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Application of Artificial Intelligence in Acute Ischemic Stroke: A Scoping Review

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Artificial intelligence (AI) is revolutionizing stroke care by enhancing diagnosis, treatment, and outcome prediction. This review examines 505 original studies on AI applications in ischemic stroke, categorized into outcome prediction, stroke risk prediction, diagnosis, etiology prediction, and complication and comorbidity prediction. Outcome prediction, the most explored category, includes studies predicting functional outcomes, mortality, and recurrence, often achieving high accuracy and outperforming traditional methods. Stroke risk prediction models effectively integrate clinical and imaging data, improving assessments of both first-time and recurrent stroke risks. Diagnostic tools, such as automated imaging analysis and lesion segmentation, streamline acute stroke workflows, while AI models for large vessel occlusion detection demonstrate clinical utility. Etiology prediction focuses on identifying causes such as atrial fibrillation or cancer-associated thrombi, using imaging and thrombus analysis. Complication and comorbidity prediction models address stroke-associated pneumonia and acute kidney injury, aiding in risk stratification and resource allocation. While significant advancements have been made, challenges such as limited validation, ethical considerations, and the need for better data collection persist. This review highlights the advancements in AI applications for addressing key challenges in stroke care, demonstrating its potential to enhance precision medicine and improve patient outcomes.

Key Words: Stroke; Artificial intelligence; Machine learning; Outcome assessment, health care; Diagnostic imaging; Risk assessment

INTRODUCTION

Artificial intelligence (AI) is revolutionizing healthcare, especially in stroke medicine where quick diagnosis and treatment are vital. The integration of AI technologies across the stroke care continuum, from initial diagnosis to outcome prediction, represents a significant advancement in our ability to deliver precise, personalized care in a timely manner. Recent years have witnessed an exponential increase in publications exploring AI applications in stroke medicine, with studies ranging from automated imaging analysis to prediction models for patient outcomes. The increase in research activity, especially since 2019, highlights the advancement of AI technologies and their acknowledged potential to address significant challenges in stroke care.

This scoping review provides an overview of the current research landscape on AI applications in stroke care, categorizing studies to assess the extent of existing advancements. It aims to summarize the available literature, offering insights into how AI is being utilized across various aspects of stroke management, including outcome prediction, stroke risk prediction, stroke diagnosis, etiology prediction, and complication or comorbidity prediction. With a systematic search using a novel automated methodology, articles were manually selected by the author with the aim to prioritize exploring

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more challenging areas that require additional investigation and development. The goal is to provide a clear understanding of the current state of AI in stroke care and its potential for advancing precision medicine.

Artificial Intelligence Models

Variety of algorithms has been used for AI. Support vector machines are trained for classification tasks by finding an optimal hyperplane that maximizes the margin between different classes in high-dimensional space.[1] Decision trees use a hierarchical structure where data is recursively split based on feature thresholds, creating an interpretable model that can handle both classification and regression tasks.[2] Random forests are an ensemble of these decision trees where each tree is trained on a random subset of the data and features.[3] Gradient boosting machines enhance predictive performance by sequentially training decision trees, where each tree corrects the errors of the previous one using gradient-based optimization.[4] Artificial neuron-based algorithms consist of interconnected artificial neurons that simulate biological neural networks by processing multiple weighted inputs and applying an activation function to produce an output.[5] Convolutional neural networks consist of multiple layers of these artificial neurons, including convolutional layers that extract spatial features, pooling layers that reduce dimensionality, and fully connected layers that perform classification.[6] These models are frequently used for image analysis. Other deep neural networks, such as recurrent neural networks and transformer-based models, are used for sequential data processing, particularly in natural language tasks.[7,8] Natural language processing models, such as Bidirectional Encoder Representations from Transformers and Generative Pre-trained Transformer, use self-attention mechanisms to understand context in text, allowing for advanced language comprehension and generation.[9,10]

METHODS

Literature Search and Screening

A systemic literature search was performed on December 10, 2024, using National Library of Medicine database (PubMed) with the search term ((artificial intelligence [Title] OR machine learning [Title] OR deep learning [Title]) AND (stroke [Title] OR thrombectomy [Title] OR thrombolysis [Title] OR cerebral infarction [Title])). The search was performed with a custom Python script that automatically performs the pre-specified search using the National Institutes of Health (NIH) application programming interface and saving the results into a spreadsheet file. The script is available in the Supplementary Material 1. Search results were screened by assessment of their titles and abstracts. All scientific literature on the topic of using AI for ischemic stroke were included. Only original research articles were included for analysis, while other types of articles such as reviews, editorials, research protocols, or literature describing experience with AI software were excluded. Research mainly on the focus of rehabilitation after stroke was excluded. Studies only concerning hemorrhagic stroke were excluded. Non-human research was excluded. Manual selection was performed for final inclusion of this review.

Literature Classification

Search results were classified into the following categories after reading the title and the abstract of the literature: 1) outcome prediction, 2) stroke risk prediction, 3) stroke diagnosis, 4) etiology prediction, 5) complication or comorbidity prediction, and 6) others. The outcome prediction category included studies that used AI to predict outcome for patients with stroke. Stroke risk prediction included research that aimed to develop models for occurrence of stroke. Studies classified as stroke diagnosis included those which used imaging, clinical variables, or novel modalities to aid in the diagnosis of stroke. Research that used AI to classify or predict the etiology of stroke was included in the etiology prediction category. The complication or comorbidity prediction category included studies that predicted the occurrence or presence of other diseases. Articles that did not fit into any of these categories were placed in the 'other' group.

