DEEPLUNGNET: LEVERAGING UNET++ AND TRANSFER LEARNING FOR PRECISE PNEUMOTHORAX SEGMENTATION IN CHEST RADIOGRAPHS

PHASE I REPORT

Submitted by

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BONAFIDE CERTIFICATE

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INTERNAL EXAMINER **EXTERNAL EXAMINER**

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ABSTRACT

"DeepLungNet: Leveraging UNet++ and Transfer Learning for Precise Pneumothorax Segmentation in Chest Radiographs" focuses on the critical medical condition of pneumothorax, characterized by the accumulation of air in the pleural space. It introduces advanced deep learning techniques to automate pneumothorax detection and segmentation, minimizing diagnostic errors and providing a reliable tool for healthcare professionals. This comprehensive solution combines classification and segmentation, making it a game-changer in the field of medical imaging. For classification, a robust model inspired by CheXNet and DenseNet-121 identifies pneumothorax presence, aided by fine-tuning layers, while the segmentation part employs UNet++ and Double UNet, known for their exceptional precision. The model's flexibility is enhanced through integrated data preparation strategies, adapting to diverse clinical scenarios, and addressing real-world medical practice's dynamic challenges. This approach not only revolutionizes pneumothorax management but also empowers healthcare professionals to make early, confident decisions based on detailed patient information, promising improved outcomes and patient care.

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LIST OF ABBREVIATIONS

CNN	Convolutional Neural Network
AI	Artificial Intelligence
DL	Deep Learning
CPU	Central Processing Unit
GPU	Graphical Processing Unit
RESNET	Residual Network
VGG	Visual Geometric Group
DICOM	Digital Imaging and Communications in Medicine
PNG	Portable Network Graphics

CHAPTER 1

INTRODUCTION

Chest radiography, a cornerstone of modern medical diagnosis, provides valuable insights into a patient's thoracic health. Among the various conditions detectable through chest radiographs, pneumothorax stands out as a potentially life-threatening concern. Pneumothorax occurs when air accumulates in the pleural space, leading to lung collapse and impaired respiratory function. Timely and accurate detection is paramount for effective patient management, making it a critical concern in clinical radiology.

Traditional pneumothorax diagnosis, reliant on manual assessment by radiologists, can be time-consuming and subject to interobserver variability. These challenges have driven the exploration of automated solutions, where deep learning and artificial intelligence play pivotal roles. In this context, we introduce our project, "Leveraging UNet++ and Transfer Learning for Precise Pneumothorax Segmentation in Chest Radiographs."

The project offers a comprehensive solution to pneumothorax diagnosis, encompassing both classification and precise segmentation. It leverages cutting-edge deep learning techniques, including the powerful CheXNet and DenseNet-121 models for classification. By adding fine-tuning layers, we enhance the model's capability to distinguish between positive and negative cases, enabling early detection.

In the domain of segmentation, we employ advanced techniques such as UNet++ and Double UNet to achieve precise delineation of pneumothorax regions within chest radiographs. This detailed information is vital for clinical decision support, promising more accurate and effective patient management. Moreover, our project integrates a wide array of data preparation strategies, enhancing the model's flexibility and adaptability to diverse clinical scenarios.

This adaptability is essential as chest radiographs can exhibit variations in quality and presentation.

By automating pneumothorax detection and segmentation, our project aims to revolutionize the management of pneumothorax cases, reducing diagnostic errors, and improving patient outcomes. Combining the power of deep learning with precise segmentation techniques offers a promising solution to this critical medical challenge. Through this project, we contribute to the broader context of leveraging artificial intelligence for medical image analysis and enhancing healthcare.

The detailed account of the methodologies, results, and insights gained throughout the project are explained. We believe that our work has the potential to significantly impact pneumothorax diagnosis and further the use of deep learning in medical imaging.

1. 1 PROJECT DEFINITION

Pneumothorax, a critical medical condition characterized by the presence of air in the pleural space (between the chest walls). The timely and accurate diagnosis of pneumothorax is significant, as misdiagnosis or delayed treatment can lead to life-threatening consequences. This is an innovative project that leverages the power of state-of-the-art deep learning techniques to automate pneumothorax detection and segmentation. The primary objective is to improve diagnostic capabilities and reduce errors in pneumothorax detection, which is a critical factor in ensuring timely and accurate treatment for affected patients. The diagnostic process involves two significant challenges: the classification of pneumothorax in chest X-rays and the precise segmentation of the affected regions. Classification involves finding whether pneumothorax is present or not and segmentation involves delineating the precise location of the affected area. Classification is achieved through the use of models such as CheXNet and DenseNet-121, ensuring precise identification of the presence or absence of pneumothorax. Simultaneously, the segmentation module employs UNet++ and Double UNet, which are well-known for their ability to delineate affected areas with high precision. It aims to minimize diagnostic errors, improve patient outcomes, support timely treatment planning, and contribute to enhanced clinical decision-making. The project offers a comprehensive solution that combines advanced classification methods with precise image segmentation to enhance diagnostic capabilities in the field of pneumothorax diagnosis.

The objectives of the project are multifaceted and designed to address critical challenges in pneumothorax diagnosis and treatment. The primary objective is to enhance diagnostic capabilities by developing an automated system that can reliably classify chest radiographs as either indicating the presence or absence of pneumothorax. Early and accurate detection is paramount, and this binary classification serves as the foundation for confident diagnosis. The secondary objective is to employ advanced image segmentation techniques to precisely delineate the affected area, thereby providing crucial information regarding the degree and location of the condition. This detailed segmentation is instrumental in facilitating treatment planning, thus improving the overall management of pneumothorax cases.

Furthermore, the project aims to reduce diagnostic errors, which are prevalent in this complex medical domain. By integrating diverse data preparation methods, leveraging well-established models, and fine-tuning them with customized layers, we intend to enhance the system's robustness and adaptability. The system's adaptability is critical, as medical images can exhibit variations in quality and presentation. These objectives offer a dependable, efficient, and adaptable solution that supports real-time clinical decision-making, enhances diagnostic accuracy, minimizes the risk of misdiagnosis, and ultimately leads to improved patient outcomes.

1.2 NEED FOR AUTOMATED PNEUMOTHORAX CLASSIFICATION AND SEGMENTATION

The critical need for automated pneumothorax classification and segmentation arises from the urgency for enhanced, accurate, and efficient diagnosis and management of this life-threatening medical condition. Pneumothorax, characterized by the presence of air in the pleural space, poses significant challenges for healthcare practitioners. Manual pneumothorax diagnosis and segmentation from chest radiographs are time-intensive and subject to human errors, resulting in delayed diagnoses, misinterpretations, and inconsistent assessments, potentially jeopardizing patients' well-being. Furthermore, variations in image quality and presentation across different healthcare settings emphasize the urgency for automation. Automated pneumothorax classification and segmentation offer compelling advantages, primarily in expediting the diagnostic process in life-threatening situations. They significantly reduce diagnosis time, allowing healthcare professionals to respond promptly and minimize subjectivity. Accurate localization and segmentation of pneumothorax regions are imperative for effective treatment planning, and automated systems excel in achieving this with exceptional precision, providing essential, detailed information vital for comprehensive patient management. The exponential growth of medical imaging data, coupled with the evolving role of artificial intelligence (AI) in healthcare, has created a conducive environment for advanced automated tools. These systems can rapidly analyze extensive datasets, facilitating early detection and alleviating the workload on medical staff. Automation not only streamlines the diagnostic process but also equips healthcare professionals with reliable and efficient tools that enhance their confidence in delivering precise diagnoses. In summary, automated pneumothorax classification and segmentation are indispensable for addressing the multifaceted challenges associated with the diagnosis and management of pneumothorax. They introduce speed, consistency, and precision into a domain where timely and accurate decisions hold life-and-death significance, ultimately revolutionizing pneumothorax care across diverse clinical scenarios and image variations, making them an invaluable addition to the realm of medical imaging and healthcare.

1.3 OVERVIEW OF ALGORITHMS USED

1.3.1 Pneumothorax Classification

The Pneumothorax Classification component of the project involves determining whether a given chest radiograph exhibits the presence or absence of pneumothorax.

Two prominent deep learning architectures are employed for this task:

1. CheXNet: CheXNet is a 121-layered Convolutional Neural Network (CNN) developed on top of the ResNet architecture. It is explicitly designed for chest radiograph analysis and medical image classification. Our implementation of CheXNet serves as the primary model for binary classification. It undergoes fine-tuning to enable it to differentiate between positive and negative cases of pneumothorax, ensuring the reliable detection of this life-threatening condition.

2. DenseNet-121: DenseNet, a dense convolutional neural network, is primarily known for image classification. In our project, DenseNet-121 complements CheXNet, providing additional feature extraction capabilities. The extracted features are concatenated with those from other layers, enhancing the model's understanding of the input image. This enriched information is subsequently employed for more accurate classification.

1.3.2 Pneumothorax Segmentation

Pneumothorax Segmentation component is focused on precisely delineating the region affected by pneumothorax within chest radiographs. Two sophisticated segmentation algorithms are used to achieve this:

1. UNet++: UNet++ is an advanced variant of the classic UNet architecture, specifically designed for medical image segmentation. It excels in spatial fidelity, making it highly suitable for accurate pneumothorax region delineation. UNet++ comprises encoder and decoder blocks with dense skip pathways, which help to propagate feature information and reduce errors effectively.

