



2025 IEEE
Symposium Series on
Computational Intelligence



CAS-GAN for Contrast-free Angiography Synthesis

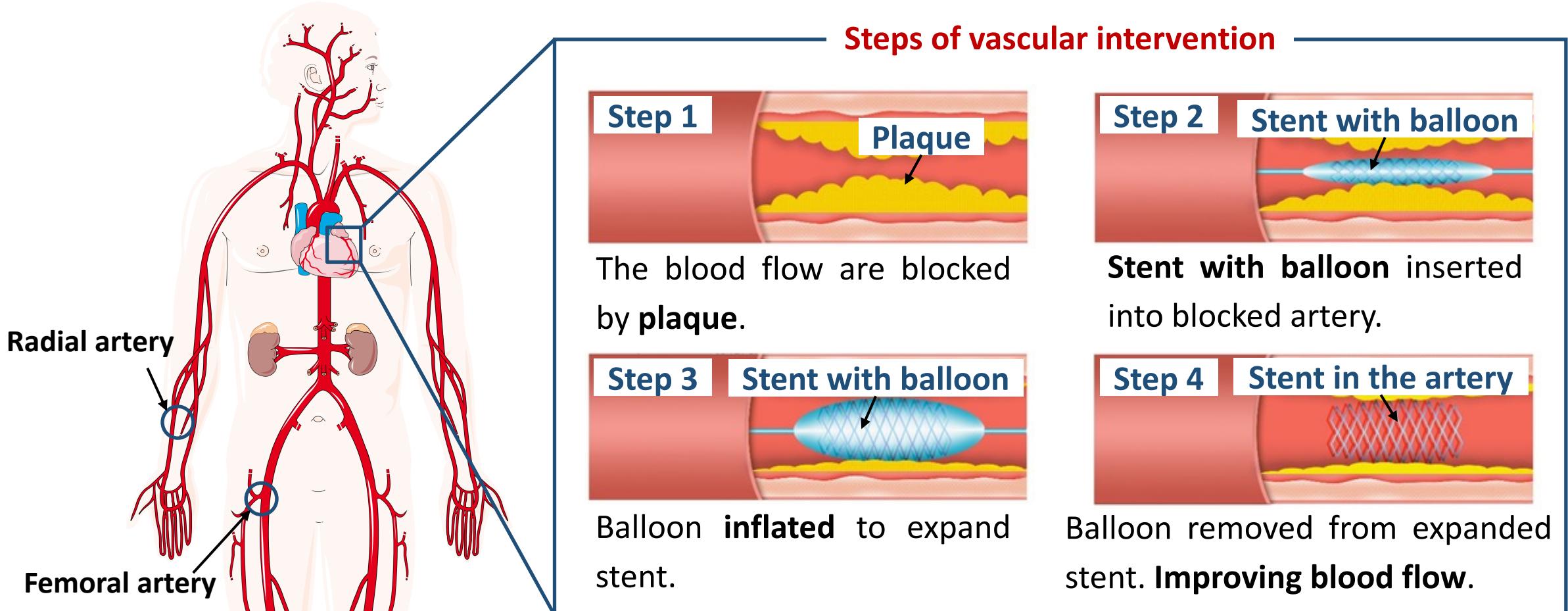
De-Xing Huang, X. Zhou*, M. Gui, X. Xie, S. Liu, S. Wang, H. Li, T. Xiang, Z.-G. Hou*

Email: huangdexing2022@ia.ac.cn

State Key Laboratory of Multimodal Artificial Intelligence Systems
Institute of Automation, Chinese Academy of Sciences
University of Chinese Academy of Sciences

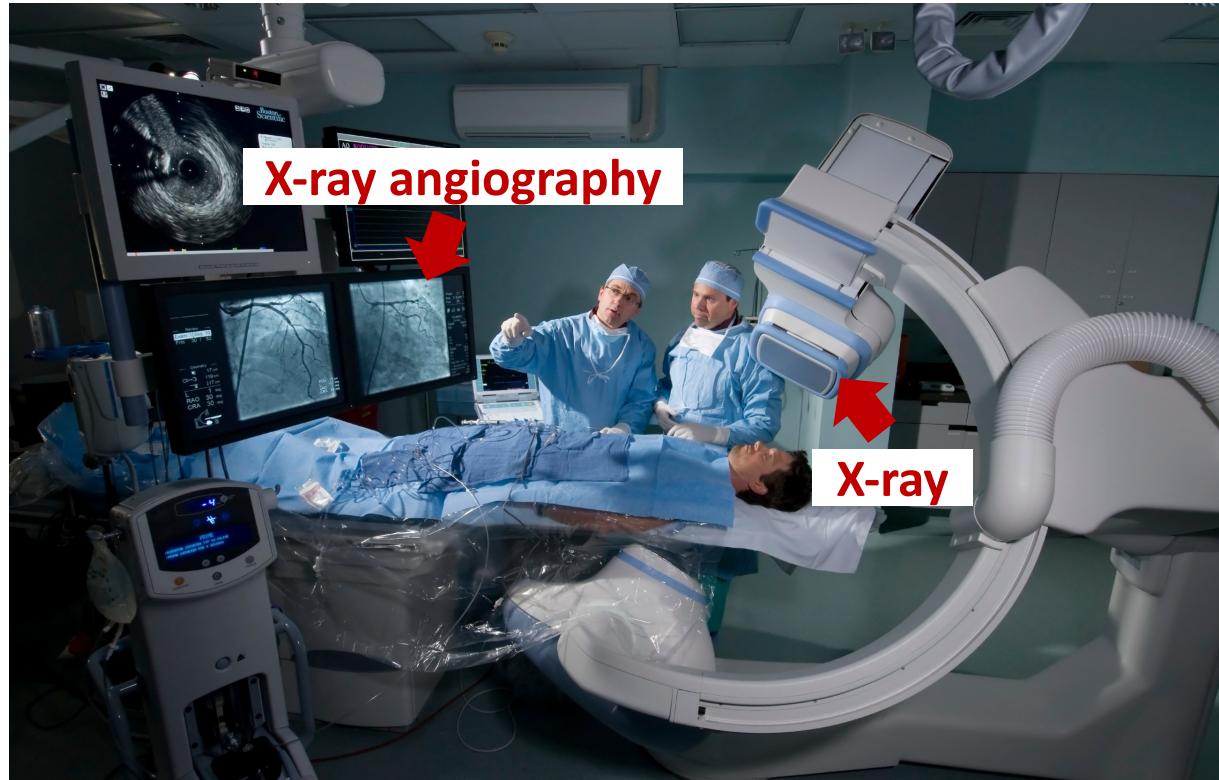
Background

- **Vascular intervention** is a minimally invasive treatment of cardiovascular diseases.



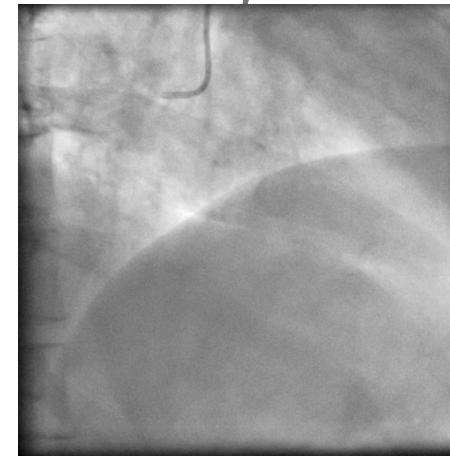
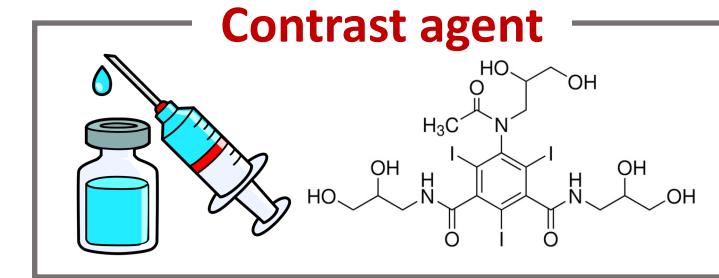
Background

- Currently, **X-ray angiography** is a must for guiding cardiologists to locate vascular lesions.

