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# DEVELOPMENT OF DEEP LEARNING MODEL FOR AUTOMATIC DIAGNOSIS OF LARGE VESSEL OCCLUSIONS


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# ROLE OF IMAGING IN TREATMENT OF LVO

- Endovascular thrombectomy has become the standard therapy for large vessel occlusion (LVO) in acute ischemic stroke.
- Timely and accurate detection of LVO is crucial for this therapy
- However, treatment is often delayed due to the shortage of experienced neuroradiologists.
- For every 5-minute delay in endovascular reperfusion, 1 in 100 patients with LVO may experience a worse disability outcome[1]

[1] *Sheth SA, Jahan R, Gralla J, Pereira VM, Nogueira RG, Levy EI, et al. Time to endovascular reperfusion and degree of disability in acute stroke. Annals of neurology. 2015;78(4):584-93.*

# ARTIFICIAL INTELLIGENCE IN RADIOLOGY

- Novel algorithms, such as Convolutional Neural Network (CNN), have revolutionized Diagnostic Radiology.
- Numerous academic research studies and commercial applications use CNN for diagnosing LVO.
- To our knowledge, there is no published research regarding use of deep learning approaches for automated detection of LVO in Vietnam.

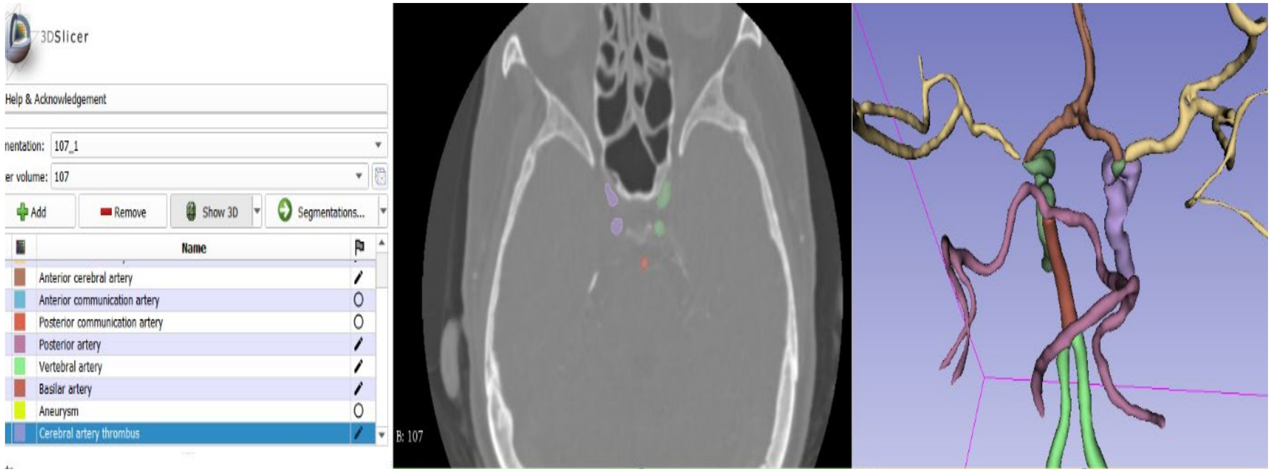
*Murray NM, Unberath M, Hager GD, Hui FK. Artificial intelligence to diagnose ischemic stroke and identify large vessel occlusions: a systematic review. Journal of neurointerventional surgery. 2020;12(2):156-64.*

