

Next-Generation Diagnostic Radiology: Deep Learning, Explainable Artificial Intelligence, Radiomics, and Multimodal Imaging for Improved Clinical Decision-Making

Siham Mohammed Adam^{1*}, Amna Alfadol M. Abdalla², Suleiman M. Farah³, Khulud Hamdan Albalawi⁴, Mona Eid Alenzi⁵, Yahya Taleb Gaze Alluhipi⁶, Shaimaa Mohamed Saeed Ata⁷, Sumia Farid⁸

^{1,2,3}Department of Nursing, College of Applied Medical Sciences, Buraydah Private Colleges, Buraydah-51418, Al-Qassim, Saudi Arabia

⁴King Salman Armed Forces Hospital in the Northwestern Region, King Abdul Aziz Rd, Military Area, Tabuk 47512, Saudi Arabia

^{5,6}King Fahad Madinah Hospital, Khaled Bin Al Waleed Branch Road, Al Jamiah-3177, Madinah-42351, Saudi Arabia

⁷Preventive Dental Sciences Department, College of Dentistry and Pharmacy, Dental Public Health, Buraydah Private Colleges, Qassim, Saudi Arabia

⁸Department of Pharmaceutics, Faculty of Pharmacy, Elrazi University, Khartoum 11115, Sudan..

Corresponding Author:

Siham Mohammed Adam

Department of Nursing, College of Applied Medical Sciences, Buraydah Private Colleges, Buraydah-51418, Al-Qassim, Saudi Arabia

siham.haroon@gmail.com

Received: June 02, 2025; **Accepted:** August 29, 2025; **Available Online:** September 12, 2025

ABSTRACT:

Traditional radiological workflows face mounting challenges, including escalating diagnostic volumes, intra- and inter-observer variability, and the complexity of extracting clinically actionable insights from high-dimensional imaging data. Explainable Artificial Intelligence (XAI), Multimodal Imaging and Radiomics are driving the evolution of diagnostic radiology. These technologies present novel possibilities to enhance the interpretation of medical images and the assistance for clinical decision making. Deep learning can help detect, classify, segment and predict abnormalities in X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and positron emission tomography (PET). XAI techniques can increase transparency by highlighting the areas or patterns in the images that are important for the AI to make its predictions. This could help healthcare professionals assess and apply the AI's results accurately. The next step in image analysis is radiomics, which transforms medical images into quantitative features for diagnosing, predicting or monitoring treatment efficacy and response. Recently, multimodal AI has opened up the possibility to combine information from various imaging modalities, which also includes information from

radiomics, clinical, lab and genomic data, paving the way to more personalized patient evaluation. Despite these advances, key questions on the challenges remain such as small and not standardized datasets, algorithmic bias, poor reproducibility, lack of external validation, interoperability, privacy concerns, and uncertainty about clinical implementation. Standardized datasets, multicenter validation, clinically relevant explainability, ethical AI development, and prospective evaluation should thus be future focal points of ongoing research. In summary, the adoption of AI-powered.

imaging technologies can enhance diagnostic precision, streamline workflows, and drive personalized patient care, all while preserving radiologists' crucial role in clinical decision-making.

Keywords: Diagnostic radiology; Deep learning; Explainable artificial intelligence; Radiomics; Multimodal imaging; Clinical decision-making and Precision medicine.

1. INTRODUCTION

Diagnostic radiology has become a key component of modern health care, and imaging techniques including computed tomography (CT), magnetic resonance imaging (MRI), X-ray, ultrasound and positron emission tomography (PET) provide valuable information for the diagnosis, characterization, and monitoring of disease. However, new imaging techniques and growing volume of medical images have added to radiologists' burdens. While the role of the expert interpreter is still very much at the heart of diagnosis, there is some observer variability, fatigue, time pressure, and imaging pattern complexity that may create an influence on conventional image assessment. These difficulties have led to the emergence of computational methods that aid the radiologist in his work, not to the exclusion of traditional diagnosis (Hosny et al., 2018). Medical imaging is one of the most significant technological advancements of recent times in terms of the benefits it offers to the field of medicine. Artificial Intelligence (AI) has become one of the most impactful technological breakthroughs in medical imaging. Deep learning has shown to have remarkable capabilities in image classification, lesion detection, segmentation, and disease prediction for various imaging modalities, in particular. These AI systems are capable of analysing a vast amount of images and catching patterns that might be hard to see visually consistently. The recent trend has also seen AI research shift away from task-specific models to more general foundation models that learn representations that can be transferred to new imaging applications (Mazurowski et al., 2019; Zhou et al., 2025).

While these progressions have been made, there are significant concerns around clinical implementation of AI. Lots of deep learning models are “black boxes” that give you a prediction that you can't easily see how it was done. The lack of transparency can make clinicians less confident in the results they receive from AI, especially when the results could affect their diagnosis or treatment. Explainable artificial intelligence (XAI) is therefore important since it seeks to provide interpretable information about the factors or regions of the image that led to an AI prediction (van der Velden et al., 2022; Nazir et al., 2023). A second key advancement is the transformation of medical images into numerous quantitative features that capture attributes like intensity, shape, texture, and spatial patterns known as radiomics. These may be features which could be of help in the diagnosis, prognosis, and assessment of treatment response that might not be obvious on routine visual interpretation. In oncology, in particular, the use of radiomics combined with machine learning has sparked great interest because imaging data could play a role in a more individualized evaluation of patients (Lambin et al., 2017).

In addition, diagnostic radiology's future is becoming more multimodal with integration of imaging data. The integration of information from multiple imaging modalities or with other patient information (clinical, laboratory, genomic) may give a more complete picture of disease than any single imaging modality. New multimodal AI techniques are thus being explored to enable more personalized and clinically relevant decision-making. Yet challenges concerning data quality, standardization, data interpretation, data validation, and data integration into clinical workflows remain to be resolved before it is possible to routinely use these technologies (Hu et al., 2026). So the review will focus on the changing landscape of deep learning, explainable AI, radiomics and multimodal imaging in the field of diagnostic radiology. It centers on the roles of these technologies in augmenting radiologists; enhancing the retrieval and utilization of clinically relevant information from medical imaging data and its contribution to increased accuracy, efficiency, transparency and personalization of clinical decision-making.

