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AI scientific evidence

Scientific publication highlights & references

Intelligent healthcare made easy

AI Scientific Evidence

AI

Artificial Intelligence (AI) is reshaping the way we interact, process information, and procure goods and services across vast industries. In healthcare, AI is already transforming the patient experience and how clinicians practice medicine in radiology and diagnostic imaging.

ALTIVITY

At Canon Medical, our aim is to evolve AI for everyone. Through Altivity, our bold new approach to AI innovation that is deeply rooted in machine learning and deep learning, we have developed smart technologies to make a whole new level of quality, insight and value possible across the entire care pathway. We are committed to supporting healthcare providers with the very best AI tools that improve clinical decision-making and streamline workflows, enabling more personalized medicine and improved patient outcomes. For this purpose, our global research teams collaborate with a range of leading academic, clinical and governmental institutions to develop and validate the next generation of AI-assisted imaging technologies.

TRUST

An important requirement for the implementation of AI solutions into daily clinical practice is trust. At Canon Medical, we understand the importance of providing you with evidence-based solutions. Therefore, we are pleased to provide you with this overview of the scientific evidence on Canon Medical AI solutions. This scientific reference list assists you in finding more in-depth information on our AI technologies. In addition, the highlighted articles provide you with quick insights into some of the demonstrated benefits of our AI applications in clinical radiology.

CT

Deep Learning Reconstruction algorithms can reduce radiation dose and improve image quality in CT angiography

Cardiac experts from the University Hospital of Dijon have incorporated cardiac CT Angiography (CTA) for all patients with stroke symptoms as part of their initial stroke work-up. While adding important information to better understand the patient's underlying etiology, the additional acquisition results in increased radiation exposure. As such, strategies to reduce radiation dose without sacrificing image quality are needed.

The potential of radiation dose reduction in cardiac CTA was investigated by Bernard et al. The authors compared Canon's CT Deep Learning-based Reconstruction (DLR) to Hybrid Iterative Reconstruction (HIR) in terms of radiation dose and image quality. 300 consecutive patients with suspected stroke underwent cardiac CTA reconstructed either with HIR or with DLR. For each CT reconstruction algorithm, image quality and radiation dose were evaluated.

The use of the DLR algorithm for cardiac CTA in an acute stroke imaging protocol showed an approximate 51% improvement in Signal-to-Noise Ratio (SNR), 49% improvement in contrast-to-noise ratio (CNR) and 40% reduction in radiation dose compared to HIR. See Table 1.

	HIR	DLR	P value
Dose-length product (DLP) [mGy·cm]	176.1±37.1	106.4±50.0	<0.001
Volume CT dose index (CTDIvol) [mGy]	11.5±2.2	6.9±3.2	<0.001
Effective dose [mSv]	2.5±0.5	1.5±0.7	<0.001

Table 1: Radiation dose comparison between Hybrid Iterative Reconstruction (AIDR 3D) and Deep Learning Reconstruction (AiCE). Data are presented as mean ± standard deviation. Table adapted from reference (Bernard et al. 2021)

Reference
Bernard et al. | *Deep learning reconstruction versus iterative reconstruction for cardiac CT angiography in a stroke imaging protocol: reduced radiation dose and improved image quality.* | Quant Imaging Med Surg. (2021)
https://pubmed.ncbi.nlm.nih.gov/33392038/

CT

How does Deep Learning Reconstruction affect image quality and radiation dose reduction in pediatric patients?

CT image quality improvement and lower patient radiation dose are important in all patients but even more essential in pediatric patients. The solution to this challenge may arise from recent technological advances such as Deep Learning Reconstruction (DLR). Recently, Brady et al. compared current clinical CT reconstruction algorithms to a DLR algorithm when pediatric patients were scanned based on the clinical indication for trauma. Image datasets were reconstructed using Model-Based Iterative Reconstruction (MBIR), Statistical-Based Iterative Reconstruction (SBIR), Filtered Back Projection (FPB), and DLR. The CT image quality of the different reconstruction algorithms was assessed subjectively by radiologists and objectively by mathematical observer models.

Compared to MBIR, SBIR, and FPB, the DLR algorithm demonstrated higher object detection ability and accuracy. The subjective image quality investigation showed that the radiologists preferred DLR images over SBIR and MBIR images because of the improved object edge definition and quantum noise texture. Therefore, DLR had higher image quality ratings with greater radiologist preference and higher confidence ratings.

