An Imaging Perspective on AI's Function in the Lung Cancer Diagnosis and Detection

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Abstract

Due in large part to late diagnosis, and the primary cause of cancer-related death globally is still lung cancer, primarily as a result of late detection and ineffective treatment at later stages. When it comes to lung cancer screening, detection, diagnosis, and staging, medical imaging is essential; yet, Growing data volumes, inter-observer heterogeneity, and the modest presence of early-stage disease pose challenges to conventional picture interpretation. Artificial intelligence (AI), which makes automated, quantitative, and repeatable analysis possible, has become a potent instrument in recent years to improve imaging-based lung cancer assessment.

The review provides an in-depth overview of the role of artificial intelligence in the diagnosis and detection of lung cancer through the imaging perspective. We discuss the way machine learning and deep learning methods are being applied to the primary imaging modalities, including computed tomography, low-dose CT, positron emission tomography-computed tomography, and chest radiography. We consider such significant AI-based application like TNM staging, segmentation, benign-malignant classification, pulmonary nodule recognition, and tumour characterisation. Radiomics and multimodal AI make personalised decision-making and non-invasive tumour characterisation possible. Also, the clinical effects of AI on the optimization of screening, workflow, diagnostic accuracy, and early detection are summarized in this paper. New solutions such as explainable AI and multimodal data integration are evaluated with seriousness and the limitations that exist today in terms of data heterogeneity, model generalizability, interpretability, and regulatory issues are also discussed. On balance, AI can dramatically transform the frame of imaging of lung cancer by helping to diagnose lung cancer earlier and make more precise clinical decisions. In order to realize the full clinical advantages of AI-based imaging in lung cancer treatment, clear models need to be developed, continuous validation is required, and the seamless integration into clinical pathways is needed.

Introduction:

The prevalence of lung cancer is among the critical international health issues, and it has remained the top cause of death associated with cancer all over the world. In spite of significant progress in treatment options, such as targeted therapy and immunotherapy, the overall survival statistics are rather low. To a great extent, this can be explained by late-stage diagnosis since early-stage lung cancer does not have symptoms or has nonspecific symptoms. As a result, a number of patients end up being diagnosed in later stages of the disease, when the form of treatment available is minimal and the patient is unlikely to make it. Medical imaging is of great importance in the detection, diagnosis, staging and monitoring of lung cancer. Traditional imaging technologies like the chest radiography, low dose computed tomography (LDCT), high resolution computed tomography and positron emission tomography-computed tomography (PET-CT) are actively used throughout the lung cancer care pathway. LDCT has shown a definite advantage in the lowering mortality due to lung cancer in high-risk groups, and is commonly advocated with respect to screening. Nevertheless, the correct interpretation of imaging findings is still a difficult task and much depends on the experience of the radiologist. Inter-observer variability, work load increase, fatigue among readers, and the gradual occurrence of the first pulmonary nodules may affect diagnostic accuracy and result in false or delayed diagnosis..(1)

The rising amount and complexity of medical imaging information have created an additional burden on the radiologists, which increase the risk of diagnostic errors and burnout. In this connection, the artificial intelligence (AI) has been a promising solution to improve the analysis of the images and assist the process of clinical decision-making. AI involves calculating mechanisms able to execute activities normally done by human intellect, such as pattern recognition, categorization, and predictive analytical efforts. Machine learning and deep learning techniques have been specifically relevant in the field of medical imaging. Conventional machine learning uses feature extraction that is usually handcrafted, and the convolutional neural networks used in deep learning learn hierarchical features directly, which is effectively produced automatically, directly on raw imaging data making it particularly well adapted to complex radiological tasks. In the last ten years, the development of AI-based imaging has been impressive in detecting and diagnosing lung cancer. These programs cover automated nodules in the lungs, segmentation, and classification, and malignancy risk. A number of papers have indicated that AI systems can perform as well as radiologists with respect to diagnostic performance in certain cases surpassing experienced radiologists, especially in LDCT-based screening programs. Computer-aided detection systems using AI have also been shown to be useful as either concurrent or second readers that enhance the sensitivity, but reduce the interpretation time and workload. (2)

In addition to detection, AI has increased the diagnosis capabilities of medical imaging via radiomics and multimodal information. Radiomics is the high-throughput process of identifying and extracting quantitative properties of medical images which allows the detailed characterization of tumor morphology, texture and heterogeneity. Radiomics combined with AI models facilitates the idea of a virtual biopsy, where it is possible to make non-invasive predictions of tumor histology, genetic changes, and treatment response without the need to perform any invasive procedures on the body, as all predictions are made based on imaging data. Moreover, AI in PET-CT imaging has improved the staging of tumors, their prognosis, and the assessment of their response to therapy through the combination of metabolic and anatomical data. Although these are encouraging progress, there are still challenges when it comes to clinical implementation of AI in the imaging of lung cancer. Problems with data quality, generalizability of models, algorithm bias, and lack of interpretability still limit broad clinical use. A large number of AI systems are black boxes, which lacks clinicians in terms of comprehension and trust, which causes ethical, legal, and regulatory issues. Subsequently, the demand to develop explainable and transparent AI with a view of safe and effective integration into everyday clinical activity is increasing. Since AI technologies develop fast and become more and more relevant in thoracic imaging, there is a need to synthesize the existing evidence in a comprehensive manner. The proposed review seeks to critically discuss the use of artificial intelligence in detection and diagnosis of lung cancer through imaging. This review has provided the recent developments, clinical advantages, and current limitations of AI applications in the major imaging modalities in the study, such as chest radiography, computed tomography, low-dose CT, PET-CT, and future perspectives of the research and clinical practice(3)(4)

Keywords: Lung cancer, artificial intelligence, medical imaging, deep learning, machine learning, computed tomography, lung cancer screening, radiomics

Overview of Lung Cancer and Imaging Modalities:

Lung Cancer Classification and Clinical Relevance

Lung cancer is a heterogeneous disease that develops as a result of the malignant transformation of respiratory epithelial cells and can be broadly divided into two major histological types: non-small cell lung cancer (NSCLC), and small cell lung cancer (SCLC). NSCLC represents about 85 percent of all lung cancers, and of this disease, there is the adenocarcinoma, squamous cell carcinoma, and large cell carcinoma. SCLC is less prevalent but aggressive in its growth, early metastasis and its prognosis is worse. Biological diversity of lung cancer is one of the factors that make this disease vary in terms of appearance during imaging, disease spread and treatment, and hence accurate detection and diagnosis of this disease is clinically challenging. Stage of lung cancer at diagnosis has a close relationship with prognosis. The survival rates with regard to early-stage disease are much higher as compared to the prognosis of the advanced-stage lung cancer. Regrettably, early lung cancer is either asymptomatic or has non-specific symptoms, and thus is diagnosed late. This makes imaging very important to identify pulmonary cancer at early stage as well as to help in the diagnosis, staging, planning of treatment and follow-up. (5)

Imaging Modalities in Lung Cancer

Chest Radiography

Chest radiography is often the first-line imaging modality used in patients with respiratory symptoms due to its wide availability, low cost, and minimal radiation exposure. It can detect large masses, pleural effusions, and advanced disease manifestations. However, chest radiography has limited sensitivity for early-stage lung cancer, particularly for small pulmonary nodules, lesions obscured by anatomical structures, or those located in the lung apices or retrocardiac regions. These limitations contribute to a significant rate of missed or delayed diagnoses when chest radiography is used alone.

Computed Tomography and Low-Dose CT

Computed tomography (CT) has become the cornerstone of lung cancer imaging due to its high spatial resolution and ability to provide detailed cross-sectional images of the lung parenchyma. CT is highly effective in detecting pulmonary nodules, characterizing lesion size, shape, margins, and internal composition, and assessing local invasion and lymph node involvement. Low-dose computed tomography (LDCT) has emerged as a key tool for lung cancer screening, particularly in high-risk populations, as it offers reduced radiation exposure while maintaining adequate diagnostic performance.

Despite its advantages, CT interpretation is complex and time-consuming. Radiologists must evaluate large volumes of image data, often under time constraints, increasing the likelihood of inter-observer variability and diagnostic errors. Differentiating benign from malignant nodules based solely on visual assessment can be challenging, especially for small or indeterminate lesions.(5) (4)

Positron Emission Tomography–Computed Tomography

Positron emission tomography–computed tomography (PET-CT) combines anatomical and functional imaging, providing valuable information on tumor metabolism, aggressiveness, and metastatic spread. PET-CT is widely used for staging, treatment response assessment, and detection of recurrence. By evaluating metabolic activity, PET-CT improves differentiation between benign and malignant lesions and enhances accuracy in lymph node and distant metastasis detection.

However, PET-CT is not without limitations. False-positive findings may occur in inflammatory or infectious conditions, while false-negative results can arise in small lesions or tumors with low metabolic activity. Interpretation remains dependent on clinical context and expert judgment, underscoring the need for advanced analytical support.(6)

Limitations of Conventional Imaging Interpretation

Although imaging modalities are indispensable in lung cancer management, conventional interpretation relies heavily on human expertise and subjective judgment. Factors such as reader fatigue, increasing imaging workload, subtle lesion characteristics, and overlapping imaging features between benign and malignant nodules contribute to diagnostic variability. Additionally, manual assessment of tumor burden and progression can be time-intensive and prone to inconsistency, particularly in longitudinal studies.

