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Deep Learning-Based Lung Nodule Classification and Lung Cancer Diagnosis: A Comprehensive Literature Review

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ABSTRACT

Lung cancer is still one of the major causes of cancer-related deaths in the world and timely and precise diagnosis is very important to enhance survival of the patients. The past decade has seen remarkable progress in the medical image analysis arena for detection, segmentation and classification of pulmonary nodules, which is driven by the recent developments in Artificial Intelligence (AI) and Deep Learning (DL). This literature review aims to provide a thorough overview of recent research articles published from 2025 to 2026 related to lung nodule classification based on computed tomography (CT) and chest radiography images within the context of deep learning. The review delves into the mechanisms of several architectures such as Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), ensemble learning, transfer learning, multi-task learning, Neural Architecture Search (NAS), and Explainable AI (XAI). Furthermore, the segmentation methods and data augmentation strategies are explored, as well as being evaluated in conjunction with hybrid AI frameworks. The review points out the advantages, weaknesses, and the data sets, measures, and clinical utility of the available approaches. Results suggest that transformer-based models, hybrid CNN-transformer models, and explainable ensemble models outperform the classification accuracy of other models, which is above 95%, in several research studies. There are many challenges that are yet to be solved, including the limited annotated datasets, interpretability of the models, generalization across clinical environments and computational complexity. Multimodal learning, federated learning, integrating explainable AI, and clinically validated real-time diagnostics are directions for future research.

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1. INTRODUCTION

Lung cancer is one of the most deadly cancers in the world, and there are many lung cancer deaths every year. The timely identification of malignant pulmonary nodules by imaging techniques, such as Computed Tomography (CT) scan and Chest X-ray (CXR) is important for planning treatment and for increased survival rates. But, manual examination of medical images by radiologists is time consuming, subjective and has a risk of diagnostic errors particularly in terms of small nodules and low contrast lesions.

In the field of automated lung nodule detection, segmentation, and classification, AI, specifically Deep Learning (DL), has proven itself to be a strong tool. By automatically extracting features that are most important for the diagnosis, deep learning models can lower the reliance on handcrafted feature engineering and enhance the uniformity in diagnosis. The application of ensemble architectures, transfer learning, and Vision Transformers (ViTs) at CNN is further improved the ability of Computer-aided Diagnosis (CAD) systems in recent years.

