Advanced imaging techniques and artificial intelligence in pleural diseases: a narrative review

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Advanced imaging techniques and artificial intelligence applications show promise in transforming the management and follow-up of pleural diseases, enhancing diagnostic accuracy while minimising the need for invasive procedures. https://bit.ly/3CAccUB

Cite this article as: Marchi G, Mercier M, Cefalo J, *et al*. Advanced imaging techniques and artificial intelligence in pleural diseases: a narrative review. *Eur Respir Rev* 2025; 34: 240263 [DOI: 10.1183/16000617.0263-2024].

Received: 24 Nov 2024
Accepted: 1 Feb 2025

Abstract

Background Pleural diseases represent a significant healthcare burden, affecting over 350 000 patients annually in the US alone and requiring accurate diagnostic approaches for optimal management. Traditional imaging techniques have limitations in differentiating various pleural disorders and invasive procedures are usually required for definitive diagnosis.

Methods We conducted a nonsystematic, narrative literature review aimed at describing the latest advances in imaging techniques and artificial intelligence (AI) applications in pleural diseases.

Results Novel ultrasound-based techniques, such as elastography and contrast-enhanced ultrasound, are described for their promising diagnostic accuracy in differentiating malignant from benign pleural lesions. Quantitative imaging techniques utilising pixel-density measurements to noninvasively distinguish exudative from transudative effusions are highlighted. AI algorithms, which have shown remarkable performance in pleural abnormality detection, malignant effusion characterisation and automated pleural fluid volume quantification, are also described. Finally, the role of deep-learning models in early complication detection and automated analysis of follow-up imaging studies is examined.

Conclusions Advanced imaging techniques and AI applications show promise in the management and follow-up of pleural diseases, improving diagnostic accuracy and reducing the need for invasive procedures. However, larger prospective studies are needed for validation. The integration of AI-driven imaging analysis with molecular and genomic data offers potential for personalised therapeutic strategies, although challenges in data privacy, algorithm transparency and clinical validation persist. This comprehensive approach may revolutionise pleural disease management, enhancing patient outcomes through more accurate, noninvasive diagnostic strategies.

Introduction

Overview of pleural diseases

Pleural diseases encompass a spectrum of disorders commonly associated with pleural effusions and typically categorised as pleural neoplasms (primary tumours such as mesothelioma and secondary metastatic lesions), non-neoplastic pleural disorders (pleural infections, pleural thickening/fibrosis and pleural plaques) and pneumothorax [1]. These conditions frequently manifest with symptoms such as dyspnoea, chest pain and cough, although they can occasionally present asymptomatically, especially in the initial stages. Pleural diseases are associated with reduced quality of life and significant morbidity and mortality [2, 3]. They represent a common cause of emergency department presentations and often necessitate comprehensive investigation and management, resulting in over 350 000 hospitalisations annually in the USA alone, with a globally rising incidence [4, 5]. This places a significant healthcare and economic burden due to the rising healthcare costs associated with diagnosis, treatment and long-term management [4, 5].

Importance of imaging in diagnosis and management of pleural diseases

Imaging plays a crucial role in the diagnosis, management and follow-up of pleural diseases. It often serves as the first step in evaluating suspected pleural conditions, providing crucial information for clinical decision-making and treatment strategies. Imaging helps detect and characterise pleural abnormalities, assess disease extent and monitor treatment responses [6]. The choice of imaging technique depends on several factors, such as suspected underlying disease, clinical presentation and available resources. Various modalities offer complementary insights, differing in accuracy and the ability to provide anatomical and functional details [7]. Imaging also guides interventional procedures such as thoracentesis, chest drain placement and biopsies, which are crucial for definitive management. Advanced techniques have improved the differentiation between benign and malignant pleural lesions, staging malignancies and assessing treatment efficacy [8]. Continuous advancements in imaging enhance detection, characterisation and management have led to more accurate diagnoses, better treatment decisions and improved patient outcomes.

Rise of artificial intelligence (AI) in healthcare

AI refers to the development of technologies capable of performing tasks that typically require human intelligence, such as integrating information, analysing data, learning, reasoning and problem-solving [9]. The application of AI spans a wide range of fields, including healthcare. In thoracic imaging, AI techniques offer promising applications for detection, diagnosis and prognosis. However, they also have significant limitations, such as reliance on monocentric data for training, which can result in poor generalisability when applied to unfamiliar or unknown data [10].

Purpose and scope of the review

This review critically assesses advancements in imaging techniques and the role of AI in diagnosing and managing pleural diseases. It explores both traditional and advanced imaging methods, highlighting their strengths and limitations, as well as AI's transformative potential to enhance diagnostic accuracy, treatment planning and patient outcomes. The review also covers AI applications in interpreting imaging data, predicting disease progression and personalising treatments, while also addressing challenges such as the need for large datasets, algorithm transparency and clinical validation. By evaluating these areas, this review aims to provide insights into future research directions and clinical applications to optimise pleural disease management.