These challenges highlight the limitations of traditional imaging workflows and emphasize the need for advanced computational tools capable of supporting radiologists in image interpretation. Artificial intelligence has therefore gained attention as a means to enhance diagnostic accuracy, reduce workload, and improve consistency across imaging-based lung cancer detection and diagnosis.

Transition to AI-Based Imaging Analysis

The complexity and volume of lung imaging data make it an ideal domain for the application of artificial intelligence. By leveraging computational power to analyze imaging features beyond human visual perception, AI-based systems offer the potential to transform lung cancer imaging from a qualitative, observer-dependent process into a more quantitative, reproducible, and efficient workflow. The following sections of this review explore the principles of artificial intelligence in medical imaging and examine its role in lung cancer detection and diagnosis across various imaging modalities.(7)

Literature Review

The application of artificial intelligence in lung cancer detection and diagnosis has grown rapidly over the past decade, driven by advances in medical imaging, computational power, and data availability. Early research efforts primarily focused on enhancing traditional imaging interpretation through computer-aided detection systems. These systems were designed to assist radiologists by highlighting suspicious regions on chest radiographs and computed tomography scans. While early computer-aided approaches improved sensitivity in detecting pulmonary nodules, they were often limited by high false-positive rates and dependence on handcrafted feature extraction, which constrained their clinical reliability.

With the evolution of machine learning techniques, researchers began exploring supervised learning algorithms such as support vector machines, decision trees, and random forests for lung cancer imaging tasks. These models relied on predefined imaging features, including shape, margin characteristics, texture, and intensity patterns, to differentiate benign from malignant lung nodules. Although machine learning-based approaches demonstrated improved classification performance compared to rule-based systems, their effectiveness remained highly dependent on feature engineering and dataset quality. Variability in imaging protocols and manual feature selection limited their scalability and generalizability across clinical settings.

The emergence of deep learning marked a significant turning point in lung cancer imaging research. Convolutional neural networks enabled automated feature learning directly from raw imaging data, eliminating the need for manual feature extraction. Numerous studies reported that deep learning models achieved high accuracy in lung nodule detection and classification tasks using chest X-ray, CT, and low-dose CT images. In particular, deep learning-based systems demonstrated strong performance in identifying small and subtle nodules that are frequently missed during routine visual inspection. These findings highlighted the potential of AI to augment radiologist performance and reduce diagnostic errors.

Low-dose CT screening has been a major focus of AI-driven lung cancer research due to its established role in early detection. Several studies have evaluated AI algorithms within LDCT screening workflows, reporting improvements in sensitivity, reduction in false-positive findings, and decreased interpretation time. AI-assisted screening systems have also been explored as second readers, supporting radiologists by prioritizing high-risk cases and flagging suspicious lesions. These approaches have shown promise in addressing the increasing workload associated with population-based screening programs while maintaining diagnostic accuracy.

Beyond detection, artificial intelligence has been increasingly applied to lung cancer diagnosis and characterization. AI models have been developed to assess tumor size, morphology, growth patterns, and invasion of surrounding structures using CT imaging. In PET-CT imaging, machine learning and deep learning techniques have enabled integration of metabolic and anatomical information, enhancing tumor staging, lymph node evaluation, and detection of distant metastases. Studies have also demonstrated the ability of AI models to predict treatment response and clinical outcomes based on imaging-derived features, suggesting a broader role for AI in personalized lung cancer management.

Radiomics has emerged as a complementary approach within the AI landscape, enabling high-throughput extraction of quantitative imaging features that capture tumor heterogeneity and biological behavior. Radiomic analyses combined with machine learning models have been applied to predict histological subtypes, genetic mutations, and prognosis in lung cancer patients. This approach has led to the concept of a “virtual biopsy,” offering a non-invasive alternative to tissue sampling in selected clinical scenarios. While radiomics-based AI models have shown encouraging results, concerns regarding reproducibility and standardization remain.(8)(9)

More recently, research has shifted toward multimodal and integrative AI frameworks that combine imaging data with clinical, pathological, and molecular information. These approaches aim to provide comprehensive decision support across the lung cancer care continuum, from risk assessment and screening to diagnosis and outcome prediction. Such integrative models reflect the growing recognition that lung cancer is a complex disease requiring multi-dimensional analysis beyond imaging alone.

Despite the significant progress documented in the literature, the majority of AI studies in lung cancer imaging are retrospective and conducted in controlled research environments. Limited external validation, small sample sizes, and heterogeneity in imaging acquisition protocols pose challenges for clinical translation. Additionally, many high-performing deep learning models lack transparency, operating as black-box systems that offer limited insight into their decision-making processes. This has prompted increasing interest in explainable artificial intelligence approaches aimed at improving interpretability and clinician trust.

Overall, the existing literature demonstrates the substantial potential of artificial intelligence to enhance lung cancer detection and diagnosis through medical imaging. However, it also highlights the need for standardized methodologies, robust validation, and clinically interpretable models to enable widespread adoption in routine practice (8)

Literature Review Gap

Even though a lot of research has been conducted on the application of artificial intelligence in the imaging of lung cancer, there are still a number of crucial gaps. First, a number of current studies are devoted to single-task studies, e.g. nodule detection or classification, with no attention to the entire imaging process, i.e. screening, diagnosis, and staging. This disjointed strategy constrains clinical implementation of AI systems to the real world environment, where end-to-end and integrated solutions are needed.

Second, high diagnostic performance was found in the experimental literature, but the external validity of AI models in various populations and imaging conditions is not discussed sufficiently. Variations in the type of scanners, acquisition protocols, and types of patients frequently lead to a drop in performance using the models in situations outside the training data. This weakness is also a significant obstacle to the large-scale clinical uptake.

Third, most existing AI implementations are black-box systems and have little interpretability of their predictions. This diminishes clinician faith and ethical and regulatory issues, especially in life and death clinical decision-making. Despite the fact that explainable AI methods have been suggested, they are not actively used in daily routine lung cancer imaging processes.

Lastly, reviews that do exist tend to emphasize either the technical development of algorithms or the individual imaging modalities, and have a little focus on an imaging-centric approach that finds a balance between clinical relevance and AI methodology. The evidence of the necessity of an updated and integrative review synthesizing AI use across different imaging modalities and critically assessing its clinical effects, limitations, and future implications is obvious.

In this regard, the current review fills these gaps by giving a detailed examination of the artificial intelligence in lung cancer detection and diagnosis in an imaging view. As a way to support the informed development and responsible clinical translation of AI-based imaging solutions, the present review will be useful in regard to lung cancer care, by integrating evidence that spans across chest radiography, computed tomography, low-dose CT, and PET-CT, and by emphasizing both achievements and challenges in this respect (9).

Artificial Intelligence in Medical Imaging

Artificial intelligence has become an integral component of modern medical imaging, offering advanced computational tools to support image interpretation, analysis, and clinical decision-making. In the context of lung cancer, medical imaging generates large volumes of complex data that exceed the limits of conventional manual analysis. AI-based approaches provide the ability to extract meaningful patterns from imaging data, enabling more accurate, consistent, and efficient assessment of disease-related features.

Concepts and Components of Artificial Intelligence

Artificial intelligence refers to computational systems designed to perform tasks that typically require human intelligence, such as pattern recognition, learning, and prediction. Within medical imaging, AI is primarily implemented through machine learning and deep learning techniques. Machine learning involves algorithms that learn relationships from data and make predictions based on predefined features. These models require careful feature selection and are often sensitive to data quality and variability.

Deep learning represents a subset of machine learning that uses multi-layer neural networks to automatically learn hierarchical representations from raw data. Unlike traditional machine learning, deep learning does not rely on handcrafted features, making it particularly suitable for image-based applications where visual patterns are complex and high-dimensional. This ability to learn directly from imaging data has made deep learning the dominant approach in contemporary medical imaging research. (10)

Machine Learning Techniques in Imaging

Early AI applications in medical imaging relied heavily on conventional machine learning algorithms such as support vector machines, random forests, decision trees, and k-nearest neighbor classifiers. These techniques were applied to imaging features describing lesion size, shape, texture, and intensity. In lung cancer imaging, such models were used to differentiate benign and malignant nodules, assess disease risk, and support diagnostic decisions.

Although these approaches demonstrated promising results, their performance was often constrained by feature engineering requirements and limited adaptability to heterogeneous datasets. As imaging datasets grew in size and complexity, the need for more robust and scalable solutions became evident, leading to the widespread adoption of deep learning methods.(9)(10)

Deep Learning and Convolutional Neural Networks

Deep Literacy has significantly enhanced medical imaging by enabling automated, end- to- end processing of image data. One of the multitudinous deep literacy models, convolutional neural networks, has shown emotional performance in imaging operations because of its capability to identify spatial correlations and original visual patterns. CNNs use a sequence of convolutional layers to prize introductory rudiments like edges, textures, and shapes. These characteristics are also gradationally added to more complex representations, which are necessary for accurate complaint categorization and opinion.

In lung cancer imaging, CNNs have been successfully applied to chest radiography, CT, low-dose CT, and PET-CT images for tasks including lung nodule detection, segmentation, classification, and risk prediction. Their capacity to analyse three-dimensional imaging data has further enhanced performance in volumetric CT and PET-CT studies, supporting comprehensive tumour assessment.

