BCSE497J ProjectI

Explainable Deep Learning Framework for Early Detection of Lung Cancer

Submitted in partial fulfilment of the requirements for the degree of

Bachelor of Technology

in

B Tech Computer Science and Engineering

by

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DECLARATION

I hereby declare that the project entitled Explainable Deep Learning Framework for Early Detection of Lung Cancer submitted by me, for the award of the degree of Bachelor of Technology in Computer Science and Engineering to VIT is a record of bonafied work carried out under the supervision of Dr . Diviya M .

I further declare that work reported in this project has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university .

Place : Vellore

Date : 05.11.2025

Signature of the Candidate

Examiner(s)

CERTIFICATE

This is to certify that the project entitled Project Title submitted by H Preyansh Nahar (22BCE3807), **School of Computer Science and Engineering**, VIT, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering*, is a record of bonafied work carried out by him / her under my supervision during Fall Semester 2024 2025, as per the VIT code of academic and research ethics.

The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university. The project fulfils the requirements and regulations of the University and in my opinion meets the necessary standards for submission.

Place : Vellore

Date : 05.11.2025

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Examiner(s)

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Name of the Candidate

H Preyansh Nahar

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List of Abbreviations

AI	Artificial Intelligence
AUC	Area Under the Curve
CAD	Computer-Aided Diagnosis
CNN	Convolutional Neural Network
CT	Computed Tomography
DL	Deep Learning
DFD	Data Flow Diagram
EA	Evolutionary Algorithms
GAP	Global Average Pooling
Grad CAM	Gradient-weighted Class Activation Mapping
GRU	Gated Recurrent Unit
IG	Integrated Gradients
LIDC-IDRI	Lung Image Database Consortium and Image Database Resource Initiative
LUNA	Lung Nodule Analysis
ML	Machine Learning
RGB	Red Green Blue
SHAP	SHapley Additive exPlanations
VIT	Vellore Institute of Technology
XAI	Explainable Artificial Intelligence

ABSTRACT

Lung cancer remains one of the leading causes of cancer related deaths worldwide, making early and accurate detection critical for improving patient survival rates. Traditional diagnostic methods often face challenges such as variability in interpretation, scalability limitations, and a lack of consistency, which hinder their reliability in clinical applications. To overcome these challenges, this project presents a deep learning based framework for lung cancer detection using transfer learning with the Xception Convolutional Neural Network (CNN) architecture. The Xception model is chosen for its efficiency, depth wise separable convolutions, and superior feature extraction capability compared to conventional CNNs. The model is trained to classify CT scan images into four categories: Normal, Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma.

During experimentation, the model achieved high training accuracy (around 99.18%) but relatively lower validation accuracy (around 88.89%), indicating overfitting due to limited dataset diversity. To mitigate this, the framework incorporates advanced preprocessing, extensive data augmentation, and cross validation techniques to improve generalization and enhance performance on unseen data. Beyond classification, the project focuses on Explainable AI (XAI) to interpret the model's decision making process. Specifically, Grad CAM is used to generate heatmaps that highlight important regions influencing the model's predictions, while SHAP provides feature level interpretability, enabling a deeper understanding of the contribution of each pixel or region to the final decision. These explainability tools help bridge the gap between deep learning models and clinical reasoning, improving transparency and trust.

Additionally, a web based user interface is developed to allow clinicians to upload CT scans, obtain automatic classification results, and visualize the AI's explanations in real time. The interface offers side by side comparisons of original images with Grad CAM overlays, customizable visualization options, and a case management dashboard, ensuring usability and accessibility for medical professionals.

In the future, the framework can be extended to integrate multimodal clinical data such as patient history, biomarkers, and genomic information to enhance diagnostic precision. By combining deep learning with explainable AI techniques, this project aims to create a transparent, interpretable, and scalable solution for early lung cancer detection. Ultimately, the proposed framework strives to assist clinicians in making faster and more informed decisions, thereby advancing the role of AI in modern healthcare.

CHAPTER 1

1. INTRODUCTION

1.1. Background

Lung cancer continues to be one of the most prevalent and life threatening diseases worldwide, contributing to a high number of cancer related deaths each year. Early detection plays a crucial role in improving survival rates, yet traditional diagnostic approaches such as manual interpretation of CT scans are prone to human error, subjectivity, and time constraints. To overcome these limitations, deep learning has emerged as a powerful approach for automating medical image analysis. In particular, Convolutional Neural Networks have demonstrated exceptional performance in identifying complex visual patterns and supporting early diagnosis of lung cancer.

In this project, the Xception Convolutional Neural Network is employed as the core model due to its efficiency in extracting fine grained features through depth wise separable convolutions. The model is trained using transfer learning on a dataset containing CT scan images categorized into four classes: Normal, Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma. The primary goal is to improve classification accuracy and optimize the model for generalization across diverse clinical conditions.

However, a major limitation of deep learning models lies in their lack of transparency, often being treated as black box systems. To address this challenge, this project integrates Explainable AI methods such as SHAP and Grad CAM, which help visualize and interpret how the model makes its predictions. Grad CAM provides heatmap visualizations that highlight the important regions influencing the model's output, while SHAP quantifies feature importance to enhance interpretability at the pixel and region levels. These techniques improve clinician trust and promote responsible AI deployment in medical environments.

By combining deep learning with explainable AI, the proposed framework not only enhances detection accuracy but also bridges the gap between algorithmic prediction and human understanding. This approach contributes toward building transparent, interpretable, and clinically reliable systems that can assist healthcare professionals in early lung cancer diagnosis and treatment planning.

1.2. Motivations

The primary motivation behind this project is to address the persistent disconnect between high performance research models and their practical implementation in clinical environments. Existing literature repeatedly points out several critical issues: the overreliance on limited or homogeneous datasets, insufficient validation across diverse patient groups, and a general lack of interpretability within current models. It is also evident that while some models report impressive training accuracy, their performance frequently deteriorates during external validation, which raises legitimate concerns regarding their overall robustness and reliability.

Additionally, the absence of user friendly interfaces tailored for clinicians poses a significant barrier to widespread adoption in everyday medical workflows. To tackle these challenges, this project proposes the development of a comprehensive framework that integrates the Xception CNN architecture for classification, explainable AI techniques such as SHAP and Grad CAM, and an accessible web based user interface. The objective is to deliver a solution that is not only accurate and interpretable, but also genuinely usable for healthcare professionals in real world settings.

1.3.Scope of the Project

This project focuses on developing and implementing a deep learning framework for lung cancer detection using CT scan images. The model employs the Xception Convolutional Neural Network architecture to classify scans into four categories: Normal, Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma. To ensure better robustness and generalization, the workflow incorporates preprocessing, data augmentation, and cross validation techniques.

A key aspect of this framework is the integration of explainable artificial intelligence methods such as SHAP and Grad CAM. These techniques help visualize and interpret the model's decision making process, providing heatmaps and attention overlays that allow clinicians to understand which regions influenced the classification results. This interpretability enhances clinical confidence and supports practical decision making.

The project also includes the design of a simple web based interface that enables real time image uploads, automated classification, and visualization of both prediction and explanation. The initial training accuracy achieved around 99.18 percent, while validation accuracy was limited to 88.89 percent, revealing the presence of overfitting and the need for better generalization. Future work will focus on increasing dataset diversity and incorporating additional clinical information such as patient history and biomarker data. These improvements aim to create a scalable and clinically relevant framework that balances performance, transparency, and usability in real healthcare environments.

CHAPTER 2

2. PROJECT DESCRIPTION AND GOALS

2.1. Literature Review

Table 1Literature Survey

No.	Title (APA)	Journal / Year	Method	Result (headline)	Dataset(s)	Pros	Cons	Future Work
1	S. Z. Reem, S. M. A. Sumon, A. Howlader and M. Sarker, "A Deep Learning Strategy for Accurate Lung Cancer Subtype Classification Using Convolutional Neural Networks," 2024 13th International Conference on Electrical and Computer Engineering (ICECE), Dhaka, Bangladesh, 2024, pp. 585590, doi: 10.1109/ICECE64886.2024.11025053.	IEEE / 2024	Custom EfficientNetB7 architecture (built on pretrained CNN) compared with DenseNet121 and ResNet50	Achieved 96.48% accuracy, 96.2% precision, 96.25% F1score, and 99.5% AUC for lung cancer subtype classification	Chest CT scan images: adenocarcinomas, large cell carcinomas, squamous cell carcinomas, normal lung tissue	High classification accuracy; robust even with smaller nodules; comprehensive comparison with other CNNs	Requires high computational resources; dependent on CT image quality; limited to four classes	Extend to larger datasets; clinical validation; integration with other diagnostic tools and modalities

2	S. Z. Ahammed, R. Baskar and G. Nalinipriya, "Advanced Deep Learning Framework for Automated Lung Cancer Detection Using DeepResNet," 2024 IEEE 6th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA), Hamburg, Germany, 2024, pp. 170175, doi: 10.1109/ICCCMLA63077.2024.10871810.	IEEE / 2024	Deep ResNet framework combining UNet for segmentation and ResNet for feature extraction	Achieved 99.89 % accuracy with near perfect F1 score, sensitivity, and specificity for lung cancer detection.	LIDCIDRI dataset (CT scan images of pulmonary nodules)	High diagnostic accuracy; effective at detecting subtle nodules; robust combination of UNet and ResNet	May require high computational resources; limited to CT scan images; model complexity is high	Apply framework to larger and multicenter datasets; integrate with clinical decision support systems; optimize for faster inference
3	T. S. Ruprah, B. Regmi, S. B. Jadhav and S. Singh, "Early Stage Lung Cancer Detection Using Deep Learning," 2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon), Pune, India, 2024, pp. 16, doi: 10.1109/MITADTSoCiCon60330.2024.10575345.	IEEE / 2024	Optimized VGG 16 CNN using Gaussian blur, SMOTE, transfer learning, and early stopping techniques.	Achieved 99% accuracy in distinguishing malignant, benign, and normal CTscan images	IQOTH/NCCDLung Cancer Dataset (CTscan images of lung nodules)	High accuracy, balanced classes, reduced overfitting, and adaptable across demographics.	Limited to VGG 16; computationally intensive; requires validation on larger and more diverse datasets.	Extend to multicenter datasets; further optimization for speed; integration with clinical diagnostic workflows

4	T. Mahmmod, N. Ayesha, M. Mujahid and A. Rehman, "Customized Deep Learning Framework with Advanced Sampling Techniques for Lung Cancer Detection using CT Scans," 2024 Seventh International Women in Data Science Conference at Prince Sultan University (WiDS PSU), Riyadh, Saudi Arabia, 2024, pp. 110115, doi: 10.1109/WiDSPSU61003.2024.00035.	IEEE / 2024	Customized deep learning framework using large CT scan dataset with advanced sampling techniques and transfer learning	Outperformed stateofthheart methods for lung cancer categorization and earlystage detection	Large chest CT image dataset (pulmonary nodules)	High accuracy and efficiency; robust earlystage detection; effective use of transfer learning	May require significant computational resources; dataset details not fully specified; implementation complexity	Expand to multicenter datasets; validate in clinical settings; further optimize model efficiency and generalizability
5	G. V. Saji, T. Vazim and S. Sundar, "Deep Learning Methods for Lung Cancer Detection, Classification and Prediction A Review," 2021 Fourth International Conference on Microelectronics, Signals & Systems (ICMSS), Kollam, India, 2021, pp. 15, doi: 10.1109/ICMSS53060.2021.9673598.	IEEE / 2021	Reviewed ML and DL methods for lung cancer detection and classification.	Summarized DL methods with their advantages, limitations, and datasets for lung nodule detection.	Multiple datasets including CT and chest Xray images	Comprehensive review outlining strengths, weaknesses, and gaps in current DL approaches.	Not an experimental study; no new model proposed; limited to literature analysis	Encourage development of hybrid or optimized DL models; suggest standardized datasets and evaluation metrics for future studies

6	A. Saboor et al., "Deep Learning Model for Lung Cancer Detection," 2024 21st International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP), Chengdu, China, 2024, pp. 14, doi: 10.1109/ICCWAMTIP64812.2024.10873732.	IEEE / 2024	Integrated CNN GRU deep learning model for lung cancer detection	CNN GRU model achieved high accuracy in lung cancer detection from CT scans using holdout validation.	CT scan images dataset of lung cancer	High accuracy; precise detection; suitable for ehealthcare applications	Dependent on dataset quality, computationally intensive, and lacks extensive external validation.	Validate on larger, multicenter datasets; explore realtime deployment in clinical Ehealthcare systems
7	S. Shiva and H. K. Kalluri, "Lung Cancer Detection Using FusionBased Deep Learning Techniques," 2024 IEEE Students Conference on Engineering and Systems (SCES), Prayagraj, India, 2024, pp. 15, doi: 10.1109/SCES61914.2024.10652562.	IEEE / 2024	Fusion DL using MobileNet, VGG 16, GooglеNet, InceptionV3, and ResNet50 with ensembling.	Achieved high accuracy in detecting lung malignancies on LC25000 CT scan dataset	LC25000 dataset (CT scans of various lung pathologies)	High accuracy; ensemble approach improves detection; adaptable to multiple architectures	High computational complexity; requires careful tuning; limited to LC25000 dataset	Test on larger and more diverse datasets; optimize ensemble for efficiency; clinical validation

