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Artificial Intelligence in Health

REVIEW ARTICLE

Applications of artificial intelligence in acute stroke imaging

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Abstract

Stroke remains a major global public health challenge, representing the second leading cause of death worldwide and a primary contributor to long-term disability. The paradigm "time is brain" underscores the importance of treating stroke patients within the critical window period, ideally within 60 min from symptom onset, to minimize damage and improve outcomes. The integration of artificial intelligence (AI) into stroke imaging has transformed diagnosis and management by increasing speed, accuracy, and efficiency. AI algorithms have been trained to detect acute stroke, assess hemorrhage, detect and quantify midline shifts, calculate automated Alberta Stroke Program Early Computed Tomography Scores, and identify dense middle cerebral artery on non-contrast computed tomography (CT) as well as large vessel occlusions on CT angiograms, with high sensitivity and specificity. AI also aids in treatment guidance and outcome monitoring. This review provides insights into AI applications in acute stroke imaging, including its role in early detection, screening, triage and prioritization, automated image analysis, workflow optimization, and system integration. Despite its benefits, AI adoption faces challenges such as clinical validation, ethical considerations, and integration into existing workflows. Future developments depend on large, diverse, and well-annotated datasets to train more robust AI systems capable of guiding treatment strategies and improving patient outcomes. The seamless integration of cloud-based AI solutions with telereporting platforms has the potential to revolutionize stroke care by enabling rapid, high-quality radiologic interpretation, even in remote locations.

Keywords: Artificial intelligence; Stroke imaging; Computed tomography angiograms; Magnetic resonance angiography; Hemorrhage; Teleradiology; Workflow integration

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1. Introduction

Stroke is the second leading cause of mortality and a major global health concern, responsible for about 5.5 million deaths annually, and was the fourth-highest Level 3 cause of disability-adjusted life years (DALYs) in 2021.[1] It is a medical emergency defined by the sudden reduction of blood flow to the brain, leading to cell death and functional impairments. According to the World Health Organization, stroke accounts for nearly 11% of global deaths.[2] Furthermore, global DALYs due to stroke have surged from 119.89 million in 1990 to 159.86 million in 2021, driven by population growth and increased life expectancy. This figure is projected to rise to 186.88 million by 2030 and 224.86 million by 2050, as reported by Cheng *et al.*[3] in the Global Burden of Disease 2021 study. In India, stroke is the fourth-leading cause of death and the fifth-leading cause of disability. The stroke-related death rate in India has increased from 44 to 55 people per 100,000 population between 1990 and 2021.[2] According to a study conducted by Pandian *et al.*,[4] India has the highest DALYs due to stroke among countries in the Southeast Asia Region.

A striking feature in India is that a large proportion of the stroke patients are from the younger population, unlike in developed countries. Nearly 20% of patients hospitalized with a first-time stroke are under 40 years of age.[5] Younger individuals are increasingly at risk due to sedentary lifestyles, substance use (including tobacco, nicotine, alcohol, and illicit drugs), and stress. Other risk factors involve elevated blood pressure, blood sugar, cholesterol, and body weight.[6,7]

The paradigm "time is brain" is pivotal in stroke care, as millions of neurons die with each minute that a stroke goes untreated. Therefore, treating stroke patients within the critical window period or the golden hour (within 60 min of symptom onset) is essential. During this time, physicians should administer medication and initiate treatment as quickly as possible.[8] Beyond this golden hour, irreversible brain damage occurs, making treatment less effective. Treatment strategies include intravenous tissue plasminogen activator for thrombolysis and endovascular treatment (EVT).[9] Timely intervention is critical to minimize damage and improve outcomes. However, disparities in stroke care persist due to delays in diagnosis, limited access to treatment, and a shortage of radiologists and stroke care experts. Teleradiology has transformed stroke care by enabling rapid, high-quality, and accurate radiologic interpretation, even from remote locations.[8,10-12] Still, the sharp rise in the volume of radiologic imaging, without a corresponding increase in the number of trained radiologists, necessitates more scalable and efficient solutions.[13]

Neuroimaging is essential for identifying acute strokes and distinguishing between ischemic and hemorrhagic types.[14] Tools such as computed tomography (CT) and magnetic resonance imaging (MRI) are pivotal in detecting, characterizing, and diagnosing strokes. Artificial intelligence (AI) is a rapidly advancing field that offers powerful tools for fast and efficient imaging analysis. Its emergence has enabled the analysis of large datasets, pattern recognition, and prediction with unprecedented speed and accuracy. In healthcare, AI is growing at a rate of 40% per annum and is projected to help decrease healthcare costs by United States Dollar 150 billion by 2026.[15] AI-powered tools further enhance radiologic image analysis, enabling fast and precise identification of ischemic and hemorrhagic strokes, as well as vascular abnormalities, thereby supporting swift and effective stroke management.