The analysis of different image thicknesses showed that DLR images at 0.5 mm and 3 mm showed equal or better detection accuracy than 3 mm SBIR images. This gives end-users multiple options such as using 0.5 mm slices to reduce partial volume artifacts, while favorably reducing quantum noise.

DLR has a greater radiation dose reduction potential than alternative algorithms in pediatric CT examinations. Without sacrificing noise texture and spatial resolution, the use of DLR provides the potential for a 52% reduction in volume CT dose index. This translates to organ-specific reductions in the order of 53% compared with SBIR. Shown in Figure 1.

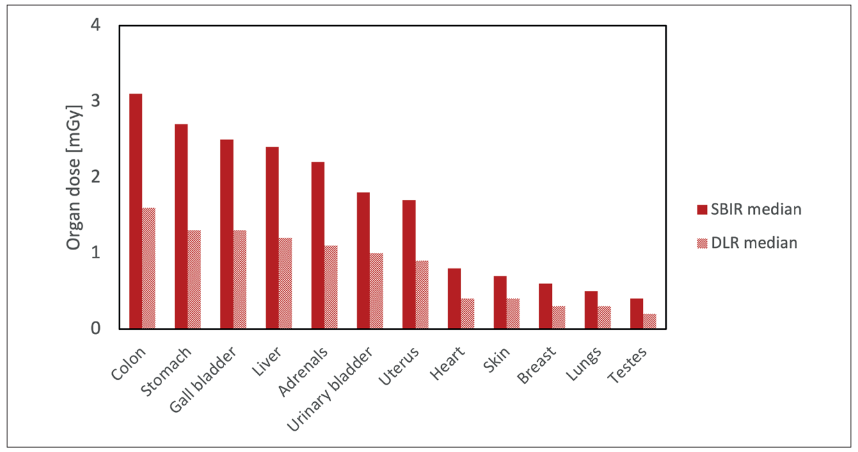

Figure 1. Organ-specific dose value comparison between DLR and SBIR. The use of DLR provides the potential for a 52% reduction in volume CT dose index and a mean of 53% in organ-specific reductions. Figure adapted from reference (Brady et al. 2021).

Reference
Brady et al. | *Improving Image Quality and Reducing Radiation Dose for Pediatric CT by Using Deep Learning Reconstruction* | Radiology | (2021)
https://pubmed.ncbi.nlm.nih.gov/33201790/

Deep Learning Reconstruction CT: low-dose, high-quality, and high-speed

Deep Learning Reconstruction (DLR) in CT is a promising application of artificial intelligence in radiology because it has the potential to improve image quality and radiological preference, as well as reduce patient radiation dose.

The review article of McLeavy et al. discusses the clinical advantages of DLR over conventional image reconstruction techniques such as Hybrid Iterative Reconstruction (HIR). The authors are affiliated with Leighton Hospital in Crewe which was one of the first institutions in the UK to use Advanced intelligent Clear-IQ Engine (AiCE) in a clinical setting. In this institution, DLR was used to develop specific protocols that achieve either ultra-low dose scans without a penalty in image quality or ultra-high image quality without increasing radiation dose.

Examples shown in this article:

- Volume CT pulmonary angiography with AiCE on pregnant women results in an effective dose of only 0.2 mSv. This is equivalent to 10 chest radiographs.

- A dual-phase and pelvis CT performed on pediatric trauma patients results in only 0.8 mSv without a compromise in the signal and contrast-to-noise ratio. A case illustration from this institution is provided in Figure 1.
- A CT scan of the urinary tract (kidney, ureter, and bladder (KUB)) using DLR with additional metal artifact reduction software reduced beam hardening in the pelvis. This exam resulted in an effective dose of only 1 mSv, an 84% dose reduction compared to HIR, without degrading image quality.

- Whereas a plain radiograph of the abdomen and pelvis has an effective dose of 1.4 mSv, the dose from CT scans of the entire urinary tract performed in this institution using DLR was only 1.2 mSv. This corresponds to 83% less radiation dose than the national dose levels.