8	A. A. Hasan, A. T. A. Salih and A. Ghandour, "Lung Cancer Detection using Evolutionary Machine learning and Deep learning: A survey," 2023 International Conference on Information Technology, Applied Mathematics and Statistics (ICITAMS), AlQadisyia, Iraq, 2023, pp. 129133, doi: 10.1109/ICITAMS57610.2023.10525500.	IEEE / 2023	Survey of ML and DL models optimized using Evolutionary Algorithms (EA) for lung cancer detection	Overviewed effectivenes s of ML and DL models on CT scans and highlighted optimization using EA	Chest CT scans (including pneumonia and lung cancer datasets)	Comprehensive review; highlights role of evolutionary optimization; identifies gaps in ML/DL models	No new experimental results; limited to literature analysis; dependent on previously published datasets	Encourage development of EAoptimized ML/DL models; propose standard benchmarks for comparison; clinical validation in future work
9	K. Muthulakshmi and T. Gopalakrishnan, "Improved Deep Learning Models for Early Detection and Classification of Lung Cancer Using Computerized Tomography–A Systematic Review," 2025 INCIP, Bangalore, India, 2025, pp. 697701, doi: 10.1109/INCIP64058.2025.11019422.	IEEE / 2025	Systematic review of deep learning models for lung cancer detection using CT scans.	Reviewed CAD methods for nodule detection and classification; summarized DL model pros and cons.	Multiple prior CT scan datasets (survey based, not experimental)	Grouped studies; outlined DL pros/cons; foundation for future CAD work.	No new dataset or experimental validation; limited to secondary analysis	Proposes improvements in DL methods for segmentation/classification; encourages CAD development for earlystage detection; highlights future research directions

10	Amirthayogam, G., S, S., Maheswari, G., James, M., & Remya, K. (2024). Lung and colon cancer detection using transfer learning. In 2024 Ninth International Conference on Science Technology Engineering and Mathematics (ICONSTEM) (pp. 16). IEEE. https://doi.org/10.1109/ICONSTEM60960.2024.10568787	ICONSTEM / 2024	Transfer learning with EfficientNetB3 on histopathology images	99% accuracy with strong precision, recall, and F1score	25,000 histopathology images	High accuracy and robust metrics; effectively distinguishes cancerous vs noncancerous tissue	Focused only on lung and colon cancer, may not generalize to other cancer types	Extend to multicancer detection; enhance dataset diversity; improve realworld applicability
11	A. Bouamrane and M. Derdour (2023). Enhancing Lung Cancer Detection and Classification Using Machine Learning and Deep Learning Techniques: A Comparative Study. 2023 International Conference on Networking and Advanced Systems (ICNAS), Algiers, Algeria, pp. 16. doi:10.1109/ICNAS59892.2023.10330504	ICNAS / 2023	Compared ML and DL models for lung cancer detection.	Deep learning models showed superior accuracy compared to traditional ML methods	LIDCIDRI dataset (CT scans of 1012 patients)	DL models show high precision, speed, and reliability for small nodule detection.	Traditional ML methods less effective; computational cost of DL models	Expand dataset diversity; explore hybrid MLDL methods; enhance realtime clinical applications

12	R. D. Mohalder, J. P. Sarkar, K. A. Hossain, L. Paul and M. Raihan (2021). A Deep Learning Based Approach to Predict Lung Cancer from Histopathological Images. 2021 ICECIT, Khulna, Bangladesh, pp. 14. doi:10.1109/ICECIT54077.2021.9641341	ICECIT / 2021	Proposed a CNN model for lung cancer detection from histopathological image	Accuracy of 99.80 % in predicting lung cancer from histopathological data	15,000 lung cancer histopathological images	Very high prediction accuracy; effective early detection; robust dataset size	Limited to histopathological images only; lacks validation on CT/X ray data	Future work to include multimodal imaging (CT, Xray + histopathology); realworld clinical validation ; scalability to larger datasets
13	M. Jaeyalakshmi, P. K. Janani, P. J. Priya, M. Bhavani and K. E. Narayanan, "Detection of Lung Cancer Using Deep Learning Model and Radiomics Method," 2024 International Conference on Communication, Computing and Internet of Things (IC3IoT), Chennai, India, 2024, pp. 15, doi: 10.1109/IC3IoT60841.2024.10550376.	International Conference on Communication, Computing and Internet of Things (IC3IoT) / 2024	Deep learning with chest CT scans and radiomics integration for lung cancer detection	Integrated deep learning and radiomics improved tumor detection and feature extraction	Chest CT scans (curated datasets)	Combines segmentation + radiomics, supports tumor feature extraction, potential clinical deployment	Does not mention dataset size, clinical validation pending, early stage web application	Future deployment as userfriendly web app; comprehensive tumor feature analyses; clinical support system

14	B. D. Rao and M. Arshad, "Early Detection of lung Cancer Using Machine Learning Technique," 2023 International Conference on Computer Communication and Informatics (ICCCI), Coimbatore, India, 2023, pp. 15, doi: 10.1109/ICCCI56745.2023.10128389.	International Conference on Computer Communication and Informatics (ICCCI) / 2023	Neural network framework for early lung cancer detection from CT images	Proposed CNN based framework improves detection accuracy and reduces diagnosis time	CT images (lung cancer cases)	Multistep framework (preprocessing, segmentation, feature extraction); lowcost solution	Lacks quantitative performance metrics; results mostly descriptive; clinical trials not reported	Extend framework with quantitative evaluation; validate in clinical settings; improve staging accuracy
15	A. S. Sakr, "Automatic Detection of Various Types of Lung Cancer Based on Histopathological Images Using a Lightweight EndtoEnd CNN Approach," 2022 20th International Conference on Language Engineering (ESOLEC), Cairo, Egypt, 2022, pp. 141146, doi: 10.1109/ESOLEC54569.2022.10009108.	20th International Conference on Language Engineering (ESOLEC) / 2022	Lightweight endtoend CNN for lung cancer detection from histopathological images	Achieved 99.5% accuracy, outperforming stateoftheart cancer detection methods	Publicly available histopathology image dataset	Computationally efficient; high accuracy; normalization improves detection performance	Only tested on histopathology dataset; generalization to clinical environments not validated	Extend to multicenter clinical data; test on larger datasets; explore realtime medical applications

16	A. Kumar Swain, A. Swetapadma, J. Kumar Rout and B. Kumar Balabantaray, "A Review on Lung Cancer Detection and Classification using Shallow Learning and Deep Learning," 2023 OITS International Conference on Information Technology (OCIT), Raipur, India, 2023, pp. 570573, doi: 10.1109/OCIT59427.2023.10431005.	OITS International Conference on Information Technology (OCIT) / 2023	Survey of shallow learning and deep learning methods for lung cancer detection and classification	Deep learning methods generally achieved higher accuracy than shallow learning methods	Survey of multiple techniques (no specific dataset)	Compares shallow vs deep learning; highlights advantages of DL in accuracy	Does not provide experimental results; survey only	Explore hybrid shallow–deep models; more benchmarking across datasets
17	M. Wahengbam, M. Sriram and T. G. Singh, "Deep Learningbased Early Lung Cancer Detection using MultiModel Image Fusion Technique," 2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS), Pudukkottai, India, 2023, pp. 884889, doi: 10.1109/ICACRS58579.2023.10405217.	2nd International Conference on Automation, Computing and Renewable Systems (ICACRS) / 2023	Deep learning with multimodel image fusion for early lung cancer detection	Proposed framework improves detection accuracy and efficiency using multimodal imaging	Medical imaging datasets (CT scans, multimodal images)	Combines deep learning and multimodal fusion; enhances early detection; realtime potential	Implementation details and clinical validation not fully reported; generalization unclear	Clinical trials; larger datasets; integration with realtime hospital systems

18	P. VB, Meeradevi, M. R. Mundada, S. P. Singh, S. Bhetariya and C. Srivastava, "Performance Analysis of Various Deep Learning Models in Lung Cancer Detection and Classification Using Medical Images," 2024 5th International Conference on Circuits, Control, Communication and Computing (I4C), Bangalore, India, 2024, pp. 219227, doi: 10.1109/I4C62240.2024.10748430.	5th International Conference on Circuits, Control, Communication and Computing (I4C) / 2024	Evaluation of CNN, ResNet50, MobileNet V2, and VGG 16 for lung cancer detection from medical images	Deep learning models effectively detect and classify lung nodules from Xrays and CT scans	Medical imaging datasets (Xrays and CT scans)	Comparative analysis of multiple deep learning models; automatic feature extraction; robust evaluation	Challenges with data scarcity, interpretability, and bias; limited clinical validation	Explore larger and more diverse datasets; address interpretability and bias; clinical trials for validation
19	H. Wang and L. Xing, "Deep Learning's Application on Radiology and Pathological Image of Lung Cancer: A Review," 2021 International Conference on Information Technology and Biomedical Engineering (ICITBE), Nanchang, China, 2021, pp. 299303, doi: 10.1109/ICITBE54178.2021.00071.	International Conference on Information Technology and Biomedical Engineering (ICITBE) / 2021	Review of deep learning applications in radiology and pathological imaging for lung cancer	Deep learning enhances tumor recognition, prognosis prediction, and pathological image analysis	Radiology and pathological imaging datasets of lung cancer	Comprehensive review of deep learning applications; highlights potential for prognosis and diagnosis	Focuses on review; lacks new experimental validation	Future work: clinical trials, realtime application, integration with medical imaging pipelines

20	L. Singh, H. K. Choudhary, S. Singh, A. K. Bisht, P. Jain and G. Shukla, "Automated Detection of Lung Cancer using Transfer Learning based Deep Learning," 2022 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 2022, pp. 500504, doi: 10.1109/CISES54857.2022.9844372.	International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES) / 2022	Transfer learning based CNN (ResNet50) for automated lung cancer detection from CT scans	Achieved 99.1% accuracy in classifying lung CT scans as cancerous or noncancerous	LUNA 2016 dataset (2478 lung CT scan images)	High accuracy; early detection; assists doctors in analysing lung cancer images	Limited dataset size; only binary classification; lacks broader clinical validation	Future work: larger datasets, multiclass classification, clinical integration, realtime deployment

2.2. Gaps Identified

2.2.1. Most existing studies on lung cancer detection using deep learning emphasize model accuracy but overlook explainability and interpretability, which are critical for clinical adoption. Although CNN based models achieve high accuracy on standard datasets, they often act as "black boxes," offering little insight into how or why a decision was made.

2.2.2. While several deep learning models such as VGG, ResNet, and Inception have been used for CT image classification, few works explore the Xception architecture, which leverages depthwise separable convolutions to achieve superior feature extraction with reduced computational cost. The potential of Xception for lung cancer classification remains underexplored in comparison to other CNNs.

2.2.3. Many current studies rely on limited or homogeneous datasets, resulting in overfitting and reduced generalization capability when applied to unseen clinical data. There is a need to address this gap through advanced preprocessing, data augmentation, and cross validation techniques to ensure robustness and reliability.

2.2.4. There is insufficient research on combining deep learning classification with Explainable AI (XAI) methods such as SHAP and Grad CAM for medical imaging. Most models stop at classification accuracy without providing visual or feature level explanations that could help clinicians interpret model predictions and validate trustworthiness.

2.2.5. Existing research often lacks an interactive and interpretable interface for real world deployment. Few frameworks enable clinicians to visualize CT scans alongside Grad CAM heatmaps or SHAP value plots for transparent decision making.

2.2.6. Lastly, most approaches do not integrate multimodal data such as patient history, biomarkers, or genomic information, which could significantly enhance diagnostic precision. A framework that unifies deep learning accuracy with explainable, transparent, and extensible design remains largely missing in the current literature.

2.3. Objectives

- The primary objective of this project is to develop an Explainable Deep Learning Framework for Early Detection of Lung Cancer using CT scan images. The proposed framework leverages transfer learning with the Xception Convolutional Neural Network (CNN) architecture to accurately classify lung cancer types, including Normal, Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma. To enhance model robustness and prevent overfitting, the system incorporates extensive data augmentation and cross validation strategies, ensuring reliable performance across diverse datasets.

- In addition to classification, the framework integrates Explainable AI (XAI) techniques specifically Grad CAM and SHAP to provide visual and feature level interpretability of model predictions. These explanations aim to improve transparency, clinical trust, and decision support for healthcare professionals.

- The system further includes a web based interface designed for practical usability, enabling clinicians to upload CT scans, view classification outputs, and visualize AI explanations in real time.

