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# Artificial Intelligence for Automated Detection of Large Vessel Occlusion: State of the Art, Clinical Applications and Future Perspectives

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## ABSTRACT

**Background:** Large vessel occlusion (LVO) is a major cause of morbidity and mortality in acute ischemic stroke (AIS) and a common indication for mechanical thrombectomy. Rapid detection is critical because the benefit of treatment is highly time-dependent. Artificial intelligence (AI)-based imaging systems have emerged as decision-support tools for automated LVO identification, image prioritisation, and rapid stroke-team notification.

**Objective:** To critically review current evidence on AI-assisted LVO detection, including diagnostic accuracy, clinical and workflow implications, commercially available platforms, barriers to implementation, and future perspectives.

**Methods:** This narrative review covers literature published from January 2015 to June 2026 on AI-based LVO identification using computed tomography angiography (CTA) and multimodal stroke imaging. Evidence relating to diagnostic performance, external validation, workflow impact, commercial platforms, implementation, and emerging technologies was reviewed.

**Results:** AI systems demonstrate high diagnostic accuracy for proximal anterior circulation LVO, with reported sensitivities of 85-97% and specificities above 90%. Clinical implementation has improved image triage, specialist notification, thrombectomy activation, and interhospital coordination. However, performance is less consistent for distal and posterior circulation occlusions, while heterogeneity in study design, imaging methods, and outcome measures limits comparisons between platforms. Additional challenges include false-positive alerts, missed occlusions, limited generalisability, algorithmic bias, explainability, regulatory oversight, interoperability, and cost.

**Conclusion:** AI-assisted LVO detection has the potential to improve the speed and coordination of acute stroke care, particularly for proximal anterior circulation occlusions, but should augment rather than replace clinician interpretation. Its long-term clinical value requires prospective multicentre validation, standardised comparative studies, transparent reporting, and evaluation of patient-centred outcomes.

**Keywords:** *Artificial Intelligence; Large Vessel Occlusion; Acute Ischemic Stroke; Mechanical Thrombectomy; Computed Tomography Angiography; Stroke Imaging; Clinical Decision Support; Machine Learning.*

## INTRODUCTION

Acute ischemic stroke (AIS) is one of the leading causes of death and permanent disability worldwide. The most severe type is large vessel occlusion (LVO) of major intracranial arteries, such as the intracranial internal carotid artery (ICA), middle cerebral artery (MCA), basilar artery, and proximal anterior cerebral artery. LVO stroke is associated with larger infarcts, more neurological deficits, higher mortality and poorer functional outcome, as compared to non-LVO stroke. So, early diagnosis is important [10]. Mechanical thrombectomy has changed the treatment of patients with LVO. Landmark trials have demonstrated endovascular thrombectomy (EVT) to be the standard of care for anterior-circulation LVO, with additional data expanding its use for selected patients beyond typical time frames and for posterior-circulation occlusions. Since the benefit of EVT diminishes with delays in treatment, early identification and referral of LVO is important [3,4]. Computed tomography angiography (CTA) imaging is the first-line modality for the detection of arterial occlusion and for the evaluation of eligibility for EVT . However, increasing imaging volumes, limited neuroradiology knowledge, interobserver variability and the complexity of regional stroke networks may cause interpretation delays, especially in primary stroke centers and resource-constrained settings [1,5,10].

One promising answer has come in the form of deep learning, a subfield of artificial intelligence (AI). Modern artificial intelligence systems can automatically detect LVO on CTA, prioritize urgent testing, identify vascular anomalies, and immediately report to the stroke teams. Numerous commercial tools are now integrated into clinical stroke workflows to assist in real time diagnosis and triage [10,11]. Performance in controlled validation tests is promising but doesn't necessarily translate to ordinary practice. Diagnostic accuracy was affected by occlusion location and image quality, with reduced accuracy in cases of distal and posterior circulation occlusion. Differences in study design, imaging methods, reference standards and training datasets further limit the ability to compare algorithms. Challenges for widespread implementation include false-positive and false-negative results, automated bias, explainability, regulatory and medico-legal issues, interoperability, cost, and equitable access [1,7,8].