Machine learning algorithms assist in analyzing CT angiograms and identifying large vessel occlusions (LVOs) in real time. Studies have shown that these AI tools reduce door-to-treatment times by promptly alerting clinicians.[16] AI can assess imaging data to determine whether a patient is eligible for procedures like mechanical thrombectomy or tissue plasminogen activator administration. AI models also analyze electronic health records, imaging data, and outputs from wearable devices to assess stroke risk. For example, predictive algorithms can detect atrial fibrillation, a major stroke risk factor, from smartwatch electrocardiogram data with high sensitivity.[17]

Several studies have evaluated the role of AI in stroke management and patient care.[18-23] A review article by Liu *et al.*[18] highlights the role of AI in areas such as automated segmentation of infarct areas, identification of LVOs, stroke outcome prediction, analysis of hemorrhagic transformation risk, prediction of recurrent ischemic stroke, and automated grading of collateral circulation. Al-Janabi *et al.*[19] provided an overview of the AI tools used to identify strokes and guide acute ischemic stroke care.

This review paper explores the transformative potential of AI in stroke care. It provides an overview of AI applications in acute stroke care imaging, focusing on the advancements in detection and screening, triaging and prioritization, quantification and prognosis, automated image interpretation, and workflow optimization, supported by published review articles on the subject.

2. Methodology

A comprehensive literature search was conducted using the PubMed and Google Scholar databases, focusing on papers evaluating the use of AI in stroke imaging, published between 2014 and 2024. Keywords used for the search included "artificial intelligence in stroke," "AI in acute stroke," "AI in hemorrhage," "AI in ASPECTS score," "AI in large vessel occlusion," and "AI in midline shift."

Studies were included if they focused on the application of AI in stroke imaging, specifically involving acute stroke, hemorrhage detection, Alberta Stroke Program Early Computed Tomography Scoring (ASPECTS), LVO detection, or midline shift assessment. Only original research articles, reviews, and systematic reviews written in English and with full-text availability were considered.

Studies were excluded if they were unrelated to medical imaging or the application of AI in stroke, or if they were duplicates, conference proceedings, commentaries, editorials, or abstracts without full-text access.

A total of 316 studies were initially retrieved through database searches. After removing 33 duplicates, 283 studies remained for title and abstract screening. Of these, 127 full-text articles were assessed for eligibility based on the inclusion and exclusion criteria. A final total of 78 studies were included in the review.

The study selection process is depicted in Figure 1.