2. Double UNet with DenseNet Backbone: Our project introduces the Double UNet architecture with a DenseNet Backbone, combining the strengths of both models. This architecture refines the segmentation process by enhancing the model's ability to capture fine details in the pneumothorax region. The inclusion of a DenseNet Backbone bolsters feature extraction and aids in achieving precise segmentation.

The combined use of these algorithms allows us to provide a comprehensive solution for pneumothorax diagnosis. By integrating robust classification with precise segmentation, our project offers a sophisticated tool for healthcare professionals to detect and manage pneumothorax cases more effectively.

CHAPTER 2

LITERATURE REVIEW

Do et al. [1] have contributed significantly to the field of medical imaging with their 2012 research published in Computational and Mathematical Methods in Medicine. They tackled the challenging task of automating pneumothorax quantification, offering a potential life-saving solution for a condition marked by air accumulation in the pleural cavity. Their study addressed the critical need for precise pneumothorax measurements, a vital component of effective patient care. By harnessing computed tomography (CT) imaging, the authors introduced automated quantification methods that significantly boost efficiency and reliability compared to manual approaches, which tend to be time-consuming and subject to variability. The research unveiled a groundbreaking methodology for the automatic estimation of pneumothorax volume and extent from CT images, highlighting the potential of automation to advance pneumothorax diagnosis and management. This work not only underscores the importance of reducing subjectivity in clinical assessments but also paves the way for further developments in automated medical image analysis, setting a model for future research endeavors in the domain.

Ronneberger et al.'s [2] paper, "U-Net: Convolutional Networks for Biomedical Image Segmentation," published in 2015, lays the foundation for precise biomedical image segmentation, a fundamental component of medical diagnostics and treatment planning. Their innovative U-Net architecture, with its encoder-decoder structure and skip connections, has emerged as a seminal model for maintaining spatial details and achieving accurate segmentation in medical imaging. The research's impact extends beyond biomedicine, providing inspiration for enhanced variants such as UNet++. It also finds applications in broader domains like natural image segmentation, image translation, and object detection. Researchers can take this work as a model for developing state-of-the-art segmentation models, and the architectural insights and principles can serve as building blocks for advancements in various computer vision

tasks, ultimately contributing to improved healthcare, as well as diverse applications in image analysis and understanding.

K. Jakhar et al. [3] "Pneumothorax Segmentation: Deep Learning Image Segmentation to Predict Pneumothorax" (2019), delves into the application of deep learning for pneumothorax segmentation in medical images. Pneumothorax, the presence of air in the pleural cavity, necessitates precise segmentation for timely diagnosis and intervention. The study introduces a specialized deep learning model designed to predict pneumothorax, highlighting its potential to advance medical image analysis. The research unveils innovative techniques and architectures tailored to tackle the unique challenges of pneumothorax segmentation, making a significant contribution to computer vision in medical imaging. By enhancing diagnostic accuracy and efficiency, this work holds promise for healthcare professionals, potentially revolutionizing pneumothorax diagnosis and patient care. Overall, K. Jakhar, A. Kaur, and M. Gupta's paper underscores the transformative role of artificial intelligence in the realm of medical image analysis, particularly in the context of pneumothorax diagnosis and management.

Wang.W et al. [4] "Automated segmentation and diagnosis of pneumothorax on chest X-rays with fully convolutional multi-scale ScSE-DenseNet," Wang et al. introduced an innovative approach to pneumothorax diagnosis through chest X-rays. They proposed the ScSE-DenseNet model, specifically tailored for precise pneumothorax detection and segmentation, a critical task given the life-threatening nature of this condition. The integration of spatial and channel-wise feature recalibration in the model enhances its ability to capture information from

X-rays, enabling pixel-level segmentation for accurate pneumothorax localization. This research underscores the effectiveness of deep learning in pneumothorax diagnosis, offering the potential for faster and more accurate clinical decision support and improved patient outcomes. Wang et al.'s work stands as a notable contribution to the field of deep learning applications in complex medical image segmentation, highlighting the significance of

fully convolutional networks in advancing AI's role in medical imaging. Researchers can further build upon this model to explore additional applications and refine pneumothorax diagnosis processes for the benefit of healthcare professionals and patients alike.

Salvaggio et al. [5] introduced a novel approach to pneumothorax diagnosis using chest X-rays in their paper titled "Automated segmentation and diagnosis of pneumothorax on chest X-rays with fully convolutional multi-scale ScSE-DenseNet," published in BMC Medical Informatics and Decision Making in 2020. They presented the ScSE-DenseNet model, designed to enhance pneumothorax detection and segmentation, a critical requirement for swift and accurate diagnosis of this life-threatening condition. Notably, this research integrates spatial and channel-wise feature recalibration to improve information capture from X-ray images, enabling precise pneumothorax localization down to the pixel level. The study demonstrates the model's effectiveness in segmentation and diagnosis, promising to enhance clinical decision support. By leveraging deep learning for pneumothorax detection, this work has the potential to significantly improve patient outcomes through quicker and more accurate diagnoses. Researchers and practitioners can take this innovative model as a basis for further developments in the application of fully convolutional networks in complex medical image segmentation, ultimately benefiting healthcare professionals and patients alike.

Tolkachev et al. present a two-stage deep learning approach for pneumothorax segmentation in chest radiographs, offering a substantial contribution to computer-aided diagnosis and the application of artificial intelligence in healthcare. Pneumothorax, a potentially life-threatening condition, necessitates swift and precise diagnosis, and this research effectively addresses that need. In the first stage, the model adeptly classifies the presence of pneumothorax in radiographs, distinguishing between images with and without the condition. The second stage is dedicated to accurately delineating pneumothorax regions within the chest radiographs, providing a detailed and localized assessment. This two-stage approach, commonly employed in deep learning-based medical image analysis, not only enables binary classification but

also fine-grained localization of the condition. Such a methodology has the potential to streamline and enhance the automation of pneumothorax diagnosis, offering benefits to both patients and healthcare providers. This research aligns with the prevailing trend of integrating advanced deep learning techniques into clinical radiology, emphasizing the potential of deep learning to revolutionize pneumothorax diagnosis, improve patient outcomes, and enhance healthcare delivery.

Cho et al. [7] introduce an innovative approach to pneumothorax detection in chest X-rays, with a specific focus on accurately localizing this life-threatening condition. The authors advocate the use of small artificial neural networks (ANNs) to pinpoint pneumothorax locations in X-ray images, significantly improving diagnostic precision. What sets this research apart is the straightforward training process for these small ANNs, making the approach accessible to a wider audience, including researchers and medical practitioners. This development of lightweight models is particularly valuable for resource-constrained environments and the swift diagnosis of pneumothorax. By introducing this pioneering method for precise pneumothorax localization using small ANNs, the study contributes to the field of computer-aided diagnosis and equips healthcare professionals with the tools to efficiently identify this critical condition. In summary, this research presents a novel approach to pneumothorax detection through precise localization using small ANNs, offering a straightforward training process and high accuracy, with the potential to advance early pneumothorax diagnosis and enhance healthcare in the field of medical imaging.

Patel et al. [8] introduce PTXNet, an extended UNet model designed for pneumothorax segmentation in chest radiography images. This research addresses the critical task of pneumothorax segmentation, essential for accurate diagnosis and treatment of the life-threatening condition. PTXNet builds upon the effective UNet architecture, tailoring it to efficiently identify pneumothorax regions in complex chest radiography images. This advancement contributes to medical image analysis and computer-aided diagnosis, aiding healthcare professionals in the rapid and accurate diagnosis of pneumothorax and enabling timely medical intervention. The authors, A. Patel and A. Vidyarthi, significantly contribute to the development of state-of-the-art techniques for pneumothorax segmentation. Their work has the potential to enhance medical practitioners' capabilities, improve patient outcomes, and advance the application of artificial intelligence in the medical field. In summary, this research introduces PTXNet, an extended UNet model for precise pneumothorax segmentation in chest radiography images, making it a valuable addition to the field of medical imaging and computer-aided diagnosis with the potential to impact pneumothorax diagnosis and treatment.

Rueckel et al. [9] present an innovative approach to optimizing artificial intelligence (AI) systems for accurate pneumothorax detection in chest radiographs. This research, published in "European Radiology" in October 2021, addresses the critical need for precise AI-driven pneumothorax diagnosis in medical imaging to support timely patient care. Recognizing the significance of mitigating bias in AI algorithms, particularly in the medical imaging domain, the authors introduce in-image annotations in the training process to enhance AI system accuracy. This pioneering approach has the potential to significantly improve AI systems' performance, benefiting radiologists and clinicians by aiding in the precise and efficient diagnosis of pneumothorax. Rueckel et al.'s article underscores the importance of bias reduction and optimization in AI systems for pneumothorax detection, promising to advance the capabilities of AI in assisting healthcare professionals to achieve accurate and efficient pneumothorax diagnosis.

