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Artificial Intelligence in Medical Imaging: Current Applications, Limitations, and Future Perspectives - Narrative Review

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ABSTRACT

Artificial intelligence (AI) has developed from a theory to a technology that has become practical in current healthcare, especially in image diagnosis. This is a review of where current usage of this technology is, its limitations at present, and its possible futures. Our findings indicate that AI systems are already augmenting radiological practice across various imaging modalities, including X-ray, CT, and MRI. These tools show real promise in speeding up diagnosis by detecting subtle or early signs that might be missed during standard screenings, particularly lung and breast cancers, and by analyzing heart and brain images. However, many unanswered questions remain regarding the reliability of AI tools in routine clinical practice, despite their impressive technical performance. Model bias, a lack of varied, high-quality data, and difficult moral conundrums related to AI use are some of the main obstacles. We observe that clearer legal and regulatory frameworks, as well as greater transparency, are increasingly required, often referred to as "explainable AI". Looking ahead, the field is evolving. The next generation of AI may involve multimodal and foundation models that integrate imaging data with other clinical information. The use of AI is focused on supporting, not replacing, radiologists and on analyzing medical images.

Keywords: Medical imaging, Artificial intelligence, Diagnostic imaging, Radiomics.

1. INTRODUCTION

In recent years, artificial intelligence (AI) has transitioned from a theoretical concept to a practical tool in medicine, significantly influencing diagnostic imaging. Radiologists have begun utilizing deep learning tools, such as complex architectures like Vision Transformers (ViTs), to facilitate easier and faster disease detection, classification, and characterization across various imaging modalities (Azad et al., 2024; Aburass et al., 2025). These technologies have been trained to be able to spot subtle or complicated details in images that even highly experienced radiologists might miss. In typical clinical settings, this often results in better patient outcomes and more efficient workflows (Noh & Lee, 2025). For example, mammography supported by AI technology was capable of reducing the radiologists' interpretation time while improving the detection of cancer.

Nevertheless, challenges also lie in its implementation in real healthcare delivery. The so-called "black box" problem is a serious worry since clinicians may be hesitant to trust AI's judgments, since they are hard to understand (Borys et al., 2023; Houssein et al., 2025). Nevertheless, in order to resolve this issue, methods such as Federated Learning have been proposed, which enable hospitals and research institutions to train models of Artificial Intelligence together without sharing sensitive data of their patients, thereby reducing privacy issues (Guan et al., 2024 & Rehman et al., 2023).

In this review, we provide a broad overview of AI's current role and progress in medical imaging, and examine the full spectrum of AI's evolution, from recent technological developments such as foundation models capable of zero- and few-shot learning (Noh & Lee, 2025) to the growing list of FDA-cleared devices and the current state of real-world clinical adoption (FDA, 2025; Singh et al., 2025). Current clinical applications include breast imaging, neuroimaging, point-of-care ultrasound, and echocardiography (Windecker et al., 2025; Al-Karawi et al., 2024). We also discuss the ethical and regulatory environment, pointing out the most important issues regarding FDA-approved AI devices, the need for standardization, and the impediments to their application in practical fields (Chang et al., 2025; East et al., 2025; Paschali et al., 2025). We look at new directions for the future, especially the development of multimodal AI models that integrate genomic, clinical, and imaging data. Such integrative approaches have the potential to improve diagnostic accuracy and push the field closer to truly personalized medicine (Horvat et al., 2024; Demircioğlu, 2025; Simon et al., 2025).

The following sections discuss the technical foundations of current AI solutions in medical imaging. We will then explore current applications of AI solutions across various modalities of image acquisition, taking into account the practical, ethical, and regulatory considerations surrounding them. Our vision concerning prospects will be presented at the close of the paper, with specific reference to multimodal data integration and the paradigm shift offered by foundation models.

2. REVIEW METHODS

This is a narrative review that employed a thorough literature search of the PubMed and Google Scholar databases. For this review, we employed the following keywords in searching for literature in the various databases: medical imaging, AI, diagnostic imaging, and radiomics. This review included randomized trials, observational studies, systematic reviews, and FDA reports that address FDA approval of various imaging technologies. It is important to point out that in screening the literature, the authors of this review adhered to PRISMA standards (Figure 1). After conducting the search, 25 articles published between 2019 and 2025 were selected to provide a current, clinical overview of AI applications in medical imaging.