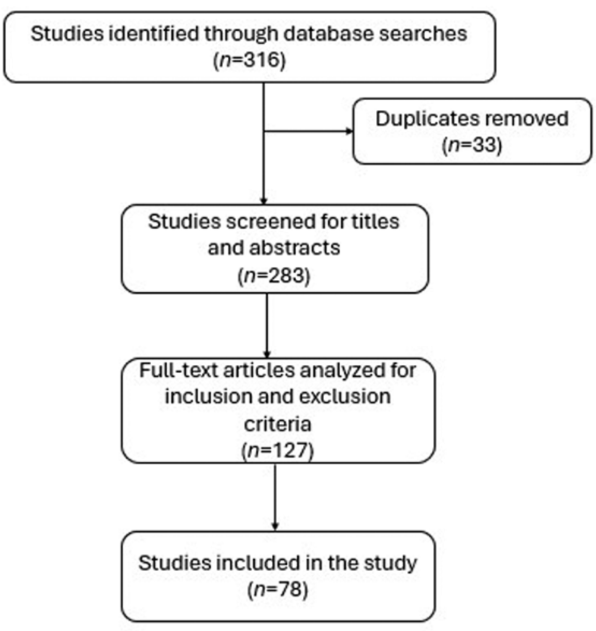


Figure 1. The article search and screening process

3. Results

AI has introduced a paradigm shift in medical imaging.[24] The application of AI in stroke imaging spans multiple domains, including screening, detection, triage, and automated diagnosis of carotid artery disease,[25-27] brain hemorrhage and infarct segmentation, quantification, and prognosis; distinguishing ischemic from non-ischemic tissue and normal versus infarcted brain;[28-36] midline shift detection and quantification;[37-41] automated ASPECT score calculation;[42-46] and detection of dense middle cerebral artery (MCA) and LVO on CT angiograms.[47-53] Several commercially available AI-integrated workflows have been developed to interpret ischemic stroke imaging automatically (Table 1). These AI-driven tools enhance workflow integration, optimize radiological interpretation, and improve stroke management.

3.1. AI in stroke screening

Carotid artery stenosis is commonly associated with plaque progression and accounts for 10 – 20% of ischemic strokes due to atherothrombotic disease. Non-invasive imaging techniques used to assess the likelihood of atherosclerotic plaque formation and evaluate lumen diameter reduction include MRI, CT angiograms (CTA), and ultrasound imaging. AI enhances imaging interpretation by identifying even minute plaques that may go unnoticed by radiologists, thereby facilitating timely diagnosis and treatment of carotid artery disease. It also helps standardize the identification and quantification of carotid plaque across various medical imaging centers and among different physicians. A study by Kordzadeh *et al.*[25] demonstrated the applicability and precision of AI in detecting carotid artery disease using grayscale static duplex ultrasound images. In their findings, the AI system achieved 91% sensitivity, 86% specificity, and 92% accuracy in identifying normal carotid arteries, and 87% sensitivity, 82% specificity, and 90% accuracy in detecting any degree of carotid artery stenosis. Skandha *et al.*[26] conducted a study using echocolor Doppler imaging on the internal carotid arteries of 345 patients and developed a diffusion convolutional neural network to distinguish symptomatic and asymptomatic plaques, achieving an accuracy of 95.66% (area under the curve [AUC] 0.956, $p<0.0001$). AI algorithms also improve the detection and characterization of carotid plaques through CTA and MRA. In CTA, AI enables early plaque detection, standardizes quantification, and assesses plaque vulnerability. In MRA, AI estimates varying degrees of carotid artery stenosis and automates risk assessment using MRI-based models, such as the high-risk plaque MRI model, which automatically estimates risk scores related to plaque vulnerability.[27] These algorithms play a pivotal role as segmentation systems, differentiating between different layers (such as the lumen, outer wall, and lipid core), and various components of atherosclerotic plaque on T1- and proton density-weighted images, enabling precise identification of plaque contours and vulnerable lesions.

3.2. AI in acute stroke imaging

3.2.1. Assessment of hemorrhage

Hemorrhagic strokes, classified based on the location of bleeding, include subarachnoid hemorrhage, intraparenchymal hemorrhage, and intraventricular hemorrhage.[28] AI algorithms have shown high sensitivity and specificity in detecting hemorrhages, even in challenging cases involving small bleeds or complex brain anatomy. These tools are capable of segmenting and quantifying hemorrhages, thereby improving classification and localization. For instance, a study by Rava *et al.*[28] demonstrated that the AI could automate the detection and triage of patients undergoing non-contrast CT (NCCT)

Table 1. List of artificial intelligence (AI) algorithms in acute stroke imaging, along with their analytical performance metrics

