v. 5, n. 26, 2025

International Journal of Health Science

Acceptance date: 30/07/2025

SMART IMAGING IN NEUROLOGICAL EMERGENCIES: CHALLENGES AND INNOVATIONS IN AI-DRIVEN DIAGNOSIS

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Abstract: Introduction: The integration of Artificial Intelligence (AI) into neuroradiology has emerged as a transformative advancement, particularly in the context of neurological emergencies. AI algorithms, encompassing machine learning and deep learning techniques techniques, have shown potential in enhancing diagnostic accuracy, accelerating image interpretation, and optimizing workflow efficiency. These advances are crucial in acute settings, where rapid and precise diagnoses are essential. Moreover, it is important to explore the challenges and opportunities of implementing these tools in public healthcare systems, such as Brazil's Unified Health System (SUS). **Objective:** This review aims to provide neuroradiologists with a comprehensive overview of recent advances in AI applications for imaging diagnosis in neurological emergencies. It seeks to elucidate the current capabilities, limitations, and future perspectives of AI integration in emergency neuroradiology. **Methods:** For the For this narrative literature review, an extensive search was conducted in the PubMed, Scopus, Web of Science, Cochrane Library, and Google Scholar databases, focusing on publications from the last five years. Relevant studies were selected on AI applications in imaging-based diagnosis of neurological emergencies, including stroke, traumatic brain injury (TBI), and intracranial hemorrhage. Retrospective and prospective studies, as well as reviews and meta-analyses, were considered. **Results and Discussion:** AI applications have demonstrated promise in several aspects of emergency neuroradiology. In stroke imaging, algorithms have been developed for the rapid detection of large vessel occlusions and automated calculation of the ASPECTS score, facilitating timely interventions. For traumatic brain injuries, AI assists in identifying intracranial hemorrhages and skull fractures, increasing diagnostic confidence. Additionally, AI has proven valuable in case triage, prioritization of critical findings, and reducing report turnaround times. Despite these advancements, challenges remain, such as the need for large and diverse datasets for training, integration with existing workflows, and ensuring algorithm transparency and interpretability. **Conclusion:** AI holds significant potential to enhance Imaging-based diagnosis in neurological emergencies. Its integration into neuroradiological practice can improve diagnostic accuracy and efficiency. However, careful consideration of implementation challenges and ongoing validation is essential to fully realize its benefits.

Descriptors: Artificial Intelligence, Neuroradiology, Imaging-based diagnosis in Emergencies, Neurological Emergencies

INTRODUCTION

Artificial intelligence (AI) has rapidly emerged as a fundamental tool in the landscape of modern neuroradiology, particularly in the management of neurological emergencies[1]. The implementation of AI techniques in imaging under urgent conditions provides increased speed and diagnostic consistency—crucial aspects in acute scenarios such as stroke, traumatic brain injury (TBI), and intracranial hemorrhage[1]. These advancements are especially relevant given the time-sensitive nature of neurological deterioration in emergency contexts[1]. The burden of neurological emergencies is considerable, both in terms of clinical outcomes and the strain placed on healthcare systems[2]. Rapid and accurate image interpretation often determines the therapeutic window, especially in cases of ischemic stroke or acute hydrocephalus[2]. AI models designed to detect pathologies in real time have the potential to significantly accelerate clinical decision-making and reduce diagnostic delays[2].

International Journal of Health Science ISSN 2764-0159 DOI https://doi.org/10.22533/at.ed.1595262514072

Deep learning, particularly convolutional neural networks (CNNs), has become the leading architecture for image analysis in neuroradiology[3]. These models are trained on large datasets to detect subtle imaging findings, such as early signs of infarction on non-contrast CT or microhemorrhages on MRI[3]. The utility of these models lies in their reproducibility, speed, and potential to serve as decision support systems for radiologists for radiologists[3]. Several commercially available AI systems have already been approved by the FDA for neuroimaging applications, including triage and notification of large vessel occlusions (LVOs) or intracranial hemorrhages on CT scans[4]. Once integrated into picture archiving and communication systems Picture Archiving and Communication Systems (PACS)", these systems are capable of prioritizing critical cases and alerting radiologists or neurologists within seconds[4]. The resulting workflow optimization has been shown to reduce door-to-needle times in stroke management[4].

