ORIGINAL RESEARCH

Performance of An Automated Algorithm in Large and Medium Vessel Occlusion Detection: A Real-World Experience

Aakanksha Sriwastwa, Yasmin N. Aziz, Kara Weiss, Robert Buse, Bin Zhang, Stacie L. Demel, Arafat Ali, Sriharsha Voleti, Lily Li-Li. Wang, and Achala S. Vagal

ABSTRACT

BACKGROUND AND PURPOSE: Fast, accurate detection of large (LVO) and medium vessel occlusion (MeVO) is critical for triage and management of acute ischemic stroke. Multiple AI-based software products are commercially available. However, their strengths and limitations for detection of vessel occlusion in the context of expanding indications for mechanical thrombectomy are not entirely understood. We aimed to investigate the performance of a fully automated commercial detection algorithm to identify large and medium vessel occlusions in Code Stroke patients.

MATERIALS AND METHODS: We utilized a single-center, institutional, retrospective registry of all consecutive code stroke patients with CTA and automated processing using Viz.ai presenting at a comprehensive stroke center between March 2020 and February 2023. LVO was categorized as anterior LVO (aLVO), defined as occlusion of the intracranial internal cerebral artery or M1-middle cerebral artery (MCA), and posterior LVO (pLVO), defined as occlusion of the basilar artery or V4-vertebral artery. MeVO was defined as occlusion of the M2-MCA, A1/A2-anterior cerebral artery, or P1/P2-posterior cerebral artery. Reports from 12 board-certified radiologists were considered the gold standard. We analyzed the performance of the automated algorithm using STARD guidelines. Our primary outcome was accuracy of anterior LVO (aLVO) by the software. Secondary outcomes were accuracy of the software to detect three additional categories: all LVO (aLVO and

pLVO), aLVO with M2-MCA, and aLVO with MeVO.

RESULTS: Of 3,590 code stroke patients, 3,576 were technically sufficient for analysis by the automated software (median age 67 years; 51% female; 68% White), of which 616 (17.2%) had vessel occlusions. The respective sensitivity and specificity for all four pre-specified categories were: aLVO: 91% (87-94%), 93% (92-94%); all LVO: 73% (68-77%), 92% (91-93%); aLVO with M2-MCA:74% (70-78%), 93% (92-94%); aLVO with all MeVO: 65% (61-69%), and 93% (92-94%).

CONCLUSIONS: The automated algorithm demonstrated high accuracy in identifying anterior LVO with lower performance for pLVO and MeVO. It is crucial for acute stroke teams to be aware of the discordance between automated algorithm results and true rates of LVO and MeVO for timely diagnosis and triage.

ABBREVIATIONS: LVO = large vessel occlusion; aLVO = anterior large vessel occlusion; pLVO = posterior large vessel occlusion; MeVO = medium vessel occlusion; EVT= endovascular thrombectomy; AI = artificial intelligence; ACA = anterior cerebral artery; PCA = posterior cerebral artery; BA = basilar artery; VA = vertebral artery.

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SUMMARY SECTION

PREVIOUS LITERATURE: Commercial automated tools for vessel occlusion detection are widely used to triage Code Stroke patients, often with minimal guidance regarding their limitations. While most of these tools have been trained, programmed, and FDA-approved for the exclusive detection of anterior large vessel occlusions (aLVO), they are frequently used for all Code Stroke patients in real-world clinical practice. Prior studies have evaluated these tools for their accuracy of aLVO detection. No study has evaluated them in the context of growing thrombectomy indications, which creates an opportunity for user error. Moreover, their modest positive predictive value and the trends in false positive and negative results have been less thoroughly explored.

KEY FINDINGS: This study systematically examined the performance of an AI-based software (Viz.ai) to detect numerous prespecified categories of vessel occlusions, developed to reflect an evolving landscape of stroke thrombectomy that surpasses the current capabilities of many AI platforms. Analysis in a large real-world sample of acute ischemic stroke patients revealed high sensitivity for detecting aLVO, with a modest positive predictive value. Worse metrics were noted when potentially treatable M2s and pLVO were included. Horizontal dominant M2-MCA occlusions were more frequently detected than non-dominant horizontal or vertical M2-MCA occlusions.

Finally, the study presents a detailed analysis of false positive and negative results by AI.

KNOWLEDGE ADVANCEMENT: Acute stroke providers should be aware of the limitations of automated vessel occlusion detection software, particularly in the setting of rapidly expanding indications for thrombectomy. The study serves as a knowledge base for understanding and improving these technologies.

INTRODUCTION

Commercially available artificial intelligence (AI) software is a valuable tool for the rapid identification and management of stroke patients due to large vessel occlusion (LVO). Such software has been instrumental in reducing the time taken to transfer patients to comprehensive stroke centers and in expediting the initiation of thrombectomy procedures, as evidenced by improved time from symptom onset to groin puncture.[1]

Automated vessel occlusion software is widely used at both primary and comprehensive stroke centers. One notable example of such software is Viz.ai, which leverages a convolutional neural network for image recognition tasks to detect LVO from the internal carotid artery terminus (ICA) to the sylvian fissure with high sensitivity (82%) and specificity (94%).[2, 3]

Multiple AI based software platforms are available for automated detection and rapid prioritization of LVO cases. However, their abilities, strengths, and limitations for detection of vessel occlusion in the context of expanding indications for mechanical thrombectomy are not entirely understood. Although AI tools were introduced predominantly to detect anterior circulation LVO (aLVO, i.e., ICA and M1 occlusions), in real-world practice, the tools are utilized for all code stroke patients. This creates a potential for acute stroke teams to rely on these tools to detect all vessel

occlusions, including detection of posterior circulation and medium vessel occlusion, rather than aLVO alone. Further, given the efficacy of endovascular therapy (EVT) to treat aLVO and advances in device technology, there is an increase in the treatment of medium vessel occlusion (MeVO), particularly M2 occlusions.[4] Hence, with the widespread use of AI tools and expanding indications of thrombectomy, it is important to understand the software's capability to detect occlusion in vessels in addition to aLVO.

