International Journal of Advances in Medicine
Vadlapudi V et al. Int J Adv Med. 2025 Nov;12(6):621-626
http://www.ijmedicine.com
pISSN 2349-3925 | eISSN 2349-3933

DOI: https://dx.doi.org/10.18203/2349-3933.ijam20253360

Review Article

Artificial intelligence in medical imaging: bridging innovation, ethics, and clinical impact

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Received: 27 August 2025
Accepted: 11 October 2025

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ABSTRACT

Medical imaging is essential for diagnosis, treatment planning, and disease monitoring. The integration of artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), is revolutionizing this field by automating image analysis and improving diagnostic performance. This review synthesizes recent advancements in AI applications for medical imaging, with a focus on radiology, oncology, and digital pathology. Core methodologies, including image classification, segmentation, reconstruction, and multimodal integration, are examined alongside emerging approaches such as federated learning and explainable AI. AI models demonstrate strong potential in enhancing diagnostic accuracy, reducing variability, and improving workflow efficiency. However, key barriers remain, including data quality limitations, algorithmic bias, lack of interpretability, and regulatory challenges. Novel strategies, including cross-modality fusion and privacy-preserving frameworks, are being explored to address these issues and improve generalizability. AI-driven medical imaging tools are poised to advance personalized care and clinical decision-making. Achieving widespread adoption will require fairness, transparency, clinician engagement, and rigorous real-world validation to ensure safe and effective integration into healthcare practice.

Keywords: Artificial intelligence, Machine learning, Deep learning

INTRODUCTION

Medical imaging techniques such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, positron emission tomography (PET), and digital pathology remain fundamental to modern healthcare, providing critical information for diagnosis, treatment planning, and patient monitoring. The increasing demand for image interpretation, coupled with the growing complexity and volume of imaging data, places a considerable burden on radiologists and clinicians. AI has emerged as a transformative solution, offering automated approaches that augment human expertise and streamline clinical workflows.[1,2] AI refers to computational systems that mimic human cognition-such as perception, reasoning, and decision-making. Within AI, ML enables algorithms to recognize patterns from data without explicit programming, while DL leverages multilayered neural networks to autonomously extract hierarchical features from raw input. In radiology, convolutional neural networks (CNNs) have become the predominant DL architecture, excelling in image classification, segmentation, and diagnostic tasks.[3,4] Radiomics, which converts images into quantitative descriptors, further enhances these models by uncovering features beyond human visual interpretation[5]. Recent developments illustrate the clinical potential of AI across specialties. For example, DL has improved detection and characterization of ophthalmic disorders, enhanced corneal disease management, and enabled prediction of surgical outcomes using generative adversarial networks (GANs).[6-9] Similarly, AI applications in oncology, neurology, and gastrointestinal imaging are advancing diagnostic precision and prognostic assessment.[10-13] Despite this progress, clinical implementation faces persistent barriers such as algorithmic bias, limited generalizability, interpretability challenges, and evolving regulatory standards. This review provides an integrated overview of current methodologies, applications, and future directions for AI in medical imaging, with a focus on both opportunities and translational hurdles.

METHODOLOGICAL FOUNDATIONS AND TECHNIQUES

ML in imaging early

ML applications in imaging relied on handcrafted features and statistical models such as support vector machines and random forests. Radiomics exemplifies this approach by extracting quantitative features from images to reveal patterns beyond human perception.[14] While useful, these approaches often lacked scalability and were limited by dependence on manual feature engineering.

DL architectures

DL, particularly CNN-based architectures, overcame these challenges by learning representations directly from data. Networks such as ResNet, DenseNet, and U-Net are now standard tools for classification and segmentation tasks.[15] DL approaches have been shown to produce encouraging results on histopathology images in various studies.[16] More advanced variants, including attention-guided CNNs and recurrent neural networks, provide contextual and temporal insights into imaging data. The concept of a convolutional neural network (CNN) to recognize handwritten digits, paving the way for the use of deep neural networks in imaging.[17] CNN algorithms enhance image analysis and reduce variability. The rising incidence of pancreatic diseases, including acute and chronic pancreatitis and various pancreatic neoplasms, poses a significant global health challenge. CNNs, have been effective in detecting and differentiating between benign and malignant lesions. DL algorithms have also been used to predict survival time, recurrence risk, and therapy response in pancreatic cancer patients.

