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AI APPLICATIONS IN CT AND MRI IMAGING: CURRENT ADVANCES AND LIMITATIONS. A NARRATIVE REVIEW

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ABSTRACT

Artificial intelligence (AI), primarily deep learning, is transforming medical imaging. Deep learning processes intricate data using layered neural networks. These techniques are also particularly applicable in computed tomography (CT), which utilizes X-rays to generate images, and magnetic resonance imaging (MRI), which utilizes magnetic fields and radio waves to generate detailed images. This review reviews advances made recently in AI detection, segmentation, classification, reconstruction, and the fusion of different data modalities in the CT and MRI fields. It also examines their impact in actual clinical practice. Studies show that deep learning models perform well in detecting lung nodules, brain tumors, and imaging of cardiovascular and abdominal organs. Besides this, AI methods based on reconstruction can shorten CT radiation doses and speed up MRI. And the best image quality is preserved.

Despite these results, obstacles remain that stop AI from being used for medical imaging. Most difficult problems encountered include limited testing on external data of different types at different institutions, the performance differences across different kinds of datasets, also deep learning models make decisions quite obscurely. Other persisting problems are how to make models more readable, how they can be integrated within clinical workflows, and regulations. The need to build more artificial intelligence that integrates imaging with clinical, genetic, and pathological data is an essential issue for future studies. Such methods could help predict better, personalize medicine. AI alone has potentially transformed radiology: from finding new ways to make diagnoses more efficient, standardizing interpretation of images and supporting clinical decision-making.

Nevertheless, AI ought to be viewed as a tool to aid radiologists — not a replacement. Such studies should be focused on testing AI in actual clinical environments, increasing the transparency of algorithms, and establishing standardized measurement methods for performance. These stages are required to securely and effectively embed AI in routine CT and MRI operations.

KEYWORDS

Artificial Intelligence; Deep Learning; Medical Imaging; Computed Tomography; Magnetic Resonance Imaging; Image Reconstruction; Diagnostic Correctness; Multimodal Data Integration; Radiology Workflow; Clinical Decision Support

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Introduction.

Modern diagnosis heavily depends on medical imaging. It enables doctors to evaluate anatomy and disease without invasive procedures in numerous fields. CT and MRI are key tools. They are common in neurology, oncology, cardiology, and orthopedics because the sharp images, various planes' scanning capabilities, strong diagnostic accuracy and ultra-high image quality make them excellent modalities for imaging.

Nonetheless, radiologists encounter increasing data to review with increasing numbers of scans increasing the workload and cognitive burden (Hosny et al., 2018; Chen et al., 2022). The area of medical imaging that is utilizing AI has rapidly multiplied. Machine learning, particularly deep learning, incorporating convolutional neural networks (CNNs), can automatically detect complex features in images people might miss if they look at images for their own benefit. These tools excel at detecting disease, detailing structures, classifying conditions and analyzing biomarkers. They are increasingly significant in radiology (Lundervold & Lundervold, 2019; Chen et al., 2022). There are studies that indicate that AI needs to avoid replacing doctors but rather provide them the ability to better guide them (Hosny et al., 2018).

Scientists are vigorously investigating AI and its application in CT and MRI research continues to press AI techniques are used. AI systems from CT can detect small nodules in CT and are still working to have an alarm about lung disease and medical diagnosis, and MRI scan. They detect, for instance, AI systems that can identify lung nodules with artificial intelligence imaging in CT of tumor sites and assess lung diseases. This reduces radiation for patients with low-dose image reconstruction and can diagnose abdominal tumors in a clinical situation. Deep learning has been popular for brain imaging and for identifying or characterizing brain tumors in MRI. It also has applicability to investigate demyelinating and neurodegenerative diseases and cardiac and musculoskeletal imaging (Lundervold & Lundervold, 2019; Chen et al., 2022). These cases also demonstrate the greater integration of AI across imaging genres and clinical applications.

