JOURNAL OF MEDICAL AND HEALTH SCIENCE

Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

ISSN 3032-1182 (online), https://anamnetic.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

JOURNAL OF MEDICAL AND HEALTH SCIENCE
Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

Table Of Contents

Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

Originality Statement

The author[s] declare that this article is their own work and to the best of their knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the published of any other published materials, except where due acknowledgement is made in the article. Any contribution made to the research by others, with whom author[s] have work, is explicitly acknowledged in the article.

Conflict of Interest Statement

The author[s] declare that this article was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Copyright Statement

JOURNAL OF MEDICAL AND HEALTH SCIENCE

Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

JOURNAL OF MEDICAL AND HEALTH SCIENCE

Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

Article information

Check this article update (crossmark)

Check this article impact (*)

Save this article to Mendeley

(*) Time for indexing process is various, depends on indexing database platform

ISSN 3032-1182 (online), https://anamnetic.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

JOURNAL OF MEDICAL AND HEALTH SCIENCE
Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

The digital revolution in medical imaging: The Role of artificial intelligence (AI) in the future of radiology: A subject review

Fathinul Fikri Ahmed Saad, fathinulfikri@upm.edu.my (*)
Universiti Putra Malaysia — Selangor — Malaysia., Malaysia

Duraid Manea Bashara, duraidalhajjaj@yahoo.com
Universiti Putra Malaysia, Selangor , Malaysia

(*) Corresponding author

Abstract

General Background: Radiology has evolved from analog image interpretation to data-intensive digital analysis, creating opportunities for artificial intelligence (AI) to support diagnostic and operationalprocesses. **Specific Background:** AI, particularly deep learning and convolutionalneural networks, is increasingly applied in lesion detection, image segmentation, image reconstruction, workflow triage, and radiomics. **Knowledge Gap:** Despite rapid adoption, a comprehensive synthesis of AI applications in radiology and the associated technical, ethical, and legal barriers remains necessary. **Aims:** This review examines current AI applications in medical imaging, their role in precision medicine, and the major challenges affecting clinical implementation. **Results:** AI demonstrated expert-level performance in detecting pulmonary nodules, breast cancer, and pancreatic lesions; automated segmentation improved quantitative assessment of tumors and neurodegenerative changes; deep learning reconstruction reduced radiation dose and shortened MRI acquisition time; triage systems prioritized urgent findings and reduced turnaround time; and radiomics and radiogenomics enabled non-invasive “virtual biopsy” and prognostic modeling. **Novelty:** This review integrates diagnostic, operational, and predictive roles of AI across the entire radiology workflow within the concept of augmented intelligence. **Implications:** AI is positioned as a collaborative tool that supports radiologists and advances precision medicine, while successful adoption depends on explainability, data generalizability, privacy protection, and clear regulatory frameworks.

Highlights:

- AI supports lesion detection, segmentation, and image reconstruction in medical imaging.
- Intelligent triage and scheduling reduce turnaround time and improve radiology workflow.
- Radiomics and radiogenomics enable non-invasive tumor characterization and prognosis prediction.

Keywords: Artificial Intelligence, Radiology, Deep Learning, Radiomics, Precision Medicine

JOURNAL OF MEDICAL AND HEALTH SCIENCE
Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

Published date: 2026-05-17

JOURNAL OF MEDICAL AND HEALTH SCIENCE
Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

1. Introduction

The field of radiology has shown a tremendous change from the discovery of X-rays last century (the 19th century) to now, where analog film images are being replaced by extremely complex digital data sets, high-order analysis [1]. In the past decade, Artificial Intelligence (AI) -particularly deep learning- has emerged as a game-changer in contemporary workflow [2]. The ever-increasing burden on the radiologists, spurred in part by rising global medical imaging volumes and no doubt fueled by the need to get it right in diagnosis, has seen intelligent algorithms change from being considered technically nice-to-haves to something far more impactful – a clinical need [3].

Essentially, AI in radiology takes advantage of the innate ability of a computer to mimic human thought processes like pattern-recognition and deep decision-making derived from analysis of immense "Big Data" sourced typically through modalities, such as MRI or CT, for example [4]. The secret to making these technologies work, as one might guess, is the ability to extract extremely fine details (some of which humans cannot see) from that image. This premise is the basis of "Radiomics" [5]. This emerging field converts standard images into measurable high-dimensional data that may help us make medical decisions in a more objective way [5].

