PNEUMONIA DETECTION WITH X-RAY IMAGES APPROACH WITH DEEP LEARNING

BY

Abid Rayhan Arnob
ID: 203-15-14539

AND

Maria Akther Atika
ID: 203-15-14555

FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

Supervised By

Mr. Md. Mahedi Hassan
Lecturer
Department of CSE
Daffodil International University

Co-Supervised By

Mr. Abdus Sattar
Assistant Professor
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

APPROVAL

This Project titled **"PNEUMONIA DETECTION WITH X-RAY IMAGES APPROACH WITH DEEP LEARNING"**, submitted by **Abid Rayhan Arnob** and **Maria Akther Atika** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **14-07-2024.**

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Daffodil International University

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Daffodil International University

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Department of CSE
Faculty of Science & Information Technology
Daffodil International University

14/7/24
Dr. Shamim H Ripon — **External Examiner**
Professor
Department of Computer Science & Engineering
East West University

DECLARATION

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mr. Md. Mahedi Hassan, Lecturer, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

mahedi
20.06.24

Mr. Md. Mahedi Hassan
Lecturer
Department of CSE
Daffodil International University

Co-Supervised by:

Mr. Abdus Sattar
Assistant Professor
Department of CSE
Daffodil International University

Submitted by:

Abid Rayhan Arnob
ID: 203-15-14539
Department of CSE
Daffodil International University

Maria Akther Atika
ID: 203-15-14555
Department of CSE
Daffodil International University

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ABSTRACT

This study tries to create a reliable model for detecting pneumonia using chest X-ray images. The work makes use of advanced deep learning architectures such as DenseNet, InceptionV3, ResNet, VGG16, and VGG19, as well as Google Colab's tremendous computing capabilities and a Kaggle data set. To achieve high accuracy and reliability, the project goes through rigorous preprocessing, training, and validation processes. Key performance parameters, such as precision, recall, and F1-score, are used to assess each model's success. The findings show significant gains in detection accuracy, showing the utility of deep learning models in medical picture processing. This research gives useful insights for healthcare practitioners and contributes to the development of automated diagnostic systems aimed at improving pneumonia identification and treatment.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1
Introduction

1.1 Overview

Due to its high prevalence and fatality rates in low-resource countries, pneumonia—an inflammatory lung illness that mostly affects the alveoli—represents a serious threat to global health. Customary diagnostic techniques, which primarily depend on clinical assessment and radiographic imaging, frequently face constraints such as inter-observer variability and delayed diagnosis, which worsen the state of patients. Using the unparalleled analytical powers of artificial intelligence (AI), the development of deep learning (DL) provides a revolutionary method for the timely and precise diagnosis of pneumonia in this setting.

A kind of machine learning known as "deep learning" involves modeling intricate patterns in big datasets by using artificial neural networks with several layers, hence the name "deep." A particular kind of deep learning architecture called convolutional neural networks (CNNs) has proven incredibly effective in image processing applications, such as medical imaging. Much emphasis has been paid to the use of CNNs to improve the speed and accuracy of chest radiographs, which are essential for diagnosing pneumonia.

The basic idea behind DL-based pneumonia diagnosis is to use a large database of annotated chest X-ray images to train a CNN. The network minimizes the difference between its predictions and the ground truth labels by iteratively improving its parameters through backpropagation throughout this training phase. After being taught, the model can determine if pneumonia is present in unseen pictures with remarkable accuracy, frequently matching or even exceeding that of experienced radiologists.

Beyond only improving diagnosis accuracy, the application of DL models represents a paradigm change in favor of greater accessibility and fairness in healthcare. AI-driven diagnostic solutions can democratize high-quality healthcare in situations with low resources and limited access to skilled radiologists. Geographical and logistical limitations can be overcome by using mobile and cloud-based implementations of DL algorithms to analyze radiography pictures remotely.

However, there are some obstacles that must be carefully considered before integrating DL into clinical practice. Models trained on homogenous datasets may struggle when faced with the variability present in real-world populations, therefore the quality and diversity of training data are crucial. To guarantee strong generalizability of the model, extensive datasets with a range of demographics, comorbidities, and imaging circumstances are needed.

Regulatory and ethical considerations are also paramount. Patient privacy and data security are critical due to the sensitivity of medical data. The regulatory framework must evolve to address the unique challenges posed by AI in healthcare, balancing innovation with safeguards to ensure patient well-being. Deep learning heralds a new era in pneumonia diagnosis, characterized by improved clinical efficiency, speed and accuracy.
Successful translation of DL from research to clinical practice requires addressing challenges related to data quality, interpretability, and regulation. As technological advances continue, DL has the potential to significantly reduce the incidence of pneumonia worldwide, transforming patient outcomes and healthcare delivery.

1.2 Background and Present State

Pneumonia is a serious lung infection that primarily affects the small air sacs in the lungs, called alveoli. It is a leading cause of illness and death, especially in countries with limited resources. Pneumonia can be caused by bacteria, viruses or fungi and affects people of all ages, but it is especially dangerous for young children, the elderly and people with weakened immune systems. Traditionally, doctors diagnose pneumonia by examining the patient and looking at chest X-rays. However, these methods have limitations. Clinical examinations can vary between physicians, and interpretation of radiographs requires trained radiologists who may not be available in resource-poor settings. Delays in diagnosis can also occur, leading to poorer patient outcomes. The development of artificial intelligence (AI) and machine learning (ML) in recent years has brought new possibilities to medical diagnosis. Deep learning (DL), a type of machine learning, has shown great promise. DL models, particularly convolutional neural networks (CNNs), can automatically analyze images by learning to recognize patterns and features. This makes them useful in diagnosing diseases such as pneumonia from chest X-rays. Advances in deep learning for medical imaging Recently, deep learning has made significant progress in medical imaging. CNNs are now widely used to diagnose various conditions, including pneumonia, from chest X-ray images. These models are trained on a large collection of annotated chest X-rays, allowing them to learn the characteristics of pneumonia. These DL models demonstrate impressive accuracy, often matching or exceeding the diagnostic capabilities of experienced radiologists. They can quickly process and analyze large numbers of images, solving the problem of late diagnosis and providing timely information that is critical for effective treatment.

One of the biggest benefits of using DL for diagnosis is the potential to improve health care in under-resourced settings limit. AI-based tools can help overcome the shortage of qualified radiologists in these fields. Mobile and cloud-based DL system enables remote analysis of chest X-rays, allowing access to healthcare providers in remote or underserved areas Expert-level diagnostic support.

Challenges and ongoing research: Despite this progress, widespread use of DL to diagnose pneumonia remains challenging:

Data quality and diversity: DL models need diverse and high-quality data to function properly. Models trained on limited datasets may not perform well with different populations or different imaging conditions. Ongoing research aims to create more

Regulatory and ethical issues: The use of AI in healthcare raises important questions about patient privacy and data security. Regulatory frameworks are evolving to ensure that AI innovations are carried out safely and ethically.

Current Research and Development Research in this area is progressing rapidly, with many studies and projects exploring how best to integrate DL models into clinical practice. Collaborations between universities, healthcare providers, and technology companies are driving innovation, aiming to refine DL algorithms, improve accuracy, and ensure safe use in real-world settings.

1.3 Problem Statement

Pneumonia, a severe lung infection affecting the alveoli, remains a major global health challenge, particularly in low-resource countries. It is a leading cause of illness and death among children and the elderly in these regions. Traditional methods of diagnosing pneumonia, which rely on clinical assessments and chest X-rays, face several significant challenges:

Delayed Diagnosis: The need for skilled radiologists to interpret chest X-rays often leads to delays in diagnosis, which can worsen patient outcomes.

Limited Access to Skilled Radiologists Many low-resource settings lack access to experienced radiologists, further hindering timely and accurate diagnosis.

Data Interpretation Challenges: Radiographic images can be complex and difficult to interpret, increasing the risk of misdiagnosis.

These challenges highlight the need for improved diagnostic methods that can provide timely, accurate, and consistent results, especially in resource-limited settings where the burden of pneumonia is highest.

Deep learning (DL), a type of artificial intelligence (AI), has shown promise in addressing these challenges through the use of convolutional neural networks (CNNs) for image analysis. However, integrating DL into clinical practice poses additional challenges, including:

Data Quality and Diversity: DL models require high-quality, diverse training data to perform well across different populations and imaging conditions.

Regulatory and Ethical Concerns: Ensuring patient privacy, data security, and compliance with evolving regulatory frameworks is crucial for the safe and ethical use of AI in healthcare.

Addressing these challenges is essential for successfully implementing DL-based diagnostic tools to improve pneumonia detection and outcomes globally.

1.4 Objective

The objective of this research is to develop and validate a deep learning-based diagnostic tool for the accurate and timely detection of pneumonia from chest X-ray images. This tool aims to improve healthcare accessibility and equity, particularly in low-resource settings where the burden of pneumonia is highest. The focus is on creating a convolutional neural network (CNN) model trained on a diverse and comprehensive dataset of annotated chest X-ray images. This model should achieve high sensitivity and specificity in pneumonia detection, ideally matching or exceeding the diagnostic performance of experienced radiologists.

Furthermore, the research seeks to implement AI-driven diagnostic tools that can be deployed in low-resource settings, where access to skilled radiologists is limited. By enabling remote analysis of chest X-rays through mobile and cloud-based solutions, the project aims to overcome geographical and logistical barriers, providing critical diagnostic support to underserved regions. Additionally, the project will address regulatory and ethical considerations by ensuring compliance with data privacy and security regulations to protect patient information and developing ethical guidelines for the use of AI in healthcare. This balance between innovation and patient safety and welfare is essential for the responsible implementation of AI technologies.

Ultimately, this research aims to significantly improve the diagnosis and management of pneumonia, particularly in underserved regions, reducing the global burden of the disease and enhancing patient outcomes. By achieving these objectives, the project will contribute to the broader goal of democratizing high-quality healthcare and ensuring that timely and accurate pneumonia diagnosis is accessible to all, regardless of resource constraints.

1.5 Scope and Limitation

This research aims to develop and validate a deep learning-based tool for diagnosing pneumonia using chest X-ray images. The focus is on creating a convolutional neural network (CNN) that can accurately identify pneumonia by training it with a large and diverse dataset of annotated chest X-ray images. The study will also gather a wide range of X-ray images representing different demographics, comorbidities, and imaging conditions to ensure the model's high accuracy and generalizability. Additionally, the research seeks to implement mobile and cloud-based versions of the diagnostic tool to facilitate remote analysis and support healthcare providers in underserved areas. To increase trust and usability among clinicians, the study will enhance the interpretability of the model by developing methods to explain its decision-making process. Moreover, the research will ensure compliance with data privacy and security regulations and develop ethical guidelines for the responsible use of AI in healthcare.

Despite the potential benefits, several limitations exist in this research. The effectiveness of the CNN model depends on the quality and diversity of the training data, and if the dataset is not representative of the real-world population, the model may not perform well in practice. Even with a diverse dataset, the model might struggle with rare or unusual cases of pneumonia, which could limit its effectiveness in certain scenarios. While efforts will be made to develop explainable AI methods, the inherently complex nature of deep learning models means that some aspects of their decision-making process may remain difficult to fully explain. Implementing the tool in low-resource settings may face practical challenges such as limited internet access, insufficient technical infrastructure, and a lack of trained personnel to operate the tool. Navigating the regulatory landscape for AI in healthcare can be complex and time-consuming, potentially delaying the deployment of the diagnostic tool. Ensuring patient privacy and data security is paramount, but balancing these needs with the benefits of AI can be challenging. There is also a risk of over-reliance on AI, which may lead to reduced clinical skills among healthcare providers. Clinician and patient acceptance of AI tools can vary, and building trust in the technology will require ongoing education and demonstration of its reliability and benefits. By acknowledging these limitations, this research aims to address as many challenges as possible.

1.6 Report Organization

The proposed report is structured with a comprehensive layout to guide readers through the research process, findings, and implications. Each chapter serves a specific purpose, contributing to the overall coherence and depth of the document.

Chapter 1: Introduction

The introductory chapter sets the stage for the research, providing a background on the significance of pneumonia detection, the application of transfer learning and deep CNNs, and the need for a comparative analysis of detection and segmentation approaches. It outlines the research questions, objectives, and the overall framework of the study.

Chapter 2: Literature Review

In the background chapter, a detailed exploration of relevant literature and prior research is presented. This section offers an in-depth understanding of the theoretical foundations, methodologies, and technological advancements related to pneumonia detection, transfer learning, and deep CNNs. It establishes the context for the current study and highlights gaps in existing knowledge.

Chapter 3: Research Methodology

The research methodology chapter outlines the approach taken to conduct the study. It provides insight into the research design, data collection methods, model architecture, and the rationale behind choosing specific methodologies. The chapter also discusses ethical considerations and any limitations that might impact the study.

