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Review Article

Integrating machine learning into medical radiology: Principles, applications, challenges, and future directions

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Abstract

Over recent decades, machine learning has been widely implemented in medical radiology. Radiologists, who are at the forefront of clinical practice, need to be aware of the benefits of machine learning to facilitate its implementation. It is crucial for them to thoroughly understand and effectively integrate machine learning into the practical realm of medical radiology.

In this review, we highlight the principles and applications of machine learning in medical radiology and provide a summary of its development in this field. Machine learning has significantly advanced diagnostic imaging, enhancing detection, segmentation, and image reconstruction, while improving workflow efficiency and radiology reporting. Current literature indicates three primary challenges in implementing machine learning: data standardization, validation of model performance, and regulatory compliance. The successful integration of machine learning in clinical practice requires robust data security protocols and clear frameworks for professional accountability. To prepare for this technological transition, radiologists must develop new competencies through enhanced educational programs and adapt their roles to focus more on clinical decision-making and multidisciplinary collaboration while leveraging machine learning as a supportive tool.

Keywords: AI, Artificial intelligence, Artificial neural network, Deep learning, Machine learning.

Introduction

Medical imaging plays an essential role in parts of patient care, from screening and diagnosing, to planning further management. The demands of medical imaging have been increasing over recent decades due to the ready availability of imaging technology and demand for higher standards of patient care [1, 2]. However, this increased demand has not been met by a proportional increase in the number of radiologists [3]. Due to time pressure, radiologists are challenged to make a decision based on integrating radiological and clinical information, and patient preferences. Furthermore, it is also difficult for radiologists to work effectively within the multidisciplinary team.

To assist radiologists in providing standard medical care despite overwhelming workloads and limited time, rigorous machine learning techniques have been developed and widely implemented in medical radiology over the last three decades (Box 1). Since the 2000s, machine learning has been increasingly applied in medical services, particularly in the field of radiology, to reduce radiologists' workload and enhance diagnostic performance. The trend of machine learning has grown exponentially since 2010, with the generation of algorithms transitioning to model-free and purely data-driven approaches, which require large datasets for training and supervision [4]. An example of a model-free and data-driven algorithm in the field of radiology is 'texture analysis' or 'radiomics,' which provides tumor segmentation and classification of tumor subtypes [4]. After 2018, AI has shifted from deep learning models to foundation models, which aim to generate new content, including text, sound, and images. While AI can now respond to complex tasks, there is a risk of AI hallucinations and biases stemming from the training data [5].

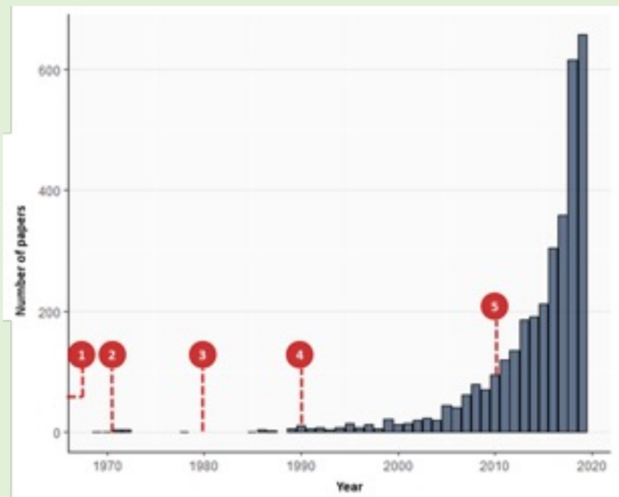
Although machine learning is a promising tool contributing to improved medical service and reducing radiologists' workload, it has been criticized in terms of how it will be integrated into routine practice. Regulatory and ethical issues have also been raised.

Comprehensively understanding and integrating machine learning into the real world of medical diagnosis is essential. Radiologists need to be prepared to adapt their roles and learn how to utilize machine learning in smart and effective ways.

Here we briefly summarise basic principles and the development of machine learning in medical radiology and highlight its applications in this field. We also discuss the current challenges and future perspectives of machine learning. Finally, we suggest how radiologists can prepare for the future integration of machine learning into workflow.

Box 1

The term 'machine learning' was first introduced in 1957 by Arthur Samuel who described algorithms for computers to solve problems by learning from existing data without explicitly predefined rules [5]. However, there were several limitations mainly caused by a lack of computational power and insufficient availability of data. Model performance was faced with overfitting and expensive computing time. Since 1980s computers were radically improved in computational capacity and widely implemented in all scientific fields; as a result, numerous machine learning techniques were adopted in scientific research. At the same time, computer-aided systems were introduced into medical radiology although they were mainly based on a set of rules defined by human knowledge [4]. After that, in the 1990s, statistical models have been mainly used for CADs to incorporate both human knowledge and statistical parameters from data [4, 6, 7]. These CADs provide the probability of the outcome of interest. However, the high dimensional data from radiological images were limited with model assumptions and data transformation. Since the 2000s, machine learning approaches, which are model-free and driven with now-available high dimensional data, therefore obtain more popularity in multiple fields with influential studies spreading from all modalities in radiology in the early 2000s [4].



Box 1 Figure. *The bar chart shows the number of papers from a MEDLINE search each year. (1) 1950 First artificial intelligence introduced; (2) 1970s Computers and Radiology Information Systems implemented; (3) 1980s Rules-based CADs mainly used; (4) 1990s Statistical based CADs implemented; and (5) 2010 Deep learning-based CADs mainly used.*

Terminology and basic principles

Computer-aided systems

Computer-aided detection (CADe) and computer-aided diagnosis (CADx) are both computer-based systems that assist radiologists in making a decision based on information obtained from radiological images [6, 7]. While CADe recognizes suspicious patterns on images and aims to assist radiologists in identifying abnormal findings, CADx analyses medical images and eventually provides a probability that a specific disease is present [8]. Both computer-based systems comprise multiple steps, including data analytic algorithms which can be based on rules, statistics, or artificial intelligence (AI).

