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Lung cancer detection using transfer learning and hybrid deep learning models: A review

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Abstract

Lung cancer remains one of the most serious health challenges worldwide and is responsible for a significant number of cancer-related deaths every year. Early detection plays a critical role in improving survival rates and treatment outcomes. Medical imaging techniques such as Computed Tomography (CT), Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and Chest X-rays are widely used for diagnosis. However, manual interpretation of these images is time-consuming, subject to human error, and dependent on the expertise of radiologists.

Recent advancements in Artificial Intelligence (AI), particularly Deep Learning (DL), Transfer Learning (TL), and Hybrid Deep Learning Models, have demonstrated remarkable potential in automated lung cancer detection. Convolutional Neural Networks (CNNs), Res Net, VGG16, Dense Net, Mobile Net, Efficient Net, Vision Transformers, and ensemble architectures have shown promising performance in identifying malignant lung nodules and classifying cancer stages.

This review paper presents a comprehensive analysis of recent research works related to lung cancer detection using transfer learning and hybrid deep learning approaches. The study discusses commonly used datasets, preprocessing techniques, segmentation methods, classification models, performance metrics, research gaps, and future research directions. The review highlights that transfer learning and hybrid architectures can improve classification accuracy, reduce computational complexity, and support reliable clinical decision-making.

Keywords: Lung cancer detection, deep learning, transfer learning, CNN, hybrid deep learning, CT scan, medical imaging, explainable AI

Introduction

Lung cancer is one of the leading causes of cancer-related mortality worldwide. According to global health reports, millions of new cases are diagnosed annually, and a significant proportion of patients are detected at advanced stages. Early diagnosis is often difficult because symptoms may remain unnoticed during the initial stages of the disease. Consequently, there is a strong need for automated diagnostic systems capable of identifying lung abnormalities at an early stage.

Medical imaging has become a fundamental component of lung cancer diagnosis. CT scans provide detailed information about lung tissues and nodules, while PET scans offer metabolic information that helps distinguish malignant tissues from normal tissues. However, manual examination of thousands of image slices is labor-intensive and susceptible to observer variability.

Artificial Intelligence has emerged as a powerful tool in healthcare. Deep learning algorithms can automatically learn complex image features and classify medical images with high accuracy. Transfer learning allows pretrained networks to be adapted to medical imaging tasks, reducing training time and data requirements. Hybrid deep learning systems combine multiple architectures to improve robustness and diagnostic performance.

This review investigates recent developments in lung cancer detection using transfer learning and hybrid deep learning models. The primary objective is to analyze current methodologies,

compare model performances, identify existing limitations, and discuss future opportunities for research and clinical deployment.

Motivation of the Study

The motivation for this review arises from the increasing prevalence of lung cancer and the growing need for reliable automated diagnostic systems. Although numerous studies report high classification accuracy, challenges remain regarding generalization, Explain ability, clinical validation, and deployment in real-world environments.

Many existing systems are evaluated using limited datasets, and their performance may vary across different imaging centers. Furthermore, clinicians require interpretable AI models that provide explanations for diagnostic decisions. Therefore, understanding current research trends and identifying future directions are essential for developing clinically useful AI systems.

Objective: The primary objective of this review is to examine recent advancements in transfer learning and hybrid deep learning approaches for lung cancer detection. It aims to compare various artificial intelligence models, including Convolutional Neural Network (CNN)-based, transfer learning, ensemble, and hybrid architectures, to evaluate their effectiveness in improving diagnostic accuracy. Furthermore, the study seeks to analyze the datasets, preprocessing methods, and image segmentation techniques commonly employed in lung cancer detection research. Another important objective is to identify the existing research gaps and limitations in current studies, highlighting challenges related to model performance, generalization, and clinical applicability. Additionally, the review discusses potential future directions for AI-assisted lung cancer diagnosis and proposes a review-based framework to guide future research toward the development of more accurate, efficient, and reliable diagnostic systems.

Background

A. Lung Cancer and Medical Imaging

Lung cancer occurs due to uncontrolled growth of abnormal cells within lung tissues. It is generally classified into Small Cell Lung Cancer (SCLC) and Non-Small Cell Lung Cancer (NSCLC). CT imaging is the most commonly used modality for lung cancer screening because it provides detailed cross-sectional views of lung structures.