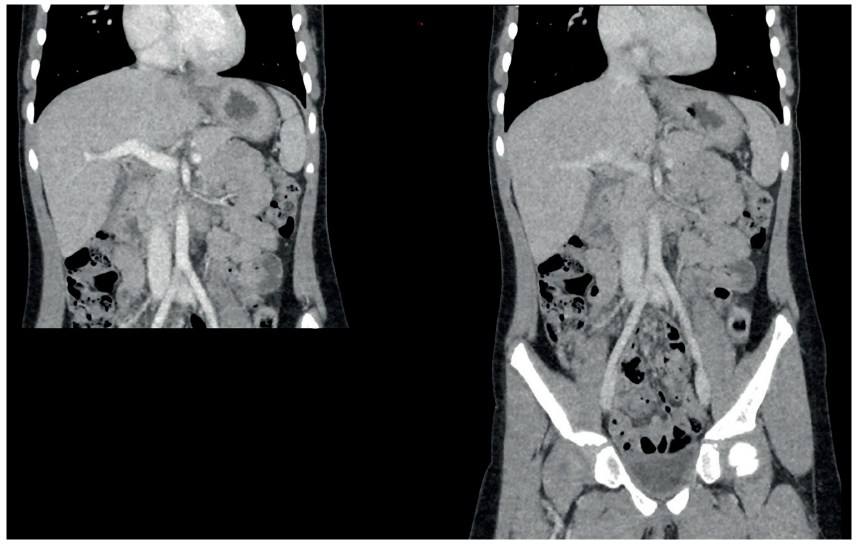

Figure 1. Dual-phase CT performed on a 7-year-old patient with suspected pancreatic trauma. Left: Coronal image from an arterial phase acquisition of the abdomen reconstructed with AiCE (0.3 mSv). Right: Coronal image from a portal venous phase acquisition of the abdomen and pelvis reconstructed with AiCE (0.5 mSv).

Other examples of dose reductions in COVID-19, coronary artery disease, bariatric and oncology patients were also demonstrated.

In addition to ultra-low-dose protocols, DLR can be used to produce ultra-high-quality images, while still achieving dose reductions when compared to traditional reconstruction methods. In both cases, DLR offers a high reconstruction speed.

In conclusion, DLR is the future in CT reconstruction as it provides the elusive triad of low dose, high quality, and high speed.

Reference
McLeavy et al. | The future of CT: deep learning reconstruction | Clin Radiol. (2021)
https://pubmed.ncbi.nlm.nih.gov/33637310/

CT

- *Nakamura et al. | Diagnostic value of deep learning reconstruction for radiation dose reduction at abdominal ultra-high-resolution CT | European Radiology | (2021)* https://pubmed.ncbi.nlm.nih.gov/33389036/
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- *Nakamura et al.| Possibility of Deep Learning in Medical Imaging Focusing Improvement of Computed Tomography Image Quality | J Comput Assist Tomogr (2019)* https://pubmed.ncbi.nlm.nih.gov/31789682/
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- *Tatsugami et al. | Deep learning–based image restoration algorithm for coronary CT angiography | Eur Radiol. (2019)* https://pubmed.ncbi.nlm.nih.gov/30963270/

AI enables high-resolution non-contrast MR Coronary Angiography

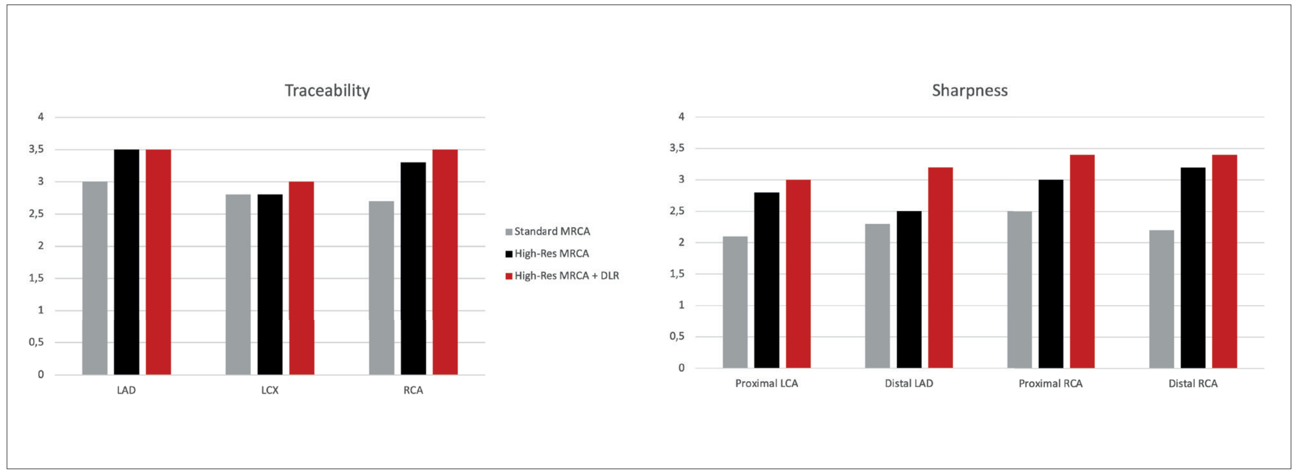

Figure 1. The sharpness and traceability of the vessels were scored by 2 experts on a scale for 1 (poor) to 4 (excellent). Except for the left circumflex (LCX) all scores were significantly different between the standard and the high-resolution MRCA+DLR. Abbreviations: left coronary artery (LCA), left anterior descending (LAD), right coronary artery (RCA)

