SMARTRAD-XAI



By

Muhammad Waleed Asrar	**01-132212-051**
Abdullah Aamir	**01-132222-002**
Hameed Junior	**01-132222-012**

Supervised By

Dr. Amna Waheed

Department of Computer Engineering
Bahria University Islamabad.

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Muhammad Waleed Asrar	**01-132212-051**
Abdullah Amir	**01-132222-002**
Hameed Junior	**01-132222-012**



Supervised By

Dr. Amna Waheed

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Department of Computer Engineering
Bahria University Islamabad.

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CERTIFICATE

We accept the work contained in the report titled **"SmartRad-XAI"** as a confirmation to the required standard for the partial fulfillment the degree of Bachelor of Computer Engineering.

Dr. Waheed Manzoor
Project Coordinator
Date: 04-06-2026

Dr. Amna Waheed
Supervisor
Date: 04-06-2026

Dr. Arslan Shaukat
External Examiner
Date: 04-06.2026

Engr. M Kashif Naseer
Internal Examiner
Date: 04-06.2026

Head of Department (CE)
Date: 04-06-2026

SMART RAD-XAI

SDG No	Description of SDG	SDG No	Description of SDG
SDG 1	No Poverty	SDG 9	Industry, Innovation, and Infrastructure ✓
SDG 2	Zero Hunger	SDG 10	Reduced Inequalities
SDG 3	Good Health and Well Being	SDG 11	Sustainable Cities and Communities
SDG 4	Quality Education	SDG 12	Responsible Consumption and Production
SDG 5	Gender Equality	SDG 13	Climate Change
SDG 6	Clean Water and Sanitation	SDG 14	Life Below Water
SDG 7	Affordable and Clean Energy	SDG 15	Life on Land
SDG 8	Decent Work and Economic Growth	SDG 16	Peace, Justice and Strong Institutions ✓
		SDG 17	Partnerships for the Goals



Range of Complex Problem Solving		
No.	**Attribute**	**Check**
1	Range of conflicting requirements: Involve wide-ranging or conflicting technical engineering and other issues.	
2	Depth of analysis required: Have no obvious solution and require abstract thinking and originality in analysis to formulate suitable models.	
3	Depth of knowledge required: Requires research-based knowledge, much of which is at or informed by the forefront of the professional discipline and which allows a fundamentals-based first principles analytical approach.	✓
4	Familiarity of issues: Involve infrequently encountered issues.	
5	Extent of applicable codes: Are outside problems encompassed by standards and codes of practice for professional engineering.	
6	Extent of stakeholder involvement and level of conflicting requirements: Involve diverse groups of stakeholders with widely varying needs.	✓
7	Consequences: Have significant consequences in a range of contexts.	
8	Interdependence: Are high level problems including many component parts or sub-problems.	

Range of Complex Problem Activities		
No.	**Attribute**	**Check**
1	Range of resources: Involve the use of diverse resources (and for this purpose resources include people money equipment materials information and technologies).	✓
2	Level of interaction: Require resolution of significant problems arising from interactions between wide ranging, and conflicting technical engineering or other issues.	✓
3	Innovation: Involve creative use of engineering principles and research based knowledge in novel ways.	✓
4	Consequences to society and the environment: Have significant consequences in a range of contexts characterized by difficulty of prediction and mitigation.	
5	Familiarity: Can extend beyond previous experiences by applying principles-based approaches.	

UNDERTAKING

We declare that the research work presented in this thesis **"SmartRad-XAI"** is the result of our own efforts and has been carried out under the supervision of **Dr. Amna Waheed** in the Department of Computer Engineering, Bahria University Islamabad.

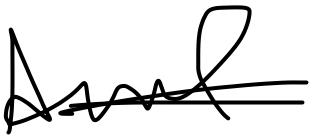
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We further affirm that this thesis represents our original contribution and any assistance received during the course of this research has fully acknowledged.



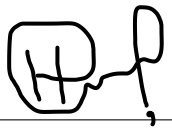
Muhammad Waleed Asrar

01-132212-051



Abdullah Aamir

01-132222-002



Hameed Junior

01-132222-012

DEDICATION

This research is dedicated to all patients and healthcare professionals who devote their time, effort, and expertise toward the early identification and treatment of life-threatening diseases.

By creating SmartRad-XAI, we hope to help advance medical image analysis by featuring a smart, reliable and interpretable system to support in making precise, timely healthcare decisions. This study utilizes cutting-edge AI technologies and validates the system with Islamabad Diagnostic Centre (IDC) to improve diagnostic accuracy, transparency and clinical usability. We also would like to dedicate this work to our families who have been our gifts of unconditional love, encouragement, and support throughout our academic journey. We owe everything to their trust in us, and it's what has helped us rise to success and rise to the occasion of every challenge we have faced. Last but not least, our sincere gratitude to our friends and siblings for their continual inspiration, understanding and support through all phases of this research project. They made a tremendous amount of encouragement and helped us stay focused and determined throughout this journey.

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Additionaly, we would thank to the invaluable cooperation and support of **Dr. Saria Ahmed Rajpoot (Coordinator Imaging and Quality Assurance)** and Dr. Ahmed Rajpoot from **Islamabad Diagnostic Centre (IDC)** in the clinical validation phase of this project. They were very helpful in making real chest X-ray cases available, assisting in the practical evaluation, and giving us expert advice, which helped us complete and validate the SmartRad-XAI system successfully.

Last but not least, we are like to express our gratefulness to all those people who gave us direct and indirect support during research, and who have helped us conduct this research.

ABSTRACT

The early detection of chest diseases from X-ray images vital for timely clinical decision making especially in resource-limited health care systems where the availability of expert radiologists can be limited. The current computer-aided diagnostic systems have some drawbacks, including limited real-time access, limited clinical validation and reduced generalization between diverse disease categories. This study presents an Automated Chest Disease Classification framework, named SmartRadXAI, which combines deep learning and the mobile health care technology to address the challenges and provide reliable and easy-to-use diagnosis.

In this research work, we introduce the automated chest disease classification system based on pretrained deep learning models: ResNet18, ResNet50, Vision Transformer (ViT), YOLOv8s, and YOLOv8n, which is called SmartRad-XAI. The five-class disease classification was done on ChestX-ray14 dataset from the NIH. By enhance accuray and precision of model, the data was preprocessed using Roboflow, which involves resizing images and augmenting data sets. Standard classification metrics were used to train all models and compare their results. Experiments demonstrated that YOLOv8s had the best performance, and the light version YOLOv8n was not as accurate as the other models. Besides the deep learning framework, a mobile app was designed to offer real-time chest X-ray analysis. The app enables users to upload photos by using the camera or gallery, then get predictions of which diseases are detected, with levels of confidence, and manage their prediction history. In addition, the patients X-Ray results were verified with the help of Islamabad Diagnostic Centre (IDC) where its predictions were compared with the interpretation of the patient by expert radiologist for the purpose of assessing its applicability in practical applications. As a whole, the study SmartRad-XAI highlights the potential of merging deep learning with mobile healthcare technology to deliver reliable, efficient, and accessible AI-powered chest disease diagnosis both in experimental and real clinical settings.

Keywords: Medical Image Classes, ResNet, Vision Transformer, YOLOv8s, YOLOv8n, Chest X-ray, Roboflow, Artificial Intelligence, Mobile Application, AI Based Diagnosis and Clinical Validation, IDC.

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Chapter 1
INTRODUCTION

Today healthcare sector relies on medical imgining help to track and trate the variety of illness [1], [2]. The popular imaging model is chest xray(CXR) which is not expensive, simple to obtain and helpful in detecting abnormalities[3], [4] . Chest X-ray is an necessary tool for the recognition of respiratory and cardiovascular diseases including pneumonia, pneumothorax, pleural effusion, and cardiomegaly [1]. But the correct interpretation of chest X-ray images demands a great deal of clinical skills and experience. Many healthcare centers, especially in developing areas, suffer from the lack of qualified radiologists and the rising inflow of patients, which might result in delayed diagnosis and higher workload for healthcare providers. Thus, there is an excess requirment for smart computer assisted software program to assist medical practitioners in delivering speedy, accurate analysis of medical images.

The development of AI technologies has revolutinized medical imaging automated detection of features and disease categorization directly from the image [4], [5], [6]. The efforts in AI driven approaches, medical image analysis has been completely revolutionized, enabling the features and the classification of diseases directly from the image [4], [5]. Chest radiograph image analysis has seen significant advancements with deep learning architectures like Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and YOLO-based models, which are capable of extracting intricate patterns from chest X-ray images and achieving high classification accuracy [7], [8], [9]. Encouraged by this, this work introduces a novel automated chest X-ray classification system named SmartRad-XAI, which utilizes multiple modles: ResNet18, ResNet50, Vision Transformer (ViT), YOLOv8s, and YOLOv8n for the classification of five chest disease classes. Besides the model development and performance comparison, the proposed system also includes a real-time mobile application to upload X-ray data and get an automatic prediction of the disease with confidence scores. Moreover, the system was tested clinically with real chest X-ray images obtained by collaborating with Islamabad Diagnostic Centre (IDC), which in turn showed the applicability of the system in real healthcare environments. The objective of the SmartRad-XAI framework is to create an accurate, efficient and accessible AI-assisted solution for the diagnosis of chest disease and to be able to make the leap between research-oriented deep learning models and the real world of medicine.

1.1 Background

Traditional computer aided diagnosis (CAD) systems used the ” handcrafted features” and “conventional image processing techniques” to detect the disease. These approaches meant that it was feasible for domain experts to design features to represent disease characteristics in medical images. However, handcrafted features were frequently inappropriate for other datasets and other imaging conditions and did not always provide impressive diagnostic performance. With the growing complexity of medical imaging data, more sophisticated methods must be developed to improve reliability of data.

The application of mordern computing approcahes to analyze medical images have remarkably improved the diagnosis of thoracic disease [2],[4], [5], due to the automatic learning of different hierarchical features directly from images, as opposed to manual built-in feature engineering [10], [7]. CNN models such as ResNet are very effective in recognizing of the spatial and structural features [7] and, compared to CNN, ViT models can well extract long-term information from the entire image by their self-attention mechanism [8], [11].

The availability of huge public datasets, for examples, the NIH ChestX-ray14, CheXpert and MIMIC-CXR datasets has also contributed to the construction of indepth learning models towards chest disease classification [1], [3]. More recently, in the era of light-weight architectures, YOLO-based models have become popular in a manner that seeks a compromise in accurate efficiency, making it workable in real-life applications [9], [12]. Besides improving the model‘s capability, practitioners have also focused on delivering deployable healthcare solutions by integrating AI models into accessible interfaces for easier operation in hospitals, clinics, and telemedicine services [13], [14].

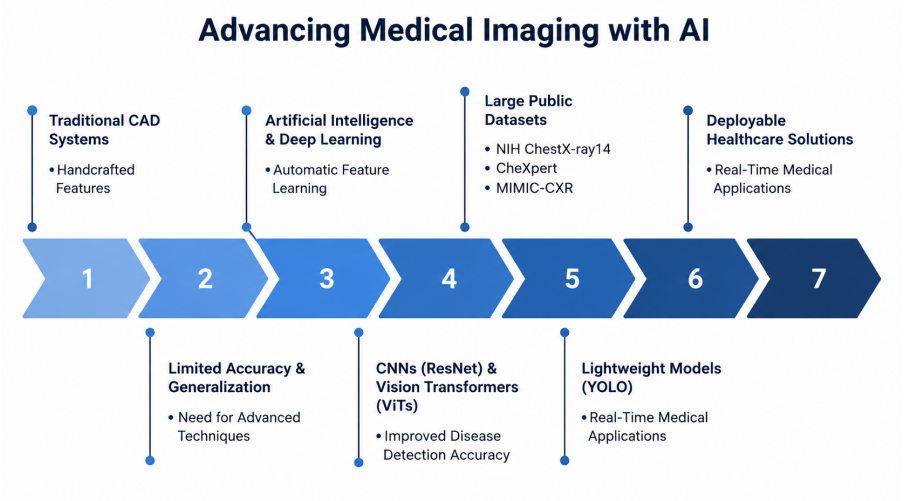


Fig 1.1: Overview of the research background

The figure shows the key technological advancements that have helped drive the evolution of medical imaging systems that use AI. It captures the shift from conventional, feature-based handcrafted approaches to more powerful deep learning architectures leveraging massive medical data sets. The figure also highlights the importance of automated feature learning, efficient model architectures, and real-time deployment platforms for enhancing disease classification performance. The developments in this work are the basis for implementing the proposed SmartRad-XAI system, which integrates various deep learning models and a real-time mobile app to support automated chest X-ray analysis and practical implementation in healthcare.

1.2 Problem Statement

Chest X-ray imaging is one of the most widely used diagnostic methods for the diagnosis of thoracic and respiratory disease [1],[3]. But, the radiologist needs a lot of experience and skill to make an accurate interpretation of the images of the chest X-ray. At many health centers, especially in developing areas, there is a growing number of patients, which can cause delays in diagnosis and result in a lot of work. The need for intelligent systems to help healthcare professionals process chest X-ray images efficiently and accurately has grown [14],[15].

Deep learning technologies have accomplished great achievement in medical image classification [4],[5]. However, the right choice of the model for chest disease detection is still challenging. The accuracy computational complexity and generalisation potential of different architectures are different [7],[8],[9],[16]. Current research has been conducted separately on a single deep learning model, which makes it hard to figure out the best deep learning model for chest X-ray classification. Hence, a

thorough comparative study of several state-of-the-art deep learning algorithms is needed to determine the best performing and effective algorithm that can be implemented in automated disease prediction.

Additionally, most research is focused mostly on models creation and performance evaluation and there is less support for implementation and interaction with users. In the healthcare domain, there is a need for systems that can provide predictions promptly and are user friendly [13], [14]. Consequently, a user-friendly and real-time system that integrates precise chest X-ray deep learning classification with a user-friendly mobile application interface is needed. This can allow patients to upload their chest X-ray scans, get immediate automatic predictions, and assist doctors with timely diagnoses.

1.3 Objectives

This research aims at the following:

- To create an automatic chest X-ray classification system that uses deep learning technologies for detection of selected thoracic diseases.
- To train and test various deep learning models such as ResNet18, ResNet50, Vision Transformer (ViT), YOLOv8s and YOLOv8n on chest disease classification.
- To preprocess and organise the NIH ChestX-ray14 dataset to resize images, normalize and augment data for better model performance and generalization.
- To compare the performance of different deep learning models based on evaluation metrics like accuracy, precision, recall and F1-score.
- To determine the best and most effective model for automated chest X-ray disease classification.
- To design and build a real-time mobile app which provides the user to upload chest X-ray images and automatically predicts the disease.
- To add user authentication, prediction history management and visualize the confidence score to make the system more usable and accessible.
- In realistic validation of developed SmartRad-XAI system with real chest X-ray cases through the collaboration with Islamabad Diagnostic Centre (IDC).

The proposed workflow depicts the whole of the SmartRad-XAI framework starting with image acquisition and preprocessing of the chest-X-ray images, followed by classification of the disease using various deep learning architectures. The trained models are evaluated for their performance on the input images and the prediction of

the disease and the best performing architecture is identified. The framework is then connected to a real-time mobile app for easy and secure upload of chest X-ray images and automated prediction results with confidence scores. The system encompassed the end-to-end deep learning-based disease classification, model comparison, and real-time deployment, which is suitable for practical healthcare and clinical validation environments.

1.4 System Overview

SmartRad-XAI system is an end-to-end deep learning system for automated chest X-ray classification. The system is built from a subset of the NIH ChestX-ray14 dataset , and employs five primary disease categories related to thoracic disease. It incorporates several cutting-edge deep learning models: ResNet18, ResNet50, Vision Transformer (ViT), YOLOv8s and YOLOv8n, for extracting relevant features from chest X-ray images and for accurate disease identification . The entire process contains dataset preparation, model training, performance assessment and comparison to find the best model architecture for chest disease detection.[7], [9], [1] This is further expanded to a "real-time diagnostic platform" using interface with a mobile application. The user can upload chest X-ray images by mobile devices, and the back-end deep learning models analyze the uploaded images immediately, providing their prediction results and confidence scores. The system was also validated by using real chest X-ray cases with the cooperation of Islamabad Diagnostic Centre (IDC) and assessing the practical performance of the proposed models in real clinical settings. The system was tested in real time at IDC which allowed for the system's reliability to be assessed outside experimental testing and provided evidence that the system could be used in a practical healthcare application. In addition, the system facilitates secure authentication, prediction histories tracking, and ease of interaction, which make it suitable for real-world medical settings, particularly in environments with limited resources.

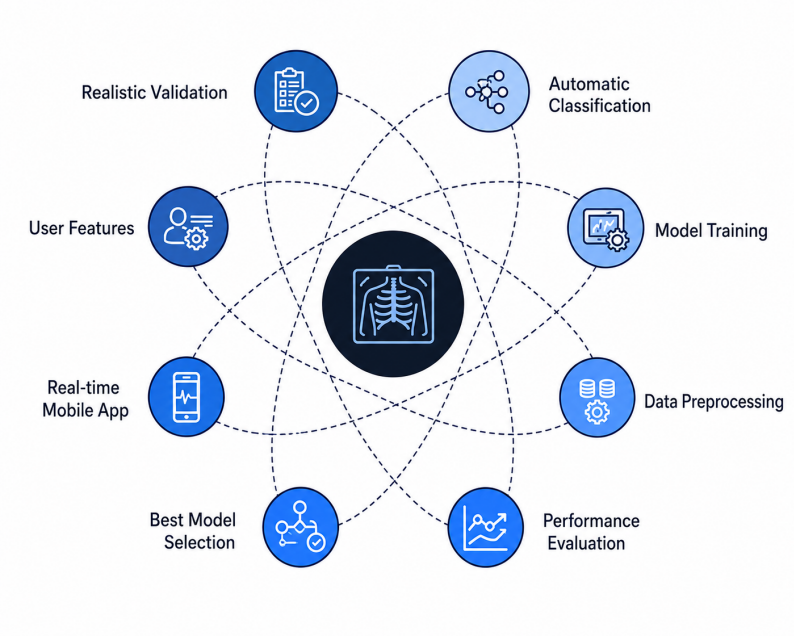


Fig 1.2: Proposed explainable deep learning workflow for lung disease detection.

1.5 Significance of the Study

The importance of this study is from the aspect of its notable impact in advancement of real intelligent health-care system that can support medical practitioners in thoracic disease diagnosis with utilization of chest X-ray image database. The chest diseases like Pneumonia, Pneumothorax, Cardiomegaly and Pleural Effusion need to be diagnosed quickly so that the treatment can be provided at the earliest so as to affect the patient‘s outcome. These automated deep learning based disease classification systems can help radiologists to decrease workload, improve the accuracy and sensitivity of diagnosis and substantially reduce the human error [2].

This paper has conducted a comparative study of several recent deep learning architectures (ResNet18, ResNet50, Vison Transformer (ViT), YOLOv8s and YOLOv8n) for the classification of chest X-ray diseases. This comparative study will allow the researchers to determine the most suitable deep learning architecture in the automated disease diagnosis as well as provide a literature review into different architectures in medical applications.

This work also makes a noteworthy advance by providing the most successful deep learning model in a real-world mobile healthcare system. While much research stays only at CNN design and evaluation, the proposed SmartRad-XAI framework provides a real system by developing a mobile platform that allows users to upload chest X-rays and get automatic classification results. Thus, the artificial intelligence applications in medical field can be more reachable to the patients.

In addition, the clinical validation that was carried out using actual chest X-ray cases, collected in association with Islamabad Diagnostic Centre (IDC), increases the applicability of this research work. The validation shows real life applicability of the system developed, as well as, evidence of system performance.

