Deep Learning for Automated Lung Cancer Detection Using CT and Chest X-ray Images: A Comprehensive Review

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Abstract: Lung cancer is still a major cause of death from cancer and early and accurate diagnosis is crucial. The deep learning based automatic lung cancer detection system for computed tomography (CT) and chest X-ray (CXR) images is discussed in detail in this review. It contains publicly available datasets, preprocessing techniques, deep learning architectures, Explainable Artificial Intelligence (XAI) techniques and measures for evaluation. The review identifies the current challenges, gaps and novel topics like multimodal learning and federated learning that will guide the creation of comprehensive and interpretable AI diagnostic devices that can be applied in the clinical setting.

Keywords: Lung Cancer Detection, Deep Learning, Computed Tomography (CT), Chest X-ray (CXR), Explainable Artificial Intelligence (XAI).

Introduction

The lung cancer is one of the top cancer killers in the world and accurate and timely diagnosis is required. In recent years, new advances in deep learning have made it much easier to automatically analyze computed tomography (CT) and chest X-ray (CXR) images for the efficient detection and classification of pulmonary abnormalities. Different CNN, transformer models, and hybrid ones have exhibited good diagnostic capacities. However, several problems such as diversity of datasets, interpretability of models, computational complexity, and clinical validation still prevent these methods from being applied in clinical practice and their use. This review opens the reader up to the latest developments, compares previous approaches, shows gaps in the research and suggests future directions to help bring reliable AI-assisted lung cancer diagnoses to the fore.

Related work

Table 1. Comparison of references on various parameter.

Ref.	Dataset	AI/Model	Key Strength	Limitation	Ref.
[1] Eftekharian & Hashemi (2026)	Multiple CT, FDG PET/CT, Multimodal	AI, ML, DL, Multimodal Review	Comprehensive review of screening, staging, prognosis, and multimodal AI	Limited quantitative comparison and explainability	[1] Eftekharian & Hashemi (2026)
[2] Kumari & Goel (2026)	LIDC-IDRI, LUNA16	CNN, ResNet, DenseNet, EfficientNet, ViT	Extensive comparison of CT-based deep learning methods	Limited clinical validation and interpretability	[2] Kumari & Goel (2026)

[3] Koutoulakis et al. (2026)	CT datasets	XAI (Grad-CAM, SHAP, LIME, CAM)	Comprehensive review of Explainable AI techniques	Limited coverage of hybrid and multimodal models	[3] Koutoulakis et al. (2026)
[4] Yousafzai et al. (2026)	CT	Hybrid CNN–Transformer	Superior local-global feature learning with high accuracy	Limited dataset and external validation	[4] Yousafzai et al. (2026)
[5] Zahid et al. (2026)	Multiple public datasets	ML, DL, Hybrid AI	Broad overview of AI techniques for lung cancer prediction	Limited preprocessing and XAI discussion	[5] Zahid et al. (2026)
[6] Herber et al. (2026)	Pulmonary nodule CT	Multiple AI Models	Clinical comparison of AI diagnostic performance	Focused only on pulmonary nodule classification	[6] Herber et al. (2026)
[7] Khan et al. (2026)	CT (2020–2025)	Preprocessing & Harmonization	Comprehensive review of normalization and harmonization	No evaluation of classification models	[7] Khan et al. (2026)
[8] Nady et al. (2026)	CT	Explainable Reinforcement DL	Improved transparency with explainable AI	High computational complexity	[8] Nady et al. (2026)
[9] Yang et al. (2026)	Lung CT	Segmentation & Classification	Improved lesion localization and diagnosis	Limited comparison with Transformer models	[9] Yang et al. (2026)
[10] Parra-Cabrera et al. (2026)	ChestX-ray14, VinDr-CXR	AI for Chest X-ray	Comprehensive review of datasets and AI methods	Limited CT multimodal and XAI coverage	[10] Parra-Cabrera et al. (2026)

Key Contribution

This paper provides a thorough comparison of deep learning techniques for lung cancer diagnosis from computed tomography (CT) and chest X-ray (CXR) images.

