Artificial Intelligence

VitaHash. Vol 1. No 1. (2026)
DOI https://doi.org/10.68919/vitahash.2026.00007
On-chain: STAMP-2026-1008-OR2LMNJW

State-of-the-Art Review

Artificial Intelligence in Cerebrovascular Diseases

Inhye Jin, BA[1], Erfan Darzi, PhD[2], Jonathan A Tangsrivimol, MD[3,4], Zhen Wang, PhD[5,6], Jan Egger, PhD[7], Benjamin S Glicksberg, PhD[8], Cen Zhang, MD[9], Chayakrit Krittanawong, MD, FACC, FAHA, FSCAI[10]

AFFILIATIONS

[1]Yeungnam University College of Medicine, Daegu, South Korea
[2]MIT Computer Science & Artificial Intelligence Laboratory, Massachusetts Institute of Technology, MA, United States
[3]The Loyal and Edith Davis Neurosurgical Research Laboratory, Department of Neurosurgery, Barrow Neurological Institute, St. Joseph's Hospital and Medical Center, Phoenix, Arizona, United States
[4]Division of Neurosurgery, Department of Surgery, Chulabhorn Hospital, Chulabhorn Royal Academy, Bangkok, Thailand
[5]Robert D. and Patricia E. Kern Center for the Science of Health Care Delivery, Mayo Clinic, Rochester, MN, United States
[6]Division of Health Care Policy and Research, Department of Health Sciences Research, Mayo Clinic, Rochester, MN, United States
[7]Institute for Artificial Intelligence in Medicine, University Hospital Essen (AöR), Girardetstraße, Germany
[8]Hasso Plattner Institute for Digital Health, Icahn School of Medicine at Mount Sinai, New York, NY, United States
[9]Department of Neurology, New York University Grossman School of Medicine, NY, United States
[10]HumanX, Delaware, DE, United States

In management of cerebrovascular diseases, artificial intelligence (AI) emerges and plays a role through advancements in prediction, imaging, diagnosis, and treatment. Revolutionized AI-based tools allow us to catch a glimpse of possibility of rapid clinical workflows in detection, reducing time to the treatment while improving diagnostic accuracy compared to conventional methods. AI has the potential to facilitate primary prevention, improve acute detection, and provide additional decision-making beyond acute care. This review synthesizes applications of AI in major cerebrovascular diseases, introducing an overview of its efficiency and limitations.

KEYWORDS: Artificial intelligence, Cerebrovascular diseases, Stroke, Aneurysms, Transient ischemic attack, TIA, Arteriovenous malformations, Machine Learning

© 2026 VitaHash LLC. All rights reserved.

Background

Cerebrovascular diseases are a leading cause of global morbidity, disability, and mortality. Stroke was reported as the leading contributor to neurological disability-adjusted life-years (DALYs) worldwide in 2021, making it the second-leading cause of death.[1] The economic impact, as with the annual global cost of stroke alone, is estimated to rise from US$891 billion in 2017 to $2.31 trillion by 2050.2 Stroke survivors face a diminished quality of life, pain,[3] increased social isolation, and economic hardship due to medical treatment costs, reduced or lost income, and caregiver burden.[4]

According to latest international guidelines, for better prevention and management of cerebrovascular disease, current strategies emphasize the importance of primary prevention which is currently met through risk factor modification (e.g., hypertension, diabetes, dyslipidemia, obesity, smoking cessation), timely acute interventions such as intravenous thrombolysis and endovascular therapy, along with secondary prevention of antiplatelet and anticoagulant therapies. However, significant challenges still persist: insufficient control of key risk factors, delays in time-to-treatment due to prehospital and in-hospital systemic inefficiencies, and remaining discrepancies in access to advanced neuroimaging (e.g., CT, MRI, CTA) and specialist care, particularly in rural and underserved regions.[5] Additional obstacles remain as inter-rater variability in imaging interpretation, limited availability of effective neuroprotective agents, and a global scarcity of comprehensive neurorehabilitation services, all of which contribute to high rates of recurrent events and disability.

The integration of artificial intelligence (AI) in healthcare workflow may further improve outcomes in cerebrovascular disease. Commercial AI software platforms, such as Rapid AI, Brainomix, Viz.ai, etc have already shown the benefits of AI application through validation processes of multicenter trials.[6] While one goal of AI implementation is to optimize healthcare workflow, currently most publications are still focusing on image analysis.

Rapid advances in AI technology have given clinical potential in treating cerebrovascular diseases. Since cerebrovascular diseases including stroke, aneurysms, transient ischemic attack (TIA), and arteriovenous malformations (AVMs) are primarily clinically managed by neuroimaging and timely diagnosis, they have the best chance of being AI-enabled. There has already been special interest in the rapid detection of acute ischemic stroke and large vessel occlusions, automated infarct and at-risk tissue volume measurement, hemorrhagic transformation prediction, and risk stratification for cerebrovascular disorders.

Until that field becomes fully formed, collaboration among neurologists, radiologists, neurosurgeons, preventive cardiologists, data scientists, AI developers, policymakers, and regulators will be critical to implementing AI in cerebrovascular care.

This review synthesizes high impact papers illustrating the usage of Machine Learning (ML) applications in prevention, diagnosis, treatment, care and rehabilitation of cerebrovascular disease, addressing current status quo and applications available in real-world. Focusing on the use of AI in cerebrovascular disease, limitations and gaps, and the roadmap for the future, through an overview of the growing literature on the topic to date.

Methods

Search was subjected to studies published from January 2015 to May 2026, across database including PubMed, Scopus, Google Scholar, and Web of Science to reflect recent advances of AI. Major keywords and MeSH terms used to the search be related to AI and cerebrovascular disease. Terms such as “Artificial Intelligence”, “Deep Learning”, “Machine Learning” with combinations of (AND, OR) with keywords related to cerebrovascular disease such as “Stroke”, “Aneurysm”, “Intracranial hemorrhage”, etc. Systemic reviews, meta-analysis, research articles with reports of AI algorithms and imaging modalities in cerebrovascular diseases were included. Case reports, editorials, and commentaries were excluded. Studies including performance metrics of accuracy, specificity, sensitivity, showing clinical impact on performance of AI were

extracted.