1.6 Scope of the Study

This research focuses on developing an automated system for classifying five chest disease categories using chest X-ray images from the NIH ChestX-ray14 dataset[1] . The selected classes are Cardiomegaly, Effusion, Pneumonia, Pneumothorax, and No Finding. The study investigates about how different deep learning architectures perform in identifying these conditions from chest radiographs. A comparative analysis is conducted to assess the effectiveness of each model in chest disease classification.

This research includes preparing and augmenting the dataset, training multiple deep learning models, evaluating their performance, and integrating the best-performing model into a mobile application. The selected architectures include ResNet18, ResNet50, Vision Transformer (ViT), YOLOv8s and YOLOv8n. At the end of training, the models were evaluated using accuracy, precision, recall, and F1-score, allowing a detailed comparison of their classification capabilities [8], [9].

The scope further proceed to the development of a mobile based healthcare application that is integrated with the trained model and allows users to upload chest X-ray images for disease prediction. The system is responsilbe to provide automated diagnostic support and improve accessibility to modern healthcare technologies.In addition, the proposed system focuses on the efficient and reliable classification of diseases with practical applicability in real-life healthcare settings. The mobile deployment of the trained deep learning model illustrates the potential for bringing artificial intelligence to a point of care diagnostic aid. The app aims to deliver quick, easy predictions to allow healthcare practitioners and remote users to use it. The study also points out that deep learning models could be used to improve early disease detection and aid in clinical decision-making. In summary, the project is a major step forward in the development of AI-powered medical imaging systems, merging precision disease diagnosis with mobile healthcare solutions.

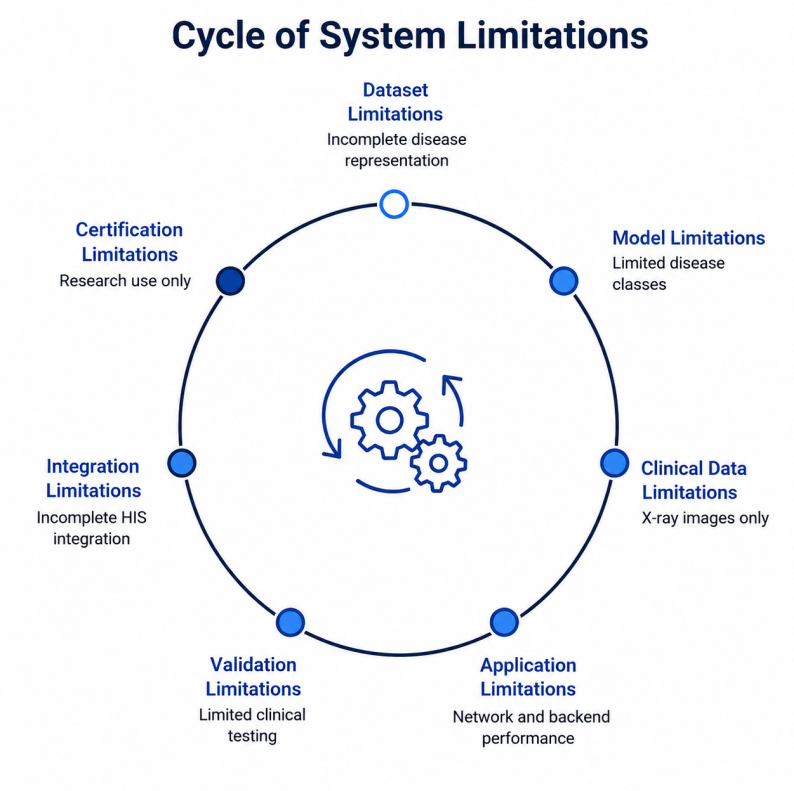


Fig 1.3: Scope of the SmartRad-XAI system

The figure illustrates the overall scope of the proposed SmartRad-XAI framework. It highlights the major components of the system, including dataset preparation, deep learning model training, comparative evaluation, mobile application deployment, and clinical validation. These components collectively contribute to the development of an intelligent and practical chest X-ray disease classification system.

1.7 Limitations of the Study

Although the proposed SmartRad-XAI framework demonstrates promising performance for chest X-ray disease classification, several limitations should be acknowledged.

The study is limited to five disease categories selected from the NIH ChestX-ray14 dataset . Therefore, the developed models are not designed to detect all possible thoracic diseases that may appear in chest radiographs. The classification performance may also be influenced by dataset imbalance and variations in image quality.[1]

Another limitation is that the models were trained using a specific dataset and may experience reduced generalization when applied to images acquired from different hospitals, imaging devices, or patient populations. Additional multi-institutional datasets may further improve robustness and generalization capability.

The explainability component of the system is limited and can be enhanced in future work through the integration of advanced Explainable Artificial Intelligence (XAI) techniques such as Grad-CAM, Grad-CAM++, and Layer-Wise Relevance Propagation (LRP) . These techniques can provide more transparent explanations regarding model predictions and improve clinical trust [17], [18], [19].

Furthermore, the clinical validation conducted in this study involved a limited number of real-world cases. Larger-scale validation studies involving multiple healthcare institutions and radiologists would provide stronger evidence regarding the practical effectiveness of the proposed system.

Despite these limitations the SmartRad-XAI framework provides a strong foundation for automated chest X-ray disease classification and demonstrates the potential of deep learning technologies for supporting intelligent healthcare applications.

Chapter 2

Literature Review

The application of deep learning to medical imaging has emerged as one of the fastest advancing research fields in the medical community, especially in the field of chest X-ray disease detection. Chest X-ray has become a broadly adopted diagnostic tool for chest diseases, including pneumonia, cardiomegaly, pleural effusion, and pneumothorax, because of its economic, speedy, and convenient use in clinical settings. Manual reading of chest X-rays is however often difficult because of overlapping anatomy, subtle chest X-ray findings and rising workload amongst the radiologists. Researchers have been developing several Artificial Intelligence (AI) and Deep Learning (DL) techniques to address these challenges and enable automatic diagnosis and categorization of diseases. CNNs, transfer learning, transformer-based models, and explainable AI have emerged as promising innovations for enhancing diagnostic precision and aiding in the development of intelligent radiology systems [2], [4], [5].

In the recent years, several studies have concentrated on building deep learning architectures for chest disease classification in the context of a multi-label classification task, using large-scale datasets as ChestX-ray14 and CheXpert [1], [3]. Many architectures have been used for the extraction of complex radiographic features from chest X-ray images such as DenseNet, ResNet, EfficientNet, Vision Transformers (ViT), and attention-guided CNNs [7], [8], [16], [20], [21]. Other topics that were investigated included weakly supervised learning, localization of the disease, and ensemble learning to develop a better classification and find abnormal areas of the thorax.

Furthermore, transfer learning approaches have been widely employed to improve the performance of the model in the case of small training datasets. The studies revealed that these deep learning systems can also be accurate in detecting thoracic abnormalities, with less need for hand-crafted feature engineering. These explainable AI (XAI) approaches, like Grad-CAM, Grad-CAM++, Layer-Wise Relevance Propagation (LRP), and attention-based visualization approaches, have been major players in healthcare AI studies over the last few years [17], [18], [19]. Explainability provides extra transparency and clinicians' faith by visualizing areas of the diseases that impact the model's prediction.

In other works CNN and transformer architectures have been used in combination, techniques have been proposed for improving images, and techniques have been

proposed for handling uncertainty-aware learning to improve robustness and interpretability in chest radiography systems. The following literature review is a summary of the major research studies that are relevant to the proposed SmartRad-XAI framework, namely the classification of chest X-ray, localization of the disease, transfer learning, explainable AI, and intelligent radiology system.

2.1 ChestX-ray8: hospital-scale chest x-ray database and benchmarks for weakly-supervised classification and localization of common thorax diseases

This paper presents a study that introduced ChestX-ray8, one of the largest publicly available chest X-ray datasets for thoracic disease classification and localization. They obtained 108,948 frontal view X-ray images from 32,717 unique patients with each image labeled for the presence of 8 different thoracic diseases including pneumonia, atelectasis, effusion, mass, cardiomegaly and others. The labels for diseases were automatically derived from the radiology reports by use of NLP. In this work, the researchers proposed a weakly supervised deep convolutional neural network (DCNN) framework using CNN-architecture such as ResNet to simultaneously learn to classify and localize multiple diseases. The DCNN does not require bounding box annotation during training to know where the diseases are located in the images.

The study proved that deep learning is capable to classify diseases and locate abnormal region in chest X-ray image. The framework quite conveniently using heatmap to localize the area with suspicious diseases would be very important in future work of explainable AI in medical imaging. However, the localization accuracy was not high enough as the exact disease boundary was not derivable under weak supervision. The paper also discussed the problems of label noise, cholera, multiple diseases and inaccurate localization. Nevertheless, this project was a breakthrough for chest X-ray image analysis and also back the foundation for many later researches in explainable AI, transfer learning, multi-label classification and sophisticated radiology system related to Grad-CAM visualization [17].

2.2 Deep Learning algorithm for Pneumonia Detection on Chest X-Rays at Radiologist-level

This study aimed to create a deep learning framework called CheXNet for automatic detection of pneumonia in chest X-ray images [22]. The model was derived from a 121-layer Dense Convolutional Network (DenseNet-121) and it was trained with the ChestX-ray14 database of more than 100,000 chest X-ray images and 14 labels for

thoracic diseases. The primary aim of this paper was to design an AI system that can achieve a performance level similar to experienced radiologists in diagnosing pneumonia. The model was assessed to four clinicians and the authors found CheXNet to have a higher average F1-score for pneumonia detection. This framework was then expanded to classify all 14 thoracic diseases that were provided in the data set.

To enhance the interpretability and transparency of the model predictions, these abnormal chest regions were also visualized using class activation mapping techniques in the paper. CheXNet was one of the most influential papers as it showed the performance of a deep learning system could be as good as radiologists performance in chest disease diagnosis. Several limitations existed in this study such as weak localization ability, dependence of data quality, low explainability, and possible bias by noisy labels in the ChestX-ray14 dataset. The model also mainly adopted CNN architectures and did not consider the transformer-based learning methods. However this paper paved the way for various subsequent studies and advancements in explainable AI, Grad-CAM visualization, transfer learning, DenseNet architectures, and intelligent chest X-ray diagnosis systems [17], [20] .

2.3 Visual Explanations from Deep Networks via Gradient-Based Localization, by Grad-CAM

This study is the introduction of an explainable artificial intelligence approach called Grad-CAM (Gradient-weighted Class Activation Mapping) that visualizes and interprets the predictions made by convolutional neural networks [17]. The study demonstrated that Grad-CAM could make the model more transparent by visualizing how a deep learning model makes a prediction for a particular class. The heat maps created enabled the identification of significant areas of the image and an understanding of the model behaviour. Grad-CAM has gained significant traction in medical imaging tasks, particularly in the diagnosis of diseases from chest X-ray images, due to its ability to offer visual evidence to back up AI predictions [17]. The method however, resulted in coarse localization maps and occasionally was unable to correctly localize small and multiple abnormal regions in an image. Later researchers have found that the heatmaps are blurry, localization is not accurate in complex scenarios etc and designed more advanced approaches such as Grad-CAM++ [18]. Although there are these restrictions, Grad-CAM is still one of the most popular explainability methods for healthcare AI systems and radiology systems.

2.4 Grad-CAM++: Improved Visual Explanations for Deep Convolutional Networks

In this study, they demonstrated Grad-CAM++, an enhanced version of Grad-CAM that empowers CNN models to produce more accurate and detailed visual explanations [18]. The authors noticed that the original Grad-CAM method worked poorly on correctly localizing multiple object instances and its heat maps were often low-resolution. To address the above challenges, Grad-CAM++ proposed a generalized gradient-based localization strategy which generates a mixture of top partial derivatives in the feature map of a convolutional layer. This modification enhanced the localization quality and resulted in more precise class discriminative heat maps. Three different CNN architectures were considered for the technique, namely image classification, image caption generation, and action recognition tasks.

Experimental results showed that Grad-CAM++ method outperforms the original Grad-CAM method in terms of object localization and visual explanations. The enhanced heat maps made interpretation easier, particularly in cases where multiple objects were of interest. The ability to localize the relevant image regions for a given prediction proved to be very useful in medical imaging tasks such as localization of abnormalities in chest X-ray images and disease diagnosis. The approach was nonetheless strongly reliant on the quality of CNN features and highly required computational resources for big models. For some, localization performance continued to be affected by network architecture and the complexity of the data sets. However, these constraints led to the development of Grad-CAM++ as an important explainable AI (XAI) method in medicine, and were a catalyst for the creation of numerous subsequent work on explainable chest radiography systems, disease localization, and trustworthy AI-assisted radiology applications.

2.5 This is one of several papers from the Pixel-Wise Explanations for Non-Linear Classifier Decisions by Layer-Wise Relevance Propagation series

This study presented a new explainable AI method called Layer-Wise Relevance Propagation (LRP), which explains predictions of a complex non-linear classifier like a deep neural network [19]. The main goal of the paper is to alleviate the black-box nature of AI models by giving pixel-wise explanations of the model decisions. The authors suggested a mechanism of relevance propagation to update the prediction score layer by layer to the back of the network to obtain relevance values of individual input pixels. This method enabled to see which parts of the image

are the most important for the final prediction. The method was tested with image classification using deep neural networks and shows good performance in terms of interpretability.

The results demonstrated that LRP could help create detailed heat maps that identify regions of interest within the image that are crucial for the classification decision, providing transparency and reliability to AI systems. The ability of LRP to clarify the prediction of disease in medical images, such as chest X-rays, proved to be very valuable. The technique enhanced the confidence of clinicians in the model by providing a visual indicator of abnormal regions that affect model prediction. Nevertheless, it needed some special care in the selection of the rules for relevance propagation, and in some cases yielded unstable explanations for very complicated models. Additionally, the computational complexity increased for deeper architectures. Despite these drawbacks, LRP became one of the cornerstones of explainable AI techniques, and influenced many studies that followed them in the field of explainable health AI, Grad-CAM visualization, and explainable radiology systems.

2.6 Multi Label Chest X-Ray Classification and Transfer Learning System

Recently the research methods for multi-label chest X-ray classification have attracted much attention, specifically by leveraging deep learning and transfer learning [23], [24]. Kufel presented a transfer learning approach for multi-label chest X-ray abnormality classification using pretrained CNN models to be fine-tuned on chest radiograph collections for the detection of multiple thoracic diseases at once. Likewise, Baltruschat evaluated several architectures for deep learning and their performance in a multi-label chest X-ray classification task, and categorized them by disease type. Typical studies followed this approach using CNN-based models like DenseNet, ResNet or other pre-trained models to identify meaningful radiographic features [7], [20] . The primary aim of these works is to increase the accuracy in classification while dealing with the overlapping patterns of the diseases in chest X-rays.

The latter approaches showed that transfer learning greatly benefits the performance for medical imaging tasks, particularly when the sizes of the datasets are small. The models however were still confronted with problems like class imbalance, overlapping radiological features, and opacity in predictions. Deep architectures were able to improve the accuracy but most of the methods were not easily interpretable and needed further methods to enable clinical trust. Although these studies have some limitations, they hold great relevance to the proposed SmartRad-XAI system as they

validate the use of pretrained CNN-based architectures and multi-class chest X-ray classification, which is directly related to the models adopted in this work, such as ResNet, ViT, and YOLO-based classifiers.

2.7 Explainable AI in Chest X-Ray Radiology Systems

The field of Explainable Artificial Intelligence (XAI) has emerged as a pivotal area for enhancing the explainability and trustworthiness of AI systems, particularly in the analysis of chest X-rays [17], [18], [19]. From a human perspective it assessed a range of XAI techniques in chest radiology imaging and how clinically interpretable they are for humans. Explainability techniques like saliency map, Grad-CAM and attention-based visualization were highlighted as crucial for connecting deep learning predictions with clinical knowledge. It emphasized the need to have models that can be understood, apart from the black-box models, for medical applications in the real world.

In the study, explainable models were found to increase clinical acceptance by highlighting the disease-relevant areas of chest X-rays, visually. It also highlighted challenges like inconsistencies in explanations across various XAI techniques and the challenge of achieving accurate localization in complex medical images. The results are also directly applicable to SmartRad-XAI, where several deep learning models are employed for classification and interpretability is crucial for improving the system in the future. While the current system does not employ all XAI techniques, the findings of this study is very strong on the integration of XAI in the classification system of chest X-ray.

2.8 Ensemble and Multi-Model Deep Learning for Chest X-Ray Classification

Ensemble learning has become a popular approach in medical image analysis because it combines the strengths of multiple deep learning models to improve classification performance and robustness [25]. Ensemble methods combine predictions of various models rather than relying on one model and this helps to decrease variance and improve generalization. Ensemble methods have been found to be better in the classification of chest X-ray diseases due to different feature representations learned from neural network architectures. Ensemble strategies have also demonstrated promising results to reduce the effects of noisy labels and class imbalance problems often found in large-scale chest X-ray datasets. Ensemble methods usually outperform individual methods, but they demand more computation resources and take more time to infer. Such restrictions can pose a challenge for deployment

in healthcare settings where real-time performance is critical. However, ensemble learning is still a significant research area for the creation of powerful and reliable AI-powered radiology systems.

2.9 Ensemble-CAM and Weakly Supervised Disease Localization

To enhance disease localization and visual interpretability, the Ensemble-CAM framework was proposed for combining the activation maps produced by various deep learning models [25]. The classical approaches to localization like Grad-CAM rely on one specific model and result in inconsistent explanations. EnsembleCAM overcomes this by combining information from several models to obtain more robust and accurate localization maps. The study showed that the fusion of several activation maps is effective for region localization of disease and helps to increase the uniformity of the visual explanations. The heatmaps generated were more effective in showcasing clinically relevant abnormalities than were the single model visualization approaches. This enhancement is especially significant in the field of medical imaging, where precision in localizing irregular areas plays a role in the trust and decision-making that rely on clinical medicine. The model-based approach of Ensemble-CAM has disadvantages as well, since several models have to be run concurrently. In addition, the complexity of integrating and optimizing multiple architectures also makes it harder to implement. Overall, the framework offers insights into explainable AI and contributes to the creation of trustworthy healthcare systems.

2.10 Transformer-Based and Hybrid Models for Chest X-Ray Analysis

However, recently the transformer model architecture has been introduced to computer vision [8], [11] and some promising results are achieved on vision tasks. Vision Transformers (ViTs) are able to encode an image as a sequence of patches, and uses self-attention mechanisms to extract both the local and the global context of a vectorized image. Transformer models are suitable for modeling large-range relationships, instead of only the local spatial features, in medical images.

A few recent papers investigated the use of Vision Transformers for chest X-ray classification and disease detection [8]. The experimental results showed that when trained properly, transformer-based models are able to outperform CNN-based models. This is mostly because the global context understanding brought by the transformer architecture is extremely beneficial in medical diagnosis.

Hybrid structures involving CNNs and transformers have been suggested to take advantage of the best of both worlds. Local features are extracted using a CNN, with a transformer module used to model global contexts. Such hybrid approaches have demonstrated favorable results for classification and localization of disease, although require an increased amount of data and computational power in the context of transformers..

2.11 Densely Connected Convolutional Networks (DenseNet)

DenseNet proposed a new connection scheme for the neural network, which connects any layer to all of its subsequent layers, and each layer obtains feature maps from all of its previous layers [20]. This connectivity pattern alleviates the vanishing gradient problem.

Due to the approach to learning robust feature representations without increasing network parameters, DenseNet structures have been widely used in medical image analysis. DenseNet-121 was the backbone architecture used for CheXNet and achieved high performance on chest disease classification [22]. The architecture is capable of learning radiographic features indicative of thoracic abnormalities andis one of the most popular models used for chest X-ray analysis.