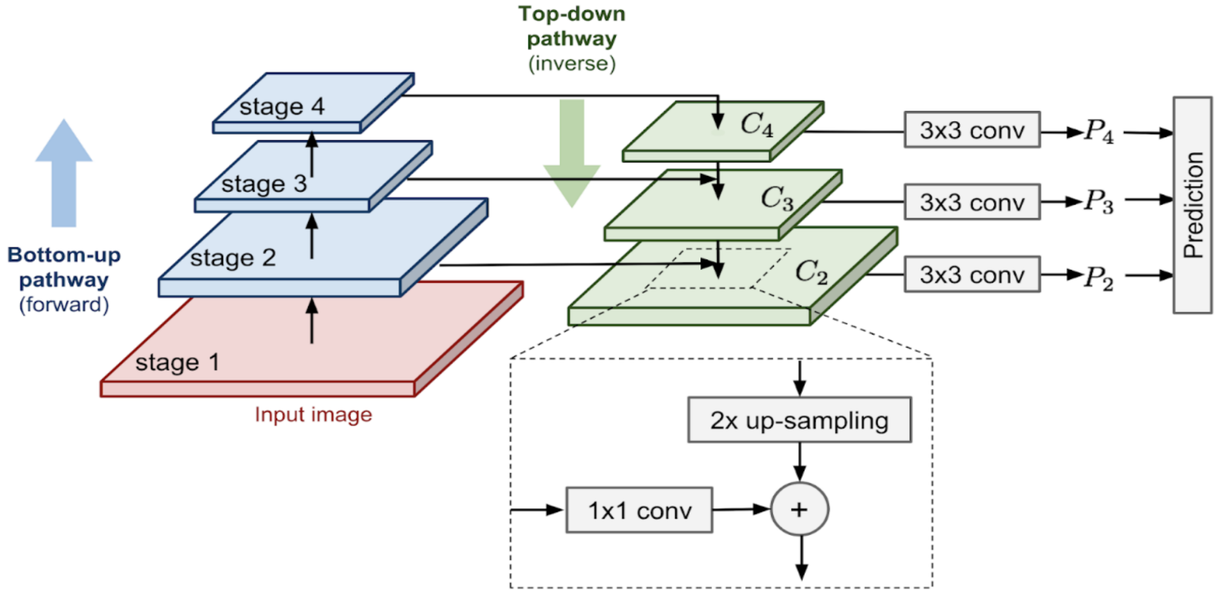
# MATERIALS AND METHODS

- CT images were retrieved from databases of 2 provincial hospitals in central Vietnam from 2017 to 2024.
- All DICOM images were anonymized.
- IRB approval was obtained from both hospitals.
- MDCT: Toshiba Aquilion 80 and GE 128.