This narrative review summarizes the available evidence on AI-assisted LVO detection in AIS with particular emphasis on diagnostic performance, algorithmic techniques, workflow integration, commercial platforms and implementation problems. It highlights the drawbacks of existing systems and the future research objectives for the safe, successful, and unbiased integration of AI into acute stroke care [1,10].

## METHODS

### Literature search strategy

A structured literature search was conducted to identify evidence related to the use of artificial intelligence (AI) to support the detection of large vessel occlusion (LVO) in acute ischemic stroke. We searched PubMed/MEDLINE, Scopus, Web of Science, Embase, and Google Scholar for studies published in English between January 2015 and June 2026. Reference lists were searched for relevant articles and recent reviews. The search terms were combinations of artificial intelligence, machine learning, deep learning, convolutional neural network, vision transformer, large vessel occlusion, acute ischemic stroke, computed tomography angiography, CTA, mechanical thrombectomy, stroke triage, neuroradiology, workflow optimization and computer-aided diagnosis with the use of appropriate Boolean operators.

The search retrieved approximately 25 records. After removal of duplicates and screening of titles, abstracts and full texts 13 studies were included in the final narrative review.

### Inclusion and exclusion criteria

Eligible publications included original research, prospective and retrospective observational studies, multi-center validation studies, randomized trials, systematic reviews, meta-analyses, clinical guidelines, consensus statements, and landmark technical reports. Studies assessing automated LVO detection on CTA or multimodal stroke imaging, diagnostic performance, external validation, workflow integration, commercial AI platforms, implementation or emerging technologies were included.

Conference abstracts without full text, case reports, non-English publications, editorials without sufficient evidence, and studies not related to acute stroke imaging or cerebrovascular occlusion were excluded. Where the study populations overlapped, the report with the most complete or the most recent information was selected.

Titles and abstracts were screened for relevance and full texts were reviewed. Special emphasis was given to multicenter validation, prospective implementation studies, systematic reviews, meta-analyses and clinical guidelines. For qualitative comparison, we retrieved diagnostic accuracy measurements (sensitivity, specificity, and area under the receiver operating characteristic curve [AUC]) and workflow outcomes.

**Justification for Qualitative Synthesis**

To provide a clinically focused overview of AI-assisted LVO detection, a narrative review was chosen as the methodology to address algorithm development, diagnostic performance, workflow integration, commercial platforms, implementation challenges, ethical considerations, and emerging technologies. Significant heterogeneity in AI models, patient populations, LVO definitions, imaging protocols, validation techniques, and outcome measures precluded meaningful quantitative synthesis.

Thus, results were narratively synthesized, and systematic reviews and meta-analyses were used to contextualize diagnostic performance where relevant. The review highlights areas of agreement, areas of disagreement between studies, limitations in external validity, and the clinical importance of the outcomes reported.

**Ethical Use of Artificial Intelligence**

Language tools for artificial intelligence were only used for language, organization and readability improvements. The authors independently selected the literature, interpreted the data, critically analyzed and drew conclusions and approved the manuscript for submission. The authors bear full responsibility for the accuracy, integrity and originality of the manuscript. No AI was used to generate, manipulate or fabricate research data, results or references.

## CLINICAL RELEVANCE OF LARGE VESSEL OCCLUSION

Large artery occlusion (LVO) comprises 20-40% of all acute ischemic strokes, but accounts for a disproportionate amount of severe disability, death, and health care burden. A sudden reduction of cerebral blood flow may be due to a significant occlusion of intracranial arteries such as the intracranial internal carotid artery (ICA), middle cerebral artery (MCA), basilar artery, vertebral artery, and proximal anterior cerebral artery. Clinical severity is determined by the location of the occlusion, the collateral circulation, systemic hemodynamics and duration of the ischemia [1,10]

Mechanical thrombectomy has revolutionized the outcomes for appropriately selected patients with LVO. Landmark trials have established endovascular thrombectomy (EVT) as the standard of care for eligible patients with anterior-circulation large vessel occlusion (LVO). Additional evidence has expanded the eligibility criteria to include selected patients beyond traditional treatment windows and to those with basilar artery occlusions. Therefore, early recognition and treatment eligibility of LVO has become a critical part of modern stroke care [3,4]