Non-contrast Magnetic Resonance Coronary Angiography (MRCA) is a technique to assess coronary morphology without a contrast agent or ionizing radiation. Despite the great potential of this technique for the diagnosis and management of coronary artery disease, it is not widely used. To make the use of non-contrast MRCA more common, a higher spatial resolution that does not prolong scan time is needed. Typically, an increase in resolution leads to a drop in SNR. Therefore, Yokota et al. chose in their study to increase the resolution but compensate the SNR drop by using Deep Learning Reconstruction (DLR) to reduce the noise.

Deep Learning Reconstruction for MR Coronary Angiography
The authors used the Advanced intelligent Clear-IQ Engine (AiCE) DLR technique from Canon Medical Systems to improve the image quality of high-resolution non-contrast MRCA. To evaluate the influence on image characteristics, the authors scanned ten healthy volunteers on Vantage Galan 3T MR system (Canon Medical Systems) using standard MRCA and a high-resolution MRCA protocol. The difference in resolution between the standard and high-resolution protocol was a factor of three. The high-resolution images were evaluated both with and without DLR (AiCE).

Significant improvements in image characteristics
The standard and high-resolution images were evaluated quantitatively by looking at the contrast-to-noise ratio (CNR) and qualitatively by a visual evaluation by two experienced observers. The CNR improved significantly when DLR was applied to the high-resolution images. Figure 1 shows the results of the qualitative analysis, which demonstrates that the sharpness and traceability of the vessels significantly improved between standard MRCA and high-resolution MRCA plus DLR.

As a next step, the authors recommend evaluating this in a patient cohort to demonstrate the clinical value. Important in clinical translation is also applicability to all field strengths. In Figure 2 we show that this technique is not just successful at 3T, but can be extended to 1.5T. These images show how DLR improves the visualization of coronary arteries in volume renderings of high-resolution non-contrast MRCA images.

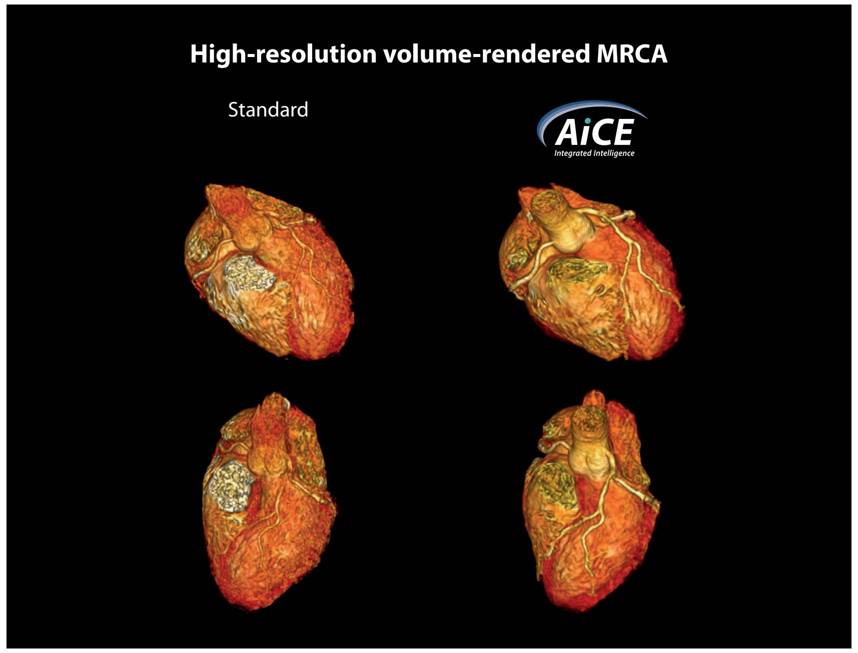

Figure 2. Example acquired on a 1.5T Vantage Orian of high-resolution non-contrast MRCA without (left) and with (right) Canon Medical's DLR technology AiCE. The volume rendered images nicely demonstrate the improved visibility of the coronary arteries with AiCE.