Our primary objective was to determine the accuracy of an automated detection tool to detect anterior LVO, defined as ICA and M1, in real-world code stroke CT angiography (CTA). Our secondary objective was to determine the accuracy of the automated tool to additionally identify MeVO and posterior vessel occlusion detection in the same population. We hypothesized that the software tool will have a high accuracy in detecting terminal ICA and M1-MCA occlusions, with lower performance in detecting posterior LVO and all MeVOs.

MATERIALS AND METHODS

Population

We performed a retrospective analysis of prospectively collected data from all consecutive code stroke patients who underwent CTA head between March 2020 and February 2023 at a large, comprehensive stroke center comprised of two distinct sites: site A and site B. Inclusion criteria were as follows: (1) code stroke patients aged 18 years or above, (2) CTA head imaging performed within 24 hours of last known normal time and, (3) automated algorithm LVO output using Viz.ai (index test) included with CTA acquisition. Technically suboptimal CTAs due to significant motion, inadequate or missed contrast bolus, or other artifact precluding appropriate assessment of the intracranial vasculature were not interpreted by the software and therefore excluded from analysis. The study was approved by the local Institutional Review Board (IRB), and informed consent was waived due to the retrospective study

design. We followed the STARD guidelines.[5]

Variables:

We recorded patient demographics, including age, sex, race, and ethnicity. Clinical characteristics and vascular risk factors including diabetes mellitus, hypertension, hyperlipidemia, congestive heart failure, atrial fibrillation, smoking history, and prior history of stroke from the electronic medical record were also collected. Among the imaging variables, we recorded the site of vessel occlusion based on the reports of board-certified radiologists.

Image acquisition and workflow:

The CTAs were acquired on four 256-slice scanners with 80 detectors. Images were acquired in the axial plane with slice thickness of 0.625 mm. All CTAs were acquired as a single arteriovenous phase contrast study with a 60 mL intravenous contrast bolus administered at a rate of 5mL per second, using bolus tracking triggered from the aortic arch with aortic arch to vertex coverage. These images were reformatted in coronal and sagittal planes post-acquisition. The post-processing also included generating maximum intensity projection (MIP) images in all three orthogonal planes. CTA images of all code stroke patients were routed to Viz.ai software (version 1.84.0, Viz.ai inc., San Francisco, California) directly from the CT scanner. A binary outcome of suspected LVO versus no suspected LVO was produced by the algorithm. If LVO is suspected, an alert is generated on the mobile application for the stroke care team. The software generated image of the segmented anterior vasculature was also instantly routed to the pictures archiving and communication systems. The software's interpretation of the study, however, was not available to the radiologists reading the CTA study. Per institutional protocol, CT perfusion was only performed for select cases presenting between 6-24 hours of last known normal or wake-up LVO cases being considered for mechanical thrombectomy. These studies were available to the radiologist at the time of CTA interpretation. The final CTA report was considered

as the reference standard. A neuroradiology fellow (AS) independently adjudicated all cases, in which the AI identified a vessel occlusion, and the clinical radiologist did not (i.e., false positive cases).

Categorization of vessel occlusions:

Based on the radiology reports, we categorized vessel occlusions into 4 groups, starting with aLVO and then adding on discrete areas of vessel occlusion with clinical relevance:

1. **Anterior LVO (aLVO):** Acute occlusion of intracranial ICA (extending from petrous segment to ICA terminus) and M1 segment of MCA (defined as MCA extending from origin at the ICA terminus to the MCA bifurcation)[6].
2. **All LVO (all LVO):** Anterior and posterior circulation LVOs (aLVO and pLVO), with pLVO including basilar artery and intracranial vertebral artery (V4 segment) occlusions.
3. **Anterior LVO with M2-MCA occlusion (aLVO plus M2):** aLVO with M2-MCA occlusions, defined as any occlusion identified distal to MCA bifurcation and inclusive of the sylvian segment.
4. **Anterior LVO with all MeVOs (aLVO plus all MeVO):** Anterior LVO with all MeVO, inclusive of occlusions in the M2-MCA, A1/A2 anterior cerebral artery (ACA), or P1/ P2 posterior cerebral artery (PCA).

M2-MCA occlusions were further trichotomized into horizontal M1-like M2 occlusion, horizontal non-M1-like M2 occlusion, and vertical M2 segment occlusion. M1-like M2 was defined as a dominant M2 or when one M2 branch caliber is more than the caliber of other M2 branch by over 50%. This classification of M2 morphology was similar to the M2 morphology categorization used for other ongoing randomized controlled trials at the institution's radiology research core laboratory. The neuroradiology fellow (AS) was trained by the senior author (AV) for morphologic classification of M2. After reviewing multiple cases

with appropriate agreement, the fellow proceeded to assess the M2 morphology in all the cases with M2-MCA occlusions.

Analyses and Statistics:

Patient demographics, clinical characteristics, vascular risk factors, and imaging interpretations of interest were reported as mean ± standard deviation (SD) or median with interquartile range (IQR) for continuous variables, and frequencies and percentages for the categorical variables. The primary outcome was the diagnostic performance of the automated algorithm for detecting aLVO compared to the reference standard of board-certified radiologists. Secondary outcomes were performance metrics for the detection of occlusions beyond the aLVO, inclusive of pLVO (i.e., all LVO), M2s (i.e., aLVO + M2), and any additional anterior or posterior circulation MeVO (i.e., aLVO + all MeVO).

Accuracy metrics, including sensitivity, specificity, positive predictive value, and negative predictive value were calculated for each vessel category (Table 2). Additionally, precision recall curve analyses were performed for each vessel category (Supplementary figure 1). The study was performed according to the STARD guidelines for assessing accuracy of the index test (Supplementary material).[5] All statistical analyses were performed using SAS version 9.4 (SAS Institute Inc., Cary, NC, USA). A p-value <0.05 was considered statistically significant.