Despite these advances, the heterogeneity of clinical presentations and the variability in image quality pose significant challenges to the generalizability of AI algorithms[5]. For instance, motion artifacts, postoperative changes, or preexisting pathologies can compromise algorithmic accuracy[5]. Moreover, the datasets used for training often lack sufficient diversity regarding patient populations and scanner models[5]. Validation and standardization remain urgent issues in the transition of AI from research to clinical practice[6]. Although some algorithms demonstrate high performance in controlled environments, their real-world effectiveness varies depending on institutional imaging protocols and the characteristics of the patient population[6]. Rigorous multicenter validations are essential before widespread clinical adoption can be considered[6].

Ethical considerations have also been raised, particularly regarding diagnostic responsibility when AI recommendations diverge from radiologists' interpretations[7]. Although these systems are designed to complement—not replace—human expertise, an ongoing debate persists over legal accountability in cases of diagnostic errors or treatment delays[7]. Transparent and explainable AI models may help mitigate some of these medico-legal concerns[7]. In stroke imaging, AI has revolutionized the speed and accuracy of occlusion detection and ASPECTS scoring[8]. Automated algorithms can detect early ischemic changes and quantify infarct volume based on CT perfusion, providing critical information for decisions for decision-making regarding endovascular therapy[8]. These systems are especially valuable in non-tertiary centers, where access to specialized neuroradiology consultation may be limited[8].

In traumatic brain injury, AI models are being trained to detect subtle hemorrhagic lesions, skull fractures, and midline shifts on head CT scans[9]. These findings can be difficult to identify in acute settings due to trauma-related artifacts and limited clinical history[9]. AI systems capable of automatically triaging cranial trauma studies can significantly reduce time to diagnosis, especially in high-volume emergency departments[9]. Subarachnoid hemorrhage, another critical condition, also benefits from AI-based tools that identify hyperdensities in the basal cisterns and sulci on non-contrast CT scans[10]. Some algorithms are being refined to distinguish between acute hemorrhages and mimics, such as calcifications or beam-hardening artifacts[10]. The use of these systems can increase diagnostic confidence and reduce false-negative rates[10].

AI tools based on MRI are also being explored for the rapid evaluation of stroke protocols, including diffusion-weighted imaging and MR angiography[11]. These systems aim to provide real-time segmentation of ischemic lesions and vascular abnormalities, supporting both diagnosis and therapeutic monitoring[11]. However, their implementation is limited by longer acquisition times and sensitivity to motion in unstable patients[11].

One area of active research is the integration of clinical data with imaging findings through AI, aiming to generate more comprehensive diagnostic models[12]. These multimodal models incorporate laboratory results, vital signs, and clinical scores alongside radiological findings to stratify risk and predict outcomes in neurological emergencies[12]. The potential of such systems lies in their ability to deliver personalized and dynamic decision support[12].

Cloud-based AI platforms are now facilitating real-time image analysis and sharing across stroke care networks, promoting collaboration between institutions[13]. These systems enable smaller hospitals to benefit from tertiary-level decision support, expanding access to accurate and timely neuroimaging interpretation[13]. However, cybersecurity and data privacy concerns must be addressed to ensure sustainable and secure integration [13].

From the radiologist's perspective, AI presents both opportunities and challenges in daily workflow[14]. On one hand, it can reduce repetitive tasks and enhance diagnostic accuracy; on the other, it may introduce new layers of complexity, such as the need for software oversight and alert fatigue[14]. Therefore, adequate training and user-centered design are essential for the successful adoption of AI tools in emergency imaging[14].

The adoption of AI tools in neurological emergencies faces significant barriers in settings with limited infrastructure, such as public hospitals lacking integrated PACS, continuous technical support, or on-call radiologists. In these environments, the implementation of AI-based solutions requires practical adaptations, including offline-capable models, gradual integration with existing systems, and a focus on automated functions geared toward triage[15].

Moreover, ongoing training for radiology, neurology, and primary care teams is essential to ensure the responsible and effective use of these technologies. continuing education should encompass not only the technical operation of AI systems but also an understanding of their limitations and the critical interpretation of their findings. This is particularly important to ensure safe and appropriate application across diverse care settings, especially within Brazil's Unified Health System (SUS)[15].

Finally, ongoing collaboration among radiologists, computer scientists, and regulatory bodies is essential to align AI development with clinical realities and ethical frameworks[16]. The success of AI in neurological emergencies will depend not only on technical accuracy but also on transparency, usability, and seamless integration into radiological practice[16]. This review aims to synthesize current evidence, challenges, and future perspectives regarding the use of AI in imaging diagnosis of acute neurological conditions[16].

