pneumonia diagnosis involves manual feature extraction and radiologist-led classification, a time-consuming and error-prone process. Moreover, these methods may miss early or subtle pneumonia signs. Recent advances in deep learning have shown promise in pneumonia detection using chest X-ray images, as these models can discern intricate image features, often escaping human detection, leading to faster and more accurate diagnoses.

#### **3.2 Current State of the Art**

Several deep learning models have been developed for pneumonia detection, including AlexNet, VGGNet, ResNet, and DenseNet. These models have achieved state-of-the-art results on various pneumonia detection benchmarks. However, there are still some challenges in developing robust and reliable deep learning models for pneumonia detection. One challenge is the limited availability of large-scale and well-curated pneumonia datasets. Another challenge is the need to develop models that can generalize to new data and different healthcare settings.

#### **3.3 Drawbacks and Limitations**

- **Accuracy:** While deep learning models have achieved high accuracy on pneumonia detection benchmarks, their performance in real-world clinical settings can be lower. This is due to factors such as the variability in image quality, the presence of artifacts, and the complexity of medical data.
- **Generalization:** Deep learning models are prone to overfitting, which can lead to poor performance on new data. This is a challenge for pneumonia detection, as datasets may vary in terms of patient demographics, imaging protocols, and disease severity.
- **Interpretability:** Deep learning models are often complex and difficult to interpret. This can make it challenging to understand why a model makes a particular prediction, which is important for medical decision-making.
- **Scalability:** Deploying deep learning models in clinical settings can be challenging due to the high computational resources required. This is especially true for resource-constrained healthcare environments.

# Chapter 4

## Proposed system

### 4.1 Introduction

Our proposed system aims to address the drawbacks and limitations of existing deep learning models for pneumonia detection. We propose a comparative analysis of AlexNet and DenseNet for pneumonia detection in chest X-ray images.

AlexNet and DenseNet are two widely used deep learning models with proven performance in image classification tasks. AlexNet is a classic CNN model, while DenseNet is a more recent CNN model with several architectural advantages.

We compare the performance of AlexNet and DenseNet on a large-scale and well-curated pneumonia dataset. We evaluate the models on various metrics, including accuracy, sensitivity, specificity, and F1 score. We also analyze the generalization ability of the models to new data.

### 4.2 Rationale for Model Selection

We have chosen to focus on AlexNet and DenseNet for several reasons:

**Proven track record:** Both AlexNet and DenseNet have demonstrated exceptional performance in image classification tasks. This suggests that they are well-suited for the task of pneumonia detection.

**Architectural differences:** AlexNet and DenseNet exhibit distinct architectural features, which allow us to compare the effectiveness of various deep learning strategies. For example, AlexNet relies on multiple convolutional layers to extract features, while DenseNet uses a dense connectivity pattern to promote feature reuse.

**Community adoption:** Both AlexNet and DenseNet are widely adopted and studied in the deep learning community. This provides a rich source of research and insights that we can leverage in our analysis.

### 4.3 Project Objectives

- To conduct a rigorous comparative analysis of AlexNet and DenseNet in the context of pneumonia detection from chest X-ray images.
- To determine which model offers superior performance, considering various metrics such as accuracy, sensitivity, specificity, and F1 score.
- To provide insights into the strengths and weaknesses of each model for this specific medical imaging task.

# Chapter 5

## Methodology

### 5.1 Introduction

AlexNet and DenseNet are two deep learning models that have been shown to achieve promising results in pneumonia detection from chest X-ray images. This methodology aims to conduct a comprehensive and rigorous comparative analysis of these two models to determine which offers superior performance in terms of accuracy, sensitivity, specificity, F1 score, generalization ability, interpretability, and scalability.