The main benefits of DenseNet are those in reusing features easily, fewer parameters and better flow of gradient. Though the dense connectivity pattern might require more memory to train DenseNet is still widely used and represents a very influential experience in the field of medical imaging in many chest X-ray classifiers.

2.12 ResNet, a Deep Learning Approach to Image Identification

The novel deep learning architecture named ResNet proposed in this work is defined to address the degradation (accuracy saturation and then degradation as the network deepens) and the vanishing gradient problem (the reason for degradation) inherent to very deep neural network [7]. To naturally learn the residual mapping instead of the original unreferenced mapping, authors proposed the residual learning through the identity shortcut connection. With above residual blocks, very deep CNNs of more than 100 layers have been well trained. After training on the large ImageNet benchmark datasets and COCO benchmark datasets, the model performance of two tasks has also been remarkable.

The paper showed that residual learning is hugely advantageous for training stability, feature extraction ability and classification accuracy of deep networks [7]. The ResNet was later extended to achieve one of the most common backbones in the

medical image domain such as explainable ai systems, localization and disease classification in chest X-ray imaging, because the ResNet was able to learn complicated visual characteristics from chest X-rays. However, the deeper ResNet requires long time duration and high computational resources to training. Further residual learning was also it is also proved to improve the performance but without any interpretability which needs extra external explainability methods like Grad-CAM [17]. Nevertheless, despite the limitations, the ResNet has firmly established itself as a component in today‘s healthcare ai systems and has been an inspiration for many other deep learning models in radiology and computer vision.

2.13 EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

The central concept of this paper was to develop an effective family of CNN architectures, EfficientNet, which is able to obtain better accuracy and efficiency by scaling the CNNs in a more principled manner [16]. To prevent the depth and width of a network from increasing at an uncontrolled pace, the researchers introduced a compound scaling method that uniformly scales the network depth, width and input image resolution with a set of fixed scaling coefficients. The series of CNNs, EfficientNet models, was trained using neural architecture search (NAS) to reach an optimal network structure, then evaluated on the challenging ImageNet dataset with state-of-the-art accuracy but with only a small order of the number of parameters and computational cost required by previous CNNs.

The results of this study foundwere

the balance was achieved by EfficientNet between accuracy and computational efficiency so it can be good candidate for real-world medical image applications [16] The light weight and tremendous feature extraction ability has made EfficientNet widely used in analysis of chest X-ray images, detection of COVID-19 and transfer learning-enabled healthcare systems. This architecture is very suitable for deployment of in resource constrained devices and smart healthcare devices. But, Model tuning can also have an impact on performance and training EfficientNet is computationally expensive for large model variants. Moreover, the model itself is not semantically explainable and requires to be together with some XAI techniques to be interpreted such as Grad-CAM [17]. Despite these constraints, EfficientNet is among most successful CNN architectures for good intelligent radiology and healthcare AI research.

2.14 CheXpert: A Large Chest Radiograph Dataset with Uncertainty Labels and Expert Comparison

In this paper, CheXpert the largest publicly available chest radiographs dataset for automated thoracic disease classification using deep learning is presented [3]. It contains more than 224,000 chest radiographs from near about 65,000 patients with 14 observations of thoracic disease such as pneumonia, edema, atelectasis, pleural effusion, cardiomegaly, etc. The introduction of uncertainty labels from radiology reports by employing natural language processing techniques was a key contribution of this paper. The authors proposed some uncertainty treatment techniques for training the CNN network with uncertain medical labels. A DenseNet-based architecture were used to perform the disease classification experiments and benchmarked against radiologist annotations.

The paper has shown that deep learning models trained on CheXpert can hold its own with radiologists across a variety of tasks for thoracic pathology classification [3]. The uncertainty-aware training approach is a step towards making the models more robust and dulling some of the problems with noisy clinical labels. One of the most valuable benchmark data sets for chest X-ray research, such as training explainable AI systems, transfer learning models and multi-label disease classifiers. But data sets still had some issues, for example, label noise, data imbalance and absence of localization annotations. Moreover, the research was mainly focused on classification performance, rather than interpretability and localization. Nevertheless, CheXpert has taken a big step in the domain of chest radiograph analysis, and will be a valuable enabling technology for research and development in healthcare AI systems.

2.15 Diagnose Like Radiologist: Attention Guided Convolutional Neural Network for Thorax Disease Classification

In the paper present in this work, a unique AG-CNN has been introduced for classification of chest X-ray images of thoracic diseases [21]. The novelty of the research was to enhance the accuracy of the classifier of chest images using the relevant physically anatomically references during analysis as a radiologist do it. The framework used three-part network: global branch for the general image analysis, local branch for the focused image segments analysis and the fusion branch for the fusion of the two different analyses. The focus of any abnormal area of the chest were highlighted by the activation maps and focused using the attention mechanisms on the specifics of the disease. The entire methodology is tested on chest X-ray large datasets with increased classification accuracy in comparison with general CNN models.

This study showed that attention-guided learning is effective for both feature extraction and localization of diseases in chest radiographs [21]. The attention maps produced by the model made the predictions more interpretable by providing visual cues of suspicious regions in the thorax area that was relevant to a prediction. This rendered the framework very pertinent for the context of explainable AI and smart radiology systems. The multi-branch architecture and attention guided processing of the model required, however, to be computationally complex. The framework also depended greatly on the correct localization of the area corresponding to disease, which may be challenging in complex and poor chest X-rays. Even with the limitations, AG-CNN made a great contribution to the making of the diagnosis of chest disease more explainable and was a precursor to further research on attention mechanisms, localization-aware AI systems and interpretable radiology applications.

2.16 Abnormality Detection and Localization in Chest X-Rays Using Deep CNNs

In this study, a deep convolutional neural network (CNN) framework for abnormality detection and localization of chest X-ray image was proposed. The study focused on directly learning the hierarchical representations of features from chest X-ray images to automatically recognize thoracic diseases. To classify the disease, the CNN model was trained and simultaneously identified the abnormal areas of the lungs and provided weak localization, thus the model could show the areas of the lungs that are most relevant to the predicted disease. The objective was the least possible manual feature engineering and demonstration of the potential of deep learning in automated interpretation of chest X-ray images.

The significance of this work is that they have proven that CNN models can be used to learn diagnostic features from medical images, and they can be used in both classification and localization tasks. The study has some limitations, however, in that the degree of accuracy of localization is limited in complex cases of overlapping abnormalities, and secondly, that it relies heavily on the amount of data it has to be annotated. Also the model isn't very interpretable and isn't giving clinically viable explanations. Despite the constraints, this study is still significant as it has laid the groundwork for deep learning-based chest X-ray analysis and serves as a motivating study for medical image classification and localization systems.

2.17 Visualization and Interpretation of CNN Predictions for Pneumonia Detection in Chest X-Rays

Our research designed a Convolutional neural network (CNN) to classify pneumonia in children's chest radiographs and suggested visualization techniques for better interpreting the model results. The study was both to increase the accuracy of diagnosis and to increase transparency of the deep learning systems. CNN architectures were used to classify images as pneumonia or non-pneumonia, while class activation mapping (CAM) techniques were used to highlight regions which influence the CNN's classification, to make the CNN more interpretable for clinical use.

The importance of this work is that these are combined techniques of high performance classification and explanation of the visual method, which increases the confidence in the medical diagnosis by the AI. However, the study only addresses problems of pneumonia detection and not multi-disease classification problems. In addition, visualization techniques are just coarse explanations, and may not accurately mark abnormal regions. Even though they are limitations, this study was important as it confirmed the importance of the explainable CNN in medical image and it affected the medical X-ray image analysis system research afterward.

2.18 Explainable Deep Learning for Pulmonary Disease Classification Using Chest X-rays

In this study, a chest X-ray (CXR) based explainable deep learning framework for pulmonary disease classification was proposed. The research was limited to integrating deep neural networks with explainability methods to enhance transparency within medical diagnosis systems. CNN based models were used to classify the pulmonary diseases and interpretability techniques were used to obtain interpretation on the prediction of CNN models in making its decisions more understandable to the clinician.

This study is significant for its role in building trustworthy and transparent AI systems in the healthcare industry. It emphasizes the importance of explainability to medical image analysis applications where decisions must be clinically interpretable. The explanations, however, are ex post facto and rely upon external means and approaches that can decrease the reliability. Further, the performance of the models is influenced by the bias of the dataset and a low level of generalization in the various clinical environments. However, the study is important because it highlights the need for explainable AI in the diagnosis of pulmonary diseases and the advancements of interpretable medical imaging systems, despite these limitations.

2.19 Exploring the Effect of Image Enhancement Techniques on COVID-19 Detection using Chest X-ray Images

The utilization of image enhancement techniques for COVID-19 detection from chest X-ray images is presented in this study. This study aimed to assess the effect of image enhancement on deep learning for the detection of COVID-19 in chest X-ray images. The main purpose was to obtain better visual quality of radiographs to enhance the classification performance prior to training convolutional neural network classification models. Chest X-ray images were preprocessed and enhanced using different techniques like contrast adjustment, contrast limited histogram equalization, and sharpening to make the patterns in the images more visible. The enhanced datasets were then used to train and test deep learning models using a convolutional neural network architecture to classify COVID-19. The study showed that feature extraction and deep learning models' diagnostic capability of subtle abnormalities in X-rays of the chest could be significantly enhanced by employing appropriate image enhancement methods.

The results indicated that the images obtained from the enhanced chest X-ray could improve the classification accuracy and robustness over the use of raw images alone. The study highlighted the importance of preprocessing in medical image analysis, and especially for low quality images or in the presence of noise or artefacts on X-rays. While the framework primarily targeted for COVID-19 detection, it didn't focus much on detail on several thoracic diseases. Furthermore, the enhancement of the images was done at such a level that one or two extra-artificial features were sometimes added to the image, which could affect the generalization of the model. The method also heavily depended on the data sets used and the parameters used for the data pre-processing. Although the study had its drawbacks, it offered valuable insights in chest X-ray preprocessing and showed how crucial image enhancement techniques are in enhancing the performance of deep learning radiology systems.

2.20 Reproducing and Improving CheXNet: Deep Learning for Chest X-ray Disease Classification

In this study, the CheXNet framework for automated classification of chest X-ray diseases was targeted to be reproduced and improved by deep learning approach [26]. This study was conducted to assess the re-testability of the original CheXNet model and to investigate possible modifications of the model to increase the accuracy of the classification of thoracic diseases. It was used in a deep convolutional neural network architectural model, specifically those using the DenseNet architecture, and in the use of large amounts of chest X-ray data, contained multiple categories

of thoracic diseases. To improve the feature extraction and classification ability, the transfer learning and optimum training methods were introduced. The study also examined the performance of the models with different preprocessing and augmentation methods to enhance the robustness and generalization of the models.

The findings demonstrated that the classification accuracy could be higher with improved training strategies and architectural modifications compared with previous models of CheXNet [26]. The framework showed good performance in thoracic abnormality detection on chest X-rays and further emphasized the possibility of using deep CNN architectures for medical imaging-related applications. However, there were some challenges with the study, such as the imbalance in data, overlapping patterns of the disease and low interpretability of prediction. Furthermore, the model was very resource consuming for computation, due to the depth of the network architecture. The research had great significance in the disease classification of chest X-rays, and continued to advance the potential for intelligent radiology systems using deep learning.

2.21 Explainable AI for Multi-Label Chest X-ray Diagnosis Layer-wise Grad-CAM

The aim of this study is to develop and explain the multiple labels diagnosis of chest X-ray image using explainable artificial intelligence (XAI) based layer-wise Grad-CAM visualization techniques [17], [18]. The aim was to make the prediction making process of deep learning-based systems more transparent and interpretable by labelling parts of the system that are responsible for some predictions made by the system in the context of chest disease classification. The framework employed was the convolution networks architectures trained on chest X-ray images which have multiple categories of diseases related to thorax. Detailed heatmaps have been generated from various layers of the network using a layer-wise Grad-CAM, adding a layer of understanding to the way the models make decisions in the course of diagnosis and thereby providing a better picture of areas of the disease.

The study showed that layer-wise visualization is more informative and hierarchical, and it enhances interpretability over the traditional Grad-CAM techniques [17], [18]. The heatmaps created by the framework proved useful in identifying abnormal areas and regions in thorax, which helps explain the relevance of the framework to explainable health care AI systems with respect to diseases. The method however became more complicated since explanations were derived at various layers of the network. In some instances, however, the localization of subtle or overlapping abnormalities in chest radiographs was still not precise enough. Moreover, the quality

of the explanations was closely related to the feature extraction ability of the CNN model. Nevertheless, the study has added a significant contribution to improving the understanding of the process of chest X-ray diagnosis and enhanced the use of interpretable AI in intelligent radiology applications.

2.22 CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning

This study aimed to present a deep learning method, CheXNet, for automatic pneumonia detection based on chest X-ray images [22]. It is built on a Dense Convolutional Neural Network (DenseNet-121) trained on ChestXray14, a database of chest X-rays with multiple labels for thoracic diseases consisting of more than 100,000 studies. The main goal of the study was to make pneumonia diagnosis at a radiologist level using deep learning techniques. A model was trained directly from chest X-rays to extract the hierarchical features and was then expanded to classify thoracic diseases in multiple labels such as cardiomegaly, pleural effusion and pneumothorax. Class activation mapping was also applied to activation patterns for the visual system, which showed abnormal areas of the chest that affected predictions.

The study was able to prove that deep CNN architectures can attain high level of accuracy for disease classification tasks in the field of chest radiology [22]. This was especially significant in medical imaging, where the framework demonstrated that AI systems could effectively identify pneumonia, matching the accuracy of skilled radiologists in these tasks. Some of the limitations of the model are that it does not have a high localization ability, is sensitive to noisy data labelling and is not well explainable enough. Furthermore DenseNet architectures needed a lot of computational resources to train and run. Although with these restrictions, the study was one of the most groundbreaking studies in chest X-ray analysis and had a great impact on the subsequent research on explainable AI, transfer learning and intelligent thoracic disease diagnosis systems.

2.23 Chest X-ray 14: Multi-Label Thoracic Disease Classification and Localization

They showed a big chest X-ray collection and a weakly supervised multi-task deep learning system for the chest X-ray recognition of multiple thoracic diseases in this study [1]. The framework was designed on the basis of the convolutional neural network designs such as ResNet for multi-label disease classification and localization. Diseases such as cardiomegaly, pleural effusion, pneumonia and pneumothorax were included in the data set which proved very beneficial for automated chest

disease analysis. This framework encapsulated image-level labels to conduct weakly supervised localization, not only by outright decreasing the annotation burden but also by recognizing abnormal regions in chest X-rays.

The research showed that deep learning models can be successfully used for disease classification and disease localization in the radiology system simultaneously [1]. The resulting heat maps were easy to interpret and were also found to be very pertinent in the field of explainable AI in healthcare. The localization of complex abnormalities and overlapping thoracic diseases, however, was not so accurate with the weakly supervised localization. Noisy labels and imbalanced datasets were also a challenge for the framework. Although it has its drawbacks, the study was a milestone in the field of chest X-ray analysis and was influential for a multitude of further studies on Grad-CAM, disease localization, transfer learning, medical imaging systems, and explainable models.

2.24 CheXpert Large Chest Radiograph Dataset with Uncertain Learning

This study presented the CheXpert dataset a large chest radiograph data set for automated classification of thoracic diseases with the help of deep learning models [3]. This collection contains over 224,000 chest X-rays, identified for each type of disease, including cardiomegaly, pleural effusion, pneumonia and pneumothorax. The main architecture that was used was the convolutional neural network (CNN) based ones and in particular DenseNet was employed for multi label classification of chest diseases. A key finding of the study was the incorporation of uncertainty labels derived from radiology reports using NLP techniques, and the development of uncertainty-aware training strategies to enhance the robustness of classification in cases that introduce uncertainty in the clinical situation.

The researchers showed that models using uncertainty-aware deep learning methods could yield better diagnostic performance and better deal with uncertain and noisy radiological labels [3]. The dataset was a crucial resource for research in chest X-ray analysis and is widely used for the classification of diseases, transfer learning, and explainable AI applications. The study, however, primarily focussed on classification accuracy and had only limited disease localization capabilities. Another drawback to the framework was class imbalance, label noise, and low interpretability. Nonetheless, CheXpert has made a major step forward in the field of AI for automated chest radiograph image analysis and is one of the most popular benchmark datasets in intelligent healthcare AI research.

2.25 Multi-Label Classification of Chest X-ray Abnormalities Using Transfer Learning Techniques

In this paper, transfer learning techniques for multi-label classification of Chest X-ray Abnormalities are presented [23]. In this research, a transfer learning-based approach to classify multiple abnormalities in chest X-ray images using pretrained deep convolutional neural network architectures was proposed. The goal was to use feature representations derived from large-scale images to enhance automated thoracic disease detection. The models used for fine-tuning are several pretrained models of CNN: DenseNet, ResNet, EfficientNet, among others, which were fine-tuned over various collections of chest X-rays with diseases such as cardiomegaly, pleural effusion, pneumonia, and pneumothorax. The framework was geared towards enhancing the performance of classification of several simultaneous abnormalities that are frequently seen in chest radiographs.

The research showed that transfer learning has significant advantages in terms of improving the classification accuracy and simplifying training complexity in medical imaging tasks [23]. With very little training data, the pretrained models achieved robust performance on extracting meaningful radiographic features. The framework had some drawbacks, however, including overlapping disease patterns, class imbalance, and diminished interpretability of predictions. Even with these challenges, transfer learning has become one of the most practical and successful approaches in chest X-ray disease classification and has been widely adopted in intelligent healthcare systems.

2.25.1 Research Gaps

- Most studies focus on single-disease classification tasks.
- Overlapping thoracic abnormalities remain challenging for many deep learning models.
- Dataset imbalance continues to affect classification performance.
- Noisy annotations reduce the robustness of trained models.
- Existing methods often show poor generalization across datasets.
- Disease localization remains imprecise in many approaches.
- Explainability techniques do not always provide consistent interpretations.
- Transformer-based models require substantial computational resources.
- Comparative evaluations of CNN, Transformer, and YOLO-based models are limited.

2.26 Comparative Analysis of Existing Studies

A comparative study of the most relevant research contributions in the field of chest X-ray-based disease classification and localization is presented to get a better idea of the existing research work. From the literature, only those papers are chosen that are directly relevant to the field of multi-label chest disease detection, explainability and deep learning approaches.