Artificial intelligence and machine learning

Artificial intelligence is a field of computer science that creates systems performing tasks that usually require human problem-solving skills [9]. Machine learning, which is a subfield of AI, comprises a set of techniques that allows a computer program to learn and improve its performance using existing data without being explicitly programmed. Machine learning can be categorized into three main groups based on tasks: supervised learning, unsupervised learning, and reinforcement learning [10]. About supervised learning, pre-defined, or "labeled", outcomes (e.g. BI-RADS classification in mammography) are required in data input. The labeled data is used to train computer algorithms that make predictions when applied to new data. In contrast, unsupervised learning does not need labeled data; the algorithms recognize data patterns and classify the data into subgroups based on the similarity of each data point. Lastly, reinforcement learning learns from iterative trial and error to achieve specific tasks. The algorithms receive rewards and penalties based on the action each round and then assemble all feedback as the weight of each network.

Artificial neural network and deep learning

The artificial neural network (ANN) is a subset of machine learning methods inspired by a biological neural network that transfers and processes information. The ANN comprises several interconnected artificial neurons, known as nodes or process elements, which are structured in at least three layers: input, hidden, and output layers (Figure 1). Each neuron in one layer connects to all neurons in another layer. The strength of connections between neurons is weighted based on the performance in a training process. Deep learning is a subset of the artificial neural network, which contains more than one hidden layer. Although many types of deep learning have been developed, the most commonly used and known is the convolutional neural network (CNN), in which a convolutional operation filters informative data through piles of information layers.

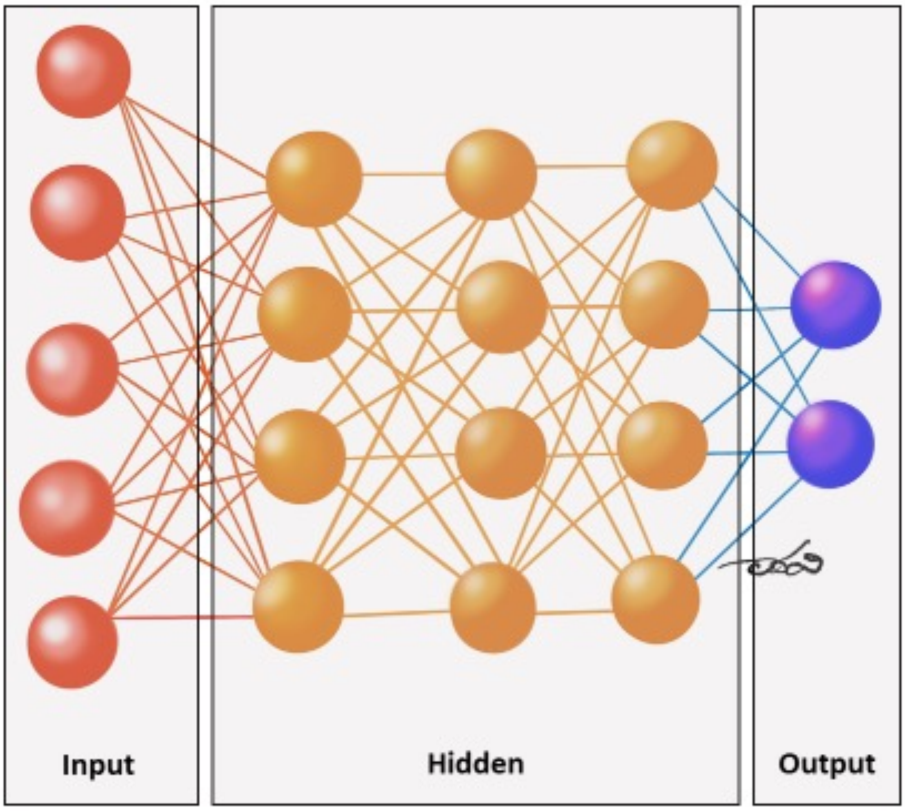


Figure 1. *Schematic presentation of an artificial neural network; a spherical shape refers to one process element, also known as a node or neuron. Nodes are structured into three main layers: input, hidden, and output layers; and each node connects to all nodes in another layer.*

Current applications of machine learning in medical radiology

The application of AI in medicine has notably increased, particularly in medical radiology, including diagnostic radiology, radiotherapy, and oncology, as well as interventional radiology. In diagnostic radiology, AI assists in disease detection, segmentation, diagnosis, and monitoring during follow-up or post-treatment. In the fields of radiotherapy and oncology, AI plays additional roles in treatment planning, outcome prediction, and advanced techniques in radiotherapy and chemotherapy for cancer [11-15]. AI also supports therapeutic radiation dose optimization in oncology and interventional radiology. In interventional radiology, AI is involved in recognizing and diagnosing diseases in medical imaging, providing intraoperative guidance, and conducting postoperative assessments, including in oncologic interventions, neurologic interventions, interventional cardiology, and robotic-supported interventional procedures [16]. AI also aids in patient registration for imaging and treatment, scheduling, appointment management, queue management, and organization during follow-up. The applications of AI in medical radiology have been described and highlighted based on radiology workflow from patient registration to radiological reports (Figure 2) [17, 18].

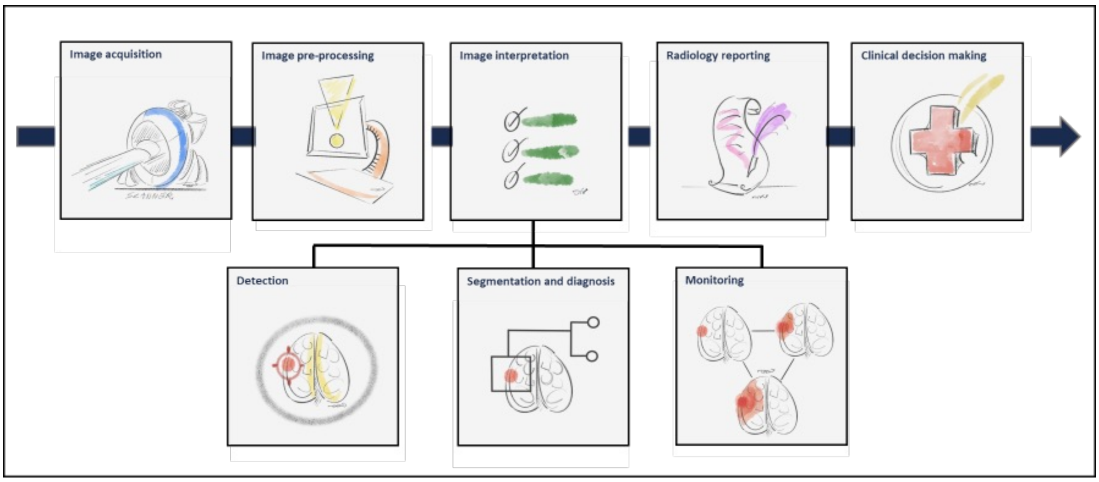


Figure 2. *Artificial intelligence implemented in radiology workflow (this figure is modified from Figure 3 in a review by Hosny et al. [17]).*

Patient schedule for radiological follow-up

Machine learning is implemented in patient-scheduling programs to reduce the number of patients who lose radiological follow-up. Machine learning has been used to determine an individual's risk of missing radiological care, following which a patient care team develops an individual solution to reduce the chance of loss of follow-up [19]. AI has been employed to analyze patient information and clinical data, as well as radiologist schedules and scanner availability. This enables the provision of optimized scheduling for patients during follow-up, thereby reducing waiting time [13, 20, 21].