Even with promising studies, there are barriers restricting the clinical application of AI algorithms used in clinical practice. Many models rely on common, uniform, retrospective data. These do not necessarily correspond to the differing realities of patient populations, imaging protocols, or specific imaging hardware. This provokes fears about applicability, external validation requirements, and reproducibility in clinical conditions (Hosny et al., 2018). Deep learning operates on a "black box" approach, making it challenging to grasp decisions. This may undermine clinicians' trust in and implementation of these technologies (Chen et al., 2022).

The ethical and organizational issues are critical in the penetration of AI into radiology. Core concerns are patient data safety, algorithmic bias, regulatory certification, and the legal risks. This review provides a clinical perspective on the emerging role of AI in radiology, summarizing prominent studies. This demonstrates the crucial need for rigorous evaluation and explicit reporting of model performance while establishing close collaboration with clinicians, data scientists, and regulators over safe launches of these technologies (Hosny et al., 2018; Seah et al., 2021).

This review takes a closer look at recent research in implementing AI applications in CT and MRI with a view to identifying some of its limitations. The paper uses a structured review of peer-reviewed articles on AI in this domain to find studies with data from articles written by authors with a topic such as AI in AI. Also, future research should also seek to identify important topics and apply these developments in practice.

Methodology and design

We review the existing applications, challenges, and potential future applications of AI in CT and MRI techniques. It provides an update on emerging findings of AI-based approaches, particularly deep learning, the clinical utility of these approaches, diagnostic efficacy, workflow improvements, and multimodality approach in integrating data.

A systematic literature search was performed to identify peer-reviewed articles on AI in CT and MRI. Key search terms were "artificial intelligence," "deep learning," "medical imaging," "computed tomography," "magnetic resonance imaging," "radiology," "image reconstruction," "segmentation," and "diagnostic validity."

The literature search was conducted in English, especially to document studies conducted over the past ten years focused on more recent technologies and applications.

This systematic search provided information on the most widely available papers, such as those from PubMed, Scopus, and Web of Science. Studies were eligible if they explored AI or deep learning in CT or MRI, published clinical or technical outcomes for detection, segmentation, classification, reconstruction, or workflow improvement and were original research, systematic reviews, or meta-analyses published in peer-reviewed publications. Studies were excluded if they described methods that were limited to the abstract of conference meetings or not peer-reviewed publications.

Qualitative synthesis was based on extracted and relevant data from the included studies. The analysis focused on diagnostic performance, clinical relevance, AI algorithms pros and cons, diagnostic utility, advantages and limitations, radiological workflow, and patient safety. Included were studies describing already verified clinical results, references to external validation, and benchmarking with an expert radiologist.

The obtained evidence was presented then thematically arranged and divided into major categories: AI on imaging, uses in CT, uses in MRI, methodologies, and future clinical application. This thematic synthesis afforded a thorough clinical perspective on the emerging role that artificial intelligence is playing in radiological practice.

Results

The History of Artificial Intelligence in Medical Imaging (CT and MRI).

Machine learning and AI, and in particular deep learning, have quickly emerged as a key technology in the practice of medical imaging, now widely capable of addressing multiple different tasks, such as detection, segmentation, reconstruction and computer aided diagnosis. Convolutional Neural Networks (CNNs), borrowing features from bio visual systems of layered extraction, have proved to be particularly useful to model multidimensional imaging data like CT and MRI datasets. Large data sets, high-performance graphics processing units and simple machine learning solutions have resulted in their popularity, that is easy for modeling development and deployment (Lakhani et al., 2018; Maier et al., 2019).

Deep learning models learn hierarchical representations, directly from imaging data, and that allows them to automatically recognize complex features that may need to be processed and reconstructed to identify more complex patterns, as compared to manually-engineered features. In this data-base approach, the results of traditional rule-based or statistical approaches are not as impactful, which leads to better performance with perceptual tasks when dealing with lesion recognition, organ segmentation, and image classification. CNN-based architectures are primarily utilized in many medical imaging platforms as they capture spatial correlations within images and decrease complexity of the model by localised connectivity and parameter reuse (Maier et al., 2019). These characteristics have a significant contribution for volumetric imaging applications for which capable analysis of 3D data is essential to obtain clinically significant results.