Radiomics and AI synergy radiomics approaches

Extracting quantitative features from imaging modalities such as CT, MRI, and endoscopic ultrasound, have enhanced the accuracy of these DL models.[18] Combining AI and radiomics improved the breast ultrasound.[19] Radiomic models may aid various processes in breast cancer research.[20] Combining radiomics with DL has enabled predictive models that integrate imaging phenotypes with genomic or molecular data-a field termed radiogenomics. These approaches show promise in oncology, where they can predict therapeutic outcomes and patient survival.[21] Recent advancements in radiomics and AI offer novel solutions by integrating ML algorithms and quantitative imaging features to enhance prognostic precision and diagnostics.[22] High-quality AI models trained on radiomics data demonstrate superior performance and helping physicians and patients in the study on thoracic trauma.[23]

Explainable and interpretable

AI interpretability is critical for clinical use. Visualization tools such as saliency maps, Grad-CAM, and attention mechanisms provide insights into model decision-making.[24] Nonetheless, the black-box nature of DL remains a barrier to clinician confidence.

Emerging approach novel

Strategies such as federated learning enable collaborative model training across institutions while preserving patient data privacy.[25] Additionally, uncertainty quantification and model calibration are becoming important for enhancing reliability and clinical safety.

CLINICAL APPLICATIONS OF AI IN MEDICAL IMAGING

Disease detection and diagnosis

DL systems have demonstrated expert-level performance in disease recognition tasks. For instance, algorithms now match ophthalmologists in detecting diabetic retinopathy from fundus photographs and achieve high sensitivity in identifying pulmonary nodules on chest CT.[26,27] Computer-aided diagnosis (CAD) powered by AI is increasingly incorporated into radiology workflows to support clinical decision-making. In neurology, AI-based methods are being developed for the early identification of neurodegenerative disorders such as Parkinson’s and Alzheimer’s disease, offering potential for timely intervention and improved patient outcomes.[28]

Oncology and digital pathology

Oncology is one of the most active areas for AI deployment. DL has shown remarkable accuracy in breast cancer detection and prognosis, utilizing both radiographic and histopathological data. Whole-slide histopathology imaging has been transformed through DL, enabling tumor subtype classification, prediction of genetic mutations, and survival outcome modeling.[29] In clinical oncology, AI tools are increasingly applied to forecast therapeutic responses and stratify patients, reinforcing the promise of precision medicine.

Image reconstruction and enhancement

AI techniques are also advancing image acquisition and post-processing. In PET, DL-based methods improve image reconstruction, compensate for noise, and enhance resolution.[30,31] In MRI and CT, these approaches reduce radiation exposure and scan times while maintaining diagnostic quality.[32] Ultrasound imaging has similarly benefited, with AI-powered denoising methods producing clearer and more interpretable images.

Multimodal integration

The integration of multiple imaging modalities, alongside genomic and clinical data, is driving personalized medicine. For example, combining MRI and PET provides complementary information that enhances diagnostic accuracy. AI has also revealed associations between genetic mutations and morphologic features captured in pathology slides, linking imaging phenotypes to molecular mechanisms.[33,34] Such multimodal frameworks enable more comprehensive patient profiling and improve prognostic modeling.

Specialty-specific applications

Beyond oncology and radiology AI has shown promise across numerous specialties. In ophthalmology, it aids in detecting retinal disorders; in cardiology, it supports echocardiographic analysis; and in pulmonology, it contributes to the diagnosis of COVID-19 from chest CT scans.[35] Furthermore, multimodal DL has enabled integrative analyses of histopathology slides and genomic datasets across diverse cancer types, opening new avenues for biomarker discovery and translational research.[36,37]

CHALLENGES AND LIMITATIONS

Data quality and bias

AI effectiveness is constrained by the quality and diversity of training datasets. AI algorithms are prone to bias at multiple stages of model development.[38] AI in healthcare gains momentum, it brings forth profound ethical challenges that demand careful consideration. The primary concerns use of AI in healthcare includes responsibility privacy trust, bias, cybersecurity, transparency, and data quality.[39-41] Inadequate representation of populations can introduce biases, potentially exacerbating health disparities.[42]

Generalizability and reproducibility models

Developed on single-center datasets often struggle to generalize across different populations or institutions due to variations in scanners, imaging protocols, and annotation standards. Beyond diagnostic imaging, artificial intelligence has also been explored for predicting clinical outcomes. For example, ML approaches designed to identify large vessel occlusions and viable brain tissue are crucial in extending the treatment window, thereby improving both patient prognosis and healthcare cost efficiency. However, for such models to be reliable, they must be reproducible-meaning the algorithms, underlying code, and datasets should be accessible, well-documented, and free of errors. At present, the absence of standardized reporting practices and the limited public availability of source code and clinical datasets pose significant challenges. These limitations not only hinder reproducibility but also conflict with the ethical principles of transparency and accountability in AI research.[43]

Interpretability and trust

Interpretability trust are critical parameters to developing transparent AI models that clinicians can trust for reliable decision support.[44] The opaque decision-making of DL models undermines clinical trust. While explainable AI methods are progressing, achieving fully transparent models remains a challenge.

