DEVELOPMENT OF A CLINICAL DECISION SUPPORT SYSTEM (CDSS) FOR THORACIC DISEASE DETECTION USING A HYBRID DEEP LEARNING MODEL

BY

OKECHUKWU BRIAN G.

GOU/U22/CSC/866

DEPARTMENT OF COMPUTER SCIENCE, FACULTY OF COMPUTING AND INFORMATION TECHNOLOGY, GODFREY OKOYE UNIVERSITY, ENUGU STATE,
IN PARTIAL FULFILLMENT OF THE AWARD OF BACHELOR OF SCIENCE (B.SC), DEGREE IN COMPUTER SCIENCE.

SUPERVISOR: ENGR. CAMILUS NJOKU

JUNE, 2026

APPROVAL PAGE

This research, titled "Development of a Clinical Decision Support System (CDSS) for Thoracic Disease Detection Using a Hybrid Deep Learning Model", has been assessed and approved by the Department of Computer Science and Mathematics Committees in the Faculty of Computing and Information Technology, Godfrey Okoye University, Enugu, Nigeria.

Mr. Camilus Njoku	....	....
Supervisor	**Signature**	**Date**
....	....	....
External Examiner	**Signature**	**Date**
Dr. Frank Okebanama	....	....
HOD, Department of Computer Science	**Signature**	**Date**
Prof. I. A. Ajah	....	....
Dean, Faculty of Computing And Information Technology.	**Signature**	**Date**

CERTIFICATION

I certify that I completed the research included therein and that it was primarily based on my observations and investigation. Consequently, I will fully accept the University's decision if I am found to have cheated on the assignment.

OKECHUKWU BRIAN G.

GOU/U22/CSC/866

DEDICATION

I dedicate this work to God and my beloved parents, whose unwavering love, sacrifices, encouragement and steadfast belief in me have been the foundation of my academic journey. Your support, guidance, and countless acts of kindness have inspired me to persevere through challenges and remain committed to achieving my goals. This accomplishment is a reflection of your dedication and the values you have instilled in me.

ACKNOWLEDGEMENTS

I give thanks to Almighty God, who made all things possible and granted me the strength, wisdom, and grace to successfully carry out this project. Words alone cannot fully express my sincere and heartfelt appreciation to everyone who supported me materially, financially, morally, and academically throughout this period.

I am deeply grateful for the knowledge, guidance, and love I received during the course of this work. My special appreciation goes to my project supervisor, Mr Camilus Njoku, for his guidance and support.

I also appreciate the Head of Department, Dr Frank Okebanama, alongside the lecturers and staff of the Department of Computing and Information Technology, for their contributions and encouragement. May God bless you all abundantly.

ABSTRACT

Thoracic diseases, especially pneumonia, continue to be one of the leading causes of death and morbidity across the globe, hence the pressing need for proper diagnosis. In this paper, a clinical decision support system is designed and implemented in order to detect thoracic diseases automatically through the development of a hybrid dheer learning model, namely, DenseNet121-EfficientNetB0, and using chest X-ray images. Here, DenseNet121 is used to acquire the details of the images at a local level while EfficientNetB0 is used to learn in-depth knowledge on the higher semantic level through transfer learning. The combination of features obtained from either of the models helps in improving the performance in classification of thoracic disease. Also, the chest images used for the purpose have been sourced from Kaggle Pneumonia dataset and processed through resizing, normalizing and augmenting the images before the learning starts. Further, during learning, Adam optimization method was utilized while accuracy, precision, recall, f1-score, confusion matrix, ROC curve and average precision metrics were used to evaluate the model. The experimental results show that the model developed had accuracy of 97.75%, AUC of 0.9976 and an average precision score of 0.9973, which clearly indicates the effectiveness of the model. The model developed has already been deployed as a web-based clinical decision support and the users are able to upload their chest X-ray images and get diagnosis.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Table **Page**

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Thoracic diseases are a significant public health problem worldwide and are still one of the most common causes of morbidity, disability and mortality. These diseases involve abnormalities of the tissues of the thoracic cavity, especially in the lungs, pleura, airways, and surrounding tissues. Common thoracic conditions include pneumonia, pulmonary fibrosis, emphysema, lung nodules and masses, pneumothorax, pleural effusion, atelectasis, tuberculosis and cardiomegaly and other respiratory abnormalities. Respiratory diseases are still responsible for the death of millions of people every year, with people living in LMICs (lower- and middle-income countries) having a higher burden of the disease because of poor healthcare infrastructure, limited access to diagnostic resources and a shortage of specialist medical personnel (WHO, 2024). The rise in respiratory diseases and the growth of the population along with urbanization, pollution, and new diseases, has brought a growing need for effective and accurate diagnostic systems.

Medical imaging technologies are extensively used in the diagnosis of thoracic diseases and the widely used diagnostic method is Chest X-ray (CXR) imaging. Chest radiographs are commonly used because they are non-invasive, relatively cheap, readily available, and when they reveal abnormalities, they can be very helpful in the diagnosis. Chest radiograph is a common imaging test used in the diagnosis of pneumonia, lung infiltration, pleural effusion, pneumothorax, thoracic nodules and many other thoracic disorders. Chest radiography was even more important during the COVID-19 pandemic, when prompt assessment of respiratory status was an important factor in patient care and disease follow-up (Apostolopoulos & Mpesiana, 2020). Although it may be widely used, the reading of the X-ray images of the chest is still in a complex and difficult process. Many thoracic diseases have similar radiologic features making them difficult to differentiate, even for the expert radiologist.

In addition, the number of imaging studies produced by health care centers has dramatically grown, causing a great burden for radiologists and physicians. Factors including clinician fatigue, workload, image complexity, and inter-observer variability in radiologists have been shown to lead to diagnostic error (Majkowska et al., 2020). These mistakes could result in delayed diagnosis, incorrect treatment decisions, extended hospital stays, and, in extreme cases, higher death rates. This is further complicated by the lack of qualified radiologists. There is a huge disparity between the demand for diagnostic facilities and available trained radiology specialists in many developing countries, among which are several regions in Africa. This shortage can lead to the delays in interpretation of images and restricted access to expert diagnostic opinions. This is why intelligent technologies that can support health care workers in their faster and more accurate diagnostic decisions are gaining more interest in development (Mollura et al., 2021).

The recent developments of Artificial Intelligence (AI), opened new prospects for the transformation of medical image analysis and healthcare delivery.New opportunities for the transformation of medical image analysis and healthcare delivery emerged lately with the advent of Artificial Intelligence (AI). Artificial Intelligence is the capability of a computer system to do tasks normally associated with human intelligence such as learning, reasoning, decision-making, pattern recognition, and problem-solving. In the healthcare industry, AI technologies have shown incredible promise in disease diagnosis, patient monitoring, treatment recommendations, drug discovery, and clinical decision support.

Machine Learning (ML) and Deep Learning (DL) are the most powerful technology branches of AI that have impacted medical imaging applications (Nguyen et al., 2022). With machine learning, computer systems can derive patterns from past data and make predictions, without having to be programmed for every possible case. In traditional ML methods, the image features are handcrafted, i.e., relevant image features are drawn by the domain experts for classification. While such approaches have moderately succeeded in medical image analysis, the quality of manually designed features and their capacity to represent highly complex images limit their effectiveness (Khan et al., 2021). To overcome these limitations, Deep Learning is a specific branch of Machine Learning that learns the hierarchically structured representations of features from raw data. In the case of deep learning models, they make use of artificial neural networks with several layers to identify more and more abstract, meaningful features in images. This capability has greatly aided in the field of computer vision (CV) including object detection, image classification, image segmentation, and pattern recognition.

For instance, in the medical field, deep learning has transformed the analysis of medical images by automating the process of disease detection from radiological images that achieves high accuracy rates similar to those of medical professionals (Yamashita et al., 2021). For medical image analysis, Convolutional Neural Networks (CNNs) are the most popular deep learning architecture. CNNs are specifically engineered to process image data by learning spatial hierarchies of features by convolutional operations. They can automatically recognize edges, textures, shapes and complex image patterns, which makes them very useful for tasks involving disease detection. CNN based architectures have proven their utility in the diagnosis of thoracic diseases from X-ray images of the chest with high accuracy in different categories of diseases (Rahman et al. 2021). With the growing use of deep learning, new and more complex architectures have been introduced to enhance classification accuracy. Dense connectivity patterns between layers of the network are one such architecture, called Dense Convolutional Network (DenseNet). The DenseNet can propagate the features better and handle the vanishing gradient problem at ease, and also reusing features across the network. A popular variant of DenseNet is DenseNet121 that has attracted a lot of attention in the field of thoracic disease recognition because of its outstanding results on large chest radiography datasets. What is noteworthy is that DenseNet121 was adopted to build several cutting-edge chest X-ray diagnostic systems and has shown excellent performance for detecting multiple thoracic abnormalities (Tariq et al., 2023).

Another important advancement in deep learning is the EfficientNet family of models. We use a compound scaling strategy to optimise network depth, width and image resolution to ensure high performance, while keeping the computation efficient. EfficientNetB0, a baseline model in the EfficientNet family, offers a good trade-off between classification accuracy and computation cost, and is suitable for real world healthcare applications and systems with limited computational resources (Tan & Le, 2021). There have been recent reports of models built on EfficientNet attaining great performance on classification tasks related to thoracic diseases with fewer computational resources than many traditional architectures (Alghamdi et al., 2024).

Although individual deep learning architectures have demonstrated considerable success, researchers have increasingly recognized the advantages of hybrid deep learning approaches. Hybrid models combine the strengths of multiple architectures to overcome the limitations associated with standalone models. For example, DenseNet121 excels at extracting disease-specific radiological features, while EfficientNetB0 offers lightweight yet highly discriminative feature extraction capabilities. The combination of these architectures allows the model to extract various data from chest radiography images, resulting in enhanced classification precision, reliability, and generalization capability (Ahmed et al., 2025).

However, disease diagnosis is not the ultimate goal of such solutions. More often than not, doctors require extra assistance with interpreting outputs and making the final decision about a diagnosis. This growing need has resulted in the rise of Clinical Decision Support Systems (CDSS). Clinical Decision Support System (CDSS) implies the use of IT solutions in the process of making decisions based on reliable statistical data and evidence-based samples (Sutton et al., 2020).

Present-day AI-enabled Clinical Decision Support Systems (CDSS) can analyze enormous amounts of clinical and imaging data, identify patterns, compute risk scores and make suggestions to medical professionals. AI-based decision-making systems in medical imaging have shown their potential to help healthcare providers with challenging decision-making tasks (Kumar et al., 2024). Another important trend in healthcare technology is the use of web-based diagnostics. New intelligent healthcare platforms based on cloud computing, web technologies and APIs have made it possible to create platforms for providing real-time diagnostic services through web browsers and connected devices. The systems allow obtaining medical images, auto-analyzing them and giving decision support recommendations, ensuring better availability to medical subject matters specialists, regardless of their locations, especially in those areas that lack specialized expertise (Chen et al., 2023).

The potential to enhance the diagnosis of thoracic disease with deep learning, web-based deployment and clinical decision support is vast. Healthcare providers can gain valuable insights for patient management and treatment planning in a timely way, by leveraging a strong deep learning model and embedding it in a clinical decision support framework. In addition, web-based deployment makes it easier to scale-up the deployment, accessibility, and remote healthcare delivery, ensuring that the benefits of advanced diagnostic technologies can be reached to a wider population. Although significant advances have been made in the research of thoracic disease detection, there are a number of drawbacks.

Existing studies are mostly concerned with maximizing classification accuracy and have limited attention to aspects of practical deployment, clinical usability, and decision support functionalities. Furthermore, a significant number of models are only tested in research settings and therefore not readily incorporated into health systems that could be used by a healthcare practitioner. Many existing thoracic disease detection models are not very practical due to the absence of comprehensive clinical decision support capabilities. Hence a system encompassing the detection of thoracic disease with precision, intelligent clinical decision support and real-time web-based availability in a single platform is needed.

To address this requirement, this paper presents the design and implementation of hybrid deep learning model Clinical Decision Support System (CDSS) for Thoracic Disease Detection based on Chest X-Ray Images and Hybrid DenseNet121–EfficientNetB0. The system aims to harness the capabilities of cutting-edge deep learning architectures and contemporary web technologies, offering precise disease detection, evidence-based clinical support, and reachable healthcare services. The overall goal of the system is to enhance the efficiency of diagnostics, assist decision-making by healthcare practitioners, mitigate diagnostic errors, and help to achieve better therapeutic results, especially in low-resource settings.

1.2 Statement of the Problem

Worldwide, thoracic diseases are still one of the major causes of mortality and morbidity, causing millions of hospital admissions and deaths each year. Meanwhile, pneumonia, tuberculosis, pneumothorax, pleural effusion, pulmonary fibrosis, emphysema, lung masses and other respiratory diseases remain a strain on healthcare systems, especially in low-resource areas of developing countries where access to specialized healthcare services is limited (World Health Organization, 2024). A diagnosis as early as possible and as accurate as possible is essential for the effective planning and management of treatment and for better patient outcomes.

Timely diagnosis, however, is a significant challenge in many health care settings. Chest X-ray imaging is one of the most frequently used imaging modalities for the diagnosis of thoracic diseases as it is inexpensive, non-invasive and widely available. Although helpful, reading chest radiographs is a very specialized procedure and can only be done with a lot of experience and expertise.

A few thoracic diseases share common radiographic characteristics and therefore it is hard to differentiate even for the most advanced radiologists. Some abnormalities are not obvious and can be overlooked and the symptoms can overlap for some diseases, leading to misdiagnosis. As such, the manual interpretation process is still subject to diagnostic variation, human mistakes, fatigue, and inconsistencies among healthcare professionals (Majkowska et al., 2020). In recent years, these pressures have been compounded by the growing number of services being delivered in the radiological field. The healthcare organizations are creating thousands of medical images per day these days and it's becoming a real challenge for radiologists and clinicians.

With the growth in volume of patients, health care workers are forced to decipher extensive amounts of images in short periods of time. This can delay diagnosis, report delays and decreased diagnostic accuracy. However, these are more extreme in resource limited health facilities where fewer highly trained radiologists and fewer good diagnostic facilities are available (Mollura et al., 2021).

In recent years with the advent of Artificial Intelligence (AI) and Deep Learning (DL), there are some AI-based solutions that are potential for automatic thoracic disease detection but many of them are still having some drawbacks. Many of the studies have focused mainly on getting to high classification accuracy with individual deep learning architectures like Convolutional Neural Networks (CNNs), DenseNet, ResNet and EfficientNet models. Although these have had good results, not all of these models are suitable for quantification of all the complex radiographic features of multiple thoracic diseases. Consequently, issues with generalization, robustness, and consistency in the diagnosis remain (Ahmed et al., 2025).

One limitation of existing research is that there are no user user-friendly, deployable platforms that allow healthcare professionals to use this technology in real-time. A large portion of published research concentrates on the development and evaluation of experimental techniques, utilizing benchmark data sets, but does not further take them into practical applications in health care.

As there are difficulties faced researchers in delivering the solution, there is a need of a smart, accurate and deployable system based on chest X-ray images that will detect numerous thoracic diseases and give efficient support to clinicians. This system needs to use advanced deep learning techniques and technologies diagnose difficult cases in real-time and decrease the load of radiologists, reduce the number of mistakes in the process of making diagnoses, and improve access to health care for those without resources.

Given these facts, the study set out to solve these challenges by developing a Clinical Decision Support System for Thoracic Disease Detection based on a Hybrid DenseNet121 - EfficientNetB0 deep learning model and using Chest X-ray images.

1.3 Aim and Objectives of the Study

The aim of this study is to design and implement a Clinical Decision Support System (CDSS) for thoracic disease detection using a Hybrid deep learning model.

The specific objectives of this study are to:

1. Collect and prepare chest X-ray images from the NIH ChestX-ray14 dataset for thoracic disease detection.
2. Design a hybrid deep learning architecture by integrating DenseNet121 and EfficientNetB0 to enhance feature extraction and classification of thoracic diseases.
3. Train and optimize the proposed hybrid model using chest X-ray images representing multiple thoracic disease categories.
4. Develop a React-based web application that enables healthcare professionals to upload chest X-ray images and obtain real-time diagnostic results.
5. Evaluate the performance of the developed model using standard classification metrics.

1.4 Significance of the Study

The study is important as it makes a contribution in the areas of artificial intelligence, medical image analysis, clinical decision support systems, and the healthcare technology. The study can be appreciated from healthcare professionals, patients, healthcare institutions, researchers, and throughout the society.

i. Healthcare Professionals The proposed Clinical Decision Support System (CDSS) will provide an intelligent assistant to radiologist, physicians and other health care practitioners by providing automated thoracic disease detection from chest X-ray images. The system will alleviate manual interpretation of images, assist the decision-making process in diagnosis, and shorten the diagnostic time and increase the diagnostic accuracy. This might result in more time being spent on patient management and treatment planning, and less on image analysis.

ii. Patients It is crucial that thoracic diseases are diagnosed early and correctly in order to be able to treat them properly and result in better patient outcome. The proposed system will enable prompt diagnosis, and thus decrease the time lag in starting treatment. Early detection of the disease can help to improve disease management, minimize complications and enhance quality of life for a thoracic patient.

iii. Healthcare Institutions The proposed system can help hospitals, clinics, and diagnostic centers to reduce the workload in the diagnostic process and improve the efficiency of the system. This system can support health institutions to control the increasing number of patients while maintaining the diagnostic quality and consistency. It can also be useful as a back-up tool in situations where there is a shortage of radiology experts.

iv. Researchers and Academics This research work is a part of the increasing body of knowledge in the field of artificial intelligence driven healthcare system. It offers insights into the implementation of hybrid deep learning architectures for medical images classification and illustrates the incorporation of deep learning models into a real clinical decision support system. The results of this research article can be used for further research on more intelligent healthcare systems in the future. AI in Medicine Development.

v. Medical Artificial Intelligence Development. The study highlights the feasibility of applying hybrid deep learning approaches to address real-world healthcare problems. The research melds the DenseNet121 and EfficientNetB0 designs, offering insights into enhancing the precision, efficiency, and dependability of AI-driven disease detection systems.

vi. Government and Healthcare Policymakers Research findings from this study can contribute to healthcare policy makers and government bodies in their consideration of AI implementation in healthcare systems. The proposed system can be used as a model for incorporating intelligent diagnostic tools into health services systems, especially in developing countries, where there is a lack of health services.