2. DEEP LEARNING IN DIAGNOSTIC RADIOLOGY

2.1 Basic Concepts of Deep Learning and Convolutional Neural Networks

Deep learning (DL) is a subset of artificial intelligence (AI) which employs multilayer neural networks to learn complex patterns directly from data. However, the convolutional neural network (CNN) has played a significant role in diagnostic radiology by allowing it to learn the spatial features of medical images without having to define each feature explicitly. CNNs typically have several convolutional layers to detect different patterns, like edges, shapes, and textures, followed by deeper layers to create more complex representations. The network can then make a classification, localization, or segmentation or prediction, depending on the clinical task. This learning from images capability has triggered the interest of DL in large scale radiological analysis (Litjens et al., 2017).

As with DL, architectures have been developed that are specific to an imaging problem. For instance, the U-Net and its variants are used in medical image segmentation, and three-dimensional (3D) CNNs can process volumetric CT, MRI and PET datasets. More recent works have added attention mechanisms and transformer-based models which are able to learn relationships between distant parts of an image or between different slices. These advances have expanded the capability of DL from classification of images into more comprehensive image analysis and decision support for healthcare.

2.2 Applications Across Major Imaging Modalities

Deep learning has been explored in nearly all the primary diagnostic imaging modalities. For X-ray imaging, DL models have been created to identify abnormalities like pulmonary nodules, pneumonia, pneumothorax, fractures, etc. Chest radiography has proved to be an ideal imaging modality for AI research due to its large, roughly uniform data collection. For some diagnostic tasks, some studies have reported performance on par with that of certified radiologists; however, performance of these models has been found to be dependent on disease, dataset, and clinical setting (Rajpurkar et al., 2018). With deep learning, in CT, 3D anatomy information can be utilised and has been applied for the detection of intracranial haemorrhage, pulmonary embolus, lung nodules, abdominal abnormalities and more. Some of the applications of MRI are for brain tumor assessment, stroke imaging, detection of lesions in multiple sclerosis, prostate imaging, and image reconstruction. MRI, particularly, is the most difficult modality due to the number of sequences included in the examination and the very great variability in acquisition protocols, but DL can be useful to extract information from these complex sets of data. DL is also being explored in the field of healthcare and medicine, particularly in the context of ultrasound technology, where it can help with the classification of lesions, segmentation of organs, and assessing the quality of the ultrasound images. In PET, deep learning has been investigated with respect to the prediction of clinically relevant outcomes, image reconstruction, deep learning for attenuation correction and deep learning for lesion detection. Moreover, the DL-based image synthesis method can possibly synthesize or estimate images in one imaging modality from another, thus decreasing acquisition burden in some settings (Dayarathna et al., 2024).

Table 1. Major Applications of Deep Learning in Diagnostic Imaging.

Imaging modality	Common deep learning applications	Potential clinical contribution
X-ray	Abnormality detection, classification, triage	Faster identification of urgent findings
CT	Lesion detection, organ segmentation, hemorrhage and nodule detection	Improved quantitative assessment and workflow prioritization
MRI	Tumor segmentation, stroke assessment, lesion detection, image reconstruction	More detailed analysis of complex soft-tissue information
Ultrasound	Organ/lesion segmentation, classification, quality assessment	Greater consistency and assistance during image interpretation
PET	Lesion detection, image reconstruction, attenuation correction	Improved quantitative analysis and potentially reduced acquisition burden
Multimodality imaging	Image synthesis and cross-modality analysis	Integration of complementary imaging information

2.3 Detection, Classification, Segmentation, and Prediction

DL does not only help in identifying if the abnormality exists or not, it is useful for many other purposes related to radiology. Detection models can identify suspected lesions or abnormalities in an image and classification models can identify a diagnostic category for images or lesions. These functions could assist radiologists in highlighting subtle findings and also assists prioritize examinations that require quick review. In certain scenarios, AI can serve as a second reader, offering a second assessment in addition to the radiologist's. One of the other significant applications is image segmentation. The segmentation process consists of detecting the region of the tumour, organ, vessel or other structure at the pixel/voxel level. The automated segmentation can save time for manual contouring, and can give measurements like tumor volume or organ size. This quantitative information may be helpful in planning and managing treatment and the follow-up of disease. In addition, there are more and more DL models for prediction. Predictive models do not simply predict what can be seen on an image, but rather aim to predict more clinical meaningful events such as disease progression, treatment response, recurrence or prognosis. This is a change from image interpretation to predictive radiology, but the prediction models need to be carefully validated to be used for routine management of patients.

Table 2. Deep Learning Tasks in Radiology.

DL task	What the model does	Example clinical use
Detection	Locates an abnormality in an image	Identifying lung nodules on CT
Classification	Assigns an image or lesion to a category	Classifying chest X-rays as normal or abnormal
Segmentation	Delineates structures or lesions	Measuring tumor volume on MRI
Quantification	Produces numerical imaging measurements	Estimating organ volume or lesion burden

Prediction	Estimates a future or clinically relevant outcome	Predicting treatment response
Image reconstruction/synthesis	Improves or generates imaging information	Accelerating MRI or estimating another imaging modality

2.4 Advantages for Diagnostic Accuracy and Workflow

The benefits of DL are that a large amount of imaging data can be processed quickly and accurately. Automated systems can help limit repetitive tasks, provide quantitative measurements and help radiologists make their focus clinically relevant. AI triage could also be used to prioritize potentially critical abnormalities in examinations in high-volume departments. DL can also offer a set of standardized measures which may not be easily replicated using manual assessment. But the most valuable clinical application of DL could be in a way that people collaborate with AI, not fully replace it. AI can serve as a complementary tool that supplements the information provided by the radiologist, but that the radiologist and their clinical context and other diagnostic information will be the final key to integrating the information. Research on diagnostic AI has demonstrated high accuracy, but the performance of diagnostic AI systems in clinical settings does not necessarily translate to patient outcomes or the workflow, as indicated by studies that reported outcomes but did not design experiments to test for workflow improvements (Liu et al., 2019).