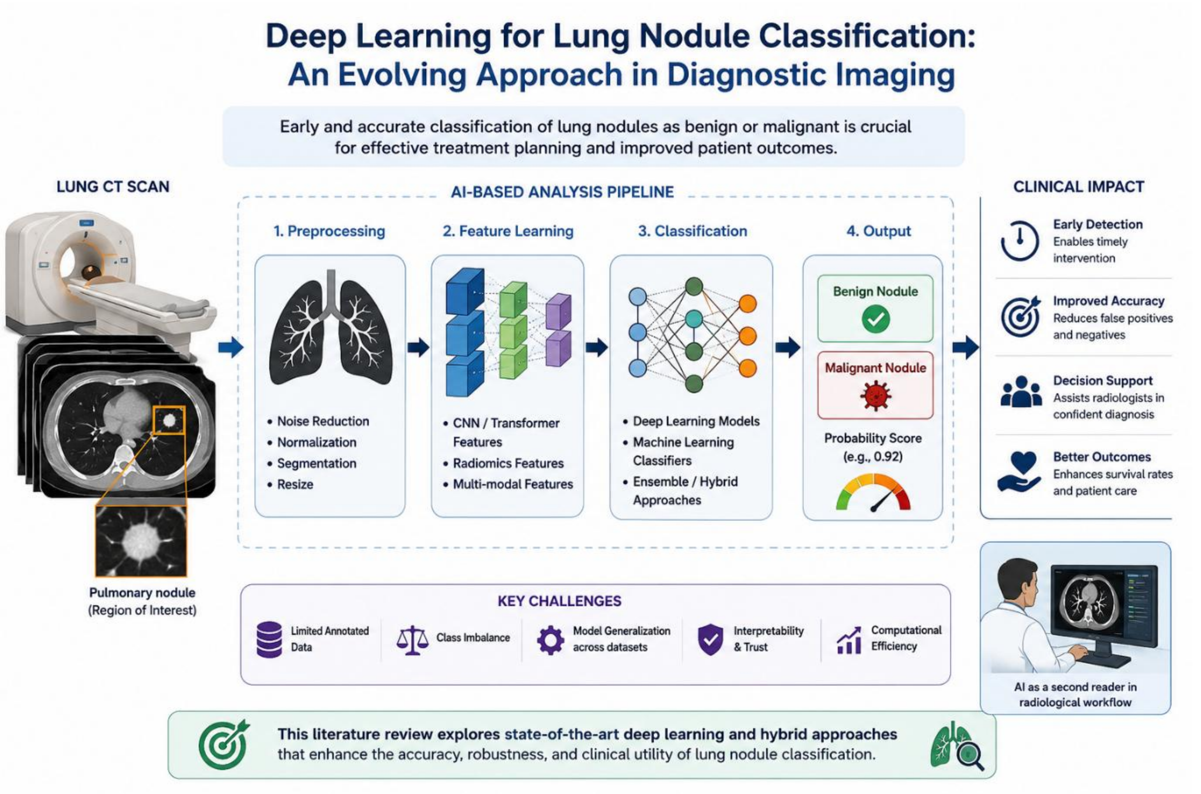

Fig.1. Deep learning for lung tumor classification

This literature review gives a detailed summary of the most recent deep learning approaches used for lung nodule classification and lung cancer diagnosis in the last two years (2025-2026). Specific features highlighted in the review include architectural innovations, performance comparisons, segmentation strategies, explainability methods, and opportunities for future research.

2. DEEP LEARNING APPROACHES FOR LUNG NODULE CLASSIFICATION

2.1 Vision Transformer-Based Approaches

Recently Vision Transformers (ViTs) have attracted much interest for their global contextual information from medical images. To classify lung nodules from CT scans using robust models, Huang et al. [1] introduced a hybrid approach that combines Vision Transformer and machine learning classifiers. They have implemented CNN layers, transformer encoders, and patch embedding. The model showed the 94% accuracy and 96% AUC on training sets and good generalization ability on external sets.

Likewise, Faizi et al. [2] proposed a dual-branch Swin Transformer (DCSwinB) network that exploits CNN-based deep local features and transformer-based deep global feature representation. The proposed model achieved high classification accuracy of 90.96% and an AUC of 0.94, better than the traditional CNN models like ResNet50 and common Swin-T models.

Recently, Pan et al. [3] proposed MSA-Net, which combines multiple self-attention mechanisms into an integrated 3D network. They extracted spatial features from their model in an efficient way reducing the computational complexity. Overall, the approach performs better than competing methods on the LUNA16 dataset, with an accuracy of 95.3% and an AUC of 0.993, demonstrating the effectiveness of attention-based feature learning in 3D medical imaging.

The results of these studies indicate the great potential of transformer-based architectures to learn long-range dependencies and context in lung CT scans.

Table 1. Lung nodule classification models comparison based on vision transformer

Ref.	Proposed Method	Dataset/Imaging	Key Features	Accuracy	Advantages	Limitations
[1]	Vision Transformer + ML Hybrid	CT Images	Transformer encoder with SHAP explainability	94%	Strong global feature extraction and interpretability	High computational cost
[2]	DCSwinB Swin Transformer	CT Images	Dual-branch CNN + Transformer	90.96%	Better contextual representation	Requires large datasets
[3]	MSA-Net	3D CT Scans	Multiple self-attention mechanism	95.3%	Efficient spatial feature extraction	Complex architecture

2.2 CNN-Based Lung Nodule Classification Models

The popularity of lung nodules analysis by Convolutional Neural Networks (CNN) stems from the fact that they extract local features well. Lavuri et al. [4] introduce a CNN based neural network for automatic lung cancer diagnosis and classification. They highlighted the real-world applications of CNN in minimizing human effort by implementing automated feature extraction and robust diagnosis of benign and malignant nodules.

Tawfeek et al. [5] proposed a Lung Cancer Risk Prediction (LCRP) model, which is a combination of three sequential, functional and transfer learning based CNN architectures. Their model was based on Mask R-CNN segmentation, two optimization strategies (Adam and Sgd) optimizers. The model showed good performance in terms of classification accuracy of 98.5%, sensitivity and specificity high.

Sudha and Maheswari [6] suggested a hybrid approach which is the combination of U-Net segmentation and Convolutional Neural Network Fish Swarm Optimization (CFSO). The swarm intelligence based feature selection method has improved the diagnostic performance of the method, with an accuracy of 97.80%, and it has also reduced the computational costs and the number of selected features.

Based on these studies, CNN-based frameworks are still capable of obtaining reliable results with segmentation and optimization processes.