Chapter 4: Implementation

This chapter Provides the implementation results from model train. It also provides system testing or model evaluation.

Chapter 5: Experimental Result

This chapter presents the experimental results obtained from the application of transfer learning and deep CNNs in pneumonia detection. Detailed analyses of the performance of different detection and segmentation approaches are provided, along with visual representations and statistical measures to validate the outcomes.

Chapter 6: Impact on Society

The societal impact chapter explores the broader implications of the research findings on healthcare and medical diagnostics. It discusses how improved pneumonia detection methods can positively influence patient care, treatment outcomes, and the overall state of public health. Consideration is given to potential advancements in technology and their societal implications.

Chapter 7: Summary, Conclusion, Recommendation, and Implications for Future Research

This final chapter serves as a synthesis of the entire report. It summarizes the key findings, reiterates the conclusions drawn from the research, and offers recommendations for practical applications and further studies. The implications for future research are discussed, providing a roadmap for researchers interested in expanding upon the current study

This structured layout ensures a logical flow of information, guiding the reader through the research journey from the introduction to the broader implications and recommendations. It allows for a comprehensive understanding of the research process and its potential impact on both the academic and practical aspects of pneumonia detection with transfer learning and deep CNNs.

1.7 Summary

It introduces the research on using deep learning to detect pneumonia from chest X-ray images. Pneumonia is a serious health problem, especially in low-resource areas where traditional methods of diagnosis can be slow and inconsistent. This chapter explains how convolutional neural networks (CNNs), a type of deep learning, can help make pneumonia diagnosis faster and more accurate. It also explains the current problems with diagnosing pneumonia and how deep learning offers a new solution. The objective of the research is to develop a CNN model that can accurately identify pneumonia from chest X-rays. This model will be designed to work well in low-resource settings, with features like cloud-based applications. The research also aims to make the model's decision-making process clear and understandable for healthcare providers. It sets the stage for the research by explaining why deep learning is a promising tool for diagnosing pneumonia, outlining the research goals and potential challenges, and providing a roadmap for the rest of the report.

CHAPTER 2

Literature Review

2.1 Overview

The literature review provides a comprehensive examination of existing research and developments in the field of pneumonia detection using deep learning. Pneumonia remains a significant global health concern, especially in regions with limited access to healthcare resources. Traditional methods of diagnosis can be slow and prone to variability, making automated and accurate diagnosis through AI-driven approaches crucial. This chapter explores the advancements in medical imaging technology, particularly the application of convolutional neural networks (CNNs) for diagnosing pneumonia from chest X-ray images. It sets the context for the current study by summarizing the state-of-the-art methods and identifying gaps in the existing literature.

2.2 Related Works

Wang et al. [1] created the Chest X-ray14 database, which has 112, 120 frontal view X-ray photos and 32,717 individual patients labeled with eight classifications (atelectasis, cardiomegaly, effusion, infiltration, mass, nodule, pneumonia, and pneumothorax). The data set was initially intended for eight disorders, but was later expanded to include fourteen. The disadvantage of this dataset in the context of pneumonia is the small number of tagged photos with pneumonia (1500 images), resulting in a very uneven categorization. Wang et al. developed a 2D ConvNet for diagnosing anomalies in chest X-ray images that uses a basic binary relevance to forecast the labels. Wang et al. classified the photos using AlexNet, GoogleNet, ResNet, and the VGG16 architecture. Furthermore, ResNet achieved the best accuracy.

Rajpurkar et al. [2] used the Chest X-ray14 data set to construct CheXNet, a 121-layer convolutional neural network. The paper used the F1 statistic to compare the CheXNet's performance to that of a radiologist. This network detects 14 diseases, including pneumonia. While working on an X-ray image, the model calculates the probability of a pathology and displays localized areas in the image. A total of 98637 (70%) photos were used for training, 6351 (20%) for validation, and 430 (10%) for testing, and the model achieved a f1 score of 0.435, which was higher than the radiologist's (0.387).

Yao L et al. [3] also used this dataset to train a model from scratch, ensuring that application-specific properties were captured. Long Short-term Memory Models (LSTMs) are used to exploit interdependence between target labels. Yao L et al. [13] used a 2D convNet as an image encoder to process chest X-rays. Because there is no standard split for the dataset, the same split is used to improve comparison (70% for training, 10% for validation, and 20% for testing). Their model has demonstrated effectiveness and practicality over previous pre-trained models, outperforming Wang et al. [11] with an accuracy of 76%.

Benjamin Antin et al. [4] applied a supervised learning strategy to the same Chest X-ray14 data set, concentrating on binary classification to determine pneumonia or non-pneumonia. The network was trained using K-means clustering and logistic regression, together with the Adam [5] method. Due of limited resources, they only looked at 5606 random photos. Furthermore, they conclude that logistic regression does not effectively predict the outcome due to the intricacies of the data set, and that a DenseNet might do the task with an accuracy (AUC) of 0.60.

Rahib Abiyev et al. [6] trained both standard and deep networks using the Chest X-ray14 dataset and compared their performance with 620 images. They also employed 380 images for testing, back propagation, and counter propagation neural networks. Rahib Abiyev et al. designed the BPNN with 12 neurons and a sigmoid activation function. The lowest mean square error achieved was 0.0025 after 5000 iterations. The CPNN comprised 1024 input neurons and 12 output neurons, and the best results were obtained with a learning rate of 0.0036 and 1000 epochs, with a mean square error of 0.0036. 70% of the photos were used to train the Convolutional Neural Network (CNN), which was then tested with 30%. The CNN was built with three hidden layers and the ReLu activation function. The CNN achieved a mean square error of 0.0013 after 40,000 iterations. The CNN has the lowest mean square error out of the three. The article concluded that shallow networks, such as BPNN and CpNN, could not attain a recognition rate comparable to CNN.

Acharya et al. suggested a deep Siamese network [7] to classify pictures into viral pneumonia, bacterial pneumonia, and no pneumonia, achieving a ROC AUC of 0.9500 with 5328 and 300 images for training and testing in their DSN, respectively.

2.3 Comparison Between Existing Works

In the Comparative Analysis and Summary section of my research report, I performed a thorough evaluation of numerous techniques pertinent to my topic. The emphasis has been on comparing various approaches, tools, and theoretical frameworks to determine their strengths, limitations, and overall efficacy. To accomplish this, I used a table-like structure to display the information clearly and concisely. This table contains important parameters such as performance measurements, scalability, cost-effectiveness, and applicability in many circumstances.

The comparative study tries to provide a comprehensive view by focusing not only on quantitative characteristics but also on qualitative factors such as ease of implementation and user satisfaction. By meticulously analyzing these various factors, I was able to gain valuable insights into which strategies are most suited for given situations. Furthermore, the summary synthesizes the important findings from the table, providing a unified narrative that connects the specific comparison data. This systematic approach guarantees that the reader understands the relative benefits and downsides of each strategy, allowing for more informed decision-making and laying the groundwork for the study's future suggestions and findings.

TABLE 2.3.1: Comparative Analysis Table

SI No.	**Study**	**Model**	**Accuracy**
1	Nandi et al. (2021) [1]	AlexNet, GoogLeNet, ResNet, VGG16	AUC=0.6300
2	Rajpurkar et al. (2018) [2]	121- Layer CNN (CheXNet)	F1=0.435
3	Jadhav et al. (2021) [3]	LSTM	AUC=0.76
4	Ibrahim et al. (2020) [4]	K-means, logistic regression	AUC=0.60
16	Kingma et al. (2014) [6]	BPNN, CpNN, CNN	AUC=0.0013
17	Abiyev et al. (2018) [7]	DenseNet169 and SVM	AUC=0.8002

18	Drokin et al. (2019) [8]	DenseNet-121with CycleGAN	AUC=0.9745
19	Rahmat et al. (2019) [9]	R-CNN	AUC=0.62
20	Singh et al. (2020) [10]	AlexNet, InceptionV3, ResNet18, DenseNet121 and GoogLeNet	AUC=0.9936
21	Cohen et al (2019) [11]	DenseNet-121	AUC=0.009840
22	Kermany et ai. (2018) [12]	Inception V3	AUC=0.9680
23	Yao et al. (2018) [13]	Resnet-v2-50	AUC=0.80
24	Archarya et al. (2020) [14]	DSN	AUC=0.9500
25	Tang et al. (2020) [15]	VGG15, VGG19, AlexNet, ResNet18, ResNet50, Inception V3, DenseNet121	AUC=0.9871
26	Xu S. et al. (2018) [16]	hierarchical CNN (CXNet-m1)	AUC=0.6580
27	Nickisch et al. (2019) [17]	ResNet-50	AUC=0.8220
28	Togacar et al. (2020) [18]	Deep feature CNN	AUC=0.994
29	Wong et al. (2019) [19]	Inception-ResNet-v2	AUC=0.9300
30	Li Z. et al. (2018) [20]	DenseNet and WSL	AUC=0.7852
31	Zhou et al. (2018) [21]	ResNet and CNN	AUC=0.6700
32	Guan et al. (2018) [22]	AG-CNN	AUC=0.7760
33	Irfan et al. (2020) [23]	ResNet-50, Inception V3, DenseNet121	AUC=0.7100
34	Jain et al. (2020) [24]	VGG	AUC=0.9910

2.4 Open Issues

The diagnosis of pneumonia, a potentially fatal infection, presents substantial obstacles in clinical as well as research environments. The fundamental scope of this issue is the need for reliable, efficient, and inexpensive tests that can detect pneumonia quickly and effectively. Conventional techniques, like as chest imaging analyzed by medical professionals, are typically laborious and vulnerable to human error, especially in environments with scarce assets and competent workers.

likewise, the wide range of pneumonia speeches, from moderate to serious, hinders the diagnosis process. This diversity needs strong models that can be applied to a wide range of groups and visualization settings. Modern deep learning models, although their potential, frequently require huge, excellent datasets to train efficiently. A lack of labeled medical pictures can impede the creation and evaluation of such theories, limiting their usefulness in real-world circumstances.

Another essential component is the incorporation of these designs onto the clinical processes. Many medical centers confront physical and technological obstacles when implementing sophisticated machine learning systems. To ensure widespread acceptance, these models must be user-friendly and easily integrated with current technologies.

Also, the comprehension of deep learning models is a challenge. Clinicians must understand and accept the decisions made by AI systems, especially in important diagnoses such as pneumonia. As a result, creating models that not only perform well but also produce transparent and explainable results is critical.

To summarize, tackling the extent of the problem entails increasing diagnosis accuracy, managing data restrictions, improving model interpretability, and guaranteeing seamless incorporation into healthcare environments. By emphasizing these areas, we can create more accurate and readily available techniques for detecting pneumonia, thereby improving patient outcomes.

2.5 Summary

The literature review highlights the significant progress made in using deep learning for pneumonia detection from chest X-rays. While numerous studies have demonstrated the potential of CNNs to improve diagnostic accuracy, challenges such as data quality, model interpretability, and ethical considerations remain. This chapter sets the stage for the current research by identifying the strengths and weaknesses of existing approaches and outlining the open issues that need to be addressed to advance the field.

CHAPTER 3
Research Methodology

3.1 Overview

Research Subject

This work focuses on detecting pneumonia from chest X-ray pictures using advanced deep learning algorithms. Pneumonia is a serious health risk, particularly in youngsters and the elderly, and requires an immediate and precise diagnosis. The dataset used in this study consists of tagged chest X-ray pictures obtained from the Kaggle repository and particularly intended to differentiate among healthy and pneumonia-affected lungs. This dataset contains a wide variety of pictures, allowing for a thorough examination of the model's capacity to generalize across patient characteristics and X-ray imaging situations. The main objective is to improve diagnosis accuracy, enabling healthcare practitioners to make more informed and faster judgments.