Abedalla et al. [10] present an innovative approach to pneumothorax segmentation in chest X-ray images. This research combines the U-Net architecture, renowned for its efficacy in medical image segmentation, with two additional architectures, EfficientNet and ResNet, to create a hybrid approach focused on enhancing segmentation model performance. By integrating different neural network architectures, the authors aim to advance the field of medical image analysis. Leveraging the strengths of U-Net, EfficientNet, and ResNet, the study aims to develop a robust and accurate system for automating pneumothorax detection and delineation in chest X-ray images. This approach contributes to the improvement of pneumothorax diagnosis and treatment by enhancing the accuracy and efficiency of image segmentation techniques, ultimately benefiting the medical community and patient care.

O. Ronneberger et al. [11] "U-Net: Convolutional Networks for Biomedical Image Segmentation" published in the "Lecture Notes in Computer Science" in 2015, present a seminal contribution to deep learning and computer vision, particularly in the context of biomedical image segmentation. The paper introduces the innovative U-Net architecture, which is purpose-built for the precise segmentation of biomedical images, a critical task in the medical field. This architecture's unique encoder-decoder structure, complemented by skip connections, empowers it to achieve highly accurate localization and preservation of spatial details during the segmentation process. Beyond its applications in biomedical imaging, the U-Net model has left a lasting impact on various domains, including natural image segmentation, image translation, and object detection. This research has significantly elevated the field of biomedical image segmentation and stands as a fundamental reference for researchers and practitioners in deep learning and computer vision, offering a model for future advancements and applications.

A. Goel et al. [12] "The Role of Artificial Neural Network and Machine Learning in Utilizing Spatial Information" published in "Spatial Information Research" in November 2022, explore the significance of artificial neural networks and machine learning in harnessing spatial information. The study delves into the role of these technologies in handling and making the most of spatial data, which has applications in various domains, including geography, geology, and environmental science. By emphasizing the role of artificial neural networks and machine learning in spatial information utilization, this research sets the stage for further advancements in the field, offering insights and a model for future developments.

CHAPTER 3

SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

The existing system employs two distinct approaches to address the challenge of pneumothorax prediction and segmentation. One approach uses the U-Net architecture with a fixed structure. But it lacks data augmentations, limiting its adaptability when dealing with diverse medical images. While this method provides a foundational framework for pneumothorax prediction and segmentation, its rigid structure may hinder its effectiveness, especially when confronted with variations in medical image data.

The second approach takes a more intricate path. It leverages the UNet++ architecture and introduces extensive data augmentation. Although this approach offers the potential for improved performance, it comes at the cost of increased resource utilization, resulting in higher computational overhead. Additionally, the complexity of this method can pose challenges in terms of interpretation, potentially impeding its practical application in clinical settings.

One of the foremost drawbacks of the existing system lies in the potential for slow processing times, which can give rise to delays in clinical decision-making. This issue is particularly critical in medical scenarios involving pneumothorax, where real-time segmentation plays a vital role in ensuring timely diagnosis and treatment planning. The system's slow response time has the potential to compromise the quality of patient care and overall medical outcomes, creating a pressing need for an alternative that can provide faster and more responsive results.

Another significant drawback of the existing system pertains to the high costs associated with misclassification and mis-segmentation errors. These errors can have severe consequences in medical applications. False negatives, where pneumothorax cases are missed, may lead to delayed diagnoses and treatment, placing patients at risk. Conversely, false positives, indicating the presence of pneumothorax when it is absent,

can result in unnecessary medical interventions. These high-cost errors underscore the need for a more accurate and efficient system, such as the proposed This project, which aims to overcome these limitations and significantly enhance patient care within the realm of pneumothorax diagnosis and treatment.

3.2 PROPOSED SYSTEM

The proposed system presents a comprehensive solution to the challenges of pneumothorax diagnosis. It encompasses both classification and segmentation phases, providing a cutting-edge approach for the medical field. The key components of the proposed system include

- Data Collection:
  Data for the proposed system is sourced from the SIIM (Society for Imaging Informatics in Medicine) dataset in the form of RLE (Run-Length Encoded) DICOM format. This dataset is substantial, comprising 12,954 training images and 3,204 testing images. Two crucial data files are utilized: 'train.csv,' which associates Image IDs with corresponding masks, and 'test.csv,' containing Image IDs for the testing dataset.

- Performance Metrics for Evaluation:
  To assess the system's performance, a range of metrics is used. The Dice coefficient, a measure of Intersection Over Union, is utilized to evaluate the accuracy of the segmentation process. In addition, the system relies on the Combo Loss, a combination of cross-entropy loss and Dice loss, to ensure the effectiveness of pneumothorax localization.

- Exploratory Data Analysis and Preprocessing:

  Data exploration and preprocessing are integral components of the proposed system. The 'pydicom' Python package is instrumental for the analysis of DICOM image formats, facilitating data understanding. The system involves the conversion of DICOM images into PNG format for further processing. Furthermore, masks for pneumothorax regions are created from the Run-Length

  Encoded (RLE) data, ensuring that the data is appropriately prepared for both classification and segmentation.

- Modeling:

  This phase is divided into two distinct parts - classification, segmentation.

1. Pneumothorax Classification:

   This part employs advanced deep learning models for classification. The CheXNet model, a 121-layered Convolutional Neural Network (CNN) developed on top of ResNet, is utilized for binary classification, distinguishing between "Pneumothorax Present" and "No Pneumothorax Present." Additionally, DenseNet, known for its image classification capabilities, is integrated into the classification phase. Performance evaluation in this phase encompasses metrics like AUC-ROC, Sensitivity, Negative Predictive Value (NPV), and Precision-Recall curves to assess the classification accuracy.

2. Pneumothorax Segmentation:

   For precise pneumothorax segmentation, the UNet++ architecture, known for its spatial fidelity, is used. An Encoder-Decoder Approach with dense skip pathways is implemented, facilitating error reduction and enhancing segmentation precision. Evaluation of the segmentation phase relies on the Dice Score, ensuring accurate localization of pneumothorax regions.

- Model Deployment:

  The proposed system is deployed as an end-to-end Flask application, offering user-friendly access. It generates output images that include pneumothorax masks and indications of pneumothorax presence or absence, making it highly accessible to healthcare professionals. Deployment is executed on the Microsoft Azure platform, ensuring a robust, scalable, and reliable system for real-world healthcare applications.

This comprehensive approach to pneumothorax diagnosis is carried out by combining advanced classification and segmentation techniques, offering adaptability,

robustness, and real-time capabilities. This system holds the promise of significantly enhancing patient care and clinical decision-making in the medical field.

3.2.1 NEED FOR PROPOSED SYSTEM

Pneumothorax, characterized by the presence of air in the pleural space, is a medical condition with potentially life-threatening implications. Accurate and timely diagnosis is paramount, as any misdiagnosis or delayed intervention can have severe consequences for patients. The existing systems in place for pneumothorax detection and segmentation often exhibit limitations in terms of accuracy, efficiency, and adaptability to the diverse clinical scenarios encountered in the real world of medical practice.

The proposed solution bridges these critical gaps in pneumothorax diagnosis. Its need arises from the pressing requirement to provide healthcare professionals with a reliable, efficient, and adaptable tool for confident diagnoses and streamlined treatment planning. The proposed system encompasses both classification and segmentation aspects, automating pneumothorax detection and precise localization. By reducing diagnostic errors, This project contributes significantly to enhancing patient outcomes and facilitating timely treatment interventions. Its adaptability to diverse clinical scenarios and robustness in handling variations in medical images make it a highly sought-after solution in the medical field. Its advanced classification techniques ensure accurate identification of the presence or absence of pneumothorax, providing clinicians with a vital first step in diagnosis. The segmentation module, employing cutting-edge techniques such as UNet++, delivers precise information about the extent and location of the condition, thereby facilitating targeted treatment planning. In critical medical scenarios, real-time clinical decision-making is paramount, and This project addresses this need efficiently.

3.2.2 APPLICATIONS OF PROPOSED SYSTEM

There are a wide variety of applications in the healthcare sector, particularly in scenarios where pneumothorax diagnosis is pivotal. This system helps in enhancing the diagnostic and treatment planning skills and proves to be an innovative change in the medical field. The following are some applications of

- Enhanced Diagnostic Capabilities: This project's utilization of advanced classification and segmentation techniques equips healthcare professionals with comprehensive insights, thereby augmenting their diagnostic capabilities. This, in turn, contributes to more accurate and effective medical assessments.
- Reduction in Diagnostic Errors: Through the automation of pneumothorax detection and segmentation, this project plays a pivotal role in minimizing diagnostic errors. By ensuring the prompt and precise identification of medical conditions, it guarantees that patients receive appropriate treatment without undue delay.
- Real-time Clinical Decision Support: This project offers the potential for real-time clinical decision support, which is particularly critical in

emergency situations and other high-stakes medical scenarios. It assists healthcare providers in swiftly making informed decisions that can significantly impact patient outcomes.

