Pneumonia Detection from Chest X-Ray Images using Deep Neural Network

By

Nazmul Shihab Shishir

ID: 213-15-4593

FINAL YEAR DESIGN PROJECT REPORT

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

Supervised by

Mr. Saiful Islam

Assistant Professor

Department of Computer Science and EngineeringDaffodil International University

Co-Supervised by

Mr. Md. Monarul Islam

Lecturer

Department of Computer Science and EngineeringDaffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

Dhaka, Bangladesh

September 17, 2025

APPROVAL

This Project titled **"Pneumonia Detection from Chest X-Ray Images using Deep Neural Network"**, submitted by Nazmul Shihab Shishir, ID No: **213-15-4593** 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 **17 September, 2025**.

BOARD OF EXAMINERS

Dr. S.M Aminul Haque — **Chairman**
Professor and Associate Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Ms. Nazmun Nessa Moon — **Internal Examiner**
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Md. Abbas Ali Khan — **Internal Examiner**
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Dr. Md. Zulfiker Mahmud — **External Examiner**
Professor
Department of Computer Science and Engineering
Jagannath University

©Daffodil International University i

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mr. Saiful Islam**, Assistant Professor, 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:

Mr. Saiful Islam
Assistant Professor
Assistant Professor, Department of CSE, FSIT
Daffodil International University

13.09.25

Mr. Md. Monarul Islam
Lecturer
Assistant Professor, Department of CSE, FSIT
Daffodil International University

Submitted by:

Nazmul Shihab Shishir
ID: 213-15-4593
Department of CSE, FSIT
Daffodil International University

©Daffodil International University ii

ACKNOWLEDGEMENTS

This work would not have been possible without the support and contributions of many individuals over the past two semesters. We are deeply grateful to everyone who has assisted us in one way or another.

First, we express our heartfelt thanks and gratefulness to the almighty for His divine blessing making it possible for us to complete the **Final Year Design Project(FYDP)** successfully.

We are grateful and wish our profound indebtedness to **Mr. Saiful Islam, Assistant Professor**, Department of Computer Science and Engineering, Daffodil International University, Dhaka, Bangladesh. Deep knowledge and keen interest of our supervisor in the field of Ecommerce to carry out this project. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

We would like to express our heartfelt gratitude to the Head of the Department of Computer Science and Engineering, for his kind help in finishing our project and also to other faculty members and the staff of the Department of Computer Science and Engineering, Daffodil International University.

We would like to thank our entire course-mates at Daffodil International University, who took part in this discussion while completing the coursework.

Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

Pneumonia is still a significant public health issue at worldwide level, especially in children and elderly, in which a not timely recognized or mistaken diagnosis may induce important and lethal complications. Pneumonia detection is a common application of chest X-ray image; however, it is time-consuming and subject to inconsistencies by the radiologists to manually interpret the results even with scarce resources in any given locale. In this thesis, a deep learning-based approach to automate the detection of pneumonia in chest X-ray images is proposed which leverages custom convolutional neural network (CNN) designs as well as transfer learning with state-of-the-art architectures such as VGG16, ResNet50, InceptionV3, and MobileNetV2. The dataset (of size 3392 X-ray images) was preprocessed and augmented for class imbalance and better generalization. Performance of models were evaluated using standard metrics such as accuracy, precision, recall and F1-score. Among all the architectures used, InceptionV3 performed best on the test set (accuracy 85.9%), It was well spread between pneumonia and normal classes. VGG16 worked fine and ResNet50 and MobileNetV2 overfit to the diminished training biased to the majority classes not even recognizing normal. These findings highlight the promise as well as challenges of transfer learning for improving diagnosis, including dataset imbalance and interpretability, as well as clinical workflow limitations. The results of this study contribute to the literature using AI in medicine and healthcare by demonstrating the feasibility of deep learning for pneumonia detection, laying a foundation for future work involving advanced clinical AI research.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Introduction

Pneumonia is one of the most common and severe respiratory diseases worldwide, causing millions of people to suffer and/or die annually in all age groups. It is due to bacterial, viral or fungal infection that cause inflammation of air sacs in the lungs, which can result in fever, cough, chest pain and breathing difficulty. A prompt and accurate diagnosis is essential for without treatment major complications or death may occur, particularly in children and the elderly. Chest radiography, or X-ray, has been the gold standard for the detection of pneumonia, since it allows to visualise visual signs, such as opacities and infiltrate within the lung tissues. Nevertheless, reading X-rays manually by a radiologist is not only time-consuming but also subject to human mistakes, especially when the medical services is not enough or not professional.

CAD (computer-aided diagnosis) has been developed to assist clinicians in decision-making with the proliferation of AI and deep learning over the years. In particular, Convolutional Neural Networks (CNNs) have demonstrated high power in medical image analysis they can learn discriminative features from raw data without the need for hand crafted features. Applications of these models in chest X-ray images analysis can significantly improve the accuracy and efficiency of pneumonia diagnosis and reduce burdens on medical staffs. Secondly, it is the generation of deep neural networks which may has potential to be used as a reliable diagnostic measure and generating clinical models via mobile or cloud solutions in resource limited setting.

In this thesis work, we focus on developing deep learning models and perform evaluation for automated detection of pneumonia using CXR images. The study aims to identify an optimal method for high diagnostic accuracy implemented by combining custom CNN architectures and the transfer learning strategy using popular pretrained networks VGG16, ResNet50, InceptionV3, MobileNetV2, and DenseNet121. The study additionally includes data preprocessing, augmentation, and comparison between various models, in order to overcome problems of little data diversity and the unbalanced nature of classes. In the end, it is hoped that the findings would contribute to the development of intelligent health care system that aids radiologists, mitigates early diagnosis and help in the struggle toward tackling pneumonia on global basis.

1.2 Motivation

The impetus for this study is the urgent necessity to change the current situation of pneumonia diagnosis with high false negative rates and inaccessibility in global communities. Pneumonia remains an important cause of hospitalisation and mortality despite the fact that it is both preventable and treatable; more so in resource-limited areas than in resource-rich areas of the world. In several rural and underdeveloped areas, the problem of lack of radiologist who in time can provide accurate interpretation of chest X-rays prevents reliable and timely delivery of interpretations. Therefore, the patients are frequently misdiagnosed or diagnosed at an advanced stage, which is likely to cause higher risk of severe complications or therapeutic failure.

The emergence of deep learning methods is paving the way to fill this gap with automatic, consistent and scalable solutions for medical image analysis. Unlike traditional ML methods which rely on handcrafted features, deep neural networks are capable of automatically learning the hierarchical visual representations from raw images. This capability allows them to notice fine-textural signals of pneumonia that can eventually escape the human eye and is a leading factor toward enhancing diagnostic reliability. Moreover, deployment of these technologies as a part of clinical protocols can reduce burden on healthcare providers and allow them to go back to patient care responsibilities and bring the diagnostic tools out into areas that are less served.

Inspired with the vision of developing a smart system that is practical and robust, which achieves high accuracy, Transfer Learning (TL) based on the analysis of chest X-ray images using Convolutional Neural Networks (CNN), motivates this work itself. Ultimately, it is our hope to help the growing field of computer-aided diagnosis combatting pneumonia and aid the healthcare community in addressing globally the illness and death that is caused by pneumonia. Such motivation is inspired by the prospect for AI to revolutionize healthcare delivery through bringing sophisticated diagnostic tools to areas where there is little expert human interpretation.

1.3 Objectives

The target of this research is to propose, and evaluate state-of-the art deep learning architectures for accurate pneumonia detection based on chest X-ray images.

Propose and Evaluate Deep Learning Architectures: The aim is to design and evaluate different deep learning architectures with emphasis in Convolutional Neural Networks (CNNs), for automated pneumonia screening in chest x-ray images. This paper will investigate the efficiency of custom CNN and pretrained models (VGG16, ResNet50, InceptionV3, MobileNetV2, and DenseNet121) to obtain an accurate classification.

Address Dataset Imbalance and Enhance Model Generalization: The motivation behind this study is to address the class imbalance problem on the dataset (more pneumonia cases are available than normal cases) using data augmentation methods. This in turn leads to the model generalizing better on unseen data, less biased towards the majority class, and improves both the pneumonia and the normal cases.

1.4 Methodology

The scope of this thesis is focused on the use of deep learning algorithms for the screening of pneumonia diagnosis from chest x-ray images. The work concentrates on the implementation of Convolutional neural networks (CNN) and transfer learning techniques to develop models that can be trained to classify healthy and pneumonia affected X-rays of the lung. The work is applied on an image-based diagnosis and cannot be rigorous in context to other diagnostic methods - CT scan, blood test, clinical symptoms, etc. The research focuses on chest X-rays, one of the most common and widely available imaging tools available in hospitals and diagnostic centers around the globe.

This thesis focuses on the performance of a few famous deep neural network architectures, e.g., VGG16, ResNet50, InceptionV3, MobileNetV2, and DenseNet121. Each of the models is trained, fine-tuned and tested with a set of standard TR metrics and both accuracy (ACC) of the models is compared to find the best architecture for pneumonia classification. The effect of pre-processing and data augmentation methods are also discussed to enhance the robustness and generalization of the model.
The work is performed using publicly available datasets and low computational resources, and subsequently the models are trained and validated on subsets of chest X-rays, and not a large-scale clinical dataset. In addition, although the study showed a good performance of the deep learning models as a supporting tool for radiologists, it did not aim to replace expertise of medical professionals or to apply for direct clinical use. Instead, the thesis seeks to provide a research blueprint, which includes practical feasibility, pros and cons when employing deep neural networks for pneumonia, and to serve as a stepping stone for follow-up investigations as well as practical applications.

1.5 Thesis Outcome

This will be a novel deep learning model that will be capable of diagnosing pneumonia accurately from chest x-ray images.! By exhaustively assessing various state-of-the-art CNN architectures, we determine which model (or ensemble thereof) provides the best tradeoff between accuracy, robustness, and computational cost. The findings are expected to demonstrate that the transfer learning with pretrained networks is much more effective than standard methodology, especially for imbalanced medical datasets.

Other than performance measures like accuracy, precision, recall, f1-score, etc. a comparison of models will be conducted to highlight the pros and cons of the models. They will further have to implement the visualization of solutions (e.g., confusion matrices and Grad-CAM heatmaps) for the purpose of infusing interpretability into predictions giving insights about how the networks make decisions. These results will not only validate the success of deep learning method for detecting pneumonia, but also demonstrate the promising segments of action for such models in decision assisting to radiologists.

Ultimately, it is this thesis aim to provide a methodology and findings that may aid future work in medical image analysis. The findings will demonstrate how feasible to improve diagnostic performance, to release HCPs from sky-rocketing workloads and eventually make high-quality healthcare convenient not only for the elites or minorities but for the majority of the population as well, particularly in resource-limited condition using deep learning models. While it remains that this work, on its own, cannot replace the expertise of clinicians, it sets a foundation for the use of AI in practice of medical diagnosis through complementing existing healthcare infrastructures.

1.6 Organization of the Report

This report is structured into six main chapters, each addressing a distinct component of the research work.

Chapter 1 – Introduction provides the background, motivation, objectives, scope, expected outcomes, and overall organization of the thesis. It establishes the context of the study and highlights the importance of applying deep learning methods to pneumonia detection.

Chapter 2 – Literature Review presents a detailed survey of existing research on pneumonia detection and medical image analysis. It reviews conventional diagnostic methods, explores the role of deep learning in healthcare, and discusses related work on pretrained models such as VGG16, ResNet50, InceptionV3, MobileNetV2, and DenseNet121.

Chapter 3 – Methodology describes the research framework and workflow followed in this study. It includes dataset details, preprocessing steps, augmentation strategies, model architectures, training procedures, evaluation metrics, and the experimental setup.

Chapter 4 – Results and Analysis reports the outcomes of model training and evaluation. Each model's performance is presented through classification reports, confusion matrices, and comparative tables, followed by an analysis of results, error patterns, and interpretability through visualization techniques.

Chapter 5 – In this chapter the results are discussed linked to research objectives and literature review. It emphasizes on study's strengths and limitations, its clinical significance, ethical considerations and practical obstacles in real life application.

Chapter 6 – Finally, conclusions and further directions for improvement are presented in Conclusion and Future Work Star Chapter 6 - Conclusion and Future Work recovering important achievements of research work, listing main findings, as well as recommending them for improvements through the development of more advanced architectures, larger feature sets (datasets) on which they are implemented, along with clinical validation on a bigger scale.

Chapter 2

Background

2.1 Introduction

Medical imaging has become an indispensable tool in modern healthcare, playing a critical role in the diagnosis, monitoring, and treatment of a wide range of diseases. Among these, chest radiography (X-ray imaging) is one of the most widely used and cost-effective diagnostic methods for detecting respiratory illnesses, including pneumonia. As a non-invasive imaging technique, chest X-rays provide detailed visualization of the lungs, making it possible to identify abnormalities such as opacities, infiltrates, or consolidations that are often associated with pneumonia. Despite its diagnostic value, the interpretation of X-rays remains a challenging task that requires specialized expertise and is subject to variability among radiologists. In many cases, subtle signs of pneumonia can be overlooked, particularly in environments with limited resources or a shortage of trained professionals.

The advancement of artificial intelligence (AI), particularly deep learning, has opened new opportunities for enhancing medical image analysis. Convolutional Neural Networks (CNNs), a class of deep learning models, have demonstrated exceptional success in computer vision tasks, ranging from object recognition to medical image classification. In recent years, their application in radiology has gained significant attention, as CNNs are capable of learning complex and subtle patterns directly from medical images without relying on handcrafted features. This ability allows them to match or even surpass human-level performance in certain diagnostic tasks.

This chapter provides a review of the background and related studies relevant to pneumonia detection using chest X-ray images. It begins with an overview of pneumonia and the significance of chest radiography in diagnosis. It then explores traditional diagnostic approaches and the limitations associated with manual interpretation. The chapter also examines recent advancements in deep learning for medical image analysis, with a focus on transfer learning and the performance of widely used pretrained CNN architectures such as VGG16, ResNet50, InceptionV3, MobileNetV2, and DenseNet121. By highlighting existing research findings, strengths, and limitations, this chapter establishes the foundation for the methodology adopted in this thesis and identifies the research gaps that the present work seeks to address.

2.2 Literature Review

2.2.1 Similar Applications

The detection of pneumonia from chest X-rays has been an area of interest for research for many years, originally starting with traditional image processing and machine learning based studies. In classical methods, the usual method was to extract handcrafted features including texture analysis, edge detection, histogram-based features, and use a classifier such as Support Vector Machines (SVM) or Random Forests. Although these techniques were moderately successful, they were frequently challenged in terms of generalisation, caused by the complexity of medical images and patients themselves, which introduced noise in the process [1].