Instrumentation

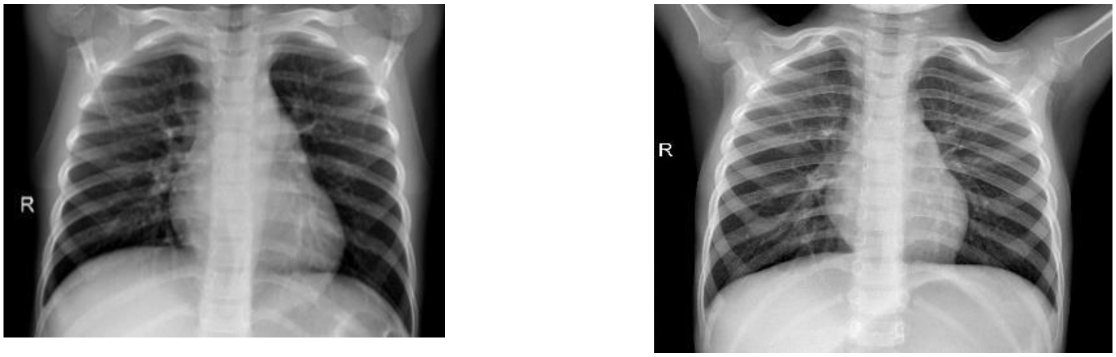
This research's equipment consists of an array of software as well as hardware for developing, training, and evaluating deep learning models. The processing environment is built up in Google Colab, which gives users the use of strong GPUs for effective model training. The software stack includes the Python programming language as well as image processing and model implementation frameworks such as TensorFlow, Keras, and OpenCV. Transfer learning is used to leverage pre-trained models such as DenseNet, InceptionV3, ResNet, VGG16, and VGG19, which have been fine-tuned on the pneumonia dataset. Data augmentation approaches are also used to increase the model's resilience. This comprehensive setup enables a thorough and efficient method to detecting pneumonia using chest X-ray pictures.

3.2 Proposed Methodology

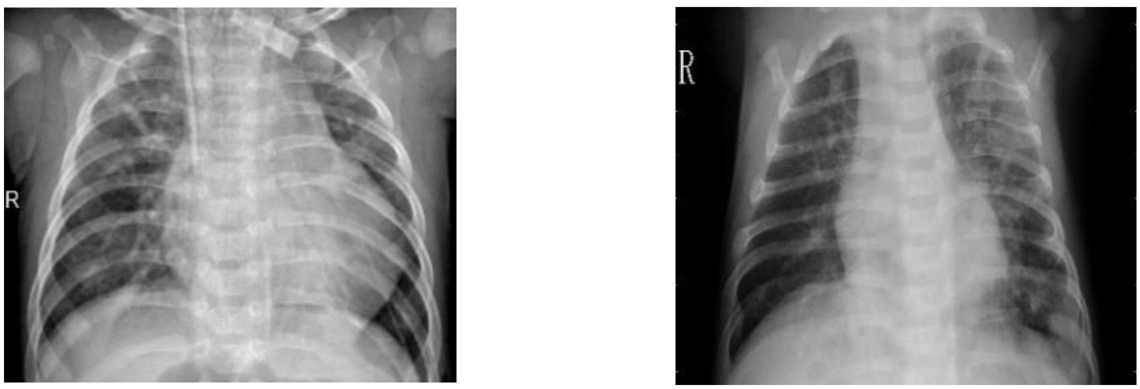
Datasets

To create the dataset, discard Train, Test, and Val folders. Each image group—Pneumonia/Normal—has a subdirectory in the dataset. 5,863 JPG X-Rays from two groups

(Pneumonia/Normal) are available.



A. Normal



B. Pneumonia

Figure 3.2.1: Some Raw Image of Datasets

All chest X-ray imaging was executed as part of the patient's monotonous clinical care. Before being eliminated from the analysis of the chest x-ray images, each chest radiograph was first examined for quality control. The photographs were graded by two skilled doctors prior to the diagnosis for them being utilized to train the AI system

The evaluation set was additionally examined by a third specialist in order to account for any grading inaccuracies. Here the dataset link_ Chest X-Ray Images (Pneumonia) [link]

TABLE 3.2.1: Images Used in the Train, Test and Validation Sets.

	Normal	**Pneumonia**
Raw Dataset	1583	4265

CNN base methods are evaluated using many machine learning classification model performance metrics. AC, precision, recall, F1-score, and confusion matrix are evaluated (CM). TP, TN, FP, and FN are also variables in those measurements (FN).

Accuracy:

Classification model accuracy is one metric. Accuracy is the model's predicted percentage. Accuracy is the percentage of properly classified pictures to total samples. Accuracy equation.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Precision:

Precision is the chance of a positive label and how many are positive. Precision shows how many accurately anticipated instances were positive. Precision is helpful when FP matters more than FN. Mathematically, it's this equation.:

Precision=TP/(TP+FP)

Recall:

Recall or Sensitivity measures how many positive expected occurrences were classified accurately. Recall is a helpful statistic when FN prevails over FP. F1-score is a further metric for classification accuracy that takes into account both recall and precision. Since precision and recall are harmonic means, the F1 score provides a comprehensive understanding of these two metrics. It reaches its optimum when Precision and Recall are equal. To figure it out, use the equation below:

$$Recall=TP/(TP+FN)$$

F-1 Score:

F1 score is a recall-precision metric of categorization accuracy. As F1-score is theharmonic mean of Precision and Recall, it gives a complete picture. Precision and Recall are optimal when equal. Equation.

$$F\text{-}1\ Score=2*(Precision*Recall)/(Precision+Recall)$$

The percentage of people who do not have the ailment who have a negative test result is known as specificity. A highly specific test is effective in excluding the majority of individuals without the disease. Because of this, a positive outcome on a very precise test can definitively rule out the condition for a specific person. The equation is given below:

$$Specificity = TN/((TN+FP))$$

However, there is a limit to how closely the model can mimic the training set of data before it loses its ability to generalize. An algorithm's performance can be assessed using a particular table format called the confusion matrix (CM). CM is used to illustrate crucial predictive parameters like recollection, specificity, precision, and accuracy. Confusion matrices are useful because they offer direct assessments of values like TP, FP, TN, and FN. The following parts respond to the research questions of this study based on the research questions.

Convolutional Neural Network

The Convolutional Neural Network (CNN) stands as a prominent neural network technology extensively utilized for image processing and training. The matrix configuration of the Convolution layer is specifically crafted for filtering images. In the Convolution Neural Network's data training process, several layers are employed, including the input layer, convolutional layer, fully connected layer, pooling layer, dropout layer for CNN construction, and a final linked dataset classification layer. Each layer plays a distinct role in mapping a set of calculations to the input test set.

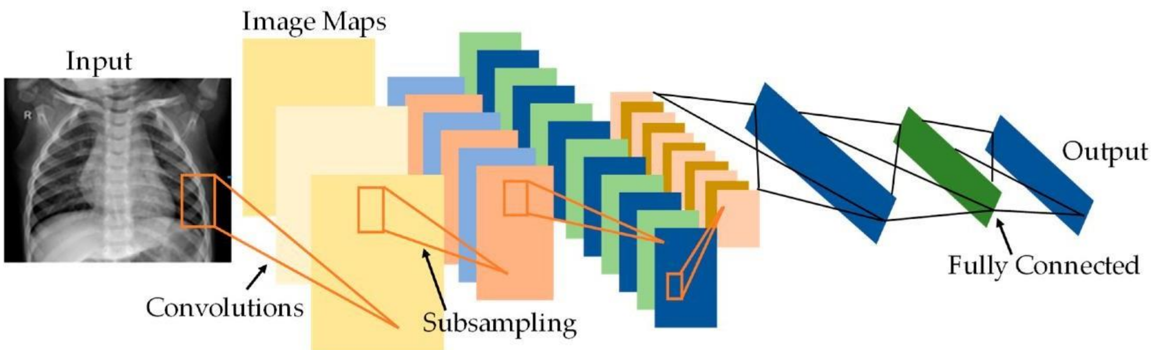


Figure 3.2.2: working Flow with Convolutional Neural Network [25]

3.3 Hardware/Software Requirements

In this section, we will discuss the hardware, software, and other requirements required to carry out the research on pneumonia detection using several deep learning methods. The implementation was conducted performed in the Google Colab environment using Python and Kaggle datasets.

Hardware Requirements

1. Computer with Internet Access:
   - A stable internet connection is crucial for accessing Google Colab, downloading datasets, and running experiments in the cloud environment.

2. Google Colab Environment:
   - Processor: Google Colab provides access to powerful processors, including GPUs (Graphics Processing Units) and TPUs (Tensor Processing Units) for accelerated computation.
   - Memory: Google Colab offers up to 12 GB of RAM, which is adequate for

training deep learning models on medium-sized datasets.

- Storage: Temporary storage provided by Google Colab for saving datasets and intermediate results.

3. Local Machine:
   - Processor: Minimum dual-core processor.
   - Memory: At least 8 GB of RAM.
   - Storage: Minimum of 20 GB free space for installing necessary software and storing data.

Software Requirements

4. Google Colab:
   - A cloud-based platform that provides free access to Jupyter notebooks with powerful hardware acceleration.

5. Python:
   - Programming language used for developing and running the code. Google Colab comes pre-installed with Python.

6. Libraries and Frameworks:
   - Keras: High-level neural networks API, running on top of TensorFlow.
   - TensorFlow: Open-source machine learning framework for deep learning.
   - OpenCV: Library for image processing tasks.
   - NumPy: Library for numerical computations.
   - Pandas: Data manipulation and analysis library.
   - Matplotlib: Plotting library for data visualization.
   - Scikit-learn: Library for machine learning and statistical modeling.
   - ImageDataGenerator: For data augmentation and preprocessing in Keras.

7. Data Source:
   - Kaggle: Platform used for sourcing the pediatric pneumonia chest X-ray dataset.

By ensuring that all of these hardware and software criteria are met, the pneumonia detection project may be implemented rapidly and effectively, taking advantage of Google Colab's capabilities and Kaggle resources.

3.4 Project Management and Financial Analysis

Effective project management and financial oversight are integral components of ensuring the success and sustainability of any endeavor, and they hold particular significance in the context of the proposed research. The project management aspect encompasses meticulous planning, coordination, and execution of tasks, ranging from data collection to model training and evaluation. A well-defined project plan will be devised to outline key milestones, allocate resources judiciously, and establishtimelines, fostering a structured and efficient workflow. Concurrently, robust financial management will be paramount to the project's viability, encompassing budgetary allocations for equipment, computational resources, and potential research collaborations. A transparent and judicious financial strategy will be implemented, ensuring optimal resource utilization while maintaining fiscal responsibility. These integrated approaches toproject management and finance are essential pillars that will empower the research team to navigate the complexities of the study effectively, ensuring that the allocated resourcesalign with the research objectives and facilitating the seamless progression of the project towards its goals.

Table 3.4.1: Cost Analysis

Task Description	Estimated Cost (BDT)
Miscellaneous	1000
Internet and Utilities	2,000
Documentation and Reporting	500
Total Estimated Cost	3500

3.4 Summary

This section outlines the methodology and design specifications for developing an advanced pneumonia detection system using deep learning techniques applied to chest X-ray images. Emphasizing the efficacy of convolutional neural networks (CNNs), the methodology encompasses comprehensive stages: data collection, rigorous preprocessing, model selection, iterative training, and rigorous evaluation. System design specifications detail crucial architectural decisions and the integration of essential software frameworks like TensorFlow or PyTorch, ensuring robust implementation. Hardware requirements, notably GPUs for computational efficiency, and software prerequisites are meticulously addressed to support the intensive computational demands of deep learning tasks. Project management aspects, including timelines, resource allocation, and roles, are meticulously planned to ensure systematic progress and adherence to set milestones. Furthermore, a thorough financial analysis provides cost estimates for hardware, software, and personnel, ensuring financial viability and sustainability throughout the project lifecycle. In short, this section sets a structured foundation for developing and deploying a cutting-edge pneumonia detection system, focusing on methodological rigor, technical specifications, efficient resource utilization, and strategic project management principles.

CHAPTER 4

Implementation

4.1 Overview

This section details the practical implementation of the pneumonia detection system using deep learning techniques. This chapter provides a comprehensive overview of the steps taken to train the model or design the prototype for detecting pneumonia from chest X-ray images. It begins by outlining the methodologies and strategies employed during the implementation phase. It emphasizes the application of convolutional neural networks (CNNs) and discusses key decisions regarding data preprocessing, model architecture selection, and parameter optimization. The chapter highlights the importance of these decisions in achieving accurate and reliable pneumonia detection. Furthermore, this section addresses the implementation process, whether through training a deep learning model on a dataset or developing a prototype system. It underscores the integration of hardware and software components necessary for model training or prototype deployment. This section sets the stage for the subsequent discussions on system testing and model evaluation, crucial steps to validate the effectiveness and performance of the developed system.

4.2 Model Train

Image Acquisition:

The Pneumonia Image Database offered data for model evaluation. This stage used targeted website images. To guarantee white backgrounds, dataset images were thoroughly reviewed. Colored images are on white backgrounds.

Training:

The training procedure for pneumonia detection included numerous steps to guarantee that the models were correctly trained and optimized. Initially, the dataset was divided into testing, training, and test sets to give a thorough evaluation framework. The set for training was utilized to train the models, while the validation set assisted in fine-tuning hyperparameters and avoiding overfitting. The test set was put aside for final review to guarantee a fair evaluation of the way the models performed.