Reference
Yokota et al. | Effects of Deep Learning Reconstruction Technique in High-Resolution Non-contrast Magnetic Resonance Coronary Angiography at a 3-Tesla Machine | Can Assoc Radiol J (2021)
https://pubmed.ncbi.nlm.nih.gov/32070116/

Deep Learning Reconstruction improves the reliability of quantitative diffusion-weighted imaging

In MR there is always a trade-off between scan time, resolution and SNR. Deep Learning Reconstruction (DLR) is a technique that alleviates this trade-off by removing noise from the images to expand diagnostic capabilities for anatomical imaging. However, the value of DLR for more quantitative techniques like Diffusion-Weighted Imaging (DWI) and Diffusion Tensor Imaging (DTI) is less investigated. For these techniques it is important for the quantitative value not to change when DLR is applied. This means that the values of the Apparent Diffusion Coefficient (ADC), Fractional Anisotropy (FA) or fiber volume are the same with and without DLR. To research this, Sagawa et al. have investigated the influence of DLR on DWI and DTI in the brain.

Fast DTI protocol combining MultiBand SPEEDER and DLR

The researchers included 20 patients with various brain diseases who were scanned on a Vantage Galan 3T (Canon Medical Systems) using a 32-channel head coil. The DTI scans were acquired with a b-value of 1000 s/mm² and 12 gradient directions. To prevent long scan times, the scans were accelerated with Canon Medical's technique for simultaneous multi-slice acquisition: MultiBand SPEEDER. Two scans were performed: one single acquisition in 1:05 min (NAQ1) and a ground-truth scan with 5 averages of 5:45 min (NAQ5). The single acquisition scan was reconstructed twice, one time using standard reconstruction and once using the Advanced intelligent Clear-IQ Engine (AiCE) DLR technique from Canon Medical Systems.

Improved reliability of quantitative values and better fiber tracking with DLR

There were no significant differences in the signal intensity of the b-1000 diffusion images or the ADC values in any of the brain regions for the three datasets (NAQ1, NAQ5 and NAQ1 plus DLR). The same holds for the FA values, except in the deep gray matter. In the deep gray matter, the FA values were lowest for NAQ5 and highest for NAQ1. It is known that for areas with a low SNR, like the deep gray matter, the FA value tends to be overestimated. This overestimation was lower when DLR was applied, indicating that DLR improves the reliability of the scan. Also the decreased standard deviation and improved SNR in most brain regions demonstrates improved reliability with DLR (Figure 1).

To evaluate the influence of DLR on Diffusion Tensor Tracking (DTT) of the pyramidal tracts, the Fiber Volume (FV) was determined. When the SNR is low, tracking points are terminated due to image noise, resulting in a low FV. Figure 2 shows the Fiber Volumes of the three datasets. Both NAQ5 and NAQ1 plus DLR are significantly better than NAQ1 (Figure 2), demonstrating the feasibility of single averaging fast DTT with DLR for depicting white matter fibers for preoperative planning.

Sagawa et al. demonstrated in their study that DLR not only reduces noise, but also improves the reliability of ADC and FA values. In this study, the scan time of the scans with DLR was five times lower than the ground truth, which can have a big impact on workflow and patient comfort.

Reference

Sagawa et al. | Deep Learning-based Noise Reduction for Fast Volume Diffusion Tensor Imaging: Assessing the Noise Reduction Effect and Reliability of Diffusion Metrics | Magn Reson Med Sci (2020)
https://pubmed.ncbi.nlm.nih.gov/32963184/