With the advent of Deep learning, mainly Convolutional Neural Network (CNN), medical image analysis has seen a transformative turn. Rajpurkar et al. [2] presented CheXNet, a 121-layer DenseNet, trained on the NIH ChestX-ray14 dataset, which performed at the radiologist level in pneumonia detection. They showed that deep networks can be trained for large scale medical image classification. Similarly, Kermany et al. [3] also employed transfer learning to pre-trained CNNs for pediatric chest X-ray classification, with high sensitivity and specificity in pneumonia diagnosis, and demonstrating the usefulness of deep learning models in real-world clinical settings.

Alternatively, other works aimed at investigating diverse CNN architectures to improve performance. Stephen et al. [4], who utilized VGG16 and ResNet50 for chest X-ray classification, and demonstrated that transfer learning outperforms training from scratch, especially when the availability of data is limited. Ayan and Ünver [5] suggested a model ensemble between VGG16 and Xception which enables better accuracy by using the best of several pretrained models. Similarly, Chowdhury et al. [6] studiedMobileNetandInceptionV3for pneumonia detection, highlighting those lightweight architectures are the most useful in the context of resource-limited environments.

2.2.2 Related Research

Recent work has also focused on model interpretability and explainability, which are important for clinical and medical deployment. Rajaraman et al. [7] used visualization methods including CAM and Grad-CAM to localize lesions in lung images that induced prediction and enhance trust in AI-assisted nucleic acid. Besides, efforts have been made to solve the problem of imbalance and enhance the generalization. Stephen et al. [8] showed that data augmentation such as rotation, flipping and brightness change contributed to combating overfitting and led to an improvement of CNNs performance.

However, there are still some challenging points in developing a better pneumonia detection system. What's more, a shortage of diverse data sources constrains the effectiveness of many such studies; most models are trained on specific populations and do not necessary to all global datasets. Moreover, although the accuracy of deep learning models is highly promising, there is a need for significant clinical validation, ethical reflection and governmental approval to implement them into clinical practice [9]. This literature underscores the necessity of ongoing research in robust, interpretable, and scalable deep learning architectures for pneumonia detection, which is the basis of the current study.

2.3 Gap Analysis

Despite the excellent results in pneumonia detection from chest X-ray images by using deep learning approaches, there are still several research directions to be explored. The majority of the studies, however, use open-access databases, such as NIH ChestX-ray14, or the XT pediatric data from Guangzhou Women and Children's Medical Center. While these datasets are potentially useful, they tend to be narrow in diversity and do not necessarily span the full range of patient demographics, imaging conditions or disease severity. This lack of diversity can question model generalizability when applied in other clinical practices [10].

Another big drawback is that the datasets are imbalanced in that pneumonia is more common than normal cases. Although re-sampling strategies and data augmentation techniques have been applied for addressing this problem, biased models comprising high general accuracy while failing to distinguish between minority classes are still often reported in the literature [11]. Moreover, most of the existing works only concentrate on binary classification (normal vs. pneumonia) and do not differentiate the subtypes of pneumonia (bacterial versus viral), which is significant from the clinical point of view [12].

Furthermore, while deep learning algorithms (e.g., VGG16, ResNet50, and DenseNet121) have produced encouraging research outcomes, their application in clinical decision-making system has been limited due to computational overhead and transparency deficiency. Lightweight models such as MobileNetV2, have been explored for resource-limited settings, but further study is required for trade-offs between accuracy, speed and hardware [13]. Furthermore, measures for interpretability such as Grad-CAM are usually treated as an additional analysis instead of a component in the development and validation phases of a model, which may decrease the confidence and adoption in the clinical setting [14].

Ethical and practical issues are largely unresolved in the end. Very few works take into account privacy-preserving training methods like federated learning which are vital in multi-institution collaboration without leaking patient privacy. Finally, there is a lack of clinical validation of these models in the real-world, with most studies restricted to retrospective dataset-based performance assessments. It is necessary to fill that gap with prospective studies in collaboration with healthcare providers to ensure the reliability, safety and conformity with regulations [15].
and model optimization for implemthe entation in real clinical use.

Table 2.3: Comparison of Intrusion Detection Approaches

Author(s) & Year	Dataset Used	Model/Method	Key Findings	Limitations	Ref.
Rajpurkar et al. (2017)	NIH ChestX-ray14	DenseNet121 (CheXNet)	Achieved radiologist-level pneumonia detection performance	Requires large-scale GPU resources; limited interpretability	[2]
Kermany et al. (2018)	Pediatric CXR dataset (Guangzhou)	Transfer Learning (CNN)	High sensitivity & specificity for pneumonia classification	Dataset limited to children; lacks adult cases	[3]
Stephen et al. (2019)	Kaggle CXR dataset	VGG16, ResNet50	Transfer learning improved accuracy significantly	Limited dataset diversity; potential overfitting	[4]
Ayan & Ünver (2019)	Chest X-ray (Kaggle)	VGG16 + Xception Ensemble	Achieved improved accuracy via ensemble approach	Computationally expensive; not suitable for real-time use	[5]
Chowdhury et al. (2020)	COVID-19 & viral pneumonia dataset	MobileNet, InceptionV3	Lightweight models feasible for low-resource settings	Lower accuracy compared to heavier models	[6]
Rajaraman et al. (2020)	NIH ChestX-ray14	Pruned Ensembles + Grad-CAM	Improved interpretability; reduced model complexity	Focused on COVID-19; limited pneumonia subtype classification	[7]
Irvin et al. (2019)	CheXpert Dataset (224k images)	Multi-label CNN with Uncertainty Labels	Addressed uncertainty in CXR interpretation	Model complexity; requires high computational resources	[10]
Varshni et al. (2019)	Kaggle CXR dataset	CNN feature extraction + SVM	Achieved promising results on pneumonia detection	Shallow model; lacks robustness compared to deep CNNs	[12]
Pham et al. (2021)	Kaggle CXR dataset	MobileNetV2, EfficientNet	Balanced accuracy and	Performance slightly lower than DenseNet/ResNet	[13]

			efficiency for real-time use		
Das et al. (2021)	Kaggle & NIH datasets	Grad-CAM + CNNs	Enhanced interpretability of predictions	Interpretability remains limited to visual heatmaps	[14]

2.4 Summary

This thesis has focused on the application of deep learning models as an aid to automated diagnosis for pneumonia from chest X-ray imagery, in a bid to address challenges of manual interpretation by clinicians (doctors and radiologists) containment, particularly in resource limited environments. The study tried to improve the diagnostic accuracy using CNN (Convolutional neural networks) models and transfer learning with pre-trained architectures like VGG16 [36], ResNet50 [37], InceptionV3 [38], MobileNetV2, DenseNet121. The dataset was augmented and over-sampled with 3,392 X-ray samples in order to balance the classes and improve model generalizability.

The results showed that the 85.9% accuracy is achieved as a best performance of InceptionV3 for sensitivity and specificity. The VGG16 resulted in a high recall score for pneumonia, that have a high FP rate, way since there were some normal class cases. Discriminatory power between the normal and the Resnet50 and MobileNetV2 where they are looking at as a misclassied normal. These findings also highlight the need for addressing class imbalance, overfitting and model generalization.

The thesis concludes with conclusion that the AI and deep learning in particular has a good chance of bringing about improvement pneumonia diagnosis especially in low-resource settings. Nevertheless, there is need for further developments to mitigate interpretability or multi-class classification in near-real-time clinical practice.

Chapter 3

Methodology

3.1 Methodology

3.1.1 Overview

Our research method is intended to sequentially construct deep learning models for pneumonia detection from chest X-ray images, and train and validate the models in a systematic manner to conclude which architecture performs the best. First, we get the dataset, the original picture should be preprocessed into a well-preferred one (that is, normalized, balanced to make the model can be trained). Because the chest X-ray datasets usually have problems of class imbalance and image quality variety, preprocessing (e.g., normalization, rescaling, and augmentation) are taken before the model training to achieve data consistency and model generalization.

After preprocessing, various deep CNN neural network architectures are applied and compared. Both crafted and transfer learning models are investigated with respect to pretrained networks including VGG16, ResNet50, InceptionV3, MobileNetV2, and DenseNet121. Transfer learning is particularly useful here given that it makes use of knowledge that has been learned from large-scale image databases such as ImageNet to enhance the performance on the relatively small data volume of the medical image.

3.1.2 Proposed Methodology

All the models are compiled with appropriate optimisers, loss functions and learning rates on the augmented dataset before trainig. During training, hyper-parameters are well tuned with validation sets to prevent overfitting and well generalize models. We evaluate the performance using standard metrics like accuracy, precision, recall, F1-score. Furthermore, confusion histograms and visualization techniques such as Grad-CAM are used as an aid for understanding the models output and what parts of the chest X-rays were taken into account to make the predictions.

Finally, the output of all models is measured for both accuracy and computational efficiency, to select the best architecture for pneumonia detection. This structured classification provides a complete panorama of deep learning applications in medical imaging with respect to scarcity of robust datasets, complexity/compactness of proposed models, and their interpretability..

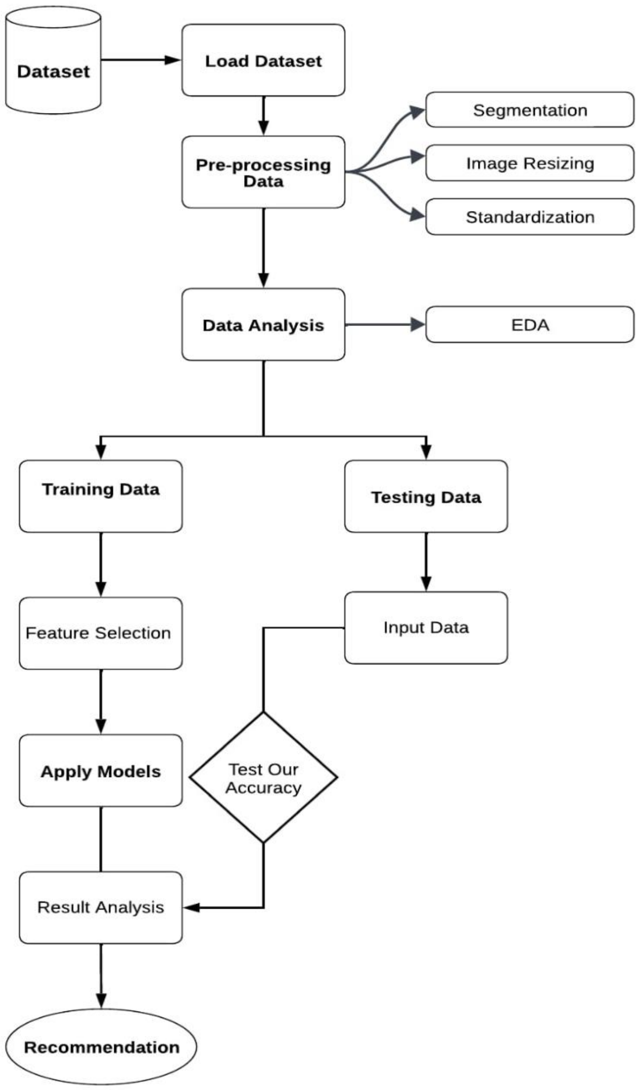

Figure 3.1.2. Overall Flowchart

3.1.3 Functional and Nonfunctional Requirements

The primary objective is to classify these images into two classes (pneumonia/normal) with the help of Convolutional Neural Networks (CNN's), and transfer learning models such as VGG16, ResNet50, InceptionV3, MobileNetV2 and DenseNet121ickers. It also needs to test the models with well-known performance metrics such as accuracy, precision, recall and F1-score as well as providing utilities for result visualization which can help understand how it came to a decision: confusion matrix and Grad-CAM heatmap. The system should also manage the class imbalance of the dataset with data augmented (such as rotate, zoom, flip) and enable a comparison between different pretrained models to improve performance.

Even on the non-functional side the system is required to be very performant as images have to be processed fast (real time response). It needs to be able to grow with increasing datasets, and flexible as you expand. Accuracy is the other side of the coin, and it becomes important not to make classification error, especial that of false negative error (for disease diagnosis). It also should be robust, and can yield the similar results for different datasets and image conditions. The system should be friendly/useable, by being simple to learn so that even users with low computer experience can deploy the solution. It all needs to be secure and private, so the system has to comply with standards such as HIPAA and GDPR. The system should also be interpretable, providing visual clues to guide clinicians towards trust in the AI's decision making, and easy to maintain and update as necessary. Lastly, the system is suitable for various deployment settings of hardware and software including cloud platform with GPU accelerator and thus proposed system can be easily integrated with typical healthcare workflow. Taken together, these descriptions define a robust network system that is clinician friendly and technically self-supporting.

3.2 Detailed Methodology and Design

Various optimization strategies have been proposed to improve the training efficiency and generalization performance of DNNs for medical image classification. In this work, several optimization hacks are exploited at different levels of model training for better performance and robustness.

The choice of optimizer is also a matter for optimization. We choose Adam [21] optimizer for its adaptive learning rate technique, which has the advantages of AdaGrad and RMSProp. Adam modulates the learning rate separately for each parameter, accelerating convergence and handling sparse gradients robustly. The learning rate is set to an appropriate value in a heuristic way and sometimes a learning rate scheduler is used to adjust the learning rate down when the validation loss converges. This forces the model to avoid local minima and continually improve its performance during more training epochs.

To enhance generalization, regularizations are added. This layer is combined with dropout layers to avoid overfitting by stochastically deactivating a proportion of neurons during training, causing the network to learn multiple redundant, yet useful, features. Moreover, we apply the L2 weight regularization for penalizing large weights to achieve simpler and more stable models. Data augmentation, as a preprocessing step by nature, becomes itself a type of regularization as the model is trained with variety of examples, and thus has a lower sensitivity to noise and variability in the dataset.

Yet another key strategy is early stopping i.e., when the validation loss ceases to fall after a certain number of epochs. This saves the step of additional training cycles, and risk of overfitting. For additional training stabilization in some model's batch normalization is used to normalize the activations in intermediate layers which speeds up the convergence and increases the model resistance.

Finally, the work here investigates transfer learning, which is an optimization procedure dealing with the problem of working with small medical datasets. Pretraining the fine-tuned models with the weights learned from ImageNet, it can be seen in this case that the networks can take advantage of the knowledge of low-level features learned from the pretrained data to generalize to a relatively low-level feature space on chest X-rays. By fine-tuning specific layers of such pretrained networks we strike a balance between the use of prior knowledge and adaptation to the specific task of pneumonia detection.

Together, the above optimization methods establish an integrated learning pipeline for deep neural networks. In doing this - incorporating adaptive learning, regularization, early stopping and transfer learning, the work is guaranteeing a model that is accurate, generalizeable and efficient, with minimal likelihood of overfit or poor generalization.