Medical imaging enables doctors to examine internal lung structures without the need for invasive procedures. CT scans are widely preferred because they provide detailed cross-sectional images of the lungs. Other imaging modalities, such as PET scans, offer metabolic information that can help identify cancer activity, while MRI and chest X-ray imaging can support diagnosis and treatment planning in specific clinical situations. Each imaging technique has its own advantages and limitations in terms of image quality, resolution, contrast, and diagnostic capability.

Therefore, artificial intelligence-based lung cancer detection systems should be designed according to the characteristics of the imaging modality being used. Factors such as image resolution, contrast, noise levels, and the specific diagnostic objective play an important role in developing accurate and reliable AI models for medical image analysis.

B. Deep Learning in Medical Imaging: Deep learning has revolutionized medical image analysis. CNNs automatically

extract hierarchical image features without manual feature engineering. Early layers capture low-level patterns such as edges and textures, while deeper layers identify complex anatomical structures and disease-specific features.

In lung cancer detection, CNN models can learn important visual characteristics such as edges, textures, shapes, lesion boundaries, and abnormal tissue patterns from medical images. The initial layers of a CNN typically capture low-level features, including edges and simple textures, while deeper layers learn more complex and high-level structures associated with disease characteristics. This hierarchical feature learning enables CNNs to identify subtle visual differences that may not be easily detectable by traditional methods.

The ability of CNNs to automatically learn discriminative features makes them highly effective for medical image classification tasks. As a result, deep learning-based CNN models have become a popular approach for lung cancer detection, offering improved diagnostic accuracy and reducing the need for manual feature extraction.

C. Data Augmentation in Lung Cancer Detection

Data augmentation is widely used to improve model generalization. Since medical image datasets are often limited, augmentation creates modified versions of existing images without changing their medical significance. Common augmentation techniques include rotation, flipping, zooming, cropping, shifting, brightness adjustment, contrast enhancement, and noise injection.

Advanced augmentation methods such as Random Pixel Swap, mixup, cutout, and generative augmentation have also been explored in recent studies. These techniques improve model robustness by exposing the network to a wider range of image variations and reducing the risk of over fitting. Data augmentation can also help address class imbalance by increasing the diversity of underrepresented classes in the dataset.

However, augmentation must be applied carefully in medical imaging because unrealistic image transformations may distort clinically important features and lead to inaccurate predictions. Properly designed augmentation strategies preserve diagnostic information while enhancing the model's ability to generalize to unseen clinical data.

D. Transfer Learning

Transfer learning is useful because medical image datasets are usually smaller than general image datasets. Training a deep model from scratch requires a large amount of labeled data, high computational power, and careful optimization. Pretrained models reduce this burden by using previously learned features.

VGG16 is simple and effective but has many parameters. ResNet50 uses residual connections and helps solve the vanishing gradient problem. Dense Net connects each layer to other layers and improves feature reuse. Mobile Net is lightweight and suitable for mobile or low-resource environments. Efficient Net balances model depth, width, and resolution. Vision Transformer (ViT) models are also gaining attention because they can capture global image relationships. Transfer learning utilizes pretrained models trained on large datasets and adapts them to medical imaging tasks. Popular architectures include VGG16, ResNet50, DenseNet121, Mobile NetV3, Efficient Net, ConvNeXt, and Vision Transformers.