Initial Literature Analysis Using Artificial Intelligence

Large language models were used for initial screening and categorization of search results. The results provided by the models were reviewed and edited by the corresponding author. Two models were used sequentially for each row of the spreadsheet file that contained the search results. The first model assessed the abstract to see if the article meets any of the exclusion criteria. If the article was not excluded, the article was sent to the second model. The second model categorized the article into the 6 pre-specified categories. The results were saved as new columns and saved as a separate spreadsheet file. The script is available in the Supplementary Material 2.

Literature Search Results

A total of 821 results were retrieved from the search. Of these results, 505 articles (61.5%) were included for analysis after exclusion (Fig. 1). Outcome prediction was the most studied category (198 articles, 39.2%), followed by stroke diagnosis (166 articles, 32.9%), stroke risk prediction (92 articles, 18.2%), etiology prediction (20 articles, 4.0%), and complication and comorbidity prediction (12 articles, 2.4%). On further classification of articles inside the outcome prediction category, functional outcome was the most studied topic (101 articles, 51.0%), followed by mortality (26 articles, 13.1%), and stroke recurrence (16 articles, 8.1%). The number of articles on AI and stroke has grown rapidly since 2019 (Fig. 2). However, the rate of increase has plateaued since 2022. Outcome prediction studies have consistently been published from 2014, while stroke diagnosis has also been studied extensively, especially in 2022. A total of 52 articles were manually selected for this review (Supplementary Table 1).

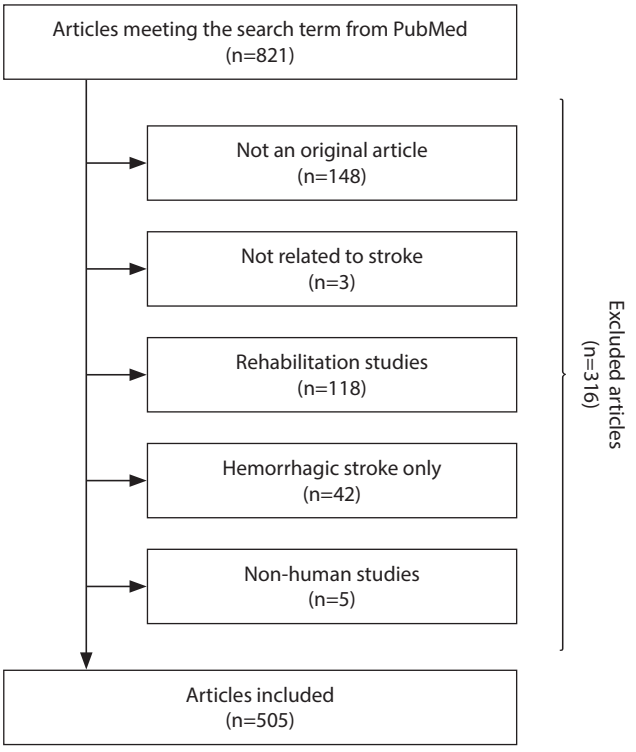

Fig. 1. Flowchart of articles screened and included in this review.

STROKE OUTCOME PREDICTION

Functional Outcome

One of the earliest large-scale studies on the topic of functional outcome prediction used the Multicenter Randomized Clinical Trial of Endovascular Treatment for Acute Ischemic Stroke in the Netherlands Registry to retrospectively develop models to predict good reperfusion (modified Thrombolysis in Cerebral Infarction≥2b) and functional independence (modified Rankin Scale≤2) at 3 months using baseline

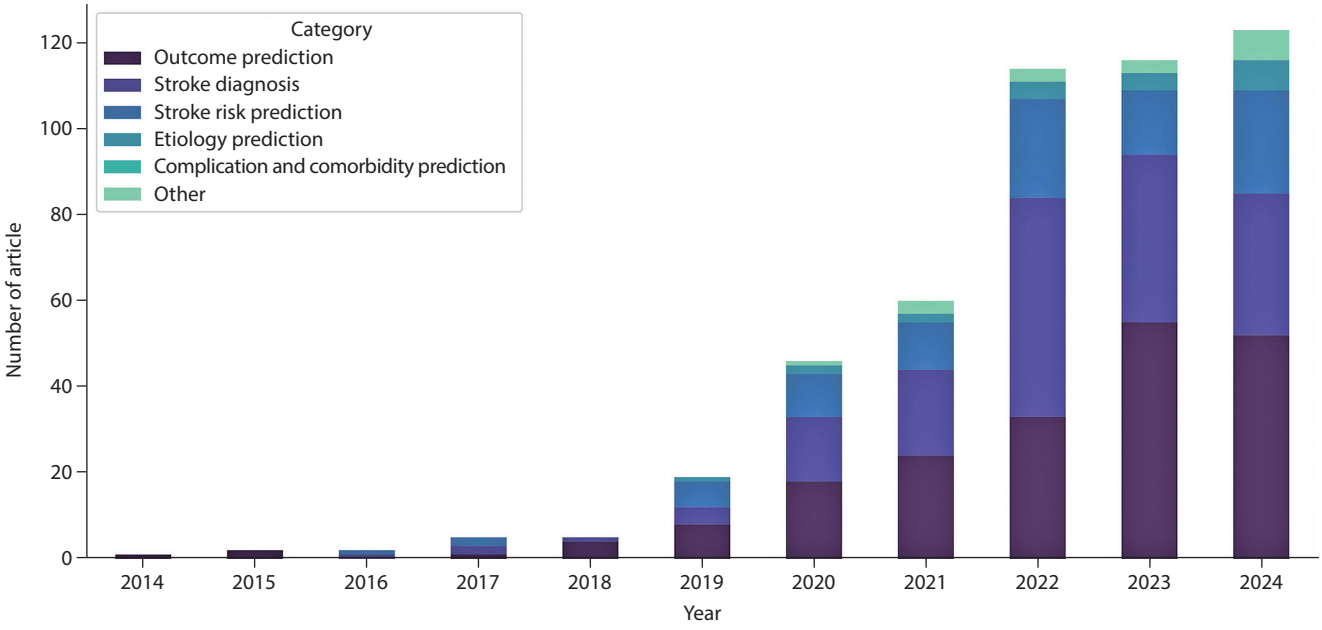

Fig. 2. Yearly trend in the number of articles categorized by classification.

