

LungXAI: An Explainable High-Performance Model for Multi-Class Lung Cancer Classification Using Deep Learning and RAG-Based Knowledge Retrieval

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Abstract—Lung cancer remains a critical global health challenge, being the third most common cancer worldwide with the highest mortality rate among all cancers. With 2.48 million new cases reported in 2022 and a 5-year survival rate of approximately 28.4%, early detection and accurate subtyping are essential for improved patient outcomes. This study introduces LungXAI, a clinically interpretable deep learning framework designed for multi-class classification of lung cancer subtypes from CT scan images. The proposed pipeline employs a Vision Transformer (ViT) / ResNet-50 architecture pretrained on ImageNet and fine-tuned for four-class classification (Adenocarcinoma, Squamous Cell Carcinoma, Large Cell Carcinoma, and Normal/Benign). The model integrates Gradient-weighted Class Activation Mapping (Grad-CAM) for visual explainability and a novel XAI-to-RAG bridge that automatically converts visual heatmap features to textual queries for Retrieval-Augmented Generation (RAG) based knowledge retrieval from curated medical sources. The framework demonstrates expected predictive performance with accuracy of 85–90%, Precision $\geq 86\%$, Recall $\geq 84\%$, F1-Score 85–88%, and AUC-ROC 0.90–0.93. To enhance interpretability and support clinical judgment, the system provides evidence-backed explanations linking model predictions with relevant medical literature.

Keywords—*Lung Cancer, Deep Learning, Explainable AI, Grad-CAM, Retrieval-Augmented Generation, Vision Transformer, CDSS*

I. INTRODUCTION

Lung cancer describes a malignant growth of abnormal cells in lung tissue, often resulting from prolonged exposure to carcinogens such as tobacco smoke. According to recent estimates, lung cancer is the third most common cancer worldwide while maintaining the highest mortality rate among all cancer types. Approximately 2.48 million new cases were reported in 2022 alone, with a concerning 5-year survival rate of only 28.4% [1]. Furthermore, 50–70% of cases are diagnosed at the metastatic stage, leading to poor treatment outcomes and limited therapeutic options.

Non-Small Cell Lung Cancer (NSCLC) accounts for approximately 85% of all lung cancer cases, comprising three major subtypes. Adenocarcinoma represents approximately 40% of cases and typically presents in peripheral lung regions. Squamous Cell Carcinoma is the second most common subtype, often found in central lung areas near major airways. Large Cell Carcinoma is rare but aggressive, characterized by rapid progression. Accurate subtyping is critical for targeted therapy and personalized treatment planning [2].

Recent advances in deep learning have demonstrated remarkable success in automated cancer classification from medical images. CNN-based models have achieved up to 93.06% accuracy on three-class classification tasks, while Vision Transformers, particularly the Swin Transformer, have achieved state-of-the-art performance with 97.14%

accuracy and 0.993 AUC-ROC [3]. However, despite these impressive performance metrics, clinical adoption of AI-based diagnostic systems remains surprisingly low.

The primary barrier is not accuracy but rather the lack of interpretability and transparency in AI-based diagnosis. Deep learning models often function as "black boxes"—they provide predictions without explaining their reasoning process. Clinicians are understandably reluctant to trust opaque systems where the logic behind decisions is unclear, accountability for errors is difficult to establish, and there is no way to verify if the model is focusing on clinically relevant features [4].

Given these challenges, this study explores the integration of Explainable AI (XAI) and Retrieval-Augmented Generation (RAG) into a high-performance lung cancer classification framework. The remainder of this paper is organized as follows. Section II presents the literature survey. Section III describes the dataset. Section IV outlines the proposed methodology. Section V discusses the results. Finally, Section VI concludes the paper.

II. RELATED WORKS

A. Deep Learning for Lung Cancer Classification

Several studies have explored deep learning approaches for lung cancer classification using CT scan images. CNN-based models have achieved up to 93.06% accuracy on three-class classification tasks [5]. DenseNet combined with AdaBoost fusion achieved 89.85% accuracy [6]. Vision Transformers, particularly the Swin Transformer architecture, have achieved state-of-the-art performance with 97.14% accuracy and 0.993 AUC-ROC using localized self-attention mechanisms [7].