Regulatory and ethical considerations

Clinicians acknowledge that the rapid development and applications of AI in medical highlighting significant progress and innovation. Ethical challenges, such as data security, fairness, system bias, patient privacy and regulatory gaps are the potential for AI to replace human practitioners.[45] The regulatory landscape for AI in healthcare is evolving. Although several AI-based imaging systems have received FDA approval, questions of liability, patient consent, and data security remain unsettled.[46]

FUTURE DIRECTIONS

Federated and privacy-preserving

AI conventional centralized AI models require pooling sensitive patient data, raising concerns about confidentiality. Federated learning (FL) addresses this by enabling multiple institutions to collaboratively train models without exchanging raw data, maintaining privacy while achieving performance comparable to centralized approaches. Advanced methods integrate FL with differential privacy, secure multiparty computation, and homomorphic encryption to further reduce risks of data leakage.[47,48] These frameworks promote cross-institutional collaboration, enhance model generalizability, and align with regulatory compliance.

Trustworthy and explainable

AI for AI systems to be widely adopted, they must not only perform accurately but also provide transparency and reliability. DL models are prone to overconfidence in uncertain scenarios and vulnerable to adversarial attacks, which undermines clinical trust. Incorporating uncertainty quantification and interpretability tools can provide confidence estimates alongside predictions, making outputs more reliable for clinical use.[49,50] This shift toward explainable AI is crucial for clinician acceptance.

Multimodal and multiscale models

The future of AI in imaging is expected to converge diverse data sources-radiology, pathology, and genomics-into unified predictive frameworks. Multimodal DL approaches have already demonstrated superior performance compared with unimodal systems, particularly for tasks such as automated reporting, outcome prediction, and CAD.[51,52] In addition, multiscale models that link imaging at cellular, organ, and physiological levels hold promise for patient-specific simulations, such as tailored cardiac models for therapy planning. Despite their potential, barriers such as data heterogeneity, interpretability, and generalizability remain pressing challenges.

Clinical translation and regulation

Although numerous high-performing AI algorithms have been published, relatively few have been integrated into routine clinical practice. Bridging this gap requires adherence to robust validation protocols, prospective trials, and standardized reporting frameworks such as CONSORT-AI and SPIRIT-AI. Once beyond initial development, models must demonstrate clinical validity (accuracy in real-world settings), clinical utility (impact on patient care), and usability (integration into daily workflows) before they can be reliably deployed.[53]

Human-AI collaboration

The trajectory of medical AI suggests a collaborative future rather than replacement of clinicians. Recent studies show that radiologists supported by large language models (LLMs), such as GPT-4, achieve modest improvements in diagnostic performance, underscoring the role of AI as a clinical assistant rather than a substitute.[54] Applications in breast cancer screening already demonstrate how human–AI interaction can improve accuracy, efficiency, and patient experience.[55] By reducing workload and enhancing diagnostic consistency, AI will increasingly function as a complementary partner to clinicians.

CONCLUSION

Artificial intelligence, particularly ML and DL, is reshaping medical imaging by enhancing automation, diagnostic accuracy, and understanding of disease processes. Its applications in radiology, oncology, and pathology highlight its ability to improve clinical efficiency and support precision medicine. Nonetheless, widespread clinical deployment is constrained by challenges, including limited data diversity, model interpretability, potential biases, and regulatory uncertainties. Emerging strategies such as federated learning, explainable AI, and multimodal integration are critical to addressing these barriers and ensuring reliable real-world adoption. Multiscale frameworks that combine imaging, molecular, and clinical data are particularly promising for building comprehensive patient profiles and advancing personalized care. However, successful translation requires more than technological innovation-it must also prioritize fairness, transparency, interoperability, and rigorous prospective validation. Ultimately, the future of AI in medical imaging lies in collaborative human-AI models that complement rather than replace clinical expertise. By integrating ethical responsibility, clinician engagement, and robust validation, AI-driven imaging solutions can achieve safe, effective, and equitable integration into healthcare practice.

Funding: No funding sources
Conflict of interest: None declared
Ethical approval: The study was approved by the Institutional Ethics Committee

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Cite this article as: Vadlapudi V, Kaladhar DSVGK. Artificial intelligence in medical imaging: bridging innovation, ethics, and clinical impact. Int J Adv Med 2025;12:621-6.