variables with or without treatment variables.[11] Random Forests, Support Vector Machine, Neural Network, and Super Learner were used and compared with logistic regression models. The area under the receiver operating characteristic curve (AUC) was 0.53–0.57 for reperfusion prediction and 0.77–0.79 for functional independence prediction. Upon adding treatment variables, the AUC increased to 0.88–0.91 on functional independence prediction, indicating the importance of reperfusion treatment in functional outcome. Another earlier large-scale study included 2,604 patients to develop models to predict functional independence at 3 months.[12] Deep neural network, Random Forest, and logistic regression was used to build models and compare outcomes with the Acute Stroke Registry and Analysis of Lausanne (ASTRAL) score. Baseline clinical variables were used as input. The deep neural network model showed an AUC of 0.888, which was significantly higher compared to the ASTRAL score (0.839, P=0.001). More recently, a study has shown that models incorporating multimodal inputs have shown higher performance compared to single-modality models.[13] An ensemble model including 3D convolutional neural networks of diffusion-weighted imaging and fluid-attenuated inversion recovery imaging performed significantly better (AUC of 0.830) than models that used either a diffusion coefficient map, fluid-attenuated inversion recovery imaging, or clinical data as predictors. When compared to stroke neurologists, AI models performed similarly when only clinical variables were used and may perform better when imaging is also used.[14,15]

Reperfusion Therapy Outcomes

AI was used to predict outcome measures associated with acute reperfusion therapies. Successful recanalization after the first thrombectomy effect, also known as first-pass effect, was predicted using pre-treatment CT and MR imaging.[16] Using a cohort of 326 patients, a hybrid transformer model with non-local and cross-attention modules was trained and validated. No manual segmentation was needed to use the model. The MR-based model showed an AUC of 0.797 and the CT-based model showed an AUC of 0.805. Models using only clinical variables were developed to also predict the first-pass effect in another study.[17] Random Forest, Support Vector Machine, and logistic regression were applied, yielding final accuracies between 65.8% and 67.1%. Of note, feature attribution analysis revealed that the most influential variable was the interventionist's choice of an aspiration catheter as the thrombectomy device, underscoring the potential bias introduced by human judgment in the model's predictions. Success after intravenous thrombolysis was predicted with clinical variables and AI.[18] The AUC was 0.765, with the initial NIH Stroke Scale (NIHSS) being the most important variable in outcome prediction, followed by glucose, neutrophil, white blood cell, and blood urea nitrogen levels.

Stroke Recurrence

Stroke recurrence was predicted using AI models. Using a large public health care-based dataset (41,975 patients with stroke), models were developed to predict early (≤90 days), late (91–365 days), and long-term (>365 days) recurrence risk.[19] Of the included patients, 16% (5,932 of 36,114) suffered stroke recurrence during follow-up (median 2.69 years). The AUCs were 0.76 for early, 0.60 for late, and 0.71 for long-term recurrence risk prediction models. The most important predictors were time from previous stroke, Barthel Index, atrial fibrillation, dyslipidemia, age, diabetes, and sex. AI models were significantly better at prediction than the Cox model. Another study that developed recurrence prediction models focused on patients with symptomatic intracranial cerebral artery stenosis.[20] The AUCs ranged from 0.813 to 0.912 for 5 models on 10-fold cross-validation. Feature attribution analysis showed radiologic characteristics of high-resolution vessel-wall imaging were important in recurrence.

STROKE RISK PREDICTION

Initial and Recurrent Stroke Risk

Prediction modelling of occurrence of stroke has been studied extensively with AI algorithms. A study investigated stroke risk in a large prospective cohort of 3,435,224 U.S. patients with multimorbidity, utilizing traditional clinical risk scores, a clinical multimorbid index, and AI approaches.[21] While common clinical scores (e.g., CHADS2, CHA2DS2-VASc) showed moderate predictive ability, the clinical multimorbid index and AI-based algorithms demonstrated superior discriminative performance (c-index of 0.866). The AI models effectively accounted for the dynamic nature of multimorbidity and showed better calibration and decision curve analysis compared to clinical rules. In addition to predicting initial stroke risk, efforts have also been made to predict the risk of recurrent strokes using AI.[22] A study developed prediction models based solely on patient-reported data easily obtained at home, eliminating the need for costly clinical or

imaging data. The best model achieved an AUC of 0.70, with good probability calibration. Key predictive factors included family and housing circumstances, rehabilitative measures, age, diet, blood pressure levels, and the frequency of family doctor home visits.

Stroke Risk Prediction in Cardiac Patients

Patients with cardiac diseases are at higher risk of developing stroke. Research has been conducted to predict stroke occurrence in patients with atrial fibrillation, coronary artery disease, and those who have undergone percutaneous coronary intervention. One of the earliest published studies on risk prediction in patients with atrial fibrillation developed a 2-year prediction model with data of 1,864 patients and achieved an AUC of 0.71–0.74.[23] Another study leveraged continuous remote monitoring data from cardiac implantable electronic devices to evaluate signatures of atrial fibrillation burden for near-term stroke risk stratification with 3,185 patients.[24] Using convolutional neural networks, random forests, and LASSO logistic regression, the study found that these models outperformed the conventional CHA2DS2-VASc score with the highest AUC of 0.702. In a case-control study involving 8,624 patients, machine learning (ML) models for predicting coronary heart disease and ischemic stroke achieved AUCs of 0.905 and 0.889, respectively, identifying key predictors such as age, brachial-ankle pulse wave velocity, hypertension, and low-density lipoprotein cholesterol.[25] Another study analyzing data from 17,356 patients developed random forest models to predict ischemic stroke after percutaneous coronary intervention, with an AUC that exceeded logistic regression models at all time points, reaching 0.662 at 6 months and 0.702 at 5 years.[26] Additionally, a cohort of 5,757 coronary artery disease patients receiving coronary revascularization showed that a CatBoost model outperformed logistic regression for predicting postoperative stroke, achieving an AUC of 0.760 in the testing set, with the Charlson Comorbidity Index identified as the most important predictor.[27]

