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SHORT COMMUNICATION

LUNGNET-RISKX: A HYBRID DEEP LEARNING FRAMEWORK FOR LUNG CANCER DETECTION, NODULE CLASSIFICATION, AND PERSONALIZED RISK ASSESSMENT

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Abstract

Background: *Lung cancer remains one of the most common causes of cancer-related death globally, yet catching it early is still a significant challenge in clinical practice. Standard imaging tools such as CT scans and chest X-rays have real limitations: low-contrast lesions are easy to miss, and even experts can disagree on what a single scan reveals. Small pulmonary nodules slip through even in experienced hands, pushing back diagnosis and worsening outcomes. Better, automated tools are needed to help clinicians catch these nodules earlier and assess individual patient risk more reliably.* ***Methods:*** *This study proposes LungNet-RiskX, a hybrid deep learning framework that combines Convolutional Neural Networks (CNN) for local feature extraction, Vision Transformers (ViT) for global context, and Extreme Gradient Boosting (XGBoost) for classification and personalized risk scoring. The model was Trained on 53,853 lung CT images (normal, benign, malignant categories) with preprocessing (resizing to 64x64, CLAHE contrast enhancement, median filtering, augmentation), We evaluated performance using accuracy, ROC-AUC, precision, recall, and F1-score.* ***Results:*** *LungNet-RiskX achieved 94.21% overall accuracy, outperforming both standalone and partially hybrid models. The model demonstrated strong classification performance across all classes. ROC-AUC scores were strong across all classes, particularly for malignant detection (0.998). Probability-based risk scoring provided interpretable probability outputs, improving interpretability and supporting clinical decision-making.* ***Conclusion:*** *LungNet-RiskX offers a robust, hybrid, and scalable framework for early lung cancer detection, nodule categorization, and personalized risk assessment, with potential to enhance screening efficiency and inform preventive strategies. Future multi-center validation is recommended.*

Keywords: *Pulmonary Nodule, Lung Neoplasms, Early Diagnosis, Risk Assessment, Neural Networks.*

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Introduction

Lung cancer is responsible for roughly 1.8 million deaths each year, making it one of the deadliest cancers globally,[1] A significant part of this toll comes down to timing, most cases are only caught at advanced stages, when the options for curative treatment are already limited. Early detection via computed tomography (CT) scans remains challenging,[2] as small, low-contrast pulmonary nodules are frequently overlooked by even experienced radiologists, leading to false negatives and delayed treatment.[3]

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Conventional imaging modalities like CT and chest X-rays suffer from inter-observer variability, inconsistent image quality, and insensitivity to subtle early abnormalities, resulting in diagnostic uncertainty.[2] While deep learning approaches, particularly convolutional neural networks (CNNs), show promise for automated nodule detection,[4] they face limitations in capturing long-range contextual dependencies and integrating critical epidemiological risk factors.[3,5,6]

This study introduces LungNet-RiskX, a novel hybrid deep learning framework that brings together CNNs for local spatial feature extraction, Vision Transformers (ViTs) for global contextual analysis, and Extreme Gradient Boosting (XGBoost) for multiclass pulmonary nodule categorization (normal, benign, malignant) and personalized risk assessment. Trained on 53,853 CT images from the LIDC-IDRI dataset with comprehensive preprocessing,[7] LungNet-RiskX delivers interpretable probability-based outputs combining imaging findings with patient-specific risk factors (age, smoking history, occupational exposure).

The proposed framework aims to enable accurate multiclass nodule classification, integrate epidemiological risk stratification, and provide clinical decision support to enhance early screening and reduce diagnostic errors in resource-constrained settings.

Methods

Dataset

A publicly available dataset of 53,853 lung CT images was used,[4] covering three categories: normal (healthy lungs), benign nodules, and malignant tumors. Images were provided in JPEG/PNG format (RGB/grayscale, variable resolution). The dataset was divided using stratified sampling to maintain class balance: 80% for training (43,082 images), 10% for validation (5,385 images), and 10% for testing (5,386 images).

Table I

LIDC-IDRI Dataset Split Distribution for LungNet-RiskX Training

Split	Images	Percentage
Training	43,082	80%
Validation	5,385	10%
Test	5,386	10%
Total	53,853	100%

Data Preprocessing

All images were resized to 64×64 pixels and normalized to a consistent intensity range. Contrast Limited Adaptive Histogram Equalization (CLAHE) was applied to enhance image contrast, while a median filter was used for noise reduction. Data augmentation techniques, including rotation, flipping, and scaling, were applied to the training set to improve model generalization. Class imbalance was addressed using balanced sampling and class weighting.