- Looking forward, the framework is designed to be extensible, allowing the integration of multimodal clinical data such as patient history, biomarkers, and genomic information to support more holistic and precise lung cancer diagnosis.

2.4.Problem Statement

While deep learning models for lung cancer detection often demonstrate impressive training accuracy, their performance tends to drop off during validation, raising concerns about realworld reliability. Interpretability is another major issue these models frequently operate as "black boxes," making it difficult for clinicians to trust or fully understand their decisions. As a result, despite their technical promise, many current systems fall short in terms of practical clinical usability. There is a clear demand for diagnostic frameworks that not only maintain strong accuracy across diverse datasets but are also explainable and easily integrated into everyday medical practice.

2.5.Project Plan

2.5.1. Gantt Chart

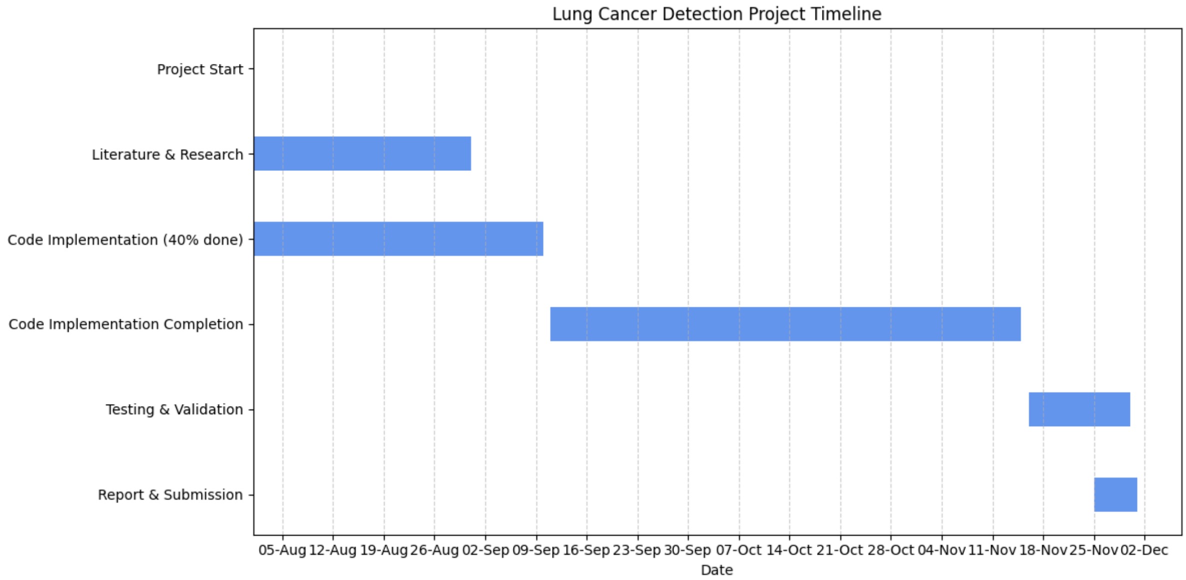

Figure 1Gantt Chart

2.5.2. Work Breakdown Structure

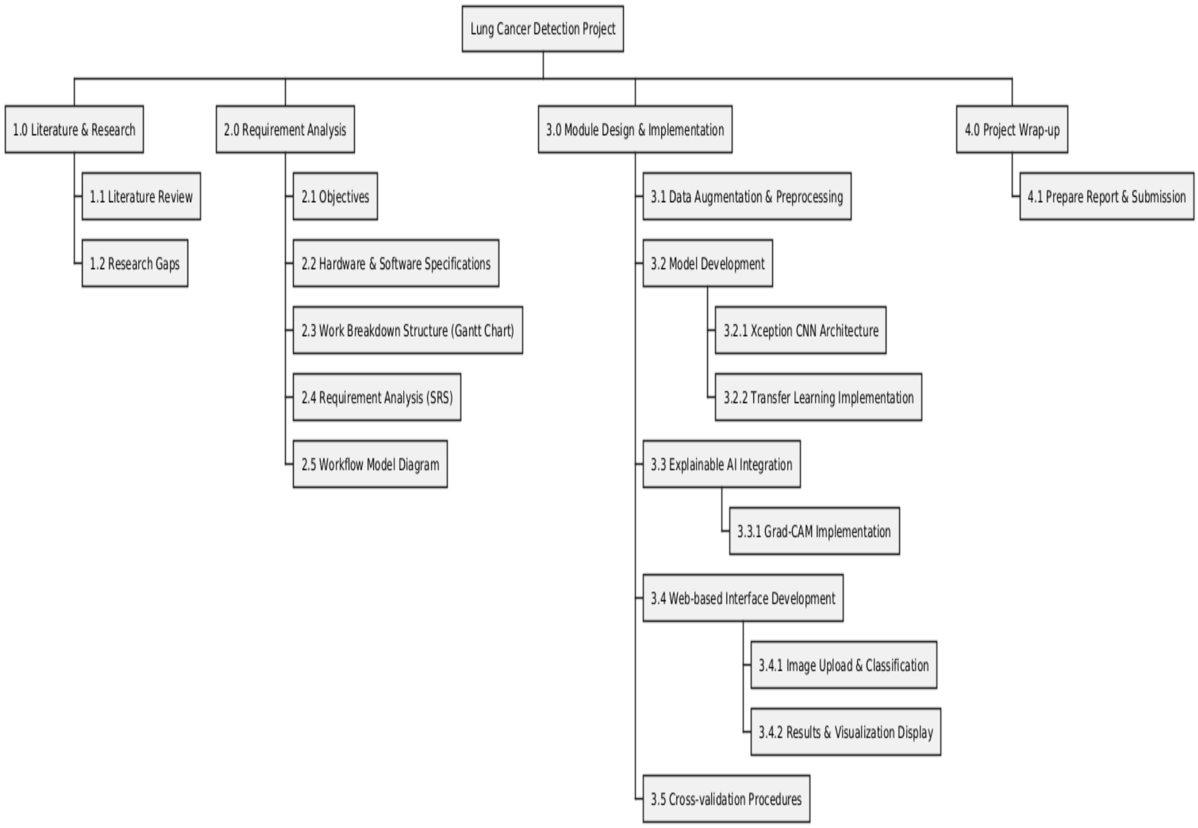

Figure 2Work Breakdown Structure

CHAPTER 3

3. REQUIREMENT ANALYSIS

3.1. Requirements

3.1.1. Functional Requirements

- Allow users to upload CT/X ray images for lung cancer detection.
- Perform *image preprocessing* including resizing, normalization, and format conversion.
- Use a deep learning model (Xception CNN) to classify lung images into multiple cancer classes or normal.
- Provide prediction probability scores for each class.
- Generate Grad CAM heatmaps to visualize regions influencing predictions.
- Generate Integrated Gradients maps for pixel level explanation of model decisions.
- Support batch evaluation of multiple images to assess overall model performance.
- Display confusion matrices and classification reports for validation/testing datasets.
- Allow users to download Grad CAM or IG visualizations for further analysis.
- Provide a web interface (Streamlit) for interaction and visualization.

3.1.2. Non Functional Requirements

- Usability: Simple and intuitive user interface for uploading images and viewing results.
- Performance: Model should return predictions within a reasonable time (<5 seconds per image).
- Reliability: Ensure consistent and accurate predictions across different images.
- Scalability: Able to handle batch evaluation for multiple images efficiently.
- Security: Uploaded images and predictions should be handled securely, preventing unauthorized access.
- Maintainability: Modular design to allow future updates such as adding new models or classes.
- Portability: The application should run on standard web browsers without installation.

3.2. Feasibility Study

3.2.1. Technical Feasibility

- The system leverages pre trained deep learning models (Xception) and TensorFlow/Keras for image classification.
- Grad CAM and Integrated Gradients are standard explainability techniques compatible with TensorFlow.
- The system can run efficiently on Google Colab (GPU enabled) and can be deployed on local machines or web servers.
- Streamlit provides a lightweight web interface for real time interaction.

3.2.2. Economic Feasibility

- The project uses open source software including Python, TensorFlow, Keras, OpenCV, and Streamlit, reducing development cost.
- Deployment costs are minimal since Google Colab or free hosting can be utilized for testing.
- No specialized hardware is required beyond a standard PC with GPU for faster training.

3.2.3. Social Feasibility

- Provides an assistive tool for radiologists and healthcare professionals, improving lung cancer detection efficiency.
- Enhances understanding of AI decisions with explainable visualizations, fostering trust in AI assisted diagnostics.
- Contributes to early diagnosis, potentially saving lives and improving patient care.

3.3. System Specification

3.3.1. Hardware Specification

Table 2Hardware Specification

Component	Minimum Requirement	Recommended Requirement
Processor	Intel i5 or equivalent	Intel i7 / AMD Ryzen 7
Ram	8 GB	16 GB or more
Storage	100 GB free disk space	200 GB SSD
GPU	Optional	NVIDIA GPU with CUDA
Display	1366×768 resolution	1920×1080 resolution

3.3.2. Software Specification

Table 3Software Specifications

Software Component	Version / Requirement
Operating System	Windows 10/11, macOS, Linux
Python	3.8 or higher
TensorFlow / Keras	2.10 or higher
OpenCV	4.5 or higher
Streamlit	1.24 or higher
Supporting Libraries	Numpy, Pandas, Matplotlib, Seaborn, PIL
Web Browser	Chrome, Firefox, Edge (latest)

CHAPTER 4

4. DESIGN APPROACH AND DETAILS

4.1. SYSTEM ARCHITECTURE

The Lung Cancer Detection System relies on a layered design that keeps things modular, scalable, and, most importantly, explainable. At its core, the system combines deep learning using the Xception model with a Grad CAM based explainable AI layer. This setup means doctors can actually see and interpret how the model comes to its conclusions, not just take its word for it. The system splits into four main layers: User Interaction, Processing, Model & Explainability, and Storage & Data Management. Every layer has a job to do, and together, they create an efficient, understandable, and reliable workflow for diagnosis.

Start with the User Interaction Layer. This is where clinicians meet the AI. Through a web interface, they upload CT scans, request predictions, and review results. The Visualization Module then displays GradCAM heatmaps, confidence scores, and previous patient results. Meanwhile, the API Gateway manages secure communication and user authentication, keeping everything both user friendly and compliant with medical data standards.

Next comes the Processing Layer. This is the workhorse between user input and the deep learning model. The Preprocessing Module takes raw CT images and gets them ready normalizing, resizing, augmenting, and denoising as needed. The Dataset Manager keeps training, validation, and test data organized and balanced. When it's time for predictions, the Inference Controller handles requests and sends them to the deployed model. The Training Orchestrator keeps tabs on model training, checkpoints, and performance. Altogether, this layer ensures data is always in shape for the model and that everything runs smoothly.

The heart of the system is the Model & Explainability Layer. Here, the Xception Model, a deep convolutional neural network analyses CT images and classifies them as benign or malignant. The Grad CAM Module steps in to highlight the regions in each image that most influenced the model's decision, giving clinicians real evidence instead of just a black box answer. The Model Management component keeps track of different trained models, handling version control and letting the system deploy whichever model performs best. This blend of deep learning and explainability builds trust, doctors see not just a prediction, but the reasoning behind it.

Finally, there's the Storage & Data Management Layer. This layer keeps everything organized and accessible for the long haul. The Dataset Repository stores CT images and metadata for training and validation. The Model Repository holds trained model weights, checkpoints, and deployment ready versions. All prediction results, Grad

CAM visualizations, and logs go into the Results Database, making it easy to audit, review, or retrain as needed. This structure keeps data safe, traceable, and easy to retrieve.