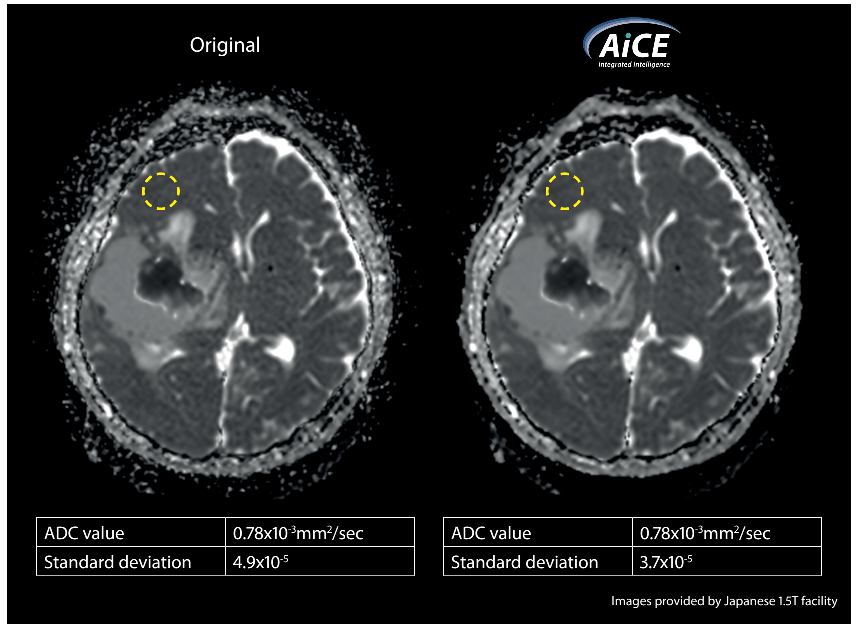

Figure 1. Example ADC map acquired at 1.5T (Vantage Orian) confirming the observations by Sagawa et al. The ADC value is the same with and without AiCE, but the standard deviation has improved for the map reconstructed with AiCE.

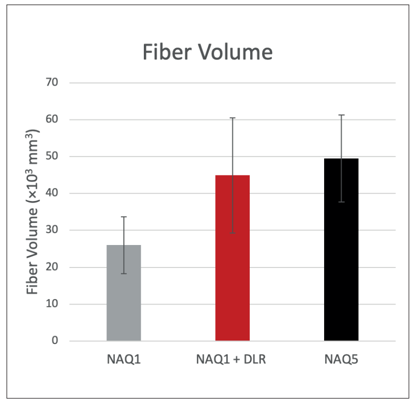

Figure 2. Fiber Volume of the pyramidal tracts. Both NAQ5 and NAQ1 + DLR are significantly better than NAQ1. There was no significant difference between NAQ5 and NAQ1+DLR.

MRI

- *Sagawa et al. | Deep Learning-based Noise Reduction for Fast Volume Diffusion Tensor Imaging: Assessing the Noise Reduction Effect and Reliability of Diffusion Metrics| Magn Reson Med Sci (2020)* *https://pubmed.ncbi.nlm.nih.gov/32963184/*
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Emergency department triage: Artificial Intelligence's gateway to radiology

The earliest adoption of artificial intelligence (AI) within clinical workflows has emerged within the emergency setting where it can manage priority for interpretation of imaging studies. In this triage role, AI does not commit to a diagnosis; rather it offers a binary decision as to whether the image contains a specific finding. The goal is to expedite the interpretation of the most critical cases, ultimately leading to improved patient outcomes.

Stroke workflow, primed for optimization

One clinical domain particularly suited to workflow optimization, due to its time critical nature, is acute stroke. Advances in treatment have resulted in continually shifting guidelines, adding complexity to the time pressured decisions.
With several key imaging features involved in stroke triage, it lends
itself to the current focus on narrow
AI solutions.

Intracranial Hemorrhage (ICH) detection

ICH is a medical emergency and timely diagnosis is critical as nearly half of resulting mortalities occur within the first 24 hours. The speed of interpretation is dependent on the priority assigned to the scan request, which is a particular risk when symptoms can be vague. Automated ICH detection, as implemented by Canon Medical Systems' Stroke CT Package, can address this problem by automatically detecting ICH and pushing the results to the neurointerventionalist. A case example is shown in Figure 1.

Performance of this algorithm, assessed in a validation cohort of 200 ICH positive and 102 non-ICH patients, yielded the following results (Table 1): a sensitivity of 0.93, specificity of 0.93, Positive Predictive Value (PPV) of 0.85 and Negative Predictive Value (NPV) of 0.98. Of note, where the algorithm performance is challenged is in cases of small volume hemorrhages. The author notes that ensemble methods using multimodal data may be used to address this limitation in the future.