Methods

A nonsystematic, narrative literature review was conducted to assess the current evidence on the use of advanced imaging techniques and AI in the diagnosis and management of pleural diseases. The PubMed database was queried to identify relevant studies, with no restrictions on publication dates. Only studies involving adult human populations and published in English were included. Article selection was based on a two-step process, namely an initial screening of abstracts followed by full-text review for relevant studies. The following search terms were combined to generate specific search strings: "pleural disease", "artificial intelligence (AI)", "imaging techniques", "diagnosis", "elastography", "mesothelioma", "malignancy", "machine learning" and "deep learning".

Traditional imaging techniques in pleural diseases

Clinical suspicion of pleural disease necessitates imaging, with chest radiography (CXR), lung ultrasound (LUS) and computed tomography (CT) being the most used modalities [11]. Chest magnetic resonance imaging (MRI) and ^{18}F-fluorodeoxyglucose positron emission tomography–computed tomography (^{18}F-FDG PET-CT) play more limited roles [8]. AI techniques offer unique advantages, with the choice depending on clinical context, suspected pathology and resource availability. A comprehensive approach guided by professional guidelines yields accurate diagnosis and appropriate management [7].

CXR

CXR is typically the first imaging test for pleural pathology due to its wide availability, accessibility and cost-effectiveness [12, 13]. It aids in diagnosing and quantifying pneumothorax and can detect pleural effusions greater than 200 mL, which present as blunting of the costophrenic angle [14–17]. Pneumothorax is characterised by the visceral pleural line and peripheral radiolucency on imaging, indicating the presence of air in the pleural space [14–17]. However, CXR has a sensitivity of only 52% for pneumothorax detection, decreasing in supine positions [18–20]. Despite this, CXR remains essential for initial assessment and follow-up of pleural diseases, particularly in resource-limited settings [21, 24]. Its role in monitoring disease progression remains important, although more advanced techniques offer higher accuracy.

LUS

LUS has revolutionised pleural imaging, with higher sensitivity than CXR for the detection of pleural effusions (93% *versus* 47%) [22]. It offers greater accuracy in estimating fluid volume, echogenicity, detecting septations and distinguishing between pleural fluid and thickening. LUS excels in detecting minimal effusions (⩾20 mL), with 94% sensitivity and 98% specificity [23], and in diagnosing pneumothorax, with 78.6% sensitivity and 98.4% specificity [24]. Effusions appear as anechoic or echogenic areas between the parietal and visceral pleura, with septations or loculations in complex effusions [25, 26]. LUS is radiation-free and real-time, allowing for safe guidance during procedures such as thoracentesis and biopsies, enhancing diagnostic yield and procedural safety [27]. Its portability and ability to accommodate various patient positions make it highly practical. For pneumothorax, LUS relies on the absence of lung sliding and comet-tail artefacts and the presence of the lung point sign [28]. Consensus guidelines have standardised LUS use in clinical contexts, improving reliability [25, 26]. However, its accuracy depends on operator skill, emphasising the importance of training [27]. Furthermore, LUS represents the most used technique to guide invasive pleural procedures (*e.g.* thoracentesis, chest drain positioning and biopsy) [29–33].

CT

CT provides detailed anatomical imaging of the pleura and lung parenchyma, offering higher resolution compared to CXR [7, 34]. It can identify complex features such as pleural thickening, nodularity or calcification in pleural masses, potentially indicating malignancy [35–37]. CT is particularly useful for detecting occult pneumothorax, especially in trauma [38], and provides valuable information on the extent and distribution of pleural disease, aiding treatment planning [7].

MRI

Conventional MRI offers superior soft tissue contrast without radiation [39, 40] and has shown promise in distinguishing malignant from benign pleural lesions, particularly using diffusion-weighted imaging [41–43]. MRI can characterise complex effusions and detect pleural-based masses but is limited by cost and acquisition time [44].

^{18}F-FDG PET-CT

^{18}F-FDG PET-CT is critical for evaluating pleural malignancy, with 95% sensitivity and 82% specificity [45–47]. It aids in staging malignant pleural mesothelioma, detecting distant metastases and guiding biopsies [48–50]. However, false positives in inflammatory conditions and false negatives in indolent tumours require careful interpretation [51, 52].

Advanced imaging techniques in pleural diseases

Pleural effusion is a common pathological condition with several potential aetiologies. Several new advanced imaging techniques are being studied (table 1).

ImageJ – pixel-density quantitative measurement

Distinguishing between transudative and exudative effusions without invasive procedures is challenging. Several studies have investigated the relationship between the US appearance and the underlying aetiology of pleural effusion, yielding inconclusive results [53–56]. The application of quantitative techniques for measuring the echogenicity of pleural fluid can predict biochemical parameters of pleural fluid, such as lactate dehydrogenase (LDH), cell count and pH [57, 58]. Kalkanis *et al.* [57] studied 62 patients with pleural effusion of unknown origin who underwent LUS. The mean echo levels of all pixels of the pleural effusion and of the 10th rib were compared in order to elaborate a hypo-echogenicity index, which was calculated as the ratio of the mean echo level of all pixels of the rib to that of the pleural effusion. All patients then received diagnostic thoracentesis. LDH levels, cell count, pH and effusion pixels (mean) were significantly associated with the pixel ratio (p-value $\leqslant$0.0001).