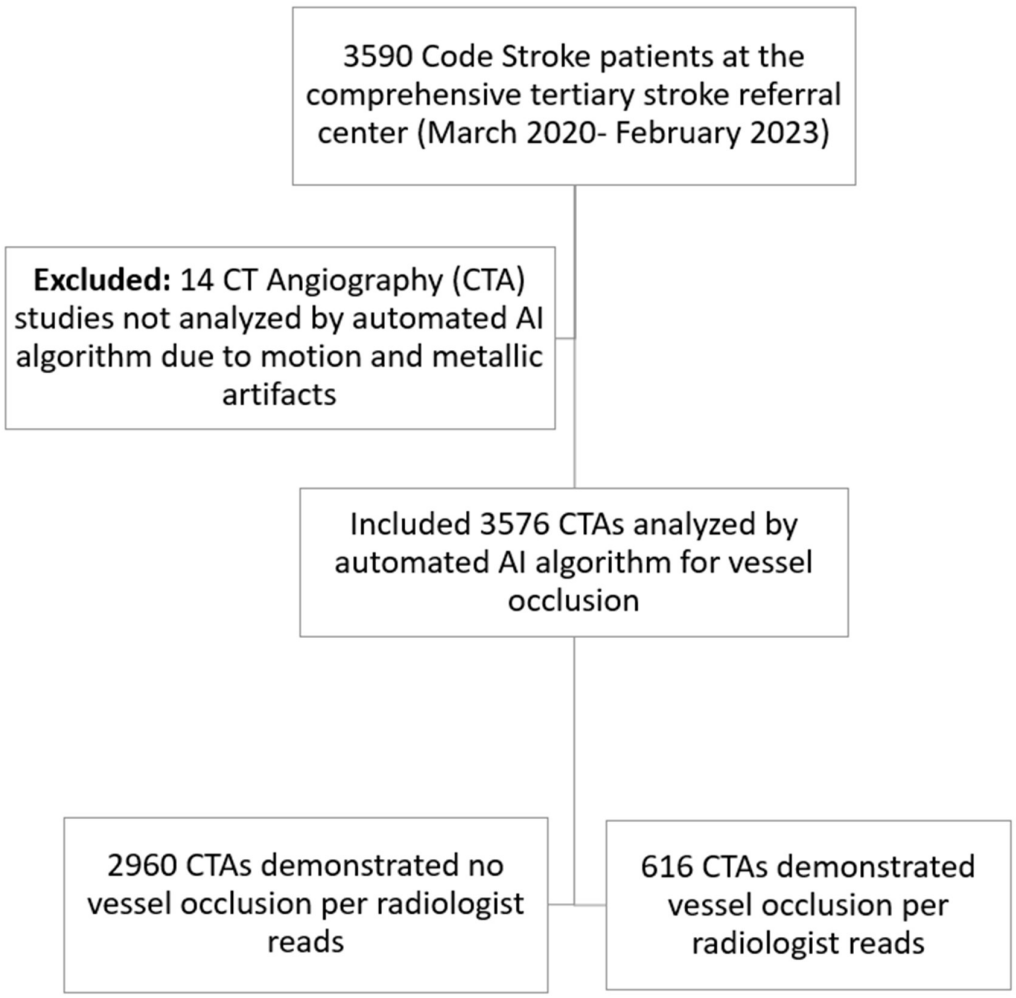

Figure 1: Flowchart. CTA = CT Angiography; AI = Artificial Intelligence.

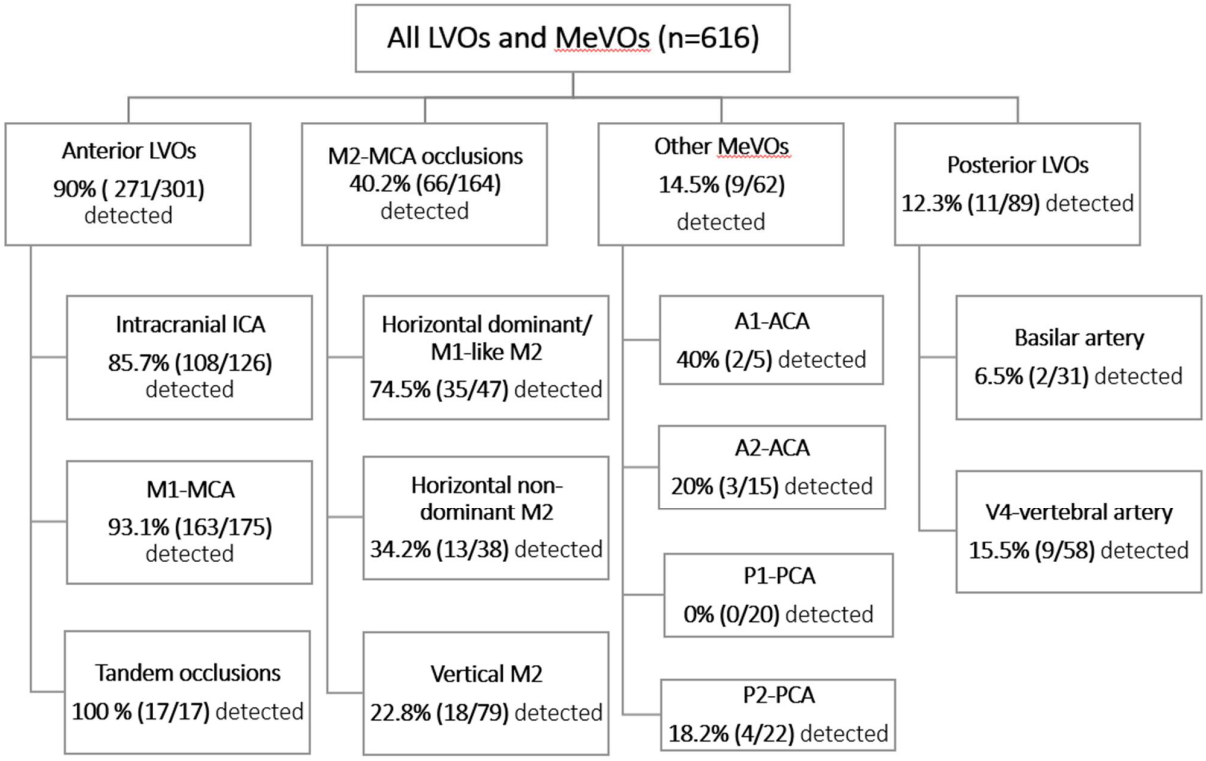

Figure 2: Automated Vessel Occlusion Detection. LVO = Large Vessel Occlusion; MeVO = Medium Vessel Occlusion; ICA = Internal Carotid Artery; MCA = Middle Cerebral Artery; ACA = Anterior Cerebral Artery; PCA = Posterior Cerebral Artery; AI = Artificial Intelligence.