AlexNet can classify more than 1000 different classes using deep layers consisting of 650k neurons and 60 million parameters. The network is made up of five convolutional layers (CLs) with three pooling layers, two fully connected layers (FCLs), and a Softmax layer [11]. The dimension of input image for the AlexNet has to be  $227 \times 227 \times 3$  and the first CL converts input image with 96 kernels sized at  $11 \times 11 \times 3$  having a stride of four pixels, which is the input to the second layer [49], and the remaining details are summarized in Figure 1.

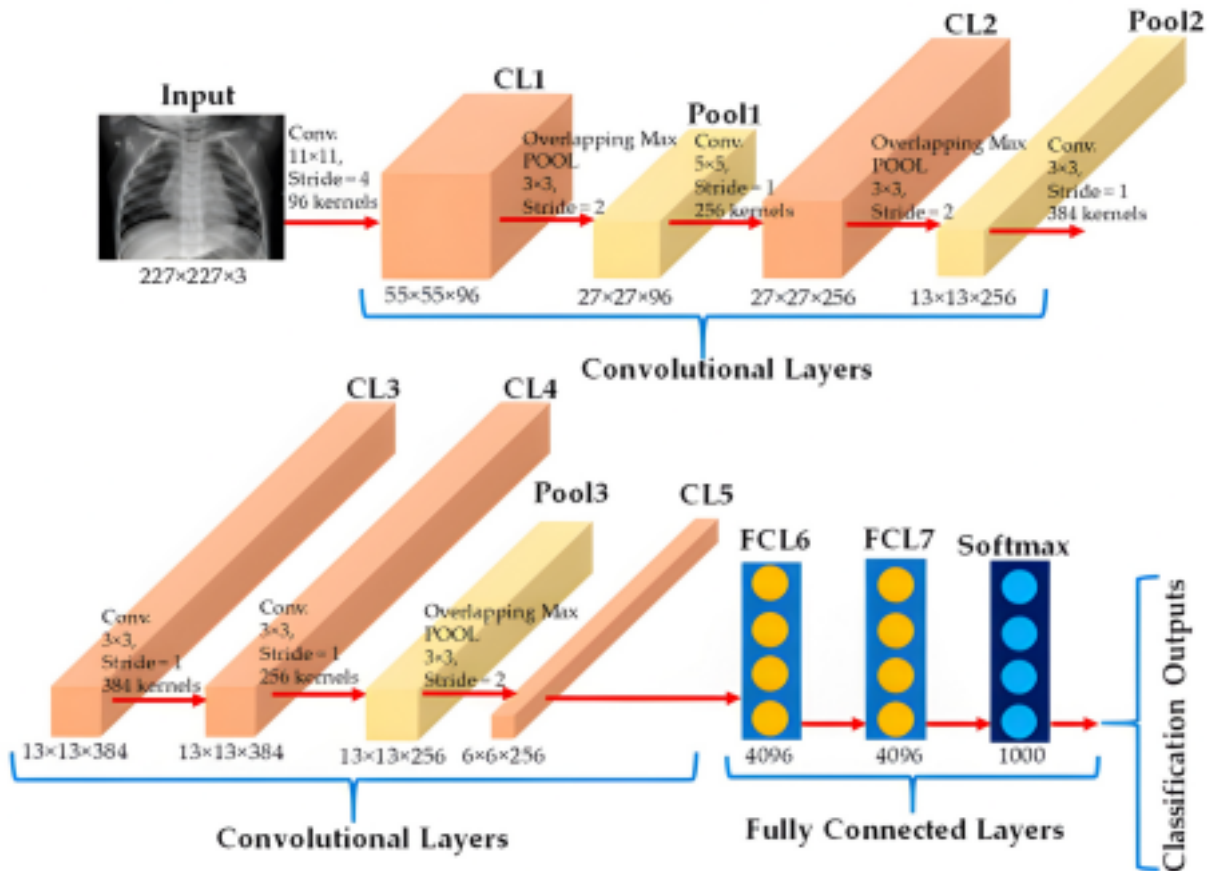


Fig 1. AlexNet Architecture

DenseNet, which is a short form of the Dense Convolutional Network, needs less numbers of parameters than a conventional CNN, as it does not learn redundant feature maps [50]. The layers in DenseNet are