Workflow of AI-Based Medical Imaging Analysis

The analysis of medical images via AI usually is a guided procedure. Image acquisition is the first step of the process where standardised protocols are used to get imaging data. This is then succeeded by image preprocessing which could involve noise reduction, normalisation, and even segmentation to enhance the quality of data and model performance. Traditional machine learning pipelines require the extraction of features manually, and deep learning models are trained to extract features.

After extracting features or learning, a classification or prediction model is used to conduct a particular clinical task, e.g., detect suspicious lesions or the risk of malignancy. The last step is validation and interpretation of findings that need to be reliable and clinically relevant. Such a workflow would allow AI systems to act as decision support systems and not to replace clinician expertise.

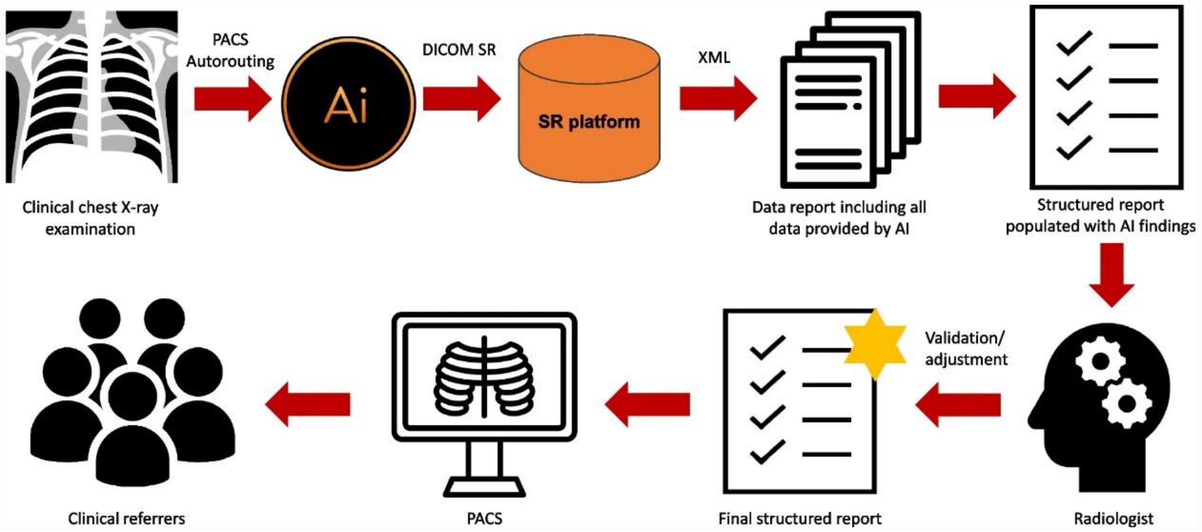


Fig 1

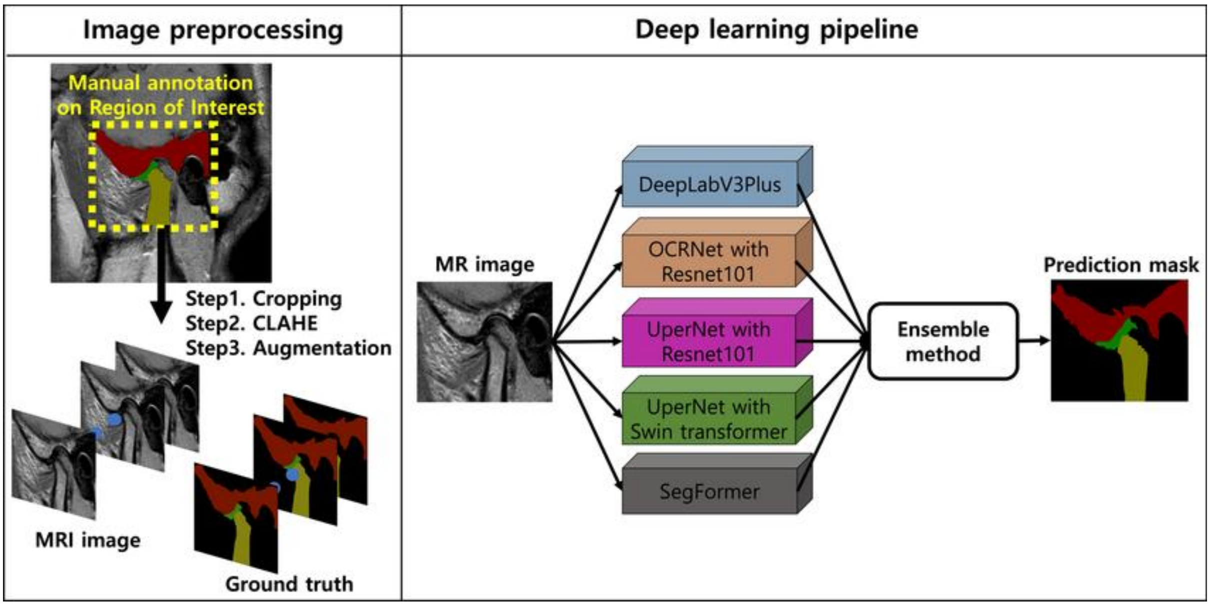


Fig 2

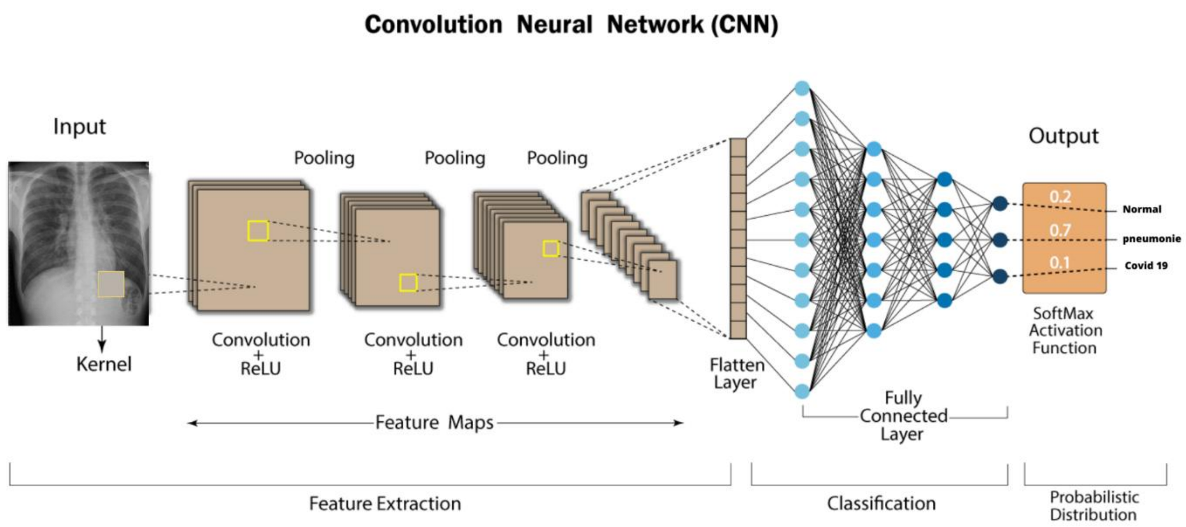


Fig 3

Role of AI as Clinical Decision Support

Instead of removing radiologists, AI in medical imaging is now being considered a decision-support technology. Artificial intelligence can support clinicians by ranking the cases at risk, identifying areas of concern, and come up with quantitative measurements that raise the level of diagnostic confidence. This support is especially helpful in the imaging of lung cancer because of the high stakes of missed or late diagnosis.

The use of AI in the medical imaging workflow can enhance the accuracy of diagnoses, lessen inter-observer variability, and streamline the workflow. Nonetheless, the successful clinical adoption cannot be undertaken without due validation, transparency, and alignment to the current clinical practices. The latter points are particularly relevant to lung cancer detection and diagnosis, with the results of imaging being directly related to patient management and outcomes.

Artificial Intelligence in Lung Cancer Detection Using Imaging

Artificial intelligence has demonstrated significant potential in improving lung cancer detection by enhancing the analysis of medical imaging data. Detection represents the earliest and most critical step in the lung cancer care pathway, as early identification of suspicious lesions directly influences diagnosis, treatment options, and patient survival. AI-based imaging systems aim to overcome the limitations of human interpretation by providing consistent, quantitative, and high-sensitivity detection of pulmonary abnormalities across imaging modalities.(10)

AI-Based Lung Nodule Detection

The automated detection of pulmonary nodules is one of the most widely researched uses of AI in lung cancer imaging. Pulmonary nodules are typical appearances of CT scans of the chest and low dose CT scans but a low percentage of them are malignant disease. It is hard to make a distinction between clinically relevant nodules and benign ones especially when the nodules are small, have indistinct margins, or are found in such areas as close to blood vessels or by pleura.

Convolutional neural networks (in particular deep learning models) have demonstrated excellent performance in the detection of pulmonary nodules, trained to acquire complex spatial and textural information on the basis of imaging data. Such models can detect nodules that can be missed out in the process of a standard visual examination, which cuts down on the false-negative rates. AI detection systems have the potential to scan the whole lung volume within a short period and indicate suspicious details that can be analyzed by radiologists later.

This can be especially useful when there are high volumes of screening involved, when time limits and reader burnout can affect diagnostic performance (11).