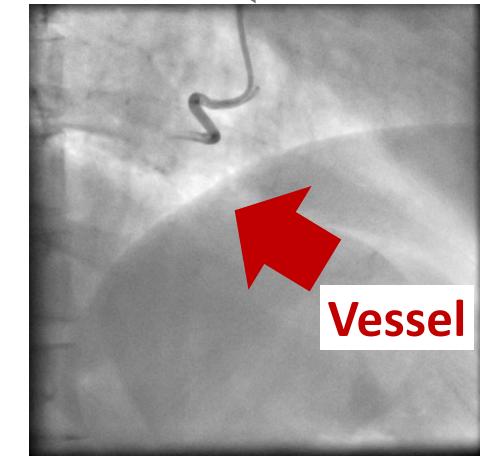


Vascular interventional procedures

(From: <https://www.dicardiology.com/>)



Non-contrast X-ray

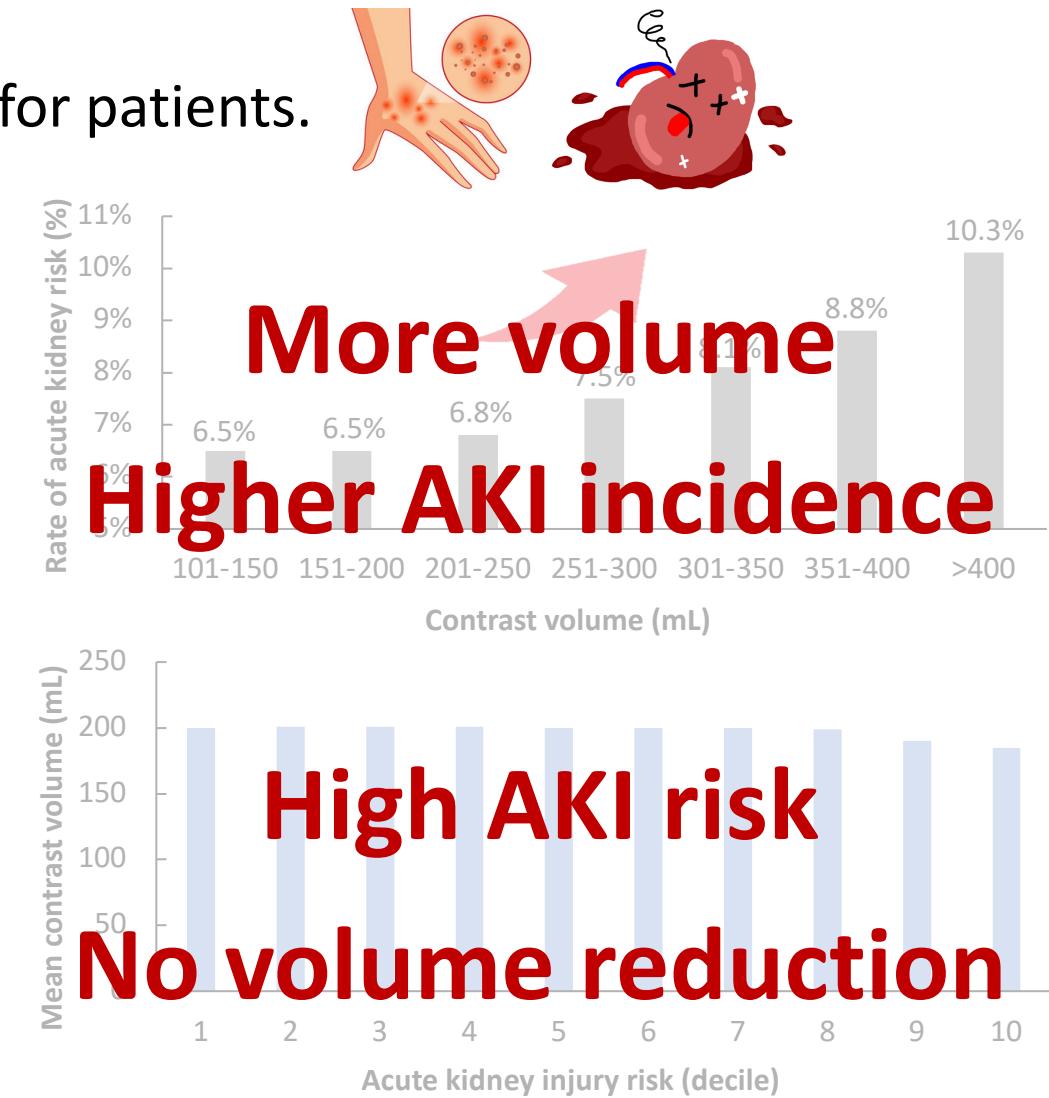
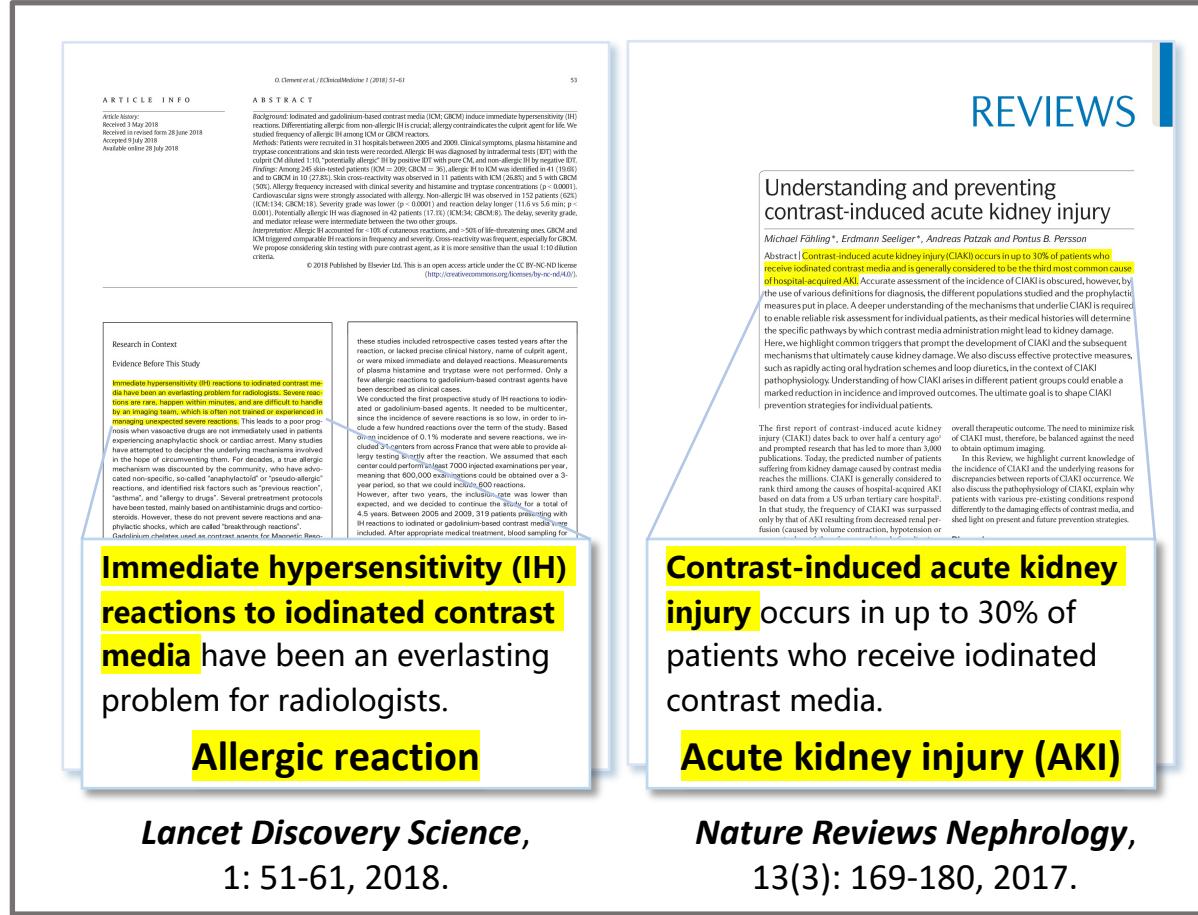


X-ray angiography

- H. Zhao *et al.*, “Large-scale pretrained frame generative model enables real-time low-dose DSA imaging: An AI system development and multi-center validation study,” *Med*, 6(1): 100497, 2025.