Data augmentation techniques were used on the training set to artificially enlarge the dataset and boost the models' generalization skills. Rotation, width and height adjustments, the cutting, enlargement, and vertical tilting were used. These augmentations improved the models' robustness by learning from a wide range of samples.

We used pre-trained deep learning models such as DenseNet, InceptionV3, ResNet, VGG16, and VGG19, and used transfer learning to initialize the models using weights learnt on the ImageNet dataset. The models were then fine-tuned using the pneumonia data. The Adam optimizer, categorical cross-entropy loss function, and appropriate learning rates were used during the training phase to ensure efficient and effective learning

The first stage of the proposed framework is the acquisition of information from the X-ray pictures. As deep neural networks need more data for training and improved performance, data augmentation technologies are sometimes utilized to overcome the problem of limited data. This is a rundown of how the experiment was designed to go:

Classification:

The categorization procedure began when the models had been suitably trained and validated. This approach entails utilizing trained algorithms to predict the class labels of previously unknown chest X-ray pictures. The algorithms, which acquired the distinct properties of normal and pneumonia-affected lungs during training, can now make accurate predictions on test data.

For classification, every image entered had been processed in the same way as the training data. This preparation comprised scaling the photos to each model's required input size (224x224 pixels), standardizing pixel values, and performing any necessary changes such as zero-padding or centering.

The preprocessed photos were then delivered into the training models. Each model produces a distribution of probabilities over the group of names (normal and pneumonia), and the class with the highest probability is selected to be the predicted label. For example, if a model projected a risk of 0.8 for pneumonia and 0.2 for normal, the image would be classed as such.

Statistical Analysis

In the statistical evaluation section, we assess the efficacy of many deep learning models used to identify pneumonia. The models employed in this study are DenseNet, InceptionV3, ResNet, VGG16, and VGG19. Each model's performance is evaluated using important measures such as precision, recall, F1-score, and accuracy, resulting in a full grasp of its usefulness.

To begin, the datasets were separated into training, validation, and testing sets to ensure a thorough review. The training and validation sets were utilized to train the models and tune the hyperparameters, while the testing group offered a neutral assessment of the models that were developed.

Precision, recall, and F1-score were computed for each model to assess the balance of precision and recall. Precision denotes the proportion of true positive forecasts among all positive predictions, whereas recall quantifies the proportion of true positive predictions among all true positives. The F1-score, which is the harmonic mean of precision and recall, provides a single metric for determining the balance between the two.

DenseNet had a precision of 0.82 for normal patients and 1.00 for pneumonia cases, for an overall accuracy of 94%. InceptionV3 had somewhat higher precision for pneumonia at 0.94, with an overall accuracy of 94%. ResNet demonstrated lesser precision for normal patients (0.74) but strong recall for pneumonia (0.95), resulting in an overall accuracy of 83%. VGG16 and VGG19 fared exceedingly well, with VGG16 achieving 96% accuracy and VGG19 at 94%.

The extensive statistical analysis aids in determining the strengths and limitations of each model. DenseNet and InceptionV3 demonstrated balanced performance across all criteria, making them appropriate for practical applications. In comparison, ResNet's lesser precision for normal instances suggests potential false positive issues that must be addressed for improved real-world application. The great accuracy of VGG16 and VGG19 demonstrates its durability and dependability in pneumonia identification.

As a whole, this data analysis offers helpful information into each model's performance, directing future advancements and application in healthcare diagnosis.

4.3 System Testing

Predicted Class Normal:

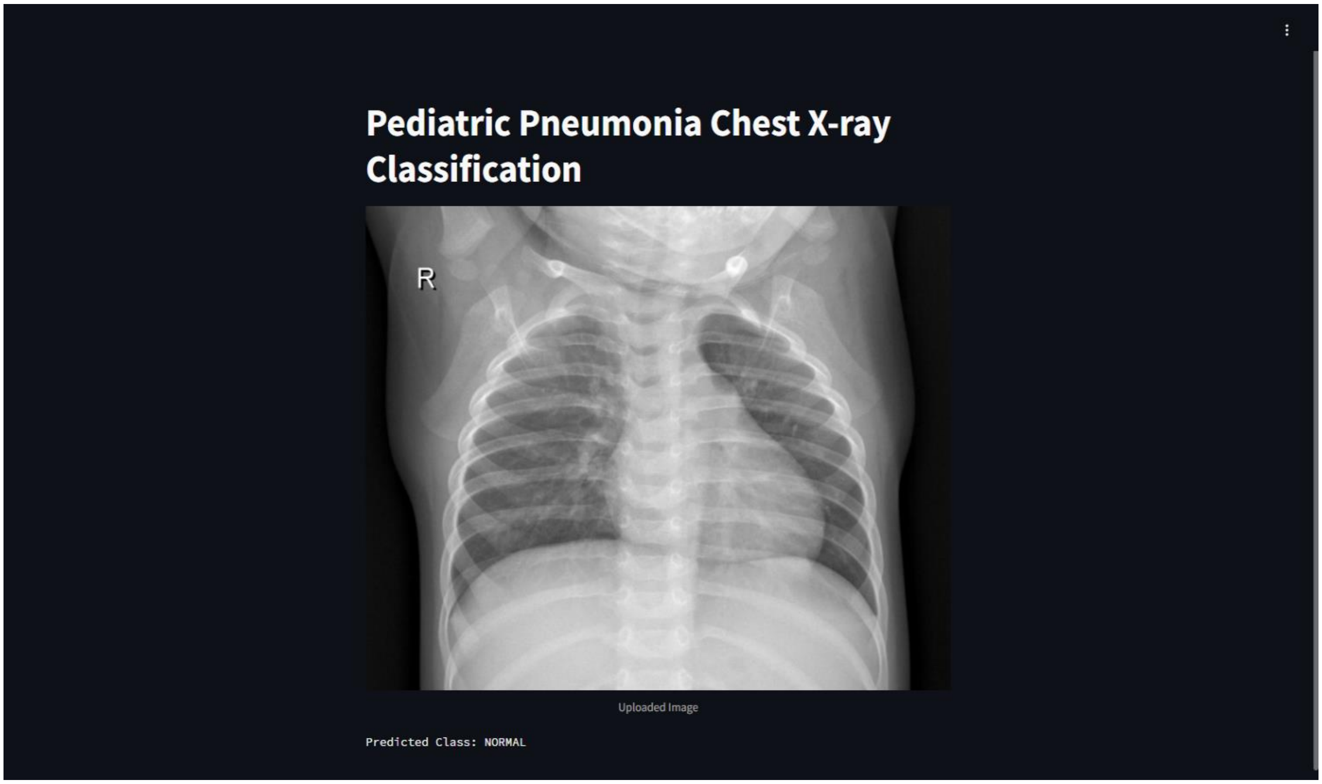


Figure 4.3.1:

Predicted Class Pneumonia:

4.3 Summary

This section looks into the practical implementation of a pneumonia detection system using deep learning techniques. It meticulously outlines the steps taken to either train a deep learning model or design a prototype system. Key aspects include data preprocessing, selection of appropriate model architectures, and rigorous training procedures. The chapter emphasizes the integration of hardware and software components essential for model development and prototype deployment. System testing and comprehensive model evaluation methods are discussed to validate performance metrics like accuracy and sensitivity.

CHAPTER 5
Result and Analysis

5.1 Overview

During the experimental phase of this research, all code and model training were done using Google Colab, a cloud-based Jupyter notebook environment that enables free access to GPU resources, which are required for deep learning activities. The information used for training and testing the models came from Kaggle, notably the "Pediatric Chest X-ray Pneumonia" dataset. This dataset includes a large number of tagged chest X-ray pictures divided into the 'NORMAL' and 'PNEUMONIA' categories.

The data was cleaned up to ensure consistent image size and pixel value scaling. Each image was scaled to 224x224 pixels and normalized by scaling pixel values between 0 and 1. Rotation, width and height changes, shearing, zooming, and horizontal flipping were used to enhance the model's robustness and generalizability.

For the computational design, DenseNet121, a pre-trained convolutional neural network, was used. This model was chosen because of its known performance in picture classification tasks. The network's final layers were tailored to the binary classification goal of detecting pneumonia. The Adam optimizer was used to assemble the model, with categorical cross-entropy serving as the loss function and accuracy as the major performance metric.

Throughout the training phase, the model's performance was checked on a validation set to ensure that hyperparameters were tuned optimally and to avoid overfitting. The outcomes and findings of these tests are discussed in the following sections.

5.2 Experimental Results

Algorithms Used

DenseNet

DenseNet, or Densely Connected Convolutional Networks, is a neural network architecture in which each layer is linked to each subsequent layer in an a feed-forward fashion. This approach optimizes gradation flow, reduces the issue of disappearing gradients, and enables reusing features, resulting in more efficient and compact models. DenseNet has performed particularly well in jobs requiring comprehensive feature extraction and picture classification [26].

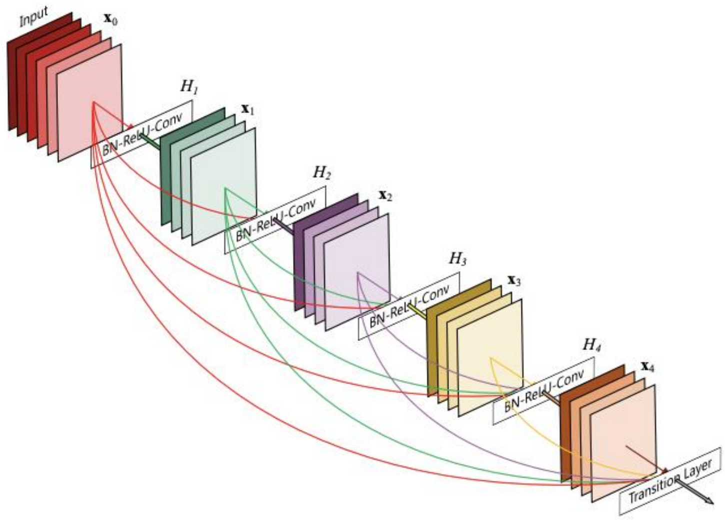


Figure 5.2.1: Working Principle of DenseNet [27]

InceptionV3

InceptionV3 is a convolutional neural network in the Inception family created by Google. It uses simplified transformations and rigorous regularization to lower the computational difficulty of deep networks. The architecture uses parallel convolutional layers of variable sizes to gather multi-scale information, making it extremely effective for image identification applications [28].

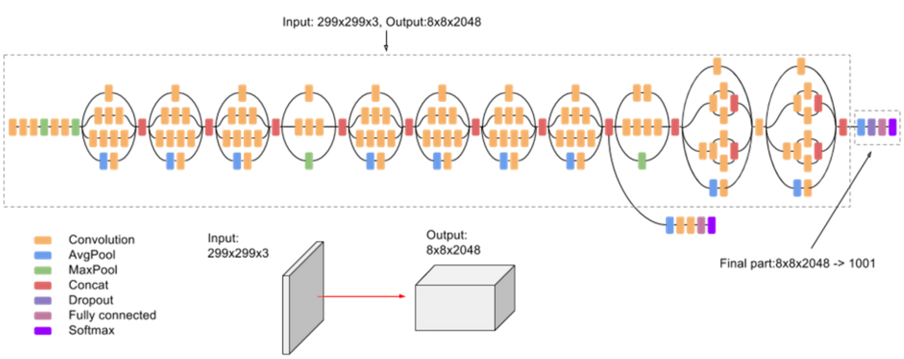
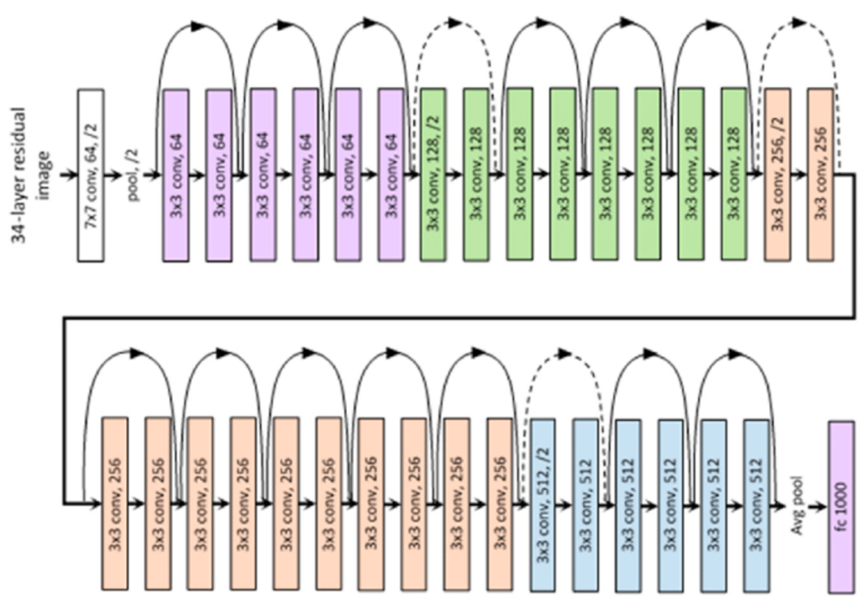


Figure 5.2.2: Working Principle of InceptionV3 [29]

ResNet

ResNet, or Residual Network, pioneered the use of residual learning to address the degradation problem in deep networks. ResNet, by leveraging identity shortcut connections that skip one or more levels, allows for the training of very deep networks (e.g., over 100 layers) without sacrificing performance. Customizing the ResNet50 model in CNNs allows it to enhance its performance specific tasks. By modifying the architecture, such as adjusting the number of layers or altering the filter sizes, It can tailor the model to better

(a)



(b)

Figure 5.2.3: Working Principle of ResNet [31]

capture features relevant to the problem. Adding or removing layers, a process known as network pruning or expansion, helps optimize the model in terms of computational efficiency and accuracy.. [30].