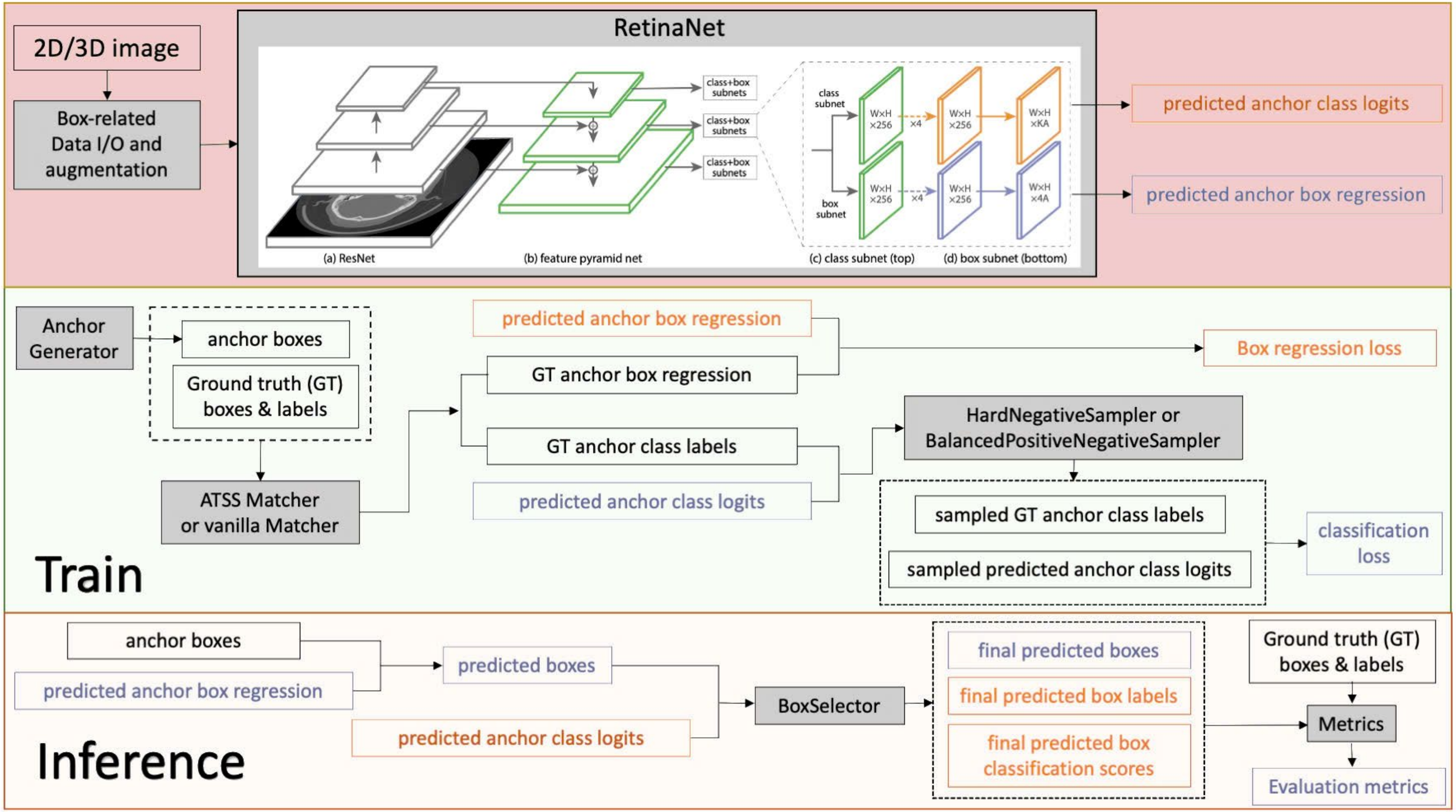
# SEGMENTATION AND MODEL TRAINING

- Manual Segmentation by 3D-Slicer.
- Segmentation Model was built based on UNET-R architecture.
- Classification Model was built based on RetinaNet architecture.
- Models were evaluated using sensitivity, specificity, and accuracy

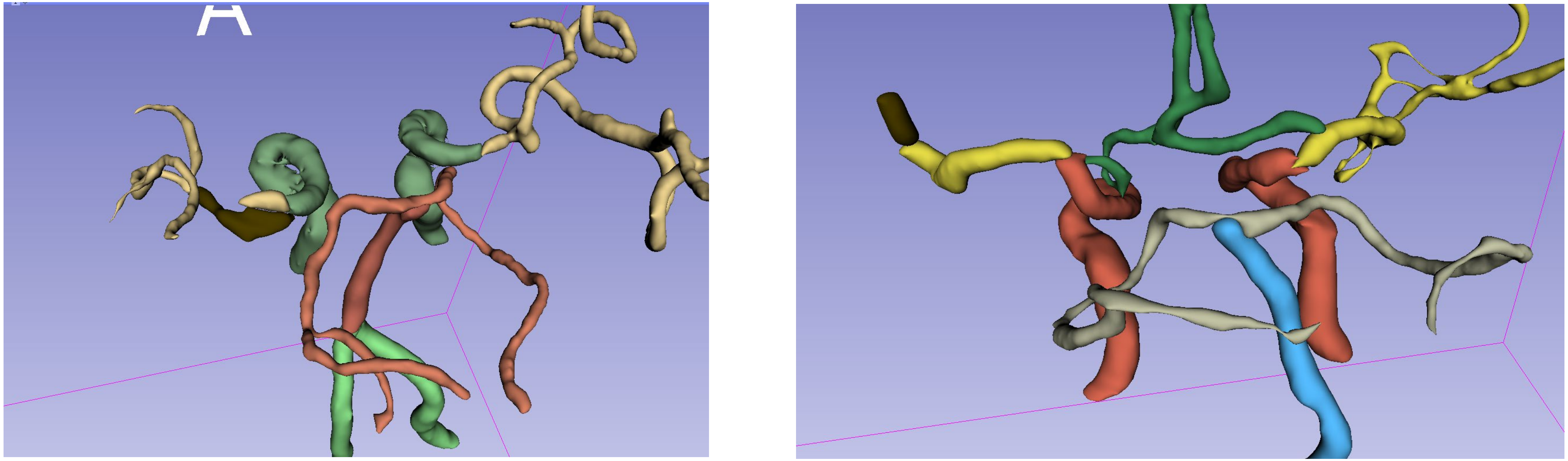


# DEEP LEARNING MODEL ARCHITECTURE



# SEGMENTATION BY 3-D SLICER



A

B

*Figure 1: Manual segmentation of the cerebrovascular anatomy and labeling of the right M1 thrombus (brown segmentation in panel A) and right M2 thrombus (brown segmentation in panel B) using 3D-Slicer.*