- Time Efficiency: This project's remarkable efficiency translates into substantial time savings within the demanding healthcare environment. This allows medical professionals to redirect their focus toward patient care, thus enhancing overall healthcare delivery.
- Confident Diagnosis: The system empowers healthcare professionals with the tools needed to make confident diagnosis. By reducing uncertainty and enhancing diagnostic accuracy, this project not only benefits the medical staff but also greatly improves the overall quality of patient care.

3.3 FEASIBILITY STUDY

Feasibility analysis is an important process in determining the viability of a project. It involves analyzing various factors such as technical, economic, legal, operational, and schedule feasibility to determine whether a proposed project is feasible and worthwhile to pursue. In the case of your project, here is a brief explanation of each feasibility analysis:

Technical Feasibility: This project leverages well-established deep learning models like CheXNet and UNet++, making it technically feasible. The availability of DICOM images and Python-based tools further enhances the project's technical viability. Scalability is also achievable, enabling adaptation to evolving technology.

Economic Feasibility: Economic analysis suggests that the project is economically viable. While initial costs include data acquisition and cloud services (Microsoft Azure), the potential return on investment (ROI) is promising. Reduced diagnostic errors, improved patient outcomes, and time savings in clinical settings can offset these costs, making the project financially sustainable. Securing funding resources remains critical.

Legal Feasibility: Compliance with healthcare data privacy and regulatory standards is vital for legal feasibility. Adhering to legal requirements is essential to ensure that the project is ethically and legally sound.

Schedule Feasibility: A well-planned project timeline and resource availability assessment indicate that the project can be completed within the allocated time frame. However, ongoing monitoring of the schedule is necessary to address potential delays.

Operational Feasibility: User acceptance and integration into existing healthcare infrastructure are key operational considerations. Early user feedback and acceptance studies are essential to ensure the project's seamless integration into clinical practice. Regulatory compliance, data privacy, and ethical considerations are additional factors that need to be addressed for operational feasibility.

In conclusion, this project exhibits robust feasibility from technical, economic, legal, schedule, and operational standpoints. Its potential to enhance pneumothorax diagnosis, reduce errors, and improve patient care is promising, provided that it continues to meet legal and regulatory requirements and receives positive user acceptance and engagement.

CHAPTER 4

SYSTEM REQUIREMENTS

To ensure the optimal functioning of the project, it is essential to meet specific hardware and software requirements. It plays a critical role in the performance and functionality of the system.

HARDWARE REQUIREMENTS

1. High-Performance CPU: Recommended Intel Core i7 or higher for efficient computation.

2. GPU Acceleration: Optimal performance with NVIDIA GeForce RTX or Tesla GPUs.

3. Memory (RAM): Suggested minimum 16 GB, ideally 32 GB or more for handling complex tasks.

4. Storage: Adequate 500 GB SSD for fast data access and system responsiveness.

SOFTWARE REQUIREMENTS

1. Operating System: Compatible with Windows, macOS, and Linux (Ubuntu, CentOS).

2. Web Application Deployment: Knowledge of Flask and web development.

3. Deep Learning Frameworks: TensorFlow and PyTorch are essential.

4. Software Dependencies: NumPy, OpenCV, Flask, and other Python libraries are needed.

5. DICOM Image Viewer: 'pydicom' or similar is required for DICOM image handling

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

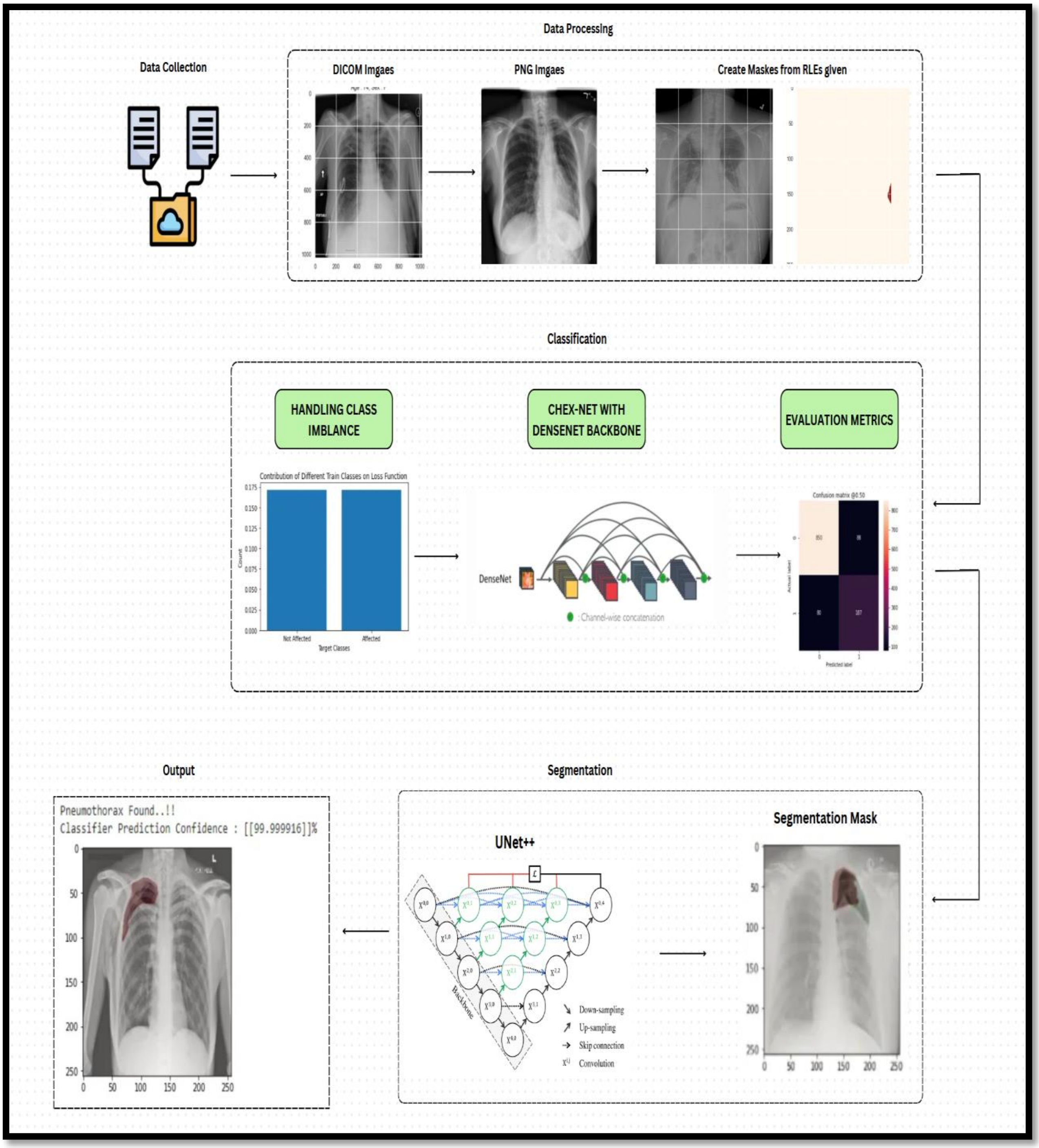

Figure 5.1 System Architecture Diagram

Figure 5.1 presents a detailed architectural diagram depicting the workflow for pneumothorax detection and segmentation. The process begins with a Chest radiograph input into a designated website. As these radiographs are commonly in dicom format, the first step is the conversion of the image into dicom format for further analysis. Once the image is preprocessed, the system's focus shifts to identifying the Run-Length Encoding (RLE) masks in images that depict individuals affected by pneumothorax. The subsequent stages involve modeling, classification, and segmentation. During the modeling phase, the system tackles the classification of pneumothorax. To address the challenge of class imbalance, it incorporates probabilistic functions and measures to make a decisive determination of whether pneumothorax is present in the image or not. In the segmentation stage, the architecture utilizes UNet++, a powerful tool for image segmentation. It is tasked with accurately outlining and highlighting the regions of pneumothorax within the image. The final output is an image that indicates the presence or absence of pneumothorax. If pneumothorax is detected, the segmented portion is highlighted, providing crucial visual information for medical professionals. This workflow illustrates a comprehensive approach to pneumothorax detection and segmentation, potentially revolutionizing the field of medical imaging by offering more accurate and efficient diagnostic tools.