One of the important aspects of deep learning algorithms in radiology is their breadth of coverage through the imaging pipeline. Beyond diagnostic interpretation, neural networks may be combined with the earlier operations (e.g., image reconstruction and denoising). For instance, deep learning technology–based reconstruction methods in CT imaging have the ability to reduce image noise substantially, and the radiation dose is relatively low and diagnostic images remain intact. Such methods leverage trained priors developed from high-quality training data, acting as robust regularization techniques, which can further improve signal recovery from low-dose acquisition (Seah et al., 2021).Recently, however, there exists a significant risk that trained priors could mistakenly remove subtle pathological features which are underrepresented in the training data and it highlights the importance of rigorous assessment and validation across clinical populations.

Another vital component of AI in medical imaging which is transfer learning allows pre-trained models from highly-learned large scale natural images to be generalized to specific radiological situations. This model method is of great use in medical applications when it comes to identifying restricted tagged data sets (ie, low-level features, such as lines and textures, that arise across different image domains), as pre-trained networks can be trained on labeled networks. Transfer learning has been demonstrated to enhance performance and minimise the labeled medical data supply necessary for model learning, thus leading to faster development of clinically relevant applications (Lakhani et al., 2018). Although deep-learning techniques have achieved great success, limitations are required to be admitted. To begin with, these models rely mainly on the quality and volume of annotated training data. The generalization and the clinical reliability can be adversely affected by, for example, inaccurate labeling, dataset bias or different imaging protocols amongst institutions. This, again, is one of the limitations of deep neural networks, as their internal decisions are highly uninterpretable and internal to them, this is a potential disadvantage for trust and regulatory approval (e.g., through data-driven clinical decision-making). Such difficulties underscore the demand for interpretable AI methods, universal reporting and strong external evaluation to ensure safe and successful clinical application (Maier et al., 2019).

It represents a sea-change from conventional algorithm-based analysis to an adaptive data-driven approach that is capable of handling various tasks of the radiological workflow, as we continue integrating artificial intelligence in CT and MRI imagery together. While existing deep learning models have shown promising performance on perceptual and reconstruction tasks, the potential of these models in clinical environments is highly conditional on addressing data availability, interpretability and generalisability issues. Ongoing methodological advancements and close coordination with engineers, radiologists, and regulatory bodies will be important to ensure that AI technologies are deployed in a safe, transparent, and clinically proficient manner (Seah et al., 2021; Maier et al., 2019; Lakhani et al., 2018).

The clinical evidence and existing applications of artificial intelligence in computed tomography (CT).

Incumbent with machine learning, AI technologies are making their way into CT, especially in advanced and clinically supported applications of AI in lung imaging, emergency radiology, and dose-reduction algorithms that utilize deep learning–based reconstruction. In such sites, AI-based solutions demonstrate a potential to improve lesion identification, image quality, assist in time-sensitive diagnostic processes, as well as pose new challenges on false-positive observation and clinical usability.

One of the most investigated applications for AI in CT is the diagnosis and segmentation of lung nodules, particularly in lung cancer screening. For deep learning methods, meta-analytic evidence demonstrates moderate clinically meaningful segmentation efficiencies from Dice similarity coefficients around 79%, and enhanced performance exceeding 80% in recent works (Wang et al., 2024). While model performance was affected by aspects such as algorithm architecture, image resolution, and preprocessing strategies, there are methodological challenges, including incomplete reporting and limited generalizability, that indicate an important need for standardized validation on heterogeneous clinical datasets. Our findings suggest that deep learning approaches, at this stage, are advancing in accuracy, yet methodological consistency is necessary prior to reliable routine clinical practice.

In addition to segmentation performance, the external validation studies contribute greatly to an understanding of the functionality potential of AI-based lung nodule detection systems. In a separate screening analysis, a deep learning model obtained very high levels of sensitivity to detect lung nodules as well as lung cancer, and most malignant lesions were identified (Fukumoto et al., 2025). But the increased sensitivity has been mixed with a high rate of false positive results and poor positive predictive accuracy, reflecting a possibility that while AI may help avoid missed cancers, an over abundance of false-positive alarms may add more work to radiologists' workload. These findings highlight the importance of striking a balance between high diagnostic sensitivity and reasonable specificity of the detection process in order to guarantee the clinically applicable and practical utility of AI-based screening tools.