# DATA ANNOTATION

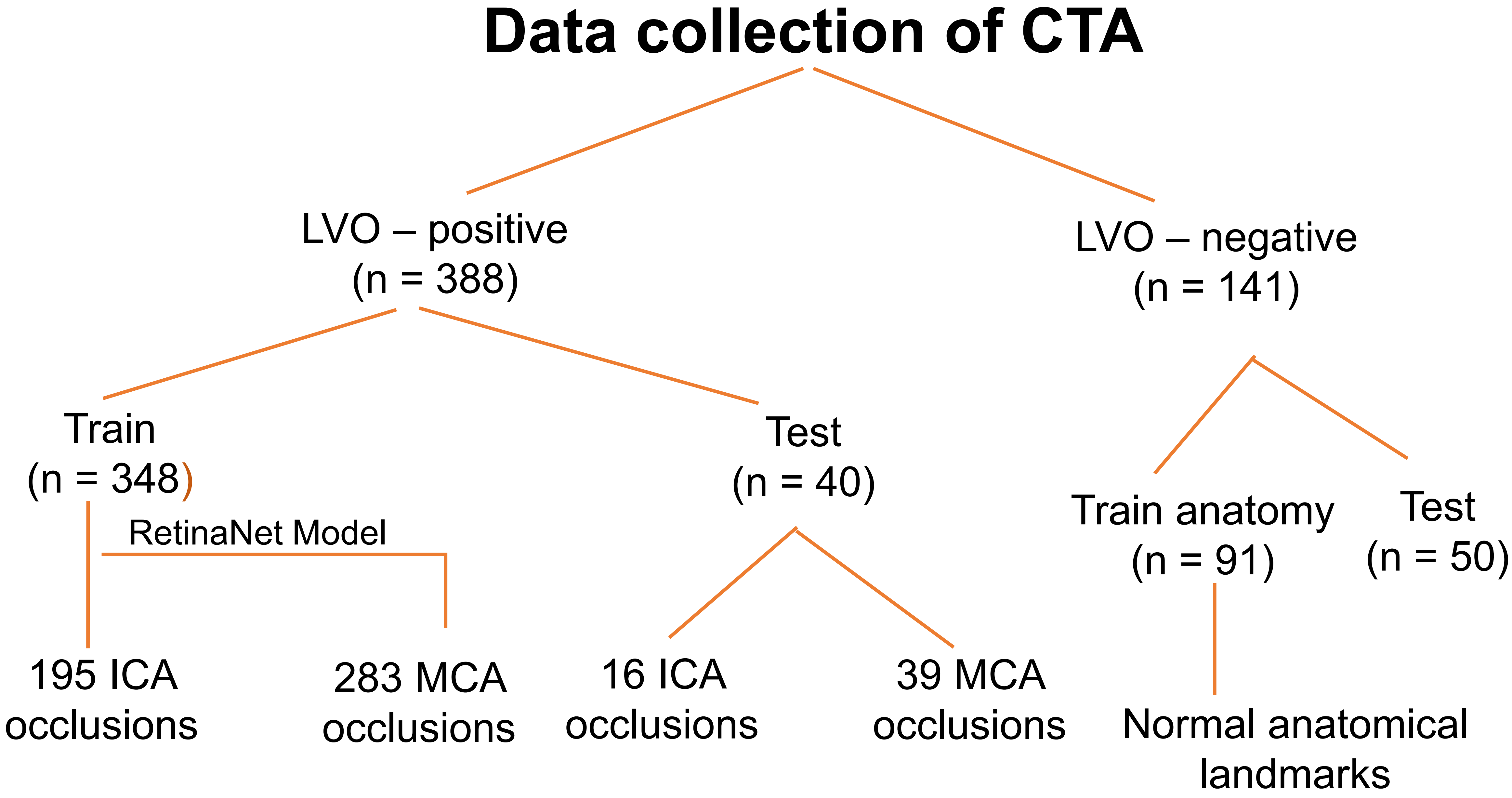
- Labels: (+)/(-) for LVO.
- 91 normal samples were segmented and used to train for normal anatomy.
- We segmented 348 positive samples (195 with ICA occlusions and 283 with MCA occlusions), totaling 478 occlusion sites as some cases had multiple occlusion locations, and used them to train the classification model to identify the vessel occlusion sites.

