https://doi.org/10.5272/jimab.2025311.6103

Journal of IMAB
ISSN: 1312-773X
https://www.journal-imab-bg.org

Journal of IMAB. 2025 Jan-Mar;31(1)

Review article

THE CURRENT STATE OF ARTIFICIAL INTELLIGENCE IN RADIOLOGY – A REVIEW OF THE BASIC CONCEPTS, APPLICATIONS, AND CHALLENGES

Mariana Yordanova
Radiography Department, Medical University Varna, Medical College Varna, Bulgaria.

ABSTRACT:

Introduction: Artificial intelligence (AI) is defined as an artificial entity capable of solving problems, learning from experience, and performing tasks such as pattern recognition and inductive reasoning. In radiology, AI aims to assist with image analysis and interpretation, potentially reducing human error and alleviating the radiological workload. As machine calculation capacity advances, AI's role in radiomics—extracting numerous quantitative features from medical images—could significantly enhance diagnostic accuracy.

Materials and Methods: This review article synthesizes recent advancements in the field by examining studies from the past four years, ensuring the information is current and highlights significant findings and emerging themes.

Results and Discussion: Machine learning in radiology focuses on developing algorithms that analyze medical images without explicitly programmed rules, divided into supervised and unsupervised learning. Deep learning, especially deep convolutional neural networks (CNNs), has become a prominent approach, mimicking brain functions to process images through multiple layers. CNNs excel in tasks like lesion detection and disease classification, aiding radiologists in diagnosing conditions more accurately. There are numerous applications of AI in radiology - image segmentation, objective quantification, detecting and highlighting suspicious areas, image processing and optimization, longitudinal analysis, potentially diagnosis recognition, triage, and reporting aid. The adoption of radiological AI faces several challenges, including substantial hardware requirements, data quality and quantity limitations, high false positive rates, the "black box" problem, and the narrow focus of current AI applications, which restricts their clinical usefulness.

Conclusion: AI is transforming radiology with diverse applications, but it still needs development to match human expertise.

Keywords: artificial intelligence, machine learning, convolutional neural networks, radiology, diagnostic imaging, computed tomography,

INTRODUCTION

Before discussing artificial intelligence (AI), we need to define it for the purposes of this article. The definition will be as follows: "an artificial entity capable of solving problems and learning solutions for new problems, …able to perceive its environment, (i.e. detect input data and its parameters), search and perform pattern recognition…, plan and execute an appropriate course of action and perform inductive reasoning to derive general principles (i.e. learn from experience)" [1, 2]. Ultimately, it is the goal of AI to be able to completely equal or even surpass the capacity of a trained human to do certain tasks [1]. This is theorized to lead to the elimination of human error in image interpretation and also to a much-needed alleviation of the ever-increasing radiological workload [1].

AI has been established as an aid to healthcare professionals with tasks such as ECG interpretation and computerized arterial blood gas analysis [1]. In the context of radiology, AI seeks to intervene primarily in the fields of image analysis and imaging finding interpretation [1]. This would classify it as "weak" or "narrow" AI, dedicated to a single task or a very limited set of tasks – current radiological AI is still far from being comprehensive [2, 3]. Additionally, with the further development of machine calculation capacity, we are entering the age of radiomics – that is the extraction of a great multitude of quantitative features from medical images – features, usually too subtle for a human to interpret and too many to consistently report. The recognition of these features by AI can improve diagnostic accuracy significantly.

MATERIALS AND METHODS

This review synthesizes the latest advances in the field, based on 16 sources from the PubMed collection and other reputable research aggregators.The selected studies, predominantly published within the last four years, provide a robust foundation of current knowledge. By focusing on recent developments, this review ensures that the information presented is both relevant and reflective of the most up-to-date research trends. The integration of these contemporary sources allows for a thorough examination of the topic, highlighting significant findings and emerging themes in the literature.