1.5 Scope of the Study

This study aims to design and implement a Clinical Decision Support System (CDSS) for thoracic disease detection that is based on chest X-ray images captured from patients and a hybrid deep learning architecture. This system is designed to help physicians to automatically detect and diagnose various thoracic diseases from images and make intelligent decisions.

This research involves data collection, data preprocessing, training, evaluation, deployment, and validation of a deep learning model for the detection of diseases from chest radiographs (CXRs) from the NIH ChestX-ray14 Dataset. The dataset comprises more than 100,000 frontal-view chest X-ray images annotated with multiple thoracic diseases, which can be used to train and test the proposed system

1.6 Limitations of the Study

While the aim of this study is to create the effective Clinical Decision Support System for the detection of thoracic diseases, there are some shortcomings that can be avoided and would affect the overall performance and application of the proposed system.

A drawback of the study is the use of the NIH ChestX-ray14 dataset. While the dataset is one of the largest publicly available chest radiography datasets, there can be inaccuracies in the labels and class imbalance that can impact model training and prediction performance.

Some disease classes have much fewer samples than other, more common classes, e.g. few samples for hernia compared to samples for more common diseases like infiltration or effusion, which can result in different levels of accuracy when classifying diseases.

The other drawback is that the study is only related to the chest X-ray images. Other imaging techniques, like computed tomography (CT) scan, magnetic resonance imaging (MRI) and ultrasound imaging can also offer more information for diagnosis and disease characterization. However, this is beyond the scope of this research to consider multiple imaging modalities.

Another crucial factor which influences the performance of the proposed deep learning model is the quality of the captured images. Low resolution, high noise, incorrect positioning or imaging artefacts can cause poor image quality, the adverse consequences of which may impact on prediction accuracy. The image is subjected to some image related challenges and then preprocessed in order to improve the image quality.

Despite these limitations, the proposed system has the potential to provide valuable support in the detection of thoracic diseases and showcase the feasibility of integrating AI and clinical decision support technologies into healthcare.

1.7 Operational Definition of Terms

The following terms used in this study are operationally defined as follows:

Artificial Intelligence (AI)

Artificial Intelligence is the ability of computer systems to complete tasks that typically require human intelligence such as learning from data, identifying patterns and making decisions. In this research, AI is used in the field of automated thoracic disease diagnosis using X-ray image of the thorax.

Chest X-ray (CXR)

Chest X-ray is a diagnostic procedure that uses x-rays to obtain pictures of the chest. It can be used to allow visual examination of the lungs, heart, ribs and other thoracic structures for abnormalities.

Clinical Decision Support System (CDSS)

A Clinical Decision Support System (CDSS) is a computer-based tool that helps healthcare providers by analysing patient information and providing diagnostic or treatment suggestions to enhance clinical decision-making.

Deep Learning (DL)

Deep Learning is a high-level field of machine learning that uses multilayer neural networks to automatically find meaningful patterns in large data sets without having to engineer features.

Feature Extraction

Feature extraction is used to convert raw image information into a set of meaningful numbers that can help a machine learning (or deep learning) model differentiate between various image classes.

Hybrid Deep Learning Model

A hybrid deep learning model is a model architecture that uses two or more neural networks to leverage the strengths of each network and enhance the final classification accuracy. The DenseNet121 and the EfficientNetB0 are used in this study for the detection of thoracic diseases.

Normalization

One of the image preprocessing methods is the Normalization method which is designed to bring pixel intensity values of image to a common range to provide stability of training, faster convergence speed and better model performance.

Pneumonia

Pneumonia is a respiratory infection that causes inflammation of the lung air sacs, often leading to fluid accumulation that can be identified from chest X-ray images.

Thoracic Disease

Thoracic disease refers to any medical condition affecting the organs and structures within the chest cavity, particularly the lungs, pleura, airways, and related tissues.

Transfer Learning

Transfer learning is a deep learning approach in which a model previously trained on a large dataset is adapted to perform a new but related task, reducing training time while improving predictive performance.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter introduces a thorough review of the literature of existing research related to the design and implementation of a Clinical Decision Support System for detecting thoracic diseases from chest X-ray images and the application of hybrid deep learning techniques. The theoretical background, concepts, technologies, and previous studies on the foundations of the development of intelligent healthcare systems for disease diagnosis are reviewed. Thoracic diseases and chest radiography, clinical decision support systems, artificial intelligence in the healthcare sector, deep learning architectures, DenseNet121, EfficientNetB0, hybrid deep learning models, and web-based health care systems are explored in the chapter specifically. In addition, empirical studies from this period from 2020 to 2026 are critically reviewed with regard to existing achievement, limitation and gaps in the studies. The result of this review will lay the theoretical and practical groundwork for the development of the proposed system.

2.2 Theoretical Framework

The theoretical foundation of this study is based on three major theories:

1. Clinical Decision Support Theory
2. Deep Learning Theory
3. Pattern Recognition Theory

These theories collectively provide the conceptual basis for developing an intelligent system capable of detecting thoracic diseases and supporting clinical decision-making.

2.2.1 Clinical Decision Support Theory

Clinical Decision Support Theory deals with how computer systems can support the health care professional in making decisions based on the evidence available in the diagnosis, treatment, and management of a patient. The Clinical Decision Support Systems (CDSS) aim to improve the delivery of health care services by integrating clinical information, medical knowledge, and computational intelligence to provide valuable recommendations (Sutton et al., 2020). The theory is based on the premise that healthcare professionals will make better decisions with accurate, timely and relevant healthcare information.

Clinical decision support systems ease the cognitive burden, increase diagnostic uniformity, lower the risk of medical errors, and aid in better patient care. The proposed system uses the following mechanism in the aforementioned context: Clinical Decision Support Theory that combines automated thoracic disease detection with intelligent diagnostic assistance. The system has the ability to predict thoracic diseases based on chest X-ray image analysis and to deliver information that can help health professionals during their diagnosis.

2.2.2 Deep Learning Theory

Deep Learning Theory is based on the principles of Artificial neural networks and is concerned with computational models being able to learn hierarchical feature representations from large amounts of data automatically (LeCun et al., 2021). In contrast to traditional machine learning methods, which are based on manually engineered features, deep learning models learn discriminative features directly from the raw image data. Deep neural networks work through various layers, gradually mapping simple features of images to more complex and meaningful representations. One of the reasons for the success of deep learning in medical imaging is the ability to learn visual patterns that are specific to medical diseases, which are not easy to learn using traditional learning methods. In recent years, deep learning models have been shown to perform at a level similar to that of advanced radiologists in a variety of medical image analysis applications (Yamashita et al., 2021). The study proposes to implement a hybrid DenseNet121–EfficientNetB0 for thoracic disease detection using Deep Learning Theory.

2.2.3 Pattern Recognition Theory

Pattern Recognition Theory is about the process of recognising regularities and meaningful structures in data. Theory is the ability to classify observations into pre-defined categories, based on learned characteristics of the computational system (Bishop, 2021). The medical image analysis is essentially a pattern recognition problem, and the diagnosis of disease is based on the recognition of abnormal patterns of images which differ from the normal ones in disease tissues. In the chest, various diseases have their own characteristic x-ray pattern. The hybrid approach is to be based on the principles of pattern recognition, which will detect disease-specific features in chest X-ray images.

2.3 Conceptual Review

2.3.1 Thoracic Diseases

Thoracic diseases are diseases of structures found within the thoracic cavity, such as diseases of the lungs, pleura, heart, airways and surrounding tissues. These diseases are major burden to healthcare all over the world and frequently require imaging diagnosis for appropriate management (WHO, 2024). Thoracic diseases can be infectious, inflammatory, obstructive, or neoplastic, or structural. Promptly identification of the disease is crucial, as it can cause serious consequences such as worsening of the disease, escalating healthcare expenses and mortality. In this study, we used the NIH ChestX-ray14 dataset, which consists of 14 categories of thoracic disease.

2.3.2 Atelectasis

Atelectasis is the collapse or inadequate expansion of a part of the lung. It decreases the exchange of oxygen and can be caused by airway blockage, compression of the lungs, or complications after surgery. Radiographically, atelectasis is seen as increased lung density with loss of lung volume.

2.3.3 Cardiomegaly

Cardiomegaly is an enlarged heart. It is often seen with hypertension, heart failure and valvular heart diseases. A cardiothoracic ratio is often measured on X-rays of the chest to evaluate cardiac enlargement.

2.3.4 Pleural Effusion

Pleural effusion is a buildup of fluid in the pleura, which is the thin tissue that covers the lungs. It can be caused by an infection, a cancer, a heart failure or inflammation. Pleural effusion appears as the blunting of the costophrenic angle and opacification of the pleura on chest X-rays.

2.3.5 Pneumonia

Pneumonia is an infection of the lungs that results in inflammation of the lung tissue and an accumulation of fluid in the air sacs. It is still one of the most common causes of hospitalization and deaths in the world, especially in children and elderly people (WHO, 2024). A chest X-ray is a key examination to identify pneumonia.

2.3.6 Pneumothorax

Pneumothorax is when air enters the pleural space and leads to partial or total collapse of the lung. Early diagnosis is very important as pneumothorax can be life threatening if left untreated. A chest X-ray will allow for rapid diagnosis of pneumothorax by detecting the presence of air between the lungs and the chest wall, and the loss of lung structure.

2.11 Review of Related Literature

The review of related literature presented in this study is divided into two sections.

The use of artificial intelligence, deep learning, and clinical decision support systems for the detection of thoracic diseases based on chest X-ray images has been the topic of numerous studies. Recent progress in deep learning has greatly enhanced the performance of automated disease diagnosis by making it possible to extract complex radiological features from medical images. This section reviews selected studies in the most critical manner from 2020 to 2026 that are relevant to the proposed Clinical Decision Support System for Thoracic Disease Detection.

Wang et al. (2025) created an automated system for thoracic disease classification from chest radiographs based on deep learning techniques. The study used DenseNet121 and tested it using a vast chest X-ray dataset. The average Area Under the Curve (AUC) for the results was 0.89 in various thoracic disease categories. While the study proved DenseNet architectures to be effective in medical image classification, it lacked the integration of clinical decision support functionalities and real-time deployment.

Alghamdi et al. (2024) introduced an EfficientNet model for detection of Thoracic disease with the aim of enhancing the computational efficiency while maintaining high classification accuracy. Study used chest radiographs from public databases and reported classification accuracy of over 92 % for common thoracic diseases. While EfficientNet had good performance, this study was not integrated with a decision support framework, and it only investigated disease classification.

Rahman et al. (2021) studied the deep learning technique for thoracic disease classification in chest X-ray images with multiple labels. This study involved several CNN architectures such as ResNet, DenseNet and VGG model. The experimental results showed that DenseNet121 outperforms the tested architectures overall. The study did not, however, look at deployment issues, and was restricted to evaluation of the model offline.

Kumar et al (2024) discussed the use of Artificial Intelligence in Clinical Decision Support Systems. Their research found that using AI-driven CDSS platforms was more efficient in diagnoses and decreased clinician workload. The authors highlighted the importance of combining predictive models with practical healthcare interfaces. They did not however have a targeted interest in the diagnosis of thoracic disease.

Ahmed et al. (2025) proposed a hybrid deep learning architecture for medical image classification using various convolutional neural networks. The hybrid model performed better than the standalone models in the classification task. It was concluded that hybrid models have more comprehensive features extraction capabilities. Nevertheless, these benefits did not include any web-based deployment or clinical decision support implementation.

The designers of the platform, Chen et al. (2023), created a web-based healthcare diagnostic platform that connected deep learning prediction models implemented by RESTful APIs. The system made information more accessible, and allowed for remote diagnosis. The results showed that the web-based deployment had a significant effect on improving health care service delivery. The study did not, however, involve diagnosis of thoracic disease.

Tariq et al. (2023) assessed DenseNet121's performance on chest X-rays and found it to be effective in detecting pneumonia, pleural effusion, and cardiomegaly. The study highlighted the benefits of using dense feature propagation in thoracic disease classification. However, this system was not explainable and did not have recommendations for clinical use.

Li et al. (2024) proposed a multi-label chest disease detection system based on transfer learning and attention mechanism. The proposed model obtained an average AUC of 0.91 in 14 thoracic disease categories. The performance was impressive, but the study did not consider deployment or interaction with the users.

Zhang et al. (2025) designed an intelligent chest X-ray analysis system based on ensemble deep learning technique. The system integrated DenseNet and EfficientNet architectures and obtained a better classification performance than the DenseNet and EfficientNet alone. The study illustrated the benefits of hybrid architectures but didn't provide the solution as far as a Clinical Decision Support System.

Nguyen et al. (2022) surveyed the use of artificial intelligence in healthcare diagnostics and came up with medical imaging as one of the successful application areas. The authors concluded that deep learning models can greatly boost the accuracy of disease detection. They also identified issues regarding explainability, deployment, and integration into the healthcare system.

Singh et al. (2024) proposed an automated system for the detection of pneumonia using deep learning and chest X-ray images. The proposed model gave classification accuracy of 94.5%. The system showed good diagnostic power but was restricted to a single disease category, and it did not give any recommendations for decisions.

Rodriguez et al. (2023) created a cloud-based medical image analysis platform that can process radiological images remotely. The study identified the advantages of web-based health care system in rural and underserved populations. The platform was primarily geared toward image storage and visualization, however, without any intelligence in disease detection.

Alhassan et al. (2025) suggested a hybrid DenseNet–EfficientNet model for the classification of chest disease. Experimental testing showed that the hybrid model architecture was more accurate, precise and recall than stand-alone architecture. Although these encouraging results, the study did not include clinical decision support functionalities.

Park et al. (2024) investigated EAI techniques for chest X-ray diagnosis. To make the model easier to understand and more trusted with, the study used Grad-CAM visualization. They found explainable models to be more acceptable to healthcare professionals. The system was still just a prototype system and not a product that could be deployed as a healthcare application.

Yusuf et al. (2026) implemented a real-time AI powered chest disease diagnosis system with FastAPI and modern web technologies.Yusuf et al. (2026) created an AI-powered real-time chest disease diagnosis platform using FastAPI and the latest web technologies. The platform enabled greater access and shortened the diagnostic turnaround time. However, this system adopted a single-model design and lacked a complex feature fusion..

2.12 Summary of Literature Review

Table 2.1 presents a summary of selected literature reviewed in this study.

Table 2.1 Summary of Literature Review

Author(s)	Technique Used	Work Done	Limitation
Wang et al. (2025)	DenseNet121	Thoracic disease classification	No CDSS implementation
Alghamdi et al. (2024)	EfficientNet	Chest disease detection	No decision support
Rahman et al. (2021)	CNN Models	Multi-label disease classification	Offline evaluation only
Kumar et al. (2024)	AI-powered CDSS	Clinical decision support framework	Not specific to thoracic diseases
Ahmed et al. (2025)	Hybrid CNN	Medical image classification	No deployment platform
Chen et al. (2023)	Web-based AI System	Remote healthcare diagnostics	Limited thoracic focus
Tariq et al. (2023)	DenseNet121	Chest X-ray analysis	No recommendation system
Li et al. (2024)	Transfer Learning	Multi-label disease detection	No real-time deployment
Zhang et al. (2025)	Ensemble Deep Learning	Thoracic disease classification	No CDSS integration
Nguyen et al. (2022)	Review Study	AI in healthcare diagnostics	No implementation
Singh et al. (2024)	Deep Learning	Pneumonia detection	Single disease focus
Rodriguez et al. (2023)	Cloud Platform	Remote image processing	Limited AI functionality

Alhassan et al. (2025)	Hybrid DenseNet-EfficientNet	Disease classification	No clinical support system
Park et al. (2024)	Explainable AI	Explainable chest diagnosis	Experimental framework
Yusuf et al. (2026)	FastAPI Deployment	Real-time diagnosis platform	Single-model architecture

2.5 Research Gap

The literature reviewed has shown significant progress in the application of artificial intelligence and deep learning for thoracic disease detection, as several studies demonstrates the effectiveness of DL and Transformer architectures in order to classify chest radiographs with high levels of accuracy.

After some progress in diagnosing thoracic diseases, research in the field has many holes. Most research is aimed at attaining high accuracy of classification without converting results into a Clinical Decision Support System that helps health practitioners in practice. Moreover, proposed solutions are tested mainly in the offline form. It should be noted that most investigated methods rely on one single deep learning model. Furthermore, while advanced deep learning techniques have been combined with modern web technologies, the work has not yet been completed. Thus, researchers should be able to develop a unified system combining hybrid deep learning and capabilities for detecting multiple thoracic diseases with clinical decision support features and real-time deployment. In this context, this research is supposed to fill these research gaps and develop a Clinical Decision Support System for the detection of thoracic diseases based on a Hybrid DenseNet121–EfficientNetB0 Deep Learning Model and images of chest X-rays.

CHAPTER THREE

SYSTEM ANALYSIS AND DESIGN

3.1 Introduction

In this chapter the system analysis and design methodology used to develop the proposed Clinical Decision Support System (CDSS) for Thoracic Disease Detection using chest X-ray images is presented. The chapter includes an in-depth description of the present diagnostic procedures in thoracic diseases and illustrates the drawbacks of those procedures. In addition, it presents the proposed intelligent system, designed to overcome the identified drawbacks by implementing the integration of artificial intelligence, deep learning and web technologies. This research aims to design a Clinical Decision Support System (CDSS) that integrates the best of two cutting edge deep learning architectures (DenseNet121 and EfficientNetB0) for detecting multiple thoracic diseases in chest X-rays. The system also utilizes these features in a web-based platform built with FastAPI and React technologies, allowing health care practitioners to have access to the diagnostic support in real-time. In this research work the methodology used is Object Oriented Analysis and Design (OOAD) and Quantitative Experimental Research techniques.

3.2 System Analysis

System analysis is an essential step in the evolution of any software system as it gives an overall view of the environment in which the proposed solution is to function. It includes the analysis of the current systems, their weaknesses, their users' needs, and their functional requirements for the new system. In hospitals, health centers, and other medical settings, system analysis is crucial because it directly impacts patient outcomes and clinical care. Chest X-ray imaging is an important tool that healthcare professionals use for diagnosing thoracic diseases, as it can provide information about any abnormalities in the lungs, pleura, or the other structures found in the thoracic cavity. This process will depend largely on the experience and expertise of the radiologists and physicians.