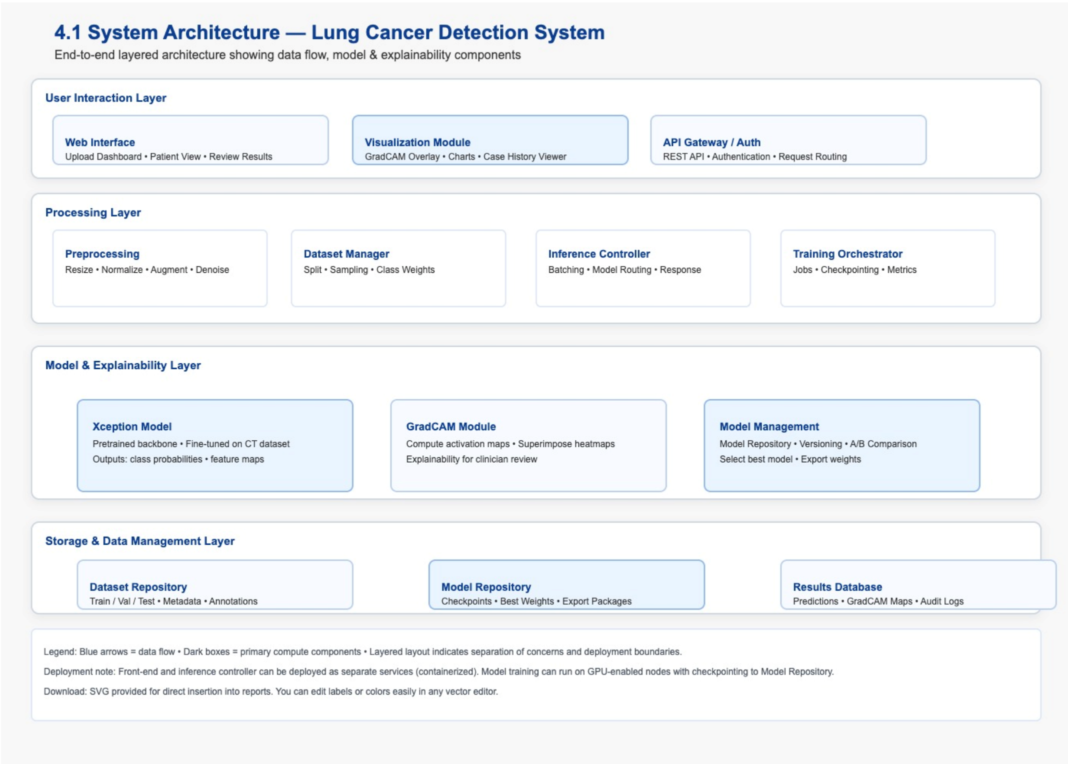

Figure 3System Architecture

4.2.DESIGN

4.2.1. DATA FLOW DIAGRAM

The Data Flow Diagram (DFD) lays out how data moves through the Lung Cancer Detection System. It maps out the main players clinicians, data storage, and the system's core modules: preprocessing, training, inference, and Grad CAM explainability. You can also spot where the data lives, like the dataset repository, model storage, and the case database. The DFD gives you a bird's eye view of the whole process, showing how CT scan images start with upload, move through each stage, and end up as predictions and visualizations.

Here's how it works: the clinician kicks things off by uploading CT images through the web interface. The system preprocesses these images, then sends them to the training and inference modules. That's where the Xception model gets to work, generating predictions. Both the predictions and Grad CAM heatmaps go into the database and appear on the clinician's dashboard. With Grad CAM in the mix, clinicians don't have to guess how the model reached its conclusions they get clear, visual explanations pointing to the relevant regions in the scans. The

DFD ties all this together, showing exactly how information moves from one part of the system to another, making the whole process efficient and easy to follow.

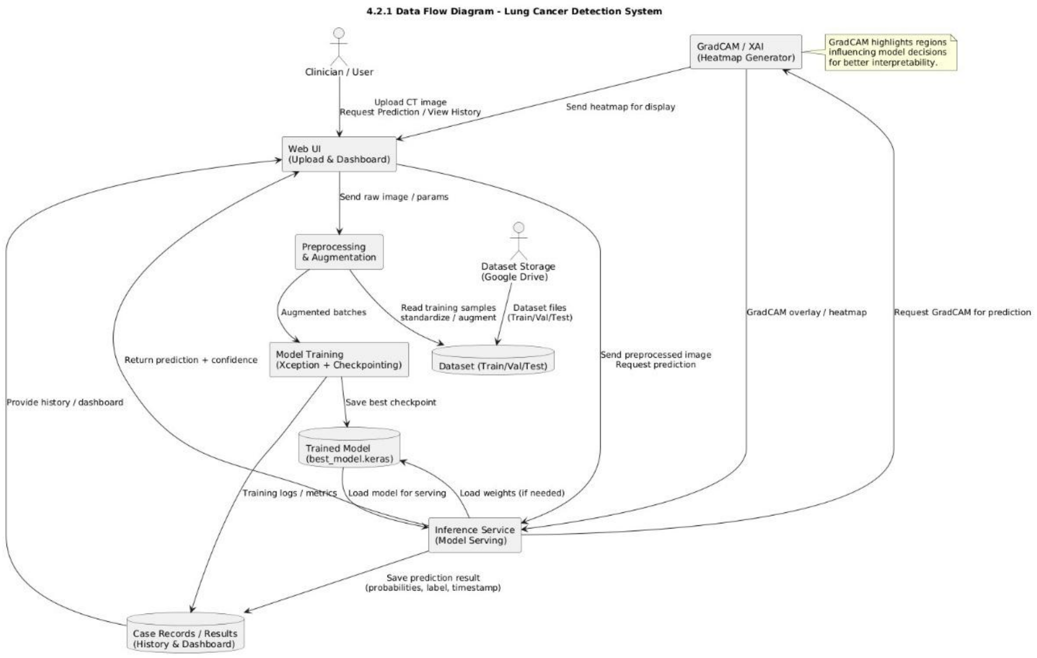

Figure 4Data Flow Diagram

4.2.2. USE CASE DIAGRAM

The Use Case Diagram lays out how the Lung Cancer Detection System actually works for its two main users: clinicians and administrators. Clinicians use the system to upload CT images, run predictions, see Grad CAM visualizations, and look back at old cases on the dashboard. Administrators handle the backend they manage datasets, keep an eye on model training, and track performance numbers. The diagram makes it clear who does what and how each person interacts with the system.

What stands out here is how modular the system is. Data preparation includes things like preprocessing and augmentation, and Grad CAM explanations are baked right into the inference process. The diagram connects each user's needs directly to the features they use, so nothing gets lost in translation. Clinicians get real help from AI driven diagnostics, while administrators stay in charge of the system's backbone. The end result? A setup that balances usability for the people on the front lines with maintainability for those behind the scenes.

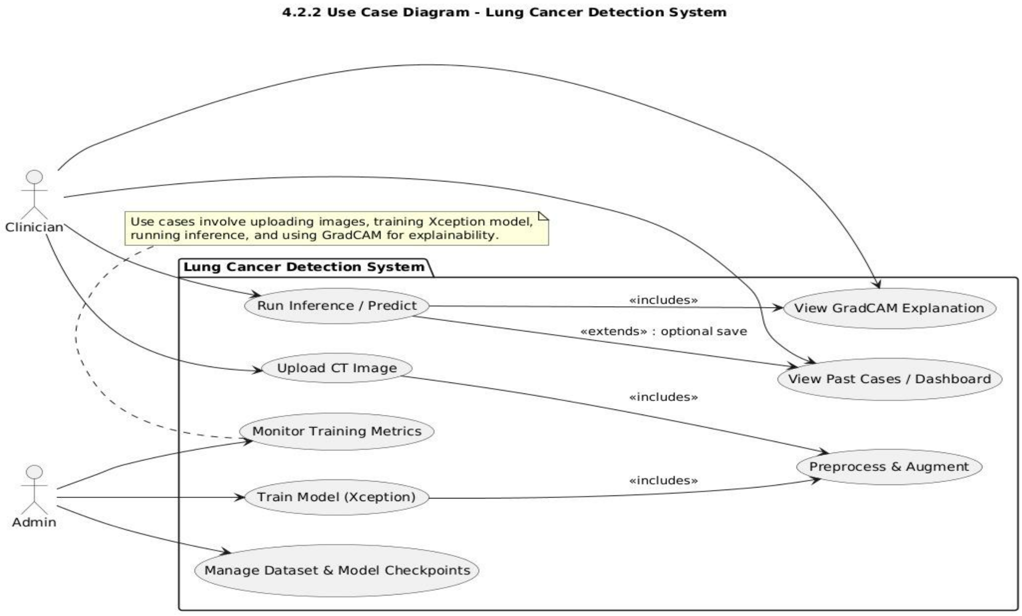

Figure 5Use Case Diagram

4.2.3. CLASS DIAGRAM

The Class Diagram lays out the system's backbone. It shows the main classes User, Image File, Dataset Manager, Preprocessor, Xception Model, Grad CAM, Inference Service, Case Record and how they connect. Each class comes with its own set of attributes and methods, and together, they make up the object oriented architecture driving features like data management, preprocessing, model training, inference, Grad CAM visualization, and case record storage.

Take the Preprocessor, for example. It takes care of image normalization and augmentation. The Xception Model steps in for model compilation, training, and prediction. Inference Service uses the trained Xception Model and Grad CAM to generate predictions and visualizations that actually help interpret results. Meanwhile, Database keeps track of storing and retrieving case results.

All these classes work together to keep data flowing smoothly and cleanly. The relationships between them make the design modular, so it's easier to scale and reuse code. The diagram isn't just a map it's proof that object oriented design can handle the complexity of machine learning in healthcare, giving you something robust and maintainable.

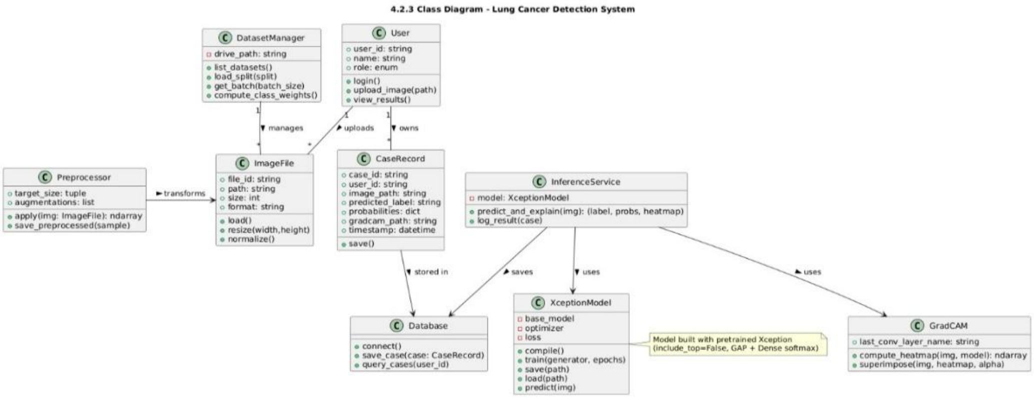

Figure 6Class Diagram

4.2.4. SEQUENCE DIAGRAM

The Sequence Diagram lays out how system components interact over time during the key process: delivering a Diagnosis Report with Explanation. Unlike a Class Diagram, which just shows structure, this one actually tracks the back and forth who talks to whom and when. You see the Clinician kick things off by sending an Upload CT Scan Image message to the Web UI. From there, the image moves into the Preprocessing Module, where it gets resized and rescaled. This step standardizes the data before it goes to the Classification Model for prediction.

What stands out in this diagram is the clear, separate invocation of the Grad CAM Module right after the prediction. That's where explainability comes in. The system splits the workflow first, it generates the classification, then it creates the visual explanation. Only after both are ready does the Web UI pull them together into a single Diagnosis Report. Before showing it to the Clinician, the system saves everything in the Case History Database

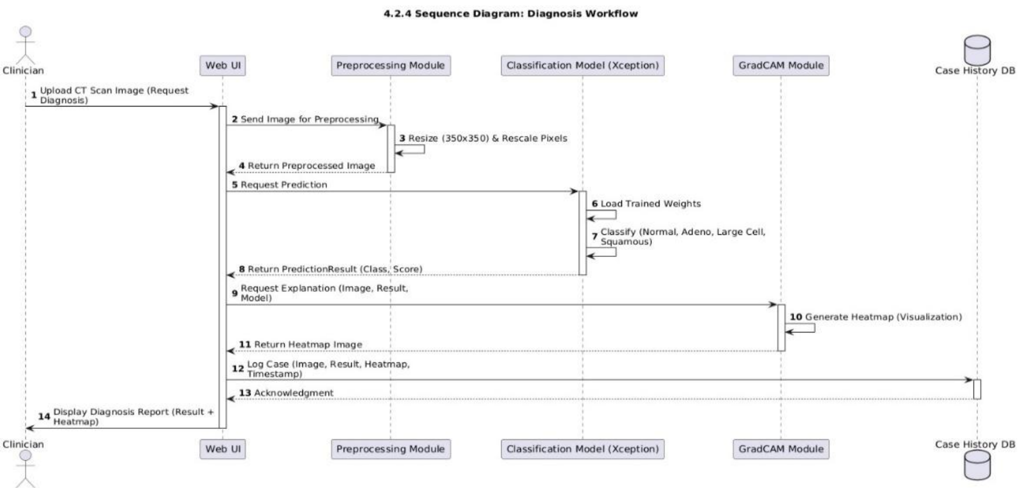

Figure 7Sequence Diagram

CHAPTER 5

5. METHODOLOGY AND TESTING

5.1.METHODOLOGY

The proposed system focuses on Lung Cancer Detection using Deep Learning (DL) with Explainable AI techniques. The methodology integrates state of the art image classification using the Xception Convolutional Neural Network (CNN) architecture and provides interpretability via Grad CAM and Integrated Gradients (IG) . The workflow is structured as follows:

1. Dataset Preparation

The dataset consists of lung CT and X ray images categorized into four classes:

- adenocarcinoma_left.lower.lobe_T2_N0_M0_Ib
- large.cell.carcinoma_left.hilum_T2_N2_M0_IIIa
- squamous.cell.carcinoma_left.hilum_T1_N2_M0_IIIa
- normal

Images are split into training, validation, and test sets with proper class labelling. Data augmentation techniques, such as horizontal flipping, rotation, zooming, and brightness adjustment, are applied to improve model generalization.