very narrow, i.e., 12 filters, which add a lesser set of new feature-maps. DenseNet has four different variants: DenseNet121, DenseNet169, DenseNet201, and DenseNet264. In this paper, we have used DenseNet201 for pneumonia detection. Each layer in DenseNet has direct access to the original input image and gradients from the loss function. Therefore, the computational cost significantly reduced, which makes DenseNet a better choice for image classification.

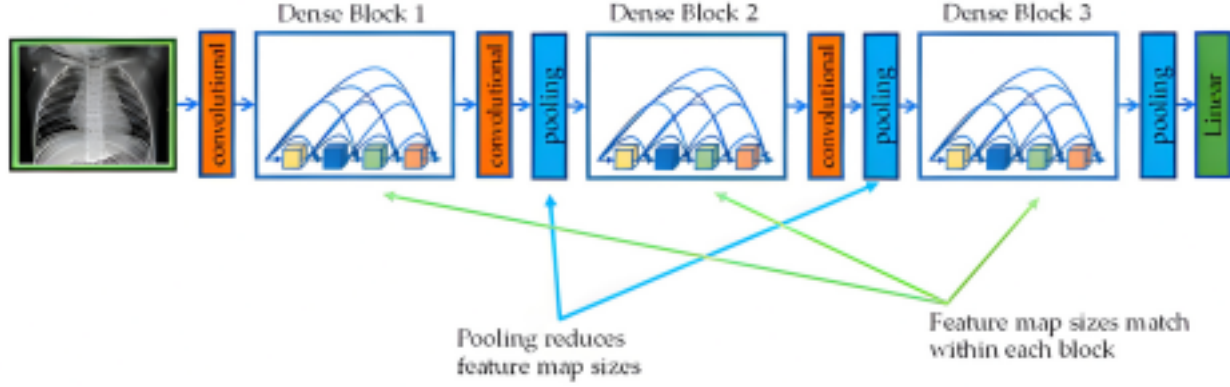


Fig 2.DenseNet Architecture

## 5.2 Dataset Collection

The Kaggle dataset for pneumonia detection in chest X-ray images will be used for this analysis. This dataset contains over 5,800 images, including both pneumonia and non-pneumonia cases. The images are labeled with ground truth annotations for pneumonia.

## 5.3 Data Preprocessing and Data Augmentation

In our data preprocessing pipeline, we conducted essential tasks to prepare the dataset for effective model training and evaluation. This included resizing the images to  $227 \times 227$  pixels for AlexNet and  $224 \times 224$  pixels for DenseNet 201, ensuring compatibility with each model's specific input requirements. Additionally, we applied image normalization to standardize pixel values, aligning them with pre-trained model standards to enhance performance and generalization. In conjunction with data preprocessing, we implemented data augmentation techniques, such as rotation, translation, and scaling, which generated new images by transforming existing ones. This approach provided our models with a more comprehensive view of the dataset, improving their ability to recognize patterns, reducing the risk of overfitting, and enhancing their overall robustness and generalization capabilities.