5.2 DATAFLOW DIAGRAM

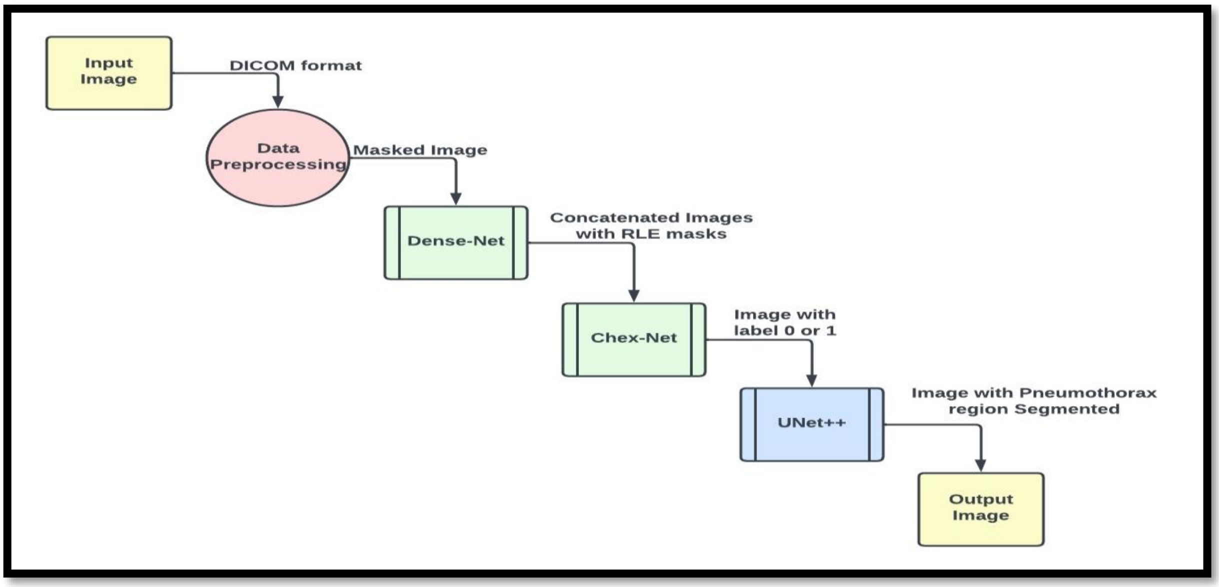

Figure 5.2 Data Flow Diagram

In Figure 5.2 the data flow diagram (DFD), the architectural workflow detailed in Figure 5.1 is further clarified. It illustrates how data and information move throughout the system during the process of pneumothorax detection and segmentation. The central component is the Chest radiograph image, which serves as the input to the system. This image is initially processed to convert it from dicom format, ensuring it's compatible with further analysis. Once the preprocessing is complete, the system focuses on pneumothorax detection. It extracts and identifies RLE masks in the images containing individuals with pneumothorax. The detected RLE masks, along with the preprocessed images, are then fed into the modeling stage. This is where the heart of the classification process takes place. The system employs sophisticated algorithms to handle class imbalance, utilize probabilistic functions, and apply various measures to make a binary determination: whether pneumothorax is present in the image or not. The outcome of the classification is essential for the subsequent segmentation process.

If pneumothorax is detected, the system invokes UNet++ for image segmentation. This advanced technique is used to precisely outline and highlight the pneumothorax-affected areas in the image. The final result of the data flow diagram is twofold: it provides an image indicating the presence or absence of pneumothorax, and if the condition is present, it also offers a segmented image where the affected area is visually highlighted. This streamlined data flow process ensures efficient pneumothorax diagnosis and enhances the capabilities of medical professionals in providing timely and accurate patient care.

The key components of the proposed system include

- Data Collection:

  Data for the proposed system is sourced from the SIIM (Society for Imaging Informatics in Medicine) dataset in the form of RLE (Run-Length Encoded) DICOM format. This dataset is substantial, comprising 12,954 training images and 3,204 testing images. Two crucial data files are utilized: 'train.csv,' which associates Image IDs with corresponding masks, and 'test.csv,' containing Image IDs for the testing dataset.

- Performance Metrics for Evaluation:

  To assess the system's performance, a range of metrics is used. The Dice coefficient, a measure of Intersection Over Union, is utilized to evaluate the accuracy of the segmentation process. In addition, the system relies on the Combo Loss, a combination of cross-entropy loss and Dice loss, to ensure the effectiveness of pneumothorax localization.

- Exploratory Data Analysis and Preprocessing:

  Data exploration and preprocessing are integral components of the proposed system. The 'pydicom' Python package is instrumental for the analysis of DICOM image formats, facilitating data understanding. The system involves the conversion of DICOM images into PNG format for further processing. Furthermore, masks for pneumothorax regions are created from the Run-Length Encoded (RLE) data, ensuring that the data is appropriately prepared for both classification and segmentation.

- Modeling:
  This phase is divided into two distinct parts - classification, segmentation.

3. Pneumothorax Classification:
   This part employs advanced deep learning models for classification. The CheXNet model, a 121-layered Convolutional Neural Network (CNN) developed on top of ResNet, is utilized for binary classification, distinguishing between "Pneumothorax Present" and "No Pneumothorax Present." Additionally, DenseNet, known for its image classification capabilities, is integrated into the classification phase. Performance evaluation in this phase encompasses metrics like AUC-ROC, Sensitivity, Negative Predictive Value (NPV), and Precision-Recall curves to assess the classification accuracy.

4. Pneumothorax Segmentation:
   For precise pneumothorax segmentation, the UNet++ architecture, known for its spatial fidelity, is used. An Encoder-Decoder Approach with dense skip pathways is implemented, facilitating error reduction and enhancing segmentation precision. Evaluation of the segmentation phase relies on the Dice Score, ensuring accurate localization of pneumothorax regions.

5.3 LIST OF MODULES

- Data Collection and Pre-processing
- Classification Module - Detects whether Pneumothorax found or not
- Segmentation Module - Segmented Region of where the pneumothorax is detected
- Model Evaluation and deployment

5.3.1 MODULE 1 - Data Collection and Processing

Data collection and processing forms the first and foremost phase in the This project project, which involves handling the collection, transformation, and enhancement of medical imaging data. This process is essential to ensure the data's compatibility and quality for subsequent classification and segmentation tasks. Below is an in-depth outline of the data processing workflow for documentation purposes:

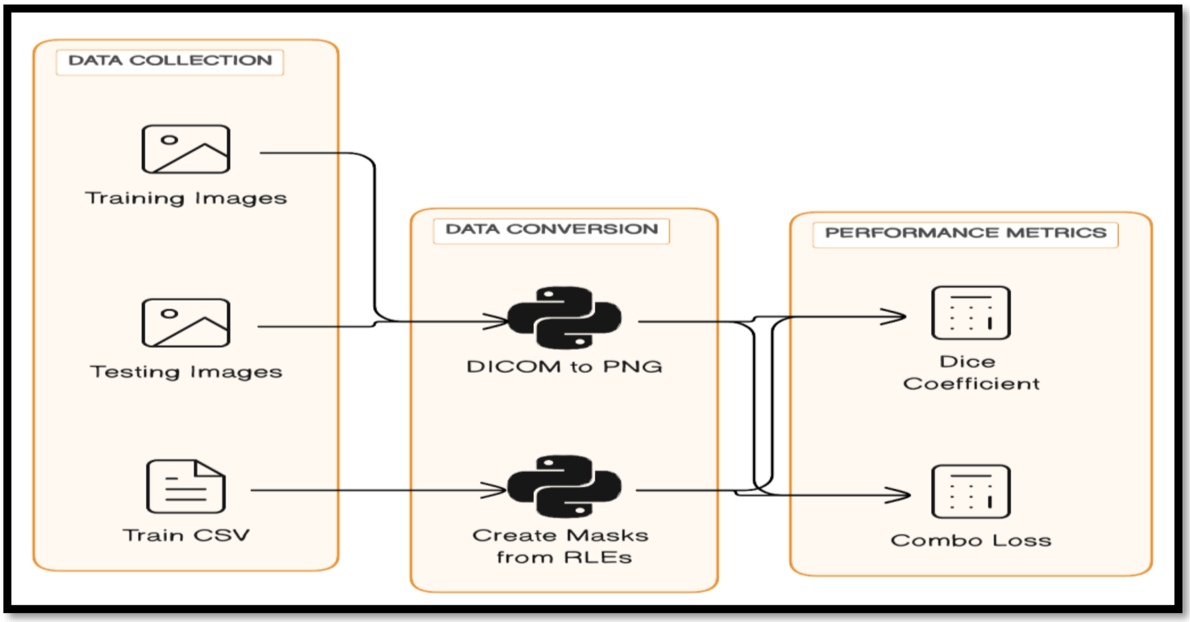

Figure 5.3 Data Flow diagram of Data Collection and Preprocessing

- Data Collection:
  The first step entails the acquisition of chest radiographs presented in Run-Length Encoded (RLE) DICOM format, utilizing the SIIM dataset. The SIIM (Society for Imaging Informatics in Medicine) dataset is a medical

imaging dataset that contains a collection of chest radiographs in DICOM format for use in healthcare research and development.

The dataset comprises:

- Training Data: A comprehensive set of 12,954 DICOM images.

- Testing Data: Comprising 3,204 DICOM images.

- Train.csv: This file contains Image IDs and their corresponding masks, specifically designated for training data.

- Test.csv: Correspondingly, Test.csv provides a record of Image IDs for the testing dataset.

● Performance Metrics for Evaluation:
The performance evaluation relies on two primary metrics:

- Dice Coefficient (Intersection Over Union): This metrics gauges the extent of overlap between the predicted pneumothorax segmentation and the ground truth mask. A higher Dice coefficient signifies more precise segmentation.

- Combo Loss (Cross-Entropy Loss + Dice Loss): The Combo Loss method combines the standard Cross-Entropy Loss and Dice Loss, offering a comprehensive assessment of segmentation quality.

● Exploratory Data Analysis and Preprocessing:
1. pydicom Package: This project leverages the 'pydicom' Python package to interpret DICOM image formats. This library enables the extraction of crucial metadata from DICOM files, facilitating a deeper understanding of the image characteristics.