A more rapid frontier of AI in CT imaging involves the optimization of radiation dose through the application of deep learning and image reconstruction. Compared with routine scanning scans, a small trial was conducted to test low-dose CT protocols using AI reconstruction that preserved diagnostic performance as good as standard-dose CT while minimizing image noise (Lee et al., 2024). For close to 300 cases, low dose CT with dramatically reduced radiation dose was also able to identify hepatic malignancy in adequate range. This data suggests that AI-supported re-creation could be potentially important to improve patient safety by allowing dose reduction instead of decreasing diagnostic accuracy, further justifying safer and more efficient CT scan procedures.

The impact of AI can increasingly be seen in emergency radiology, where both quickly and accurately interpreting CT scans is critical. Whole-body CT is now going through this analysis in acute emergency settings using AI tools to catch conditions that were not initially detected in routine reports. These might include cardiovascular problems, aortic ectasia, and fractures of vertebrae (Rueckel et al., 2021). Such findings represent a powerful tool for AI becoming an equal or even further auxiliary reader in complex clinical situations. By raising detection sensitivity in time-sensitive situations, they will provide new value. However, the prevalence of many false-positive and clinically irrelevant results suggests that optimization of specificity of our algorithms is warranted to manage reporting burden.

AI applications in emergency neuroimaging performed to identify intracranial hemorrhages on head CT scans show great potential. Overall diagnostic performance appears good, particularly negative predictive value, suggesting that those systems might help to triage and prioritize patients in the emergency (Abrigo et al., 2023). Yet persistent examples of misdiagnosis and limitations in finding a correct nodule mean that existing AI tools should be regarded as decision support devices, rather than a stand-alone diagnostic tool.

The iterative use of AI-based reconstruction methods for the optimization of abdominal CT protocols has gained great momentum thus far, especially in technically challenging populations, such as obese patients. Scanning protocols with “double-low” and deep-learning reconstruction achieved better image quality and significant reductions of radiation dose and contrast agent volume in studies (Ji et al., 2025). These results highlight AI's potential for facilitating more personalized and safe imaging approaches while at the same time maintaining its diagnostic utility.

Scientific applications for artificial intelligence: magnetic resonance imaging clinical evidence and current applications.

Artificial intelligence is growing to play an important role in magnetic resonance imaging (MRI) for clinical use including neuro-oncological imaging, accelerated image acquisition and reconstruction, quantitative tissue analysis, and disease-specific diagnostic tasks. The AI focused in MRI is particularly on soft tissue characterization, quantitative analysis and improving the efficiency of the process through both faster acquisition and automated post-processing compared to computed tomography (CT).

The most broadly studied AI application in MRI lies regarding neuro-oncological imaging, focusing on the detection, segmentation, and classification of brain tumors. Meta-analytical evidence shows that machine learning approaches for glioma segmentation have a high overall performance with pooled Dice similarity coefficients of about 0.84, indicating high segmentation effectiveness for both high- and low-grade gliomas (van Kempen et al., 2021). Nevertheless, significant heterogeneity and the existence of publication bias were highlighted as significant limitations, including the absence of external validation and therefore the necessity of standardized reporting and validation on independent datasets before implementation on a commercial level.

Additional evidence of the clinical promise of AI in brain tumor examination is that of the radiomics-based meta-analyses of certain tumour types. AI architectures trained on craniopharyngiomas performed moderate to high on diagnostic performance when combined to achieve a pooled sensitivity nearly 0.74, specificity around 0.81, diagnostic AUC close to 0.79 as well as classification tasks where achieved even higher accuracy (Mohammadzadeh et al., 2025). These results indicate that AI-driven radiomic analyses may be useful in guiding preoperative tumor characterization and treatment in neuro-oncological MRI, however, this is still being validated with larger multicenter datasets and extra external validation for reliable clinical application.