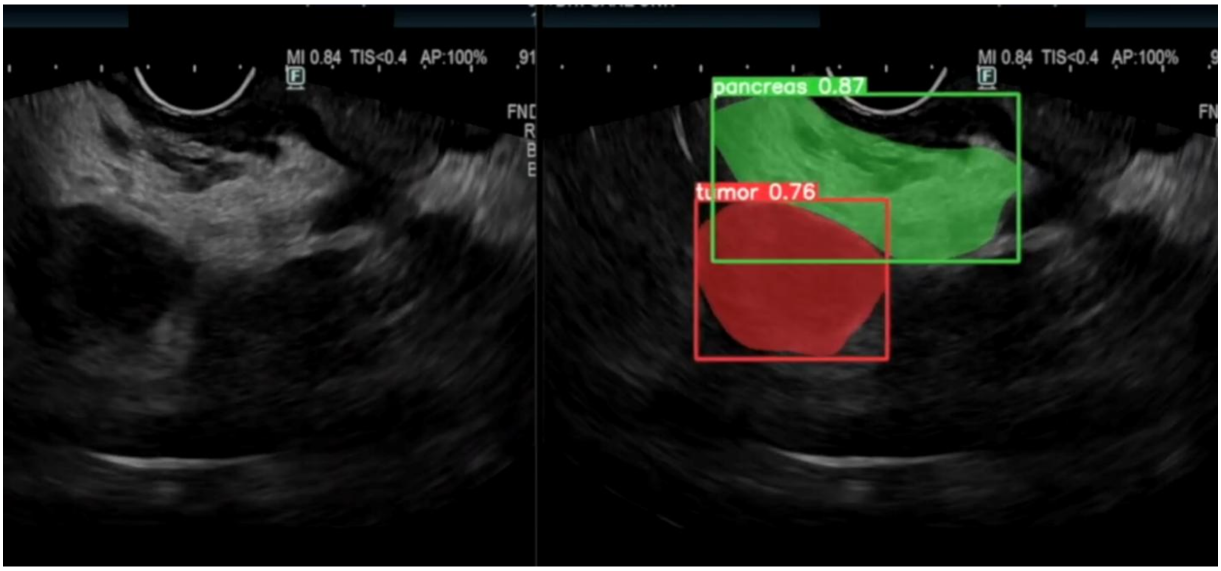
But utilization of AI in a radiology suite is not to replace the radiologist, but to be one where you have "Augmented Intelligence." This modality focuses on optimizing the radiological workflow, and thematic focuses are image quality, radiation dose saving, and early triage for intervention of live-threading diagnosis [6]. Notwithstanding these promising outlooks, several challenges must be addressed, including the "black box" of algorithm decision making, data protection problems, and complex legal issues concerning diagnostic liability [7,8]. The purpose of this review is to illustrate the state of current AI applications within radiology, barriers to adoption across specialties, and how the future may unfold for a specialty in an increasingly automated health care setting.

2. Artificial Intelligence in Analysis of Radiographic Images

At the heart of this, one might argue that AI is at its most useful for radiology in the ability to execute those higher-order tasks that were hitherto only within the remit of human perception. These applications could be generally classified into three main tasks on CCC cases: automated detection, segmentation, and image enhancement. For instance, a small lesion configuration that appears irregular on a low-resolution digital radiography could be segmented further utilizing image analysis segmentation to enhance the lesion margins and density[9].

2.1. Computer-Aided Detection and Diagnosis (CADe/CADx)

The application of Deep Learning, especially Convolutional Neural Network (CNN), has greatly increased the sensitivity of CAD systems. In thoracic radiology, AI has become so advanced that it can detect pulmonary nodules on chest CT scans as accurately or more accurately than attending radiologists [10]. In breast imaging, for example, AI-controlled mammography screening has proven highly effective in cutting down on "false negatives," or missed early-stage malignancies resulting from human fatigue and error [11].



The hypoechoic mass which was uncertained on ultrasound, it was clearly detected clearly on the AI-aided deteecton (red color) suggesting a pancreatic tumour[12].

Convolutional neural networks to detect a small pancreatic small lesion. CNN improve diagnostic capability and standardize the performance of EUS, we have developed a convolutional neural network to detect very small lesions in the pancreas[13].