# DATA ANNOTATION

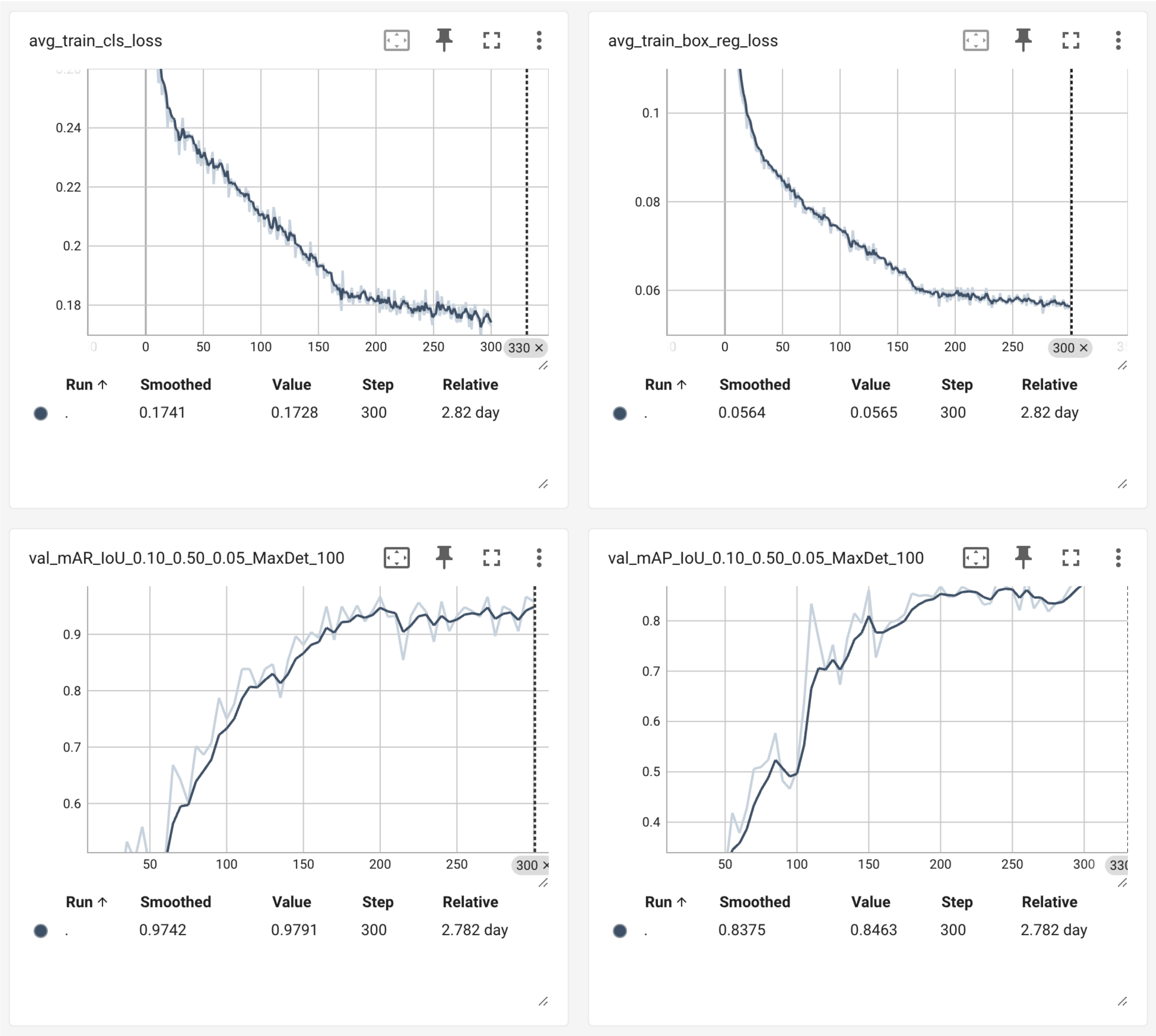
- Readers: 2 independent experienced neuroradiologists.
- Non-concordant results were excluded from dataset.
- We focused on the (+) in the anterior circulation, including the intracranial internal carotid artery (ICA) and middle cerebral artery (MCA).

# RESULTS

- 90 new samples were included in the test set.
- 40 positive samples (16 with ICA occlusions and 39 with MCA occlusions), totaling 55 occlusion sites as some cases had multiple occlusion locations, were reviewed by two radiologists in Vietnam and one neuroradiologist at Mayo Clinic Jacksonville, all with the same result, along with 50 negative samples.


Data collection of CTA
LVO – positive
(n = 388)
LVO – negative
(n = 141)
Train
(n = 348)
Test
(n = 40)
Train anatomy
(n = 91)
Test
(n = 50)
RetinaNet Model
195 ICA
occlusions
283 MCA
occlusions
16 ICA
occlusions
39 MCA
occlusions
Normal anatomical
landmarks

# Training & Validation Performance over 300 Epochs




*The upper row shows the training losses for box regression and classification. The bottom row shows the validation mAP and mAR for IoU ranging*