No.	Findings	AI model	Vendor	Sensitivity (%)	Specificity (%)	Accuracy (%)	Cohort size	Study design type	Reference
1	Hemorrhage	AUTOStroke Solution	Canon	93	93	NA	200	Retrospective	Rava *et al.*[28]
		Qure.ai	Qure.ai	NA	NA	NA	21,095	Retrospective	Chilamkurthy *et al.*[29]
		Neural Assist	TeleradTech	92	84	84	21,420	Prospective	-
2	Midline shift	qER-Quant software	Qure.ai	95	95	NA	313,318 head CT	Retrospective	Chilamkurthy *et al.*[29]
		Neural Assist	TeleradTech	84	89	89	22,729	Prospective	-
3	ASPECT score	AI DLAD	D.LABS	65	82	80	258	Retrospective	Chiang *et al.*[43]
		Deep-ASPECTS	Qure.ai	77	99	NA	5,000	Retrospective	Upadhyay *et al.*[44]
		RAPID ASPECTS	iSchemaView	NA	NA	NA	100	Retrospective	Maegerlein *et al.*[45]
		e-ASPECTS	Brainomix	44	93	87	2,640	Retrospective	Nagel *et al.*[46]
4	Dense MCA	Xception Model	viso.ai	82.90	89.70	86.50	18,396	Retrospective	Shinohara *et al.*[48]
		Neural Assist	TeleradTech	56.25	94	89.7	22,708	Prospective	-
5	LVO	Viz-LVO	Viz.ai	80.3	82.9	82.70	610	Retrospective	Rodrigues *et al.*[51]
		AUTOStroke Solution	Canon	73	98	81	303	Retrospective	Rava *et al.*[52]
		RAPID-CTA	Rapid AI	94	76	NA	477	Retrospective	Amukotuwa *et al.*[53]
6	CT Perfusion analysis	Viz CTP	Viz.ai	80	86.20	NA	94 labeled training images and 62 unlabeled testing images	Retrospective	Soun *et al.*[1]
		e-CTP	Brainomix®	NA	NA	NA	111	Retrospective	Shahrouki *et al.*[57]

Note: This table enlists selected examples of AI algorithms currently available on the market and does not represent a complete list.
Abbreviations: ASPECTS: Alberta Stroke Program Early Computed Tomography Score; CT: Computed tomography; CTA: Computed tomography angiograms; CTP: Computed tomography perfusion; DLAD: Deep learning-based automatic detection; LVO: Large vessel occlusion; MCA: Middle cerebral artery; NA: Not available.

by classifying them as intracranial hemorrhage positive or negative, with a specificity of 0.93 ± 0.01, sensitivity of 0.93 ± 0.03, positive predictive value of 0.85 ± 0.02, and negative predictive value of 0.98 ± 0.01. Similarly, the AI algorithm *Neural Assist* by TeleradTech classifies, localizes, and quantifies hemorrhages with 92% sensitivity and 83% specificity, as prospectively studied in a cohort of 21,420 scans. It accurately detects various hemorrhage types with an overall accuracy of 85% (Figures 2A-D and 3). *Neural Assist* processes non-contrast adult head CT Digital Imaging and Communications in Medicine (DICOM) files and analyzes them to detect intracranial hemorrhage, midline shift, cranial fractures, and dense MCA signs. It prioritizes critical scans by generating priority flags and automatically produces a preliminary report to support specialist review (Figure 4). The output is a structured report available in DICOM, PDF, or DOC formats. Additionally, a study by Chilamkurthy *et al.*[29] reported that their AI algorithms achieved AUC values of 0.8977, 0.9559, 0.9194, 0.9161, 0.9044, and 0.9288 for detecting intraparenchymal hemorrhage, intraventricular hemorrhage, intracranial hemorrhage, subdural hematoma (SDH), subarachnoid hemorrhage, and epidural hematoma, respectively.

3.2.2. Detection of midline shift

Midline shift is a crucial indicator of the lateral displacement of midline structures of the brain due to trauma or mass effects resulting from hematomas, tumors, abscesses, or intracranial lesions. It serves as a key prognostic feature in stroke.[37] AI tools used to measure midline shift are generally categorized into two types: Symmetry-based approaches, which calculate the curve of the deformed midline, and landmark-based approaches, which detect anatomical landmarks such as the septum pellucidum within specified ventricular regions and measure midline shift accordingly.[38] Chilamkurthy *et al.*[29]

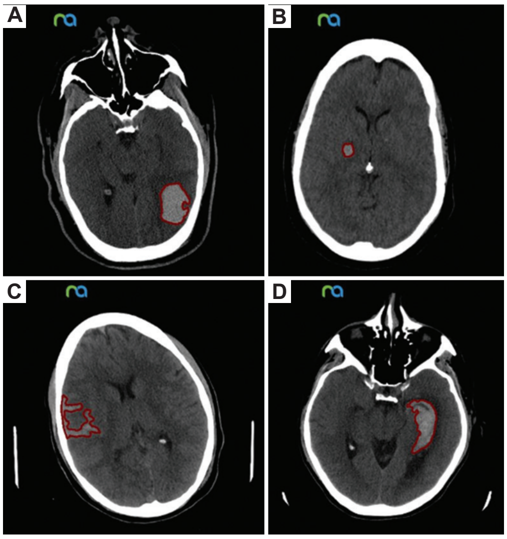


Figure 2. TeleradTech artificial intelligence *Neural Assist* algorithm in detection of hemorrhages: (A) and (B) intraparenchymal hemorrhage, (C) subarachnoid hemorrhage, (D) intraventricular hemorrhage