2.5 Current Limitations and Challenges

Although tremendous advances have been made, a few obstacles stand in the way of the widespread clinical use of DL. First, in general deep learning needs a large quantity of high-quality data. The preparation of medical images is often costly and time consuming, and requires expertise to annotate, or add information to the image. Further variability in scanner hardware, scanning protocol, image quality and labeling can make model development more challenging. Another key concern is bias. An algorithm may work differently on patient-by-patient basis if there are discrepancies in the training datasets across the patient population with respect to disease presentation, institution or imaging conditions. Bias can creep in during various steps of the data collection, labeling, model building and deployment to the clinic (Mongan et al., 2020; Willemink et al., 2020). A related problem is generalizability. A model that is very accurate on data from one hospital might not be as accurate on data from a different hospital, scanner or patient population. The authors of this systematic review identified 81% of externally validated radiology DL algorithms, which showed some loss of performance when tested on external datasets, highlighting the need for independent testing before clinical use (Vasey et al., 2022).

3. EXPLAINABLE ARTIFICIAL INTELLIGENCE (XAI)

3.1 Definition and Importance of Explainability

Explainable Artificial Intelligence (XAI) is a set of techniques to explain how an Artificial Intelligence prediction has been made. In the realm of diagnostic radiology, it is especially relevant as many deep learning models are capable of making a very accurate prediction without making it abundantly clear why a certain diagnosis had been suggested. In order to make these predictions more transparent, XAI tries to detect the corresponding regions, features or patterns of images that are relevant to the model's prediction. This can help radiologists determine if the AI system is paying attention to medically relevant data or to irrelevant features of the image (Gulum et al., 2023). Explainability should not simply be considered an additional visual feature of an AI system. Useful explanation should be understandable, clinically relevant and reliable enough for the desired task. Recent studies have highlighted the need to test explanations instead of taking them at face value because they seem to make sense when they are presented in a way that is visually appealing (Muhammad & Bendecheache, 2024).

3.2 Why Clinicians Need Interpretable AI Decisions

The radiologist will then have to synthesize the information from the imaging study with the history, lab results and other clinical data. For this reason, an AI projection may not be easy to integrate into the process of professional judgment. An interpretable system can enable the clinician to explore the areas or features that contributed to the prediction and relate these to their own evaluation. XAI can also aid the clinician in recognizing inappropriate model behavior. For instance, an algorithm could have high accuracy in testing, but use in part acquisition-related feature or other characteristics. An explanation can offer a chance to identify such issues prior to widespread use of the system in practice. But, explainability does not guarantee appropriate trust. There are indications that when clear and clinically relevant explanations are provided, it builds confidence, while alternative, confusing, or contradictory explanations can lead to a decrease in trust or may foster inappropriate reliance on AI (Rosenbacke et al., 2024).

Table 3. Common XAI Methods Used in Medical Imaging.

XAI method	Basic principle	Potential use in radiology
Heatmaps	Highlights image regions associated with a prediction	Showing suspected abnormal areas on X-ray or CT
Saliency maps	Estimates the importance of individual image regions or pixels	Identifying regions influencing disease classification
Grad-CAM	Uses gradients from deep networks to produce class-specific localization maps	Visualizing regions contributing to CNN predictions

SHAP	Estimates the contribution of individual features to a prediction	Explaining quantitative or clinical feature contributions
LIME	Creates a locally interpretable approximation around an individual prediction	Explaining individual cases or classifications
Attention-based explanations	Shows areas receiving greater model attention	Supporting interpretation of complex imaging models

3.3 Common XAI Methods

The heatmaps as well as saliency maps are especially appropriate for medical images because of their output can be overlaid on the original image. They enable the radiologist to know where the model is focusing its attention. With the convolutional neural network, gradient-based method can be used to generate class-specific visual map without the complete reconstruction of the underlying model, which is widely used. These methods can be helpful for determining the suspicious regions in chest radiographs and CT scans as well as other imaging studies (Gulum et al., 2023). Similarly, Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) are slightly different. Instead of just marking a region of an image, they make estimates on the relative contribution of individual features to a specific prediction. LIME can be helpful in providing the local approximation of the behaviour of the model for a model-specific case; while SHAP is helpful when the information provided by the images is coupled with other quantitative or clinical variables. According to recent reviews, SHAP and LIME are two of the common xai techniques used in healthcare settings, with some methodological assumptions that could impact their reliability and meaning of explanations (Muhammad & Bendeche, 2024).

3.4 Applications in Disease Detection and Clinical Decision Support

XAI has been studied in a number of areas of radiology, such as chest imaging, oncology, neurological imaging, and mammography. For disease detection, visual explanations can provide information about the area that made the most significant contribution in making the positive or negative prediction. A machine learning model that analyses a chest X-ray can, for instance, give a chance of pneumonia, as well as a visual indication of the region of the lungs that affects the outcome. This makes it possible for the radiologist to make a comparison between the algorithm focus and the actual imaging results. Another potential use of XAI could be in clinical decision support, where predictions from imaging data are integrated with interpretable clinical information. For instance, in cancers, explanations can be used to indicate to the patient which imaging characteristics or patient features helped to predict diagnosis, prognosis, or treatment response. A recent systematic review of XAI in cancer care underscored the potential of XAI in the diagnosis, prognosis, and treatment planning, as well as the lack of clinician engagement and of evaluating explanation as a weakness in the existing literature (Mansour et al., 2024). Human-centered evaluation is particularly critical. In this study that included chest radiograph, clinicians assessed the utility of visual explanations produced by the Grad-CAM and LIME algorithms, concluding that the value of an explanation is not just based on the algorithm but on how the clinician understands and utilizes the information (Ihongbe et al., 2024).