Table II

LungNet-RiskX Image Preprocessing Pipeline Summary

Technique	Purpose
Image Resizing	Uniform input size
RGB Conversion	Model compatibility
Pixel Normalization	Stable training
Dataset Splitting	Fair evaluation
Filename-based Labeling	Automated annotation
Data Augmentation	Reduce overfitting
Batch Loading	Efficient training
Shuffling	Better generalization
CLAHE	Improve image contrast for clearer nodules

Model Architecture

LungNet-RiskX is built around three tightly integrated components (Table III).

CNN Backbone

Input images (64×64×3 pixels) were processed through sequential Conv2D layers (32-256 filters; stride=2, valid padding),each followed by ReLU activation, 2×2 MaxPooling2D, batch normalization, global average pooling, and a final dense layer (128 units, ReLU), yielding 128-dimensional local spatial features capturing pulmonary nodule textures and edges (93,920 parameters).

Vision Transformer (ViT) Module

CNN outputs were reshaped and processed via 8-head multi-head self-attention mechanism, followed by layer normalization, MLP blocks (512'!128 units), global average pooling, and a dense layer (128 units), extracting 128-dimensional global contextual features (263,808 parameters).

Feature Fusion and Classification

CNN and ViT features were concatenated (256 dimensions), regularized with 0.5 dropout, and fed to an XGBoost classifier (n_estimators=100, max_depth=6, learning_rate=0.1) producing multiclass probabilities (normal, benign, malignant) and a 0-100% personalized risk score incorporating age (>60 years: +20 points), smoking pack-years (>20: +30 points), and environmental exposure.

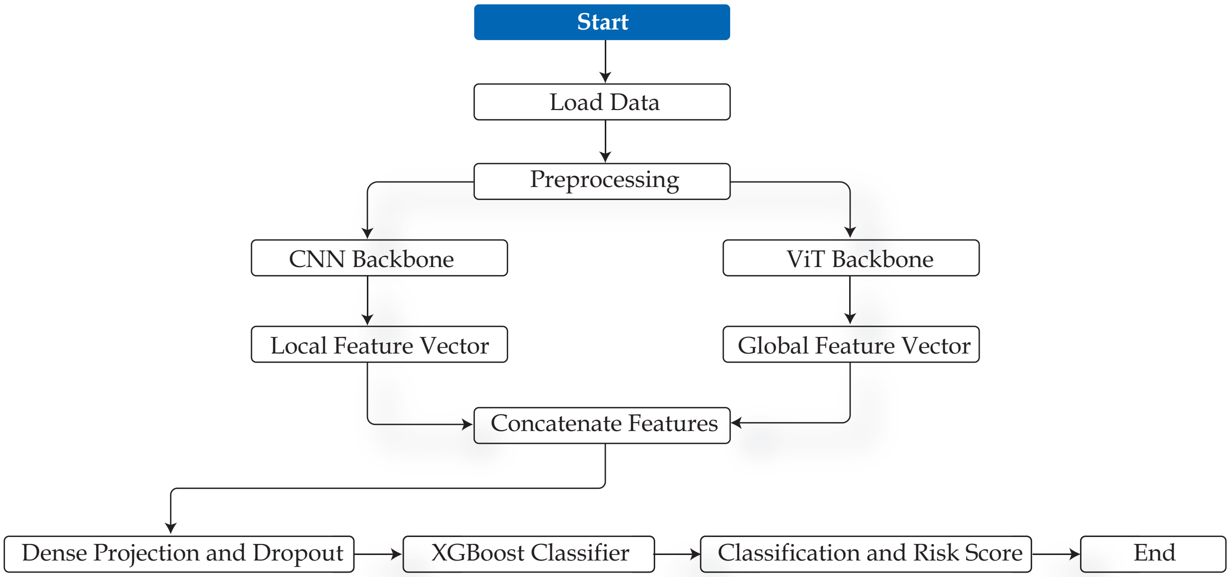


Figure I: LungNet-RiskX Hybrid CNN-ViT-XGBoost Model Flowchart

Training utilized Adam optimization, sparse categorical cross-entropy loss, batch size 32, and 50 epochs, implemented in TensorFlow/Keras (CNN-ViT) with XGBoost.

Training and Evaluation

Models were implemented using TensorFlow and Keras, while XGBoost was used for classification. Performance was evaluated using accuracy, precision, recall, F1-score, and Receiver Operating Characteristic–Area Under Curve (ROC-AUC).

