Department of Electrical and Computer Engineering
North South University

Senior Design Project

Image-based Detection and Classification of Pulmonary Abnormalities using Deep Learning-Techniques

Md. Mudachir Uddin	**ID# 1921849042**
Rasa Jebin Hossain	**ID# 1921698042**
Naima Mohsin Raian	**ID# 2011799642**

Faculty Advisor:

Dr. Shahnewaz Siddique

Assistant Professor

ECE Department

Summer, 2024

APPROVAL

Md. Mudachir Uddin (ID # 1921849042), Rasa Jebin Hossain (ID # 1921698042) and Naima Mohsin Raian (ID # 2011799642) from Electrical and Computer Engineering Department of North South University, have worked on the Senior Design Project titled "Image-based-Detection-and-Classification-of-Pulmonary-Abnormalities-using-Deep-Learning Techniques" under the supervision of Dr. Shahnewaz Siddique partial fulfillment of the requirement for the degree of Bachelors of Science in Engineering and has been accepted as satisfactory.

Supervisor's Signature

....

Dr. Shahnewaz Siddique

Assistant Professor

Department of Electrical and Computer Engineering

North South University

Dhaka, Bangladesh.

Chairman's Signature

....

Dr. Mohammad Abdul Matin

Professor

Department of Electrical and Computer Engineering

North South University

Dhaka, Bangladesh.

DECLARATION

This is to declare that this project is our original work. No part of this work has been submitted elsewhere partially or fully for the award of any other degree or diploma. All project related information will remain confidential and shall not be disclosed without the formal consent of the project supervisor. Relevant previous works presented in this report have been properly acknowledged and cited. The plagiarism policy, as stated by the supervisor, has been maintained.

Students' names & Signatures

1. Md. Mudachir Uddin

_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _

2. Rasa Jebin Hossain

_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _

3. Naima Mohsin Raian

_ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _ _

ACKNOWLEDGEMENTS

For his unwavering support, insightful direction, and practical counsel throughout this project, we would like to thank our project supervisor, Dr. Shahnewaz Siddique, Assistant Professor, Department of Electrical and Computer Engineering, North South University, Bangladesh. His guidance has been crucial to the completion of our experiments, research, and report. We also thank North South University's Department of Electrical and Computer Engineering for providing the tools and assistance required to finish this project. Lastly, we would like to express our gratitude to our families and loved ones for their unwavering support, encouragement, and sacrifices, all of which have given us strength along this journey.

ABSTRACT

Image-based Detection and Classification of Pulmonary Abnormalities using Deep Learning-Techniques

Lung diseases such as COVID-19, pneumonia, and lung opacity pose significant global health challenges, necessitating early and accurate diagnosis for effective treatment. Traditional diagnostic methods, relying on manual interpretation of chest X-rays, often face limitations like human error, time constraints, and the unavailability of skilled radiologists in resource-limited settings. To address these challenges, our project leverages deep learning techniques for the automated detection and classification of pulmonary abnormalities in chest X-ray images.

We utilized advanced models such as VGG16, ResNet-152, and EfficientNet-B7, fine-tuned with transfer learning techniques, to classify X-rays into four categories: normal, COVID-19, pneumonia, and lung opacity. These models were trained on a diverse dataset of 4,219 images, employing data augmentation techniques to enhance robustness and generalization. The weighted ensemble approach of ResNet-152 and EfficientNet-B7 achieved the highest accuracy of 93%, surpassing individual models while ensuring reliable performance.

Our results highlight the potential of deep learning in improving diagnostic accuracy, reducing human error, and enhancing healthcare accessibility. By automating the diagnostic process, our system significantly reduces the workload on medical professionals and enables early detection of lung diseases, particularly in under-resourced areas. This innovation not only advances medical imaging but also contributes to equitable healthcare delivery, ultimately improving patient outcomes and saving lives.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter-1

Project Overview

1.1 Introduction

Lung diseases, such as COVID-19, pneumonia, and lung opacity, are serious global health problems that affect millions of people every year. The arrival of Covid-19 has brought significant threat to human life which started from China in November 2019 and later on spread across the world. It has been reported that more than 63.2 million people have already been infected in the world which includes approximately 1.47 million deaths. The world health organization (WHO) continuously provides the necessary information for nations to protect against Covid-19 [10]. However, people suffered from severe pneumonic conditions in their lungs that resulted in death as well [10]. Early and accurate diagnosis of these conditions is critical for effective treatment and better patient outcomes. In past studies, researchers had employed hand crafted feature extraction methods for transforming raw images into useful features for classifying a medical image for disease classification. This requires domain expertise for performing feature engineering by extracting relevant features, transforming and removing redundant features. More promising results have been shown by deep neural network approaches where feature engineering has been replaced by feature learning where better features are learnt [3]. Traditionally, doctors rely on chest X-rays and manual interpretation to identify these diseases. Pneumonia is an infection in one or both the lungs because of virus or bacteria through breathing air [3]. It infames air sacs in lungs which fill with fluid which further leads to problems in respiration [3]. Pneumonia is interpreted by radiologists by observing abnormality in lungs in case of fluid in Chest X-Rays [3]. Another drawback for the early diagnosis of pneumonia is the human-dependent detection. Expert radiologists need to have sufficiently trained eyes in order to be able to differentiate between the heterogeneous color distribution of air while flowing in the lungs. This may be seen in different colors on the x-ray image taken, yet not be the dense pneumonia fluid. Thus, it’s highly significant for a radiologist to be able to tell whether the white spots on the x-ray film actually correspond to the fluid itself. As a result of the error margin of the human eye, there are many cases where the radiologists fail to make the correct diagnosis. In both cases, whether it's a false positive or false negative diagnosis, it has substantial impacts on the human body [1]. However, this process can be time-consuming and prone to human error, especially when faced with a large number of cases or poor-quality images. In resource-limited settings, where access to expert radiologists is scarce, these challenges are even more significant.

With advancements in technology, artificial intelligence (AI) and deep learning have emerged as powerful tools to address these challenges. The recently developed algorithms of deep learning promote the quantification, identification, and classification of patterns within medical images. Deep learning algorithms are capable of learning features simply from data, rather than hand-designing features depending on field-specific knowledge [5]. Deep learning models have shown great potential in analyzing medical images, offering faster and more accurate results than traditional methods. These models can automatically detect patterns and abnormalities in chest X-rays, helping doctors make informed decisions more efficiently. Using AI in this way not only reduces the workload on medical professionals but also ensures that patients in remote or underserved areas get the care they need.

Our project focuses on using deep learning techniques to develop a system that can automatically detect and classify pulmonary abnormalities from chest X-ray images. We trained advanced models, such as ResNet-152 and EfficientNet-B7, on a diverse dataset of chest X-rays. These models were fine-tuned using transfer learning to ensure high accuracy and reliability in detecting four categories: COVID-19, pneumonia, lung opacity, and normal cases.

This system aims to assist doctors by providing quick and accurate diagnostic support, especially in areas with limited healthcare resources. By automating the detection process, it reduces the chances of misdiagnosis and allows healthcare professionals to focus on treatment. This project highlights the potential of AI-driven solutions to transform medical diagnostics, making healthcare more accessible, efficient, and equitable. Ultimately, our goal is to contribute to better patient care and save lives through the use of advanced technology.

1.2 Background and Motivation

Radiology plays an essential role in diagnosing and monitoring a range of diseases [8]. The demand for radiological services is increasing. A lack of proper equipment or a lack of service causes severe consequences in the treatment process, by introducing additional risks of obtaining a positive result in the treatment of many diseases, in particular neoplastic diseases [8]. The urgent need to improve the diagnosis of lung conditions, such as COVID-19, pneumonia, lung opacity, and other pulmonary abnormalities, is what inspired this initiative. Because of their slight differences in imaging characteristics and overlapping symptoms, these illnesses are sometimes difficult to identify quickly and effectively. The skill of radiologists is a major component of current diagnostic procedures, which might result in interpretation variability and possible delays, particularly in high-pressure clinical settings. In urgent or emergency situations, such delays or misclassifications can lead to inadequate treatment regimens and worsened patient outcomes. The shortcomings of conventional diagnostic techniques have come to light in the aftermath of international health emergencies such as the COVID-19 pandemic. The tremendous strain on healthcare systems throughout the world has highlighted the need for creative solutions that might lessen the workload for medical practitioners while increasing the precision of diagnoses. In order to close that gap, our study uses cutting-edge deep learning techniques to create a system that can quickly and accurately analyze chest X-ray pictures autonomously.

The diagnosis of lung disorders might be completely changed by the use of artificial intelligence into medical imaging. We hope to create a system that not only produces correct results but also guarantees efficiency and scalability by utilizing cutting-edge deep learning models, such as ResNet-152 and EfficientNet-B7, in conjunction with strategies like transfer learning. Specifically, transfer learning allows the model to modify pre-trained networks to fit our dataset, improving its performance even when there is a little amount of labeled data. This method achieves great diagnostic accuracy while drastically cutting down on the time and computing resources needed for model training. For environments with low resources and restricted access to radiology specialists, such a system has enormous potential. Lack of qualified personnel and diagnostic tools can cause treatment delays and less-than-ideal care in many regions of the world.

Deep learning over the period of time has evolved in the form of a number of architectures of convolution neural networks which can extract features in an object, especially an image or a video [4]. Any deep learning architecture can be extended to its quaternion domain by customizing convolution operations, batch normalization, max pooling to quaternion values instead of real values [4]. This gap may be filled by an automated, AI-driven diagnostic tool that gives reliable, fast, and accurate findings, enabling medical professionals to make well-informed judgments.This is especially important in isolated or impoverished areas where prompt access to medical treatment might mean the difference between life and death. Reducing human error in diagnosis is another important healthcare issue that our research seeks to solve. Fatigue or cognitive bias can cause misinterpretations even for seasoned radiologists. By acting as a trustworthy second opinion, an AI-assisted diagnostic tool may enhance the skills of medical professionals and guarantee more sound decision-making. The suggested approach enables efficiency in medical imaging processes in addition to increasing diagnostic accuracy. The system can process enormous numbers of chest X-ray pictures in a short amount of time because of significant developments in computer technology, which speeds up patient triage and improves the distribution of healthcare resources.