This is where neuroimaging is relevant. NCCT is useful to exclude cerebral bleeding and to assess early ischemia changes with methods such as the Alberta Stroke Program Early CT Score (ASPECTS). Computed tomography angiography (CTA) allows immediate visualization of the cerebral vasculature to identify arterial occlusion, while CT perfusion (CTP) and magnetic resonance imaging (MRI) can be used to further determine infarct core, salvageable tissue, collateral circulation and tissue viability in selected individuals [4,5]

CTA interpretation is complicated although widely used. The accuracy of diagnosis is influenced by image quality, motion artifacts, contrast timing, vascular calcification, anatomical variance, tandem lesions and reader expertise. Occlusions in the distal and posterior circulation are more challenging to detect and access to neuroradiologists or neurointerventional specialists is generally limited outside comprehensive stroke facilities [5,7]

These challenges are magnified in hub-and-spoke stroke networks where delays in CTA interpretation, specialist consultation, patient transfer and thrombectomy team activation can increase the time to reperfusion. Thus, the necessity of technologies that can identify LVO fast and uniformly has become more crucial, laying the groundwork for AI-assisted stroke imaging systems [6]

## ARTIFICIAL INTELLIGENCE IN STROKE IMAGING: BASICS

Artificial Intelligence (AI) has evolved from a basic computer aided detection to a sophisticated tool for medical picture analysis. In acute stroke care AI is already used for automatic detection of cerebral bleeding, large vessel occlusion (LVO), ASPECTS rating, perfusion analysis, collateral assessment, and calculation of the ischemic core. Among these, automated LVO identification is especially important as a rapid diagnosis directly impacts the patient's eligibility for mechanical thrombectomy [10,11]

Early computer-assisted systems relied on hand-crafted image features such as vessel diameter, intensity, morphology and geometry, and were therefore limited in their ability to detect complicated patterns. Machine learning changed this paradigm by providing algorithms to learn from annotated imaging datasets. The majority of today's applications of stroke imaging use supervised learning, in which models are trained on labeled images [11]. Deep learning has progressed further. CNNs have been the dominant LVO detection solution because of their ability to learn hierarchical spatial information from CTA images. 3D CNNs are designed to handle volumetric data while preserving spatial correlations. More recently, Vision Transformers (ViTs) and hybrid CNN-transformer models have shown promise in capturing long-range image associations, while their clinical usefulness in LVO detection remains less established [11]

The regular AI pipeline consists of image pre-processing and vessel segmentation. CTA images are normalized, registered, artifact corrected and segmented prior to analysis. Arterial occlusions are subsequently identified by algorithms that analyze vascular continuity, contrast enhancement, branching patterns and hemispheric asymmetry. Modern systems incorporate these phases into automated workflows that can deliver results in clinically relevant timeframes [1,11]. The complexity of AI models is growing, and so is the need for interpretability. Explainable AI (XAI) techniques, e.g. saliency maps, Gradient-weighted Class Activation Mapping (Grad-CAM) and attention maps, can be used to highlight the regions of an image that influence the model's predictions, which may be useful for clinician assessment and error analysis . But these approaches do not fully capture the thinking of the model [10,11]

Ultimately, technical excellence alone does not guaranty a clinical benefit. The standard artificial intelligence algorithms for acute stroke must be timely and accurate across a broad spectrum of patient populations, imaging protocols, scanner types, and clinical settings. Therefore, research has gradually shifted from algorithm development to external validation and real-world clinical deployment [1,7,10].

### Artificial intelligence algorithms for automatic detection of large vessel occlusion

Artificial intelligence-based detection of LVO has evolved from conventional machine learning with manually selected imaging variables to deep learning-based methods that directly analyze computed tomography angiography (CTA). Current approaches typically involve multiple steps like image pre-processing, vessel segmentation, feature extraction and classification for detecting vascular discontinuity, reduced distal contrast opacification or hemispheric asymmetry suggestive of occlusion. Convolutional neural networks (CNNs), particularly three-dimensional models, have the most research, and attention-based and hybrid CNN-transformer architectures provide promising approaches to capturing complex vascular interactions [1,8,11]. Published studies consistently demonstrate good diagnostic accuracy for proximal anterior-circulation LVO, particularly intracranial internal carotid artery (ICA) and M1 occlusions . Sensitivities of 85–97%, specificities >90% and area under the receiver operating characteristic curve (AUC) >0.90 have been reported in systematic reviews and validation studies . In several trials, AI has been on par with professional readers, supporting their role in settings where direct neuroradiology expertise is unavailable [1,7,8].