2. Conversion of DICOM to PNG Images: A pivotal preprocessing step involves converting DICOM images into the PNG format. PNG images are

universally supported and seamlessly integrated into deep learning frameworks, ensuring their suitability for model training.

3. Generation of Masks from RLEs: This project generates masks that delineate regions within the images where pneumothorax is present. These masks are constructed from the provided Run-Length Encoded (RLE) data, serving as the ground truth reference for precise segmentation.

Data processing serves as the basis for aligning the input data with the model's requirements, guaranteeing compatibility and quality. It encompasses the conversion of DICOM to PNG, mask creation, and an exploratory data analysis to set the stage for model development and the subsequent phases of classification and segmentation.

5.3.2 MODULE 2 - Pneumothorax Classification

The pneumothorax classification component of the project assumes a pivotal role by ascertaining the presence or absence of pneumothorax in chest radiographs. This process leverages two well-established deep learning architectures, ChexNet and DenseNet, each fulfilling distinct functions in the classification task:

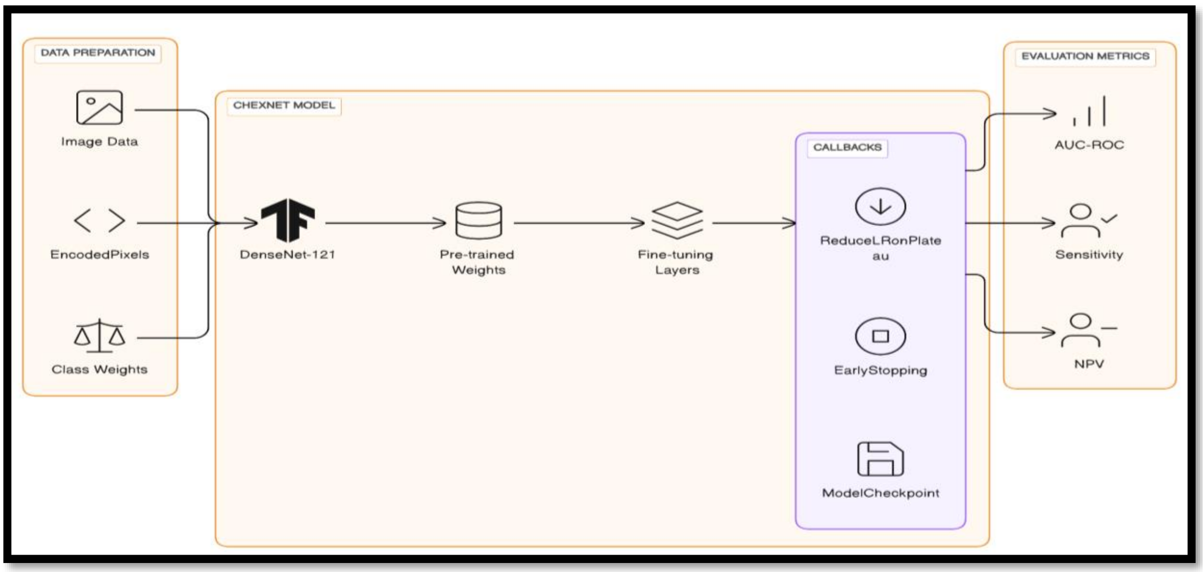

Figure 5.4 Data flow Diagram of Pneumothorax Classification

1. ChexNet:

- ChexNet is an intricate 121-layered Convolutional Neural Network (CNN) strategically built upon the ResNet architecture. Its specialization lies in chest radiograph analysis and medical image classification, having undergone extensive training on a vast dataset of chest X-rays. It excels in discerning a spectrum of thoracic pathologies, including pneumothorax.

- Operation: ChexNet commences by extracting intricate features from the input chest radiograph. These features undergo progressive transformations through the numerous network layers. Subsequently, they contribute to a binary classification decision, distinctly indicating the presence or absence of pneumothorax. The model's proficiency results from its exposure to diverse chest X-rays, enabling it to identify distinct patterns and anomalies associated with pneumothorax.

2. DenseNet:

- DenseNet, recognized as a Densely Connected Convolutional Network, primarily serves as an image classification architecture. In the context of the project, its role predominantly revolves around image feature concatenation, amplifying the wealth of information accessible for the classification process.

- Integration: DenseNet's application is not direct classification but feature extraction. The features extracted are thoughtfully amalgamated with those derived from other layers. This synergistic data enrichment bolsters the model's comprehension of the input image. The augmented feature set is then supplied to the ChexNet model, augmenting its classification prowess.

The classification process commences with the presentation of a chest radiograph as the input. Subsequently, ChexNet and DenseNet collaboratively engage in feature extraction from the image. While ChexNet primarily handles the central classification task, DenseNet's contribution lies in fortifying the feature representation, ultimately culminating in augmented classification precision. The binary classification outcome decisively conveys the presence or absence of pneumothorax, thereby facilitating expedited diagnosis and informed clinical decision-making.

This classification facet is pivotal in the prompt identification of pneumothorax cases, thus curtailing diagnostic inaccuracies and ensuring timely medical interventions.

CHAPTER 6

PERFORMANCE EVALUATION

The performance evaluation is a critical aspect of the project, encompassing both training and testing phases to ensure the accuracy and reliability of the pneumothorax detection system. This section provides a comprehensive insight into the training and testing evaluation processes:

6.1 TRAINING EVALUATION

The training phase involves the development and fine-tuning of the machine learning models, ensuring they are well-equipped to handle pneumothorax classification and segmentation tasks.

1. Training Data: The model is trained on a substantial dataset (SIIM) consisting of 12,954 chest radiographs. These images serve as the foundation for model development.

2. Performance Metrics: This project employs a range of performance metrics during training to gauge the model's accuracy. Key metrics include:

- AUC-ROC (Area Under the Receiver Operating Characteristic Curve): This metric quantifies the model's ability to discriminate between positive and negative pneumothorax cases. A higher AUC-ROC score indicates better discrimination in table 6.1

Model	AUC-ROC Score
CheXNet	0.908
VGG16	0.884
ResNet 50	0.912

Table 6.1 Performance metric comparison of Models

- Sensitivity: Sensitivity measures the model's ability to correctly identify true positive cases of pneumothorax, minimizing false negatives.

- NPV (Negative Predictive Value): NPV assesses the model's capacity to correctly identify true negative cases, reducing false positives.

- Precision-Recall Curves: These curves provide a comprehensive overview of the trade-off between precision and recall, offering valuable insights into model performance.

6.2 TESTING EVALUATION

Once the model is trained, it undergoes rigorous testing to evaluate its performance on unseen data. The testing evaluation phase is equally important, and it includes the following elements:

1. Testing Data: A separate dataset comprising 3,204 chest radiographs is used for testing the trained model. This dataset serves as an independent benchmark to assess the model's generalization and robustness.

2. Dice Coefficient: The Dice coefficient, calculated as the Intersection Over Union (IoU), is employed for the evaluation of pneumothorax segmentation. It measures the degree of overlap between the predicted and ground truth

pneumothorax regions. A higher Dice coefficient indicates more precise segmentation.

3. Combo Loss: The Combo Loss is a comprehensive evaluation metric that combines the Cross-Entropy Loss and Dice Loss. It provides a holistic assessment of segmentation quality, considering both pixel-wise arrangements and segmentation accuracy.

The combination of training and testing evaluations ensures that This project not only performs well during model development but also maintains its efficacy on new, unseen data. This rigorous evaluation process guarantees the reliability and accuracy of the system, contributing to its potential in revolutionizing pneumothorax diagnosis in healthcare.

By systematically applying these performance evaluation metrics, This project can provide accurate and reliable results, supporting medical professionals in making critical decisions regarding pneumothorax cases.