	All (n = 258)	Small ICH (n = 93)	Medium ICH (n = 117)	Large ICH (n = 48)
ICH volume (mL)	17.2 ± 2.7	1.7 ± 0.3	13.2 ± 1.2	57.3 ± 6.1
Accuracy	0.94 ± 0.01	0.94 ± 0.02	0.93 ± 0.02	0.95 ± 0.02
Sensitivity	0.93 ± 0.03	0.89 ± 0.05	0.94 ± 0.04	0.99 ± 0.01
Specificity	0.93 ± 0.01	0.94 ± 0.02	0.92 ± 0.02	0.92 ± 0.04
Positive predictive value	0.85 ± 0.02	0.81 ± 0.05	0.86 ± 0.03	0.91 ± 0.04
Negative predictive value	0.98 ± 0.01	0.98 ± 0.01	0.98 ± 0.01	0.99 ± 0.01
F1 score	0.86 ± 0.03	0.81 ± 0.06	0.87 ± 0.04	0.94 ± 0.02
Matthews correlation coefficient	0.87 ± 0.02	0.83 ± 0.04	0.87 ± 0.03	0.90 ± 0.04
Proper triage as ICH positive, % (n)	95 (245)	92.5 (86)	94.9 (111)	100.0 (48)

Table 1. 95% Confidence Intervals for ICH volume, accuracy, sensitivity, specificity, positive predictive value, negative predictive value, F1 score, and Matthews correlation metrics corresponding to the ICH detection algorithm for all, small (≤5 mL), medium (>5 and <30 mL), and large (≥30 mL) ICHs. The percentage of times the algorithm correctly detects an ICH is also indicated.

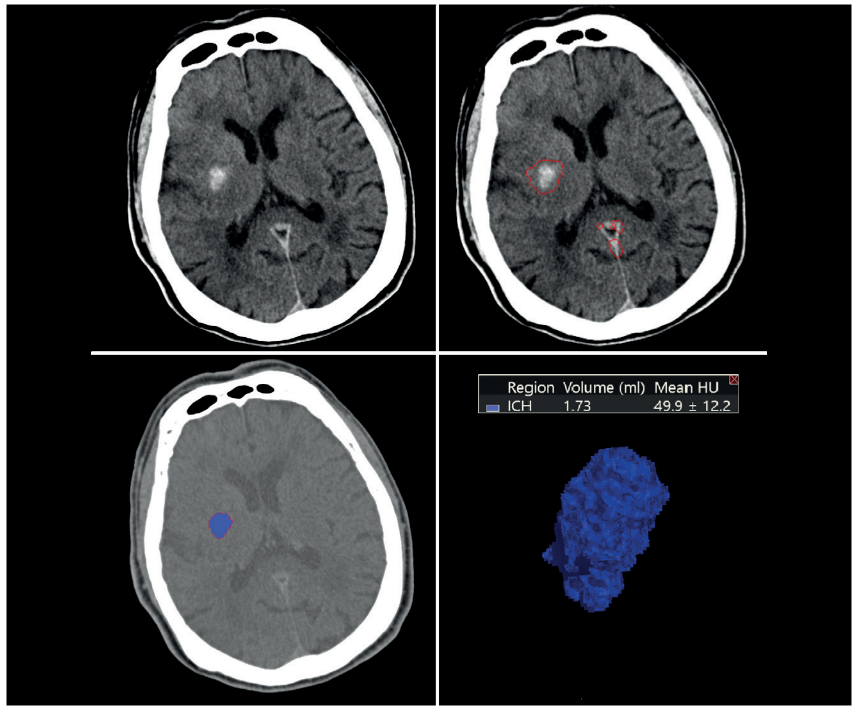

Figure 1: Stroke CT Package was used to detect and segment the hemorrhage regions from the non contrast computed tomography (NCCT) image. The top left image shows an axial slice from the NCCT volume which is processed by the software. The boundary of the detected hemorrhagic region is shown in top right for the same axial slice. Automatic detection is performed throughout entire volume. Bottom left image shows the segmented hemorrhage in purple (using Vitrea Advanced Visualization), with a manually adjustable outline in red. The bottom right image displays an volume view of the segmented hemorrhage (using Vitrea Advanced Visualization) along with the automated volume measurement and mean Hounsfield unit (HU).*

** Not available in all geographies.*

Reference
Rava et al. | Assessment of an Artificial Intelligence Algorithm for Detection of Intracranial Hemorrhage | World Neurosurgery (2021)
https://pubmed.ncbi.nlm.nih.gov/33684578/

Large Vessel Occlusion (LVO) detection
With the introduction of endovascular clot retrieval to routine clinical workflows, the identification of those patients who would benefit from the treatment quickly became top priority in stroke workflows. Implementing the automated detection of large vessel occlusions (LVO) in CTA, as provided by Canon Medical Systems' Stroke CT Package, addresses this triage need.

