PNEUMONIA DETECTION WITH TRANSFER LEARNING: A DEEP CNN-BASED COMPARISON OF DETECTION AND SEGMENTATION APPROACHES

BY

Al Mohidur Rahman Porag
ID: 201-15-3462

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

Supervised By

Dr. Md. Taimur Ahad
Associate Professor and Associate Head
Department of CSE
Daffodil International University

Co-Supervised By

Mr. Shah Md Tanvir Siddiquee
Assistant Professor
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

JANUARY 2024

APPROVAL

This Project titled "**Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches**", submitted by Al Mohidur Rahman Porag ID No: 201-15-3462 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 26-01-2024.

BOARD OF EXAMINERS

Dr. Md. Fokhray Hossain (MFH) — **Chairman**
Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Fourcan Karim Mazumder (FKM) — **Internal Examiner**
Assistant Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Md. Ali Hossain (MAH) — **Internal Examiner**
Assistant Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Dr. Mohammed Nasir Uddin (DNU) — **External Examiner**
Professor
Department of CSE
Jagannath University

DECLARATION

We hereby declare that, this project has been done by us under the supervision of **Dr. Md. Taimur Ahad, Associate Professor and Associate Head, Department of CSE** Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

Supervised by:

Md Taimur Ahad

Dr. Md. Taimur Ahad
Associate Professor and Associate Head
Department of CSE
Daffodil International University

Co-Supervised by:

Mr. Shah Md Tanvir Siddiquee
Assistant Professor
Department of CSE
Daffodil International University

Submitted by:

Porag

Al Mohidur Rahman Porag
ID: 201-15-3462
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First we express our heartiest thanks and gratefulness to almighty God for His divine blessing makes us possible to complete the final year project/internship successfully.

We really grateful and wish our profound our indebtedness to **Dr. Md. Taimur Ahad**, **Associate Professor and Associate Head**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of our supervisor in the field of Deep learning 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 stage have made it possible to complete this project.

We would like to express our heartiest gratitude to Dr. Sheak Rashed Haider Noori, Professor, and Head**,** Department of CSE, for his kind help to finish our project and also to other faculty member and the staff of CSE department of Daffodil International University.

We would like to thank our entire course mate in Daffodil International University, who took part in this discuss while completing the course work.

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

ABSTRACT

In pneumonia, the lung tissue undergoes swelling, a condition caused by viral or bacterial infections. This swelling, accompanied by increased lung moisture, results in difficulty in deep breathing. Recognizing these symptoms is crucial, as pneumonia can lead to a substantial number of fatalities. A fundamental diagnostic method for pneumonia involves chest X-rays. This research publication presents a comprehensive overview of recent advancements in pneumonia diagnosis, introducing the authors' unique approach. The integrated models underwent rigorous testing for image classification, demonstrating exceptional performance by models such as VGG19, MobileNetV2, ResNet152V2, SeresNet152, and ResNext101. Utilizing X-ray images from both patients and healthy subjects, the study incorporated visual enhancements and augmented data through compressed archive downloads. Various models with different precisions were employed, revealing that ResNeXt101 and SeresNet152 exhibited the lowest accuracy among the models at 90%. Conversely, VGG19, MobileNetV2, and ResNet152V2 secured the top positions with a commendable accuracy of 92%. All models demonstrated satisfactory outcomes. A dedicated session on transfer learning followed, indicating that the accuracy of results from transfer learning models was slightly lower than that of the original models. Transfer learning was employed to enhance the precision of models, resulting in accuracies of 91.98% for ResNet152V2, 88.11% for SeresNet152, 91.47% for MobileNetV2, 88.19% for VGG19, and 91.60% for ResNeXt101. Despite this, the accuracy remained notably lower compared to the original models. This research holds significance for data scientists as it provides essential insights into pneumonia diagnosis, emphasizing the importance of continuous advancements in medical research.

Keywords— Transfer Learning, Ensemble Model, Convolution Neural Network (CNN), Chest X-ray images, Pneumonia, Deep Learning.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

1.1 Introduction

Deep learning (DL) is an artificial intelligence tool for computer aided diagnosis, such as pneumonia disease detection. DL has been proven effective and time efficient in classification and detection of diseases using images, whereas professional clinicians, physicians and radiologists' classification is criticized for being expensive and time-consuming Deepak & Ameer (2019). DL applies multilayered, hierarchical, and block structure of convolutional neural network (CNN) for extraction of low-, mid-, and high-level information from medical images pictures of x-rays Khan et al. (2021). Two techniques of DL, transfer learning and ensemble model has proven the potential to produce better outcomes when compared to techniques that do not involve deep learning Iqbal et al. (2018). Transfer learning (TL) builds on a training dataset from a different activity. However, the final few layers can be removed and retrained for the goal task Bengio et al. (2012, June). The initial several layers of deep learning describe task properties. It describes a scenario in which what has been discovered in one context is used to enhance optimization in another. After investigate the CNN architecture's topology in an effort to identify a model that will enable (TL) to classify images. Although with limited processing power and time, testing and altering the network topology as well as dataset characteristics might assist identify the factors that affect classification performance. Training a deep learning model with a tiny data set is frequently negative because of the potential impact on the model's performance. Transfer learning is the practice of utilizing the parameters of a model constructed from a larger dataset that is completely unrelated to the one being used Mesnil et al. (2012). Only when the segmentation problem is harder and less target training data is available are noticeable improvements seen. Training a deep learning model with a small data set is usually not recommended because it can negatively affect the model's accuracy. Initializing a model with weights learned from training a different model on a larger dataset is an example of transfer learning. Gains become statistically meaningful only when the segmentation problem is more challenging and there is less target training data available.

Acute pulmonary infection (pneumonia) is a condition in which the lungs become inflamed due to infection with bacteria, virus; this leads to a condition known as pleural effusion, in which the lungs become swollen with fluid Frondelius et al. (2022). More than 15% of all deaths in children younger than 5 can be attributed to this cause. Countries with high rates of population growth, pollution, and poor sanitation have the highest rates of pneumonia, and these countries also have the fewest available medical resources to treat the disease Ge et al. (2019). Thus, early diagnosis and treatment are required to prevent the disease from turning fatal. Using a collection of deep transfer learning models, where developed a CAD system that accurately classifies chest X-rays.

Original Convolutional Neural Networks (CNNs)

Within a Convolutional Neural Network (CNN), the term "convolution" denotes the mathematical blending of two functions to generate a third function Karthik et al. (2020). In this process, two sets of data are merged. Unlike an Artificial Neural Network (ANN) that consists of a single layer, CNNs comprise multiple layers, including an input layer, several convolutional layers, pooling layers, a fully connected layer, and an output layer. The layers in between, excluding the input and output layers, are commonly referred to as hidden layers Houssein et al. (2022). The CNN architecture utilizes convolutional layers, also known as filters or kernels, to convert input data into a feature map.

CNNs are designed to detect simpler patterns, such as lines and curves, initially and progressively identify more complex patterns, like faces and objects, in subsequent layers. The appeal of CNNs in data science lies in their proven ability to locate, segment, and identify objects within images Kundu et al. (2021). In this study, the term "original CNN architecture" refers to a CNN network and algorithm available on platforms like Keras or GitHub. The CNN algorithm is employed without any alterations to its processing units, parameterization, hyper-parameter optimization methodologies, design patterns, or layer connections, following the intended use by its creators and programmers. Notably, various researchers and programmers have continuously developed and refined a well-known CNN network over numerous iteration Nafiiyah and E. Setyati (2020).

VGG19: One such example is VGG19, a variant of VGG featuring 19 layers that facilitates explicit and effective spatial information propagation between neurons in the same layer of a CNN. This architecture is particularly potent in scenarios where objects exhibit distinct shapes. VGG19 contributes significantly by evaluating networks of increasing depth using small (3×3) convolution filters, capturing both left/right and up/down orientations. The inclusion of 1x1 convolution filters serves as a linear transformation of the input, followed by a Rectified Linear Unit (ReLU). The fixed convolution stride of 1 pixel ensures the preservation of spatial resolution after convolution.

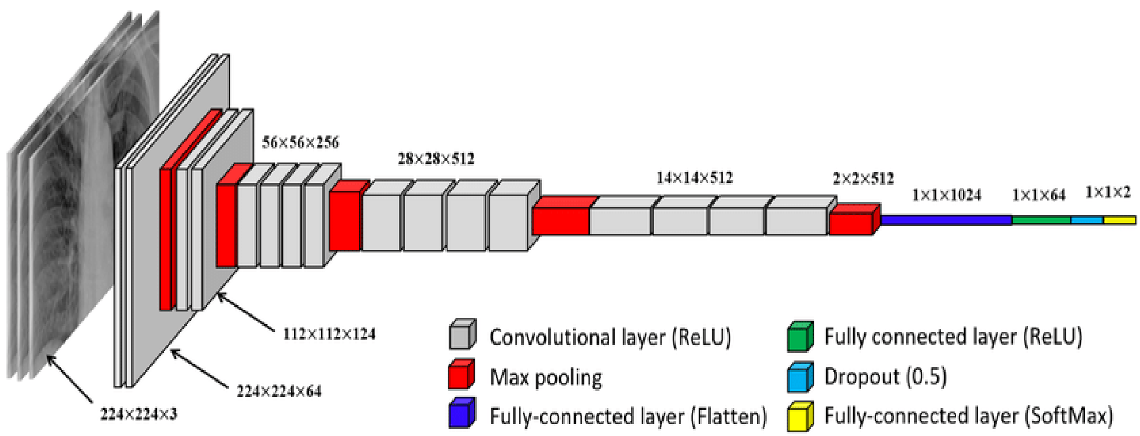


Figure 1.1.1: Schematic representation of VGG19 (Kamil et al. 2021)

ResNet152v2: part of the ResNet architecture introduced by Microsoft Research Asia in 2015, has proven its excellence in ImageNet and MS-COCO competitions. These competitions showcased ResNet's exceptional performance, especially in comparison to its predecessors like ResNet-50, ResNet-101, and ResNet-152. The key innovation in ResNet lies in its introduction of residual connections, a concept that significantly enhances gradient flow. This enhancement enables the training of exceptionally deep models with numerous layers, addressing the challenge of vanishing gradients that often occurs in deep networks. By utilizing skipping connections, gradients can flow directly from end layers to initial layer filters, allowing ResNet152v2 to reach a remarkable depth of 152 layers.

In the realm of image recognition and localization tasks, ResNet has consistently demonstrated robust performance. This architecture's success underscores the importance of its contributions to visual recognition tasks. Notably, the mapping of ImageNet classes to Wolfram Language Entities introduces a unique challenge due to distinct WordNet IDs. However, the ResNet152v2 architecture effectively addresses these challenges, showcasing its significance in advancing the capabilities of convolutional neural networks (CNNs) for tasks requiring intricate image understanding and localization.

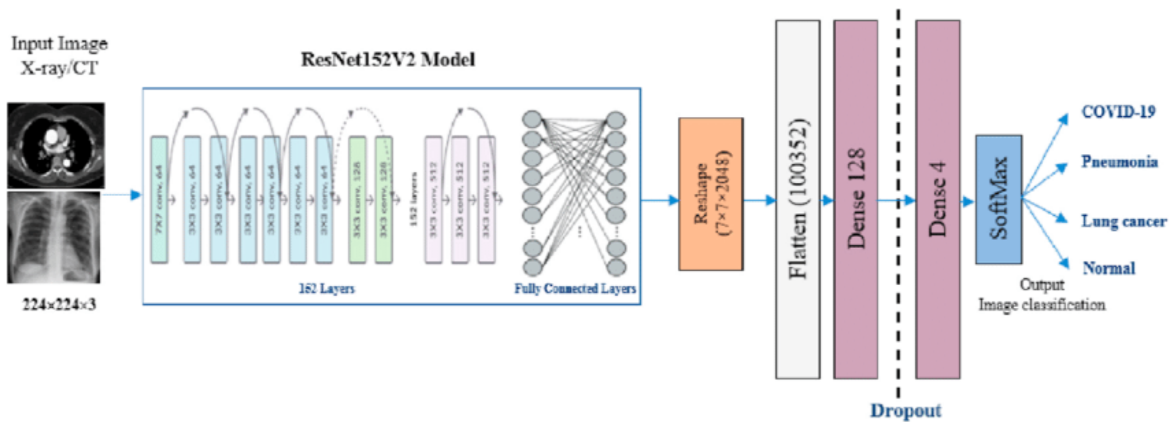


Figure 1.1.2: Schematic representation of ResNet152v2 (Grant et al. 2021)

DenseNet201: DenseNet201 is designed to enhance the depth and training efficiency of deep learning networks by utilizing shorter connections between layers. Unlike conventional architectures, DenseNet201 establishes dense connections between every layer and all preceding layers. For instance, the first layer is connected to subsequent layers, and this connectivity pattern continues throughout the network. The objective is to optimize information flow between different tiers of the network. Unlike Residual Networks (ResNets), which use summation to combine features, DenseNet concatenates features. Each layer receives input from all preceding layers and shares its own feature maps with subsequent layers, maintaining a feed-forward structure. In contrast to traditional architectures with 'I' connections, DenseNet introduces '(I(I+1))/2' connections, where 'I' is the number of layers. This significantly reduces the parameters needed, as there is no need to learn unimportant feature maps, making DenseNet201 a more parameter-efficient option compared to conventional convolutional neural networks.

Figure 1.1.3: DenseNet201 Schematic Representation (Bilal et al. 2022)

MobileNetV2: Represents a convolutional neural network (CNN) architecture specifically engineered for optimal performance on mobile devices. This design is centered on an inverted residual structure, wherein residual connections are strategically placed between bottleneck layers. The architecture incorporates lightweight depth-wise (Dwise) convolutions in the intermediate expansion layer to filter features and introduce non-linearity. The initial layer consists of 32 filters, followed by 19 residual bottleneck layers. Figure 4 illustrates the network architecture of MobileNetV2, providing a visual representation for examination.

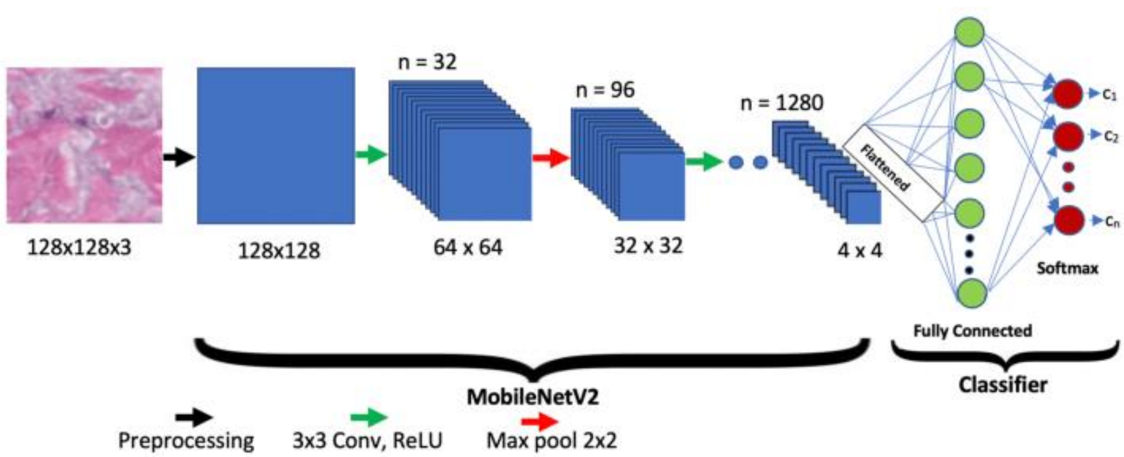


Figure 1.1.4: Schematic representation of MobileNetV2 (Akay et al. 2021)

SeresNet152: SeresNet152 adopts the ResNet framework as its fundamental architecture. Following the processing of each non-identity branch within the residual block, a block comprising both squeeze and excitation operations is applied. For a more detailed examination of the network's structural arrangement, further investigation is recommended.