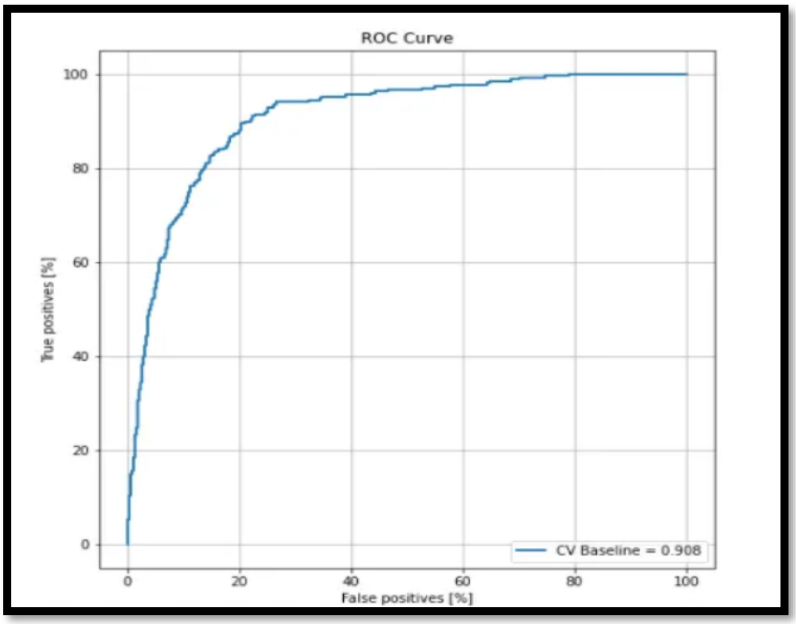

Figure 6.1 ROC Curve for checking Classification accuracy

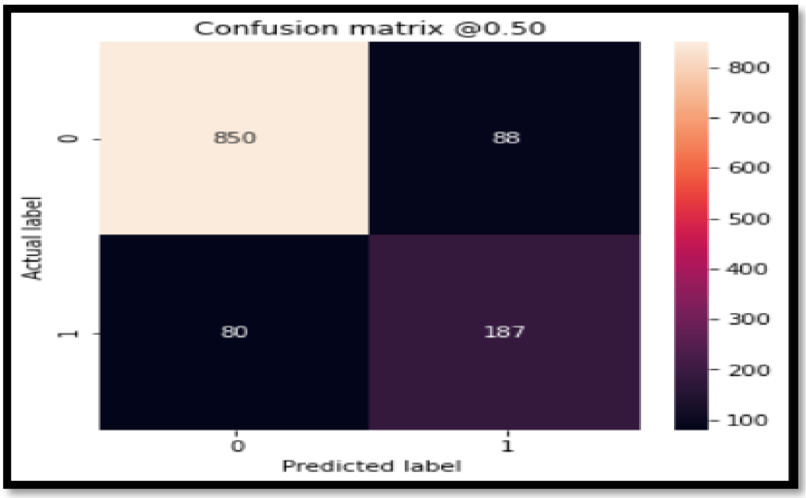

Figure 6.2 Confusion Matrix for checking classification accuracy

6.3 COMPARATIVE ANALYSIS

In the context of our comparative analysis, it's imperative to address the issue of class imbalance, a common challenge encountered within the medical domain. Specifically, we observe a substantial disparity between the positive class, denoting cases with pneumothorax, and the negative class, representing cases without pneumothorax. To mitigate this imbalance and prevent our model from exhibiting bias toward the majority class, we adopt a class weighting strategy. This entails assigning weights to each class, inversely proportional to their respective frequencies, which are calculated as the class count divided by the total number of records. Unsurprisingly, the positive class exhibits a lower frequency due to its minority status within the dataset. By incorporating these class weights into the training process, we ensure equitable contribution from both classes, thereby averting the model's inclination towards the majority class. This balanced weighting mechanism empowers our model to learn effectively from both positive and negative cases, fostering enhanced sensitivity and fairness in predictions, and ultimately, improving overall classification performance.

S No.	Aspect	Existing System	Proposed System
1	Classification Method	U-Net architecture without data augmentations	Combination of CheXNet and DenseNet-121 with fine-tuning
2	Segmentation Method	U-Net++ architecture with data augmentations	UNet++ and Double UNet for precise segmentation
3	Adaptability	Less adaptable to diverse medical image types	Enhanced adaptability to varying clinical scenarios
4	Latency	Potential for slow processing times	Real-time segmentation for timely diagnosis
5	Error Consequences	High-cost errors with missed diagnoses or unnecessary interventions	Minimized diagnostic errors and improved patient care

Table 6.2 Comparative Study

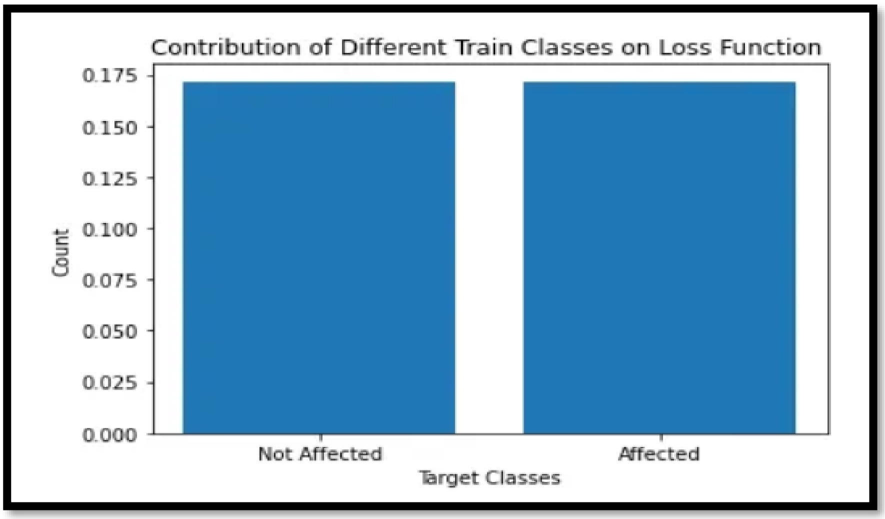

Figure 6.3 Bar graph representation of Class Imbalance

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 CONCLUSION

In conclusion, the proposed model represents a significant step forward in addressing the challenges of pneumothorax diagnosis and treatment. By combining advanced deep learning techniques for classification and precise segmentation, it offers a promising solution for the medical field. This project's integration of diverse data preparation strategies, state-of-the-art model architectures, and efficient deployment methods positions it as a valuable tool for healthcare professionals. The project's potential to enhance diagnostic capabilities, reduce errors, and support real-time clinical decision-making is a testament to its impact in the field of medical imaging. With applications spanning across healthcare, the system not only improves patient outcomes but also streamlines medical workflows, saving valuable time in busy clinical environments. This project's adaptability to diverse clinical scenarios and its technical robustness makes it a forward-looking project, poised to revolutionize the management of pneumothorax cases and contribute to better patient care.

7.2 FUTURE ENHANCEMENT

Many future enhancements can be made to this comprehensive approach. These potential improvements can further elevate the project's impact in the field of pneumothorax diagnosis and medical imaging.

Advanced Model Architectures: Exploring more advanced deep learning architectures, such as Transformer-based models or custom-designed networks, can enhance the project's classification and segmentation capabilities, leading to even greater precision and efficiency.

Real-time Integration: Expanding the project's real-time capabilities, including real-time video streaming and image analysis, can facilitate rapid clinical decision-making, particularly in emergency medical scenarios.

Multimodal Data Fusion: Integrating data from multiple imaging modalities, such as X-rays, CT scans, and ultrasounds, can provide a holistic view of patient conditions, allowing for comprehensive diagnosis and treatment planning.

Clinical Decision Support Systems: Developing the project into a comprehensive clinical decision support system that integrates with Electronic Health Records (EHRs) and assists healthcare professionals in making well-informed decisions can significantly enhance patient care.

Mobile Application: Creating a mobile application that allows medical professionals to access This project on their smartphones or tablets can increase its accessibility and usability in various healthcare settings.

These future enhancements aim to reinforce the project’s position as an indispensable tool in the medical field, with a commitment to continually improving patient care, diagnostic accuracy, and clinical workflows.

APPENDIX

A1.1 SAMPLE CODE

<u>pneumo_EDA_Seg.ipynb</u>

```
import os

import sys

import glob

import random

import cv2

import pydicom

import numpy as np

import pandas as pd

from tqdm.notebook import tqdm

from PIL import Image

import tensorflow as tf

from tensorflow.keras import *

from tensorflow.keras.layers import *

from tensorflow.keras import backend as K

from keras.losses import binary_crossentropy

from keras import Model

from keras.layers import Input, Conv2DTranspose

from keras.layers import Conv2D, MaxPooling2D
```

```
from keras.layers import Dropout, BatchNormalization
from keras.losses import binary_crossentropy
import keras.callbacks as callbacks
from keras.applications.xception import Xception
from keras.layers.merge import concatenate
import matplotlib.pyplot as plt
plt.style.use('seaborn-white')
import seaborn as sns
def dicom2png(file):
    '''
    This function inputs the path of the image to be read
    and create a .png format for the same image and store in the path created.
    '''
    ds = pydicom.read_file(str(file))
    img = ds.pixel_array
    # formatting the image to make training the network faster.
    img = cv2.resize(img, (256,256) )
    fname = file.replace('.dcm','.png')
    fname = fname.replace('_dicom','_png')
    cv2.imwrite(fname, img)
def rle2mask(rle, width, height):
```

```
    '''
    RLE to mask conversion as given.
    It inputs the rle (EncodedPixel value) and return the mask value.
    '''
    mask= np.zeros(width* height)
    array = np.asarray([int(x) for x in rle.split()])
    starts = array[0::2]
    lengths = array[1::2]
    current_position = 0
    for index, start in enumerate(starts):
        current_position += start
mask[current_position:current_position+lengths[index]] = 1
        current_position += lengths[index]
    return mask.reshape(width, height).T
n_imgs = 3
root = "/kaggle/input/pneumothorax/train/dicom_files/"
for i in range(n_imgs):
    f_id = train["ImageId"][i]
    sample = pydicom.dcmread(f"{root}{f_id}.dcm")
    if train[" EncodedPixels"][i] == ' -1':
        plot_pixel_array(sample, title="No pneumotorax")
```

```
    else:
        plt.figure(figsize=(8,8))
        plt.imshow(sample.pixel_array, cmap=plt.cm.bone)
        mask = rle2mask(train[" EncodedPixels"][i][1:], sample.Rows, sample.Columns) * 255
        plt.imshow(mask, alpha=0.3, cmap="Reds")
        plt.axis("off")
        plt.title("Pneumotorax present")
        plt.show()
```