Hemorrhage findings

Type of hemorrhage	Hemorrhage location	Quantification
Intraparenchymal hemorrhage (IPH)	Right ganglio-thalamus (Slice -13)	Length: 7 mm, Width: 1.2cm

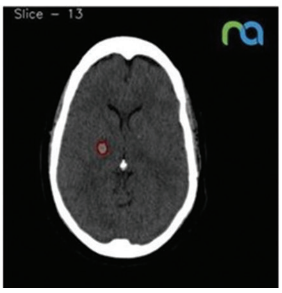
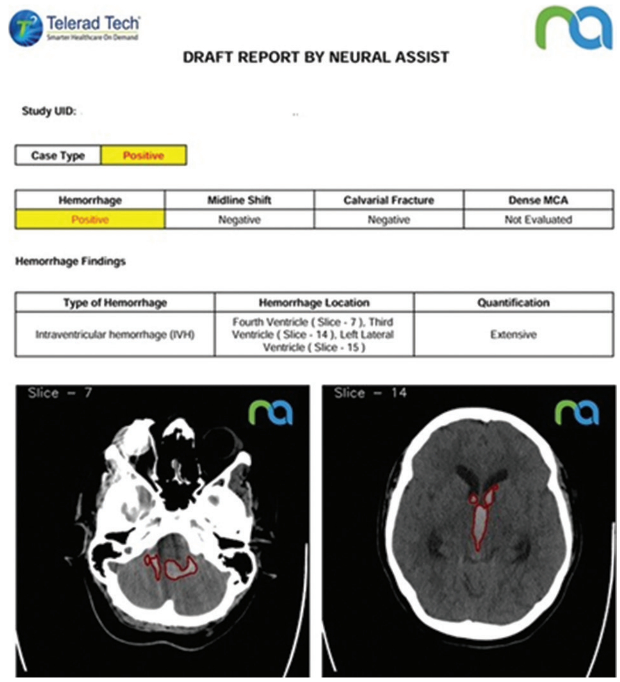


Figure 3. Classification, localization, and quantification of hemorrhage by TeleradTech's artificial intelligence *Neural Assist* algorithm

proposed an AI model that detects midline shift (MLS) with an AUC of 0.9276. Nguyen *et al.*[39] developed a deep learning algorithm that attained a case-level midline shift identification AUC of 95.3%, utilizing a testing dataset of 2,545 NCCT head scans, and measured midline shift with an average absolute error of 1.20 mm across 228 midline shift-positive cases. Chen *et al.*[40] described an automated process using CT imaging to quantify MLS and triage for elevated intracranial pressure. The AI Neural Assist algorithm developed by TeleradTech detects midline shift with 84% sensitivity and 89% specificity, based on a cohort of 22,729 patients (Figure 5).

3.2.3. ASPECTS analysis

The ASPECTS is a scoring system generally used to guide treatment strategies for patients presenting with MCA



Telerad Tech

DRAFT REPORT BY NEURAL ASSIST

Study UID:

Case Type	Positive

Hemorrhage	Midline Shift	Calvarial Fracture	Dense MCA
Positive	Negative	Negative	Not Evaluated

Hemorrhage Findings

Type of Hemorrhage	Hemorrhage Location	Quantification
Intraventricular hemorrhage (IVH)	Fourth Ventricle (Slice - 7), Third Ventricle (Slice - 14), Left Lateral Ventricle (Slice - 15)	Extensive

Slice – 7

Slice – 14

Figure 4. Draft radiology report generated by TeleradTech's artificial intelligence *Neural Assist* algorithm