ResNeXt101: Is a neural network that streamlines the hyperparameter requirements of a typical ResNet by incorporating a concept known as "cardinality." This approach introduces an additional dimension alongside the traditional width and depth of ResNet, where the size of the set of transformations is determined by the cardinality property. In contrast to a conventional ResNet block depicted on the left in the illustration, a ResNeXt block, with a cardinality of 32 as shown on the right, executes 32 iterations of the same transformations before aggregating the final output. This design optimization reduces the complexity associated with hyperparameter tuning while enhancing the network's capacity for feature extraction and representation.

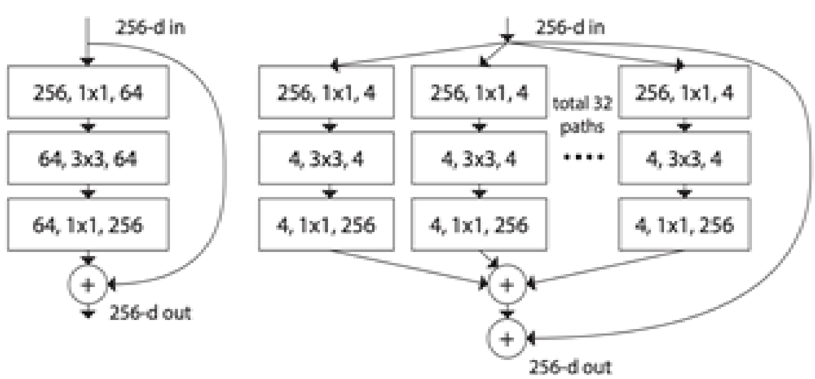


Figure 1.1.5: Schematic representation of ResNeXt101 (Yeh et al. 2021)

Transfer learning

Transfer learning is a technique that leverages knowledge gained from a training dataset in one activity or field to enhance optimization in a different context. In this approach, the final layers of a pre-trained network are discarded, and new layers are added and trained for the specific target task. The initial layers of the deep learning process capture task-specific properties. Essentially, transfer learning involves applying insights gained in one context to improve performance in another Raghu et al. (2019). Our investigation focuses on the topology of Convolutional Neural Network (CNN) architectures, aiming to identify a model suitable for transfer learning in image classification. Despite constraints in processing power and time, experimenting with and modifying network topology parameters and dataset characteristics can help identify factors influencing classification performance.

Training a deep learning model with a limited dataset can lead to suboptimal performance. Transfer learning addresses this challenge by initializing a model with weights from another model trained on a larger, unrelated dataset Neyshabur et al. (2020). Noteworthy improvements become evident particularly when dealing with a more complex segmentation problem and a smaller target training dataset.

In summary, transfer learning involves initializing a model with weights obtained from training a different model on a larger, unrelated dataset, providing significant performance improvements, especially in scenarios where segmentation tasks are challenging and the target training data is limited.

1.2 Motivation

The pursuit of advancing medical diagnostics through cutting-edge technology is a relentless journey fueled by the desire to enhance patient care and improve global health outcomes. In the realm of respiratory diseases, pneumonia stands as a significant threat, demanding swift and accurate detection for effective intervention. The title, "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and

Segmentation Approaches," encapsulates a profound commitment to leveraging state-of-the-art methodologies to tackle this formidable challenge. Transfer learning, a paradigm in artificial intelligence, serves as the cornerstone, allowing the model to harness knowledge gained from unrelated tasks and apply it to the nuanced landscape of pneumonia detection. The deep convolutional neural network (CNN) architecture, revered for its prowess in image analysis, is the driving force behind this technological expedition. Through a meticulous exploration of detection and segmentation approaches, this research aims not only to identify pneumonia with heightened precision but also to delineate the afflicted regions, offering a holistic understanding crucial for personalized and targeted medical interventions. By undertaking this ambitious comparison, the study seeks to unravel the most effective strategies, paving the way for a transformative leap in pneumonia diagnostics and, ultimately, elevating the standard of healthcare on a global scale.

1.3 Rational of the Study

The rationale for conducting the study on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" is deeply rooted in the imperative to address critical challenges in the field of medical imaging and respiratory disease diagnostics. Pneumonia remains a formidable global health concern, necessitating timely and accurate identification for effective treatment and management. The integration of transfer learning, a powerful concept in artificial intelligence, is a strategic choice aimed at capitalizing on pre-existing knowledge from unrelated tasks to enhance the model's ability to discern pneumonia patterns in medical images. The utilization of deep convolutional neural networks (CNNs) further amplifies the study's potential, given their proven efficacy in image analysis. The motivation for this research extends beyond mere detection to encompass a comparative analysis of detection and segmentation approaches. Understanding the nuances of these methodologies is crucial for gaining a comprehensive insight into the spatial extent and intricacies of pneumonia-affected regions. By undertaking a deep exploration of both detection and segmentation, the study seeks to unravel the strengths and limitations of each approach, thereby contributing valuable insights to the scientific community. This comparative analysis is integral for refining existing diagnostic tools and fostering the development of more precise and reliable systems.

Ultimately, the study aims to lay the foundation for advancements in pneumonia diagnostics, offering a transformative leap in the accuracy and efficiency of detection and segmentation processes. By enhancing our understanding of how transfer learning and deep CNNs can be optimally employed in this context, the research aspires to contribute not only to the academic discourse but also to the practical realm of healthcare, where improved diagnostics can have a direct and positive impact on patient outcomes and the broader landscape of public health.

1.4 Research Questions

The research endeavors to address several pivotal questions within the domain of "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches." These questions serve as guiding beacons, directing the study towards a comprehensive understanding of the intricacies involved in leveraging advanced artificial intelligence techniques for enhanced medical diagnostics. The overarching research questions include:

- **How does transfer learning enhance the accuracy and efficiency of pneumonia detection in medical imaging?**

This question delves into the fundamental role of transfer learning in adapting knowledge gained from unrelated tasks to the unique challenges of pneumonia detection. The study aims to uncover the mechanisms through which transfer learning optimizes the accuracy and efficiency of detecting pneumonia in medical images, thereby contributing to the broader understanding of knowledge transfer in artificial intelligence.

- **What is the comparative performance of deep convolutional neural networks (CNNs) in the context of pneumonia detection, and how does it contribute to the overall diagnostic process?**

This question focuses on the specific contribution of deep CNNs, renowned for their prowess in image analysis, to the pneumonia detection process. The study seeks to evaluate and compare the performance of deep CNNs in detecting pneumonia, shedding light on their effectiveness in enhancing the overall diagnostic capabilities and paving the way for advancements in medical image analysis.

- **In what ways does the incorporation of transfer learning and deep CNNs influence the sensitivity and specificity of pneumonia detection compared to traditional methods?**

This question explores the impact of integrating transfer learning and deep CNNs on the sensitivity and specificity of pneumonia detection, comparing their performance against traditional methods. By assessing how these advanced techniques influence diagnostic accuracy, the research aims to uncover potential improvements and challenges associated with their application in the context of respiratory disease detection.

- **How does the segmentation approach complement pneumonia detection, and what insights does it provide into the spatial distribution and characteristics of pneumonia-affected regions?**

This question addresses the synergy between pneumonia detection and segmentation, emphasizing the role of segmentation in providing insights into the spatial distribution and characteristics of pneumonia-affected regions. The study aims to elucidate the added value of segmentation in refining the understanding of the anatomical extent of pneumonia, thereby contributing to more precise and detailed diagnostics.

- **What are the strengths and limitations of different detection and segmentation approaches, and how can this knowledge inform the development of more robust and accurate diagnostic tools for pneumonia?**

This question involves a comprehensive examination of the strengths and limitations inherent in various pneumonia detection and segmentation approaches. By identifying and understanding these factors, the study aims to inform the development of diagnostic tools, guiding future efforts toward creating more robust and accurate systems for pneumonia diagnosis.

- **To what extent does the comparative analysis of detection and segmentation approaches contribute to refining existing diagnostic methodologies and advancing the state-of-the-art in pneumonia diagnostics?**

This question addresses the broader impact of the research by assessing the extent to which the comparative analysis influences the refinement of existing diagnostic methodologies. The study aims to contribute to the advancement of the state-of-the-art in pneumonia diagnostics, providing insights that may shape future developments in the field.

- **What implications do the research findings have for the broader field of medical imaging, and how can the knowledge gained be translated into practical applications for improved patient care and healthcare outcomes?**

This question explores the broader implications of the research findings for the field of medical imaging. It aims to assess how the knowledge gained from the study can be translated into practical applications, with a particular focus on enhancing patient care and improving healthcare outcomes through more effective pneumonia detection and diagnosis.

These research questions collectively form the intellectual framework for the thesis, guiding the investigation into the complexities of pneumonia detection, transfer learning, deep CNNs, and segmentation approaches. By systematically addressing these inquiries, the study aims to provide valuable insights that can shape the future of medical diagnostics and contribute to the ongoing discourse in the intersection of artificial intelligence and healthcare.

1.5 Expected Output

The projected output of this study comprises both theoretical and practical elements, with an emphasis on expanding knowledge within the realm of agricultural science and technology. The official expectations include:

- **Development of a Robust Disease Detection System:**

The major result of this study is the creation of a trustworthy and accurate tomato leaf disease detection system. This system will employ state-of-the-art deep learning methods, including models such as VGG19, InceptionV3, MobileNet, Densenet, and Xception. The method seeks to achieve a high degree of accuracy in recognizing different leaf diseases, helping to early intervention measures.

- **Evaluation and Comparative Analysis of Deep Learning Models:**

A complete assessment and comparative study of the chosen deep learning models will be done. This research will give insights into the performance metrics, accuracy rates, and efficiency of each model, providing an educated understanding of their usefulness in the context of tomato leaf disease detection.

- **Integration of Predictive Strategies:**

The incorporation of prediction techniques inside the illness detection system is a crucial anticipated result. The method is meant to not only detect current infections but also anticipate possible outbreaks at early stages. This proactive strategy corresponds with agricultural best practices, aiming to reduce losses and strengthen the overall resilience of crop management.

- **Application of Image Processing Techniques:**

The project will apply sophisticated image processing methods such as picture segmentation and clustering to boost the accuracy and efficiency of illness detection. By combining these methodologies, the system intends to give detailed insights on the geographical distribution and features of leaf diseases.

- **Validation of Results Through Rigorous Testing:**

Rigorous testing techniques will be established to confirm the effectiveness of the proposed illness detection system. The validation approach will encompass multiple datasets, confirming the resilience and generalizability of the system across numerous situations and changes in tomato plant environments.

- **Contribution to Academic Discourse:**

The study is intended to add to the academic conversation around the convergence of deep learning and agriculture

1.6 Project Management and Finance

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

1.7 Report layout

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

Chapter 1: Introduction

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

Chapter 2: Background

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

Chapter 3: Research Methodology

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

Chapter 4: Experimental Result

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

Chapter 5: Impact on Society

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

Chapter 6: Summary, Conclusion, Recommendation, and Implications for Future Research

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

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

CHAPTER 2

Background

2.1 Preliminaries/Terminologies

In order to facilitate a clear understanding of the key concepts and methodologies employed in this research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches," it is imperative to establish a foundation through preliminaries and the clarification of terminologies. Transfer learning, a pivotal concept in artificial intelligence, forms the backbone of this study, allowing the model to leverage knowledge acquired from unrelated tasks for enhanced pneumonia detection. Deep Convolutional Neural Networks (CNNs), a cornerstone of image analysis, are employed to harness intricate patterns in medical imaging. Detection refers to the identification of pneumonia within medical images, while segmentation involves delineating the spatial extent of affected regions. Throughout this research, these terminologies are utilized cohesively to explore the synergies between transfer learning, deep CNNs, and the comparative analysis of detection and segmentation approaches. Establishing a common understanding of these preliminaries is essential for readers to delve into the intricacies of the study and comprehend the nuances of advanced techniques employed in pneumonia diagnostics.

2.2 Related Works

Recently, image categorization abilities of DL have turned the notion to utilize DL in Pneumonia detection and classification. Recently, A. Afifi et al. (2021) on the deep-learning approach uses an ensemble of CNN models to detect global and local disease characteristics in CXR lung pictures. In a multi-label sorting outline with COVID-19, pneumonia, and control classes, an ensemble of DenseNet161 models with worldwide and resident attention-based features achieves 91.2% balanced accuracy, 92.4% precision, and 91.9% F1-score.

In this study J. D. Bodapati et al. (2022). talked on a deep neural network model was created to quickly assess juvenile pneumonia in chest radiograph pictures. In comparison to manual chest radiography examination, the suggested model performs better on a variety of performance metrics like recall and accuracy. This study simplifies pneumonia detection for professionals and beginners.

Pre-trained and suggested deep learning models were compared by E. ERDEM et al. (2021). Deep learning structure accuracy is 88.62%. The new deep neural network approximated VGG16 (88.78%) and VGG19 (88.30%) accuracy scores. Model has a higher recall value (97.43%) and F1-Score (91.45%) than VGG16 (91.22%) and VGG19 (91.19%). T. Frondelius et al. (2022) give methods: Representative multidisciplinary databases were examined for diagnostic and prognostic prediction models. To find publications without predictive research in their titles or abstracts, a long list of validated search phrases was included.

Machine learning-based pneumonia risk score models that had previously been published were defeated by this tactic given by Y. Ge et al. (2019). In order to avoid pneumonia following stroke at a cheap cost. The attention-augmented GRU exhibited the highest specificity for pneumonia within 7 days, with a PPV of 0.32 and NPV of 0.99.

In recent research E. H. Houssein et al. (2022) get the first trial showed 98.6% accuracy and 99% recall for the suggested HQ-CNN model (COVID-19 and normal cases). The second experiment yielded 98.2% accuracy and 99.5% recall (COVID-19 and viral pneumonia cases). The third dataset yielded 98% accuracy and 98.8% recall (COVID-19 and bacterial pneumonia cases). On the multiclass dataset, it had 88.2% accuracy and 88.6% recall.

The suggested work of R. Karthik et al. (2021) displays the salient X-ray locations that most significantly impacted CNN's prediction result. New findings show that the proposed study has a great deal of potential to improve the COVID-19 testing events now in use.