2. Preprocessing

Each image is resized to 350×350 pixels and normalized to scale pixel values between 0 and 1. Images are converted to RGB format to ensure compatibility with the pre trained Xception model.

3. Model Architecture

The Xception model pre trained on ImageNet is used as the feature extractor. The last 20 layers of Xception are fine tuned , while earlier layers are frozen to retain generic features. A Global Average Pooling (GAP) layer and a Dense SoftMax output layer are added for multi class classification. The model is trained using the Adam optimizer with a learning rate of 1e 4 and categorical cross entropy loss. Class imbalance is addressed by computing class weights , which are applied during training.

4. Explainable AI Techniques

To improve interpretability and trust in the model's predictions:

- Grad CAM (Gradient weighted Class Activation Mapping) : Highlights regions of the lung images that influence the model's prediction. The last convolutional layer block14_sepconv2_act is used for generating heatmaps.
- Integrated Gradients (IG) : Measures feature attribution for input pixels, providing an attribution map that identifies the most important areas contributing to the prediction.

5. Implementation

The model training, evaluation, and explainability modules are implemented in Google Colab using TensorFlow and Keras. A Stream lit web interface is developed to allow users to upload lung images and visualize predictions along with Grad CAM and IG heatmaps. Batch evaluation functionality is included for testing multiple images in a folder and generating performance metrics.

5.2.TESTING

The model performance and explainability were evaluated using the validation and test datasets , ensuring both classification accuracy and interpretability.

1. Single Image Prediction

Each uploaded image is pre processed and passed through the trained Xception based model. The predicted class and probability are displayed Grad CAM heatmaps overlay the original image to highlight regions contributing to the prediction. Integrated Gradients attribution maps show pixel level importance for model decisions.

2. Batch Evaluation

Images from the validation/test folder are evaluated in batch mode. The confusion matrix visualizes the model's class wise prediction accuracy. Classification reports are generated including precision, recall, F1 score, and overall accuracy.

3. Performance Metrics

Training Accuracy: Achieved high accuracy (>88%) after fine tuning.
Validation Accuracy: Similar performance on unseen data demonstrates good generalization.

Class wise Evaluation: Confusion matrices indicate reliable prediction across all four classes.

4. Explainability Testing

Grad CAM heatmaps successfully highlight the affected regions of the lungs, helping radiologists understand model focus areas. Integrated Gradients maps provide a complementary explanation by attributing importance to individual pixels. These visualizations confirm that the model relies on medically relevant areas rather than spurious features.

5. Conclusion of Testing

The testing demonstrates that the system not only accurately detects lung cancer types but also provides interpretable explanations for its decisions. This ensures that the model can assist clinicians in decision making with both performance and transparency .

CHAPTER 6

6. PROJECT DEMONSTRATION

6.1. METHODOLOGY OVERVIEW

1. Data Preparation

- Collected CT and X ray images of lungs, categorized into four classes.
- Split data into training, validation, and test sets.
- Applied data augmentation (rotation, flipping, zoom, brightness) to increase dataset diversity.

2. Image Preprocessing

- Resized all images to **350×350 pixels**.
- Normalized pixel values to the range [0, 1].
- Converted images to RGB for compatibility with the pre trained Xception model.

3. Model Architecture & Training

- Used Xception CNN pre trained on ImageNet as a feature extractor.
- Fine tuned the last 20 layers for lung cancer classification.
- Added Global Average Pooling (GAP) and Dense softmax layer for multi class output.
- Trained using Adam optimizer with learning rate 1e 4 and categorical cross entropy loss.
- Applied class weights to handle data imbalance.

4. Explainable AI Integration

- **Grad CAM**: Highlights lung regions influencing predictions using the last convolutional layer block14_sepconv2_act.
- **Integrated Gradients (IG)**: Provides pixel level attribution to explain the model's decisions.

5. Deployment

- Stream lit app allows uploading of images.
- Outputs include predicted class, probability scores, Grad CAM heatmaps**,** and Integrated Gradients maps**.**

- Supports batch evaluation of images with confusion matrix and classification report.

6.2. ALGORITHMIC STEPS

1. Input Image Acquisition

- Take a lung CT or X ray image as input.
- Ensure the image is in a supported format (PNG, JPG, or JPEG).

2. Preprocessing

- Resize the image to a standard size of 350×350 pixels.
- Normalize pixel values to a range of 0 to 1.
- Convert the image to RGB format to be compatible with the model.

3. Prediction using Deep Learning Model

- Pass the preprocessed image through the Xception CNN model**.**
- Extract features using the convolutional layers of Xception.
- Apply Global Average Pooling and Dense layers to classify the image.
- Output a probability score for each class and determine the predicted class.

4. Grad CAM Visualization (Explainability)

- Identify the last convolutional layer in the model.
- Compute the gradient of the predicted class score with respect to this layer.
- Multiply the gradients with the feature maps to generate a heatmap.
- Overlay the heatmap on the original image to visualize the regions influencing the prediction.

5. Integrated Gradients (Pixel Level Explanation)

- Compare the input image with a baseline image (e.g., a blank image).
- Gradually interpolate between the baseline and input image.
- Calculate gradients at each step and average them to determine pixel importance.
- Generate an attribution map showing which areas of the image contributed most to the prediction.

6. Output Display

- Display the predicted class along with the probability score.

- Show Grad CAM heatmap highlighting influential regions.
- Show Integrated Gradients map showing pixel level contributions.

6.3. OUTPUT AND EXECUTION

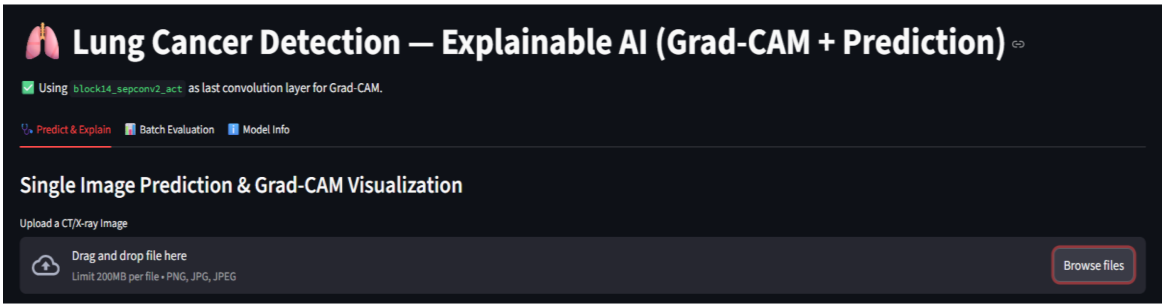

Figure 8Upload lung CT/X ray image for Prediction.

This interface allows the user to upload a single lung CT or X ray image. The uploaded image will be processed by the system for classification into one of the four lung cancer categories, initiating the prediction workflow.

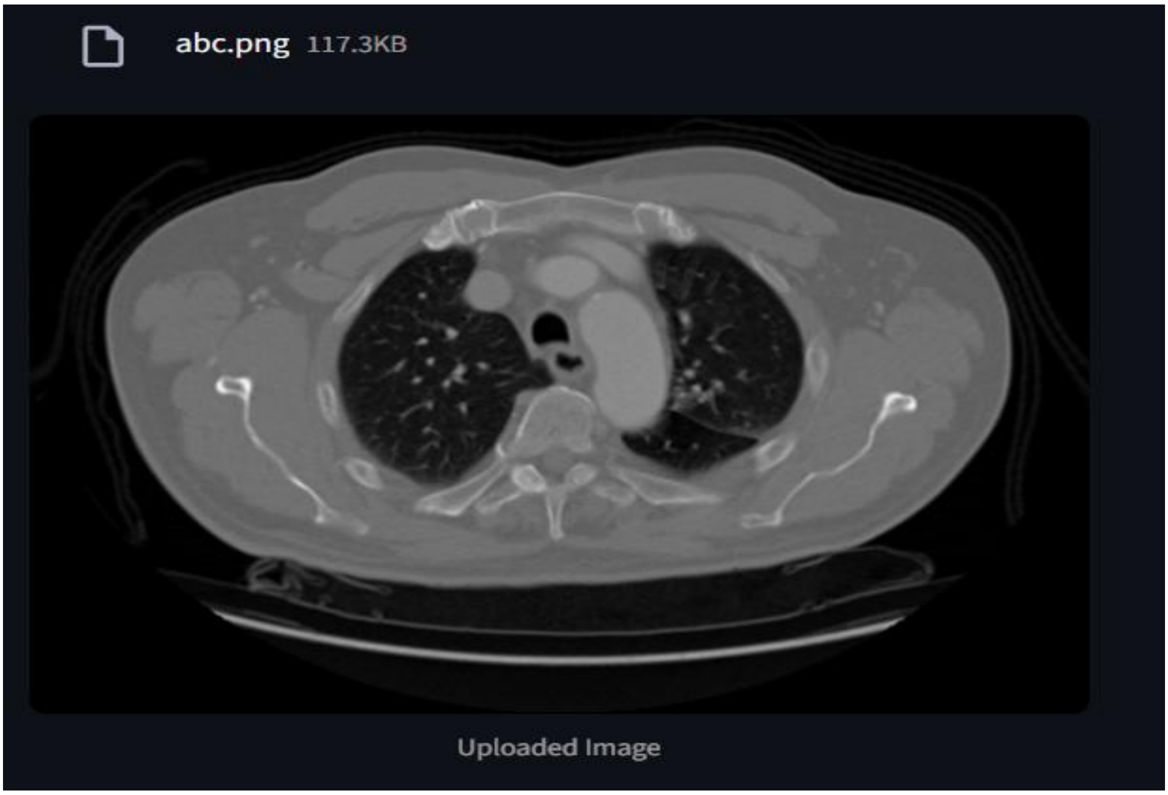

Figure 9 Uploaded lung image displayed.

Once a user uploads an image, it is displayed on the interface. This provides a visual confirmation of the selected image before the system performs classification, ensuring the correct input is processed.

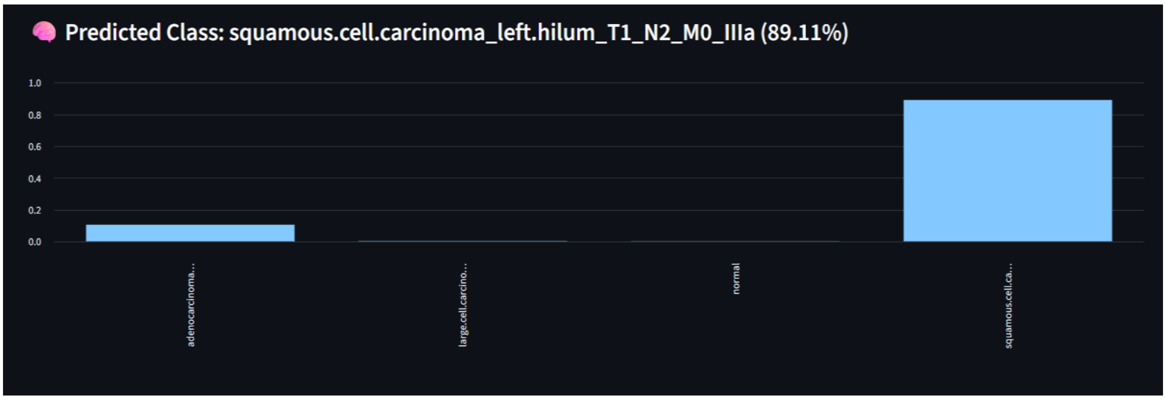

Figure 10Predicted class and probability of the uploaded lung image.

After processing the uploaded image through the trained model, the system predicts the most likely class (Normal, Adenocarcinoma, Large Cell Carcinoma, or Squamous Cell Carcinoma) and displays the associated probability score. This helps users understand the model's confidence in its prediction.