# ILLUSTRATION OF MODEL PREDICTIONS

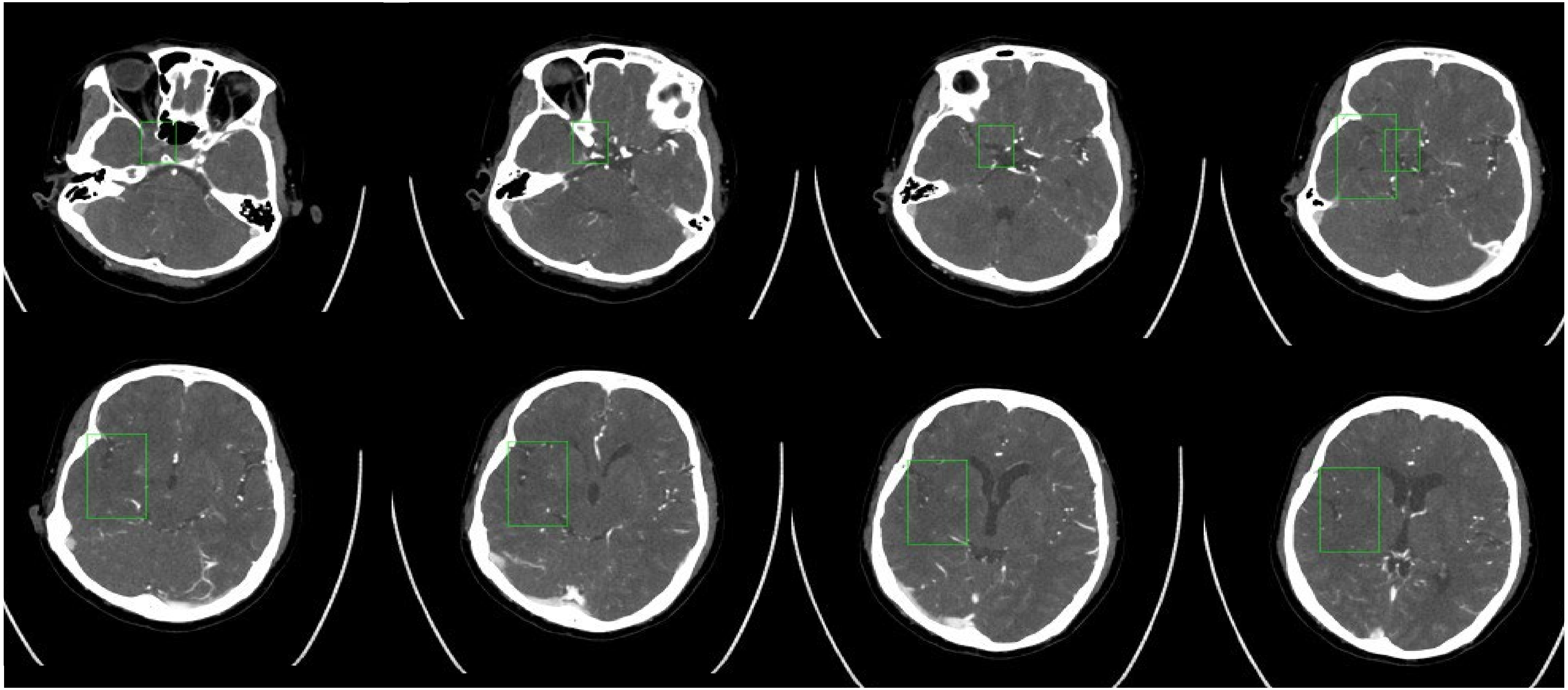


*Figure 2: Automatic detection of the right ICA and MCA occlusions performed by the DL model*