The performance of this LVO detection solution was assessed in a cohort of 202 acute ischemic patients, 100 of whom had an occlusion within the Internal Carotid Artery (ICA), M1 or M2 regions of the Middle Cerebral Artery (MCA) and 102 patients with no occlusion. Analysis including all patients produced the following metrics (Table 1): a sensitivity of 0.73, specificity of 0.98, PPV of 0.99 and NPV of 0.64. As with ICH detection, it seems size matters. As the occlusions become more distal, within the MCA M2 region, they decrease in size and a drop off in performance is seen, with sensitivity falling to 0.5. With any such automated detection task there is a trade off in sensitivity versus specificity, however in this clinical scenario this algorithm, for all vessel locations, may benefit from further weighting to improve sensitivity. Figure 1 shows a clinical case example with detected LVO.

These triage applications of narrow AI have become a reality within acute stroke workflows and now the discussion of the effectiveness of these solutions is coming to the fore. It's clear that further improvement is needed to address the challenges around the smaller, more subtle examples of pathologies, which will be tackled by additional training examples and techniques such as ensemble learning.

	All (n = 303)	ICA (n = 160)	MCA M1 (n = 183)	MCA M2 (n = 162)
Accuracy	0.81	0.95	0.89	0.80
Sensitivity	0.73	0.90	0.77	0.51
Specificity	0.98	0.98	0.98	0.98
Positive predictive value	0.99	0.96	0.97	0.94
Negative predictive value	0.64	0.94	0.84	0.77
F1 score	0.84	0.93	0.86	0.66
Matthews correlation coefficient	0.67	0.89	0.78	0.59

Table 1. Accuracy, sensitivity, specificity, positive predictive value, negative predictive value, F1 score and Matthews correlation metrics corresponding to the LVO detection algorithm for all and each occlusion site.

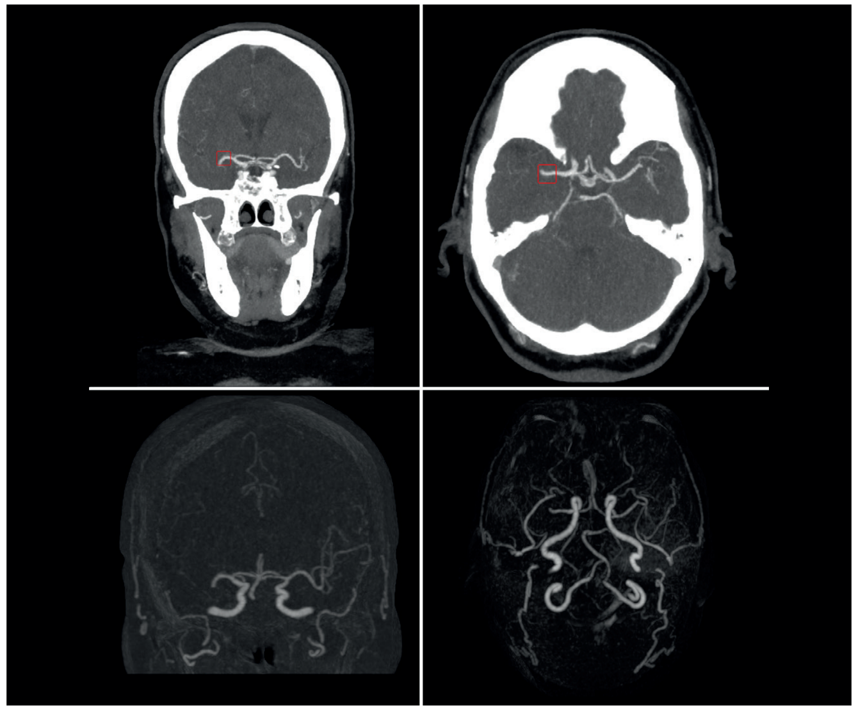

Figure 1: Correctly predicted large vessel occlusion (LVO) in case with right middle cerebral artery (MCA) occlusion. Top row shows coronal and axial views of the correctly labeled LVO, as indicated by the red box. Bottom row shows the same case with 2D MIP subtraction and 3D MIP subtraction (right) where you can visualize the lack of contrast distal to the occlusion.*

** Not available in all geographies.*

Reference
Rava et al. | Validation of an Artificial Intelligence Driven Large Vessel Occlusion Detection Algorithm for Acute Ischemic Stroke Patients | The Neuroradiology Journal (2021)
https://pubmed.ncbi.nlm.nih.gov/33657922/

Healthcare Information Technology
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