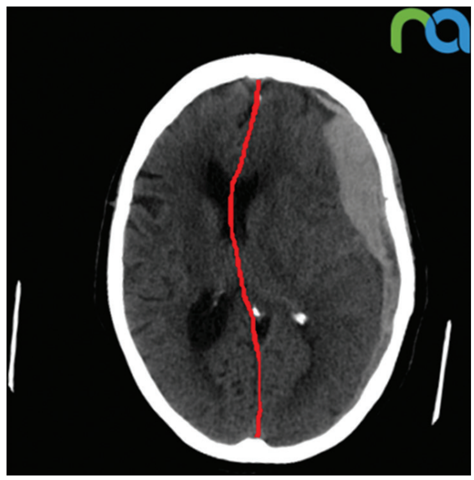


Figure 5. Detection of midline shift by TeleradTech artificial intelligence *Neural Assist* algorithm

ischemic strokes using NCCT brain scans.[42] AI algorithms assist in automating ASPECTS calculation, enabling rapid and accurate evaluation of acute ischemic stroke severity on NCCT scans and ultimately improving stroke care. For example, Chiang *et al.*[43] studied the potential of a deep learning-based automatic detection (DLAD) algorithm for ASPECT scoring on NCCT images in patients with symptoms of acute ischemic stroke. The DLAD achieved 65% sensitivity, 82% specificity, and 80% accuracy in ASPECTS prediction, thus enhancing and expediting physician decision-making. Upadhyay *et al.*[44] evaluated an AI algorithm for automated ASPECT scoring, which decreased diagnosis time for NCCT scans and demonstrated a 76.19% agreement with radiologists. AI-assisted ASPECT scoring systems have shown outcomes comparable to, or in some cases better than, manual assessments by clinicians. They demonstrate good to excellent reliability, with intraclass correlation coefficients indicating strong agreement with expert consensus and reference standards. In a study by Maegerlein *et al.*,[45] AI-generated ASPECTS in acute MCA stroke showed better agreement with predefined consensus scores than human readers alone. AI tools not only reduce inter-observer variability but also enhance clinical decision-making by providing quick and reliable ASPECT scores, which are critical for assessing the severity of acute ischemic stroke and determining patient eligibility for treatments like thrombectomy and thrombolysis.[46,47] Additionally, features such as heat maps indicate the probability of low attenuation and sulcal effacement.

3.2.4. MCA

In a study conducted by Shinohara *et al.*[48] on a cohort of patients with acute ischemic stroke, the diagnostic performance of a deep convolutional neural network model (Xception) was evaluated for the identification and prioritization of the hyperdense MCA sign on NCCT. The model demonstrated a sensitivity of 82.9%, specificity of 89.7%, and accuracy of 86.5% using leave-one-case-out cross-validation. Furthermore, the AI *Neural Assist* algorithm developed by TeleradTech detected dense MCA with an accuracy of 89.7% (Figure 6).

3.2.5. LVO

AI algorithms enable rapid and accurate detection of LVO, facilitating timely alerts and swift decision-making for reperfusion treatments or transfer to specialized stroke centers when needed. Various studies have demonstrated that AI tools can precisely identify LVO on CTA in real time.[49-53] Le *et al.*[50] demonstrated that a machine learning algorithm used for automated LVO detection on CTA, coupled with secure communication at non-EVT-performing primary stroke centers, significantly reduced door-in-door-out time by promptly alerting clinicians. This intervention increased the number of patients undergoing EVT after transfer, ultimately improving patient outcomes. In a retrospective study by Rodrigues *et al.*[51] found that the AI Viz-LVO Algorithm® version 1.4 detected internal carotid artery and MCA-M1 LVOs with a sensitivity of 87.6%, specificity of 88.5%, and accuracy of 87.9% (AUC 0.88). Similarly, Rava *et al.*,[52] in a study on acute ischemic stroke patients, reported that the AUTOStroke Solution LVO achieved 73% sensitivity, 98% specificity, and 81% accuracy in correctly identifying and localizing LVOs. The accuracy, sensitivity, and Matthews correlation coefficients of the algorithm for detecting different occlusion types were as follows: 0.95, 0.90, and 0.89, respectively, for the internal carotid artery; 0.89, 0.77, and 0.78, respectively, for the M1 segment of the MCA; and 0.80, 0.51, and 0.59, respectively, for the M2 segment of the MCA. Additionally, the RAPID CTA AI solution showed strong potential in detecting intracranial LVO, with a sensitivity of 94% and specificity of 76%, as revealed in a study conducted by Amukotuwa *et al.*[53]