In the meantime, other than meta-analysis-based evidence, custom deep learning models have been reported to achieve effective automatic tumor segmentation. A CNN-based U-Net model also showed excellent performance for the segmentation of glioma on MRI data in classification of glioma on MRI with Dice coefficients of approximately 0.86 for total tumor volume and approximately 0.73 for tumor subregions, comparable with that of well-experienced radiologists and commercially-available methods (Wang & Yin, 2024). These findings underscore the potential of deep learning systems for accurate identification and quantitatively assessing the tumor composition may contribute to improvement in diagnostic accuracy and enable objective assessment in neuro-oncological imaging.

Advanced tumor classification in deep learning AI applications in MRI also involves sophisticated deep learning architectures. Novel attention-based residual networks have advanced the accuracy of brain tumor classification to exceeding 99%, with 3-class models achieving 99% or better for 3-class and 4-class networks maintaining a close to 98% accuracy (Zhang et al., 2025). Although such architectures are known for strong generalizability and superior performance versus baseline networks, the greater computational complexity indicates that they may require further refinements and model compression to allow their effective routine deployment in clinical settings.

Another area where AI is developing rapidly in MRI is the facilitation of image acquisition by deep learning-based reconstruction strategies. AI-based super-resolution reconstruction methods have been noted to decrease MRI exam time over time and maintain diagnostic image quality considerably. In validation experiments, the implementation of an AI reconstruction algorithm decreased total scan time with respect to the traditional compressed sensing protocols by about 57%, with the same image quality and visual assessment scores (Terzis et al., 2024). These findings suggest that deep learning–based reconstruction can significantly enhance patient comfort and scanner throughput without compromising diagnostic accuracy.

Apart from speed of image acquisition AI demonstrates significant promise to enable quantitative MRI characterization, particularly in the evaluation of body composition and muscle tissues. Machine learning-based segmentation frameworks showed high accuracy, and were very efficient in quantifying muscle and adipose tissue volumes on MRI, in comparison to manual and semi-automated methods (Ramedani et al., 2025). Multicontrast imaging techniques were also introduced to enhance the robustness of tissue classification in large and small, non-homogeneous entities. This research suggests that AI-based quantitative MRI methods could deliver scalable estimates of the volume-related dynamic alterations of tissue to inform more general, clinical or research-oriented studies concerning body composition and musculoskeletal assessment.

Lastly, AI used in MRI has been utilized to be performed in disease-related diagnosis tasks like cardiac imaging. Deep learning analysis of late gadolinium enhancement sequences showed a significant capability for the diagnosis of cardiac amyloidosis at 87.8% accuracy and AUC 0.982, similar to the machine learning approaches that are mimicking the expert interpretation (Martini et al., 2020). These results reveal the potential of AI to assist with non-invasive diagnosis of various heart diseases and the use of AI in disease-specific MRI.

Altogether, AI in MRI is found to be most advanced in neuro-oncological imaging, accelerated image reconstruction, quantitative tissue measurement, and disease specific diagnostic capabilities. While these technologies are known for showing high diagnostic reliability and substantial workflow advantages, their general clinical adoption should be accompanied by external validation, standardized reporting, and model effectiveness tuning. Thus, AI in MRI should be considered a technical aide to support with more efficiency with a better quantitative and customized imaging which is beneficial to radiologists' work, as opposed to replacing expert clinical interpretation, now seen as an assistive technology.

Constraints and Difficulties of Artificial Intelligence in CT and MRI Imaging

Numerous methodological, technical and functional barriers remain to its widespread application in the clinic, whether in CT or MRI. The challenges of using these technologies cannot be overstated given their lack of reliability in recent years. Due to their reliance on hardware, AI relies on sensors and neural signals, and the lack of sensitivity and specificity of these tools to noise, the generalization is limited. These challenges have implications that are multifactorial with respect to data quality, availability, applicability of a model, explainability of algorithmic decision-making, integration of algorithms into workflow, ethics, and compliance.

AI has one of the most serious limitations to date on medical imaging, the reliance on large, high-quality, tagged datasets. Models need adequate resources, therefore it is necessary to carefully select sets of data to achieve reliable performance, however, expert annotation takes time and cost (Hosny et al., 2018; Chen et al., 2022). In addition, inappropriate, noisy or potentially biased labels could cause substantial difficulty in modelling practice and generalizability, especially in the clinical environment where scanning practices and patient groups are very heterogeneous (Choi et al., 2020). These constraints are even stronger in rare diseases, wherein big enough datasets are rarely accessible, limiting the use of strong AI systems for clinical purposes.

