

# Unsupervised Feature Orthogonalization for Learning Distortion-Invariant Representations

Sebastian Doerrich, Francesco Di Salvo, Christian Ledig

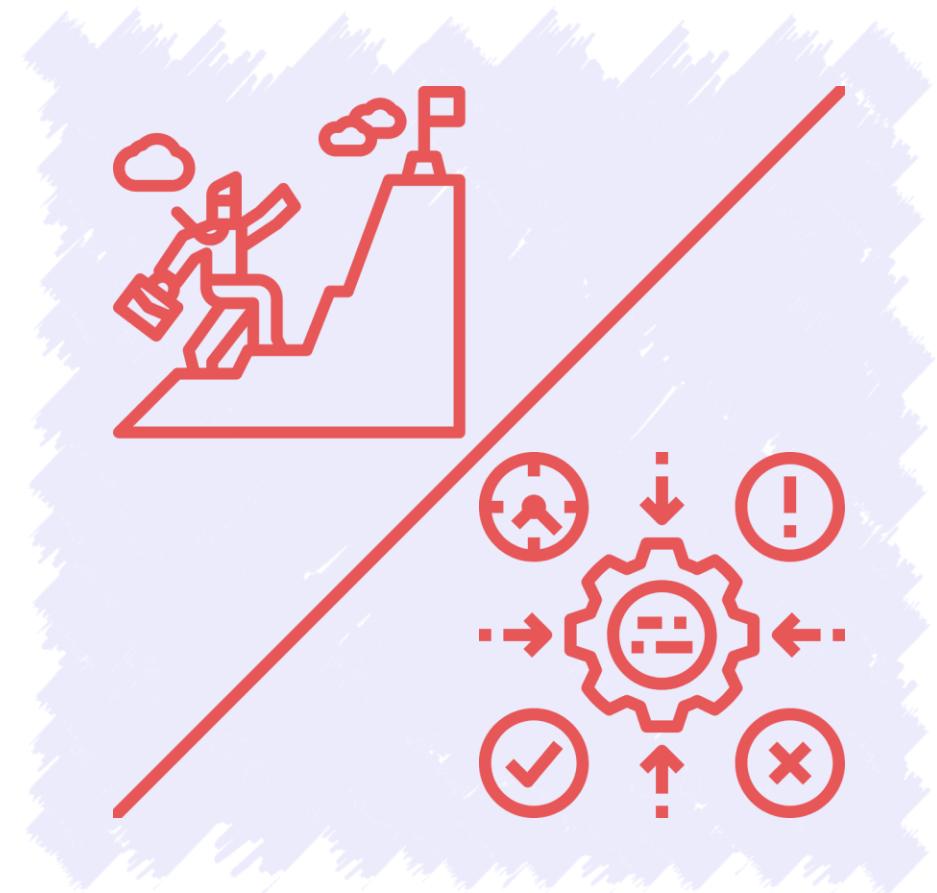
xAI Lab Bamberg

University of Bamberg

17 July 2025