Image acquisition

Deep learning has been used in image reconstruction that enhances mapping between machine sensors and images. Indeed, deep learning has outperformed conventional acquisition methods in terms of noise tolerance and artifact reduction [22]. Many studies have utilized deep learning to reduce artifacts in digital subtraction angiography (DSA), computed tomography (CT), and magnetic resonance imaging (MRI) [16, 23-31]. These studies have shown that deep learning techniques significantly improve diagnostic quality by effectively reducing artifacts and shortening image acquisition time. In the field of radio-oncology, deep learning methods are employed to reconstruct CT images from cone beam CT, resulting in noise reduction, enhanced image quality, and reduced radiation doses [32-35]. In addition, AI methods have been used to solve the problem of missing data from CT scans, in cases where a scanner cannot perform full rotations of the target objects. CNN has also been used to correct the artifact problem in CT using a combination of original and corrected image information to reduce metal artifacts [36].

Image pre-processing

Selected similarity criteria and reference images can bias the interpretation of radiological images. Deep learning allows us to achieve better motion compensation for sequential images and better handling of complex tissue deformations [17]. The multimodal ability in deep learning methods also allows for multiple quantitative measures of several imaging modalities, which thus improves the accuracy of image assessment [37]. For example, the application of multimodal imaging in oncologic evaluation has enabled the combination of various quantitative functional measurements, as seen in positron emission tomography (PET) scans and single-photon emission computed tomography (SPECT) imaging. This approach enhances the precision of tumor characterization and assessment [17, 38].

Image interpretation: detection, characterization and monitoring

Detection is a basic task used to identify a suspicious abnormality in medical images. While radiologists use cognitive skills to confirm or reject their hypotheses based on their knowledge and experiences, machine learning employs pre-defined rule-based programs or the recognition of abnormal data patterns from images. Rule-based CADe has been criticized mostly in terms of false positives which reduce radiologists' acceptability. Although machine learning-based CADe remains susceptible to false-positive results, it has demonstrated comparable predictive performance when used by radiologists. Breast cancer and lung cancer are the main fields that have been investigated with machine learning [39]. A breast cancer screening program has been implemented in the United States as a second radiologist or pre-screening process to reduce radiologists' workload and increase medical access for patients. Regarding lung cancer, machine learning has also been used to detect abnormal lymph nodes, which may be a sign of metastases. It has been demonstrated that the performance of machine learning-based CADe is comparable to that of radiologists. In addition, there is evidence demonstrating that the use of machine learning as a second radiologist provides more accurate results compared with either machine learning or radiologists alone [40-42].

Characterization refers to a task covering the segmentation and diagnosis of radiological images. While segmentation is used to identify the margins of abnormal areas in images, diagnosis is employed to estimate the probability that the specific conditions are present or absent. Probabilistic Atlas software uses machine learning algorithms to demarcate ill-defined image pixel intensity and locate abnormalities in radiological images, such as the segmentation of gliomas from a brain MRI and the estimation of prostate volume based on a prostate MRI [43, 44].

To provide examples of applying AI in detection, classification, and monitoring within musculoskeletal radiology, machine learning tools have been developed to assist radiologists in detecting fractures related to trauma on radiographs and CT scans, as well as detecting knee cartilage lesions on MRIs in osteoarthritis cases [45]. For characterization, AI assists radiologists in grading tumors such as osteosarcoma and soft tissue sarcoma on CT and MRI. AI is also used to classify post-operative instruments, such as spinal hardware or shoulder arthroplasty components. Additionally, AI monitors implant-related complications from plain radiographs and MRIs in cases of knee or hip arthroplasty loosening [45-47]. AI assists in the measurement of body composition, including skeletal muscle parameters and adipose tissue distribution, to predict survival outcomes and adverse events in cancer patients—a growing trend in contemporary oncological research [48, 49]. Figure 3 demonstrates the application of AI in segmenting skeletal muscle areas and adipose tissue from CT slices at the third lumbar vertebral level (L3) to assess sarcopenia and quantify visceral, subcutaneous, and intramuscular fat deposits in cancer patients for survival prediction. These examples illustrate the significant potential of AI applications in enhancing the accuracy and efficiency of musculoskeletal radiology. As AI continues to evolve, its integration into clinical practice will likely expand, offering further advancements in patient care.

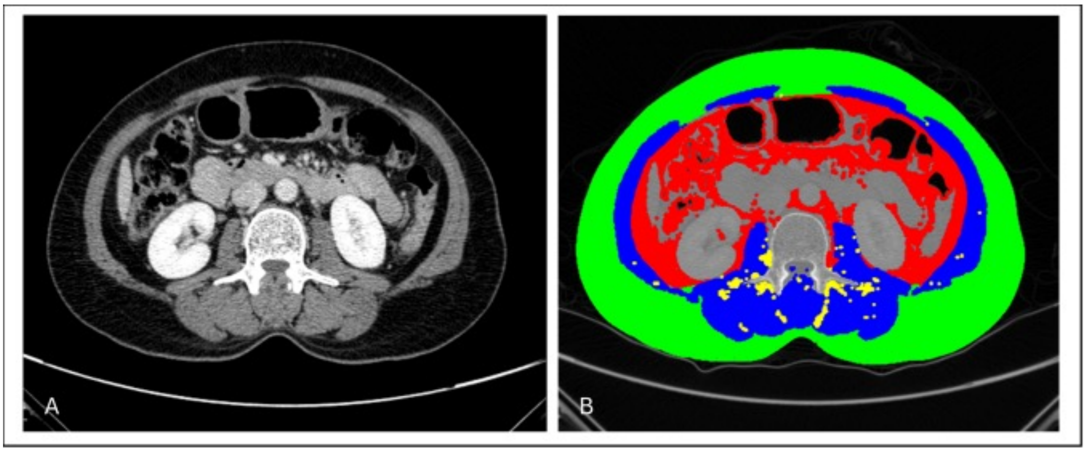


Figure 3. *Body composition analysis using CT imaging; (A) Axial CT image at the L3 vertebral level (B) Color-coded segmentation map depicting different tissue components: skeletal muscle area (blue), subcutaneous adipose tissue (green), visceral adipose tissue (red), and intramuscular adipose tissue (yellow).*