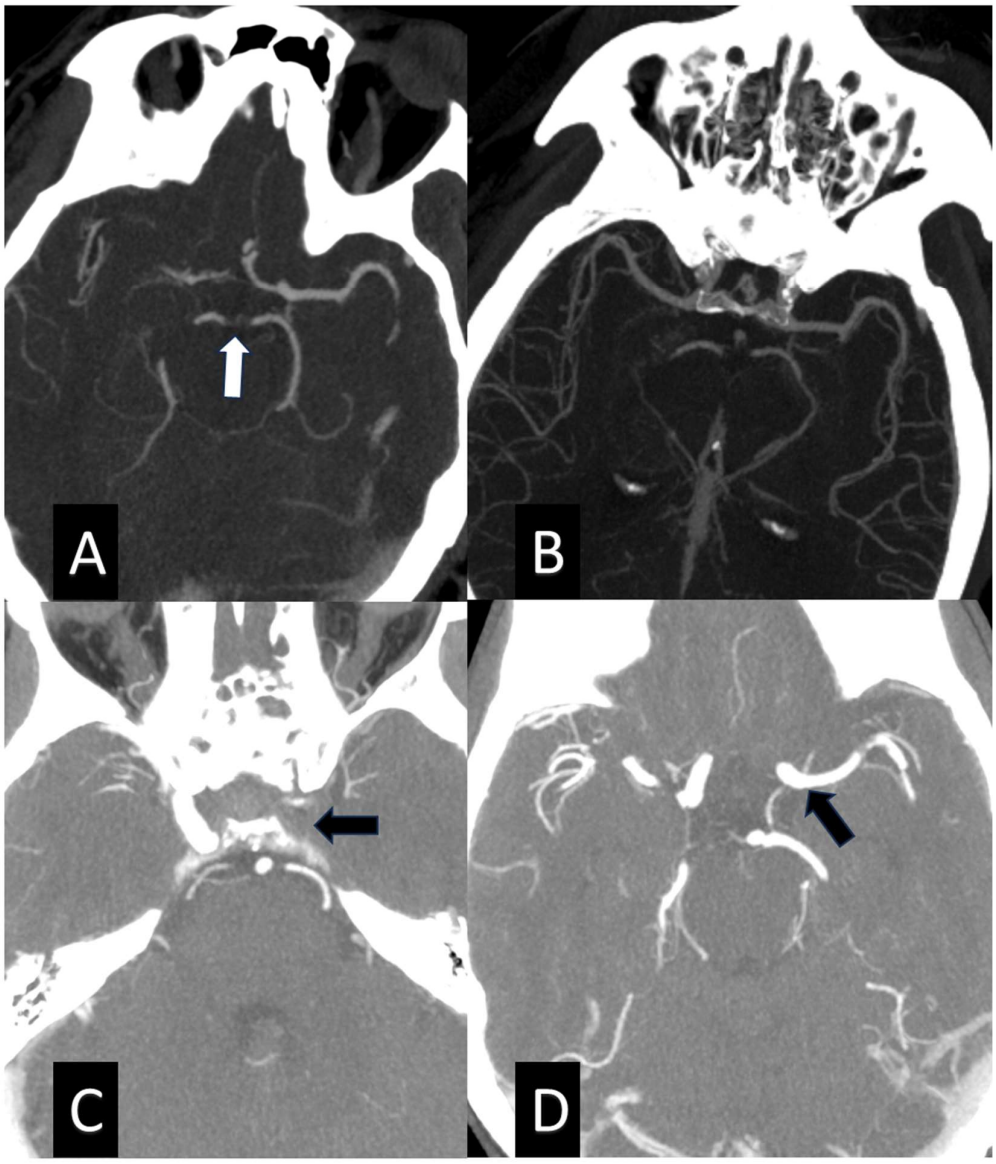

Figure 3: Representative examples of false negative cases using automated AI algorithm. **Figures 3A and 3B:** CT angiography image demonstrates occlusion of distal basilar artery and bilateral proximal posterior cerebral arteries (arrow in A). Automated AI algorithm's reconstruction of vessel tree (B) did not detect an occlusion. **Figure 3C and 3D:** CT angiography image at the level of skull base demonstrates occlusion of left petrous and intracavernous ICA (arrow in C) with reconstitution in supraclinoid segment (arrow in D). This occlusion was not detected by the automated AI algorithm.