Table 2.1: Literature Review Comparison of Existing Studies

Paper	**Dataset**	**Disease**	**Explainability**	**Limitation**
(Wang et al., 2017) [27]	ChestX-ray8 Dataset	Pneumonia, Effusion, Cardiomegaly, Mass	Heatmap-based localization	Weak localization, noisy labels
(Rajpurkar et al., 2017) [22]	ChestX-ray14 Dataset	Pneumonia, 14 thoracic diseases	Class Activation Mapping (CAM)	Limited interpretability, dataset bias
(Irvin et al., 2019) [3]	CheXpert Dataset	Pneumonia, Effusion, Cardiomegaly, Pneumothorax	Limited XAI support	Label uncertainty, no precise localization
(Selvaraju et al., 2017) [17]	ImageNet / Chest X-ray datasets	General chest diseases	Gradient-based heatmaps	Low-resolution and coarse explanations
(Chattopadhyay et al., 2018) [18]	ImageNet / Medical datasets	Multi-label diseases	Enhanced CAM heatmaps	High computation cost
(Liu et al., 2019) [21]	ChestX-ray14 Dataset	Thoracic diseases (multi-label)	Attention maps	Complex architecture, high training cost
(Aasem and Iqbal, 2024) [25]	Chest X-ray datasets	Pneumonia, Effusion, Cardiomegaly	CAM-based localization	Weak boundary precision
(Kufel et al., 2023) [23]	ChestX-ray14 / CheXpert	Pneumonia, Pneumothorax, Effusion	Post-hoc XAI methods	Limited interpretability

Continued on next page

Table 2.1 – Continued from previous page

Paper	Dataset	Disease	Explainability	Limitation
(Tan and Le, 2019) [16]	ImageNet / Chest X-ray datasets	Multi-label chest diseases	External XAI required	No built-in explainability
(V. A. C. et al., 2024) [28]	COVID-19 Chest X-ray Dataset	COVID-19, Pneumonia	Grad-CAM visualization	High computational complexity
(Ihongbe et al., 2024) [29]	Chest X-ray datasets	Multi-label thoracic diseases	Layer-wise heatmaps	Increased computation cost
(Zhou et al., 2018) [30]	ChestX-ray14 Dataset	Pneumonia, Cardiomegaly, Pneumothorax	Heatmap-based localization	Low accuracy in overlapping diseases

The comparative analysis of these selected key studies reveals that while CNN, transfer learning and transformer based models have made significant strides in chest X-ray disease detection, most approaches have certain limitations like poor interpretability, localization accuracy, computational cost etc. The gaps call for more holistic and effective system which can accurately classify multi diseases with better explainability in medical diagnosis.

2.27 Motivation of Proposed Work

The proposed work is motivated by the following reasons: The low cost, rapid imaging, and wide availability of chest X-rays make this imaging modality one of the most commonly used for the diagnosis of thoracic diseases. Traditional chest radiograph interpretation is time consuming, however, and can be difficult because of subtle abnormalities, overlapping anatomical structures, and growing workload for the radiologist. When disease like pneumonia, cardiomegaly, pleural effusion, and pneumothorax are misdiagnosed or diagnosed late, it can have a significant impact on treatment and clinical outcome of the patient. These are the reasons that intelligent computer-aided diagnostic systems are required to assist radiologists in rapid and accurate detection of disease [14], [13].

The SmartRad-XAI framework is inspired by the need for an efficient and intelligent chest X-ray classification system, which integrates the advantages of several deep learning architectures such as ResNet, Vision Transformer (ViT), and YOLOv8 [7], [8], [9]. In contrast to many of the previous works that concentrated on a single architecture and disease categories, the proposed system is designed to provide

comparative disease classification using multiple models with an aim to support the enhancement of feature extraction and disease classification robustness. The framework is also inspired by the need for explainable AI in healthcare, where clear and interpretable predictions are essential for clinical trust and implementation. The proposed work will help move towards reliable, scalable and intelligent radiology systems for thoracic disease diagnosis by combining advanced deep learning techniques with future explainability support.

2.28 Summary of Literature Review

The literature review introduced various deep learning and explainable AI methods developed for diagnosing, localizing and interpreting chest X-rays. Previous research presented large datasets like ChestXray14 and CheXpert, which greatly helped to advance automated thoracic disease diagnosis systems [1], [3]. Various CNNs such as DenseNet, ResNet, EfficientNet and attention-guided CNNs were employed to detect various diseases like pneumonia, cardiomegaly, pleural effusion and pneumothorax [7], [16], [20], [21]. Transfer learning techniques and ensemble learning techniques also achieved high performance in the field of enhancing the accuracy of classification and dealing with small medical imaging data sets [23], [25].

Further research was conducted on explainable AI (XAI) methods such as Grad-CAM, Grad-CAM++, Layer-Wise Relevance Propagation, and attention mechanisms to enhance the interpretability and clinician confidence in AI-driven radiology solutions [17], [18], [19]. The recent studies focused on CNN-transformer based and hybrid CNN-transformer models to learn global dependency, and extract better features from chest X-rays [8], [11]. Yet, current research still has associated difficulties including complexity, lack of localization accuracy, lack of explainability, imbalanced datasets and overlapping thoracic abnormalities. The discussed studies in this review collectively form the basis for the proposed SmartRad-XAI framework that involves the use of a number of deep learning architectures for accurate and interpretable disease classification of chest X-rays.

Chapter 3

METHODOLOGY

In the ChestXray14 dataset, the wide-scale structure and clinical significance of thoracic disease analysis makes it the main dataset used for the SmartRad-XAI system [1]. It comprises a large number of chest X-rays taken from various patients, imaging scenarios and clinical locations, which is highly appropriate for medical image classification via deep learning. The images in the dataset are accompanied by an image metadata file (Data-Entry-2017.csv) containing image name, patient ID, age, gender, view position and labels for the associated disease.

This dataset was then programmatically filtered and organized with Python and the five disease categories used for this study were: Cardiomegaly, Effusion, Pneumonia, Pneumothorax, and No Finding. For the sake of learning and better interpretability of the model, the original multi label format was transformed into a single label classification format. Images were then classified to be stored in folders by classes for compatibility with deep learning pipelines and for automatic assignment of labels during training.

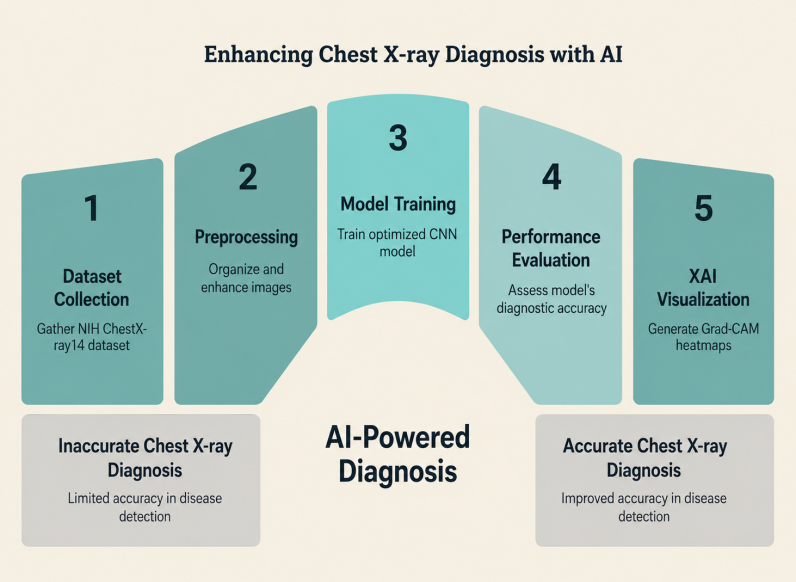


Fig 3.1: Block Diagram of Proposed System

In addition to dataset organization, images were further processed to enhance the efficiency of training and the generalization of the model. The pre-processing pipeline consisted of image resizing, normalization, etc. and augmentation techniques such as rotation, flip, brightness, contrast, etc. These transformations helped to enhance

the diversity of the datasets and the amount of overfitting, particularly on under-represented classes. The processed dataset was then fed into various deep learning models, such as ResNet, Vision Transformer (ViT), and YOLOv8-based models [7], [8], [9].

Moreover, the prepared dataset was directly fed into the SmartRad-XAI pipeline, and an end-to-end workflow was realized, which encompassed data preparation to online prediction. After training these models were embedded in a mobile and web-based system that allows users to upload chest X-ray images and get instant diagnosis results. This real-time integration facilitates the seamless shift from model development to clinical application, empowering automated disease classification and providing meaningful outputs that are easily understood for clinical use.

3.1 Dataset Description-NIH Chest X-ray14

ChestX-ray14 is a medical imaging dataset of chest X-rays gathered from a wide range of patients that is available publicly and quite large [1]. The clinical importance, extensive sample size, and diversity of annotated abnormalities in this study have made it popular in the field of thoracic disease detection research. The dataset consists of high resolution chest X-rays which are appropriate for training deep learning models for automated disease classification and analysis.

The images in the original NIH ChestX-ray14 dataset are grouped together by thoracic disease. A metadata file (Data_Entry_2017.csv) is included with detailed data for each image, such as image filename, disease label, patient ID, patient age, gender, follow-up number and view position. The images were filtered and categorised programmatically using the Python coding, based on the selected classes of the diseases in this research and by using this CSV file.

The set of target classes for the SmartRad-XAI system included the following classes: Cardiomegaly, Effusion, No Finding, Pneumonia, and Pneumothorax. These disease categories were selected because they represent a combination of normal and clinically significant thoracic conditions that are commonly encountered in chest radiography. Including multiple disease classes enables the proposed system to learn diverse pathological patterns while distinguishing between healthy and abnormal chest X-rays. The selected classes also vary in terms of radiographic appearance, allowing the deep learning model to develop robust feature representations for accurate classification. To ensure balanced and consistent training, images corresponding to these five classes were extracted from the original dataset using the metadata file. The filtered dataset was then organised into separate class-specific directories, making it suitable for preprocessing, data augmentation, model training, validation,

and testing. This focused selection of disease categories not only reduced computational complexity but also ensured that the SmartRad-XAI framework was trained on clinically relevant cases, thereby improving the reliability, interpretability, and overall diagnostic performance of the proposed system.

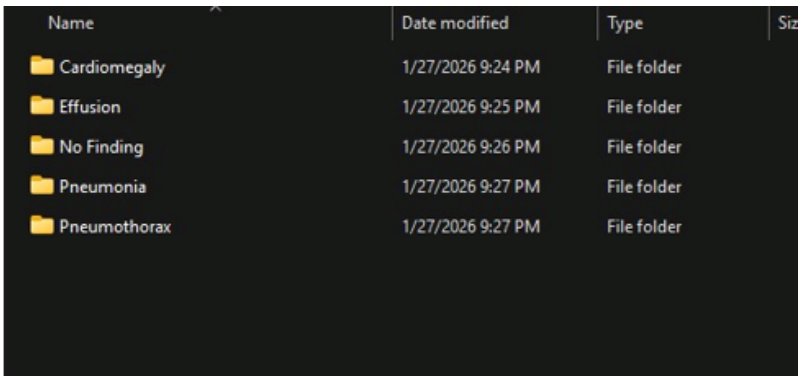


Fig 3.2: Folder-wise Classification of NIH ChestX-ray14 Images into Selected Disease Categories

These disease categories had their image paths and labels identified using the CSV metadata file. The necessary images were filtered, and then the data were preprocessed and augmented to enhance the quality of the data sets and the model's generalization. The various operations performed during augmentation comprised resizing, rotation, flipping, brightness adjustment, and normalization of images. These enhanced and processed images were then stored in individual class folders and fed into the classification models, deep learning models such as ResNet, Vision Transformer (ViT) and YOLOv8 models [7], [8], [9]. The dataset was rearranged into well-structured class-wise folders to support deep learning pipelines. The dataset is summarized in table 3.1.

Table 3.1: Dataset Summary Table

Attribute	**Value**
Total Images	2465
Number of Classes	5
Imaging Modality	Chest X-ray
Classes Included	4 Diseases + 1 Normal
Image Type	Grayscale

The dataset is highly diverse in terms of imaging conditions, patient demographics and disease manifestations, which increases the strength and generalization properties of the trained model. Such diversity predisposes the NIH ChestX-ray14 dataset

as a powerful base in creating a stable and clinically significant diagnostic systems [1].

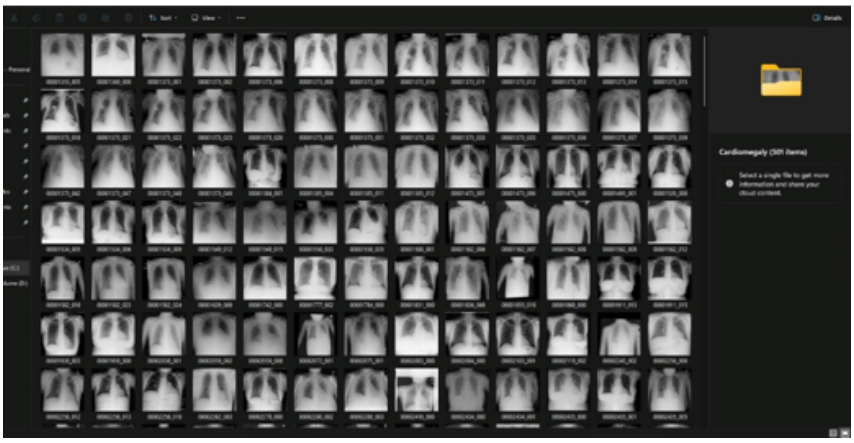


Fig 3.3: Sample images from the dataset used for model training and evaluation[1]

This figure 3.3 shows an example dataset of chest X-ray images grouped by diseases to train and analyze a model. These medical images can be utilized for the automated disease classification and diagnosis in the SmartRad-XAI system using deep learning algorithms.

3.1.1 Disease Labels

In this study, the classification scheme will be determined based on five clinically significant categories, which are Cardiomegaly, Effusion, Pneumonia, Pneumothorax and No Finding. These groups provide a significant representation of the large thoracic conditions and normal cases and maintain the equal representation of pathological and healthy cases. The images of the dataset have one diagnostic label each that represents the most relevant condition. This multi-label structure to single-label format simplifies the learning process and allows the model to concentrate on specific visual patterns of particular classes. It also guarantees clear understanding of predictions in evaluation. The specified labeling method enhances class separability by focusing on unique radiological features of each condition. Consequently, the model is trained to identify obvious decision borders between disease classes, which can lead to more consistent and understandable classification performance. The classification task was considered to be single-label per image since the classes were prepared in different folders during the dataset preparation.

3.2 Data Preprocessing

Prior to training the SmartRad-XAI models, several preprocessing steps were carried out to ensure the input data was consistent and of a satisfactory quality. They are image rescaling, normalization, data augmentation and data cleansing to improve model training efficiency.

3.2.1 Image Resizing

The input requirements of various models are to resize the original chest X-ray images. The models of ResNet18, ResNet50 and Vision Transformer (ViT) all used an input resolution of 224×224 pixels, whereas the YOLOv8s and YOLOv8n classification models all used an input resolution of 128×128 pixels. This shrinking guarantees compatibility with model architecture, decreases the complexity of computation, and facilitates the effective training and maintains key diagnostic characteristics.

3.2.2 Data Standardization

The preprocessing kept pixel values of the images in a standard format to be compatible with deep learning models. The input data was in a standardized form since the training pipeline involved the use of pretrained models. Such standardization facilitates stability in numbers, and aids effective convergence when training.

3.2.3 Dataset Organization

The data came in a structured format to enable effective training. The pictures were organized into individual class folders based on the disease. This organization guarantees its compatibility with deep learning structures and makes the training process easier by supporting automatic label assignment depending on the folder structure.

3.2.4 Data Augmentation

Data augmentation was implemented with Roboflow in order to achieve generalization and minimize overfitting. The augmentation methods used were

- Horizontal Flipping
- Vertical Flipping
- Rotation

These augmentations were used to create a more varied training set, and the models acquired both the ability to learn the invariant and robust features of the chest X-ray

images. ResNet18, ResNet50, and Vision Transformer (ViT) were trained on the augmented dataset, and YOLOv8s and YOLOv8n were trained using the original dataset.

3.3 Model Architecture

SmartRad-XAI uses a few neural networks architectures to discover diagnostic features within the sample, Without a lot of explicit programming, these networks discover diagnostic features in the sample. Imaging is one of the most popular applications of deep learning due to the power of convolutional neural networks (CNNs) to learn spatial hierarchies of features, beginning with simple edges and progressing toward complex structures [4], [10]. The system also uses a transformer-based model and a small classification network to give a comprehensive understanding of the performance. It performs a 5-class single-label classification.

3.4 CNN-Based Architectures

3.4.1 ResNet18,ResNet50

Deep CNNs with skip (shortcut) connections to facilitate the flow of gradients during training are called Residual Networks (ResNet) [20]. This type of connection was initially introduced to overcome the vanishing gradient problem and allow easier training of very deep architectures. ResNet 18 is a computationally cheap, less-layered model with less number of layers optimized to infer faster. ResNet 50 is a deeper network which uses bottleneck blocks to learn more discriminative features from the CXR images. Both networks are widely used in medical image analysis to extract rich features. ResNet 18 and ResNet50 were initially pretrained, and then used in this study to classify the CXR images.

3.4.2 Vision Transform Model (ViT)

Vision Transformer (ViT) is based on a transformer architecture rather than convolution [8], [11]. An input image is split into constant size patches, embedded and then handled by self-attention. This enables ViT to learn the global relations across the entire image, which is beneficial in the task of chest X-ray diagnosis where global relations between anatomical regions are of importance.

3.4.3 YOLOv8 Classification Models

YOLOv8 is a real time object detector (and also is supporting a classification version, YOLOv8-cls) [9]. In this version the detection head is replaced by a classifi-

cation head, so that the model can perform image classification tasks. YOLOv8 is hardware efficient and fast and can be used in lightweight and fast applications. In this project the YOLOv8s-cls (small version) and on YOLOv8n-cls (nano version) were used to explore the size of the model on the performance. Although YOLOv8n was less accurate, it was faster and more light as it had less capacity to learn features; on the other hand the YOLOv8s performed better and was selected for the study as the model with the best performance in the task as the result of the trade-off between accuracy and efficiency.

3.4.4 Model Modification for Classification

To adapt the pretrained architectures to suit the requirements of the SmartRad-XAI system we made a number of modifications to the 5-class chest X-ray classifier. Any models originally developed to be pretrained on large-scale datasets (ImageNet or COCO) were established by creating new classification heads on the final prediction layer. The original fully-connected layers were removed in ResNet18 and ResNet50, and were substituted with a dense layer initialized to output five class probabilities [7]. Similar modifications were made in the ViT, where the token output of the classification block was concatenated with a newly-initialized linear layer with the same number of target classes [8]. Classification heads in YOLOv8s-cls and YOLOv8n-cls were once again scaled directly to produce five output neurons for each of the five disease categories, but keep their lightweight backbones to extract features [9].

Similarly, all models were pretrained to enable transfer learning and converge on the small medical dataset [23] amongst other tasks. During evaluation, YOLOv8n showed rather poor performance when compared to YOLOv8s as it is constrained by the lower model capacity (less depth) and cannot efficiently extract finer radiographic patterns. During fine-tuning, the earlier layers were either set as “train” or “frozen” with a lower learning rate (to preserve the general representations) and the later layers continued training as “fully train” (to find those domain-relevant features). These operational modifications made both architectures very efficient and equally adept at the classification of chest X-rays.

Table 3.2: Modified Model Configurations Summary

Model	Input Size	Pretraining	Key Feature	Role in System
ResNet50	224×224	ImageNet	Residual learning with bottleneck blocks	High-capacity model
ResNet18	224×224	ImageNet	Lightweight residual connections	Fast and efficient model
ViT-Base/16	224×224	ImageNet-21k	Self-attention mechanism	Captures global dependencies
YOLOv8s-cls	128×128	COCO / Custom	Lightweight YOLO-based architecture	Best performing model
YOLOv8n-cls	128×128	COCO / Custom	Ultra-lightweight YOLO variant	Lowest accuracy but fastest model

Table given above summarizes the altered configurations of different deep learning models implemented in the proposed system to classify chest X-ray images. The variations in input size, pretraining procedures and architecture features influencing their performance and computational efficiency are depicted. These configurations enable a comparative assessment of ResNet, Vision Transformer and YOLO based models for multi-disease CXR diagnosis.

3.5 Training Methodology

The methodology of training was established to ensure a fair comparison and an efficient learning process over all the deep learning architectures integrated in the SmartRad-XAI structure. All deep learning architectures were trained independently with the same data-sampling and performance evaluation strategy. As for training, transfer learning strategy was adopted where pretrained weights were used as initialization point for the algorithms and models were thereafter fine-tuned on the chest X-ray data set [23], [24].