However, with the expanding patient numbers, the increasing diagnostic workload and the shortage of health care specialists have revealed the limitations of currently existing diagnostic practice. It is therefore important to have intelligent systems that can assist healthcare professionals who require timely and accurate diagnosis. The Clinical Decision Support System (CDSS) proposed in this work looks forward to solving these problems with the aid of an Artificial Intelligence (AI) and Deep Learning (DL) system, which is capable of automating the detection of thoracic diseases while providing useful decision support information to healthcare practitioners. The existing diagnostic process is explored and the proposed solution is motivated by specific limitations found in the current process.

3.2.1 Analysis of the Existing System

Currently, the diagnosis of thoracic disease is mainly based on manual examination and interpretation of the chest X-ray image by radiologists and physicians. Here, physicians and other healthcare workers visually examine radiographs for signs of disease including opacities, abnormalities of the pleura, infiltrates, nodules, masses and other pathological changes related to diseases of the thorax. Chest X-ray is considered one of the most commonly used imaging techniques due to its low cost, availability, and ability to yield useful information quickly.

Chest X-rays are used regularly in healthcare settings all over the world for the diagnosis of respiratory conditions such as pneumonia, tuberculosis, pleural effusion, pneumothorax, and other thoracic abnormalities. The process usually starts with image acquisition, radiological interpretation and taking clinical decisions based on the acquired image. Although widely used, the manual analysis of chest X-rays has a lot of difficulties. Diagnosis can be accurate to a great degree, depending on the skill, experience and judgment of the individual health care provider. There may be inter-observer variability with different radiologists interpreting the same image. In addition, some thoracic diseases have less obvious radiographic characteristics, and it can be challenging to detect especially during early stages of disease. This can lead to incorrect diagnoses, misdiagnoses and a failure to diagnose abnormalities.

Besides manual diagnosis, the last few years have seen the introduction of Artificial Intelligence based diagnostic systems. A machine learning or Deep Learning technique is applied in many of these systems to automatically classify chest X-ray images. Several architectures, like Convolutional Neural Networks (CNNs), ResNet, DenseNet, EfficientNet, and Vision Transformers, have shown promising performance on the task of thoracic disease detection. Such systems have the ability to learn complex image features and to generate disease prediction with high accuracy. But much of the current AI-based systems are still research systems and are tested mostly in controlled experimental settings. Numerous studies have been conducted that only focus on the accuracy of the classification and leave out the issues of deployment and integration into clinical workflow. As a result, the use of these technologies is limited for physicians and other healthcare practitioners, even though they are successful. Figure 3.1 presents a diagrammatic overview of the current system.

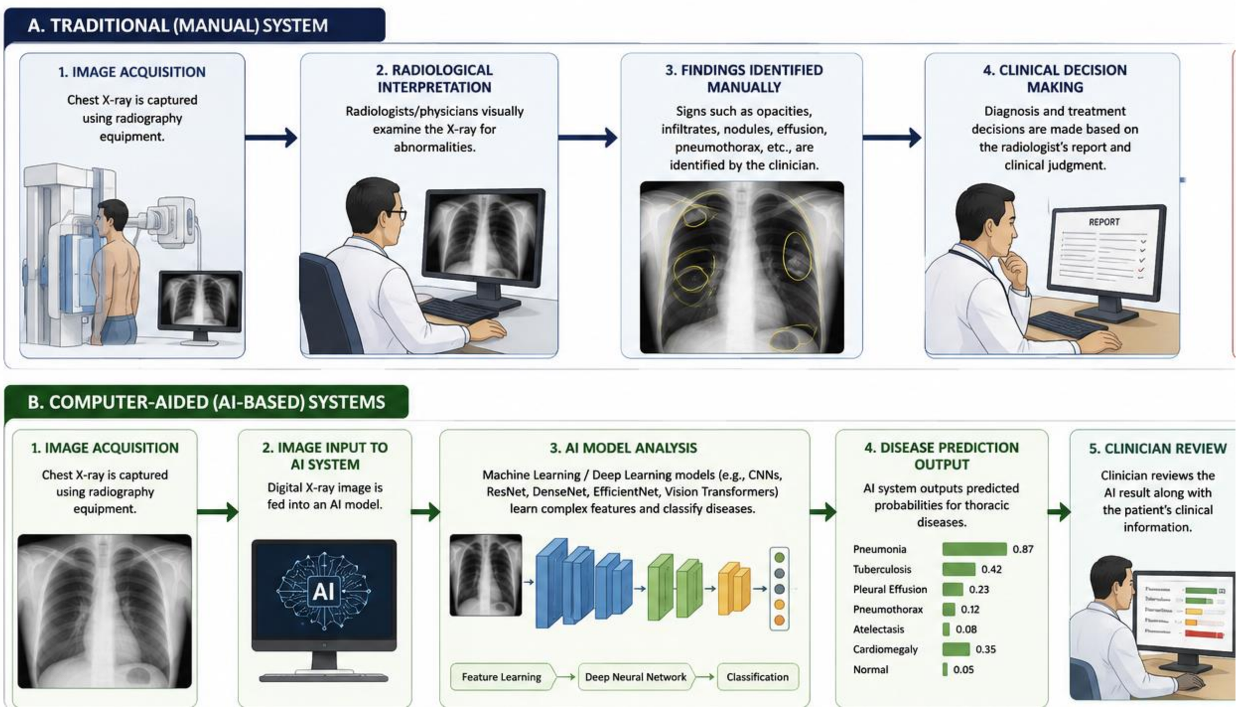

Figure 3.1 Proposed system Architecture

Furthermore, most of the current solutions are just image classification systems, and do not offer full Clinical Decision Support features. Disease predictions are made, but the information that could be useful to a health care practitioner to interpret results and make clinical decisions is missing. The constraint limits the real-world applicability of numerous AI-powered diagnostic tools in clinical settings.

3.2.2 Limitations of the Existing System

The existing system is limited in the following ways: While the traditional method of diagnosing thoracic disease has played a large role in the delivery of healthcare over the years, there are still a number of issues that impact the effectiveness and efficiency of the traditional method.

i. The current system heavily relies on the skill of radiologists and can result in different diagnoses.
ii. Heavy workloads can be a burden to radiologists and may lead to fatigue, delays, and the failure to detect abnormalities.
iii. Limited access to timely diagnosis due to shortage of radiologists, particularly in rural areas.
iv. Some AI systems just predict disease categories without providing confidence scores, explanations, clinical guidance.
v. The majority of AI models are still in research labs and are not yet working in real-world applications in healthcare.
vi. Single-model methods might not be able to fully characterize the wide variety of chest X-ray characteristics.

The gaps indicate the need for an accurate, accessible, decisions-support based thoracic disease detection system.

3.2.3 Analysis of the Proposed System

This study aims to overcome these drawbacks of the current diagnosis method by proposing the development of a Clinical Decision Support System for Thoracic Disease Detection based on a Hybrid DenseNet121–EfficientNetB0 Deep Learning Model and Chest X-ray Images. The suggested system integrates cutting-edge AI methods with internet-based technologies to develop an intelligent diagnostic platform that can help healthcare practitioners in real-time clinical decision-making. The system is designed to be able to take chest X-ray images that are uploaded via a web-based user interface which is intended to be created with React.

When the image is submitted, it is preprocessed with a series of actions such as image resizing, normalization, and image enhancement. These pre-processing steps are crucial in enhancing the clarity and quality of the images and in making them suitable for the deep learning model. After preprocessing, the image is passed to the hybrid deep learning architecture. The architecture is composed of 2 parallel feature extracting branches. The first branch is DenseNet121 which is used to extract detailed radiological features related to the disease from the chest X-ray image. By leveraging its dense connectivity structure and efficient feature reuse capabilities, DenseNet121 is well suited to detect subtle pathological features of thoracic diseases. The second branch is based on a scaled down and yet very effective deep learning architecture EfficientNetB0, which is characterized by balanced scaling. EfficientNetB0 is an efficient network that extracts complementary image features.

The union of the two architectures is able to extract a much wider spectrum of discriminative features than either one can do on their own. These features are then fused together using a feature fusion mechanism and fed to a classification layer. The classification layer makes disease predictions for fourteen classes of thoracic disease included in the NIH ChestX-ray14 dataset. Apart from disease prediction, the system also calculates confidence scores which denote the probability of every prediction. The system incorporates a Clinical Decision Support module to make the system more useful in practice. This module decodes the predictions and creates additional information that can help healthcare professionals in the diagnosis.

The decision-support element of the system integrates the disease descriptions and level of confidence on thoracic disease diagnosis. Its entire framework is implemented on FastAPI back end and React front end technology, which makes this system easy to get and operate as real-time applications. Thus, health care providers have access to this system through their usual web browsers, not requiring any kind of installation of specialized software. As a result, the proposed system presents an integrated health application with automatic diagnosis of diseases, smart support decision capability, and web-based accessibility.

3.2.4 Advantages of the Proposed System

Conventional diagnostic techniques and any existing AI systems have several limitations; thus, the dedicated Clinical Decision Support System is characterized with the following benefits::

i. Facilitates automatic identification of thoracic diseases, thus minimizing the time required for manual image analysis;
ii. Improves accuracy of diagnosis due to its hybrid architecture of DenseNet121–EfficientNetB0.
iii. For more accurate disease classification, extracts complementary image features.
iv. Aids radiologist in the diagnostic process, thereby minimizing workload and fatigue.
v. Offers Clinical Decision Support information in addition to basic disease forecasting.

vi. Improves clinical decisions by providing more insights and recommendations for diagnosis.
vii. Allows access remotely via a web application created using FastAPI and React.

3.2.5 System Requirements

System requirements specify the resources and constraints of a proposed Clinical Decision Support System that are required to ensure its successful functioning. These requirements are divided into functional and non-functional requirements.

A. Functional requirements

i. The system needs to offer a secure and easy-to-use UI enabling healthcare practitioners to upload chest X-ray images for analysis.
ii. The images uploaded must be checked and approved for processing by the system to only process images that are supported.
iii. Once the image is submitted to the system, it should automatically convert the images into preprocessed images (resizing, normalization and enhancement).
iv. The system should also be able to extract image features with Deep ResNet50, DenseNet121 and EfficientNetB0 architectures and then classify thoracic diseases.
v. After classification the system should produce confidence scores and information supporting decisions on the detected disease conditions.
vi. The results should be presented on an interactive dashboard to enable users to see predictions and download diagnostic reports as needed.

B. non-functional requirements

i. The proposed solution needs to be high performing and be able to produce predictions within a short response time for real-time clinical use.
ii. Reliability is also key, as the system needs to give consistent and reliable results in repeated operations.
iii. The usability is another important requirement.
iv. The system should offer an easy-to-use interface with reduced learning curve for the healthcare practitioners.

v. Safety measures will also need to be put in place to secure uploaded medical images and make sure that delicate health information is dealt with properly.
vi. Furthermore, the system should be scalable to support future updates, like adding more disease categories, expanding datasets, and connecting with hospital information systems.
vii. Maintainability should also be addressed during development, in order to make future modifications to the model, system changes and software changes as easy as possible without adversely affecting the operation of the system.

3.2.6 Input-Process-Output (IPO) Analysis

The Input-Process-Output (IPO) is a commonly used analytical framework to demonstrate the basic method of transformation of input information into meaningful outputs, through the means of certain processing activities. The IPO model allows understanding the working process of the proposed Clinical Decision Support System and describes how the chest X-ray images are processed to yield predictions regarding thoracic diseases and clinical suggestions.

In the proposed system, the main input refers to the chest X-ray images uploaded by health practitioners through the online interface. Those images show the radiographic data necessary for disease analysis. Apart from that, such inputs as users' inquiries, metadata of images, and the system's commands, which launch the diagnostics process, are also provided in the input.

Once the image has been submitted, the system starts a series of processing activities. The first stage is connected with image preprocessing, which allows resizing, normalizing, and adjusting uploaded images in a way that they become compatible with the deep learning model. After preprocessing is completed, the image is sent to the hybrid architecture of DenseNet121–EfficientNetB0 in order to conduct feature extraction, disease classification, etc. Finally, the classification results are referred to the Clinical Decision Support module where confidence scores and diagnostic recommendations will be generated.

The final output consists of thoracic disease predictions, with its associated confidence levels, and decision-support information which will be shown or presented through the user interface. These outputs assist healthcare professionals in making informed clinical decisions regarding patient diagnosis and management.

Table 3.1: Input-Process-Output Analysis of the Proposed System

Input	Process	Output
Chest X-ray Image	Image Preprocessing	Enhanced Chest X-ray Image
Enhanced Image	DenseNet121 Feature Extraction	Disease-Specific Features
Enhanced Image	EfficientNetB0 Feature Extraction	Generalized Features
Extracted Features	Feature Fusion	Combined Feature Representation
Combined Features	Disease Classification	Thoracic Disease Prediction
Prediction Results	Clinical Decision Support Analysis	Recommendations and Confidence Scores
Processed Results	User Interface Display	Diagnostic Report and Visualization

Results of the IPO analysis show how the proposed system extracts clinically meaningful information out of the raw medical images. This controlled flow enhances system efficiency and reliability, and provides useful diagnostic help to healthcare practitioners as needed.

3.2.7 Feasibility Study

Feasibility study would be conducted to find out whether a proposed system can be successfully developed, implemented and utilized in its intended environment or not. It assesses the feasibility of the solution suggested from technical, economic, operational and organizational aspects. The proposed Clinical Decision Support System (CDSS) is feasible and has the potential to be valuable in today's healthcare landscape.

A. Technical Feasibility

Technical Feasibility: It is an assessment of the technologies, tools and resources that are available to develop and implement the system. The proposed system uses well-known technologies such as Python, FastAPI, React, TensorFlow, DenseNet121, EfficientNetB0, and the latest web development frameworks. These technologies are popular and have been employed in many AI and health-related applications with good results. The ChestX-ray14 is a large and diverse dataset that is suitable for model training and testing. Moreover, cloud computing environments and

Graphics Processing Units (GPUs) are readily available that can assist in developing and experimenting with deep learning models. This means that the technical requirements to implement the proposed system can be met.

B. Economic Feasibility

The study of economic feasibility determines if the benefits that the system is expected to provide are worth the costs during development and operation of the system. The proposed system has the advantage of using open-source software tools and public data, thus lowering the cost of software development. TensorFlow, FastAPI, React and Python are examples of frameworks that can be used without any licensing fees. The advantages of increased diagnosis efficiency, less workload for healthcare workers, and increased healthcare accessibility outweighs the costs of increasing the system development and deployment. Hence, the project is deemed to be economically viable.

C. Operational Feasibility

Operational feasibility is a test of the proposed system's ability to operate in the environment that it is intended to work within and the extent to which the user will adopt and use the proposed solution. Digital healthcare technologies and medical imaging systems are routinely used in healthcare by the professionals in clinical practice. The proposed web-based platform will be designed to be user-friendly and accessible to users, enabling them to interact with the system via easily recognizable web interfaces. The Clinical Decision Support functionality is to augment the current diagnostic workflows, not to replace clinical judgment. This strategy is effective for enhancing the acceptance of the users and the possibility of using it in real practice in healthcare settings.

D. Organizational Feasibility

Organizational Feasibility assesses the ability of the proposed system to adapt to the healthcare institutions and their goals. Artificial Intelligence is becoming more and more popular in the healthcare sector, offering enhanced service delivery and diagnostic efficiency. The vision proposed in this system is consistent with these goals and features intelligent diagnosis support and evidence-based clinical decision making.

Future implementation may be as standalone application or in integration to larger healthcare infrastructure. This versatility makes it an ideal choice for healthcare facilities. The technical, economic, operational and organizational evaluations indicate the proposed Clinical Decision Support System is feasible and should provide benefit to healthcare practitioners and patients.

3.3 System Architecture

System architecture refers to the structural design of the proposed Clinical Decision Support System and shows the interactions between the different components of the system for the disease detection and decision support functions. To achieve system efficiency, scalability, maintainability, and reliability, a well-designed architecture is crucial.

The proposed architecture is based on a layered approach with five key layers:

the Presentation Layer, Application Layer, Preprocessing Layer, Deep Learning Layer, and Clinical Decision Support Layer. Every layer has its own functions and interacts with other layers to accomplish the goals of the system.

The topmost layer of the architecture is the Presentation Layer, which represents the user interface of the system. The layer is made using React and offers access to functionalities of the system for healthcare practitioners. This interface allows users to upload X-ray images of patients' chest, start a diagnosis, check disease predictions, look at confidence scores and clinical recommendations. The design prioritizes usability and responsiveness, ensuring that users can interact with it effectively and efficiently.

The second layer is implemented using FastAPI, and it is the Application Layer. This layer serves as a communicative interface between the frontend interface and the deep learning parts. The FastAPI processes incoming requests, validates images uploaded, manages API endpoints, and orchestrates communication between various system modules. It also guarantees efficient processing as well as delivery of results to users.

The third layer is a Preprocessing Layer. The chest radiograph image files are needed to be preprocessed before they can be analyzed. Such operations involve normalising and resizing images, as well as image enhancements. The goal of the preprocessing is to enhance the quality of the images, to minimize the variations and to prepare the data for the feature extraction of the deep learning model.

The fourth layer is the Hybrid Deep Learning Module which is the main intelligence of the proposed system. This module contains two parallel architectures of a neural network: DenseNet121 and EfficientNetB0. DenseNet121 focuses on extracting comprehensive radiographic characteristics related to the disease and EfficientNetB0 uses computationally efficient mechanisms to extract general representations of the images. A feature fusion layer is used to fuse the outputs of both architectures to obtain a consolidated feature representation for classification.

After feature fusion, the classification layer uses these features to make predictions on the disease categories of the thoracic diseases in the ChestX-ray14 dataset. Classifier learns probabilities of each disease category, and determines most probable pathological conditions in an image.

The last layer is the Clinical Decision Support Layer. This component decodifies the classification and creates additional information that may help healthcare practitioners in the diagnosis process. The decision-support module offers confidence scores, disease descriptions, and diagnostic suggestions to improve clinical reasoning and decision-making.