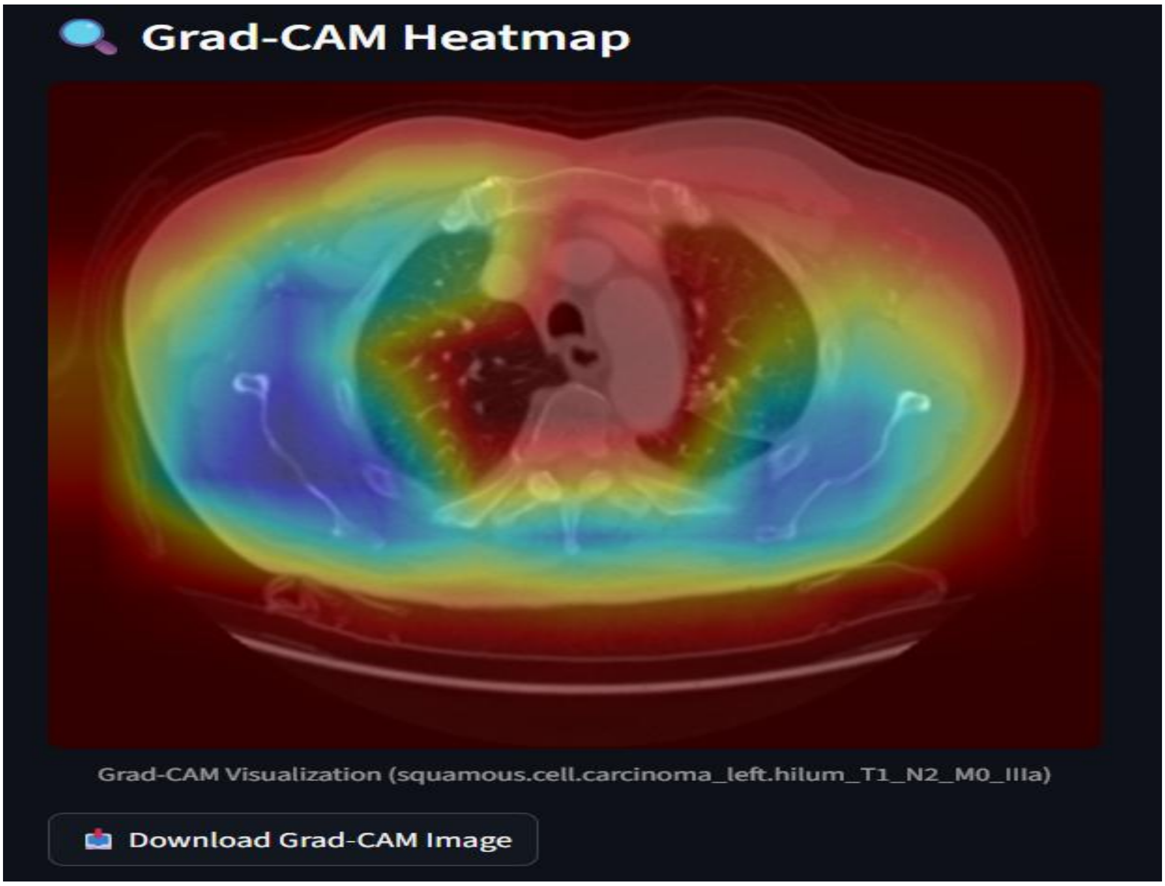

Figure 11Grad CAM heatmap on lung image.

Grad CAM heatmap overlaid on the uploaded lung CT/X ray image, highlighting regions that contributed most to the model's prediction. This visualization helps in understanding which areas of the image influenced the model's diagnostic decision, enhancing interpretability and trust in the results.

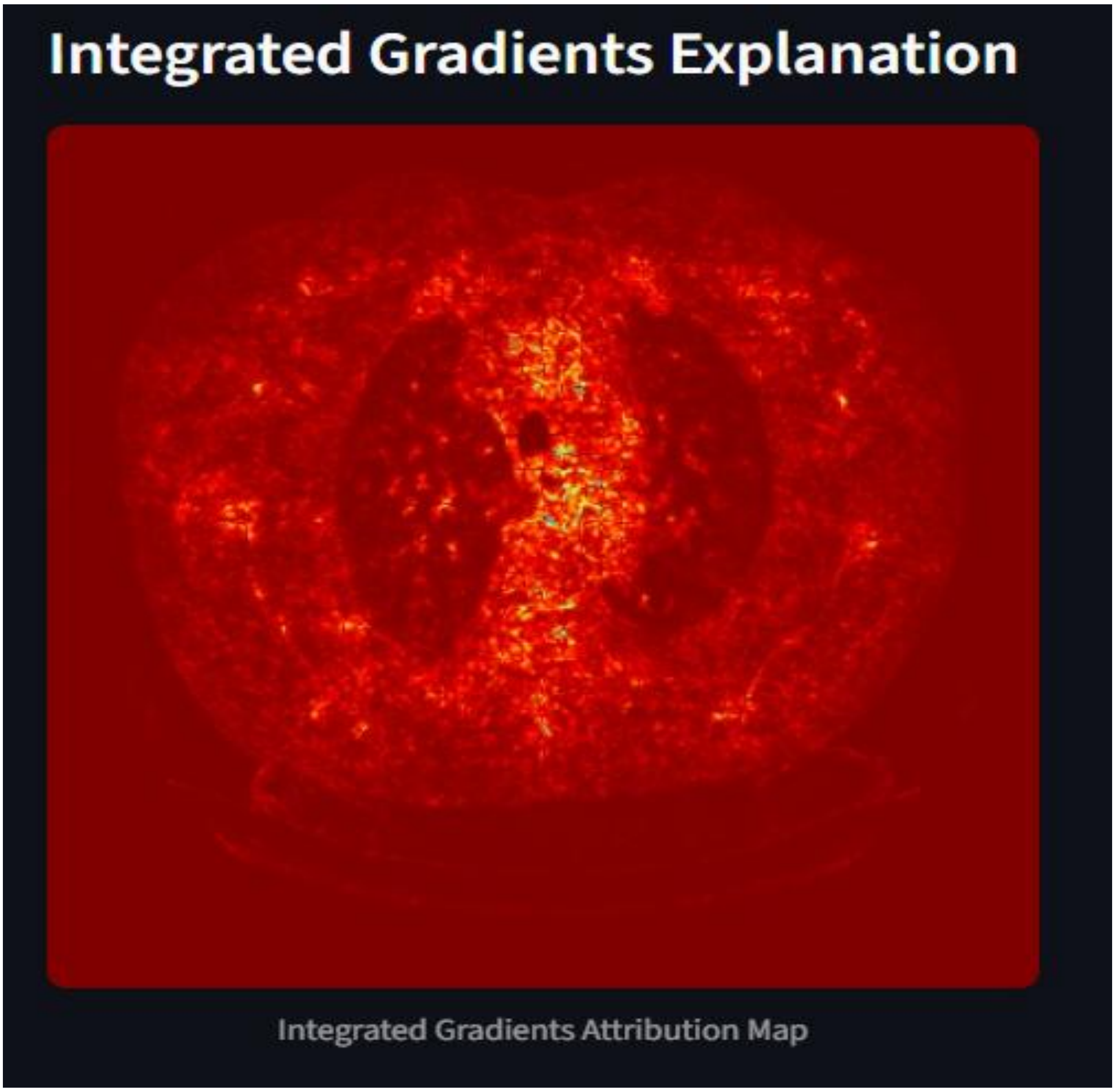

Figure 12Integrated Gradients map.

Integrated Gradients attribution map illustrating pixel level contributions that influenced the model’s prediction for the uploaded lung CT/X ray image. This visualization provides insights into how different regions of the image impact the model’s decision, aiding interpretability and highlighting critical areas associated with specific lung conditions.

CHAPTER 7

7. RESULT AND DISCUSSION

7.1.RESULT

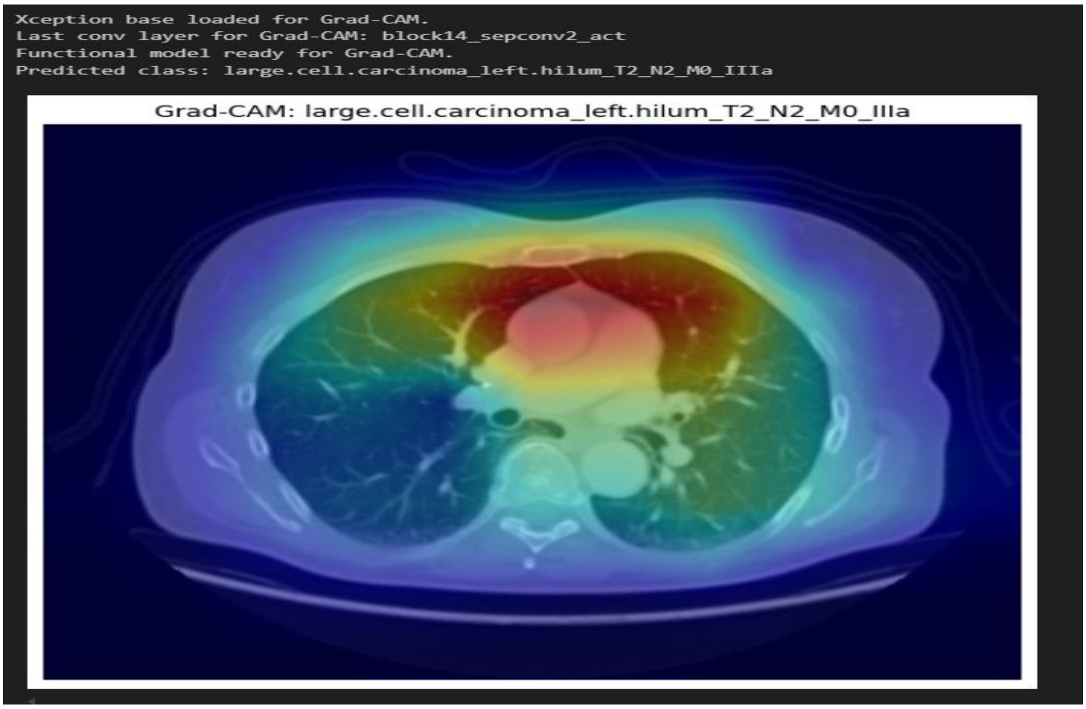

Figure 13Sample Grad Cam of large cell carcinoma

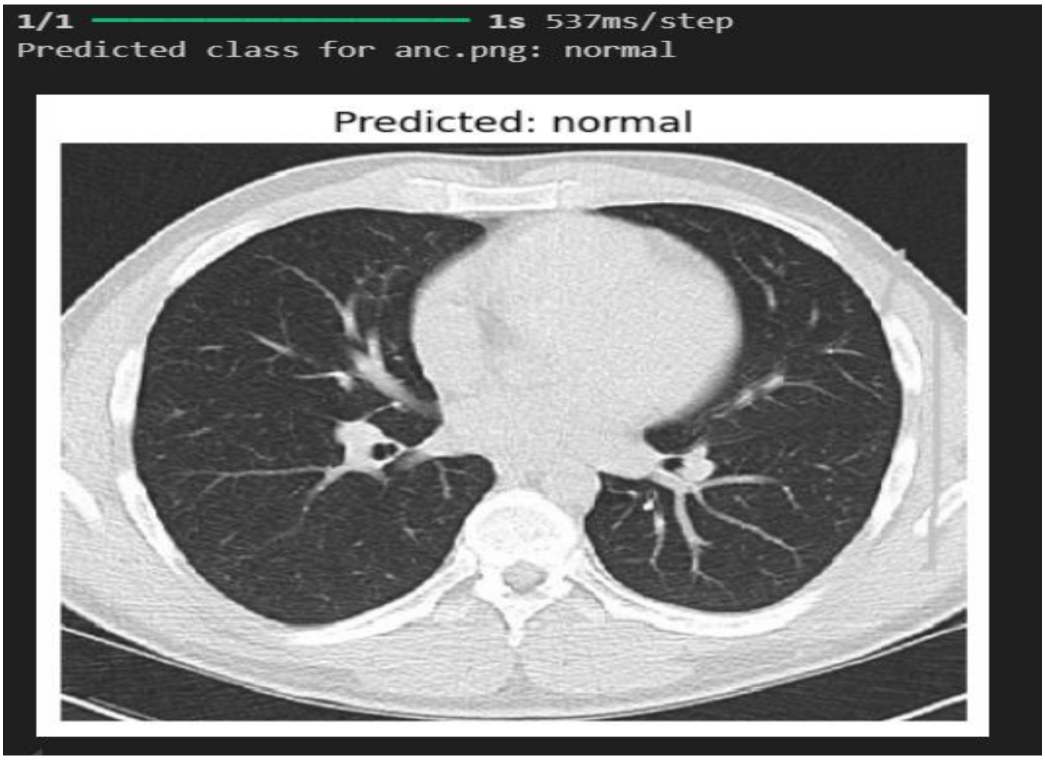

Figure 14Sample Prediction Class(Normal)