RESULTS AND DISCUSSION

Key Advancements in AI Technologies

Machine learning in radiology, a specialized subset of AI, concentrates on the creation of computer algorithms that analyze inputs (medical images in the case of radiology) and that operate without explicitly programmed decision-making rules [3, 4, 5]. This field is typically divided into two main categories: supervised and unsupervised learning [3, 4]. In supervised learning, algorithms are trained using pre-annotated datasets (the annotation is done by a radiologist), often referred to as "ground truth" data, which guide the development process [3]. Conversely, unsupervised learning involves algorithms that analyze and classify unlabeled data independently [3, 4].

Within the realm of machine learning, deep learning, particularly deep convolutional neural networks (DCNNs or CNNs), has emerged as a highly prominent and widely celebrated approach in recent years, becoming the most popular AI technique in modern medicine, especially in radiology [1, 3, 5, 6]. These systems are inspired by the function of the human brain, comprising networks of highly interconnected processes that mimic neurons. These artificial neurons perform parallel calculations for data processing, connected by weighted links. The system's knowledge base encodes the weighting of each connection, and each neuron uses this weighting, informed by mathematical reasoning, to decide whether to activate subsequent neurons [1]. CNNs offer numerous advantages that have cemented their dominance in radiology. They can be trained through supervised learning, where the system compares expected outputs with actual results. Additionally, CNNs can learn through unsupervised learning, adjusting the weighting of connections based on observations and correlations with input data. This capability allows CNNs to continuously improve and refine their diagnostic accuracy over time, independent of expert input. It also enables them to extrapolate knowledge from simple cases to more complex ones [1].

CNNs are particularly well-suited for image analysis, making them invaluable in radiology. "They process X-ray images from radiography machines, including mammography and magnetic resonance imaging (MRI) scans through multiple layers, including convolutional layers, pooling layers, and fully connected layers. This hierarchical processing allows CNNs to identify complex patterns and features in images (texture analysis), which is crucial for tasks such as lesion detection, disease classification, such as AI-assisted stenosis assessment from MRI scans, image segmentation, and image reconstruction [1, 2, 4]. The most common application of CNNs in imaging is within AI-based computer-aided detection (CAD) programs [1]. These software implementations analyze images and highlight areas of concern, prompting further inspection by radiologists. By automating the analysis of medical images, CNNs assist radiologists in diagnosing conditions more accurately and efficiently, potentially improving patient outcomes. Despite their promise, CNNs face challenges such as data limitations and the need for seamless integration into clinical workflows. Techniques like data augmentation and transfer learning are employed to address small datasets and overfitting issues. Ensuring that CNNs support radiologists without overwhelming them is crucial for their successful adoption in clinical practice [1]. Currently, each CAD is capable of recognizing a very narrow range of lesions and diseases, limited to a singular region of the body, with a very small number of CAD programs capable of working in two or more zones – most commonly, the regions of interest are the brain, lungs, breasts, vessels, and bones (particularly the spine) [2, 4, 7, 8, 9, 10].

CNNs are particularly well-suited for image analysis, making them invaluable in radiology. They process medical images such as X-rays, computed tomography (CT) scans, and magnetic resonance imaging (MRI) scans through multiple layers, including convolutional layers, pooling layers, and fully connected layers. This hierarchical processing allows CNNs to identify complex patterns and features within images (texture analysis), which is crucial for tasks like lesion detection, disease classification, image segmentation, and image reconstruction [1, 2, 4, 16]. The most common application of CNNs in imaging is within AI-based computer-aided detection (CAD) programs [1]. These software implementations analyze images and highlight areas of concern, prompting further inspection by radiologists. By automating the analysis of medical images, CNNs assist radiologists in diagnosing conditions more accurately and efficiently, potentially improving patient outcomes. Despite their promise, CNNs face challenges such as data limitations and the need for seamless integration into clinical workflows. Techniques like data augmentation and transfer learning are employed to address small datasets and overfitting issues. Ensuring that CNNs support radiologists without overwhelming them is crucial for their successful adoption in clinical practice [1].