# ILLUSTRATION OF MODEL PREDICTIONS

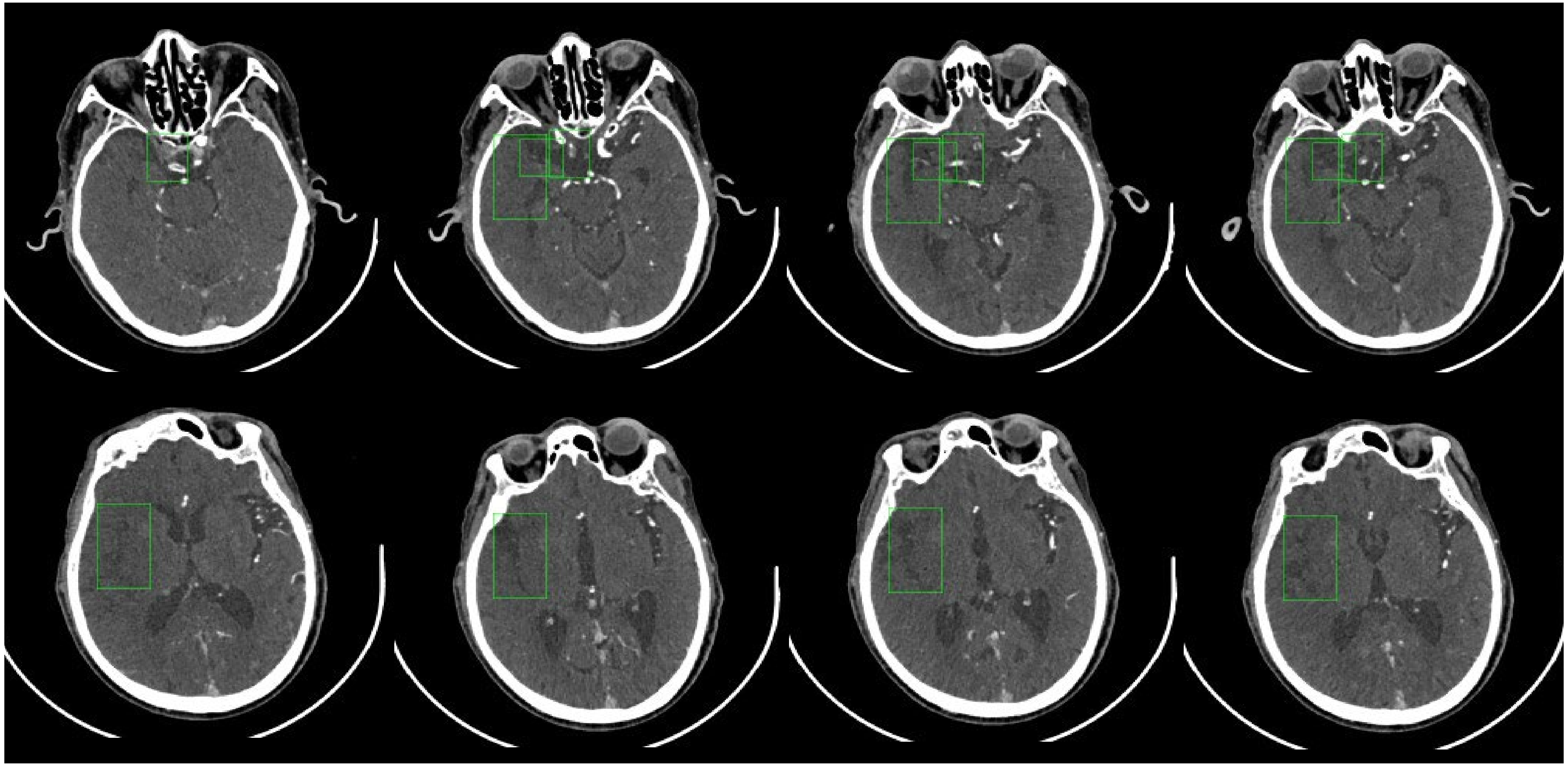


*Figure 3: Automatic detection of the right ICA and MCA occlusions performed by the DL model*

# MODEL PERFORMANCE ON TEST SET

The resulting model was evaluated on a data set of 90 patients, including 40 patients with LVO and 50 patients without LVO

**LVO**

A

| | Ground Truth | | |
|---|---|---|---|
| | LVO | No LVO | |
| LVO | True positive | False positive | PPV |
| | 30 | 1 | **96.8%** |
| No LVO | False negative | True negative | NPV |
| | 10 | 49 | **83.1%** |
| | Sens. | Spec. | Acc. |
| | **75.0%** | **98.0%** | **87.8%** |

**ICA**

B

| | Ground Truth | | |
|---|---|---|---|
| | LVO | No LVO | |
| LVO | True positive | False positive | PPV |
| | 14 | 3 | **82.4%** |
| No LVO | False negative | True negative | NPV |
| | 2 | 71 | **97.3%** |
| | Sens. | Spec. | Acc. |
| | **87.5%** | **95.9%** | **94.4%** |

**MCA**

C

| | Ground Truth | | |
|---|---|---|---|
| | LVO | No LVO | |
| LVO | True positive | False positive | PPV |
| | 24 | 3 | **88.9%** |
| No LVO | False negative | True negative | NPV |
| | 15 | 49 | **76.6%** |
| | Sens. | Spec. | Acc. |
| | **61.5%** | **94.2%** | **80.2%** |

*Figure 4:* Sensitivity, specificity, and accuracy of LVO at any location (ICA, MCA) in **A**; ICA occlusion in **B**; and MCA occlusion in **C**

**Sens**.: Sensitivity, **Spec.**: Specificity, **NPV**: Negative Predictive Value, **PPV**: Positive Predictive Value**, Acc:** accuracy

# DISCUSSION

- The model has similar performance to that of other academic studies.
- The results are still lower than commercial software models like RapidAI Model, Brainomix and Viz.