Table 2. Comparison result of CNN-based lung nodule classification models

Ref.	Proposed Method	Segmentation Technique	Optimization Method	Accuracy	Strengths	Weaknesses
[4]	CNN-based Neural Network	Not specified	Standard CNN training	High performance	Automated feature extraction	Limited explainability
[5]	LCRP Model	Mask R-CNN	Adam + SGD	98.5%	Excellent diagnostic accuracy	High training complexity
[6]	CNN + Fish Swarm Optimization	U-Net	Fish Swarm Optimization	97.80%	Improved feature selection	Increased computational time

2.3 Ensemble and Transfer Learning Models

Transfer learning and ensemble learning are now becoming very effective solutions to address the small number of medical datasets and robustness of the classification.

Noman et al. [7] have proposed LungCT-NET, which is an ensemble model that combines five different deep networks: VGG-16, DenseNet-121, EfficientNet-B0, MobileNet-V2, and ResNet152-V2. They had an accuracy of 98.99% using their stacking ensemble approach and added an explainability component using SHAP to enhance the clinical trustworthiness.

Rahman et al. [8] proposed a model named Self-DenseMobileNet which combines DenseNet201, MobileViTv2, ResNet152, and a stacking-based meta-classifier. They had an outstanding internal validation accuracy of 99.28% and external validation accuracy of 89.40%. ScoreCAM and class activation mapping (CAM) were used to enhance model interpretability.

The methods emphasize the merits of using several pre-trained architectures to achieve robustness and generalization over heterogeneous data sets.

Table 3. Comparison of ensemble and transfer learning models

Ref.	Ensemble Components	Explainability Method	Accuracy	Major Contribution	Limitation
[7]	VGG16, DenseNet121, EfficientNetB0, MobileNetV2, ResNet152V2	SHAP	98.99%	Explainable ensemble framework	Large model size
[8]	DenseNet201, MobileViTv2, ResNet152	ScoreCAM	99.28%	Stacking-based meta-classifier	External validation variability

3. SEGMENTATION AND MULTI-TASK LEARNING APPROACHES

Segmentation is one of the key pre-processing steps to be performed for precise lung nodule analysis. Gao et al. [9] did an extensive review that focuses on the significance of accurate segmentation for lung cancer diagnosis. Their analysis revealed that CNN-based segmentation methods are the predominant ones in pulmonary nodule analysis.

Xue et al. [10] introduced a prior knowledge guided multi-task learning network to simultaneously segment, classify benign-malignant and score images. They incorporated hypergraph neural networks and channel-wise cross-attention blocks, which were able to capture complex attribute correlations. The model was able to achieve the state-of-the-art performance with an accuracy of 91.04% when it comes to classification.

To segment and classify the images, Akintola et al. [11] used a hybrid pipeline with Mask R-CNN and CNNs. They developed a model automated localization and diagnosis method which successfully reached an accuracy of 95.6% with good scalability for clinical implementation.

These studies indicate that integration of segmentation and classification in a single framework improves the accuracy of the diagnosis and helps to minimize error propagation.

Table 4. Comparison of segmentation and multi-task learning approaches

Ref.	Proposed Framework	Main Tasks	Key Techniques	Performance	Advantages
[9]	Systematic Review	Detection & Segmentation	CNN-based segmentation	Comprehensive review	Summarizes latest segmentation methods
[10]	Multi-task Learning Network	Segmentation + Classification	Hypergraph Neural Networks	91.04%	Joint learning improves accuracy
[11]	Mask R-CNN + CNN	Segmentation + Diagnosis	Integrated deep learning pipeline	95.6%	End-to-end automated framework

4. DATA AUGMENTATION AND SYNTHETIC DATA GENERATION

In medical imaging, there are still a few problems with limited annotated datasets. Patel et al. [12] studied image augmentation based on Variational Autoencoder (VAE) for lung nodule classification in order to tackle this problem. Generative augmentation techniques were found to be effective with an increase in test sensitivity of 3.13% in synthetic image generation.

Besides boosting generalization, data augmentation helps to prevent overfitting in deep learning models with limited data or skewed data distributions. Future CAD systems will incorporate the use of synthetic data generation, which should be of increasing importance.

5. EXPLAINABLE AI AND CLINICAL INTERPRETABILITY

Many deep learning models are not transparent enough, which hinders clinical use. Some of the recent studies have incorporated explainable AI (XAI) techniques like SHAP, ScoreCAM, and class activation maps.

Some other researchers, like Noman et al. [7] used SHAP explanations to improve their confidence in the model predictions and other like Rahman et al. [8] used ScoreCAM heatmaps to explain model reasoning for classification. Huang et al. [1] also used SHAP analysis to determine texture and intensity to be two significant discriminative features.

These are ways to enhance the trustworthiness and collaboration of AI systems and radiologists.