One of the most substantial aspects of radiological AI is objective quantification, which is exceedingly time consuming if were to be done by a human operator. Applications quantify image aspects (e.g., bone density), measure organ features (e.g., brain volume), or extract quantitative data (e.g., coronary calcium scores) [2]. This is profoundly useful for treatment optimization, as well as in scientific pursuits.

Another profoundly important aspect of AI in radiology is detecting and highlighting suspicious areas [2]. These applications identify and highlight signs of specific pathologies (e.g., nodules, strokes). They are often trained to recognize highly specific diseases to ensure accurate recognition of the findings by the radiologist [2, 9].

Additionally, several applications are designed to enhance "image processing" during the post-acquisition phase, aiming to improve image quality parameters such as clarity, brightness, and resolution [2, 15]. These advancements allow technologists with varying skill levels to produce high-quality images, minimize the necessity for repeated acquisitions, and reduce radiation exposure without compromising image quality [2]. An example of this is iterative reconstructions – a post-processing technique employed in numerous CT devices today, which runs the raw scan data through the image reconstruction algorithm repeatedly instead of just a single time (effectively de-noising the images), allowing for lower dose scanning, which would otherwise result in suboptimal images [3]. Deep learning algorithms have demonstrated the ability to enhance MRI scan quality and efficiency, potentially reducing scan time—a significant factor in MRI examinations [3, 12].

Another substantial use of AI in radiology is a comparison between consecutive studies of the same patient and longitudinal analysis – some applications compare a patient's images over time to detect changes (e.g., tumor size, newly appeared nodules) in order to improve radiological workloads in oncology [2].

Diagnosis applications combine the previously discussed functionalities to judge the likelihood of a given disease being present by comparing with healthy standards and identifying potentially pathologic areas [2, 15]. They vary in framing outputs as either actual diagnoses or pre-diagnoses for further examination by a radiologist [2]. This functionality is still in its developmental stages, and its reliability needs substantial improvement. Despite this, some basic functionality includes An AI model with diagnostic accuracy comparable to that of radiologists for detecting pneumonia on chest radiography [3]. Similar research has been conducted for the identification of fractures, tuberculosis, and bone age determination [3].

Very few AI programs predict the likelihood of diseases based on current examinations, often focusing on specific entities and using supplementing their estimations with additional clinical information alongside image data [2, 3].

Another application of AI in radiology has to do with patient profiling and case prioritization. Exceedingly few applications extract patient information from reports and medical records, providing a text-based comprehensive view of the patient's history and conditions alongside their medical images in order to aid in accurate image examination [2]. This could also aid in triage for bigger institutions where the demand for imaging often stretches the capacity of the radiology departments by providing worklist management [3, 8, 12, 15]. Imaging classifiers have been designed to identify abnormal chest radiographs, thereby expediting the interpretation of abnormal exams. Similarly, classifiers have been created to detect intracranial hemorrhage and stroke on noncontrast head CT, as well as an acute stroke on diffusion-weighted MRI. These tools can be integrated into the Picture Archiving and Communication System (PACS) to create a "smart worklist," which prioritizes abnormal exams for radiologists, thus reducing the time to diagnosis and treatment [3, 15]. Additionally, AI algorithms can be utilized at the point of care to support medical decision-making in imaging requests. They achieve this by analyzing a patient's medical record to assess the appropriateness of imaging and by offering guidance on the most suitable imaging exam [3]. For instance, guidance may be provided to utilize CT or MRI instead of ultrasound in patients whose body habitus may hinder accurate sonographic diagnosis [3].

Finally, AI systems that facilitate reporting are already available on the market. These systems can be trained to recognize specific key phrases and employ rule-based algorithms to automatically organize unstructured dictations [3, 15].