# PERFORMANCE OF THE BRAINOMIX AND RAPIDAI

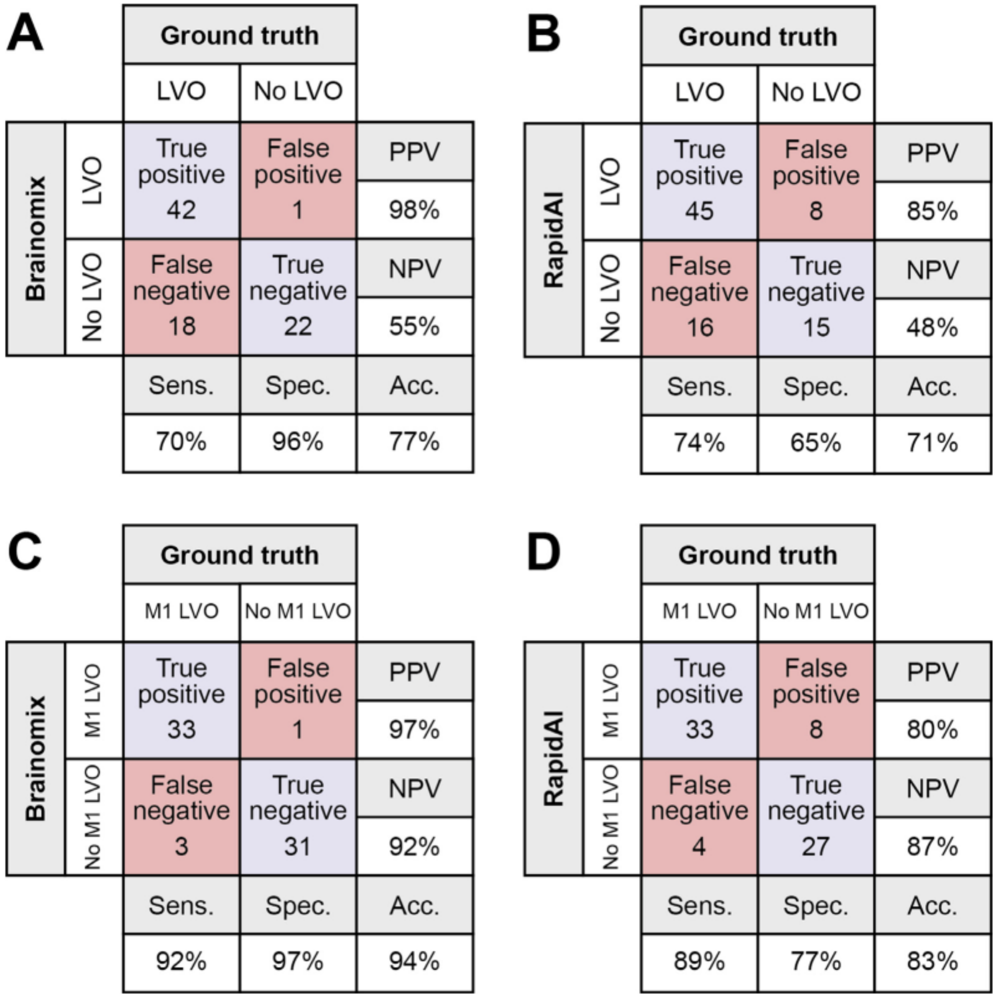



**Figure 2.** *Confusion matrix with diagnostic statistics for Brainomix and RapidAI for LVO of all sizes (ICA, M1 and M2) (A) and for M1 LVO (B). For all LVOs considered together and for M1 occlusions only, Brainomix had a higher accuracy than RapidAI.*

Mallon DH, Taylor EJ, Vittay OI, Sheeka A, Doig D, Lobotesis K. Comparison of automated ASPECTS, large vessel occlusion detection and CTP analysis provided by Brainomix and RapidAI in patients with suspected ischaemic stroke. *Journal of Stroke and Cerebrovascular Diseases*. 2022;31(10):106702.

# PERFORMANCE OF THE VIZ MODEL

Table 4:

Prediction of LVO by the Viz LVO system

| System LVO Detection | Sensitivity | 95% CI | Specificity | 95% CI | NPV | 95% CI | PPV | 95% CI | Accuracy | 95% CI |
|---|---|---|---|---|---|---|---|---|---|---|
| Entire cohort (*n* = 1167) | 0.81 | 0.74–0.91 | 0.96 | 0.95–0.97 | 0.99 | 0.98–0.99 | 0.65 | 0.55–0.74 | 0.94 | 0.92–0.96 |
| Stroke protocol subgroup (*n* = 404) | 0.82 | 0.71–0.89 | 0.90 | 0.86–0.93 | 0.96 | 0.93–0.98 | 0.64 | 0.53–0.73 | 0.89 | 0.86–0.94 |

Open in a separate window

**Note:**—NPV indicates negative predictive value.

Yahav-Dovrat A, Saban M, Merhav G, Lankri I, Abergel E, Eran A, et al. Evaluation of artificial intelligence–powered identification of large-vessel occlusions in a comprehensive stroke center. American Journal of Neuroradiology. 2021;42(2):247-54.

# DISCUSSION

- Future directions:
  - Increase training size/locations to improve the accuracy.
  - Experiment with more advanced architecture.
  - Include other data (medical records) to the diagnostic model.

# Thank You