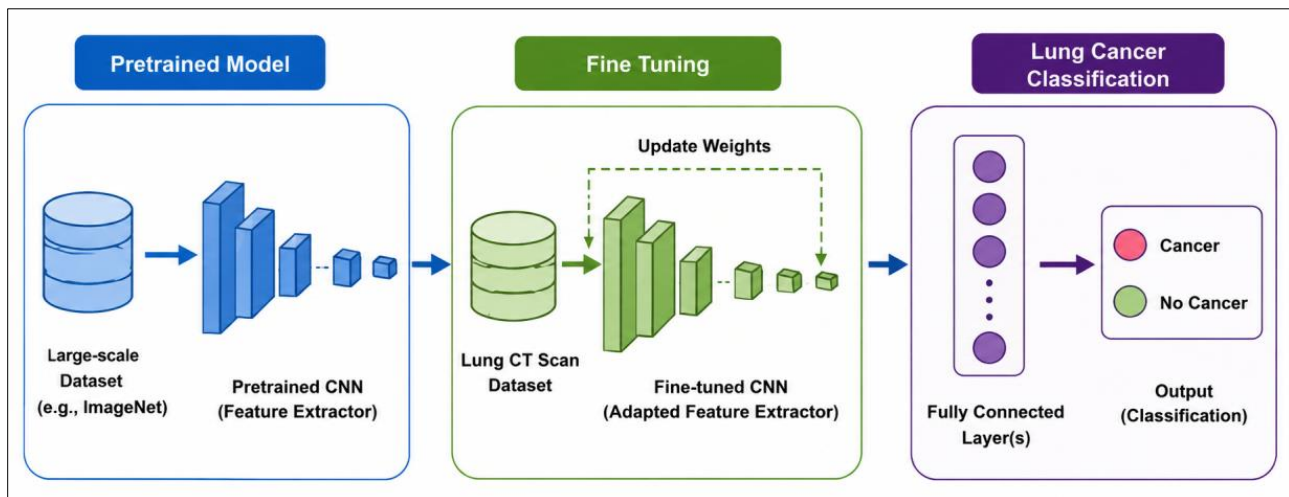


Fig 1: Transfer Learning Architecture

Transfer learning offers several benefits in medical image classification

- It reduces training time because the model already contains learned visual features.
- It requires fewer medical images compared with training a model from scratch.
- It improves convergence speed during training.
- It helps overcome the problem of limited labeled medical datasets.
- It supports fine-tuning for specific cancer classification tasks.
- It can improve performance when data augmentation is properly applied.
- It enables lightweight deployment when combined with efficient architectures.

These advantages make transfer learning one of the most widely adopted approaches in modern medical image analysis.

E. Hybrid Deep Learning Models: Hybrid models combine multiple deep learning techniques such as segmentation

networks, feature extractors, transformers, auto encoders, and ensemble classifiers. These systems often achieve superior performance because they leverage complementary strengths of different architectures.

Hybrid deep learning models combine different methods to improve performance. In lung cancer detection, hybrid systems may include preprocessing, segmentation, feature extraction, feature selection, and classification. U-Net can be used for lung nodule segmentation, CNNs can extract meaningful features, auto encoders can reduce feature dimensions, and lightweight deep learning models can perform the final classification.

Hybrid models are particularly useful because lung cancer detection involves more than a simple classification task. A comprehensive diagnostic system may need to identify lung nodules, remove irrelevant background regions, classify different types of cancer, and provide interpretable results for clinical decision-making. By integrating multiple techniques, hybrid models can effectively handle these complex tasks and often achieve better accuracy and robustness than a single deep learning model

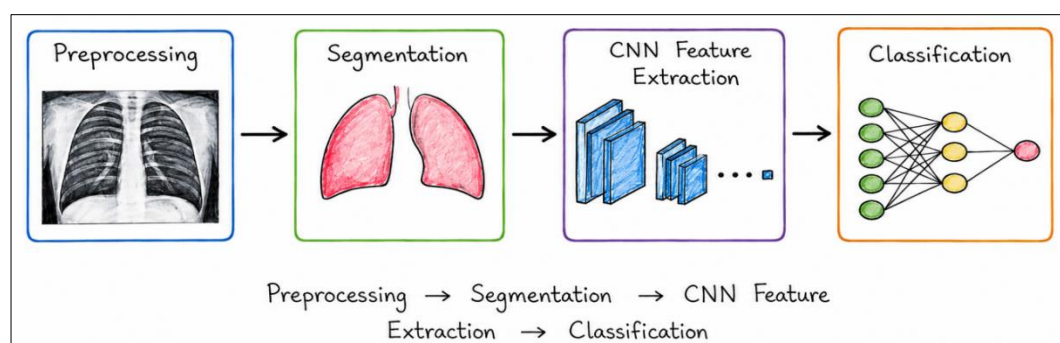


Fig 2: Hybrid Deep Learning Framework

F. Hybrid Deep Learning Models

Preprocessing is an important step in lung cancer detection because medical images may contain noise, low contrast, and irrelevant background regions. Common preprocessing techniques include resizing, normalization, contrast enhancement, denoising, and data augmentation. These steps improve image quality, reduce unwanted variations, and make the dataset more suitable for deep learning models.