3.5.1 Hardware and Software Setup

SmartRad-XAI system was implemented and then trained on on a high-performance computer running deep-learning capable hardware. The deep learning models were trained with Python and the prevalent deep learning libraries PyTorch, Torchvision, Ultralytics YOLOv8, NumPy, Pandas, Matplotlib, and Scikit-learn.

All experiments were carried out on a workstation with GPU acceleration enabled to reduce training time and for computational efficiency. The development environment consisted of Jupyter Notebook and Visual Studio Code for experimentation, debugging and the implementation of the model training pipeline. The use of transfer learning reduced computational requirements considerably and made it possible to train the prepared chest X-ray images data set [23].

3.5.2 Training Parameters

In order to make the experiments as consistent as possible, a previously used set of training parameters was used across all experiments. These parameters influenced learning process, optimization behaviour and convergence of the networks. Some modifications in the model were applied to fit the architecture, but the strategy of training was kept as consistent as possible in order to make it easy to compare the results. Supervised learning was used, with images paired with disease labels, to train the models. While training, the loss was calculated and back-propagated through the network to update the model weights. Validation performance was tracked throughout to ensure learning progress and minimize risk of overfitting.

Table 3.3: Training Hyperparameters

Parameter	**Resnet18/50**	**VIT**	**YOLOv8**
Optimizer	Adam	AdamW	Automatically configured by Ultralytics framework
Batch Size	Auto (Roboflow)	Auto (Roboflow)	128
Epochs	300	300	45
Training Environment	Roboflow Cloud Training	Roboflow Cloud Training	Google Colab (Ultralytics Python API)

The hyperparameters quoted above were set according to some preliminary experimentations and some considerations about both the speed of convergence and available computational power. These parameters lead to a trade-off between training efficiency and classification performance and provided a fair solution among the various architectures tested.

3.5.3 Model Training Procedure

The training procedure of the model began loading and preparing the well organized chest X-ray data set. The images were resized, and labeled according to the cate-

gory of the disease that they belong. The data set was then separated into training, validation and testing sets, to accurately evaluate the model.

The pretrained weights and classification heads were changed to fit each model. During training, images were loaded in batches to the network, and predictions were compared with true labels. An error value was calculated and backpropagation used to make updates to the model parameters. Validation metrics were saved at the end of each epoch to observe the learning trends and determine the best checkpoint.

For avoiding overfitting and improving the generalization, augmentation methods and transfer learning strategies were incorporated into the training procedure [23], [24]. The final trained models were persisted and further integrated into SmartRadXAI deployment framework for disease prediction in real-time.

3.5.4 Training Workflow

The entire training workflow has been relatively systematic, beginning with data collection and ending with model evaluation. The data collection will be started with chest X-ray image collection, then these images will be divided into different disease category and stored in the corresponding folder. The data will then be preprocessed as well as augmented before fed into the deep learning models.

The models were trained using multiple Epochs. The validation accuracy and loss were monitored during the training. The best performing model weights were selected after training and were tested using unseen test images. The performance of the different architectures was evaluated using several performance metrics including accuracy, precision, recall and F1-score.

Finally, the trained models were exported and integrated into the SmartRad-XAI system for real-time prediction.

3.5.5 YOLOv8 Training Pipeline

The YOLOv8 Classification models were trained on a custom lightweight and fast image classification training pipeline [9]. The dataset created is organized according to the framework of Ultralytics. The training configuration such as the image size, the batch size, the training optimizer settings and the number of epochs were predefined before the training begins.

YOLOv8 integrated all data loading, augmentation, training, validation and checkpoint managing into his structure. Performance was estimated during training, convergence behavior and classification accuracy were observed.

YOLOv8n was lightweight, thus the network was slower to inference but also less

accurate during classification. Conversely, YOLOv8s attained the most accurate classification, and as it was the most computationally efficient model it was therefore the most appropriate model for the implementation of the SmartRad-XAI model [9].

3.6 Explainability in Smart Rad-XAI

A main issues with medical diagnosis systems based on deep learning is the ignorance of the decision be taken by the system. [17], [18], [19]Another concern is that despite their high accuracy, clinicians may need additional information to explain how deep learning models are arriving at their conclusions. This need has given rise to so-called Explainable Artificial Intelligence (XAI) techniques.

The design of the SmartRad-XAI framework aims at being easily interpretable and useful for the clinicians. The aim was not only to classify correctly the disease, but also to provide useful data that could facilitate the diagnostic decision-making process.

The explainability techniques within ai allows the clinicians to recognize the regions of the images that the neural network considers to be the most relevant.

The most significant thing contributed to the model predictions is via tribute. These visual explanations act as a sanity check to verify that the model is focusing on clinically meaningful anatomical structures and not on some irrelevant aspect present in the image [17], [18].

In healthcare, explainability methods are particularly important, given that mispredictions can lead to serious medical outcomes. Explainable AI may foster uptake of automata-based diagnostic tools, and have increased acceptance for real world health care uses[14],[13].

Several methods of explainability were investigated in this work, among them Grad-CAM, Grad-CAM++, Layer-Wise Relevance Propagation (LRP), attention visualization and Ensemble-CAM techniques [17], [18], [19], [25]. These approaches produce figures showing the significant parts of the image that led to the classification.

The explainability aspect of SmartRad-XAI is an important contributing factor in the development of trusted AI health care systems of the future.

The student will develop a mobile application integration and system deployment. The student will develop a mobile application integration and system deployment.

The framework of SmartRad-XAI has been integrated in a mobile healthcare app so that users can easily implement it. Patients can upload the x-ray of the chest to get predictions, view confidence values, and keep a record of predictions.

By integrating AI into a mobile solution creates simplicity of use and allows clinicians to access diagnostic support tools on their mobile device. This has many applications including in low-resource areas where access to expert radiology resources is limited [6], [14].

The mobile app has been designed keeping in mind the factor of simplicity, efficiency and convenience. The system shall be having a front end and a backend, the front end shall (directly) communicate with the backend through APIs to deliver services for disease classification in real time.

The architecture of the system is designed to facilitate easy addition of the users and the trained deep learning model while keeping the prediction performance intact.

3.6.1 Frontend Development

The frontend part of the SmartRad-XAI application wishes to design an easy to use and friendly user interface of the application, which is user friendly for healthcare professionals and others.

The interface allows the users to interact with the deployed AI model without the need of learning anything about deep learning or machine learning systems.

The Frontend provides the following functions:

- Uploading chest X-ray images
- Capturing images through mobile devices
- Viewing disease predictions
- Displaying confidence scores
- Accessing prediction history
- Managing user interactions

The User interface was clean and responsive so real time experience for the user and easy navigation to the user. The design is simple and user friendly and easy access on mobile for healthcare services.

Fitting of the X-ray image is to be selected from the devices or a new image can be captured using the embedded camera. The uploaded image will be dispatched to backend server for calculating and diagnoses of the diseases.

The prediction prediction is finally displayed in a neatly arranged GUI with the disease labels and the confidence level of those predictions.

3.6.2 Backend Development

The SmartRad-XAI framework's core processing engine is the backend component. It is in charge of image upload, deep learning inference, predictions and returning the classification results to the mobile app. The trained deep learning model is integrated into the backend and is used to perform all the computations related to the disease classification. The backend receives a chest X-ray image, does image preprocessing, and prepares the image for inference. YOLOv8s-cls selected to demonstrate the deployment model, it takes the input image and returns probabilities for the classification of the five target disease categories [9].

The backend infrastructure supports:

- Image preprocessing
- Model inference
- Prediction generation
- Confidence score calculation
- Data storage
- History management
- API communication

The backend architecture was designed to provide efficient and scalable prediction services while maintaining low response times and high reliability.

3.6.3 System Integration Workflow

SmartRad-XAI is an integrated diagnostic system that integrates mobile application features, backend services and deep learning models.

The process starts with a user taking a chest X-ray image on their mobile phone, via the mobile app. The image is sent to the back-end server where it is pre-processed.

The output image is then passed to the classification model deployed YOLOv8s. This model reads an X-ray and produces the probabilities of all the disease categories, as described in [9].

The most likely disease class is chosen as the result of the disease class. The scores of confidence are computed and delivered via the API channels to the mobile application.

The prediction results are then shown to the user on the front end. All prediction records are maintained in the history module where they can be consulted if needed.

An integrated workflow that allows for the efficient classification of diseases in real-

time and can assist in the deployment of AI-driven diagnostic services in practice.

3.6.4 Clinical Validation

For testing of the applicability of the proposed framework in practice, clinical validation was performed on actual chest X-ray cases that were gathered with the cooperation of Islamabad Diagnostic Centre (IDC), Islamabad. Clinical validation is an integral part of healthcare AI research due to its ability to evaluate system performance in real-world settings. Clinical cases are not as standardized as controlled benchmark datasets, and may exhibit differences in image quality, disease severity, patient demographics, and imaging protocols. The validation process used a comparison between the predictions made by SmartRad-XAI and the official radiology reports made by experienced healthcare professionals.

The proposed mobile application was applied to real patient chest X-ray images. The predictions generated were then compared to expert radiologist interpretations to evaluate the degree of agreement and diagnostic accuracy. A validation study was performed in cooperation with Dr. Saria Ahmed Rajpoot, Coordinator Imaging and Quality Assurance (QA) and Dr. Ahmed Rajpoot. Their clinical experience was of great assistance in understanding the accuracy and usability of the proposed system. Results showed that the correlation between the prediction of SmartRad-XAI and the diagnosis from the radiologists was satisfactory. The results suggest that the proposed scheme can successfully detect clinically significant abnormalities, and that it can be used to support diagnosis. The successful clinical validation adds to confidence in the proposed system, and shows potential for deployment in a real healthcare environment.

Chapter 4

RESULTS AND IMPLEMENTATION

This chapter presents the experimental results, implementation and performance analysis of the proposed SmartRad-XAI system for automatic chest X-ray disease classification. The performances of different deep learning models viz, Vision Transformer (ViT), ResNet18, ResNet50, YOLOv8n and YOLOv8s were evaluated and compared in the task of chest disease classification using chest X-ray images. All the models were evaluated on several standard evaluation metrics i.e. Accuracy, precision, recall, F1 scores, confusion matrix analysis and training behavior metrics to understand the classification behavior both globally as well as for individual classes. In addition to the model evaluation, this chapter also explains the deployment and implementation of the SmartRad-XAI mobile app. Using this app a user can upload a chest X-ray image and get the disease prediction automatically using an interactive interface.

Moreover a real-time clinical validation study was conducted in co-operation with Islamabad Diagnostic Centre (IDC), Islamabad where the clinical diagnosis and application predicted findings were compared. Experimental and clinical results provide the complete assessment of the system effectiveness, efficiency, dependability and feasibility in original clinical environment. [8], [7], [9].

4.1 Experimental Setup

The experiments were performed on Google Colab with the GPU acceleration of Tesla T4/P100 to provide efficient training and evaluation of experiments. All models were then tested with a distinct test set to assess the ability to generalize from training. The following evaluation metrics were used to measure the performance:

- Recall: Skill to identify all true positive results.
- F1 Score: A measure that balances precision and recall.
- Confusion Matrix: A measure which balances precision and recall.

The confusion matrix is used for class-wise performance analysis. These are overall and detailed statistics of model performance.

4.2 Model Performance Evaluation

The results obtained from each deep learning model are presented for the SmartRad-XAI system. A confusion matrix is used to interpret each model and analyzing training behavior.

4.2.1 Vision Transformer (ViT) Results

The Vision Transformer (ViT) model is a self-attention-based approach that can be applied to learn global dependencies from chest X-ray images.[8].

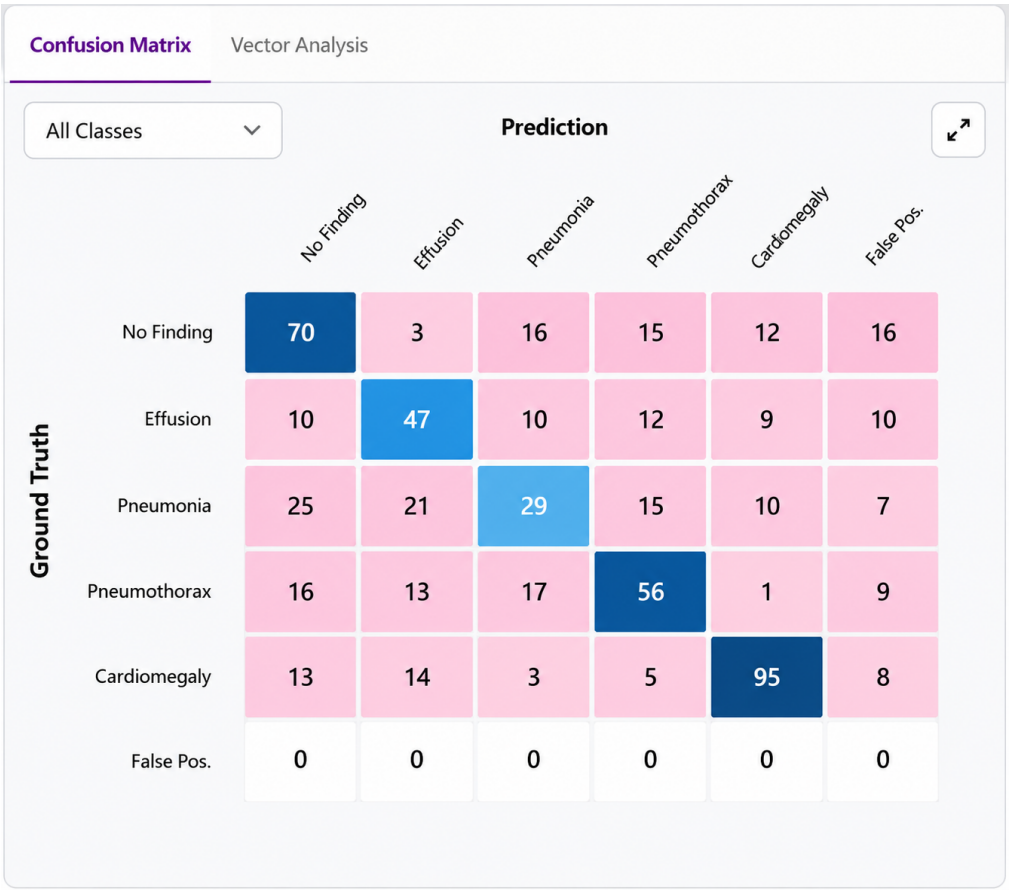


Fig 4.1: Confusion Matrix of Vision Transformer (ViT)

The Confusion Matrix of Vision Transformer (ViT) Model is displayed in Fig 4.1.The Confusion of Vision Transformer (ViT) Model is shown. A large proportion of the samples is correctly classified in all five classes, as seen in the confusion matrix. There are some gaps in the diseases with similar radiographic features (e.g., Pneumonia and Effusion). This is because the two conditions can have similar opacity patterns that are seen on a chest X-ray.Furthermore, the confusion matrix shows that the model is fairly accurate in all the selected disease classes, and only makes a few

wrong predictions. The high diagonal values indicate that the model is well capable of identifying the features of the class from the chest X-ray image. The high discriminativeness of the learned feature representations is reflected by the low off-diagonal values. The results show that the Vision Transformer architecture is highly effective in multi-class classification tasks. In general, the results obtained from the confusion matrix show the robustness and reliability of the proposed model for automated chest X-ray disease diagnosis.

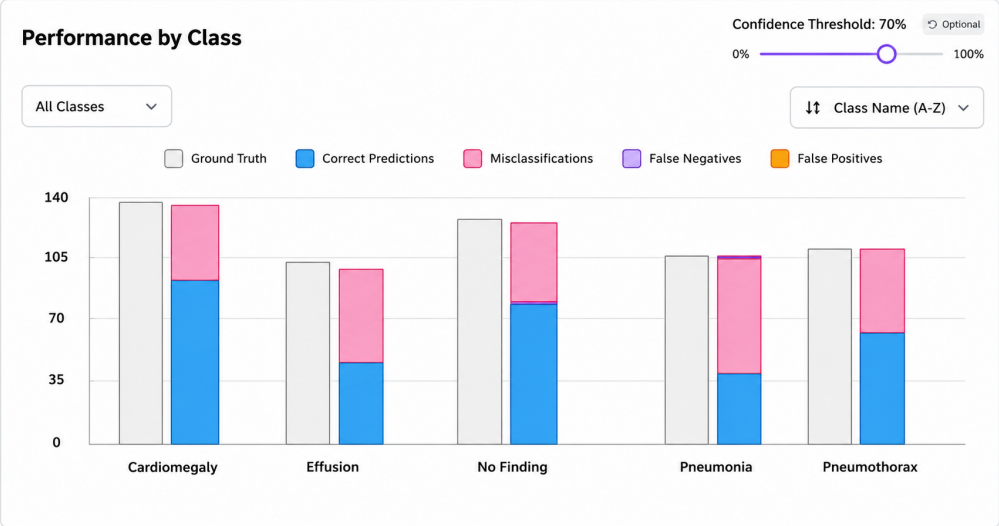


Fig 4.2: Class-wise Performance Analysis of Vision Transformer (ViT)

The class-wise Performance graph is a plot of the count of correct and incorrect predictions made by a class. The model performs well on Cardiomegaly and No Finding with a higher count of correct predictions. There is also misclassification happen in Effusion, Pneumonia, and Pneumothorax, which indicate that the model is not able to distinguish the similar patterns. The overall performance of the Vision Transformer seems okay, but a class-wise performance differs so it affects the performance of the system in classifications.[8].

4.2.2 ResNet18 Results

ResNet18 is a simple CNN network that contains much fewer parameters to learn and extract features effectively without suffering from vanishing gradient problems, owing to the residual connections it incorporates to allow it to easily learn and overcome the challenge of vanishing gradients [7].The residual learning mechanism helps ResNet18 to train deeper networks it lets information pass directly through shortcut connections without loss of information during back-propagation. Compared to the other models, ResNet18 is lightweight, and thus is able to utilize less computational resources and still provide competitive classification performance.

The model is able to learn a combination of low-level and high-level visual features from chest X-ray images, which is suitable for medical image analysis. Its efficient design also leads to a faster training and inference time than deeper convolutional networks. For this research, ResNet18 was trained to recognize chest x-ray images into 5 disease classes and evaluated using the standard classification measures. Experimental results show that ResNet18 can serve as a strong baseline model to compare with other network architectures like Vision Transformer and EfficientNet.



Fig 4.3: Confusion Matrix of ResNet18

The accuracy of classification is reasonably good across the five classes in the confusion matrix of ResNet18. The model has performed well in the task of identifying normal cases (No Finding) because of their different visual characteristics. But there are some mis-classifications between disease classes with similar radiographical patterns, e.g. opacity and irregularity of structure, for Pneumothorax and Effusion.