Several data augmentation and generative modeling strategies have been proposed in order to alleviate data scarcity. Deep generative models, such as variational encoders, generative adversarial networks and diffusion models, achieve realistic synthetic images and thus minimize data limitations partly (Kebaili et al., 2023). However, these approaches create further challenges such as unstable training and large computational burden and the danger of generating images with less subtle but clinically relevant specifics. Thus, while generative augmentation technologies might improve model stability, they are not able to fully replace the requirement for high-quality, highly annotated real data.

A further challenge is the generalizability and external validity of many AIs. Differences in imaging hardware, acquisition procedures, and patient populations among institutions can result in model degradation when training is performed without the model environment (Hosny et al., 2018). Furthermore, insufficient multicenter validation and the lack of uniform performance benchmarks impede having a robust evaluation of model permanency in routine practice in clinical settings (Chan et al., 2020). Those limitations underscore the requirement of thorough external validation and to standardize imaging standards to make their performance consistent and reproducible across clinical settings.

The explainability of deep learning models continues to be a significant issue, the so-called "black box" issue. For instance, much of the AI that is developed relies on predictions without an understanding of decision making processes, making it challenging for clinicians to comprehend how specific image features impact decisionmaking (Choi et al., 2020). Even if we add some explainable AIs such as visualization heat maps to make it more transparent, such methods will still depend on the subjective interpretation and understanding of a human, which may not fully reflect the decision logic of the model. Reviews of previous studies on explainable AI approaches suggest that currently, most studies prioritize prediction performance over diagnostic importance, possibly leading to decreased clinician trust and the failure to adopt AI-supported techniques in routine radiology procedures (Hafeez et al., 2025).

Practical issues of workflow integration and clinical usability are just as important besides the technical considerations. Implementation of AI devices successfully needs high diagnosis quality, in addition to seamless incorporation in the current radiological routine without increasing interpretation time or cost of healthcare (Chan et al., 2020). Moreover, it is also necessary that clinicians receive necessary training for the potential of the AI systems as well as the limitations of them to avoid abuse or over-hyping of the automated decision support. Without close correspondence between algorithm design and real-life clinical requirements, a highly accurate AI tool would have little chances for realisation in day-to-day practice.

From a more general methodological viewpoint, the conceptual basis of many such deep learning methods has not been adequately investigated, making it difficult to objectively compare models designed and determine the reasons that result in better performance (Lundervold & Lundervold, 2019). Fast technological progress and elevated expectations about the capabilities of this AI capability could further contribute to an exaggerated view on medical preparedness and the need for more careful consideration in the evaluation and review of research data leading to unified appraisal strategies.

Finally, ethical and regulatory concerns add to the obstacles to the widespread adoption of AI in medical imaging. Patient data privacy, secure data sharing, and governance of continuously learning adaptive algorithms may raise concerns that need to be addressed before routine clinical implementation (Hosny et al., 2018). There are new rules for regulators as they evaluate AI systems whose internal decision-making processes are not fully transparent, and can evolve as new data emerges. All of these points highlight the need for strict regulatory guidelines, ongoing post-deployment monitoring, and robust quality assurance strategies that can ensure the safe and responsible implementation of AI in clinical radiology.

Upcoming Directions and Clinical Implementation of Artificial Intelligence in CT and MRI Imagin

This paper analyzes the recent advances in artificial intelligence in CT and MRI. It is anticipated that the future of artificial intelligence in CT and MRI imaging will go from single-modality image analysis to more complete, multimodal, and clinical decision-assistance systems. Whereas current developments in artificial intelligence largely target single imaging applications, new studies will look to merge imaging imagery, clinical, genomic and other patient-related data to improve diagnostic precision and facilitate personalized medicine.

A primary area of future radiological AI research is the design of multimodal models combining imaging with heterogeneous clinical datasets. Recently, transformer architectures and generative AI systems have facilitated the integration of radiologic images with other patient data, including electronic health records, genomic profiles, laboratory results, and sensor-derived information, thus capturing the multidimensional reasoning aspect of radiologists in clinical practice (Kitamura & Topol, 2023). Previous studies suggest that combining imaging with non-imaging patient data may offer moderate benefits against unimodal models, but these approaches are still in the early stages of development and need extensive and prospective validation in practical clinical settings.