Pixel density, combined with other qualitative US parameters (*e.g.* presence of loculations or debris), could help to distinguish between transudative and exudative pleural effusions, without further invasive procedures. Soni *et al.* [59] retrospectively recruited 83 patients who underwent thoracentesis during hospitalisation for unexplained pleural effusion. A pre-procedural US examination was performed. Pleural fluid echogenicity was quantified by measuring pixel density with image-processing software (ImageJ; National Institutes of Health) (figure 1). Pleural effusions were categorised as exudative if one or more of

TABLE 1 Summary of advanced imaging techniques and their application

Advanced imaging technique	Main application	Strengths	Limitations
ImageJ – Pixel-density quantitative measurement [56–59]	Differentiate exudative *versus* transudative pleural effusions	Can be part of a conventional US examination Can be performed at bedside Repeatability	Absence of internal validation No standardised ultrasound parameters Absence of confirmatory prospective studies
Contrast-enhanced ultrasound sonography [61–64]	Improve pleural lesions characterisation in suspected malignancy	Use of non-nephrotoxic contrast Can be performed at bedside Repeatability Can distinguish malignant and benign pleural lesions	Absence of large prospective studies Need for compatible ultrasound scanners
Ultrasound elastography [65–71]	Improve pleural lesions characterisation (tissue stiffness) in suspected malignancy Guide US-guided pleural biopsy	Can be part of a conventional US examination Can be performed at bedside Repeatability Helps identify the optimal target area during biopsy	Operator dependency Tissue attenuation can limit assessment of deeper tissues System settings may bias results
FAPI-PET-CT [77–80]	Detect specific tumours, *i.e.* solitary fibrous tumour of the pleura	Use of highly specific tracer Higher accuracy than FDG-PET in detecting specific pleural neoplasms	Expensive Limited scientific evidence (case series)
DWI/VIBE-DCE-MRI [39, 81]	Pleural lesions characterisation in suspected malignancy Distinguish exudative *versus* transudative pleural effusions	Can correct false positives on PET-CT caused by inflammation or talc pleurodesis	Expensive Need for specific software and scanners

DWI/VIBE-DCE-MRI: diffusion-weighted imaging/volumetric interpolated breath-hold examination sequences for dynamic contrast-enhanced magnetic resonance imaging; FAPI-PET-CT: radiolabelled fibroblast activation protein inhibitor–positron emission tomography–computed tomography; FDG-PET: fluorodeoxyglucose–positron emission tomography; PET-CT: positron emission tomography–computed tomography; US: ultrasonography.

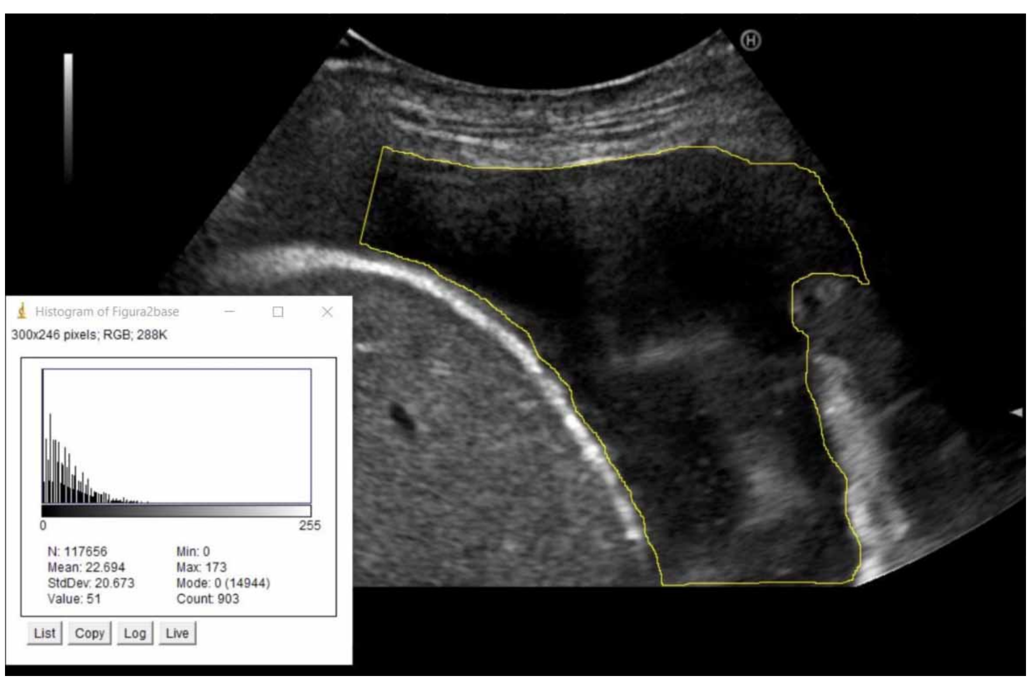

FIGURE 1 Image cropping technique used for analysis in ImageJ software. The freehand selection tool is employed to define the region of interest. Histogram analysis is then applied, automatically calibrating tissue echogenicity levels, with white pixels set to a value of 255 and black pixels to 0. The mean pixel count within the selected area is calculated automatically by the software.

the criteria reported by LIGHT *et al.* [60] were met. A pleural fluid US score was calculated based on the following criteria: floating debris, fibrinous stranding, loculations, pixel density of 3–10 and pixel density of at least 10 at the image processing software. Median pleural fluid pixel density was higher in exudates than transudates (3.53 *versus* 2.32; p=0.038). A pixel density cutoff of more than 10 was only recorded in the presence of exudates. A pleural fluid US score of at least 3 indicated a very high likelihood of being exudative and relatively low likelihood (10%) of being transudative. However, the lack of internal validation, the variation in echogenicity while changing US parameters (*e.g.* gain regulation) and the lack of confirmatory prospective studies represent limitations of this approach and warrant further investigation.