However, these data should be treated with caution. Diagnostic performance depends on the site of occlusion, image quality, patient population, reference standards, and LVO definitions. Distal medium vascular (M2–M3), tandem and posterior circulation occlusions are far more complex due to lower caliber, anatomical heterogeneity and less conspicuity. Therefore, the good accuracy reported for proximal anterior-circulation occlusions cannot be generalized to all LVOs. [1,5,8].

Comparisons to human readers also need to be put in context. AI is often compared to neuroradiologists, the subspecialists in this area, but it may be more useful for emergency physicians, general radiologists, or readers with less experience. Also, AI and physicians err differently; false negatives can lead to a delay in thrombectomy, while false positives can lead to unnecessary evaluation or transfer. Thus, evaluation should be based on the clinical implications of errors and not on diagnostic accuracy alone [1,7].

The big problem is the problem of generalization. Many of the early algorithms were developed using retrospective, single-center data, making their performance susceptible to changes in scanner type, imaging procedures, contrast timing, patient demographics, and disease prevalence. The multicenter external validation more strongly supports clinical utility, and interinstitutional variability highlights the need for local validation and ongoing post deployment surveillance [1,7,8]. New techniques such as CTA in combination with non-contrast CT, CT perfusion, MRI and clinical data are helping to identify the infarct core, collateral circulation, perfusion mismatch and eligibility for therapy. Foundation models and self-supervised learning may improve transferability and reduce dependence on large annotated datasets, but are experimental and need prospective validation [10,12].

To summarize, current evidence supports a role for artificial intelligence as a rapid and accurate adjunct to the diagnosis of proximal LVO, but performance varies across vascular territories and studies. Future research should focus on independent validation from multiple centers, standardized reporting, head-to-head comparisons of platforms, and prospective evaluation of patient-centered outcomes [1,8].

| Category | Model / Evidence | Target Population / Vascular Territory | Validation Setting | Performance Range* | | AUC (ROC) | Key Interpretation |
|---|---|---|---|---|---|---|---|
| | | | | Sensitivity | Specificity | | |
| Overall across studies | AI systems across validation studies (systematic reviews and cohorts) | Predominantly proximal anterior-circulation LVO (ICA, M1) | Retrospective and prospective studies; multicenter and single-center | 85 – 97% | > 90% | Often > 0.90 | • Strongest performance for proximal anterior-circulation LVO. • Range reflects between-study heterogeneity in design and cohorts. |
| Commercial Platform (Viz.ai) | Viz.ai (CTA-based LVO detection) | Proximal anterior-circulation LVO (ICA, M1) | Multicenter observational and implementation studies | High (≈ 85 – 97%) | High (> 90%) | Reported > 0.90 | • Extensively implemented with workflow impact evidence. • Performance varies with occlusion location and imaging quality. |
| Commercial Platform (RapidAI) | RapidAI / RAPID CTA (CTA-based LVO detection) | Proximal anterior-circulation LVO (ICA, M1) | Multicenter observational studies; research cohorts | High (≈ 85 – 97%) | High (> 90%) | Reported > 0.90 | • Strong performance for proximal LVO. • Results should be interpreted according to vascular territory. |
| Commercial Platform (JLK-LVO) | JLK-LVO (CTA-based LVO detection) | Proximal anterior-circulation LVO (ICA, M1) | Multicenter and institutional validation studies | High (≈ 85 – 97%) | High (> 90%) | Reported > 0.90 | • Comparative studies report platform-specific strengths and failure patterns. • Evidence primarily for proximal LVO. |
| Vascular Territory (Distal / Medium) | Commercial AI systems overall | Distal / medium-vessel occlusions (M2–M3 and more distal) | Multiple retrospective and prospective studies | Lower and more variable (≈ 50 – 80%) | Variable (≈ 70 – 90%) | Lower and variable (< 0.90) | • Smaller vessel caliber and anatomical variability reduce detection reliability. • Performance consistently below that for proximal LVO. |
| Vascular Territory (Posterior Circulation) | Commercial AI systems overall | Posterior-circulation LVO (vertebrobasilar and branches) | Multiple retrospective and prospective studies | Variable (≈ 50 – 85%) | Variable (≈ 70 – 90%) | Variable (< 0.90) | • Evidence and performance less consistent than for anterior circulation. • Heterogeneity in definitions and imaging protocols. |
| Comparison with Human Readers | AI versus experienced neuroradiologists and radiologists | Primarily proximal anterior-circulation LVO (ICA, M1) | Direct comparison studies | Comparable in some studies | Comparable in some studies | Comparable (≈ 0.90+) | • Performance depends on reader expertise and case complexity. • AI and humans may err differently. |