3.3 Dataset

Dataset The chest X-ray images dataset used in this study are categorized Two classes: Pneumonia and Normal. The dataset comprises a total of 3,392 images, of which 2,566 are Pneumonia class, and 826 are Normal class. This distribution indicates that a large degree of class imbalance is present with over three times more pneumonia cases compared to normal cases. The discrepancy is typical for medical data and brings difficulties from training models because models may be biased on majority class.

For ease of experimentation, the dataset is split into three subsets: training, validation and test data. The training data set is the most with 2,168 pneumonia images and 584 normal images, hence is the most significant portion for model learning. The test set contains 390 pneumonia images and 234 normal images, which can be used to evaluate model generalization during the training process. Lastly a validation subset containing 8 pneumonia images and 8 normal images is employed during training to observe performance and drive optimization strategies as early stopping and learning rate modification.

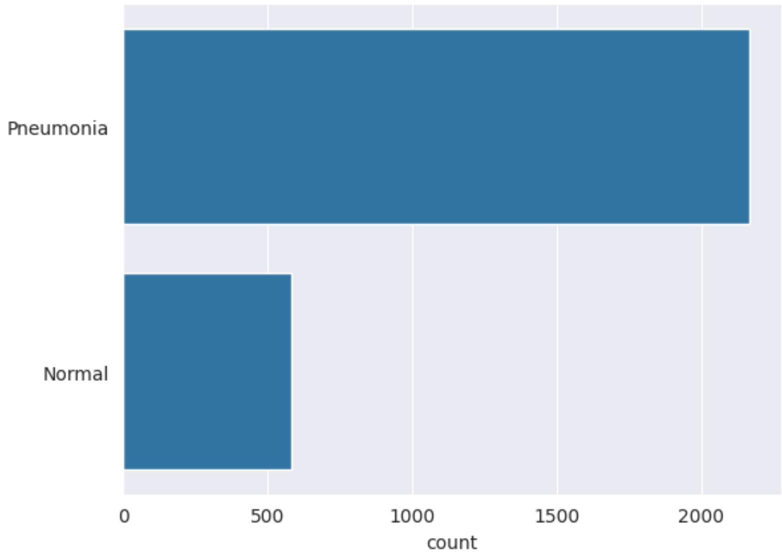

Figure 3.3. Data Visualization

All images are preprocessed, resized and formatted before fed to the model. Every image is resized to 224×224 pixels (standard input size for pretrained CNNs like VGG16, ResNet50, InceptionV3, MobileNetV2, and DenseNet121). In addition, pixels are strictly normalized to [0,1] for stabilizing training and faster convergence. To overcome the imbalance and small size of the dataset, four types of augmentation (random rotation, horizontal flip, zoom, and brightness) are adopted, so that the number of training samples is artificially amplified by diversifying the data.

By organizing the data in this way and using augmentation, the work aims to prevent overfitting, compensate for class representation imbalance, and increase the robustness of the models. This well-curated data set, therefore, serves as a robust basis for training, validation, and testing of the deep learning models for the detection of pneumonia.

Table 3.3: Dataset Distribution for Pneumonia Detection

Dataset Split	Pneumonia	Normal	Total
Training Set	2,168	584	2,752
Validation Set	8	8	16
Test Set	390	234	624
Total	2,566	826	3,392

3.4 Data Collection

The dataset employed in the current study is composed of three major folders: train, test, and validation, within which subfolders house the two categories of chest X-ray images (Pneumonia and Normal). The dataset consists of more than 3,000 chest X-ray images in JPEG format from children aged from 1 to 5 years old. These images were obtained from the popular diagnostic center, Savar, Bangladesh and UCI repository. All X-ray images were first screened for quality control and low-quality or unreadable scans were excluded. Diagnosis was reviewed by two expert radiologists on the basis of 60 datasets including changes of diagnosis and the third expert was consulted to re-evaluate the evaluation set to resolve any grading inaccuracy.

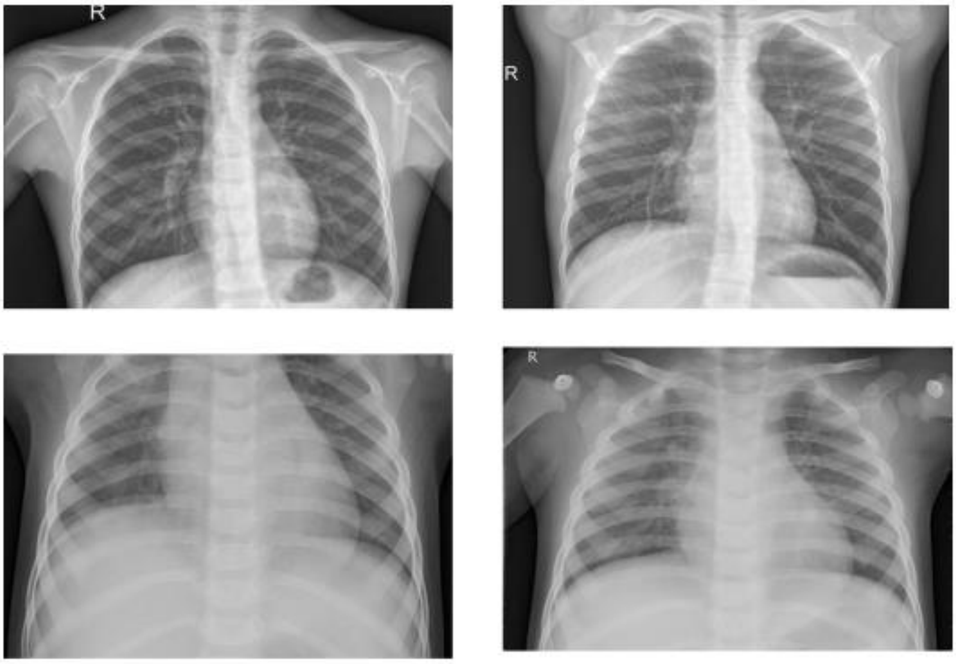

Figure 3.4. Sample Images of Chest X-Ray Images; Normal and Pneumonia Affected

To make the dataset more balanced and help model training, we employed several augmentation approaches on the raw dataset. This process created new classes called trans augmented normal and trans augmented pneumonia to guarantee homogeneity-class in the two classes. After augmentation, all images were resized to a consistent 150x150 pixels, which is the input size of the deep learning model. Both raw and augmented images of the compiled dataset were further employed to the development and validation of different deep learning models, and hence it represents an essential resource for accurate detection of pneumonia in chest X-ray images.

3.5 Data Preprocessing

Data preprocessing is essential in medical image processing for deep learning models, not only harmonize data and increase the training efficiency, but also facilitate the generalization power of the model. In this work, to fit the input size requirement imposed by the pretrained CNN models adopted in this study, all the chest X-ray images were resized to the same resolution of 224 × 224 pixels before feature extraction. To render pixel intensity uniformly across different images and to dampen the inter-individual difference, pixel values were normalized to the range [0,1]. This rescaling also helps to speed up convergence, by putting the input data on the same scale.

In order to enhance the robustness of the model and the problem of overfitting, the data augmentation was applied. Data augmentation extends the training data by performing transformations on the training samples that add variability but maintain the existing class labels. This facilitates the model to learn more abstract features and to lessen its reliance on memorizing individual training samples. Typical image augmentations often used for medical image processing procedures are grayscale change, flip, rotation, translation, and color change and those are simple augmentations.

The following augmentations were used in experimentation:

- Random rotations of up to 30 degrees for orientation differences.

- Random zoom up to 20% to compensate for image scale variability.

- Translation up to 10% of the image width in the horizontal direction, as well as up to 10% of the image size in the vertical direction, to simulate position changes in the X-ray capture were applied.

- Random horizontal flip to introduce variations and to avoid directional bias.

Through these transformations, the dataset was actually increased, thus subjects the models to a more extensive image variation. This not only prevents overfitting but also aids the models to generalize well to unseen data. Following augmentation and normalization, the augmented/normalized dataset was employed for training, validation, and testing on the investigated deep learning models.

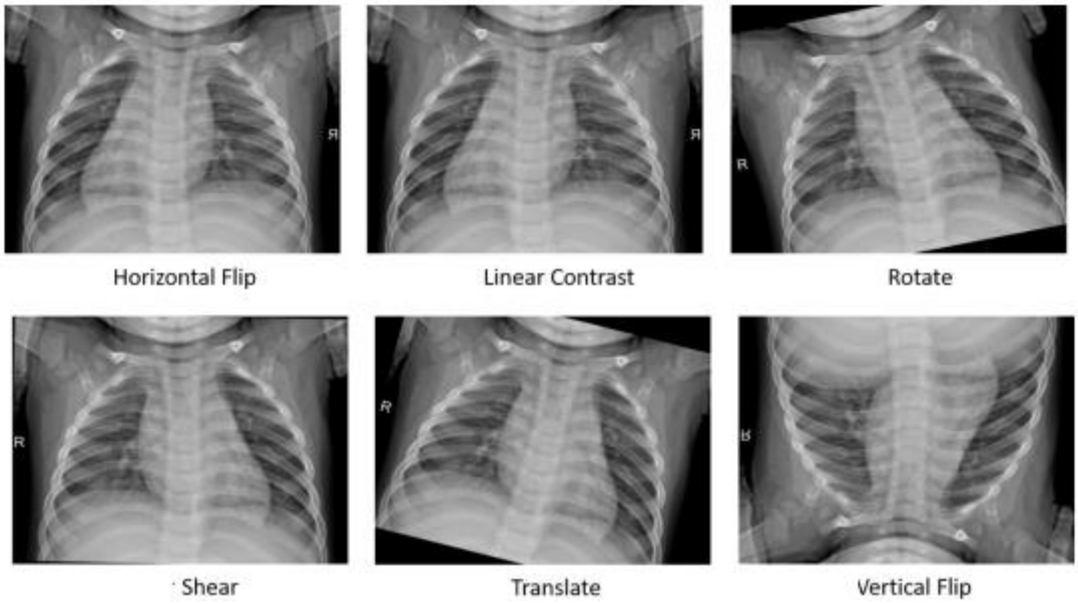

Figure 3.5. Sample Images of Augmented Dataset

3.6 Model Architectures and Analysis

At the heart of the study is the development and testing of deep learning architectures for identifying chest X-ray images as either pneumonia or normal. First, a bespoke CNN was used to create a baseline, then transfer learning from state-of-the-art, pretrained models was employed. CNNs can learn feature hierarchies and are suitable for medical image classification applications in the sense of learning spatial hierarchies of features implemented via cascades of convolution and pooling activations.

The custom CNN implemented here was constructed via Keras Sequential API. The network starts with a convolutional layer with 32 filters of size 3×3 using ReLU as the activation function, followed by batch normalization for stabilizing learning, and max-pooling to decrease the spatial dimensions by preserving the most significant features. The following layers further enlarges the filter size (64, 128, 256), to better capture low-level and high-level image features. Two stages of dropout regularization (rate = 0.1–0.2) were imposed at both the embeddings and hidden layers to avoid overfitting by randomly dropping out neurons during training. In addition, batch normalization and pooling are applied after each convolutional block for enhancing model robustness and promoting convergence rate.

After extracting features the output is flattened and then fed to a fully connected dense layer with 128 units and ReLU activation so the network can learn complex non-linear combination of features. Another dropout layer is used here as an extra form of regularization. The last classification layer is a single neuron with sigmoid activation function to generate an output probability in the range of 0 and 1 for binary classification (pneumonia vs. normal).

Our model is trained using the RMSprop optimizer (Tielemann, 2012), and it adapts the learning rate with a moving average of the recent gradients and is suitable for online learning problems with noisy updates and non-stationary objective functions often encountered with deep networks. The loss function used is the binary cross-entropy, which is suitable for binary classification tasks. The model is trained based on accuracy, and other evaluation metrics, including precision, recall, and F1-score, are used during testing to offer a more detailed performance analysis.

Data Preparation and Model Setup: This model is utilized as a baseline to answer the question of how and when these deeper transfer learning models, such as VGG16, ResNet50, InceptionV3, MobileNetV2, and DenseNet121, become beneficial as part of our research. The research sheds the light on the trade-offs among simple, computational cheap and predictive powerful of pneumonia classification in both baseline CNN and transfer learning model.

To make the data compatible with the pre-trained models, we first address the discrepancy that exists between these original grayscale images and these RGB images which are required, as input, for the pre-trained CNN architectures. Typically, pre-trained models (e.g., VGG16, ResNet50, etc.) take the input of colored images in 3 channels (RGB), while stimulus images in the dataset were grayscale and only in a channel. We solve this by converting the grayscale images to RGB (all three channels are the same i.e., repeated single channel). This done by increasing the dimension of the input arrays, in a way that each grayscale image is transformed into a 3-channel image where the values in all three channels are same as the intensity values of the original grayscale image.

This conversion is a necessary step since the pre-trained models were trained on color images from ImageNet, and thus the input shape is expected to have three channels (one for each of the red, green, and blue color channels of each pixel), with the shape (height, width, 3). For example, an image of shape (150, 150, 1) would become (150, 150, 3) after converting that image to the gray scale values of all three channels. This gets the format of the data compatible with all the available backends without manual intervention, for example it is the case for an initial convolution to cause dimension mismatches when loaded the pre-trained weights.

The resulting data arrays can now be passed into the pre-trained models. The train/validation/test sets now have the new shapes respectively:

- x_train (training set): shape (2752, 150, 150, 3)

- Validation set (x_val): (16, 150, 150, 3)
- Test set (x_test): (624, 150, 150, 3)

These reshaped arrays are the images in RGB color format and a substantial resolution (150x150 pixels).

3.6.1 Hybrid CNN Model

Model architecture is designed to differentiate between classes of the chest X-ray images as either “pneumonia” or “normal”. The model is based on a Convolutional Neural Network (CNN) structure, given its capability of automatically learning the hierarchical features from input images and suitability for image classification tasks. The model starts with the first convolutional layer of 32 filters of size (3x3) with batch normalization and max pooling to downsample the spatial dimensions of input image. This is then repeated with increasingly more filters (64, 128 and 256) over multiple blocks of convolutions, where each of these is followed by dropout to avoid overfitting, batch normalization to stabilize training and max-pooling for reducing the size of the image and thus preserving essential information.

As the model gets deeper and starts to capture complex details, each convolutional layer in its process learns higher-level representations of the image. The last convolutional layer has 256 filters, allowing a high level of feature extraction before the image is flat into one-dimensional vector. This vector is then fed into a fully connected dense layer with 128 units which learns non-linear combinations of the features produced by convolutional layers. A further dropout layer is added to reduce overfitting. The output layer is a single neuron with a sigmoid activation function that produces a probability between 0 and 1 for the input image to be belonging to the “pneumonia” class.