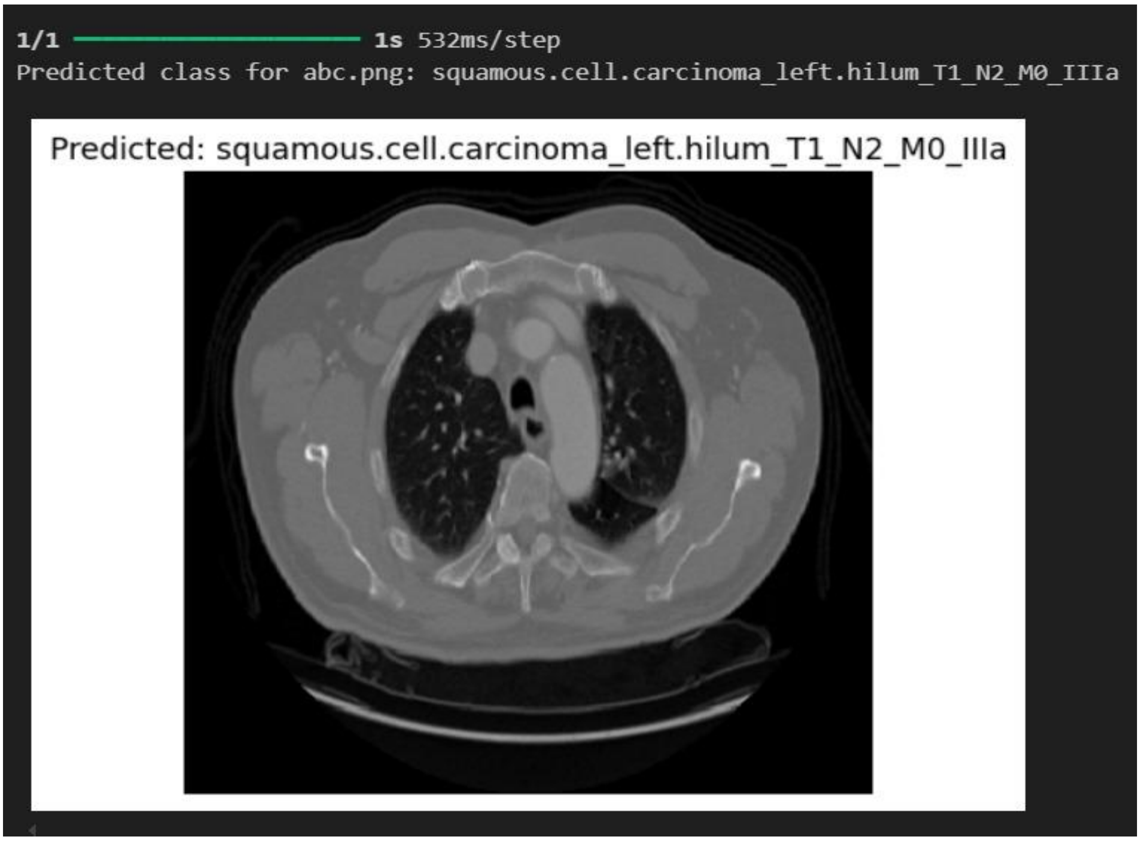

Figure 15Sample Prediction Class (Squamous Cell)

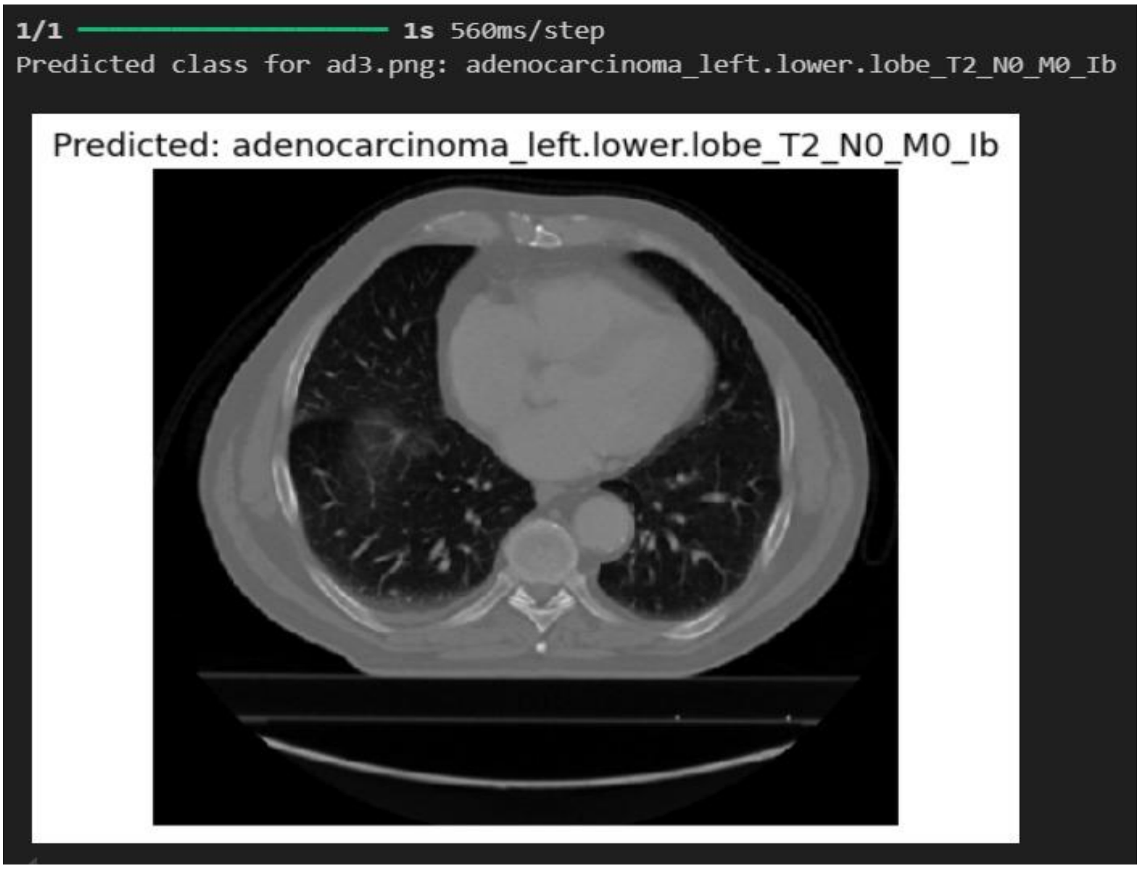

Figure 16Sample Prediction Class(Adenocarcinoma)

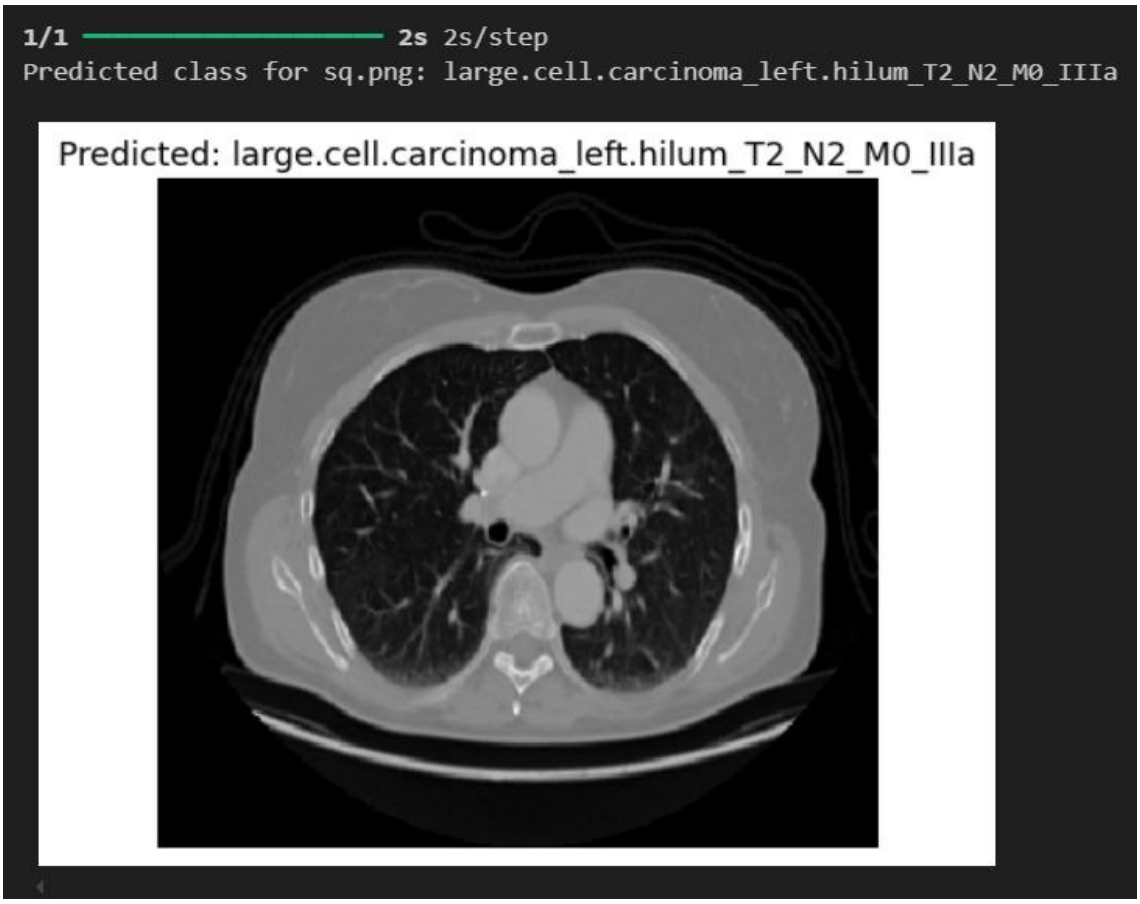

Figure 17Sample Prediction Class(Large Cell Carcinoma)

