Artificial Intelligence in Neurointerventions

A comprehensive review of AI technologies utilized in diagnosis and outcome prediction for ischemic stroke, intracranial aneurysms, and brain arteriovenous malformations.

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Cerebrovascular disease covers a wide range of conditions that pose a significant risk of severe, potentially life-threatening sequelae largely due to ischemic and hemorrhagic stroke. Management involves a balance between alleviating the risk associated with the natural history of the disease process and avoiding deleterious iatrogenic complications associated with highly technical interventions. Therefore, prompt diagnosis and judicious decision-making are crucial for averting poor patient outcomes, making the field ideal for the application of artificial intelligence (AI) and machine learning.

This review aims to provide a comprehensive assessment of AI technologies utilized in cerebrovascular disease, focusing on diagnosis of and outcome prediction for acute ischemic stroke (AIS), intracranial aneurysms (IAs), and brain arteriovenous malformations (AVMs). An extensive literature review was conducted to identify recent studies employing the latest AI and machine learning techniques, and we present the clinical significance of AI in cerebrovascular disease, enabling practicing neurointerventionalists to grasp its current and future potential applications.

ISCHEMIC STROKE

Stroke Detection

The diagnosis of AIS hinges on timely and precise imaging techniques. Although noncontrast CT is typically the initial step in suspected stroke cases, its limited sensitivity restricts its utility mainly to ruling out intracerebral hemorrhage.[1] Conversely, MRI diffusion-weighted imaging (DWI) surpasses noncontrast CT with a sensitivity of at least 83% in detecting early AIS.[1] This method has not proved more effective than CT. However, challenges in MRI accessibility and availability lead to potential diagnostic delays. Hence, attempts have been made to integrate AI to improve time to diagnosis.

AI excels in detecting subtle findings imperceptible to human observers.[2-4] For example, Lu et al developed a deep-learning model comprising two deep convolutional neural networks (CNNs) to enhance the identification of AIS. The first CNN acted as a localization tool, outlining suspicious regions of infarction on preannotated CT scans. Subsequently, the output fed into the second CNN, a classification model that assigned a probability of AIS to each case. Following training, the model underwent both internal and external validation demonstrating robust performance across various metrics. Notably, it outperformed two experienced radiologists and enhanced their performance, highlighting the potential synergy between human expertise and machine assistance.[4]

Time of Stroke Onset

The time elapsed since the onset of stroke symptoms is pivotal in treatment decisions, yet this information isn't always readily available, as up to 25% of AISs occur during sleep.[5-7] Thomalla et al demonstrated that combining DWI and T2-weighted fluid-attenuated inversion recovery (FLAIR) imaging can estimate stroke onset within 4 to 5 hours.[8] However, identifying this mismatch is challenging even for experienced radiologists. Recent research suggests deep learning can enhance detection, outperforming human interpretation.[9,10] Polson et al developed a deep learning model to predict stroke onset time within the tissue plasminogen activator window and reached an area under the curve (AUC) of 0.814, which was significantly improved compared to a baseline of three neuroradiologists utilizing DWI-FLAIR mismatch.[10]

Large vessel occlusion (LVO) is a major reversible cause of AIS,[11-13] and rapid identification of LVO is crucial in initial stroke assessment. AI has become pivotal in this regard, leading to platforms like Rapid CTA (RapidAI), Viz LVO (Viz.ai), and aiOS (Aidoc) with commendable sensitivity and specificity.[14,15] Mobile stroke units (MSUs) are specialized ambulances equipped with basic CT capabilities; however, the quality can be suboptimal. Recent studies have demonstrated AI's efficacy in detecting LVO using CTA scans from MSUs.[16] Despite MSU CTA limitations in visualizing ischemic events due to image quality variations and early acquisition post–stroke onset, Czap et al developed a model that achieved an AUC of 0.84 on in-hospital CTAs and 0.80 on MSU CTAs.[16] These findings highlight the potential of MSUs, coupled with proficient AI algorithms, to expedite acute diagnoses.

Predicting Outcomes After Stroke

Clinicians navigating the complexities of stroke management often face the added challenge of addressing the concerns of patients' families regarding both short- and long-term prognoses. Predicting these outcomes involves considering various factors, including clinical symptoms, radiologic findings, medical history, and available treatment options at the time of assessment. ASPECTS (Alberta Stroke Program Early CT Score) emerged as a valuable tool for forecasting outcomes following a middle cerebral artery stroke by quantifying ischemic changes using noncontrast head CT.[17] Originally designed to identify candidates for thrombolytic therapy, ASPECTS has since aided decisions about which patients might benefit from mechanical thrombectomy.[18-20]

Initially, manual ASPECTS interpretation was cumbersome and prone to variability due to human error.[21,22] However, the advent of commercially available AI software, such as Rapid ASPECTS (RapidAI) and e-ASPECTS (Brainomix), has automated this process, enhancing interrater agreement.[23-25] Additionally, several studies have developed models capable of generating ASPECTS scores from CT scans, showing strong agreement with scores derived from DWI.[26,27] These AI-driven advancements have surpassed the performance of experienced clinicians, suggesting AI's potential role in managing AIS beyond diagnosis.

Furthermore, AI models have been deployed to forecast outcomes following AIS. AI has been leveraged to predict negative sequelae of stroke, including malignant cerebral edema and hemorrhagic transformation.[28-31] Such predictive tools may allow clinicians to gauge disease severity earlier in stroke patient management. Various studies have aimed to develop AI algorithms for predicting functional outcomes at different post-discharge stages,[32-34] indicating significant promise for prognostication after stroke.