Segmentation is used to isolate the lung region or suspected nodules from the complete medical image. U-Net and its variants are widely used for medical image segmentation because they preserve spatial information through encoder-decoder connections. Accurate segmentation enables the model to focus on clinically relevant regions while reducing the influence of background structures and artifacts.

Effective preprocessing and segmentation can significantly enhance the performance of lung cancer detection systems by

improving feature extraction and classification accuracy. These techniques also contribute to better model robustness

and reliability, making automated diagnostic systems more suitable for real-world clinical applications.

Table 1: Common Preprocessing Techniques

Technique	Purpose
Resizing	Makes all input images uniform for model training.
Normalization	Scales pixel intensity values to improve convergence.
Denoising	Removes unwanted noise from medical images.
Contrast Enhancement	Improves visibility of nodules and tissue boundaries.
Augmentation	Increases training diversity and reduces overfitting.
Segmentation	Separates lung regions or nodules from the background.

General Workflow of Lung Cancer Detection

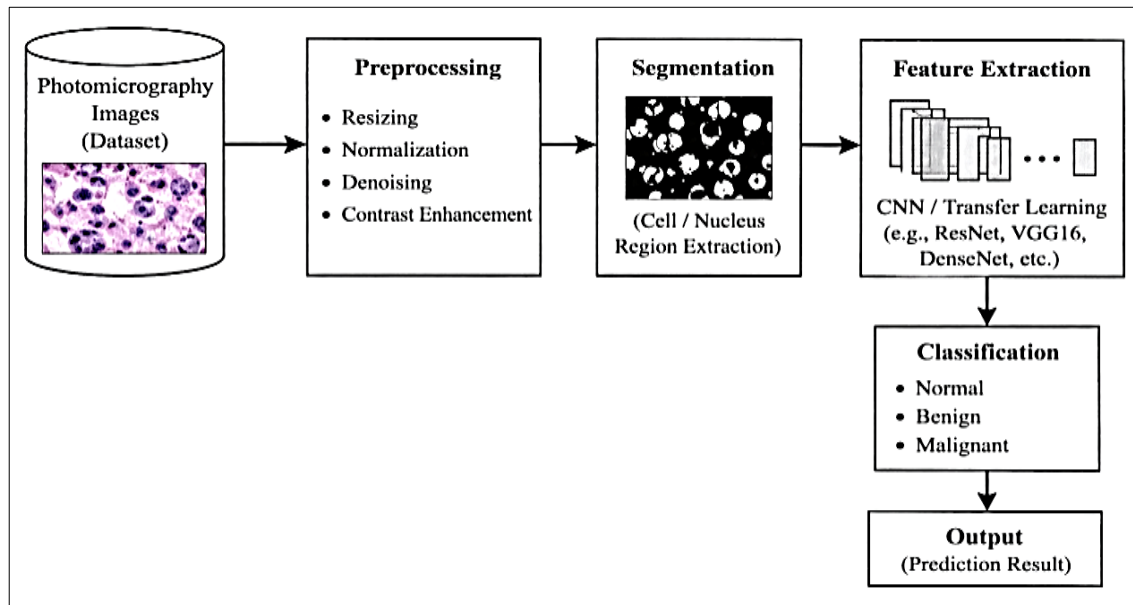


Fig 3: General workflow of lung cancer detection using photomicrography

Medical Images → Preprocessing → Segmentation → Feature Extraction → Classification → Diagnosis
The workflow begins with image acquisition, followed by preprocessing operations such as resizing, normalization, and

denoising. Segmentation isolates lung regions and nodules. Feature extraction is performed using deep learning architectures, and classification identifies normal, benign, or malignant cases.