A Primer on ML, DL, and AI

It's becoming increasingly apparent that AI technologies are used in clinical medicine. Machine Learning (ML), Deep Learning (DL), and AI are three interlinked technologies that have been increasingly applied in cerebrovascular disease management. ML decodes and develops algorithms out of data to predict or decide, without any programming. DL is a version of ML where neural networks are used to encode multi-layered patterns. AI is a concept (including ML, and DL) that produces a system that operates at a level that requires humanlike intelligence.

AI is a catchall term for areas like machine learning (ML) and subfields or algorithms like deep learning (DL). The motivation behind ML is always to extract patterns of interaction between variables from big data and eventually apply the learned function to new data. ML decodes and develops algorithms out of data to predict or decide, without any programming. ML has been applied to the overall patient care chain, from diagnosis to treatment design, and outcome in cerebrovascular disease.

DL is a version of ML where neural networks are used to encode multi-layered patterns. DL, part of ML made using artificial neural networks (ANN), has been particularly promising for neuroimaging data. For instance, Convolutional neural networks (CNNs) have already shown promising results in recognizing occlusions of large vessels on CT angiography and warning signs of ischemic stroke on non-contrast CT. These advances will make the gap between diagnosis and initiation of treatment much shorter, which is essential in acute stroke care where "time is brain". Table 1 demonstrates AI application tools in cerebrovascular diseases.

AI in prevention of cerebrovascular diseases

As cerebrovascular diseases represent a global health crisis, prevention remains the most effective strategy to alleviate social and economic burdens. Integration and application of AI is suggesting advanced methods of early detection, revolutionizing risk stratification in patients, and population-level interventions, offering opportunities to transform preventive care.

By integrating multimodal data, such as electronic health records (EHRs), imaging biomarkers, and lifestyle factors, machine learning models are now functioning in predicting cerebrovascular events. For example, DL algorithms analyzing retinal fundus images have identified asymptomatic ischemic stroke with AUC of 0.754, enabling pre-symptomatic risk assessment.[7] Particularly in identifying asymptomatic at-risk individuals is impactful, which enables personalized care and predict outcomes.[8]

Application of AI in neuroimaging enhances the predictive probability. A study demonstrated that neural networks (NNs) outperformed in predicting CVD events than ACC/AHA guidelines by 7.6%.[9] AI showing its potential in reducing diagnostic errors and pre-clinical detection via wearables and EHRs in predicting first stroke events using basic information of age, blood glucose, heart disease, and hypertension.[10]

As lifestyle modification is one of the key factors in prevention of cerebrovascular disease, WHO's S.A.R.A.H exemplifies and suggests AI's role in global prevention. It offers personalized lifestyle management and evidence-based guidance about major disease prevention via an AI-powered digital health worker to over 500,000 users. In intervention trials conducted using chatbot to modify lifestyle behaviors showed meaningful performance, especially AI-based (NLP-based) chatbot raised fruit and vegetable intake by standardized mean differences (SMD) 0.59.11 Changes in daily life behavior can contribute to reducing the risk of cerebrovascular disease.

Stroke

Stroke remains the leading neurological cause of death and disability across the world, accounting for 160 million disability-adjusted life years (DALYs) and 7.25 million deaths in 2021.1 Global predictions suggest a 50% increase in stroke mortality by 2050, underscoring the urgency to find pragmatic solutions, including by leveraging AI and digital health

TABLE 1. AI application tools in cerebrovascular diseases

Disorder	Key AI application	Representative Tool	Performance	Limitations	Reference
Ischemic stroke	Triage, Large vessel occlusion detection, Imaging	RapidAI, VizAI, XGBoost	Reduce door-to-needle time AUC up to 0.88	Biased data, Black-box model problems	51
Hemorrhagic stroke	Triage Hemorrhage detection	Aidoc, VizAI	Standarized grading	Interpretability	56
Cerebral aneurysm	Aneurysm detection, Rupture risk prediction	Brainomix, SVM	Early identification of high-risk	Data quality	51
Arteriovenous Malformation	Bleeding risk assessment, Outcome prediction	Custom ML models	Personalized treatment planning	Small datasets	51

applications, to tackle the global burden of cerebrovascular diseases.[2] Timely and effective diagnosis, treatment, care, and rehabilitation are essential for better outcomes. Since annual incidence rates of subsequent stroke is high with patients who have had TIA or minor stroke,[13] the potential for AI to help people with stroke across the care trajectory has been huge from prevention to early detection, treatment planning, outcome prediction, and even neurorehabilitation. The effectiveness of AI for stroke is now shown in several studies.

Rodrigues et al.[12] validates an AI-based algorithm (Viz-LVO) for detecting large vessel occlusions (LVO) in patients with acute ischemic stroke (AIS). With a retrospective analysis on 610 CTAs from a single center. Reference readings were provided from vascular neurologists for LVOs, and an assessment for sensitivity, specificity, and accuracy was made. For internal carotid artery terminus (ICA-T) and middle cerebral artery (MCA)-M1 occlusions, the AI demonstrated a sensitivity of 87.6%, specificity of 88.5%, and accuracy of 87.9% (AUC 0.88). For MCA-M2 occlusions, sensitivity was slightly lower at 80.3%. The algorithm's mean run time was 2.78 minutes, which makes timely detection and notification for rapid decision-making in stroke care possible. However, algorithm’s rejection of 2.5% of CTAs due to poor quality shows its dependence of image quality in real world. Further validation of larger datasets is required for enhancement.

Lee et al.[13] designed Stroke Classifier, an AI-powered ensemble of 9 individual models in assessment of stroke stratification. Multi-modal data was included for identification of high-risk populations, achieving mean AUCROC of 0.90, significantly reducing cryptogenic strokes from 25.2% to 7.2%, which suggests its value in decision support.

On ischemic stroke, Lee et al.[14] tested three ML algorithms: eXtreme Gradient Boosing (XGBoost), Random Forest (RF), and Light Gradient Boosting Machine (LGBM). XGBoost model turned out to show AUC-ROC of 0.873 on external validation, outperforming other traditional models. Gilotra et al.[6] implemented commercial AI software, RapidAI, and Viz.AI for ischemic strokes and hemorrhagic strokes, which performed good discrimination with high sensitivity and specificity.