Motivation

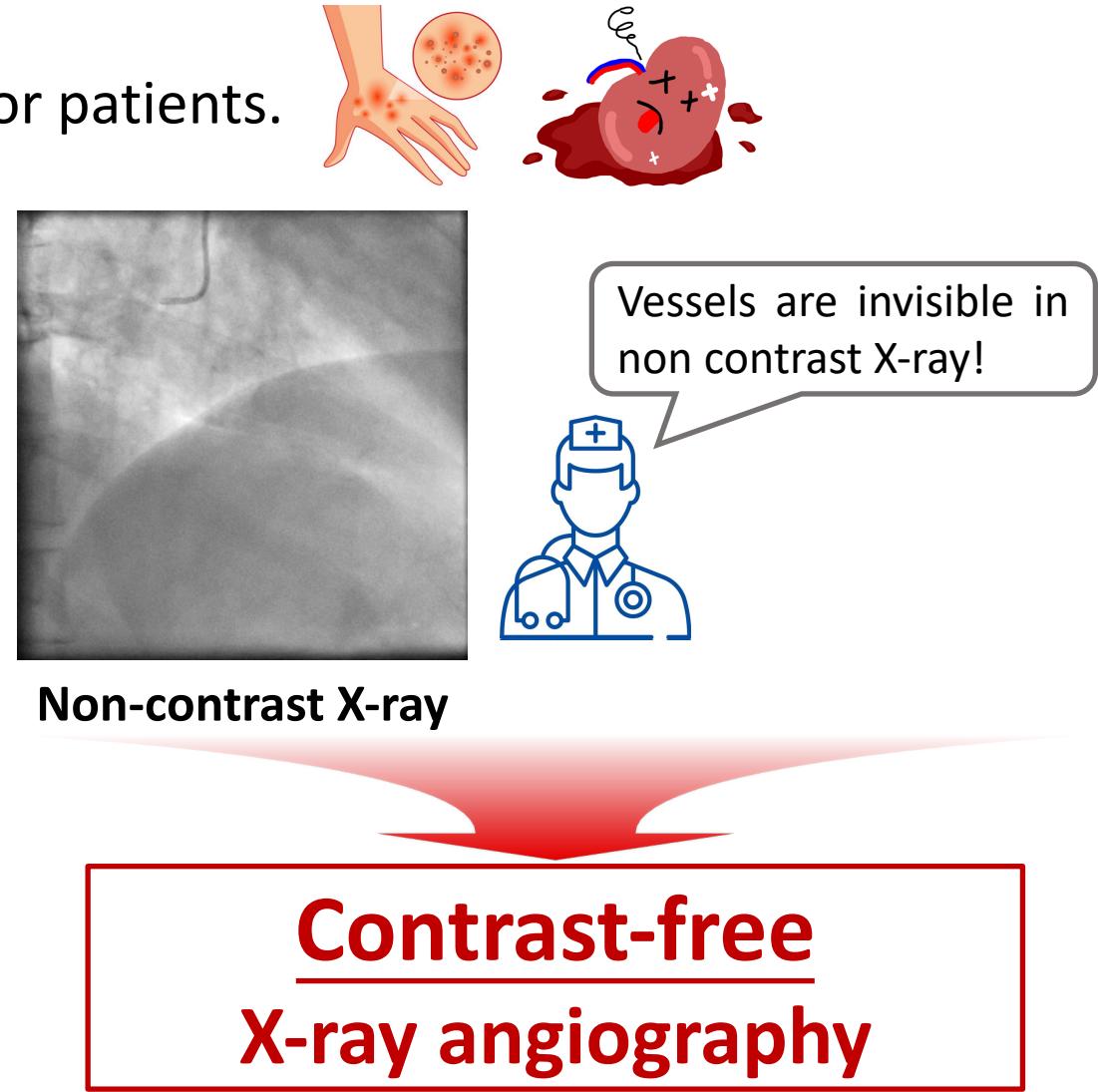
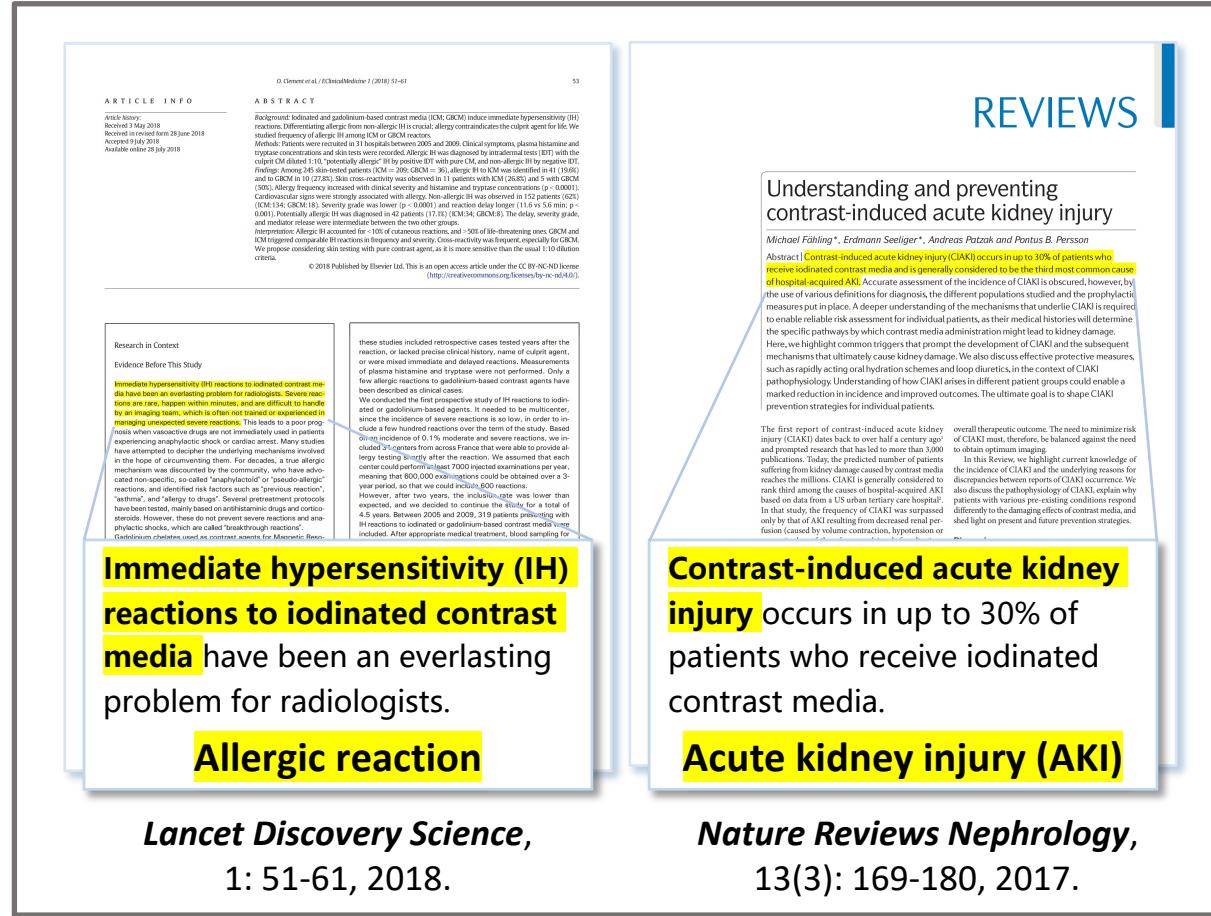
- Contrast agents pose **significant health risks** for patients.



- A. P. Amin et al., "Association of variation in contrast volume with acute kidney injury in patients undergoing percutaneous coronary intervention," *JAMA Cardiol.*, 2017, 2(9): 1007-1012.

Motivation

- Contrast agents pose **significant health risks** for patients.



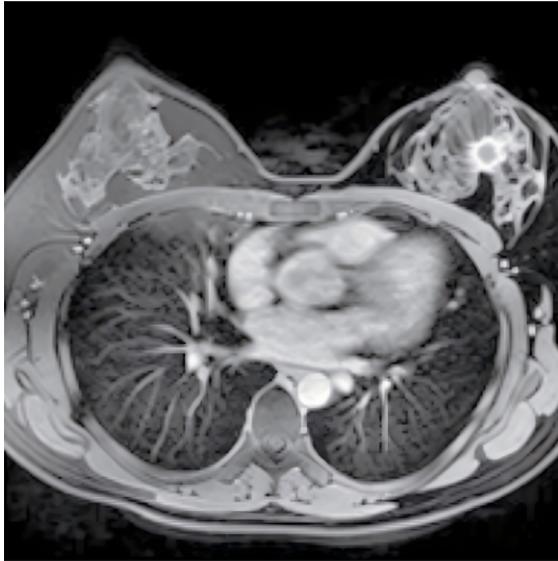
- A. P. Amin *et al.*, "Association of variation in contrast volume with acute kidney injury in patients undergoing percutaneous coronary intervention," *JAMA Cardiol.*, 2017, 2(9): 1007-1012.

Solution

- Generative models can create **photorealistic images** based on specific constraints.