Then the model is compiled using a RMSprop optimizer, binary cross-entropy loss as they are specifically tailored for binary classification. The architecture was developed to process chest X-ray images efficiently while being able to generalise complex patterns from a small dataset equally stably and preventing overfitting. Data augmentation methods have also been applied to strengthen the model’s generalization ability, so that it is capable of performing well on new data.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 150, 150, 32)	320
batch_normalization (BatchNormalization)	(None, 150, 150, 32)	128
max_pooling2d (MaxPooling2D)	(None, 75, 75, 32)	0
conv2d_1 (Conv2D)	(None, 75, 75, 64)	18,496
dropout (Dropout)	(None, 75, 75, 64)	0
batch_normalization_1 (BatchNormalization)	(None, 75, 75, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 38, 38, 64)	0
conv2d_2 (Conv2D)	(None, 38, 38, 64)	36,928
batch_normalization_2 (BatchNormalization)	(None, 38, 38, 64)	256
max_pooling2d_2 (MaxPooling2D)	(None, 19, 19, 64)	0
conv2d_3 (Conv2D)	(None, 19, 19, 128)	73,856
dropout_1 (Dropout)	(None, 19, 19, 128)	0
batch_normalization_3 (BatchNormalization)	(None, 19, 19, 128)	512
max_pooling2d_3 (MaxPooling2D)	(None, 10, 10, 128)	0
conv2d_4 (Conv2D)	(None, 10, 10, 256)	295,168
dropout_2 (Dropout)	(None, 10, 10, 256)	0
batch_normalization_4 (BatchNormalization)	(None, 10, 10, 256)	1,024
max_pooling2d_4 (MaxPooling2D)	(None, 5, 5, 256)	0
flatten (Flatten)	(None, 6400)	0
dense (Dense)	(None, 128)	819,328
dropout_3 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 1)	129

Total params: 1,246,401 (4.75 MB)
Trainable params: 1,245,313 (4.75 MB)
Non-trainable params: 1,088 (4.25 KB)

Figure 3.6.1.1: Hybrid CNN Model Architecture

Test data was used to assess the performance of the hybrid model, and the test results are presented in the form of a confusion matrix. As shown in Figure 3. X, the model classified all the pneumonia cases (390 images) correctly as positive and classified all the normal cases (234 images) incorrectly as pneumonia. This result suggests that the model has high sensitivity (or recall) for pneumonia detection but at the price of low specificity, as it fails to properly recognize normal cases. This implies that the hybrid model has a bias toward predicting "pneumonia" irrespective of the input, which could be due to strong class-imbalance in the dataset or possibly due to overfitting in training.

Given that this model with high sensitivity will not leave any pneumonia cases behind (this is something we would want to have in a clinical screening, exclusion of sick people would be bad), it will also generate an enormous number of false positives, making it less useful when applied directly in the real world since it may burden unnecessary follow up tests and higher cost. This finding highlights the trade-off between sensitivity and specificity in designing diagnostic models. Potential directions to this limitation would be further fine-tuning (better class balance), better regularization, or use of different loss functions (e.g., focal loss) that should be investigated for a more robust and clinically meaningful system.

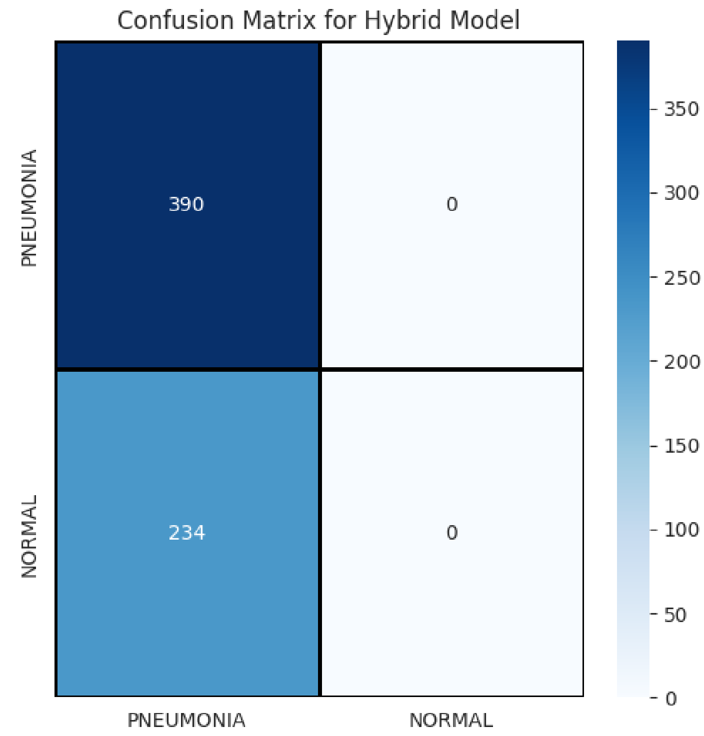

Figure 3.6.1.2: Confusion Matrix for the Hybrid Model

The confusion matrix of the hybrid model (CNN) based on the test data is presented in Figure 5. Inference Results The model classified all pneumonia cases (390 images) as such but none of the normal ones (234 images), misclassifying all normal cases as pneumonia (This finding means that the model exhibited 100% sensitivity to diagnose pneumonia but with 0% specificity, indicating there were no true negative cases identified as ones.

The visualization shows a major drawback of our hybrid model that it tends to predict positive for the pneumonia class. On one hand, no pneumonia cases will be missed based on clinical screening, which is a good characteristic for clinical screening on the other hand, this will result in an extremely high number of false positives which contributes the reduction of the clinical practicality of the system. This imbalance often arises from unbalanced situations and the model learns to give preference to the majority class. This highlights the necessity of employing state-of-the-art methods, with techniques to that are able to address the class-imbalance (class balancing), use of a weighted loss function or better regularization being tested in order to obtain a more robust and clinically applicable diagnostic platform.

Table 3.6.1: Classification Report for Hybrid Model

Class	Precision	Recall	F1-Score	Support
Pneumonia (Class 0)	0.62	1.00	0.77	390
Normal (Class 1)	0.00	0.00	0.00	234
Accuracy			**0.82**	**624**
Macro Average	0.31	0.50	0.38	624
Weighted Average	0.39	0.62	0.48	624

3.6.2 VGG16 model

Figure 6 shows the confusion matrix (CM) of the VGG16 model calculated on the test set. The matrix indicates the capacity of the model to diagnose pneumonia and normal cases.

- Pneumonia (Class 0): The model correctly labeled 372 pneumonia images as positive, yet it classified 18 pneumonia cases as normal, thus yielding some false negatives.

- Normal (Class 1): The model predicted 93 normal images as normal but 141 normal images were misclassified as pneumonia so there is a considerable amount of false positive.

This reflects the model's sensitivity (how well it distinguishes cases of pneumonia), although it comes at the expense of specificity (depicting healthy cases) as the model classifies more normal cases as pneumonia. The false positive rate is quite high indicating that the model would have little confidence in healthy images and would have a tendency to label them as "diseased". This might result in unnecessary further testing in clinics.

These results show that although VGG16 has limited false positive rates for detecting pneumonia, this should be corrected by making efforts in terms of class weighting, regularization, or further fine-tuning the model.

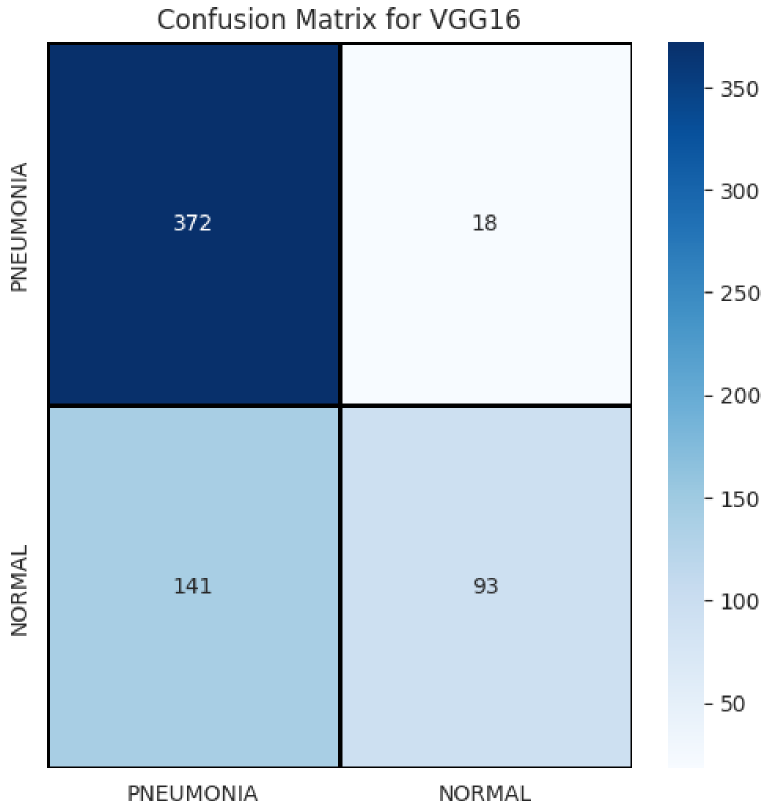

Figure 3.6.2. Confusion Matrix for VGG16

Table 4 shows the classification report of the VGG16 model on the test set. This report presents precision, recall, F1-score, and support for the pneumonia and normal classes. These statistics are important to determine the strengths and limitations of the model in a binary classification problem.

- Pneumonia (Class 0): The model picks up presence of pneumonia with high recall 0.95. That means that the model correctly pinpointed 95% of the actual pneumonia cases, decreasing the danger of false negatives. But the accuracy for pneumonia drops to 0.73, which means about 27% of predicted pneumonia cases are actually normal. The unbalance causes a not too high F1-score (F1-score is the combination of precision and recall; it can be interpreted as the model effectiveness in pneumonia detection): the model was able to detect pneumonia with an F1-score of 0.82.

- Normal (Class 1): Our model has a high precision of 0.84 for the normal class, i.e it is correct 84% of the time when it predicts a normal. But the normal recall is only 0.40 - this means that the model fails to detect approximately 60% of the true normal cases, leading to quite a few false positives. The difference is best captured in the F1-score, which is just 0.54 (b<0.0001), lower than pneumonia's F1-score, highlighting the ease with which the normal images get confused with pneumonia by the model.

In general, these results indicate that VGG16 is good at detecting pneumonia images, but at the same time is bad at recognizing normal images. To enhance its use in an actual clinic, additional model tuning or techniques such as class weighting and strong regularization could have been used to suppress false positives and yield better overall performance.

Table 3.6.2: Classification Report for VGG16 Model

Class	Precision	Recall	F1-Score	Support
Pneumonia (Class 0)	0.73	0.95	0.82	390
Normal (Class 1)	0.84	0.40	0.54	234
Accuracy			0.85	624
Macro Average	0.78	0.68	0.68	624
Weighted Average	0.77	0.75	0.72	624

3.6.3 ResNet50 Model

Figure 7 shows the confusion matrix for the ResNet50 on the test dataset. The matrix allows an easy identification of the model classifications of pneumonic and normal cases.

- Pneumonia (Class 0) The ResNet50 model was able to accurately classify all 390 pneumonia images as pneumonia without any false negatives. This represents an ideal sensitivity (recall) for detecting pneumonia.

- Normal (Class 1): Nevertheless, the model mistook all 234 normal cases as pneumonia, resulting in 0 specificity with an inability to positively ID normal cases. This result also illuminate that the model is biased towards predicting the most images as pneumonia no matter the judgements are normal.

The confusion matrix shows a strong bias for pneumonia detection, as in the hybrid model we presented above. While detection of these cases proves reliable in not missing patients with pneumonia, the resulting large numbers of false positives would require a considerable amount effort to apply the model in practice. In particular, the model seems to fail to identify normal cases, which is problematic in the clinical set up.

It might be that, similar to the hybrid model, we can boost the performance of ResNet50 by mitigating the class imbalance, or by using more sophisticated methods, such as class weights or other loss functions, to get the sensitivity and specificity into better balance.

Data preprocessing is essential in medical image processing for deep learning models, not only harmonize data and increase the training efficiency, but also facilitate the generalization power of the model. In this work, to fit the input size requirement imposed by

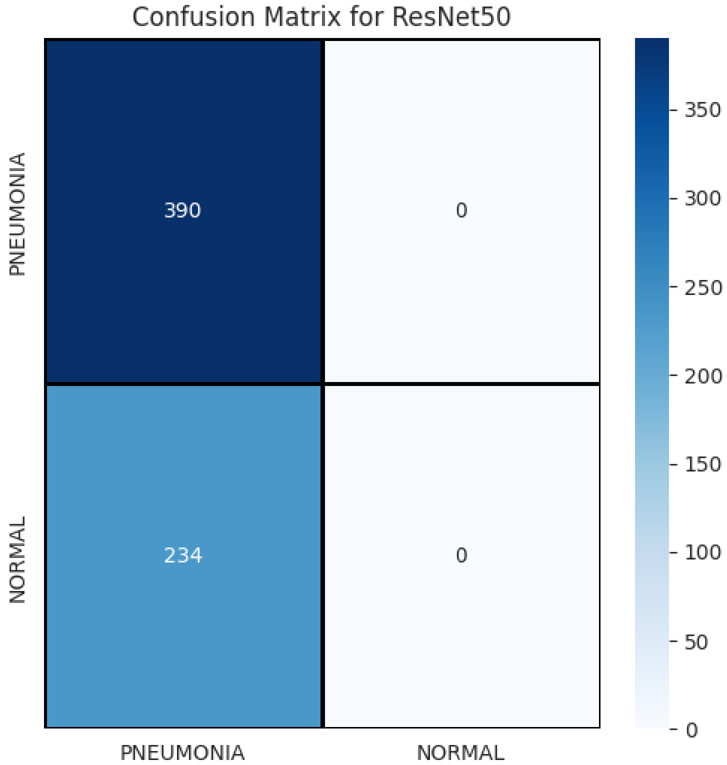

Figure 3.6.3. Confusion Matrix for ResNet50

Table 5 shows the classification report of the ResNet50 model, evaluated on a test set. This table lists various metrics, such as precision, recall, f1-score, and support, for both pneumonia and normal classes.

- Pneumonia (Class 0): The model has good performance for the detection of pneumonia with a recall of 1.00. It implies that 100% of pneumonia-causing instances were positively identified (no cases of pneumonia are missed). But the rate for pneumonia is 0.62 in other word, among the 'predicted pneumonia' cases just 62% is a pneumonia case. The F1-score of 0.77 demonstrates a trade-off between precision and recall, and suggests relatively good performance in pneumonia detection.