Deep learning can be considered a promising technology for radiology since the work of radiologists mainly concerns image interpretation [8]. This feature is especially helpful in emergency situations where prompt and precise diagnosis is essential to life preservation. The ultimate goal of this project is to provide quicker, more dependable, and scalable diagnostic technologies in order to significantly improve patient care. Our goal is to enhance healthcare delivery by lowering diagnostic mistakes, increasing speed, and producing reliable outcomes. If this approach is implemented successfully, it may establish a standard for incorporating AI into medical imaging, opening the door for more widespread uses in the diagnosis of various illnesses. Our goals are to save lives, enhance patient outcomes, and revolutionize the global healthcare system in the process.

1.3 Purpose and Goal of the Project

Our project's goal is to create an intelligent system that can recognize and categorize lung conditions from chest X-ray pictures, such as COVID-19, pneumonia, and lung opacity, using deep learning techniques. Early and precise diagnosis is essential for successful treatment and better patient outcomes for many illnesses, which are important global health issues. But conventional diagnostic techniques, which depend on manually interpreting X-rays, are frequently laborious, prone to mistakes, and highly reliant on the availability of qualified radiologists. By developing a dependable and automated solution that improves the diagnostic procedure, our initiative seeks to address these issues. Providing quicker and more accurate diagnoses is one of the project's main objectives, particularly in environments with limited resources and restricted access to medical specialists and cutting-edge equipment. By automating the detection process, lowering their burden, and lowering the possibility of mistakes brought on by human weariness or inexperience, the system is intended to assist medical personnel. This is especially crucial in dire circumstances, like a pandemic, when prompt detection might save lives and stop the spread of the illness. We used sophisticated deep learning models, such ResNet-152 and EfficientNet-B7, which are renowned for their excellent performance in picture classification tasks, to accomplish this. We improved the system to produce reliable and accurate findings by training these models on a

dataset of more than 4,000 chest X-ray pictures that were divided into COVID-19, pneumonia, lung opacity, and normal cases. By using transfer learning approaches, the system maintains a high level of dependability while managing its computing requirements.
Making healthcare more equal and accessible is the project's ultimate objective. Our goal is to assist medical practitioners by offering an economical and effective diagnostic tool, especially in underprivileged regions with limited access to infrastructure and knowledge. In addition to assisting in closing the gap in healthcare inequities, this initiative establishes the foundation for further developments in AI-powered medical technology.
This technology not only helps medical professionals but also gives local clinics and hospitals the ability to provide better treatment. By cutting down on diagnostic delays and freeing up physicians to concentrate on treatment rather than laborious diagnostic procedures, it contributes to the overall improvement of healthcare systems' efficiency. In the end, our effort helps to improve healthcare systems, save lives, and make high-quality treatment available to everyone, regardless of resources or geography.

1.4 Advantages

Our project has a number of benefits that make it a worthwhile addition to the medical field. The capacity to quickly and accurately detect lung conditions including COVID-19, pneumonia, and lung opacity is one of the main advantages. Effective treatment depends on early diagnosis, and our system guarantees that patients may get timely medical attention, possibly saving their lives.

It also lessens the workload on medical experts, which is another benefit. Physicians and radiologists frequently have to evaluate a lot of chest X-rays, which can be tiring and time-consuming, which raises the possibility of mistakes. Our solution helps doctors spend less time on picture analysis and more time on therapy by automating the diagnostic process.

Accessibility to healthcare is another issue that the project tackles. There is limited access to skilled radiologists and cutting-edge medical facilities in many rural or undeveloped places. In these situations, our system can be used to deliver dependable diagnostic assistance, guaranteeing that even underprivileged areas obtain high-quality medical care.

The system is also reasonably priced. It saves costs for patients and healthcare providers by automating the diagnosis process, which eliminates the need for repeated testing and decreases human error. Additionally, it makes use of already-existing X-ray imaging equipment, which facilitates integration into modern medical procedures.

Finally, our project promotes accuracy and consistency in diagnosis. Because the algorithm is neither biased or tired like humans are, it consistently produces accurate findings. These benefits make our initiative a useful and significant instrument for enhancing healthcare around the globe.

1.5 Difficulty

We ran across several practical and technological roadblocks while we worked on the project, which slowed down our progress and made things more complicated. One of the most difficult parts of training our deep learning models was handling runtime errors. These errors were often the result of faulty code, incompatible libraries, or a lack of resources to handle large datasets and complex computations. Debugging these errors took a long time, and we had to make constant changes to our code.

Another major barrier was the model training time. Deep learning models such as ResNet-152 and EfficientNet-B7 require a significant amount of processing time and computing resources to process thousands of chest X-ray images. When utilizing Google Colab's free edition, we encountered several issues, such as GPU use limitations and session timeouts. Because it was difficult to complete the training all at once, we frequently had to repeat sessions and run our models again as a result of these constraints, wasting a lot of time and effort.

Due to the limitations of free resources, we also had to cope with slower processing speeds and less memory, especially when working with large datasets. This was inconvenient since it delayed our research and made it impossible for us to test our models as thoroughly as we would have liked. Additionally, uploading and analyzing large datasets utilizing free platforms usually caused major delays and network issues.

In order to overcome these challenges, we decided to get Colab Pro. Colab Pro's ability to give us faster GPUs, additional RAM, and longer session durations significantly increased our productivity. Because of the enhanced processing power, we were able to train our models faster and manage larger datasets without any problems. This move allowed us to save a significant amount of time and focus more on improving our model's accuracy rather than fixing resource-related problems.

Despite these challenges, we learned valuable lessons about managing large-scale deep learning initiatives. The incident taught us how important it is to have reliable computer resources, efficient coding methods, and reliable backup plans. Despite the difficult journey, overcoming these challenges made our project stronger and allowed us to gain skills that would be useful later on. We were able to complete the project on time and with improved results by making the necessary upgrade to Colab Pro.

1.6 Organization of the Report

In our project, from now on, we will discuss step by step. In Chapter 2, we added the literature reviews related to this project. Chapter 3 presents the methodology of this project. Chapter 4 presents the experiment, result analysis and discussion of our project. In chapter 5, we added the impacts of the project. Chapter 6 presents the planning and budget. And Last chapter, which is Chapter7 presents the conclusion part.

Chapter-2

Literature Review

2.1 Existing Research and Limitations

The research Early Diagnosis of Pneumonia with Deep Learning addresses the urgent need for timely pneumonia diagnosis, utilizing deep learning to automate detection from chest X-ray images. Pneumonia, a leading global cause of mortality, requires early detection to improve outcomes. Traditional methods, relying on radiographs and expert interpretation, face limitations in accuracy and efficiency. This work proposes a convolutional neural network (CNN)-based model enhanced by novel preprocessing techniques brightness adjustment, contrast enhancement, and color expansion to improve image clarity and feature extraction. Additionally, a Residual Neural Network (ResNet) is integrated to enhance feature preservation across layers.The approach achieves a classification accuracy of 78.73%, outperforming the CheXNet model (76.8%) while maintaining lower computational complexity (three layers vs. 121). This improvement, attributed to the tailored preprocessing and ResNet integration, ensures faster training and greater scalability, making it suitable for clinical deployment. Despite these advances, the authors suggest potential improvements through object detection frameworks (e.g., YOLO, SSD) for region localization and dataset diversification to enhance model generalization.In conclusion, this work presents a significant advancement in automated pneumonia detection, offering a computationally efficient, accurate alternative to traditional diagnostic methods and setting the stage for broader applications in medical imaging. [1].

The paper explores the use of deep learning to enhance pneumonia detection from chest X-rays, addressing challenges in traditional diagnosis, which relies heavily on human interpretation. By employing convolutional neural networks (CNNs), the study automates the classification of bacterial and viral pneumonia, as well as normal cases, using a dataset of 9,057 images from the NIH. The authors adapt a pre-trained VGG16 network, incorporating dropout layers and Adam optimization to improve model performance.Key steps include data preprocessing (resizing, normalization, augmentation), followed by training for 10 epochs, achieving 100% accuracy on both validation and testing sets. The research aligns with and builds upon prior work in the domain of medical AI. For instance, the CheXNet model, a 121-layer convolutional network, previously achieved high performance in detecting pneumonia from X-rays. However, the current study demonstrates comparable accuracy with a less complex architecture, underscoring its computational efficiency. Other studies have explored similar applications of AI in healthcare, ranging from multi-modality imaging for Alzheimer's diagnosis to CNN-based identification of lung nodules. The current study distinguishes itself by its focus on rapid

and accurate pneumonia detection, which holds particular relevance for under-resourced healthcare settings. The model demonstrates comparable performance to more complex models like CheXNet while being computationally efficient.The research underscores the potential of deep learning in addressing pneumonia diagnosis, particularly in resource-limited settings. Future directions involve expanding the dataset, incorporating more augmentation techniques, and developing broader AI models to detect multiple chest diseases. The study highlights deep learning's promise for transforming medical diagnostics, offering scalable, efficient solutions with global healthcare impact [4].

The paper Detection of Pneumonia Using Convolutional Neural Networks and Deep Learning presents a novel CNN model for automated pneumonia detection, addressing the global need for efficient diagnostic tools. The model integrates dropout layers within the convolutional segments to reduce overfitting, achieving 97.21% accuracy, 97.34% recall, and 97.40% precision. Trained on a pediatric dataset of 5,856 X-ray images, the model outperforms state-of-the-art architectures (e.g., InceptionV3, ResNet50) while maintaining a compact architecture (10.6 million parameters) and fast inference time (122ms per image). Despite the dataset's limitations in diversity, the study offers a scalable, computationally efficient solution for rapid pneumonia diagnosis, with future potential for multi-modal data integration and explainable AI tools. The dataset, while robust, is limited to a specific population and lacks diversity in terms of age, imaging techniques, and geographic representation. Future work could address these gaps by incorporating multi-modal imaging data and expanding the dataset to include global demographics. Additionally, integrating explainable AI tools could ensure that diagnostic decisions are interpretable and clinically actionable. [2].

CNNs have revolutionized the detection of lung diseases like pneumonia and tuberculosis, with significant public health impact. They excel in medical image analysis due to their ability to extract features, resist noise, and achieve high classification accuracy. Recent studies show strong performance, with Kamila et al. (2024) achieving 97.79% accuracy in pneumonia detection through optimized preprocessing. Despite challenges like computational intensity and image variations, CNNs continue to improve with innovations like hybrid architectures and model optimization. Future advancements could integrate

CNNs with techniques like ChexNet and LSTMs, offering enhanced diagnostic accuracy, especially in low-resource settings. In comparison, studies like Rahman et al. (2021) reported accuracies of 95.11% using ensemble CNN architectures, while Gm et al. (2021) achieved 92.16% accuracy with hybrid CNN-ANN models. These findings emphasize the potential for further enhancements through model innovation and architecture refinement. The integration of CNNs with advanced techniques, such as ChexNet, Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, offers promising avenues for improving diagnostic accuracy. These hybrid approaches can incorporate spatial and temporal data, enabling more robust disease classification. Furthermore, extending CNN applications to low-resource settings could support early detection and treatment of lung diseases in regions with high disease prevalence [9].