A photo of Bakklandet in
Trondheim, 4k,
photorealistic



MRI: breast tumor with
HER2 mutation from the
view of T1c



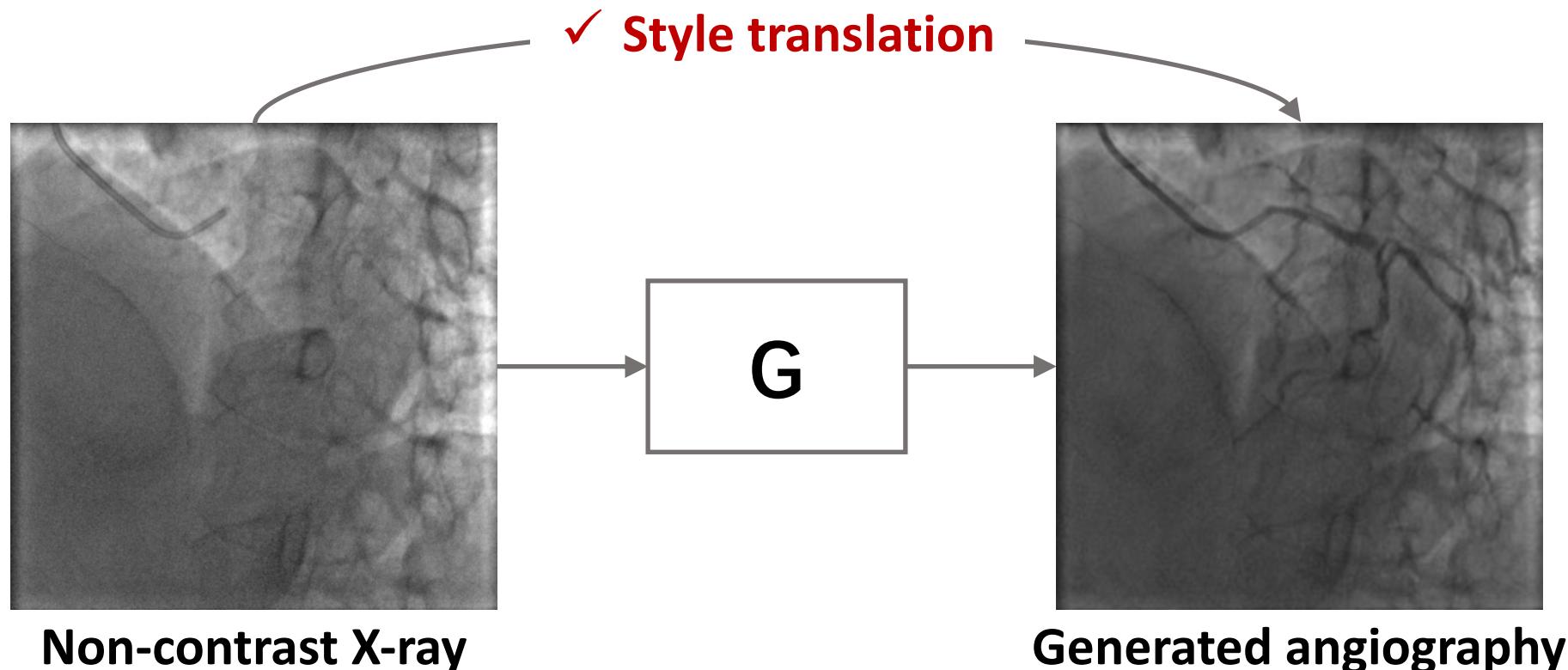
Can we use
generative models as
“virtual contrast agent”?

• R. Rombach *et al.*, “High-resolution image synthesis with latent diffusion models,” in *Proc. CVPR*, 2022: 10684-10695.

• J. Wang *et al.*, “Self-improving generative foundation model for synthetic medical image generation and clinical applications,” *Nat. Med.*, 31, 609-617, 2025. **5/15**

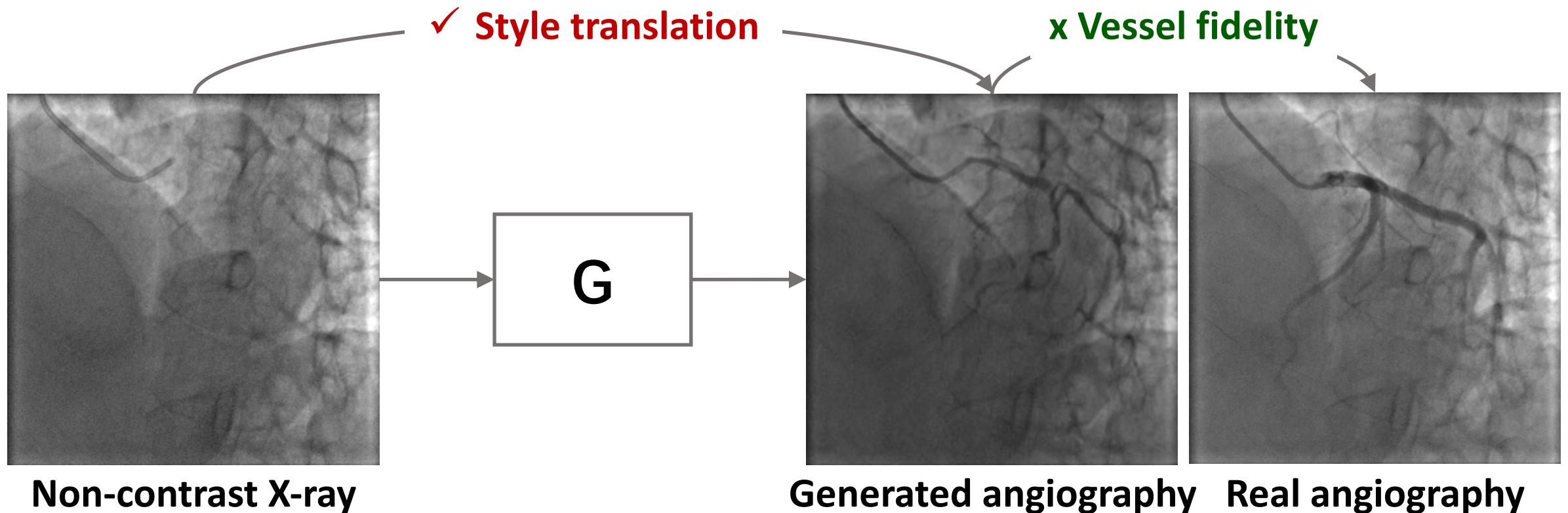
Challenge

- Current methods focus on **style translation** but fail to preserve **vessel fidelity**.



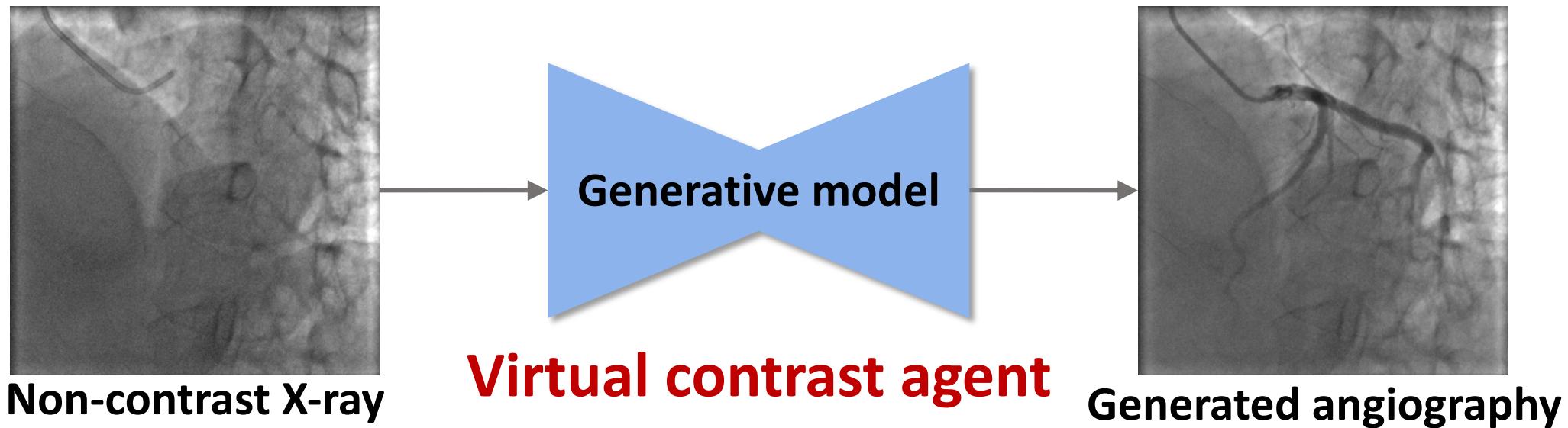
Challenge

- Current methods focus on **style translation** but fail to preserve **vessel fidelity**.