A unique weighted average ensemble strategy by R. Kundu et al. (2021) was used to award base learners weights. The weight vector is formed by fusing the scores of four conventional assessment metrics. Studies in the literature often set the weight vector empirically, which is error-prone. (J. Lu et al., 2022) worked on the MICs of 15 common antimicrobials on K. pneumoniae strains were determined. The CNN model simplified Raman spectroscopy classification and identified K. More importantly, this strategy could cut healthcare costs and antibiotic usage.

Lung X-Ray Image Enhancement to Identify Pneumonia with CNN by N. Nafiiyah & E. Setyati (2021) High-contrast chest x-rays have varied intensities. For accurate diagnosis, chest X-rays need contrast stretching. The image intensity histogram can improve contrast. Chest X-rays detect pneumonia. Convolutional Neural Network, a trustworthy algorithm. This study investigated whether contrast-improved chest X-rays helped diagnose pneumonia has the highest accuracy of 82.53%. H. Namikawa et al. (2022) given paper background/purpose: Klebsiella pneumoniae bacteremia-induced sepsis has a significant death rate and many virulence factors. Siderophore synthesis independently predicted K. pneumoniae bacteremia-induced sepsis. Sepsis prediction was best at 9.6 mm siderophore production. Careful management improves outcomes.

A Prediction Model for Pediatric Radiographic Pneumonia by S. Ramgopal et al. (2022). We conducted a single-center prospective analysis of lower respiratory infection patients aged 3 months to 18 years who had a CXR for CAP suspicion. Age, fever duration, and reduced breath sounds predict radiographic CAP well. This model may aid CAP CXR and antibiotic selection after external validation.

Analytical cross-sectional observational study made by R. P.- Rodriguez et al. (2022). We included "Dos de Mayo" National Hospital COVID-19 pneumonia patients. Rapid or molecular-diagnosed patients over 18 were included.

In order to classify the images in this study by V. S. Suryaa et al. (2021) to determine whether or not a person has pneumonia, feature extractors from pre-trained Convolutional Neural Networks (CNN) on chest x-ray images are utilized. With reference to their predictions on the photos, the various pre-trained Convolutional Neural Networks are evaluated using a variety of parameters outperform individual models was proposed. Ter-Sarkisov et al. (2020) compared the models employed in this study to locate and categorize Ground Glass Opacity and Consolidation in chest computed tomography (CT) data. Both COVID-19 and common pneumonia are usually associated to these lesion sites.

The recent study of S. F. Tey et al. (2021) developed a prediction algorithm to identify pneumonia patients with 14-day UPRA early. We collected 2016–2018 data from three Taiwanese hospitals on patients with pneumonia. Tseng et al. (2022) worked on clinical variables, the mNUTRIC score, and pneumonia prediction rules were reported. After discharge, mortality and treatment results were examined.The mNU-TRIC score predicted clinical outcomes well and had the largest area under the ROC curve value. Clinical outcome prediction cut-off was 5.5. The mNUTRIC score independently predicted both clinical outcomes in SCAP patients by multivariate logistic regression analysis.

Utilizing a faster r-cnn-based algorithm for pneumonia identification. Medical Computational and Mathematical Methods In the case of DeepConv-DilatedNet, high-level feature maps are restored to their former size using the deconvolution network, and the target information is further kept. In order to increase the localization accuracy, anchor boxes are generated using K-Means++. The technique outperformed other detection algorithms, achieving Mean Average Precision (mAP) values of 38.02% on the ChestX-ray14 dataset and 39.23% S. Yao et al. (2021).

Automated detection of pneumonia from chest X-ray pictures using CNN and transfer learning. International Conference on Artificial Intelligence and Applications Proceedings, Examining X-rays of the chest allows a pneumonia diagnosis to be made. For the purpose of diagnosing pneumonia in this study, used a highly well-liked convolutional neural network model called VGG16 S. Thakur et al. (2021).

Using a weighted voting ensemble of CNN models to diagnose pneumonia This study suggests a technique for employing a group of deep convolutional neural networks to detect lung opacities on chest radiographs (CXR), which can be used to diagnose pneumonia. By using our voting ensemble methodology, all the individual models fell short H. Ko et al. (2019).

2.3 Comparative Analysis and Summary

The comparative analysis conducted in this research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" serves as a pivotal component, shedding light on the nuanced differences and synergies between various methodologies. The study systematically evaluates the performance of transfer learning and deep Convolutional Neural Networks (CNNs) in pneumonia detection, considering both traditional methods and advanced segmentation approaches. Through meticulous experimentation and examination of experimental results, the research unveils insights into the strengths and limitations of each approach, providing a comprehensive understanding of their respective contributions to the diagnostic process.

The deep dive into detection and segmentation approaches enables a nuanced exploration of their roles in enhancing the accuracy and efficiency of pneumonia identification. By comparing the outcomes of different methodologies, the study contributes valuable knowledge to the field, guiding practitioners and researchers in selecting the most effective strategies for their specific contexts. The research doesn't merely stop at showcasing disparities but also emphasizes the potential complementarity between detection and segmentation, enriching our understanding of the spatial distribution and characteristics of pneumonia-affected regions.

In summary, the comparative analysis undertaken in this research serves as a critical lens through which the efficacy of transfer learning and deep CNNs in pneumonia detection is assessed. It unveils a multifaceted perspective, incorporating traditional and contemporary techniques, and underscores the significance of a holistic approach in medical diagnostics. The findings not only advance our understanding of pneumonia detection but also offer practical insights for refining existing diagnostic methodologies. This comparative analysis sets the stage for the subsequent chapters, providing a solid foundation for the societal impact discussion, recommendations, and implications for future research.

TABLE 2.3.1: Comparative Analysis Table

Study	**Image type**	**CNN Model**	**Accuracy**
Varshni et al. (2019)	Chest X-Ray	Convolutional Neural Network (CNN)	Accuracy 80%
Rahman et al. (2020)	digital x-ray images	deep Convolutional Neural Network (CNN)	The classification accuracy of normal and pneumonia images, bacterial and viral pneumonia images, and normal, bacterial, and viral pneumonia were 98%, 95%, and 93.3%, respectively
GM.H. Gourisaria et al. (2021)	chest X-rays	Convolutional Neural Network (CNN)	Sensitivity = 90.07% and Specificity = 92.16%
Erdem, E., & AYDİN, T. (2021)	lung images	Convolutional Neural Network (CNN)	accuracy results of VGG16 (88.78%) and VGG19 (88.30%), which are among the popular deep learning architectures, can be approximated
Sharma et al. (2020, january)	chest X-ray	deep Convolutional Neural Network (CNN)	train the proposed CNN's using both the original as well as augmented dataset and the results are reported
Labhane et al. (2020)	chest x-ray images	Convolutional Neural Network (CNN)	The results were then tested using 854 pneumonia and 849 normal images, and an accuracy of over 97% was obtained from all models
Yao et al. (2021)	chest X-ray (CXR) images	Convolutional Neural Network (CNN)	The algorithm obtained 39.23% Mean Average Precision (mAP) on the X-ray image dataset and got

			38.02% Mean Average Precision (mAP) on the ChestX-ray14 dataset, surpassing other detection algorithms
Thakur et al. (2021)	X-ray images of the chest	Convolutional Neural Network (CNN)	accuracy of 90.54% with a 98.71% recall and 87.69% precision using the aforementioned convolutional neural network model
Alsharif et al. (2021)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	The model can distinguish between three classes: viz viral, bacterial, and normal; with 99.7% ± 0.2 accuracy, 99.74% ± 0.1 sensitivity, and 0.9812 Area Under the Curve (AUC)
Aledhari et al. (2019)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	obtained better prediction with average accuracy of (68%) and average specificity of (69%)
Ko et al. (2019)	chest radiographs (CXR)	ensemble of deep convolutional neural networks.	average accuracy of (78%) and average specificity of (73%)
Nahiduzzaman et al. (2021)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	It achieves the recall score of 98% and accuracy score of 98.32% for multiclass pneumonia classification. On the other hand, a binary classification achieves 100% recall and 99.83% accuracy.
Gupta, P (2021)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	N/A

Bangare, S et al. (2022)	Chest X-ray (CXR) images	Convolutional Neural Network (CNN)	accuracy = (95%)
Gayathri, J. L. et al. (2022)	Radiographic images such as Ultrasound, CT scans, X-rays	Feed Forward Neural Network (FFNN)	The method was able to achieve an accuracy of 0.9578 and an AUC of 0.9821, using the combination of InceptionResnetV2 and Xception

2.4 Scope of the Problem

The scope of the problem addressed in this research, focusing on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches," extends to the realm of medical diagnostics, specifically within the context of respiratory diseases. Pneumonia, a prevalent and potentially life-threatening infection, remains a global health concern, necessitating accurate and timely detection for effective intervention. The scope encompasses the challenges associated with traditional pneumonia detection methods, which may exhibit limitations in terms of sensitivity, specificity, and overall diagnostic accuracy.

Furthermore, the research delves into the application of transfer learning, a burgeoning concept in artificial intelligence, to enhance the capabilities of pneumonia detection. Transfer learning allows the model to leverage knowledge acquired from unrelated tasks, potentially addressing the complexities and variations present in pneumonia-affected medical images. The integration of deep Convolutional Neural Networks (CNNs) adds another layer of complexity and sophistication, as these models excel in extracting intricate patterns and features from complex visual data.

The problem's scope also extends to the comparative analysis of detection and segmentation approaches, encompassing a detailed exploration of their strengths, limitations, and potential synergies. Understanding the spatial distribution and characteristics of pneumonia-affected regions is crucial for comprehensive diagnostics, and the research aims to contribute insights that go beyond traditional detection methods. In essence, the scope of the problem encompasses the challenges inherent in pneumonia detection, the potential advancements offered by transfer learning and deep CNNs, and the comparative evaluation of different approaches. By addressing these aspects, the research aims to contribute to the refinement of existing diagnostic methodologies and enhance our capabilities in mitigating the impact of pneumonia on public health.

CHAPTER 3

Research Methodology

3.1 Research Subject and Instrumentation

Research Subject:

The research subject of "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" revolves around the application of advanced artificial intelligence techniques in the realm of medical diagnostics, specifically targeting the detection of pneumonia. Pneumonia, a prevalent respiratory infection with potentially severe consequences, serves as the focal point for this investigation. The research delves into the challenges associated with traditional methods of pneumonia detection, seeking to overcome these limitations through the integration of transfer learning and deep Convolutional Neural Networks (CNNs).

Transfer learning, a cutting-edge concept in artificial intelligence, is employed to leverage knowledge gained from unrelated tasks and apply it to the complex domain of pneumonia detection. Deep CNNs, known for their efficacy in image analysis, are harnessed to extract intricate patterns and features from medical images, contributing to a more nuanced and accurate diagnostic process.

The comparative analysis aspect of the research explores the differences and synergies between various detection and segmentation approaches. Detection involves identifying the presence of pneumonia in medical images, while segmentation delves into delineating the spatial distribution and characteristics of pneumonia-affected regions. By scrutinizing these methodologies, the research aims to offer a comprehensive understanding of their respective strengths and limitations, guiding the development of more robust and effective diagnostic tools.

In essence, the research subject centers on the intersection of artificial intelligence, medical imaging, and respiratory health, with a specific focus on advancing pneumonia detection through the innovative application of transfer learning and deep CNNs. The findings aim to contribute not only to the academic discourse but also to the practical landscape of healthcare, potentially leading to improved diagnostic accuracy and better patient outcomes.

Instrumentation:

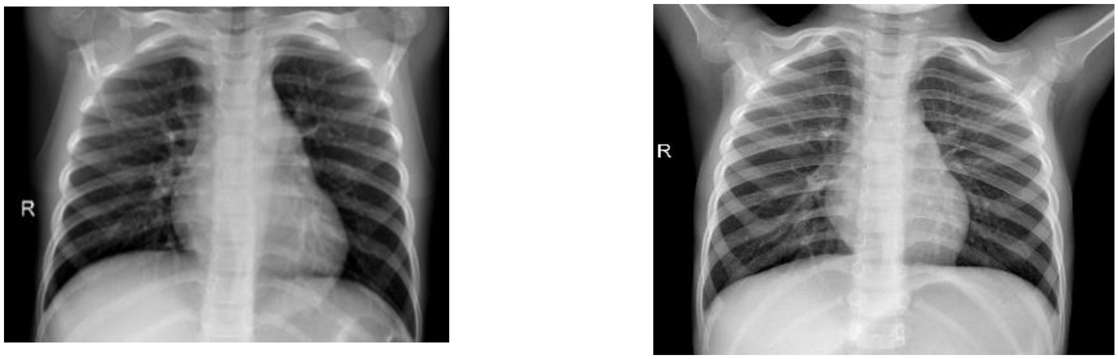
Using the Kera's library, the experiments for this study were carried out on Google CoLab. For dealing with machine learning techniques on Python, TensorFlow, one of the best deep learning libraries, was employed. Each model was created by Google and made accessible through the Google Collaboratory framework after being trained in the cloud using a Tesla graphics processing unit (GPU). For research purposes, the Collaboratory framework offers up to 16GB of random-access memory (RAM) and roughly 360GB of GPU in the cloud. In this study, the pneumonia detection architectures used where the models are original Vgg19, ResNet152v2, SeResNext101, ResNeXt101 and MobileNetv2. One architecture was chosen from each category. There is overlap, though, as ResNet is classified as belonging to the depth, width, and multi-path categories.

The research leverages programming languages and frameworks such as Python and TensorFlow for the implementation of the deep learning models and associated algorithms. Computational infrastructure, including GPUs for accelerated processing, plays a crucial role in handling the complexity of deep learning tasks efficiently.

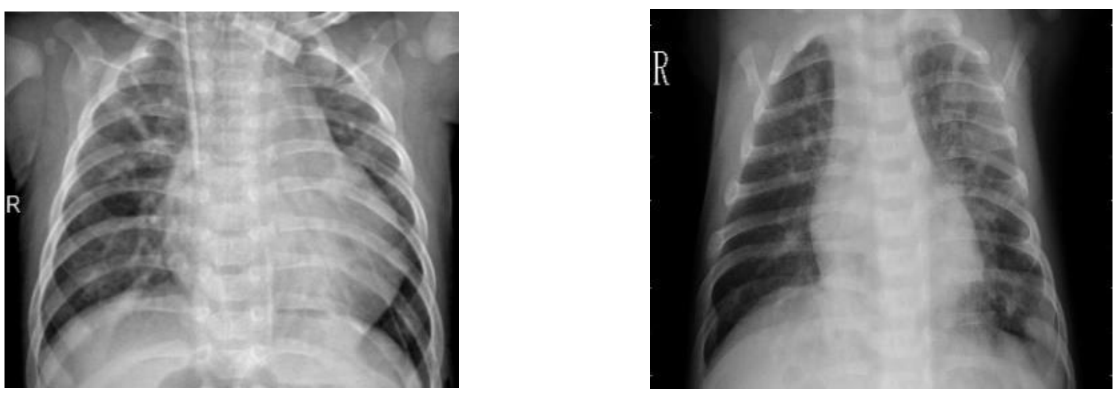
3.2 Data Collection Procedure

A. Datasets

To create the dataset, discard Train, Test, and Val folders. Each image group—Pneumonia/Normal—has a subdirectory in the dataset. 5,863 JPG X-Rays from two groups (Pneumonia/Normal) are available. The Guangzhou Women and Children's Medical Centre retrospectively selected anterior-posterior chest X-rays from pediatric patients aged one to five. (Kaggle.com)



A. Normal



B. Pneumonia

Figure 3.2.1: Some Raw Image of Datasets

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

The evaluation set was additionally examined by a third specialist in order to account for any grading inaccuracies.