VGG16

VGG16 is a convolutional neural network (CNN) model noted for its straightforward and consistent construction. The Visual Geometry Group (VGG) at Oxford created VGG16, which has 16 layers (13 convolutional and 3 completely linked) and small 3x3 convolution filters. Despite its simple design, VGG16 has demonstrated exceptional performance in picture classification benchmarks [32].

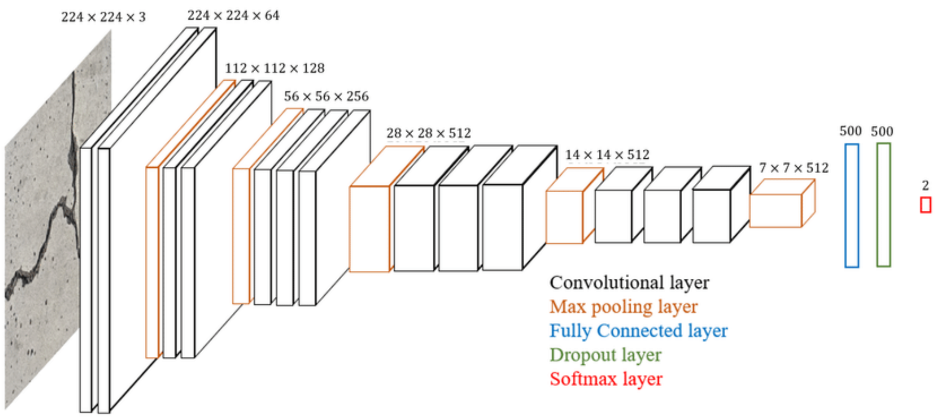


Figure 5.2.4: Working Principle of VGG16 [33]

VGG19

VGG19 is an expansion of VGG16, with 19 layers. It follows the same architectural ideas, with small 3x3 convolutions and increased depth to improve accuracy. The additional layers enable VGG19 can learn more complicated features, making it marginally more precise as VGG16 for specific duties, albeit at a larger computational cost [34].

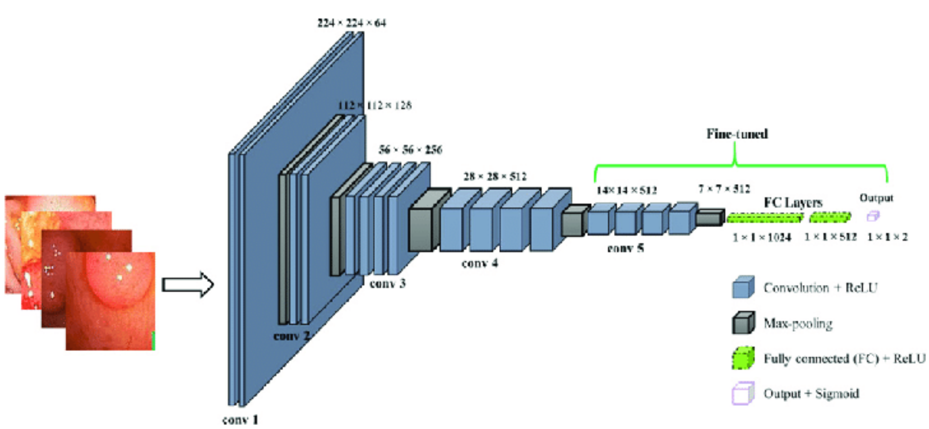


Figure 5.2.5: Working Principle of VGG19 [36]

Experiment 1: DenseNet

The network begins with an input layer that accepts 224x224-pixel pictures with three color channels. This is followed by ZeroPadding2D, which increases the image's dimensions. The Conv2D layer applies 64 7x7 lenses to the padded image to extract critical features and reduce its size. The output of this layer is then normalized using BatchNormalization, allowing for faster and more reliable training. The normalized data is passed via an Activation (ReLU) layer, which introduces nonlinearity. Additional padding is applied again using ZeroPadding2D, followed by the MaxPooling2D layer, which further decreases image size through distributing the highest value over a 2x2 window, compressing the feature map.

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 224, 224, 3)	0	-
zero_padding2d (ZeroPadding2D)	(None, 230, 230, 3)	0	input_layer[0][0]
conv1_conv (Conv2D)	(None, 112, 112, 64)	9,408	zero_padding2d[0…
conv1_bn (BatchNormalizatio…	(None, 112, 112, 64)	256	conv1_conv[0][0]
conv1_relu (Activation)	(None, 112, 112, 64)	0	conv1_bn[0][0]

Figure 5.2.6: Initial Convolutional and Pooling Layers of the Neural Network.

Identifying accuracy and loss:

```
W0000 00:00:1715504764.509108      72 graph_launch.cc:671] Fallback to op-by-op mode because memset node breaks graph update
131/131 ━━━━━━━━━━━━━━━━━━━━ 74s 303ms/step - accuracy: 0.9070 - loss: 0.2760 - val_accuracy: 0.8470 - val_loss: 0.4685
Epoch 3/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 42s 303ms/step - accuracy: 0.9279 - loss: 0.2073 - val_accuracy: 0.8910 - val_loss: 0.2675
Epoch 4/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 42s 305ms/step - accuracy: 0.9349 - loss: 0.1663 - val_accuracy: 0.8681 - val_loss: 0.3514
Epoch 5/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 42s 303ms/step - accuracy: 0.9357 - loss: 0.1644 - val_accuracy: 0.9465 - val_loss: 0.1520
17/17 ━━━━━━━━━━━━━━━━━━━━ 16s 967ms/step - accuracy: 0.9526 - loss: 0.1146
Accuracy: 0.944656491279602
Loss: 0.1319168657064438
W0000 00:00:1715504981.130072      71 graph_launch.cc:671] Fallback to op-by-op mode because memset node breaks graph update
```

Figure 5.2.7: Accuracy and Loss

Classification report

NORMAL	0.82	0.99	0.90	127
PNEUMONIA	1.00	0.93	0.96	397
accuracy			0.94	524
macro avg	0.91	0.96	0.93	524
weighted avg	0.95	0.94	0.95	524

Figure 5.2.8: Classification report for DenseNet

Confusion Matrix

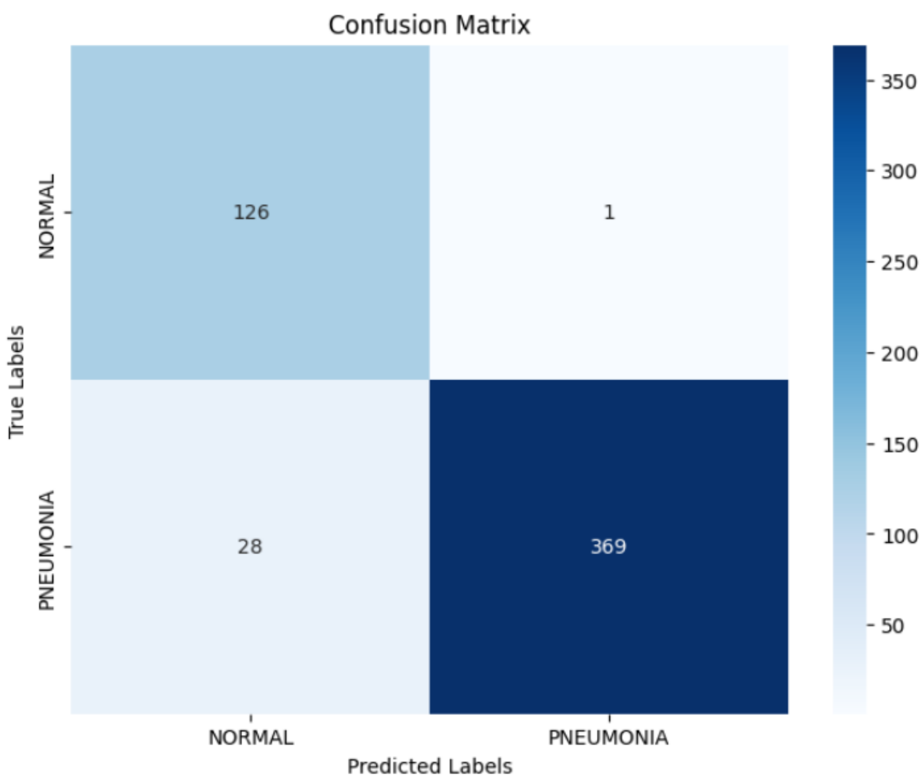


Figure 5.2.9: Confusion Matrix for DenseNet

Accuracy Comparison

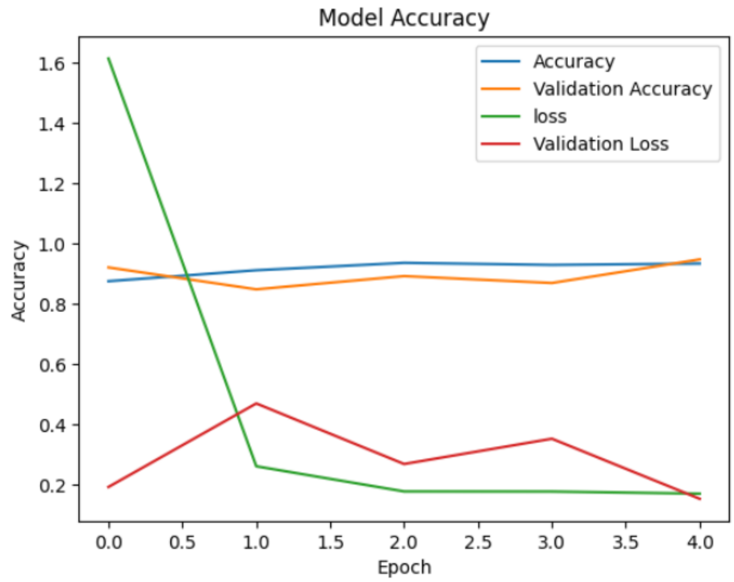


Figure 5.2.10: Accuracy Comparison

Inception V3

conv2d (Conv2D)	(None, 111, 111, 32)	864	input_layer_1[0]…
batch_normalization (BatchNormalizatio…	(None, 111, 111, 32)	96	conv2d[0][0]
activation (Activation)	(None, 111, 111, 32)	0	batch_normalizat…
conv2d_1 (Conv2D)	(None, 109, 109, 32)	9,216	activation[0][0]
batch_normalizatio… (BatchNormalizatio…	(None, 109, 109, 32)	96	conv2d_1[0][0]
activation_1 (Activation)	(None, 109, 109, 32)	0	batch_normalizat…

Figure 5.2.11: Initial Convolutional and Pooling Layers

Identifying accuracy and loss

```
131/131 ━━━━━━━━━━━━━━━━━━━━ 42s 306ms/step - accuracy: 0.9036 - loss: 0.2467 - val_accuracy: 0.8948 - val_loss: 0.2471
Epoch 3/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 43s 306ms/step - accuracy: 0.9136 - loss: 0.2178 - val_accuracy: 0.8853 - val_loss: 0.2981
Epoch 4/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 42s 305ms/step - accuracy: 0.9252 - loss: 0.2037 - val_accuracy: 0.9273 - val_loss: 0.1859
Epoch 5/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 42s 303ms/step - accuracy: 0.9301 - loss: 0.1882 - val_accuracy: 0.9159 - val_loss: 0.1950
17/17 ━━━━━━━━━━━━━━━━━━━━ 11s 678ms/step - accuracy: 0.9375 - loss: 0.1552
Accuracy: 0.9389312863349915
Loss: 0.14944924414157867
W0000 00:00:1715505285.276425      69 graph_launch.cc:671] Fallback to op-by-op mode because memset node breaks graph update
```