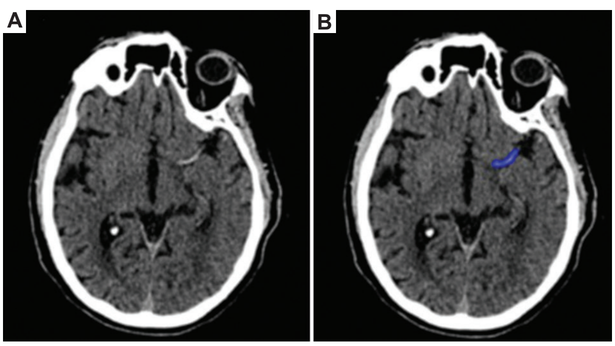


Figure 6. TeleradTech artificial intelligence (AI) *Neural Assist* algorithm for detection of dense middle cerebral artery (MCA): (A) Original image; (B) AI-interpreted image showing dense MCA (blue margin)

3.3. Perfusion analysis

CT perfusion (CTP) imaging has emerged as a key imaging technique for assessing acute ischemic stroke and determining eligibility for endovascular clot retrieval in cases of LVO.[54,55] Cerebral blood flow and volume, mean transit time, and other pseudocolor perfusion variables are leveraged to evaluate the condition of ischemic brain tissue. Research by Hu *et al.*[56] emphasized that the quality of AI-based CTP pseudocolor images was superior compared to the control group ($p<0.05$), enabling easier, faster, and more precise identification of ischemic strokes, hemorrhagic strokes, and vascular abnormalities. This aids physicians in detecting the infarct location and assessing cerebral blood flow. A retrospective study by Shahrouki *et al.*[57] demonstrated the ability of the AI tool e-Stroke Suite (Brainomix®) in accurately estimating ischemic core volumes using both NCCT and CTP, with mean volumes of about 21 mL and 20 mL, respectively, in a cohort of 111 patients.[19,57] Mallon *et al.*[58] prospectively evaluated the Brainomix® e-Stroke AI in 551 patients and found it demonstrated 58.6% sensitivity, 83.5% specificity, and 77% accuracy for acute ischemic stroke. The tool also showed strong concordance in perfusion data for both core and penumbra zones, facilitating rapid and definitive diagnosis.

3.4. Automation: Workflow and triage

Commercially available algorithms are being integrated into the clinical workflows of numerous large institutions, both in practice and trials, to provide automated triage and segmentation of acute stroke cases. These tools help decrease the workload on radiologists and enhance diagnostic accuracy. Automated ASPECT scoring supports treatment teams in selecting patients for endovascular therapy. Overall, such tools offer rapid and efficient analyses to improve stroke care at both spoke and hub hospitals and reduce the turnaround times in medical workflows. In a retrospective study by Colasurdo *et al.*,[59] a convolutional neural network was incorporated into the institutional workflow to detect SDH from NCCT head scans. The subdural convolutional neural network showed 91.4% sensitivity, 96.4% specificity, and 95.1% accuracy; for the subgroup with SDH thickness greater than 10 mm, the sensitivity reached 100%.

Retrospective research by Soun *et al.*[1] also demonstrated that the integration of an AI algorithm into the hospital system supported triage of CTA in ischemic stroke cases, enabling automatic identification of LVO cases with 96% sensitivity and 85% specificity, and a turnaround time of 22 min. The AI was accessible in the Picture Archival and Communication System via a web or mobile application.

3.5. Integration with teleradiology workflow

Teleradiology has been addressing the global challenge of radiologist shortages.[60-64] The seamless integration of cloud-based AI solutions with telereporting platforms enhances workflow by prioritizing critical cases, sharing automated alerts to stroke teams for prompt action, and extending the benefits of AI across multiple domains, including remote or underserved areas.[65-71] However, data security poses a significant challenge for cloud-based AI algorithms. Implementing robust cybersecurity systems is pivotal to ensure secure integration of AI into the teleradiology workflow. Another challenge is ensuring that AI outputs are accessible within the teleradiologist's viewer. The use of aggregator platforms and workflows that consolidate outputs from multiple AI tools would support seamless telereporting. Furthermore, leveraging clinical data from teleradiology, incorporating feedback from teleradiologists, and collaborating with AI developers for training, upgrading, and validating AI systems will further streamline integration in real time. A potential obstacle is the lack of adequate infrastructural support for AI integration. Employing Graphic Processing Units would allow efficient and fast processing of large volumes of data for AI development.[13,72]