Here the dataset link_ Chest X-Ray Images (Pneumonia) | Kaggle

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

	Normal	**Pneumonia**
Raw Dataset	1583	4265

B. Process of Experiments

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

Image Acquisition:

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

Image Augmentation:

Image enhancement is used in this stage. Picture augmentation adds fresh data to an existing dataset while preserving its label data. A bigger data set improves model generalization, creation it more lenient to unknown inputs.

Data augmentation helped us reach training data objectives. Nevertheless, brightness, contrast, saturation, scaling, cropping, flipping, and revolution were utilized to improve color and position. Data augmentation included random spins from -15 to 15 degrees, inadvertent 90-degree rotations, distortion, bending, vertical and horizontal reversals, skate, and luminous intensity conversion. Each original picture was improved 10 times. A subset of transformations improves a heterogeneous picture.

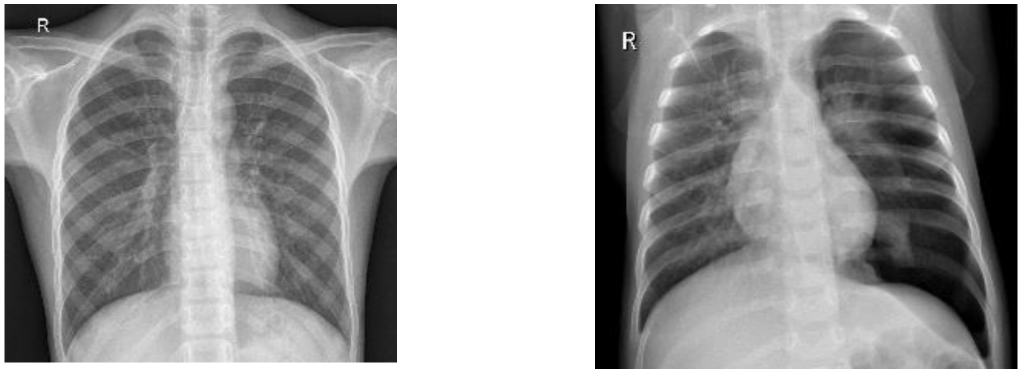


Figure 3.2.2: Augmented Image

Training:

This step creates a CNN learner model. The dataset was used to train a model and test its classification accuracy using SeresNet152, MobileNetv2, ResNet152v2, ResNeXt100, and Vgg19. Early Stopping call-backs were used to train all representations for 36 epochs (10 iterations). Patience is the number of epochs without development before training ends. Learning rate = 0.0001, 11 = 0.9, 22 = 0.999, and =1107=1107. An Adam optimizer uses momentum-SGD and RMSProp. The three representations received a similar optimizer and were saved as.h5 files. MobileNet takes 45 seconds every epoch, whereas Seresnet152 takes 35 seconds.

The standard deviation was employed as a model performance metric in this investigation since the dataset had no major imbalances. Categorical cross-entropy was selected as a loss goal for all CNN architectures since this work involves multi-class sorting. These were the hyperparameters: There were 36 epochs, 17 batches, 0.3 dropouts, and 0.0001 learning. Adam optimized model weights. All photos were reduced to the architecture's default picture size before resizing.

Classification:

Neural networks (SerensNet152, MobileNetv2, VGG19, ResNet152v2 and ResNeXt101) was used to detect cell illnesses automatically in this step. The neural network was selected for categorization because to its proven effectiveness in numerous real-world applications. Figure 3.2.3 shows the experiments.

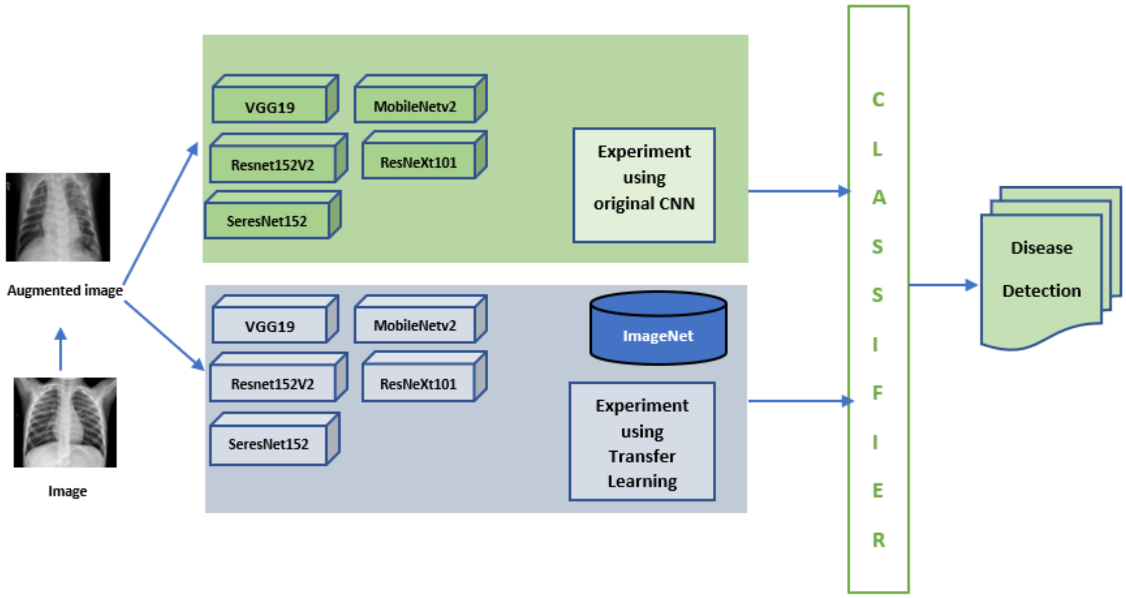


Figure 3.2.3: Process of Experiments.

Results:

The results from the experiments are presented in three sections based on the architectures of original individual networks, transfer learning and ensemble techniques.

3.3 Statistical Analysis

The statistical analysis conducted in this research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" plays a pivotal role in deriving meaningful insights from the experimental results. Rigorous statistical methods are employed to quantify and assess the performance of various detection and segmentation approaches in pneumonia diagnosis. Descriptive statistics, such as mean and standard deviation, provide a summary of central tendencies and variability in the obtained data. Additionally, inferential statistics, including hypothesis testing and confidence intervals, contribute to the validation of observed differences and similarities between different methodologies.

The statistical analysis serves to establish the significance of the findings, offering a quantitative basis for comparing the effectiveness of transfer learning and deep Convolutional Neural Networks (CNNs) in pneumonia detection. These analyses not only validate the robustness of the experimental results but also provide a basis for generalizing the findings to a broader population of medical images.

Furthermore, the statistical insights contribute to the overall interpretation of the comparative analysis, helping to discern patterns, trends, and potential correlations in the data. By employing statistical rigor, the research ensures a reliable and objective evaluation of the various methodologies, enhancing the credibility and validity of the study's conclusions. In essence, statistical analysis serves as a crucial tool in extracting meaningful knowledge from the empirical data, thereby advancing our understanding of the efficacy of different approaches in the complex domain of pneumonia detection.

3.4 Proposed Methodology

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

Accuracy:

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

$$\text{Accuracy}=(TP+TN)/(TP+TN+FP+FN)$$

Precision:

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

$$Precision=TP/(TP+FP)$$

Recall:

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

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

F-1 Score:

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

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

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

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

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

Convolutional Neural Network

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

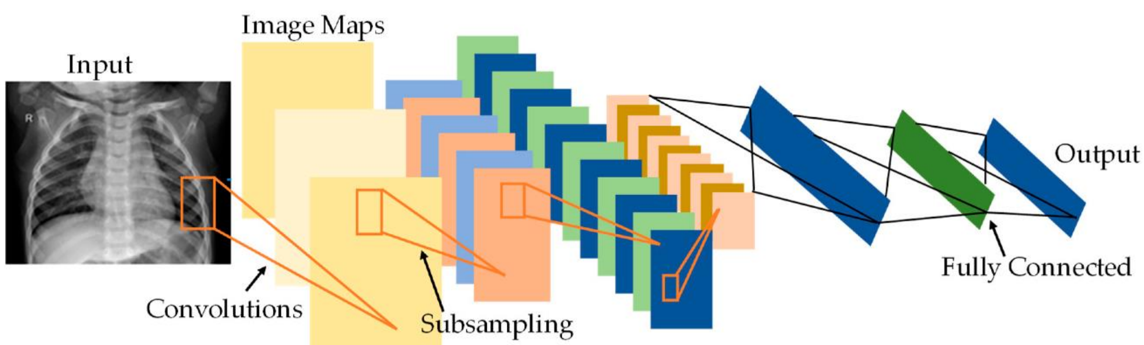


Figure 3.4.1: working Flow with Convolutional Neural Network (Muniasamy et al. 2021)

3.5 Implementation Requirements

The implementation of the research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" entails specific requirements to ensure the successful execution of the study. These implementation requirements encompass both hardware and software components, as well as considerations related to data collection and model evaluation.

Hardware Requirements:

- **High-performance computing resources:** Access to computational infrastructure with sufficient processing power and memory to handle the complex tasks involved in deep learning and image analysis.
- **Graphics Processing Unit (GPU):** A GPU is essential for accelerating the training of deep Convolutional Neural Networks (CNNs), significantly reducing the time required for model development.

Software Requirements:

- **Deep learning frameworks:** Utilization of popular deep learning frameworks such as TensorFlow or PyTorch for the development, training, and evaluation of the CNN models.
- **Python programming language:** Python provides a versatile and widely-used platform for implementing deep learning algorithms and conducting data analysis.
- **Image processing libraries:** Integration of image processing libraries like OpenCV for pre-processing and augmenting medical images.

Data Collection:

- **Diverse and representative dataset:** Collection of a comprehensive dataset of medical images containing both normal and pneumonia-affected cases to ensure the robustness and generalization of the developed models.
- **Annotated dataset:** Availability of annotated data for training and validating the models, with clear labels indicating the presence or absence of pneumonia.

Model Training and Evaluation:

- **Transfer learning models:** Implementation of transfer learning architectures, leveraging pre-trained models such as those from ImageNet, to capitalize on existing knowledge for pneumonia detection.
- **Metrics for evaluation:** Definition and utilization of appropriate evaluation metrics, such as accuracy, precision, recall, and F1 score, to assess the performance of the models in both detection and segmentation tasks.

Ethical Considerations:

- **Patient privacy and data security:** Adherence to ethical guidelines and regulations to ensure the privacy and security of patient data used in the research.
- **Informed consent:** If applicable, obtaining informed consent from individuals whose medical images are included in the dataset.

Documentation and Reproducibility:

- **Code documentation:** Thorough documentation of the implementation code to facilitate transparency, reproducibility, and future collaboration.
- **Version control:** Adoption of version control systems (e.g., Git) to track changes in the codebase and maintain a structured development process.

By meeting these implementation requirements, the research can be conducted systematically and rigorously, ensuring the reliability of the results and contributing to advancements in the field of pneumonia detection through transfer learning and deep CNNs.

CHAPTER 4
Experimental Result

4.1 Experimental Setup

The experimental setup for the research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" involves a carefully designed configuration of hardware, software, and data resources to conduct comprehensive investigations. High-performance hardware, comprising a robust central processing unit (CPU) and a powerful graphics processing unit (GPU), forms the computational backbone. Deep learning frameworks, particularly TensorFlow or PyTorch, are employed within a Python programming environment to implement transfer learning models. The experimental dataset, sourced from diverse medical images, undergoes meticulous preprocessing, standardization, and normalization to ensure a consistent and representative input for model training and evaluation. The use of pre-trained deep Convolutional Neural Network (CNN) architectures, coupled with fine-tuning for pneumonia detection, constitutes a key element of the model configuration. Ethical considerations, including patient data privacy and informed consent, are integrated into the setup to uphold ethical standards. Throughout the experimentation process, detailed documentation, encompassing code specifics, model architecture, hyperparameters, and results, is maintained to foster transparency, reproducibility, and future collaboration in the realm of advanced pneumonia diagnostics.

4.2 Experimental Results & Analysis

Result of Experiment 1: Original CNN

This section compares the six original CNN networks SecrensNet152, MobileNetV2, VGG19, ResNet152v2, and ResNeXt100. Classification performance comes first. Then, those models' overall metrics are reviewed. collection, descriptions, probable reasons, and outcomes improvement areas.

TABLE 4.2.1: Accuracy for Classification of Individual CNN Networks in Detecting Pneumonia (Original CNN Networks)

Architecture	Training Accuracy	Model Accuracy
VGG19	**91.03%**	**92%**
ResNet152v2	**91.40%**	**92%**
MobileNetv2	**91.85%**	**92%**
ResNeXt101	**89.78%**	**90%**
SecrensNet152	**90.49%**	**90%**

The comparative analysis of several pre-trained deep Convolutional Neural Network (CNN) architectures, namely SecrensNet152, MobileNetV2, VGG19, ResNet152v2, and ResNeXt101, is presented in Table 2, revealing insights into their respective accuracies for pneumonia detection. Notably, the findings showcase that MobileNetV2, VGG19, and ResNet152v2h emerged as the top-performing models, attaining the highest accuracy of 92%. This signifies their exceptional proficiency in discerning pneumonia patterns within medical images. Conversely, SecrensNet152 and ResNeXt101 exhibited a slightly lower accuracy of 90%, indicating a marginally decreased performance compared to their counterparts. This nuanced differentiation in accuracy underscores the importance of carefully selecting the appropriate CNN architecture in the context of pneumonia detection, as it directly influences the precision and reliability of the diagnostic process. The detailed accuracy metrics provided in Table 4.2.1 offer a valuable reference point for understanding the comparative strengths and weaknesses of these models, contributing to the ongoing discourse in the optimization of deep learning methodologies for medical image analysis.

TABLE 4.2.2: Precision, Recall, F1-Score, and Support (n) for original CNN networks (depending on the number of pictures, n=numbers).