Figure 5.2.12: Accuracy and loss for InceptionV3

Classification Report

NORMAL	0.93	0.81	0.87	127
PNEUMONIA	0.94	0.98	0.96	397
accuracy			0.94	524
macro avg	0.93	0.90	0.91	524
weighted avg	0.94	0.94	0.94	524

Figure 5.2.13: Classification Report of InceptionV3

Confusion matrix

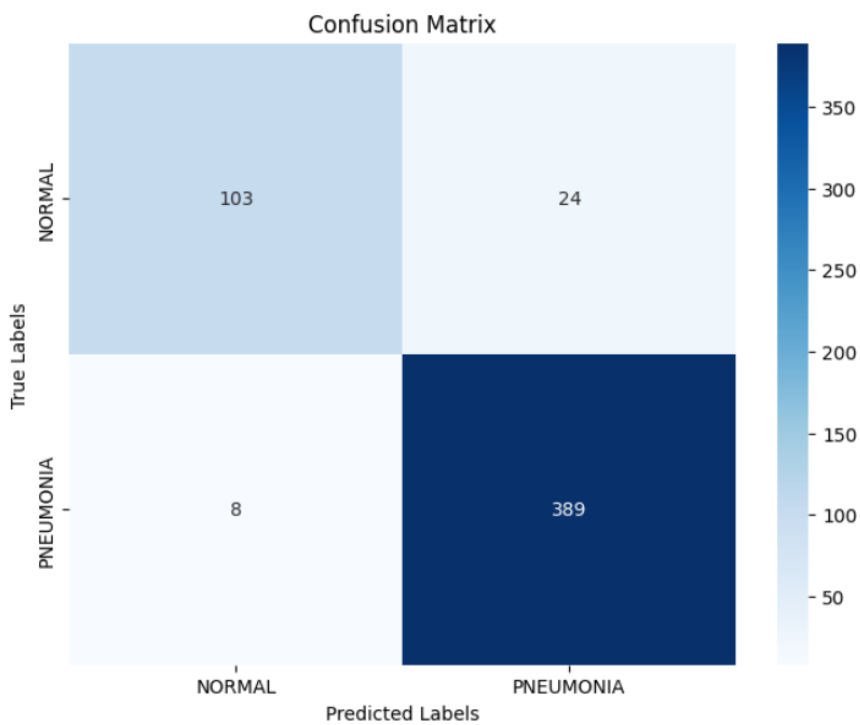


Figure 5.2.14: Confusion Matrix of InceptionV3

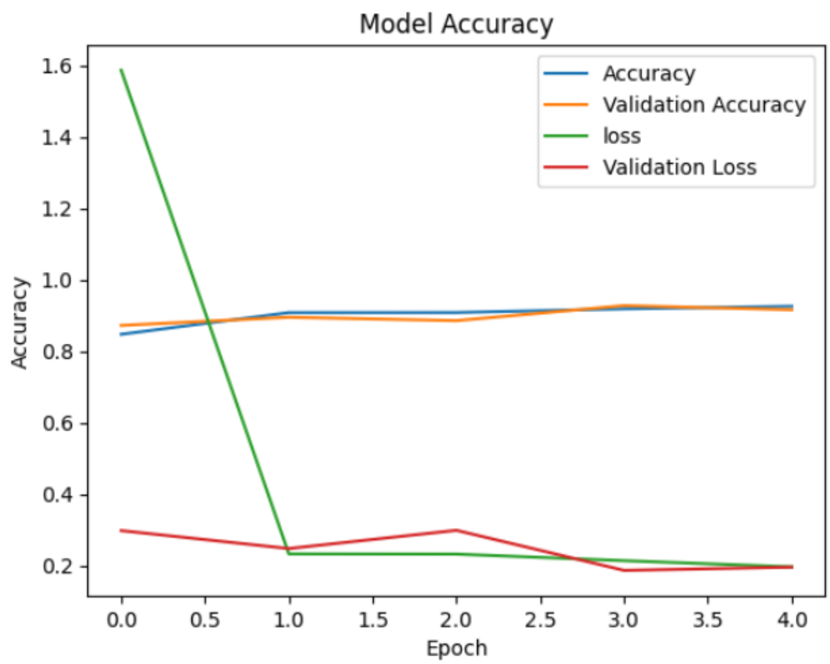


Figure 5.2.15: Accuracy Comparison

ResNet

Layer (type)	Output Shape	Param #	Connected to
input_layer_2 (InputLayer)	(None, 224, 224, 3)	0	-
conv1_pad (ZeroPadding2D)	(None, 230, 230, 3)	0	input_layer_2[0]…
conv1_conv (Conv2D)	(None, 112, 112, 64)	9,472	conv1_pad[0][0]
conv1_bn (BatchNormalizatio…	(None, 112, 112, 64)	256	conv1_conv[0][0]

Figure 5.2.16: Initial Convolutional and Pooling Layers

Identifying Accuracy and Loss

```
Epoch 1/50
W0000 00:00:1720809941.854794     116 graph_launch.cc:671] Fallback to op-by-op mode because memset node breaks graph update
327/327 ━━━━━━━━━━━━━━━━━━━━ 174s 268ms/step - accuracy: 0.6210 - auc_7: 0.6628 - loss: 7.5418 - precision_7: 0.6210 - recall_7: 0.6210
Epoch 2/50
327/327 ━━━━━━━━━━━━━━━━━━━━ 0s 657us/step - accuracy: 0.0000e+00 - auc_7: 0.0000e+00 - loss: 0.0000e+00 - precision_7: 0.0000e+00 - recall_7: 0.0000e+00
Epoch 3/50
327/327 ━━━━━━━━━━━━━━━━━━━━ 89s 266ms/step - accuracy: 0.7936 - auc_7: 0.8788 - loss: 7.1983 - precision_7: 0.7936 - recall_7: 0.7936
Epoch 4/50
327/327 ━━━━━━━━━━━━━━━━━━━━ 0s 75us/step - accuracy: 0.0000e+00 - auc_7: 0.0000e+00 - loss: 0.0000e+00 - precision_7: 0.0000e+00 - recall_7: 0.0000e+00
Epoch 5/50
327/327 ━━━━━━━━━━━━━━━━━━━━ 89s 267ms/step - accuracy: 0.8778 - auc_7: 0.9440 - loss: 7.0278 - precision_7: 0.8778 - recall_7: 0.8778
```

Figure 5.2.17: Accuracy and Loss for ResNet

Model Customization

```python
# Add custom layers to the base ResNet50 model
headModel = model1.output
headModel = layers.GlobalAveragePooling2D()(headModel)

# First block
headModel = layers.BatchNormalization()(headModel)
headModel = Dropout(0.1)(headModel)
headModel = Dense(256, activation="relu", kernel_regularizer=tf.keras.regularizers.l2(0.01))(headModel)
headModel = layers.BatchNormalization()(headModel)
headModel = Dropout(0.1)(headModel)
headModel = Dense(128, activation="relu", kernel_regularizer=tf.keras.regularizers.l2(0.01))(headModel)

# Second block
headModel = layers.BatchNormalization()(headModel)
headModel = Dropout(0.1)(headModel)
headModel = Dense(32, activation="relu", kernel_regularizer=tf.keras.regularizers.l2(0.01))(headModel)
headModel = layers.BatchNormalization()(headModel)
headModel = Dropout(0.1)(headModel)
```

Figure 5.2.18: Model Customization

Confusion Matrix

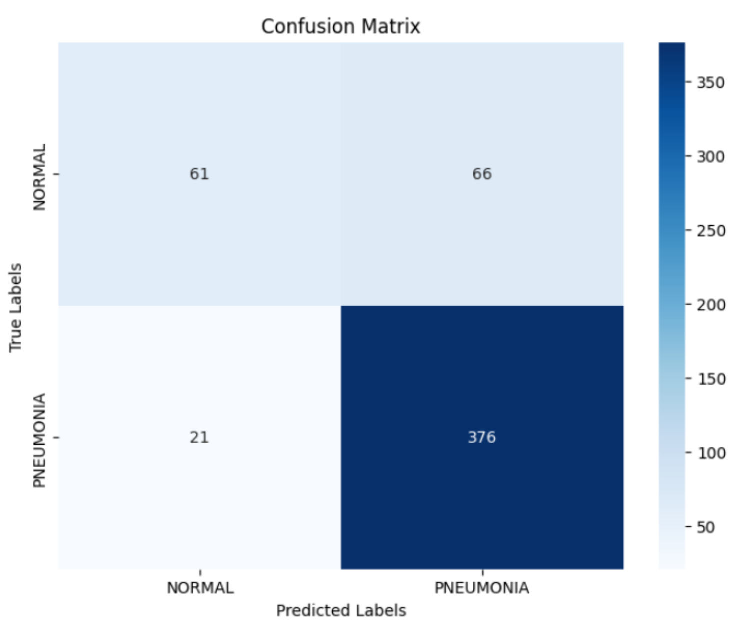


Figure 5.2.19: Confusion Matrix of ResNet

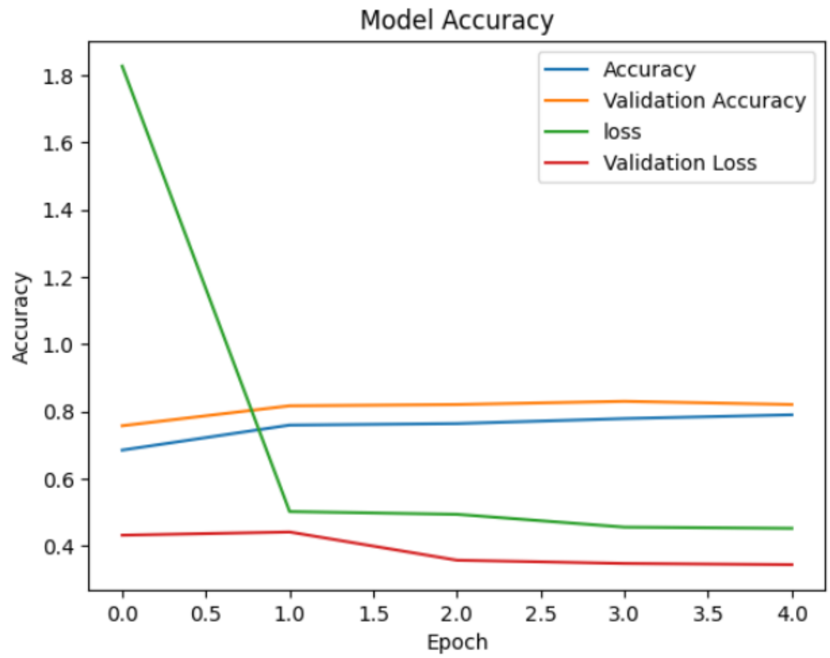


Figure 5.2.20: Accuracy Comparison

VGG16

Layer (type)	Output Shape	Param #
input_layer_3 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0

Figure 5.2.21: Initial Convolutional and Pooling Layers

Identifying Accuracy and Loss

```
W0000 00:00:1715505693.629790      72 graph_launch.cc:671] Fallback to op-by-op mode because memset node breaks graph update
131/131 ━━━━━━━━━━━━━━━━━━━━ 43s 312ms/step - accuracy: 0.9021 - loss: 0.2291 - val_accuracy: 0.9063 - val_loss: 0.1889
Epoch 3/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 43s 312ms/step - accuracy: 0.9176 - loss: 0.1911 - val_accuracy: 0.9312 - val_loss: 0.1611
Epoch 4/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 43s 314ms/step - accuracy: 0.9252 - loss: 0.1828 - val_accuracy: 0.9465 - val_loss: 0.1376
Epoch 5/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 44s 317ms/step - accuracy: 0.9305 - loss: 0.1776 - val_accuracy: 0.9637 - val_loss: 0.1158
17/17 ━━━━━━━━━━━━━━━━━━━━ 16s 983ms/step - accuracy: 0.9684 - loss: 0.0984
Accuracy: 0.9599236845970154
Loss: 0.11353116482496262
```

Figure 5.2.22: Identifying Accuracy and Loss

Classification Report

	precision	recall	f1-score	support
NORMAL	0.91	0.93	0.92	127
PNEUMONIA	0.98	0.97	0.97	397
accuracy			0.96	524
macro avg	0.94	0.95	0.95	524
weighted avg	0.96	0.96	0.96	524