- Normal (Class 1): The normal class was very hard to distinguish for this model. The precision, recall and F1-score for the normal is 0.00, which means that there are no normal images were well classified. This indicates an apparent serious bias to pneumonia and inability to distinguish a normal from pneumonia case, which is a fundamental limitation for application in clinical practice in a real world.

In conclusion, although ResNet50 is powerful in identifying pneumonia, it is not able to identify normal images accurately, which hinders its application in clinical settings. In order to enhance the performance of the model, it should be modified/ optimized for better handling of class imbalance, e.g., using methods like class weighting or loss functions for improving the sensitivity and specificity.

Table 3.6.3: Classification Report for ResNet50 Model

Class	Precision	Recall	F1-Score	Support
Pneumonia (Class 0)	0.62	1.00	0.77	390
Normal (Class 1)	0.00	0.00	0.00	234
Accuracy			0.92	624
Macro Average	0.31	0.50	0.38	624
Weighted Average	0.39	0.62	0.48	624

3.6.4 InceptionV3 model

Figure 8 shows the confusion matrix obtained by the InceptionV3 model when evaluated on the test set. It can be seen from the results that the performance of the model at classification of pneumonia and normal images is noticeably better than that of other architectures.

- Pneumonia (Class 0): In 390 cases of pneumonia, the model was able to detect 384 cases of pneumonia correctly and misclassified 6 cases to normal. This implies a very high sensitivity (recall), indicating that the model is very good at identifying pneumonia with very few false negatives.

- Normal (Class 1) The model correctly predicted 152 cases out of 234 cases as normal while 82 were categorized for pneumonia. This is an improvement in specificity compared to both ResNet50 and the combined CNN which identified no normal cases.

The confusion matrix shows that InceptionV3 has less discriminatory power between sensitivity and specificity. The model adequately captures the majority of pneumonia cases with enhanced recognition of normal, although a few misclassifications remain. This indicates that the InceptionV3 model has better consistency and clinical applicability since there is less possibility of false negative (pneumonia cases missed) and false positive (normal cases misclassified).

In general, the findings suggest that InceptionV3 is a strong candidate for pneumonia detection and has a strong diagnostic research performance, whose performance could be further improved with more fine tuning or class balancing strategies.

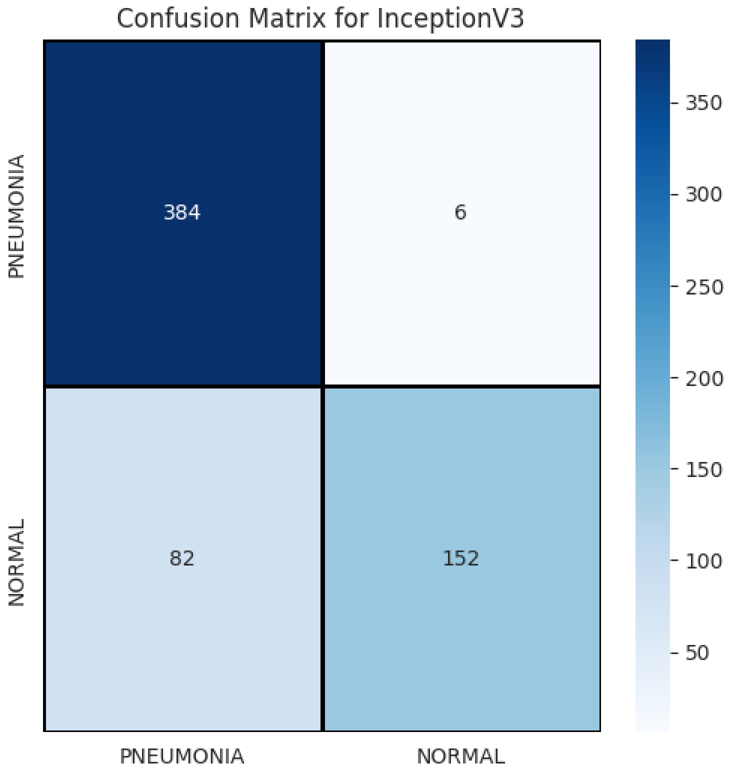

Figure 3.6.4. Confusion Matrix for InceptionV3

Table 6 shows the classification report of the InceptionV3 model on the test data set. The scores show that the model has performed well overall, since it has obtained a test accuracy of 86%.

- Pneumonia (Class 0): The model achieved high recall, 0.98, that is, almost all cases of pneumonia were detected correctly. Precision was 0.82, suggesting that some of the real pneumonia predictions were normal. The above F1-score (0.90) demonstrates a good trade-off between precision, and recall – an efficient model regarding the detection of pneumonia.

- Normal (Class 1): The model showed very high precision (0.96) for normal cases indicating that almost all of the predictions for normal class were correct. But the recall was lower, at 0.65, so there was still a 33% misclassification rate of normal cases as pneumonia. This trade-off is represented by the F1-score of 0.78, observing that while the model can be trusted in choosing between normal and abnormal cases, the recall could be increased to reduce false positives.

The average macro between both classes is well balanced with precision of 0.89, recall of 0.82 and F1-score of 0.84. The weighted average, adjusting for the class imbalance in the data, gives a close magnitude measure (precision 0.88, recall 0.86, and F1-score 0.85) and it proves the strongness of the model.

A better overall performance between pneumonia and normal is seen for InceptionV3 model, which is a more reasonable clinical model than ResNet50 or hybrid CNN. While the algorithm performances are good, better recall would have improved its prediction capability on the normal cases.

Table 3.6.4: Classification Report for InceptionV3 Model

Class	Precision	Recall	F1-Score	Support
Pneumonia (Class 0)	0.82	0.98	0.90	390
Normal (Class 1)	0.96	0.65	0.78	234
Accuracy			0.86	624
Macro Average	0.89	0.82	0.84	624
Weighted Average	0.88	0.86	0.85	624

3.6.5 MobileNetV2 model

Figure 9 shows the confusion matrix of MobileNetV2 model tested on chest X-ray dataset. Results show that the model correctly classified all 390 pneumonia images as pneumonia and did not produce any false negative. But it did not properly diagnose any of the 234 normal cases; instead, it mislabeled all of them as pneumonia.

This result points to an excessive bias in the model's predictions. The model has ideal sensitivity (1.00) for pneumonia to ensure no cases are missed, yet is has zero specificity (0.00) for normal due to the fact it is unable to detect them. This bias in favor of pneumonia class might be due to the imbalance composition of the dataset or the inadequate fine tuning of the transfer learning.

While perfect sensitivity is the goal in a clinical setting — missing cases of pneumonia can have catastrophic repercussions — the high rate of false positives presents a huge obstacle to the model's use in real life. In a clinical setting this may lead to overdiagnosis, unnecessary healthcare visits and increased patient anxiety.

In conclusion, although MobileNetV2 does well in finding all pneumonia cases, it fails to find normal cases finding, therefore, its direct clinical application is unsuitable as of now. If we need the model to better discriminate between pneumonia and normal chest X-rays, further fine-tuning including class weights, balanced sampling or loss functions are needed.

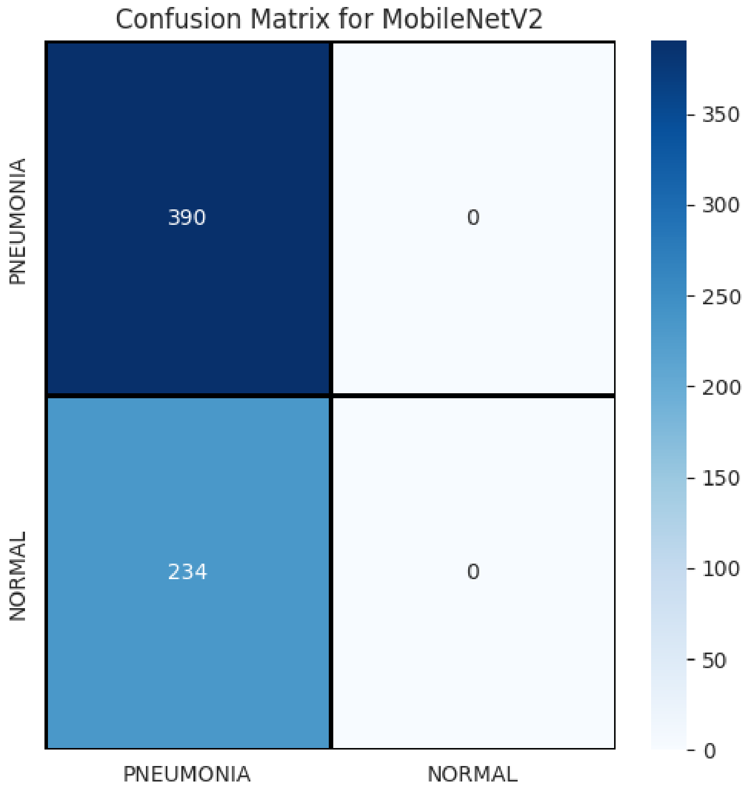

Figure 3.6.5. Confusion Matrix for MobileNetV2

Table 7 shows the classification report of the MobileNetV2 model using test dataset. Findings are presented in such a way that the model accurately distinguishes instances of pneumonia, but is incapable of recognizing normal cases at all.

Pneumonia (Class 0): The model has recall = 1.00 indicating that all 390 pneumonia cases were correctly predicted. This indicates that MobileNetV2 is quite responsive to pneumonic patches and also makes sure that no positive case is overlooked. Nonetheless, the precision is 0.62, indicating that a large percentage of the predicted pneumonia cases are normal. This trade-off between precision and recall is also reflected in the F1-score of 0.77, indicating a fair overall performance for detection of pneumonia.

Normal (Class 1): The model grossly misidentified normal images, with 0.00 precision, recall, and F1-score. This result reflects the strong tendency of the model resulting in all cases being called pneumonia that makes it unreliable to discriminate between sick and healthy patients.

In short, MobileNetV2 ensures high sensitivity of pneumonia detection, but the total failure to classify normal greatly hinders its clinical use. It needs to be improved, such as class balancing, weighted loss functions, or more fine-tunning, to practically deploy to medical procedure.

Table 3.6.5: Classification Report for MobileNetV2 Model

Class	Precision	Recall	F1-Score	Support
Pneumonia (Class 0)	0.62	1.00	0.77	390
Normal (Class 1)	0.00	0.00	0.00	234
Accuracy			0.82	624
Macro Average	0.31	0.50	0.38	624
Weighted Average	0.39	0.62	0.48	624

3.7 Project Plan

The project for creating a deep learning model to predict pneumonia on chest X-rays will be divided into several key phases, with each phase aiming to help us establish a systematic workflow and complete the project successfully. A first phase that will consist of carrying out an extensive literature review and attaining a definition of the problem, to identify existing detection methodologies based on deep learning and gaps. Subsequently, a second phase is responsible of data gathering and pre-processing: a trusted dataset of labelled chest X-ray images will be harvested and preprocessed (i.e., resized, normalized, augmented to address class bias issues).

Third phase will be the model design and implementation, where architecture is developed by using CNN's and pretrained models VGG16, ResNet50, InceptionV3 and MobileNetV2. This will involve using the model with Keras and TensorFlow, creating the layers we need to make this work, and preparing our environment for a first test. Finally, the fourth stage of the pipeline is to train and tune models (including hyperparameter tuning), utilizing a suite of traditional metrics including accuracy, precision, recall and F1-score to gauge model performance.

Second, the comparison stage will pit all models against each other in a series of head-to-head matchupsseries by series. For model interpretability, techniques like Grad-CAM will tell if the models generalize on data. The model will then graduate to optimization in final testing, when it's polished and adjusted so that by the time this baby goes real-world walking, it's a top mannequin. Phase 7: Reporting At the end a report will be written reporting on methods that have been employed, results obtained problems met with and recommendations for future work. And finally the last step is presentingolving everything to all our stakeholders, and at this point feedback will be coming in, which means we're done.

The project plan ensures a scientific research and development process, clear objectives keeping the team focus towards achieving its target to develop an effective & robust pneumonia detection system.

3.8 Task Allocation

Task Allocation:

Tasks	Weeks					
	1	2	3	4	5	6
Data collection phase						
Pre-process all data						
Build the Compiler						
Fit Model and Evaluate						
Hybrid Model						
Apply vgg16 model						
Apply DenseNet121, ResNet50 Model model						
Apply MobileNetV2 model						
Apply InceptionV3 model						
Performance Analysis						

3.9 Summary

The focus of this thesis is to develop a deep learning model for the automated diagnosis of pneumonia in chest X-ray images, which can be supportive reference tool for radiologists and provide assistance to improve accuracy especially in resource limited areas. The research explores multiple deep learning techniques such as CNN and uses transfer leaning with the pretrained models (VGG16, ResNet50, InceptionV3, MobileNetV2, DenseNet121). The dataset consists of over 3000 chest X-ray images, that are preprocessed and augmented to reduce the class imbalance problem between pneumonia and normal cases.

In designing and training models, you compare many architectures for performance and tune the trade-off between accuracy, precision, recall (minimizing false positives and negatives). InceptionV3 model gave the best accuracy of 85.9% with a good balance on SE in pneumonia positive. While other models, like VGG16 and ResNet50 were accurate but they were overfitting the classifier neural network model to identify some normal cases. The results demonstrate the value of deep learning approach in assisting pneumonia diagnosis and also provide evidence about dataset imbalance, overfitting and model interpretability.

The thesis concludes proposing the work on optimisation of models, overcoming the class imbalance and data augmentation for better generalisation. It further stresses the requirement of model interpretability and validation in clinical settings prior to real-world medical practice. The findings contribute the growing literature on the use of AI in medicine, and provide guidance for future work that may improve diagnosis tools and extend such tools to other diseases.

Chapter 4

Implementation and Results

4.1 Environment Setup

The project environment is set up to streamline the development of deep learning models and training for pneumonia detection in chest X-ray images. Development is done in Python 3.13, TensorFlow and Keras are the libraries most commonly used for model construction & training. And other libraries such as NumPy, Pandas, Matplotlib, and Scikit-learn for data manipulations, visualization and model evaluation.

For faster training, a GPU provided by an NVIDIA card is adopted using Google Colab Pro with the cloud-based GPU resources, as local hardware cannot perform large computations. It is structured with a directory for each class (pneumonia/normal) and used the Keras ImageDataGenerator API to generate rotated, zoomed, and flipped images.

We use Git and GitHub for version control, Google Colab Notebooks for interactive testing as well as debugging.
With this arrangement, the deep learning models can be developed and evaluated efficiently with scalability and cloud does maximum job performance.