Nodule Segmentation and Quantitative Analysis

Following detection, accurate segmentation of pulmonary nodules is essential for quantitative assessment. Segmentation involves delineating the boundaries of a lesion from surrounding lung tissue, enabling precise measurement of size, volume, shape, and growth rate. Manual segmentation is time-consuming and subject to inter-observer variability, especially for irregular or poorly defined lesions.

AI-driven segmentation models, including fully convolutional networks and three-dimensional CNNs, have demonstrated high accuracy in automatically outlining lung nodules on CT images. These models support consistent and reproducible quantification of tumor characteristics, facilitating longitudinal monitoring and treatment response assessment. Automated segmentation also forms the foundation for advanced analyses such as radiomics, where quantitative features are extracted from precisely defined regions of interest.

Classification of Benign and Malignant Nodules

Beyond detection and segmentation, AI has been applied to classify pulmonary nodules as benign or malignant. This task is clinically significant, as it influences decisions regarding follow-up imaging, biopsy, or surgical intervention. Traditional imaging assessment relies on subjective evaluation of nodule features such as size, margin irregularity, density, and growth pattern, which can vary between observers.

AI-based classification models integrate multiple imaging features simultaneously, allowing more objective and data-driven risk assessment. Deep learning models can capture subtle differences in texture and spatial arrangement that may not be easily perceived by the human eye. Machine learning approaches combined with radiomic feature extraction have also been used to estimate malignancy probability, supporting risk stratification and personalized patient management.(12)

Role of AI in Low-Dose CT Screening Programs

Low-dose CT screening has emerged as an effective strategy for reducing lung cancer mortality in high-risk populations. However, LDCT screening generates a large number of detected nodules, the majority of which are benign, leading to increased follow-up imaging, patient anxiety, and healthcare costs. AI has been proposed as a solution to optimize LDCT screening workflows by improving specificity while maintaining high sensitivity.

AI-assisted screening systems can prioritize high-risk nodules, reduce false-positive findings, and assist radiologists in managing the high volume of screening examinations. These systems may function as concurrent readers or second readers, providing additional support without replacing clinical judgment. By enhancing efficiency and consistency, AI has the potential to make large-scale lung cancer screening programs more sustainable and clinically effective.(13)

Clinical Impact of AI in Lung Cancer Detection

There are clinical benefits of the introduction of AI into lung cancer diagnosis processes. Greater sensitivity of detection could allow earlier diagnosis, and there is a higher chance of curative therapy. Automated analysis saves on interpretation time and workload enabling radiologists concentrate on complex cases and clinical decision-making. Also, any standardized AI-based assessment has the ability to minimize inter-observer variability, which leads to more coherent patient care.

Although these are the advantages, one should remember that AI systems are meant to supplement and not to override human expertise. To be successfully implemented, it is necessary to carefully validate, incorporate into clinical workflows, and monitor the performance in order to make sure of reliability and safety in real-world practice. (14)

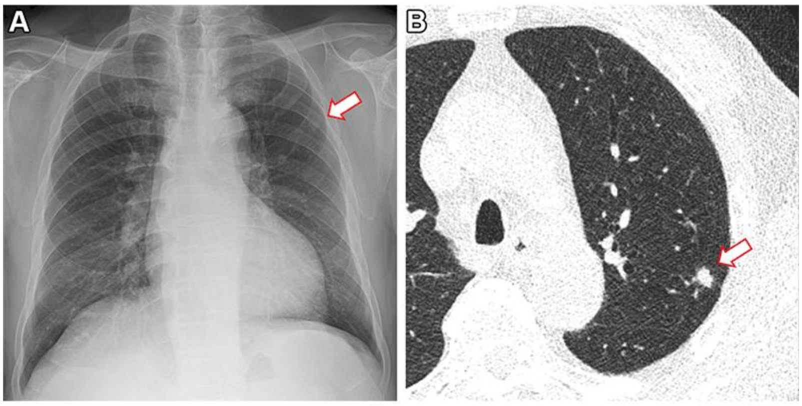


Fig 4

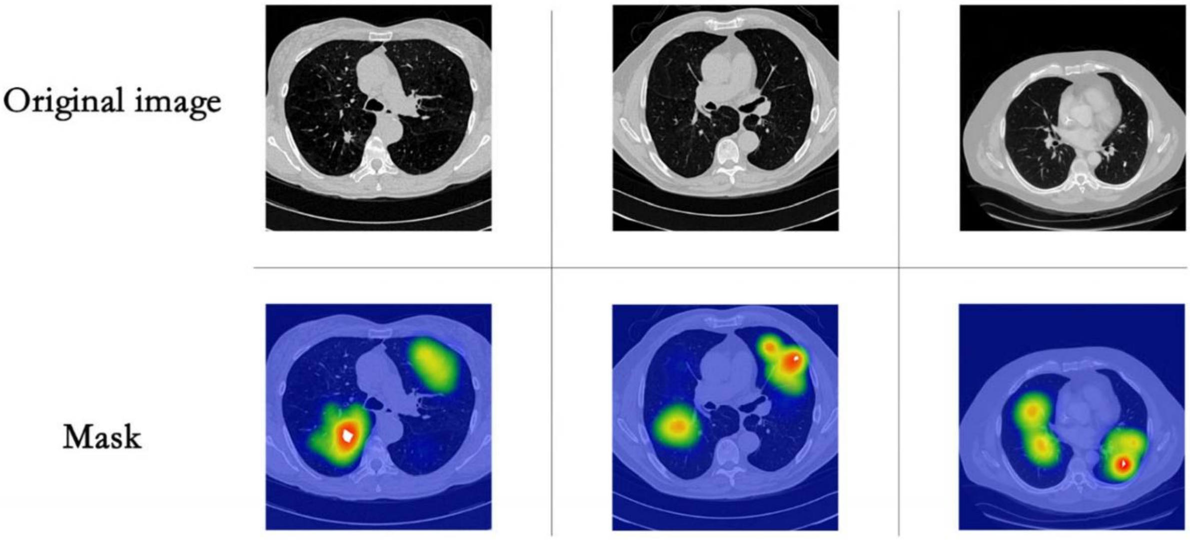
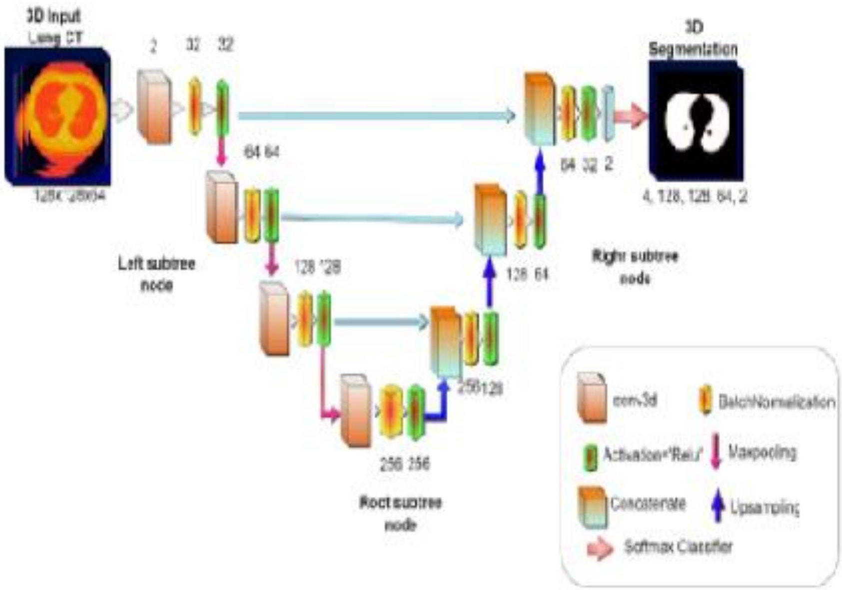


Fig 5



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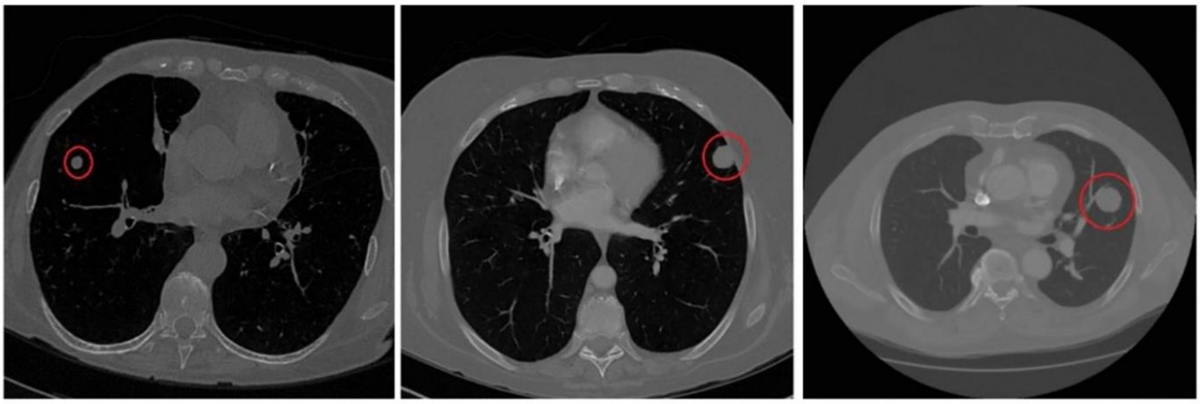


(a) (b) (c)