Contributions of this work

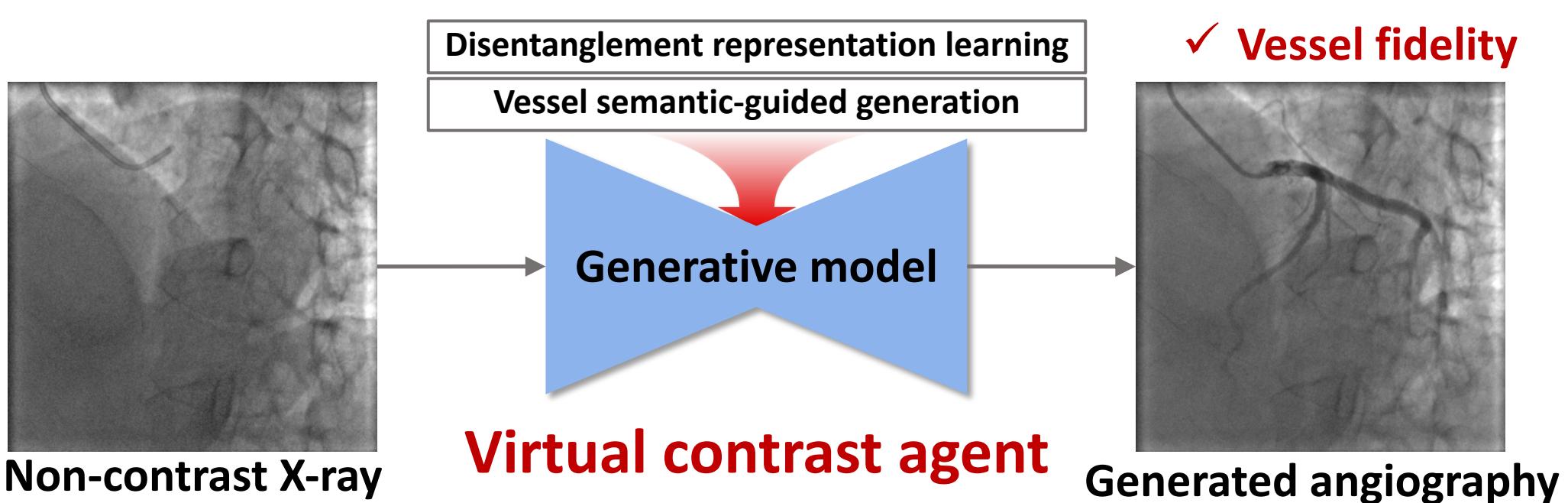
- ✓ Novel **generative model** for more accurate contrast-free X-ray angiography synthesis.



Contributions of this work

- ✓ Novel **generative model** for more accurate contrast-free X-ray angiography synthesis.
- ✓ Novel **disentanglement representation learning** approach for capturing relationships between anatomical and vessel features.
- ✓ Novel **vessel semantic-guided generation process** for X-ray angiography synthesis with enhanced attention mechanism and loss function.

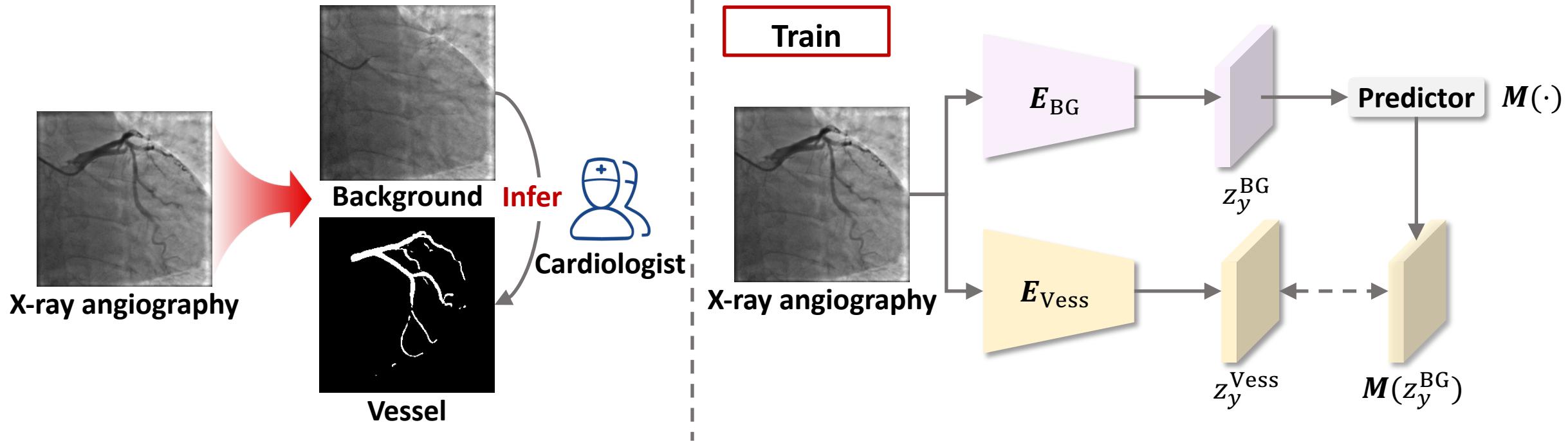
- ✓ **Style translation**
- ✓ **Vessel fidelity**



Part I: Disentanglement Representation Learning

**Novel representation learning approach
inspired by cardiologists**

Part I: Disentanglement Representation Learning



- **Disentanglement encoding**

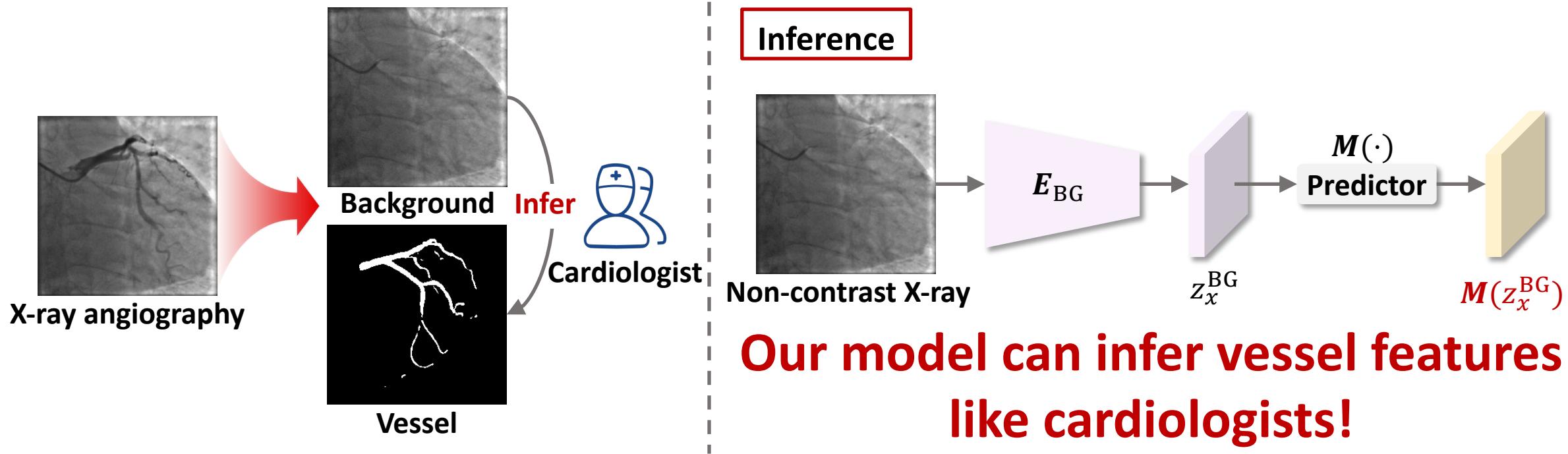
For an X-ray angiography (y), using the background encoder (E_{BG}) and vessel encoder (E_{Vess}) to extract its background (z_y^{BG}) and vessel (z_y^{Vess}) features.

$$z_y^{BG} = E_{BG}(y), z_y^{Vess} = E_{Vess}(x)$$

- **Explicitly formulating the relationship between background (z_y^{BG}) and vessel (z_y^{Vess}) features**

$$\mathcal{L}_{\text{Pred}} = \mathbb{E}_{y \sim p} \left\{ \| M(z_y^{BG}) - z_y^{Vess} \|_1 \right\}$$