# Motivation & Context

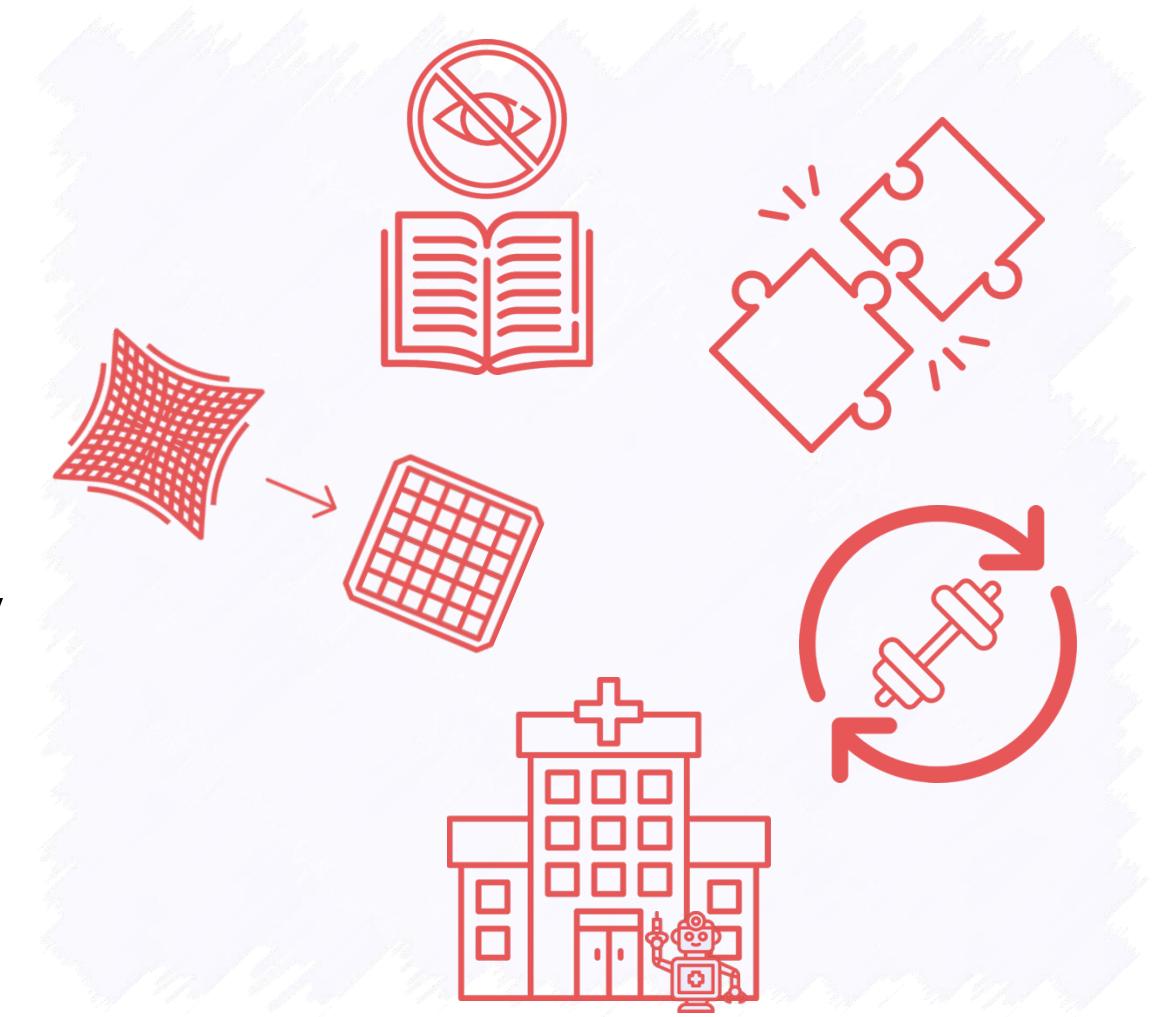
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# Categorization of Core Concepts

- Unsupervised learning
- Feature orthogonalization
- Distortion-invariance
- Robustness and generalizability
- Medical domain

→ With Deep Learning!