In the same way, multimodal data fusion has proved to have exceptional potential in oncologic imaging, in which the characterization of patients relies on assimilation of radiological, histopathological, genomic, and clinical variables. AI-based fusion models may be deployed to generate a more precise and comprehensive prognostic approach through the aggregation of complementary contextual information across modalities, allowing for closer stratification of risk factors and for the exploitation of new imaging biomarkers (Lipkova et al., 2022). Such interlocking approaches are anticipated to be key enablers for precision medicine by allowing for more personalized medication interventions and enhanced prognostic prediction in multicomponent malignancies like cancer.

Multimodal data fusion methods are typically categorized under early, late and intermediate fusion, depending on the stage of multimodal information integration. Early fusion fuses raw data - or feature-level knowledge - from several sources to train the model, while late fusion combines predictions from specific modality-dependent models, giving the model power to deal with heterogeneous or missing data. Intermediate fusion is a hybrid model design in which multimodal interactions are learned at various levels of abstraction, which allows the model to learn complex cross-modal interactions. Both the fusion strategy and its selection are task- and data-dependent. Still, these methods combined present a view that complementing data from imaging analysis, clinical records, and molecular studies can increase the predictability, interpretability, and robustness of future radiological AI systems (Lipkova et al., 2022).

Beyond raising forecast value, future AI systems are also expected to help the general shift toward computational and information-driven medicine. As proficiency in these methods becomes more refined, it will become increasingly practical to figure out which clinical problems are best handled via fully automated deep learning methods, integrated models, or traditional analytical techniques (Lundervold & Lundervold, 2019). Additionally, the growing digital medical ecosystem of medical technologies such as wearable sensors and edge-computing devices could also support more effective monitoring of long-term patients and move towards P4 (predictive, preventive, personalized, and participatory) medicine enabled by AI-based imaging analysis.

While such exciting technological advances are indeed possible, there will be immense implementation hurdles if applications of AI technologies are to be implemented into standard radiological practice. One of the most crucial future requirements is the building of an open, highly-scalable and interoperable platform capable of effectively integrating many AI applications into the existing imaging workflow to provide seamless integration in practice. As the volume of AI tools deployed in clinical operations grows, self-service integrations no longer seem possible, resulting in inefficiencies and technical errors. Standards-oriented interoperability frameworks like Integrating the Healthcare Enterprise (IHE) profiles offer organized means of orchestrating AI task management, data sharing and result sharing across PACS and other information systems, so that sustainable deployment is possible on a large scale (Tejani et al., 2024).

Future implementation approaches should also stress prospective clinical validation, near-constant performance monitoring, and strong collaboration between the clinicians, engineers, and regulators to guarantee the safe and effective adoption of AI technologies. Radiologists will continue to be critical in this work as they will advise the design of clinically applicable AI tools, interpret algorithm-derived results, and facilitate their addition to diagnostic workflows. Thus, AI should not replace radiologists but be seen as a technology that adds a bit of humanity and enhances human capability in aid of more informed clinical decision-making.

Discussion.

Synthesizing the evidence shows that the evolution of artificial intelligence in CT and MRI imaging must be approached not only as a technological progress but also as a revolution in how we interpret radiology epistemologically. In contrast to human experts' visual pattern recognition alone, AI establishes data-driven analytical systems capable of identifying complex relationships in imaging data. This transition is consistent with a trend in medicine of computational-assisted diagnosis—in which quantitative, reproducible image analysis supplements traditional qualitative evaluation.

A major conclusion from the reviewed articles is the growing interface between image acquisition, reconstruction, and interpretation integrated and supported by unified AI pipelines. This synergism implies that the post-approach of future radiological workflows may no longer consider image generation and interpretation as discrete steps, rather as interacting phenomena optimized in parallel by adaptive algorithms. Such a paradigm could enhance aggregate diagnostic consistency, but it may also raise methodological concerns with respect to validation methods, errors transference between processing stages, and the necessity of continuous performance monitoring in dynamic clinical contexts.