Radiology reporting

Radiology reports are a key tool for communication between radiologists and other professionals. These reports are created in various formats depending on the radiologist making the report. As such, it is a challenge to generate a standardized pattern, which is a benefit in terms of quality control and standard communication. Al could enable this task to generate uniform and standardized radiology reports. Radiological images can be transformed into natural language processing and matching with the narrative radiology reports [50]. This allows machine learning to extract radiological reports for quality improvement and future analysis. In addition, machine learning could be linked to radiologists' recommendations, thus reducing the loss of communication and follow-up [51].

The development of AI can lead to a decrease in mistakes in radiology reports. For example, errors such as reporting the wrong anatomical structures, like identifying a prostate in a female patient or a uterus and ovaries in a male patient, can be reduced. Another common issue is reporting a lesion on the wrong side; the lesion may be on one side in the findings section, but the radiologist might mention it on the other side in the impression section [52]. In some countries, such as Thailand, radiologists often type reports in English, which is not their mother tongue. This can lead to misspellings, inappropriate grammar, and irrelevant sentences and phrases within the same report. The developed AI can assist radiologists in reducing these reporting problems.

Another challenge for AI is assisting in the longitudinal reporting of lesions, especially in oncologic cases. A crucial task is comparing lesions over the follow-up period. Complex cases with multiple lesions can be time-consuming and tedious. AI can simplify this complexity by structuring and organizing the sequence of measurements and comparisons of changes in serial follow-up images over time, making the process easier [52].

Challenges of machine learning in medical radiology

Data for developing machine learning

The development of machine learning-based systems requires not only a large data set but also high-quality data. The amount of data required for the development of machine learning-based systems depends on the tasks. If the task is specific, such as a segmentation task, the required data set is relatively small compared with that needed for complex classification tasks.

Apart from data quantity, machine learning also needs high data quality to avoid inaccurate models. Radiological images used in the same machine-learning task should have low heterogeneity in data quality. The data should be produced using standardized imaging processes and imaging protocols. Data curating also requires a standardized set of criteria that is specific to a machine learning task, and data storing needs to be managed systematically, which enables future data access. Moreover, labeled data should be created according to standardized and generally accepted diagnostic criteria.

AI has been developed to enhance radiology reports by making them more concise, patient-friendly, and tailored with specific recommendations for each individual. Research has demonstrated that AI improves both the quality of reports and the efficiency of radiologists' workflows [53]. Recent advancements use the Natural Language Processing (NLP) tools and AI techniques to annotate, summarize, and extract key findings from these reports [52, 54]. Since radiology reports are often written in unstructured free text, they can be challenging to read, extract data from, and utilize effectively. Structured reports, on the other hand, are preferred because they offer standardization, completeness, and easier information retrieval. To train AI systems to convert unstructured reports into structured formats, a large dataset is necessary. The process involves meticulous preprocessing, entity recognition, manual annotation by domain experts, and data normalization. This approach not only ensures accuracy and reliability but also uses medical ontologies for standardization. By implementing validation steps such as inter-annotator agreement and expert reviews, the resulting structured data provides a solid foundation for training advanced NLP models. This methodology significantly enhances the development of AI tools that can improve the accuracy, efficiency, and overall quality of radiological diagnostics and patient care.

Model performance

Machine learning is developed based on existing data or training data without an explicit model assumption, as is the case with conventional statistics. As a result, machine learning is considerably dependent on the quality and amount of training data. If training data contains considerable random noise, the model is fitted to unnecessary information and provides poor model accuracy with new data. In addition, as a complex model that is still developing, machine learning is prone to be overfitted, in which machine learning algorithms are too fitted with the training data and perform very inaccurately with new data that models have not met before. This drastically reduces the value of the model in terms of generalisability.

There are many metrics used to evaluate the performance of AI algorithms in medical radiology. Accuracy, sensitivity, specificity, overlap-based metrics, distance metrics, and data quality are some of the well-known metrics [55]. However, there is no single, universally accepted metric for evaluating AI model performance. Given these challenges, regulatory standards, protocols, and best practices are crucial for AI implementation. Organizations should actively work to combine data science skills with the pertinent areas of drug development and safety monitoring. In Thailand, the Thailand Food and Drug Administration (TFDA) has not approved any machine learning or AI in use in the field of Radiology. The European Medicines Agency (EMA), a key agency of the European Union (EU) responsible for the scientific evaluation, supervision, and safety monitoring of medicines, has released a Reflection Paper on the use of AI in the medicinal product lifecycle. This paper aims to initiate dialogues with all stakeholders in this rapidly evolving field [56]. The EMA emphasizes high accuracy, sensitivity, and specificity for AI models used in clinical settings. Specific ranges are defined based on the use case and risk classification of the AI application. The Food and Drug Administration (FDA) of the United States has approved the use of machine learning and AI in medicine and radiology. The trend of these approvals has increased exponentially over the past decades [57]. Although AI has received approvals for use in radiology, its application in daily practice must be approached with caution. There have been reports of misinterpretations involving AI in radiologic images. Additionally, many radiologists are reluctant to use AI tools because they are concerned about the reliability of predictions, especially when the tool was tested on retrospective data but is now being used for prospective data [57].

AI has a significant potential to revolutionize radiology practice, but specific metrics are necessary to objectively measure its impact. The promises surrounding AI have been substantial, claiming to enhance technical performance, improve the detection and quantification of pathologies, streamline radiologists' workflows, and ultimately improve patient outcomes [18, 58-60].

Integration into the radiologists' workflow

AI has gradually refined the traditional roles of radiologists and integrated itself into radiology practice, becoming an integral part of every aspect of the radiologist's workflow. In scheduling, AI assists in patient list management, reducing patient waiting time and optimizing scan queues. During scanning, AI helps select optimized procedures and processes to reduce radiation doses [61]. Image quality from various imaging modalities has improved with AI, which also reduces scan times [13, 20, 21]. Radiologists benefit from AI in detecting abnormalities, interpreting images, and writing radiology reports.