Part I: Disentanglement Representation Learning



- Infer vessel (z_x^{Vess}) features from background (z_x^{BG}) features

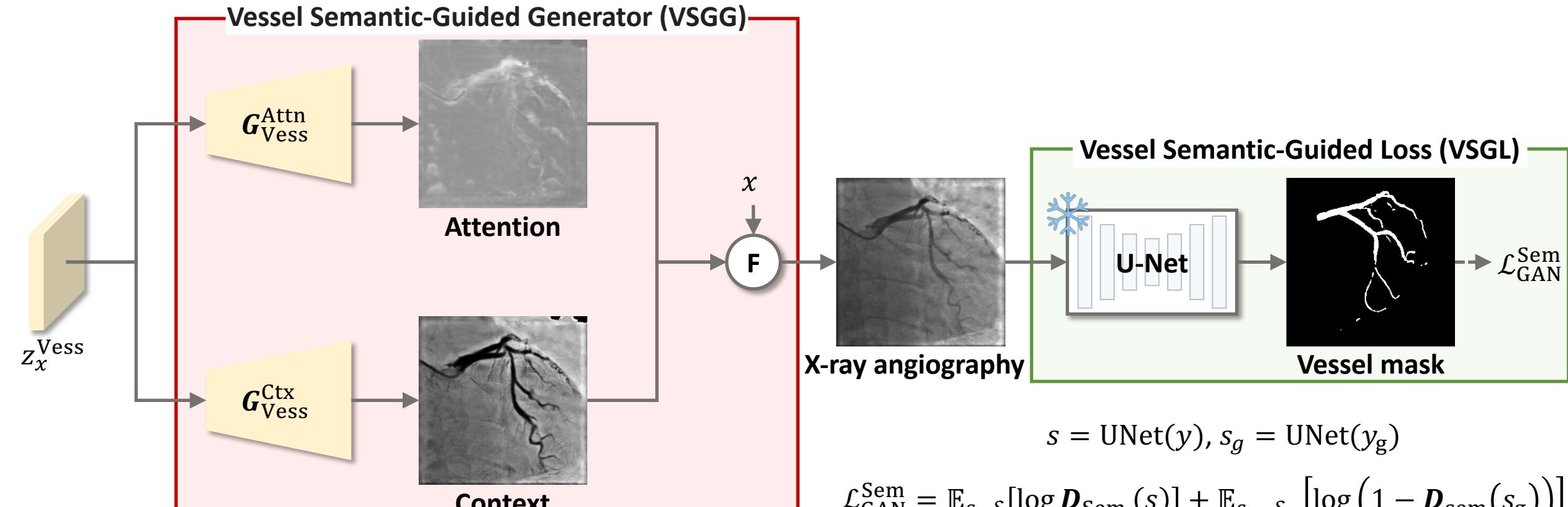
For a non-contrast X-ray (x), using the background encoder (E_{BG}) to extract its background (z_x^{BG}) features. Then, the predictor is utilized infer vessel features (z_x^{Vess}) based on background (z_x^{BG}) features.

$$z_x^{BG} = E_{BG}(x), z_x^{Vess} = M(z_x^{BG})$$

Part II: Vessel Semantic-Guided Generation

**Novel angiography generation process focuses on
vascular details**

Part II: Vessel Semantic-Guided Generation



$$A_g = \mathbf{G}_{\text{Vess}}^{\text{Attn}}[\mathbf{M}(z_x^{\text{BG}})], C_g = \mathbf{G}_{\text{Vess}}^{\text{Ctx}}[\mathbf{M}(z_x^{\text{BG}})]$$

$$y_g = x \odot (1 - A_g) + C_g \odot A_g$$

$$s = \text{UNet}(y), s_g = \text{UNet}(y_g)$$

$$\mathcal{L}_{\text{GAN}}^{\text{Sem}} = \mathbb{E}_{s \sim \mathcal{S}} [\log \mathbf{D}_{\text{Sem}}(s)] + \mathbb{E}_{s_g \sim \mathcal{S}_g} [\log (1 - \mathbf{D}_{\text{sem}}(s_g))]$$

- H. Tang *et al.*, “AttentionGAN: Unpaired image-to-image translation using attention-guided generative adversarial networks,” *IEEE Trans. Neural Networks Learn. Syst.*, 34(4): 1972-1987, 2021.
- O. Ronneberger *et al.*, “U-Net: Convolutional networks for biomedical image segmentation,” in *Proc. MICCAI*, 2015: 234-241.

Main Results – Comparisons with SOTAs

- The proposed CAS-GAN significantly outperforms baselines in both FID and MMD.

Evaluation metrics
Frechet Inception Distance (FID) $\text{FID} = \ \mu - \hat{\mu}\ _2^2 + \text{Tr} \left\{ \Sigma + \hat{\Sigma} - 2(\Sigma \hat{\Sigma})^{\frac{1}{2}} \right\}$
Maximum Mean Discrepancy (MMD) $\begin{aligned} \text{MMD} &= \frac{1}{n(n-1)} \sum_{i \neq j} k(f_i^R, f_j^R) + \frac{1}{m(m-1)} \sum_{i \neq j} k(f_i^G, f_j^G) \\ &\quad - \frac{2}{mn} \sum_{i=1}^n \sum_{j=1}^m k(f_i^R, f_j^G) \end{aligned}$

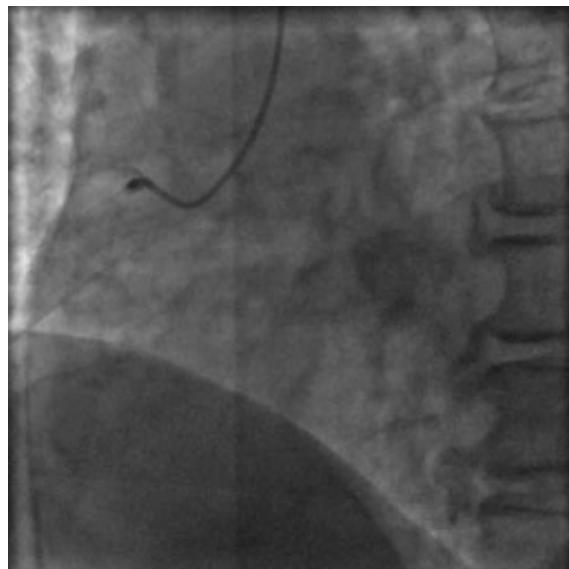
Table I. Quantitative comparisons with SOTAs.

Method	FID ↓	MMD ($\times 10$) ↓
CycleGAN [<i>ICCV' 17</i>]	6.54	0.28
UNIT [<i>NeurIPS' 17</i>]	9.99	<u>0.22</u>
MUNIT [<i>ECCV' 18</i>]	8.87	0.33
CUT [<i>ECCV' 20</i>]	7.09	0.26
AttentionGAN [<i>TNNLS' 21</i>]	<u>6.34</u>	0.31
QS-Attn [<i>CVPR' 22</i>]	7.20	0.24
StegoGAN [<i>CVPR' 24</i>]	10.80	2.26
CAS-GAN [Ours]	5.87	0.16

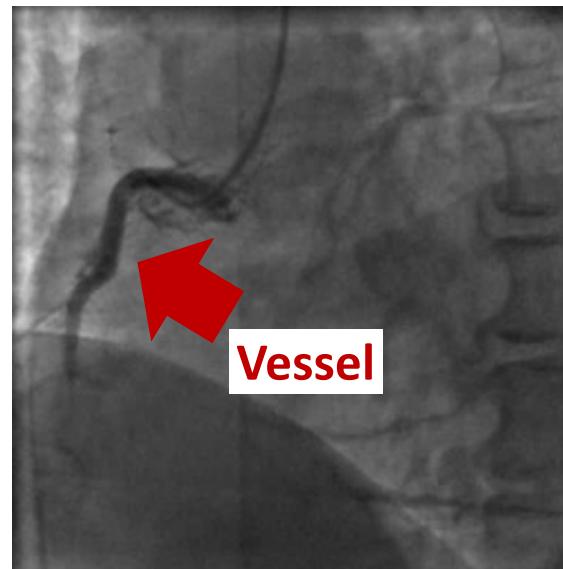
- Best results are highlighted in **bold** and second best are underlined.

Main Results – Comparisons with SOTAs

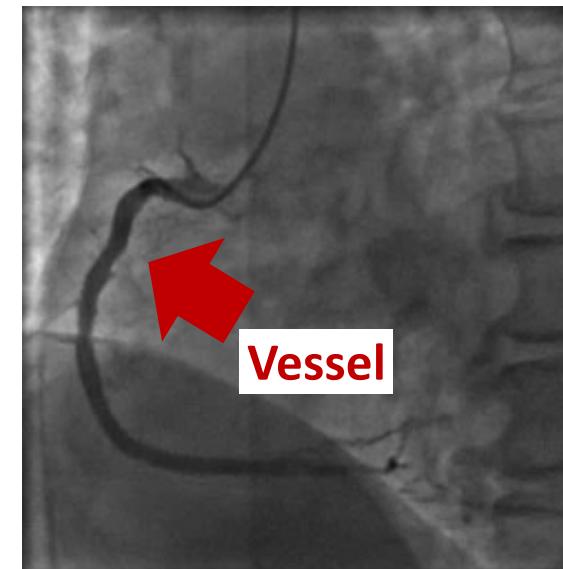
- Case 1: CAS-GAN can effectively **preserve structural consistency** of vessels.