* Performance ranges reflect approximate values reported across studies included in recent reviews and validation cohorts.

AI, artificial intelligence; AUC, area under the receiver operating characteristic curve; CTA, computed tomography angiography; ICA, internal carotid artery; LVO, large vessel occlusion; ROC, receiver operating characteristic.

**Clinical Applications and Integration into Workflow**

The advantages of AI-assisted LVO detection are not confined to its diagnostic accuracy but also encompass the capability to expedite time-sensitive stroke therapy. AI tools have the potential to evaluate CT angiography (CTA) directly after acquisition and prioritize suspected LVO cases and provide clinicians with information that can help reduce delays between imaging, specialist assessment, transfer choices and mechanical thrombectomy [2,6,10].

Another important use is automatic image triage. In routine practice, urgent CTA studies often compete with other imaging, especially in times of high volume or low neuroradiology coverage. AI is able to identify LVO cases that are more likely to be true positives and prioritize these for examination, especially for smaller hospitals and centers that do not have specialists available 24/7. But AI should augment, not replace, image interpretation skills [2,6,9]. Commercial platforms are embracing integrated communications with automated picture analysis. When LVO is detected alerts can be sent at the same time to neurologists radiologists neurointerventionalists and stroke coordinators so that they can evaluate the images and plan the treatment at the same time. In hub-and-spoke networks, these systems can allow for earlier communication between referring and comprehensive stroke centers for patient transfer and preparation for thrombectomy [2,6,9].

Observational studies have suggested that AI adoption is associated with shorter CTA to notification time, thrombectomy team activation, door to groin puncture time, and in some networks, door in door out time. However, the degree of improvement varies by institution, and depends on current procedures, manpower, transfer infrastructure and system integration. Most of the research is observational, making it difficult to separate the influence of AI from broader workflow improvements [2,6,7]. Importantly, improved process metrics do not necessarily translate into improved clinical outcomes. Earlier reperfusion is associated with better recovery but there is little evidence that AI improves functional outcomes or mortality independently. Hence, future research is vital in patient-centered outcomes [2,7].

Another problem is workflow integration. False-positive alerts may lead to unwarranted picture inspection and warning fatigue, and false-negative results may delay therapy if physicians over-rely on automated outputs. Integration with PACS , RIS , EHR and communication systems is essential with well-defined institutional guidelines for successful adoption . Human supervision is still needed, particularly when AI results differ from clinical or imaging assessments. [2,9,10]. Besides, the implementation is of great economic importance. Commercial AI platforms have licensing, infrastructure, integration, maintenance and staff training costs. Early treatment can reduce long-term impairment and health care costs. Information on cost-effectiveness according to stroke volume and health care context is limited and likely to be variable. [9,10]

AI-assisted LVO identification may improve coordination and efficiency along acute stroke pathways by automated picture processing, prioritizing, communication and transfer support. The benefits of the workflow are routinely reported but prospective studies are necessary to ascertain the effect on patient outcomes, cost-effectiveness and equitable access. [2,6,9]

**Commercial AI Platforms for Automated Detection of Large Vessel Occlusion**

Commercial artificial intelligence systems have helped the clinical adoption of AI-assisted LVO identification by incorporating automated image analysis into established stroke workflows. Unlike research algorithms, these systems offer real-time interpretation of CTA, worklist prioritization, automated alarms, image sharing and multidisciplinary collaboration [9].