3. RESULT AND DISCUSSION

Evolution of AI Architectures: From CNNs to Foundation Models

The way medical images are analyzed has undergone significant changes in recent years. This shift has been driven mainly by progress in model architecture. Traditionally, the convolutional neural networks (CNNs) were the primary means of image processing, and they formed the basis of past breakthroughs in the application of vision in medicine. The Vision Transformers (ViTs) that exhibit added flexibility and have proven superior to the conventional models in image processing tasks have gained much attention in recent years (Azad et al., 2024). Unlike the CNNs, which were dependent on certain regions, ViTs allow analysis of the complete visual field, including images in the health sector. They are able to capture fine spatial relationships owing to this global attention mechanism, which improves segmentation as well as classification tasks to a significant extent (Azad et al., 2024; Aburass et al., 2025).

Based on these advances, a new set of large-scale foundation models has been developed. These are general-purpose systems that can be adapted to various tasks and have been pre-trained on large datasets before fine-tuning them for medical use. Surprisingly, they frequently require very little extra data to achieve competitive performance. This flexibility represents a fundamental change in how AI systems are created for the healthcare sector, by reducing reliance on time-consuming manual image annotation and facilitating quick adaptation to new clinical situations (Noh & Lee, 2025). One of the biggest paradigm leaps in the current state of medical imaging AI is the move from task-specific designs to widely pre-trained models. Table 1 summarizes the main architectural paradigms that have influenced the development of AI in medical imaging, detailing their benefits, drawbacks, and illustrative uses.