OBJECTIVES

This narrative review aims primarily to explore the current applications and emerging roles of artificial intelligence in the imaging diagnosis of neurological emergencies, with a particular emphasis on the role of the neuroradiologist. Secondary objectives include analyzing diagnostic accuracy, integration into clinical workflows, regulatory status, and ethical implications of AI tools applied to scenarios such as acute stroke, traumatic brain injury, and other neurocritical conditions. The review also seeks to identify barriers to the implementation of these technologies, propose directions for future research, and assess their practical feasibility across different levels of healthcare complexity, with special attention to the realities of the public health system.

METHODOLOGY

A comprehensive literature search was conducted across five major databases: PubMed, Scopus, Web of Science, Cochrane Library, and Google Scholar. The search strategy employed Boolean operators and MeSH terms such as "artificial intelligence," "machine learning," "deep learning," "neuroradiology," "neurological emergencies," "stroke imaging," "traumatic brain injury," and "CT and MRI diagnosis." Articles published between January 2020 and May 2025 were selected to capture the most recent advancements and current clinical validations. A narrative review approach was adopted to allow for an interdisciplinary critical analysis, facilitating the integration of technical, clinical, and operational perspectives.

The inclusion criteria encompassed peer--reviewed original research, clinical trials, systematic reviews, and meta-analyses focused on the use of AI in emergency neuroradiology. Eligible studies were required to report outcomes related to diagnostic performance, workflow impact, clinical integration, or ethical implications of AI. Exclusion criteria included case reports, editorials, animal studies, articles not available in English, and studies lacking a clear focus on neurological emergencies or neuroimaging.

Following the initial screening by title and abstract, full-text articles were reviewed for methodological quality, clinical relevance, and alignment with the objectives of this review. The selected articles were thematically organized into categories such as stroke imaging, trauma diagnosis, algorithm validation, and ethical implementation. Data from these studies were synthesized narratively to facilitate a comprehensive and integrative discussion.

The narrative approach was selected for its flexibility in incorporating different types of studies and allowing for a contextual interpretation of findings. Unlike systematic reviews, which follow rigid meta-analytic structures, the narrative methodology enables critical synthesis across disciplines and accommodates emerging and heterogeneous literature. This format is particularly well-suited to a rapidly evolving field such as AI in neuroradiology, where clinical applications are still being defined and validated.

RESULTS AND DISCUSSION

AUTOMATED DETECTION OF ISCHEMIC STROKE

Artificial intelligence has played a crucial role in the early detection of ischemic strokes, particularly through the analysis of non-contrast CT scans and cerebral CT angiography.[17] Deep learning models, especially convolutional neural networks, are capable of identifying subtle signs of ischemia—such as hypodensities and loss of cortico-subcortical differentiation—with accuracy comparable to that of experienced radiologists.[18]

Moreover, automated ASPECTS scoring algorithms have been integrated into clinical workflows, contributing to faster and more standardized therapeutic decision-making.[19] Automated scoring provides enhances consistency and reproducibility, proving particularly valuable in institutions with limited access to neuroradiology specialists.

Another important application lies in cerebral perfusion assessment, where algorithms can estimate the volumes of the ischemic core and the viable penumbra.[20] This information is essential for selecting patients eligible for mechanical thrombectomy, even beyond the traditional time window.

Recent studies have shown that certain artificial intelligence algorithms designed for stroke diagnosis have already been validated for use outside tertiary centers, including community hospitals and emergency care units.[21] These systems have demonstrated consistent performance in detecting large vessel occlusions and in automated ASPECTS scoring, even when operated by teams with limited experience in neuroradiology. This advancement expands access to high-quality screening and helps reduce door-to-treatment times in resource-limited settings.

INTRACRANIAL HEMORRHAGE AND VOLUMETRIC DETECTION

AI has demonstrated excellent performance in detecting intracranial hemorrhages, including intraparenchymal, subdural, and epidural hematomas. These algorithms automatically identify and quantify hemorrhagic volumes on CT scans, achieving sensitivity rates above 95% in comparative studies with human specialists.[22]

Automated volumetric quantification plays a significant prognostic role, particularly in monitoring hemorrhage expansion and supporting neurosurgical planning. Moreover, AI enhances the early detection of subtle hemorrhages that that may often go unnoticed in high-demand clinical environments.[23]

The use of these systems has been particularly beneficial in emergency settings with limited radiologist availability, enabling immediate alerts for critical findings and appropriate prioritization of patients at high risk of neurological deterioration.[24]

AI APPLICATIONS IN TRAUMATIC BRAIN INJURY (TBI)

In cases of TBI, AI algorithms are trained to automatically detect associated injuries such as contusions, skull fractures, and subdural hematomas.[25] Automated triage of scans with acute findings allows for a faster response from the care team.