INTRACRANIAL ANEURYSMS

IAs affect about 2% to 3% of adults and pose a risk of rupture with a high mortality rate. The purpose of intervention is to mitigate the risk of rupture in the future.[35-37] Current models for quantifying the risk of rupture rely on patient-specific risk factors such as hypertension and tobacco use and radiographic features such as aneurysm location and morphology; however, these methods remain imperfect. AI, especially deep learning algorithms, offers promise in enhancing aneurysm detection and prognostication.

Aneurysm Detection

Digital subtraction angiography (DSA) remains the gold standard for diagnosis due to its high sensitivity in detecting aneurysms of all sizes.[38] However, two-dimensional (2D) modalities such as CTA and MRA have several advantages, including being noninvasive, less expensive, and more widely available. Thus, work has gone into amplifying their sensitivity using AI. CNN classifiers have shown promising results, with reported sensitivity ranging from 79% to 100%.[39-43] Various algorithms such as RAG (retrieval-augmented generation) and U-Net have been examined. For example, Hainc et al used a commercially available AI system on 2D images, demonstrating a sensitivity of 79%.[40] With improvements, this application of AI may provide benefit to less experienced interventionalists or in resource-limited settings.

With regard to stratifying IA instability, Bizjak et al demonstrated the application of models in predicting IA growth based on morphologic features.[44] Utilizing CTA and MRA scans, they employed "deep shape" learning via the PointNet++ model to predict future aneurysm growth and rupture, achieving high sensitivity and accuracy.[44] Xiong et al developed an AI model using a support vector machine algorithm, which outperformed the commonly used PHASES score in predicting aneurysm rupture, identifying maximum size, location, and irregular shape of the IAs as major predictors.[45]

The highest predictive capacity for assessing rupture risk in IAs emerges when algorithms integrate hemodynamic features and clinical information.[43,46-48] Chen et al found that hemodynamic features were more significant predictors than imaging alone, demonstrating comparable performance to logistic regression modeling.[46] Similarly, integrating hemodynamic features improved accuracy across metrics in various AI algorithms.[47]

Predicting Outcome

AI has broadened its scope to not only predicting clinical outcomes but also forecasting occlusion rates after endovascular intervention. Various AI systems like elastic net and U-Net have been employed, yielding sensitivities from 75% to 98%.[49-52] Paliwal et al analyzed 84 internal carotid artery sidewall aneurysms treated with flow-diverting stents, incorporating AI algorithm parameters such as hemodynamics and morphology metrics,[49] achieving 90% accuracy for IA occlusion.

Jadhav et al used AI techniques to predict occlusion of bifurcation aneurysms using intrasaccular flow-diverting devices.[52] Random forest modeling integrating clinical and imaging features exhibited the highest accuracy of 75.3% and sensitivity of 91.8%. Shiraz Bhurwani et al investigated radiographic outcomes at 6 months for patients treated with flow-diverting stents, achieving an average sensitivity of 0.92 but a specificity of 0.57.[50] The DIANES (IA diameter, indication, parent artery diameter ratio, neck ratio, side branch artery, and sex) score developed by Guédon et al achieved 89% sensitivity and 81% accuracy, emphasizing the role of imaging and clinical factors in predicting occlusion.[51] Williams et al introduced the Aneurysm Occlusion Assistant, utilizing open-source libraries including Keras, TensorFlow, and scikit-learn, alongside angiographic parametric imaging and segmented DSA imaging, which predicted 6-month occlusion within 7 seconds post–device placement, with an accuracy of 0.84.[53] These studies highlight the potential for AI to influence procedure planning as well as decision-making during intervention.

ARTERIOVENOUS MALFORMATIONS

Brain AVMs are congenital lesions that are characterized as an abnormal tangle of connected arteries and veins without intervening capillary beds. They most commonly present with intracerebral hemorrhage with high rates of morbidity and mortality. Management options include surgical resection, stereotactic radiosurgery, and/or endovascular embolization. Similar to IAs, the decision to treat unruptured lesions is centered around predicting the lifetime risk of rupture, which remains an imperfect art and has resulted in several AI applications.

Saggi et al employed AI algorithms, including random forest models and gradient-boosted decision trees, to predict hemorrhage risk in 189 pediatric AVM patients, identifying smaller AVM sizes, left-sided AVMs, and concurrent arterial aneurysms as predictors not discernible through conventional methods.[54] In adults, Oermann et al developed a three-dimensional surface AI algorithm accurately forecasting adverse events post-radiosurgery in 1,810 AVM patients, with comparisons to established scoring systems yielding AUC values from 0.6 to 0.7.[55] Jiao et al investigated AI-based indicators for postoperative motor deficits in AVM resection recipients, achieving the highest AUC of 0.88 compared to the Spetzler-Martin grading scale.[56,57]

CONCLUSION

Prediction and risk stratification are at the heart of diagnosis and treatment of cerebrovascular disease, making it ideal for the adoption of AI. Over the last 5 to 10 years, significant work has been devoted to the development of AI technology applied specifically to cerebrovascular disease. Despite its relative nascency, some AI software has already been implemented in the clinical setting underlining the potential of AI in this realm.

As we gather more robust data to input, AI algorithms will continue to improve and impact management of cerebrovascular pathology, resulting in improved cost-effectiveness and, more importantly, patient outcomes. It is only a matter of time before AI is ubiquitously used in the neurointerventional sphere and revolutionizes clinical care of cerebrovascular disease. ■

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