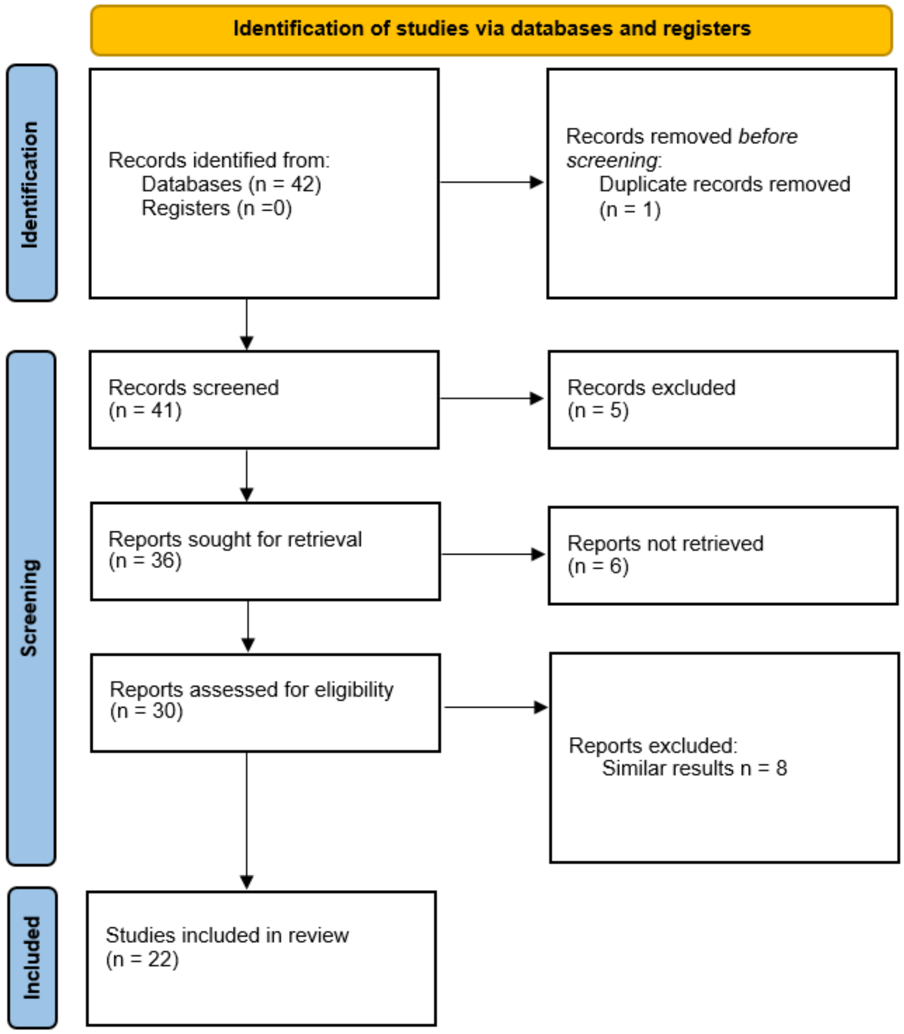

Figure 1. Prisma flow chart

Table 1. Overview of Key AI Architectures Used in Medical Imaging

Architecture / Model Type	Core Principle	Key Advantages	Limitations	Representative Applications	Representative References
CNN (Convolutional Neural Network)	Localization of features in images through convolutional filters	Robust performance capabilities when working with structured data types, such as images	Lack of global understanding of images	Lesion detection, segmentation, and classification	(Azad et al., 2024; Aburass et al., 2025)
Vision Transformer (ViT)	Global self-attention mechanism, considers entire visual context	Captures long-range spatial relations well, achieves high accuracy in complex images	Computationally expensive, data-hungry	Brain tumor segmentation, lesion detection in breast images	(Azad et al., 2024; Aburass et al., 2025)

Foundation Models	Large-scale pretraining on heterogeneous datasets, followed by fine-tuning	Adaptable across modalities; zero-/few-shot learning; minimal labeling	Regulatory uncertainty; interpretability challenges	Cross-modality segmentation, clinical adaptation	(Noh & Lee, 2025; Paschali et al., 2025)
Radiomics Models	Quantitative extraction of handcrafted features	High interpretability; links imaging features to biology	Sensitive to acquisition variability; less flexible	Oncologic prognosis, risk stratification	(Horvat et al., 2024; Demircioğlu, 2025)
Vision-Language Models (VLMs)	Processing of inputs in vision and text domains	Allows report creation and multimodal inference	Research in its infancy stage, validation is limited	Automated reporting, Clinical summarization	(Simon et al., 2025; Kalpelbé et al., 2025; Kurz et al., 2025)

Interpretability, Privacy, and Collaborative Learning in Medical AI

As these models continue to become more advanced, the decision-making process that happens within them becomes less interpretable. This is what is meant by the "black box" problem. It is reportedly one of the reasons that has contributed to a lack of adoption in a clinical setting. It is only logical that a clinician wouldn't choose to use algorithmic predictions if the decision-making process in the algorithm is unintelligible (Borys et al., 2023). Addressing such an issue, one significant topic in current studies was given to Explainable AI, aimed at enhancing the interpretability of predictions made by AI models. (Borys et al., 2023) Saliency maps/Attention maps refer to visualizations used to depict areas with the highest possible influence on the predictive outcomes of AI models. However, one major hindrance in such an approach is ensuring the explanations generated relate to their clinical application. (Houssein et al., 2025) Finding a balance between model accuracy and interpretability will probably be essential to the long-term success of AI integration in medicine.

Accessibility and data privacy are two more important issues. AI development requires large and diverse datasets. For ethical and legal reasons, patient data in healthcare must be strictly protected (Guan et al., 2024). There are significant privacy and governance risks when moving sensitive data to centralized repositories. The Federated Learning (FL) approach is a good substitute. It is predicated on a network that several institutions share. Each region has its own confidential data of patients that is utilized in creating a model. Among the basic assumptions of this proposed model is that data of patients is not leaked out of an organization, but instead, it is only the adjusted parameters of a model that are used in improving the overall system's efficiency. Privacy of data is ensured in such a decentralized approach. Technical problems still exist, nevertheless, such as variations in imaging procedures and data quality among locations (Rehman et al., 2023). But the major advantage remains strong: it enables organizations to work together to train reliable models without ever having to share or reveal private patient information. Therefore, Federated Learning is a crucial component of privacy-protection and scalability in Artificial Intelligence (Rehman et al., 2023).

Development and Deployment: Regulatory Context

In addition to the technical difficulties related to model-building and data protection, regulatory approval is an important challenge in this field. Before entering clinical practice, every AI technology must first get regulatory certification. In the United States, oversight of medical AI systems falls primarily to the Food and Drug Administration (FDA).

The current status of clinically deployed systems can be better understood by examining AI tools that have successfully negotiated this path. Examples of FDA-approved AI diagnostic imaging tools are shown in Table 2, arranged by clinical area and primary purpose.