# Areas of Impact for DL in Healthcare



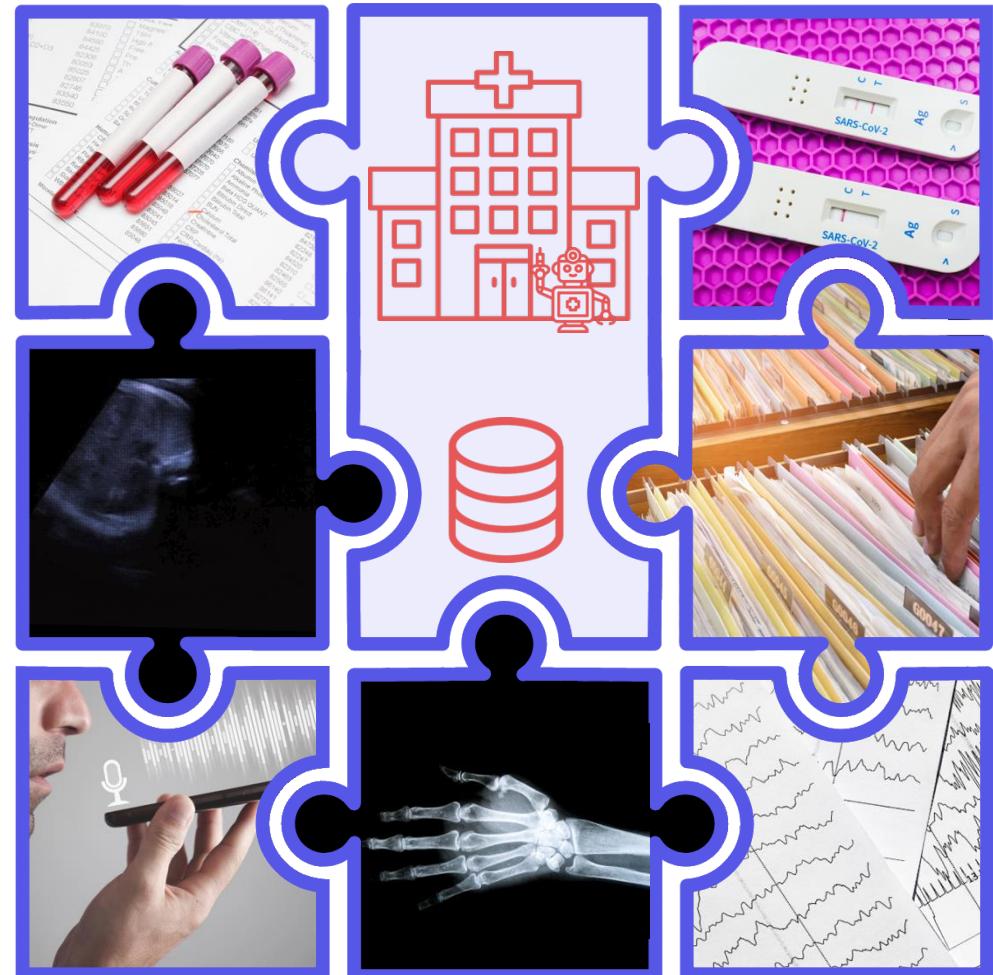
Kumar et al. (2023) Eng Appl Artif Intell, 120

Al Kuwaiti et al. (2023) J Pers Med. 13(6):951

Jimma (2023) Telemat Inform Rep. 9

# Types of Medical Data with DL

- Video (e.g., Ultrasound)
- Text (e.g., anamnesis reports)
- Image (e.g., X-ray)
- Numerical (e.g., blood reports)
- Categorical (e.g., test results)
- Speech (e.g., doctor instructions)
- Signals (e.g., ECG)



# Inherent Challenges with Medical Data



## Ideal

- Large, diverse, high-quality datasets
- Homogeneous data acquisition
- Equal representation of disease classes and severities
- Equal representation of demographics
- Consistent imaging parameters and scanner models.