3.6. Ethical, legal, and social implications of AI in stroke imaging

The application of AI has revolutionized stroke imaging; however, ethical, legal, and societal implications present barriers that need to be addressed. Potential biases in training data and the decision-making process of AI (often referred to as the "black box" nature) raise ethical and societal concerns. These can be mitigated by implementing a robust framework that emphasizes data security, patient privacy, and fair and equitable access to AI applications in healthcare.[73]

Multidisciplinary discussions on the advantages and limitations of using AI in healthcare, among all stakeholders, including clinicians, AI developers, administrative personnel, and policymakers, are essential. Standardized protocols and regulations should be established to promote impartiality, clarity, trustworthiness, accountability, confidentiality, and compassion in the development of AI within an ethical framework.[74]

4. Challenges and future directions

The development and deployment of AI platforms in clinical settings have been instrumental in transforming stroke care by lowering mortality and improving quality of life. However, several challenges constrain their widespread adoption. One major challenge is the limited generalizability of datasets, i.e., AI models are often trained on single-center or homogeneous datasets, which may result in underperformance when applied to external populations or systems with different scanners, imaging protocols, electronic health record systems, laboratory equipment, and varying clinical and administrative procedures. To improve generalizability and performance, continuous learning from large, diverse, multicenter, and high-quality annotated datasets is essential.[29,75]

Another challenge is the "black box" nature of numerous AI models, which limits interpretability, reliability, and transparency in their decision-making processes, hindering widespread acceptance (1). The development and implementation of heat maps, prediction-based modules, user-friendly interfaces, interactive dashboards, and visualization tools can help make AI insights more understandable, thereby addressing the "black box" problem.[76] The white paper of the Italian Society of Medical and Interventional Radiology emphasizes the urgent need for explainable AI (xAI), which can reveal the rationale behind AI decision-making, offering insights into its strengths, limitations, and potential future performance.[77] Furthermore, the ongoing training of technologists, radiologists, and physicians through workshops and continuous medical education is vital for keeping pace with advancements in AI tools and techniques.

The lack of historical records also limits diagnostic accuracy. Integrating multimodal data, including clinical history and laboratory results, with stroke imaging is crucial for prognostic analysis, allowing timely diagnosis, early intervention, treatment guidance, and outcome monitoring.[78]

Finally, regulatory compliance and the integration of AI into clinical workflows are paramount. AI tools must be rigorously validated and approved by regulatory bodies such as the Food and Drug Administration prior to their deployment in clinical settings. Despite these challenges, AI algorithms hold immense promise as transformative tools in stroke care.[13]

5. Conclusion

Acute stroke is a time-sensitive clinical situation where swift assessment and treatment are critical. The refinement of guidelines and protocols, along with the implementation of technologies that reduce time to treatment, will remain central areas of focus in stroke care. The development and integration of AI algorithms into clinical workflows can detect subtle signs of stroke, quantify infarct size, assess collateral status, predict patient outcomes, and guide prognosis and post-stroke recovery planning. AI has revolutionized stroke imaging by improving detection, enabling synchronous communication, and enhancing triage, diagnosis, and prognosis assessment.

Emerging AI technologies should be leveraged with transparency, supported by appropriate legislation and regulation, to enhance both clinical impact and the credibility of these algorithms.

In conclusion, the integration of AI tools into the teleradiology workflow can significantly address global workforce shortages in stroke care and tackle several challenges, including ethical, legal, and societal implications.

Glossary

Term	Definition
Alberta Stroke Program Early Computed Tomography Score (ASPECTS)	A 10-point quantitative scoring system used to assess the extent of early ischemic changes in the brain on computed tomography scans following an acute ischemic stroke
Deep learning	A subset of machine learning that uses multilayered neural networks, known as deep neural networks, to simulate complex decision-making processes similar to those of the human brain
Artificial intelligence vendors	Companies that provide access to their proprietary artificial intelligence models, typically via Application Programming Interfaces (APIs)

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Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Arjun Kalyanpur
Formal analysis: Neetika Mathur
Investigation: All authors
Methodology: Neetika Mathur
Supervision: Arjun Kalyanpur
Visualization: Arjun Kalyanpur
Writing – original draft: Neetika Mathur
Writing – review & editing: Arjun Kalyanpur

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data

Not applicable.

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