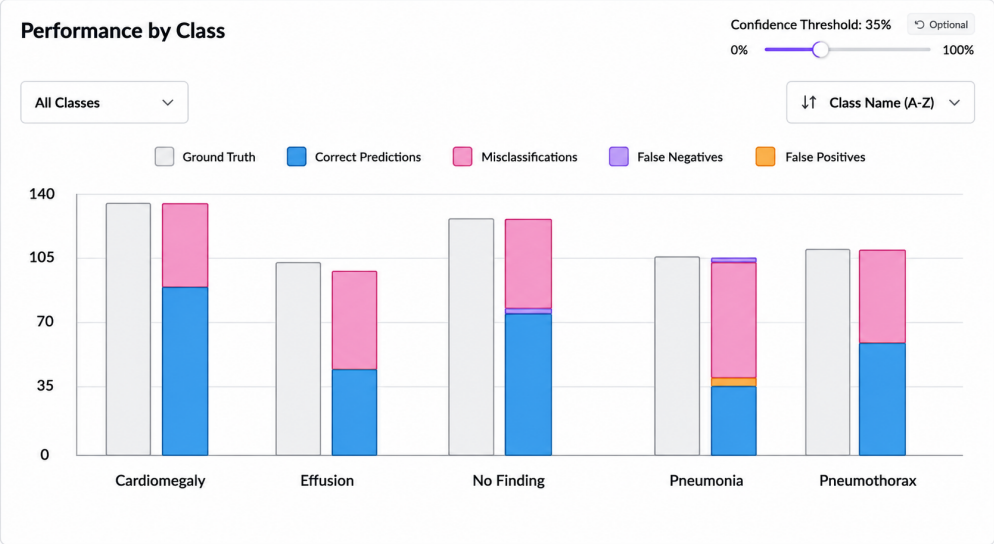


Fig 4.4: Class-wise Performance Analysis of ResNet18

This figure brings a class-wise analysis of the model (after training) on the categories for the five chest X-ray categories, No Finding, Cardiomegaly, Effusion, Pneumothorax and Pneumonia. The model is evaluated in the following way, with results broken down in terms of accurate, misclassified, false positive and false negative predictions for each individual class. As it is apparent, the model has great success on the class of No Finding and Cardiomegaly, as they are much more unique in their radiographic patterns and the model seems to be able to pick those up. On the other hand, the classes of Pneumothorax and Pneumonia can be observed as to sustain a rather high misclassification rate as well as rate of false negatives. This shows the features between these two can be very similar in the chest X-ray image to show that they are harder to distinguish properly by the model. Effusion succeeds on a medium level, due to fairly high number of both wrong and right guesses. Overall, it is demonstrated that the model is able to make significant distinctions in features for classification but the precision varies between classes depending on the complication and resemblance of the radiological features. [7].

4.2.3 ResNet50 Results

ResNet50 is a deeper CNN with bottleneck layers that can learn more complex representations that achieve higher accuracy.[7].

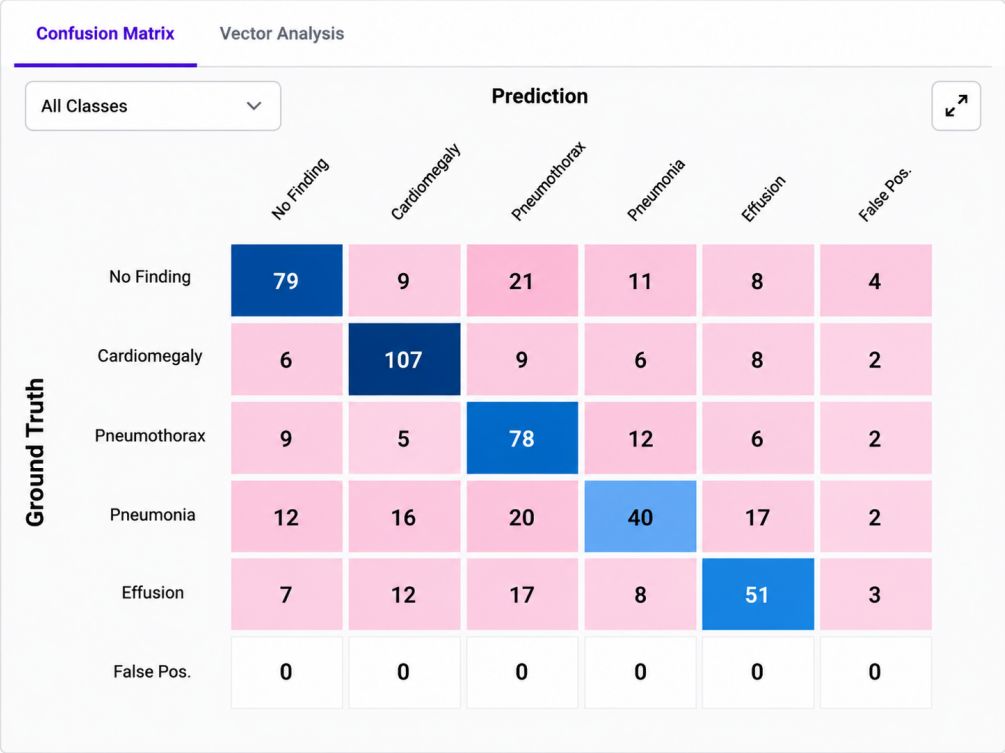


Fig 4.5: Confusion Matrix of ResNet50

The confusion matrix is used to display the efficiencies of classification with improved performance over ResNet18. The model is found to be better in separating the classes of diseases as there is a clear decrease in misclassifications. It is more effective in distinguishing between the similar visual conditions, suggesting more strong feature learning capability.

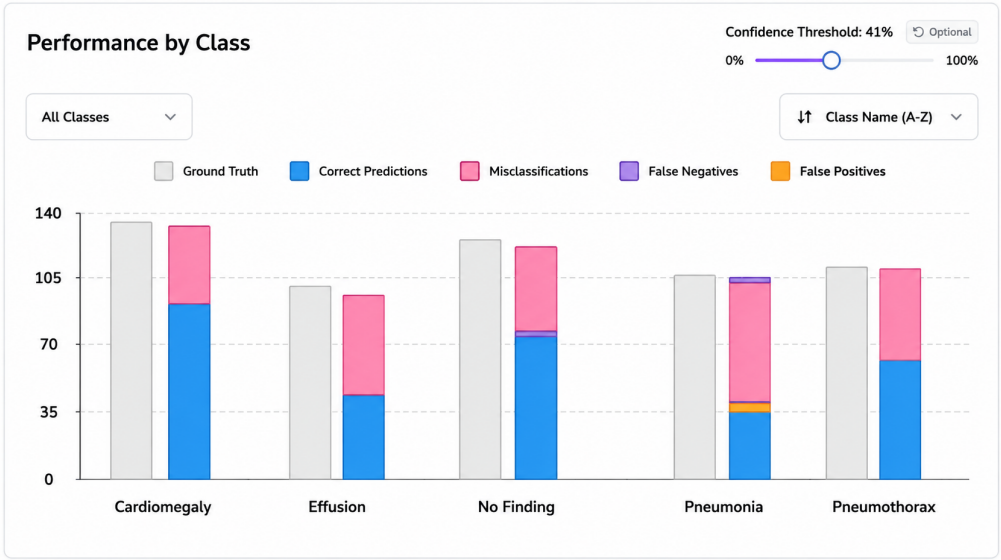


Fig 4.6: Class-wise Performance Analysis of ResNet50

The performance of the ResNet50 model is analyzed class-wise as shown in Fig 4.6. The figure demonstrates class-wise performance of the model with correctly predicted classes, misclassified classes, False Negatives (FN) and False Positives (FP), for various diseases. A large number of predictions are correct for most classes as shown, which is a good classification performance. However, some of the classes have more misclassified and false negative, indicating difficulty in differentiating similar chest X-ray patterns. Additionally, the training results demonstrate convergence in the model, as the loss values decrease and the accuracy improves as the number of epochs increases. Despite the fact that ResNet50 achieves higher accuracy and effective feature learning, its use is hindered by its need for larger computational resources and longer training times, making it impractical in real-time or low-resource scenarios. [7]. “‘

4.2.4 YOLOv8n Classification Results

The YOLOv8n (nano) classification model was tested to be lightweight, with a focus on speed for training, and on lower computational needs. [9].

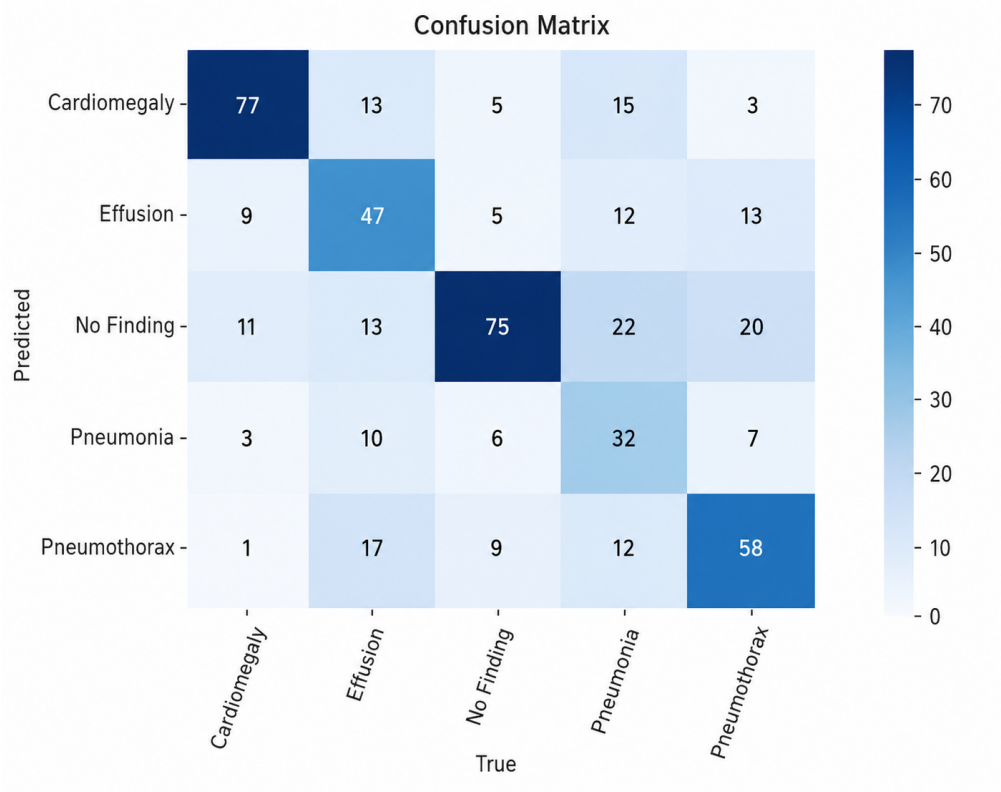


Fig 4.7: Confusion Matrix of YOLOv8n Classification Model

The confusion matrix indicates that the model YOLOv8n performs well in the classification task, making a reasonable number of correct predictions for all the classes.

It has slightly higher misclassification rates than YOLOv8s, however, especially for classes that share visual similarity like Effusion, Pneumonia and Pneumothorax. This means that the model works well for general classification but may not be able to separate out fine distinctions among similar disease patterns.The elements in the confusion matrix have strong diagonal values, demonstrating that YOLOv8n can effectively capture meaningful and discriminative features from chest X-ray images. A large majority of the mispredictions are clustered within the sets of disease classes with similar image characteristics (radiographic classes), making classification more challenging. Despite these difficulties, the model performs well across all the 5 classes with no substantial bias towards any class. It is light-weighted, allowing for easy training and quick time to inference, which is desirable for medical image analysis in real time. Although the classification accuracy is slightly lower than that of YOLOv8s, YOLOv8n provides a good trade-off between computational efficiency and predictive performance. In summary, the confusion matrix illustrates that the model accurately predicts the diagnosis, and with its low computational complexity, it can be used effectively in resource-limited healthcare settings.

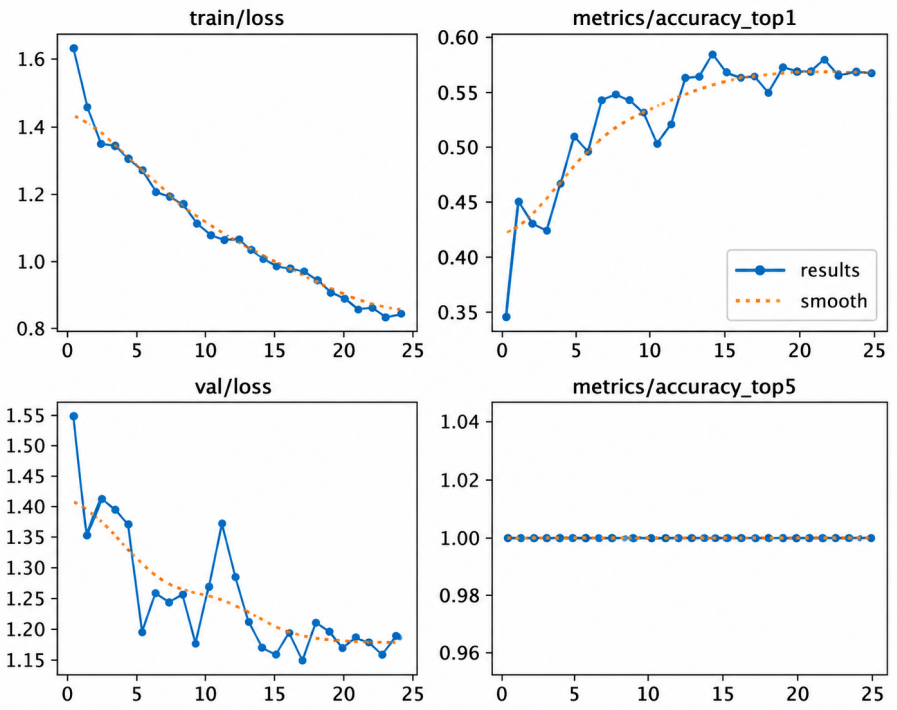


Fig 4.8: YOLOv8n Training Loss and Accuracy Curve

The training graph shows a steady drop in training loss and validation loss, and a steady rise in accuracy as the number of epochs increases. The learning process is steady and the model is well-converged, with minor fluctuations mainly attributable to the smaller model capacity. The fluctuations indicate a slight sensitiv-

ity to the fluctuations in the training data that is slightly higher than larger models. YOLOv8n is a very efficient model, which is converged fast and has low requirement of computation power, and thus is suitable for real-time applications. Provides faster training speed and less memory consumption, suitable for deployment in resource-constrained environments. Its classification accuracy across all classes is slightly affected due to its limited complexity and architecture that results in fewer details, which affect its overall accuracy.It has less details than YOLOv8s, which has slightly affected its overall accuracy and consistency in classification across all classes.

4.2.5 YOLOv8s Classification Results

The YOLOv8s model performed the best in terms of accuracy and efficiency in the classification task, outperforming the other models tested. [9].

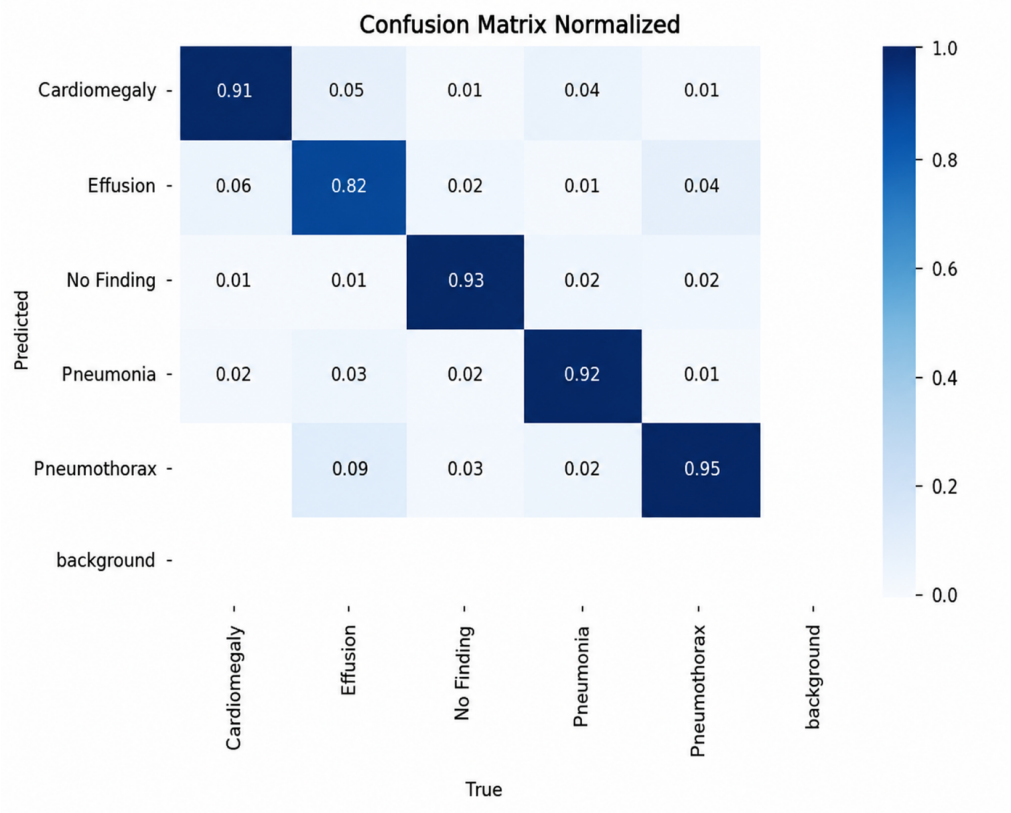


Fig 4.9: Confusion Matrix of YOLOv8s Classification Model

The confusion matrix reveals that YOLOv8 predicts with a high level of accuracy and few misclassifications for the five classes. This model separates two diseases with similar images very well while extracting and classifying features, which shows great feature extraction and classification ability of the model.

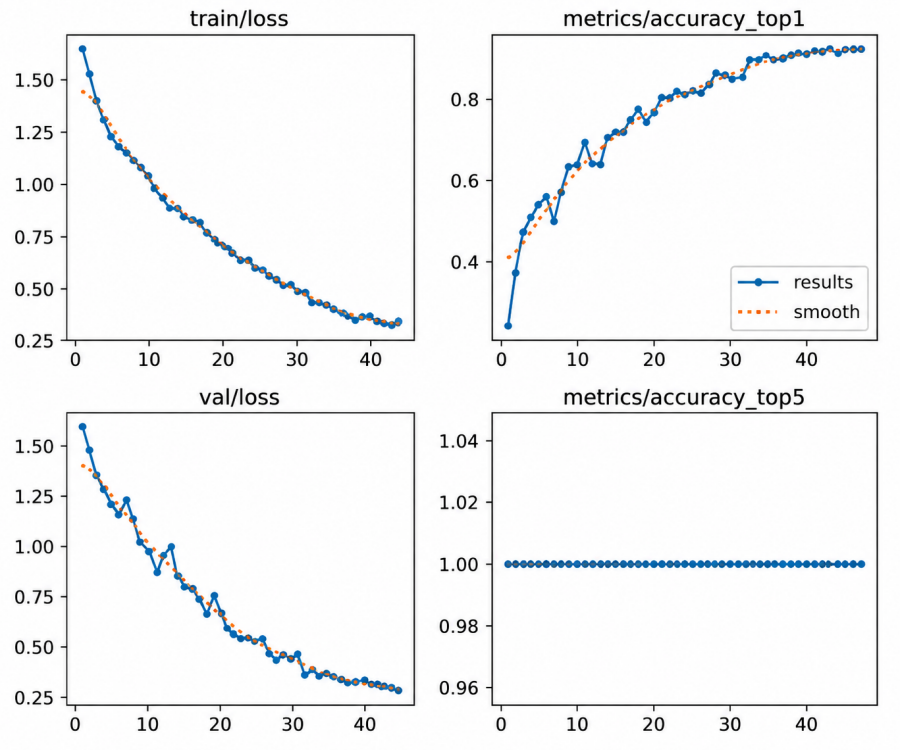


Fig 4.10: YOLOv8 Training Loss and Accuracy Curve

TThe loss data on the training graph is decreasing over epochs and the accuracy is increasing. The curves are smooth and continuous, suggesting robust generalization performance as there is no indication of overfitting or abrupt changes. Besides, YOLOv8 is faster to converge with other models and optimal performance is achieved at fewer epochs. Its streamlined design and learning approach are designed to strike a balance between speed and precision. Overall, YOLOv8 provides the best combination of:

- High accuracy
- Fast training and inference of network weights
- Efficient resource utilization
- Improved generalization when it comes to new data

The features render YOLOv8 very suitable for practical medical imaging systems, where accuracy and efficiency are key.