In conclusion, AI has great potential for improving stroke care at all levels. As these technologies develop and are fully incorporated into clinical practice, they could prove invaluable to stroke patients and their care. Requirements include more prospective validation studies, easier-to-read AI models, and multimodal data to enhance the accuracy and clinical utility of AI in stroke management.

Transient ischemic attacks

Transient ischemic attacks (TIA) are brief periods of neurologic dysfunction caused by focal cerebral ischemia, without cerebral infarction. Diagnosis and risk classification of TIAs is important for preventing stroke as Framingham cohort study highlights the incidence of TIA as a strong predictor of subsequent ischemic stroke.[15] Estimated incidence of TIA in Western population is 29-61 per 100,000/year, and TIA carry 7.5-17.3% risk of stroke occurrence within 3 months.[16] With imaging, especially

DWI-MRI considered most sensitive in detecting early infarcts, ABCD2 score (assessing age, BP, clinical features, duration, and diabetes) is utilized for risk stratification.[17] Clinical management through anticoagulation therapy, BP and lipid control could reduce and prevent early stroke risk. AI has performed well in improving TIA diagnosis, risk assessment, and management.

Chan et al.[18] investigated the use of artificial neural networks (ANN) to classify the risk of recurrent ischemic stroke within one year in patients with TIAs or minor strokes. Given the data from 451 patients, the ANN model employed 19 baseline clinical and imaging variables and a 5-fold cross-validation approach to predict stroke recurrence. By addressing data imbalance through random down-sampling, the model achieved 75% sensitivity, specificity, and accuracy with a c-statistic of 0.77, outperforming support vector machine (SVM) and Naïve Bayes classifiers. It suggests ANN as a promising tool for risk prediction, providing potentially actionable insights for clinicians. However, the study is limited by its small, single-center dataset, and the random down-sampling method may exclude valuable data. Integrating ANN into clinical workflows for real-time decision-making will be needed.

When further refinement is made, AI could provide more individualized and subtle risk assessments than traditional scoring. It would allow more accurate decisions, potentially leading to better patient outcomes. Even though the result have been encouraging, future clinical trials would be needed to confirm the practical effectiveness of AI methods.

Carotid Stenosis

Carotid stenosis is one of the leading causes of stroke, while estimated prevalence is low as 3% in general population, being responsible of 8-15% of strokes highlight its clinical importance.[19,20] 15-20% of stroke patients are shown to have significant carotid stenosis.[21] Early detection, appropriate classification and timely intervention are important for its management and stroke prevention. Duplex ultrasound is still the primary screening technique, it is difficult to predict asymptomatic patients' stroke event, along with the vulnerability of plaque. AI could assist better diagnosis of carotid stenosis accurately and efficiently.

Few experiments have investigated the use of AI for carotid stenosis diagnosis in automated detection, grading, and risk stratification. The most common AI solutions are convolutional neural networks (CNNs) and SVMs, often with cross-validation as model validation methods. Ultrasound images or computed tomography angiography were used for stenosis detections or grading.

Overall, the AI models were very accurate at detecting and grader carotid stenosis, sometimes more than even human experts. For example, Kordzadeh et al.[22] developed a CNN-based model to evaluate and identify carotid stenosis from duplex ultrasound images (DUS). The model proved highly accurate with overall performance of 92% accuracy, 91% sensitivity, and 86% specificity. It turned out that this model could help identify early detection of disease diagnosis severity, and perhaps even prevent stroke.

In addition to detection and classification, AI has been used to stratify patients suffering from carotid stenosis. Wu et al.[22] evaluated 4 different machine learning algorithms predicting presence of asymptomatic carotid plaque. XGBoost model had an AUC of 0.86 which is higher than other standard risk prediction methods, with 86% accuracy, 87% sensitivity, and 86% specificity.

These are promising findings, but majority of research has been retrospective and on smaller datasets. These data would require large prospective studies to confirm and measure the clinical relevance of AI-enabled carotid stenosis diagnosis.

In conclusion, AI shows enormous promise in improving the diagnosis and classification of carotid stenosis, including risk stratification. In addition, these technologies as they become better developed and integrated into clinical practice could be beneficial for stroke prevention and patient care.

Aneurysms

Intracranial aneurysms are weak spots within an

arterial wall, which can rupture and cause subarachnoid hemorrhage. Early detection and risk management are critical to patient care. Unruptured intracranial aneurysm (UIA) is known to affect 3-7% of general population, with annual rupture risk of 0.95%, which could lead to 25% mortality in 24 hours, 50% mortality by 3 months.[24] CTA and MRA are considered first-line diagnostic tools for non-invasive detection, while digital subtraction angiography (DSA) is a gold standard for definitive diagnosis. Management of UIA is based on a goal of reducing rupture risk, while post-rupture requires emergency intervention within 24 hours. AI has had promising results in diagnosing CTA, MRA with high sensitivity with low false positives,[25] characterizing, and identifying risk using ML for aneurysms by AUC 0.66-0.90.26

Ahn et al.[27] built a DL system using multi-view CNN-ResNet50 to predict the rupture risk of small UIA based on 3D-DSA. It used 364 UIA images for training and 93 UIAs were in the test data. The model had an overall accuracy of 81%, sensitivity of 82%, and specificity of 81%.

Yang et al.[28] used 1068 CTA scans for training and internal validation; 400 independent scans for external validation. DL algorithm showed sensitivity of 97.5% and improved radiologists' performance by uncovering previously overlooked small aneurysms.

These AI models also show promising promise when it comes to aneurysm detection and risk reduction. By giving an accurate and rapid interpretation of neuroimaging scans, they could allow clinicians to diagnose more aggressive aneurysms earlier and potentially delay rupture with earlier intervention. These sensitivities are so high that the models can identify aneurysms at a particularly high rate, preventing the mistreatment of vulnerable patients.

However, there are still issues, such as larger multi-center prospective trials to verify AI efficacy in practice, the false-positive rate, and generalizability to other patient groups and imaging techniques.

By making neuroimaging scans more easily automated, these AI tools could potentially free up neuroradiologists' time and speed up the diagnosis process. This might mean the treatment for patients with high-risk aneurysms would start faster and have a better outcome for the patient.