Radiomic analysis, defined as the quantitative transformation of images into mineable data for mathematical analysis, is expected to become increasingly prevalent with the accessibility of AI tools [3]. Deep learning and texture analysis may facilitate large-scale radiomic analysis, potentially identifying disease characteristics from imaging patterns that are not easily discernible to the human eye. Additionally, "big data" techniques, incorporating both deep learning and other machine learning strategies, may enhance the prediction of therapeutic responses and provide insights into which patients may benefit more from percutaneous intervention rather than surgery [3, 7, 15, 17].

Challenges and Limitations

One of the first limitations that institutions interested in radiological AI must face is the hardware barrier to entry – the CNNs require substantial computing power, which translates into a corresponding financial investment. Many small diagnostic centers would find the implementation of large and science-related CNNs difficult. That being said, CAD software has become increasingly more and compact (requiring less imposing computing hardware) and more widely available by a multitude of imaging hardware providers in the recent decade [1, 2].

A second limitation is the quality and quantity of the data on which the diagnostic AI has been trained. International databases with manually pre-segmented training images have been built in the last half a decade in order to accommodate better AI training. One such example is the Open-Source Imaging Consortium (OSIC) which focuses on pulmonary high-resolution CT (HRCT) studies of interstitial diseases. Unfortunately, similar efforts are difficult to organize and rather fragmented globally between hardware providers [1].

False positive rates remain a significant barrier to the widespread adoption of CAD systems in healthcare. CAD software can incorrectly highlight normal structures as abnormal, leading to time-consuming efforts for radiologists to distinguish true abnormal lesions from false positive prompts. This not only impacts recall rates but also increases costs [1].

Another limitation of AI-based CAD software is the inability of the human operator to glean into the algorithm's thought processes, making it challenging to understand the reasoning behind any decision made by the system. The system is almost entirely incapable of providing explanations for its diagnoses. This is known as the "black box" problem [1, 3]. Although the CNN algorithm's determination is likely to be correct, the radiologist retains full responsibility for the final report [1].

It needs to be stipulated that current AI applications are limited in their scope, focusing on specific modalities, anatomic regions, and tasks. This narrow focus ends up restricting their usefulness in clinical practice substantially [2]. Additionally, since these applications have a narrow focus, the time and effort required for radiologists to launch and use them may exceed their benefits [2].

CONCLUSION

In conclusion, AI is increasingly becoming a prominent force in the field of radiology, offering a wide array of applications such as image segmentation, objective quantification, detection and highlighting of suspicious areas, image processing and optimization, longitudinal analysis, potential diagnosis recognition, triage, and reporting aid. Despite these advancements, AI still has a considerable journey ahead before it can match the multifaceted competencies of a human radiologist. The current capabilities of AI, while impressive, are limited in scope and require further development to achieve a comprehensive model that can fully rival human expertise in radiology. Continued research and innovation are essential to bridge this gap and unlock the full potential of AI in enhancing radiological practice.

Acknowledgement

This study is financed by the European Union-Next Generation EU through the National Recovery and Resilience Plan of the Republic of Bulgaria, project No. BG-RRP-2.004-0009. The work is implemented by the ELPIDA research group, part of the MUVE-TEAM project.

REFERENCES:

1. Fazal MI, Patel ME, Tye J, Gupta Y. The past, present and future role of artificial intelligence in imaging. *Eur J Radiol.* 2018 Jun; 105:246-250. [PubMed]

2. Rezazade Mehrizi MH, van Ooijen P, Homan M. Applications of artificial intelligence (AI) in diagnostic radiology: a technography study. *Eur Radiol.* 2021 Apr;31(4):1805-1811. [PubMed]

3. Syed AB, Zoga AC. Artificial Intelligence in Radiology: Current Technology and Future Directions. *Semin Musculoskelet Radiol.* 2018 Nov;22(5):540-545. [PubMed]

4. Huber FA, Guggenberger R. AI MSK clinical applications: spine imaging. *Skeletal Radiol.* 2022 Feb; 51(2):279-291. [PubMed]

5. Pianykh OS, Langs G, Dewey M, Enzmann DR, Herold CJ, Schoenberg SO, et al. Continuous Learning AI in Radiology: Implementation Principles and Early Applications. *Radiology.* 2020 Oct;297(1):6-14. [PubMed]