Table 2. FDA-Authorized AI Tools in Diagnostic Imaging (as of 2025)

Application Area	Representative AI Tool / Function	Clinical Task	Validation / Deployment Setting	Key Benefit	References
Breast Imaging	AI-STREAM	Automated detection in mammography screening	Prospective multicenter study	Improved cancer detection rates, reduced reading time	(Chang et al., 2025; East et al., 2025)
Cardiac Imaging - Echocardiography, POCUS	AI-assisted echo	Image acquisition guidance, LV function quantification	Point-of-care and bedside	Enhances image quality, supports novice users	(East et al., 2025; Trost et al., 2025)
Neuroimaging - CT, MRI	FDA-cleared algorithms for triage	Intracranial hemorrhage diagnosis, stroke triage	Emergency conditions	Rapid prioritization of emergency cases	(Singh et al., 2025; Windecker et al., 2025)
Ophthalmology	Ai-assisted fundus camera	Diabetic retinopathy screening	Primary care and outpatient	Decentralized diagnostic availability	(Chang et al., 2025; Paschali et al., 2025)
General Radiology	Quantitative analysis software	Lesion segmentation, volumetric analysis	Multi-institutional	Standardizes measurement and reduces workload	(Singh et al., 2025; Windecker et al., 2025; Paschali et al., 2025)

According to a current analysis of over one thousand approved devices, the vast majority of algorithms were developed with narrow, task-specific purposes in mind, rather than more flexible, general-purpose applications (Singh et al., 2025). These systems tend to be designed with specific, usually pre-existing, diagnostic processes in mind. Representative categories include:

- Triage algorithms that flag urgent findings - such as intracranial hemorrhage - to expedite radiologist review.
- Quantitative analysis tools that perform automated measurements of organ size, lesion volume, or disease progression.
- Detection aids that identify and highlight suspicious abnormalities on radiographs, mammograms, or CT images.

The growing number of devices in the real world confirms the practical application of this task-specific approach to AI. There are several cases in which regulatory approval led to the development of practical clinical solutions, which were, in turn, used outside of the clinic, such as in the development of mobile AI-powered fundus cameras to diagnose diabetic retinopathy (Chang et al., 2025; East et al., 2025; Paschali et al., 2025). These applications emphasize the importance of assessing AI performance in both controlled and real-world scenarios.

In this landscape, models that are predictable in behavior and limited in function are preferred by current regulatory frameworks, making validation easier. However, more advanced, adaptive foundation models that can learn zero- or few-shot are still largely limited to research settings because it is difficult to ensure secure, dependable performance across a variety of patient populations and imaging environments (FDA, 2025; Singh et al., 2025; Chang et al., 2025).

For next-generation AI systems to be securely incorporated into clinical practice, regulatory bodies will need adaptable but responsible evaluation procedures. Performance audits, multi-center validation, and continuous post-market surveillance play important roles in ensuring the continued accuracy and usefulness of such devices (FDA, 2025; Paschali et al., 2025). However, ultimately, the regulatory environment represents the balance between nurturing innovation, ensuring patient safety, and helping in the application of AI in medical images.

Clinical Applications Across Imaging Modalities

As AI develops, it is impacting many imaging modalities, each with its own opportunities and challenges for diagnosis. Standardized, two-dimensional imaging, like radiographs and mammograms, was the primary focus of early AI applications. Today, AI is being deployed in dynamic and multi-dimensional contexts, including ultrasound, CT, MRI, and point-of-care devices, expanding the scope of clinical utility.

Breast imaging is one of the most thoroughly validated uses of AI. Deep learning algorithms have been found to improve the detection of subtle malignancies as well as reduce inter-reader variability and radiologic workload. Prospective studies conducted on large groups of screening populations have indicated that AI-assisted mammography enables a higher cancer detection rate with equal specificity (Windecker et al., 2025). Many of these systems have obtained FDA clearance, providing early examples of AI integration into real-world clinical screening workflows (Chang et al., 2025; East et al., 2025).

In cardiovascular imaging, particularly in echocardiography and point-of-care ultrasound (POCUS) imaging, one of the greatest barriers remains the dependence on operator expertise. With the development of AI-based techniques, the problem is eliminated since AI techniques can help the clinician during imaging, track the quality of the images in real time, as well as quantify the functioning of the heart automatically. AI-based techniques that can automatically assess the functioning of the heart, guide imaging, as well as assess the quality of the images in real time are a lifesaver in bedside imaging (Al-Karawi et al., 2024). Also, in POCUS, practical applications of handheld ultrasound systems demonstrate improved ease of making a positive diagnosis, particularly in emergencies (Paschali et al., 2025). AI is being used more and more in cross-sectional imaging, like CT and MRI, for complex tasks including volumetric quantification, lesion segmentation, and automated report generation. Vision Transformers and foundation models offer the greatest potential in these data-intensive modalities, and it was observed and proven that they perform well in detecting pathologies, such as brain tumors, ischemic stroke, and neurodegenerative disorders (Azad et al., 2024; Noh & Lee, 2025). By completing detection, localization, and characterization all at once, multi-task models further improve efficiency by expediting workflow and cutting down on interpretation time.

