https://doi.org/10.5469/neuroint.2025.00052

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 multi-center 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 multi-center 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

https://doi.org/10.5469/neuroint.2025.00052

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.

https://doi.org/10.5469/neuroint.2025.00052