Contrast-enhanced ultrasound (CEUS)

CEUS is an advanced imaging technique that utilises an intravascular injection of microbubble contrast agents to improve pleural lesion characterisation. Parameters assessed during CEUS, such as contrast agent distribution into the target lesions and wash-out time, when combined with pleural thickness measurements, can help differentiate between benign and malignant pleural diseases [61–64]. YANG *et al.* [62] demonstrated that pleural thickness derived from B-mode US and CEUS were significantly greater in the malignant group (with a cutoff value of 7.8 mm, sensitivity of 70%, specificity of 95.0% and an area under the curve (AUC) of 0.848). Arrival time (AT), the time to peak (TTP) of the time intensity curve (TIC), peak intensity and the area under the TIC were respectively significantly shorter and higher in the malignant group. The combined pleural thickness from CEUS, along with morphology, CEUS enhancement mode, AT, TTP, peak intensity and the area under the TIC, yielded a sensitivity of 93.3%, specificity of 90.0%, and an AUC of 0.975. Application of CEUS for characterising pleural lesions is still experimental and has yet to gain broad acceptance in clinical practice. Further research is needed to fully incorporate this innovative approach into standard medical care.

Elastography

US elastography measures tissue stiffness by quantifying its strain in response to mechanical stress [65]. Quantitative elastography provides numerical measurements of tissue stiffness. The most commonly used US technology for pleural evaluation is shear wave elastography (SWE), which quantifies tissue stiffness by measuring the speed of shear waves propagating through the tissue. Faster shear wave velocities indicate stiffer tissues. Conversely, qualitative elastography offers visual or semi-quantitative assessments of tissue stiffness. This is achieved through a colour gradient superimposed on grayscale ultrasound images, employing either strain elastography or SWE technology [65].

Recent studies suggest that US elastography could be a valuable method for distinguishing malignant pleural mesothelioma or pleural metastases from benign conditions [66, 67], although conflicting findings are still present in evaluating soft tissue lesions [68] (figure 2). Additionally, multiple studies have reported that US elastography enhances the diagnostic accuracy of US-guided pleural biopsies. Stiffness was assessed three times in the same area and in the same sequence to calculate the mean elasticity index [69, 70]. The diagnostic yield of the index for all cases and the sensitivity for malignant pleural effusions (MPEs) were 92.9% and 88.7%, respectively [69].

A potential application of elastography in pneumothorax has been described. Elastography performed at the "lung point" enhances the visualisation of the air–tissue interface by distinguishing normal lung parenchyma, where the elastographic colour signal terminates at the pleural line, from the air column in pneumothorax, where the elastographic colour signal extends beyond the pleural line. This phenomenon has been termed the "elasto lung point". Further studies are needed to determine the clinical significance of this finding [71].

US-based techniques in the diagnosis of nonexpandable lung (NEL)

The concept of "nonexpandable lung" describes a spectrum of conditions where the lung cannot expand adequately to maintain normal pleural interactions [72]. Pleural manometry (PM) describes the measurement of intrapleural pressures using a water or digital manometer. It aims to derive a measure of pleural elastance and, therefore, indirectly predict the presence of an NEL. However, CHOPRA *et al.* [73] showed that 25% of patients with elevated pleural elastance may reach a complete lung re-expansion following pleural effusion removal. SALAMONSEN *et al.* [74] showed that incorporating US with PM could increase the sensitivity in diagnosing NEL by assessing various parameters, such as the displacement of the collapsed lung during a breath hold using M-mode US. PETERSEN *et al.* [75] showed that M-mode US effectively rules out NEL with superior accuracy to B-mode and shear wave elastography, achieving an AUC of 0.81 and offering a simpler, efficient alternative. HASSAN *et al.* [76] evaluated patients undergoing chest ultrasonography before medical thoracoscopy. During breath-hold, US M-mode was used to quantify the displacement of the collapsed lower lobe. In addition, the echogenicity of the collapsed lung and the