When integrated with each other, they form a complete system that can detect thoracic diseases in an automated fashion and can provide useful decision-support data. The layered architecture also facilitates scalability and potential future additions, like explainable artificial intelligence capabilities, new disease categories, and hospital information system integration. Fig 3.1 will present the system the proposed system architecture

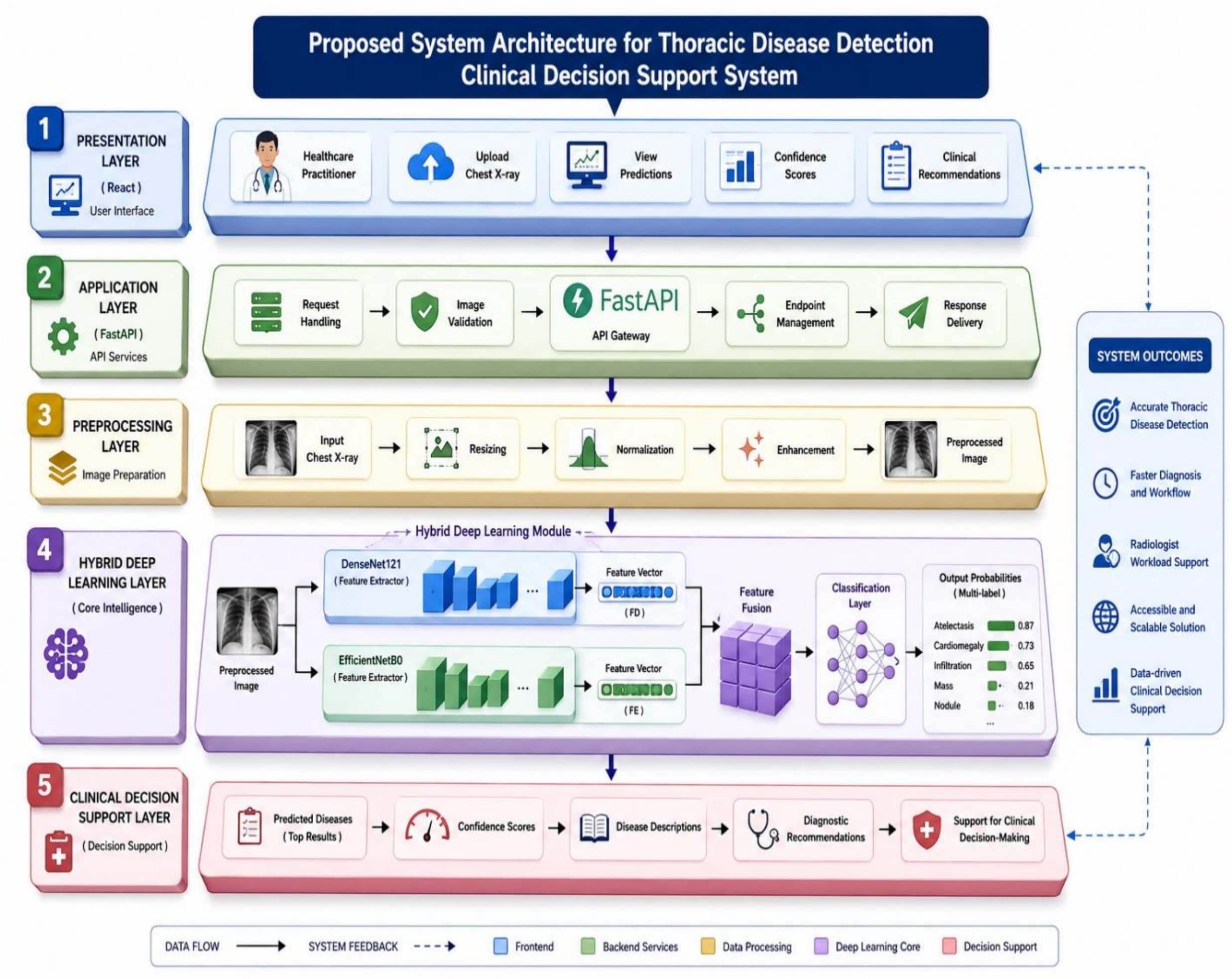

Figure 3.2: Proposed System Architecture for Thoracic Disease Detection

The proposed Clinical Decision Support System for thoracic disease detection is shown in Figure 3.1, where data is fed into the system from the chest X-ray image upload, followed by preprocessing, hybrid deep learning analysis (DenseNet121 and EfficientNetB0), feature fusion, and finally, the disease classification. The architecture combines the React and FastAPI framework with a hybrid deep learning model alongside a Clinical Decision Support module for giving disease predictions, confidence scores and diagnostic suggestions for healthcare professionals.

3.4 System Design

The transformation of system requirements and analysis results to a structured blueprint to guide the development and implementation of the proposed system is called system design. It offers a graphically detailed model of the interaction between the different parts of the system, working towards the desired ends. The system design in this research is aimed to build a web-based Clinical Decision Support System (WDCCS) for detecting thoracic disease in chest X-ray image by implementing a hybrid deep learning architecture. The design process is based on the software engineering principles, modeling techniques of object-oriented, and artificial intelligence methodologies to ensure the proposed system is scalable, maintainable, efficient, and user-friendly. During the design phase, the design can be represented in form of Unified Modelling Language (UML) diagrams that give a visual representation of the functionality of the system to stakeholders, thus allowing them to understand the behavior and structure of the system before it is implemented.

3.4.1 Design Methodology

The proposed system design has been developed using Object-Oriented Analysis and Object Oriented Design Methodologies (OOAD). OOAD is a software engineering methodology for describing a system as a set of interacting objects that are used to represent real-life entities. The methodology is modular, reusable, maintainable and scalable, suitable for the development of complex healthcare applications. This study makes use of OOAD because of its ability to break down complex processes into manageable components which facilitate system development. The methodology helps to identify actors in the system, the processes of the system, flows of data and interactions between the system actors, thus creating a clear structure to implement software. OOAD also offers a set of modelling tools for visualising the functionality and structure of the system, as well as supporting software development. These tools involve Use Case Diagram, Class Diagram, Activity Diagram, Sequence Diagram used in this study to depict different aspects of the proposed Clinical Decision Support System. The OOAD methodology also makes the system easily extensible and thus it is easy to add new modules and functionalities to the system without significantly modifying its structure.

3.4.2 Use Case Diagram

Use Case Diagram is a behavioural modelling diagram that shows how system users interact with functionalities of the system. It highlights the different users of the system and what services they can use. The Use Case Diagram gives a high level view of how the system is going to work for the user. The proposed Clinical Decision Support System contains two main actors, the Healthcare

Practitioner and the System Administrator. The use case diagram of the proposed clinical decision support system is shown in figure 3.2.

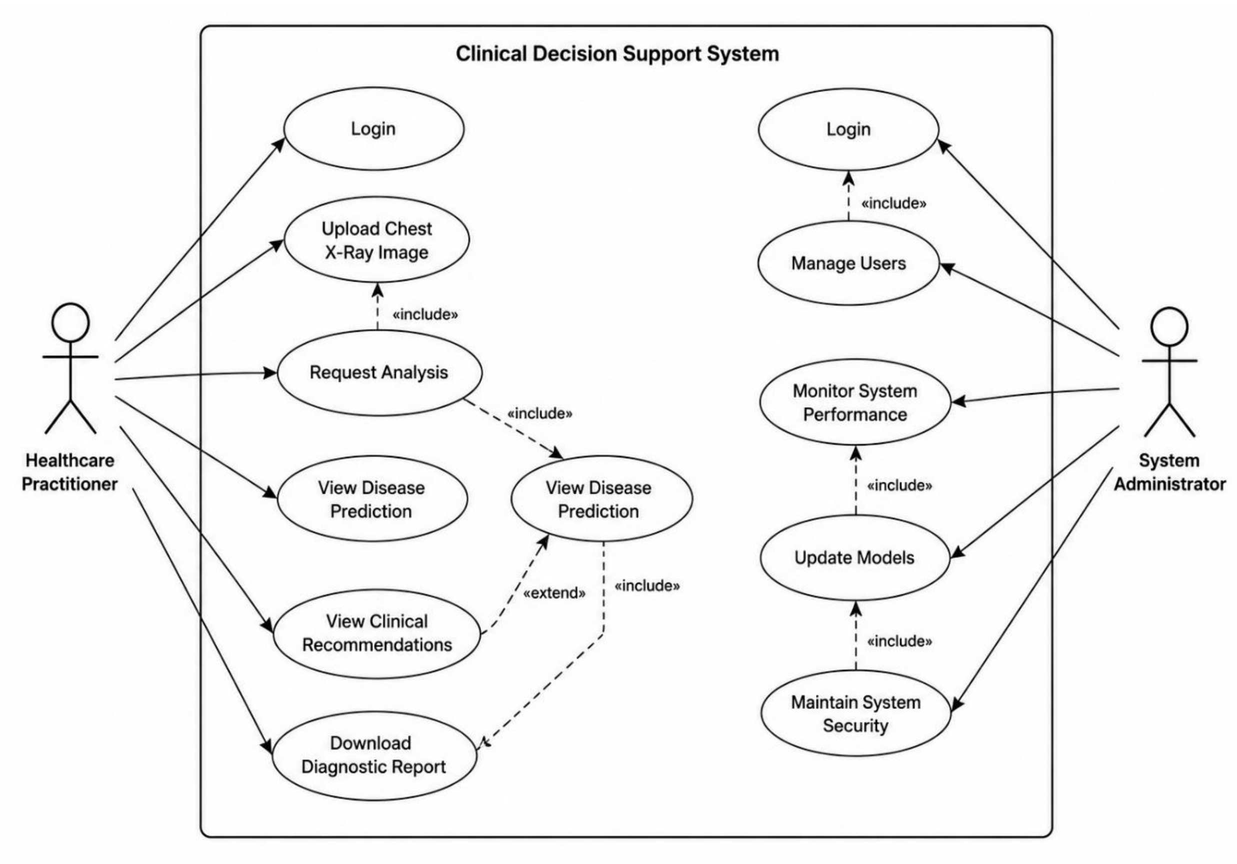

Figure 3.3 Use case Diagram

A Healthcare Practitioner consists of various healthcare professionals like doctors, radiologists, medical laboratory technicians, and others who work in diagnosing thoracic diseases. He works with the proposed system by uploading X-ray images, requesting analysis, checking predicted diseases, obtaining clinical recommendations, and downloading reports. On the other hand, the System Administrator is responsible for operating the system properly. The person ensures that duties such as user accessing, managing the system, maintenance activities, model updates, and performance supervising are properly performed.

Among the most important use cases related to the actor are Login, Upload X-Ray Image, Request Analysis, View the Prediction, Check Recommendations and Download Report. As for the System Administrator, the actor conducts functions like Manage Users, Monitor System Performance, Update Models, and Maintain System Security. The Use Case Diagram reflects the relationship between the actors and the system proposed and specifies the functional scope of the system.

3.3.3 Class Diagram

Class Diagram is a structural UML diagram describing the classes in the system along with their attributes, methods, and relations. It gives the static overview of the architecture of the system and forms the basis for software implementation. The model includes several classes that fulfill the task of disease detection and provide decision support. Figure 3.3 presents the Class Diagram of the Proposed Clinical Decision Support System.

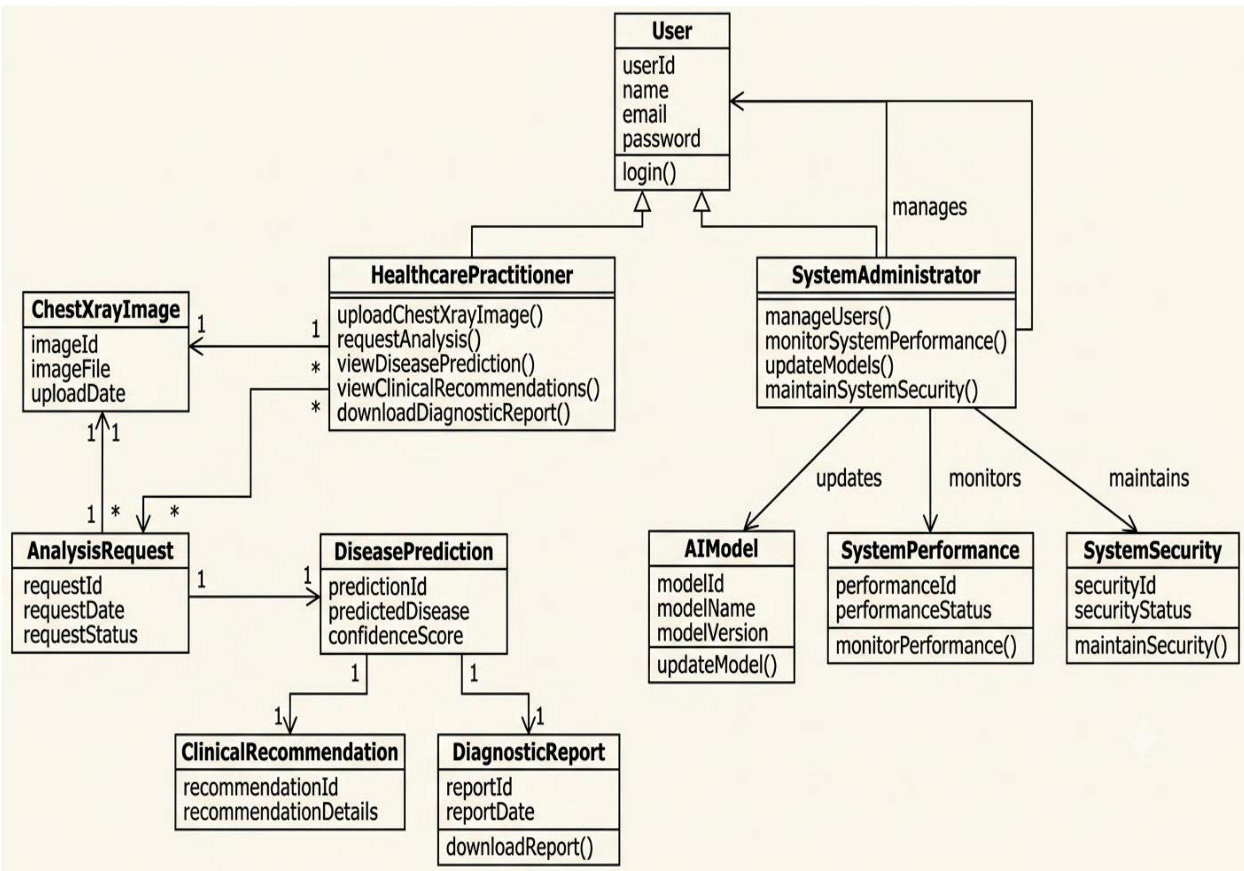

Figure 3.4: Class Diagram of the Proposed Clinical Decision Support System.

The User class denotes users of the system. Some of the attributes that the User class consists of are User ID, Name, Email Address, Password, and User Role. It has the following methods: Login, Logout, and Profile Management. The ChestXRayImage class signifies the uploaded X-ray images. The features of this class are Image ID, File Name, Upload Date, and Image Path. The methods of this class are Validate Image, Store Image, and Retrieve Image. The Preprocessor class is responsible for modifying the images for analysis. It uses the methods Resize Image, Normalize Image, Enhance Image Quality, and Prepare Input Data. The DenseNet121Extractor class executes feature extraction using the DenseNet121 framework. Similarly, the EfficientNetB0Extractor class implements extraction of additional features using EfficientNetB0. Both classes are important in the feature extraction process found in the hybrid model.

The FeatureFusion class integrates outputs from both artificial neuronal network architectures which gives one representation of features for classification. The DiseaseClassifier class uses the output features in making predictions about some thoracic diseases. It estimates the reliability of prediction for every disease. The ClinicalDecisionSupport class interprets the results of prediction and gives confidence coefficients, descriptions of diseases, and diagnostic recommendations. Last but not least, it should be noted that the ReportGenerator class performs the generation of diagnostic reports that are downloadable and contain the results of analysis and recommendations. The relationships among these classes are what defines the internal structure of the proposed system which will in turn assist the implementation.

3.3.4 Activity Diagram

An Activity Diagram can be defined as a type of UML diagram that is used to display the interaction of activities within a certain system. It describes how tasks are carried out in a certain order from beginning to end. The process flow of the suggested Clinical Decision Support System starts when a healthcare professional opens the service and logs into the system. In the figure 3.4 is the shown activity diagram based on the system of clinical decision support.

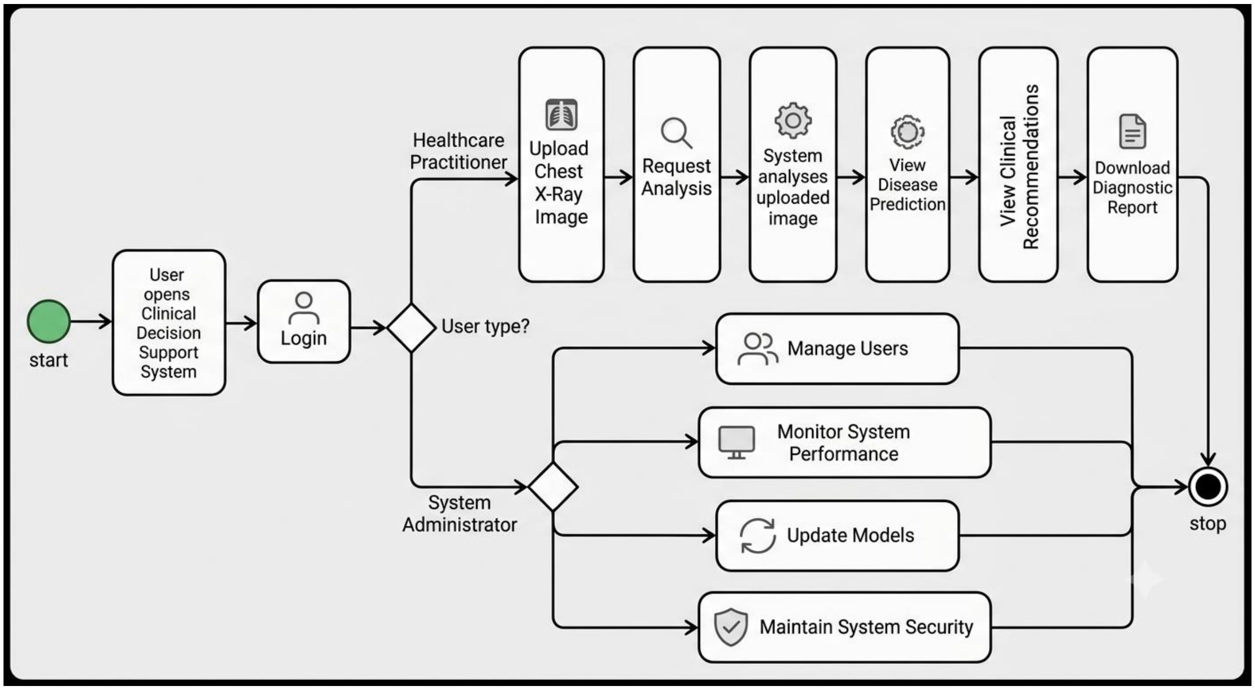

Figure 3.5: Activity Diagram of the Proposed Clinical Decision Support System.