Table 2: Comparative Analysis of Existing Studies

Author(s)	Data / Modality	Method Used	Task	Accuracy	Major Observation
Shatnawi <i>et al.</i>	CT Scan Images	Enhanced CNN, VGG16, ResNet50, ConvNeXt, Efficient NetB0	Classification	100% (Enhanced CNN)	Optimized CNN achieved the best performance.
Endalew <i>et al.</i>	CT Scan Images	Preprocessing, Segmentation, U-Net, 3D CNN	Detection and Classification	77%	Complete pipeline developed, but accuracy remained moderate.
Shah <i>et al.</i>	LUNA16 CT Dataset	Ensemble CNN	Nodule Detection	95%	Ensemble learning improved prediction accuracy.
Sait <i>et al.</i>	PET and CT Images	DenseNet-121, Autoencoder, Mobile NetV3-Small	Classification	98.6%	Efficient model with fewer parameters and high performance.
Takale <i>et al.</i>	LIDC-IDRI CT Images	ResNet50	Classification	Not Specified	ResNet50 helped reduce the vanishing gradient problem.
Kutaphale <i>et al.</i>	CT Scan Images	Machine Learning Algorithms, CNN, SMOTE	Classification	98.89% (Training Accuracy)	Balanced dataset improved training results.
Abe <i>et al.</i>	CT Scan Images	Random Pixel Swap, ResNet, Vision Transformer	Classification	97.78%	Data augmentation improved model.
Faruqui <i>et al.</i>	CT and IoT Sensor Data	LungNet Hybrid CNN	Five-Class Classification	96.81%	Hybrid data sources enhanced diagnostic performance.
Klangbunrueang <i>et al.</i>	CT Scan Images	VGG16, ResNet50, InceptionV3, Mobile NetV2	Normal, Benign, and Malignant Classification	98.18%	VGG16 achieved the best overall results.
Cimpeanu <i>et al.</i>	CT Images	CNN with Data Augmentation	Benign and Malignant Classification	77.01% (Validation Accuracy)	Useful approach but requires performance improvement.

Review of Existing Studies

Mohammad Q. Shatnawi *et al.* proposed an Enhanced CNN model for lung cancer detection that outperformed several

pretrained models, demonstrating the effectiveness of optimized CNN architectures for medical image classification. Simie Endalew *et al.* developed a lung cancer

detection pipeline using preprocessing, U-Net segmentation, and 3D CNN classification, achieving 77% accuracy on CT scan images. Asghar Ali Shah *et al.* introduced an ensemble CNN approach using the LUNA16 dataset and achieved 95% accuracy, showing the benefits of combining multiple CNN models. Abdul Rahaman Wahab Sait *et al.* used DenseNet-121, deep autoencoders, and Mobile NetV3-Small for PET/CT image classification, achieving 98.6% accuracy with low computational complexity. Mohseena Thaseen *et al.* highlighted the effectiveness of CNN-based methods for detecting malignant lung nodules and classifying cancer severity. Dr. Dattatray G. Takale *et al.* applied ResNet50 on the LIDC-IDRI dataset and demonstrated improved lung cancer classification performance using deep learning techniques. Yash Kutaphale combined machine learning algorithms and CNN models with SMOTE-based balancing, achieving high diagnostic performance on CT scan images. Ayomide Adeyemi Abe *et al.* proposed a Random Pixel Swap augmentation technique that improved the performance of CNN and Vision Transformer models for lung cancer detection. Nuruzzaman Faruqui *et al.* developed Lung Net, a hybrid CNN model integrating CT images and IoT sensor data, achieving 96.81% accuracy. Helena Liz-Lopez *et al.* reviewed deep learning approaches for lung cancer detection and highlighted the importance of CNNs, explainable AI, and publicly available datasets. Dunke Siddhi *et al.* proposed a CNN-based framework for classifying malignant and benign lung nodules from CT scan images. Vishal Nayakwadi *et al.*

utilized a VGG16-based transfer learning model for multi-class lung cancer classification with strong diagnostic performance. Rapeepat Klangbunrueang *et al.* demonstrated that VGG16 achieved 98.18% accuracy and outperformed several popular deep learning architectures. Gayathri Devi Nagalapuram *et al.* combined machine learning and deep learning methods for lung cancer risk prediction, stage analysis, and early diagnosis. Abhishek Kumar Murgunde *et al.* discussed the importance of CT-based lung cancer screening programs and their impact on reducing mortality rates. OvidiuCimpeanu *et al.* developed a CNN model for classifying benign and malignant lung lesions, achieving 77.01% validation accuracy. Unai Muñoz-Aseguinolaza *et al.* explored CNN-based and 3D medical image analysis techniques for disease prediction and abnormality detection.