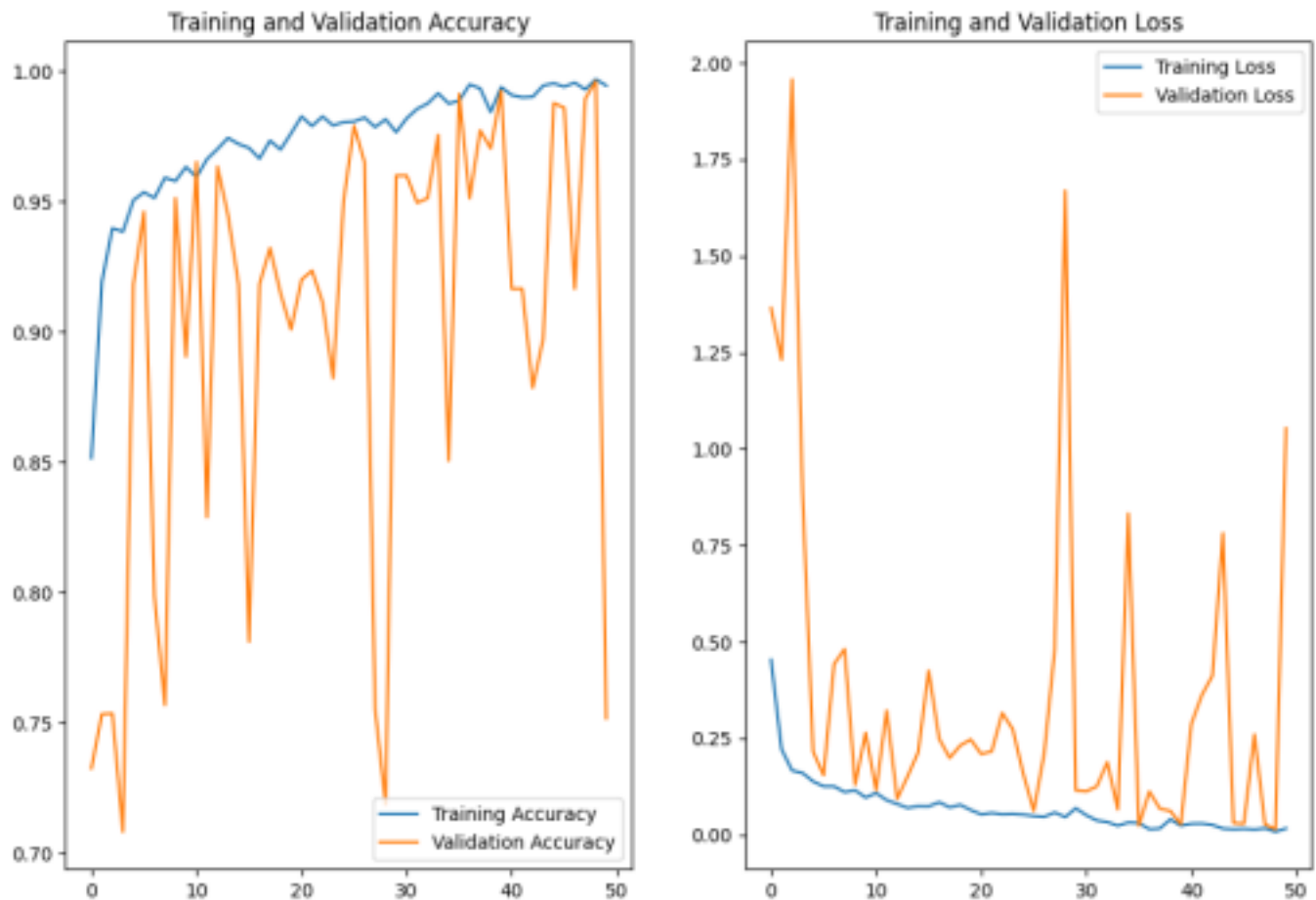
## 5. Model Selection and Training

AlexNet and DenseNet will be selected as the two deep learning models for comparison. Both models will be trained on the preprocessed Kaggle dataset using a framework such as TensorFlow. The hyperparameters of each model, such as the learning rate, optimizer, and number of epochs, will be tuned to achieve optimal performance.