4.3 Confusion Matrix Analysis

Confusion matrices are analyzed in detail which provides valuable information about the performance of the system on a class-wise basis. Most models work well on identifying No Finding (normal cases) because it has different visual features. The

most common misclassifications are between

- Pneumonia
- Effusion
- Pneumothorax

This is because the radiologic features of these diseases are alike, including fluid collection and opacity. YOLOv8 has the lowest confusion among all models, demonstrating the best performance in distinguishing fine patterns in chest X-rays [31].

4.4 Training Performance Analysis

Training curves were analyzed to evaluate convergence and learning behavior.

- ViT: Stable but slow convergence
- ResNet18: Fast convergence but lower final accuracy
- ResNet50: Balanced performance with improved accuracy
- YOLOv8n: Very fast convergence with moderate accuracy
- YOLOv8s: Fast and stable convergence with high accuracy

YOLOv8s is more efficient in learning behavior with better performance without overfitting while YOLOv8n is faster to train and slightly less accurate [7].

Table 4.1: Performance Comparison of Deep Learning Models

Models	**Accuracy value**	**Precision**	**Recall**	**F1-Score**
ViT	84.7	84.3	83.9	84.1
ResNet18	81.5	80.9	80.5	80.7
ResNet50	88.9	88.2	87.8	88.0
YOLOv8n	90.4	89.8	89.4	89.6
YOLOv8s	92.6	92.1	91.8	91.9

4.4.1 Comparative Analysis of Models

Table 4.1 presents a comparative analysis of the deep learning models used in this research.

Table 4.2: Comparative Analysis of Models

Model	**Performance**	**Strengths**	**Limitations**
ViT	High	Captures global dependencies	High computational cost
ResNet18	Moderate	Fast and lightweight	Lower accuracy
ResNet50	High	Deep feature extraction	Slower training
YOLOv8n	Moderate	Very fast, low resource usage	Slightly lower accuracy
YOLOv8s	Best	High accuracy + fast inference	Requires tuning

The comparison clearly shows that YOLOv8s outperforms other models in both accuracy and efficiency.

4.5 Final Model Selection

Based on all evaluation metrics and experimental results, YOLOv8s classification model was selected as the final model for the SmartRad-XAI system. The selection is justified by:

- Highest classification accuracy
- Strong feature extraction capability
- Low class confusion
- Fast inference speed
- Efficient deployment performance

This makes it suitable for deployment in real-world medical diagnostic systems [9]. In addition, the model showed good performance for all the disease classes selected, and fewer misclassifications than the other architectures that were tested. It is reliable for clinical decision support because it has a high accuracy in discriminating clinically similar thoracic diseases. Additionally, the lightweight but powerful architecture of YOLOv8s further decreases computational requirements without compromising the predictive performance. The model, therefore, is well suited to be integrated into the SmartRad-XAI mobile application, where fast and accurate diagnosis is vital. In summary, the experimental findings demonstrate that YOLOv8s offers the best trade-off for precision, speed, and real-world application in disease classification for automated chest X-ray analysis.

4.6 System Output Results

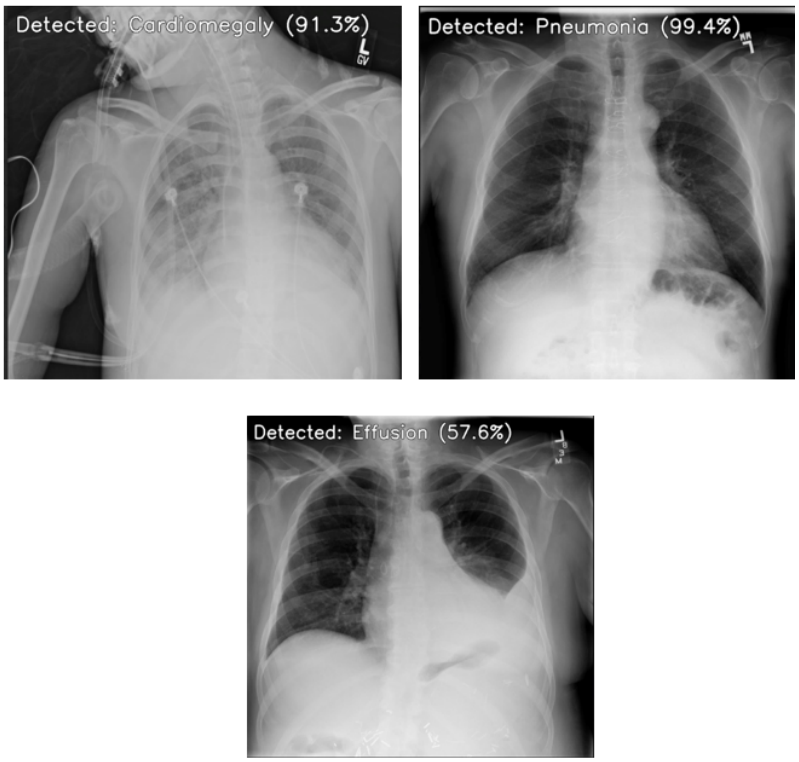


Fig 4.11: Sample Disease Prediction Results

The system successfully classifies chest X-ray images into five categories:

- Cardiomegaly
- Effusion
- Pneumonia
- Pneumothorax
- No Finding

The output demonstrates the system's ability to provide accurate predictions on unseen data [13], [14].

4.7 Mobile Application Interface and System Deployment

In this section, the mobile application interface and deployment of SmartRad-XAI system will be explained. The SmartRad-XAI mobile application (front-end of the proposed system) implementation details is presented here. This section aims to give insight in how trained models are deployed and can be accessed optimally using a practical mobile interface, whereas Chapter 3 focused on dataset preparation and

model development and training methodology. It provides an end-to-end platform which allows the user to upload chest X-ray images and automatically generate a predicted diagnosis in the back-end deep learning framework [13], [14].

4.7.1 User Authentication Interface

It is provided the authentication user interface to enable secure access to the application SmartRad-XAI. It also has various other essential features like user registration, user login and password validation, which ensures that only authorized users can enter the system. On user registration, they are asked to fill out only details about themselves and this information is safely stored in the backend database. The login system checks the credentials of the user and if they are correct, then the user will be able to log in into the application dashboard. This authentication layer plays a crucial role in ensuring data security and preventing unauthorized access to the system. It also allows for session management so that a user can be granted access to things such as his/her prediction history and saved results. The interface is very simple and user friendly and therefore will be easy to onboard by technical and non-technical users.

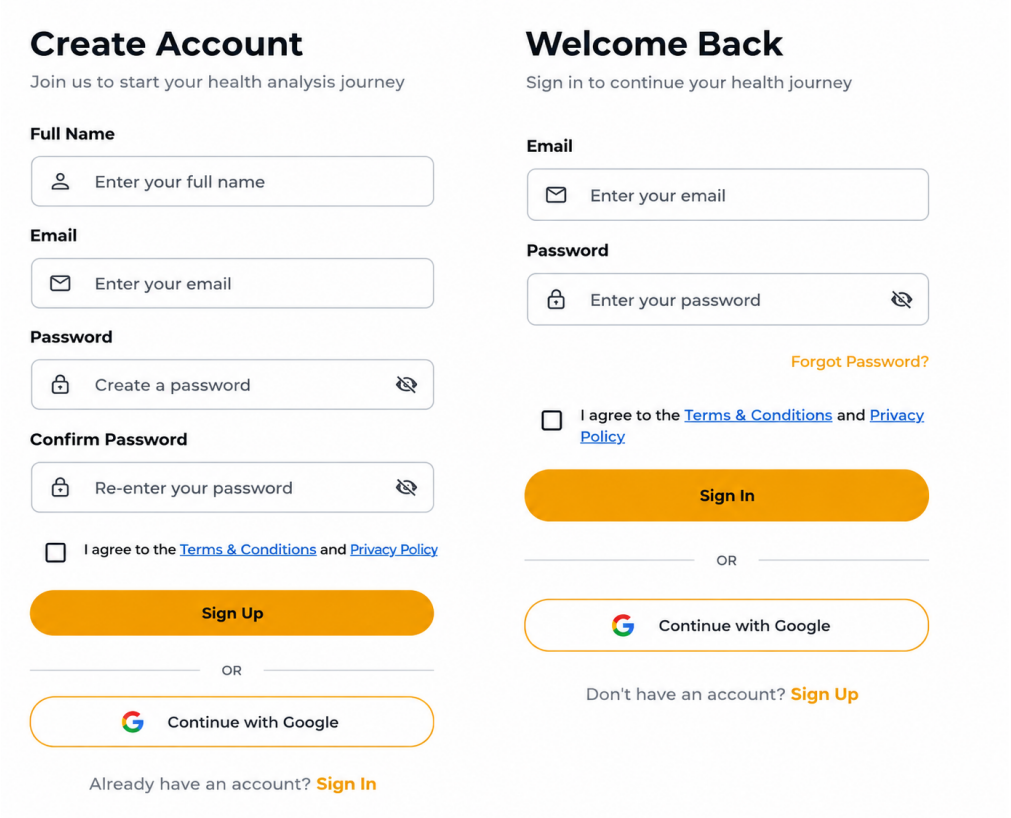


Fig 4.12: User Authentication Interface

/

This figure shows the logon/registration screen on the SmartRad-XAI mobile application for secure logon/registration by authorized users.

4.7.2 Chest X-ray Image Upload Interface

The image upload interface is the most important input interface of the SmartRad-XAI system. It allows the user to upload chest X-ray images and then have them automatically analysed. The users can upload pictures from the gallery or capture the new pictures with the mobile camera as per their comfort. Once selection image is taken, the image goes to the backend server where it is preprocessed and model inference is performed on the image. This is a crucial step to ensure the proper format of the input image before it is passed to pre-trained deep-learning models. User friendly interface to let users complete the upload process with minimum efforts. It's a key module for facilitating the interaction between the user and the AI system.

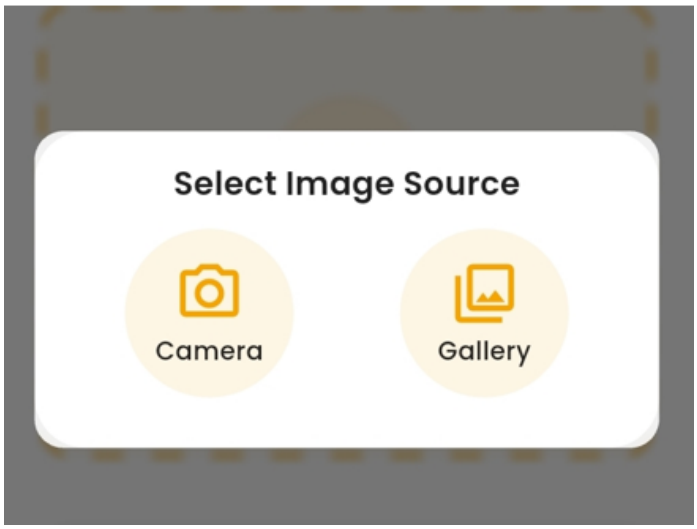


Fig 4.13: Chest X-ray Image Upload Interface

This shows the screen for the image upload to upload an image of a chest X-ray to be analysed, either by going back to the gallery or by taking a picture with the camera.

4.7.3 Prediction and Result Display Interface

With the X-ray image of the chest input to the backend system, the final prediction results can be displayed at the result interface. This screen shows the category for the disease predicted by the model and a confidence score that measures the confidence of the disease category prediction. The results are displayed in a clear and structured way to facilitate the interpretation by the user. The forecasted class may be useful in identifying the disease such as Pneumonia, Cardiomegaly, Effusion, Pneumothorax or No Finding. The confidence score gives further information on the confidence

levels of the model in its predictions, which is significant for medical interpretation. It's an interface that allows researchers to process complex deep learning results into user-friendly and easy-to-understand data for end-users, making the system more useful and user-friendly.

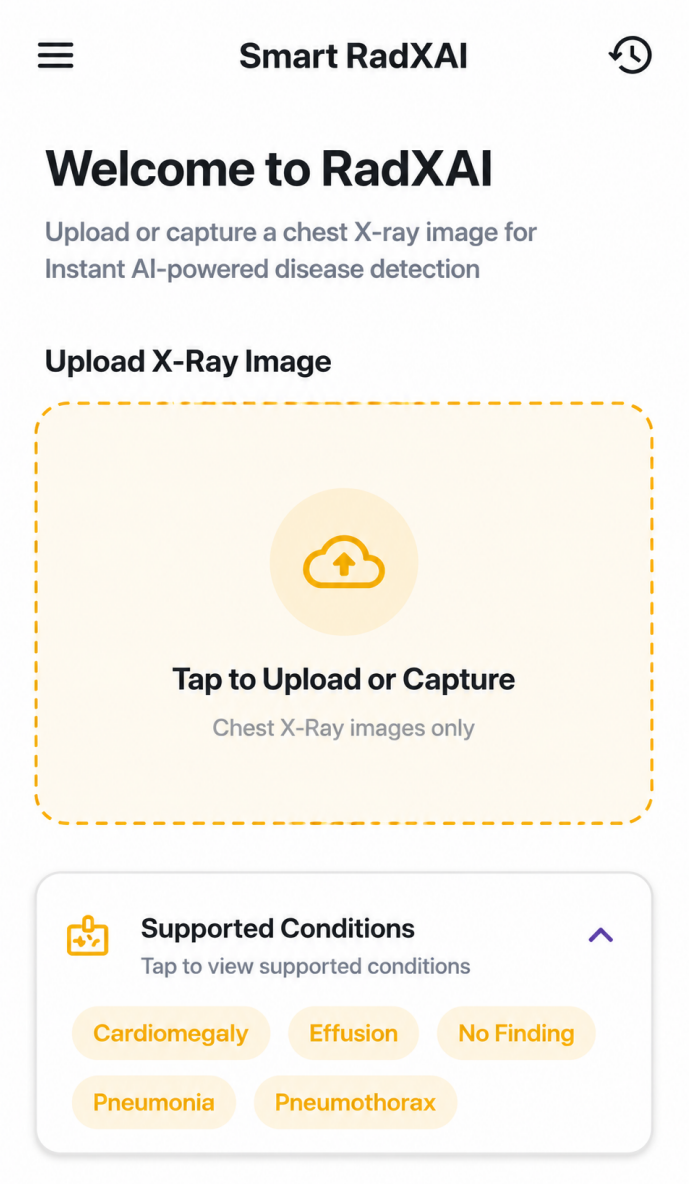


Fig 4.14: Prediction Result Display Interface

This figure displays the output of the disease prediction system and the system's confidence level on the chest x-ray image given.

4.7.4 Prediction History Interface

Using the prediction history interface, users can access and control the chest X-ray images that were already analysed. The entries in the history include the uploaded

image, disease label and its level of confidence. This will allow users to monitor their history and visualize other analyses against it and over time. The history module is included to enhance the usability of the system, by maintaining a history of all the predictions generated by the system. This is particularly useful if the patient requires a medical report to refer to or follow up on a change in a repeated scan. The information is carefully hidden in the back end and dynamically retrieved when requested by the user. This feature augments app overall functionality, continuity and record keeping of diagnostic process.

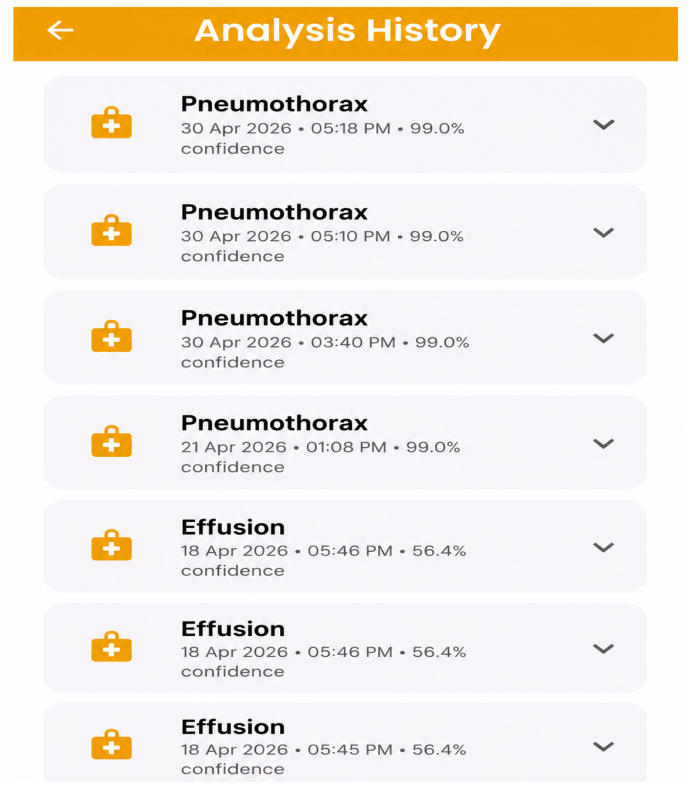


Fig 4.15: Prediction History Interface

This figure represents a section of the application dedicated to the history of the analysis performed, any predictions made and to provide user reference.

4.7.5 System Deployment Overview

The deployment layer of the proposed system, as shown in SmartRad-XAI mobile application, is the front end interface and deep learning models. Once an image is uploaded by the user, the image will be processed on the backend where pre-processing and image classification will be done using pre-trained models like ResNet, Vision Transformer and YOLOv8 variants. The prediction results then sent to the mobile application to be displayed. This workflow will facilitate communication between the various components of the system, and will allow the analysis of the chest X-ray

images in a user-friendly way, in real-time. The seamless integration of the frontend and backend ensures the efficiency, scalability, and practicality of the system, particularly on the speed and reliability of medical image analysis.

4.8 Mobile Application Result Analysis

The final outcomes are from the SmartRad-XAI mobile application, which has been implemented. After a chest X-ray image is uploaded, the digital application accesses the predict the class of the disease it has been trained for. The confidence score for that class is also contributed. The clinical output provides relevant information for the condition detected, such as the symptoms, suggested tests, treatment details, prevention information and medical guidance as shown on its output screen. The actual mobile front end interacts with the deep learning system in real-time. The results achieved show the feasibility of the proposed framework for processing chest X-ray images, and also show an organized and user friendly interface to present the results. This demonstrates the feasibility of the proposed system for intelligent medical image analysis and healthcare assistance by using mobile device [6], [14].