The classification of pneumonia using deep learning has garnered significant attention due to its potential to augment diagnostic accuracy and reduce radiologists' workload. Traditional methods of pneumonia diagnosis, reliant on chest X-rays (CXRs), are often time-consuming and subjective, making automated solutions invaluable. Deep neural networks, particularly CNNs, have consistently demonstrated good performance in analyzing medical images. Real-valued CNNs have been employed extensively in pneumonia detection. For instance, studies using ResNet and DenseNet architectures have reported high accuracies ranging between 82% and 92%, demonstrating the potential of CNNs for binary and multi-class classification tasks. Deep learning, particularly CNNs, has shown promise in automating pneumonia detection from chest X-rays, improving accuracy and reducing radiologists' workload. However, traditional CNNs struggle with preserving inter-channel relationships in color images. Quaternion CNNs (QCNNs) address this by treating RGB channels as a single quaternion entity, improving feature extraction and classification. Singh and Tripathi (2021) achieved 93.75% accuracy using a quaternion residual network, outperforming DenseNet121 with fewer parameters. Preprocessing steps like resizing and ELU activation further optimized performance. Future research could explore hypercomplex networks, such as Octonion networks, and tackle dataset limitations through augmentation and synthetic data. [3].

Pneumonia detection using AI, particularly Convolutional Neural Networks (CNNs), has shown significant advancements in improving diagnostic accuracy. Studies such as Ayan and Ünver (2019) and Hashmi et al. (2020) demonstrated strong results, with CNNs achieving up to 98.43% accuracy using ensemble models. Jain et al. (2020) and Chouhan et al. (2020) further highlighted the effectiveness of custom and ensemble CNN architectures, with recall rates surpassing 99%. However, challenges such as computational costs, model complexity, and dataset limitations (e.g., class imbalance) persist. The current study addresses these issues by proposing a balanced CNN model, optimizing feature extraction and maintaining computational efficiency, resulting in superior performance across key metrics such as precision, recall, and F1 score. The proposed model achieved an accuracy of 96.07% but required further refinement for better precision. Manickam et al. (2021) incorporated U-Net segmentation along with pre-trained Inception V3 and ResNet50 models. The ResNet50 model outperformed its counterparts, achieving a recall of 96.78% and accuracy of 93.06%. While existing studies demonstrate the efficacy of deep learning models, several limitations persist. The trade-off between model complexity and accuracy remains a key concern. Pre-trained models, though effective, often involve high computational costs and require fine-tuning for optimal performance. Additionally, smaller datasets or unbalanced class distributions can negatively impact model generalizability. In response to these challenges, the current study proposes a novel CNN model tailored for pneumonia detection. Unlike traditional approaches, the proposed method focuses on a balanced architecture that enhances feature extraction while maintaining computational efficiency. The model demonstrates significant improvements over existing frameworks, achieving superior performance metrics, including precision, recall, and F1 scores [5].

Deep learning, particularly through CNNs, has significantly advanced the automated detection of chest abnormalities in X-ray images, addressing challenges in manual interpretation like misdiagnosis and time inefficiency. Notable models like CheXNet and AlexNet have shown high accuracy in pneumonia detection. This study leverages SqueezeNet, a lightweight CNN, to classify chest X-rays into “normal” and “abnormal” categories, achieving 90.95% accuracy on the ChestX-ray14 dataset. By employing pre-processing techniques such as CLAHE and using transfer learning with pre-trained weights, the model maintains competitive performance with fewer parameters. These results highlight the effectiveness of efficient, smaller networks for medical image analysis, especially in resource-limited environments. Future research could focus on comparative network studies and real-world clinical validation to enhance model robustness and generalizability [6].

Chest X-ray imaging is essential for diagnosing respiratory diseases, including COVID-19, but accurate interpretation remains challenging, especially in multi-abnormality cases. Deep learning (DL) models, particularly Convolutional Neural Networks (CNNs), have shown promise in enhancing diagnostic accuracy through multi-class classification and object detection. However, existing approaches often struggle with class imbalance and low sensitivity for certain abnormalities, limiting their reliability.Recent advancements propose ensemble models combining object detection networks like YOLOv7, Faster R-CNN, and EfficientNet to address these challenges. These methods, particularly when integrated with weighted box fusion, improve detection by refining bounding box predictions and boosting mean average precision (mAP). This collaborative approach enhances both classification and localization of abnormalities in chest X-rays.In summary, DL techniques, especially multi-classification and object detection models, are crucial for improving the accuracy and efficiency of medical image analysis. Future research should focus on overcoming data imbalance and computational challenges while refining ensemble strategies and exploring novel architectures to advance the field [7].

Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized medical imaging, particularly in chest X-ray analysis for diseases like pneumonia and tuberculosis. Notable models like CheXNet and EfficientNet have demonstrated exceptional performance in disease detection, with approaches such as transfer learning and LSTMs addressing dataset limitations and enhancing accuracy. However, challenges remain, including dataset imbalance, overfitting, and the need for model interpretability. Techniques like data augmentation, regularization, and Grad-CAM have been employed to mitigate these issues, with recent work integrating dynamic routing to improve interpretability. EfficientNet's scalable architecture balances high accuracy with computational efficiency, highlighting its potential for clinical applications. Future research should focus on overcoming dataset biases and computational constraints to further solidify CNNs as a dependable tool in medical diagnostics [8].

Deep learning, especially Convolutional Neural Networks (CNNs), has significantly advanced the detection of lung diseases like pneumonia and COVID-19 through chest X-rays (CXRs). CNNs have shown superior accuracy in classifying diseases, as seen in works by Abiyev and Maaitah (2018) and Lin et al. (2019). Recent models, such as COVIDetectioNet (Turkoglu, 2021), further enhance accuracy using transfer learning.Challenges remain, particularly in region-of-interest (ROI) extraction and high computational costs. Recent research combining Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) units has improved feature extraction and accuracy, achieving 95.04% detection for COVID-19. These advances highlight the potential of deep learning to revolutionize lung disease detection, especially in resource-limited settings [10].

Chapter-3

Methodology

3.1 System Design

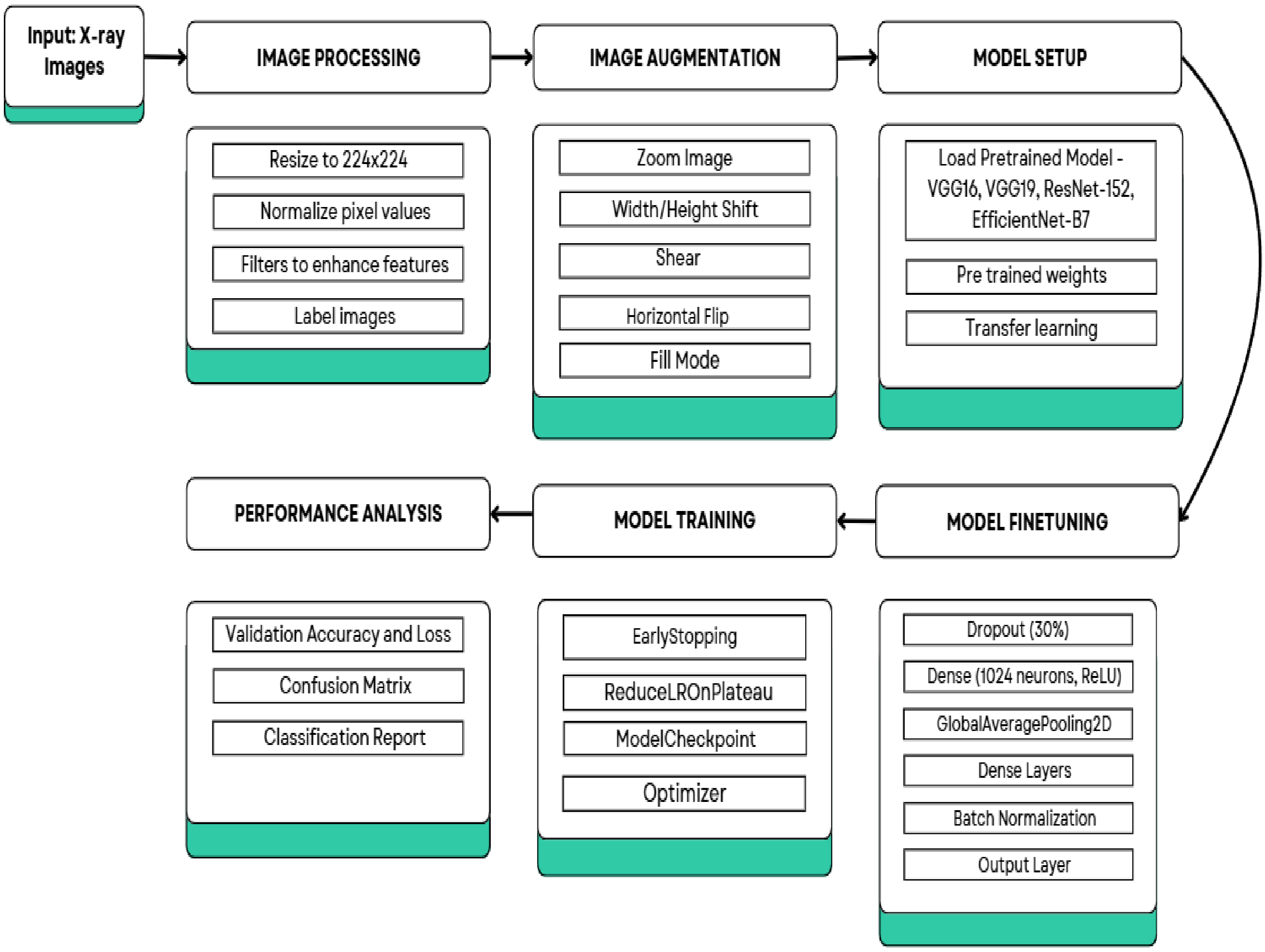

Figure 1: Block Diagram of the Proposed Model

The deep learning models will be use in this proposal are:

1. **VGG-16 and VGG-19**:
   - These are Convolutional Neural Networks (CNNs) designed to process and classify images effectively.
   - Their ability to extract features hierarchically enables the detection of subtle abnormalities in medical images.
   - These models are simple yet powerful and act as the baseline for more advanced architectures.
2. **ResNet-152**:

- This model employs residual connections, which solve the problem of vanishing gradients, enabling the training of deeper and more accurate networks.
- ResNet-152 has shown significant improvements in stability and performance when applied to medical imaging.