Table 5. Comparison of explainable ai techniques

Ref.	Explainability Technique	Purpose	Benefits
[1]	SHAP	Feature importance analysis	Improved interpretability
[7]	SHAP	Explain ensemble predictions	Enhances clinical trust
[8]	ScoreCAM	Heatmap visualization	Better diagnostic transparency

6. NEURAL ARCHITECTURE SEARCH AND EFFICIENT LEARNING

Neural Architecture Search (NAS) is an automatic method to find the best architectures of deep learning networks.

In order to solve the problem, Yu et al. [13] proposed an efficient multimodal one-shot NAS framework (EMTMO-NAS) for PET/CT lung nodule classification. The searched architecture was able to reach accuracy of 94.23% with much fewer parameters than the traditional CNN architectures. The study proved that the accuracy of the diagnosis remained satisfactory after the reduction of the model complexity with the use of NAS.

The efficient architectures are critical for real-time clinical use, especially if the computational resources are limited [14-16].

7. COMPARATIVE ANALYSIS OF EXISTING STUDIES

Recent works have shown that these hybrid and transformer architectures reliably achieve superior performance over traditional architectures based on CNNs in lung nodule classification tasks. The robust and high generalization performance of ensemble learning approaches combined with the reliability in clinical use of explainable AI techniques is ensuring high quality performance.

Table 6. Overall comparative analysis of reviewed studies

Study Category	Best Performing Method	Highest Accuracy	Key Strength	Major Challenge
Vision Transformers	MSA-Net	95.3%	Global contextual learning	High computational complexity
CNN-Based Models	LCRP Model	98.5%	Robust feature extraction	Limited explainability
Ensemble Learning	Self-DenseMobileNet	99.28%	Superior generalization	Large model complexity
Segmentation Models	Mask R-CNN + CNN	95.6%	Accurate localization	Requires annotated masks
Explainable AI	LungCT-NET	98.99%	Clinical interpretability	Increased processing overhead
NAS Models	ETMO-NAS	94.23%	Automated architecture optimization	High search complexity

But there are a number of issues that are unanswered:

- There are not many annotated medical datasets available.
- No standard preprocessing pipelines.
- Transformer models are generally complex to compute.
- Lacks and Henrietta were not the only two patients from whom the HeLa cells were derived.
- The black box models are not as intelligible.

Future systems should be lightweight, explainable, and clinically validated and be deployable in real time.

Table 7. Summary of research gaps and future directions

Research Gap	Current Limitation	Future Direction
Limited datasets	Small annotated medical datasets	Federated and collaborative learning

Model interpretability	Black-box behavior	Explainable AI integration
Computational complexity	Transformer models are resource-intensive	Lightweight architectures
Generalization issues	Poor cross-hospital validation	Multi-center clinical validation
Data imbalance	Scarcity of malignant samples	GAN/VAE-based augmentation
Real-time deployment	Slow inference speed	Edge AI and optimized hardware

8. FUTURE RESEARCH DIRECTIONS

Future research in lung nodule classification should focus on the following areas:

The research needed in lung nodule classification in future should be directed to the following areas:

- Multimodal Learning - Integrating clinical data, genomic data and CT and PET for better diagnostic accuracy.
- Federated Learning - Creating a collaborative learning environment across hospitals without compromising patients' privacy.
- Explainable AI - Increasing the model transparency and interpretability for clinical acceptance.
- Lightweight Models - Architectures that are efficient from a computational point of view and can be used for edge devices and real-time diagnosis.
- Large-Scale Clinical Validation - Running multiple center prospective studies for good external validation.
- Synthetic Data Generation - Data Augmentation using Generative AI models like GANs and diffusion models.

9. CONCLUSION

By making it possible to detect, segment, and classify pulmonary nodules and diagnose lung cancer with high accuracy, deep learning has transformed the analysis of these nodules and diagnosis of lung cancer. The recent progress in the field of Vision Transformers, hybrid CNN-transformer architectures, ensemble learning, multi-task learning, and explainable AI has greatly enhanced diagnostics capabilities. The various studies covered in this paper show that, in many instances, the accuracy of the classification is over 95%, which indicates that AI-based CAD systems have a great potential in clinical situations. Although there has been significant progress in this area, the problem of data sparseness, generalization, interpretability, and computational efficiency still remains. Multimodal integration, explainable AI, federated learning and real-world clinical validation should be the focus of future research work for real-world adoption. In summary, the deep learning approach to classification of lung nodules has tremendous potential to advance lung cancer detection at an early stage and ultimately improve patient outcomes.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

Data can be provided on genuine request.

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