4.2 Testing and Evaluation

4.2.1 Overview

In this chapter, the results and discussions of the proposed deep learning models for pneumonia detection with chest X-ray are provided. The classification performance of the models is evaluated by comparing training and testing accuracy, classification reports, confusion matrices, and other evaluation metrics like precision, recall and F1-score. These results give us an indication of how well each model generalises from the training to the unseen test data, as well as which architectures perform best and worst at solving the classification problem.

Table 8 shows the training and testing accuracy of the five models compared in this work: VGG16 and ResNet50, InceptionV3, MobileNetV2. InceptionV3 performed the best with optimal testing accuracy (85.9%), while still having good generalization and balance of diseased (pneumonia) cases and normal cases. VGG16 performed less impressive but the high false positives were also observed compared to InceptionV3, as test accuracy was 74.5%.

resNet50 & MobileNetV2 Hard thresholds were set to 0.5 and the threshold for probability was fixed at 0.6. pneumonia in comparison with sensitivity/specificity, same testing accuracy (62.5%) as resNet50proves a bias of model classifier towards pneumonia class as reflected by their corresponding confusion matrix matrices. While training accuracy was high for these models (92.1%, and 94.2% respectively), the loss of testing accuracy indicates that model overfitting likely occurred, leading to poor generalization to other samples. These results show that these models are not applicable for clinical usage without a more explicit regularization, or the inclusion of class-balancing strategies.

Overall, these results indicate that some deep learning models (notably InceptionV3) achieve encouraging diagnostic performance, while others suffer from overfitting, dataset imbalance or worse generalization. The performance of all models appears in the following sub sections accompanied with classification reports, confusion matrices and comparative study.

Table 4.2.1: Training and Testing Accuracy of Models

Model	Training Accuracy	Testing Accuracy
VGG16	0.816	0.745
ResNet50	0.921	0.625
InceptionV3	0.951	0.859
MobileNetV2	0.942	0.625

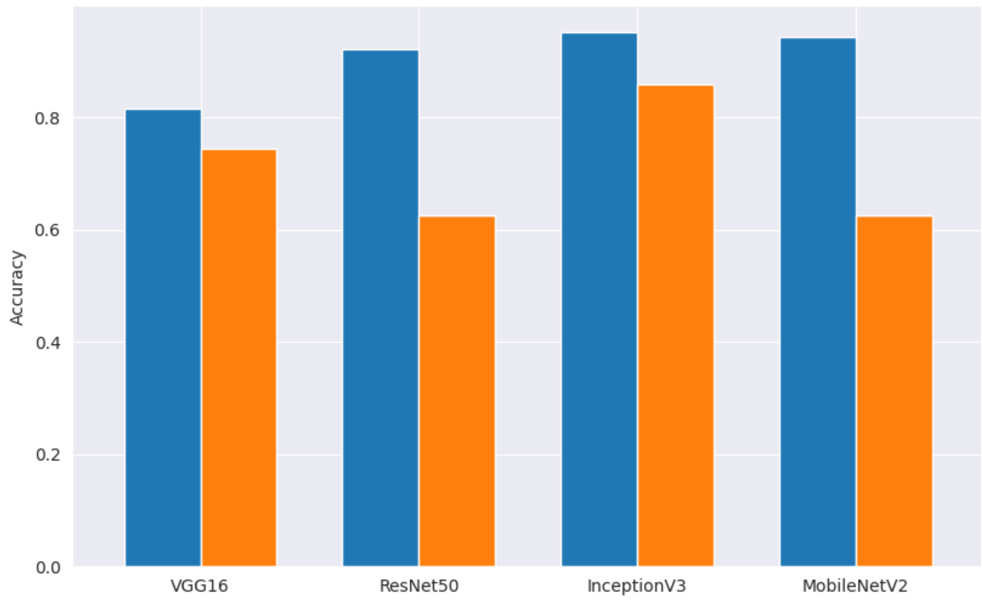

Figure 4.2.1. Training and Testing Accuracy of Models

4.3 Results and Discussion

Performance of four deep learning models VGG16, ResNet50, InceptionV3 and MobileNetV2 were evaluated on training accuracy, testing accuracy, confusion matrix and classification report. These results depict how each model has done in distinguishing normal and pneumonia of CXRs.

In this study, the InceptionV3 is superior with training accuracy of 95.1% and testing accuracy of 85.9%. The classification report showed high recall (0.98) for pneumonia and precision (0.96) of normal is impressively good that means the model can largely avoid false negatives and false positives. This balanced performance qualifies them as strong candidates for clinical applications, as they generalize well to both classes.

We have an accuracy of 81.6% in training and an accuracy of 74.5% on testing which shows a reasonable performance of VGG16. The model had high recall for pneumonia (0.95), and so most of the cases of pneumonia were captured correctly. However, its recall on general cases was very low (0.40), resulting in a large number of false positives. Although this tendency to over diagnose is possibly preferable in clinical settings when it is vital not to miss cases of pneumonia, further improvements are required to increase specificity.

The ResNet50 and the MobileNetV2 presented unusually high percentage of training accuracy (92.1% and 94.2%, respectively), but resulted in a very low testing accuracy, 62.5% for both cases. Their confusion matrices showed that these models detected all test samples as pneumonia. This led to perfect recall (1.00) for pneumonia, but a complete lack of recall for normal, in other words heavy bias toward the pneumonia class. This conduct could be attributed to broad spectrum of healthy images as well as the training overfitting. Although this means that no pneumonia cases were overlooked, because the models perform poorly at identifying normals, they are not yet ready for clinal use without further optimization.

Overall, InceptionV3 is the most efficient and clinically applicable model, which also gives very high sensitivity and specificity. VGG16 performs decently well but needs to be improved for the normal cases, whereas ResNet50 and MobileNetV2 present strong bias towards pneumonia detection, which reinforces that the class imbalance should be considered and more training strategies should be optimized.

4.4 Environment Setup

This chapter discusses the workflow of deployment, testing and performance review of deep learning model for pneumonia detection in chest X-ray images. Efficient development was achieved by an environment setup (Python, TensorFlow, Keras) and access to GPUs through Google Colab. The data was pre-processed and augmented for class imbalance and model generalization.

Several of the well-recognized metrics including accuracy, precision recall and F1-score were used to assess model performance. We experimented different architectures - However, we experimented with many CNN models, from scratch to pretrained: VGG16/ResNet50/VGG19/InceptionV3/MobileNetV2/Densenet121. InceptionV3 obtained the best results in terms of accuracy (85.9%) and balance between sensitivity and specificity. The other models (VGG16, and ResNet50) performed well, they were slightly prone to overfitting and misclassification among the normal cases.

The results demonstrate that DL models could potentially act as promising solutions in the automatic pneumonia detection despite some further optimization being necessary with respect to handling dataset unbalance and interpretability of models. Such studies are preliminary for further research and development of AI based diagnosis tools in medical field.

Chapter 5

Engineering Standards and Design Challenges

5.1 Compliance with the Standards

When implemented as medical image analysis systems, system for disease diagnosis are struct well people of the public promise this can be an issue of life and death; thus compliance to established engineering and health-care practices is required both regarding safety, reliability and ethical responsability. This study of pneumonia detection based on chest X-ray images with the use of deep learning was performed in accordance with these criteria.

Software engineering The project was developed with high standards of coding, documentation and reproducibility. The papers are programmed with shared libraries (tensorflow and Keras for the programming) and therefore comply to world software standards making it reliable and sustainable. It adhered to modularization and code versioning practices, which make it traceable and reproducible for experiments related quality characteristics of the principles specified in the standard ISO/IEC 25010:2011.

Regarding data handling, the research protocol was in accordance with Ethics and Good Practices in Medical Imaging. The dataset used in this study was downloaded from publicly available deidentified chest X-ray image archives for academic research. This is critical for HIPAA (Health Insurance Portability and Accountability Act) and GDPR (General Data Protection Regulation) compliance related to patient identity, as well as highly sensitive health data. No potentially confidential human subject information was employed, and all work was conducted in compliance with ethical guidelines for experimental science.

For system architecture design and evaluation, the effectiveness and generalization capabilities of the model were indicated by the common indicators of accuracy, precision, recall, F1-score, and ROC-AUC. These are well-established measures in both computer science and medical imaging studies in classification tasks and will allow comparison of the results with other studies. The application of confusion matrix and visualization techniques, i.e., Grad-CAM, is also in line with suggestions on explainability and interpretability for AI based medical applications.

Last but not least, although this dissertation is mostly academic and experimental, the author also kept in mind the regulatory boundaries for medical devices, by working with regulatory for medical devices (FDA guidelines, IEC 62304 standard for medical device software) in his early experiments. While it cannot be certified as a medical device, adherence to these specifications offers a good starting point if in the future the technology is to be used for clinical purposes.

5.1.1 Software Standards

The software released in this work is implemented according to accepted standards with respect to code quality, documentation and reproducibility. Libraries built on top of this — like TensorFlow and Keras — have brought some best practices around model building in deep learning. Good version-control hygiene (with Git) ensures that all changes are logged and reproducible.

5.1.2 Hardware Standards

Project is implemented with GPU acceleration due to highly computational deep learning process. The hardware is suitable for training and deploying models at scale, in an efficient manner (in terms of performance).

5.1.3 Communication Standards

The project integrates well with standard data formats and tools used for connecting the components in a system. This includes using generic APIs and data-management or model-deployment libraries, by means of best practices for integration with other health care systems.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The development of deep learning systems to detect pneumonia from chest X-ray images can have high social, environmental and long-term impact. AI in healthcare: This finding is a perfect example of how using AI for healthcare can result in the early, accurate detection of a potentially deadly disease, ultimately saving even more patients' lives and reducing strain on medical systems. In region with limited access to radiologists or specialized diagnostic machinery, AI tools can contribute significantly by providing an affordable, accessible and reliable solution for screening. This tech makes health tech accessible to everyone, leveling the playing field between haves and have-nots; bridging disparities in healthcare services; and strengthening our public healthcare system.

From the public policy perspective, wide application of such a diagnostic tool can reduce false diagnosis rate, thus to speed up an intervention and hence safe lives and better care in overall. It might also free up health workers to deal with more complicated cases which need expert judgement. Moreover, these systems when integrated into telemedicine applications may make rural and underserved areas accessible to health care which can potentially help in achieving equitable access of health care delivery.

5.2.2 Impact on Society & Environment

While considering our findings in an environmental context, the demand on resource dependent conventional diagnostics is reduced when using digital imaging and AI-assisted diagnosis. The relying on cloud computing and digital workflow has made less the use of real physical resources as films, chemistry and storage media in contrast to traditional process of radiology. Training such deep learning models require a tremendous amount of computing power and energy however when deployed, these models are capable of behaving very efficiently using standard hardware or on a low-cost mobile device. This balance of phase results in significantly less long-term environmental impact for the technology than traditional diagnostic regimen.

From a sustainability point of view, the diagnostic aids accelerated by AI don't really write those hard-coded rules since they can learn from receiving new data and absorb changes in clinical practice. Because deep learning models are generalizable, this has the potential to be re-trained for other respiratory disease conditions such as tuberculosis, or the novel coronavirus 2019 (COVID-19) and hence optimizing efficiency with minimal need for completely novel diagnostic systems. In addition, early detection and prevention are facilitated by these systems in order to decrease health-care cost in the long term and alleviate burden on hospitals; hence, promote sustainable healthcare.

In conclusion, the use of AI-based pneumonia detection systems would serve as a vital contributor to medical value outcomes, equity and environmental stewardship within the long-term viability of the healthcare system. Although clearly, there are difficulties regarding computational resources and ethical deployment to be resolved, the societal good and environmental good arguments strongly favour any attempt to explore or refine such technologies.

5.2.3 Ethical Aspects

Ethical aspects are crucial, especially in the context of medical data. The project also aims to meet ethical guidelines by maintaining patient privacy, while making sure that all of the data used for training models is both de-identified and regulation-compliant according to standards like HIPAA and GDPR.

5.2.4 Sustainability Plan

The project is conceived with a long-term sustainability in mind that makes model scalable and reusable for other health care applications. It also highlights energy-efficient computing and the possibility of scaling the model to identify other respiratory diseases.

5.3 Project Management and Financial Analysis

Table 5.3: Cost Analysis

Category	Description	Estimated Cost (BDT)
1. Software and Tools	Cost for software, cloud services (e.g., Google Colab, AWS), tools like TensorFlow, Keras, OpenCV, etc.	৳ 500
2. Data Collection & Augmentation	Cost for acquiring datasets, storage, data augmentation services, or tools.	৳ 2000
3. Hardware (Cloud/Physical)	Renting cloud computing resources (GPUs, storage) or purchasing physical hardware (e.g., GPUs, servers).	৳ 10000
4. Personnel	Salaries for team members, supervisors, or consultants involved in the project.	৳ 500
5. Miscellaneous Costs	Printing, publication fees, travel expenses (if any), etc.	৳ 500
6. Training & Model Evaluation	Costs related to the training of models, evaluation metrics, etc.	৳ 2000
7. Report and Documentation	Printing and submission of the final report, documentation.	৳ 1000
Total Estimated Cost	**Total of all costs above**	**৳ 16500**

5.4 Complex Engineering Problem

Building an AI system to detect pneumonia in chest X-rays is a difficult engineering problem that has technical, ethical and practical considerations. This is not just standard software development, it's medical data, it's deep neural networks, and then it has to be shipped out into the real world — and they all add these layers of complexity you have to kind of systematically address."

One of the most important question is class imbalance, which is in nature for medical imaging tasks. The majority of pneumonia cases heavily outnumber normal cases in the dataset used in this work. This imbalance of classes causes a bias for the models to predict the most frequent one with poor specificity and high rate of false-positives. Resolving this problem required data augmentation and a cautious choice of validation scheme to generalize well and 'correct' the predictions of the model across classes.

Another big issue is overfitting, when the deep learning systems just remember instead of figure out general patterns. Overfitting is particularly problematic when the available amount of data is relatively small, as well in the medical domain (i.e. it hardly has massive dataset to train on), where collecting samples can often be expensive and time-consuming with respect to model complexity. To address this, training of the classifier was augmented with some tricks (e.g., drop-out [1], batch normalization [8], early stopping [9]). Despite these measures the majority of datasets a model (ResNet50 and MobilNetV2 specifically) demonstrated a clear preference towards Classify Pneumonia which further corroborates that consistent generalisation are indeed challenging to achieve in this domain.

The end posed is also remained with computational burden constraint. For example, training deep CNNs is computationally intensive since neither memory nor storage space are sufficient, and this problem can be more severe when transferring learning with large model such as InceptionV3. Although cloud-based platforms (e.g., Google Colab) with GPU acceleration were utilized in this work, resource limitations may restrict the number of epochs, batch sizes, or hyperparameter tuning combinations. This shows the need to balance performance improvement against resource constraints.