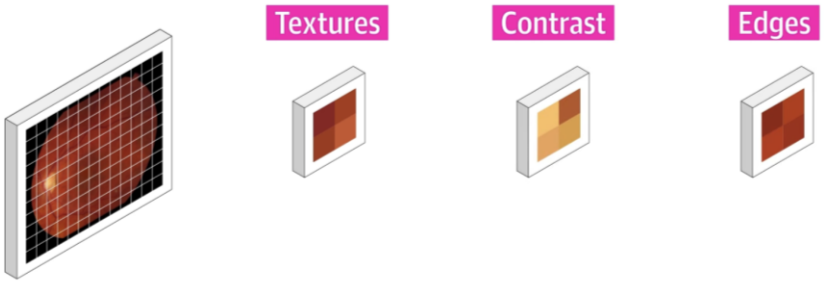
Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

2.2. Image Segmentation and Quantitative Analysis

Segmentation is the precise outlining of anatomical structures or pathologic lesions. AI would clearly welcome this task, by automatically "contouring" tumors in three dimensions - a critical part of calculating the volume and tracking its growth over time [14]. Neuroradiology In neuroradiology, AI for segmentation is utilized to provide quantitative measures of brain atrophy and ventricular dilation in neurodegenerative diseases such as Alzheimer's Disease or volume measuring of white matter lesions in Multiple Sclerosis, enabling objective measures as opposed to only qualitative descriptions by clinicians [15].

When working with deep convolutional neural networks to solve a problem related to computer vision, machine learning experts engage in stacking more layers. These additional layers help solve complex problems more efficiently as the different layers could be trained for varying tasks to get highly accurate results[16]. While the number of stacked layers can enrich the features of the model, a deeper network can show the issue of degradation. In other words, as the number of layers of the neural network increases, the accuracy levels may get saturated and slowly degrade after a point. As a result, the performance of the model deteriorates both on the training and testing data[17].

Figure 1. RES NET



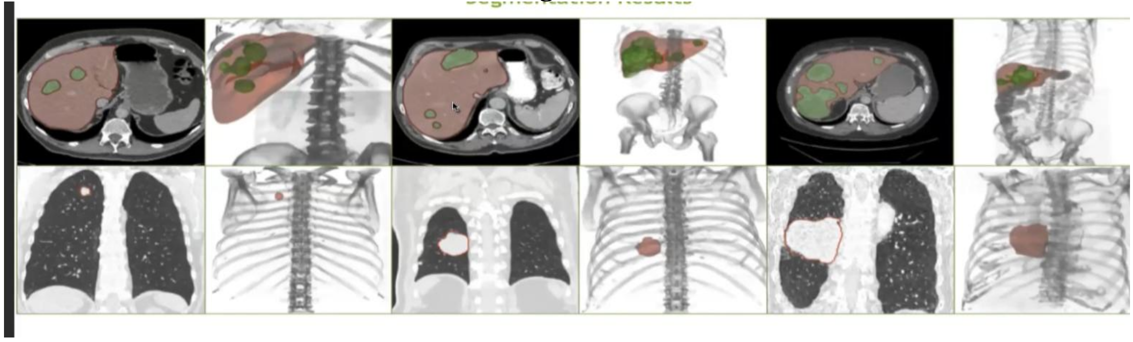
2.3. Image quality improvement and dose sparing

The ability of AI in restoring high-quality images from their low-quality versions is one such application that holds great promise. Reconstruction Contributions Deep learning reconstruction (DLR) methods are capable of generating high-resolution CT and MRI images at a much lower radiation dose in CT or scanning time in MRI [18]. This promotes patient safety as it reduces X-ray exposure, but also optimizes the capacity of the imaging department to accommodate a greater number of patients faster [19].

The segmentation system comprises of different stages to finally reach its target which is to segment the lung tumor. Image pre-processing takes place first where some enhancement techniques are used to enhance and reduce noise in images[20].

The next stage is where the different parts in the images are seperated to be able to segment the tumor in later stages. In this phase threshold was selected automatically which assures the right selection of all images since the tumor have different gray-levels intensities in each image[21]. Another technique was also used here to remove the tumor from the thresholded image. Finally, the lung tumor is accurately segmented by subtracting the thresholded and the other image.[22]

Figure 2



2.4. Triage and Prioritization Systems

AI is the "first responder" in the digital workflow. For instance, AI algorithms can be used to auto-detect intracranial hemorrhages or pneumothorax and bump these cases instantly to the top of a radiologist's worklist [23].