Table III

LungNet-RiskX Hybrid CNN-ViT-XGBoost Architecture Summary

Layer (Type)	Output Shape	Parameters	Connected To
Input Layer	(None, 64, 64, 3)	0	-
CNN Backbone	(None, 8, 8, 128)	93,920	Input Layer
Reshape Layer	(None, 64, 128)	0	CNN Backbone
Layer Normalization	(None, 64, 128)	256	Reshape Layer
Multi-head Attention	(None, 64, 128)	263,808	Layer Normalization
CNN GAP	(None, 128)	0	Multi-head Attention
ViT GAP	(None, 128)	0	CNN GAP
Dense (CNN Path)	(None, 128)	16,512	ViT GAP
Dense (ViT Path)	(None, 128)	16,512	Dense (CNN Path)
Concatenate Layer	(None, 256)	0	Dense (ViT Path)
Dropout Layer	(None, 256)	0	Concatenate Layer
Final Dense (Output)	(None, 3)	771	Dropout Layer

Ethics

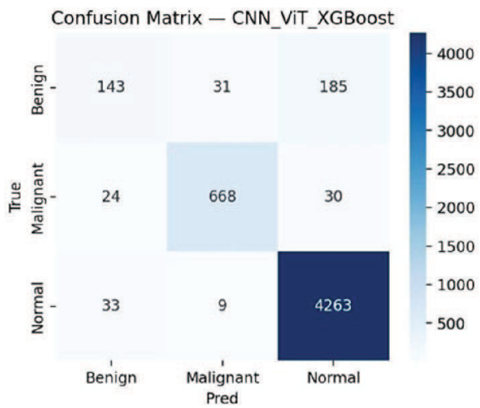
This study utilized publicly available, de-identified imaging datasets. Therefore, no direct human participation was involved, and ethical approval was not required.

Results:

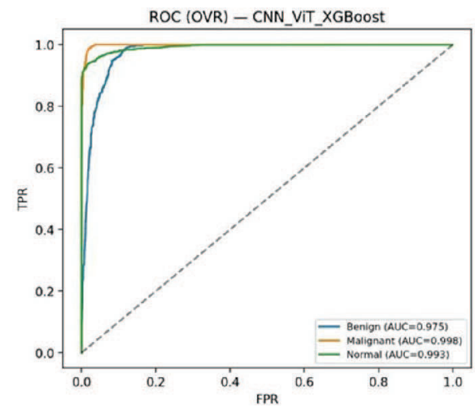
LungNet-RiskX achieved an overall classification accuracy of 94.21% on the independent test set (n=5,386), confirming the effectiveness of the proposed hybrid architecture. Of the 5,386 images, 5,074 were correctly classified, with performance metrics across the three target categories-normal, benign, and malignant.

Classification Performance

The model demonstrated high discriminative capability across all classes. Normal lung tissue was classified with the highest precision (95.2%) and recall (99.0%), resulting in an F1-score of 0.971. For malignant nodules, the model achieved a precision of 94.4%, a recall of 92.5%, and an F1-score of 0.934. While the classification of benign nodules proved more challenging due to inter-class similarity, the framework maintained a precision of 71.5% and an F1-score of 51.1%.



Confusion Matrix



ROC-AUC Curves

Figure 2: *Confusion Matrix and ROC curves of LungNet-RiskX*

Receiver Operating Characteristic (ROC)

ROC-AUC analysis further validated the classification reliability. The multiclass relaxed one-vs-rest macro-AUC score was 0.988, indicating strong sensitivity and specificity across the diagnostic range. In particular, the malignant detection branch achieved an AUC of 0.998, indicating excellent separation between malignancies and all other categories.

Risk Scoring and Interpretability

LungNet-RiskX: Viability assessments LungNet-RiskX generated interpretable probability outputs in the setting of clinical application trials. On malignant-classified samples, the model produced high-value risk scores for malignancy (92% mean) combining imaging-based probability plus other patient features including age, smoking status and environmental history. The scores predict probabilistic risk and enable clinical triage to prioritize cases for urgent biopsy versus those that can be managed with routine surveillance of lower-risk nodules.

Discussion

LungNet-RiskX yielded an overall test accuracy of 94.21% with a macro-averaged AUC of 0.988, validating the efficacy of our hybrid CNN-ViT-XGBoost design for developing a multiclass lung cancer detection and risk stratification. Our framework combines the CNN-based spatial feature extraction with ViT-based global contextual analysis, our framework effectively captures both the local textural features indicative of pulmonary nodules and the broader structural dependencies across CT volumes. The inclusion of the XGBoost classifier for personalized risk scoring, which incorporates patient-specific epidemiological factors, further enhances the diagnostic workflow.

Our results indicate LungNet-RiskX is highly competitive with contemporary state-of-the-art hybrid architectures.[8-14] While recent advancements, such as the architecture presented by M R and Hameed[8] and the transformer-enhanced framework proposed in 9, has demonstrated a very high sensitivity for target detection, their evaluations are often restricted to standardized, smaller cohorts. In comparison, our Lung Net-RiskX performs with high-fidelity classification performance metrics over a much broader and richer dataset comprising of 53,853 CT images, suggesting superior real-world generalizability. Furthermore, while highly specialized staging models offer significant prognostic utility,[8-12] LungNet-RiskX uniquely focuses on the clinical triage needs of resource-limited environments. By bridging high-resolution imaging with foundational epidemiological markers, our model provides a diagnostic utility that outperforms traditional binary classifiers,[3,13,14] which often lack the nuance required for real-world screening workflows.