Fig 7

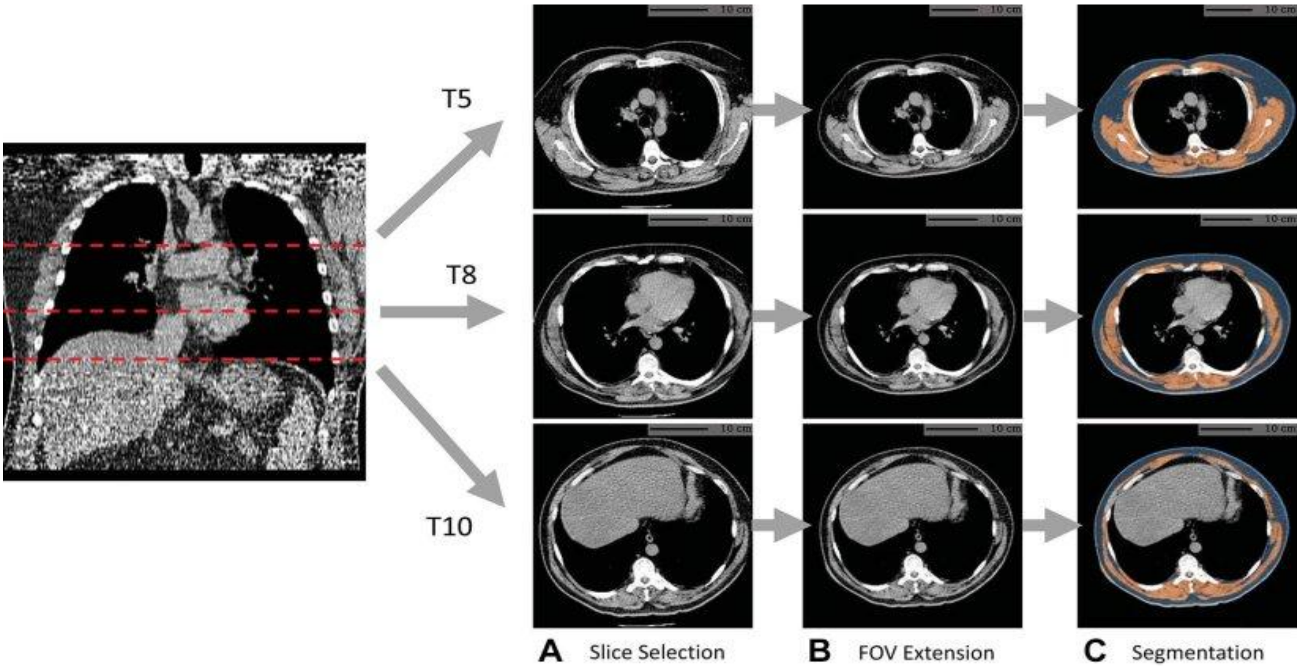


Fig 8

Artificial Intelligence in Lung Cancer Diagnosis and Staging

Following the detection of pulmonary abnormalities, accurate diagnosis and staging are critical steps that guide treatment decisions and determine prognosis in lung cancer patients. Medical imaging plays a central role in this process by providing information on tumor characteristics, local invasion, lymph node involvement, and distant metastases. Artificial intelligence has increasingly been applied to imaging-based diagnosis and staging to enhance precision, reduce subjectivity, and support clinical decision-making.(14)

AI in Tumour Characterisation

Tumor characterization involves the assessment of lesion size, shape, margins, density, and growth patterns, all of which are essential for distinguishing malignant tumors from benign or inflammatory lesions. Conventional interpretation of these features relies heavily on radiologist expertise and may vary between observers, particularly in borderline or complex cases.

AI-based models, especially deep learning algorithms, can analyse multiple tumor characteristics simultaneously and identify subtle imaging patterns associated with malignancy. By learning from large imaging datasets, these models provide objective and reproducible assessments of tumor morphology and behavior. Such quantitative evaluation supports more consistent diagnosis and facilitates longitudinal monitoring of tumor progression or response to therapy.(15)

AI in CT-Based Lung Cancer Diagnosis

Computed tomography remains the primary imaging modality for lung cancer diagnosis due to its high spatial resolution and ability to visualize lung anatomy in detail. AI applications in CT imaging have focused on improving diagnostic accuracy by assisting in lesion classification and risk stratification. Deep learning models trained on CT images can differentiate malignant tumors from benign nodules by integrating complex spatial and textural features that may not be readily apparent on visual inspection.

In addition to improving diagnostic confidence, AI-assisted CT analysis reduces inter-observer variability and supports standardized reporting. These advantages are particularly valuable in clinical settings with high imaging volumes, where consistent interpretation is essential for timely and accurate patient management.

AI in PET-CT Imaging for Diagnosis

Positron emission tomography–computed tomography provides complementary functional and anatomical information, making it a powerful tool for lung cancer diagnosis and staging. PET-CT evaluates metabolic activity, which is often elevated in malignant tumors, thereby aiding differentiation between benign and malignant lesions.

Artificial intelligence has enhanced PET-CT interpretation by integrating metabolic parameters with anatomical features to improve lesion characterization. Machine learning and deep learning models can analyze complex uptake patterns, quantify tumor heterogeneity, and reduce false-positive findings caused by inflammatory or infectious processes. These AI-driven approaches improve diagnostic accuracy and provide valuable insights into tumor aggressiveness and biological behaviour.(13)