Carotid Plaque Imaging for Stroke Risk Assessment

Carotid plaque imaging and advanced analytics have demonstrated utility in stroke risk prediction. Automated segmentation of grayscale carotid plaques achieved high classification accuracies of 95.08% and 93.47% for far and near walls, respectively.[28] Deep learning models applied to color Doppler images classified carotid plaques as high-risk or stable with a maximum accuracy of 93.81%, using pretrained Inception V3 and VGG-16 models fine-tuned for this task.[29] MRI-based analyses showed 94.81% accuracy in identifying carotid plaques with YOLOv3 models, emphasizing operator independence and the superior soft-tissue contrast of MRI in stroke risk assessment.[30] Plaque morphology shown in CT was also utilized.[31] A combined model incorporating clinical factors such as age, body mass index, and a history of transient ischemic attack or stroke with plaque morphology variables like perivascular adipose tissue and lipid-rich necrotic cores achieved an AUC of 0.759 for 30-day stroke or mortality.

Fundus Imaging for Stroke Risk Assessment

Fundus imaging has been utilized with AI to predict stroke occurrence. A study involving 250 participants with atrial fibrillation analyzed fundus images captured at wavelengths of 548, 605, and 810 nm using 3 classical deep neural networks (Inception V3, ResNet50, SE50).[32] The models achieved an accuracy of over 78%, with the 605 nm wavelength showing the most stable detection performance in prediction of stroke occurrence. Multi-spectral combinations of images yielded higher AUC scores compared to single-spectrum models. Another study analyzed retinal vasculometry data from 88,052 and 7,411 participants across 2 large cohorts to assess its potential in improving risk algorithms for incident stroke, myocardial infarction, and circulatory mortality.[33] The addition of retinal vasculometry data to the Framingham risk scores did not significantly enhance prediction; however, a simpler model using retinal vasculometry data, age, smoking status, and medical history performed equally or better than Framing risk scores, with C-statistics ranging between 0.75–0.77 for circulatory mortality prediction. Furthermore, a deep learning-based system trained on retinal biomarkers from fundus images achieved AUC of 0.83 and 0.93 in 2 datasets, demonstrating superior performance over traditional benchmarks in predicting stroke risk and timing of occurrence.[34]

STROKE DIAGNOSIS

Large Vessel Occlusion Detection

AI was used to automatically estimate Alberta Stroke Program Early CT score.[35] Numerous commercially approved software solutions offer this functionality and are frequently used in clinical settings.[36] Studies have shown that these

software improved efficiency in imaging analysis.[37,38] Similarly, AI models were developed and validated for detection and segmentation of ischemic lesions in non-contrast brain CT imaging.[39,40] Models focused on large vessel occlusion detection have also been extensively studied and validated, currently available as commercial software certified for use in clinical settings.[41-43] Performance of large vessel occlusion detection using AI was studied for CT imaging obtained from mobile stroke units.[44] Automatically detecting large vessel occlusion at the mobile stroke unit before arrival at the emergency room could facilitate faster reperfusion times, leading to better treatment outcomes.

Ischemic Lesion Segmentation

Ischemic lesion segmentation on non-contrast brain CT was performed with AI.[39,45,46] One of the main challenges in developing a segmentation model for non-contrast brain CT is the low correlation of 'ground truth' segmentation between experts. The decision of the 'right' lesion after manual delineation by experts was performed by reaching a consensus.[46] Although with a limited number of images (260 CT studies), developing a model with a dataset consisted of randomly choosing 1 out of 3 experts' segmentation for each CT study showed better performance than a merged segmentation map.[39] An alternative approach, despite its limitations, is indirectly deriving the segmentation map using expert-labeled ischemic lesion volumes from diffusion-weighted MRI scans.[45]

AI-Enhanced Imaging

AI-accelerated ultrafast MRI, which takes about a fourth the time to acquire compared to traditional MRI, was validated.[47] Interchangeability on detection of cerebral infarction of the ultrafast MRI compared to traditional MRI was assessed with 3 radiologists as primary outcome. Secondary findings such as microbleeds or neoplasms, vascular territory of the infarction, and image quality assessment were also compared. There was no significant difference in the assessment results by the radiologist between the 2 modalities. A Cycle-GAN-based deep learning model was developed to generate high-resolution synthetic time of flight (TOF) images from time-resolved MRA for improved collateral evaluation in acute ischemic stroke.[48] Image quality assessments showed that synthetic TOF images had better overall quality compared to time-resolved MRA but were inferior to real TOF in some areas. Clinical validation demonstrated synthetic TOF enhanced diagnostic confidence and reduced decision time in detecting large-vessel occlusion, showing the potential for use in stroke centers.