3. **EfficientNet-B7**:
   - EfficientNet-B7 optimizes network depth, width, and resolution to achieve superior accuracy with lower computational requirements.
   - This model's balance of efficiency and performance makes it suitable for deployment in resource-limited healthcare environments.
4. **Ensemble Approach:**
   - To improve accuracy further, we propose combining the outputs of ResNet-152 and EfficientNet-B7 in an ensemble model.
   - This approach leverages the strengths of both models, providing classifications that are more reliable with reduced variability.

3.2 Software Components

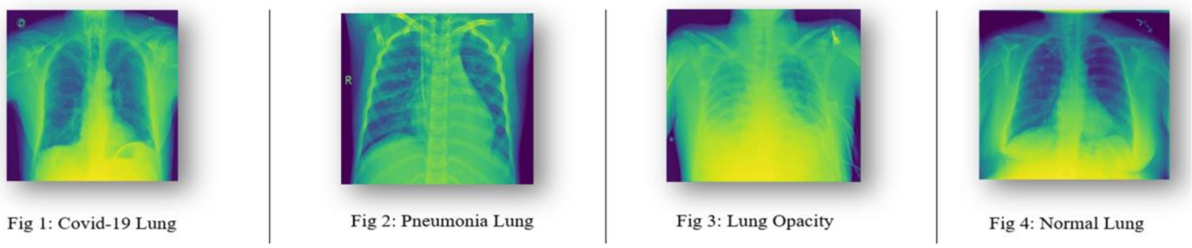

Figure 2: Dataset for anomaly detection

The dataset used in this project contains a total of 4,219 chest X-ray images, distributed across four classes: COVID-19 (1,069 images), Normal (975 images), Lung Opacity (1,150 images), and Viral Pneumonia (1,025 images). This dataset was sourced from Talukder, Md Alamin (2023), "Chest X-Ray Image," Mendeley Data, V1, doi: 10.17632/m4s2jn3csb.1.

Table I: Software and Hardware Tools Used in the Project

Tool	Functions	Other similar Tools (if any)	Why selected this tool
Google Colab Pro	A cloud-based platform that offers enhanced GPU/TPU support, making it easier to train and fine-tune deep learning models.	Jupyter Notebook, Kaggle Kernels	Paid version offers faster GPUs, longer runtimes, and priority access to resources, enhancing training efficiency.
TensorFlow/Keras	A deep learning library used to build, train, and fine-tune models for tasks like image classification.	PyTorch, MXNet	It's widely used, has pre-trained models, and offers excellent community support and documentation.
VGG16	A pre-trained CNN model used for transfer learning in image classification tasks.	ResNet, EfficientNet, Inception	It's simple yet effective, and a proven performer for image classification tasks.
VGG19	Another pre-trained CNN model with a slightly deeper architecture than VGG16, used for transfer learning.	ResNet, EfficientNet, Inception	It allows experimentation with deeper networks to improve accuracy.
EfficientNet B7	A state-of-the-art CNN model that balances accuracy and computational efficiency for image classification.	ResNet 152, DenseNet	It's highly efficient and achieves great accuracy while using fewer resources compared to other models.

ResNet 152	A very deep pre-trained model with 152 layers, ideal for feature extraction and image classification.	EfficientNet, DenseNet	Its depth helps capture complex patterns, making it a strong choice for classification.
Ensemble (EffNet + ResNet)	Combines predictions from EfficientNet B7 and ResNet 152 to improve classification accuracy.	Ensembles with other models	This approach leverages the strengths of both models, boosting overall performance and handling weaknesses.
ImageDataGenerator	A Keras utility for augmenting images during training with transformations like rotation (10°), shear (5%), and brightness (±5%).	Albumentations, imgaug	It's simple to use and works seamlessly with TensorFlow models.
AdamW Optimizer	An optimizer with weight decay (0.01) and learning rate (1e-4), used for training models efficiently and preventing overfitting.	SGD, Adam, RMSprop	It offers adaptive learning rates and better generalization for model training.
ExponentialDecay	A method to reduce the learning rate gradually (decay factor 0.9 every 10,000 steps) for better convergence during training.	StepDecay, PolynomialDecay	It helps fine-tune the model training process without sudden learning rate drops.

OpenCV	A library for processing images, such as resizing to (224x224), converting to RGB, and normalizing pixel values to [0, 1].	PIL, skimage	It's powerful, flexible, and works well for various image manipulation tasks.
Matplotlib/Seaborn	Libraries used to create plots for visualizing training/validation accuracy and loss, and confusion matrices for evaluation.	Plotly, Bokeh	These tools are simple to use and produce high-quality visualizations.
Google Drive	Used as a cloud storage solution for saving datasets, trained models, and best weights.	Dropbox, AWS S3	It integrates easily with Colab and offers ample free storage.
Scikit-learn	A library used for computing metrics like precision, recall, F1-score, and confusion matrices.	Statsmodels, PyCaret	It's versatile and provides reliable tools for evaluating model performance.
Compute Class Weights	A Scikit-learn function that assigns weights to classes (e.g., COVID: 1.2, Normal: 1.3) to handle imbalanced datasets.	Manual calculation	It makes handling class imbalances easier by automating the weight calculations.
Compute Class Weights	A Scikit-learn function that assigns weights to classes (e.g., COVID: 1.2, Normal: 1.3) to handle imbalanced datasets.	Manual calculation	It makes handling class imbalances easier by automating the weight calculations.

Hyperpara-meter Optimization	Techniques include adjusting learning rates (1e-4), dropout rates (0.4), batch size (32), and weight decay (0.01).	Optuna, Hyperopt, Keras Tuner	Optimizing these parameters improved accuracy, reduced overfitting, and sped up convergence.

3.3 Software Implementation

Model Development and Training	Developed deep learning models (VGG-16, VGG-19, ResNet-152, EfficientNet-B7) using TensorFlow and Keras. Leveraged transfer learning with ImageNet pre-trained weights for feature extraction and domain-specific adaptation. Fine-tuned top layers for dataset-specific training.
Data Preprocessing	Preprocessed images by resizing to 224 × 224 224×224, normalizing to [0,1], and augmenting data (rotation, shear, flipping, brightness adjustment) using ImageDataGenerator to improve robustness.
Hyperparameter Tuning	Optimized learning rate, batch size, and dropout rates to enhance model accuracy and reduce overfitting. Implemented ExponentialDecay for learning rate adjustment.
Model Integration	Combined predictions from ResNet-152 and EfficientNet-B7 using a weighted ensemble approach to improve classification reliability and generalization.

Evaluation and Visualization	Evaluated models using precision, recall, F1-score, and confusion matrices. Visualized accuracy and loss curves using Matplotlib and Seaborn to monitor training progress.
Deployment Environment	Used Google Colab Pro for model training and experimentation with high-performance GPUs. Saved model checkpoints for best-performing results.
Output and Results	Generated class probabilities for chest X-ray images, enabling classification into four categories (COVID-19, Pneumonia, Lung Opacity, Normal). Created post-processing scripts for summarizing performance metrics.

Chapter 4

Experiment, Result, Analysis and Discussion

4.1 Investigation / Experiment

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
Number of images in COVID class: 1069
Number of images in Normal class: 975
Number of images in Lung Opacity class: 1150
Number of images in Viral Pneumonia class: 1025
```

Figure 3: Dataset Verification and Class Distribution

We checked the output to ensure that the data was loaded correctly from each class and to verify the distribution of images across the four categories: COVID, Normal, Lung Opacity, and Viral Pneumonia. This step was important to confirm that there were no missing files or imbalances in the dataset that could impact the model's performance during training. It also helped us ensure that the dataset was ready for preprocessing and augmentation.