After verification is successful, the user proceeds to upload the chest X-ray image using the web interface. The system executes validation as soon as the image has been uploaded in order to check whether the file format and quality of the photo meet the relevant standards. The preprocessing operations will take place if validation is successful. The preprocessing process includes operations such as image resizing and normalization as well as having an image enhanced. Once the preprocessing is complete, the chest X-ray image passes through the DenseNet121 and EfficientNetB0 branches at the same time. Each of the branches is responsible for different features extraction. Once the image features have been extracted, they are merged first and sent afterwards to the classification module. The classification module analyzes already merged image features and generates prognoses making recommendations based on the preliminary analysis. Ultimately, health professionals get the prognosis and advice through the web interface, and they also have the opportunity to download the diagnostic report or analyze the X-ray image further if needed. The Activity Diagram illustrates the workflow.

3.4 Model Design and Development

To build a successful Clinical Decision Support System for detecting thoracic diseases, a strong machine learning framework is needed that is capable of accurately recognizing the pattern of disease from chest X-ray images. In this section, we discuss the processes of acquiring the dataset, preparing the data, designing the model architecture, training the model, and evaluating the performance.

The aim is to design a hybrid deep learning system capable of making accurate diagnosis of various thoracic diseases and assisting the health care providers with intelligent diagnostic recommendations. The model development process is systematic with collecting the datasets, preprocessing, extracting features, classification, and evaluation. The overall workflow is structured to ensure the developed model has high predictive performance with computational efficiency that is appropriate for deployment in a real-world healthcare environment.

3.4.1 Dataset Collection

This study used the NIH ChestXray14 Dataset, which is one of the largest public chest radiography datasets created by the United States National Institutes of Health (NIH). It was developed specifically for research in automated detection of thoracic disease, and is a state-of-the-art data source to test deep learning models for medical image analysis. The ChestX-ray14 data set consists of chest X-rays from 30,805 patients, resulting in a collection of 112,120 frontal chest X-rays. Each image has a set of one or more disease labels corresponding to thoracic abnormalities detected in the radiological reports. The dataset was created by applying NLP techniques to obtain the disease annotations from the clinical reports associated with the diseases. The availability of a large number of images makes the dataset highly suitable for training deep learning models. It also has a wide spectrum of patients and disease representation, which improves the generalization capability of well-trained models in various clinical settings. This data set includes images in Portable Network Graphics (PNG) format, along with metadata on patient characteristics, image acquisition parameters, and disease labels. The images are used as the main input data in the proposed Clinical Decision Support System.

3.4.2 Dataset Description

The NIH ChestX-ray14 dataset consists of 14 categories for thoracic disease conditions that span a broad spectrum of pathological conditions commonly seen in clinical practice. Atelectasis, Cardiomegaly, Effusion, Infiltration, Mass, Nodule, Pneumonia, Pneumothorax, Consolidation, Edema, Emphysema, Fibrosis, Pleural Thickening, and Hernia are the categories of disease. One special feature of the data set is that it has multiple labels. The ChestX-ray14 dataset is different from the regular image classification datasets, in which every image is labeled with one disease only. This is true in the real world, where patients can have more than one coexisting thoracic anomaly.

In this data there are images that are marked with "No Finding" which means there is no thoracic disease that is detected. These normal images are vital to training the model to discriminate between normal and abnormal radiographs. The variety of diseases and patients included in the dataset renders it suitable for creating a powerful multi-label classification system for detecting multiple thoracic diseases from a single chest radiograph**.**

Table 3.2: Thoracic Disease Categories in the NIH ChestX-ray14 Dataset

S/N	**Disease Category**
1	Atelectasis
2	Cardiomegaly
3	Effusion
4	Infiltration
5	Mass
6	Nodule
7	Pneumonia
8	Pneumothorax
9	Consolidation
10	Edema
11	Emphysema
12	Fibrosis
13	Pleural Thickening
14	Hernia

The dataset serves as the foundation upon which the proposed hybrid deep learning model is trained and evaluated.

3.4.3 Data Preprocessing

In the development of the deep learning model, preprocessing of the data is a very important step since the quality of the data used as an input will have a significant effect on the performance of the model. Medical images frequently vary in their size, brightness, contrast and image quality as a result of the use of different imaging equipment and protocols. As a result, before the images are used for the feature extraction operation, it is necessary to preprocess them in order to standardise them.

In this work, resizing of the images is the first preprocessing step performed. All X-ray images are resized to a common image size of 224 × 224 pixels, to fit both DenseNet121 and EfficientNetB0 architectures. The common image sizes are provided for batch processing and for faster training because it reduces the complexity of computation. Once the image has been resized, normalization of the image is performed. Normalization is the act of scaling the intensity of the values of each pixel to a common range, typically from 0 to 1. This process can be numerically stable to train the model and can aid to converge the optimization algorithm. Data augmentation is then used to further improve the capabilities of the model, and the resulting data is added to the training set. Generating artificial diversity of the data set, based on existing images, using data augmentation. The augmentation techniques applied in this work are: Rotation, Horizontal Flip, Zoom, Shift Wide, Shift High, Brightness Adjustment.

Rotation allows the model to be trained from images captured over a range of slight orientations, capturing disease patterns. Preserving some pathological structures and adding some variation by flipping horizontally. The model is animated and moved, showing various locations and sizes of images, making the model less sensitive to image alignment. Brightness adjustment enables the model to adjust to variations in exposure of an image. All the above preprocessing methods make the model more robust and do not overfit the model, which helps the model to predict new chest X-rays images.

3.4.4 Hybrid DenseNet121–EfficientNetB0 Architecture

The proposed Clinical Decision Support System is based on a hybrid deep learning model made up of DenseNet121 and EfficientNetB0. The rationale behind the hybrid architecture was to take advantage of the complementary advantages of both approaches in the retrieval of information from chest X-ray images from informative radiological features. The proposed Hybrid DenseNet121–EfficientNetB0's architecture is illustrated in figure 3.5**.**

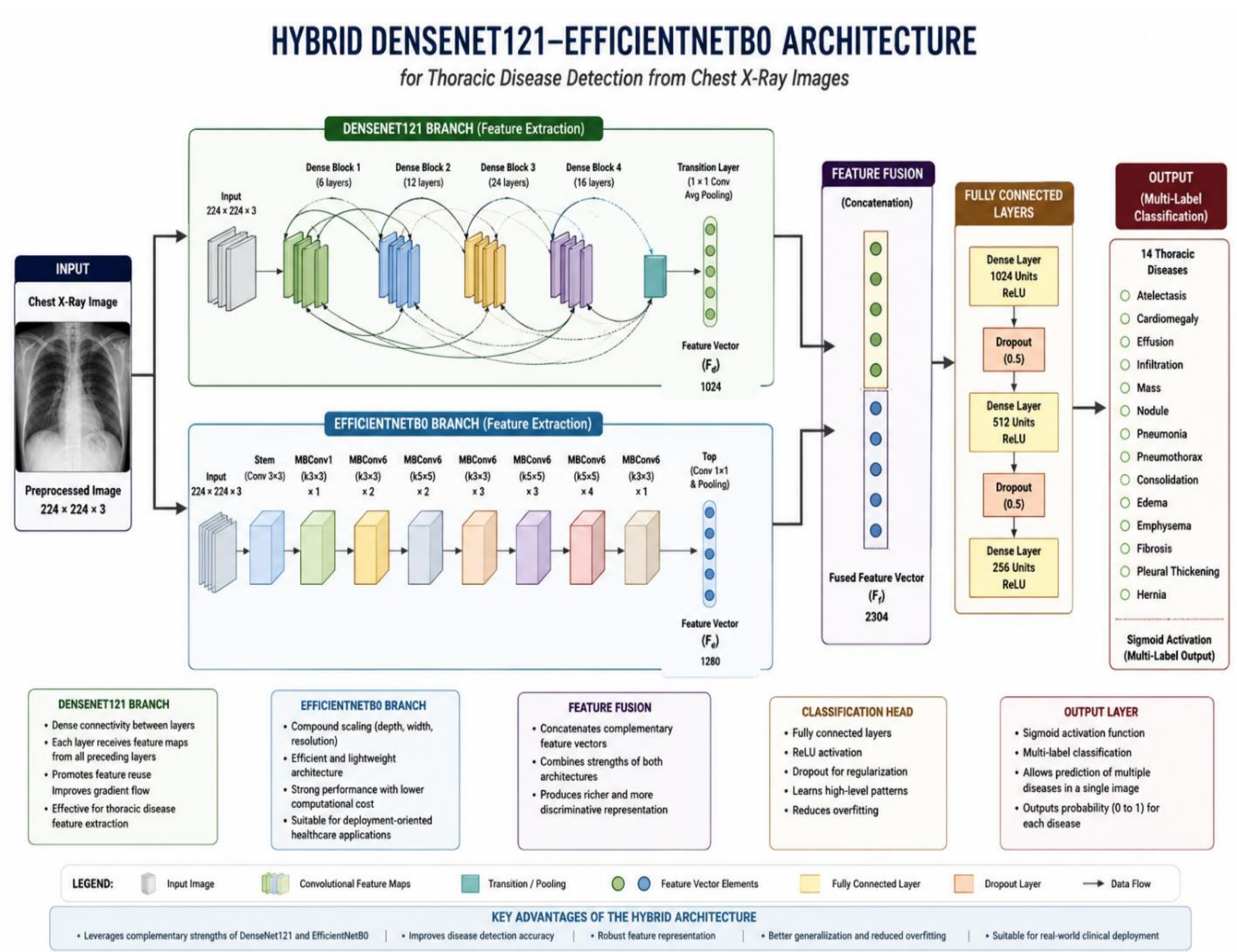

Figure 3.6 Hybrid DenseNet121–EfficientNetB0 Architecture

DenseNet121 is the first feature extraction branch. In DenseNet121, layers are connected densely to each other, and the feature maps of each layer input to the next layer in the network. This design enables efficient feature re-use, better gradient flow and minimises information loss during training. DenseNet121 has proven to be an outstanding architecture for analyzing chest radiograph images, and is considered one of the best-performing models for detecting thoracic diseases.

The second branch takes advantage of a deep learning architecture, called EfficientNetB0, designed to follow compound scaling principles. EfficientNetB0 is a network that combines good classification performance, relatively low computational cost, a network depth, width and image resolution. This is a characteristics that makes it ideal for Healthcare applications that require deployment. For both architectures, feature representations are simultaneously and independently extracted from the same input image. The feature vectors of DenseNet121 and EfficientNetB0 are then fused together using a feature fusion layer. This represents a fusion of complementary information captured by both the models, resulting in a more informative and discriminative representation of the chest X-ray image.

The fused feature representation is then fed to fully connected layers that are used for disease classification. To enable multi-label classification, the model uses a sigmoid activation function in the output layer, which enables the prediction of multiple thoracic diseases in a single image. The hybrid architecture is expected to perform better than the standalone models, leveraging the best of both the DenseNet121 and EfficientNetB0 models while addressing their respective weaknesses.

3.4.5 Model Training Procedure

In the model training process, the hybrid architecture is fed with a vast amount of labelled chest X-ray images to learn meaningful patterns related to disease. The input images and disease labels in the NIH ChestX-ray14 dataset are the data used to train the model. The set of data is split into three data subsets: training, validation and testing. The training set is used to tune the model parameters and to monitor the performance, the validation set is used to tune the hyperparameters and to monitor the performance, and the testing set is used to tune the hyperparameters and to monitor the performance.

In this study, transfer learning is used to enhance the training efficiency and predictive performance. The DenseNet121 and EfficientNetB0 architectures are initialized with pre-trained weights that were trained on large-scale image datasets. This transfer learning allows the model to transfer pre-trained visual representations, which saves time and enhances the convergence. The losses function used is the Binary Cross-Entropy loss function as it is a multi-label classification problem. Because of its efficient implementation and adaptive learning rate, the Adam optimizer is used to optimize the parameters of the model during training. Regularization methods like dropout and early stopping are used to avoid overfitting. The Dropout randomly turns off the neurons during training, whereas early stopping prematurely ends training if the validation performance doesn't improve. The process of training is repeated for several epochs until optimal performance is obtained on the validation set.

3.4.6 Model Evaluation Metrics

Several evaluation measures are used and widely adopted in medical image classification studies to evaluate the effectiveness of the hybrid deep learning model proposed. These metrics give complete picture of the various performance aspects of the model. Accuracy is the percentage of samples that are classified correctly out of the total number of samples that were tested. It gives an overall, not detailed, picture of the performance of the model. Precision is the number of correct positive predictions divided by the total number of positive predictions. If the precision is high, the false-positive rate is low. Recall which is also called Sensitivity quantifies the proportion of cases correctly detected by the model. This is a critical measurement in healthcare, where a misdiagnosis can be extremely costly. The F1-Score is the weighted average of the precision and recall, and makes a balanced judgment on classification performance.

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) assesses how well the model can separate the positive and negative disease cases at different classification levels. The larger the AUC is, the better the discriminative ability. A Confusion Matrix is also used to get a detailed breakdown of the classification results, such as True Positive, True Negative, False Positive, and False Negative. This analysis can be used to pinpoint strengths and weaknesses in the prediction of diseases. In summary, the evaluation metrics collectively offer a holistic approach to evaluating the effectiveness, reliability, and clinical applicability of the proposed Clinical Decision Support System.

3.5 Development Tools and System Requirements

To achieve the proposed Clinical Decision Support System's success, suitable software tools, hardware resources and development platforms need to be selected. These are components to process the datasets, build deep learning models, deploy the web applications, and test the system. The selection of development tools was made based on their performance, scalability, integrations, the community support.

3.5.1 Software Requirements

Software requirements are the software, software frameworks, software libraries, and software operating environments required for developing and operating the proposed system. It is built using state-of-the-art open-source tools that can facilitate machine learning, web app development, and healthcare software deployment.

Python Programming Language

The proposed system will be developed using Python as the main programming language. It was chosen due to its simplicity, a large library ecosystem and a wide range of adoption across the Artificial Intelligence and Machine Learning communities. Python offers a range of tools for image processing, building deep learning models, analyzing data, and integrating with web applications.

TensorFlow and Keras

The hybrid DenseNet121–EfficientNetB0 architecture is implemented using TensorFlow and Keras. TensorFlow offers a computational model for training and deploying deep learning models, and Keras offers a high-level application programming interface for developing neural networks. These frameworks enable functions of transfer learning, optimization, evaluation, deployment, and other functions needed by the proposed system.

FastAPI

The Clinical Decision Support System uses FastAPI as its back-end framework. It offers a high-performance environment to build Application Programming Interfaces (APIs) for linking the front-end interface with the deep learning model. FastAPI allows for the processing of image uploads, making inferences on models, generating results, and communicating between different parts of the system. Its asynchronous design allows it to process multiple requests efficiently, which helps to enhance system responsiveness

React

React is a library used to create the frontend aspect of this system. The library comes with a modern framework that ensures responsive user interfaces. The medical community can upload inputs of chest X-rays, obtain predictions of disease, find confidence scores, and retrieve recommendations using the dashboard. The component-architecture of React is favorable for system maintenance and upgrades.

OpenCV

This is a library that is utilized for preprocessing images. The library can be used to resize, enhance, normalize, filter and transform images.

NumPy and Pandas

They are utilized for performing calculations and conducting data management, where NumPy caters to the requirement of numerical calculations, while Pandas organizes and works with the dataset.

Scikit-Learn

Scikit-Learn adds functions to process data and evaluate the results, completing the TensorFlow package.

3.5.2 Hardware Requirements

Hardware requirements refer to the physical computing resources necessary for developing, training, testing, and deploying the proposed Clinical Decision Support System. Deep learning applications typically require substantial computational resources due to the complexity of neural network training and image processing operations.

Processor

A multi-core processor is required to support data preprocessing, model development, and application execution. For effective system development, an Intel Core i5 processor or higher is recommended. Multi-core processors improve computational efficiency and support concurrent execution of development tools.

Random Access Memory (RAM)

Memory capacity plays an important role in dataset processing and model training. A minimum of 8 GB RAM is required for development activities, while 16 GB RAM or higher is recommended for improved performance during large-scale data processing and experimentation.

Storage

Solid-State Drive (SSD) storage is recommended for efficient data access and system performance. SSDs provide faster read and write speeds compared to traditional hard disk drives, thereby reducing dataset loading times and improving development productivity.

Graphics Processing Unit (GPU)

Deep learning model training benefits significantly from GPU acceleration. A GPU with CUDA support is recommended to accelerate matrix computations and neural network training. Cloud-based GPU environments may also be utilized when dedicated hardware is unavailable.

Internet Connectivity

Reliable internet access is required for downloading datasets, accessing cloud computing resources, installing software packages, and deploying the web-based application. Internet connectivity also supports remote access to the deployed Clinical Decision Support System.

3.5.3 Development Environment

The environment encompasses the entire architecture employed for constructing and testing the system being put forth. It combines pieces of software programs, computer systems, and components of a computer needed throughout the process of development. The deep learning model has been created using Python, TensorFlow, and Keras in Visual Studio Code. The primary libraries utilized in preprocessing and manipulating images are OpenCV, NumPy, and Pandas. The training and assessment of the model are performed using the computational power of GPUs to ensure high efficiency in terms of computation.

The backend part is built with FastAPI, which is responsible for the API needed for image processing and predicting disease. The visual front end is incorporated utilizing React so that healthcare professionals can easily navigate the system while using it. The final version of the system is made to function as a web application that can be used with the help of modern browsers like Google Chrome, Mozilla Firefox, MS Edge, and Safari, which means that it can work on different types of devices and platforms.