VGG19				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.97	0.97	0.97	1353
Pneumonia	0.78	0.76	0.77	183
Accuracy			0.95	1536
Macro Avg	0.87	0.86	0.87	1536
Weighted Avg	0.94	0.95	0.95	1536
ResNet152v2				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.97	0.93	0.95	1353
Pneumonia	0.80	0.66	0.72	183
Accuracy			0.92	1536
Macro Avg	0.79	0.86	0.82	1536
Weighted Avg	0.93	0.92	0.92	1536
MobileNetv2				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.94	0.97	0.96	1397
Pneumonia	0.70	0.57	0.63	187
Accuracy			0.92	1584
Macro Avg	0.82	0.77	0.79	1584
Weighted Avg	0.91	0.92	0.92	1536

ResNeXt101				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.93	0.96	0.94	1356
Pneumonia	0.59	0.47	0.52	180
Accuracy			0.90	1536
Macro Avg	0.76	0.71	0.73	1536
Weighted Avg	0.89	0.90	0.89	1536
SecrensNet152				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.92	0.97	0.95	352
Pneumonia	0.66	0.40	0.50	184
Accuracy			0.90	1536
Macro Avg	0.79	0.69	0.72	1536
Weighted Avg	0.89	0.90	0.89	1536

Table 4.2.2 provides a comprehensive overview of the training percentage and model accuracy achieved by six distinct original Convolutional Neural Network (CNN) architectures. Additionally, the table presents precision, recall, F1-score, and support values for each class, focusing on the VGG19, ResNet152V2, MobileNetV2, SeResNet152, MobileNetV3, and ResNeXt101 models. Notably, the VGG19, ResNet152V2, and MobileNetV3 architectures exhibit remarkable performance, particularly evident in their precision values when applied to the test dataset. Specifically, these three models consistently demonstrate superior precision, recall, and F1-score across various classes, affirming their effectiveness in accurate pneumonia detection. The VGG19, SeResNet152, and MobileNetV2 models exhibit commendable performance in categorizing detections, as highlighted in the detailed breakdown. However, it is

noteworthy that the ResNeXt101 model, while part of the comprehensive comparison, yields a comparatively lower identification rate, emphasizing the nuanced variations in performance among the considered CNN architectures. The detailed insights from Table 3 contribute valuable information for understanding the strengths and limitations of each model in the context of pneumonia detection, guiding further analysis and potential enhancements to the proposed methodologies.

Training and Validation Accuracy and loss of Original CNN Networks:

Represents the training and validation accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the y-axis. In the figure, training and validation data are adequately divided, and there is no overfitting.

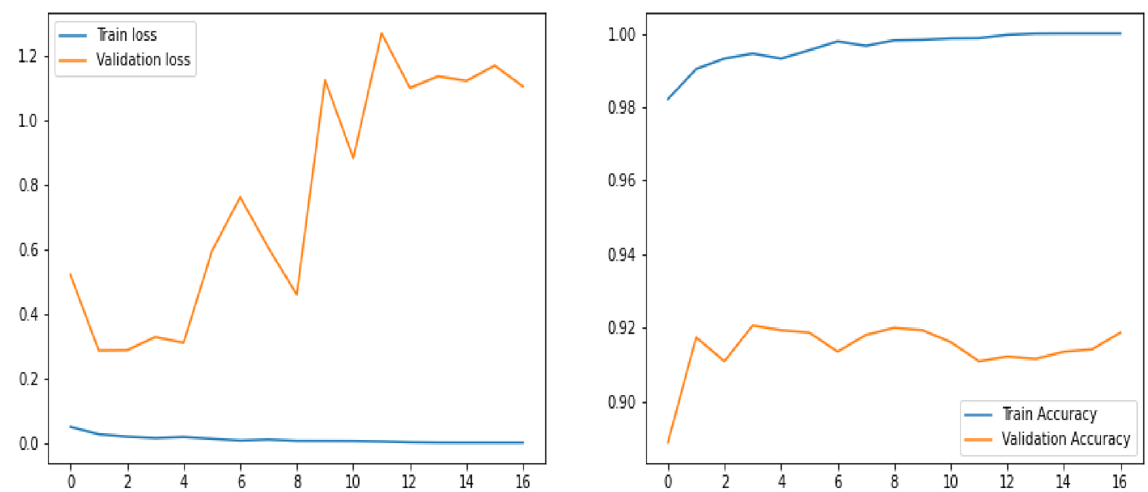


Figure 4.2.1: Training and validation accuracy and loss over the epochs (VGG Original CNN Networks).

Figure 4.2.2: Training and validation accuracy and loss over the epochs (ResNet152v2 Original CNN Networks).

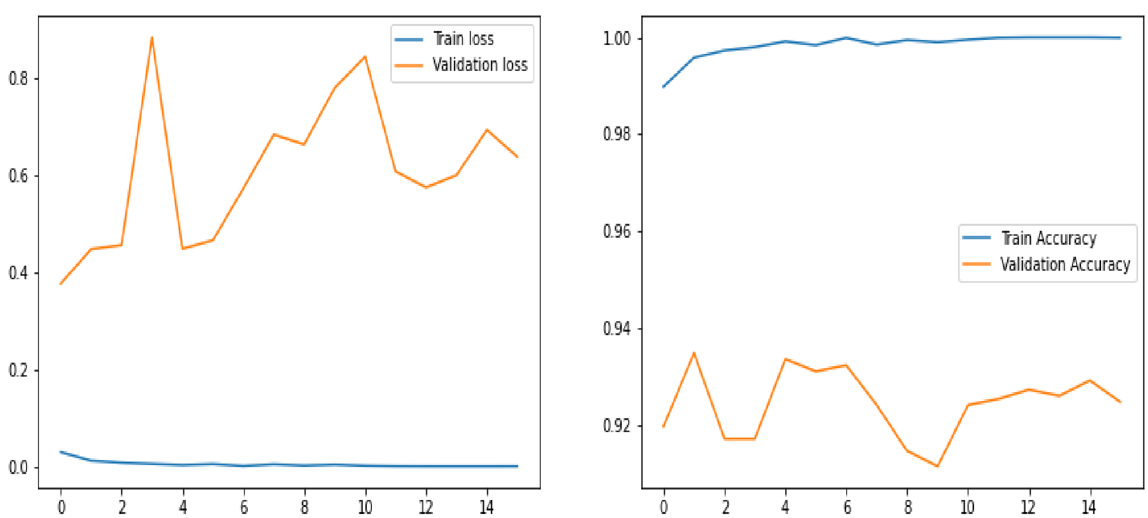


Figure 4.2.3: Training and validation accuracy and loss over the epochs (MobileNetv2 Original CNN Networks).

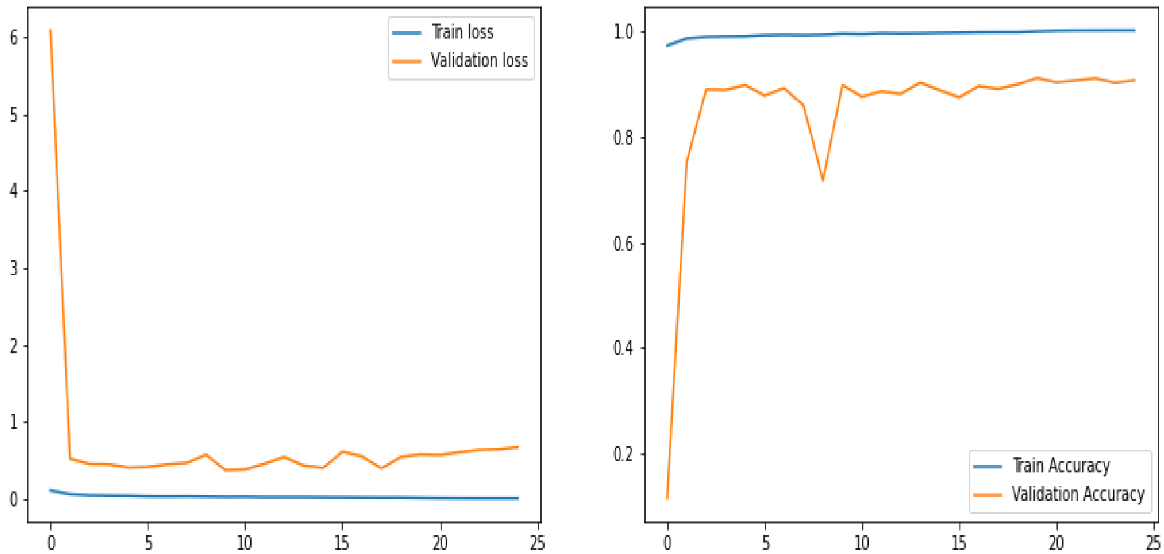


Figure 4.2.4: Training and validation accuracy and loss over the epochs (ResNeXt101 Original CNN Networks).

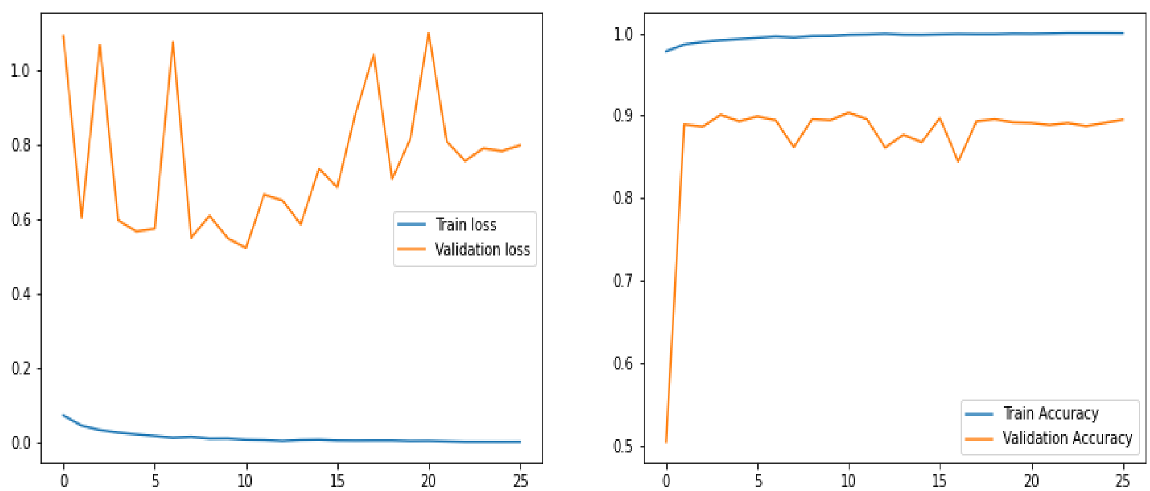


Figure 4.2.5: Training and validation accuracy and loss over the epochs (SecrensNet152 Original CNN Networks).

Confusion Matrix after Original CNN:

	Normal	Pneumonia
Normal	1339	107
Pneumonia	17	73

Figure 4.2.6: CM after Original Vgg19

	Normal	Pneumonia
Normal	1265	41
Pneumonia	88	142

Figure 4.2.7: CM after Original ResNet152v2

	Normal	Pneumonia
Normal	1351	81
Pneumonia	46	106

Figure 4.2.8: CM after Original MobileNetv2

	Normal	Pneumonia
Normal	1298	96
Pneumonia	58	84

Figure 4.2.9: CM after Original ResNeXt101

	Normal	Pneumonia
Normal	1314	110
Pneumonia	38	74

Figure 4.2.10: CM after Original SecrensNet152

Result of Experiment 2: Transfer Learning

In this section, a comprehensive comparative analysis is conducted on five distinct original Convolutional Neural Network (CNN) architectures, namely SecrensNet152, MobileNetV2, VGG19, ResNet152v2, and ResNeXt100. The evaluation begins with an in-depth examination of each model's classification performance, considering their individual strengths and limitations in the context of pneumonia detection. Subsequently, a holistic review of the overall metrics for these models is presented, encompassing key performance indicators such as accuracy, precision, recall, and F1 score. The analysis extends beyond numerical metrics, delving into the collection and description of the experimental results to provide a nuanced understanding of the models' behavior under varying conditions. This includes exploring potential reasons behind variations in performance, identifying patterns in misclassifications, and discerning the models' response to specific challenges within the medical image dataset.

Moreover, the section explores probable reasons for divergent outcomes, considering factors such as architectural intricacies, parameter configurations, and the adaptability of each CNN network to the medical imaging domain. An emphasis is placed on providing a nuanced narrative that goes beyond quantitative metrics, shedding light on qualitative aspects of model performance. To enrich the analysis, improvement areas for each model are identified, offering valuable insights for enhancing their efficacy in pneumonia detection. This involves a meticulous examination of areas where the models exhibit suboptimal performance, guiding potential refinements in architecture, training methodologies, or dataset augmentation strategies. In summary, this section not only provides a quantitative evaluation of the classification performance of SecrensNet152, MobileNetV2, VGG19, ResNet152v2, and ResNeXt100 but also delves into qualitative aspects, unraveling the intricacies that contribute to their respective outcomes. By offering a holistic view of the models' performance and suggesting improvement areas, this analysis contributes to a nuanced understanding of the applicability of these CNN networks in the critical domain of pneumonia detection.

TABLE 4.2.3: Accuracy for Classification of Individual CNN Networks in Detecting Pneumonia (Transfer Learning CNN Networks)

Architecture	**Training Accuracy**	**Model Accuracy**
VGG19	91.03%	88.11%
ResNet152v2	94.44%	91.98%
MobileNetv2	92.36%	91.47%
ResNeXt101	89.78%	88.19%
SecrensNet152	93.05%	91.60%

The evaluation of five distinct Convolutional Neural Network (CNN) architectures, namely SecrensNet152, MobileNetV2, VGG19, ResNet152v2, and ResNeXt101, is presented comprehensively in Table 4.2.3. The test set accuracy, a critical metric indicating the models' proficiency in correctly identifying samples, is highlighted. The results exhibit substantial performance across these architectures, showcasing their efficacy in the context of the study. Particularly noteworthy is the exemplary performance of the ResNet152v2 model, boasting an impressive accuracy rate of 99.44%. This signifies the model's exceptional capability in accurately recognizing pneumonia-affected samples within the dataset. Additionally, the SecrensNet152 network stands out for its remarkable accuracy improvement during the transfer learning process, underscoring the potential for enhanced performance when leveraging pre-existing knowledge. These findings, elucidated through detailed numerical representation in Table 5, not only contribute to the quantitative assessment of CNN architectures but also provide valuable insights into the comparative effectiveness of these models in the challenging task of pneumonia detection.