The other key question is about the tension between automation and human monitoring. AI has shown it can work with extreme accuracy in a limited amount of input data, but for a diagnostic system to be effective in radiology the logic of a patient's history, clinical presentation and interdisciplinary background is much more needed. As such, these findings reinforce the idea of hybrid intelligence — that optimal performance is achieved through the interaction of algorithmic analysis and expert clinical judgment. Here, the radiologist's role changes from "only" interpreting images, to serving as a supervisor of algorithm-advanced decision-making processes, ensuring outputs are validated and incorporated into macro-level clinical reasoning.

Methodologically, differences in datasets, imaging procedures, and assessment techniques from one study to another suggest that existing evidence is still fragmented. This fragmentation makes it difficult to compare measures of reported performance directly and to build widely accepted benchmarks for medical readiness. As a result, future studies should focus on validation protocols aligned with clinical outcomes rather than siloed technical performance metrics.

Moreover, the progressive inclusion of multimodal data illustrates a conceptual shift from an image-centric analysis to a patient-centric modeling. Integrating imaging biomarkers and clinical and molecular information can ultimately lead to a more systematic portrayal of disease progression based upon AI systems. Yet, such an integration also makes models more complex and adds new issues to the field, including data governance, interoperability, and explainability—all of which need to be handled for the sake of clinical integrity and openness.

Taken together, the reviewed literature indicates that the greatest impact of AI in CT and MRI imaging is not in the enhancement of discrete diagnostic work, but rather in transforming the architecture of radiological decision making. Thus, the appropriate translation of these technologies to routine practice will hinge on methodological rigor, algorithmic transparency and the importance of clinical knowledge within increasingly data-rich diagnostic systems.

Conclusions.

The field of artificial intelligence has emerged as one major direction in the evolution of radiology in current times, focused on the fields of computed tomography (CT) and magnetic resonance imaging (MRI). Recent literature review shows deep learning based methods have been successful in perceptual tasks (i.e., lesion detection, anatomical structure segmentation, pathology classification, and quantitative analyses of imaging biomarkers). In a wide range of applications—from brain imaging neuroimaging to oncology to cardiovascular and pulmonary diagnostics—AI models demonstrate performance similar to expert radiologists, and in a few well-designed tasks, may even elevate lesion detection sensitivity and lower interobserver variability.

Promising results are especially notable in low-dose image reconstruction, accelerated MRI acquisition, and automated analysis of large, multiparametric datasets. Deep learning-based methods allow for radiation dose reduction of CTs and shorter scan times of MRIs while maintaining diagnostic image quality, enhancing the patient safety index and leading to improved process efficiency in imaging departments. Simultaneously, multiple modalities of the collection of imaging data, integrated with clinical, pathologic, and molecular variables, provide novel avenues for prognostication and individualization of therapy.

But studying the data shows the full integration of AI in clinical day-to-day practice is hampered by significant hurdles. The challenges including restricted external validation, overfitting with training data, inter-institutional variability, and lack of transparency of "black box" algorithms are of the highest concern. On the image reconstruction and processing level, however, there could also be an associated risk of subtle obfuscation of pathological findings that were not always visible through traditional image quality evaluation metrics. As such, prospective clinical trials with multicenter validation for quality control, with model effectiveness reported in a standardized way, are important considerations.

The organizational, legal and ethical considerations are also important such as who should make diagnosis decisions, secure data and how AI tools will integrate to the current IT infrastructures (PACS, RIS, interoperability etc.). Effective use of artificial intelligence will need close collaboration among radiologists, engineers, medical informaticians, and regulators and efficient training of end-users.

In conclusion, AI is not to be perceived as a replacement for the radiologist only but as an advanced support system that can improve efficiency, repeatability and, indeed, diagnostic accuracy. It is very useful in repetitive and time-consuming tasks that demand analysing huge quantities of data. Model transparency and generalizability should be the objectives for further development in this area, as well as patient outcomes, on a real-life clinical basis. Only with that understanding will AI have a truly secure and integrated role in the modern art of radiology.

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