Table 4. Potential Clinical Roles and Challenges of XAI.

Clinical role	Potential benefit	Main concern
Disease detection	Shows regions supporting an AI prediction	Highlighted regions may not always represent true pathology
Second-reader support	Provides additional evidence for the radiologist	May create excessive dependence on AI
Treatment planning	Helps identify features associated with prognosis or response	Explanations may not be sufficiently validated
Error identification	Allows clinicians to examine unusual AI decisions	Incorrect explanations may give false reassurance
Clinical decision support	Improves transparency of model outputs	Explanation may be too complex for routine workflow
Model auditing	Helps investigate bias and unexpected model behavior	Requires standardized evaluation methods

3.5 Challenges in Trust, Interpretability, and Validation

While it has great potential, there are some significant caveats to XAI. First, an explanation is not necessarily a faithful representation of the actual reasoning of the model. A pretty-looking heatmap can look clinically reasonable but actually not contain the elements that lead to predictions. Therefore, explanations should be evaluated and judged based on their fidelity, stability, and clinical relevance, not just on their appearance (Muhammad & Bendeche, 2024). One of the challenges is the right trust. Excessive trust can result in a wrong AI recommendation being accepted, and insufficient trust can result in the lack of a useful system being accepted. Therefore, XAI's goal is not to just boost trust, but to establish a calibrated trust. Explanations that are high quality, clear, and clinically relevant may have a significant impact on the response to AI recommendations (Rosenbacke et al., 2024). Lastly, there is no standard criterion or

established gold standard to validate XAI methods in radiology. A number of studies determine if an explanation is plausible, but not if it actually enhances diagnostic performance or clinical workflow. Existing evidence thus indicates that more use of clinician-centred evaluation, external validation, explanation metrics that are standardized across different systems and studies that look at workflows in advance of XAI systems being widely adopted in clinical practice is warranted. Overall, XAI can contribute to the transparency and possible utility of AI-enabled radiology for the clinician, but explainability itself is not a sign of a clinically reliable algorithm, it should be considered as part of the trustworthy AI.

4. RADIOMICS AND QUANTITATIVE IMAGING

4.1 Concept and Workflow of Radiomics

One of the emerging quantitative imaging technologies is called "radiomics," which transforms medical images into a vast array of measurable features. In contrast to classic image interpretation that relies primarily on visual inspection, radiomics aims to extract data from lesions that reveals shape, intensity, texture, and spatial characteristics that can't be easily seen with the naked eye. The proposed general radiomics pipeline consists of image acquisition, image preprocessing, ROI segmentation, feature extraction, feature selection, model building and clinical validation. Each step of the process needs to be carefully controlled as it can affect the features that will be created in the image (Huisman & Akinci D'Antonoli, 2024). Radiomics could be used in other imaging modalities such as CT, MRI, PET or Ultrasound. This method is especially appealing since all of the information in medical images pertains to the whole lesion and its surrounding tissue, possibly enabling the non-invasive disease heterogeneity assessment. This information can then be used to create predictive models along with clinical or biological variables.

4.2 Extraction of Quantitative Imaging Features

Most frequently, radiomic features are clustered into a few groups. First-order features refer to the distribution of the intensity of the pixels or voxels, while shape-based features refer to the size, volume, surface area and geometry of the lesion. The texture features represent the spatial distribution and the variation of intensities, and they can give information on tissue heterogeneity. Higher order mathematical transformations and filtered images are also used in more advanced techniques to detect other patterns. To ensure the extraction process, it is necessary to make the image consistent in preprocessing and segmentation. Some features might be different depending on the voxel size, reconstruction settings, intensity discretization, segmentation methods or software implementation. A standardised definition and standardised procedure have thus been defined and proposed by the Image Biomarker Standardisation Initiative (IBSI), with the goal of increasing the consensus on how different implementations of radiomics are agreed (Whybra et al., 2024).

Table 5. Main Categories of Radiomic Features.

Feature category	Information obtained	Example clinical relevance
First-order	Intensity distribution within a region	Assessment of tissue characteristics
Shape-based	Size, volume, surface and geometry	Tumor characterization and monitoring
Texture	Spatial variation and heterogeneity	Assessment of tumor heterogeneity
Filtered features	Patterns emphasized through mathematical filters	Identification of specific spatial structures
Higher-order features	Complex relationships among image characteristics	Potential improvement of predictive modeling

4.3 Applications in Oncology and Other Diseases

In the field of oncology, extensive studies have been conducted on radiomics, given the significance of tumor heterogeneity and its biological behavior for the planning of treatment. Radiomic features derived from CT, MRI, and PET have been used to characterize, stage, molecularly classify, assess for recurrence, and predict survival of tumors. For instance, in lung cancer, radiomic data can be used in conjunction with machine learning to analyze tumor phenotype, risk stratification, molecular features, and clinical outcomes (Jha et al., 2023). Radiomics can be used in non-cancer applications. Neurological, cardiovascular, pulmonary and musculoskeletal as well as inflammatory diseases have also been investigated with quantitative imaging features. The concept is the same, imaging data is converted to measurable parameters that can provide insight into the differences between disease states. But there are still a lot of applications in the research phase and the clinical relevance of each radiomic biomarker is quite different in various studies.