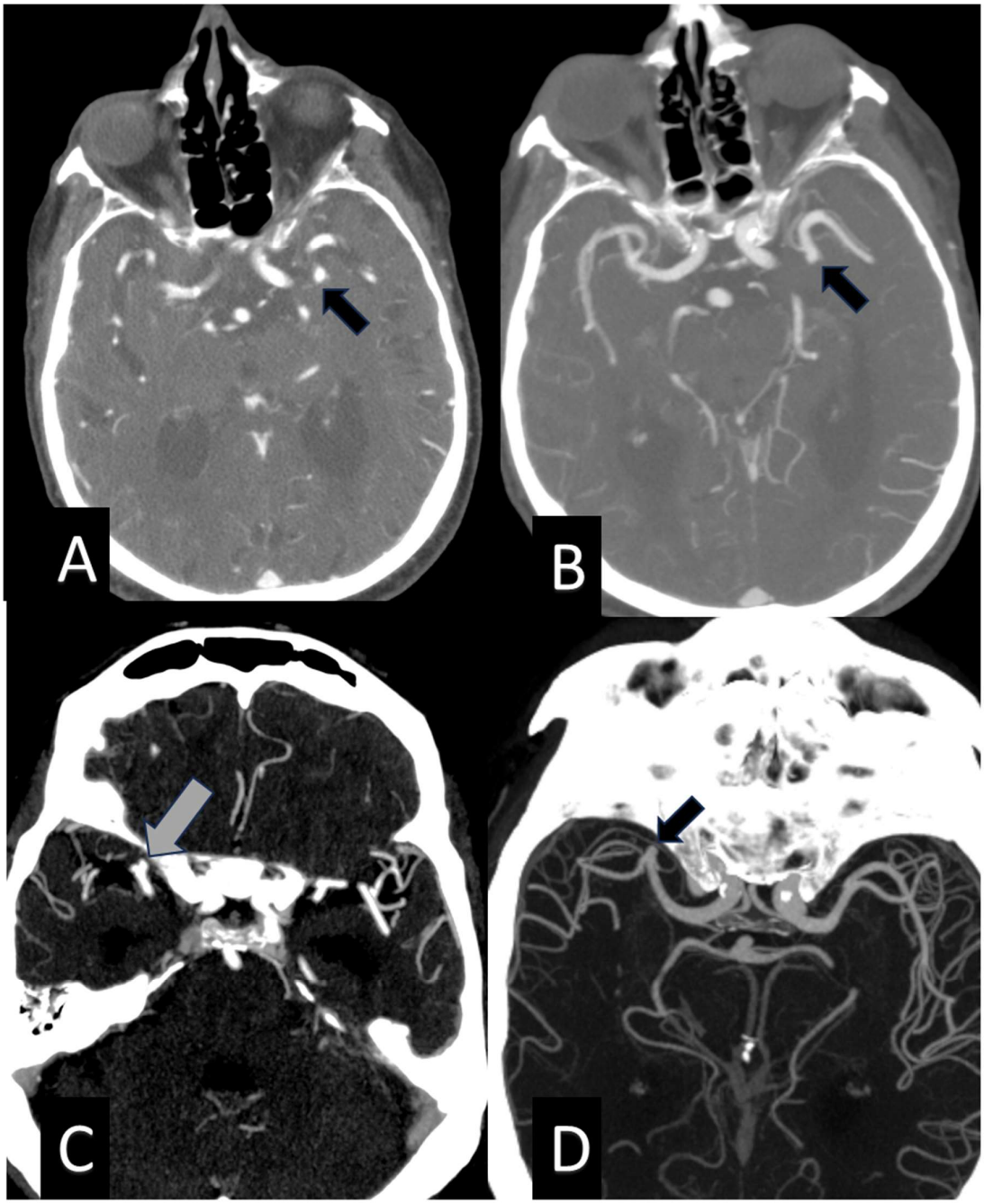

Figure 4: Representative examples of false positive cases by automated AI algorithm. **Figures 4A and 4B:** CT angiography images demonstrating dolichoectatic vessels traversing in and out of the axial planes (arrows), falsely perceived as occlusion by the automated AI algorithm. **Figures 4C and 4D:** CT angiography image demonstrating a saccular aneurysm (arrow in C) at the right distal MCA pointing anteriorly adjacent to its bifurcation. No flow limiting stenosis or occlusion was noted. Vessel tree segmented and reconstructed by automated AI algorithm (D) falsely detected an occlusion.

RESULTS

A total of 3,590 consecutive code stroke patients underwent CTA and automated algorithm detection analysis between March 2020 and February 2023. Fourteen of these cases were flagged by the automated AI tool as technically inadequate and were therefore excluded from analysis, leaving 3,576 patients (2,451 patients from site A and 1,139 patients from site B), who met the inclusion criteria (Figure 1). Of these patients, 50.4% were female, 67.9% were White, and 27.7% were Black with a median age of 67 (IQR: 54-82). Patient demographics, clinical characteristics, and radiographic characteristics are summarized in Table 1.

Acute vascular occlusions were identified in 616 (17.2%) patients by radiology reports: 301 aLVO (126 ICA, 175 M1), 89 pLVO (31 BA, 58 VA), 184 anterior MeVO (164 M2, 20 A1/A2), and 42 posterior MeVO (20 P1-PCA and 22 P2-PCA). The automated AI tool alerted a possible vessel occlusion in 505 cases (Figure 2). A total of 263 (8.6%) cases were false negatives (i.e., presence of vascular occlusion per the radiology report but not identified by the automated AI tool). Of the 2,960 cases discriminated as non LVO by radiologists, 152 were incorrectly identified by the software as LVO (i.e., false positive cases). Independent adjudication of all 152 false positive cases by a neuroradiology fellow (AS) indicated true absence of LVO.

Anterior LVO

Anterior LVO was identified in 301 radiology reports, of which 126 were ICA and 175 were M1 occlusions. Tandem occlusions, defined as discrete ICA and M1 occlusions with an intervening segment of normal vessel caliber and vascular flow, comprised 17 of these cases. The automated AI tool detected 271 (90.1%) aLVOs. The performance metrics and specifications of the aLVO missed by the AI tool are elaborated in Tables 2 and 3. All 17 cases of tandem occlusions were detected by the AI tool.

All LVO (anterior and posterior LVO)

Intracranial LVO was identified in 390 radiology reports, of which 89 were pLVO (31 BA and 58 V4). The performance metrics and specifications of the anterior and posterior LVOs not detected by the AI tool are elaborated in Tables 2 and 3. The automated algorithm did not detect 90.3% of all BA occlusions (Figure 3) and 86.2% of all V4 occlusions. All the 11 pLVO cases alerted by the automated algorithm had an associated chronic occlusion or severe stenosis in the proximal anterior circulation. It is likely that the pathology in the anterior circulation prompted the software to detect LVO rather than true identification of pLVO. Analysis of software detected MeVOs other than M2 also resulted in a similar finding.

Anterior LVO + M2

Anterior LVO plus M2 segment occlusions were identified by radiologists in 465 cases, of which 164 were M2 occlusions. The automated AI tool was able to successfully detect 66 (40.2%) of the 164 M2 occlusions. Further analysis of all 164 M2 occlusions according to their location and orientation revealed 47 horizontal dominant (i.e., “M1-like”) M2 occlusions, 38 non-dominant (i.e., non “M1-like”) M2 horizontal occlusions, and 79 vertical M2 segment occlusions (Figure 2). The performance metrics and specifications of the occlusions not detected by the AI tool are elaborated in Tables 2 and 3.

Anterior LVO + MeVO

Anterior LVO with all MeVO were identified in 527 (85.6%) of all occlusions detected. MeVOs were detected in 226 patients, including 164 M2, 5 A1, 15 A2, 20 P1, and 22 P2 segment occlusions. The performance metrics and specifications of the occlusions not detected by the AI tool are elaborated in Tables 2 and 3. All the ACA and PCA occlusions detected by the automated AI algorithm had an

associated chronic occlusion or severe stenosis in the proximal anterior circulation.