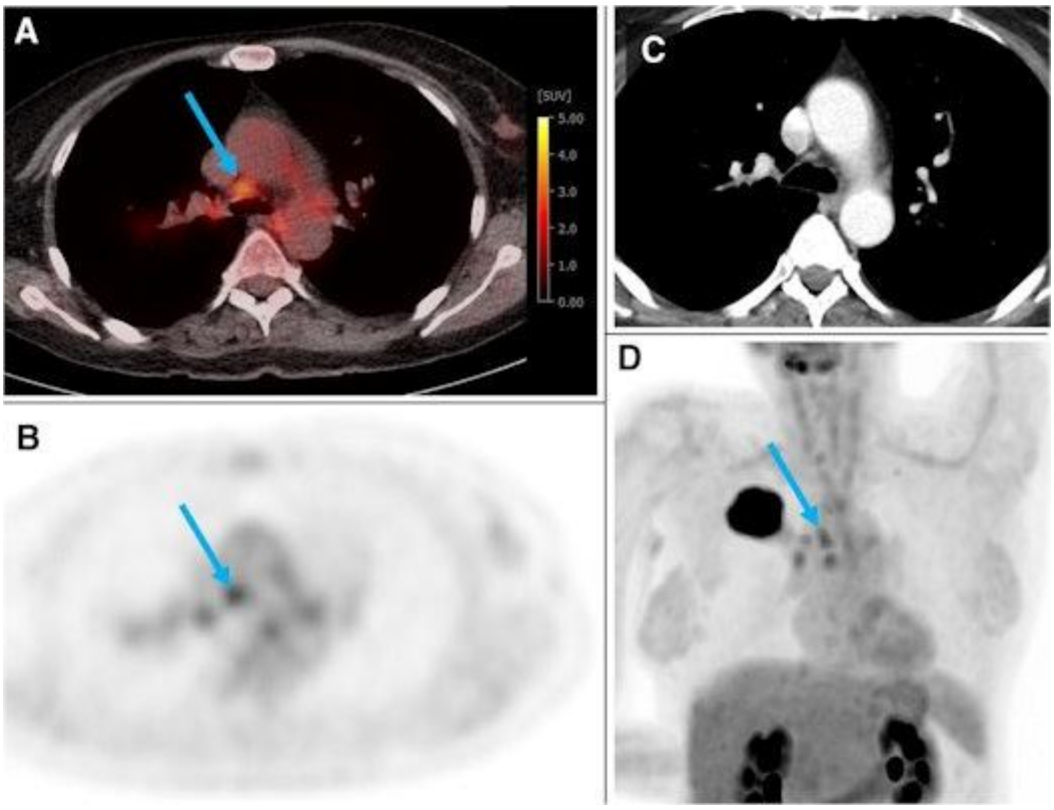


Fig 9

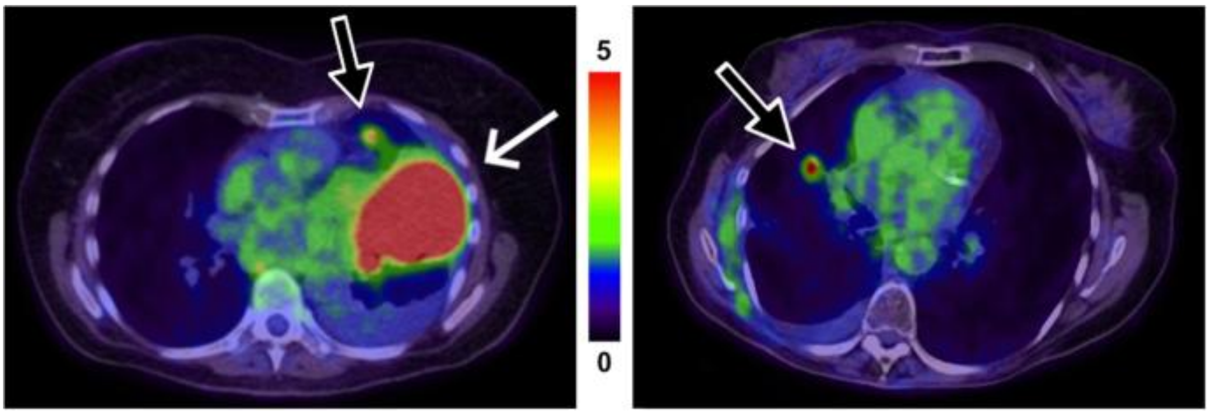


Fig 10

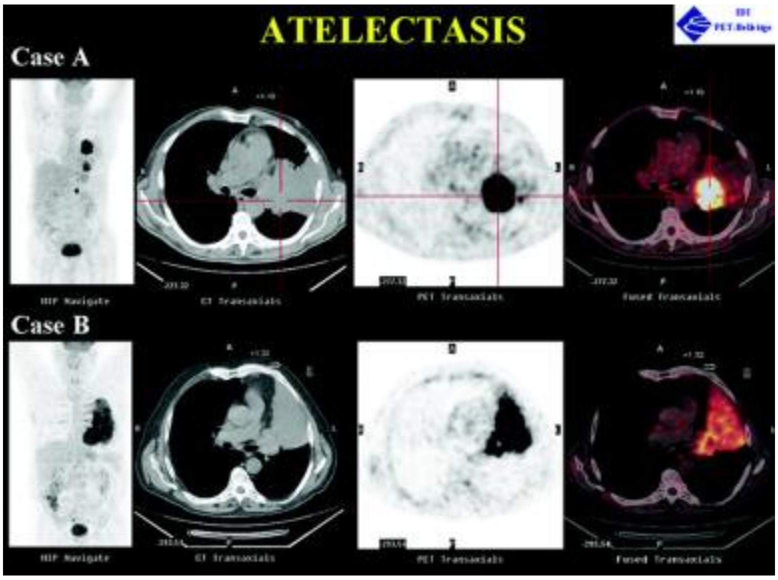


Fig 11

AI in TNM Staging

Accurate staging is essential for treatment planning and prognostic evaluation in lung cancer. The TNM staging system assesses tumor size and invasion (T), lymph node involvement (N), and distant metastasis (M). AI has shown promise in supporting each component of this staging process through automated and quantitative image analysis.

For tumor staging, AI models can precisely measure tumor dimensions and assess invasion into adjacent structures using CT imaging. In nodal staging, AI-assisted PET-CT analysis improves detection of metastatic lymph nodes by combining size, morphology, and metabolic activity. For metastasis assessment, AI systems can analyze whole-body imaging to identify distant metastatic lesions, supporting comprehensive staging with reduced interpretation time.

Clinical Significance of AI in Diagnosis and Staging

The integration of artificial intelligence into lung cancer diagnosis and staging offers several clinical benefits. Enhanced diagnostic accuracy and standardized assessments contribute to improved treatment selection and personalized care. AI-driven staging support can facilitate earlier initiation of appropriate therapy and improve prognostic stratification. Moreover, by reducing interpretation time and variability, AI systems allow clinicians to focus on complex decision-making and patient-centered care.

Despite these advantages, AI-based diagnostic and staging tools must be carefully validated in diverse clinical environments to ensure reliability and safety. When integrated responsibly, artificial intelligence has the potential to significantly enhance imaging-based lung cancer diagnosis and staging, ultimately improving patient outcomes.(16)

Radiomics and Multimodal Artificial Intelligence in Lung Cancer

Radiomics has emerged as a powerful extension of medical imaging analysis, enabling the extraction of high-dimensional quantitative information from standard radiological images. Unlike conventional visual interpretation, which relies on qualitative assessment, radiomics converts imaging data into measurable features that describe tumor shape, texture, intensity, and spatial heterogeneity. When combined with artificial intelligence, radiomics offers a data-driven approach to uncover clinically relevant tumor characteristics that may not be visible to the human eye.

Concept and Workflow of Radiomics

Radiomics is a regular procedure that begins with the gathering of images and accurate segmentation of the region of interest, which is generally the excrescence or a worrisome lesion. multitudinous quantitative rudiments are taken out of the prints after segmentation is finished. These comprise texture- grounded features that represent intratumoral diversity, first- order features that characterize intensity distributions, and advanced- order features produced by sophisticated fine operations. In order to support clinical operations including complaint opinion, outgrowth vaticination, and remedy response evaluation, the uprooted data are coming subordinated to machine literacy or deep literacy algorithms.

In lung cancer imaging, radiomic features derived from CT and PET-CT scans have demonstrated strong associations with tumor aggressiveness, histological subtypes, and patient outcomes. This quantitative approach enhances the value of routine imaging by transforming it into a source of rich, mineable data.(17)

Radiomics-Based AI for Lung Cancer Characterization

Radiomics combined with AI has shown promise in improving lung cancer characterization beyond conventional imaging assessment. By analyzing subtle textural and spatial variations within tumors, AI-driven radiomic models can help differentiate benign from malignant nodules and identify aggressive tumor phenotypes. These models integrate multiple imaging features simultaneously, enabling more objective and reproducible classification compared to subjective visual analysis.

Radiomics-based AI has also been explored for predicting histopathological subtypes and molecular characteristics of lung cancer. This capability supports the concept of a non-invasive “virtual biopsy,” where imaging data provide insights into tumor biology without the need for invasive tissue sampling. Such approaches are particularly valuable when biopsy is contraindicated or when tumor heterogeneity limits the representativeness of sampled tissue.(18)(19)

Multimodal AI and Data Integration

While imaging provides critical structural and functional information, lung cancer is a complex disease influenced by clinical, pathological, and molecular factors. Multimodal artificial intelligence aims to integrate imaging data with additional sources such as patient demographics, clinical history, laboratory findings, and genomic information. By combining these heterogeneous data streams, multimodal AI models offer a more comprehensive understanding of disease behavior and patient-specific risk.

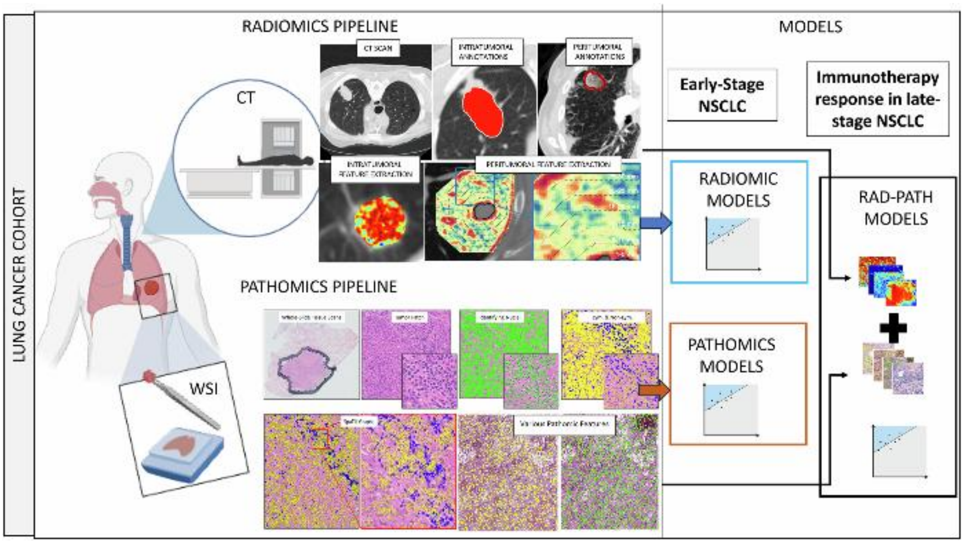
In lung cancer, multimodal AI frameworks have been developed to enhance risk stratification, improve diagnostic accuracy, and predict treatment response. For example, integrating radiomic features with clinical variables can improve malignancy risk prediction compared to imaging alone. Similarly, combining PET-CT radiomics with molecular data has shown potential for prognosis assessment and therapy selection.

Clinical Value of Radiomics and Multimodal AI

The integration of radiomics and multimodal AI into lung cancer imaging workflows offers several clinical advantages. These approaches support personalized medicine by enabling patient-specific risk assessment and treatment planning. Quantitative imaging biomarkers derived from radiomics can assist in monitoring disease progression and evaluating therapeutic response, particularly in longitudinal studies.