```
Found 3376 images belonging to 4 classes.
Found 843 images belonging to 4 classes.
```

Figure 4: Dataset Partitioning for Training and Validation

We divided the dataset into two parts: training and validation sets. A total of 3,376 images, covering the four classes (COVID, Normal, Lung Opacity, and Viral Pneumonia), were used for training the model, while 843 images were set aside for validation. This split was implemented using the validation_split parameter in the ImageDataGenerator, ensuring an 80-20 ratio between training and validation data. We performed this split to train the model on one subset and evaluate its performance on another, unseen subset, which is essential for checking how well the model generalizes to new data and minimizing the risk of overfitting.

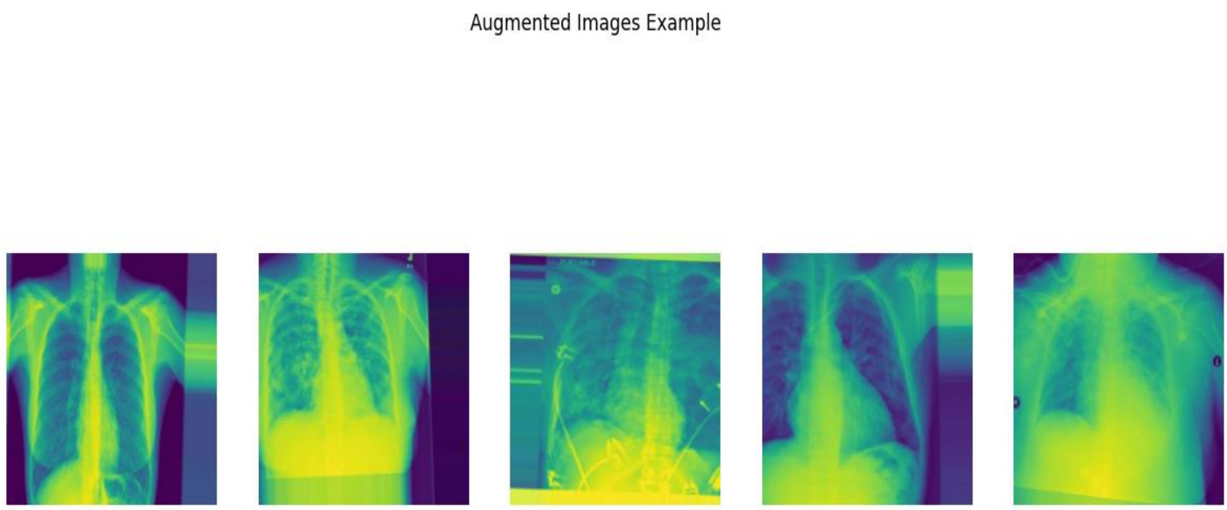

Figure 5: Example of Augmented Chest X-ray Images

Data augmentation is crucial to improve the generalization of our model, as it helps simulate variations that the model might encounter in real-world scenarios. To ensure the augmentation process was working correctly, we inspected the output images after applying transformations like rotation, brightness adjustment, and flipping. This step was necessary to confirm that the augmented images preserved the essential features of the chest X-rays while introducing meaningful variations. By checking the outputs, we ensured that the augmented images aligned with our expectations and contributed to better training results.

4.2 Results

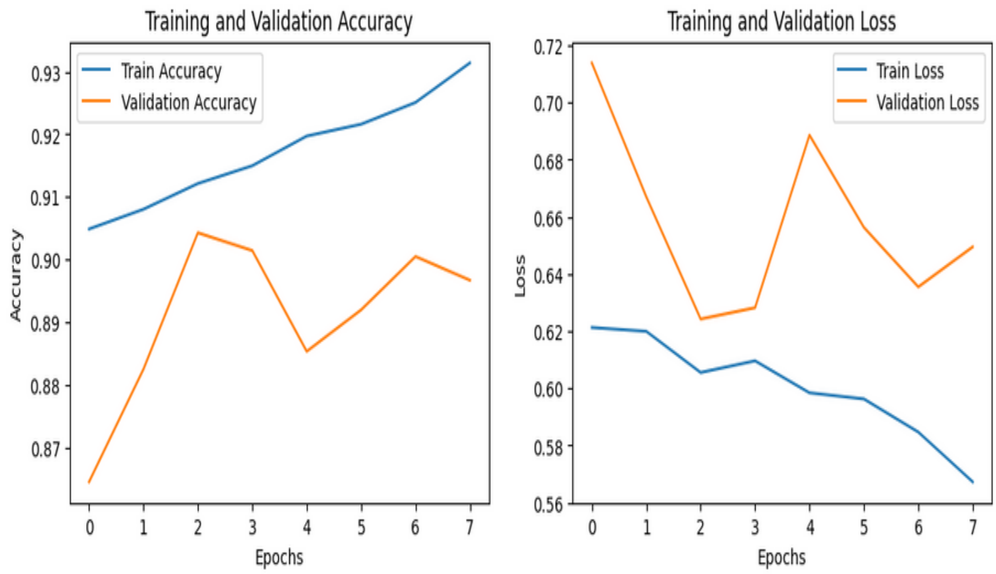

Figure 6: Model Accuracy and Loss Over Epochs: Training vs Validation (VGG-16)

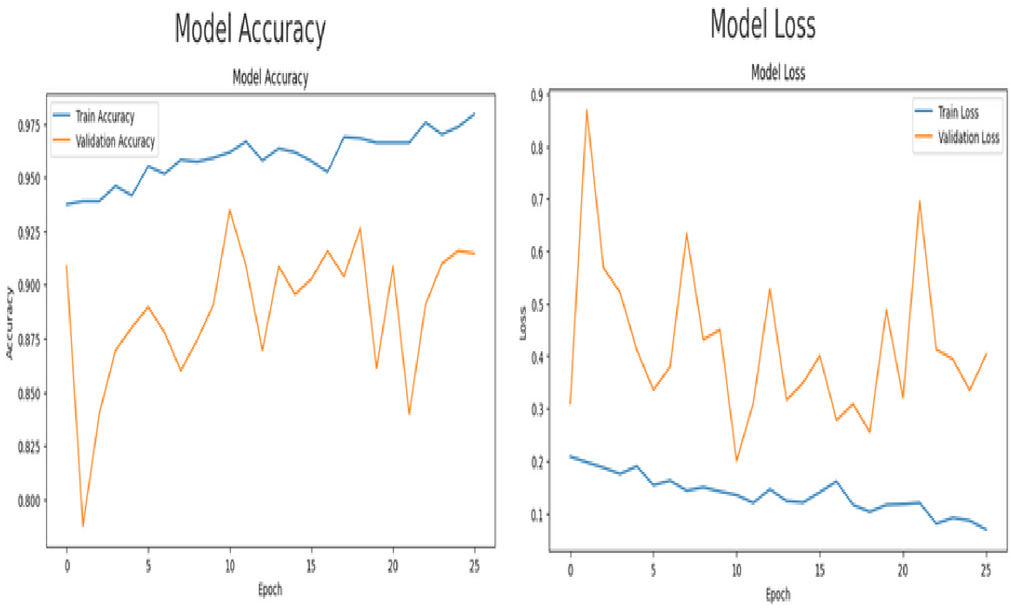

Figure 7: Model Accuracy and Loss Over Epochs: Training vs Validation (VGG-19)

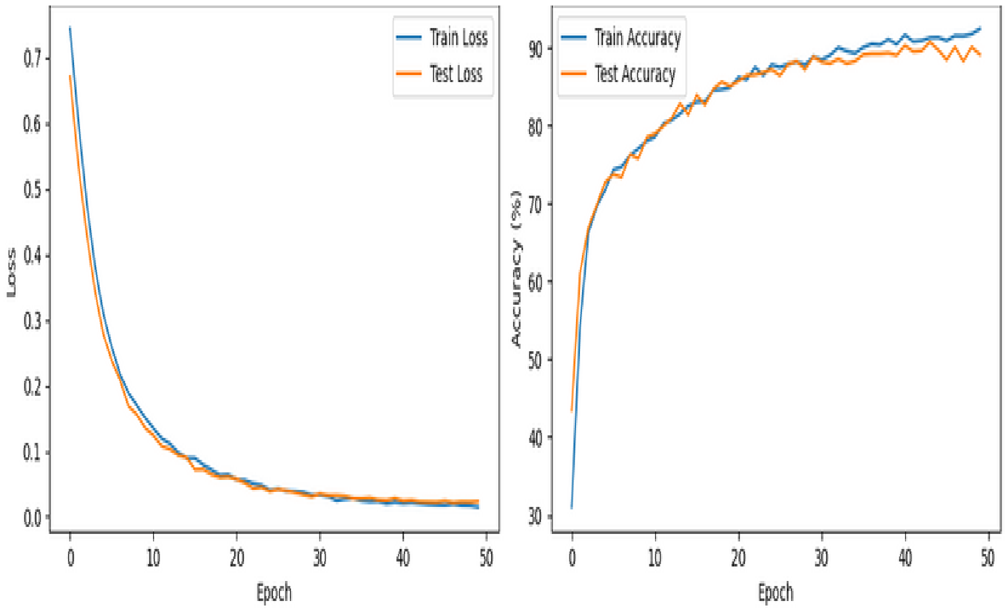

Figure 8: Model Accuracy and Loss Over Epochs: Training vs Validation (ResNet-152)

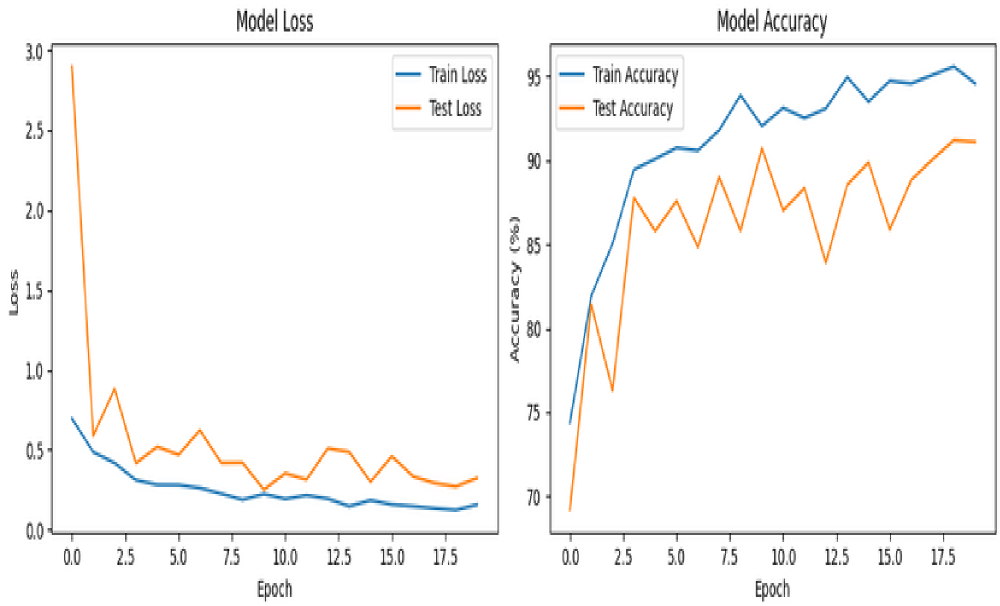

Figure 9: Model Accuracy and Loss Over Epochs: Training vs Validation (EfficientNet-B7)

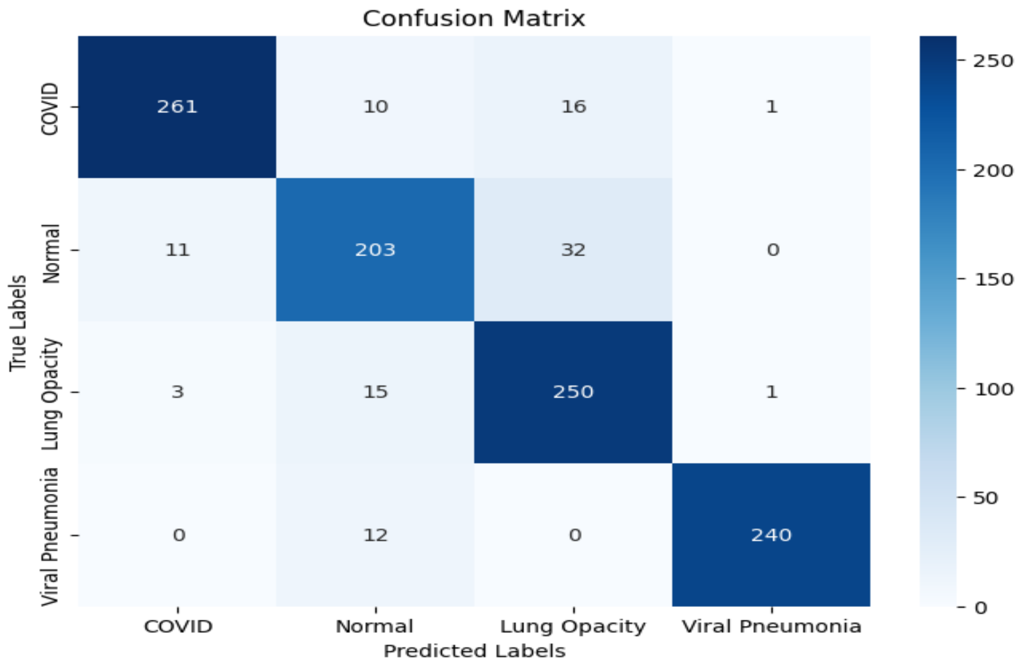

Figure 10: Confusion Matrix for VGG-16

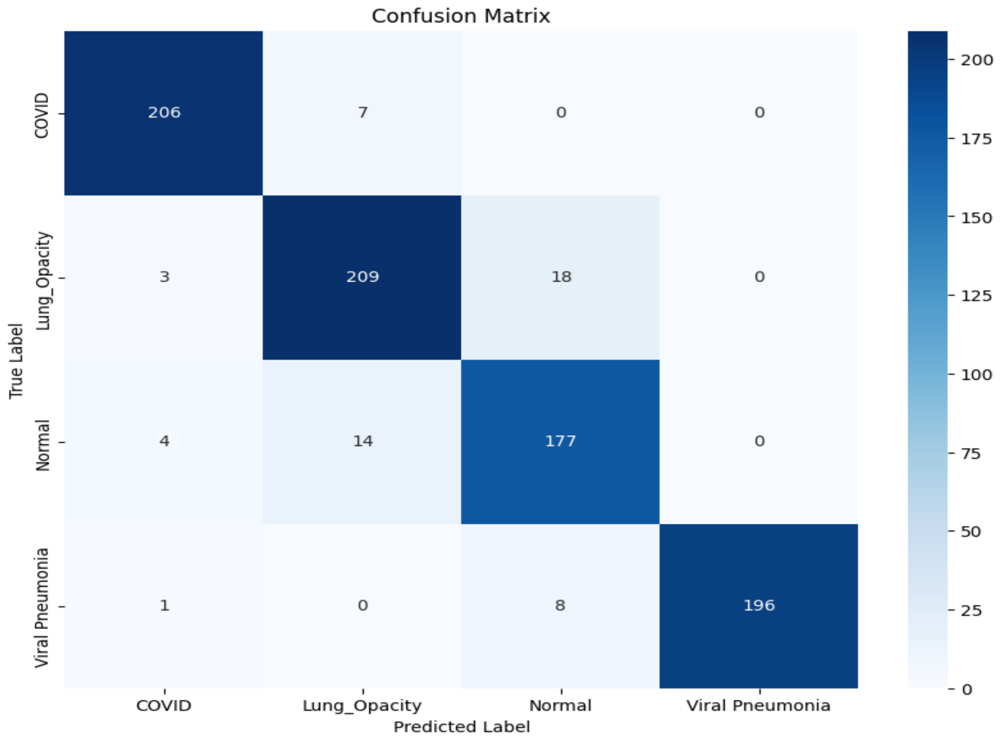

Figure 11: Confusion Matrix for VGG-19

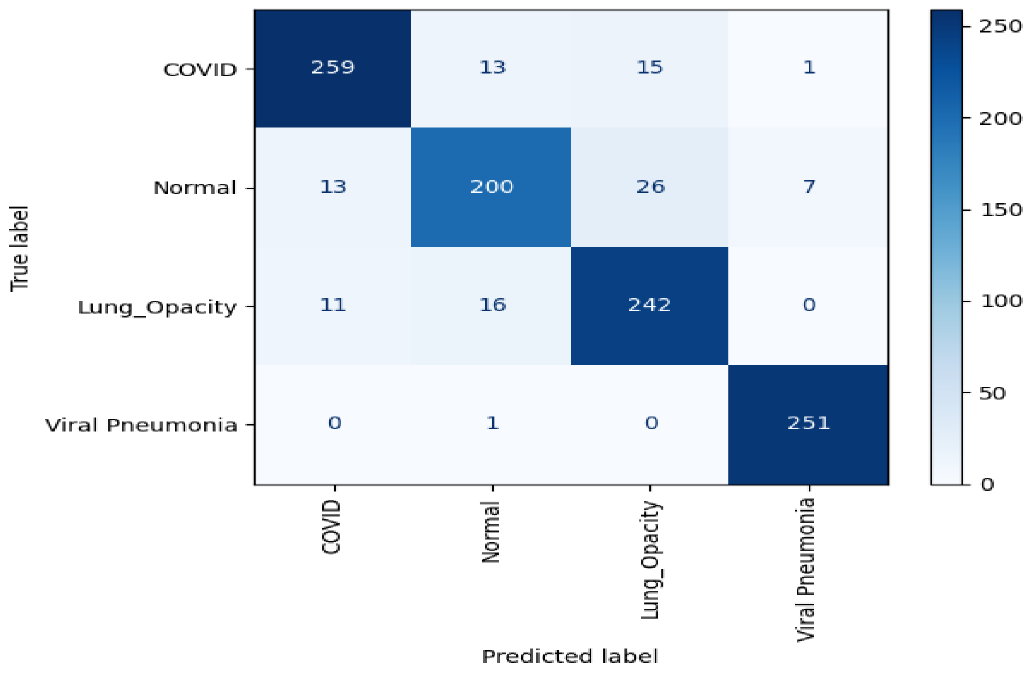

Figure 12: Confusion Matrix for ResNet-152

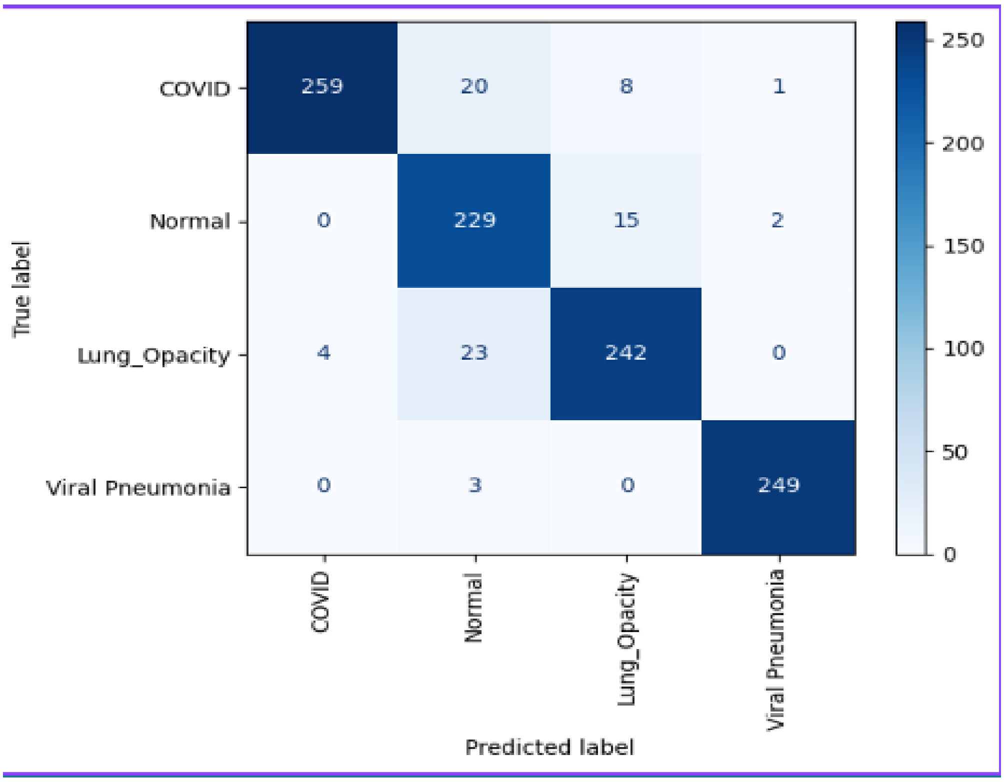

Figure 13: Confusion Matrix for EfficientNet-B7

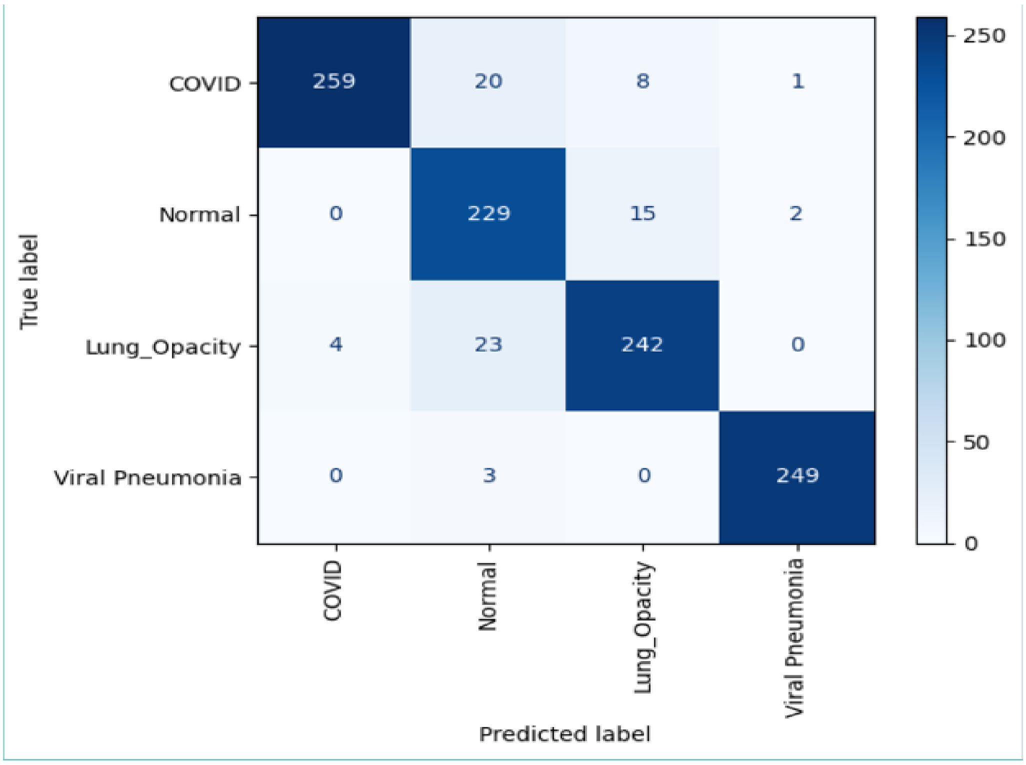

Figure 14: Confusion Matrix for ENSEMBLE OF EFFICIENT NET-B7 AND RESNET-152

Method	Precision (%)	Recall (%)	Accuracy (%)	F1 Score (%)
CNN with VGG-16 (Transfer Learning)	91	90	90	90
VGG-19	93	93	93	93
RESNET-152	90	90	90	90
EFFICIENTNET-B7	92	92	92	92
Weighted Ensemble (B7 and RESNET-152)	93	93	93	93

Table 2: Classification Report (Precision, Recall, F1-Score)

4.3 Analysis

A thorough grasp of the performance, advantages, drawbacks, and consequences of ResNet-152, EfficientNet B7, and their weighted average ensemble for medical image classification—specifically, the diagnosis of COVID-19 and other lung disorders from X-ray images—is provided by the examination of these models. With a test accuracy of 90%, ResNet-152 demonstrated its capacity to learn complex patterns and features because to its deep design, which consists of 152 layers and uses residual connections to avoid vanishing gradient problems. Its computationally expensive deep structure, however, presents difficulties for real-time or resource-constrained applications and may raise the danger of overfitting if improperly regularized.

Using its compound scaling technique, which appropriately balances network width, depth, and resolution to achieve excellent performance with fewer parameters, EfficientNet B7 surpassed ResNet-152 with a 92% test accuracy. Because of the intricacy of its 'b7' variant, EfficientNet B7 is computationally demanding, needing substantial computer resources for both training and inference, even if it is more efficient than ResNet-152 in terms of parameter count. With a test accuracy of 93%, the weighted average ensemble—which included ResNet-152 and EfficientNet B7—produced the greatest results, proving that ensemble approaches are successful at utilizing the strengths of many models to improve accuracy and resilience. The ensemble lowers the possibility of overfitting to any one model and enhances generalization to unknown data by allocating weights to each model according to their individual accuracies. However, this comes at the expense of higher computational demands during inference because both models must be run concurrently. These findings demonstrate how much more resilient and generalizable the ensemble model is than its constituent parts. Both ResNet-152 and EfficientNet B7 require a lot of computing power, and the ensemble technique raises resource requirements even more. This might make implementation impractical, especially in low-resource settings.

The ensemble's increased accuracy in generalization implies that it could perform better on unknown data, but further testing on bigger, more varied datasets is required to verify this. The models—particularly the ensemble—have a great deal of promise to help physicians diagnose lung conditions by offering quick, accurate, and trustworthy evaluations, which will simplify procedures and lessen diagnostic burdens. Future studies should concentrate on refining the models to minimize computing demands while maintaining accuracy using methods like knowledge distillation, quantization, or pruning. By providing straightforward information into the models' decision-making procedures, interpretability techniques like Grad-CAM and saliency maps will be crucial for fostering confidence among medical practitioners. Furthermore, it is essential to validate these models using datasets from various clinical settings, imaging equipment, and demographics in order to guarantee their generalizability, fairness, and dependability in various situations. Medical imaging diagnostics could undergo a revolution if these models are successfully incorporated into clinical workflows. This would allow for real-time decision support, particularly in high-pressure situations, while resolving important issues like resource utilization and comprehension to guarantee their dependability and moral application.