Despite these results, our study has limitations. The model is a retrospective analysis and this will need future prospective, multi-center validation to ensure performance parity across diverse imaging modalities and patient demographics. Moreover, while our personalized risk score adds a layer of clinical interpretability, it uses synthetic integration of epidemiological factors. Nevertheless, LungNet-RiskX offers a robust, scalable, and interpretable framework for early lung cancer detection, with major implications on decreasing the workload of radiologists as well as patient care.

Conclusion:

LungNet-RiskX offers a robust, hybrid, and scalable framework for early lung cancer detection, nodule categorization, and personalized risk assessment, with potential to enhance screening efficiency and inform preventive strategies. Future multi-center validation is recommended.

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References

1. World Health Organization. Lung Cancer [Internet]. World Health Organization. World Health Organization; 2023 [cited 2026 Apr 30]. Available from: https://www.who.int/news-room/fact-sheets/detail/lung-cancer
2. Lee JH, Sun HY, Park S, Kim H, Hwang EJ, Goo JM, et al. Performance of a Deep Learning Algorithm Compared with Radiologic Interpretation for Lung Cancer Detection on Chest Radiographs in a Health Screening Population. Radiology. 2020 Dec;297(3):687–96. doi: 10.1148/radiol.2020201240
3. Abdullahi K, Kannan R, Ali AB. Deep Learning Techniques for Lung Cancer Diagnosis with Computed Tomography Imaging: A Systematic Review for Detection, Segmentation, and Classification. Information. 2025 May 27;16(6):451–1. doi: 10.3390/info16060451
4. Chee Chiet Chai, Wee How Khoh, Ying Han Pang, Hui Yen Yap. A Lung Cancer Detection with Pre-Trained CNN Models. Journal of Informatics and Web Engineering. 2024 Feb 14;3(1):41–54. doi: 10.33093/jiwe.2024.3.1.3
5. Thanoon MA, Zulkifley MA, Mohd Zainuri MAA, Abdani SR. A review of deep learning techniques for lung cancer screening and diagnosis based on CT images. Diagnostics. 2023;13(16):2617. doi:10.3390/diagnostics13162617.
6. Basety S, Gudepu R, Velidandi A. Artificial Intelligence in Lung Cancer: A Narrative Review of Recent Advances in Diagnosis, Biomarker Discovery, and Drug Development. Pharmaceutics. 2026;18(2):201. doi: 10.3390/pharmaceutics18020201
7. LIDC-IDRI Collection [Internet]. The Cancer Imaging Archive; [cited 2026 Apr 30]. Available from: https://www.cancerimagingarchive.net/collection/lidc-idri/
8. M R V, Hameed HHS. PulmoNet: A Hybrid CNN-Vision Transformer Architecture for Enhanced Lung Nodule Classification in CT Imaging. Engineering, Technology & Applied Science Research. 2026;16(2):33278-84. doi: 10.48084/etasr.16612
9. M. D A, B V. Enhancing lung cancer classification through a double attention hybrid CNN-HiFuse approach. Scientific Reports. 2026;16:13099. doi: 10.1038/s41598-026-42290-9
10. Nady G, Salem A, Badawy O, Abo-ElNour S. Explainable active reinforcement deep learning improves lung cancer detection from CT images. Scientific Reports. 2026;16(1):7510. doi: 10.1038/s41598-026-38239-7
11. Matsuyama E, Watanabe H, Takahashi N. Performance Comparison of Vision Transformer- and CNN-Based Image Classification Using Cross Entropy: A Preliminary Application to Lung Cancer Discrimination from CT Images. Journal of Biomedical Science and Engineering. 2024;17(9):157–70. doi: 10.4236/jbise.2024.179012
12. Bannela R, Praneeth RPG, Madhusudhan RK, Arun BP. Hybrid CNN–Vision Transformer Framework for Enhanced Lung Nodule Detection. International Journal of Engineering Research and Science & Technology. 2026;22(2): 563-570.
13. Shariff V, Paritala C, Ankala KM. Optimizing non small cell lung cancer detection with convolutional neural networks and differential augmentation. Scientific Reports. 2025;15(1): 15640. doi: 10.1038/s41598-025-98731-4
14. T. Meeradevi, S. Sasikala, Murali L, N. Manikandan, Ramaswamy K. Lung cancer detection with machine learning classifiers with multi-attribute decision-making system and deep learning model. Scientific Reports. 2025;15(1): 8565. doi: 10.1038/s41598-025-88188-w