To convert medical images into high-dimensional data for prognostic and predictive modeling, researchers are still exploring quantitative feature-extraction techniques, such as radiomics, in addition to deep learning (Horvat et al., 2024). This strategy frequently enhances deep learning by giving interpretable, manually created features that can be associated with certain biological properties.

Multimodal integration, which combines imaging data with genomics, laboratory results, or clinical metadata, offers promising diagnostic insights (Horvat et al., 2024; Demircioğlu, 2025). Vision-language models (VLMs) are designed to interpret images and accompanying text; by combining these sources, AI can perform tasks such as automated report writing, structured interpretation, and clinical decision support. Even with these advances, implementing VLMs remains challenging. Reliable use depends on validating them across different patient groups, standardizing devices and centers, and ensuring they work with hospital PACS and EHR systems. Ongoing monitoring of FDA-approved devices is also important to ensure they continue to perform well.

AI is improving clinical practice in a variety of modalities. By increasing access to high-quality imaging interpretation in a number of healthcare settings, decreasing cognitive load, and enhancing diagnostic accuracy, the most successful systems complement physicians rather than replace them.

Unreported Pitfalls of Clinical AI

The practical limitations of AI must be critically examined. These flaws are ignored in the scientific literature to counteract the dominant narrative of its success in medical imaging. While performance metrics in controlled, retrospective studies are frequently impressive, these findings do not always translate to the complex and unpredictable environment of real-world clinical practice. This gap between research and reality is a primary source of challenges for AI adoption.

A fundamental issue is the problem of generalization. When used at a different hospital with different equipment or patient demographics, an AI model trained on data from one institution may produce almost flawless results, but its performance may drastically deteriorate. A systematic review of 48 AI studies on breast cancer detection was conducted, and found that it is also a practical concern. The results showed that the reported sensitivity and specificity of AI systems varied significantly. It ranges from 50% to 99% and from 20% to 98%, respectively. This enormous discrepancy emphasizes the gap between performance in a controlled laboratory setting and reliability in the real world, as well as the fact that many models are not sufficiently robust for a variety of clinical settings (Musa et al., 2025; Evans, 2024). This poor performance on new data is frequently a sign of overfitting. This happens when the model learns the training data too perfectly, including its noise and specific details, instead of identifying the actual, generalizable features of the pathology. Consequently, the model becomes unreliable when applied to images it hasn't seen before.

Furthermore, the nature of AI errors differs fundamentally from human errors. While human radiologists may miss a subtle finding (an error of omission), AI is prone to making "silent errors" of commission with high confidence. It can confidently identify a life-threatening condition based on an image artifact that a human would instantly dismiss, or hallucinate pathologies in ways that are logically incomprehensible. These errors are particularly dangerous because they lack the element of doubt, creating a significant clinical risk if not carefully monitored (Evans, 2024).

This points to the recognized problem of automation bias, in which clinicians tend to become overly reliant on a system simply because it's accurate most of the time. Consequently, based on growing trust in an AI system, one is likely to become less vigilant, leading one to overlook a failure of an AI system that is likely to fail at least occasionally. This was supported by a study. In it, it was demonstrated that when radiologists are given a misleading cue of an AI system's failure to identify a present cancer, their identification of cancer was lower by 12 percentage points than it should have been. This led to 31% more cancers being missed by radiologists using an AI system than those radiologists not receiving an AI system's assistance. In essence, it has been ascertained that an overdependence on an unfaithful AI system's assistance is likely to have a directly negative and profound impact on treatment outcome (Dratsch et al., 2023).