In the field of radio-oncology, deep learning approaches are used to reconstruct CT images from cone beam CT, providing noise reduction, improved image quality, and reduced radiation doses [32-35]. AI also assists radio-oncologists in treatment planning and offers advanced techniques in radiotherapy and chemotherapy [11-15, 17]. Additionally, AI supports interventional radiologists in recognizing and diagnosing diseases in medical imaging, offering intraoperative guidance, and conducting postoperative assessments [16]. Furthermore, AI aids clinicians in clinical decision-making by helping patients choose treatment options based on diagnosis, outcome prediction, complication forecasting, and treatment efficacy.

AI also helps in scheduling follow-up scans, tracking disease progress by comparing previous images, predicting outcomes, and evaluating treatment responses across various modalities, including radiotherapy, chemotherapy, surgery, medication, and intervention [20].

Furthermore, AI's integration into radiology practice represents a transformative shift in medical imaging and treatment methodologies. By automating and optimizing numerous tasks, AI not only enhances the efficiency and accuracy of radiologists but also significantly improves patient outcomes. Its applications in oncological and interventional radiology demonstrate its versatility and potential to revolutionize these fields. As AI technology continues to advance, its ability to support and augment the capabilities of healthcare professionals will undoubtedly lead to more precise diagnoses, personalized treatment plans, and overall better healthcare delivery. The ongoing development and implementation of AI in radiology promise a future where medical imaging and intervention are more effective, efficient, and accessible to patients worldwide.

Regulation and ethical issues

The regulation of AI in medicine is rapidly evolving. In addition, the evaluation of AI for approval is difficult due to the nature of the machine, i.e. it is learning and developing from the existing training data. Thus, the evaluation should be performed in a timely and regular manner to remain up to date [62, 63].

Data security is another issue, as the data required for machine learning is big data taken from patients' medical records. The data resource should be legal and well-known. Patients have a right to decide how their data is to be used. To use patient data in developing machine learning systems, we must obtain informed patients.

A common question is who should take responsibility and accountability for the data used and developed in machine learning. If data belongs to model developers, and in the case of data hacking, who should have a role in data protection? In case the machine provides an incorrect result, who will take responsibility for the mistake? Program developers and designers are one of the options, but clinicians and radiologists might also be involved in this responsibility.

Future of machine learning in medical radiology

The aims of the next-generation machine learning-based systems in medical radiology have been suggested as follows: improving radiologists' performance, saving time, ensuring cost-effectiveness, and integration with the radiologists' workflow [64].

The use of machine learning will be broadened not only with cancers but also with chronic and degenerative diseases such as Alzheimer's disease [17]. In addition to their detection role, machine learning-based clinical decision support systems (CDSS) might be used in a way similar to self-driving cars. This would reduce radiologists' workloads and time spent in terms of integrating clinical information and communicating with multidisciplinary teams to improve patients' outcomes. Machine learning-based CDSS will be very helpful in primary care settings, where clinicians have less experience in medical radiology [64]. This also allows improved access to medical imaging for patients in the primary care setting with less relatively increased workloads for radiologists.

Machine learning could be implemented into the radiologists' workflow in multiple tasks which are relatively routine works. Radiologists will still play a vital role in all decision-making regarding radiology fields and patient care. They will employ a part of machine learning systems to ensure that radiological reports are judicious and transparent. This also results in legal liability, as the decisions are made by human initiation.

In terms of CDSS development, unsupervised machine learning would become more useful in routine practice due to the massive number of data inputs lacking standardized labeled data [13]. Fully anonymized patient data could be shared on a large cloud platform to develop machine learning-based models that are more generalizable [65]. In addition, machine learning could be linked together across imaging modalities to improve the accuracy of diagnosis.

Regarding steps for the implementation of machine learning in medical radiology, these have been mentioned in a previous study [42]. It should start with setting up an implementation team consisting of experts from multiple disciplines (informatics officer, healthcare manager, and radiologist teams) and assigning jobs to each member. The team members will be given the jobs of Chief Informatics Officer (CIO), radiology committee, and individual radiologists. The CIO will take responsibility for safeguarding the use of data. The team in general will also manage other data governance issues. In addition, the CIO must ensure that newly implemented models are compatible with existing infrastructure and programs, such as picture archiving, the communication system (PACS), and Radiology Information Systems (RIS). The radiology committee will be responsible for creating a framework of machine learning throughout the radiologist's workflow and also for ensuring the seamless integration of this framework into the workflow. The committee will be responsible for clinical governance including the development of standards for the radiology service. Individual radiologists will be invited to participate in the development process and evaluation of clinical and radiological information governance using machine learning-based CDSS.

Preparation for integration of machine learning

Medical education in the machine learning age

In terms of education in AI for radiologists, they must understand the foundations of AI and its applications as both developers and end users. Radiologists must also understand the principle of the techniques applied in AI as well as the data used to develop it. In an ideal scenario, the radiologist will be in a team establishing how AI can be applied based on evidence-based medicine. As a result, they should be trained in the clinical relevance and applicability of AI, in addition to the principle of how AI functions. Radiologists should appraise whether the application of AI is reliable and if it has meaning in terms of clinical practice. Additionally, the results from the AI-assisted system can be explained in terms of knowledge of clinical pathophysiology knowledge.

In addition, data protection and ethical issues related to AI development and its application should be taught in a radiology residency program. Radiologists produce medical images which are a type of personal medical data. Therefore, they should take responsibility for future data use and data protection. This training would need to provide a framework for radiologists to inform patients that their data is being used to advance AI applications, or that the patient's diagnosis partially originates from AI-assisted systems. Global healthcare databases will gather other clinical data. This will be a significant opportunity for radiologists to take part and prepare themselves in the creation and analysis of combined big data [21].

AI training in radiology residency programs should be started as early as possible. Continuing medical education should also be promoted to update AI involving applications that rapidly develop and change.

Future roles of radiologists after the implementation of machine learning

Here we explore the role of radiologists in the future after machine learning is integrated into their workflow. First of all, we have to accept that, in the foreseeable future, machine learning will not be able to replace radiologists, who use both knowledge and experience in decision-making in order to form accurate clinical judgments. Radiologists' tasks are much more complex than interpreting medical images. They use both data analysis and interpretation, as well as decision-making which employs not only data from radiology but also clinical data, and patient preferences; moreover, these radiologists rely on their trainings from medical schools and experiences from work they have already carried out. However, radiologists have to adapt their roles beyond the interpretation of medical images. Radiologists must act in more of a clinician role, applying their clinical knowledge in answering diagnostic questions and guiding decision-making. In addition, radiologists should maintain their presence in clinical pathways, considering clinical, personal, and societal contexts in ways that AI alone is not able to replicate.