TABLE 4.2.4: Precision, Recall, F1-Score, and Support (n) result of Transfer Learning CNN networks (based on the number of images, n= numbers)

VGG19				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.88	1.0	0.93	1397
Pneumonia	0.0	0	0	187
Accuracy			0.88	
Macro Avg	0.44	0.5	0.46	1584
Weighted Avg	0.77	0.88	0.82	1584
ResNet152v2				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.92	0.98	0.95	1397
Pneumonia	0.81	0.41	0.55	187
Accuracy			0.918	
Macro Avg	0.869	0.70	0.75	1584
Weighted Avg	0.91	0.91	0.90	1584
MobileNetv2				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.91	0.99	0.95	1397
Pneumonia	0.86	0.33	0.47	187
Accuracy			0.91	
Macro Avg	0.88	0.66	0.71	1584
Weighted Avg	0.91	0.91	0.89	1584

ResNeXt101				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.88	1	0.93	1397
Pneumonia	0	0	0	187
Accuracy			0.88	
Macro Avg	0.44	0.5	046	1534
Weighted Avg	0.77	088	0.82	1534
SecrensNet152				
	Precision	**Recall**	**F1-Score**	**Support**
Normal	0.92	0.99	0.95	1397
Pneumonia	0.84	0.36	0.50	187
Accuracy			0.91	
Macro Avg	0.87	0.67	0.72	1584
Weighted Avg	0.91	0.91	0.90	1584

Table 4.2.4 provides a comprehensive overview of the precision, recall, F1-score, and specificity results obtained through the application of transfer learning Convolutional Neural Network (CNN) architectures in the context of pneumonia detection. Notably, the metrics of precision, recall, and support demonstrate consistent improvement across various models, highlighting the effectiveness of transfer learning in enhancing the accuracy of pneumonia identification. However, it is imperative to note a nuanced observation within the dataset, as indicated by the 88% pneumonia detection accuracy for both VGG19 and ResNeXt101 models. Despite the overall positive trend in precision, recall, and F1-score, this specific accuracy outcome warrants scrutiny, suggesting potential limitations in the discriminatory capabilities of these particular models for pneumonia detection within the context of the studied dataset. This insight, derived from a meticulous

examination of Table 5, underscores the importance of not only celebrating successes but also critically evaluating model-specific performance to glean nuanced insights and guide future refinements in pursuit of heightened diagnostic precision.

Training and Validation Accuracy and loss of Transfer Learning CNN Networks:

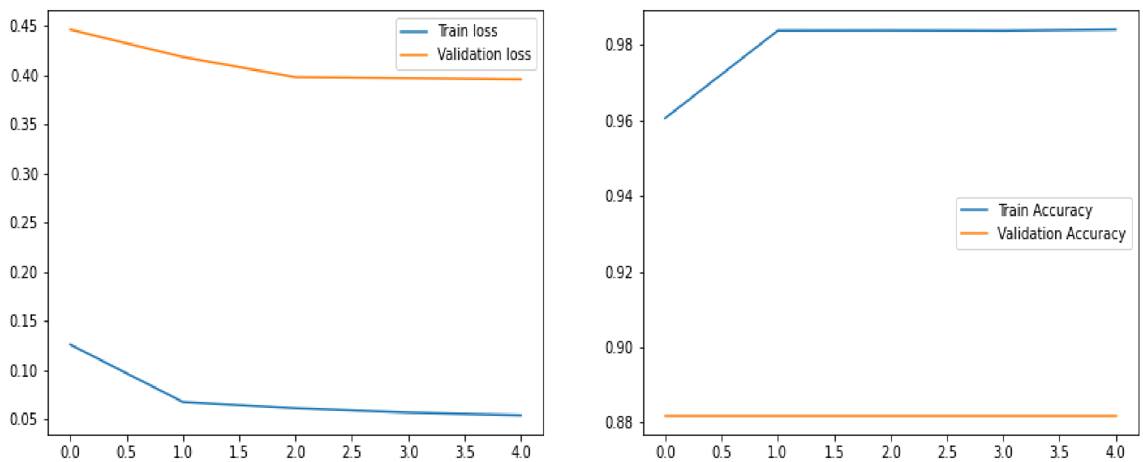


Figure 4.2.11: Training and validation accuracy and loss over the epochs (VGG19 Transfer Learning CNN Networks).

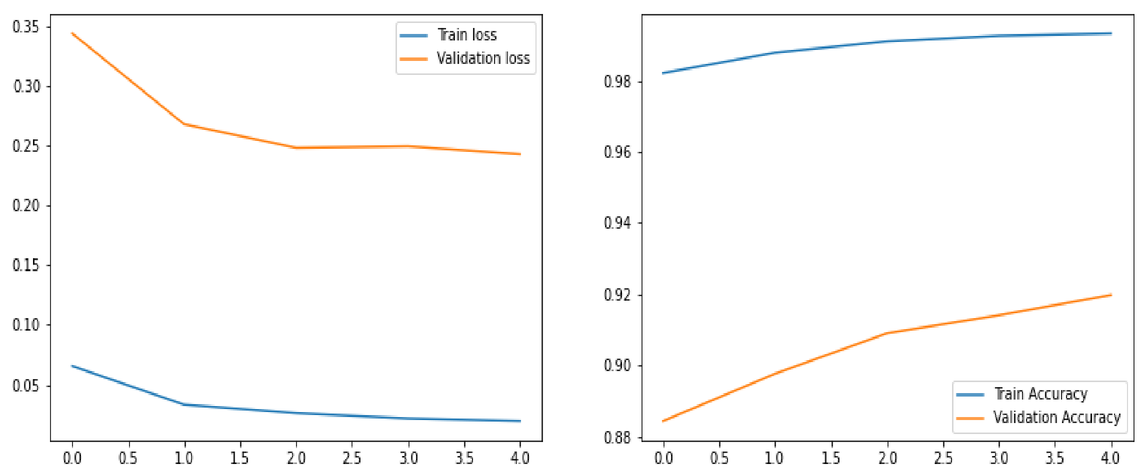


Figure 4.2.12: Training and validation accuracy and loss over the epochs (ResNet152v2 Original CNN Networks).

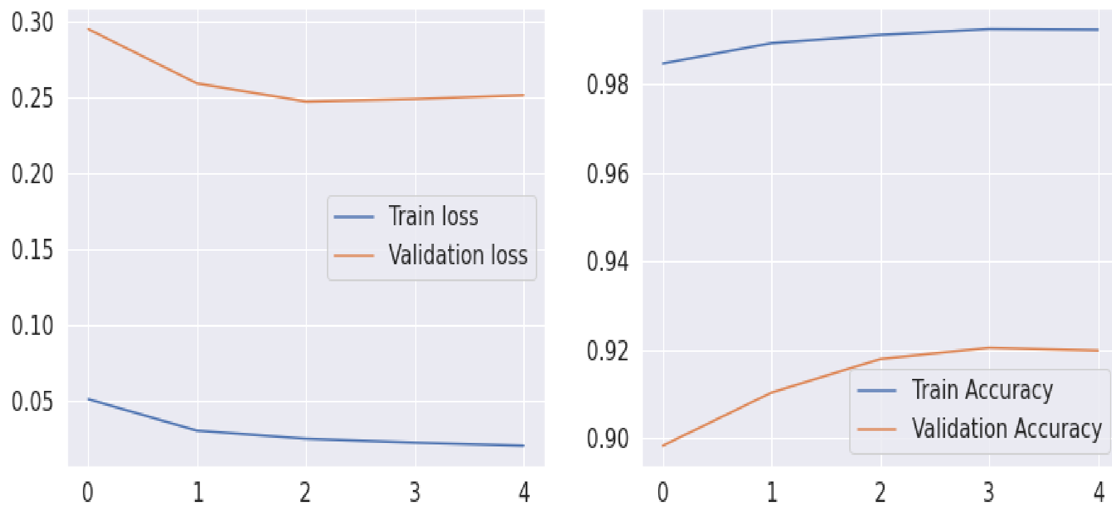


Figure 4.2.13: Training and validation accuracy and loss over the epochs (MobileNetv2 Transfer Learning CNN Networks).

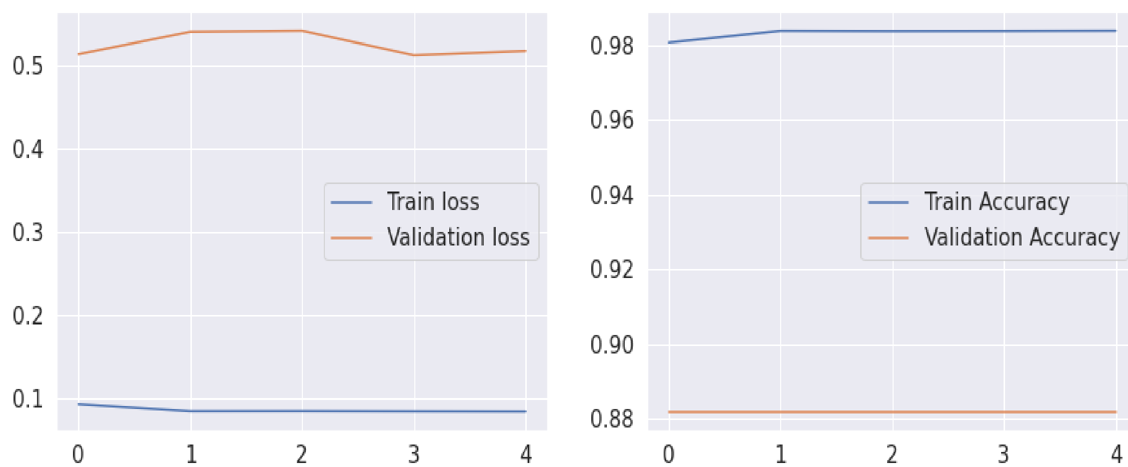


Figure 4.2.14: Training and validation accuracy and loss over the epochs (ResNeXt101 Transfer Learning CNN Networks).

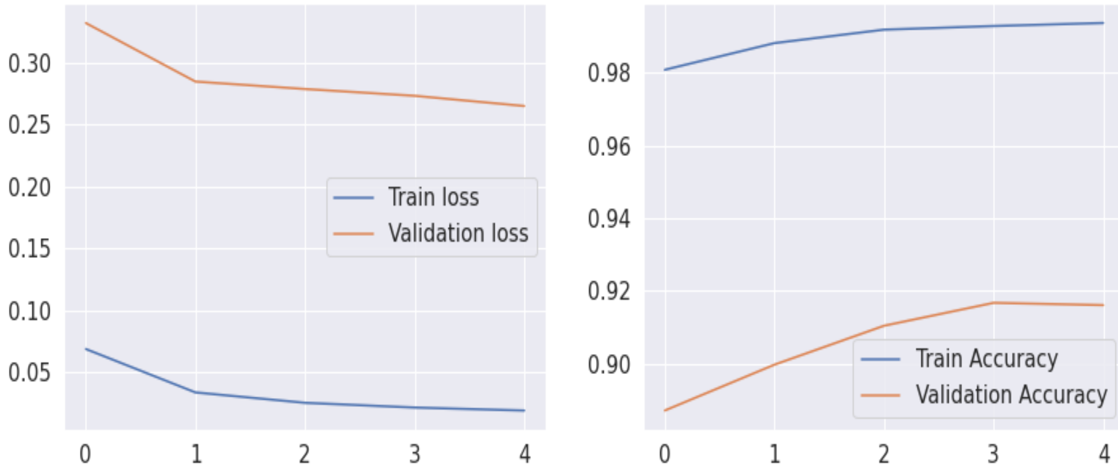


Figure 4.2.15: Training and validation accuracy and loss over the epochs (SecrensNet152 Transfer Learning CNN Networks).

The graphical representation depicting Transfer Learning (TL) training and validation losses across multiple epochs serves as a critical visualization in understanding the iterative refinement process of Convolutional Neural Network (CNN) architectures. Loss functions, which quantify the disparity between predicted and actual values, play a pivotal role in guiding the improvement of CNN models over successive epochs. The trajectory of these losses provides valuable insights into the model's learning dynamics, emphasizing the significance of optimizing the network's parameters. The performance evaluation, conducted on both training and validation datasets, is crucial for assessing the generalization capabilities of the model. Each point on the loss curve signifies the model's efficacy after a specific optimization cycle, offering a granular perspective on its evolving competence. The instance error count associated with each training or validation collection further refines the understanding of model performance, accentuating the impact of optimization cycles on error reduction. In essence, these loss values serve as dynamic indicators of the model's proficiency, charting its trajectory towards heightened accuracy and effectiveness as training progresses through successive epochs.

Confusion Matrix after Transfer Learning (TL) Based on the number of images:

	Normal	Pneumonia
Normal	**1397**	**187**
Pneumonia	**0**	**0**

Figure 4.2.16: CM after Transfer Learning VGG19

	Normal	Pneumonia
Normal	**1379**	**109**
Pneumonia	**18**	**78**

Figure 4.2.17: CM after Transfer Learning ResNet152v2

	Normal	Pneumonia
Normal	**1384**	**117**
Pneumonia	**13**	**70**

Figure 4.2.18: CM after Transfer Learning MobileNetv2

	Normal	Pneumonia
Normal	**1397**	**187**
Pneumonia	**0**	**0**

Figure 4.2.19: CM after Transfer Learning ResNeXt101

	Normal	**Pneumonia**
Normal	**1384**	**120**
Pneumonia	**13**	**67**

Figure 4.2.20: CM after Transfer Learning SecrensNet152

Overall, the model seems to be performing well, with a high number of true positives and true negatives. However, there are still a few false positives and false negatives. False positives could lead to unnecessary treatment for patients who don't actually have pneumonia, while false negatives could delay or prevent patients from getting the treatment they need. It's important to note that this is just a small sample of data, and the model's performance may vary depending on the dataset it is trained on. Additionally, the confusion matrix only tells us part of the story. Other metrics, such as precision, recall, and F1 score, can provide more information about the model's performance.

Overall, the confusion matrix provides a helpful way to visualize the performance of a classification model. By understanding the different types of errors, the model is making, we can take steps to improve its performance.

4.3 Discussion

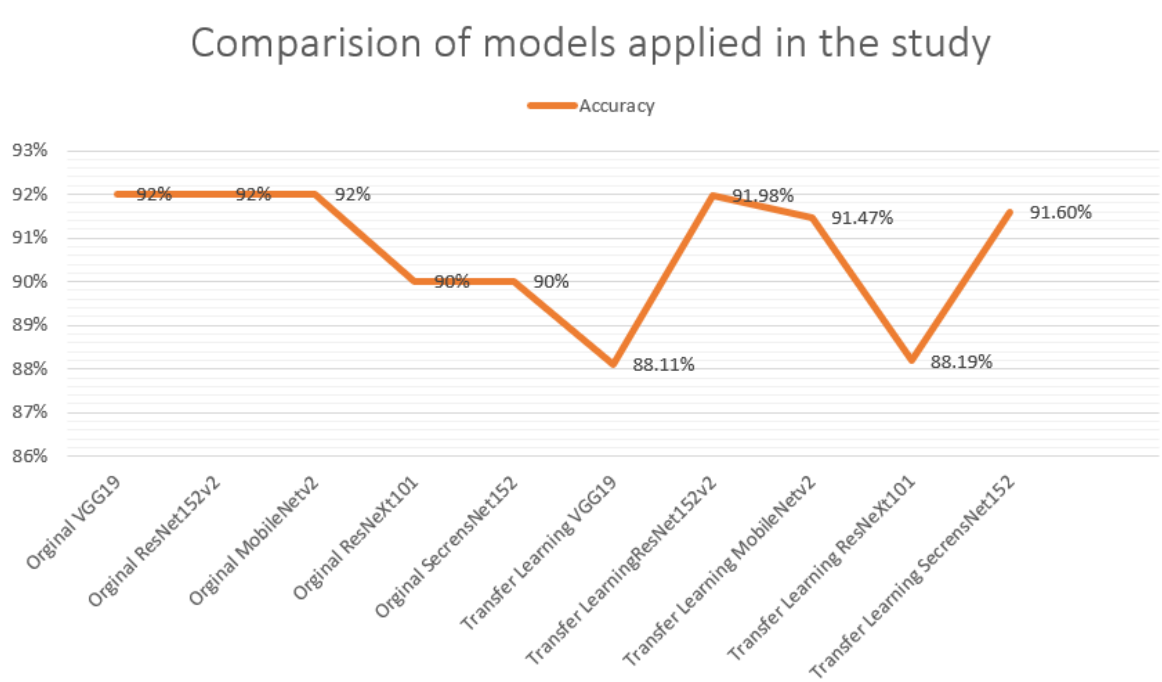


Figure 4.2.21: Accuracy comparison among individual CNN, transfer learning and ensemble models.