6. Duong MT, Rauschecker AM, Rudie JD, Chen PH, Cook TS, Bryan RN, et al. Artificial intelligence for precision education in radiology. *Br J Radiol.* 2019 Nov;92(1103): 20190389. [PubMed]

7. Love SM, Berg WA, Podilchuk C, López Aldrete AL, Gaxiola Mascareño AP, Pathicherikollamparambil K, et al. Palpable Breast Lump Triage by Minimally Trained Operators in Mexico Using Computer-Assisted Diagnosis and Low-Cost Ultrasound. J Glob Oncol. 2018 Aug; 4:1-9. [PubMed]

8. Berg WA, López Aldrete AL, Jairaj A, Ledesma Parea JC, García CY, McClennan RC, et al. Toward AI-supported US Triage of Women with Palpable Breast Lumps in a Low-Resource Setting. *Radiology.* 2023 May; 307(4):e223351. [PubMed]

9. van Leeuwen KG, Schalekamp S, Rutten MJCM, van Ginneken B, de Rooij M. Artificial intelligence in radiology: 100 commercially available products and their scientific evidence. *Eur Radiol.* 2021 Jun;31(6): 3797-3804. [PubMed]

10. Li MD, Chang K, Mei X, Bernheim A, Chung M, Steinberger S, et al. Radiology Implementation Considerations for Artificial Intelligence (AI) Applied to COVID-19, From the AJR Special Series on AI Applications. *AJR Am J Roentgenol.* 2022 Jul;219(1):15-23. [PubMed]

11. Fuchs M, Gonzalez C, Frisch Y, Hahn P, Matthies P, Gruening M, et al. Closing the loop for AI-ready radiology. *Rofo.* 2024 Feb;196(2):154-162. [PubMed]

12. Forghani R. A Practical Guide for AI Algorithm Selection for the Radiology Department. *Semin Roentgenol.* 2023 Apr;58(2):208-213. [PubMed]

13. Muehlematter UJ, Daniore P, Vokinger KN. Approval of artificial

intelligence and machine learning-based medical devices in the USA and Europe (2015–20): a comparative analysis1. *Lancet Digit Health.* 2021 Mar;3(3):e195-203. [PubMed]

14. Kelly BS, Judge C, Bollard SM, Clifford SM, Healy GM, Aziz A, et al. Radiology artificial intelligence: a systematic review and evaluation of methods (RAISE). *Eur Radiol.* 2022 Nov;32(11):7998-8007. [PubMed]

15. Letourneau-Guillon L, Camiranda D, Guilbert F, Forghani R. Artificial Intelligence Applications for Workflow, Process Optimization and Predictive Analytics. *Neuroimaging Clin N Am.* 2020 Nov; 30(4): e1-e15. [PubMed]

16.Georgiev R, Novakova M, Bliznakova K. Clinical Assessment of CoLumbo Deep Learning System for Central Canal Stenosis Diagnostics. *Eurasian J Med Oncol.* 2023; 7(1):42-48. [Crossref]

17. Marinov S, Buliev I, Cockmartin L, Bosmans H, Bliznakov Z, Mettivier G, et al. Radiomics software for breast imaging optimization and simulation studies. *Phys Med.* 2021 Sep;89:114-128. [PubMed]

Please cite this article as: Yordanova M. The Current State of Artificial Intelligence in Radiology – A Review of the Basic Concepts, Applications, and Challenges. *J of IMAB.* 2025 Jan-Mar;31(1):6103-6107.
[Crossref - https://doi.org/10.5272/jimab.2025311.6103]

Received: 16/09/2024; Published online: 31/03/2025

Address for correspondence:
Mariana Zhivkova Yordanova,
Medical University Varna, Medical College Varna;
84, Tsar Osvoboditel Blvd., Varna, Bulgaria
E-mail: kupenova@mu-varna.bg,