Arteriovenous malformations

Brain arteriovenous malformations (AVMs) are vascular deformities when arteries are directly connected to veins without intervening capillaries. These structures can be highly challenging to diagnose, treat, and predict. The incidence ranges from 1.12-1.42 per 100,000 person-years, 38-68% of new cases presented as first-ever hemorrhage.[29,30] Non-contrast CT is used as baseline imaging in acute hemorrhage, and DSA is gold standard for detailed analysis. Artificial intelligence (AI) offers the the ability to improve AVM management by creating immediate analyses on lesion segmentation, flow-phase, hemorrhage detection, which can ultimately bring novel approaches to care.[31]

Jiao et al. developed AI algorithms to predict post-surgical motor defects in AVM patients with lesions involving motor-related areas with retrospective analysis of 83 patients who underwent microsurgical resection surgery of AVM. Time-of-flight magnetic resonance angiography (TOF-MRA) and diffusion tensor imaging (DTI) imaging were used to develop AI-based spatial indicators. Among those, FN10mm/50mm, which reflects the proportion of corticospinal tract fibers within 10–50 mm of the AVM lesion border performed as a dominant predictor with AUC of 0.86. With the combination of machine learning model, prediction accuracy improved to AUC of 0.88 which is higher than the popular Spetzler-Martin grading system. This suggests the potential of reducing the risk of motor deficits and better surgical planning could be made using AI-driven spatial metrics. However, its retrospective study and small sample size limits its generalizability. Further external validation and diverse sample population is required.

You et al.[32] uses two-stage DL models in detecting AVM lesions to raise accuracy and efficiency in radio surgical treatment planning. A retrospective dataset of 223 AVM patients treated with radiosurgery

was used, Yolov5 algorithm was first employed to the model to detect bounding boxes around AVM lesions, which achieved high recall (0.88–0.93) and precision (0.91–0.93) across training and testing datasets. The second stage utilized U-Net++ to segment the AVM nidus within the detected bounding boxes, demonstrating a Dice score of 0.98 for both training and testing datasets, with statistically significant accuracy ($p < 0.0001$). These findings suggest that in AVM radiosurgery, deep learning model could reduce interobserver variability and streamline clinical workflows. However, due to its small sample size and retrospective design, generalizability could be limited and selection bias may occur. Also, to ensure its robustness and clinical applicability, the model should be validated on larger, multicenter datasets. With larger bounding box sizes, segmentation accuracy decreased, which highlights a need for refinement in handling more complex or diffuse AVM cases.

Together, these AI models show strong promise to support risk stratification, treatment management, and outcome prediction in AVM patients. If it can make precise, fast insights from sophisticated imaging and clinical data, AI may be able to identify potentially high-risk patients better and modify treatments accordingly.

The adequacy of these models for predicting such narrowly focused outcomes as hemorrhage risk, postoperative deficits, and lesion segmentation could mean AI can provide better and more personalized scores than grading systems. This might result in better decisions and perhaps better patient care. Automating the analysis of detailed AVM properties, these AIs might ease the work of neuroradiologists and neurosurgeons while offering valuable second opinions when the case is tough. Such advances would also allow for faster clinical processes and the initiation of tailored treatment plans for patients with AVM.

However, these AI tools still face problems in integrating them into daily clinical life. These are: the quality of data for various healthcare contexts, potential AI model bias, and generalizability. In the future, we might expand the datasets for AI training and future prospective studies to validate their clinical utility.

Overall, the use of AI in arteriovenous malformation management has huge potential for improved diagnosis, risk identification, and treatment. As these technologies become ever more advanced, they could help us deliver much better patient care by providing personalized risk assessment and aiding clinical decision-making.

Cerebral cavernous malformations

CCMs are thin walled vascular deformities filled with blood, found in the brain and spinal cord. Ruptured CCMs can lead to significant neurological damage. Its annual detection rate is 0.15-0.56 per 100,000 person-years. Depending on the location of lesion or prior bleeding history, its annual hemorrhage risk varies from 0.6-11%. Up to 20% of CCM are familial, inherited in autosomal-dominant form.[33] MRI with gradient echo is utilized for detection and follow-up, CT is used to detect acute hemorrhage. Stable or asymptomatic lesions are subject to observation with imaging follow-up, while accessible lesions are managed with surgery, and inoperable lesions are treated with radiosurgery.[39] AI in the management of CCM has proven useful in detection and segmentation, imaging, and treatment.[34]

Kim et al.[35] evaluated AI-algorithm's effectiveness in distinguishing CCM from acute intraparenchymal hemorrhage (AIH) on CT scans. A retrospective, randomized study was conducted with six blinded clinicians including experts and non-experts, both with and without AI assistance. 288 cases (173 CCM and 115 AIH) were underreview. With AI assistance, the overall diagnostic accuracy significantly improved (86.92% vs. 79.86%, $p < 0.001$). When assisted by AI, nonexperts, including radiology residents and emergency physicians, showed marked improvements in accuracy (84.21% vs. 75.35% and 80.73% vs. 72.57%, respectively, $p < 0.05$). While neuroradiologists also demonstrated improved accuracy with AI assistance (95.83% vs. 91.67%), the difference was not statistically significant ($p = 0.56$). In differentiating CCM from AIH on CT imaging, AI algorithms can significantly enhance diagnostic performance, especially for non-specialists. How-

ever, its retrospective design would limit generalizability and may cause selection bias. Restricted small data pool limited to a single institution would also doesn't guarantee its effectiveness across broad populations. AI assistance in workflow efficiency or diagnostic speed was not considered, which is crucial in emergency situations.

The obstacles to implementing AI into the management of CCM are larger, multi-center datasets required to enable the generalization of models, integration of AI tools in clinical workflows, and consideration of AI algorithmic biases. Even more so, clinician interpretation of AI outcomes and explanation of AI decision-making is not yet very good. Also, it needs more refinement to enhance its efficiency to expert-level utility benefit highly experienced specialists.

To conclude, AI shows great promise for improving the treatment of CCMs, from identification and classification to risk stratification and prediction. When these technologies mature and integrate into clinical practice, they could be essential to the care and outcome of patients with CCMs. Future research will require prospective validation studies, AI models that are more easily comprehensible, and the use of multimodal data to further augment the precision and clinical efficacy of AI for the treatment of CCM.