JOURNAL OF MEDICAL AND HEALTH SCIENCE
Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

3. Increasing Business and Operational Process: The Heart of The Matter

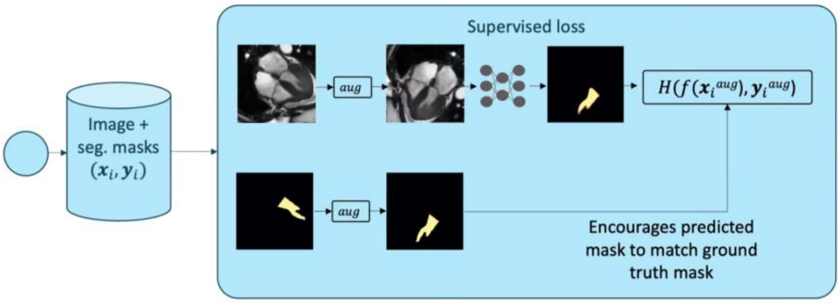
The role of AI in the radiology workflow extends beyond image interpretation to involve systemic bottlenecks that undermine care and clinician satisfaction. The new landscape of imaging is defined by an exponential increase in data volume, dramatically outstripping the bandwidth of radiologists [24, 25].

3.1. Advanced Scheduling and Predictive Analytics

Inefficiency starts in patient scheduling. As business intelligence became available to the medical industry, it has become clear that inefficiencies often start with patients and their appointments. Predictive models based on AI analyze multidimensional data (such as patient demographics, historical appointments, and weather patterns), aiming to estimate the probability of "no-show" [26]. AI technology for overbooking strategies and appointment reminders has been proven to be capable of reducing the idle scanner time by 25% [27, 28]. Moreover, AI realizes the "machine-protocol match," which sends advanced cases to high-end scanners without sending patients back for rescans [29].

Segmentation mask visualization plays a significant role in the process of image segmentation and computer vision. Masks, which are colored overlays on images that highlight segmented regions, provide a clear and precise outlook for AI systems to identify and classify objects or areas within an image. This technique allows for more efficient and accurate results in applications and segmentation tasks such as object detection, medical imaging, autonomous driving, and robotics[30].(Fig 3)

Figure 3



3.2. Real-Time Quality Assurance and Protocoling

Mistakes in the choice of culture play a large part in diagnostic delay. AI tools are already integrated in Electronic Health Records (EHRs), applying Natural Language Processing (NLP) to check clinical measures against ACR (American College of Radiology) Appropriateness Criteria [31, 32]. Whilst scanning, AI-driven computer vision detects patient motion or machine artifacts in real-time. Should a series be corrupted, the technologist is alerted, and the sequence can be reacquired immediately while the patient remains in place [33, 34].

3.3. Elements of an Intelligent Triage and "Critical Result" Assistance

FIFO as well as "Near-By The Worst First" (NBTWF): take what you will closest to the worst patient. This represents a fundamental error for emergency department reporting. AI functions as a persistent background interceptor of process scanning/ordering of the PACS [35] for acute pathologies. We already have validated algorithms for ICH, LVO, and tension pneumothorax that result in automatic alerts that are independent of the standard queue [36, 37]. Studies have shown that AI-based triage could decrease the "turnaround time" (TAT) of critical findings by more than an hour to less than three minutes, with significant enhancement of patients' outcome in the setting of "time is brain" [38, 39].

4. Radiomics and predictive analysis: the era of quantitative imaging

Radiomics usher in an era that considers images not as pictures but high-dimensional minefields. This area is concerned with the process of deriving feature representation for tumor shape, intensity, and texture (the local distribution of gray levels) [40, 41].

4.1. Radiomics Workflow and Machine Learning

The process includes four major steps: image acquisition, segmentation (manual or AI-assisted), feature extraction, and statistical modeling [42,43]. Recently, the state-of-the-art radiomics uses "Deep Features" by Convolutional Neural Networks (CNNs), which are usually more stable than traditional "hand-crafted" features [44]. These representations may be indications of a complex process referred to as "Intratumoral Heterogeneity, known as one of the most important resistance concepts that has been ignored in single-site needle biopsies [45, 46].

ISSN 3032-1182 (online), https://anamnetic.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

4.2. Radiogenomics: The Non-Invasive Genetic Map

Radiogenomics connects imaging phenotypes with molecular genotypes [47]. In neuro-oncology, AI can predict the IDH1 mutation and 1p/19q co-deletion in gliomas with high AUC/Az values on conventional MRIs [47,48]. Additionally, radiomic signatures in lung cancer have the ability to detect EGFR/ALK mutations for the targeted treatment choice [49,50]. This concept of "Virtual Biopsy" presents the actual fingerprint of the whole tumor, not just a few millimeters of tissue [51].