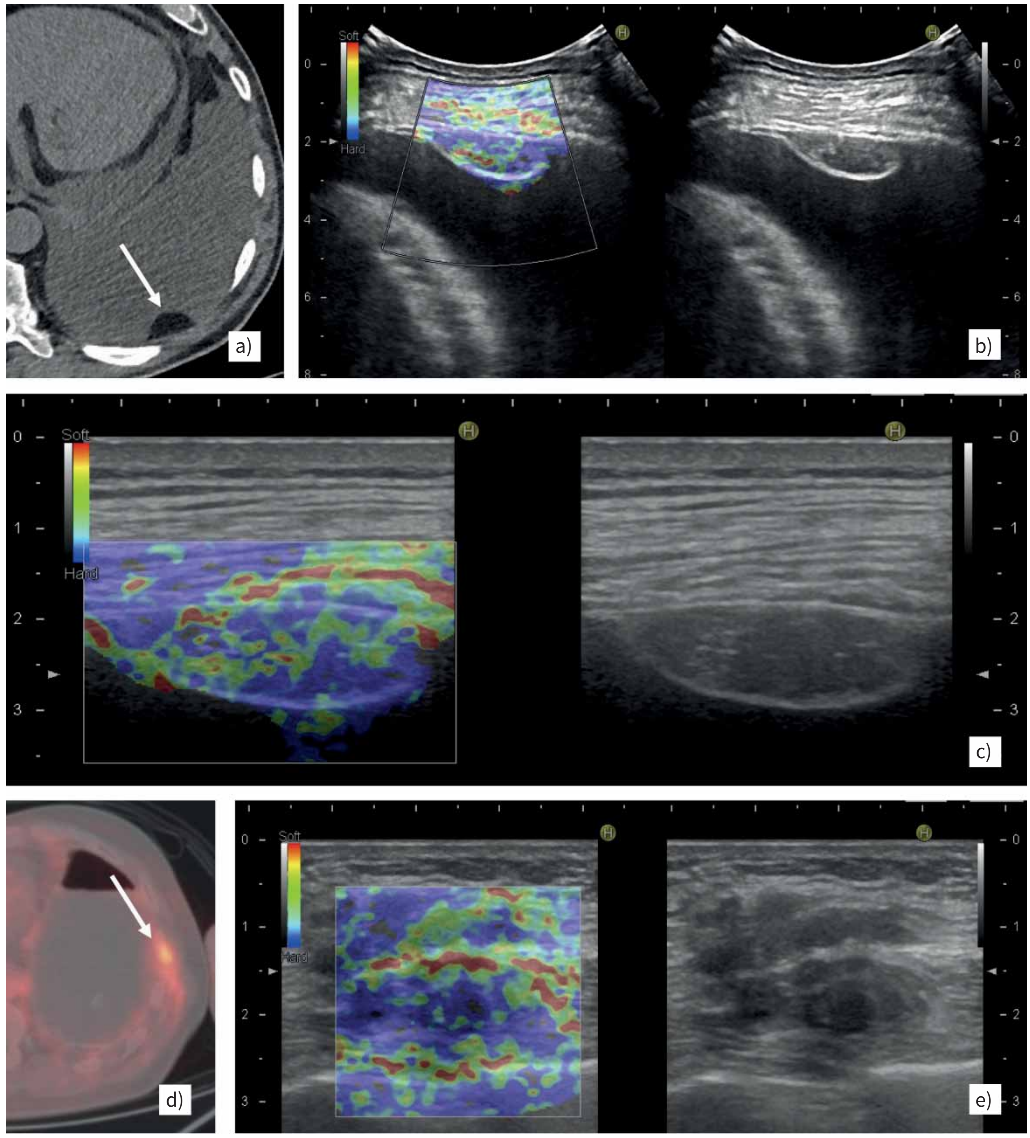

FIGURE 2 Pleural lipoma seen with a) computed tomography (CT), b) conventional B-mode ultrasonography and c) ultrasound elastography. Ultrasound elastography shows an intermediate stiffness pleural lesion. d) Positron emission tomography–CT scan showing fluorodeoxyglucose-avid pleural lesion (malignant pleural mesothelioma). e) Chest B-mode ultrasonography and ultrasound elastography show a hypoechoic, stiff lesion invading the chest wall.

liver were quantified using US images with the help of a software (ImageJ). Lung/liver echogenicity was used as a marker of lung stiffness (failure of lung de-aeration despite effusion) to predict NEL. The AUC of lung/liver echogenicity to predict NEL was 0.77 (p=0.03). A cut-off of >1.6 had a sensitivity and specificity of 71% and 83%, respectively [76].

Radiolabelled fibroblast activation protein inhibitor–positron emission tomography–computed tomography (FAPI-PET-CT)

Fluorodeoxyglucose (FDG)-positron emission tomography (PET) is widely used for malignancy assessment. New, more specific, PET tracers have been developed to improve accuracy, compared to the commonly used FDG. FAPI-PET-CT has been shown to be a promising tracer for the diagnosis of several tumours, such as the solitary fibrous tumour of the pleura (SFTP) [77–79]. Lococo *et al*. [80], in a case series of five patients with SFTP, reported that all tumours had a significant uptake of gallium-68 tetraazacyclododecane-tetraacetic acid tyrosine-3-octreotide with a mean±SD tumour maximum standardised uptake value of 9.9±5.7.

Diffusion-weighted imaging/volumetric interpolated breath-hold examination sequences for dynamic contrast-enhanced-magnetic resonance imaging (DWI/VIBE-DCE-MRI)

MRI has been underused for lung imaging due to some key limitations, *e.g.* low signal-to-noise ratio in lung tissues and artefacts from air and motion. However, the use of free-breathing diffusion-weighted imaging (DWI) and volumetric interpolated breath-hold examination (VIBE) sequences for dynamic contrast-enhanced (DCE) imaging can greatly enhance accuracy and specificity of the technique in distinguishing malignant pleural tumours from benign lesions and can help correct false positives on PET-CT caused by inflammation or talc pleurodesis [39]. FROLA *et al.* [81] investigated the imaging features of pleural effusions on MRI following intravenous administration of gadolinium-diethylenetriaminepentaacetic acid (Gd-DTPA). Quantitative analysis was performed by measuring signal intensities of pleural effusions in an operator-defined region of interest relating to muscle signal intensity. None of the transudative pleural effusions showed visual enhancement after Gd-DTPA, whereas 10 out of 12 exudative effusions showed enhancement in the late phase (sensitivity of 83%).