Current artificial neural networks have accuracy rates that surpass those of human radiologists in narrow-based tasks [66, 67]. It is impossible to exclude the possibility that the efficiency gain provided by AI may lead to a need for fewer radiologists. However, the roles of radiologists will expand as they become more connected to technology and have access to better tools. Radiologists may play a pivotal role in the identification of clinical applications where AI may make a difference. Radiologists could also play a crucial role in data interpretation, cooperating with data scientists in defining clinically useful results. Radiologists should negotiate the supply of these valuable data sets and clinical knowledge while playing a guiding role in the clinical application of AI programs. Creating this kind of "multidisciplinary AI team" will help to ensure that patient safety standards are met and will make the radiologist's responsibilities transparent to patients and regulatory authorities.

Discussion

The integration of machine learning into medical radiology has the potential to significantly enhance diagnostic accuracy, streamline workflows, and improve patient outcomes. Over recent decades, advancements in machine learning have led to its widespread application in various aspects of radiology, including disease detection, image analysis, and radiology reporting. These technologies offer promising solutions to address the increasing demands on radiologists and the growing complexity of medical imaging.

However, the successful integration of machine learning into clinical practice is not without challenges. Issues related to data quality, model performance, and regulatory considerations need to be addressed to fully realize the benefits of these technologies. Ensuring that machine learning systems are robust, reliable, and ethically sound is crucial for their effective implementation in routine radiological practice.

Future developments in machine learning are likely to continue transforming the field of radiology. As technology evolves, there will be increased opportunities for enhancing diagnostic capabilities, optimizing patient care, and refining clinical decision-making processes. Radiologists will need to adapt to these changes by acquiring new skills and embracing the evolving role of machine learning in their practice.

Preparing for the future integration of machine learning involves not only understanding the principles and applications of these technologies but also addressing regulatory, ethical, and educational aspects. By fostering collaboration among radiologists, data scientists, and policymakers, and by investing in ongoing education and training, the medical community can ensure that machine learning contributes positively to the advancement of medical radiology.

In summary, while machine learning presents transformative opportunities for medical radiology, careful consideration of its implementation and continuous evaluation of its impact will be essential to harness its full potential and improve patient care.

References

1. O'Sullivan JW, Stevens S, Hobbs FDR, Salisbury C, Little P, Goldacre B, et al. Temporal trends in use of tests in UK primary care, 2000-15: retrospective analysis of 250 million tests. BMJ 2018;363:k4666. doi: 10.1136/bmj.l444.

2. Smith-Bindman R, Miglioretti DL, Larson EB. Rising use of diagnostic medical imaging in a large integrated health system. Health Aff (Millwood) 2008; 27:1491–502. doi: 10.1377/hlthaff.27.6.1491.

3. Rimmer A. Radiologist shortage leaves patient care at risk, warns royal college. BMJ 2017;359:j4683. doi: 10.1136/bmj.j4683.

4. Savadjiev P, Chong J, Dohan A, Vakalopoulou M, Reinhold C, Paragios N, et al. Demystification of AI-driven medical image interpretation: past, present and future. Eur Radiol 2019;29:1616–24. doi: 10.1007/s00330-018-5674-x.

5. Howell MD, Corrado GS, DeSalvo KB. Three epochs of artificial intelligence in health care. JAMA 2024;331:242- 4. doi: 10.1001/jama.2023.25057.

6. Doi K. Computer-aided diagnosis in medical imaging: historical review, current status and future potential. Comput Med Imaging Graph 2007;31:198–211. doi: 10.1016/j.compmedimag.2007.02.002.

7. Chen CM, Chou YH, Tagawa N, Do Y. Computer-aided detection and diagnosis in medical imaging. Comput Math Methods Med 2013;2013:790608. doi: 10.1155/2013/790608

8. Castellino RA. Computer-aided detection (CAD): an overview. Cancer Imaging 2005;5:17–9. doi: 10.1102/1470-7330.2005.0018.

9. Wang S, Summers RM. Machine learning and radiology. Med Image Anal 2012 ;16:933–51. doi: 10.1016/j.media.2012.02.005.

10. Deo RC. Machine learning in medicine. Circulation 2015;132:1920–30. doi: 10.1161/CIRCULATIONAHA.115.001593.

11. Khajuria R, Sarwar A. Review of reinforcement learning applications in segmentation, chemotherapy, and radiotherapy of cancer. Micron 2024;178: 103583. doi: 10.1016/j.micron.2023.103583.

12. Howard FM, Kochanny S, Koshy M, Spiotto M, Pearson AT. Machine learning-guided adjuvant treatment of head and neck cancer. JAMA Netw Open 2020;3:e2025881. doi: 10.1001/jamanetworkopen.2020.25881.

13. Xie L, Xu D, He K, Tian X. Machine learning-based radiotherapy time prediction and treatment scheduling management. J Appl Clin Med Phys 2023;24:e14076. doi: 10.1002/acm2.14076.

14. Li T, Wang J, Yang Y, Glide-Hurst CK, Wen N, Cai J. Multi-parametric MRI for radiotherapy simulation. Med Phys 2023;50:5273–93. doi: 10.1002/mp. 16256.

15. Fechter T, Sachpazidis I, Baltas D. The use of deep learning in interventional radiotherapy (brachytherapy): A review with a focus on open source and open data. Z Med Phys 2024;34:180–96. doi: 10.1016/j.zemedi.2022.10.005.

16. Zhang J, Fang J, Xu Y, Si G. How AI and robotics will advance interventional radiology: narrative review and future perspectives. Diagnostics 2024 ;14:1393. doi: 10.3390/diagnostics14131393.

17. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. Nat Rev Cancer 2018;18:500–10. doi: 10.1038/ s41568-018-0016-5.

18. Choy G, Khalilzadeh O, Michalski M, Do S, Samir AE, Pianykh OS, et al. Current applications and future impact of machine learning in radiology. Radiology 2018 ;288:318–28. doi: 10.1148/radiol.2018171820.