VII. Discussion

The literature indicates that CNN-based approaches remain dominant in lung cancer detection. Transfer learning architectures such as VGG16, ResNet50, DenseNet121, and Efficient Net consistently achieve strong performance even when limited medical data are available.

Hybrid architectures demonstrate improved robustness by combining segmentation, feature extraction, and classification components. Ensemble methods also improve reliability by aggregating predictions from multiple models.

Although many studies report accuracies above 95%, direct comparison is difficult because different datasets, preprocessing techniques, and evaluation protocols are used.

Table 3: Common Datasets

Dataset	Modality	Application
LIDC-IDRI	CT	Lung Nodule Detection
LUNA16	CT	Lung Nodule Analysis and Detection
Lung-PET-CT-Dx	PET/CT	Lung Cancer Classification
IQ-OTH/NCCD	CT	Multi-class Lung Cancer Classification
Private Hospital Datasets	CT / PET / X-ray	Clinical Validation and Performance Evaluation

Explainable Artificial Intelligence

Explainable AI improves transparency and trust in AI systems. Techniques such as Grad-CAM, saliency maps, attention visualization, and occlusion sensitivity highlight image regions responsible for model predictions.

Explainable artificial intelligence is important in medical diagnosis because doctors need to understand why a model gives a particular prediction. Deep learning models often work as black boxes, which makes clinical trust difficult.

Explainable AI methods provide visual or numerical explanations of model decisions. Grad-CAM is one of the commonly used techniques for CNN-based medical image interpretation. It generates heat maps that highlight image regions influencing the model prediction. Saliency maps, occlusion sensitivity, and attention visualization are also used to interpret model behavior. In lung cancer detection, explainability can help radiologists verify whether the model is focusing on actual nodules or irrelevant image regions.

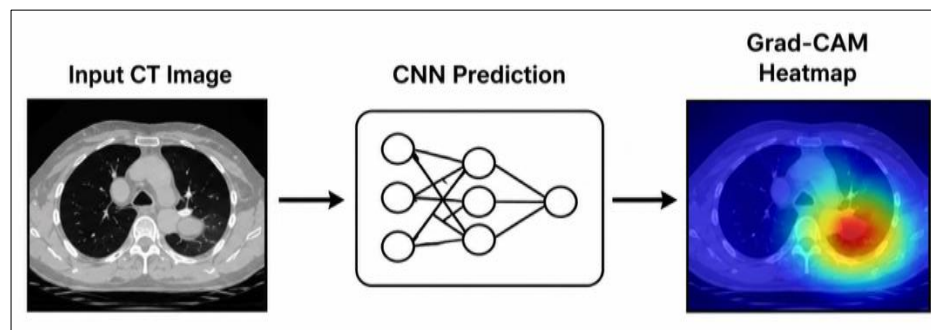


Fig 4: Explainable AI Heat map.

Research Gaps

Several important research gaps remain

- Limited dataset diversity.
- Lack of external validation.
- Dataset imbalance.
- Insufficient explain ability.
- High computational complexity.
- Limited multimodal learning.
- Lack of real-world deployment studies.

Limitation of Existing Studies

Although remarkable progress has been achieved, several limitations remain:

- Many studies use small datasets.
- External validation is often missing.
- Class imbalance affects model reliability.
- Explain ability is limited in many deep learning models.
- Some models require high computational resources.
- Dataset bias can reduce generalization.
- Real-world hospital deployment is still limited.
- Data privacy and security concerns restrict data sharing between healthcare institutions.
- Variations in imaging protocols and equipment can affect model performance.
- Lack of standardized evaluation metrics makes it difficult to compare different models.
- Integration of AI systems into existing clinical workflows remains a significant challenge.

Addressing these limitations is essential for successful clinical adoption and for developing reliable, accurate, and trustworthy lung cancer detection systems.

Future Scope: Future research should focus on developing robust hybrid deep learning models that integrate

segmentation, classification, and explainable AI techniques. Transfer learning models need to be evaluated on diverse datasets to improve generalization and reliability. Lightweight architectures such as Mobile Net and Efficient Net can support real-time clinical deployment.