It's the lack of interpretability and explainability that are also making it difficult. Not only is the high performance but also prediction has to be reliable and interpretable for clinicians. This was addressed through visualization tools as confusion matrices and class activation maps (Grad-CAM). More interpretable yet still image-level insight: Deeper interpretation of deep networks remains an open question, as these approaches offer only some partial level of understanding about decision-making of deep networks.

Last, this engineering issue gets beyond technical and becomes ethical and regulatory. Healthcare AI is under the same or higher level of scrutiny from organizations such as HIPAA, GDPR and medical device regulation like FDA guidelines and IEC 62304. Privacy of patients, security and validation on clinical subjects add further shades of complexity so that the design of this kind of systems stands out as a multidisciplinary engineering challenge.

To conclude, DL-based pneumonia detection is a challenging engineering task and must consider data imbalance, overfitting, computational constraints, interpretability and regulatory/post-deployment costs. Addressing these challenges requires more than advances in technology and includes ethical, multidisciplinary cooperation to ensure that artificial intelligence (AI) systems are incorporated rationally and efficiently in care.

5.4.1 Complex Problem Solving

Table 5.4.1.1: Mapping with Complex Engineering Problem

Complex Engineering Problem (EP)	**Dept of Knowledge (EP1)**	**Range of Conflicting Requirements (EP2)**	**Depth of Analysis (EP3)**	**Familiarity of Issues (EP4)**
Pneumonia Detection using Deep Learning	Computer Science, AI, Medical Imaging	High (Data imbalance, model accuracy, interpretability)	Deep (Model design, hyperparameter tuning, training)	Moderate (AI in healthcare is evolving)

Table 5.4.1.2: Mapping with Knowledge Profile

Knowledge Profile (K)	**K1: Natural Science**	**K2: Mathematics**	**K3: Engineering Fundamentals**	**K5: Engineering Design**
Pneumonia Detection using Deep Learning	✔ (Understanding of biological systems)	✔ (Modeling and algorithms)	✔ (Deep learning architecture basics)	✔ (AI model design)

5.4.2 Engineering Activities

In this section, we review the overall pneumonia detection task with deep learning from a perspective of different Engineering Activities (EAs). These are part and parcel of the project, involving several dimensions such as, resource provision, interacting levels of innovation, social and environmental impacts and experience with problems at hand.

Table 5.4.2: Mapping with Complex Engineering Activities

Complex Engineering Activity (EA)	**EA1: Range of Resources**	**EA2: Level of Interaction**	**EA3: Innovation**	**EA4: Consequences for Society and Environment**
Pneumonia Detection Using Deep Learning	High (Computational resources, cloud storage, GPUs, datasets)	High (Collaboration with healthcare professionals, AI researchers)	High (Application of AI in healthcare, novel model designs)	Positive (Improved diagnostics, accessibility in underserved regions)

5.5 Summary

The engineering standards, the social dimensions and the technology challenges that are involved in building a deep learning-based pneumonia detection system from chest X-ray images have been introduced in this chapter. It resulted in the ethical and ethic (responsible) requirements-based system with regard to compliance with known software quality standards and medical legal regulations. Using good practices of software engineering, knowledge in data management and performance monitoring, the study conforms to well-recognized frameworks i.e. ISO/ IEC standards, HIPAA and GDPR.

The chapter spotlighted also the impacts of the designed system on society, environment and sustainability. The scientists said diagnostic tools based on AI could revolutionise access to healthcare in developing parts of the world and could be used to bring about an end misdiagnoses, as well as earlier intervention. On the environmental side, digital imaging and AI are much less resource-intensive and environmentally costly compared to traditional manners of doing it, and on the sustainability end, these models are scalable up; they can be moved over into other diseases.

The description further mentioned the issue of imbalanced datasets, overfitting, high computational costs and the need for interpretability in this work. These are complications that make the problem of detecting pneumonia not only a classification issue, but a cross-domain issue involving technical, ethical and clinical elements.

Overall, this chapter has demonstrated that there is potential and promise in the development of AI-assisted medical diagnosticians. But to create a reliable, explainable and ethical system is anything but trivial, requiring careful engineering, thorough testing and iterative development. These findings underpin the conclusions and recommendations in the next chapter.

Chapter 6

Conclusion

6.1 Summary

This research aimed to develop, and evaluate deep learning models for automated diagnosis of pneumonia in chest X-ray images. This study shows that CNNs, especially with transfer learning, display strong performance when it comes to the classification of medical images. With a consistent methodology that includes data pre-processing, data augmentation, training and evaluation, four architectures, VGG16, ResNet50, InceptionV3, and MobileNetV2, were developed and compared.

Regarding the results shown InceptionV3 is the model which performed best the entire time, obtaining the highest test accuracy of 85.9% as well as balanced sensitivities and specificities. Detected pneumonia efficiently with very high recall (0.98) and high precision for normal cases (0.96), therefore, being best-suited for clinical use. For VGG16-26, the testing accuracy was 74.5%, pneumonia detection (recall 0.95) surpassed normal cases (recall 0.40), indicating that there was a relatively high false positive rate.

By contrast, the ResNet50 and MobileNetV2 displayed high training accuracy (92%) and strikingly low testing accuracy (62.5%). Their classification events demonstrated the marked imbalance between the pneumonia class and normal class, achieving perfect recall [1.00] for pneumonia and failing completely in non-pneumonia cases. Here is sounded an alarm bell learning law penalty thanks to regularization sensitive to stock imbalance that is not strong enough.

Another point of notice is the imbalanced data; most of them are pneumonia cases, and this condition inevitably affects the results. This imbalance was a cause of model bias, and ResNet50 and MobileNetV2 detected more than 95% of the cases as pneumonia. The effect of data augmentation helped to alleviate this issue somewhat, however one would need some additional trick like class weights or perhaps even syntethic generation algorithms for the results being more balanced.

In summary, this study demonstrates that pneumonia detection can be successfully implemented based on deep learning, and use of transfer learning can improve the performance with small datasets. But it also draws out the need of dealing with class imbalance, overfitting and model interpretability when deploying for clinical purpose. In practice, InceptionV3 is found to be a good choice for applications, by achieving relatively high accuracy and balanced classification behavior.

6.2 Contribution to the Field

The major limitation of this thesis is the dataset used for training and testing; it contains a small size imbalanced data with a greater number of pneumonia cases than normal cases. This type of imbalance may introduce model bias because the network could potentially over-favor learning from example of the majority class cases and perform relatively poor in normal case recognition. Although data augmentation methods were used to correct for this, additional advanced techniques such as class weighting or synthetic data generation may also benefit the generalization of the model. Furthermore, the models selected in this study have not been validated in clinical practice scenarios and therefore are less likely to be applied immediately for medical purposes. Another issue is the interpretability of some models, especially deep CNNs since being capable to know why a model reaches a certain prediction is essential to gain trust among clinicians. Additionally, the research does not take multi-class classification into account, for example classifying the type of pneumonia as bacterial or viral which would yield more refined diagnostic information. Finally, computational resources and hardware constraints can limit access to training on larger and more variant datasets, potentially challenging model performance and scalability.

6.3 Future Work

This study has shown the promising capability of deep learning models in pneumonia detection with chest X-ray images, however, there are a few possible ways to improve and extend. To improve the sensitivity and specificity of the system, further studies will be required to overcome the problems encountered in this report.

The problem of dataset imbalance needs to be remedied better. Even though we used data augmentation in this study, more advanced methods such as class weighting, over-sampling the minority classes or synthetic data using GANs (Generative Adversarial Networks) could further improve the capacity of the models in discriminating pneumonia from normal cases. A more representative dataset with images from more sources, with different patient demographics, and under divergent imaging conditions would alos enhace the generalizability of the models.

Second, multi-class classification should be considered in future work. Rather than only a two-way classification problem of pneumonia versus normal, models could be trained to classify bacterial pneumonia from viral pneumonia, and potentially other respiratory conditions including but not limited to TB or COVID-19. This would enhance a clinical utility of the system as it will produce an elaborate diagnostic information.

3 Large presence on the Interpreting or explaining the models. Approaches like Grad-CAM allowed to interpret decision making, however more sophisticated methods combining interpretability with the training process could enhance the trust between the machine and the doctor's decisions. Increasing transparency is an important move toward clinical deployment.

Moreover, computational efficiency and deployment capacity can also be explored in the future. Lightweight architectures or model compression method like pruning and quantization could further enable the deployment on mobile or embedded systems (36), and AI-based diagnostic will then be made available to low-resource setting.

Finally, the models proposed in this thesis needs to be validated in practice where data has to be collected with the co-operation of healthcare providers. Comprehensive live hospital testing is still required to validate the system across mixed clinical populations and settings, as well as to confirm that reliability, usability and regulation compliance are met. Privacy-preserving techniques such as federated learning could enable even multi-institutional collaborations without harming patient security as well.

All in all, the future studies need to enlarge the datasets, balance the class, as well as investigate multi-class effect, interpretability, computation efficiency, and clinical validation by real patients. This will contribute not only to increased accuracy and robustness of pneumonia detection systems but also to the speed of their deployment in practical healthcare environments.

References

[1] T. Ojala, M. Pietikäinen, and D. Harwood, "A comparative study of texture measures with classification based on featured distributions," Pattern Recognition, vol. 29, no. 1, pp. 51–59, 1996.

[2] P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, et al., "CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning," arXiv preprint arXiv:1711.05225, 2017.

[3] D. Kermany, K. Zhang, and M. Goldbaum, "Identifying medical diagnoses and treatable diseases by image-based deep learning," Cell, vol. 172, no. 5, pp. 1122–1131, 2018.

[4] O. Stephen, M. Sain, U. Maduh, and D. Jeong, "An efficient deep learning approach to pneumonia classification in healthcare," Journal of Healthcare Engineering, vol. 2019, pp. 1–7, 2019.

[5] E. Ayan and H. M. Ünver, "Diagnosis of pneumonia from chest X-ray images using deep learning," in 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT), pp. 1–5, 2019.

[6] A. Chowdhury, R. Khandakar, M. Mahbub, et al., "Can AI help in screening viral and COVID-19 pneumonia?," IEEE Access, vol. 8, pp. 132665–132676, 2020.

[7] S. Rajaraman, J. Siegelman, P. O. Alderson, L. S. Folio, L. R. Folio, and S. Antani, "Iteratively pruned deep learning ensembles for COVID-19 detection in chest X-rays," IEEE Access, vol. 8, pp. 115041–115050, 2020.

[8] O. Stephen, M. Sain, U. Maduh, and D. Jeong, "Comparative study of deep learning methods for pneumonia detection," Healthcare Technology Letters, vol. 7, no. 6, pp. 152–160, 2020.

[9] E. Topol, "High-performance medicine: the convergence of human and artificial intelligence," Nature Medicine, vol. 25, no. 1, pp. 44–56, 2019.

[10] J. Irvin, P. Rajpurkar, M. Ko, et al., "CheXpert: A large chest radiograph dataset with uncertainty labels and expert comparison," in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 33, no. 01, pp. 590–597, 2019.

[11] T. Rahman, M. Chowdhury, A. Khandakar, et al., "Reliable tuberculosis detection using chest X-ray with deep learning, segmentation, and visualization," IEEE Access, vol. 8, pp. 191586–191601, 2020.

[12] M. Varshni, S. Thakral, A. Agarwal, et al., "Pneumonia detection using CNN based feature extraction," in 2019 IEEE International Conference on Electrical,

Computer and Communication Technologies (ICECCT), pp. 1–7, 2019.

[13] D. Pham, T. Do, and M. Ngo, "Evaluation of lightweight CNN architectures for pneumonia detection from chest X-ray images," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 12, no. 6, pp. 398–405, 2021.

[14] S. Das, M. Ghosh, and S. Pal, "Interpretability in deep learning for medical imaging: The case of pneumonia detection," IEEE Reviews in Biomedical Engineering, vol. 14, pp. 205–218, 2021.

[15] F. Xu, X. Li, Y. Zhu, and Y. Wang, "Federated learning for healthcare informatics," Journal of Healthcare Engineering, vol. 2021, pp. 1–9, 2021.

Plagiarism

Nazmul Shihab Shishir

213-15-4593

Quick Submit

Quick Submit

Daffodil International University

Document Details

Submission ID

trn:oid:::1:3339833499

Submission Date

Sep 15, 2025, 12:27 PM GMT+6

Download Date

Sep 15, 2025, 2:33 PM GMT+6

File Name

Full_thesisxx.pdf

File Size

1005.0 KB

58 Pages

16,148 Words

93,483 Characters

23% detected as AI

The percentage indicates the combined amount of likely AI-generated text as well as likely AI-generated text that was also likely AI-paraphrased.

Caution: Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Detection Groups

33 AI-generated only 23%
Likely AI-generated text from a large-language model.

0 AI-generated text that was AI-paraphrased 0%
Likely AI-generated text that was likely revised using an AI-paraphrase tool or word spinner.

Disclaimer
Our AI writing assessment is designed to help educators identify text that might be prepared by a generative AI tool. Our AI writing assessment may not always be accurate (i.e., our AI models may produce either false positive results or false negative results), so it should not be used as the sole basis for adverse actions against a student. It takes further scrutiny and human judgment in conjunction with an organization's application of its specific academic policies to determine whether any academic misconduct has occurred.

Frequently Asked Questions

How should I interpret Turnitin's AI writing percentage and false positives?
The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI paraphrase tool or word spinner.

False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.

AI detection scores under 20%, which we do not surface in new reports, have a higher likelihood of false positives. To reduce the likelihood of misinterpretation, no score or highlights are attributed and are indicated with an asterisk in the report (*%).

The AI writing percentage should not be the sole basis to determine whether misconduct has occurred. The reviewer/instructor should use the percentage as a means to start a formative conversation with their student and/or use it to examine the submitted assignment in accordance with their school's policies.

What does 'qualifying text' mean?
Our model only processes qualifying text in the form of long-form writing. Long-form writing means individual sentences contained in paragraphs that make up a longer piece of written work, such as an essay, a dissertation, or an article, etc. Qualifying text that has been determined to be likely AI-generated will be highlighted in cyan in the submission, and likely AI-generated and then likely AI-paraphrased will be highlighted purple.

Non-qualifying text, such as bullet points, annotated bibliographies, etc., will not be processed and can create disparity between the submission highlights and the percentage shown.