Among the 152 false positive cases (30.1% of all positive alerts by the automated tool) in the entire study, 49 (32.2%) were chronic occlusions including six instances of moyamoya disease, 24 (15.8%) had atherosclerotic luminal narrowing/ irregularity of the anterior large vessels, 8 (5.3%) had cervical ICA occlusion with no concurrent intracranial vessel occlusion (possibly due to poor ipsilateral intracranial vascular contrast opacification), 7 (4.6%) scans were compromised by motion impairment, and 4 (2.6%) had mass effect due to an intracranial space occupying lesion. There were 2 cases each of saccular aneurysm at MCA bifurcation, dolichoectasia (Figure 4), venous contamination, intracranial foci of contrast extravasation, and low ejection fraction leading to poor contrast bolus. The majority of the false positive cases with significant atherosclerotic plaque burden demonstrated moderate (approximately 50-70%) luminal stenosis of the cavernous and supraclinoid ICA segments, and the ICA terminus. In the remaining 50 (32.9%) false positive cases, no definite reason potentially leading AI algorithm to detect a vessel occlusion could be identified on imaging review.

DISCUSSION

In this real-world cohort, automated detection software (Viz.ai) demonstrated a high accuracy for aLVO agreement with board-certified radiologists, with lower agreement when M2-MCA, pLVO, or all MeVOs were included. We found the sensitivity and specificity for detecting anterior circulation LVO was 91% and 93% respectively. These results are consistent with the manufacturer's stated performance and multiple prior studies in the literature.[2, 7, 8] However, the AI tool demonstrated a modest positive predictive value of 64.1% for anterior LVO detection, given the relatively high number of false positive cases. These findings are in alignment with results from previously published

studies performed using the same AI tool (positive predictive value 48%-77%) and a different AI tool (RAPID AI, positive predictive value 43%).[2, 9-11]

When M2 segment occlusions are added to the aLVO category, the sensitivity decreases to 74%. Other studies have demonstrated similar accuracy of the automated AI algorithms for anterior LVO and M2 occlusion detection, with sensitivity ranging between 68.5% and 74.6% [7, 8], suggesting that automated vessel detection tools can miss a significant percentage of potentially treatable anterior vascular occlusions. Given the increasing rates of M2 thrombectomy [12], the lower accuracy of automated software to detect aLVO and M2-MCA occlusions highlights the discrepancy between real-world practice and the ability of automated software to consistently detect occlusion in this location.[4]

M2-MCA morphology can be highly variable, with some proximal M2-MCAs being more similar to M1-MCA occlusions ("M1-like" M2) than other MeVOs.[13] We attempted to analyze the M2-MCA in further detail based on the M2 morphology and M2 orientation (horizontal versus vertical segment) at the occlusion site that might influence the automated detection. Most of the M2 occlusions missed by the automated AI algorithm were in the vertical or insular M2 segment (62.2%), and most of the M2 occlusions detected were in the horizontal M2 segment (72.7%). Horizontal M2 occlusions were further dichotomized into M1-like M2 and non M1-like M2 morphology. 74.5% of "M1-like" M2 occlusions were detected by the automated AI tool compared to 34.2% of horizontal non "M1-like" M2 occlusions. This difference in detection rate is intuitive, as a larger caliber vessel occlusion and consequent difference in contrast opacification are more likely to be interpreted correctly by the software. Our findings highlight a lower detection rate of occlusion in vertical M2 and non "M1-like" M2 occlusions (26.5%), compared to "M1-like" M2 occlusions (74.5%).

We found that the sensitivity for aLVO and pLVO detection (73%) is significantly lower compared to only aLVO detection (91%). Other studies have found similar results when posterior circulation vascular occlusions were included in the performance analyses.[7] Thrombectomy in acute

BA occlusion is associated with improved functional outcome, reiterating the significance of prompt pLVO detection and notification.[14, 15] Given the high mortality associated with BA occlusion and frequently atypical symptoms associated with these occlusions, strong caution should be taken to avoid delayed diagnoses.[16] Of note, we included V4 occlusions with BA occlusions in the pLVO category. Of the two recent randomized clinical trials to support thrombectomy in BA occlusion, only a small subset of vessel occlusions in the thrombectomy for acute BA occlusion trial were V4 occlusions.[14, 17] Our findings demonstrate that centers routinely performing thrombectomy on only aLVO and pLVO should be aware that reliance on this and other AI platforms, which are not trained to detect pLVO, could lead to delays in diagnosis for occlusions in this location.

Expectedly, the sensitivity of the automated software to detect occlusion was even lower when anterior and posterior MeVOs were added. The sensitivity for this subgroup was 65% in our study, similar to the sensitivity for this subgroup (59.4%) reported by previous studies[7]. Posterior circulation LVOs and MeVOs are not included in the segmentation and analysis by automated AI algorithms, resulting in 78 (87.6%) missed posterior LVOs and 38 (90.5%) missed posterior MeVOs in our series.

The high number of false positives (30% of all positive alerts) can likely be attributed to the emphasis on achieving high sensitivity for automated occlusion detection. A majority of the false positive cases can be attributed to non-emergent intracranial radiological findings as described above, most importantly, atherosclerosis and chronic occlusions.

Our study is strengthened by the analysis of a large dataset obtained from multiple locations comprising the region's largest comprehensive stroke center. CTA studies included in the analyses were reported by board-certified neuroradiologists and emergency radiologists, closely mirroring the typical work distribution among radiologists at numerous stroke centers nationwide. Additionally, we characterized the morphology and anatomical location of M2 occlusions that were more likely to be detected by AI, an analysis that is novel to the literature. Finally, we categorized vascular occlusions based on the changing landscape of thrombectomy.

Given the rapidly expanding indications for thrombectomy, providers, particularly at experienced centers, are frequently changing practice in advance of formal guideline changes following landmark studies.[14, 15, 18, 19] This creates a dynamic in which BA and M2 thrombectomy, depending on the clinical scenario, are already considered treatment options. Reliance upon automated vessel detection tools without awareness of their limitations could create diagnostic delays. Additionally, while AI is an extremely valuable tool for early detection, the commercial software cannot take patient presentation or context into consideration like human assessment. For these reasons, the manufacturer of this and many other software programs utilized in stroke have marketed their product as a tool for assessment rather than diagnosis.