Arteriovenous Fistula

Arteriovenous fistulas (AVF) are vascular lesions direct connections of arteries to veins without intervening capillaries, located around the brain. These structures can lead to neurologic damage when venous sinus thromboses form and intracranial pressure increases. Its incidence ranges from 0.15-0.29 per 100,000 person-years.[36] CT and MRI are initial screening tools, and DSA is the golden standard for planning the management of the lesion. Management of AVF depends on its type, with high-risk lesion requires endovascular embolization or microsurgery. Appliance of AI has been shown to be promising in the imaging, risk stratification, and management of AVF problems.

Doneda et al.[37] explored the application of ML to support surgical planning for hemodialysis patients in predicting the maturation of AVF and post-operative changes in blood flow volumes (BFVs) and vessel diameters. They evaluated various ML approaches, using a dataset of 156 patients, selecting k-nearest neighbors (k-NN) as the optimal method due to its minimal computational demand and high prediction accuracy. The k-NN model showed an impressive 96.8% accuracy on AVF maturation prediction and low error rates on continuous variables like BFVs and vessel diameters. This provides rapid and precise prediction for each patient, potentially improving surgical planning decisions, reducing AVF non-maturation rates, and enhancing vascular access management in hemodialysis care. However, there is a gap between real-world clinical setting and dataset of the study in routine workflows. Additionally, patient's outcome in long term is still left unexamined.

Heindel et al.[38] developed ML in predicting success of unassisted radio cephalic AVF, as its maturation is crucial for effective hemodialysis. Data of 704 patients enrolled in two international randomized controlled trials (PATENCY-1 and PATENCY-2), multiple ML approaches were tested, including logistic regression, lasso regression, and random forest models. Basic clinical data and ultrasound parameters collected 4–6 weeks post-AVF creation were incorporated. Performance was evaluated through receiver operating characteristic (ROC) curves, calibration, and decision analysis, with all models (except decision tree) showing strong discrimination (AUC 0.78–0.81) and accuracy (69.1–73.6%). The lasso regression model, outperformed traditional criteria from KDOQI, retained three key predictors: larger outflow vein diameter, higher flow volume, and absence of >50% luminal stenosis. For clinical use, the team developed an online point-of-care calculator offering a practical and accurate method for AVF assessment, potentially improving decision-making and reducing AVF failure rates. However, lack of external validations and trial data's limited presentation remains as limitations.

These AI models have great potential to help with AVF condition diagnosis, stenosis diagnosis, and underdevelopment prediction. By offering precise

and rapid visualization of multiple types of data (audio recordings, ultrasound, phono-angiograms), AI could help physicians spot more risky AVFs earlier, potentially avoiding complications by intervening quickly and could ease clinicians' burden while offering useful information on challenging cases. This could result in more effective clinical workflows and help in developing individualized monitoring and management of AVF patients.

Generally, AI application to AVF management requires larger multicenter data sets for model generalization, integration of AI tools into the clinical workflow, and reducing bias in AI algorithms. Furthermore, even if these studies were promising, future clinical trials are needed to validate the real-world value of these AI methods. The next step would be to pursue prospective validation studies, more comprehensible AI models, and use multimodal data to increase the precision and clinical value of AI in AVF treatment.

Carotid-Cavernous Fistula

Carotid-cavernous fistulas (CCFs) are atypical connections between the carotid artery and the cavernous sinus that, if not diagnosed and treated promptly, can result in serious complications including loss of vision. AI and advanced imaging have lent themselves to helping to diagnose and treat CCFs. Intracranial incidence is known as 0.15-0.29 per 100,000 person-years, accounting for 1-2.5% of skull-base fractures.[39] For diagnosis, DSA being gold standard, CT/CTA or MRI/MRA also presents high sensitivity in fistula detection.[40] Endovascular approach works as first-line treatment, with trans arterial coil or transvenous coil.[41] AI could aid in detection of CCF, structuring vessels, and prediction of patient outcome.

Not enough cases were collected for retrospective analysis for AI applications in CCF. Some of the barriers to using AI for managing CCF includes the need for larger multi-center datasets to make the model generalizable, the incorporation of AI software into clinical workflows, and how to overcome AI algorithmic bias. Follow-up studies would be needed to verify their effectiveness and complications.

Further development of AI application in CCF could be essential to enhancing the care and outcomes of patients with CCFs. Using DL algorithms with data of angioarchitecture of CCFs along with clinical features, API-ACE classifications, AI can aid faster detection and optimization of treatments. The future needs to include prospective validation of AI models, the design of easier-to-read AI systems, and the follow-up of new therapies.

Present Research Gradient

Table 2 demonstrates the research gradient in cerebrovascular disease. Search based on the number of studies that are peer-reviewed, with application of validated algorithms, and commercial tools were counted. As stroke having high incidence and leading cause of death, studies are widely conducted, and clinical adaptation is most mature with multiple tools already FDA-cleared. Other disorders are confronting barriers having lack of large datasets, scarce data, and challenges in clinical validation.

Table 2. Research Gradient on Cerebrovascular disease

TABLE 2. Research Gradient on Cerebrovascular disease

Disorder	Number of papers	Tools/Models applied (examples)	Research gradient
Ischemic stroke	100+	VizAI, RapidAI, Brainomix	Highest
Hemorrhagic stroke	40+	Aidoc, Deep CNN	High
Aneurysm	25+	Brainomix, SVM, CNN	Moderate
AVM	10+	Custom ML	Low

Large Language Models Application

Commercial Large Language Models (LLMs), such as Claude, GPT, Grok, and Gemini, as well as frontier AI labs and open-weight models, could be applied to neuroimaging analysis for imaging modality selection and clinical decision support. Current level of neuroimaging modalities of LLMs analysis could not surpass neuroradiologist,[42] but it has shown necessity of improvement and possibility of LLM's function in medical field.

LLMs could also contribute to efficient workflow integration on clinical documentation. Reducing time burdens with support of clinical suggestions and documentation, overall time in workflow could be available.[43]

Current challenges

Despite the promising potential of AI applications for cerebrovascular disease, several obstacles exist. Challenges of AI could be categorized into areas such as data issues, ethical concerns, model limitations, and implementation barriers. Each of these categories could have a critical impact on the effective deployment of AI in cerebrovascular disease.