19. Marella WM, Sparnon E, Finley E. Screening electronic health record–related patient safety reports using machine learning. J Patient Saf 2017;13:31–6. doi: 10.1097/PTS.0000000000000104.

20. Najjar R. Redefining radiology: a review of artificial intelligence integration in medicaliImaging. Diagnostics (Basel) 2023;13:2760. doi: 10.3390/diagnostics 13172760.

21. SFR-IA Group, CERF, French Radiology Community. Artificial intelligence and medical imaging 2018: French Radiology Community white paper. Diagn Interv Imaging 2018 ;99:727–42. doi: 10.1016/j.diii.2018.10.003.

22. Zhu B, Liu JZ, Cauley SF, Rosen BR, Rosen MS. Image reconstruction by domain-transform manifold learning. Nature 2018;555:487–92. doi: 10.1038/nature25988.

23. Gao Y, Song Y, Yin X, Wu W, Zhang L, Chen Y, et al. Deep learning-based digital subtraction angiography image generation. Int J Comput Assist Radiol Surg 2019 ;14:1775–84. doi: 10.1007/s11548-019-02040-x.

24. Nagayama Y, Emoto T, Kato Y, Kidoh M, Oda S, Sakabe D, et al. Improving image quality with super-resolution deep-learning-based reconstruction in coronary CT angiography. Eur Radiol 2023;33:8488–500. doi: 10.1007/s00330-023-09888-3.

25. Zhang J, Gong W, Ye L, Wang F, Shangguan Z, Cheng Y. A Review of deep learning methods for denoising of medical low-dose CT images. Comput Biol Med 2024 ;171:108112. doi: 10.1016/j.compbiomed.2024.108112.

26. Fujita N, Yasaka K, Katayama A, Ohtake Y, Konishiike M, Abe O. Assessing the effects of deep learning reconstruction on abdominal CT without arm elevation. Can Assoc Radiol J 2023;74:688–94. doi: 10.1177/08465371231169672.

27. Wang T, Yu H, Wang Z, Chen H, Liu Y, Lu J, et al. SemiMAR: semi-supervised learning for CT metal artifact reduction. IEEE J Biomed Health Inform 2023 ;27:5369–80. doi: 10.1109/JBHI.2023.3312292.

28. Man C, Lau V, Su S, Zhao Y, Xiao L, Ding Y, et al. Deep learning enabled fast 3D brain MRI at 0.055 tesla. Sci Adv 2023;9:eadi9327. doi: 10.1126/sciadv.adi9327.

29. Safari M, Eidex Z, Chang CW, Qiu RLJ, Yang X. Fast MRI reconstruction using deep learning-based compressed sensing: A systematic review. arXiv: 2405.00241v1 [Preprint]. 2024 [cited 2024 Dec 17]. Available from: https://arxiv.org/abs/2405.00241.

30. Wessling D, Gassenmaier S, Olthof SC, Benkert T, Weiland E, Afat S, et al. Novel deep-learning-based diffusion weighted imaging sequence in 1.5 T breast MRI. Eur J Radiol 2023;166:110948. doi: 10.1016/j.ejrad.2023.110948.

31. Xie Y, Tao H, Li X, Hu Y, Liu C, Zhou B, et al. Prospective comparison of standard and deep learning-reconstructed turbo spin-echo MRI of the shoulder. Radiology 2024 ;310:e231405. doi: 10.1148/radiol.231405.

32. Cui Z, Fang Y, Mei L, Zhang B, Yu B, Liu J, et al. A fully automatic AI system for tooth and alveolar bone segmentation from cone-beam CT images. Nat Commun 2022;13:2096. doi: 10.1038/s41467-022-29637-2.

33. Rusanov B, Hassan GM, Reynolds M, Sabet M, Kendrick J, Rowshanfarzad P, et al. Deep learning methods for enhancing cone-beam CT image quality toward adaptive radiation therapy: A systematic review. Med Phys 2022; 49:6019–54. doi: 10.1002/mp.15840.

34. Zhang Y, Huang X, Wang J. Advanced 4-dimensional cone-beam computed tomography reconstruction by combining motion estimation, motion-compensated reconstruction, biomechanical modeling and deep learning. Vis Comput Ind Biomed Art 2019;2:23. doi: 10.1186/s42492-019-0033-6.

35. Szczykutowicz TP, Toia GV, Dhanantwari A, Nett B. A Review of deep learning CT reconstruction: concepts, limitations, and promise in clinical practice. Curr Radiol Rep 2022;10:101–15. doi: 10.1007/s40134-022-00399-5

36. Muller B, Wang G, editors. Developments in X-Ray tomography XI. Proceedings volume 10391. SPIE optical engineering application; 2017 Aug 6-10; San Diego, California, United State. Bellingham (WA): SPIE Digital Library; 2024 [cited 2024 Dec 17]. Available from: https://www.spiedigitallibrary.org/conference-proceedings-of-spie/10391.toc?webSyncID=7a434259-d750-205b-5837-e5e3b52e1a93&sessionGUID=a61b9741-6734-4428-b5d6-4bb0bbb9456a37.

37. Yankeelov TE, Abramson RG, Quarles CC. Quantitative multimodality imaging in cancer research and therapy. Nat Rev Clin Oncol 2014;11:670–80. doi: 10.1038/nrclinonc.2014.134.

38. Jimenez-Mesa C, Arco JE, Martinez-Murcia FJ, Suckling J, Ramirez J, Gorriz JM. Applications of machine learning and deep learning in SPECT and PET imaging: General overview, challenges and future prospects. Pharmacol Res 2023;197:106984. doi: 10.1016/j.phrs.2023.106984.

39. Pesapane F, Codari M, Sardanelli F. Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine. Eur Radiol Exp 2018;2:35. doi: 10.1186/s41747-018-0061-6.

40. Shiraishi J, Li Q, Appelbaum D, Doi K. Computer-aided diagnosis and artificial intelligence in clinical imaging. Semin Nucl Med 2011;41:449–62. doi: 10.1053/j.semnuclmed.2011.06.004.

41. Zhang J, Wang Y, Yu B, Shi X, Zhang Y. Application of computer-aided diagnosis to the sonographic evaluation of cervical lymph nodes. Ultrason Imaging 2016;38:159–71. doi: 10.1177/0161734615589080.

42. Liew C. The future of radiology augmented with artificial intelligence: A strategy for success. Eur J Radiol 2018;102:152–6. doi: 10.1016/j.ejrad.2018.03.019.