Our study is limited by retrospective design from patients at a single academic center using a single AI detection system. Importantly, we did not investigate the effect of false positive and false negative results produced by the software on key clinical time metrics, such as time to groin puncture, or on the decision making and patient outcomes. Although all cases included in this analysis were within 24 hours of the last known well, the time from symptom onset to imaging for individual cases was not available. Further, CTP, which can aid in the diagnosis of vessel occlusion, was not available for all studies analyzed based on institutional protocols limiting its use to 6-24 hours of last known normal. Additionally, the accuracy of LVO discrimination of the software may be influenced by uniform CT quality metrics and true LVO incidence inherent to a single center study.

Table 1: Demographics.

Patient Characteristics	**N=3,576**
Age (in years), median (interquartile range)	67 (54-82)
Male sex, *n* (%)	1,775 (49.6)
Race	
White patients, *n* (%)	2,428 (67.9)
Black patients, *n* (%)	990 (27.7)
Hispanic or Latino patients, *n* (%)	54 (1.5)
Asian patients, *n* (%)	61 (1.7)
Other, *n* (%)	49 (1.4)
Clinical and vascular risk factors	
Congestive Heart Failure, *n* (%)	576 (16.1)
Hypertension*, *n* (%)	2,708 (75.7)
Hyperlipidemia*, *n* (%)	2,029 (56.7)
Diabetes mellitus, *n* (%)	1,266 (35.4)
Atrial Fibrillation, *n* (%)	613 (17.1)
Smoking, *n* (%)	1,560 (43.6)
Prior stroke history, *n* (%)	839 (23.5)

LVO, Large Vessel Occlusion;

*Medical diagnoses of hypertension and hyperlipidemia were abstract from the electronic medical record (based on current or historical admission)

Table 2: **Accuracy Metrics of an Automated AI Tool's Performance.**

Occlusion Category	Occlusions detected by AI (n/N)	Sensitivity (95% CI)	Specificity (95% CI)	Positive Predictive Value (%)	Negative Predictive Value (%)	Accuracy (%)
Anterior LVO*	271/301	91 (87-94)	93 (92-94)	64.1	99.1	92.8
All LVO ^	282/390	73 (68-77)	92 (91-93)	65	96.5	90.7
Anterior LVO with M2-MCA occlusions**	337/465	74 (70-78)	93 (92-94)	67.3	95.9	91.9
Anterior LVO with all MeVOs***	346/527	65 (61-69)	93 (92-94)	68.5	93.6	90.1

LVO, Large Vessel Occlusion; MeVO, Medium Vessel Occlusion; n/N, number of occlusions detected by AI algorithm over total number of occlusions

*Anterior LVO, defined as occlusion of ICA or M1;

^All LVO, defined as anterior LVO or occlusion in the basilar artery or V4- vertebral artery;

**Anterior LVO with M2-MCA occlusions, defined as anterior LVO or occlusion in the M2- middle cerebral artery;

***Anterior LVO with all MeVOs, defined as anterior LVO or occlusion in the M2- middle cerebral artery, occlusion in the A1 or A2 segments of the anterior cerebral artery, or occlusion in the P1 or P2 segments of the posterior cerebral artery

Table 3: Descriptive analyses of vessel occlusions not detected by the AI tool.

Anterior LVO	
Total occlusions missed by AI tool	30/301 (9.9%)
Petrous and cavernous segment occlusions reconstituted in supraclinoid segment	15
Distal M1-MCA occlusion near MCA bifurcation	8
Short segment occlusion with distal collateral mediated reconstitution	7
All LVO	
Total occlusions not detected by AI tool	109/390 (27.4%)
V4-vertebral artery occlusions not detected (total=58)	50
Basilar artery occlusions not detected (total=31)	29
Anterior LVO (total=301)	30
Anterior LVO with M2-MCA occlusion	
Total occlusions not detected by AI tool	128/465 (27.5%)
Horizontal dominant M2/ M1-like M2 (total=47)	12
Horizontal nondominant M2/ non-M1-like M2 (total=38)	25
Vertical M2 occlusions (total= 79)	61
Anterior LVO (total=301)	30
Anterior LVO with all MeVOs	
Total occlusions not detected by AI tool	181/527 (34.3%)

A1-ACA occlusions (total=5)	3
A2-ACA occlusions (total=15)	12
P1-PCA occlusions (total=20)	20
P2-PCA occlusions (total=22)	18
M2-MCA occlusions (total=164)	98
Anterior LVO (total=301)	30
AI, Artificial Intelligence; LVO, Large Vessel Occlusion; MeVO, Medium Vessel Occlusion; ACA, Anterior Cerebral Artery; PCA, Posterior Cerebral Artery.	

CONCLUSIONS

Evaluation of AI's ability to detect vessel occlusions in a large real-world sample of acute ischemic stroke patients revealed a high sensitivity for detecting aLVO, with a modest positive predictive value. Worse metrics were noted when potentially treatable M2s and pLVO were included. Acute stroke providers should be aware of the limitations of automated vessel occlusion detection software, particularly in the setting of rapidly expanding indications for thrombectomy.