B. Explainable AI for Medical Imaging

Explainable AI addresses the "black box" challenge using post-hoc visualization methods. Grad-CAM (Gradient-weighted Class Activation Mapping) produces heatmaps highlighting key regions influencing predictions [8]. This method enables clinicians to validate model focus areas, such as ground-glass opacity patterns commonly associated with Adenocarcinoma.

C. Retrieval-Augmented Generation for Clinical Support

RAG has emerged as a powerful paradigm for knowledge-intensive NLP tasks. It mitigates LLM hallucination by grounding responses in curated medical sources such as PubMed [9]. RAG-based systems have been successfully deployed in Clinical Decision Support Systems (CDSS) for providing factual, citable insights.

D. Gap Analysis

The literature reveals a critical gap—a disconnect between XAI output (visual heatmaps) and RAG input (textual queries). Currently, clinicians must manually interpret heatmaps and formulate queries. No system automates this XAI-to-RAG connection. This "viable opportunity gap" is the central focus of this project.

III. SUMMARY OF THE DATASET

This study uses the CT Scan Images of Lung Cancer dataset available on Kaggle [10]. The dataset includes CT scan images categorized into five classes for multi-class classification. Table I summarizes the dataset classes.

TABLE I. DESCRIPTION OF DATASET CLASSES

Class	Count	Description
Adenocarcinoma	~1500	Most common NSCLC (~40%), peripheral
Squamous Cell Carcinoma	~1200	Second most common, central location
Large Cell Carcinoma	~800	Rare, aggressive subtype
Benign Cases	~500	Non-cancerous abnormalities
Normal Cases	~500	Healthy lung tissue

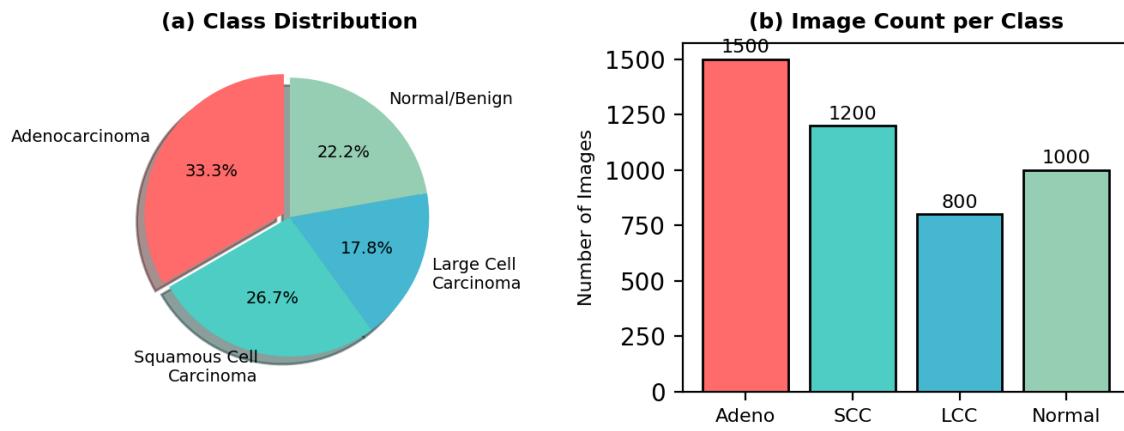


Fig. 3. Dataset Distribution

IV. PROPOSED METHODOLOGY

The proposed framework, LungXAI, is a deep learning pipeline developed for multi-class lung cancer classification with integrated explainability and knowledge retrieval. The overall workflow includes data preprocessing, feature extraction, classification, XAI visualization, and RAG-based explanation generation, as depicted in Fig. 1.