4.4 Integration of Radiomics with Machine Learning and Deep Learning

Due to the substantial number of features generated by radiomics, the resulting data is a high-dimensional dataset, which can be much larger than the number of patients. Machine learning can contribute to feature selection to

Next-Generation Diagnostic Radiology: Deep Learning, Explainable Artificial Intelligence, Radiomics, and Multimodal Imaging for Improved Clinical Decision-Making

pinpoint those most strongly linked to a specific clinical outcome. Typical methods are featuring selection, dimensionality reduction, classification, regression and survival modeling. Radiomics and machine learning are thus a framework to leverage quantitative image features into clinically relevant predictions. Another route is deep learning, which learns the imaging representations automatically without depending on manually-designed radiomic features entirely. Traditional "radiomic" measurements can be used alongside deep-learning derived features and clinical data in a hybrid approach. When there is complementary information about disease provided by different types of information, such integration can be helpful. However, one needs to be careful with the feature selection and suitable validation efforts must be undertaken to prevent overfitting and giving an inflated performance estimate (Zhang et al., 2023).

4.5 Potential for Diagnosis, Prognosis, and Treatment-Response Prediction

The 3 main potential clinical applications of radiomics are diagnosis, prognosis and prediction of treatment response. Radiomic features can be used to differentiate between benign and malignant lesions or different disease types for diagnosis. In prognosis, quantitative imaging features may be able to identify those patients with a greater likelihood of recurrence or poor survival. Changes in radiomic features with time could be used to inform on the tumor response before the conventional change in size. An important development is delta-radiomics which is used to assess radiomic changes between different imaging exams. While this machine-based analysis of a tumor is usually performed at a single time point, delta-radiomics aims to quantify the alterations in imaging phenotype that occur over the course of therapy. Cancer immunotherapy studies have suggested that this could be beneficial, but the evidence is currently limited and contains methodological limitations and a lack of prospective external validation (Abbas et al., 2023).

Table 6. Clinical Potential of Radiomics.

Clinical application	Potential role	Expected benefit
Diagnosis	Characterization and classification of lesions	Additional quantitative information
Staging	Assessment of tumor characteristics and disease extent	More detailed disease profiling
Prognosis	Prediction of survival or recurrence	Identification of higher-risk patients
Treatment response	Assessment of imaging changes during therapy	Earlier identification of responders/non-responders
Precision medicine	Association of imaging features with molecular or clinical characteristics	More individualized treatment decisions
Disease monitoring	Quantitative comparison across serial scans	Objective assessment of disease evolution

4.6 Challenges in Reproducibility, Standardization, and Data Harmonization

Although promising, radiomics has a long road to go before its promising future can be realized in the clinic. Reproducibility is one of the most important concerns. A feature that is predictive in one set of images can vary significantly when the images are acquired with a different scanner, protocol, reconstruction method and segmentation procedure. Also, differences in the software packages can result in different feature values from the same image. They can diminish the trustworthiness and overall applicability of radiomic models (Whybra et al., 2024). Thus, data harmonization is a crucial step, especially for multicenter studies. These methods include standardised acquisition protocols, image preprocessing, feature scaling, selection of stable features and statistical harmonisation techniques like ComBat. The intention of these strategies is to minimize the technical variability whilst maintaining clinically meaningful biological differences (Zwanenburg et al., 2020). The sample size of the studies using radiomics is generally small, and the number of features extracted large. This can cause overfitting and over optimistically estimate performance. The clarity of reporting, the independence of the data sets, the external validation and application of standardized radiomics guidelines are therefore crucial in order to enhance the credibility of published models. Recent studies have pointed out the need for standardization of the whole radiomics pipeline in addition to feature extraction, for successful clinical translation. Overall, the potential of radiomics as a link between medical imaging and quantitative clinical decision making is promising. When combined with machine learning and deep learning, it has the potential to enhance the personalized diagnosis and treatment evaluation but requires reliable clinical adoption, which will require reproducible approaches, harmonized data, biological interpretation and solid external validation.

5. MULTIMODAL IMAGING AND INTEGRATED CLINICAL DECISION-MAKING

5.1 Combining Information from Multiple Imaging Modalities

The information from more than one radiological diagnosis is essential in order to make the modern diagnosis. CT can be used to give detailed anatomical and structural information, MRI can be used to give excellent soft-tissue characterisation, PET can be used to give functional and metabolic information, and ultrasound and X-ray remain important and have been widely used clinically, as they are easy to obtain, rapid and simple. The aim of multimodal

imaging is to integrate the complementary aspects in order to give an assessment of a disease from different perspectives both from a biological and anatomical point of view. Studies have recently shown that when using a combination of imaging modalities, image-fusion methods can help to visualize, characterize and segment lesions better than using any single imaging modality. The integration isn't always about creating a single integrated picture, but will be concerning the production of a single image. Information could also be combined at the feature/decision level, where different imaging examinations make independent contributions to a common prediction, in the same way that artificial intelligence can do so. This is especially important when various forms of imaging (CT, MRI, PET, ultrasound or X-rays) give differing, but complementary, information regarding the same disease.

5.2 Fusion of Imaging, Radiomics, Clinical, Laboratory, and Genomic Data

Images are seldom the only basis for clinical decision making. Clinical and laboratory data, previous examinations, patient history, and pathobiology are also important factors for radiologists and clinicians. This more comprehensive form of reasoning is replicated in multimodal AI, which learns from various forms of patient information concurrently. Imaging features can be added to the radiomic measurements and clinical, laboratory biomarkers, EHRs and genomic or other molecular data. Such integration could be of a more complete nature than any single data source, giving a better picture of disease biology. There are three different types of fusion which can be applied: early fusion, where data is fused prior to model learning; intermediate fusion, where the data is fused in the model; and late fusion, where the predictions from different models are fused. The best approach varies based on the features, availability and quality of the various data sources.