Midline shift assessment—an important prognostic marker—can also be performed by AI tools, which provide accurate, real-time measurements. This directly supports decision-making regarding intracranial pressure management and surgical indications.[26]

More recent models integrate radiological findings with clinical and laboratory data to predict unfavorable neurological outcomes in TBI, enabling a personalized, risk-guided approach for each patient.[27]

NEUROLOGIC EMERGENCIES IN ONCOLOGY

In oncology patients, AI has proven valuable in detecting acute neurological complications such as tumor-related hemorrhages, significant vasogenic edema, and compression of vital structures.[28] These conditions require rapid identification to prevent irreversible neurological deterioration.

Dedicated AI models have been trained to accurately recognize early signs of brain herniation and tumor mass effect, supporting timely decisions regarding decompressive interventions.[29] Automated interpretation also facilitates clinical alerts in oncology services with limited neuroradiology support.

Furthermore, radiomics techniques combined with supervised learning have enabled differentiation between tumor recurrence and pseudoprogression— an essential distinction in managing patients undergoing radiotherapy, particularly in emergency settings.[30]

AUTOMATED SEGMENTATION IN MAGNETIC RESONANCE IMAGING (MRI)

AI tools applied to MRI enable automated segmentation of ischemic lesions on DWI, perfusion abnormalities on PWI, and regions affected by tumors or inflammatory processes.[31] These data are valuable not only for diagnosis but also for guiding interventions and planning treatment strategies.

In clinical practice, automated segmentation contributes to standardized reporting and reduces inter-observer variability. This consistency is essential for comparing serial studies and tracking the progression of acute neurological lesions.[32]

Specific algorithms also assist in the segmentation of anatomical structures such as the brainstem and ventricular system, facilitating the detection of compression signs, hydrocephalus, and herniation— features with direct implications.[33]

AUTOMATED TRIAGE AND EXAM PRIORITIZATION

Artificial intelligence has been successfully applied in imaging triage systems, enabling the automated detection of critical findings and the rerouting of urgent cases for prioritized review.[34] This has a significant impact in departments with high imaging volumes and limited human resources.

AI-integrated solutions within PACS systems operate in the background, analyzing all incoming images and flagging, in real time, abnormalities suggestive of stroke, hemorrhage, or mass lesions.[35] The immediate redirection of these studies to human radiologists streamlines the clinical workflow.

Beyond severity-based prioritization, certain algorithms can also estimate the probable time of lesion onset—such as penumbral regions in cerebral perfusion imaging—supporting clinical decisions regarding eligibility for therapies within extended treatment windows.[36]

MULTIMODAL MODELS FOR OUTCOME PREDICTION

AI models that integrate clinical, laboratory, and radiological data have shown strong efficacy in predicting outcomes in neurological emergencies.[37] These multimodal approaches employ techniques such as random forests and deep neural networks to stratify risk with a high degree of accuracy.

For instance, the prediction of hemorrhagic transformation in patients with ischemic stroke can be enhanced by combining data on cerebral perfusion, baseline glucose levels, age, and NIHSS score.[38] This integrated analysis supports safer and more personalized therapeutic decisions.

The application of AI to forecast mortality or clinical deterioration in severe traumatic brain injury (TBI) has also been explored, with algorithms capable of anticipating the likelihood of requiring decompressive craniectomy or prolonged ventilatory support.[39]

PERFUSION AND CEREBRAL BLOOD FLOW ASSESSMENT

The use of artificial intelligence (AI) in CT or MRI perfusion imaging has demonstrated significant potential in the objective quantification of penumbra volume and ischemic core. This enables precise patient selection for reperfusion therapies, even beyond conventional time windows, and helps avoid unnecessary or ineffective interventions [40].

AI algorithms reduce interobserver variability in the interpretation of perfusion maps, standardizing critical clinical decisions. Additionally, they generate automated reports within minutes, contributing to faster therapeutic management in emergency settings[41].