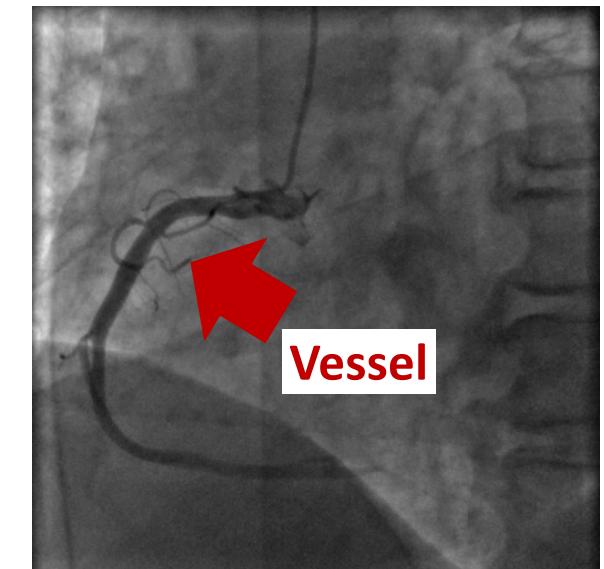
Non-contrast X-ray



AttentionGAN
(TNNLS' 21)



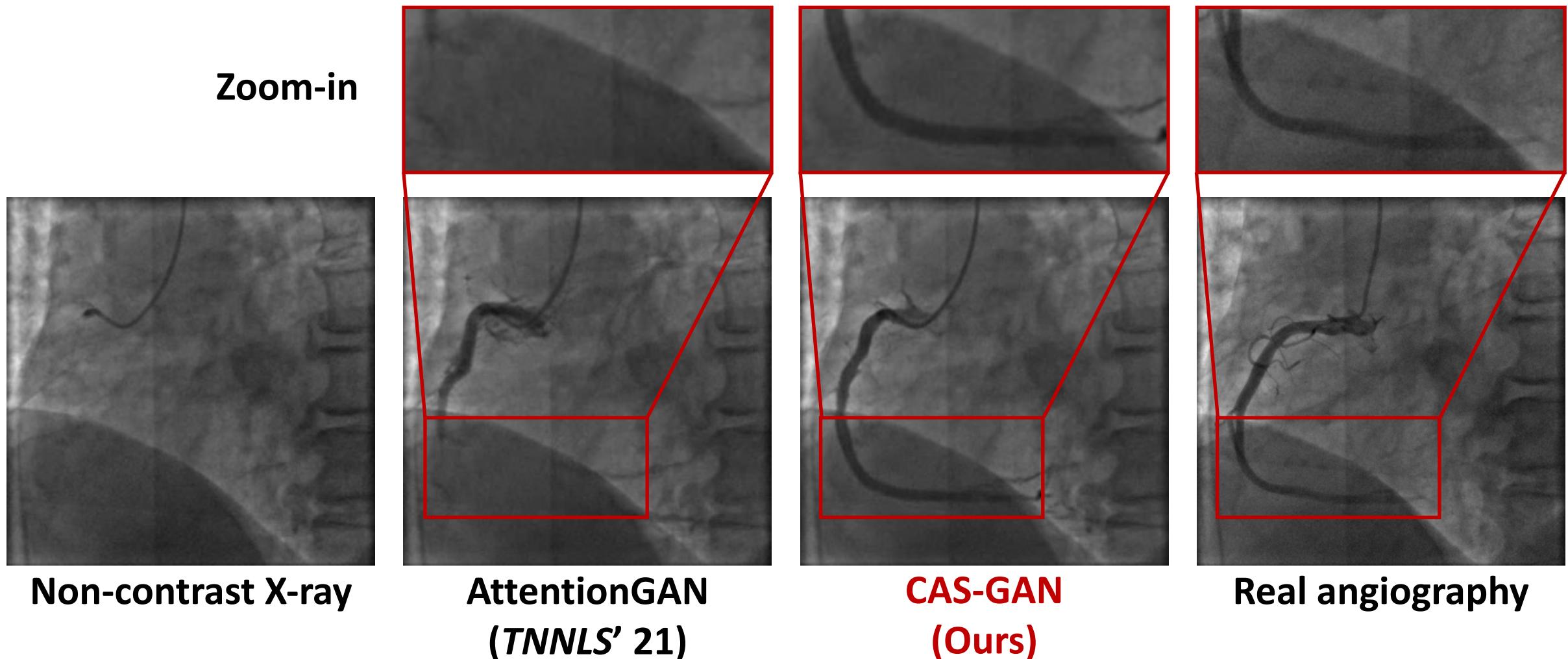
CAS-GAN
(Ours)



Real angiography

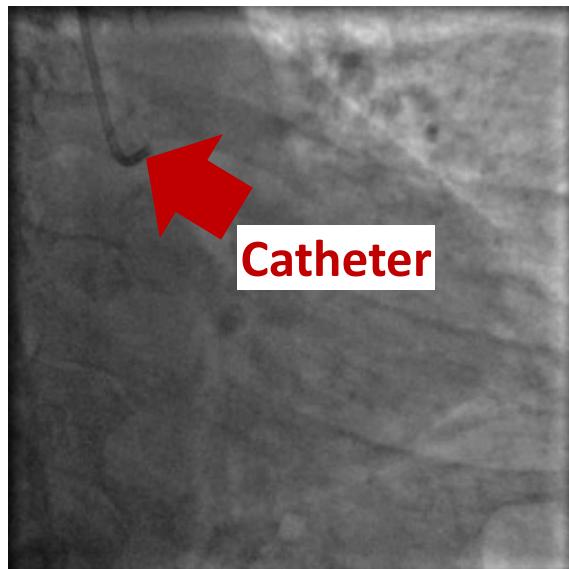
Main Results – Comparisons with SOTAs

- Case 1: CAS-GAN can effectively **preserve structural consistency** of vessels.

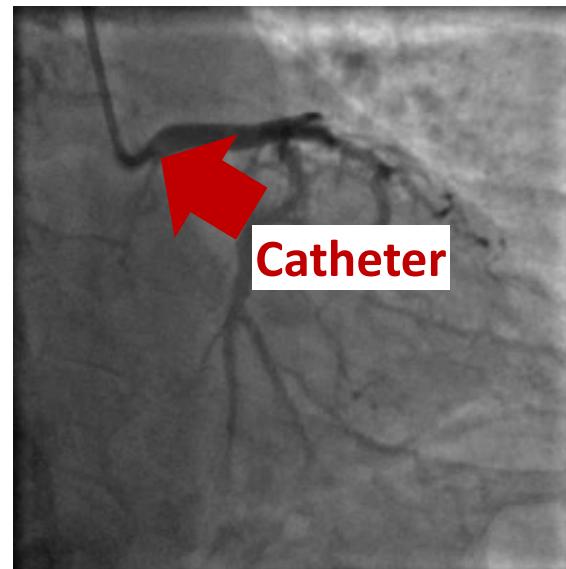


Main Results – Comparisons with SOTAs

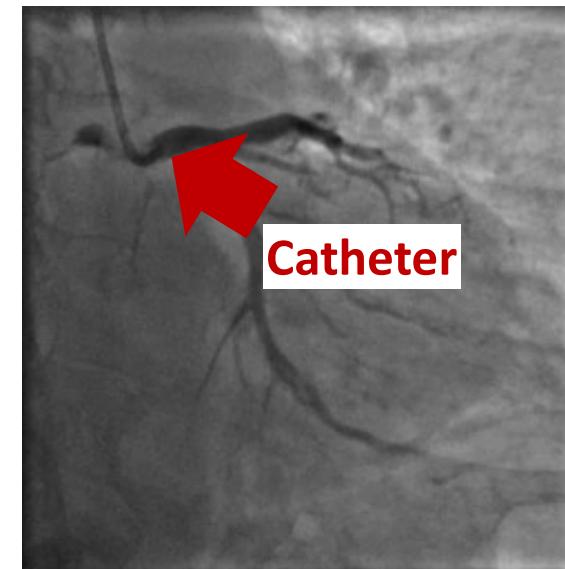
- Case 2: CAS-GAN can **accurately synthesis critical vessel bifurcations.**