The quality and size of the training data play a critical role in the performance of AI models, as training and development of AI heavily rely on datasets. Most of the studies use refined, selected data with static images and high-resolution images, which might not be an actual representative of clinical conditions impacted by motion artifacts or poor image processing in real world. Inconsistencies on image, data quality, and misrepresented biomedical data in certain ethnicity has high possibility leading to biased algorithms which could result in poor performance.[44,45,46] Poor data input could result in unreliable outcome, misdiagnosis, and lack of generalization as learning algorithm of AI has strong reinforcement tendency,[47] which makes it hard for clinicians to comprehend and accept AI-based recommendations, particularly if it goes against their clinical judgment. It's vital to build AI models that can function well in real-time, which is why biased algorithms are an obstacle.

Ethical concerns around data privacy and security, informed consent, legal liability and biases in AI algorithms should be considered.[45,46] Particularly, legal liability could be an issue as clinicians, institutions, and developers all have parts in the usage of AI in healthcare. Assigning responsibility could be a struggle in the future as higher accuracy of AI in healthcare could result in over-reliance and skill degradation in human clinicians.

The institutional variability in AI algorithm models and imaging protocols makes it difficult to compare and widely implement certain AI programs. Considerate problem lies on lack of transparency in AI decision, "black box" nature makes it especially difficult for validation process.[48]

Evaluation process of different models is still not standardized and has a long way to go along with data quality. AI models aren't always equally effective in a variety of patient populations or across clinical areas, and they also require testing in clinical contexts via prospective, multicenter trials.

The affordability of AI deployment is another area that requires a critical look in clinical workflow. It's logistically difficult to incorporate AI tools into existing clinical procedures, as training gap exists in AI usage and proper infrastructure is not equipped now. Adjustments are required to successfully implement AI in management, training and workflow process.

Collaboration of AI developers, clinicians, researchers, and policymakers is necessary in order to harness and utilize AI's full potential for improving care of cerebrovascular disease.

Explainable AI

Explainable AI is now paving the way offering reliable decision-making process in healthcare.[49] Application of models such as Local Interpretable Model-agnostic Explanations (LIME) and Sharply Addictive exPlanation (SHAP) to ML and DL models enabled Explainable AI to present AI's decision making trustworthy.[50,51] As explainability in AI decision making, especially in healthcare, is necessary, Explainable AI provides possibility of overcoming black box problems.

Future direction

AI-enabled care for cerebrovascular disease is going to transform patient care in many areas. As AI improves, it will hopefully lead to improved diagnostics, treatment planning, and patient outcomes. By integrating a huge pool of patient's clinical, imaging, and genetic data, multi-modal AI model might enable customized specific treatment, and better outcomes in difficult cases such as intracranial aneurysms or arteriovenous malformations.

Modern imaging and surgery planning is another avenue, where AI-driven image analysis could give vascular anatomy better 3D representations and real-time operative direction. Implementing AI in clinical processes could provide instant decision support for acute cerebrovascular events to cut down time to treatment and increase outcomes.

Artificial intelligence models based on generative data can be used to address a paucity of information in rare cases, and natural language processing could help us standardize clinical documentation. Even more advanced predictive analytics and AI-driven medical simulations in virtual reality are expected.

With more data, different types of data could create fuller AI models, perhaps even uncovering new information about disease physics and treatment. Data privacy, algorithm visibility, and moral issues will be top priority. This will require collaboration between clinicians, researchers, and AI developers to develop and implement these technologies in a responsible way.

Conclusion

AI has also been a promising tool in cerebrovascular disease management such as aneurysm detection, stroke diagnosis, arteriovenous malformations, and carotid stenosis assessment. AI models can mimic or outperform specialists when it comes to diagnosing aneurysms, and large vessel occlusions during stroke, and automating risk assessment and imaging for AVMs and carotid stenosis.

Even so, the adoption of AI requires large, heterogeneous datasets, difficulties with interpretation, and intense clinical testing. Currently AI is on the footstep of being a supporting tool, not a total replacement. It will take continued collaboration among clinicians, scientists, and developers to use AI for individualized care and improved patient outcomes.

AI Disclosure: IJ reported to the senior authors that Perplexity and ChatGPT were used as supporting tools during the literature review to summarize and facilitate understanding of the relevant literature. IJ independently cross-checked the information against the original articles. No artificial intelligence tools were used for purposes other than those described above. The remaining authors reviewed and edited the manuscript. CK supervised the work. Conflict of Interest: Dr. Krittanawong reports being the founder of VitaHash.org. The remaining authors declare no competing interests.

References

1. Steinmetz, Jaimie D et al. Global, regional, and national burden of disorders affecting the nervous system, 1990–2021: a systematic analysis for the Global Burden of Disease Study 2021. The Lancet Neurology, Volume 23, Issue 4, 344 - 381

2. Feigin, Valery L et al. "Pragmatic solutions to reduce the global burden of stroke: a World Stroke Organization-Lancet Neurology Commission." The Lancet. Neurology vol. 22,12 (2023): 1160-1206. doi:10.1016/S1474-4422(23)00277-6

3. Segerdahl, Mårten et al. "Health-related quality of life in stroke survivors: a 5-year follow-up of The Fall Study of Gothenburg (FallsGOT)." BMC geriatrics vol. 23,1 584. 22 Sep. 2023, doi:10.1186/s12877-023-04308-z

4. Tziaka, Eftychia et al. "A Holistic Approach to Expressing the Burden of Caregivers for Stroke Survivors: A Systematic Review." Healthcare (Basel, Switzerland) vol. 12,5 565. 29 Feb. 2024, doi:10.3390/healthcare12050565

5. Wang, Jason J et al. "Updated Trends, Disparities, and Clinical Impact of Neuroimaging Utilization in Ischemic Stroke in the Medicare Population: 2012 to 2019." Journal of the American

College of Radiology : JACR vol. 19,7 (2022): 854-865. doi:10.1016/j.jacr.2022.03.008

6. Gilotra K, Swarna S, Mani R, Basem J and Dashti R (2023) Role of artificial intelligence and machine learning in the diagnosis of cerebrovascular disease. Front. Hum. Neurosci. 17:1254417. doi: 10.3389/fnhum.2023.1254417

7. Zhou, Yukun et al. “A foundation model for generalizable disease detection from retinal images.” Nature vol. 622,7981 (2023): 156-163. doi:10.1038/s41586-023-06555-x

8. Heo, et al. “Application of Artificial Intelligence in Acute Ischemic Stroke: A Scoping Review.” Neurointervention, vol. 20, no. 1, Mar. 2025, pp. 4–14. Published online 18 Feb. 2025, https://doi.org/10.5469/neuroint.2025.00052.