pneumothorax_classification.ipynb

```
def build_dataset(paths, labels=None, bsize=32, cache=True,
                  decode_fn=None, augment_fn=None,
                  augment=True, repeat=True, shuffle=1024,cache_dir=""):
    if cache_dir != "" and cache is True:
        os.makedirs(cache_dir, exist_ok=True)
    if decode_fn is None:
        decode_fn = build_decoder(labels is not None)
    if augment_fn is None:
        augment_fn = build_augmenter(labels is not None)
    AUTO = tf.data.experimental.AUTOTUNE
    slices = paths if labels is None else (paths, labels)
```

```
    dset = tf.data.Dataset.from_tensor_slices(slices)
    dset = dset.map(decode_fn, num_parallel_calls=AUTO)
    dset = dset.cache(cache_dir) if cache else dset
    dset = dset.map(augment_fn, num_parallel_calls=AUTO) if augment else dset
    dset = dset.repeat() if repeat else dset
    dset = dset.shuffle(shuffle) if shuffle else dset
    dset = dset.batch(bsize).prefetch(AUTO)
    return dset
#Creating the Augmented Train and Valid Datasets:
dtrain = build_dataset(
    trainPath, trainLabels, bsize=16, decode_fn=decoder,cache_dir='Kaggle/tf_cache'
)
dvalid = build_dataset(
    validPath, validLabels, bsize=16,
    repeat=False, shuffle=False, augment=False, decode_fn=decoder,cache_dir='Kaggle/tf_cache'
)
#Defining the model:
base_model = densenet.DenseNet121(weights = None, include_top=False, input_shape=(256,256,3))
```

#Adding a dummy layer so that pre-trained weights can be loaded properly. This dummy layer is removed later

predictions = tf.keras.layers.Dense(14,activation='sigmoid', name='predictions')(base_model.output)

base_model2 = tf.keras.Model(inputs = base_model.input, outputs = predictions)

#Loading the pre-trained chexnet weights

base_model2.load_weights('/content/drive/MyDrive/Self Case Study 2/DATASET/brucechou1983_CheXNet_Keras_0.3.0_weights.h5')

#Removing the dummy layer

base_model2.layers.pop()

#Freezing the model

#base_model2.trainable = False

#Adding a pooling layer

new_base_model = tf.keras.layers.GlobalAveragePooling2D()(base_model2.layers[-3].output)

new_base_model = tf.keras.layers.Dense(1024, activation='relu')(new_base_model)

new_base_model = tf.keras.layers.BatchNormalization()(new_base_model)

new_base_model = tf.keras.layers.Dropout(0.4)(new_base_model)

new_base_model = tf.keras.layers.Dense(512, activation='relu')(new_base_model)

new_base_model = tf.keras.layers.BatchNormalization()(new_base_model) new_base_model = tf.keras.layers.Dropout(0.4)(new_base_model)

new_base_model = tf.keras.layers.Dense(64, activation='relu')(new_base_model)

#Adding the final Dense layer for prediction

new_base_model = tf.keras.layers.Dense(1, activation='sigmoid')(new_base_model)

#Model built

final_new_model = tf.keras.Model(base_model2.input, new_base_mod

A1.2 SCREENSHOTS

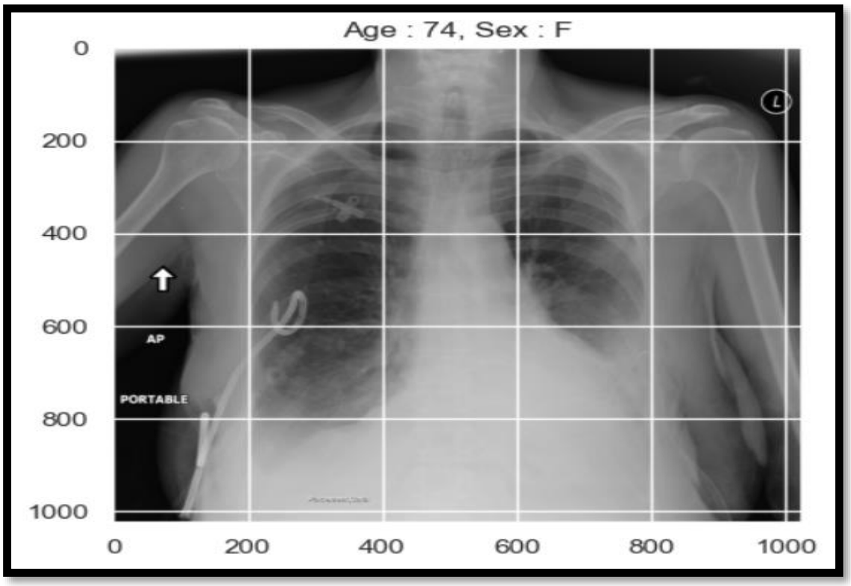

Figure A2.1 Dicom Image Representation

The figure A2.1 illustrates a chest radiograph of a person who underwent a test to check for the presence of Pneumothorax.

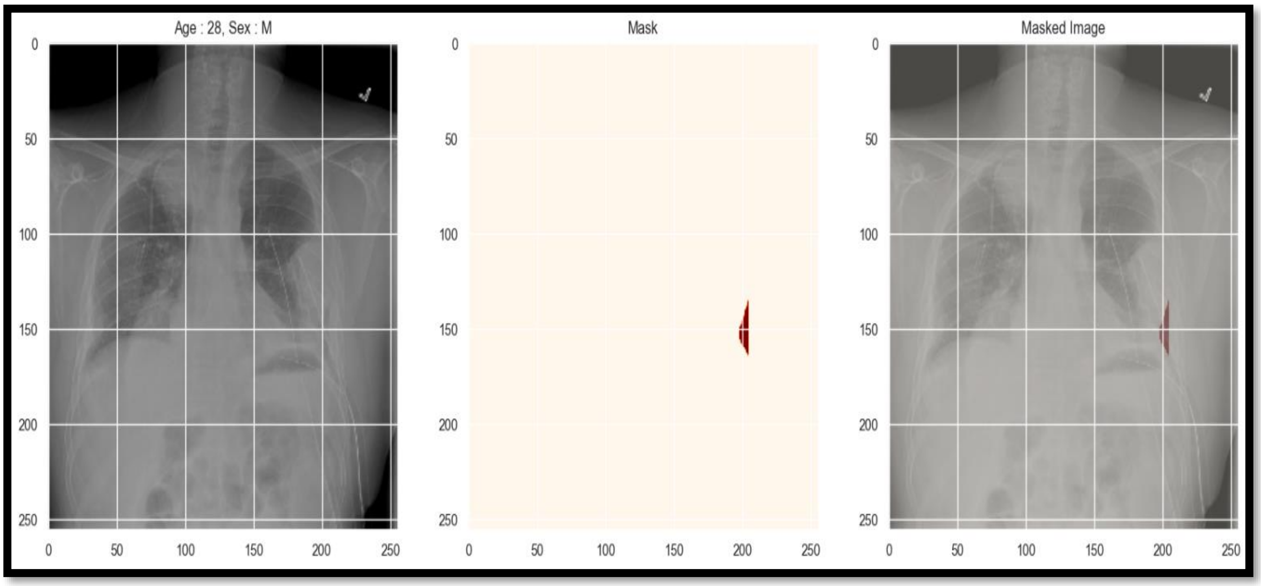

Figure A2.2 RLE Mask Generation

The figure A2.2 depicts the Run-Length Encoded (RLE) masks extracted from the 'Encoded Pixels' column of the Training-rle.csv file. These masks were utilized to determine the classification of pneumothorax.

Figure A2.3 Output Image of Pneumothorax Negative

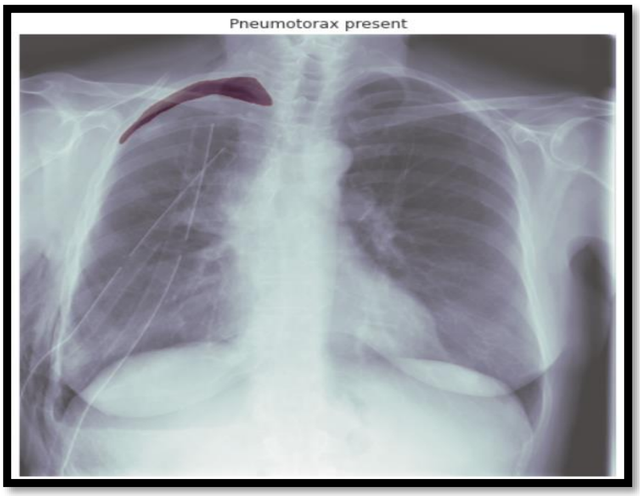

Figure A2.4 Output Image of Pneumothorax Positive

Figures A2.3 and A2.4 represent the final classified images, distinguishing between individuals without pneumothorax and those affected by pneumothorax

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