Research suggests that AI can perform numerous activities in the same way that humans do. Nevertheless, it rarely outperforms them in exceptional or complex situations that require clinical expertise. For instance, a meta-analysis of a systematic review published in The BMJ found that a deep learning algorithm's pooled sensitivity was 87.0%, while healthcare workers' was 86.4%, a difference that was not statistically significant. In comparison, AI has a slightly higher pooled specificity (92.5% versus 90.5%). The authors concluded that these assertions of superiority are likely to be optimistic in the face of the poor quality of comparative studies that lack any form of validation in a clinical setting (Shen et al., 2019).

These issues, however, do not diminish the great power of AI, as they emphasize the importance of a paradigm shift. More importance needs to be given to the validation of AI in a pragmatic way rather than concentrating only on algorithm development. Accepting AI's shortcomings and limitations is a critical step toward properly implementing AI in medical practices.

Ethical Considerations, Standardization, and Future Perspectives

Ethical, legal, and practical considerations are becoming increasingly relevant as AI is implemented in medical imaging. Therefore, to ensure accountability in patient care, joint decisions and transparency in results of AI must be explainable to ensure that proper logic is applied or followed (Borys et al., 2023; Houssein et al., 2025). Examples of Explainable AI (XAI) techniques include saliency maps and visualizing attention. It is still challenging to make sure that these justifications are reliable, consistent, and clinically significant in practical contexts (Borys et al., 2023; Houssein et al., 2025).

Using AI in ethical ways means that it is thoroughly tested on various individuals, monitored constantly, and approaches are adjusted to avoid bias. Using techniques that help preserve user privacy, such as federated learning (FL), ensures that this balance between utility and ethics is reached (Guan et al., 2024; Rehman et al., 2023).

Companies, medical groups, and regulators are increasingly speaking with one voice: we need standards for how to build, check, and report on these algorithms. This ensures the tools are safe for clinical use, reliable - giving reproducible results, and consistent in their performance (Chang et al., 2025; East et al., 2025; Paschali et al., 2025). Moreover, post-market surveillance studies are also important in identifying performance drift issues as well as ensuring that high quality is sustained.

Multimodal and foundation models have been projected to bring a revolution in terms of how we undertake a diagnosis in the days to come. In addition to that, it is also possible with such models to have a well-rounded perspective of a body of data in terms of images, as well as such data as lab results, genomics, and meta-data, thereby making it easy to pursue a diagnosis in terms of personalized medicine (Horvat et al., 2024; Demircioğlu, 2025; Simon et al., 2025). Nevertheless, if the ideal of these systems is to be realized in a clinical environment, there is a great need to continue a collaboration between technologists, clinicians, and those in regulatory agencies.

Lastly, the integration of AI in point-of-care environments is presently accelerating. AI-infused portable imaging tools will soon allow greater access and productivity in remote, resource-scarce environments (Paschali et al., 2025). A particularly important advancement in this type of environment is giving less experienced individuals greater power. As indicated in a recent study, AI tools will benefit new individuals in preparing them to derive diagnostic images from echocardiograms by offering them directional data on transducer placement as well as picture quality (Trost et al., 2025). That's why we really need solid ethical ground rules. These rules need to ensure the AI's logic is clear to everyone using it. We also have to be smart about how we use it, considering its impact on radiologists and the way hospitals function (Houssein et al., 2025; Washington Post Editorial, 2025). The safe and successful integration of these potent instruments into standard clinical practice will depend on standardized assessment metrics.

4. CONCLUSION

Artificial Intelligence is no longer an emerging field but a backbone of current biomedical imaging, bringing a paradigm shift in diagnostics. This paper focuses on how research that progressed from Convolutional Neural Networks to new Vision Transformers and Foundation Models has already led to practical benefits in neurological, cardiovascular, or cancer diagnosis. Despite this progress, however, full integration of AI is still a challenge. A clinical trust needs a solution to the "black-box problem," protecting a patient's privacy via federated learning, as well as regulatory approval & standardization. It will be important to balance innovation with safety, equity, and transparency.

"The future of medical imaging will be based on personalized medicine, which will be enabled by multimodal imaging systems that will integrate imaging data with clinical, laboratory, as well as genomic data." At the same time, the increasing adoption of AI-based point-of-care imaging devices is expected to democratize access to diagnosis. Ultimately, AI is not intended to substitute human clinicians, but rather to support them in making them better diagnosticians. AI in medical imaging is not only a technological challenge to be met but also a socio-technical issue that needs continued collaboration between innovators, practitioners, and policymakers in this field to ensure that this technology is a benefit to patients.

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Data and materials availability

All data associated with this work are present in the paper.

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