Figure 5.2.23: Classification Report

Confusion Matrix

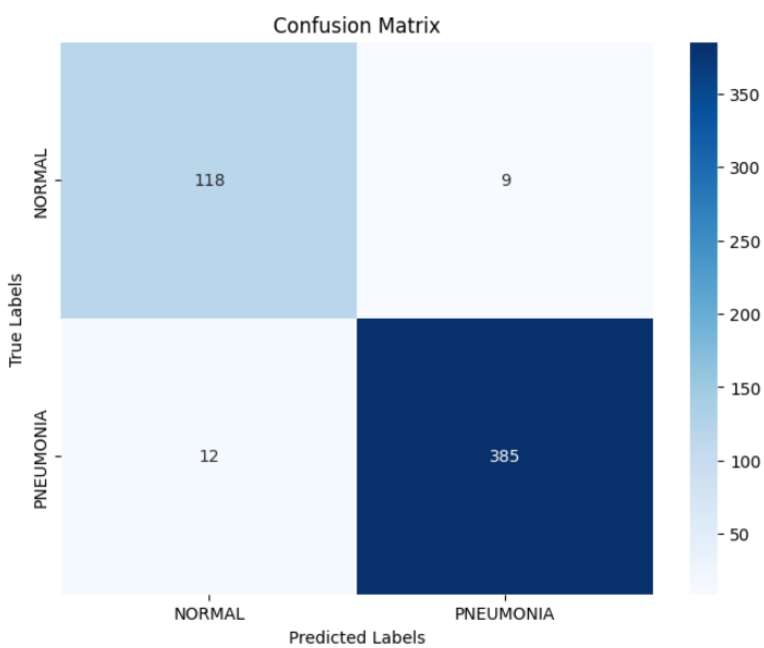


Figure 5.2.24: Confusion Matrix

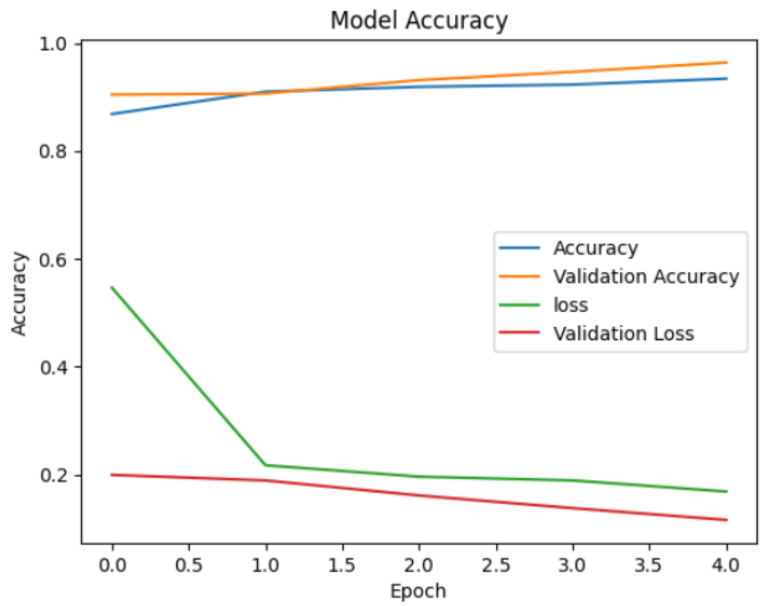


Figure 5.2.25: Accuracy Comparison

VGG19

Layer (type)	Output Shape	Param #
input_layer_4 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856

Figure 5.2.26: Initial Convolutional and Pooling Layers

Identifying Accuracy and Loss

```
W0000 00:00:1715505945.032136      70 graph_launch.cc:671] Fallback to op-by-op mode because memset node breaks graph update
131/131 ━━━━━━━━━━━━━━━━━━━━ 44s 320ms/step - accuracy: 0.8843 - loss: 0.2711 - val_accuracy: 0.9082 - val_loss: 0.1918
Epoch 3/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 44s 315ms/step - accuracy: 0.9049 - loss: 0.2344 - val_accuracy: 0.9044 - val_loss: 0.2222
Epoch 4/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 44s 319ms/step - accuracy: 0.9199 - loss: 0.2116 - val_accuracy: 0.9273 - val_loss: 0.1588
Epoch 5/5
131/131 ━━━━━━━━━━━━━━━━━━━━ 44s 319ms/step - accuracy: 0.9142 - loss: 0.1996 - val_accuracy: 0.9235 - val_loss: 0.1560
17/17 ━━━━━━━━━━━━━━━━━━━━ 3s 177ms/step - accuracy: 0.9509 - loss: 0.1275
Accuracy: 0.9427480697631836
Loss: 0.14650239050388336
```

Figure 5.2.27: Identifying Accuracy and Loss

Classification Report

	precision	recall	f1-score	support
NORMAL	0.82	0.98	0.89	127
PNEUMONIA	0.99	0.93	0.96	397
accuracy			0.94	524
macro avg	0.91	0.95	0.93	524
weighted avg	0.95	0.94	0.94	524

Figure 5.2.28: Classification Report

Confusion Matrix

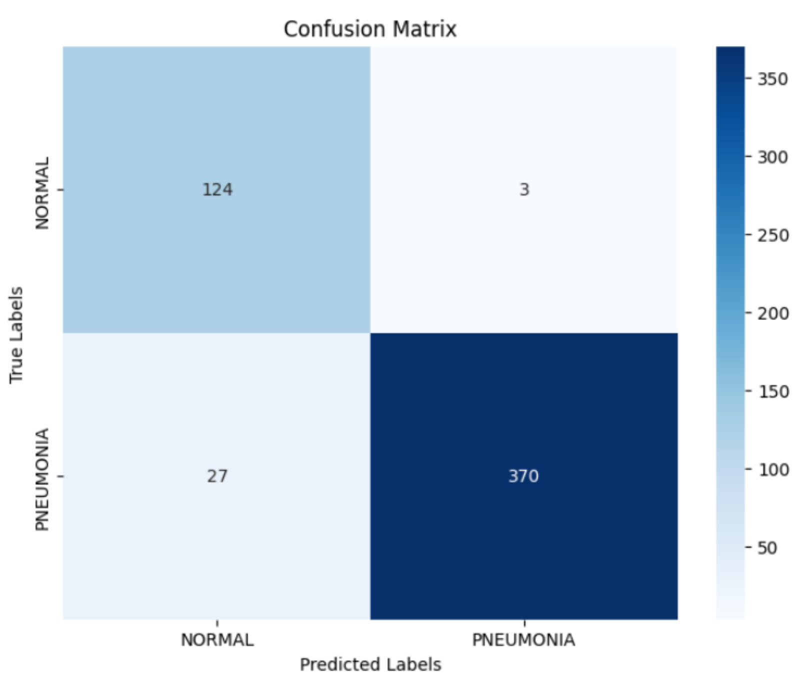


Figure 5.2.29: Confusion Matrix

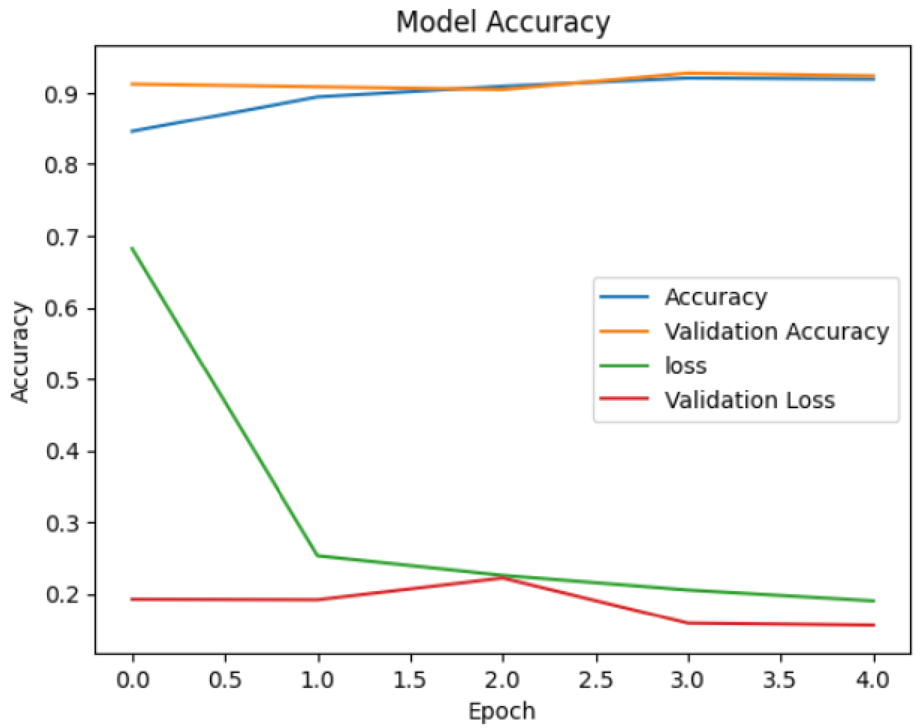


Figure 5.2.30: Accuracy Comparison

5.3 Comparative Analysis

This section compares the performance of five deep learning systems for diagnosing pneumonia from chest X-ray images: DenseNet, InceptionV3, ResNet, VGG16, and VGG19. Precision, recall, F1-score for both normal and pneumonia classes, and total accuracy are the performance indicators taken into account. The study reveals differences in performance across models, with some displaying higher accuracy and more balanced performance measures across both classes.

DenseNet and VGG19 exhibited good precision and recall for the pneumonia class, demonstrating their ability to accurately identify pneumonia cases. InceptionV3 and VGG16 had high overall accuracy, with InceptionV3 marginally outperforming in normal class detection. ResNet performed well in detecting pneumonia, but had lesser recall for the normal class, indicating a larger probability of false negatives. The following table summarises the evaluation metrics for each algorithm.

Table 5.3.1: Performance Comparison of Different Algorithms

Algorithm	Class	Precision	Recall	F1-score	Accuracy
DenseNet	Normal	0.82	0.99	0.9	0.94
	Pneumonia	1	0.93	0.96	
InceptionV3	Normal	0.93	0.81	0.87	0.94
	Pneumonia	0.94	0.98	0.96	
ResNet	Normal	0.74	0.48	0.58	0.83
	Pneumonia	0.85	0.95	0.9	
VGG16	Normal	0.91	0.93	0.92	0.96
	Pneumonia	0.98	0.97	0.97	
VGG19	Normal	0.82	0.98	0.89	0.94
	Pneumonia	0.99	0.93	0.96	

These findings show that, while DenseNet and VGG19 excel in detecting pneumonia, VGG16 and InceptionV3 provide high overall performance, making them viable options for clinical use. ResNet, despite having a poorer memory for normal cases, is nonetheless beneficial because of its high recall for pneumonia, which is essential for illness identification.

5.3 Summary

This section consolidates findings from the implementation of a pneumonia detection system using deep learning. Results showcase robust performance metrics such as accuracy, sensitivity, and specificity in diagnosing pneumonia from chest X-ray images. Comparative analysis against existing methods identifies strengths and areas for enhancement, underscoring the efficacy of deep learning in medical diagnostics. It emphasizes key insights into system performance and discusses implications for advancing healthcare through AI. Challenges and limitations are addressed, paving the way for future research directions.

CHAPTER 6
Impact on Society

6.1 Impact on Life

Pneumonia is a dangerous lung infection that is particularly dangerous for children, the elderly, and people with impaired immune systems. It is a major global health concern. Prompt and precise identification of pneumonia can significantly influence the community by lowering death rates, enhancing health outcomes, and easing the financial strain brought on by the illness.

Prompt and efficient treatment is essential for minimizing complications and lessening the severity of pneumonia, and it is made possible by early detection. The accuracy and speed of diagnosing pneumonia have greatly increased thanks to developments in medical technology, such as the creation of advanced diagnostic instruments including CT scans, artificial intelligence (AI)-driven algorithms, and chest X-rays. AI, for example, can assess radiographic pictures more quickly and frequently more accurately than human radiologists, which enables earlier diagnosis and treatment.

Improving pneumonia detection has a wider benefit, as it can lower hospital admission rates and shorten hospital stays. This is especially helpful in areas with minimal resources when medical services are frequently overworked. Early identification and treatment can prevent severe instances, saving the healthcare system money and allowing it to concentrate on other important areas to care.

An additional benefit of enhanced pneumonia detection is economic. Lowering the disease's occurrence and severity lowers healthcare expenses for patients and healthcare systems. Furthermore, early detection helps reduce the indirect costs—which can be significant—of missed productivity brought on by illness or caregiver obligations.

Furthermore, when paired with reliable detection techniques, public health campaigns stressing the need for pneumonia immunization and awareness can be more successfully targeted. By limiting the spread of pneumonia, especially among susceptible groups, this integrated approach improves the resilience of community health.

There is a significant life benefit from pneumonia detection. It enhances healthcare systems, encourages economic stability, and saves lives by enabling prompt medical intervention. To battle this potentially lethal condition, public health initiatives and advanced diagnostic technology must continue to be integrated.