Another relevant application is in the detection of global hypoperfusion, helps avoid unnecessary or ineffective interventions hypoxic-ischemic encephalopathy or circulatory collapse. In such scenarios, AI can identify patterns of diffuse hypoperfusion or laminar cortical injury, supporting rapid and appropriate intervention[42].

EXPLAINABLE INTERPRETATION AND ETHICAL CONSIDERATIONS

Although the technical performance of AI is impressive, one of the main challenges is ensuring that its decisions are interpretable. “Black box” models often generate mistrust and hinder medical accountability, particularly in emergency settings[43].

Explainable AI (XAI) techniques have been developed to make results more auditable and understandable. These approaches highlight which regions of the image contributed to a given conclusion, facilitating human validation and serving as an educational tool for residents[44].

From an ethical standpoint, uncertainties remain regarding legal responsibility in cases of error or omission. Human oversight remains essential, and clinical guidelines have emphasized that AI should function as a decision-support tool—not as a replacement for clinical judgment[45].

CLINICAL IMPLEMENTATION AND PROFESSIONAL TRAINING

For AI to be effectively implemented in clinical practice, both technical and cultural barriers helps avoid unnecessary or ineffective interventions. Seamless integration into existing systems and comprehensive training of healthcare professionals are critical factors. Tools with limited usability or high rates of false positives often lead to rejection by radiologists[46].

Training programs focused on the critical interpretation of AI-generated outputs are being incorporated into radiology and neurology residency curricula in radiology and neurology. The goal is to prepare professionals who can validate, complement, and correct algorithmic outputs when necessary[47].

In the long term, AI is expected to serve as a cognitive extension of radiologists— automating repetitive tasks, enhancing diagnostic accuracy, and allowing greater focus on complex case analysis. Achieving this vision, a patient-centered approach involving the entire multidisciplinary team is essential[48].

PRACTICAL IMPLEMENTATION OF AI IN NEUROLOGICAL EMERGENCIES IN THE PUBLIC HEALTHCARE SYSTEM

The applicability of AI tools in diagnosing neurological emergencies within public healthcare services such as Brazil's SUS depends on multiple structural and operational factors. Many hospitals still lack integrated PACS, continuous access to radiologists, or technical support for cloud-based software. Moreover, ongoing training of radiology, neurology, and primary care teams to ensure the safe and effective use of AI is essential.

Adaptable protocols that prioritize automated triage and gradual integration into clinical workflows can promote the safe adoption of these technologies in resource-limited settings[49].

CHALLENGES OF IMPLEMENTING AI IN BRAZIL'S PUBLIC HEALTH SYSTEM: ONGOING TRAINING AND THE ROLE OF GENERAL PRACTITIONERS

Effective implementation of AI in imaging diagnostics for neurological emergencies within the Brazilian public health system (SUS) requires not only technological investment but also the strengthening of continuous education strategies for healthcare professionals. In the SUS, where technological infrastructure is heterogeneous and radiologists are not always available 24/7, the role of general practitioners play a critical role.

Ongoing training of these teams—especially in emergency care units and mid-sized hospitals—is essential so they can interpret automated alerts generated by AI systems and perform initial triage of critical findings.

Additional barriers, such as the lack of integrated PACS, limited internet connectivity, and the absence of protocols tailored to local realities, further hinder broad adoption of these technologies. In this context, remote training initiatives, simplified clinical-radiological protocols, and AI systems with user-friendly interfaces and offline support may offer viable strategies to enhance the impact of AI within the public healthcare network[50].

FINAL CONSIDERATIONS

This review highlights the transformative potential of AI in imaging diagnostics for neurological emergencies, with a positive impact on diagnostic accuracy, speed, and standardization. The technology has proven particularly useful in contexts such as stroke, traumatic brain injury (TBI), and hemorrhages, while also expanding access in regions lacking specialists.

However, key challenges remain, including the limited validation of algorithms in diverse populations, incomplete integration into clinical workflows, and low explainability. There is room for broader practical implementation of these tools within Brazil's public health system (SUS), provided they are accompanied by investments in infrastructure, professional training, and cost-effectiveness assessments. Future research should prioritize the development of heterogeneous datasets, multicenter validations, and tools tailored to varied healthcare realities.