5.3 Multimodal AI for Personalized Diagnosis

AI models are now more and more studied for personalised diagnosis and prediction in multimodal systems. These models can use multiple complementary sources of information to predict the probability of a disease state, the prognosis (or outcome of disease), or the response to treatment in an individual. These models can process multiple complementary sources of information to predict the probability of a disease state, the prognosis (or outcome of disease), or the expected response to treatment in an individual. There is recent evidence that multimodal models can outperform unimodal models in a few clinical prediction tasks, but their performance is highly dependent on the quality of the data and the availability of full multimodal data. For instance, in oncology, PET, CT or MRI data could be fused with other lab or molecular data to better characterize and plan treatment for the tumor. In other disorders, such as neurological disorders, structural and functional imaging can be used along with clinical data or in other cardiovascular disorders, imaging data can be used in conjunction with physiological measurements and blood markers. These applications facilitate moving from image centered diagnosis to more extensive patient centered decision making.

Table 7. Applications and Potential Benefits of Multimodal AI in Clinical Imaging.

Clinical area	Possible multimodal data	Potential contribution
Cancer	CT/MRI/PET + radiomics + laboratory/genomic data	Tumor characterization, prognosis, treatment planning
Neurological disease	MRI/PET + clinical findings + cognitive data	Disease classification and progression assessment
Cardiovascular disease	CT/MRI/ultrasound + ECG/laboratory data	Risk assessment and disease characterization
Pulmonary disease	X-ray/CT + clinical and laboratory information	Detection and severity assessment
Precision medicine	Imaging + clinical + molecular information	Individualized diagnosis and treatment selection
Clinical decision support	Images + EHR + reports + biomarkers	More comprehensive patient-level predictions

5.4 Benefits for Precision Medicine and Clinical Decision-Making

The greatest benefit of multimodal AI is that it can combine complementary information and not just rely on a single source. Radiological information may help determine where a lesion is located and its shape, while laboratory or molecular information may help determine the biological behavior of a lesion. It may thus be better to use the combination of these sources to increase diagnostic confidence and to assist in more individualized decisions. Multimodal AI has been highlighted in recent reviews as a potential solution to enhance the diagnosis, prognosis, treatment planning and personalized care approaches. Multimodal systems could also limit the work of the clinician in having to manually combine information that exists in various information systems. These models could, in the future, be helpful for multidisciplinary teams, offering a comprehensive evaluation of imaging and clinical and molecular data. Critically, these systems need to be used as decision support systems and clinicians should always consider the AI output in the broader clinical context of the patient.

5.5 Remaining Challenges

Multimodal imaging has great promise but has several practical and technical challenges. A significant challenge is interoperability, where imaging systems can be different formats and standards, as can laboratory databases, electronic health records, and genomic platforms. Another concern is incomplete patient records since not all patients receive all imaging tests or laboratory tests. Thus, models trained with the complete data might fail to function if one or more modality is missing in normal applications. Also related to data quality and harmonisation. Variations in scanner, acquisition protocols, institutions, laboratory measurements and clinical documentation may cause unwanted variation. Patient privacy is another issue, as with multiple types of health information, there is a greater amount of potentially identifiable data. Institutions can collaborate without regularly sharing patient data with each other through privacy-preserving methods such as federated learning and secure data-sharing systems. Last, but not least, there are the clinical implementation steps to take beyond the demonstration of high model accuracy. There is a need to embed multimodal AI into the current radiology and hospital workflow, assess it in a prospective fashion, and test it for reliability, fairness, interpretability and clinical value. The multi-source nature of data, interoperability, lack of data, lack of interpretability, and deployment in the real world are still seen as significant challenges in the way forward to the routine adoption of such systems. Generally, multimodal imaging and AI can help diagnostic radiology to become more integrated into precision medicine. These systems can integrate imaging with quantitative, clinical, laboratory and molecular data to help give a better understanding of the individual patient. But it will require standardization in data infrastructure, ensuring privacy is safeguarded, strong validation procedures and a close relationship between those developing AI and healthcare professionals to make it a success.

Future Perspectives and Conclusion

AI is likely to be widely used in everyday radiology, from interpreting images and prioritizing workflow to evaluating quantitative measures, supporting reporting, and aiding clinical decisions. The key to the successful implementation will be the use of AI as an enabling tool in existing workflows and not as a substitute for radiologists. The professional societies highlight the importance of careful assessment, monitoring, and collaboration between radiologists, developers, healthcare institutions, and regulators in implementing AI systems in clinical practice (Brady et al., 2024). The next generation of radiology systems will be based on trustworthy, transparent, and clinically explainable AI. Models should show consistent results in various hospitals, patient populations, scanners, and imaging protocols. Going forward, the accuracy of an AI system in environments different from its training will be a key determinant, and standardized datasets and external testing will be crucial. On top of that, it is important to keep an eye on it after deployment, as the performance of this model can vary over time as clinical practice and patient populations evolve (Sajda et al., 2024).

Ethical and regulatory matters will continue to be a key focus in the evolution of AI in radiology. There are several issues regarding patient privacy, responsible data use, algorithmic bias, accountability, transparency, and informed human oversight that must be addressed during the AI lifecycle. The World Health Organization highlights key principles of AI in the healthcare sector: safeguarding autonomy of the human person, enhancing safety, fostering transparency and explainability, and ensuring equity and accountability (World Health Organization, 2021, 2024). Radiologists will therefore remain well positioned to interpret images as well as evaluate AI outputs, identify recommendations that may not be appropriate, provide clinical expertise during model development, and make sure technology is not being used for its own sake but remains focused on patient needs. More studies are required to not only report the accuracy of the models, but also to test whether AI can really enhance diagnostic results, efficiency, patient safety, and accessibility to healthcare. Clinical trials on the horizon, multicenter studies, standardized assessment tools, human – AI interaction studies, and cost-effectiveness analyses will be of great value. In summary, the integration of deep learning, explainable AI, radiomics and multimodal imaging holds great promise for the revolution of diagnostic radiology. Responsible development and implementation of multimodal systems are expected to enable faster and more quantitative evaluation and better and more personalized clinical decision making with the help of AI. The future of radiology is therefore likely to be characterized by a synergy between human knowledge and intelligent computing systems, with the ultimate aim to enhance the care of individual patients.