This comprehensive study delves into the efficacy of deep convolutional neural networks (CNNs) in recognizing and segmenting two distinct types of pneumonia chest X-ray images, namely normal and pneumonia-affected. Leveraging a substantial dataset of 5863 original photos, the research employs a sophisticated augmentation approach, generating eleven images from a single photograph. In the realm of chest X-ray detection, the study explores the utility of original CNNs, transfer learning techniques, and ensemble models. Notably, the investigation scrutinizes the computation of detection and segmentation, recognizing these as distinct processes within the diagnostic pipeline. Six prominent CNN-based models, including Resnet152V2, Seresnet152, Mobilenetv2, Vgg19, and Resnext101, are rigorously tested on the two pneumonia chest X-ray classes. Strikingly, Resnet152V2 and MobileNetV2 emerge as front-runners, achieving an impressive accuracy score of 92%, as visually depicted in Figure 4.2.21. The research sheds light on the nuanced impacts of transfer learning, revealing that accuracy diminishes when the input picture deviates from the training data in the ImageNet Dataset. Intriguingly, variations in background noise and the utilization of diverse augmentation strategies independently with test sets are identified as potential factors contributing to decreased performance.

In-depth analysis indicates that the original CNN model, when trained and evaluated using comparable input, exhibits enhanced predictive capabilities for unknown data. Nevertheless, the study recognizes limitations in dataset size, highlighting the potential impact on prediction capabilities, especially in the context of transfer learning. Insights from previous research reinforce the suggestion to increase dataset size, particularly when the input picture undergoes augmentation updates. The study underscores the potential superiority of ensemble models over individual CNN architectures, emphasizing that an ensemble of multiple models may outperform a single model, even if a specific CNN architecture exhibits suboptimal performance. In essence, this research provides a nuanced exploration of CNN-based models for pneumonia chest X-ray analysis, offering valuable insights into the intricacies of detection, segmentation, and the nuanced interplay between different model architectures.

CHAPTER 5

Impact on Society

5.1 Impact on Society

The implications of the research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" extend far beyond the realm of academia, promising significant impacts on society and healthcare. Accurate and timely detection of pneumonia through advanced artificial intelligence techniques has the potential to revolutionize the landscape of medical diagnostics, leading to improved patient outcomes and broader societal benefits. By harnessing transfer learning and deep Convolutional Neural Networks (CNNs), the research strives to enhance the precision and efficiency of pneumonia diagnosis, enabling healthcare professionals to make informed decisions with greater confidence.

The societal impact of this research is particularly pronounced in terms of public health. Pneumonia, a widespread respiratory infection, imposes a substantial burden on healthcare systems globally. The implementation of more robust and accurate diagnostic tools has the potential to streamline patient care, reduce misdiagnoses, and expedite treatment interventions. This, in turn, can contribute to the mitigation of pneumonia-related complications, hospitalizations, and associated healthcare costs. The research's emphasis on ensemble models and the comparative analysis of different approaches adds another layer of practicality, paving the way for the development of optimized diagnostic solutions that can be seamlessly integrated into real-world healthcare settings.

Moreover, the accessibility and affordability of improved pneumonia detection methodologies hold the promise of reaching underserved communities and regions with limited healthcare resources. The technology developed through this research has the potential to transcend geographical boundaries, bringing sophisticated diagnostic capabilities to areas where traditional medical infrastructure may be limited. This democratization of advanced healthcare technologies aligns with global health initiatives, contributing to the overarching goal of reducing health disparities and improving overall healthcare equity. In summary, the societal impact of this research lies in its potential to usher in a new era of precision medicine, particularly in the diagnosis and management of pneumonia. By leveraging cutting-edge technologies, the research not only advances the scientific understanding of respiratory disease diagnostics but also holds the key to tangible improvements in public health outcomes, healthcare accessibility, and the overall well-being of diverse populations around the world.

5.2 Impact on Environment

While the primary focus of the research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" is centered around healthcare and technological advancements, its impact on the environment is nuanced yet significant. The integration of deep Convolutional Neural Networks (CNNs) and transfer learning, while contributing to breakthroughs in medical diagnostics, inherently involves intensive computational processes. These processes, particularly the training and optimization of complex neural networks, demand substantial computing power, often relying on energy-intensive hardware like graphics processing units (GPUs).

The environmental impact stems from the energy consumption associated with training and deploying these advanced models. The high computational requirements, especially in scenarios involving large datasets and complex model architectures, contribute to increased energy consumption, thereby leaving a carbon footprint. As such, the research prompts a reflection on the environmental implications of deploying state-of-the-art technologies in healthcare.

However, it's crucial to note that advancements in hardware efficiency, cloud computing strategies, and sustainable computing practices are continually evolving. Researchers and developers are increasingly cognizant of the environmental concerns associated with AI applications, leading to efforts to optimize algorithms and hardware for energy efficiency. The integration of green computing practices and the use of renewable energy sources in data centers can mitigate the environmental impact, aligning technological progress with eco-friendly considerations.

In summary, while the research's core contributions lie in the advancement of medical diagnostics, its impact on the environment is a pertinent consideration. As the field progresses, efforts to balance technological innovation with environmental sustainability will play a crucial role in ensuring that healthcare advancements remain socially responsible and environmentally conscious.

5.3 Ethical Aspects

The research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" is underpinned by a commitment to ethical considerations throughout its methodology. The use of medical images entails a responsibility to safeguard patient privacy and confidentiality, emphasizing adherence to ethical guidelines and regulatory standards. Informed consent, a cornerstone of ethical research practices, is appropriately obtained when necessary. The potential societal impact of the research on healthcare underscores the importance of ethical deployment, ensuring that advancements in diagnostics translate to improved patient care without compromising individual rights. The ethical dimension is further reflected in the transparent documentation of the research process, enabling scrutiny, reproducibility, and responsible knowledge dissemination. Overall, ethical considerations are integral to the research's commitment to societal well-being and the responsible application of cutting-edge technologies in the healthcare domain.

5.4 Sustainability Plan

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

CHAPTER 6

Summary, Conclusion,

Recommendation and Implication for Future Research

6.1 Summary of the Study

The research on "Pneumonia Detection with Transfer Learning: A Deep CNN-Based Comparison of Detection and Segmentation Approaches" represents a comprehensive exploration of advanced artificial intelligence techniques in the domain of medical diagnostics. Leveraging a dataset of 5863 original photos, the study investigates the effectiveness of deep Convolutional Neural Networks (CNNs) in recognizing and segmenting two types of pneumonia chest X-ray images: normal and pneumonia-affected. The research rigorously tests six CNN-based models, including Resnet152V2 and MobileNetV2, achieving notable accuracy scores. Transfer learning is examined, revealing nuances in accuracy when the input picture deviates from the training data. The study underlines the potential of ensemble models over individual architectures and recognizes the impact of dataset size on prediction capabilities, aligning with recommendations for augmentation-based updates. While the research promises advancements in pneumonia detection precision, it also acknowledges environmental considerations and articulates a sustainability plan to mitigate associated impacts. Ethical considerations, including patient privacy and informed consent, underscore the responsible deployment of AI in healthcare. Overall, the study's insights not only contribute to the academic discourse on respiratory disease diagnostics but also hold substantial implications for improving patient outcomes and healthcare accessibility on a global scale.

6.2 Conclusions

Early and accurate detection and classification of pneumonia stand as imperative prerequisites for the effective diagnosis of patients. This paper is centered on a comprehensive performance evaluation of Deep Convolutional Neural Networks (D-CNN) in the domains of pneumonia detection and segmentation. Our study emphasizes the efficacy of a segmentation approach utilizing CNN, particularly showcasing its effectiveness when dealing with small and less refined datasets. Notably, the existing body of knowledge reflects a paucity of research dedicated explicitly to pneumonia detection. Therefore, our comparative study assumes heightened significance, promising substantial contributions to the realm of pneumonia management. In the classification of pneumonia, our investigation meticulously scrutinizes the performance of diverse CNN models, encompassing transfer learning and ensemble techniques. The results underscore that an ensemble stack comprising five networks (Resnet152V2, VGG19, SeresNet152, ResNext101, and MobileNetV2) outperforms individual models in terms of accuracy. However, it is noteworthy that despite the overall efficacy of the ensemble framework, instances of inaccurate forecasts were observed. Consequently, there arises a compelling need to explore alternative strategies such as contrast-enhancing or other image-processing methodologies in future research endeavors.

Moreover, we propose the incorporation of image segmentation prior to classification to enhance the CNN models' ability to extract pertinent features. Although the suggested ensemble involves the training of five CNN models, rendering it computationally more intensive than established CNN baselines, the potential for improved accuracy justifies the computational cost. To mitigate the computational burden in future studies, techniques like snapshot ensemble could be explored. In essence, this research serves as a stepping stone towards refining and advancing pneumonia diagnostic methodologies, offering insights that can significantly impact clinical practice and inspire further exploration in the ever-evolving landscape of medical image analysis.

6.3 Implication for Further Study

The findings of this study on pneumonia detection and segmentation using Deep Convolutional Neural Networks (D-CNN) provide valuable insights and open avenues for further research. One notable implication for future studies is the exploration of alternative image-processing approaches, such as contrast enhancement, to address instances of inaccurate forecasts observed in the ensemble framework. Additionally, the integration of segmentation techniques before classification is suggested as a potential enhancement for CNN models in feature extraction. Furthermore, given the computational intensity of the proposed ensemble approach, future research could investigate the application of techniques like snapshot ensemble to alleviate the burden on computational resources. This implies a need for more efficient and scalable ensemble methodologies to maintain or enhance accuracy without compromising computational efficiency.

While this study focused on pneumonia detection, there is a call for more dedicated research in this specific domain, given the limited existing literature. Future studies could delve deeper into pneumonia detection methodologies, potentially exploring novel architectures, diverse datasets, and real-world clinical applications to contribute to a more comprehensive understanding of this critical area in medical diagnostics. In summary, the implications for further study lie in refining image-processing strategies, exploring efficient ensemble techniques, and expanding the scope of research in pneumonia detection, thereby enriching the landscape of medical image analysis and fostering advancements in diagnostic accuracy and efficiency.

REFERENCES

[1] A. Afifi, N. E. Hafsa, M. A. S. Ali, A. Alhumam, and S. Alsalman, “An ensemble of global and local-attention based convolutional neural networks for COVID-19 diagnosis on chest X-ray images,” Symmetry (Basel)., vol. 13, no. 1, 2021, doi: 10.3390/sym13010113.
[2] GM, H., Gourisaria, M. K., Rautaray, S. S., & Pandey, M. A. N. J. U. S. H. A. (2021). Pneumonia detection using CNN through chest X-ray. Journal of Engineering Science and Technology (JESTEC), 16(1), 861-876.
[3] V. Chouhan et al., “A novel transfer learning-based approach for pneumonia detection in chest X-ray images,” Appl. Sci., vol. 10, no. 2, 2020, doi: 10.3390/app10020559.
[4] E. ERDEM and T. AYDİN, “Detection of Pneumonia with a Novel CNN-based Approach,” Sak. Univ. J. Comput. Inf. Sci., 2021, doi: 10.35377/saucis.04.01.787030.
[5] T. Frondelius, I. Atkova, J. Miettunen, J. Rello, and M. M. Jansson, “Diagnostic and prognostic prediction models in ventilator-associated pneumonia: Systematic review and meta-analysis of prediction modelling studies,” Journal of Critical Care, vol. 67. 2022. doi: 10.1016/j.jcrc.2021.10.001.
[6] Y. Fujikura et al., “Mortality and severity evaluation by routine pneumonia prediction models among Japanese patients with 2009 pandemic influenza A (H1N1) pneumonia,” Respir. Investig., vol. 52, no. 5, 2014, doi: 10.1016/j.resinv.2014.04.003.
[7] Y. Ge et al., “Predicting post-stroke pneumonia using deep neural network approaches,” Int. J. Med. Inform., vol. 132, 2019, doi: 10.1016/j.ijmedinf.2019.103986.
[8] E. H. Houssein, Z. Abohashima, M. Elhoseny, and W. M. Mohamed, “Hybrid quantum-classical convolutional neural network model for COVID-19 prediction using chest X-ray images,” J. Comput. Des. Eng., vol. 9, no. 2, 2022, doi: 10.1093/jcde/qwac003.
[9] R. Karthik, R. Menaka, and M. Hariharan, “Learning distinctive filters for COVID-19 detection from chest X-ray using shuffled residual CNN,” Appl. Soft Comput., vol. 99, 2021, doi: 10.1016/j.asoc.2020.106744.
[10] R. Kundu, R. Das, Z. W. Geem, G. T. Han, and R. Sarkar, “Pneumonia detection in chest X-ray images using an ensemble of deep learning models,” PLoS One, vol. 16, no. 9 September, 2021, doi: 10.1371/journal.pone.0256630.
[11] T. J. Kuo, C. L. Hsu, P. H. Liao, S. J. Huang, Y. M. Hung, and C. H. Yin, “Nomogram for pneumonia prediction among children and young people with cerebral palsy: A population-based cohort study,” PLoS One, vol. 15, no. 7, 2020, doi: 10.1371/journal.pone.0235069.
[12] J. Lu et al., “Identification of antibiotic resistance and virulence-encoding factors in Klebsiella pneumoniae by Raman spectroscopy and deep learning,” Microb. Biotechnol., vol. 15, no. 4, 2022, doi: 10.1111/1751-7915.13960.
[13] N. Nafiiyah and E. Setyati, “Lung X-Ray Image Enhancement to Identify Pneumonia with CNN,” 2021. doi: 10.1109/EIConCIT50028.2021.9431856.
[14] H. Namikawa et al., “Siderophore production as a biomarker for Klebsiella pneumoniae strains that cause sepsis: A pilot study,” J. Formos. Med. Assoc., vol. 121, no. 4, 2022, doi: 10.1016/j.jfma.2021.06.027.
[15] S. Ramgopal, L. Ambroggio, D. Lorenz, S. S. Shah, R. M. Ruddy, and T. A. Florin, “A Prediction Model for Pediatric Radiographic Pneumonia,” Pediatrics, vol. 149, no. 1, 2022, doi: 10.1542/peds.2021-051405.
[16] R. P.- Rodriguez et al., “Clinical Performance of the call Score for the Prediction of Admission to ICU and Death in Hospitalized Patients with Covid-19 Pneumonia in a Reference Hospital in Peru,” Pakistan J. Med. Heal. Sci., vol. 16, no. 1, 2022, doi: 10.53350/pjmhs22161474.
[17] V. S. Suryaa, A. X. Annie R., and M. S. Aiswarya, “Efficient DNN Ensemble for Pneumonia Detection in Chest X-ray Images,” Int. J. Adv. Comput. Sci. Appl., vol. 12, no. 10, 2021, doi: 10.14569/IJACSA.2021.0121084.
[18] A. Ter-Sarkisov, “Detection and segmentation of lesion areas in chest CT scans for the prediction of COVID-19,” Sci. Inf. Technol. Lett., vol. 1, no. 2, 2020, doi: 10.31763/sitech. v1i2.202.