We observed that the **VGG19 model** performed effectively during training and validation. As the base architecture, the model utilized pre-trained weights from ImageNet for feature extraction. We fine-tuned the last **15 layers** of the VGG19 model while freezing the earlier layers, enabling the network to retain its ability to detect generic patterns while learning domain-specific features from chest X-ray images. This fine-tuning approach allowed the model to adapt specifically to the unique characteristics of our dataset. The training was carried out using a learning rate of **1e-4**, adjusted gradually using an **ExponentialDecay schedule**. We trained the model for **26 epochs**, with early stopping enabled to terminate training when the validation performance stopped improving. **Figure 7** shows the accuracy and loss curves during training, where we observed steady improvements in training accuracy. Validation accuracy stabilized at **91.5%**, indicating that the model successfully avoided overfitting and effectively learned meaningful patterns from the data. The data augmentation techniques, including **rotation (10°)**, **shear (5%)**, **brightness adjustment (±5%)**, and **horizontal flipping**, were essential for simulating real-world variations and enhancing the generalization capabilities of the model. The confusion matrix, shown in **Figure 11**, highlights that most predictions were correct across all classes. However, occasional misclassifications were noted between the Lung Opacity and Normal classes, likely due to overlapping visual features. Despite these challenges, the model achieved strong metrics, with precision, recall, and F1-scores consistently above **90%**, as summarized in **Table 2**. This demonstrates robust performance across all metrics and highlights the reliability of the model in classifying chest X-ray images. In conclusion, while the **VGG19 model** performed well with an accuracy of **91.5%**, the results suggest that further improvements, such as addressing class-specific misclassifications or incorporating ensemble methods, could enhance overall performance. The visual results in **Figures 7 and 11** and the metrics in **Table 2** confirm the model's strong ability to generalize and classify effectively within the dataset.

We used the **VGG16 model** as the base architecture for transfer learning. Its pre-trained weights from ImageNet allowed us to leverage general image features while adapting the model to our specific task. We froze the initial layers to retain these pre-trained features and fine-tuned the higher layers to learn domain-specific patterns from the chest X-ray dataset. To enhance model performance, we also employed data augmentation techniques, including **rotation (10°)**, **shear (5%)**, **brightness adjustment (±5%)**, and **horizontal flipping**. These techniques, as illustrated in the augmented image examples, improved the model's robustness by simulating real-world variations, thereby enhancing generalization on unseen data. The training was carried out using a learning rate of **1e-6**, which was gradually reduced using the **ReduceLROnPlateau** callback when the validation loss plateaued. Training was conducted for up to **30 epochs**, with early stopping applied to avoid overfitting. The batch size was set to **32**, balancing memory constraints with computational efficiency.As shown in **Figure 6**, the accuracy and loss curves demonstrate consistent improvement in training accuracy, while validation accuracy stabilized around **90.5%**. These trends indicate that the model successfully generalized to unseen data without significant overfitting. However, slight fluctuations in validation loss suggest sensitivity to certain variations in the validation set. The confusion matrix in **Figure 10** highlights that the model correctly classified the majority of images across all four classes. Misclassifications were primarily observed between the Lung Opacity and

Normal classes, likely due to similar visual features in these categories. Despite this, the model achieved strong performance metrics, with precision, recall, and F1-scores consistently at or above **90%**. Comparing the VGG16 results with other models, we observed that while it performed well with an accuracy of **90%**, it was slightly outperformed by the VGG19 and ensemble models (both achieving **93%** accuracy). As shown in **Table 2**, this suggests that deeper architectures or combined models can capture more nuanced features for improved classification.

4.4 Discussion

We noticed that the deep learning models performed exceptionally well in classifying chest X-ray images, with the ensemble of ResNet-152 and EfficientNet-B7 achieving the highest accuracy. We observed that the ensemble approach effectively combined the strengths of both models, improving overall reliability and generalization. However, we noticed occasional misclassifications, particularly between Lung Opacity and Normal classes, which may be due to overlapping visual features. We also observed that the computational demands of the models, especially during training, could be a limitation in low-resource settings. Despite these challenges, we believe the system demonstrates significant potential to assist medical professionals by providing fast and accurate diagnostic support. Moving forward, we aim to address these issues by optimizing the models for diverse datasets and resource-efficient implementations, ensuring broader usability and impact.

Chapter-5

Impacts of the Project

5.1 Impact of this project on societal, health, safety, legal and cultural issues

Our research aims to improve early and accurate detection of lung disorders like COVID-19, pneumonia, and lung opacity, addressing significant legal, cultural, health, safety, and social concerns. By leveraging advanced deep learning algorithms, we provide a fast, reliable, and accessible diagnostic tool for various contexts. We observed that this system can bridge the gap in underserved and rural areas, offering affordable and accurate diagnoses where access to radiologists is limited. Early detection reduces healthcare costs, prevents severe complications, and supports efficient resource utilization, significantly improving patient outcomes. Additionally, automating diagnoses relieves overburdened medical staff, enabling them to focus on patient care. The system ensures safety by reducing diagnostic errors caused by human fatigue and enhances trust in healthcare during emergencies like pandemics. Adhering to strict data privacy regulations ensures legal compliance and protects patient confidentiality. Moreover, the tool is adaptable to different cultural and geographical needs, promoting equitable healthcare access. Overall, this initiative has the potential to revolutionize global healthcare systems, improving lives and ensuring high-quality care for all.

5.2 Impact of this project on environment and sustainability