Common platforms include Viz.ai which uses CTA-based LVO detection, automated alerts and mobile communication to accelerate image review and stroke team collaboration. Studies of implementation have shown reduced times for notification and treatment workflows RapidAI offers a multimodal platform that combines LVO detection with CT perfusion analysis and other imaging assessments needed to inform reperfusion decisions. Brainomix e-Stroke performs ASPECTS grading, LVO detection and collateral assessment and Aidoc is an automated triage and worklist prioritization system that flags suspected abnormalities for physician rapid review. Table 2 summarizes the main features of these platforms [2,9].

Performance comparisons should be taken with a grain of salt. Published studies differ widely in terms of patient population, definition of LVO, vascular regions, imaging protocol, reference standard, and outcome measures. Most are retrospective or single center with few direct independent head-to-head comparisons. Proprietary algorithms restrict transparency around model design, training data, and updates, making it difficult to compare models [1,9]. Commercial systems were most accurate for proximal anterior-circulation LVO and least consistent for distal, medium-vessel and posterior-circulation occlusions. Interchangeability between systems may be limited, and vendor-specific processing methods may potentially influence perfusion and other quantitative imaging data [1,8,9].

Successful deployment depends not only on diagnostic performance, but Real-world effectiveness depends on integration with imaging and communications systems, local stroke workflow, alert configuration, technical assistance, licensing fees and staff training. Therefore, the platform selection should be guided by local clinical needs and independent validation and not by accuracy measures alone [9]. Commercial AI platforms have moved LVO detection from experimental research to routine clinical decision support. But different testing methods and a lack of comparisons make it impossible to rank them definitively. Their relative therapeutic value has to be established by independent external validation, standardized reporting, prospective comparisons, and assessment of patient-centred and economic outcomes [2,9].

| Platform | Principal stroke-imaging applications | Workflow role | Key strengths | Important limitations |
|---|---|---|---|---|
| Viz.ai | CTA-based LVO detection | Automated alerts, image sharing, multidisciplinary communication | Extensive workflow-oriented implementation evidence | Performance varies by occlusion location; proprietary system |
| RapidAI | LVO detection, CTP and multimodal imaging analysis | Imaging analysis and treatment decision support | Broad multimodal stroke assessment | Vendor-dependent processing; direct comparative evidence limited |
| Brainomix e-Stroke | LVO detection, ASPECTS, collateral assessment | Standardized multimodal stroke-imaging assessment | Integrates multiple imaging biomarkers | Comparative LVO-specific evidence remains heterogeneous |
| Aidoc | Detection and triage of suspected neurovascular emergencies | Worklist prioritization and clinical notification | Integrates AI triage into radiology workflow | Less focused on comprehensive stroke management |

Abbreviations: AI, artificial intelligence; ASPECTS, Alberta Stroke Program Early CT Score; CTA, computed tomography angiography; CTP, CT perfusion; LVO, large vessel occlusion.

## CHALLENGES, LIMITATIONS, AND ETHICAL ISSUES

While the diagnostic and workflow performance is promising, autonomous application AI-assisted LVO detection shows encouraging diagnostic and workflow performance, but substantial technological, clinical, ethical and regulatory hurdles remain. Current literature supports its role as a decision-support tool for clinicians rather than replacing expert interpretation, with performance dependent on occlusion characteristics, image quality, patient population and clinical context [1,8,10]. The variable precision in the vascular areas is a major problem. Most algorithms are trained and tuned on proximal anterior-circulation occlusions, especially ICA and M1 lesions. Distal, medium-vessel, posterior-circulation, and tandem occlusions are more difficult to detect. Motion artifacts, suboptimal contrast enhancement, vascular calcification and anatomic variability may further reduce the accuracy. These limitations are clinically relevant, as false-negative results could delay thrombectomy, and false-positive alerts could lead to unnecessary evaluations and alert fatigue [1,5,8].