Despite these benefits, challenges remain in standardization, reproducibility, and validation of radiomic features across institutions and imaging platforms. Differences in acquisition protocols, reconstruction parameters, and segmentation methods can influence feature stability. Addressing these challenges is essential for translating radiomics and multimodal AI from research settings into routine clinical practice.(21)(22)

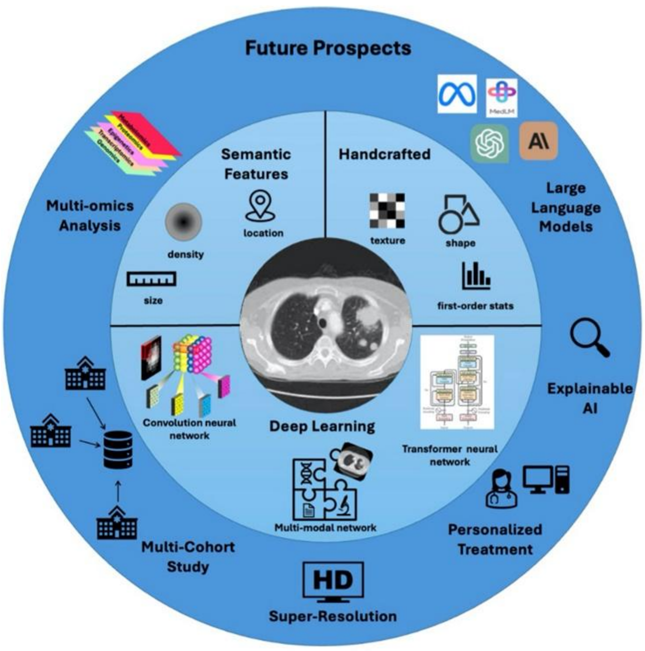
Fig 12



Clinical Impact and Benefits of Artificial Intelligence in Lung Cancer Imaging

The integration of artificial intelligence into lung cancer imaging has the potential to significantly influence clinical practice by improving diagnostic accuracy, efficiency, and consistency. As imaging plays a central role across the lung cancer care continuum, AI-based tools offer meaningful support to clinicians in managing the growing complexity and volume of imaging data. The clinical impact of AI extends from early detection and diagnosis to treatment planning and follow-up, ultimately contributing to improved patient outcomes.(23)

Fig 13



Improvement in Early Detection and Diagnostic Accuracy

One of the most significant clinical benefits of AI in lung cancer imaging is its ability to enhance early detection. Early-stage lung cancer is often subtle on imaging and may be missed during routine interpretation, particularly in high-volume screening environments. AI-based detection systems can identify small or visually inconspicuous pulmonary nodules with high sensitivity, supporting radiologists in recognizing early malignancies that may otherwise go undetected. Earlier diagnosis increases the likelihood of curative treatment and is associated with improved survival rates.

In diagnostic settings, AI-assisted image analysis improves accuracy by providing objective and quantitative assessments of imaging features. By reducing reliance on subjective interpretation, AI helps minimize diagnostic variability and supports more confident clinical decision-making, especially in complex or borderline cases.

Reduction in Radiologist Workload and Inter-Observer Variability

The increasing demand for medical imaging has placed a substantial burden on radiologists, contributing to fatigue and potential diagnostic errors. AI systems can automate time-consuming tasks such as image screening, lesion detection, and quantitative measurements, thereby reducing workload and allowing radiologists to focus on complex diagnostic and clinical responsibilities.

In addition, AI-driven analysis promotes consistency in image interpretation by standardizing assessments across different readers and institutions. Reduced inter-observer variability is particularly important in lung cancer imaging, where differences in interpretation can lead to variations in patient management and outcomes.

Support for Clinical Decision-Making and Personalized Care

Artificial intelligence serves as a valuable clinical decision-support tool by integrating imaging findings with clinical and, in some cases, molecular information. AI-based risk stratification models can assist clinicians in determining the likelihood of malignancy, guiding decisions regarding follow-up imaging, biopsy, or surgical intervention. In staging and prognosis assessment, AI contributes to more accurate treatment planning and individualized patient care.

Radiomics and multimodal AI further enhance personalized medicine by enabling non-invasive evaluation of tumor heterogeneity and biological behavior. These insights support tailored therapeutic strategies and facilitate monitoring of treatment response over time.(24)

Optimization of Lung Cancer Screening Programs

In population-based lung cancer screening programs, AI can improve efficiency and sustainability by reducing false-positive findings and prioritizing high-risk cases. AI-assisted screening workflows help manage the large volume of imaging studies generated by low-dose CT screening while maintaining high diagnostic performance. This optimization has the potential to reduce unnecessary follow-up procedures, lower healthcare costs, and minimize patient anxiety associated with indeterminate findings.

Impact on Workflow Efficiency and Healthcare Systems

Beyond individual patient care, AI has broader implications for healthcare systems. Improved workflow efficiency, reduced interpretation time, and enhanced diagnostic consistency contribute to more effective utilization of radiology resources. As AI tools mature and integrate seamlessly into clinical workflows, they may help address workforce shortages and support equitable access to high-quality lung cancer imaging services.(25)

Limitations and Challenges of Artificial Intelligence in Lung Cancer Imaging

Despite the promising clinical benefits of artificial intelligence in lung cancer imaging, several limitations and challenges continue to restrict its widespread adoption in routine clinical practice. Addressing these challenges is essential to ensure that AI-based systems are reliable, safe, and clinically meaningful.

Data Quality and Heterogeneity

One of the primary challenges in developing robust AI models is the availability and quality of imaging data. AI systems require large, well-annotated datasets for training and validation. However, medical imaging data often vary across institutions due to differences in scanner types, acquisition protocols, reconstruction parameters, and patient populations. This heterogeneity can negatively affect model performance and limit generalizability when AI systems are applied outside their original training environment.

In addition, many datasets used for AI development are retrospective and may not adequately represent real-world clinical diversity. Imbalanced datasets, where certain disease stages or patient groups are underrepresented, can introduce bias and reduce model reliability.(26)

Limited Generalizability and External Validation

Although many AI models demonstrate high performance in experimental settings, their effectiveness often declines when tested on external datasets. Limited multicenter validation remains a major barrier to clinical translation. Without rigorous external and prospective validation, it is difficult to assess whether AI systems can perform consistently across diverse clinical scenarios.

This lack of generalizability raises concerns regarding the safety and reproducibility of AI-based imaging tools, particularly in high-stakes applications such as cancer diagnosis and staging.

Interpretability and the Black-Box Problem

Most high-performing AI models, particularly deep learning systems, operate as black boxes, providing predictions without clear explanations of how decisions are made. This lack of transparency can reduce clinician trust and limit acceptance in clinical practice. In lung cancer imaging, where diagnostic decisions directly influence patient management, clinicians must be able to understand and justify AI-assisted recommendations.

Although explainable AI approaches have been proposed to improve transparency, their integration into routine imaging workflows remains limited. Ensuring that AI outputs are interpretable and clinically meaningful is a critical challenge for future development.(27)

Regulatory, Ethical, and Legal Considerations

The clinical implementation of AI in medical imaging is subject to complex regulatory and ethical considerations. Regulatory approval requires robust evidence of safety, effectiveness, and clinical benefit, which can be difficult to achieve given the dynamic nature of AI algorithms. Continuous learning systems, in particular, pose challenges for traditional regulatory frameworks.

Ethical concerns include data privacy, informed consent, algorithmic bias, and accountability in cases of diagnostic error. Clear guidelines are needed to define responsibility when AI systems influence clinical decisions. Addressing these issues is essential to ensure ethical and responsible use of AI in lung cancer imaging.

Integration into Clinical Workflow

Successful adoption of AI tools requires seamless integration into existing clinical workflows. AI systems that disrupt routine practices or increase complexity may face resistance from healthcare professionals. User-friendly interfaces, interoperability with hospital information systems, and appropriate training for clinicians are necessary to facilitate effective implementation.

Moreover, AI should be viewed as a supportive tool rather than a replacement for human expertise. Maintaining a balanced human–AI collaboration is essential to ensure safe and effective patient care.(28)

Future Perspectives and Research Directions

The future of artificial intelligence in lung cancer imaging depends on its elaboration from primarily experimental operations to reliable decision- support tools that are completely bedded in clinical practice. With ongoing advances in imaging technologies and computational ways, AI is anticipated to come an integral part of the lung cancer care continuum, supporting processes ranging from threat evaluation and early webbing to opinion, remedy planning, and long- term outgrowth assessment.

The development of dependable and astronomically applicable AI models is a major area of unborn exploration. Reliable performance in factual clinical settings requires large- scale, multicentre prospective studies with harmonious imaging ways and a variety of patient demographics. likewise, styles like allied literacy and collaborative data- sharing ways enable experimenters to train models on larger and further representative datasets while furnishing promising answers to sequestration issues.

Explainable artificial intelligence will also be critical for future adoption. Improving model transparency and interpretability can enhance clinician trust and support informed decision-making. Future AI systems should not only provide predictions but also offer clinically meaningful explanations that align with radiological reasoning. This shift toward trustworthy AI will be particularly important in high-risk applications such as cancer diagnosis and staging.

Another promising direction is the integration of multimodal data. Combining imaging with clinical, pathological, genomic, and molecular information can give a more comprehensive understanding of lung cancer biology and case-specific threat. similar integrative approaches support individualized drug by enabling acclimatized webbing strategies, personalized treatment planning, and more accurate prognostic vaticination.(26)

Advances in real-time AI and workflow integration are also expected to improve clinical efficiency. Seamless incorporation of AI tools into picture archiving and communication systems and radiology reporting platforms will facilitate routine use without disrupting established workflows. In parallel, continued education and training of healthcare professionals will be essential to ensure effective human–AI collaboration.