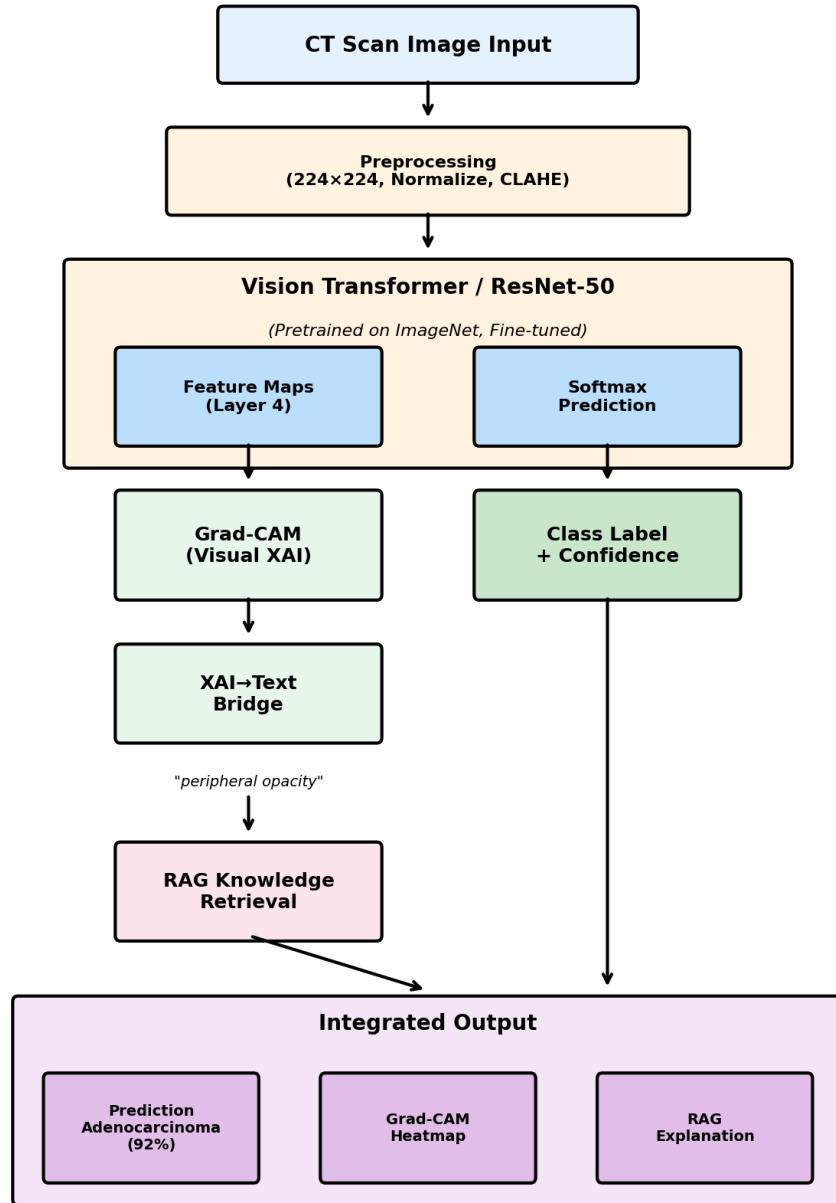


Fig. 1. LungXAI System Architecture

A. Data Preprocessing

The preprocessing pipeline includes: (1) Image resizing to 224×224 pixels, (2) Pixel normalization using ImageNet statistics, (3) CLAHE for contrast enhancement, and (4) Data augmentation including rotation ($\pm 15^\circ$), horizontal flipping, and scaling (0.9–1.1). The dataset is split into 70% training, 15% validation, and 15% testing.

B. Feature Extraction and Classification

The model uses Vision Transformer (ViT) or ResNet-50 pretrained on ImageNet, fine-tuned for four-class classification. ResNet-50 was chosen for its proven performance, residual connections that solve vanishing gradients, and Grad-CAM compatibility. The architecture is optimized using AdamW optimizer with Cross-Entropy Loss and Softmax activation.