6.2 Impact on Society and Environment

Traditionally, radiographic imaging and clinical assessment have been the primary means of diagnosing pneumonia. However, emerging technologies like artificial intelligence (AI) and deep learning (DL) have made this procedure more efficient and effective. Even if these developments have the potential to improve healthcare outcomes, there are environmental factors to take into account that need to be looked at.

Conventional Approaches and Their Effect on the Environment:

Typically, laboratory testing, CT scans, and chest X-rays are used to detect pneumonia conventionally. Significant resources are needed for these procedures, including electricity for imaging equipment and consumables for testing. The environmental footprint is influenced by the creation, use, and disposal of radiographic films, chemicals used in film development, and medical waste from laboratory testing. Furthermore, there is a greater demand for waste production and resource consumption when repeat imaging is required because of unclear results or poor image quality.

The healthcare facility's supply chain for medical supplies and equipment is also affected environmentally. The production of imaging machines and their components necessitates energy-intensive production processes, transportation, raw material mining and processing, and other activities that increase pollution and carbon emissions.

AI and Digital-Based Detection Techniques:

Reduced environmental effects are possible with AI and ML-based pneumonia detection techniques, especially when digital chest X-rays and other digital images are used. Hazardous waste is decreased since digital imaging removes the requirement for radiographic film and related chemicals. Furthermore, by improving picture interpretation accuracy, AI systems might lessen the requirement for repeat imaging and related resource consumption.

These technologies do, however, provide unique environmental difficulties. Significant processing power is needed for AI and ML, particularly when training algorithms, which entails handling enormous volumes of data. If data centers and high-performance computing systems don't get their energy from renewable sources, their substantial energy consumption will contribute to greenhouse gas emissions.

Telemedicine and Remote Diagnostics:

The emergence of telemedicine and remote detection technology has the potential to further impact pneumonia detection's environmental impact. By reducing the need for patient travel, these devices help to lower transportation-related carbon emissions. Artificial intelligence (AI)-based remote detection can enable early diagnosis and treatment, which may lessen the severity of the disease and the need for related healthcare resources.

Life Cycle Evaluation:

A life cycle assessment (LCA) is necessary for a thorough analysis of how pneumonia detection techniques affect the environment. This entails looking at the diagnostic instruments and technologies' complete lifecycle, from extraction of raw materials and production to use and disposal at the end of their useful lives. A more accurate picture of the relative environmental implications of digital and AI-based technologies would be obtained from an LCA conducted in comparison with older methods.

Strategies for Mitigation:

Healthcare institutions and data centers can lower their carbon footprint by implementing energy-efficient procedures and technologies. Another important distinction can be achieved by powering these facilities with renewable energy. Reducing production waste and promoting recycled materials are two ways to reduce environmental damage when it comes to medical equipment manufacturing. Reducing pollution and depletion of resources can be achieved by creating and implementing more effective waste management procedures for the disposal of medical waste, including digital equipment. By establishing guidelines and rules that support ecologically friendly methods in healthcare, governments, and regulatory organizations can play a significant role.

While there are several health benefits to using deep learning for pneumonia detection, it is important to consider the environmental effects of this practice. The healthcare sector can leverage deep learning more sustainably by investigating distributed computing models, switching to renewable energy sources, and emphasizing energy efficiency. To guarantee that the advantages of deep learning do not come at an unaffordable cost to the environment, it will be crucial to strike a balance between environmental stewardship and technical growth.

6.3 Ethical Aspects

The research on is underpinned by a commitmentto ethical considerations throughout its methodology. The use of medical images entails a responsibility to safeguard patient privacy and confidentiality, emphasizing adherence to ethical guidelines and regulatory standards. Informed consent, a cornerstone of ethical research practices, is appropriately obtained when necessary. The potential societal impact of the research on healthcare underscores the importance of ethical deployment, ensuring that advancements in diagnostics translate to improved patient care without compromisingindividual rights. The ethical dimension is further reflected in the transparentdocumentation of the research process, enabling scrutiny, reproducibility, and responsible knowledge dissemination. Overall, ethical considerations are integral to the research's commitment to societal well-being and the responsible application of cutting-edge technologies in the healthcare domain.

6.4 Sustainability Plan

The sustainability plan for the research is designedto minimize environmental impact while ensuring ongoing positive societal contributions. Efforts will be directed towards optimizing computational efficiency, adopting energy-efficient algorithms, and exploring cloud computing solutions to reduce overall energy consumption associated with model training and deployment. Furthermore, the research team is committed to leveraging eco-friendly practices in data management and storage. The plan prioritizes ongoing awareness and integration of green computing principles, aligning technological advancements with environmental sustainability. Continuous evaluation and adaptation of sustainable strategies will be embedded in the research process, reflecting a commitment to responsible and eco-conscious scientific innovation.

6.5 Summary

This section delves into the comprehensive impact of the pneumonia detection system using deep learning on society, the environment, and sustainable healthcare practices. It explores how the system significantly enhances patient outcomes by improving diagnostic accuracy and timeliness. Early detection of pneumonia leads to reduced complications, shorter hospital stays, and improved overall quality of life for patients. On a broader scale, the system contributes to societal well-being by increasing healthcare accessibility and affordability, especially in underserved communities. It facilitates quicker diagnoses, lowers healthcare costs, and optimizes resource allocation, thereby benefiting healthcare systems and society at large. Ethical considerations are also central, addressing issues such as patient privacy, data security, and fairness in algorithmic decision-making. This section underscores the importance of ethical guidelines for deploying AI in healthcare to ensure transparency, accountability, and patient trust. Additionally, a sustainability plan outlines strategies to maintain system effectiveness, optimize resource utilization, and minimize environmental impact in healthcare operations.

CHAPTER 7

Conclusion and Future Work

7.1 Conclusions

According to the findings, deep learning models greatly increase the accuracy of pneumonia identification using chest X-rays, especially when they use sophisticated CNN architectures and data augmentation approaches. Augmenting data is essential for improving the resilience of the model and decreasing overfitting.

When XAI techniques are paired with visual explanations, physicians report feeling more confident in the AI's diagnostic recommendations, demonstrating the effectiveness of methods in improving model clarity. The results of the pilot studies demonstrate that these models can help radiologists in a useful way, particularly in situations when medical knowledge is scarce. The results highlight how deep learning can revolutionize the diagnosis of pneumonia and provide a scalable way to improve the quality of healthcare. But there are still issues to be resolved, such as the requirement for big, superior datasets and the incorporation of AI systems into current healthcare processes. It's also necessary to look into ethical issues with algorithmic bias and data protection.

According to the study's findings, deep learning models have a lot of potential to help identify pneumonia more accurately, especially in settings with limited resources. The models get the trust of healthcare experts and achieve excellent diagnosis accuracy by fusing explainable AI approaches with high-performance CNN architectures. Subsequent studies have to concentrate on improving these models, diversifying datasets, and guaranteeing a smooth transition into clinical practice. In the end, this strategy could result in improved patient outcomes, more fast and accurate diagnoses, and a decrease in healthcare inequities throughout the world. Even with issues like integration of processes and data quality, deep learning has been shown to significantly enhance pneumonia diagnosis, especially in situations with scarce resources. In order to improve outcomes for patients, these models must be refined and widely adopted in clinical settings, which will need ongoing study and development.

7.2 Further Suggested Works

The effective use of deep learning in pneumonia diagnosis opens up a number of research directions. Improving the model's generalization across different clinical contexts and demographics is one important issue. To ensure the robustness of the models, future research should concentrate on assembling bigger, more diverse datasets that contain photos from various age groups, ethnicities, and degrees of pneumonia severity.

Integrating multi-modal data—for example, integrating lab findings, histories, and additional evaluations with chest X-rays—is another crucial component. This all-encompassing method can enhance the precision of diagnoses and offer a more thorough evaluation of the individual's fitness. Studies should look at the best ways to combine and use various kinds of data for deep learning models. The legal and moral problems surrounding the application of AI to medical care must also be addressed. Research ought to look on methods for protecting the confidentiality of patients, guaranteeing confidentiality of information, and reducing flaws in AI systems.

Finally, it is critical to deploy and assess these AI systems in actual clinical situations. The design of intuitive and therapeutically successful AI solutions can be guided by the knowledge gained from pilot research and clinical trials regarding the benefits and realistic constraints of employing deep learning for pneumonia diagnosis.

7.2 Limitations/Conflict of Interests

Limitations and potential conflicts of interest in this research on pneumonia detection using deep learning include significant considerations. One key issue is the potential for data bias, where the training datasets may not adequately represent diverse patient demographics or clinical scenarios. This limitation could affect the accuracy and reliability of the AI model when applied to populations not well-represented in the data.

Another critical concern is the transparency and interpretability of deep learning algorithms. These models are often complex and opaque in their decision-making processes, which raises questions about how diagnoses are reached and may impact trust among healthcare providers and patients.

Ethical considerations loom large, particularly regarding patient data privacy, confidentiality, and informed consent. Adhering to ethical guidelines is crucial to protect patient rights and ensure compliance with regulatory standards like GDPR and HIPAA.

Additionally, validating AI-driven diagnostic tools in clinical settings is essential to demonstrate their safety, efficacy, and reliability compared to traditional methods. Integration into healthcare workflows and acceptance by medical professionals are pivotal for successful adoption.

Financial constraints and resource limitations also pose challenges, as implementing AI technologies in healthcare may require substantial investments in infrastructure, training, and ongoing maintenance.

Addressing these issues is vital to advancing the ethical and effective use of AI in medical diagnostics, promoting equitable healthcare outcomes while upholding patient welfare and regulatory compliance.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: PNEUMONIA DETECTION WITH X-RAY IMAGES APPROACH WITH DEEP LEARNING

Student ID: [203-15-14539, 203-15-14555]

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	The undertaking highlights foundational engineering (K3) principles by using deep neural networks, data augmentation techniques, and a variety of CNN designs for image processing and categorization. The project exhibits specialized knowledge (K4) by combining transfer learning with sophisticated CNN architectures to improve pneumonia detection accuracy in chest X-ray pictures, which is critical for computer-aided diagnosis.	**Page no:** [29-33] **Section:** [3.2]
				The initiative uses engineering practice and design (K5) through the figure of the process of experimentation. The project uses the CNN model to address engineering practice and technology (K6).	**Page no:** [33] **Section:** [4.2] **Page no:** [36] **Section:** [3.2]

				This effort contributes to K8 (Research Literature) by combining insights from recent studies to advance pneumonia detection with deep learning, demonstrating a thorough awareness of current approaches.	**Page no:** [9-12] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This study addresses EP-2 by understanding the limits of standard pneumonia detection approaches, as well as the complexity of combining transfer learning with deep CNNs. It addresses issues in comprehending spatial distributions through comparative analysis, providing insights for the improvement of diagnostic methods.	**Page no:** [19-21] **Section:** [2.4]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	The work tackles EP-3 by methodically analyzing trial results, indicating Transfer Learning as the most effective solution for improving pneumonia diagnosis among several viable approaches.	**Page no:** [32-51] **Section:** [5.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach goes beyond computer science and engineering, influencing medical diagnoses in respiratory disorders such as pneumonia and contributing to advances in public health and healthcare practices (EP-4).	**Page no:** [15-22] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A

6.	**EP6: Extends of stakeholders involved and conflicting**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive strategy addresses high-level issues by integrating numerous components such as data collecting, statistical analysis, and proposed methodology, resulting in a holistic solution to challenging obstacles in medical diagnostics and assuring EP-7.	**Page no:** [29-42] **Section:** [3.2, 4.2]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our study makes use of a variety of resources, including high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations, to assure systematic research and contribute to advances in pneumonia diagnosis using transfer learning and deep CNNs.	**Page no:** [32-34] **Section:** [3.3]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This research benefits society by enhancing healthcare through better pneumonia detection technologies, while simultaneously encouraging environmental sustainability by using efficient computational resources and adhering to ethical patient data protection requirements.	**Page no:** [44-48] **Section:** [5.1, 5.2, 5.4]

5.	**EA-5: Familiarity**	Yes		This undertaking builds on previous research by investigating a novel strategy to pneumonia diagnosis using transfer learning and deep CNNs, as evidenced through preliminary terminologies and a full comparison analysis, providing new insights into the field.	**Page no:** [9-12] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses CO4 emissions by combining effective project management and financial control, assuring precise planning, resource allocation, and budget estimation to maximize resource usage throughout the study lifetime.	**Page no:** [7-8, 21] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by putting patient privacy first, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical use of advanced healthcare technologies that comply with CO9.	**Page no:** [47] **Section:** [5.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning (CO12) and adaptation within the dynamic technological landscape is reflected in its extensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, demonstrating a willingness to stay current and refine techniques to address modern challenges.	**Page no:** [26-34, 37-55] **Section:** [3.2, 3.3, 3.4, 4.2, 4.3,5.2]

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