Other Studies on Stroke Detection

A study was performed to automatically recognize stroke by using AI on transcription of medical helpline calls.[49] The model performed significantly better than the call-takers with a sensitivity of 63%. The most important words in identification of stroke were 'ambulance,' 'blood clot,' 'left,' 'right,' and 'double vision.' AI was used in the analysis of movement data of patients to diagnose stroke. The pronator drift test, an important neurologic examination for stroke, was performed using accelerometer signals from wearable devices on the wrist.[50] Stroke was predicted using ML of signals acquired from the sensors. The AUCs ranged from 0.913 to 0.975 in the prediction of stroke. In another study, based on the Face Arm Speech Test clinical test, multi-modal deep learning models were developed to analyze the movement and speech data of the patients under specific instructions (i.e., raise both arms or pronounce a pre-specified sentence).[51]

ETIOLOGY PREDICTION

Determining the etiology of stroke is crucial for effective secondary prevention. However, despite thorough evaluations, the cause remains unknown in over a third of stroke patients. Innovative approaches leveraging AI could help address this unmet need.

Detection of Atrial Fibrillation

Using demographics, comorbidities, vitals, laboratory results, and echocardiograms, a model was developed to classify between cardioembolic and non-cardioembolic strokes.[52] The model was applied to patients with embolic stroke of undetermined source and compared the results with eventual diagnosis of atrial fibrillation in these patients. The model's prediction was associated with eventual atrial fibrillation detection. Electrocardiography during sinus rhythm was used for its potential in prediction of hidden paroxysmal atrial fibrillation.[53] A model was developed for prediction of underlying atrial fibrillation with electrocardiography results from patients with paroxysmal atrial fibrillation. This model was applied to patients initially classified as embolic stroke of undetermined source and compared with prolonged

ambulatory monitoring. The probability of atrial fibrillation in the prediction model was significantly associated with detection of atrial fibrillation on prolonged monitoring.

Imaging-Based Subtype Classification

Automatic subtype classification was performed with AI using diffusion weighted MR imaging and presence of atrial fibrillation, achieving performance comparable to expert consensus.[54] By utilizing the presence of atrial fibrillation and patterns of infarction in diffusion weighted imaging, the AI model showed high agreement (72.9% agreement) with the expert consensus. A model using only the diffusion weighted imaging data showed a lower agreement (58.1%) with the expert consensus. These agreement values of the models were comparable to the agreement between the experts, which was only 76%.

Thrombi-Based Subtype Classification

AI was used for analysis for thrombi to predict etiology of stroke. In a multicenter study, whole-slide scanned images of immunohistochemically-stained thrombi retrieved from mechanical thrombectomy were used for detection of underlying cancer as the etiology for stroke.[55] The model utilizing the platelet-stained slides showed a high AUC of 0.949 on external validation, reconfirming the importance of platelet in cancer-associated thrombi in stroke. *Ex-vivo* multiparametric MR imaging was also studied for prediction of dichotomized red blood cell component of the thrombi.[56] In this experimental study, MR imaging was obtained with the thrombi retrieved from thrombectomy. After the MR imaging, the thrombi were stained to analyze the red blood cell component. A model was developed using the MR image to predict if the thrombi contain a high percentage of red blood cells. The AUC was 0.84 on cross-validation.

COMPLICATION OR COMORBIDITY PREDICTION

Stroke-Associated Pneumonia

The most studied complication after stroke was pneumonia. An XGBoost model was developed to predict stroke-associated pneumonia in 3,160 patients with stroke, achieving an AUC of 0.841 and outperforming traditional risk scores.[57] This model relied on 6 commonly available clinical variables: age, pre-morbid modified Rankin Scale score, NIHSS at admission, fasting blood glucose level, sex, and history of atrial fibrillation. Occurrence of pneumonia within 1 year after discharge was predicted with a large dataset of 5,754 hospitalized stroke patients.[58] The C-index was 0.787 on the test set, and the most important features were Glasgow Coma Scale score, age, and length of hospital stay.

Acute Kidney Injury

AI was used to predict acute kidney injury, analyzing data from 3,920 patients.[59] Among 9 model, the XGBoost model demonstrated superior performance, achieving AUCs of 0.940 and 0.887 in internal and external validation sets, respectively. SHapley Additive exPlanations analysis identified glomerular filtration rate, low-density lipoprotein, total cholesterol, hemiplegia, and serum potassium as the most important predictors.

Hidden Coronary Artery Disease

A study developed and validated ML models to predict hidden coronary artery disease in patients with stroke using clinical variables.[60] A total of 2,058 patients were included for this study, and the best performing model showed an AUC of 0.763 on validation. Additionally, major adverse cardiovascular events were more frequent for the patients who were predicted to have a high possibility of coronary artery disease during 5-year follow-up. This study highlighted the potential of AI to identify hidden coronary artery disease and inform risk stratification in stroke patients.

OTHER STUDIES

Two recent studies highlight the potential of AI to optimize acute stroke care pathways. The first study developed a mobile app integrating ML-based prediction models with historical data on air and land medical transport to guide healthcare providers in Northwestern Ontario on the most efficient patient transfer options for stroke care.[61] Using a decision tree model trained on over 70,000 transport records, the app accurately accounts for variables like patient location, available treatments, and imaging facilities, aiming to improve outcomes and reduce healthcare costs. However, the study was based on retrospective data, and the usage results of the developed app is needed. The second study explored the feasibility of Wi-Fi fingerprinting with ML algorithms, such as random forest and support vector machines,

to create a real-time location system for streamlining acute stroke endovascular interventions.[62] With an accuracy of 98% in tracking patient and staff movements across hospital zones, this technology could significantly enhance workflow efficiency during time-sensitive procedures like mechanical thrombectomy.

AI may have potential in optimizing mechanical thrombectomy for acute stroke patients by addressing procedural challenges. A model demonstrated that acute internal carotid artery angles (≤90°) are associated with longer mechanical thrombectomy durations, achieving high segmentation accuracy (Dice scores of 0.94 for the aorta and 0.86 for internal carotid artery) and robust performance in predicting internal carotid artery angles (AUC of 0.92). Similarly, a model trained on anatomical features extracted from CT angiography effectively predicted difficult transfemoral access during mechanical thrombectomy, outperforming expert assessments with an AUC of 0.76.