Ground truth segmentation is the authoritative label map used as the reference standard for evaluating, training, or validating image segmentation algorithms. It specifies, for every pixel (or voxel), the correct class or region membership according to human annotation, expert judgment, or a validated measurement process. Key elements and uses

Format: discrete label images (per-pixel integers) or binary masks per object/class; can include instance IDs, boundaries, or probabilistic labels[52].

Creation methods:

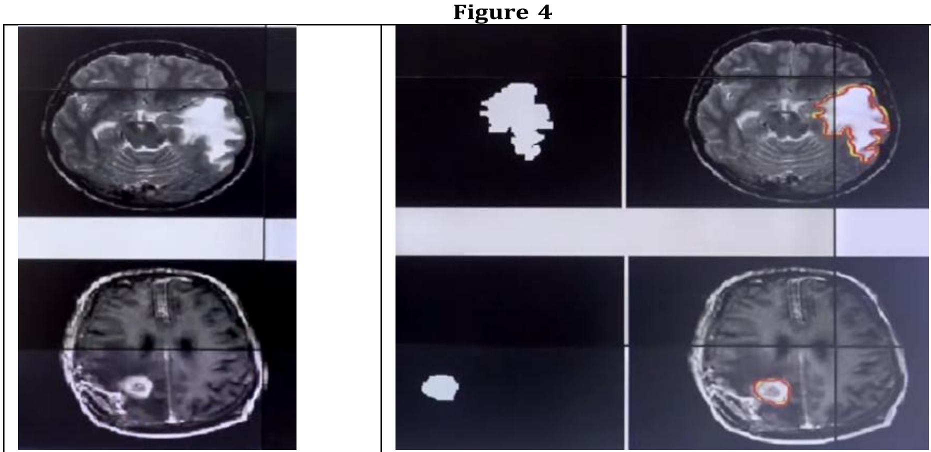
Manual annotation by experts using polygons, brush tools, or boundary tracing.

Semi-automatic annotation refined by humans (e.g., interactive segmentation).

Consensus or aggregated labels from multiple annotators (majority vote, STAPLE).

High-fidelity sensors producing proxy ground truth (e.g., LIDAR-derived depth masks, medical imaging modalities with histology correlation).

Figure 4



Original image	Segmentation ---- Red margin (Ai-aided) over Yellow margin (Ground truth)

https://youtu.be/ryUCJHk2ckU?si=gnrAu1JgxLY6PzvV

4.3. Prognostics and Longitudinal Treatment Monitoring

Prediction of clinical endpoints, such as "Overall Survival" (OS) and "Disease-Free Survival" (DFS), is a strong suit of AI. Through the analysis of longitudinal images, AI can identify "Delta-Radiomics" (feature changes over time), which are indicative of early treatment response [53, 54]. AI is very useful in such an immunotherapy setup where it works to distinguish "Pseudo-progression" and the real disease progression, stopping timely withdrawal of life-saving drugs [55, 56].

5. Challenges, Limitations, and Ethical Considerations

Although AI has the potential to transform radiology, technical, moral, and legal barriers are preventing it from being routinely applied in clinical practice. Facing up to these challenges is fundamental in order to protect patient safety and sustain the confidence of healthcare professionals [57].

5.1. The 'Black Box' Issue and Explainability

ISSN 3032-1182 (online), https://anamnetic.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

One of the key technical problems is that models created by Deep Learning are a "Black Box". Current deep neural networks are typically based on counterintuitive non-linear relationships that can be difficult to understand for human radiologists [58]. This lack of "Explainable AI" (XAI) results in a trust gap: clinicians are understandably hesitant to utilize diagnostic recommendations when the rationale behind them is not understood, particularly in high-risk clinical situations [59, 60].

5.2. Data Standardization and Algorithmic Bias

AI models are only as solid as the data they are trained on. The majority of algorithms to date are trained with datasets derived from a single institute or region, which gives rise to "overfitting" [61]. However, if such models are deployed on other patient populations or images from different scanner manufacturers, their performance substantially decreases: a phenomenon referred to as "Lack of Generalizability" [62]. Additionally, if the reference data are biased due to human biases (e.g., some ethnicities were under-represented), AI could reinforce and exacerbate Adam's vulnerabilities or even make those problems worse [63, 64].