AI

Overview of AI

AI is transforming numerous sectors by enabling systems to perform tasks that traditionally require human intelligence, such as learning, reasoning and decision-making. Driven by advances in algorithms, computational power and data availability, AI encompasses various technologies that can process multiple types of information to identify patterns, make predictions and perform complex functions. The impact of AI is particularly profound in medicine, where it has the potential to revolutionise healthcare delivery, diagnostics and treatment strategies.

AI applications in healthcare range from automating routine tasks, such as appointment scheduling and billing, to supporting complex clinical decisions. The adoption of AI in medicine has led to improved efficiency in healthcare delivery, reduced diagnostic errors and the ability to provide more personalised treatment plans [82]. While AI has demonstrated considerable potential, its implementation varies across different healthcare settings due to factors such as technological readiness, regulatory considerations and the need for clinical validation (table 2).

AI methods and applications in medicine

AI in medicine can be categorised into several techniques, each with specific applications that contribute to healthcare improvements.

TABLE 2 Applications and challenges of artificial intelligence (AI) in medicine

Applications	
Medical imaging and diagnostics	AI analyses medical images, aiding in the detection and classification of diseases such as cancer, cardiovascular conditions and neurological disorders [84]
Predictive analytics and patient monitoring	Analyses patient data to predict outcomes, enabling early interventions and personalised treatment strategies [83]
Drug discovery and development	Accelerates drug discovery by analysing biological data, predicting new compounds' efficacy and repurposing existing drugs [89]
Personalised medicine	Integrates genetic, proteomic and clinical data to develop individualised treatment plans, identifying suitable therapies [90–93]
NLP in clinical documentation	Extracts insights from unstructured data, such as clinical notes, to support decision-making and improve EHR quality [86]
Challenges	
Clinical implementation	Integrating AI into clinical workflows requires system interoperability, clinician training and thorough validation
Data challenges	AI models need large, diverse datasets, while ensuring patient privacy and data security is paramount
Technical challenges	Lack of transparency in AI models can hinder the ability to explain decisions; explainable AI is a key focus
Ethical and social challenges	AI may perpetuate biases, impacting marginalised populations; ethical frameworks are essential for fairness
Governance and regulation	Clear guidelines are needed to regulate AI development and use, ensuring safety, privacy and ethical deployment

EHR: electronic health record; NLP: natural language processing.

Machine learning (ML)

ML is a core component of AI that involves training models on datasets to recognise patterns and make data-driven predictions. In medicine, ML algorithms are applied to analyse complex medical data, including electronic health records (EHRs), genetic information and imaging results. They support the early detection of diseases, risk stratification and the development of personalised treatment plans [83]. For example, ML models can predict patient outcomes by analysing trends or different types of features.

Deep learning (DL)

DL is an advanced ML subset that uses artificial neural networks with multiple layers to extract complex features from high-dimensional data. In medical imaging, DL models, particularly convolutional neural networks (CNNs), have demonstrated exceptional performance in detecting abnormalities such as tumours, fractures and lesions in radiographs, CT scans and MRI results [84]. DL has also been employed in pathology to identify cancerous cells in histopathology slides with high accuracy, assisting pathologists in making faster and more reliable diagnoses [85].

Natural language processing (NLP)

NLP enables AI systems to interpret and interact with human language. In the medical field, NLP is used to analyse unstructured data, such as clinical notes, research articles and patient records, extracting relevant information for clinical decision support and research purposes [86]. For instance, NLP algorithms can automatically identify and categorise information about symptoms, treatments and patient outcomes from free-text clinical notes, enhancing the accuracy of EHRs and enabling more efficient information retrieval for healthcare providers [87].

Robotics

AI-driven robotics has made significant advancements in healthcare, particularly in surgical procedures. Robotic systems such as the da Vinci Surgical System enhance the precision and control of surgical interventions, allowing for minimally invasive procedures that reduce patient recovery times and improve outcomes [88]. Robotics is also employed in rehabilitation to provide personalised physical therapy, and in hospital logistics, where autonomous robots assist in medication dispensing and patient transportation, improving efficiency and reducing the workload on healthcare staff.

Applications and challenges of AI in medicine

AI applications in medicine are diverse and continue to grow, offering innovative solutions to some of healthcare's most pressing challenges:

- *Medical imaging and diagnostics*: AI, especially DL, analyses medical images to detect and classify diseases such as cancer, cardiovascular and neurological disorders with high accuracy [84].
- *Predictive analytics and patient monitoring*: AI analyses EHRs and patient data to predict outcomes, enabling early interventions and tailored treatments [83].
- *Drug discovery and development*: AI accelerates drug discovery by analysing biological data, predicting compound efficacy, identifying candidates and suggesting drug repurposing, reducing time and costs [89].
- *Personalised medicine*: AI integrates genetic, proteomic and clinical data to develop personalised treatments, identify biomarkers, and predict therapy responses, particularly in oncology [90–93].
- *NLP in clinical documentation*: NLP extracts insights from unstructured data, supporting clinical decisions and enhancing EHRs. It also powers virtual assistants for patient engagement [86].