CONCLUSION

While AI shows significant promise, its role in healthcare, including stroke management, is still evolving. Continued focus on methodical validation, ethical considerations, and practical implementation will determine the extent to which AI can be effectively applied to improve clinical outcomes. Although further evidence is needed, AI has the potential to play an important role in enhancing stroke care and addressing current challenges in the field.

SUPPLEMENTARY MATERIALS

Supplementary materials related to this article can be found online at https://doi.org/10.5469/neuroint.2025.00052.

Fund
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This article was exempted from the review by the institutional ethics committee. This article does not include any information that may identify the person.

Conflicts of Interest
The author has no conflicts to disclose.

Author Contributions
Concept and design: JNH. Analysis and interpretation: JNH. Data collection: JNH. Writing the article: JNH. Critical revision of the article: JNH. Final approval of the article: JNH. Overall responsibility: JNH.

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Supplementary Table 1. Summary of literature included in this review

Author	Year	Study design	Endpoint	Performance	AI model	Other
Stroke outcome prediction						
van Os et al.[11]	2018	Observational cohort	3-month mRS≤2	AUC: 0.91	Random Forests, SVM, Neural Network, Super Learner	Best performance when both baseline and treatment variables were included
Heo et al.[12]	2019	Retrospective from prospective cohort	3-month mRS≤2	AUC: 0.888	Deep Neural Network, Random Forest, Logistic Regression	Deep Neural Network outperformed ASTRAL score
Jung et al.[13]	2024	Prospective multicenter stroke registry	3-month mRS≤2	AUC: 0.779	Ensemble Deep Neural Network	Multimodal model outperformed single modality models
Herzog et al.[14]	2023	Observational study	3-month mRS≤2	AUC: 0.766	Deep Neural Network	Models outperformed neurologists when imaging was included
Liu et al.[15]	2024	Retrospective single-center registry	3-month mRS≤2	AUC: 0.81	Deep Neural Network	Model was noninferior to expert clinicians
Zhang et al.[16]	2024	Retrospective single-center thrombectomy cohort	First-pass recanalization	AUC: 0.7967 (MR-based), 0.8051 (CT-based)	Hybrid Transformer model with self-supervised learning	Outperformed prior AI-based approaches without manual clot segmentation
Velagapudi et al.[17]	2021	Retrospective single-center thrombectomy cohort	First-pass reperfusion	AUC: 0.67	Random Forest, SVM, Logistic Regression, Naive Bayes, XGBoost	Feature importance analysis identified aspiration as key predictor
Wang et al.[18]	2024	Retrospective single-center cohort	Thrombolysis resistance (24 hours NIHSS improvement 30%)	AUC: 0.765	Random Forest, SVM, Logistic Regression, Naive Bayes, XGBoost	NIHSS at admission, blood glucose, WBC, neutrophil count, and BUN were key predictors
Colangelo et al.[19]	2024	Retrospective multicenter cohort	Stroke recurrence (early: ≤90 days, late: 91–365 days, long-term: >365 days)	AUC: 0.76 (early), 0.60 (late), 0.71 (long-term)	Random Forest, AdaBoost, XGBoost, Cox Regression	Machine learning models outperformed Cox regression for stroke recurrence prediction
Gao et al.[20]	2024	Retrospective single-center cohort	Stroke recurrence in symptomatic intracranial atherosclerotic stenosis	AUC: 0.912	Gaussian Naive Bayes, Logistic Regression, SVM, kNN, Complement Naive Bayes	Stenosis rate, NWI, plaque enhancement, and IPH were key predictors
Stroke risk prediction						
Lip et al.[21]	2022	Prospective cohort study	Stroke occurrence	C-index: 0.866	Gradient Boosting, Neural Network, Logistic Regression, Decision Tree	Models performed better than traditional clinical risk scores
Vodencarevic et al.[22]	2022	Prospective population-based registry	1-year stroke recurrence	AUC: 0.70	Linear SVM, Logistic Regression, Naive Bayes, Random Forest, XGBoost	Patient-reported variables were key predictors