213-15-4593

ORIGINALITY REPORT

23%	14%	15%	12%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	6%
2	Thangaprakash Sengodan, Sanjay Misra, M Murugappan. "Advances in Electrical and Computer Technologies", CRC Press, 2025 Publication	1%
3	Submitted to Kaplan College Student Paper	1%
4	www.ijraset.com Internet Source	<1%
5	www.researchgate.net Internet Source	<1%
6	Submitted to The Robert Gordon University Student Paper	<1%
7	dspace.daffodilvarsity.edu.bd:8080 Internet Source	<1%
8	H.L. Gururaj, Francesco Flammini, S. Srividhya, M.L. Chayadevi, Sheba Selvam. "Computer Science Engineering", CRC Press, 2024 Publication	<1%
9	Pushpa Choudhary, Sambit Satpathy, Arvind Dagur, Dhirendra Kumar Shukla. "Recent Trends in Intelligent Computing and Communication", CRC Press, 2025 Publication	<1%

10	Submitted to Dublin Business School Student Paper	<1 %
11	lcjstem.com Internet Source	<1 %
12	de Sousa, Lúcia Maria Bessa. "Detecting a Poker Face", Universidade de Aveiro (Portugal), 2024 Publication	<1 %
13	ebin.pub Internet Source	<1 %
14	Submitted to Higher Education Commission Pakistan Student Paper	<1 %
15	assets.researchsquare.com Internet Source	<1 %
16	arxiv.org Internet Source	<1 %
17	ijain.org Internet Source	<1 %
18	Dinesh Goyal, Bhanu Pratap, Sandeep Gupta, Saurabh Raj, Rekha Rani Agrawal, Indra Kishor. "Recent Advances in Sciences, Engineering, Information Technology & Management - Proceedings of the 6th International Conference “Convergence2024” Recent Advances in Sciences, Engineering, Information Technology & Management, April 24–25, 2024, Jaipur, India", CRC Press, 2025 Publication	<1 %
19	ray.yorksj.ac.uk Internet Source	<1 %

20	repository.dl.itc.u-tokyo.ac.jp Internet Source	<1 %
21	Urdal, Jarle. "Image Processing and Classification of Urothelial Carcinoma Using Tissue Sample Images", University of Stavanger (Norway) Publication	<1 %
22	Arvind Dagur, Karan Singh, Pawan Singh Mehra, Dhirendra Kumar Shukla. "Intelligent Computing and Communication Techniques - Volume 1", CRC Press, 2025 Publication	<1 %
23	H L Gururaj, Francesco Flammini, V Ravi Kumar, N S Prema. "Recent Trends in Healthcare Innovation", CRC Press, 2025 Publication	<1 %
24	pure.aber.ac.uk Internet Source	<1 %
25	Tawsifur Rahman, Amith Khandakar, Yazan Qiblawey, Anas Tahir et al. "Exploring the Effect of Image Enhancement Techniques on COVID-19 Detection using Chest X-rays Images", Computers in Biology and Medicine, 2021 Publication	<1 %
26	Submitted to Sheffield Hallam University Student Paper	<1 %
27	Sushil Kamboj, Pardeep Singh Tiwana. "Innovations in Computing", CRC Press, 2025 Publication	<1 %
28	ijircce.com Internet Source	<1 %

29	Ghimire, Aamod Raj. "Evaluating State-of-the-Art CNN Architectures for Multi-Class Casting Defect Detection in Smart Manufacturing.", The University of Texas at San Antonio Publication	<1 %
30	R. N. V. Jagan Mohan, B. H. V. S. Rama Krishnam Raju, V. Chandra Sekhar, T. V. K. P. Prasad. "Algorithms in Advanced Artificial Intelligence - Proceedings of International Conference on Algorithms in Advanced Artificial Intelligence (ICAAAI-2024)", CRC Press, 2025 Publication	<1 %
31	Mohit Chhabra, Rajneesh Kumar. "An Efficient ResNet-50 based Intelligent Deep Learning Model to Predict Pneumonia from Medical Images", 2022 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS), 2022 Publication	<1 %
32	Submitted to University of Carthage Student Paper	<1 %
33	www.mdpi.com Internet Source	<1 %
34	Debnath Bhattacharyya, Yu-Chen Hu. "Data-Driven Decision Support Systems in Intelligent Healthcare", CRC Press, 2025 Publication	<1 %
35	Submitted to University of Hertfordshire Student Paper	<1 %
36	aircconline.com Internet Source	<1 %

37	link.springer.com Internet Source	<1 %
38	r-libre.teluq.ca Internet Source	<1 %
39	N. Amoroso, R. Errico, E. Pantaleo, A. Monaco, R. Bellotti. "Artificial intelligence in medical physics", La Rivista del Nuovo Cimento, 2025 Publication	<1 %
40	"Medical Image Computing and Computer Assisted Intervention – MICCAI 2019", Springer Science and Business Media LLC, 2019 Publication	<1 %
41	"Transforming Healthcare with Artificial Intelligence", Springer Science and Business Media LLC, 2025 Publication	<1 %
42	Bui Thanh Hung, M. Sekar, Ayhan Esi, R. Senthil Kumar. "Applications of Mathematics in Science and Technology - International Conference on Mathematical Appplications in Science and Technology", CRC Press, 2025 Publication	<1 %
43	Chirala, Venkata Sesha Sai Vamsi Krishna. "Enhancing Metastatic Cancer Detection: Implementation of Hybrid Transformer-CNN With Swin Transformer and Convnext Models", California State University, Sacramento Publication	<1 %
44	Debasis Chaudhuri, Jan Harm C Pretorius, Debashis Das, Sauvik Bal. "International Conference on Security, Surveillance and	<1 %

Artificial Intelligence (ICSSAI-2023) - Proceedings of the International Conference on Security, Surveillance and Artificial Intelligence (ICSSAI-2023), Dec 1–2, 2023, Kolkata, India", CRC Press, 2024
Publication

45	Orestis Papadimitriou, Athanasios Kanavos, Manolis Maragoudakis. "Automated Pneumonia Detection from Chest X-Ray Images Using Deep Convolutional Neural Networks", 2023 14th International Conference on Information, Intelligence, Systems & Applications (IISA), 2023 Publication	<1 %
46	Yu Fu, Peng Xue, Zhili Zhang, Enqing Dong. " PKA -Net: Prior Knowledge-Based Active Attention Network for Accurate Pneumonia Diagnosis on Chest X-Ray Images ", IEEE Journal of Biomedical and Health Informatics, 2023 Publication	<1 %
47	internationalpubls.com Internet Source	<1 %
48	"Artificial Neural Networks and Machine Learning – ICANN 2019: Workshop and Special Sessions", Springer Science and Business Media LLC, 2019 Publication	<1 %
49	nano-ntp.com Internet Source	<1 %
50	B. Sundaravadivazhagan, Sekar Mohan, Balakrishnaraja Rengaraju. "Recent Developments in Microbiology, Biotechnology and Pharmaceutical Sciences - International	<1 %

Conference on Recent Development in Microbiology, Biotechnology and Pharmaceutical Science", CRC Press, 2025
Publication

51	Submitted to EC-Council University Student Paper	<1 %
52	Rachna Jain, Preeti Nagrath, Gaurav Kataria, V. Sirish Kaushik, D. Jude Hemanth. "Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning", Measurement, 2020 Publication	<1 %
53	Chuprov, Sergei. "Robust Machine Learning Under Vulnerable Cyberinfrastructure and Varying Data Quality", Rochester Institute of Technology, 2024 Publication	<1 %
54	Mohammed Alarfaj, Mosleh Hmoud Al-Adhaileh, M. Irfan Uddin, Muhammad Adnan, Theyazn H. H. Aldhyani. "Enhancing Seizure Detection Accuracy in Wearable EEG Devices Using Deep Learning Algorithms", Journal of Disability Research, 2025 Publication	<1 %
55	Samsul Ariffin Abdul Karim, Aslina Baharum. "Intelligent Systems of Computing and Informatics in Sustainable Urban Development", CRC Press, 2025 Publication	<1 %
56	Submitted to University of Huddersfield Student Paper	<1 %
57	dokumen.pub Internet Source	<1 %

58	v1.overleaf.com Internet Source	<1 %
59	S.P. Jani, M. Adam Khan. "Applications of AI in Smart Technologies and Manufacturing", CRC Press, 2025 Publication	<1 %
60	Salve, Roshni Rajendra. "Fake News Detection: Leveraging Natural Language Processing and Machine Learning for Reliable Information Verification.", Rochester Institute of Technology Publication	<1 %
61	Tariq Qayyum, Asadullah Tariq, Muhammad Waqas Haseeb, Saed Alrabae, Zouheir Trabelsi, Farag Sallabi, Mohamed Adel Serhani. "Chapter 19 Harnessing thePower ofQuantum Computing forURL Classification: A Comprehensive Study", Springer Science and Business Media LLC, 2026 Publication	<1 %
62	Submitted to University of Durham Student Paper	<1 %
63	Submitted to University of Stirling Student Paper	<1 %
64	Xiaohong Wang, Zhongkang Lu, Su Huang, Yonghan Ting, Jordan Sim Zheng Ting, Wenxiang Chen, Cher Heng Tan, Weimin Huang. "TransMVAN: Multi-view Aggregation Network with Transformer for Pneumonia Diagnosis", Journal of Imaging Informatics in Medicine, 2024 Publication	<1 %

65	Submitted to Asia Pacific University College of Technology and Innovation (UCTI) Student Paper	<1 %
66	ijnrd.org Internet Source	<1 %
67	vdocuments.net Internet Source	<1 %
68	Lalit Mohan Goyal, Tanzila Saba, Amjad Rehman, Souad Larabi-Marie-Sainte. "Artificial Intelligence and Internet of Things - Applications in Smart Healthcare", CRC Press, 2021 Publication	<1 %
69	Submitted to Liverpool John Moores University Student Paper	<1 %
70	Sajal Misra, Satish Kumar, Sameer Sayyad, Arunkumar Bongale et al. "Fault Detection in Induction Motor Using Time Domain and Spectral Imaging-Based Transfer Learning Approach on Vibration Data", Sensors, 2022 Publication	<1 %
71	www.dovepress.com Internet Source	<1 %
72	Frank Y. Shih. "AI Deep Learning in Image Processing", CRC Press, 2025 Publication	<1 %
73	Submitted to Taylor's Education Group Student Paper	<1 %
74	www.intechopen.com Internet Source	<1 %

75	Gewida, Mariam Hani. "Leveraging Machine Learning and Large Language Model to Mitigate Smart Home IoT Password Breaches.", Colorado Technical University, 2024 Publication	<1 %
76	Mohammed Abdulrahman, Abdallah Abdulfattah. "Deepfake Image Detection Using Explainable AI and Deep Learning", Rochester Institute of Technology Publication	<1 %
77	Submitted to University of Hull Student Paper	<1 %
78	"International Conference on Smart Systems and Emerging Technologies", Springer Science and Business Media LLC, 2025 Publication	<1 %
79	Cirillo, Marco Domenico. "A Path Along Deep Learning for Medical Image Analysis With Focus on Burn Wounds and Brain Tumors", Linkopings Universitet (Sweden), 2024 Publication	<1 %
80	Fatemeh Hosseinabadi, Mohammad Mojtaba Rohani. "Deep Learning Approach for the Diagnosis of Pediatric Pneumonia Using Chest X-ray Imaging", Springer Science and Business Media LLC, 2025 Publication	<1 %
81	Submitted to Technical University of Cluj-Napoca Student Paper	<1 %
82	dspace.bracu.ac.bd:8080 Internet Source	<1 %

83	itegam-jetia.org Internet Source	<1 %
84	shsu-ir.tdl.org Internet Source	<1 %
85	www.bio-conferences.org Internet Source	<1 %
86	www.degruyterbrill.com Internet Source	<1 %
87	www.hindawi.com Internet Source	<1 %
88	Submitted to Coventry University Student Paper	<1 %
89	Gaobo Liang, Lixin Zheng. "A transfer learning method with deep residual network for pediatric pneumonia diagnosis", Computer Methods and Programs in Biomedicine, 2020 Publication	<1 %
90	Wahyudi Setiawan, Fitri Damayanti. "Layers Modification of Convolutional Neural Network for Pneumonia Detection", Journal of Physics: Conference Series, 2020 Publication	<1 %
91	export.arxiv.org Internet Source	<1 %
92	www.irjmets.com Internet Source	<1 %
93	www.medrxiv.org Internet Source	<1 %
94	wwww.easychair.org Internet Source	<1 %

95	Baihe Chen, Jinling Chen, Hao Lu, Jie Chen. "Cell classification based on affine transformed convolutional parallel networks", Biomedical Signal Processing and Control, 2026 Publication	<1 %
96	Chiranji Lal Chowdhary. "Intelligent Systems - Advances in Biometric Systems, Soft Computing, Image Processing, and Data Analytics", CRC Press, 2019 Publication	<1 %
97	Denck, Jonas. "Machine Learning-Based Workflow Enhancements in Magnetic Resonance Imaging", Friedrich-Alexander-Universitaet Erlangen-Nuernberg (Germany), 2023 Publication	<1 %
98	Mohammad Javad Shayegan. "A brief review and scientometric analysis on ensemble learning methods for handling COVID-19", Heliyon, 2024 Publication	<1 %
99	S. Prasad Jones Christydass, Nurhayati Nurhayati, S. Kannadhasan. "Hybrid and Advanced Technologies", CRC Press, 2025 Publication	<1 %
100	api.deepai.org Internet Source	<1 %
101	digitalrepository.fccollege.edu.pk Internet Source	<1 %
102	docs.neu.edu.tr Internet Source	<1 %
	dspace.uiu.ac.bd:8080	

103	Internet Source	<1%
104	easychair-www.easychair.org Internet Source	<1%
105	openneuroimagingjournal.com Internet Source	<1%
106	thesai.org Internet Source	<1%
107	www.ijsr.net Internet Source	<1%
108	www.mccormick.northwestern.edu Internet Source	<1%
109	Arvind Dagur, Karan Singh, Pawan Singh Mehra, Dhirendra Kumar Shukla. "Artificial Intelligence, Blockchain, Computing and Security", CRC Press, 2023 Publication	<1%
110	Ayush Pant, Akshat Jain, Kiran C Nayak, Daksh Gandhi, B. G. Prasad. "Pneumonia Detection: An Efficient Approach Using Deep Learning", 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT), 2020 Publication	<1%
111	Paolo Vecchiotti, Ning Ma, Stefano Squartini, Guy J. Brown. "End-to-end Binaural Sound Localisation from the Raw Waveform", ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2019 Publication	<1%

112	Rachna Jain, Preeti Nagrath, Gaurav Kataria, V. Sirish Kaushik, D. Jude Hemanth. "Pneumonia Detection in chest X-ray images using Convolutional Neural Networks and Transfer Learning", Measurement, 2020 Publication	<1%

Exclude quotes	Off	Exclude matches	Off
Exclude bibliography	Off		