CHAPTER FOUR

SYSTEM IMPLEMENTATION AND RESULTS

4.1 Introduction

The proposed Clinical Decision Support System for the detection of Thoracic Disease is implemented in this chapter with the use of the Hybrid Deep Learning Model DenseNet121–EfficientNetB0 on Chest X-Ray Images. The chapter explains the practical processes of the system development, dataset preparation, image pre-processing, implementation of the model, development of web application, training, testing and performance evaluation of the model. They implement the design specifications discussed in Chapter Three and create a working software program that can determine thoracic disease status from chest radiographs and assist health care practitioners in the diagnostic process. The chapter also introduces the development tools used, implementation process and the outcomes from the evaluation of the models. The main goal of implementation process is to create a trustful and easy to use Clinical Decision Support System which, using automated thoracic disease diagnosis, is accessible on the internet in real time. The final system allows health workers to upload chest X-ray images, receive predictions on the disease, see a confidence score, and get clinical recommendations via an interactive web interface.

4.2 System Implementation

System implementation is the process of building up, combining, and testing all the software parts necessary for the functioning of the proposed Clinical Decision Support System. To ensure efficiency, scalability, and maintainability, modern deep learning frameworks, web technologies, and software development tools were employed during the implementation process. The process involved in the implementation included data preparation, image preprocessing, development of the hybrid model, training and testing of the model, backend development, frontend development, integration of the system, and testing. The success for the deployment of the proposed system was achieved by all the stages.

4.2.1 Development Environment

To develop the proposed system, a combination of software frameworks and hardware resources were chosen that can be used in artificial intelligence and web application development.

Software Development Environment

Python was the main programming language for the development of the systems. The choice of Python was made due to its widespread support for machine learning, deep learning, image processing and web application development. To implement the hybrid DenseNet121–EfficientNetB0 model, TensorFlow and Keras were used. The functionalities for transfer learning, training the model, optimization, and deployment were provided by these frameworks. The backend framework used is FastAPI which is responsible for the image uploads, request handling, model inference, and generating the prediction responses. Frontend development was done using React, an interactive user interface to communicate with the system for healthcare practitioners. Various libraries such as OpenCV, NumPy, Pandas, and Scikit-Learn were used to process the images, manipulate the data, and assess the performance.

Hardware Environment

The implementation process needed a computing environment to support the deep learning operations and image processing tasks. The system used for development and testing has a multi-core processor, adequate amount of memory resources, adequate amount of SSD storage, and supports GPU acceleration for model training..

Table 4.1 Development Tools Used

Tool	Purpose
Python	Programming Language
TensorFlow	Deep Learning Framework
Keras	Neural Network Development
FastAPI	Backend Development
React	Frontend Development
OpenCV	Image Processing

NumPy	Numerical Computation
Pandas	Dataset Management
Scikit-Learn	Model Evaluation
Visual Studio Code	Development Environment

4.3 System Implementation

The proposed hybrid deep learning model was implemented according to the model proposed in Chapter Three. The implementation process began by acquiring the dataset, preprocessing the image data, extracting features from the data, fusing the features, classifying the images, evaluating the model, and finally implementing the model for automatic thoracic disease detection.

The Chest X-ray Pneumonia dataset has been sourced from Kaggle in this study. The data were chest radiographic images (X-ray) of two diagnostic classes: Normal and Pneumonia. The data has been divided into a training set, a validation set, and a testing set to facilitate the development and testing of the model. The training set was employed for the learning of image representations, the validation set was employed to monitor the performance of the model throughout the training process and the testing set was used to determine the final predictive capability of the developed model.

After acquiring the datasets, multiple preprocessing steps were applied to enhance the quality of the images and make them suitable for deep learning models. To ensure consistency in data, all chest X-ray images were resized to a common size before training. The intensity of the pixels was normalised to enhance numerical stability in optimising the pixel intensity. In addition, data augmentation methods such as random horizontal flipping, rotation, zooming and translation were used to artificially expand the training data sets. These augmentation techniques decreased the amount of overfitting and enhanced the model's capacity to generalise to unseen chest X-ray images.

The hybrid dual-branch network model DenseNet121 and EfficientNetB0 were used for feature extraction. The DenseNet121 was used to learn the fine-grained local features from the chest X-ray images by using densely connected convolutional layers. These tight connections allowed for easier reusability of features, better propagation of gradients, and the ability to extract subtle pathological features, including lung opacities, infiltrates, and abnormalities in texture that are frequently seen in pneumonia.

At the same time, a second feature extraction branch was used, called EfficientNetB0, and trained using transfer learning. EfficientNetB0 used the pretrained ImageNet weights to boost the capability of capturing high-level semantic representations of thoracic images while keeping the computational efficiency thanks to the compound scaling of network depth, width and resolution. The architecture of this branch was able to capture more contextual information and complex feature relationships, to complement the local discriminative features extracted by DenseNet121.

The feature vectors obtained from both networks were then fused together using a feature fusion approach, resulting in more discriminative and informative representation of each chest X-ray image. The integration of the detailed local texture information from DenseNet121 and the high-level semantic information obtained from EfficientNetB0 not only made the features more diverse but also minimized the risk of losing out on diagnostically important information during training. Fully connected classification layers with a Softmax activation function were used to classify each chest X-ray image into Normal or Pneumonia, using the fused feature representations. The network parameters were optimized by categorical cross-entropy as a loss function and the Adam optimiser.

The trained model is DenseNet121–EfficientNetB0, which is deployed as a web application on the cloud platform using Flask framework for practical application. The web platform gives the healthcare professionals or researchers an intuitive graphical user interface to upload chest X-ray images for automatic analysis. After submitting images, the application automatically preprocesses, extracts features, fuses features, and classifies images to display the disease category predicted by the application with the predicted confidence score. The deployment shows the potential of the proposed framework in the practical application of supporting computer-aided diagnosis of thoracic diseases in a real clinical environment.

4.4 Model Training and Results

To ensure efficient convergence and robust classification accuracy, the proposed Hybrid DenseNet121–EfficientNetB0 model was trained by meticulously tuning the hyperparameters. Table 4.1 shows the adopted hyperparameters.

Table 4.1 Hyperparameter Configuration

Hyperparameter	**Configured Value**
Optimisation Algorithm	Adam
Initial Learning Rate	0.001
Number of Training Epochs	22
Batch Size	32

Objective Function	Binary Cross-Entropy

4.4.1 Evaluation Metrics

The performance of the suggested hybrid DenseNet121–EfficientNetB0 model was tested with commonly used performance measures for binary medical image classification. The metrics used were Accuracy, Precision, Recall (Sensitivity), F1-score, Confusion Matrix, Receiver Operating Characteristic (ROC) Curve, Area Under the ROC Curve (AUC) and Precision – Recall (PR) Curve.

The overall accuracy is the percentage of correctly classified chest X-ray images. Precision refers to the percentage of images correctly predicted as pneumonia that were actually pneumonia cases. The model's performance on the recall is evaluated by the recall score and the F1 score is the harmonic mean of precision and recall. The confusion matrix shows the number of correct predictions of each diagnostic class and the number of incorrect predictions in each. Additionally, ROC-AUC and Precision–Recall curves measure the discriminative power at all the decision thresholds. All these evaluation metrics give a complete picture of the classification accuracy, robustness and diagnostic reliability of the proposed hybrid model.

4.4.2 Training Performance

Figures 4.1 and 4.2 show that the proposed Hybrid DenseNet121–EfficientNetB0 model has learned very well throughout the learning process. The plots show the training and validation accuracy and the corresponding loss over 22 training epochs, providing insight into the convergence behaviour and the stability of learning and the generalisation ability of the proposed model.

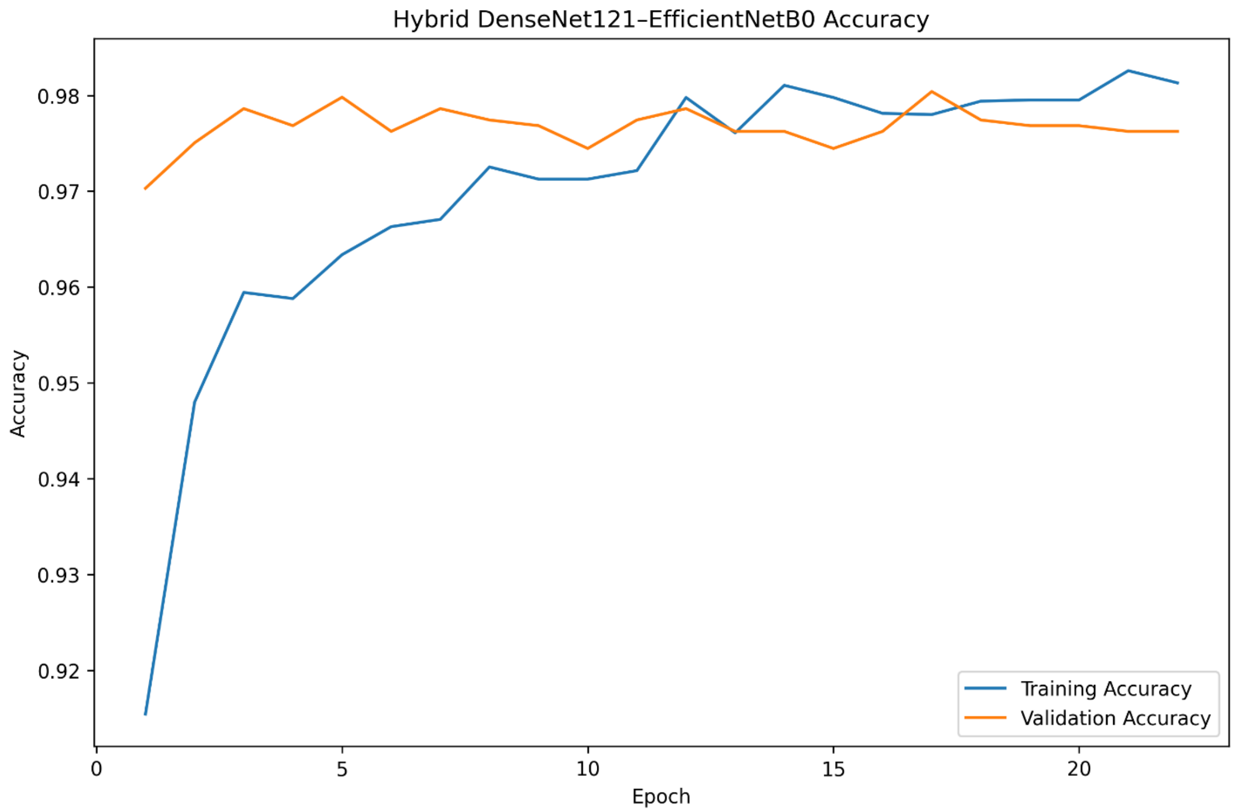

Figure 4.1. The Training Accuracy Curve

The accuracy during training was improved gradually from about 91.5% accuracy at the first epoch to more than 98% accuracy at the last epoch as displayed in figure 4.1. Likewise, during training, the validation accuracy was always at a high level (97% to 98%). The near-identical training and validation accuracy curves suggest that the hybrid model was able to learn relevant discriminative features without serious overfitting. The convergence of both curves showed that DenseNet121 with EfficientNetB0 improved feature learning, resulting in an excellent classification result in the previously unseen chest X-ray images.

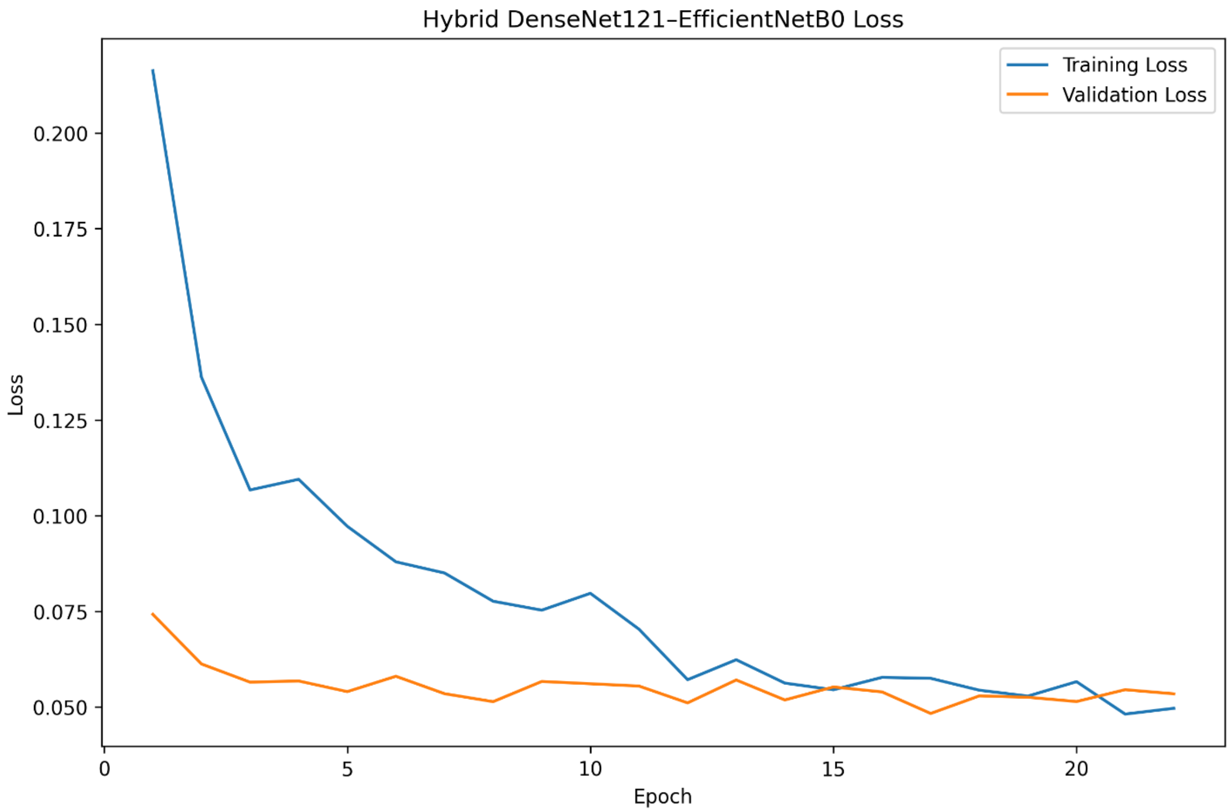

Figure 4.2 Training Loss Curve

The training and validation loss curves of the proposed hybrid model is displayed in figure 4.2. The training loss reduced significantly from about 0.22 at the beginning epoch to less than 0.05 at the end of the training. Similarly, the validation loss was low, and it stayed close to 0.05 for the rest of the training epochs.

As seen in both the training and validation losses decreasing over time, it is a testament to the success of the network's parameter optimisation and the ability to minimise prediction errors. Moreover, the similarity of the two loss curves indicates strong generalisation performance and indicated that the hybrid DenseNet121–EfficientNetB0 architecture was able to result in stable convergence without any apparent overfitting.

4.4.3 Confusion Matrix Analysis

The confusion matrix of the proposed Hybrid DenseNet121–EfficientNetB0 model for classification of chest X-ray images into Normal and Pneumonia classes is shown in Figure 4.3. The confusion matrix reveals that there were 844 normal chest X-ray images, with 833 being correctly identified as Normal and 11 being inaccurately identified as Pneumonia. Likewise, the pneumonia images were correctly identified in 817 out of 844 images and 27 images were wrongly labeled as Normal. The overall classification accuracy achieved is around 97.75% in which the model have successfully classified 1650 out of 1688 testing images. The corresponding classification report gives Normal class Precision: 96.86%, Recall: 98.70%, F1 score: 97.77% and for the Pneumonia class it is Precision: 98.67%, Recall: 96.80%, F1 score: 97.73%. The accuracy of the proposed model was also found to be well balanced, with the weighted average precision, recall and F1 score values near to 97.75%, respectively.

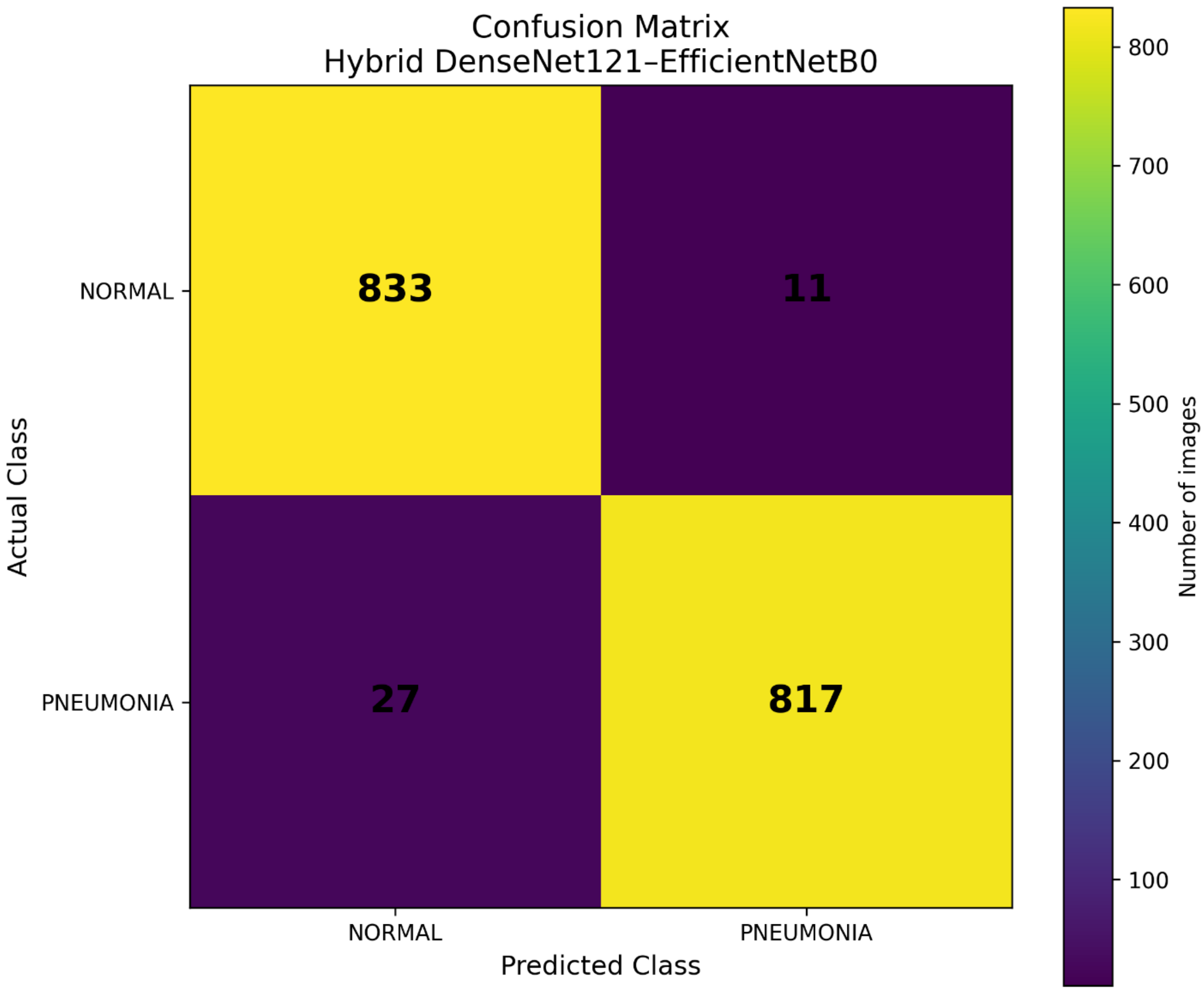

Figure 4.3 Confusion Matrix

The results presented in the confusion matrix show that the proposed hybrid architecture is capable of giving a good separation between healthy lungs and pneumonia infected lungs with minor misclassifications. The high level of diagnostic accuracy shows high performance of DenseNet121 and EfficientNetB0 for the detection of thoracic diseases, and demonstrates the potential of the proposed framework as a reliable computer-aided diagnostic (CAD) tool for chest X-ray image analysis.