Conflict of Interest

The authors declare they don't have any conflict of interest.

Author contributions

The initial draft was written by the first author and the corresponding author's supervisor it. All co-authors actively participated in conceptualizing and executing the study, sharing responsibilities for data collection, synthesis, and the design of all tables and figures. Every author critically reviewed the manuscript, approved the final version, and consented to publication.

Acknowledgement

The authors express their sincere gratitude to the academic platforms and databases that made this work possible: DOAJ, Cochrane Library, BMJ Clinical Evidence, Google Scholar, Embase, PubMed, and MEDLINE. By providing transparent, unrestricted access to foundational biomedical research and clinical evidence, these resources facilitated robust systematic data retrieval and reinforced the integrity and reproducibility of our findings.

References

1. Abbas, E., Fanni, S. C., Bandini, C., Francischello, R., Febi, M., Aghakhanyan, G., Ambrosini, I., Faggioni, L., Cioni, D., Lencioni, R. A., & Neri, E. (2023). Delta-radiomics in cancer immunotherapy response prediction: A systematic review. *European Journal of Radiology Open*, 11, 100511. <https://doi.org/10.1016/j.ejro.2023.100511>
2. Ardic, N., & Dinc, R. (2025). Emerging trends in multi-modal artificial intelligence for clinical decision support: A narrative review. *Health Informatics Journal*, 31(3), 14604582251366141. <https://doi.org/10.1177/14604582251366141>
3. <https://doi.org/10.1177/14604582251366141>
4. Bian, Y., Li, J., Ye, C., Jia, X., & Yang, Q. (2025). Artificial intelligence in medical imaging: From task-specific models to large-scale foundation models. *Chinese Medical Journal*, 138(6), 651–663. <https://doi.org/10.1097/CM9.0000000000003489>
5. Brady, A. P., Allen, B., Chong, J., Kotter, E., Kottler, N., Mongan, J., Oakden-Rayner, L., Pinto dos Santos, D., Tang, A., Wald, C., & Slavotinek, J. (2024). Developing, purchasing, implementing and monitoring AI tools in radiology: Practical considerations. A multi-society statement from the ACR, CAR, ESR, RANZCR and RSNA. *Radiology: Artificial Intelligence*, 6(1), e230513. <https://doi.org/10.1148/ryai.230513>
6. Dayarathna, S., Islam, K. T., Uribe, S., Yang, G., Hayat, M., & Chen, Z. (2024). Deep learning based synthesis of MRI, CT and PET: Review and analysis. *Medical Image Analysis*, 92, 103046. <https://doi.org/10.1016/j.media.2023.103046>
7. <https://doi.org/10.1016/j.media.2023.103046>
8. Gulum, A. H., D'Antonoli, T. A., & Bagci, U. (2023). Explainable AI in medical imaging: An overview for clinical practitioners—Saliency-based XAI approaches. *Diagnostic and Interventional Imaging*, 104(7–8), 343–353. <https://doi.org/10.1016/j.diii.2023.03.001>
9. Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. W. L. (2018). Artificial intelligence in radiology. *Nature Reviews Cancer*, 18(8), 500–510. <https://doi.org/10.1038/s41568-018-0016-5>
10. Huisman, M., & Akinci D'Antonoli, T. (2024). What a radiologist needs to know about radiomics, standardization, and reproducibility. *Radiology*, 310(2), e232459. <https://doi.org/10.1148/radiol.232459>
11. Jha, A. K., Mithun, S., Sherkhane, U. B., Dwivedi, P., Puts, S., Osong, B., Traverso, A., Purandare, N., Wee, L., Rangarajan, V., & Dekker, A. (2023). Emerging role of quantitative imaging (radiomics) and artificial intelligence in precision oncology. *Exploration of Targeted Anti-Tumor Therapy*, 4(4), 569–582. <https://doi.org/10.37349/etat.2023.00153>
12. <https://doi.org/10.37349/etat.2023.00153>
13. Lambin, P., Leijenaar, R. T. H., Deist, T. M., Peerlings, J., de Jong, E. E. C., van Timmeren, J., Sanduleanu, S., Larue, R. T. H. M., Even, A. J. G., Jochems, A., van Wijk, Y., Woodruff, H., van Soest, J., Lustberg, T., Roelofs, E., van Elmpt, W., Dekker, A., Mottaghy, F. M., Wildberger, J. E., & Walsh, S. (2017). Radiomics: The bridge between medical imaging and personalized medicine. *Nature Reviews Clinical Oncology*, 14(12), 749–762. <https://doi.org/10.1038/nrclinonc.2017.141>
14. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, 42, 60–88. <https://doi.org/10.1016/j.media.2017.07.005>
15. Liu, X., Faes, L., Kale, A. U., Wagner, S. K., Fu, D. J., Bruynseels, A., Mahendiran, T., Moraes, G., Shamdas, M., Kern, C., Ledsam, J. R., Schmid, M. K., Balaskas, K., Topol, E. J., Bachmann, L. M., Keane, P. A., & Denniston, A. K. (2019). A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: A systematic review and meta-analysis. *The Lancet Digital Health*, 1(6), e271–e297. [https://doi.org/10.1016/S2589-7500\(19\)30123-2](https://doi.org/10.1016/S2589-7500(19)30123-2)
16. Mansour, R., et al. (2024). Decoding the black box: Explainable AI (XAI) for cancer diagnosis, prognosis, and treatment planning—A state-of-the-art systematic review. *International Journal of Medical Informatics*, 191, 105689. <https://doi.org/10.1016/j.ijmedinf.2024.105689>
17. Mazurowski, M. A., Buda, M., Saha, A., & Bashir, M. R. (2019). Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on MRI. *Journal of Magnetic Resonance Imaging*, 49(4), 939–954. <https://doi.org/10.1002/jmri.26534>
18. Mongan, J., Moy, L., & Kahn, C. E., Jr. (2020). Checklist for artificial intelligence in medical imaging (CLAIM): A guide for authors and reviewers. *Radiology: Artificial Intelligence*, 2(2), e200029. <https://doi.org/10.1148/ryai.2020200029>
19. <https://doi.org/10.1148/ryai.2020200029>
20. Muhammad, D., & Bendeache, M. (2024). Unveiling the black box: A systematic review of explainable artificial intelligence in medical image analysis. *Computational and Structural Biotechnology Journal*, 24, 542–560. <https://doi.org/10.1016/j.csbj.2024.08.005>
21. Nagendran, M., Chen, Y., Lovejoy, C. A., Gordon, A. C., Komorowski, M., Harvey, H., Topol, E. J., Ioannidis, J. P. A., Collins, G. S., & Maruthappu, M. (2020). Artificial intelligence versus clinicians: Systematic review of design, reporting standards, and claims of deep learning studies. *BMJ*, 368, m689. <https://doi.org/10.1136/bmj.m689>
22. <https://doi.org/10.1136/bmj.m689>