## Chapter 6 Results

**Alex Net :**

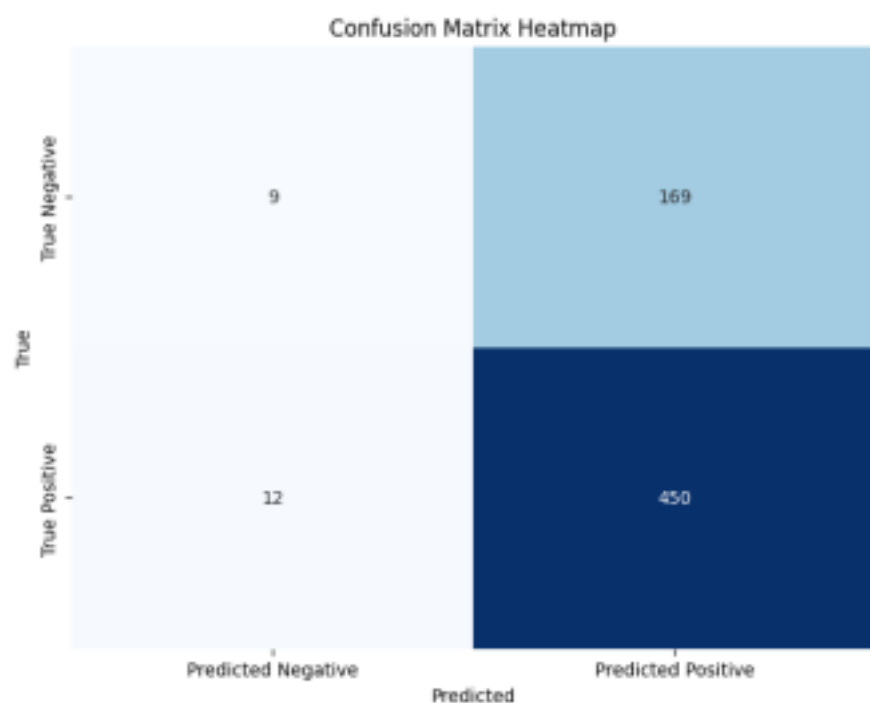
Training and Validation Graphs:



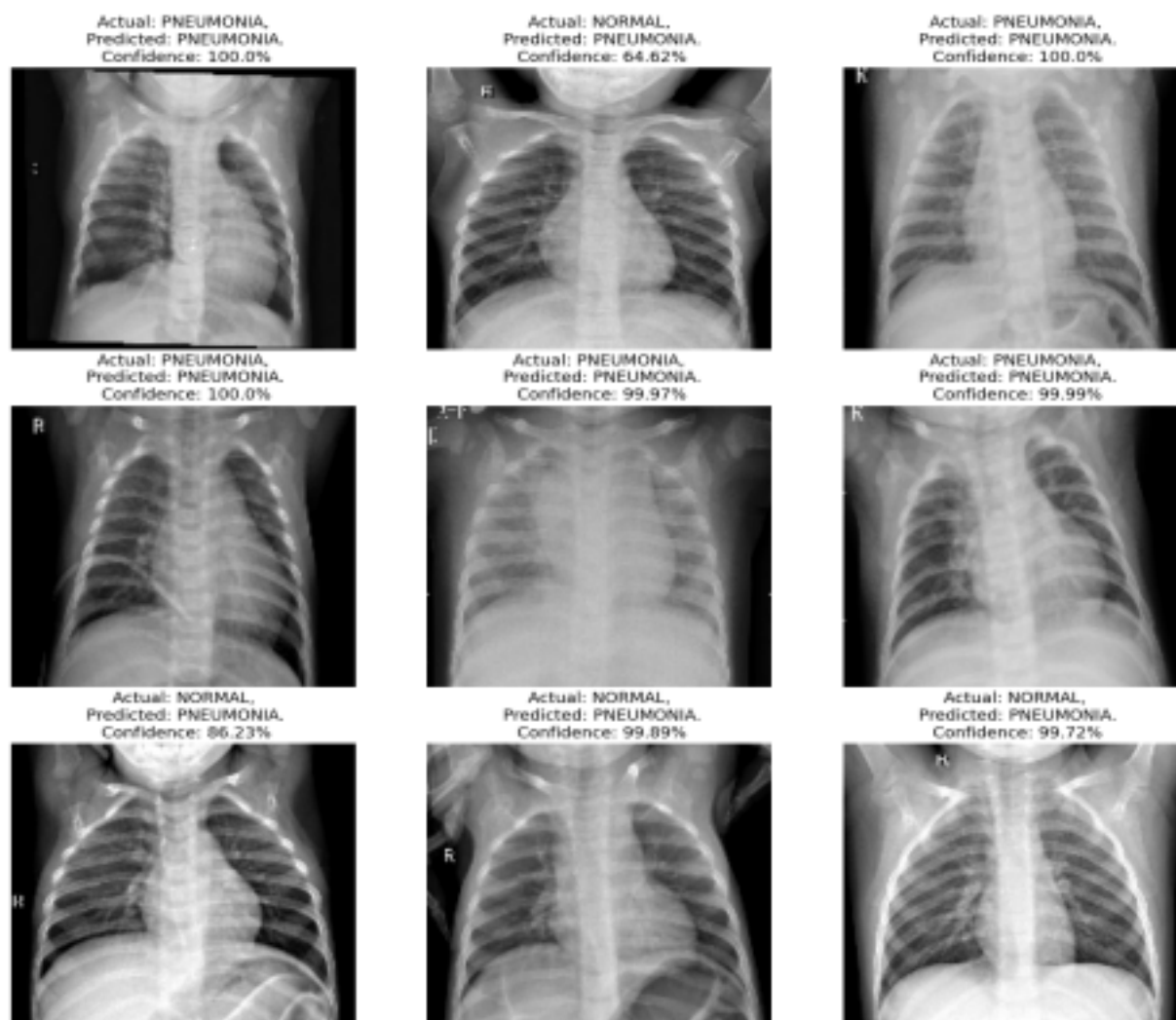
Performance Metrics:

	precision	recall	f1-score	support
0	0.43	0.05	0.09	178
1	0.73	0.97	0.83	462
accuracy			0.72	640
macro avg	0.58	0.51	0.46	640
weighted avg	0.64	0.72	0.63	640

## Confusion Matrix:



## Test Data Results:



## DenseNet :

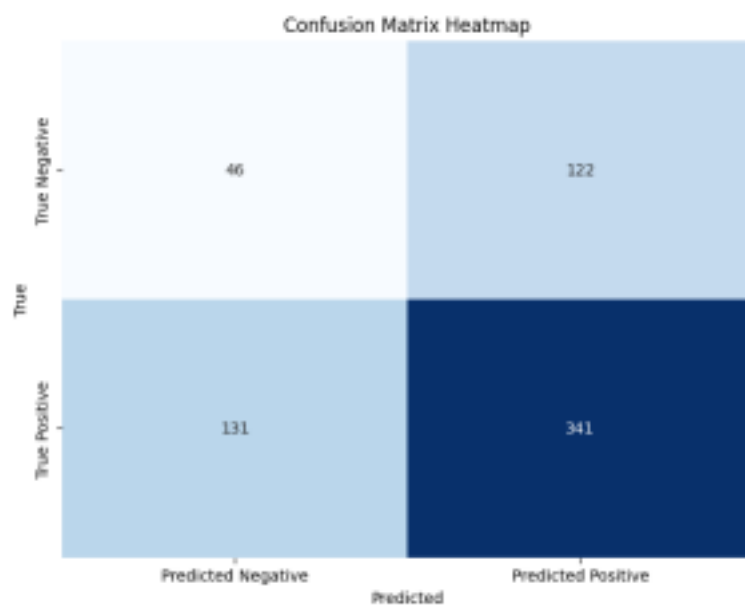
Training and Validation graphs:



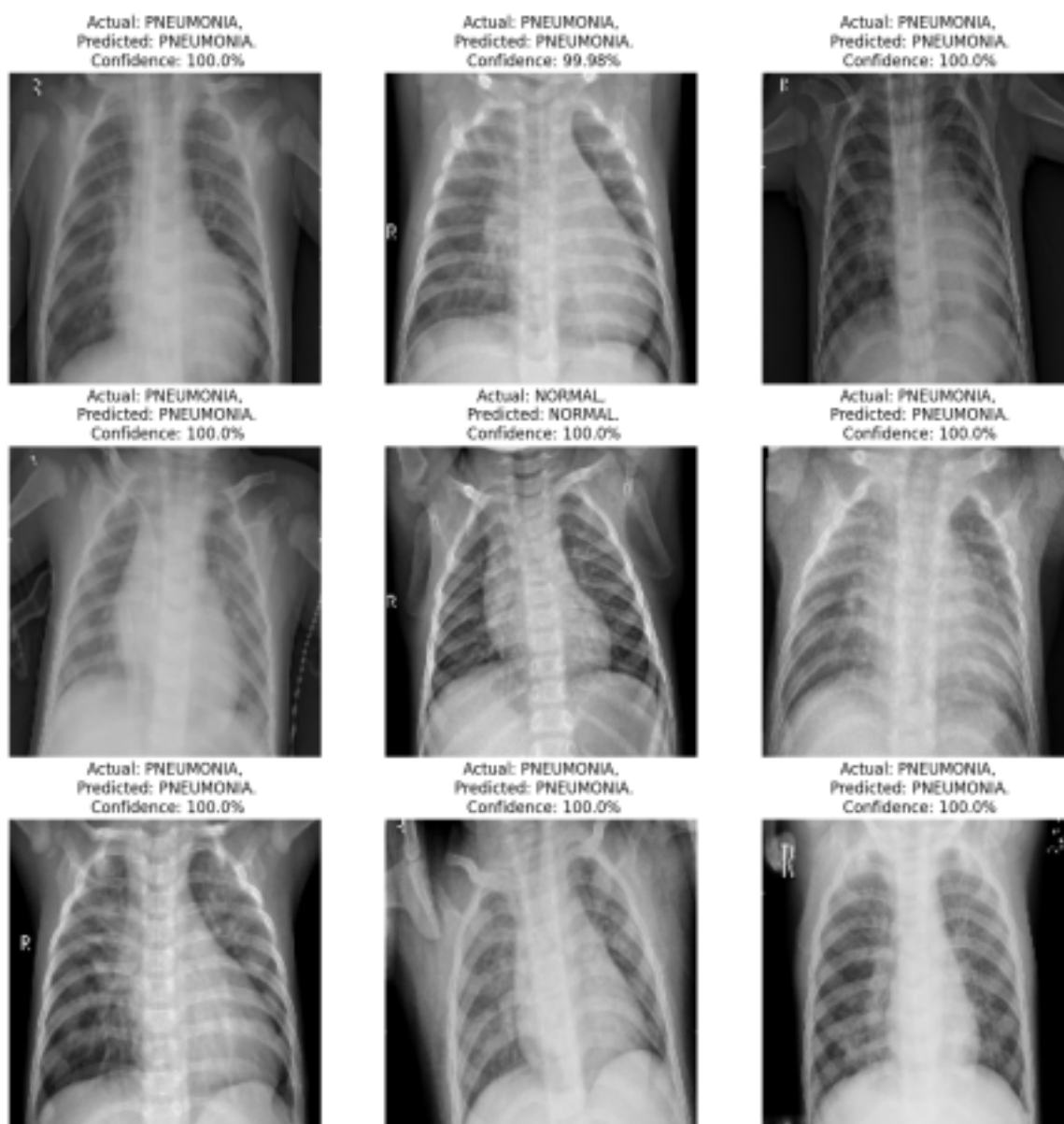
Performance Metrics:

	precision	recall	f1-score	support
0	0.26	0.27	0.27	168
1	0.74	0.72	0.73	472
accuracy			0.60	640
macro avg	0.50	0.50	0.50	640
weighted avg	0.61	0.60	0.61	640

## Confusion Matrix:



## Test Data Results:



## **Chapter 7**

### **Conclusion and future enhancements**

#### **7.1 Results**

In our comparative analysis of AlexNet and DenseNet for pneumonia detection using chest X-ray images, we obtained insightful results that shed light on the performance of these two deep learning models.