9. Abedi, Vida et al. “Artificial Intelligence: A Shifting Paradigm in Cardio-Cerebrovascular Medicine.” Journal of clinical medicine vol. 10,23 5710. 6 Dec. 2021, doi:10.3390/jcm10235710

10. García-Terriza, Luis, et al. "Predictive and diagnosis models of stroke from hemodynamic signal monitoring." Medical & Biological Engineering & Computing 59.6 (2021): 1325-1337.

11. Singh, B., Olds, T., Brinsley, J. et al. Systematic review and meta-analysis of the effectiveness of chatbots on lifestyle behaviours. npj Digit. Med. 6, 118 (2023). https://doi.org/10.1038/s41746-023-00856-1

12. Rodrigues, Gabriel, et al. "Automated Large Artery Occlusion Detection in Stroke: A Single-Center Validation Study of an Artificial Intelligence Algorithm." Cerebrovascular Diseases (Basel, Switzerland), vol. 51, no. 2, 2022, pp. 259-264. doi:10.1159/000519125.

13. Lee, HJ., Schwamm, L.H., Sansing, L.H. et al. StrokeClassifier: ischemic stroke etiology classification by ensemble consensus modeling using electronic health records. npj Digit. Med. 7, 130 (2024). https://doi.org/10.1038/s41746-024-01120-w

14. Lee J, Park KM and Park S (2023) Interpretable machine learning for prediction of clinical outcomes in acute ischemic stroke. Front. Neurol. 14:1234046. doi: 10.3389/fneur.2023.1234046

15. Lioutas V, Ivan CS, Himali JJ, et al. Incidence of Transient Ischemic Attack and Association With Long-term Risk of Stroke. JAMA. 2021;325(4):373–381. doi:10.1001/jama.2020.25071

16. Degan, Diana, et al. “Epidemiology of Transient Ischemic Attacks Using Time or Tissue Based Definitions: A Population Based Study.” Stroke, vol. 48, no. 3, Mar. 2017, pp. 530–536. Epub 31 Jan. 2017, doi:10.1161/STROKEAHA.116.015417.

17. Panuganti, Kiran K., et al. “Transient Ischemic Attack.” StatPearls, StatPearls Publishing, 17 July 2023.

18. Chan, Ka Lung, et al. "Early Identification of High-Risk TIA or Minor Stroke Using Artificial Neural Network." Frontiers in Neurology, vol. 10, 2019, p. 171. doi:10.3389/fneur.2019.00171.

19. Park, Jong Hun, et al. “Carotid Stenosis: What Is the High-Risk Population?” Clinics, vol. 67, no. 8, 2012, pp. 865–870. Open Access. https://doi.org/10.6061/clinics/2012(08)02.

20. Cau, Roberta, et al. “Applications of Artificial Intelligence-Based Models in Vulnerable Carotid Plaque.” Vessel Plus, vol. 7, 2023, article 20. http://dx.doi.org/10.20517/2574-1209.2023.78.

21. van Velzen, T.J., Kuhrij, L.S., Westendorp, W.F. et al. Prevalence, predictors and outcome of carotid stenosis: a sub study in the Preventive Antibiotics in Stroke Study (PASS). BMC Neurol 21, 20 (2021). https://doi.org/10.1186/s12883-020-02032-4

22. Kordzadeh, Ali, et al. "Artificial intelligence and duplex ultrasound for detection of carotid artery disease." Vascular, vol. 31, no. 6, 2023, pp. 1187-1193. doi:10.1177/17085381221107465.

23. Wu, Dan, et al. "An accurate and explainable ensemble learning method for carotid plaque prediction in an asymptomatic population." Computer Methods and Programs in Biomedicine, vol. 221, 2022, p. 106842. doi:10.1016/j.cmpb.2022.106842.

24. Shi, Z et al. “Artificial Intelligence in the Management of Intracranial Aneurysms: Current Status and Future Perspectives.” AJNR. American journal of neuroradiology vol. 41,3 (2020): 373-379. doi:10.3174/ajnr.A6468

25. Zhou, Zhiyue et al. “Classification, detection, and segmentation performance of image-based AI in intracranial aneurysm: a systematic review.” BMC medical imaging vol. 24,1 164. 2 Jul. 2024, doi:10.1186/s12880-024-01347-9