5.3. Ethical Accountability and Legal Liability

The question of liability for an AI that misses a life-threatening finding is equally fraught from a legal perspective once automated diagnosis becomes widespread. [65]. Underlying legal foundation based on the assumption of human error and a "liability gap" between developer software, hospital, and radiologist has not been well drawn [66]. From an ethical perspective, there's also Automation Bias, where radiologists will begin to over-trust in AI findings and become lazy downstream in their own diagnostic abilities [67, 68].

5.4. Data Privacy and Security

Teaching AI to do so requires an egregious amount of patient feeding the beast gobs and gobs of data. Tim Date Restricting access to this data, similarly demanding regimes such as GDPR and HIPAA are hard to maintain [69]. There is an ever-present danger of "re-identification" whereby a clever enough algorithm can re-connect the disembodied source of the anonymized medical images to as few as a handful of people and invade their privacy in turn [70, 71].

6. Conclusion and Future Directions

The radiology AI is not merely new technology; it's a disruption to Precision Radiology. As these and other examples in this review illustrated, the AI impact stretches across the entire imaging value chain, from raw data acquisition/derivation through to complex interpretation of radiomic features allowing for "virtual biopsies" [72]. Whilst concern for AI's inevitability overtaking all radiologists was very much a topic of early discussion, the collective mindset has certainly shifted towards Augmented Intelligence. In this scenario, the radiologist continues to be the center of clinical integration, utilizing IA tools to dehumanize repetitive low-energy tasks and focusing their attention on complex diagnostic issue-solving problems and patient engagement [73].

The future achievement of AI in this domain will be based on our ability to address the "black box" nature of algorithms via Explainable AI (XAI), and to establish that models are trained on a diverse, multi-institutional dataset to eradicate demographic bias [74]. Restricted by the regulation system and liability laws, the integration of human precision with machine efficiency would probably be a future direction of diagnostic medicine, which will enable health care become more prospective, accurate, and available [75, 76].

References

1. Mazurowski MA, Buda M, Saha A, Bashir MR. Deep learning in radiology: An overview of the concepts and a survey of the state of the art with focus on MRI. J Magn Reson Imaging. 2019;49(7):e37-e54.
2. Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL. Artificial intelligence in radiology. Nat Rev Cancer. 2018;18(8):500-514.
3. 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(2):318-328.
4. Bi WL, Hosny A, Schabath MB, Giger ML, Birkbak NJ, Mehrtash A, et al. Artificial intelligence in cancer imaging: Clinical challenges and applications. CA Cancer J Clin. 2019;69(2):127-157.
5. Gillies RJ, Kinahan PE, Hricak H. Radiomics: Images are more than pictures, they are data. Radiology. 2016;278(2):563-577.
6. 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):504-508.
7. Pesapane F, Codari M, Sardanelli F. Artificial intelligence in medical imaging: Threat or opportunity? Radiologists are again at the forefront of innovation in medicine. Eur Radiol Exp. 2018;2(1):35.
8. Yasaka K, Abe O. Deep learning and artificial intelligence in radiology: Current applications and future directions. PLoS Med. 2018;15(11):e1002707.
9. Irshad H, Veillard A, Roux L, Racoceanu D. Methods for nuclei detection, segmentation, and classification in digital histopathology: A review-current status and future potential. IEEE Rev Biomed Eng. 2013;7:97-114.
10. Nam JG, Park S, Hwang EJ, Lee JH, Jin KN, Lim KY, et al. Development and validation of a deep learning-based automatic detection algorithm for malignant pulmonary nodules on chest radiographs. Radiology. 2019;290(1):218-228.
11. McKinney SM, Sieniek M, Godbole V, Godwin N, Antropova N, Ashrafian H, et al. International evaluation of an AI