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None

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SUPPLEMENTAL FILES

Supplementary Material: STARD Checklist

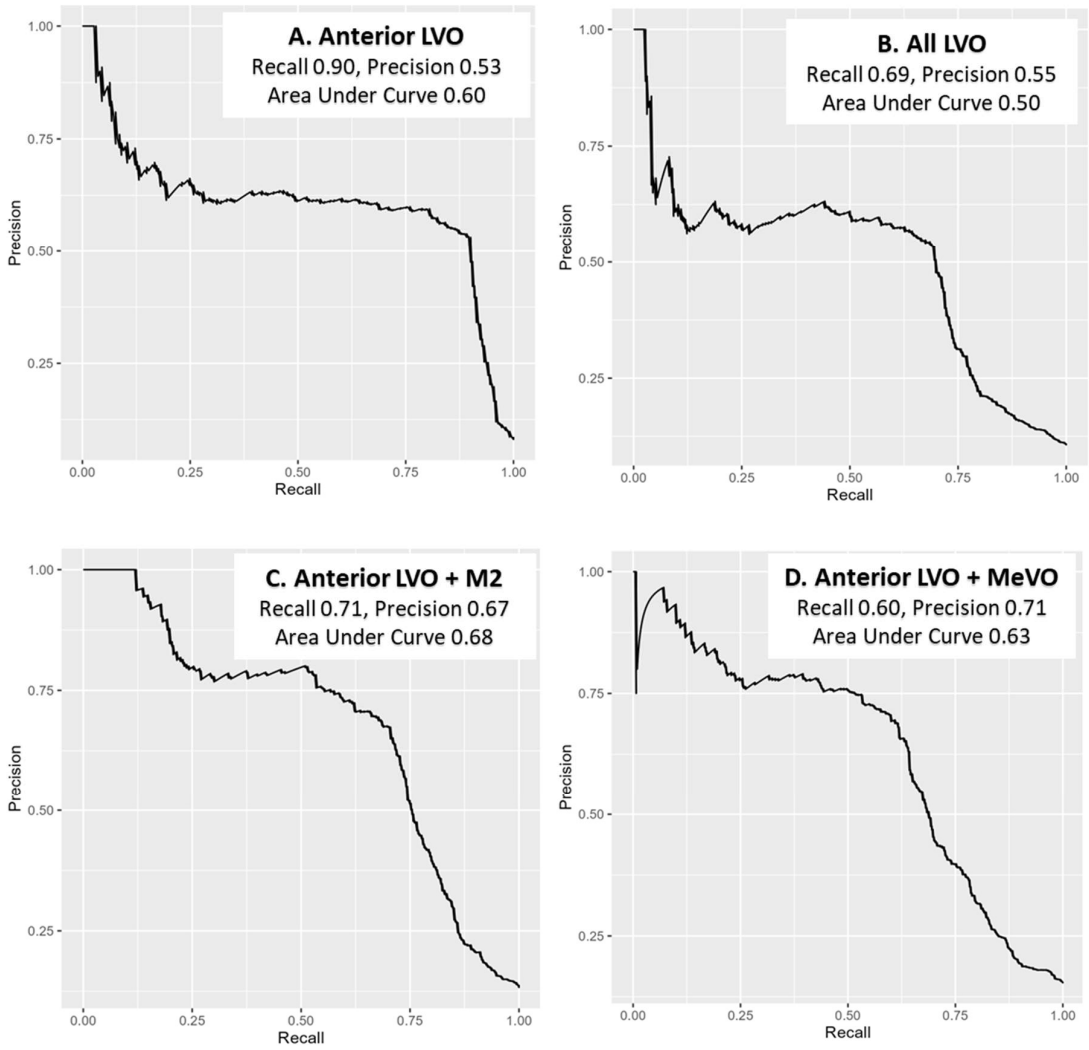
Section & Topic	No	Item	Reported on page #
TITLE OR ABSTRACT			
	1	Identification as a study of diagnostic accuracy using at least one measure of accuracy (such as sensitivity, specificity, predictive values, or AUC)	1
ABSTRACT			
	2	Structured summary of study design, methods, results, and conclusions (for specific guidance, see STARD for Abstracts)	1,2
INTRODUCTION			
	3	Scientific and clinical background, including the intended use and clinical role of the index test	4,5
	4	Study objectives and hypotheses	5
METHODS			
Study design	**5**	Whether data collection was planned before the index test and reference standard were performed (prospective study) or after (retrospective study)	5 (retrospective)
Participants	**6**	Eligibility criteria	5,6

	7	On what basis potentially eligible participants were identified (such as symptoms, results from previous tests, inclusion in registry)	5,6
	8	Where and when potentially eligible participants were identified (setting, location and dates)	5,6
	9	Whether participants formed a consecutive, random or convenience series	5 (consecutive)
Test methods	**10a**	Index test, in sufficient detail to allow replication	7
	10b	Reference standard, in sufficient detail to allow replication	7,8
	11	Rationale for choosing the reference standard (if alternatives exist)	6,7
	12a	Definition of and rationale for test positivity cut-offs or result categories of the index test, distinguishing pre-specified from exploratory	8,9
	12b	Definition of and rationale for test positivity cut-offs or result categories of the reference standard, distinguishing pre-specified from exploratory	7
	13a	Whether clinical information and reference standard results were available to the performers/readers of the index test	7
	13b	Whether clinical information and index test results were available to the assessors of the reference standard	7
Analysis	**14**	Methods for estimating or comparing measures of diagnostic accuracy	8,9

	15	How indeterminate index test or reference standard results were handled	5, 8
	16	How missing data on the index test and reference standard were handled	5
	17	Any analyses of variability in diagnostic accuracy, distinguishing pre-specified from exploratory	9
	18	Intended sample size and how it was determined	5
RESULTS			
Participants	**19**	Flow of participants, using a diagram	Figure 1
	20	Baseline demographic and clinical characteristics of participants	Table 1
	21a	Distribution of severity of disease in those with the target condition	Figure 2
	21b	Distribution of alternative diagnoses in those without the target condition	16
	22	Time interval and any clinical interventions between index test and reference standard	6,7
Test results	**23**	Cross tabulation of the index test results (or their distribution) by the results of the reference standard	Figure 2
	24	Estimates of diagnostic accuracy and their precision (such as 95% confidence intervals)	Table 2
	25	Any adverse events from performing the index test or the reference standard	14-16
DISCUSSION			
	26	Study limitations, including sources of potential bias, statistical uncertainty, and generalisability	20

	27	Implications for practice, including the intended use and clinical role of the index test	17-20
OTHER INFORMATION			
	28	Registration number and name of registry	5 (LVO registry #2016-6858)
	29	Where the full study protocol can be accessed	5-8, from the corresponding author upon reasonable request
	30	Sources of funding and other support; role of funders	2,3

Supplementary Figure



Supplementary Figure 1: **Precision-Recall Curve Analysis** for detection of (A) Anterior LVO, (B) All LVO, (C) Anterior LVO plus M2, and (D) Anterior LVO plus MeVO.