Our study contributes to environmental sustainability by using deep learning to detect and classify lung disorders like COVID-19, pneumonia, and lung opacity. While primarily software-based, it indirectly optimizes healthcare systems and reduces resource consumption, making it a step toward a sustainable future. By automating the diagnostic process, we reduce the need for repeated testing, X-ray films, and diagnostic equipment, minimizing waste and energy use. This also lowers the environmental footprint of producing and disposing of consumables. Additionally, our system reduces patient travel for multiple diagnoses, cutting transportation-related carbon emissions—a critical benefit for rural or remote areas.

We emphasized energy-efficient computing by using transfer learning and pre-trained models, which significantly decrease computational power requirements. This ensures the system remains environmentally friendly, even at scale. The project also decentralizes healthcare by providing portable diagnostic tools that reduce reliance on energy-intensive centralized infrastructures, supporting sustainability in resource-limited environments.

Finally, digitizing medical records eliminates the need for paper-based methods, saving trees and reducing waste. Overall, while indirect, our project supports sustainability by reducing waste, optimizing resources, lowering emissions, and promoting eco-friendly healthcare digitization. This aligns with the broader goal of creating a sustainable future with accessible, high-quality healthcare for all.

Chapter-6

Project Planning and Budget

Tool	Unit Price(In BDT)	Quantity	Total Cost (In BDT)	Compute Unit (Per)	Total Comput Unit
Colab Pro	1198.8	5	5994	100	500

Table 3: Project Budget

Chapter-7

Conclusions

7.1 Summary

Lung conditions including COVID-19, pneumonia, and lung opacity are among the most common health issues in the globe and need to be diagnosed accurately and promptly in order to guarantee adequate treatment and save lives. Time limits, interpretation variability, and a need for trained radiologists are some disadvantages of traditional diagnostic methods, such as manually reading chest X-rays. These challenges are particularly apparent in low-resource settings when access to state-of-the-art medical facilities and specialists is restricted. To overcome these issues, we developed a deep learning-based system that automatically detects and classifies pulmonary abnormalities from chest X-ray images.

Advanced deep learning models such as ResNet-152 and EfficientNet-B7 are used in our study. These models were trained on a dataset with 4,219 chest X-ray pictures that were divided into four groups: normal cases, pneumonia, COVID-19, and lung opacity. We improved these models for high accuracy and dependability by using transfer learning, guaranteeing consistent performance in a variety of intricate medical situations. By offering quick and automatic diagnostic assistance, this technology can lessen the effort for medical personnel and lower the possibility of mistakes.

Given that ResNet-152 achieved a 93% classification accuracy, the results are quite encouraging. ResNet-152 and EfficientNet-B7 were used in an ensemble manner to further enhance performance and strengthen the system. By offering dependable and easily available instruments for early detection, this technology has the potential to greatly improve healthcare diagnostics, especially in underprivileged regions. It helps physicians make choices more quickly and accurately, which eventually improves patient outcomes and saves lives.

For us, this initiative has also been a priceless educational opportunity. It made it possible for us to learn more about medical imaging, deep learning, and AI applications in healthcare. Working on a real-world issue gave us hands-on experience with medical datasets, model construction and training, and overcoming issues like generalizability and accuracy. Beyond its technical features, this initiative strengthened our resolve to use technology to address pressing social issues. In addition to enhancing healthcare systems, our work motivates us to keep looking for creative answers to pressing global issues.

7.2 Limitations

There are several issues that need to be resolved, even if our initiative has demonstrated significant promise in identifying and categorizing lung conditions including COVID-19, pneumonia, and lung opacity. Understanding these difficulties is crucial since they point out areas where the system may be enhanced for increased usability and performance. The dataset is one of the main drawbacks. Despite its diversity, the dataset we used might not accurately reflect all the many types of lung disorders that are observed in actual instances. For instance, the system may not be completely trained to manage the diversity introduced by chest X-rays from various populations, imaging equipment, or environmental circumstances. This can have an impact on the model's accuracy when used with fresh or untested data.

The system's computational needs represent yet another constraint. Our models, such as ResNet-152 and EfficientNet-B7, are quite sophisticated and demand a lot of processing power to train and run. Because of this, the system is challenging to utilize in low-resource environments where access to powerful hardware may be restricted. Furthermore, the approach only considers chest X-rays and four distinct categories: normal cases, pneumonia, lung opacity, and COVID-19. It doesn't take into consideration systemic disorders or other lung problems that might possibly show up on chest X-rays. Its use as a thorough diagnostic tool is constrained by its narrow breadth.

Deep learning models, like ours, frequently function as "black boxes," which means they make predictions without providing an explanation for how they arrived at them. This presents another difficulty. In severe circumstances, clinicians may find it challenging to fully trust the system's results due to this lack of interpretability. Finally, there hasn't been much testing of the technology in actual clinical situations. Its efficacy in hospitals, where variables like imaging quality, unpredictability, and time restrictions change, is yet unknown, despite the encouraging results in a controlled setting.

These restrictions point to areas that need to be improved, such as adding new illness categories, optimizing the model for contexts with limited resources, growing the dataset, and enhancing the explainability of the system. The system will become more strong, dependable, and broadly applicable in actual healthcare situations if these issues are resolved.

7.3 Future Improvement