Overall, future research should focus on translating technological innovation into measurable clinical benefit, ensuring that AI-driven imaging solutions are safe, ethical, and aligned with patient-centered care.(28)(29)

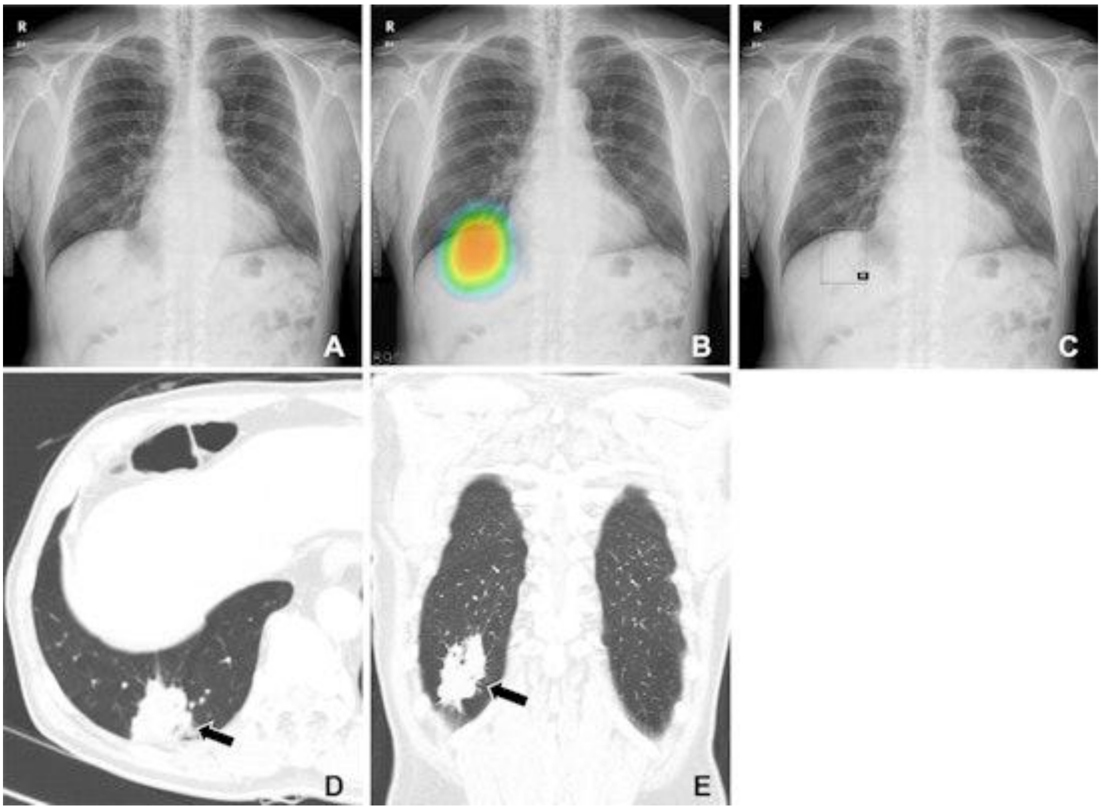


Fig 14

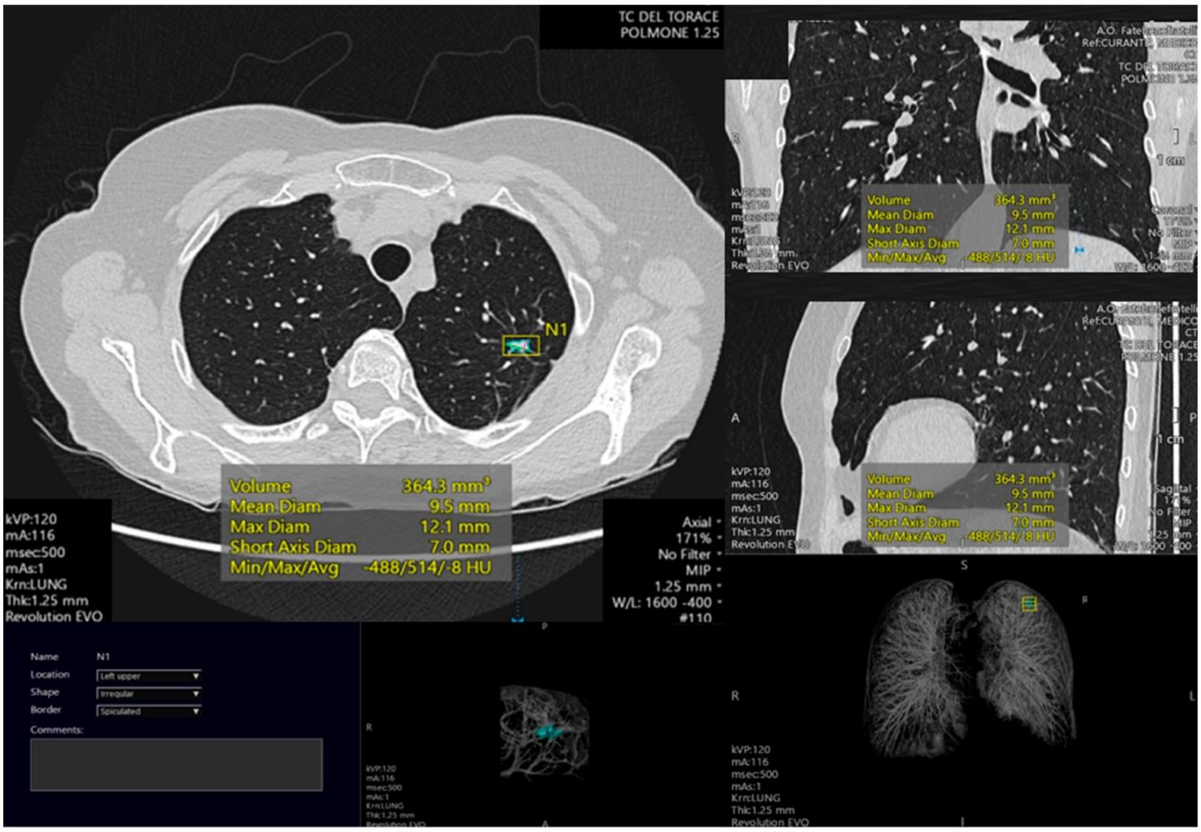


Fig 15

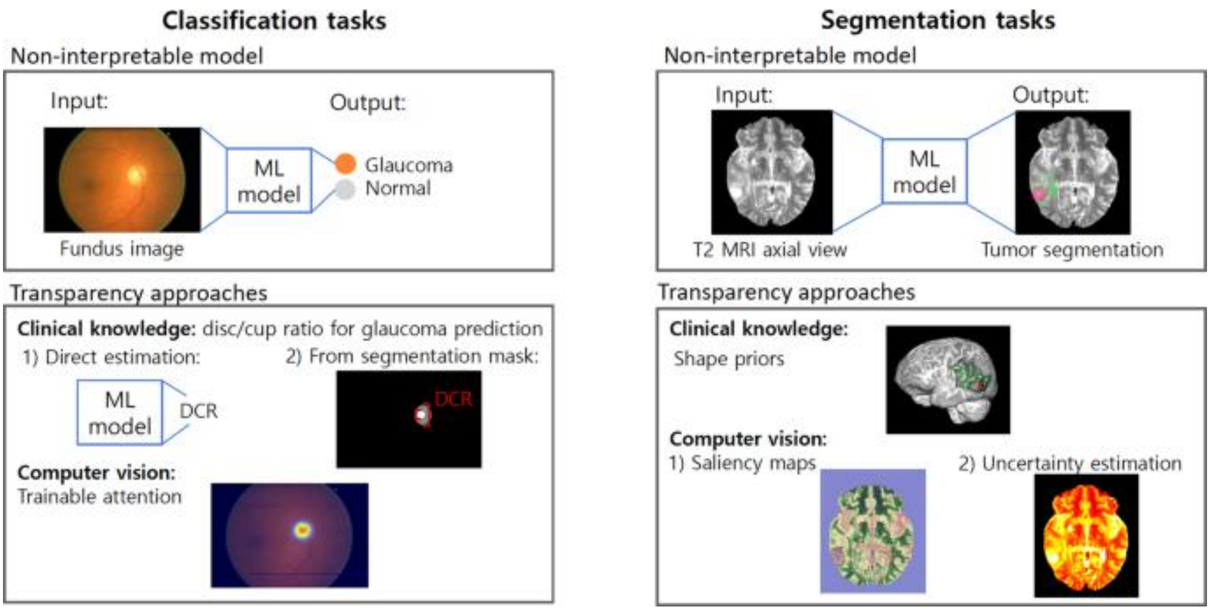


Fig 16

Conculsion

Particularly when considering imaging, artificial intelligence has come a game- changer in the discovery and opinion of lung cancer. AI overcomes numerous of the downsides of traditional image interpretation by perfecting the analysis of reckoned tomography, PET- CT imaging, low- cure CT, and casket radiography by exercising sophisticated computational approaches. Artificial intelligence (AI)- grounded systems have shown great pledge in enhancing early discovery, easing precise opinion and staging, and easing quantitative and unremarkable evaluation of excrescence features.

Medical imaging has come indeed more precious with the integration of radiomics and multimodal artificial intelligence. Together, these approaches allow deeper understanding of excrescence diversity, underpinning natural characteristics, and implicit clinical issues. By rooting and combining information from multiple imaging and data sources, these advancements ameliorate the delicacy of lung cancer webbing and opinion, support more informed treatment planning, and promote substantiated remedial strategies acclimatized to individual cases.

While these advancements hold substantial pledge, several challenges still hamper their broad relinquishment in routine clinical care. Variability in data quality, limited generalizability across different patient groups, lack of translucency in model decision- timber, and nonsupervisory hurdles remain crucial enterprises. Addressing these issues will bear comprehensive confirmation sweats, the development of secure and interpretable AI models, and thoughtful integration of these systems into being clinical workflows to support safe and ethical clinical use.

In conclusion, artificial intelligence holds substantial promise to reshape lung cancer imaging and improve patient outcomes. With continued research, multidisciplinary collaboration, and careful clinical integration, AI-based imaging solutions are poised to become an integral component of future lung cancer care.

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