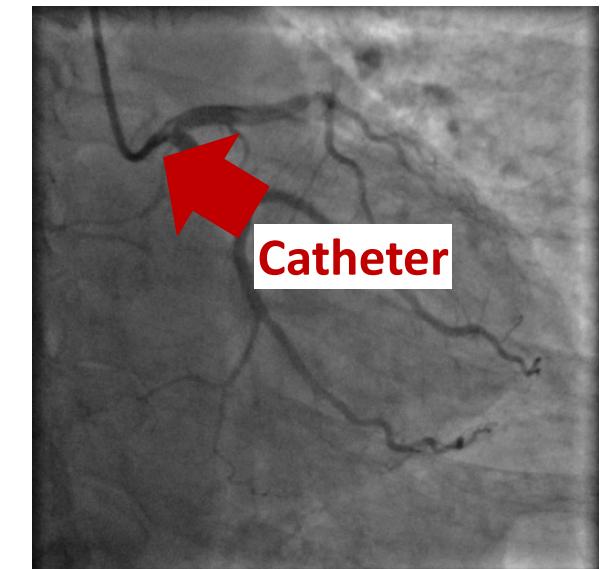
Non-contrast X-ray



AttentionGAN
(TNNLS' 21)



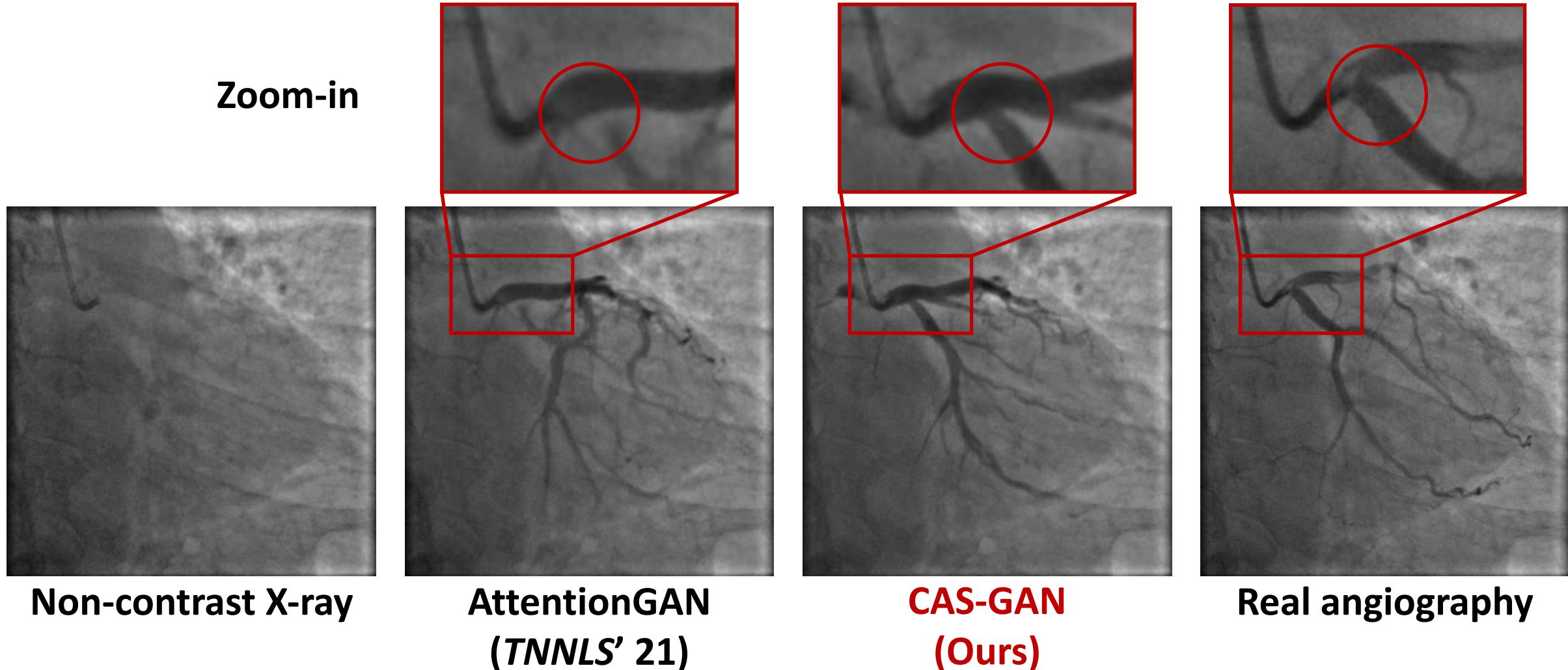
CAS-GAN
(Ours)



Real angiography

Main Results – Comparisons with SOTAs

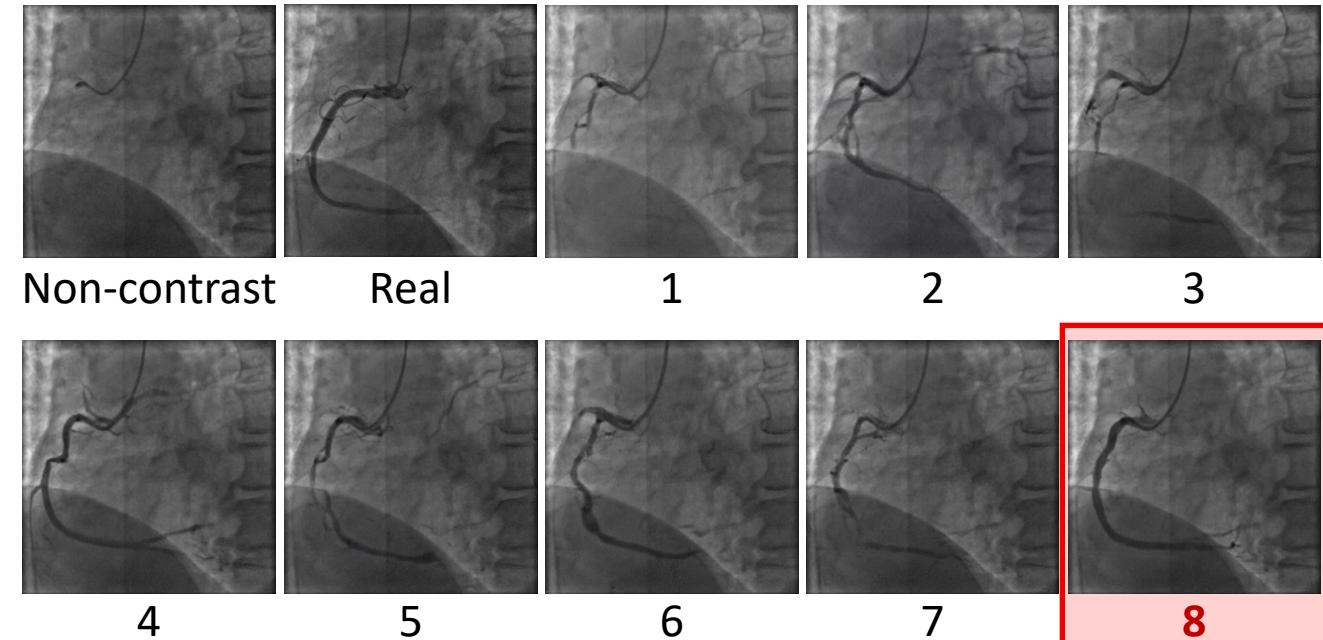
- Case 2: CAS-GAN can **accurately synthesis critical vessel bifurcations.**



Main Results – Ablation Studies

Table II. Effects of several designs.

Index	DRL	VSGG	VSGL	FID ↓	Δ
1				7.14	+1.27
2			✓	8.59	+2.72
3		✓		6.57	+0.70
4		✓	✓	5.98	+0.11
5	✓			6.87	+1.00
6	✓		✓	6.70	+0.83
7	✓	✓		5.93	+0.06
8	✓	✓	✓	5.87	—



- DRL: Disentanglement representation learning
- VSGG: Vessel semantic-guided generator
- VSGL: Vessel semantic-guided loss

Each module within the CAS-GAN plays an integral role
in precisely generating vascular structures

Summary

- ✓ This is the **first attempt** to utilize a generative model for **contrast-free angiography synthesis**, offering a promising way to reduce reliance on contrast agents.
- ✓ The **disentanglement representation learning approach** and **vessel semantic-guided generation process** can ensure high fidelity of generated images.
- ✓ In future works, CAS-GAN will be validated on a **large-scale dataset**, and **downstream applications** will be conducted in vivo animal experiments.



2025 IEEE Symposium Series on Computational Intelligence



Thanks! & QA

Email: huangdexing2022@ia.ac.cn



arXiv



Poster