Although the results of our experiment in identifying and categorizing lung problems from chest X-rays have been encouraging, there are a number of ways we may enhance it to make it more useful, dependable, and significant in actual healthcare. A crucial first step toward future development is improving the dataset. Despite its effectiveness, our present dataset may be enlarged to include more X-rays from a wider range of imaging technologies, medical settings, and people. The system can learn to manage real-world unpredictability better by including photos from patients with different demographics and situations, guaranteeing more reliable and accurate performance. Making the system more accessible in environments with limited resources is another significant enhancement. The existing concept depends on sophisticated technology with a lot of processing power, which may not be accessible in undeveloped or rural locations. In order to solve this, we intend to create a system that is lightweight and capable of operating well on less expensive gadgets like smartphones or portable laptops. This will increase the system's viability for implementation in resource-constrained clinics and hospitals, therefore reaching underprivileged areas.

By adding additional illness categories, we also want to improve the system's functionality. The system now concentrates on normal cases, lung opacity, pneumonia, and COVID-19. We intend to train the program in the future to identify more lung conditions such pleural effusion, emphysema, and TB. The system can develop into a complete diagnostic tool that helps physicians diagnose a range of lung-related health disorders by expanding the spectrum of illnesses it can detect. Another important area of effort is making the system easier to understand. Because deep learning models make predictions without revealing how they arrived at them, they are sometimes referred to as "black boxes." Explainable AI approaches that emphasize the parts of the X-ray that contribute to the diagnosis will be used to remedy this. Physicians will be better able to trust and confidently employ the system's outputs in clinical situations because of this increased openness. Lastly, evaluating the system in actual settings, such medical facilities and diagnostic labs, can yield insightful information on how well it functions in various scenarios, allowing for more improvement. By tackling these advancements, we want to provide a more adaptable, dependable, and easily available diagnostic tool that benefits medical professionals and enhances patient outcomes globally. Through early and precise diagnosis, this study might close gaps in healthcare access and save lives.

References

[1]D. Urey, C. Saul, and C. Taktakoglu, “Early Diagnosis of Pneumonia with Deep Learning.” Available: https://arxiv.org/pdf/1904.00937

[2]P. Szepesi and L. Szilágyi, “Detection of pneumonia using convolutional neural networks and deep learning,” *Biocybernetics and Biomedical Engineering*, vol. 42, no. 3, Aug. 2022, doi: https://doi.org/10.1016/j.bbe.2022.08.001.

[3]S. Singh and B. K. Tripathi, “Pneumonia classification using quaternion deep learning,” *Multimedia Tools and Applications*, Oct. 2021, doi: https://doi.org/10.1007/s11042-021-11409-7.

[4]N. Krishnamoorthy, K. Nirmaladevi, T. Kumaravel, K S Sanjay Nithish, S Sarathkumar, and M Sarveshwaran, “Diagnosis of Pneumonia Using Deep Learning Techniques,” *2022 Second International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)*, pp. 1–5, Apr. 2022, doi: https://doi.org/10.1109/icaect54875.2022.9807954.

[5]D. S. Al-Dulaimi, A. G. Mahmoud, N. M. Hassan, A. Alkhayyat, and S. A. Majeed, “Development of Pneumonia Disease Detection Model Based on Deep Learning Algorithm,” *Wireless Communications and Mobile Computing*, vol. 2022, p. e2951168, Jun. 2022, doi: https://doi.org/10.1155/2022/2951168.

[6]K. N. Akpinar, S. Genc, and S. Karagol, “Chest X-Ray Abnormality Detection Based on SqueezeNet,” *IEEE Xplore*, Jun. 01, 2020. https://ieeexplore.ieee.org/abstract/document/9179404 (accessed Nov. 22, 2022).

[7]Abdussalam Elhanashi, S. Saponara, and Q. Zheng, “Classification and Localization of Multi-type Abnormalities on Chest X-rays Images,” *IEEE Access*, vol. 11, pp. 83264–83277, Jan. 2023, doi: https://doi.org/10.1109/access.2023.3302180.

[8]J. Kufel *et al.*, “Multi-Label Classification of Chest X-ray Abnormalities Using Transfer Learning Techniques,” *Journal of Personalized Medicine*, vol. 13, no. 10, pp. 1426–1426, Sep. 2023, doi: https://doi.org/10.3390/jpm13101426.

[9] I. P. Kamila, C. A. Sari, E. H. Rachmawanto, and N. R. D. Cahyo, "A Good Evaluation Based on Confusion Matrix for Lung Diseases Classification using Convolutional Neural Networks," Advance Sustainable Science, Engineering and Technology, vol. 6, no. 1, p. 0240102, Dec. 2023, doi: 10.26877/asset.v6i1.17330.

[10]S. Goyal and R. Singh, "Detection and classification of lung diseases for pneumonia and Covid-19 using machine and deep learning techniques," *Journal of Ambient Intelligence and Humanized Computing*, Sep. 2021, doi: https://doi.org/10.1007/s12652-021-03464-7.

[11]T. Rahman *et al.*, "Transfer Learning with Deep Convolutional Neural Network (CNN) for Pneumonia Detection Using Chest X-ray," *Applied Sciences*, vol. 10, no. 9, p. 3233, May 2020, doi: https://doi.org/10.3390/app10093233.

[12]A. Mabrouk, R. P. Díaz Redondo, A. Dahou, M. Abd Elaziz, and M. Kayed, "Pneumonia Detection on Chest X-ray Images Using Ensemble of Deep Convolutional Neural Networks," *Applied Sciences*, vol. 12, no. 13, p. 6448, Jan. 2022, doi: https://doi.org/10.3390/app12136448.

[13]S.-M. Cha, S.-S. Lee, and B. Ko, "Attention-Based Transfer Learning for Efficient Pneumonia Detection in Chest X-ray Images," *Applied Sciences*, vol. 11, no. 3, p. 1242, Jan. 2021, doi: https://doi.org/10.3390/app11031242.

[14]M. F. Hashmi, S. Katiyar, A. G. Keskar, N. D. Bokde, and Z. W. Geem, "Efficient Pneumonia Detection in Chest Xray Images Using Deep Transfer Learning," *Diagnostics*, vol. 10, no. 6, p. 417, Jun. 2020, doi: https://doi.org/10.3390/diagnostics10060417.

[15]V. Chouhan *et al.*, "A Novel Transfer Learning Based Approach for Pneumonia Detection in Chest X-ray Images," *Applied Sciences*, vol. 10, no. 2, p. 559, Jan. 2020, doi: https://doi.org/10.3390/app10020559.

[16]S. T. H. Kieu, A. Bade, M. H. A. Hijazi, and H. Kolivand, "A Survey of Deep Learning for Lung Disease Detection on Medical Images: State-of-the-Art, Taxonomy, Issues and Future Directions," *Journal of Imaging*, vol. 6, no. 12, p. 131, Dec. 2020, doi: https://doi.org/10.3390/jimaging6120131.

[17] The source code and implementation details for the project are publicly available at the following GitHub repository: https://github.com/Mudachir/IMAGE-BASED-DETECTION-AND-CLASSIFICATION-OF-PULMONARY-ABNORMALITIES-USING-DEEP-LEARNING-TECHNIQUES.git