Methods, Experiments & Results

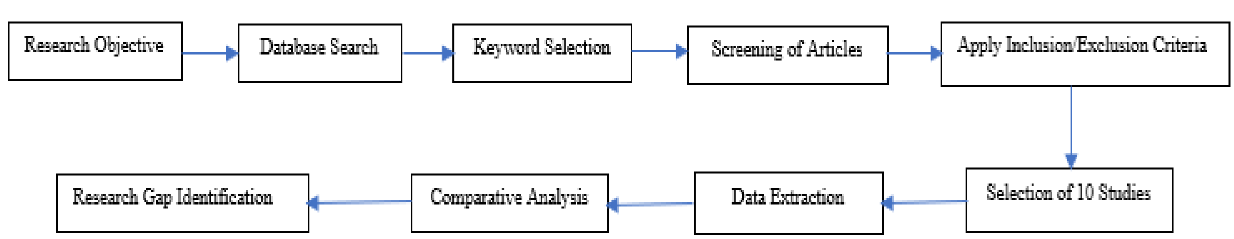

***Figure 1**. Proposed Architecture for the systematic review of deep learning-based lung cancer detection.*

Table 2. Comparison of Deep Learning Architectures for Lung Cancer Detection

Architecture	Feature Extraction	Global Context Learning	Computational Complexity	Interpretability	Common Application	Advantages	Limitations	Representative Study
CNN	Automatic local feature extraction	Low	Low	Moderate	Nodule detection, classification	Simple architecture, effective feature learning, fast training	Limited long-range dependency learning	Zahid *et al.* [5]
ResNet	Residual feature learning	Low	Moderate	Moderate	CT image classification	Solves vanishing gradient problem, supports deeper networks	High computational cost with deeper variants	Kumari and Goel [2]
DenseNet	Dense feature reuse	Low	Moderate	Moderate	Lung cancer classification	Efficient feature propagation, reduced parameter redundancy	High memory consumption	Kumari and Goel [2]
EfficientNet	Compound-scaled feature extraction	Moderate	Low–Moderate	Moderate	CT-based classification	High accuracy with fewer parameters	Requires careful hyperparameter tuning	Kumari and Goel [2]
Vision Transformer (ViT)	Patch-based feature representation	High	High	Low	Classification and feature representation	Captures long-range dependencies and global context	Requires large-scale datasets and computational resources	Kumari and Goel [2]
Hybrid CNN–Transformer	Combines local CNN features with global Transformer attention	High	High	Moderate	Lung cancer detection and classification	Superior feature representation, improved diagnostic accuracy	Increased computational complexity and longer training time	Yousafzai *et al.* [4]

Lung cancer detection is mostly performed using the CNNs like CNN, ResNet, DenseNet, EfficientNet, ViT, and CNN–Transformer hybrid. More computational resources are needed for hybrid models which combine local feature extraction and global attention, but are likely to give better results.

Table 3. Explainable AI Technique Comparison

Technique	Purpose	Working Principle	Advantages	Limitations	Representative Study
CAM	Visualize discriminative regions	Uses feature maps from the final convolutional layer	Simple and easy to interpret	Requires architecture modification	Koutoulakis *et al.* [3]
Grad-CAM	Highlight important image regions	Computes gradients with respect to feature maps	Model-independent, widely applicable	Produces coarse localization maps	Nady *et al.* [8]
SHAP	Explain feature contributions	Based on Shapley values from game theory	Provides global and local explanations	Computationally expensive	Koutoulakis *et al.* [3]
LIME	Explain individual predictions	Builds a local surrogate model around a prediction	Model-agnostic and interpretable	Sensitive to perturbation sampling	Koutoulakis *et al.* [3]

These methods, such as CAM, Grad-CAM, SHAP and LIME, improve the explainability and the clinical interpretability of an AI-based diagnosis, which makes it more reliable.

Table 4. Comparison of Metrics

Ref.	Model	Dataset	Accuracy (%)	Precision (%)	Recall/Sensitivity (%)	F1-score (%)	ROC-AUC
[4]	C-Swin	IQ-OTH/NCCD	96.26	97.48	96.39	97.42	NR
[6]	Commercial AI Models	158 CT Nodules	NR	NR	53.1–70.3	NR	0.50–0.60
[8]	ARXAF-Net	30,020 CT Images	99.00	NR	NR	NR	NR
[9]	CNN/U-Net/Transformer Review	Multiple Public Datasets	NA	NA	NA	NA	NA

FUTURE RESEARCH & DIRECTION

The multimodal AI application of CT, chest X-ray, PET/CT, clinical and genomic data to improve diagnosis needs to be explored further. Foundation models and federated learning, lightweight architectures, and Explainable AI (XAI) can be applied to lung cancer diagnosis to make it reliable, scalable, and suitable for real-time deployment with high level of privacy, interpretability and generalization.

CONCLUSION

Recent studies on deep learning in lung cancer detection by CT and chest X-ray images are summarized here. The advantages of hybrid CNN–Transformer models, their enhanced diagnostic performance and interpretability, along with the difficulties encountered with datasets diversity, clinical validation and standardization, are summarized. Solutions to these challenges will help in the robust clinical uptake of AI systems.

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