Supplementary Table 1. Continued

Author	Year	Study design	Endpoint	Performance	AI model	Other
Li et al.[23]	2017	Retrospective cohort	2-year ischemic stroke or thromboembolism	AUC: 0.74	Logistic Regression, Naive Bayes, Decision Tree, Random Forest, Cox Model	Models outperformed traditional risk scores
Han et al.[24]	2019	Retrospective cohort	Near-term stroke prediction (30-day window)	AUC: 0.696	Random Forest, Convolutional Neural Network, LASSO	Ensemble models performed best
Chen et al.[25]	2022	Retrospective case-control study	Stroke occurrence	AUC: 0.884	Random Forest, Ensemble Learning	Hypertension, baPWV, and LDL as key predictors
Chao et al.[26]	2023	Retrospective single-center registry	Ischemic stroke post-PCI (6-month, 1-, 2-, and 5-year)	AUC: 0.87 (6 months), 0.81 (1 year), 0.77 (2 years), 0.77 (5 years)	Random Forest, Logistic Regression	Periprocedural stroke was the strongest predictor
Lin et al.[27]	2024	Retrospective cohort	Postoperative stroke in patients undergoing coronary revascularization	AUC: 0.760	CatBoost, Logistic Regression, SVM, Random Forest, XGBoost, AdaBoost, Naive Bayes, kNN	Charlson Comorbidity Index was the most important predictor
Araki et al.[28]	2017	Retrospective single-center cohort	Stroke risk based on carotid plaque morphology	Accuracy: 95.08% (far wall), 93.47% (near wall)	SVM	Using grayscale texture analysis of near and far carotid wall plaques
Bai et al.[29]	2020	Retrospective single-center cohort	Postoperative stroke after carotid endarterectomy	Not reported	XGBoost, Decision Tree, Random Forest, Neural Network, Naive Bayes, SVM	Blood pressure variability, body mass index, and age were key predictors
Su et al.[30]	2023	Retrospective single-center cohort	Stroke risk based on carotid plaque classification	Accuracy: 93.81%	Inception V3, VGG-16	Classifies carotid plaques into high-risk and stable
Chen et al.[31]	2023	Retrospective single-center cohort	Stroke risk based on MRI carotid plaque	Accuracy: 94.81%	YOLOv3, RCNN, MobileNet	High accuracy in carotid plaque detection
Li et al.[32]	2023	Retrospective single-center cohort	Ischemic stroke occurrence within 1 year of atrial fibrillation	AUC: 0.954	Inception V3, ResNet50, SE50	Multi-spectral fundus images improved stroke risk prediction
Rudnicka et al.[33]	2022	Prospective cohort	Circulatory mortality, incident stroke, and myocardial infarction	C-statistic: 0.750 (circulatory mortality), 0.730 (stroke), 0.670 (MI)	SVM, Deep Learning	Retinal vasculometry as a non-invasive vascular health marker
Messica et al.[34]	2024	Retrospective cohort	Stroke risk prediction (ischemic & hemorrhagic) and timeframe estimation	AUC: 0.83–0.93	Gradient-boosted tabular model	Retinal biomarkers significantly improved stroke risk prediction

Supplementary Table 1. Continued

Author	Year	Study design	Endpoint	Performance	AI model	Other
Stroke diagnosis						
Guberina et al.[35]	2018	Retrospective single-center cohort	ASPECTS	Sensitivity: 83%, specificity: 57%, accuracy: 67%	Machine Learning	e-ASPECTS software, Brainomix; e-ASPECTS showed valid results in normal brains but underperformed in patients with pre-existing cerebral changes
Hoelter et al.[36]	2020	Retrospective single-center cohort	ASPECTS	AUC: 0.759 (Brainomix), 0.752 (Frontier V2), 0.734 (RAPID)	Brainomix e-ASPECTS, Syngo.*via* Frontier ASPECT Score V2, RAPID ASPECTS	Brainomix showed the highest correlation with expert readings
Wei et al.[37]	2025	Multicenter retrospective and prospective cohort	ASPECTS	AUC: 84.97%, ICC: 0.84	3-stage CNN: 3D ResNet, U-Net, 2.5D ResNet	AI-based ASPECTS scoring reduced time by 74.8%
Delio et al.[38]	2021	Retrospective cohort	ASPECTS scoring agreement with expert neuroradiologists	Agreement: 72% (typical readers), 77% (AI alone), 78% (AI-assisted)	Automated ASPECTS Software	AI-assisted reading improved agreement with expert consensus
Ostmeier et al.[39]	2025	Retrospective cohort	Segmentation of acute ischemic stroke on non-contrast CT	Surface Dice at Tolerance 5 mm: 0.70±0.03, Dice: 0.50±0.04	U-Net	Random expert sampling model outperformed majority vote and inter-expert agreement
Mohapatra et al.[40]	2023	Retrospective single-center cohort	Localization of early infarction on NCCT	AUC: 0.73	VGG16, GoogleNet, ResNet50, Inception-v3, Inception-v4, Inception-ResNet-v2	Model performed well for cortical, subcortical, and mixed regions
Matsoukas et al.[41]	2023	Prospective Multihospital Stroke Network data	LVO detection	AUC: 0.95 (ICA-T/M1), 0.86 (ICA-T/M1/M2)	Viz LVO AI	High performance for ICA-T/M1 occlusions
Dehkharghani et al.[42]	2021	Multicenter retrospective cohort	LVO detection	AUC: 0.99	Rapid-LVO software, Vessel Tracking Algorithm	High performance across scanner manufacturers; rapid detection within 3 minutes 30 seconds
Grunwald et al.[43]	2019	Prospective single-center cohort	CTA collateral scoring	ICC: 0.93 (e-CTA *vs.* consensus), sensitivity: 0.99, specificity: 0.94	e-CTA module, e-STROKE SUITE by Brainomix	Automated collateral scoring improved inter-rater agreement
Czap et al.[44]	2022	Retrospective cohort	LVO detection in mobile stroke unit	AUC: 0.80 (mobile stroke unit CTA), AUC: 0.84 (in-hospital CTA)	DeepSymNet-v2 CNN	LVO detected with high accuracy in mobile stroke unit CTAs