4.4.4 Receiver Operating Characteristic (ROC) and Precision–Recall Curve Analysis

Characteristic (ROC) and Precision–Recall Curve Analysis are also used. The Receiver Operating Characteristic (ROC) curve and Precision–Recall (PR) curve were analysed to evaluate further the effectiveness of the proposed Hybrid DenseNet121–EfficientNetB0 model. These graphical evaluation techniques focus on the model's performance over a range of decision thresholds, offering valuable insights into the model's behavior when applied to medical image classification, where both false positives and false negatives can impact clinical decision-making.

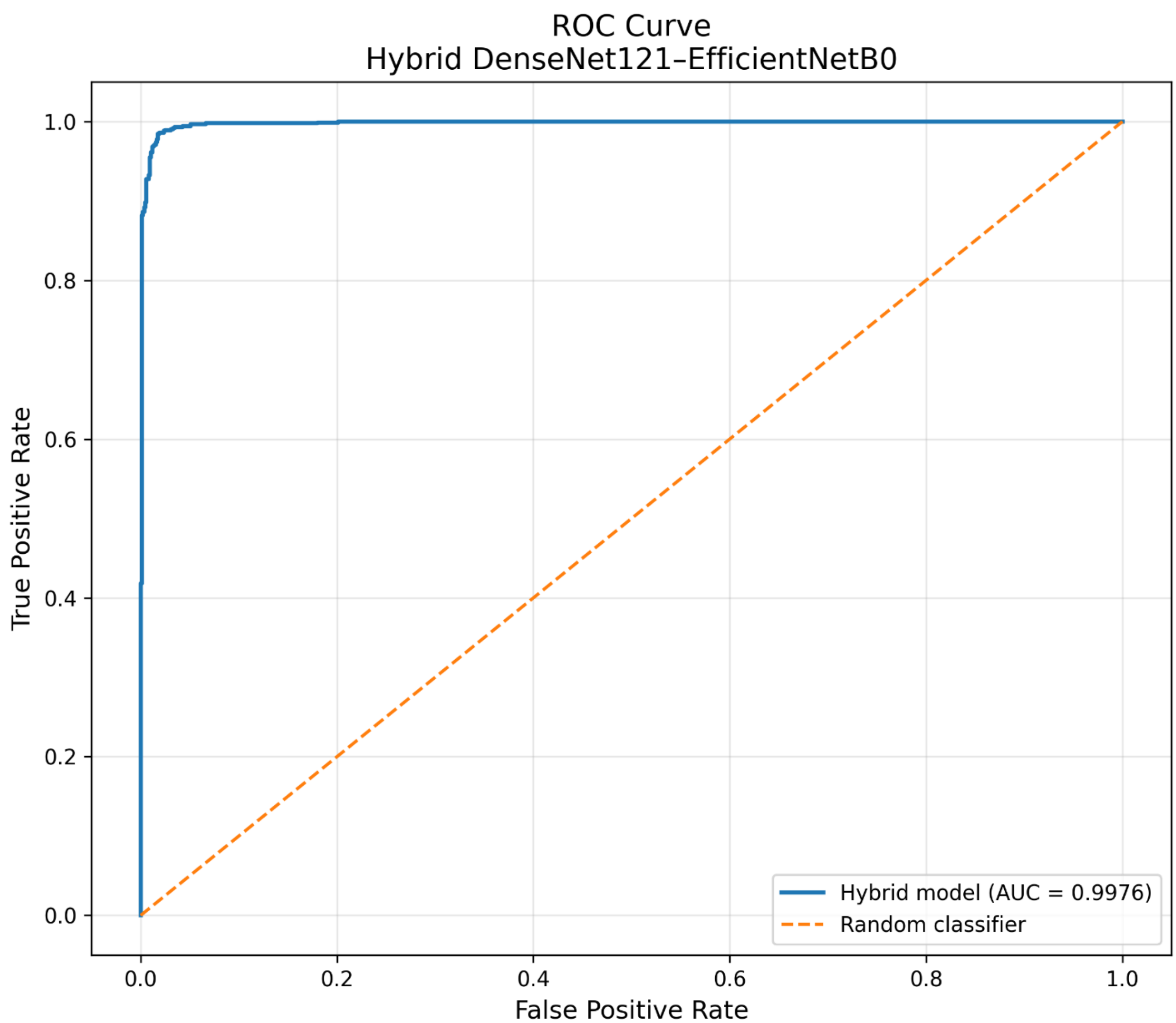

Figure 4.4 Receiver Operating Characteristic (ROC) Curve

The ROC curve of the proposed hybrid model is shown in figure 4.4. The curve illustrates how the true positive rate/false positive rate changes with the threshold used for classification. Ideals classifiers produce a curve that is close to the upper left corner of the graph due to the high sensitivity and low false alarm rate.

The ROC curve, as shown in Figure 4.4, is desired and the proposed model always gives a good separation between Normal and Pneumonia chest X-ray images with a high accuracy. The model had an Area Under the Curve (AUC) score of 0.9976, which means it has nearly perfect class separability. The high AUC score suggests that the classifier has a very high ability to accurately classify pneumonia and normal chest radiographs. The sharp increase in the curve at very low false-positive rates again illustrates this, showing that the hybrid architecture does not compromise the sensitivity of the test even though it keeps the specificity high. The results confirm DenseNet121+EfficientNetB0 is an extremely robust approach to automated thoracic disease detection.

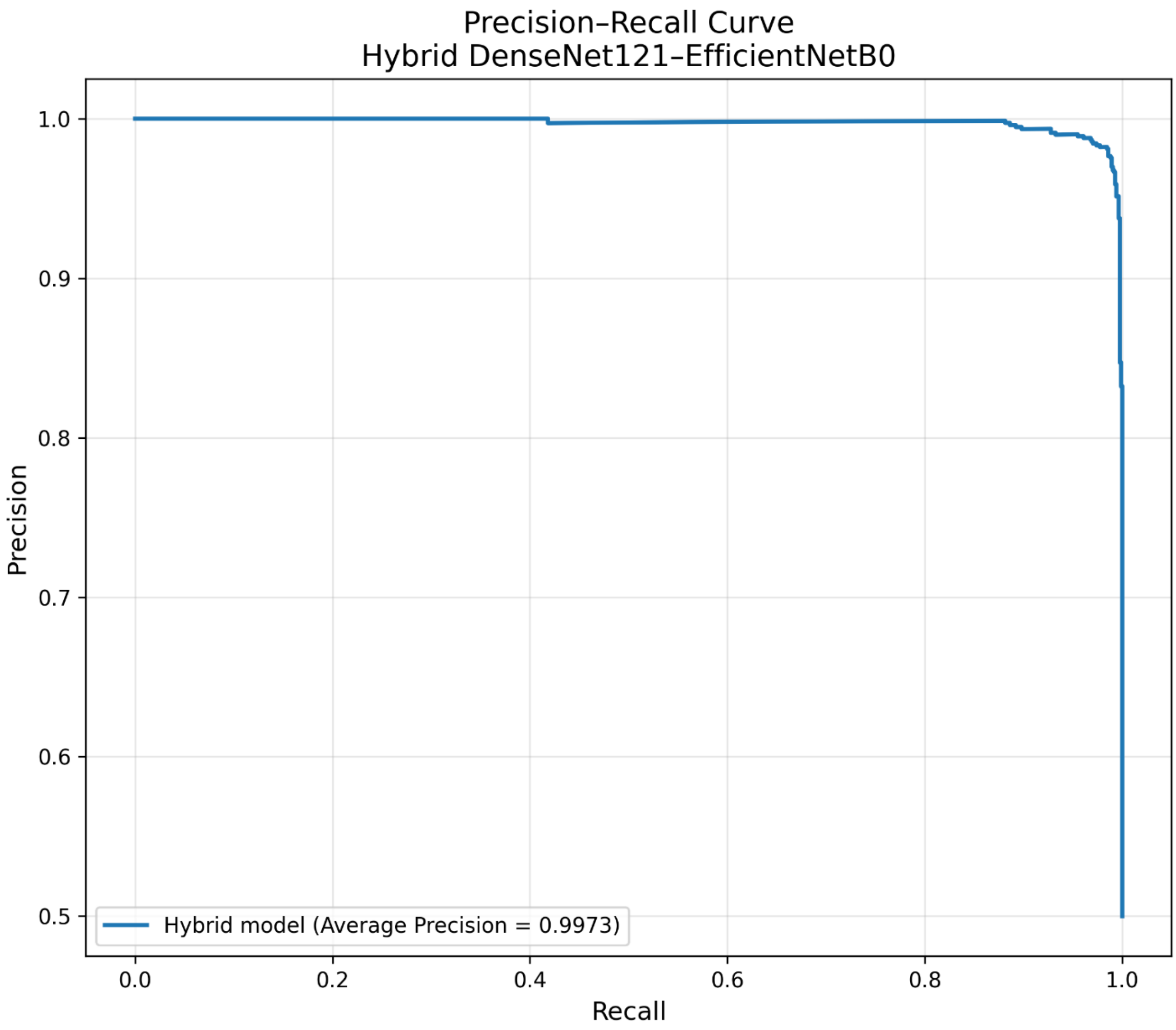

Figure 4.5 Precision–Recall (PR) Curve

Another aspect of the predictive power of the model developed is the Precision-Recall curve shown in Figure 4.5. This evaluation criterion will be considered as the balance between precision and recall; this is particularly valuable in the medical diagnosis context since it reveals how well the model is able to identify positive disease cases while minimizing false positive predictions. The PR curve stays close to the maximum of the graph all along the recall range, reflecting the fact that the classifier maintained a high precision even during the increase in recall. The proposed model achieved an Average Precision (AP) score of 0.9973, which indicated that the model made accurate predictions across the various operating points. The small loss of accuracy when the recall rate was close to 100% suggests that the classifier had a minimal number of false-positive classifications while maintaining high accuracy in classifying pneumonia when the recall rate was high. This is very desirable from a clinical point of view as it enables proper disease screening without raising too many false positive alerts. Based on the results of both ROC and Precision–Recall analyses, the proposed Hybrid DenseNet121–EfficientNetB0 model thus has a very good discriminative power, stable predictive behaviour and good generalisation ability in the task of detecting thoracic disease from chest X-ray images.

4.4.5 Classification Report Analysis

The performance of the proposed Hybrid DenseNet121–EfficientNetB0 was also evaluated with a classification report to complement the graphical evaluation. The report is a summary of the model's accuracy, recall, F1 score and the number of samples tested per diagnostic category. The following results are displayed in the table: Table 4.2.

Table 4.2 Classification Performance of the Proposed Hybrid DenseNet121–EfficientNetB0 Model

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Normal	96.86%	98.70%	97.77%	844
Pneumonia	98.67%	96.80%	97.73%	844
Overall Accuracy	97.75%	–	–	1,688
Macro Average	97.77%	97.75%	97.75%	1,688
Weighted Average	97.77%	97.75%	97.75%	1,688

Table 4.2 presents the results of the proposed hybrid model, which had consistently high predictive performance for both diagnostic categories. The results for the Normal class showed a precision of 96.86%, meaning that most of the images classified as normal were indeed correct. The almost 100% recall value indicates that nearly all normal chest X-rays in the test set were correctly identified. The two measures gave an F1 score of 97.77% which indicated a good balance of classification accuracy. In the Pneumonia

category, the model had a precision of 98.67% which indicates that the model predictions were highly accurate with very few false positive predictions. A recall of 96.80% means that the classifier was able to identify almost all of the pneumonia cases in the test set. The resulting F1-score of 97.73% therefore indicates a good level of balance between the identification of the diseased patients and the avoidance of misclassifications. The other interesting thing that can be noted from Table 4.2 is the fact that the macro-average and weighted-average performance values closely agree with each other with a value of 97.75%. The uniform performance of the classifier on both classes indicates that the classifier has not been biased for any one class over the other. The overall classification accuracy of 97.75% also confirms that the hybrid feature learning strategy was able to effectively learn and extract the features that are unique to chest x-ray images essential for accurate disease classification. The classification report, along with the confusion matrix, ROC curve and Precision–Recall analysis, demonstrates the potential for the proposed Hybrid DenseNet121–EfficientNetB0 architecture to yield accurate, stable and clinically meaningful predictions. The results provide further evidence for the applicability of the developed Clinical Decision Support System as an intelligent solution to support healthcare professionals in the diagnosis of thoracic diseases in chest X-ray images.

4.5 System Interface

This section presents the interface results of the design system which is a mobile application integrated with the developed model through FAST API.

A. Home Page

This page or screen shows the landing page or the first user access page of the designed system. Figure 4.6 presents the diagrammatic illustration of the Home Page.

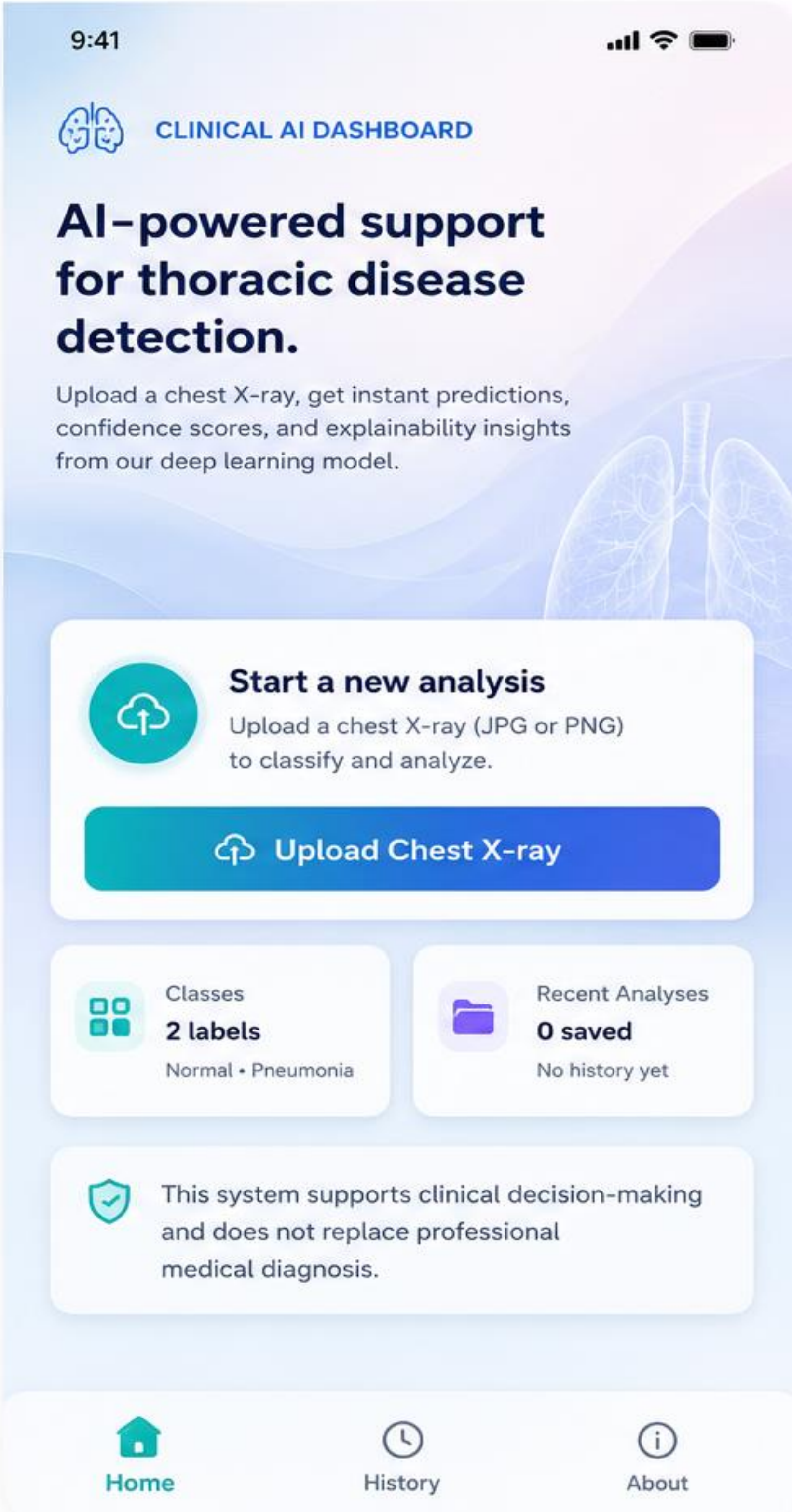

Figure 4.6 Home Page.

B. Upload Screen

This page or screen shows the upload page where the user inputs the data which is in CT scan for the designed system to predict. Figure 4.7 presents the diagrammatic illustration of the Upload Page.