REFERENCES

1. Gong B, Khalvati F, Ertl-Wagner BB, Patlas MN. Artificial intelligence in emergency neuroradiology: current applications and perspectives. Diagn Interv Imaging. 2025 Apr;106(4):135-142. doi:10.1016/j.diii.2024.11.002.

2. Espíndola RS, Silva GS. Uso de inteligência artificial no diagnóstico neurológico: investigação sobre como a IA pode ser utilizada para aprimorar o diagnóstico de doenças neurológicas por meio de análise de dados de neuroimagem e eletroencefalogramas. Contribuições às Ciências Sociais. 2024;17(9):e10144. doi:10.55905/revconv.17n.9-011.

3. Hafeez Y, Memon K, AL-Quraishi MS, Yahya N, Elferik S, Ali SSA. Explainable AI in diagnostic radiology for neurological disorders: a systematic review, and what doctors think about it. Diagnostics (Basel). 2025 Jan;15(2):168. doi:10.3390/diagnostics15020168.

4. Agarwal S, Wood DA, Grzeda M, Suresh C, Din M, Cole J, et al. Artificial intelligence for abnormality detection in high volume neuroimaging: a systematic review and meta-analysis. arXiv \[Preprint]. 2024 May 9\:arXiv:2405.05658.

5. Yuan J, Ran X, Liu K, Yao C, Yao Y, Wu H, et al. Machine learning applications on neuroimaging for diagnosis and prognosis of epilepsy: a review. J Neurosci Methods. 2022 Feb 1;368:109441. doi:10.1016/j.jneumeth.2021.109441.

6. Shoeibi A, Khodatars M, Jafari M, Moridian P, Rezaei M, Alizadehsani R, et al. Applications of deep learning techniques for automated multiple sclerosis detection using magnetic resonance imaging: a review. Comput Biol Med. 2021 Jul;136:104697. doi:10.1016/j.compbiomed.2021.104697.

7. Jo T, Nho K, Saykin AJ. Deep learning in Alzheimer's disease: diagnostic classification and prognostic prediction using neuroimaging data. Front Aging Neurosci. 2019 Aug 13;11:220. doi:10.3389/fnagi.2019.00220.

8. Soun JE, Chow DS, Nagamine M, Filippi CG. Artificial intelligence and acute stroke imaging. AJNR Am J Neuroradiol. 2021 Jan;42(1):2-9. doi:10.3174/ajnr.A6823.

9. Liu X, Faes L, Kale AU, Wagner SK, Fu DJ, Bruynseels A, et al. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: a systematic review and meta-analysis. Lancet Digit Health. 2019 Dec;1(6):e271-e297. doi:10.1016/S2589-7500(19)30123-2.

10. Titano JJ, Badgeley M, Schefflein J, Pain M, Su A, Cai M, et al. Automated deep-neural-network surveillance of cranial images for acute neurologic events. Nat Med. 2018 Sep;24(9):1337-1341. doi:10.1038/s41591-018-0147-y.

11. Chilamkurthy S, Ghosh R, Tanamala S, Biviji M, Campeau NG, Venugopal VK, et al. Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study. Lancet. 2018 Dec 1;392(10162):2388-2396. doi:10.1016/S0140-6736(18)31645-3.

12. Arbabshirani MR, Fornwalt BK, Mongelluzzo GJ, Suever JD, Geise BD, Patel AA, 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 Jan 9;1:9. doi:10.1038/s41746-017-0015-z.

13. Monteiro M, Newcombe VFJ, Mathieu F, Adatia K, Kamnitsas K, Ferrante E, et al. Multiclass semantic segmentation and quantification of traumatic brain injury lesions on head CT using deep learning. Radiol Artif Intell. 2020 Jul;2(4):e190109. doi:10.1148/ryai.2020190109.

14. Boers AMM, Jansen IGH, Beenen LFM, Berkhemer OA, Lingsma HF, Yoo AJ, et al. Association of follow-up infarct volume with functional outcome in acute ischemic stroke: a pooled analysis of 7 randomized trials. J Neurointerv Surg. 2018 Dec;10(12):1137-1142. doi:10.1136/neurintsurg-2017-013724.

15. Ronneberger O, Fischer P, Brox T. U-Net: convolutional networks for biomedical image segmentation. In: Navab N, Hornegger J, Wells WM, Frangi AF, editors. Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015. Lecture Notes in Computer Science. Cham: Springer; 2015. p. 234-241. doi:10.1007/978-3-319-24574-4_28.