Supplementary Table 1. Continued

Author	Year	Study design	Endpoint	Performance	AI model	Other
Qiu et al.[45]	2020	Single-center observational registry	Segmentation of infarction on NCCT	Correlation: r=0.76 (*vs.* MRI lesion volume), mean difference: 11 mL	Random Forest with Deep Learning features, U-Net for hypoattenuation detection	Good agreement with expert MRI-based lesion volumes
Nishi et al.[46]	2023	Multicenter retrospective cohort	Ischemic core estimation on NCCT	ICC: 0.90, AUC: 0.91 (large core>70 mL)	U-Net, 3D fully convolutional network, brain hemisphere comparison algorithm	Achieved high correlation with MRI-based reference
Altmann et al.[47]	2024	Prospective single-center cohort	Interchangeability of deep learning-accelerated MRI with conventional MRI for stroke detection	Interrater reliability ICC: 0.8, Interchangeability IEI: −0.002 (90% CI: −0.007, 0.004)	Multishot Echo-Planar Imaging, Deep Learning-based MRI Reconstruction	AI-accelerated MRI was 4 times faster than conventional MRI
You et al.[48]	2023	Retrospective single-center study	Synthetic TOF-MRA from time-resolved MRA	Structural similarity index measurement: 0.67, Peak signal to noise ratio: 15.56 dB	CycleGAN with Adaptive Layer-Instance Normalization	Synthetic TOF improved diagnostic confidence and reduced decision time for LVO
Wenstrup et al.[49]	2023	Retrospective study	Stroke recognition in medical helpline calls	Sensitivity: 63.0%, positive predictive value: 24.9%	Automatic Speech Recognition+Text Classification Ensemble	Model outperformed human call-takers in stroke recognition
Park et al.[50]	2017	Retrospective single-center study	Neurological deficit detection *via* pronator drift test with smartphones	AUC: 0.975	SVM, Radial Basis Function Network, Random Forest	Using accelerometer signals accurately detected stroke-related motor deficits
Ou et al.[51]	2025	Cross-sectional single-center observational study	Stroke identification using speech and movement data	AUC: 0.882	Multi-modal Transformer, Video Contrastive Learning, VGGish for audio features	Multi-modal approach combining action video and speech audio outperformed single-modality models
Etiology prediction						
Kamel et al.[52]	2020	Retrospective single-center cohort	Cardioembolic stroke in ESUS	AUC: 0.85 (cardioembolic *vs.* non-cardioembolic), c-statistic: 0.68 (AF prediction)	Super Learner ensemble (L1 regularization, XGBoost, Random Forests, multivariate adaptive splines)	Classifier estimated 44% of ESUS cases were cardioembolic
Rabinstein et al.[53]	2021	Retrospective single-center cohort	Atrial fibrillation in ESUS	AUC: 0.85	Deep Learning (AI-enabled Electrocardiogram)	AF detection by ambulatory monitoring
Ryu et al.[54]	2024	Multicenter retrospective cohort	Stroke subtypes using diffusion MRI	AUC: 0.90 (LAA), 0.93 (SVO), 0.95 (CE)	U-Net for infarct segmentation, EfficientNetV2 for classification	DWI+AF model outperformed DWI-only model

Supplementary Table 1. Continued

Author	Year	Study design	Endpoint	Performance	AI model	Other
Heo et al.[55]	2023	Multicenter retrospective cohort	Cancer prediction using thrombi	AUC: 0.949	Transfer Learning with CNN	Platelet-rich thrombi associated with cancer
Christiansen et al.[56]	2024	Retrospective single-center cohort	Thrombus RBC content using multiparametric MRI	AUC: 0.84, accuracy: 80%	3-layer CNN	Predicted thrombus erythrocyte content with high accuracy
Complication or comorbidity prediction						
Li et al.[57]	2020	Retrospective single-center cohort	Stroke-associated pneumonia	AUC: 0.841	XGBoost, Logistic Regression, SVM, Random Forest, Deep Neural Network	Outperformed clinical scores
Lee et al.[58]	2024	Retrospective single-center cohort	Post-stroke pneumonia	C-index: 0.787	Random Survival Forest, Cox Regression, XGBoost, Elastic Net Regression	Glasgow Coma Scale, age, and length of hospital stay were key predictors
Lu et al.[59]	2024	Retrospective single-center cohort	Acute kidney injury	AUC: 0.887	XGBoost, Logistic Regression, LightGBM, Random Forest, AdaBoost, GaussianNB, MLP, SVM, kNN	Glomerular filtration rate, LDL, total cholesterol, hemiplegia, and serum kalium were key predictors
Heo et al.[60]	2022	Retrospective single-center cohort	Hidden coronary artery disease	AUC: 0.763 (any CAD), 0.714 (obstructive CAD)	XGBoost, Logistic Regression, Random Forest, Deep Neural Networks, Gradient Boosting	Worse long-term outcomes when predicted of coronary artery disease
Other studies						
Hassan et al.[61]	2024	Retrospective single-center cohort	Optimization of stroke patient transport	Mean squared error 0.001	Decision Tree, Support Vector Regression, Random Forest	Developed NWO Navigate Stroke app for improving transport decision-making
Lim et al.[62]	2022	Proof-of-concept study	Real-time location tracking for stroke workflow optimization	Accuracy: 98%	Random Forest, SVM, Decision Tree, kNN, Ensemble models	Wi-Fi fingerprinting to tract personnel

Representative performance metrics are shown.

AI, artificial intelligence; mRS, modified Rankin Scale; AUC, area under the receiver operating characteristic curve; SVM, support vector machine; ASTRAL, Acute Stroke Registry and Analysis of Lausanne score; NIHSS, National Institutes of Health Stroke Scale; WBC, white blood cell; BUN, blood urea nitrogen; kNN, k-Nearest Neighbors; NWI, Normalized Wall Index; baPWV, brachial-ankle pulse wave velocity; LDL, low-density lipoprotein; PCI, percutaneous coronary intervention; ICC, intraclass correlation coefficient; CNN, convolutional neural networks; ASPECTS, Alberta Stroke Program Early CT Score; NCCT, non-contrast computed tomography; LVO, large vessel occlusion; ICA-T, internal carotid artery terminus; M1, middle cerebral artery M1 segment; M2, middle cerebral artery M2 segment; IEI, interchangeability error interval; TOF, time-of-flight; ESUS, embolic stroke of undetermined source; LAA, large artery atherosclerosis; SVO, small-vessel occlusion; CE, cardioembolic; IPH, intraplaque hemorrhage; RCNN, region-based convolutional neural network; MI, myocardial infarction; CTA, computed tomography angiography; CI, confidence interval; AF, atrial fibrillation; DWI, diffusion weighted imaging; RBC, red blood cells; MLP, multi-layer perceptron.