For the AlexNet model, we achieved an overall accuracy of 72%. It exhibited a significantly higher recall for class 1 (97%), indicating that it was very effective at identifying pneumonia cases, with a corresponding high F1-score of 0.83. However, the model's performance on class 0 was not satisfactory, with a low recall of 5% and a low F1-score of 0.09, suggesting that it struggled in correctly identifying non-pneumonia cases.

On the other hand, the DenseNet model yielded an accuracy of 60%. This model showed a more balanced performance with recall values of 72% and 27% for classes 1 and 0, respectively. This indicates that DenseNet was better at identifying both pneumonia and non-pneumonia cases compared to AlexNet. The F1-score for class 1 was 0.73, demonstrating its effectiveness in pneumonia detection, while the F1-score for class 0 was 0.27, indicating some room for improvement in identifying non-pneumonia cases.

In summary, our analysis indicates that DenseNet outperformed AlexNet in terms of overall classification accuracy and showed a more balanced performance in identifying both pneumonia and non-pneumonia cases. However, AlexNet exhibited a higher recall and F1-score for pneumonia cases, suggesting its potential in more accurate pneumonia detection. Further optimization and fine-tuning of these models could lead to improved results in pneumonia detection using chest X-ray images.

#### **7.2 Future enhancements**

- Explore other deep learning models: In addition to AlexNet and DenseNet, there are several other deep learning models that have been shown to achieve promising results in pneumonia detection. Future work could explore the performance of other models, such as ResNet, VGGNet, and EfficientNet.
- Use larger and more diverse datasets: Our study used the Kaggle dataset for pneumonia detection in chest X-ray images, which is a large and well-curated dataset. However, future work could use even larger and more diverse datasets to train and evaluate deep learning models. This would help to improve the generalization ability of the models to new data and different patient populations.
- Develop ensemble models: Ensemble models combine the predictions of multiple models to produce a more accurate prediction. Future work could develop ensemble models of deep learning models to improve the performance of pneumonia detection systems.

## References:

- [1] Tawsifur Rahman , Muhammad E. H. Chowdhury, Amith Khandakar, Khandaker R. Islam, Khandaker F. Islam, Zaid B. Mahbub, Muhammad A. Kadir and Saad Kashem (2020) Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray.
- [2] Alisha Imran (2019) Training a CNN to detect Pneumonia.  
<https://medium.datadriveninvestor.com/training-a-cnn-to-detect-pneumonia-c42a44101deb>
- [3] Vikash Chouhan, Sanjay Kumar Singh, Aditya Khampari, Deepak Gupta, Prayag Tiwari, Catarina Moreira, Robertas Damaševičius and Victor Hugo C. de Albuquerque (2020) A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images.
- [4] A. A. Saraiva, D. B. S. Santos, Nator Junior C. Costa, Jose Vigno M. Sousa, N. M. Fonseca Ferreira, Antonio Valente and Salviano Soares (2019) Models of Learning to Classify X-ray Images for the Detection of Pneumonia using Neural Networks.
- [5] Rachna Jain, Preeti Nagrath, Gaurav Kataria, V. Sirish Kaushik, D. Jude Hemanth (2020) Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning.
- [6] Patrik Szepesi and Laszlo Szilagyi (2022) Detection of pneumonia using convolutional neural networks and deep learning.