Additionally, multimodal approaches combining CT scans, PET images, clinical records, and patient information may enhance diagnostic accuracy. Emerging techniques such as transformer-based architectures, federated learning, self-supervised learning, and synthetic data generation also offer promising opportunities for improving lung cancer detection systems while reducing dependence on large labeled datasets.

Future research should focus on

- Federated learning for privacy-preserving training.
- Multimodal learning using CT, PET, symptoms, and genomic data.
- Explainable AI integration.
- Lightweight deployment on edge devices.
- Transformer-based medical imaging systems.
- Self-supervised learning techniques.
- Clinical validation across multiple healthcare institutions.

Proposed Review-Based Framework

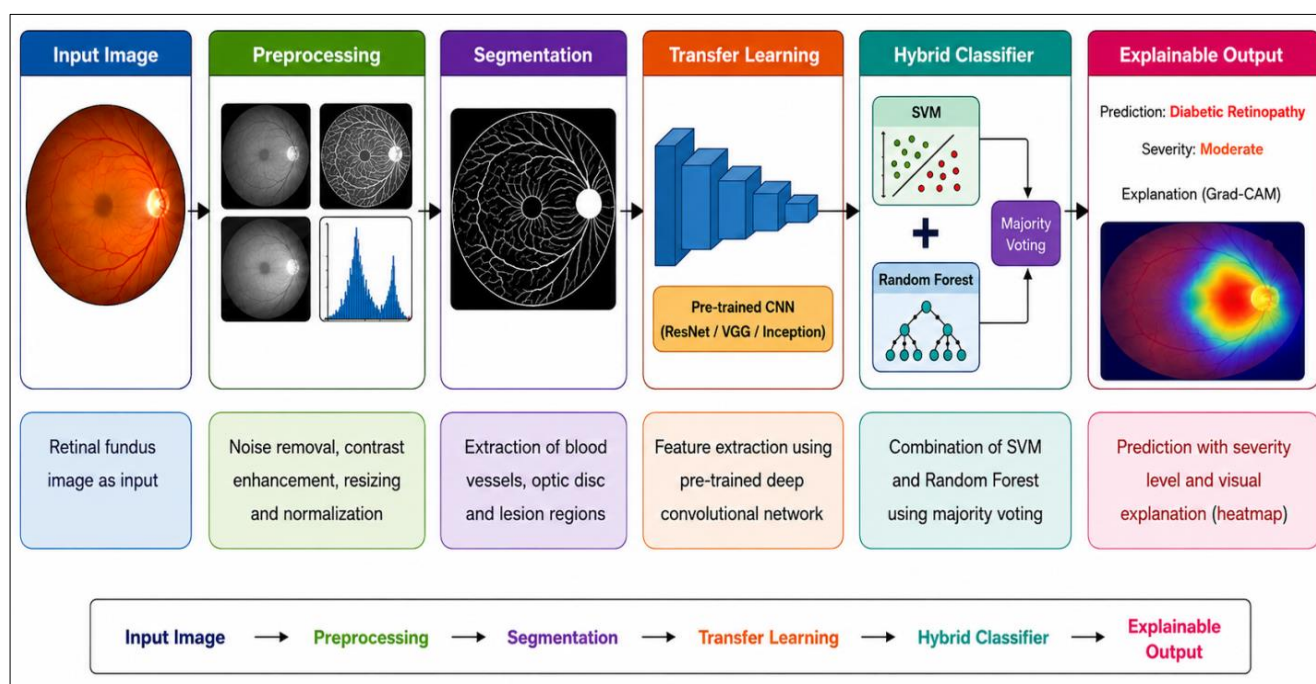


Fig 5: Proposed Review – Based Framework

Conclusion

This review analyzed recent developments in lung cancer detection using transfer learning and hybrid deep learning models. The literature demonstrates that CNNs, transfer learning architectures, segmentation networks, and ensemble methods significantly improve diagnostic accuracy. Transfer learning reduces training complexity and enables effective learning from limited medical datasets. Hybrid architectures further enhance robustness by combining complementary techniques.

Despite remarkable progress, challenges related to Explainability, dataset diversity, clinical validation, and deployment remain unresolved. Future research should focus on multimodal learning, explainable AI, federated learning, and lightweight deployment. Such developments will support the

integration of AI systems into routine clinical workflows and contribute to improved patient outcomes.

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