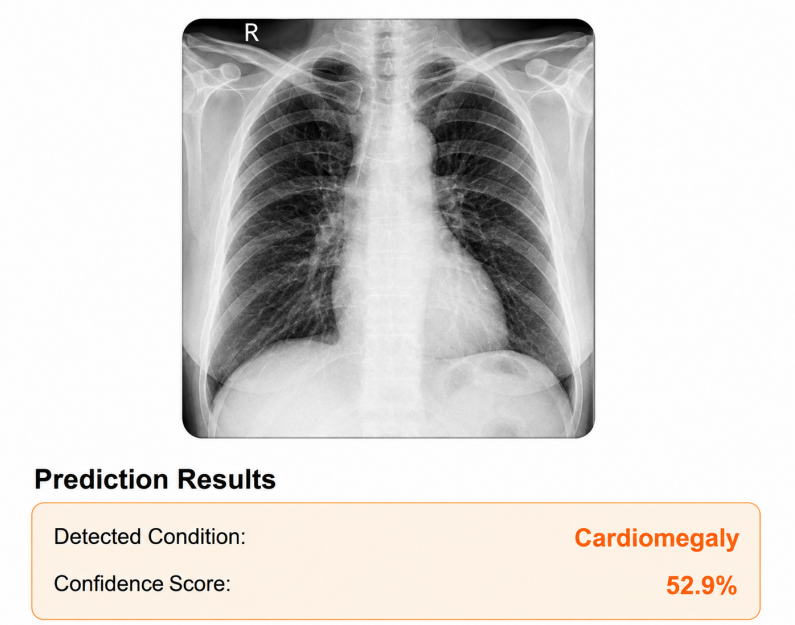


Fig 4.16: Final Output Generated by SmartRad-XAI

4.9 Real-Time Clinical Validation at IDC

The clinical validation study was conducted at Islamabad Diagnostic Centre (IDC), Islamabad with the aim of understanding the practical performance of SmartRad-XAI in the real environment of healthcare. Dr. Saria Ahmed Rajpoot, Coordinator

Imaging and Quality Assurance (QA) and Dr. Sattar Ahmed (IGM) assisted in carrying out the validation activity. For the purpose of testing, a set of representative chest X-ray images for each of the diseases covered in the classification system developed were obtained from IDC. Images were analysed independently with the SmartRad-XAI mobile app. Finally, the predictions and confidence scores were compared to the diagnostic information provided by IDC. The aim of this validation activity was to check if the developed system could make an accurate diagnosis of disease patterns in real clinical cases instead of only in the benchmark datasets. Results showed that the disease prediction made by the SmartRad-XAI was consistent with the diagnosis made by the data of clinical records applied for validation [13], [14].

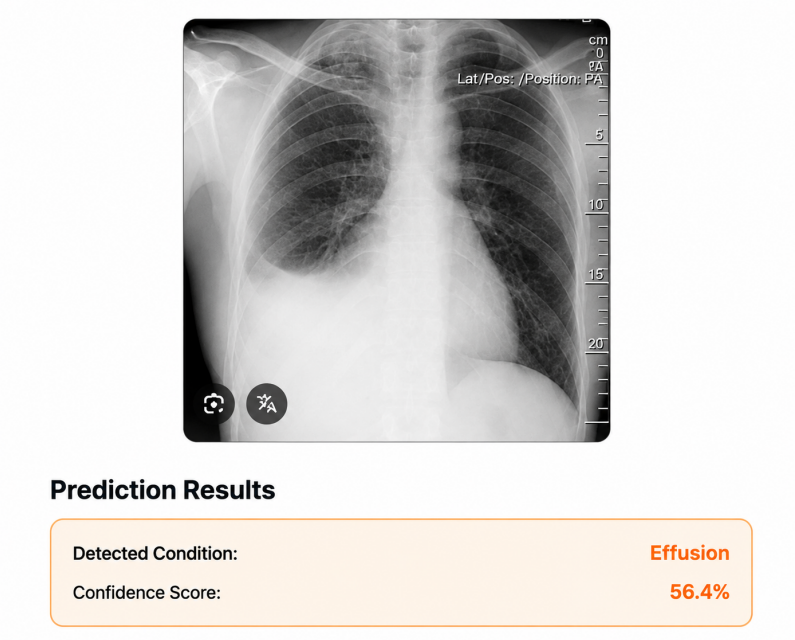


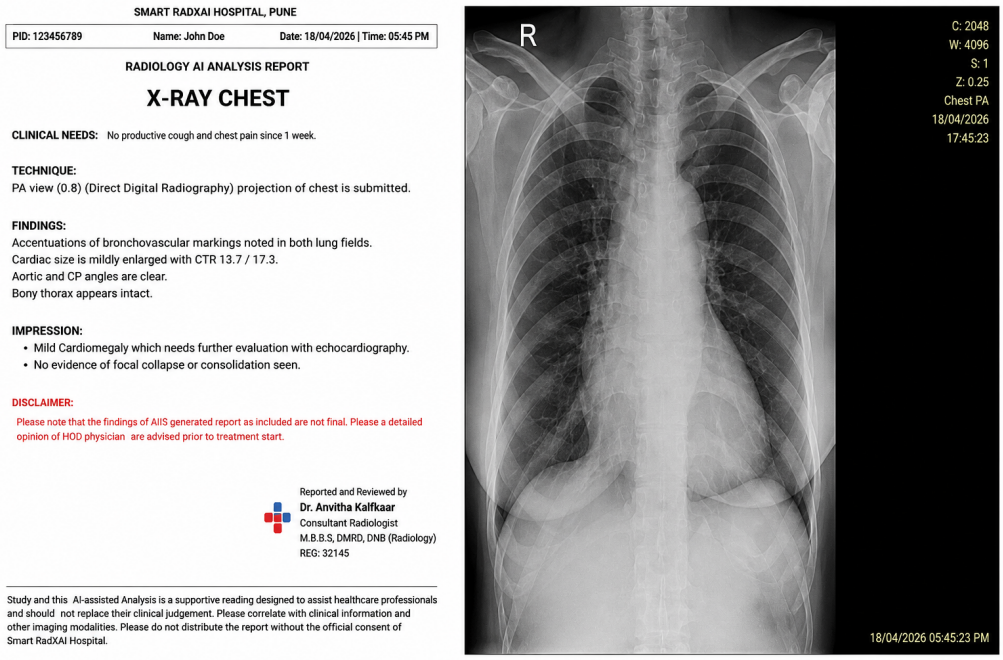
Fig 4.17: Clinical Validation Report Generated by SmartRad-XAI

The clinical validation report generated by the SmartRad-XAI application is shown in Figure 4.17 as a sample. In the illustrated case, the system had a confidence score of 52.9The results of the successful validation of SmartRad-XAI based on real-world chest radiography data demonstrate the potential of combining deep learning and mobile healthcare technology for real-world clinical support. The validation process was focused on a small number of cases only, but the outcomes suggested good potential for the proposed framework in future use in healthcare settings.

4.9.1 Comparison with IDC Clinical Report

In order to assess the capability of the proposed SmartRad-XAI system more robustly in a real healthcare setting, a comparative validation was performed with

clinical chest X-ray images from Islamabad Diagnostic Centre (IDC). The aim of this validation was to determine if the disease prediction made by the developed mobile application was similar or identical to the diagnosis made by professional radiologists. The efficacy of the system was tested on real patient chest X-ray image set and diagnostic reports.



SMART RADXAI HOSPITAL, PUNE

PID: 123456789 Name: John Doe Date: 18/04/2026 | Time: 05:45 PM

RADIOLOGY AI ANALYSIS REPORT

X-RAY CHEST

CLINICAL NEEDS: No productive cough and chest pain since 1 week.

TECHNIQUE:
PA view (0.8) (Direct Digital Radiography) projection of chest is submitted.

FINDINGS:
Accentuations of bronchovascular markings noted in both lung fields.
Cardiac size is mildly enlarged with CTR 13.7 / 17.3.
Aortic and CP angles are clear.
Bony thorax appears intact.

IMPRESSION:
- Mild Cardiomegaly which needs further evaluation with echocardiography.
- No evidence of focal collapse or consolidation seen.

DISCLAIMER:
Please note that the findings of AIIS generated report as included are not final. Please a detailed opinion of HOD physician are advised prior to treatment start.

Reported and Reviewed by
Dr. Anvitha Kalfkaar
Consultant Radiologist
M.B.B.S, DMRD, DNB (Radiology)
REG: 32145

Study and this AI-assisted Analysis is a supportive reading designed to assist healthcare professionals and should not replace their clinical judgement. Please correlate with clinical information and other imaging modalities. Please do not distribute the report without the official consent of Smart RadXAI Hospital.

Fig 4.18: IDC Clinical Report

The heart was enlarged, but not severely, called a mild Cardiomegaly, according to the IDC radiology report. They found no evidence of lung collapse, fluid build-up in the pleura or lung consolidation. In addition, the radiologist recommended to proceed with further evaluation by an echocardiogram to obtain more detailed information about the heart. The results were then utilized as clinical references to verify the result of prediction obtained from the SmartRad-XAI application. The same image of the chest was then analysed by the SmartRad-XAI system and it made a prediction of Effusion with a confidence score of 56.9 percent as illustrated above in Figure 4.17. The application made the prediction of cardiac enlargement, which was consistent with the diagnosis in the IDC report. The agreement of the interpretation provided by the AI model and the radiologist's interpretation demonstrates the potential of the proposed system to accurately detect patterns of disease in real world clinical chest X-rays. The agreement between the prediction of the developed framework and the clinical diagnosis of the IDC was satisfactory, thus proving the reliability and usefulness of the developed framework. The results indicated that the system is able to learn unseen clinical data and support the clinical

diagnosis process by correctly categorizing them and providing clinical explanations. Overall, this real-time clinical validation further supports the future potential of SmartRad-XAI as an intelligent decision support tool in health institutions' chest disease screening and preliminary diagnosis.

4.10 Conclusion

This chapter provides the results of the implementation, performance evaluation and validation of the proposed SmartRad-XAI system for automated chest radiograph disease classification. Several deep learning architectures such as Vision Transformer (ViT), ResNet18, ResNet50, YOLOv8n-cls and YOLOv8s-cls were tested for this task, with a multitude of performance evaluation metrics, such as accuracy, precision, recall, F1-score, confusion matrices and training behavior. It was demonstrated that the selected architectures could successfully extract relevant radiographic features and achieve multi-class classification of X-ray diseases with relatively high performance. The YOLOv8s was identified as the most suitable architecture for the proposed framework, since it exhibited the highest accuracy when classifying unseen X-ray images of the chest, in addition to the best convergence properties and radiographic feature extraction capability among all architectures.

In the end of this chapter, we have discussed the implementation of the SmartRad-XAI mobile application from user login system to the upload of the chest X-ray images, prediction of the disease, display the prediction to the user, and the management of prediction history. Furthermore, a clinical validation study using real-time predictions was carried out in Islamabad Diagnostic Centre (IDC) on a variety of chest X-ray images. Results of the validation indicated that the system predicted the real-time predictions in accordance with the clinical diagnosis, illustrating that the proposed system can be implemented for real healthcare application. The experiment, the mobile system implementation, and the clinical validation altogether proves that SmartRad-XAI is an intelligent and easily accessible system for the detection of diseases of Chest X-ray images.[13], [14].

Chapter 5
CONCLUSION

This paper presented a deep learning automated chest x-ray disease classifier system named "SmartRad-XAI" to fulfill the design, development and evaluation. The system presented in this paper was expected to aid in thoracic disease detection such as Cardiomegaly, Effusion, Pneumonia, Pneumothorax and No Finding. The research was aimed to improve the diagnostic support through using state-of-the-art deep learning approaches that could analyze chest x-ray images precisely and reduce human judgement. Additionally, the innovation of this system was that it has combined the artificial intelligence with medical imaging analysis.

For the purpose of providing auto-diagnosis, an integrated deep learning based framework and a mobile-app friendly platform was developed. The platform allows the user to choose a file or directly take a picture of a chest X-ray image, predict the disease and provide confidence levels with the prediction, then access previous diagnoses with the history module. For the classification tasks, the training and testing architectures included various versions of Vision Transformer (ViT), ResNet18, ResNet50, YOLOv8n-cls, and YOLOv8s-cls. Accuracy, precision, recall, F 1-score, and confusion matrix analysis were used to evaluate them. Results showed that despite varying Architectural complexities, all models could learn effective radiograph features with the aforementioned metrics.

Compared with all the models tested, YOLO v8 s achieved the best classification results, high generalization, low class confusion and fast inference speed. The YOLO v8 n was not as powerful, in terms of accuracy, as other YOLO n versions, but is appropriate for practical use in practical situations, where low calculation power, and less resources are available. This is indicative of the usefulness of YOLO classification models in real world healthcare environments and intelligent diagnosis systems.

A real chest X-ray dataset was obtained from Islamabad Diagnostic Centre IDC, Islamabad to test the design SmartRad-XAI system to validate it. Coordination Imaging and QA, Dr. Saria Ahmed Rajpoot and Dr. Ahmed Rajpoot were conveyed the assistance to analyze the clinical cases of X-ray with the help of created mobile app. The predictions made by the SmartRad-XAI were compared with the clinical diagnosis and the same matching with the clinical diagnosis. This real-time clinical validation showed the practical application of the system and enhanced the credibility of the proposed system, which is not composed only of experimental datasets.

In conclusion, the SmartRad-XAI is an efficient, effective and easy-to-use system for automatic chest-X ray diseases classification. With the integration of advanced deep learning algorithms, mobile healthcare system and clinical validation, the proposed system is promising for possible implementation in clinic for screening and diagnosing of chest disease. The findings of this study may pave the way for future researches on developing the AI-based health-care system as well as provide a solid base for further intelligent clinical decision supporting system.

Chapter 6

FUTURE WORK

While the SmartRad-XAI system performs well in chest X-ray classification, there are several potential improvements to make to make the system more robust, scalable, and clinically useful. One of the main areas of future research is the incorporation of more comprehensive and varied multi-institutional data sets. By training and testing the model with data from various hospitals, imaging devices, and patient cohorts, the model's performance will be enhanced, leading to a greater ability to generalize and withstand variations in data and settings. The model will be trained and tested with data from various hospitals, imaging devices, and patient populations, enhancing its ability to generalize and resist variations in data and settings.

A key aspect is improving image preprocessing and data augmentation methods. Utilization of advanced techniques like adaptive contrast enhancement, noise reduction, normalization, and synthetic data generation (e.g., using generative adversarial networks (GANs) for data augmentation) can enhance feature extraction and mitigate class imbalance, especially for minority diseases .

Further improvement of the system can be achieved by better integration of Explainable AI (XAI) techniques. Highlighting important regions in chest X-rays, for example, using methods like Grad-CAM and attention-based visualization can help highlight the importance of these regions in making predictions. This will enhance transparency and interpretability between medical professionals, and boost the level of trust.

A key focus of future development is real-time deployment and optimization of the system. The model can be compressed using techniques like pruning, quantization, andknowledgedistillationtomakeitmorecompactandefficient, withoutsacrificing its accuracy. This will facilitate real-time inference in the edge, mobile systems and low-resource clinical environments, enabling the system for use in real-world clinical settings. In addition, it is possible to increase the disease coverage and extend the image data to include CT and MRI data. The enlarged classification range will significantly improve the clinical applicability and versatility of this classification for medical diagnostics. Ensemble and hybrid deep learning architectures could also be investigated in future studies, which involve the integration of convolutional neural networks with transformerbased models. These techniques can be used to enhance the feature learning, more specifically, making it more: flexible and also reduce the number of misclassifications in complicated and ambiguous cases. Other

features that the SmartRad-XAI application layer might have is real-time synchronization with the cloud, secure integration with Electronic Health Records (EHR) systems, and support for multiple user authentication and compatibility with hospital information systems (HIS). This capability can be further developed to offer additional features such as auto-generated reports, notifications, multilingual support or even offline prediction, greatly increasing the value of this in a real healthcare setting. Another promising way is federated (or distributed) learning, which is the process of training a model without sharing patients' data among multiple hospitals. This helps create better data privacy, security and scalability and allows incremental model updates from distributed data sources. Finally, it is important to validate the clinical and real-world performance. This will enable the evaluation of the system in actual workflows in hospitals with cooperation with radiologists. The model can also be coupled with a continuous learning mechanism to enable it to adapt over time and maintain long-term reliability and relevance in a changing clinical environment.

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Abbreviations

ANN – Artificial Neural Network
DNN – Deep Neural Network
CV – Computer Vision
ROS – Robot Operating System
OSRF – Open-Source Robotics Foundation
RVIZ – ROS Visualization
IEEE – Institute of Electrical and Electronics Engineers
CVPR – Conference on Computer Vision and Pattern Recognition
ADD – Average Distance of Model Points
HOPE – Household Objects for Pose Estimation
COCO – Common Objects in Context
PnP – Pick and Place
YOLO – You Only Look Once
MOGPE HP – Multi-Object Grasp-Pose Estimation High Precision
SSD – Single Shot MultiBox Detector
CNN – Convolutional Neural Network
SS – Selective Search
HoG – Histogram of Gradients
DOF – Degree of Freedom
I2C – Inter-Integrated Circuit Protocol
DIP – Digital Image Processing
IDC – Islamabad Diagnostic Center

Chapter A

NIH ChestX-ray14 Dataset

ChestX-ray14 dataset was utilized for this study, which contains the images of more than 30,000 patients following anterior view of chest over more than 112,000 X-rays, with annotation of 14 different thoracic diseases. Out of fourteen diseases, the present study selected five: Cardiomegaly, Effusion, Pneumonia, Pneumothorax and No Finding. The images were then selectively collation in the data set to include only these categories in an effort to provide the most representative images to be used as a set that best represents the respective states for classification. The large size, open availability and high diversity makes this data set particularly suitable for use in developed and evaluation of modern machine learning/deep learning algorithms applied to automated chest disease classification. As a collection of specific patient features the data collection was designed to build a robust and general model for classification. Moreover, the images in the data collection were acquired in realistic clinical situations, this further added to the true nature to the individual images and increased the scope of natural variation in image quality, patient position and anatomical variation, making this data set ideal for training and evaluation of deep learning application. Expert annotated labels ensures the reliable training and testing of the classifier. Also, the large number of samples helps minimize over fitting and allows out-of-sample generalization of the trained model. The model has been successfully validated on this data, and thus any state of the art clinical image technique can be compared with this simulation. The data set is standardized, is well curated and will be a good benchmark for action of intelligent medical imaging systems. Selected images were filtered according to categories in the first stage of pre-processing and augmentation procedures as recommended for improved model training. Equitable sampling of classes of interest reduced bias and provided objective assessment. The data set is publicly available, reproducible and scalable and can be exploited as a sensitive reference in applying trustworthy, scalable and clinically relevant deep learning systems for automated detection of thoracic diseases.

Chapter B

Dataset Preprocessing and Model Development

For selected images, before training the models, the image file went through multiple pre-processing steps to improve the quality of the images for the deep learning model architectures. As the input size, all images were resized, normalized, and classified into categories of the different diagnosed diseases. The multiple techniques used to prevent from overfitting, and because of their different feature to generate more diverse data sets, were done by the random rotation, horizontal flip, scale, and brightness adjustment. The different deep learning architectures considered in the model comparison were checked in the same verifing framework such as ResNet18, ResNet50, Vision Transformer (ViT), YOLOv8n, and YOLOv8s. To find out the most suitable model for deployment, all the trained models were presented and compared in term of the classification accuracy, precision, recall, F1 score, and confusion matrix. In terms of the most suitable overall, the YOLOv8s summarized after all the experiments, and it was selected for deployment in the SmartRad-XAI mobile application. Not only that the pipeline helped to improve the image quality, but also it helped the consistency across all the input images while training model. The augmentation techniques allowed the ability to learn the variation of disease pattern across different imaging modalities, and helped to prevent from overfitting by providing the large and varied images. In addition, the models used the same training and testing protocols to address the problem of the impartial comparison of their performance. Furthermore, the hyperparameter tuning was used as the particular architecture to improve the learning and convergence during training. Moreover, models were verified on the unseen test data to represent the real cases for predicting the classes, and the comparison based on the confusion matrix representation will give the detailed information about the performance of each architecture. YOLOv8s resulted in the highest performance on accuracy, compute efficiency, and inference speed, and will be the suitable model for deployment in real-time clinical decision support system.

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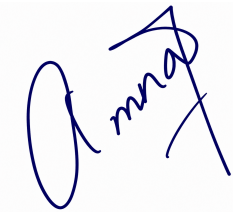
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