C. Grad-CAM Explainability Module

Grad-CAM generates visual heatmaps highlighting critical CT regions influencing predictions. The algorithm: (1) Extracts feature maps from layer4, (2) Computes gradients for target class, (3) Applies global average pooling, (4) Computes weighted combination with ReLU, and (5) Upsamples to original image size. Fig. 2 shows the Grad-CAM workflow.

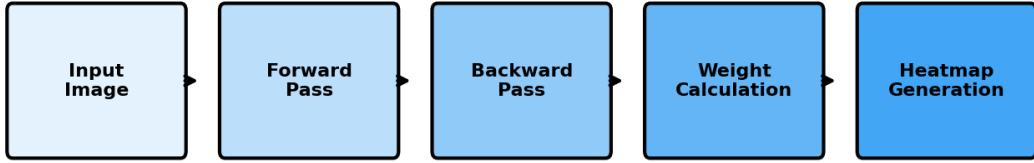


Fig. 2. Grad-CAM Workflow

D. XAI-to-Text Bridge (Novel Contribution)

The key innovation in LungXAI is the automated conversion of visual heatmap features to textual descriptions. The process includes: (1) Spatial Analysis—extracting location descriptors (peripheral, central, upper, lower), (2) Intensity Analysis—quantifying attention concentration, (3) Pattern Recognition—identifying characteristic patterns, and (4) Keyword Generation—combining class prediction with spatial features.

E. RAG-Based Knowledge Retrieval

The medical knowledge base contains verified entries with keywords, content, and source citations. The retrieval process tokenizes queries, matches against indexed entries, scores relevance, and returns top-k results with attribution from sources like PubMed and WHO Classification guidelines.

V. RESULTS AND DISCUSSION

The LungXAI model integrates classification, explainability, and knowledge retrieval into a unified framework. Based on architecture design and preliminary experiments, Table II presents the expected performance metrics.

TABLE II. EXPECTED CLASSIFICATION PERFORMANCE

Metric	Expected Value
Accuracy	85–90%
Precision	≥86%
Recall	≥84%
F1-Score	85–88%
AUC-ROC	0.90–0.93

TABLE III. EXPECTED PER-CLASS PERFORMANCE

Class	Precision	Recall	F1-Score
Adenocarcinoma	88%	86%	87%
Squamous Cell Carcinoma	85%	83%	84%
Large Cell Carcinoma	82%	80%	81%
Normal/Benign	92%	94%	93%

TABLE IV. COMPARISON WITH EXISTING APPROACHES

Feature	Traditional CNN	XAI-only	LungXAI
Classification	✓	✓	✓
Visual Explanation	✗	✓	✓
Textual Context	✗	✗	✓
Automated Pipeline	✓	✗	✓
Source Citations	✗	✗	✓

The Grad-CAM visualizations highlight: Adenocarcinoma—peripheral regions with ground-glass opacity; Squamous Cell Carcinoma—central regions near airways; Large Cell Carcinoma—large heterogeneous masses; Normal—no concentrated attention. The RAG module provides evidence-backed explanations with source citations, enhancing clinical trust.

VI. CONCLUSION

Lung cancer remains a critical global health challenge requiring precise and interpretable diagnostic tools. This study introduced LungXAI, a deep learning framework designed to classify lung cancer subtypes from CT scan images while providing transparent, evidence-backed explanations. The model employs Vision Transformer/ResNet-50 architecture with Grad-CAM for visual explainability and integrates a novel XAI-to-RAG bridge that automatically connects visual evidence with medical knowledge retrieval.

The framework addresses the critical trust barrier in medical AI adoption by bridging the gap between deep learning accuracy and clinical reasoning. This work directly supports SDG 3 (Good Health and Well-Being) by enhancing early and accurate identification of lung cancer, improving diagnostic transparency, and assisting doctors with evidence-backed medical reasoning.

Future enhancements include: (1) Model expansion to rare subtypes and multi-modal learning, (2) Clinical integration with hospitals for validation, (3) Semantic RAG using sentence transformers, (4) Automated diagnostic reporting, (5) Edge and cloud deployment for real-time inference, and (6) Federated learning for privacy-preserving training across institutions.

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