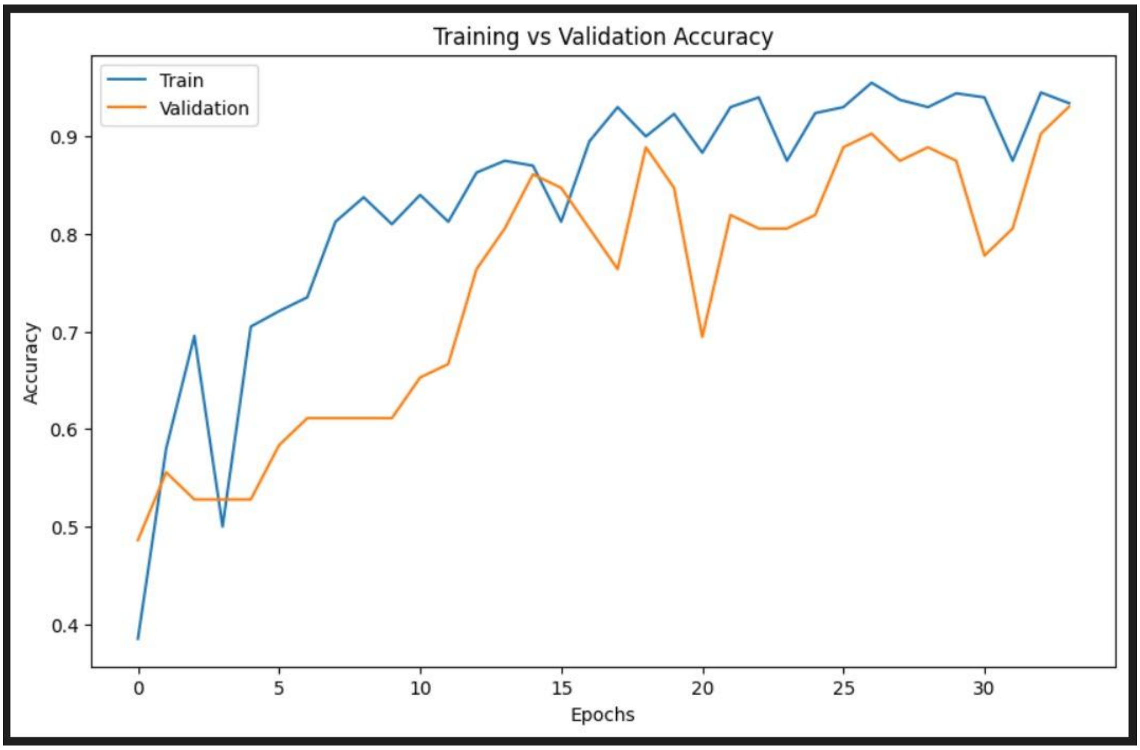

Figure 18Training vs Validation Accuracy

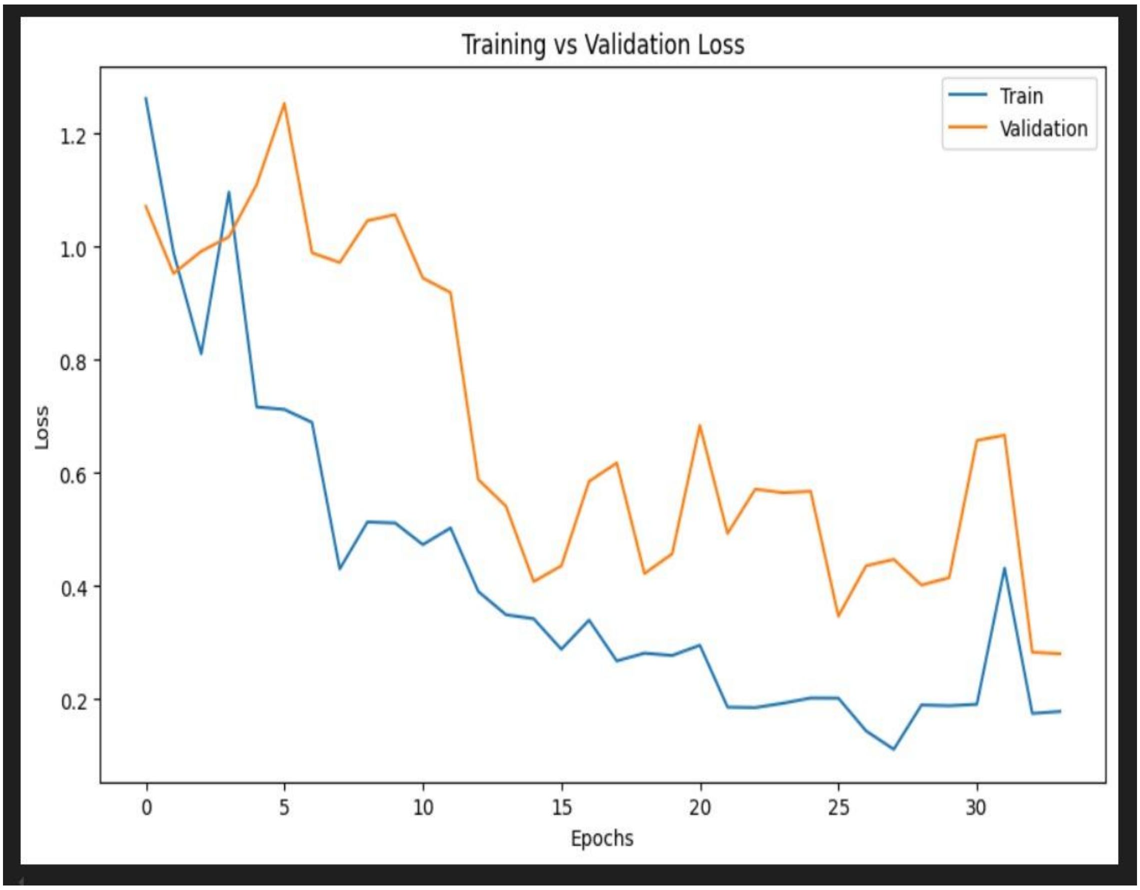

Figure 19Training vs Validation Loss

```
Found 613 files belonging to 4 classes.
Found 72 files belonging to 4 classes.
Found 315 files belonging to 4 classes.
Model: "functional"
```

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 350, 350, 3)	0
xception (Functional)	(None, 11, 11, 2048)	20,861,480
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0
dense (Dense)	(None, 4)	8,196

```
Total params: 35,538,822 (135.57 MB)
Trainable params: 7,334,572 (27.98 MB)
Non-trainable params: 13,535,104 (51.63 MB)
Optimizer params: 14,669,146 (55.96 MB)
```

Figure 20Layer Level and Parameter Classification

Table 4Model Performance Metrics

Metric	Training Set	Validation Set	Test Set	Interpretation
Accuracy	99.18%	88.89%	83.81%	High training accuracy; reasonable generalization. Slight overfitting present.
Precision	99.19%	88.92%	87.52%	Model predicts positives reliably; fewer false positives.
Recall	99.18%	88.89%	83.81%	Captures most actual positive cases; slight misses on test set.
F1 Score	99.18%	88.88%	84.25%	Balances precision and recall; good overall predictive ability.
Loss	0.04%	0.30%	0.41%	Very low loss indicates predictions closely match true labels.

7.2. DISCUSSION

- The proposed Explainable Deep Learning Framework for Early Detection of Lung Cancer was implemented using transfer learning with the Xception Convolutional Neural Network (CNN) architecture. The model was trained on a labelled CT scan dataset comprising four classes Normal, Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma. The dataset was divided into training, validation, and testing subsets to evaluate performance consistency and avoid overfitting.
- Comprehensive data augmentation techniques such as rotation, flipping, scaling, and contrast adjustments were applied to enhance dataset diversity and improve model generalization. Additionally, k fold cross validation was conducted to ensure that the reported metrics were not dependent on a specific data split.
- The Xception model demonstrated strong learning capability during training, achieving an overall training accuracy of approximately 99.18 % and a validation accuracy of 88.89 %. The performance was further assessed using precision, recall, F1 score, and overall accuracy to provide a balanced evaluation of classification performance across all classes.
- To interpret the model's decisions and enhance transparency, Explainable AI (XAI) tools were integrated. The Grad CAM visualizations successfully highlighted the discriminative lung regions contributing to each prediction, clearly indicating the presence of malignant patterns in the carcinoma classes. These heatmaps enabled clinicians to visually validate whether the network's focus aligned with known diagnostic regions.
- Further, SHAP (SHapley Additive exPlanations) analysis provided a quantitative understanding of pixel level importance by assigning contribution

values to each input region. SHAP plots revealed how subtle textural and density variations influenced the model's decisions, reinforcing the interpretability of the framework.

- Overall, the combination of Xception's deep feature extraction and explainable AI methods resulted in a model that not only achieved high diagnostic performance but also offered interpretability and clinical trust. The integration of a web based interface enabled real time visualization of both classification outcomes and corresponding explanation maps, making the system practical for use in medical environments.
- In conclusion, the proposed framework demonstrates the potential of explainable deep learning for accurate and transparent lung cancer detection, paving the way for clinically reliable AI assisted diagnostics.

CHAPTER 8

8. CONCLUSION

- This project presented an Explainable Deep Learning Framework for Early Detection of Lung Cancer that combines the power of deep neural networks with the transparency required for clinical decision making. By leveraging transfer learning using the Xception Convolutional Neural Network (CNN) architecture, the system efficiently extracted high level features from CT scan images to classify them into four diagnostic categories: Normal, Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma.
- To ensure model robustness, extensive data augmentation and cross validation techniques were employed to address overfitting and enhance generalization to unseen data. The model achieved strong predictive performance, demonstrating its potential to assist radiologists in accurately identifying early signs of lung cancer.
- A key contribution of this framework lies in its explainability. Through Grad CAM heatmaps and SHAP visualizations, the system provides both visual and quantitative explanations of its predictions. These explainability tools make it possible to verify whether the model's focus areas correspond to clinically relevant lung regions, thereby enhancing trust and interpretability two critical requirements for AI adoption in healthcare.
- Furthermore, the implementation of a web based interface allows clinicians to upload CT scans, view automated classification results, and visualize AI generated explanations in real time. This user centric design bridges the gap between complex deep learning algorithms and practical clinical use.
- In conclusion, the proposed framework demonstrates that integrating Explainable AI with deep learning can significantly improve the transparency, reliability, and usability of automated lung cancer detection systems. Future extensions may include incorporating multimodal clinical data such as patient history, genomic information, and biomarkers to achieve a more comprehensive and precise diagnostic model. Ultimately, this work contributes to advancing trustworthy AI in medical imaging, paving the way toward early detection and improved patient outcomes.

CHAPTER 9

9. REFERENCES

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APPENDIX A – SAMPLE CODE

A.1 LIBRARIES AND DEPENDENCIES

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import tensorflow as tf

from tensorflow.keras.preprocessing.image import ImageDataGenerator, load_img,
img_to_array

from tensorflow.keras.models import Model, load_model

from tensorflow.keras.layers import GlobalAveragePooling2D, Dense

from tensorflow.keras.optimizers import Adam

from tensorflow.keras.callbacks import ModelCheckpoint, ReduceLROnPlateau,
EarlyStopping

from sklearn.utils.class_weight import compute_class_weight

from sklearn.metrics import confusion_matrix, classification_report

import cv2
```

A.2 DATASET PATHS AND PARAMETERS

```
train_folder = '/content/drive/MyDrive/dataset/train'

validate_folder = '/content/drive/MyDrive/dataset/valid'

test_folder = '/content/drive/MyDrive/dataset/test'

IMAGE_SIZE = (350, 350)

BATCH_SIZE = 8
```

A.3 DATA GENERATORS

```
train_datagen = ImageDataGenerator(

    rescale=1./255, horizontal_flip=True, rotation_range=20,

    width_shift_range=0.2, height_shift_range=0.2, zoom_range=0.2,

    brightness_range=[0.8,1.2])

test_datagen = ImageDataGenerator(rescale=1./255)
```

```
train_generator = train_datagen.flow_from_directory(
    train_folder, target_size=IMAGE_SIZE, batch_size=BATCH_SIZE,
class_mode='categorical'
)
validation_generator = test_datagen.flow_from_directory(
    validate_folder, target_size=IMAGE_SIZE, batch_size=BATCH_SIZE,
class_mode='categorical'
)
class_labels = list(train_generator.class_indices.keys())
OUTPUT_SIZE = len(class_labels)
```

A.4 MODEL DEFINITION (XCEPTION BASED)

```
pretrained_model = tf.keras.applications.Xception(
    weights='imagenet', include_top=False, input_shape=(*IMAGE_SIZE,3)
)
pretrained_model.trainable = True
for layer in pretrained_model.layers[: 20]:
    layer.trainable = False
inputs = tf.keras.Input(shape=(*IMAGE_SIZE,3))
x = pretrained_model(inputs, training=False)
x = GlobalAveragePooling2D()(x)
outputs = Dense(OUTPUT_SIZE, activation='softmax')(x)
model = Model(inputs=inputs, outputs=outputs)
model.compile(optimizer=Adam(1e 4), loss='categorical_crossentropy',
metrics=['accuracy'])
```

A.5 CLASS WEIGHTS AND CALLBACKS

```
class_weights = compute_class_weight(
    'balanced', classes=np.arange(OUTPUT_SIZE), y=train_generator.classes
)
class_weight_dict = dict(enumerate(class_weights))
callbacks = [
```

```
    ReduceLROnPlateau(monitor='loss', patience=5, factor=0.5, min_lr=1e 6, verbose=2),
    EarlyStopping(monitor='loss', patience=6, verbose=2),
    ModelCheckpoint('best_model.keras', save_best_only=True, verbose=2)
]
```

A.6 MODEL TRAINING

```
history = model.fit(
    train_generator, steps_per_epoch=25, epochs=50,
    validation_data=validation_generator, validation_steps=20,
    class_weight=class_weight_dict, callbacks=callbacks
)
model.save('/content/drive/MyDrive/dataset/trained_lung_cancer_model.keras')
```

A.7 PREDICTION Function

```
def predict_image(img_path, model, IMAGE_SIZE, class_labels):
    img = load_img(img_path, target_size=IMAGE_SIZE)
    img_array = np.expand_dims(img_to_array(img)/255.0, axis=0)
    preds = model.predict(img_array)
    predicted_class = class_labels[np.argmax(preds[0])]
    print(f"Image {img_path} belongs to class: {predicted_class}")
    plt.imshow(img)
    plt.title(f"Predicted: {predicted_class}")
    plt.axis('off')
    plt.show()
```

A.8 GRAD CAM VISUALIZATION

```
last_conv_layer = model.get_layer('xception')  # Xception base
def display_gradcam(img_path, model, last_conv_layer, class_labels, IMAGE_SIZE=(350,350), alpha=0.4):
    img = load_img(img_path, target_size=IMAGE_SIZE)
    img_array = np.expand_dims(img_to_array(img)/255.0, axis=0)
```

```
grad_model = tf.keras.models.Model(
    inputs=model.input,
    outputs=[last_conv_layer.output, model.output]
)
with tf.GradientTape() as tape:
    conv_outputs, preds = grad_model(img_array)
    pred_index = tf.argmax(preds[0])
    class_channel = preds[:, pred_index]
grads = tape.gradient(class_channel, conv_outputs)
pooled_grads = tf.reduce_mean(grads, axis=(0,1,2))
heatmap = tf.reduce_sum(tf.multiply(pooled_grads, conv_outputs[0]), axis= 1)
heatmap = np.maximum(heatmap,0)/np.max(heatmap)
img_orig = cv2.imread(img_path)
img_orig = cv2.resize(img_orig, IMAGE_SIZE)
heatmap = cv2.resize(heatmap, (img_orig.shape[1], img_orig.shape[0]))
heatmap = np.uint8(255*heatmap)
heatmap = cv2.applyColorMap(heatmap, cv2.COLORMAP_JET)
superimposed_img = cv2.addWeighted(img_orig,1 alpha,heatmap,alpha,0)
plt.imshow(cv2.cvtColor(superimposed_img, cv2.COLOR_BGR2RGB))
plt.axis('off')
plt.title(f"Grad CAM: {class_labels[pred_index.numpy()]}")
plt.show()
```

A.9 EVALUATION METRICS

```
val_preds = model.predict(validation_generator)
val_preds_classes = np.argmax(val_preds, axis=1)
cm = confusion_matrix(validation_generator.classes, val_preds_classes)
print(classification_report(validation_generator.classes, val_preds_classes, target_names=class_labels))
```