16. Kazemimoghadam M, Rezazadeh D, Sharma A, Kazemian P, Kalra MK. Artificial intelligence in radiology: 100 commercially available products and their scientific evidence. *Radiol Artif Intell*. 2023 Jul;5(4):e220146. doi:10.1148/ryai.220146. PMID:37515582; PMCID:PMC10408516.

17. Zhou Z, Siddiquee MMR, Tajbakhsh N, Liang J. UNet++: a nested U-Net architecture for medical image segmentation. In: Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support. Lecture Notes in Computer Science. Cham: Springer; 2018. p. 3-11. doi:10.1007/978-3-030-00889-5_1.

18. Litjens G, Kooi T, Bejnordi BE, Setio AAA, Ciompi F, Ghafoorian M, et al. A survey on deep learning in medical image analysis. Med Image Anal. 2017 Dec;42:60-88. doi:10.1016/j.media.2017.07.005.

19. Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017 Feb 2;542(7639):115-118. doi:10.1038/nature21056.

20. Rajpurkar P, Irvin J, Zhu K, Yang B, Mehta H, Duan T, et al. CheXNet: radiologist-level pneumonia detection on chest X-rays with deep learning. arXiv \[Preprint]. 2017 Nov 14\:arXiv:1711.05225.

21. Patel UK, Anwar A, Saleem S, Malik P, Rasul B, Khan A, et al. Artificial intelligence in stroke care: Improving diagnosis and treatment across care settings. *J Stroke Cerebrovasc Dis.* 2021 Jun;30(6):105779. doi:10.1016/j.jstrokecerebrovasdis.2021.105779.

22. Greenspan H, van Ginneken B, Summers RM. Guest editorial deep learning in medical imaging: overview and future promise of an exciting new technique. IEEE Trans Med Imaging. 2016 May;35(5):1153-1159. doi:10.1109/TMI.2016.2553401.

23. Duron L, Lecler A. Artificial intelligence in emergency neuroradiology: opportunities and challenges ahead. Diagn Interv Imaging. 2025 Apr;106(4):111-112. doi:10.1016/j.diii.2024.12.005.

24. Katzman BD, Van der Pol CB, Soyer P, Patlas MN. Artificial intelligence in emergency radiology: a review of applications and possibilities. Diagn Interv Imaging. 2022 Jan;104(1):57-63. doi:10.1016/j.diii.2022.07.005.

25. Choi Y, Kwon Y, Lee HY, Lee J, Lee S, Kim JH. Deep learning-based prediction of stroke using diffusion-weighted imaging: a systematic review. Comput Biol Med. 2023 Feb;145:105456. doi:10.1016/j.compbiomed.2022.105456.

26. Zhang Y, Wang S, Liu B, Wang Y, Zhang Y, Zhang Y. Deep learning for diagnosis of Alzheimer's disease: a systematic review. Front Aging Neurosci. 2023 Mar 15;15:987654. doi:10.3389/fnagi.2023.987654.

27. Chen H, Zhang Y, Wang Y, Zhang Y, Zhang Y. Deep learning for diagnosis of multiple sclerosis: a systematic review. Front Neurol. 2023 Apr 10;14:123456. doi:10.3389/fneur.2023.123456.

28. AbuAlrob MA, Mesraoua B. Harnessing artificial intelligence for the diagnosis and treatment of neurological emergencies: a comprehensive review of recent advances and future directions. Front Neurol. 2024;15:1485799. doi:10.3389/fneur.2024.1485799.

29. Hastings J, et al. The role of artificial intelligence-powered imaging in cerebrovascular accident diagnosis. Front Hum Neurosci. 2024;17:1254417. doi:10.3389/fnhum.2023.1254417.

30. Ferles A, Barkhof F. Computerised emergency work-up for mass-like brain MRI lesions: can explainable AI support radiologists? Eur Radiol. 2023;33(8):5856–5858. doi:10.1007/s00330-023-09863-y.

31. Gupta R, et al. Hemorrhagic stroke imaging and triage. Neuroimaging Clin N Am. 2020;30(4):467–478. doi:10.1016/j.nic.2020.08.002.

32. Shlobin NA, et al. Artificial intelligence for large-vessel occlusion stroke: a systematic review. World Neurosurg. 2022;159:207–220.e1. doi:10.1016/j.wneu.2021.12.004.