Another big issue is generalizability. A plethora of algorithms have been developed using retrospective datasets from high-volume academic centers and may behave differently across different scanners, imaging protocols, patient groups, and health care systems. Some demographic groups or rare stroke cases may be underrepresented, which could lead to algorithmic bias. Therefore, validation studies in multiple centers, subgroup analysis and post-deployment surveillance are needed [1,7,8]. Models are still not very well explained. Saliency maps, Gradient-weighted Class Activation Mapping (Grad-CAM) and attention visualization methods improve transparency but do not fully clarify the prediction process of the deep learning models. This lack of interpretability can impact clinician trust, error investigation, and regulatory assessment [10,11].

Regulatory and medico-legal issues also remain unresolved. AI stroke imaging software is generally considered as Software as a Medical Device (SaMD) . However, physicians, health care organizations or developers are at risk of erroneous or missed AI results, especially when algorithms are updated after deployment . Hence the need for clear institutional protocols, human-recorded oversight and ongoing performance evaluation [10]. There are other issues with data governance. AI-powered stroke networks require rapid sharing of imaging and clinical data between institutional, cloud-based and mobile platforms, as well as strong protections for patient privacy, cybersecurity, secure authentication and compliance with data-protection legislation [10].

Barriers to implementation are of particular relevance in LMICs where the cost of licensing, information technology infrastructure, network connectivity, technical assistance, and access to sophisticated imaging may limit uptake. Many algorithms are developed in well-resourced settings, and their performance and therapeutic impact may not easily translate to resource-limited situations [9,10].

Implementation is also influenced by human considerations. Automation bias can cause clinicians to depend too much on the AI's suggestions, while repeated false-positive alerts can erode trust in the system. But too much distrust can undermine any workflow advantages. Successful adoption requires defined responses to conflicting findings, routine performance audits, and clinical education [10]. The therapeutic value of AI-assisted detection of LVO depends not only on diagnostic accuracy but also on generalizability, transparency, safety, accountability, cost and equitable access. Combining these considerations with traditional performance measures is needed when evaluating AI-enabled stroke care. [1,8,10]

## FUTURE DIRECTIONS

Next generation stroke systems with AI-help are predicted to evolve from stand-alone LVO detection to integrated decision-support platforms with imaging, clinical and process data. But advances in technology have to be matched by evidence of safety, generalizability and real patient benefit across a range of health settings [10,12]. Foundation models and self-supervised learning are promising ways to increase adaptability. Rather than training task-specific models on large annotated datasets, foundation models can learn general imaging representations and be adaptable to multiple tasks including LVO detection, vascular segmentation, ASPECTS scoring, collateral assessment, and outcome prediction. But although they promise to reduce annotation needs and increase transferability, they are yet to be proven in ordinary clinical practice [12].

Multimodal AI that integrates CTA with other imaging modalities, lab results, NIHSS scores, and EHRs could further improve decision support. Such methods may help to predict infarct progression, treatment response, hemorrhagic risk and functional outcome. The model complexity increases as well as the difficulty of bias, missing data and interpretability and therefore prospective evaluation is needed [10,12]. Federated learning allows institutions to work together to train AI models without sharing patient-level data, which can improve model diversity and reduce privacy concerns. But there are still major challenges, including variability in imaging procedures, data quality, infrastructure and governance [12]
Generative AI and large language models may improve computer vision for automated reporting, clinical documentation, and interdisciplinary collaboration. Given the high stakes of acute stroke care, these apps will need to be thoroughly validated, with well-defined roles and ongoing human supervision [13].

Artificial intelligence can also be applied to prehospital stroke triage, integrating clinical evaluation tools, mobile technologies, wearable sensors, and portable imaging. Pre-hospital suspicion of LVO may allow direct transfer to thrombectomy-capable hospitals and avoid secondary transfer if it is outweighed by improved triage at the cost of some misclassification [10]. Future studies should be prospective, multicenter evaluations of real-world clinical effectiveness, rather than retrospective assessments of diagnostic accuracy. We need standardized reporting, independent external validation, head-to-head comparisons and evaluation in different demographics and health care systems. Outcomes should include functional recovery, mortality, safety, cost-effectiveness and equity, and diagnostic performance and workflow efficiency [1,7,8].