43. Parisot S, Darlix A, Baumann C, Zouaoui S, Yordanova Y, Blonski M, et al. A probabilistic atlas of diffuse WHO grade II glioma locations in the brain. PLoS One 2016;11:e0144200. doi: 10.1371/journal.pone.0144200.

44. Pejavar S, Yom SS, Hwang A, Speight J, Gottschalk A, Hsu IC, et al. Computer-assisted, atlas-based segmentation for target volume delineation in whole pelvic IMRT for prostate cancer. Technol Cancer Res Treat 2013;12:199–206. doi: 10.7785/tcrt.2012.500313.

45. Gitto S, Serpi F, Albano D, Risoleo G, Fusco S, Messina C, et al. AI applications in musculoskeletal imaging: a narrative review. Eur Radiol Exp 2024;8:22. doi: 10.1186/s41747-024-00422-8.

46. Lacroix M, Aouad T, Feydy J, Biau D, Larousserie F, Fournier L, et al. Artificial intelligence in musculoskeletal oncology imaging: A critical review of current applications. Diagn Interv Imaging 2023;104:18–23. doi: 10.1016/j.diii.2022.10.004.

47. Park CW, Oh SJ, Kim KS, Jang MC, Kim IS, Lee YK, et al. Artificial intelligence-based classification of bone tumors in the proximal femur on plain radiographs: System development and validation. PLoS One 2022;17:e0264140. doi: 10.1371/journal.pone.0264140.

48. Pakdee W, Laohawiriyakamol T, Tanutit P, Laohawiriyakamol S, Liabsuetrakul T. Association of body composition and survival in patients with locally advanced breast cancer: a historical cohort study. Acta Radiol 2024;65:575–87. doi: 10.1177/02841851241241528.

49. Anjanappa M, Corden M, Green A, Roberts D, Hoskin P, McWilliam A, et al. Sarcopenia in cancer: Risking more than muscle loss. Tech Innov Patient Support Radiat Oncol 2020 ;16:50–7. doi: 10.1016/j.tipsro.2020.10.001.

50. Sevenster M, Buurman J, Liu P, Peters JF, Chang PJ. Natural language processing techniques for extracting and categorizing finding measurements in narrative radiology reports. Appl Clin Inform 2015;6:600–10. doi: 10.4338/ACI-2014-11-RA-0110.

51. Oliveira L, Tellis R, Qian Y, Trovato K, Mankovich G. Follow-up recommendation detection on radiology reports with incidental pulmonary nodules. Stud Health Technol Inform 2015;216:1028.

52. Bizzo BC, Almeida RR, Alkasab TK. Artificial intelligence enabling radiology reporting. Radiol Clin North Am 2021;59:1045–52. doi: 10.1016/j.rcl.2021.07.004.

53. Park J, Oh K, Han K, Lee YH. Patient-centered radiology reports with generative artificial intelligence: adding value to radiology reporting. Sci Rep 2024;14: 13218. doi: 10.1038/s41598-024-63824-z.

54. C. Pereira S, Mendonça AM, Campilho A, Sousa P, Teixeira Lopes C. Automated image label extraction from radiology reports — A review. Artif Intell Med 2024;149:102814. doi: 10.1016/j.artmed.2024.102814.

55. Erickson BJ, Kitamura F. Magician's Corner: 9. Performance metrics for machine learning models. Radiol Artif Intell 2021;3:e200126. doi: 10.1148ryai. 2021200126.

56. European Medicines Agency [Internet]. Amsterdam: The Agency; c1995 - 2024 [cited 2024 Jul 29]. The use of artificial intelligence (AI) in the medicinal product lifecycle. Available from: https://www.ema.europa.eu/en/use-artificial-intelligence-ai-medicinal-product-lifecycle.

57. Zhang K, Khosravi B, Vahdati S, Erickson BJ. FDA review of radiologic AI algorithms: Process and challenges. Radiology 2024;310:e230242. doi: 10.1148/radiol.230242.

58. Thrall JH, Li X, Li Q, Cruz C, Do S, Dreyer K, et al. Artificial intelligence and machine learning in radiology: opportunities, challenges, pitfalls, and criteria for success. J Am Coll Radiol 2018;15(3 Pt B):504–8. doi: 10.1016/j.jacr.2017.12.026.

59. Gallix B, Chong J. Artificial intelligence in radiology: who's afraid of the big bad wolf? Eur Radiol 2019;29:1637–9. doi: 10.1007/s00330-018-5995-9.

60. Mayo RC, Leung JWT. Impact of artificial intelligence on women's imaging: cost-benefit analysis. AJR Am J Roentgenol 2019;212:1172–3. doi: 10.2214/AJR.18.20419.

61. Brady SL. Implementation of AI image reconstruction in CT-how is it validated and what dose reductions can be achieved. Br J Radiol 202396:20220915. doi: 10.1259/bjr.20220915.

62. Pesapane F, Volonté C, Codari M, Sardanelli F. Artificial intelligence as a medical device in radiology: ethical and regulatory issues in Europe and the United States. Insights Imaging 2018;9:745–53. doi: 10.1007/s13244-018-0645-y.

63. Jaremko JL, Azar M, Bromwich R, Lum A, Alicia Cheong LH, Gibert M, et al. Canadian Association of Radiologists white paper on ethical and legal issues related to artificial intelligence in radiology. Can Assoc Radiol J 2019;70:107–18. doi: 10.1016/j.carj.2019.03.001.

64. Mayo RC, Leung J. Artificial intelligence and deep learning – Radiology's next frontier? Clin Imaging 2018;49:87–8. doi: 10.1016/j.clinimag.2017.11.007.

65. Fazal MI, Patel ME, Tye J, Gupta Y. The past, present and future role of artificial intelligence in imaging. Eur J Radiol 2018;105:246–50. doi: 10.1016/j.ejrad.2018.06.020.

66. Wang H, Zhao T, Li LC, Pan H, Liu W, Gao H, et al. A hybrid CNN feature model for pulmonary nodule malignancy risk differentiation. J XRay Sci Technol 2018;26:171–87. doi: 10.3233/XST-17302.

67. Becker AS, Marcon M, Ghafoor S, Wurnig MC, Frauenfelder T, Boss A. Deep learning in mammography: Diagnostic accuracy of a multipurpose image analysis software in the detection of breast cancer. Invest Radiol 2017;52:434–40. doi: 10.1097/RLI.0000000000000358.