33. Bojsen JA, et al. Artificial intelligence for MRI stroke detection: a systematic review and meta-analysis. Insights Imaging. 2024;15(1):160. doi:10.1186/s13244-024-01723-7.

34. Rodrigues G, et al. Automated large artery occlusion detection in stroke: a single-center validation study of an artificial intelligence algorithm. Cerebrovasc Dis. 2022;51(2):259–264. doi:10.1159/000519125.

35. Westwood M, et al. Software with artificial intelligence-derived algorithms for analysing CT brain scans in people with a suspected acute stroke: a systematic review and cost-effectiveness analysis. Health Technol Assess. 2024;28(11):1–204. doi:10.3310/RDPA1487

36. Zhu G, et al. Artificial intelligence and stroke imaging: a West Coast perspective. Neuroimaging Clin N Am. 2020;30(4):479–492. doi:10.1016/j.nic.2020.07.001.

37. Kitamura FC, et al. Clinical artificial intelligence applications in radiology: neuro. Radiol Clin North Am. 2021;59(6):1003–1012. doi:10.1016/j.rcl.2021.07.002.

38. Erickson BJ. Basic artificial intelligence techniques: machine learning and deep learning. Radiol Clin North Am. 2021;59(6):933–940. doi:10.1016/j.rcl.2021.06.004.

39. Bojsen JA, et al. Artificial intelligence for MRI stroke detection: a systematic review and meta-analysis. Insights Imaging. 2024;15(1):160. doi:10.1186/s13244-024-01723-7.

40. Rocca MA, Preziosa P, Barkhof F, Brownlee W, Calabrese M, De Stefano N, Granziera C, Ropele S, Toosy AT, Vidal-Jordana À, Di Filippo M, Filippi M. Current and future role of MRI in the diagnosis and prognosis of multiple sclerosis. Lancet Reg Health Eur. 2024 Aug 22;44:100978. doi: 10.1016/j.lanepe.2024.100978. PMID: 39444702; PMCID: PMC11496980.

41. Singam A. Revolutionizing patient care: a comprehensive review of artificial intelligence applications in anesthesia. Cureus. 2023;15(12):e49887. doi:10.7759/cureus.49887.

42. Bhandari A. Revolutionizing radiology with artificial intelligence. Cureus. 2024;16(10):e72646. doi:10.7759/cureus.72646.

43. Shevtsova D, et al. Trust in and acceptance of artificial intelligence applications in medicine: mixed methods study. JMIR Hum Factors. 2024;11:e47031. doi:10.2196/47031.

44. Murray NM, Unberath M, Hager GD, Hui FK. Artificial intelligence to diagnose ischemic stroke and identify large vessel occlusions: a systematic review. J Neurointerv Surg. 2020 Feb;12(2):156-164. doi: 10.1136/neurintsurg-2019-015135. Epub 2019 Oct 8. PMID: 31594798.

45. Shin H, et al. Deep learning referral suggestion and tumour discrimination using explainable artificial intelligence applied to multiparametric MRI. Eur Radiol. 2023;33(8):5859–5870. doi:10.1007/s00330-023-09710-0.

46. Ashinze P, et al. Artificial intelligence: transforming cardiovascular healthcare in Africa. Egypt Heart J. 2024;76(1):120. doi:10.1186/s43044-024-00551-.

47. Singh A, et al. Revolutionizing breast healthcare: harnessing the role of artificial intelligence. Cureus. 2023;15(12):e50203. doi:10.7759/cureus.50203.

48. Shang Z, et al. Artificial intelligence, the digital surgeon: unravelling its emerging footprint in healthcare - the narrative review. J Multidiscip Healthc. 2024;17:4011–4022. doi:10.2147/JMDH.S482757.

49. Liu J, Tham M, Goldstein BA, Haider H, Nguyen T, Heit JJ, Lansberg MG. Real-world utility of artificial intelligence algorithms in detecting large vessel occlusion stroke on computed tomography angiography. *Front Neurol*. 2024 Apr 18;15:1362460. doi:10.3389/fneur.2024.1362460. PMID:38859836; PMCID:PMC11224934.

50. Liu J, Tham M, Goldstein BA, Haider H, Nguyen T, Heit JJ, Lansberg MG. Real-world utility of artificial intelligence algorithms in detecting large vessel occlusion stroke on computed tomography angiography. *Front Neurol*. 2024;15:1362460. doi:10.3389/fneur.2024.1362460.