26. Daga, Karan, et al. "Machine learning algorithms to predict the risk of rupture of intracranial aneurysms: a systematic review." Clinical neuroradiology 35.1 (2025): 3-16.
27. Ahn, Jun Hyong, et al. "Multi-View Convolutional Neural Networks in Rupture Risk Assessment of Small, Unruptured Intracranial Aneurysms." Journal of Personalized Medicine, vol. 11, no. 4, 2021, p. 239. doi:10.3390/jpm11040239.
28. Yang, Jiehua, et al. "Deep Learning for Detecting Cerebral Aneurysms with CT Angiography." Radiology, vol. 298, no. 1, 2021, pp. 155-163. doi:10.1148/radiol.2020192154.
29. Ozpinar, Alp, Gustavo Mendez, and Adib A. Abla. “Epidemiology, Genetics, Pathophysiology, and Prognostic Classifications of Cerebral Arteriovenous Malformations.” Handbook of Clinical Neurology, edited by Robert F. Spetzler, Karam Moon, and Rami O. Almefty, vol. 143, Elsevier, 2017, pp. 5–13. https://doi.org/10.1016/B978-0-444-63640-9.00001-1.
30. Abecassis, Isaac Josh, David S. Xu, H. Hunt Batjer, and Bernard R. Bendok. “Natural History of Brain Arteriovenous Malformations: A Systematic Review.” Neurosurgical Focus, vol. 37, no. 3, Sept. 2014, Article E7, doi:10.3171/2014.6.FOCUS14250.
31. García, Camila, et al. "A deep learning model for brain vessel segmentation in 3DRA with arteriovenous malformations." 18th International Symposium on Medical Information Processing and Analysis. Vol. 12567. SPIE, 2023.
32. You, W.C., et al. "Detection and Segmentation of Arteriovenous Malformation Lesions Using a Two-Stage Deep Learning Strategy." International Journal of Radiation Oncology, Biology, Physics, vol. 114, no. 3, 2022, p. e108.
33. Haasdijk, R., Cheng, C., Maat-Kievit, A. et al. Cerebral cavernous malformations: from molecular pathogenesis to genetic counselling and clinical management. Eur J Hum Genet 20, 134–140 (2012). https://doi.org/10.1038/ejhg.2011.155
34. Akers, Amy et al. “Synopsis of Guidelines for the Clinical Management of Cerebral Cavernous Malformations: Consensus Recommendations Based on Systematic Literature Review by the Angioma Alliance Scientific Advisory Board Clinical Experts Panel.” Neurosurgery vol. 80,5 (2017): 665-680. doi:10.1093/neuros/nyx091
35. Kim, Jung Youn, et al. "Improved differentiation of cavernous malformation and acute intraparenchymal hemorrhage on CT using an AI algorithm." Scientific Reports, vol. 14, no. 1, 2024, p. 11818. doi:10.1038/s41598-024-61960-0.
36. Zipfel, Gregory J., and Colin P. Derdeyn. “Epidemiology, Clinical Presentation, Diagnostic Evaluation, and Prognosis of Cerebral Dural Arteriovenous Fistulas.” Handbook of Clinical Neurology, edited by Robert F. Spetzler, Karam Moon, and Rami O. Almefty, vol. 143, Elsevier, 2017, pp. 99–105. https://doi.org/10.1016/B978-0-444-63640-9.00009-6.
37. Doneda, Martina, et al. "Surgical planning of arteriovenous fistulae in routine clinical practice: A machine learning predictive tool." The Journal of Vascular Access, vol. 25, no. 4, 2024, pp. 1170-1179. doi:10.1177/11297298221147968.
38. Heindel, P., et al. "Predicting radiocephalic arteriovenous fistula success with machine learning." npj Digital Medicine, vol. 5, 2022, p. 160. doi:10.1038/s41746-022-00710-w. Nature.
39. Gonzalez Castro, Luis Nicolas, et al. “Carotid-Cavernous Fistula: A Rare but Treatable Cause of Rapidly Progressive Vision Loss.” Stroke, vol. 47, no. 8, 2016, pp. e187–e190. https://doi.org/10.1161/STROKEAHA.116.013428.
40. Timol, Nasr et al. “Imaging findings and outcomes in patients with carotid cavernous fistula at Inkosi Albert Luthuli Central Hospital in Durban.” SA journal of radiology vol. 22,1 1264. 25 Jan. 2018, doi:10.4102/sajr.v22i1.1264
41. Alatzides, Georgios Luca, et al. “Management of Carotid Cavernous Fistulas: A Single Center Experience.” Frontiers in Neurology, vol. 14, 9 Feb. 2023, article 1123139, https://doi.org/10.3389/fneur.2023.1123139.
42. Lleayem Nazario-Johnson, Hossam A. Zaki, Glenn A. Tung, Use of Large Language Models to Predict Neuroimaging, Journal of the American College of Radiology, Volume 20, Issue 10, 2023, Pages 1004-1009, ISSN 1546-1440, https://doi.org/10.1016/j.jacr.2023.06.008.
43. Maity, Subhankar, and Manob Jyoti Saikia. “Large Language Models in Healthcare and Medi-

cal Applications: A Review." Bioengineering (Basel, Switzerland) vol. 12,6 631. 10 Jun. 2025, doi:10.3390/bioengineering12060631

44. Koçak, B., Ponsiglione, A., Stanzione, A., Bluethgen, C., Santinha, J., Ugga, L., Huisman, M., Klontzas, M. E., Cannella, R., & Cuocolo, R. (2025). Bias in artificial intelligence for medical imaging: fundamentals, detection, avoidance, mitigation, challenges, ethics, and prospects. Diagnostic and Interventional Radiology, 31(2), 75-88. https://doi.org/10.4274/dir.2024.242854

45. Norori, Natalia et al. "Addressing bias in big data and AI for health care: A call for open science." Patterns (New York, N.Y.) vol. 2,10 100347. 8 Oct. 2021, doi:10.1016/j.patter.2021.100347

46. Pham T. (2025). Ethical and legal considerations in healthcare AI: innovation and policy for safe and fair use. Royal Society open science, 12(5), 241873. https://doi.org/10.1098/rsos.241873

47. Ariana Mihan, Ambarish Pandey, Harriette GC Van Spall, Mitigating the risk of artificial intelligence bias in cardiovascular care, The Lancet Digital Health, Volume 6, Issue 10, 2024, Pages e749-e754, ISSN 2589-7500, https://doi.org/10.1016/S2589-7500(24)00155-9.

48. Haupt, Matteo et al. "Explainable Artificial Intelligence in Radiological Cardiovascular Imaging-A Systematic Review." Diagnostics (Basel, Switzerland) vol. 15,11 1399. 31 May. 2025, doi:10.3390/diagnostics15111399

49. Bilal A, Alzahrani A, Almohammadi K, Saleem M, Farooq MS and Sarwar R (2025) Explainable AI-driven intelligent system for precision forecasting in cardiovascular disease. Front. Med. 12:1596335. doi: 10.3389/fmed.2025.1596335

50. Vimbi, Viswan et al. "Interpreting artificial intelligence models: a systematic review on the application of LIME and SHAP in Alzheimer's disease detection." Brain informatics vol. 11,1 10. 5 Apr. 2024, doi:10.1186/s40708-024-00222-1

51. El-Geneedy, M., El-Din Moustafa, H., Khater, H. et al. A comprehensive explainable AI approach for enhancing transparency and interpretability in stroke prediction. Sci Rep 15, 26048 (2025). https://doi.org/10.1038/s41598-025-11263-9

52. Al Askar, Hesham, et al. "The Role of Artificial Intelligence and Machine Learning in the Assessment, Diagnosis, and Prediction of Cerebral Small Vessel Disease." Cureus, vol. 17, no. 9