AI has the potential to transform medicine by enhancing diagnostic accuracy, enabling predictive analytics, personalising treatment and improving healthcare delivery. However, the integration of AI into clinical practice requires addressing various challenges, including clinical validation, data quality, interpretability, ethical considerations and regulatory compliance. Continued interdisciplinary collaboration, research and thoughtful governance are essential to harness the full potential of AI in healthcare while ensuring equitable and safe patient care.

AI in pleural diseases: advantages and current drawbacks

AI is becoming an essential tool in medicine, with a significant impact on the diagnosis, management and treatment of pleural diseases. These conditions pose diagnostic challenges due to their diverse causes and overlapping clinical manifestations. Traditional diagnostic methods, such as imaging and biopsy, often require invasive procedures and can be time-consuming. In this context, AI offers the potential to revolutionise the approach to pleural diseases, providing clinicians with more accurate, efficient and less invasive diagnostic and management tools (table 3).

TABLE 3 Artificial intelligence (AI) in pleural diseases

Application areas		AI technique	Potential implementation in pleural diseases
Diagnosis	Medical imaging analysis	CNNs, deep learning	Detection and classification of pleural effusions and pneumothorax in chest radiographs and CT scans; analysis of fluid accumulation, lung retraction, and pleural line abnormalities [94–99]
	Chest radiography interpretation	Deep learning	Automated interpretation of chest radiographs for common pleural abnormalities Detection of subtle signs of fluid or air in pleural space [94–99]
	CT/MRI radiomics	Machine learning	Evaluation of radiomic features to distinguish malignant from benign pleural effusions [101–103]
	Liquid biopsy analysis	AI-enhanced analysis	DNA methylation analysis of cell-free DNA in pleural fluid to distinguish malignant from benign pleural effusion [104]
	Pleural region segmentation	Deep learning	Segmentation of pleural regions and quantification of fluid volumes using lung ultrasound or CT scans [109–113]
	Point-of-care ultrasound analysis	Deep learning	Automated interpretation of lung ultrasound for pleural effusion diagnosis [99, 108]
Prognostication and treatment planning	Prognostic stratification	Predictive models	Risk stratification and outcome prediction in malignant pleural mesothelioma Identification of patients who may benefit from specific therapeutic interventions (surgery, chemotherapy, immunotherapy) [105, 106]
	Treatment decision support	Machine learning	Assistance in selecting appropriate interventions for pleural effusions (thoracentesis, chest tube placement, pleurodesis) based on individualised risk assessment [107]
	Multimodal data integration	AI-driven predictive models	Integration of patient demographics, clinical features, imaging findings and laboratory results to predict disease progression or treatment response [105, 118]
Monitoring and follow-up	Disease monitoring	Deep learning	Automated analysis of follow-up imaging studies to assess pleural fluid volume, lung re-expansion and pleural thickening over time Early detection of complications (*e.g.*, trapped lung, pleural infection) [108, 114, 115]

CNN: convolutional neural network; CT: computed tomography; MRI: magnetic resonance imaging.

One of the most significant applications of AI in pleural disease is in medical imaging analysis. CXR, CT and LUS are crucial tools in evaluating pleural pathology. However, the interpretation of these images is often subject to inter-operator variability and can be challenging, particularly in complex cases. AI algorithms have demonstrated promising performance in image analysis by identifying subtle patterns and anomalies that may be overlooked by the human eye [94, 95]. This includes identifying early signs of conditions such as cancer, brain abnormalities or cardiac issues in fields different from pulmonology [94]. In the context of pleural diseases, AI can enhance the detection of pleural effusions and pneumothorax by analysing imaging characteristics such as fluid accumulation, lung retraction and pleural line abnormalities [96]. For example, DL models, including CNNs, can analyse CXRs and CT scans to identify subtle signs of fluid presence or air in the pleural space, which might be challenging for human radiologists to detect consistently [97, 98]. These models have demonstrated high sensitivity (95%) and specificity (97%), making them effective tools in clinical settings for supporting faster and more accurate diagnoses [99].

To date, AI-driven analysis of imaging data can improve the accuracy of noninvasive diagnostic modalities. In thoracic imaging, AI algorithms have achieved high performance, with models demonstrating an area under the receiver operating characteristic curve range of 0.9–1.0 for detecting common abnormalities in CXRs [100]. ML algorithms can evaluate radiomic features, quantitative imaging biomarkers that capture underlying tissue characteristics, in CT or MRI scans to differentiate malignant from benign pleural effusions [101–103]. DNA methylation analysis of cell-free DNA in pleural fluid has proven effective in distinguishing MPEs from benign ones. Bixby *et al*. [104] have shown that such AI-enhanced analysis can achieve AUC of 0.918, demonstrating high accuracy in detecting malignancy.