The future of AI in stroke treatment is bright, but it will be human-AI collaboration, not machine-only decision-making. AI should be an adjunct to clinical knowledge, improving the speed and consistency of decision making, and offering clear benefits without unacceptable diagnostic, ethical or socio-economic concerns [10,12,13].

**Table 3. Current Challenges and Future Opportunities in AI-Assisted LVO Detection**

| Current Challenge | Clinical / Technical Implication | Future Opportunity |
|---|---|---|
| Reduced performance for distal and posterior-circulation occlusions | False negatives may delay recognition of thrombectomy candidates; performance is less reliable than for proximal ICA/M1 LVO. | • Improved architectures, multimodal imaging, and larger diverse training datasets. |
| Limited external generalizability | Performance may decline across scanners, imaging protocols, institutions, and patient populations. | • Multicenter external validation, standardized benchmarking, and postdeployment surveillance. |
| Algorithmic bias | Underrepresented populations or uncommon stroke presentations may experience unequal diagnostic performance. | • Diverse international datasets, subgroup analysis, and federated learning. |
| Limited explainability | Black-box predictions may reduce clinician trust and complicate error analysis. | • Explainable AI, uncertainty estimation, and interpretable outputs. |
| False-positive alerts and automation bias | Alert fatigue, unnecessary review, or inappropriate reliance on AI may affect clinical decisions. | • Human-in-the-loop workflows, optimized alert thresholds, clinician training, and regular auditing. |
| Regulatory and medico-legal uncertainty | Responsibility for incorrect AI recommendations or missed diagnoses may be unclear. | • Defined accountability frameworks, regulatory standards, and continuous post-market monitoring. |
| Data privacy and cybersecurity | Cloud-based image sharing and communication create privacy and security risks. | • Secure infrastructure, robust governance, privacy-preserving approaches, and federated learning. |
| Cost and infrastructure requirements | Licensing, integration, maintenance, and technical support may restrict implementation, particularly in LMICs. | • Health-economic evaluation, scalable deployment models, and resource-appropriate AI systems. |
| Limited evidence for patient-centered outcomes | Workflow improvements do not necessarily demonstrate better functional recovery or survival. | • Prospective multicenter trials assessing functional outcomes, mortality, safety, cost-effectiveness, and equity. |
| Fragmented decision support | Current systems often focus on individual imaging or workflow tasks. | • Integrated multimodal platforms combining imaging, clinical, laboratory, and potentially prehospital data. |

**Abbreviations:** AI, artificial intelligence; ICA, internal carotid artery; LMICs, low- and middle-income countries; LVO, large vessel occlusion.

## CONCLUSION

Artificial intelligence-assisted identification of large vessel occlusion has become a useful decision support tool in acute ischemic stroke. Currently the systems have a high diagnostic accuracy for proximal anterior circulation occlusions and have the ability to improve the image prioritization, specialist notification, interhospital communication and activation of thrombectomy pathways helping to reduce treatment delays.

However, AI should not replace expert clinical and radiological interpretation. However, performance for occlusions in the distal and posterior circulation is not as reliable. The reported accuracy depends on patient population, imaging protocol and validation setting. Other issues include false positive and false negative results, algorithmic bias, limited interpretability, interoperability, regulatory and medico-legal issues, cost and unequal access. Regular reports show improvements in workflow, but evidence for an independent benefit on functional outcomes and death is sparse.

Future work should focus on prospective multicenter validation, standardization of reporting and independent comparison of commercial platforms, post-deployment surveillance and assessment of patient-centered outcomes, cost-effectiveness and equity. New technologies may enable AI to transition from image interpretation to integrated decision assistance for stroke but will require rigorous validation and ongoing clinical oversight. AI should be considered as an adjunct to expedite and streamline LVO detection, with the clinicians making the diagnosis and treatment decisions. The long-term effect will depend not only on the accuracy of the diagnosis, but on the ability to improve the quality efficiency and equity of stroke care.

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