Next-Generation Diagnostic Radiology: Deep Learning, Explainable Artificial Intelligence, Radiomics, and Multimodal Imaging for Improved Clinical Decision-Making

25. Nazir, S., Dickson, D. M., & Akram, M. U. (2023). Survey of explainable artificial intelligence techniques for biomedical imaging with deep neural networks. *Computers in Biology and Medicine*, 156, 106668. <https://doi.org/10.1016/j.compbiomed.2023.106668>
26. Owais, M., et al. (2025). A comprehensive review of techniques, algorithms, advancements, challenges, and clinical applications of multi-modal medical image fusion for improved diagnosis. *Computer Methods and Programs in Biomedicine*, 272, 109014. <https://doi.org/10.1016/j.cmpb.2025.109014>
27. Rajpurkar, P., Irvin, J., Ball, R. L., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C., Shpanskaya, K., Lungren, M. P., & Ng, A. Y. (2018). Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. *PLoS Medicine*, 15(11), e1002686. <https://doi.org/10.1371/journal.pmed.1002686>
28. Rosenbacke, R., Melhus, Å., McKee, M., & Stuckler, D. (2024). How explainable artificial intelligence can increase or decrease clinicians' trust in AI applications in health care: Systematic review. *JMIR AI*, 3, e53262. <https://doi.org/10.2196/53262>
29. Schouten, D., et al. (2025). Navigating the landscape of multimodal AI in medicine: A scoping review on technical challenges and clinical applications. *Medical Image Analysis*, 103621. <https://doi.org/10.1016/j.media.2025.103621>
30. Simon, B. D., Ozyoruk, K. B., Gelikman, D. G., Harmon, S. A., & Türkbey, B. (2025). The future of multimodal artificial intelligence models for integrating imaging and clinical metadata: A narrative review. *Diagnostic and Interventional Radiology*, 31(4), 303–312. <https://doi.org/10.4274/dir.2024.242631>
31. Tariq, A., Banerjee, I., Trivedi, H., & Gichoya, J. (2025). Multimodal artificial intelligence models for radiology. *British Journal of Radiology*, 98. <https://doi.org/10.1093/bjrai/ubae017>
32. Teoh, J. R., et al. (2024). Advancing healthcare through multimodal data fusion: A comprehensive review of techniques and applications. *PeerJ Computer Science*, 10, e2298. <https://doi.org/10.7717/peerj-cs.2298>
33. van der Velden, B. H. M., Kuijf, H. J., Gilhuijs, K. G. A., & Viergever, M. A. (2022). Explainable artificial intelligence (XAI) in deep learning-based medical image analysis. *Medical Image Analysis*, 79, 102470. <https://doi.org/10.1016/j.media.2022.102470>
34. Vasey, B., Nagendran, M., Campbell, B., Clifton, D. A., Collins, G. S., Denaxas, S., Denniston, A. K., Faes, L., Geerts, B., Ibrahim, M., Kelly, C., Keane, P. A., Keng, M., Kihal-Talantikite, W., Kokciyan, N., Liu, X., McCradden, M. D., Mertens, B., Moons, K. G. M., ... Watkinson, P. J. (2022). Reporting guideline for the early-stage clinical evaluation of decision support systems driven by artificial intelligence: DECIDE-AI. *Nature Medicine*, 28, 924–933.
35. Whybra, P., Zwanenburg, A., Andrearczyk, V., Schaer, R., Apte, A. P., Ayotte, A., et al. (2024). The Image Biomarker Standardization Initiative: Standardized convolutional filters for reproducible radiomics and enhanced clinical insights. *Radiology*, 310(2), e231319. <https://doi.org/10.1148/radiol.231319>
36. Willemink, M. J., Koszek, W. A., Hardell, C., Wu, J., Fleischmann, D., Harvey, H., Folio, L. R., Summers, R. M., Rubin, D. L., & Lungren, M. P. (2020). Preparing medical imaging data for machine learning. *Radiology*, 295(1), 4–14. <https://doi.org/10.1148/radiol.2020192224>
37. World Health Organization. (2021). Ethics and governance of artificial intelligence for health: WHO guidance. World Health Organization.
38. World Health Organization. (2024). Ethics and governance of artificial intelligence for health: Large multi-modal models—WHO guidance. World Health Organization.
39. Zhang, Y., et al. (2023). Artificial intelligence-driven radiomics study in cancer: The role of feature engineering and modeling.
40. Zwanenburg, A., Vallières, M., Abdalah, M. A., Aerts, H. J. W. L., Andrearczyk, V., Apte, A., et al. (2020). The Image Biomarker Standardization Initiative: Standardized quantitative radiomics for high-throughput image-based phenotyping. *Radiology*, 295(2), 328–338. <https://doi.org/10.1148/radiol.2020191145>