AI also plays a growing role in management and prognostication. AI-driven predictive models can be trained on multimodal datasets, including patient demographics, clinical features, imaging findings and laboratory results, to identify patterns that may predict disease progression or treatment response [105]. For instance, in patients with malignant pleural mesothelioma, AI can assist in prognostic stratification by identifying patients who may benefit from specific therapeutic interventions, such as surgery, chemotherapy or immunotherapy [106]. ML algorithms can also support decision-making in the management of pleural effusions, aiding in the selection of appropriate interventions like thoracentesis, chest tube placement or pleurodesis, based on individualised risk assessment [107].

Furthermore, AI has the potential to enhance the monitoring of pleural diseases. Patients with recurrent pleural effusions or pneumothorax often require serial imaging to assess disease stability or progression. AI algorithms can automate the analysis of follow-up imaging studies, providing consistent and objective evaluations of pleural fluid volume, lung re-expansion and pleural thickening over time [108]. These models, often based on DL frameworks, can consistently segment pleural regions and quantify fluid volumes using data from imaging techniques such as LUS or CT scans [109–113]. This automation aids in providing objective assessments, which can enhance clinical decision-making and improve the accuracy of tracking patient progress during treatment (mean average precision score of 0.964) [114]. This capability can facilitate early detection of complications, such as trapped lung or pleural infection, and guide timely interventions.

The integration of AI into the field of pleural diseases, however, is not without challenges. The development of AI models requires access to large, high-quality datasets for training and validation [114]. In pleural diseases, this necessitates the collection of comprehensive imaging and clinical data across diverse patient populations to ensure generalisability and minimise biases. Data privacy and security are critical concerns, given the sensitive nature of medical information. Ensuring compliance with regulations such as the General Data Protection Regulation is essential to protect patient confidentiality during data acquisition, processing and analysis [115]. Additionally, the "black box"" nature of many AI algorithms, particularly DL models, poses a challenge in clinical practice. Clinicians may be hesitant to rely on AI-generated recommendations without a clear understanding of the underlying decision-making process [116]. Therefore, efforts to improve the interpretability and transparency of AI models are crucial for their acceptance and integration into routine clinical workflows.

Another consideration is the need for rigorous clinical validation and standardisation of AI tools before they can be widely adopted. Prospective studies and randomised controlled trials are necessary to assess the real-world impact of AI on clinical outcomes in pleural diseases [117]. Furthermore, integrating AI into clinical practice requires a multidisciplinary approach, involving collaboration between clinicians, radiologists, data scientists and regulatory bodies [118]. Developing standardised protocols and guidelines for AI implementation can help ensure consistency and safety in its application [119, 120].

Conclusions and future perspectives

In conclusion, imaging plays a key role in diagnosis, management and follow-up of pleural diseases. New imaging techniques, mostly based on LUS, are being studied to predict biochemical fluid characteristics and discriminate transudative from exudative effusion, predict malignancy and detect NEL, without the need for invasive procedures. Preliminary findings reported in the literature need confirmatory, larger and prospective studies.

AI represents a transformative force in the field of pleural diseases, offering innovative solutions to longstanding challenges in diagnosis, management and prognosis. By harnessing the power of AI, clinicians may improve the accuracy of pleural disease diagnoses, reduce the need for invasive procedures and tailor treatment strategies to individual patients, ultimately enhancing patient outcomes.

While the integration of AI into clinical practice presents challenges, such as data privacy, algorithm transparency and the need for robust validation, the potential benefits underscore the importance of continued research and collaboration in this area. Before fully integrating AI technologies into the healthcare market, specific legislation will be needed to adequately address the current concerns and long-term risks associated with the technology. International scientific societies might be the adequate host for AI development. Although these challenges exist, the future of AI in pleural disease management holds significant promise.

The development and validation of AI algorithms will require multicentric prospective studies, supported by representative datasets, to ensure their generalisability across different population and clinical settings. Furthermore, the integration of AI into clinical workflows demands close collaboration between clinicians, data scientists and engineers, alongside robust training programmes to enhance digital literacy among healthcare providers, ensuring the proper use and interpretation of AI tools. A patient-centred approach should also be prioritised, actively involving patients in the design and implementation of AI solutions to address their concerns and needs. Additionally, while the identification of novel biomarkers and therapeutic targets *via* AI is promising, it is essential to mitigate expectations by acknowledging the lengthy translation process from discovery to clinical application.

The establishment of shared guidelines and ethical frameworks for the use of AI in pleural disease management will be crucial to navigating challenges related to data privacy, bias mitigation and medico–legal accountability.

Ongoing advancements in AI technology, including the development of more sophisticated algorithms and the integration of multi-modal data, are expected to further enhance the diagnostic accuracy and prognostic capabilities of AI systems.

The combination of imaging analysis with molecular and genomic data has the potential to provide a more comprehensive understanding of pleural diseases, leading to more personalised and targeted therapeutic strategies. AI-driven models could facilitate the identification of novel biomarkers and therapeutic targets, opening new avenues for research and treatment.

Provenance: Submitted article, peer reviewed.

Acknowledgements: The authors would like to thank Luigi De Angelis (Italian Society for Artificial Intelligence in Medicine-SIIAM – Società Italiana Intelligenza Artificiale in Medicina, Rome, Italy) for his valuable contribution. The authors would also like to thank SIP-IRS (Società Italiana di Pneumologia - Italian Respiratory Society) for its support of this work.

Conflict of interest: All authors have nothing to disclose.

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