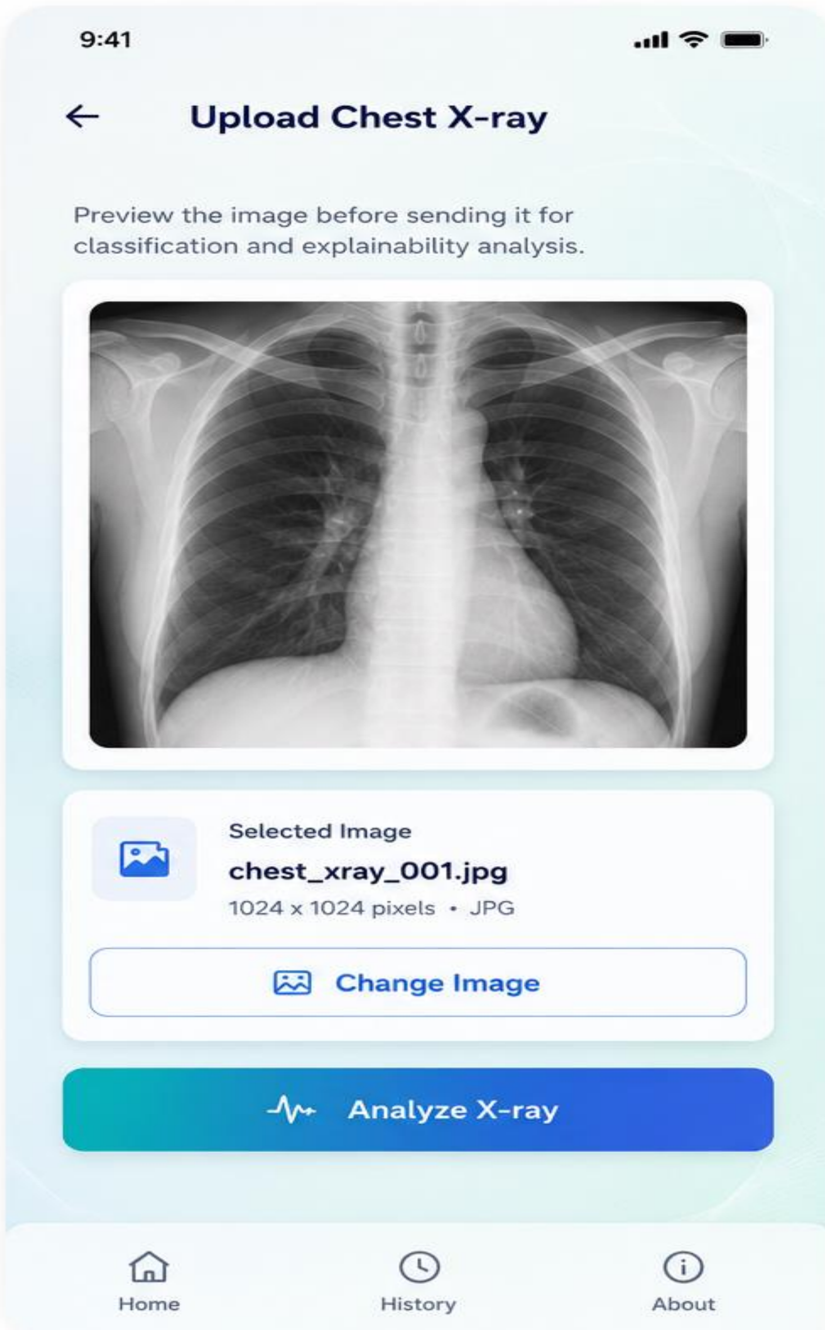

Figure 4.7 Upload Page

C. Result Display Screen

This page or screen shows the result of the input the user fed to the system after the inference engine has done processing it. Figure 4.8 presents the diagrammatic illustration of the Upload Page.

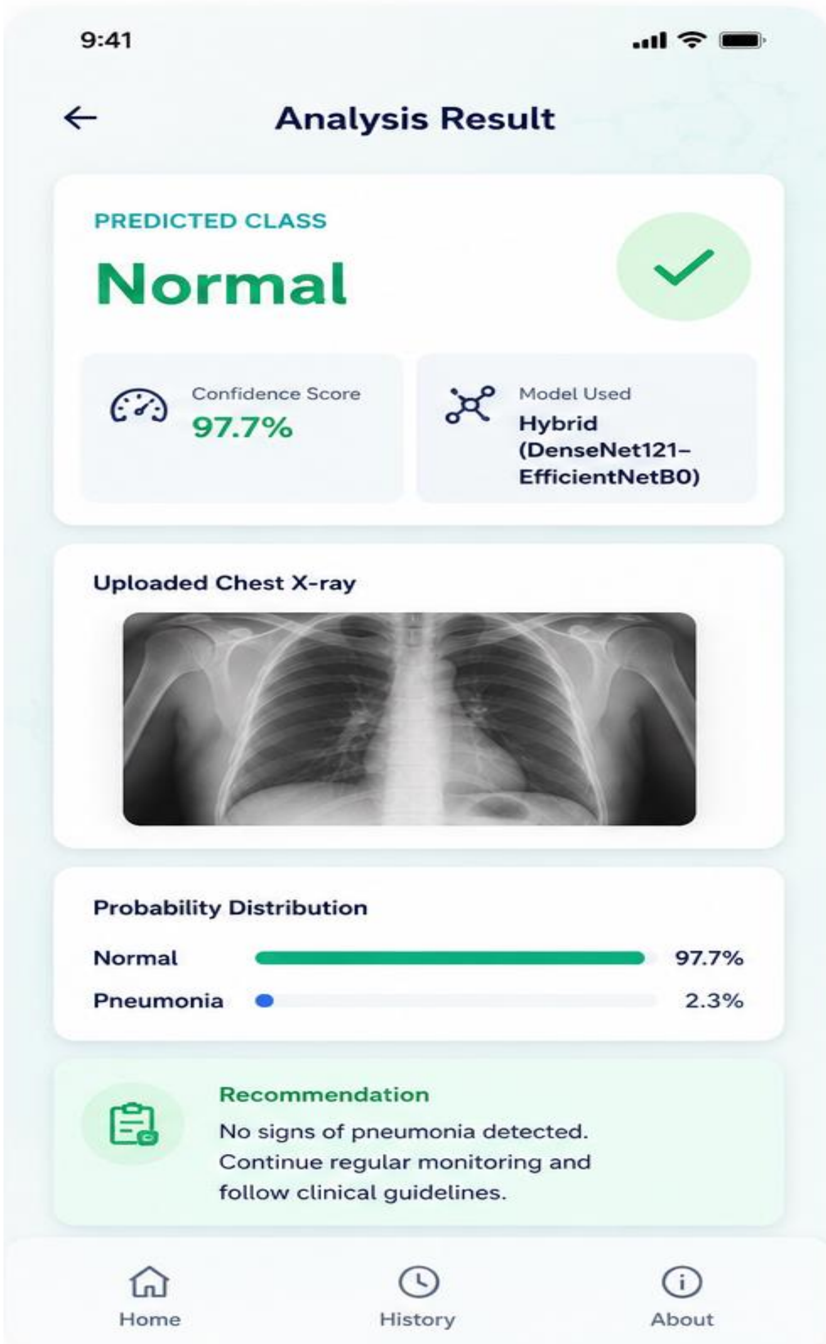

Figure 4.8 Upload Page

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

In this study, the authors introduce the design and implementation of a Clinical Decision Support System (CDSS) for detecting thoracic diseases based on chest X-ray images and a hybrid Deep Learning Model DenseNet121–EfficientNetB0. Motivation for the study was the increasing demand for quick, reliable and accurate computer-aided diagnosis which assists health professionals to diagnose the thoracic diseases, especially pneumonia in early stages. A hybrid deep learning architecture was designed by integrating DenseNet121 and EfficientNetB0, taking advantage of the complementary advantages of both models. Detailed image features at the local level were captured with DenseNet121, whereas high level semantic features at the semantic level were extracted with EfficientNetB0 using the transfer learning strategy. The extracted features were combined to create richer feature representations, for accurate classification.

The Chest X-ray Pneumonia (CXR-PN) dataset was collected from Kaggle, and the patients' images were used for training, validation and testing. The images were preprocessed before training, including resizing, normalization, and data augmentation to enhance the data quality and increase the model's capacity to generalise to novel images. Adam was employed as an optimiser for the model training, and metrics like accuracy, precision, recall, F1-score, confusion matrix, ROC AUC and Precision–Recall curve were used for evaluation. The experimental results showed that the proposed hybrid model has good classification results, with an overall accuracy of 97.75%, an AUC of 0.9976, and an Average Precision score of 0.9973, which is effective to differentiate normal and pneumonia chest X-ray images.

The trained model was implemented in a web-based Clinical Decision Support System based on the Flask framework to show its applicability. The application enables the user to upload chest X-ray images, automatically categorize and diagnose the disease and view the prediction level and diagnostic outcomes via an intuitive user interface. In general, the research accomplished its goal of creating an intelligent, efficient and accessible decision support system which can aid the thoracic disease diagnosis by healthcare professionals.

5.2 Conclusion

The results from this study prove that hybrid deep learning has a great potential to enhance the performance of the computer-aided diagnosis of thoracic diseases. The proposed model, DenseNet121 + EfficientNetB0, effectively exploited the best aspects of both architectures: it achieved very discriminative feature representations and high classification accuracy.

The evaluation results indicated a high degree of precision, recall and F1 score of the model developed and low classification errors. The confusion matrix also verified the accuracy of the classification of most chest X-ray images, and the ROC and Precision–Recall analyses showed high discriminative power at various classification thresholds.In addition to its predictive accuracy, the implementation of the trained model as a Clinical Decision Support System demonstrates its applicability in healthcare settings. The developed system offers an easy-to-use analysis interface for chest X-ray images, and offers fast diagnostic support for healthcare practitioners. While not intended to replace clinical skills, the system can be a valuable assistive tool to increase diagnostic efficiency and guide informed clinical decision.

Based on this, it can be concluded that the proposed Clinical Decision Support System (Hybrid DenseNet121-EfficientNetB0) is an effective, reliable, and practical solution for automatic thoracic disease detection from chest X-ray images.

5.3 Contributions to Knowledge

This study has added to the knowledge as follows:

1. It designed a hybrid deep learning model to detect thoracic diseases automatically using X-ray images, based on DenseNet121 and EfficientNetB0.

2. It showed that the fusion of features from two complementary convolutional neural networks enhances the classification accuracy and diagnostic reliability.

3. It developed and deployed a web-based Clinical Decision Support System (CDSS) that can automatically process X-ray images of the chest and make diagnoses in real time.

4. It was able to perform very well for the diagnosis as it could be seen that the overall classification accuracy was at 97.75%, the AUC was 0.9976, and the Average Precision was 0.9973, which indicated that the proposed approach was effective and valid.

5. It offers a practical platform to assist healthcare professionals in early thoracic disease diagnosis, and in an effort to decrease the diagnostic burden.

5.4 Recommendations

From the above information, the following recommendations are made:

1. Future studies need to test the proposed hybrid model with larger and more varied clinical data sets from multiple hospitals, to strengthen it and increase its generalisability.

2. The Clinical Decision Support System developed should be expanded to include other thoracic conditions like pneumothorax, pleural effusion, COVID-19, lung cancer and tuberculosis.

3. The system should be equipped with techniques for Explainable Artificial Intelligence (XAI) to enhance the transparency of the models and boost the trustworthiness of the predictions made by the clinicians.

4. Implement fully Explainable Artificial Intelligence (XAI) techniques like Grad-CAM, SHAP or LIME to increase transparency of the models, and therefore boost trustworthiness of the predictions generated by the clinicians.

5. Further research is needed to explore lightweight deep learning architectures, allowing for deployment at mobile devices and resource-constrained healthcare environments.

6. To support clinical adoption in real-time, integration with hospital information systems, Picture Archiving and Communication Systems (PACS) and Electronic Health Record (EHR) should be considered.

7. Before widespread deployment, further clinical validation with radiologists and medical practitioners is required to meet healthcare standards and promote clinical acceptance.

References

Apostolopoulos, I. D., & Mpesiana, T. A. (2020). Covid-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. *Physical and Engineering Sciences in Medicine*, *43*(2), 635–640. https://doi.org/10.1007/s13246-020-00865-4

Gadicha, A. B., Kale, P. V., Dalvi, G. D., Mohod, M. M., Pakhale, S. C., & Khan, S. M. (2025). Computer-aided diagnosis techniques for brain tumor segmentation and classification using MRI. *EPJ Web of Conferences*, *328*, 01052. https://doi.org/10.1051/epjconf/202532801052

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

Gundogan, E. (2025). A novel hybrid deep learning model enhanced with explainable AI for brain tumour multi-classification from MRI images. *Applied Sciences*, *15*, 5412. https://doi.org/10.3390/app15105412

Hussain, U. N., Khan, M. A., Lali, I. U., Javed, K., Ashraf, I., Tariq, J., & Din, A. (2020). A unified design of ACO and skewness-based brain tumour segmentation and classification from MRI scans. *Journal of Control Engineering and Applied Informatics*, *22*(2), 43–55.

Iantsen, A. (2022). *Automated tumour segmentation in multimodal PET/CT/MR imaging* (Doctoral dissertation). Université de Bretagne Occidentale.

Jia, H., Zhang, J., Ma, K., Qiao, X., Ren, L., & Shi, X. (2024). Application of convolutional neural networks in medical images: A bibliometric analysis. *Quantitative Imaging in Medicine and Surgery*, *14*(5), 3501–3518. https://doi.org/10.21037/qims-23-1600

Karim, S., Tong, G., Yu, Y., Laghari, A. A., Khan, A. A., Ibrar, M., & Mehmood, F. (2024). Developments in brain tumor segmentation using MRI: Deep learning insights and future perspectives. *IEEE Access*. https://doi.org/10.1109/ACCESS.2024.3365048

Kaur, S., Singh, N., Kumar, A., W. S., P., Verma, V. K., Patil, A. K., Bhardwaj, R., & Riar, A. (2025). Evaluating the impact of hyperparameters on the performance of a 1D CNN model for nutritional profiling of underutilised crops using NIRS data. *Smart Agricultural Technology*, *11*, 101025. https://doi.org/10.1016/j.atech.2025.101025

Kaur, H., Singh, M., & Kaur, J. (2025). Brain tumor detection and classification using MRI images and machine learning in MATLAB: A review. *International Research Journal of Innovations in Engineering and Technology*, *9*(11), 399–407.

Kingma, D. P., & Ba, J. (2015). Adam: A method for stochastic optimisation. *International Conference on Learning Representations (ICLR)*.

Kourounis, G., Elmahmudi, A. A., Thomson, B., Hunter, J., Ugail, H., & Wilson, C. (2023). Computer image analysis with artificial intelligence: A practical introduction to convolutional neural networks for medical professionals. *Postgraduate Medical Journal*, *99*(1178), 1287–1294. https://doi.org/10.1093/postmj/qgad095

LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, *86*(11), 2278–2324. https://doi.org/10.1109/5.726791

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, *42*, 60–88.

Liu, X., Gao, K., Liu, B., Pan, C., Liang, K., Yan, L., Ma, J., He, F., Zhang, S., Pan, S., & Yu, Y. (2021). Advances in deep learning-based medical image analysis. *Health Data Science*, *2021*, 8786793. https://doi.org/10.34133/2021/8786793

Liu, X., Hu, Y., & Chen, J. (2023). Hybrid CNN-transformer model for medical image segmentation with pyramid convolution and multi-layer perceptron. *Biomedical Signal Processing and Control*, *86*, 105331. https://doi.org/10.1016/j.bspc.2023.105331

Majlatow, M., Shakil, F. A., Emrich, A., & Mehdiyev, N. (2025). Uncertainty-aware predictive process monitoring in healthcare: Explainable insights into probability calibration for conformal prediction. *Applied Sciences*, *15*(14), 7925. https://doi.org/10.3390/app15147925

Mathivanan, S. K., Srinivasan, S., Koti, M. S., Kushwah, V. S., Joseph, R. B., & Shah, M. A. (2025). A secure hybrid deep learning framework for brain tumor detection and classification. *Journal of Big Data*, *12*, 72. https://doi.org/10.1186/s40537-025-01117-6

Mithun, M. S., & Jawhar, S. J. (2024). Detection and classification of MRI images of brain tumours using a YOLO NAS deep learning model. *Journal of Radiation Research and Applied Sciences*, *17*, 101113. https://doi.org/10.1016/j.jrras.2024.101113

Naeem, A. B., Osman, O., Alsubai, S., Cevik, T., Zaidi, A., & Rasheed, J. (2025). Lightweight CNN for accurate brain tumor detection from MRI with limited training data. *Frontiers in Medicine*, *12*, 1636059. https://doi.org/10.3389/fmed.2025.1636059

Nassar, S. E., Yasser, I., Amer, H. M., & Mohamed, M. A. (2024). A robust MRI-based brain tumor classification via a hybrid deep learning technique. *The Journal of Supercomputing*, *80*, 2403–2427. https://doi.org/10.1007/s11227-023-05549-w

Netshamutshedzi, N., Netshikweta, R., Ndogmo, J. C., & Obagbuwa, I. C. (2025). A systematic review of hybrid machine learning models for brain tumour segmentation and detection in medical images. *Frontiers in Artificial Intelligence, 8*, 1615550. https://doi.org/10.3389/frai.2025.1615550

Majkowska, A., Mittal, S., Steiner, D. F., Reicher, J. J., McKinney, S. M., Duggan, G. E., Eswaran, K., Cameron Chen, P. H., Liu, Y., Kalidindi, S. R., Ding, A., Corrado, G. S., Tse, D., & Shetty, S. (2020). Chest radiograph interpretation with deep learning models. *Radiology*, *294*(2), 421–431. https://doi.org/10.1148/radiol.2019191293

Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., & Kroeker, K. I. (2020). An overview of clinical decision support systems: Benefits, risks, and strategies for success. *NPJ Digital Medicine, 3*(17), 1–10. https://doi.org/10.1038/s41746-020-0221-y

Tan, M., & Le, Q. V. (2020). EfficientNet: Rethinking model scaling for convolutional neural networks. *Proceedings of the 36th International Conference on Machine Learning*, 6105–6114. https://proceedings.mlr.press/v97/tan19a.html

World Health Organization. (2024). *Global tuberculosis report 2024*. World Health Organization.