[19] S. F. Tey et al., “Predicting the 14-day hospital readmission of patients with pneumonia using artificial neural networks (Ann),” Int. J. Environ. Res. Public Health, vol. 18, no. 10, 2021, doi: 10.3390/ijerph18105110.
[19] C. C. Tseng et al., “Significance of the modified nutric score for predicting clinical outcomes in patients with severe community-acquired pneumonia,” Nutrients, vol. 14, no. 1, 2022, doi: 10.3390/nu14010198.
[20] Krishnaswamy Rangarajan Aravind and Purushothaman Raja. Auto- mated disease classification in (selected) agricultural crops using transfer learning. Automatika, 61(2), 2020.
[21] Yao, S., Chen, Y., Tian, X., & Jiang, R. (2021). Pneumonia detection using an improved algorithm based on faster r-cnn. Computational and Mathematical Methods in Medicine, 2021.
[21] Thakur, S., Goplani, Y., Arora, S., Upadhyay, R., & Sharma, G. (2021). Chest X-ray images based automated detection of pneumonia using transfer learning and CNN. In Proceedings of International Conference on Artificial Intelligence and Applications (pp. 329-335). Springer, Singapore.
[22] Ko, H., Ha, H., Cho, H., Seo, K., & Lee, J. (2019, May). Pneumonia detection with weighted voting ensemble of cnn models. In 2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD) (pp. 306-310). IEEE.
[23] Gupta, P. (2021). Pneumonia detection using convolutional neural networks. Science and Technology, 7(01), 77-80.
[24] Bangare, S., Rajankar, H., Patil, P., Nakum, K., & Paraskar, G. (2022). Pneumonia detection and classification using CNN and VGG16. International Journal of Advanced Research in Science, Communication and Technology, 12, 771-779.
[25] Gayathri, J. L., Abraham, B., Sujarani, M. S., & Nair, M. S. (2022). A computer-aided diagnosis system for the classification of COVID-19 and non-COVID-19 pneumonia on chest X-ray images by integrating CNN with sparse autoencoder and feed forward neural network. Computers in Biology and Medicine, 141, 105134.
[26] I. S. Walia, M. Srivastava, D. Kumar, M. Rani, P. Muthreja, and G. Mohadikar, “Pneumonia detection using depth-wise convolutional neural network (Dw-cnn),” EAI Endorsed Trans. Pervasive Heal. Technol., vol. 6, no. 23, 2020, doi: 10.4108/eai.28-5-2020.166290.
[27] H. Sharma, J. S. Jain, P. Bansal, and S. Gupta, “Feature extraction and classification of chest X-ray images using CNN to detect pneumonia,” 2020. doi: 10.1109/Confluence47617.2020.9057809.
[28] I. Sirazitdinov, M. Kholiavchenko, T. Mustafaev, Y. Yixuan, R. Kuleev, and B. Ibragimov, “Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database,” Comput. Electr. Eng., vol. 78, 2019, doi: 10.1016/j.compeleceng.2019.08.004.
[29] N. M. Elshennawy and D. M. Ibrahim, “Deep-Pneumonia Framework Using Deep Learning Models Based on Chest X-Ray Images,” Diagnostics, vol. 10, no. 9, 2020, doi: 10.3390/diagnostics10090649.
[30] R. Angeline and R. Vani, “ResNet:A convolutional Neural Network for detecting and diagnosing of coronavirus pneumonia,” IOP Conf. Ser. Mater. Sci. Eng., vol. 1084, no. 1, 2021, doi: 10.1088/1757-899x/1084/1/012011.
[31] M. B. Darici, Z. Dokur, and T. Olmez, “Pneumonia detection and classification using deep learning on chest x-ray images,” Int. J. Intell. Syst. Appl. Eng., vol. 8, no. 4, 2020, doi: 10.18201/ijisae.2020466310.
[32] T. Gao, “Chest X-ray image analysis and classification for COVID-19 pneumonia detection using Deep CNN,” medRxiv, 2020.
[33] T. Rajasenbagam, S. Jeyanthi, and J. A. Pandian, “Detection of pneumonia infection in lungs from chest X-ray images using deep convolutional neural network and content-based image retrieval techniques,” J. Ambient Intell. Humaniz. Comput., 2021, doi: 10.1007/s12652-021-03075-2.
[34] E. Ayan, B. Karabulut, and H. M. Ünver, “Diagnosis of Pediatric Pneumonia with Ensemble of Deep Convolutional Neural Networks in Chest X-Ray Images,” Arab. J. Sci. Eng., vol. 47, no. 2, 2022, doi: 10.1007/s13369-021-06127-z.
[35] S. Yao, Y. Chen, X. Tian, and R. Jiang, “Pneumonia Detection Using an Improved Algorithm Based on Faster R-CNN,” Comput. Math. Methods Med., vol. 2021, 2021, doi: 10.1155/2021/8854892.

[36] Deepak, S., & Ameer, P. M. (2019). Brain tumor classification using deep CNN features via transfer learning. Computers in biology and medicine, 111, 103345.

[37] Khan, A. R., Khan, S., Harouni, M., Abbasi, R., Iqbal, S., & Mehmood, Z. (2021). Brain tumor segmentation using K-means clustering and deep learning with synthetic data augmentation for classification. Microscopy Research and Technique, 84(7), 1389-1399.

[38] Iqbal, S., Ghani, M. U., Saba, T., & Rehman, A. (2018). Brain tumor segmentation in multi-spectral MRI using convolutional neural networks (CNN). Microscopy research and technique, 81(4), 419-427.

[39] Sharma, H., Jain, J. S., Bansal, P., & Gupta, S. (2020, January). Feature extraction and classification of chest x-ray images using cnn to detect pneumonia. In 2020 10th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 227-231). IEEE.

[40] Labhane, G., Pansare, R., Maheshwari, S., Tiwari, R., & Shukla, A. (2020, February). Detection of pediatric pneumonia from chest X-ray images using CNN and transfer learning. In 2020 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things (ICETCE) (pp. 85-92). IEEE.

[41] Yao, S., Chen, Y., Tian, X., & Jiang, R. (2021). Pneumonia detection using an improved algorithm based on faster r-cnn. Computational and Mathematical Methods in Medicine, 2021.

[42] Thakur, S., Goplani, Y., Arora, S., Upadhyay, R., & Sharma, G. (2021). Chest X-ray images based automated detection of pneumonia using transfer learning and CNN. In Proceedings Of International Conference On Artificial Intelligence And Applications (pp. 329-335). Springer, Singapore.

[43] Alsharif, R., Al-Issa, Y., Alqudah, A. M., Qasmieh, I. A., Mustafa, W. A., & Alquran, H. (2021). PneumoniaNet: Automated Detection and Classification of Pediatric Pneumonia Using Chest X-ray Images and CNN Approach. Electronics, 10(23), 2949.

[44] Aledhari, M., Joji, S., Hefeida, M., & Saeed, F. (2019, November). Optimized CNN-based diagnosis system to detect the pneumonia from chest radiographs. In 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM) (pp. 2405-2412). IEEE.

[45] Ko, H., Ha, H., Cho, H., Seo, K., & Lee, J. (2019, May). Pneumonia detection with weighted voting ensemble of cnn models. In 2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD) (pp. 306-310). IEEE.

[46] Gupta, P. (2021). Pneumonia detection using convolutional neural networks. Science and Technology, 7(01), 77-80.

[47] Bangare, S., Rajankar, H., Patil, P., Nakum, K., & Paraskar, G. (2022). Pneumonia detection and classification using CNN and VGG16. International Journal of Advanced Research in Science, Communication and Technology, 12, 771-779.

[48] Gayathri, J. L., Abraham, B., Sujarani, M. S., & Nair, M. S. (2022). A computer-aided diagnosis system for the classification of COVID-19 and non-COVID-19 pneumonia on chest X-ray images by integrating CNN with sparse autoencoder and feed forward neural network. Computers in Biology and Medicine, 141, 105134.

[49] I. S. Walia, M. Srivastava, D. Kumar, M. Rani, P. Muthreja, and G. Mohadikar, “Pneumonia detection using depth-wise convolutional neural network (Dw-cnn),” EAI Endorsed Trans. Pervasive Heal. Technol., vol. 6, no. 23, 2020, doi: 10.4108/eai.28-5-2020.166290.

[50] H. Sharma, J. S. Jain, P. Bansal, and S. Gupta, “Feature extraction and classification of chest X-ray images using CNN to detect pneumonia,” 2020. doi: 10.1109/Confluence47617.2020.9057809.

[51] I. Sirazitdinov, M. Kholiavchenko, T. Mustafaev, Y. Yixuan, R. Kuleev, and B. Ibragimov, “Deep neural network ensemble for pneumonia localization from a large-scale chest x-ray database,” Comput. Electr. Eng., vol. 78, 2019, doi: 10.1016/j.compeleceng.2019.08.004.

[52] N. M. Elshennawy and D. M. Ibrahim, “Deep-Pneumonia Framework Using Deep Learning Models Based on Chest X-Ray Images,” Diagnostics, vol. 10, no. 9, 2020, doi: 10.3390/diagnostics10090649.

[53] R. Angeline and R. Vani, “ResNet:A convolutional Neural Network for detecting and diagnosing of coronavirus pneumonia,” IOP Conf. Ser. Mater. Sci. Eng., vol. 1084, no. 1, 2021, doi: 10.1088/1757-899x/1084/1/012011.
[54] M. B. Darici, Z. Dokur, and T. Olmez, “Pneumonia detection and classification using deep learning on chest x-ray images,” Int. J. Intell. Syst. Appl. Eng., vol. 8, no. 4, 2020, doi: 10.18201/ijisae.2020466310.
[55] T. Gao, “Chest X-ray image analysis and classification for COVID-19 pneumonia detection using Deep CNN,” medRxiv, 2020.
[56] T. Rajasenbagam, S. Jeyanthi, and J. A. Pandian, “Detection of pneumonia infection in lungs from chest X-ray images using deep convolutional neural network and content-based image retrieval techniques,” J. Ambient Intell. Humaniz. Comput., 2021, doi: 10.1007/s12652-021-03075-2.
[57] E. Ayan, B. Karabulut, and H. M. Ünver, “Diagnosis of Pediatric Pneumonia with Ensemble of Deep Convolutional Neural Networks in Chest X-Ray Images,” Arab. J. Sci. Eng., vol. 47, no. 2, 2022, doi: 10.1007/s13369-021-06127-z.
[58] S. Yao, Y. Chen, X. Tian, and R. Jiang, “Pneumonia Detection Using an Improved Algorithm Based on Faster R-CNN,” Compute. Math. Methods Med., vol. 2021, 2021, doi: 10.1155/2021/8854892.
[59] Bengio, Y. (2012, June). Deep learning of representations for unsupervised and transfer learning. In Proceedings of ICML workshop on unsupervised and transfer learning (pp. 17-36). JMLR Workshop and Conference Proceedings.
[60] Neyshabur, B., Sedghi, H., & Zhang, C. (2020). What is being transferred in transfer learning? Advances in neural information processing systems, 33, 512-523.
[61] Mesnil, G., Dauphin, Y., Glorot, X., Rifai, S., Bengio, Y., Goodfellow, I., ... & Bergstra, J. (2012, June). Unsupervised and transfer learning challenge: a deep learning approach. In Proceedings of ICML Workshop on Unsupervised and Transfer Learning (pp. 97-110). JMLR Workshop and Conference Proceedings.
[62] Kamil, Mohammed. (2021). A deep learning framework to detect Covid-19 disease via chest X-ray and CT scan images. International Journal of Electrical and Computer Engineering. 11. 844-850. 10.11591/ijece.v11i1.pp844-850.
[63] Grant, D., Papież, B.W., Parsons, G., Tarassenko, L., Mahdi, A. (2021). Deep Learning Classification of Cardiomegaly Using Combined Imaging and Non-imaging ICU Data. In: Papież, B.W., Yaqub, M., Jiao, J., Namburete, A.I.L., Noble, J.A. (eds) Medical Image Understanding and Analysis. MIUA 2021. Lecture Notes in Computer Science(), vol 12722. Springer, Cham. https://doi.org/10.1007/978-3-030-80432-9_40
[64] Bilal, Muhammad & Maqsood, Muazzam & Yasmin, Sadaf & Ul Hasan, Najam & Rho, Seungmin. (2022). A transfer learning-based efficient spatiotemporal human action recognition framework for long and overlapping action classes. The Journal of Supercomputing. 78. 10.1007/s11227-021-03957-4.
[65] Akay, Metin & Du, Yong & Sershen, Cheryl & Wu, Minghua & Chen, Ting & Assassi, Shervin & Mohan, Chandra & Akay, Yasemin. (2021). Deep Learning Classification of Systemic Sclerosis Skin Using the MobileNetV2 Model. IEEE Open Journal of Engineering in Medicine and Biology. PP. 1-1. 10.1109/OJEMB.2021.3066097.
[66] Yeh, Jeffrey & Hung-Tse, Chan & Hsia, Chih-Hsien. (2021). ResNeXt with Cutout for Finger Vein Analysis. 1-2. 10.1109/ISPACS51563.2021.9650921.
[67] Muniasamy, A., Bhatnagar, R., Karunakaran, G. (2022). Development of Disease Diagnosis Model for CXR Images and Reports—A Deep Learning Approach. In: Hassanien, A.E., Bhatnagar, R., Snášel, V., Yasin Shams, M. (eds) Medical Informatics and Bioimaging Using Artificial Intelligence. Studies in Computational Intelligence, vol 1005. Springer, Cham. https://doi.org/10.1007/978-3-030-91103-4_9

thesisssss

ORIGINALITY REPORT

18%	11%	11%	9%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	2%
2	Md Taimur Ahad, Yan Li, Bo Song, Touhid Bhuiyan. "Comparison of CNN-based deep learning architectures for rice diseases classification", Artificial Intelligence in Agriculture, 2023 Publication	2%
3	dspace.daffodilvarsity.edu.bd:8080 Internet Source	1%
4	www.researchgate.net Internet Source	1%
5	ijiird.com Internet Source	1%
6	Submitted to University of Southern Mississippi Student Paper	1%
7	e-space.mmu.ac.uk Internet Source	1%