ISSN 3032-1182 (online), https://anamnetic.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

system for breast cancer screening. Nature. 2020;577(7788):89-94.
12. Hameed BS, Krishnan UM. Artificial intelligence-driven diagnosis of pancreatic cancer. Cancers. 2022;14(21):5382.
13. Fang D, Huang Y, Li S, Shi C, Bao J, Du D, et al. A semi-supervised convolutional neural network for diagnosis of pancreatic ductal adenocarcinoma based on EUS-FNA cytological images. BMC Cancer. 2025;25(1):495.
14. Menze BH, Jakab A, Bauer S, Kalpathy-Cramer J, Farahani K, Kirby J, et al. The multimodal brain tumor image segmentation benchmark (BRATS). IEEE Trans Med Imaging. 2015;34(10):1993-2024.
15. Akkus Z, Galimzianova A, Hoogi A, Rubin DL, Erickson BJ. Deep learning for brain MRI segmentation: State of the art and future directions. J Digit Imaging. 2017;30(4):449-459.
16. Yoo HJ. Deep convolution neural networks in computer vision: A review. IEIE Trans Smart Process Comput. 2015;4(1):35-43.
17. Lin CL, Wu KC. Development of revised ResNet-50 for diabetic retinopathy detection. BMC Bioinformatics. 2023;24(1):157.
18. Geyer LL, Schoepf UJ, Meinel FG, Nance JW Jr, Bastian ML, Canstein C, et al. State of the art: Iterative CT reconstruction techniques. Radiology. 2015;276(2):339-357.
19. Knoll F, Hammernik K, Zhang C, Moeller S, Pock T, Sodickson DK, et al. Deep-learning methods for parallel magnetic resonance imaging reconstruction: A review of the current state of the art. IEEE Signal Process Mag. 2020;37(1):128-140.
20. Uzelaltinbulat S, Ugur B. Lung tumor segmentation algorithm. Procedia Comput Sci. 2017;120:140-147.
21. Heit JJ, Iv M, Wintermark M. Continuous high-performance artificial intelligence: The future of neuroradiology. AJNR Am J Neuroradiol. 2019;40(10):1618-1620.
22. Branstetter BF, et al. The radiology report: Are we getting better? J Am Coll Radiol. 2017;14(10):1335-1341.
23. McDonald RJ, et al. The effects of changing radiology report turnaround time. AJR Am J Roentgenol. 2015;204(6):1220-1227.
24. Merali Z, et al. AI for reducing no-show rates in radiology. J Am Coll Radiol. 2021;18(9):1280-1289.
25. Harvey H, et al. AI in radiology: The opportunity for efficiency. Clin Radiol. 2019;74(5):379-384.
26. Chong J, et al. Utilization of AI in radiology operations. Radiol Artif Intell. 2021;3(5):e200193.
27. Sodickson DK, et al. Modernizing radiology workflows through AI. Nat Mach Intell. 2019;1(5):215-224.
28. Lakhani P, et al. Machine learning in radiology. Radiographics. 2018;38(6):1662-1679.
29. Gichoya JW, et al. AI in medical imaging. J Digit Imaging. 2020;33(1):1-3.
30. Suess C, et al. AI for quality control. J Digit Imaging. 2020;33(2):345-352.
31. Samala RK, et al. Deep learning in medical imaging. Phys Med Biol. 2018;63(24):24TR01.
32. Annarumma S, et al. Automated triaging of chest radiographs. Radiology. 2019;291(1):196-202.
33. Chilamkurthy S, et al. Deep learning algorithms for the detection of critical findings in head CT scans. Lancet. 2018;392(10162):2388-2396.
34. Titano JJ, et al. Automated deep-learning triage of head CT. Nat Med. 2018;24(9):1337-1341.
35. Lambin P, et al. Radiomics: Extracting more information from medical images using advanced feature analysis. Eur J Cancer. 2012;48(4):441-446.
36. Aerts HJ, et al. Decoding tumour phenotype by noninvasive imaging using a quantitative radiomics approach. Nat Commun. 2014;5:4006.
37. Kumar V, et al. Radiomics: The process and the challenges. Magn Reson Imaging. 2012;30(9):1234-1248.
38. Limkin EJ, et al. Promises and challenges for the implementation of computational medical imaging (radiomics) in oncology. Ann Oncol. 2017;28(6):1191-1206.
39. Kuo MD, Jamshidi N. Behind the numbers: Decoding molecular phenotypes with radiogenomics-guiding principles and technical considerations. Radiology. 2014;270(2):320-325.
40. Kickingereder P, et al. Radiomic profiling of glioblastoma: Identifying an imaging predictor of patient survival with improved performance over established clinical and radiologic risk models. Radiology. 2016;280(3):880-889.
41. Gevaert O, et al. Non-small cell lung cancer: Identifying prognostic imaging biomarkers by leveraging public gene expression microarray data-methods and preliminary results. Cancer Res. 2012;72(10):2720-2728.
42. Coroller TP, et al. Radiomic phenotype features predict pathological response in non-small cell lung cancer. Radiother Oncol. 2016;119(3):480-486.
43. Rizzo S, et al. Radiomics: The facts and the challenges of image analysis. Eur Radiol Exp. 2018;2(1):36.
44. Trebeschi S, et al. Predicting response to cancer immunotherapy using noninvasive radiomic biomarkers. Ann Oncol. 2019;30(6):998-1004.
45. Sun R, et al. A radiomics approach to assess tumour-infiltrating CD8 cells and response to anti-PD-1 or anti-PD-L1 immunotherapy: An imaging biomarker, retrospective multicohort study. Lancet Digit Health. 2019;1(5):e232-e239.
46. Braman NM, et al. Intratumoral and peritumoral radiomics for the pretreatment prediction of pathologic complete response to neoadjuvant chemotherapy in breast cancer. Breast Cancer Res. 2017;19(1):57.
47. Nie K, et al. Rectal cancer: Assessment of neoadjuvant chemoradiation outcome based on radiomics of multiparametric MRI. Clin Cancer Res. 2016;22(21):5256-5264.
48. Jaremko JL, 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(2):107-118.
49. Castelvecchi D. Can we open the black box of AI? Nature. 2016;538(7623):20-23.
50. Tjoa E, Guan C. A survey on explainable artificial intelligence (XAI): Toward medical XAI. IEEE Trans Neural Netw Learn Syst. 2021;32(11):4793-4813.
51. Ghassemi M, et al. The false hope of current approaches to explainable artificial intelligence in health care. Lancet Digit Health. 2021;3(11):e745-e750.
52. Zech JR, et al. Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study. PLoS Med. 2018;15(11):e1002683.
53. Kelly CJ, et al. Key challenges for delivering clinical impact with artificial intelligence. BMC Med. 2019;17(1):195.
54. Seyyed-Kalantari L, et al. Underdiagnosis bias of artificial intelligence algorithms applied to chest radiographs in under-served patient populations. Nat Med. 2021;27(12):2176-2182.
ISSN 3032-1182 (online), https://anamnetic.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo

Vol. 4 No. 1 (2026): July
DOI: 10.21070/anamnetic.v4i1.1655

55. Larrazabal AJ, et al. Gender imbalance in medical imaging datasets produces biased classifiers for computer-aided diagnosis. Proc Natl Acad Sci U S A. 2020;117(23):12592-12594.
56. Price WN, Gerke S, Cohen IG. Potential liability for physicians using artificial intelligence. JAMA. 2019;322(18):1765-1766.
57. Geis JR, et al. Ethics of artificial intelligence in radiology: Summary of the Joint European and North American Multisociety Statement. J Am Coll Radiol. 2019;16(11):1516-1521.
58. Parasuraman R, Manzey DH. Complacency and bias in human use of automation: An attentional integration. Hum Factors. 2010;52(3):381-410.
59. Lyell D, et al. Automation bias in mammography: The effect of artificial intelligence decision support on reader performance. J Am Med Inform Assoc. 2021;28(11):2379-2388.
60. Price WN, Cohen IG. Privacy in the age of medical big data. Nat Med. 2019;25(1):37-43.
61. Kaissis GA, et al. Secure, privacy-preserving and federated machine learning in medical imaging. Nat Mach Intell. 2020;2(6):305-311.
62. Pesapane F, et al. Artificial intelligence as a medical device in radiology: Ethical and regulatory issues in Europe and the United States. Insights Imaging. 2018;9(5):745-753.
63. Langlotz CP. Will artificial intelligence replace radiologists? Radiol Artif Intell. 2019;1(3):e190058.
64. Curtis C, et al. The future of radiology in the age of artificial intelligence. J Am Coll Radiol. 2021;18(3):450-455.
65. Arbabshirani MR, et al. Advanced machine learning in action: Identification of intracranial hemorrhage on computed tomography scans of the head with clinical workflow integration. NPJ Digit Med. 2018;1:9.
66. European Society of Radiology (ESR). What the radiologist should know about artificial intelligence: An ESR white paper. Insights Imaging. 2019;10(1):44.
67. Giger ML. Machine learning in medical imaging. J Am Coll Radiol. 2018;15(3 Pt B):512-520.

ISSN 3032-1182 (online), https://anamnetic.umsida.ac.id, published by Universitas Muhammadiyah Sidoarjo