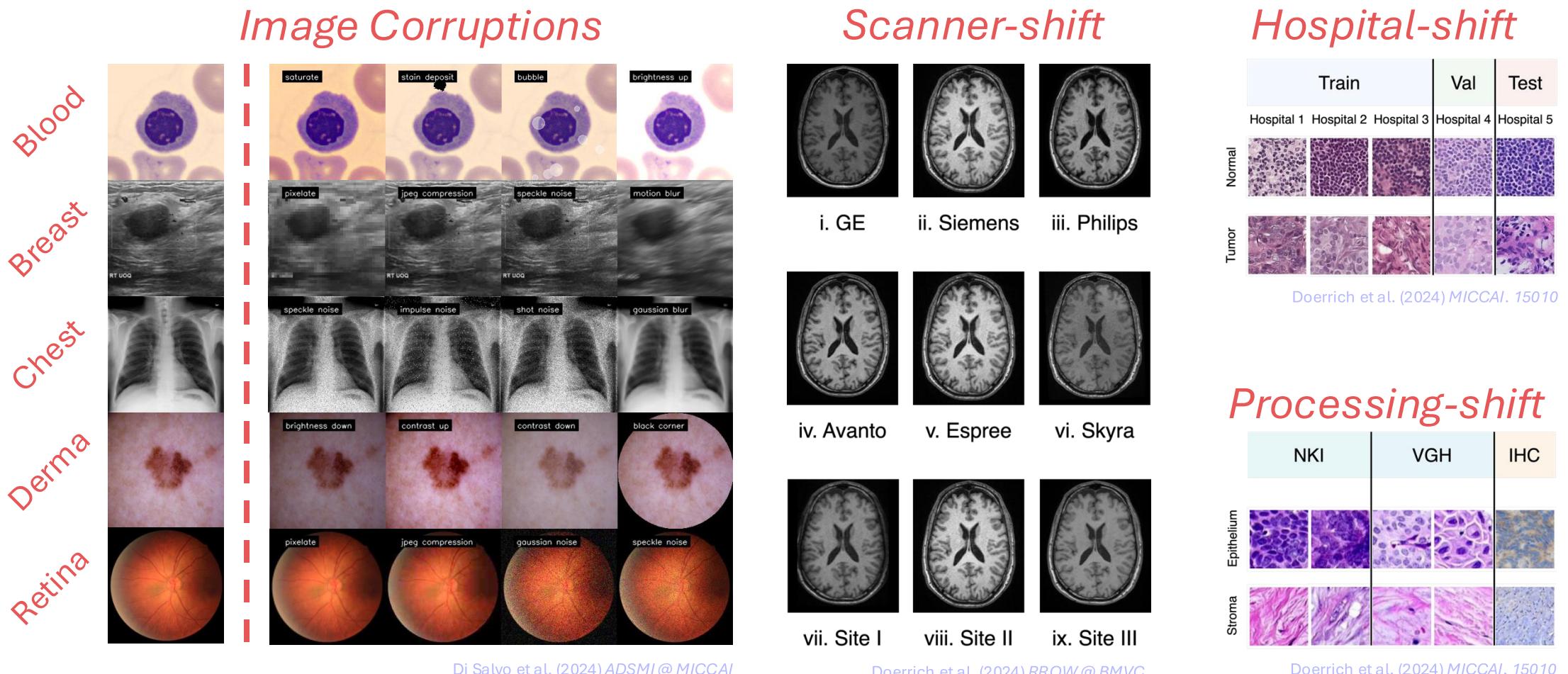


## Real

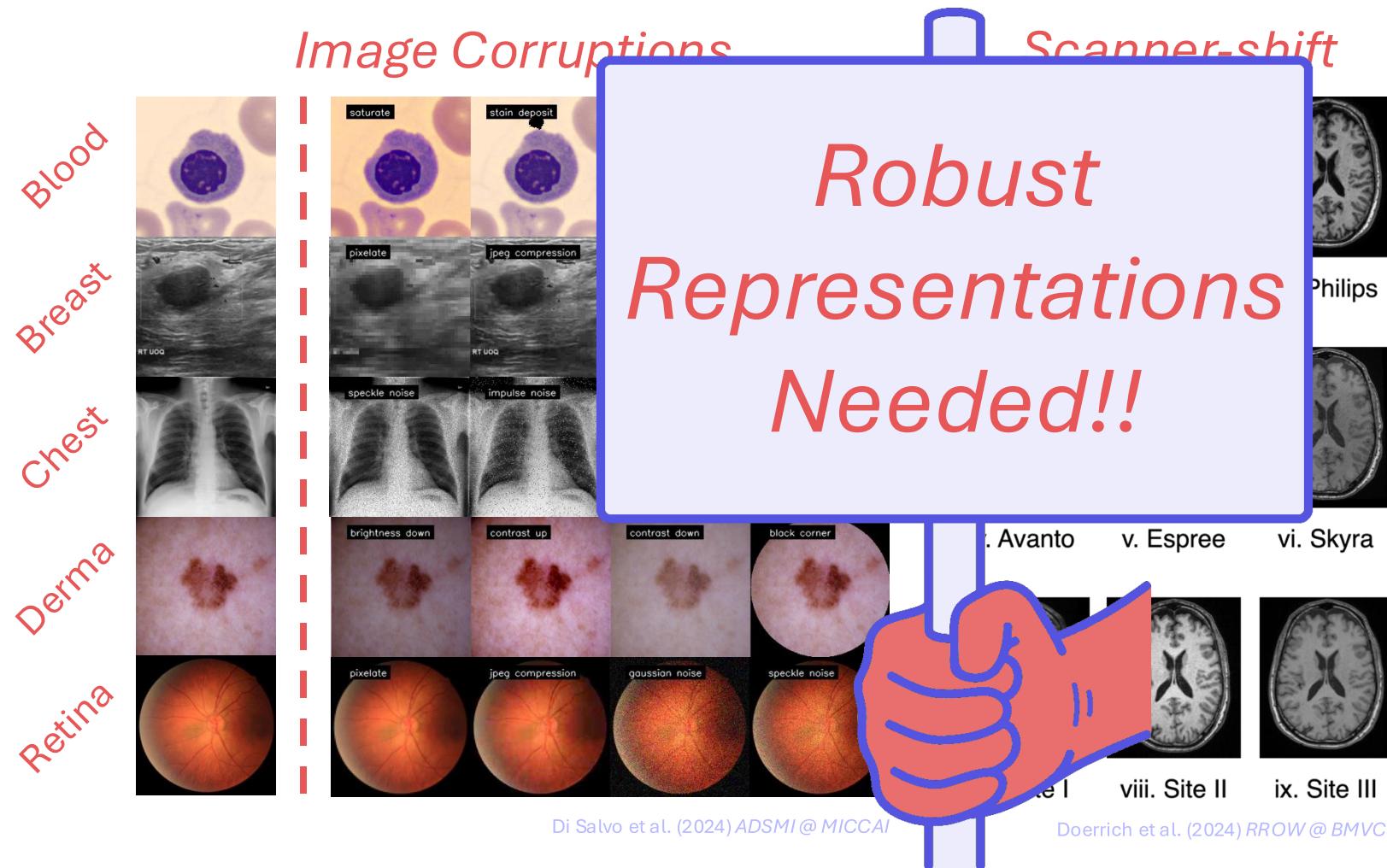
- Scarce and distorted data  
Upadhyay et al. (2024) *Arch Comput Methods Eng.* 31:1701-1719
- Inhomogeneous data acquisition  
Lafarge et al. (2017) *Lecture Notes in CS.* 10553
- Underrepresented disease classes and severities  
Afrose et al. (2022) *Commun Med.* 2:111
- Underrepresented demographic groups  
Moor et al. (2023) *Nature.* 616:259-265
- Scanner-induced domain shifts  
Stacke et al. (2021) *IEEE J Biomed Health Inform.* 25:325-336

Zhou et al. (2024) *IEEE Conf Artif Intell Test.* 120-131

# Distorted / Corrupted Data Scanner-Induced Domain Shift



# Distorted / Corrupted Data Scanner-Induced Domain Shift



## Hospital-shift

	Train	Val	Test
Normal	Hospital 1	Hospital 2	Hospital 3
Tumor	Hospital 4	Hospital 5	

Doerrich et al. (2024) MICCAI, 15010

## Processing-shift

	NKI	VGH	IHC
Epithelium			
Stroma			

Doerrich et al. (2024) MICCAI, 15010

# Method

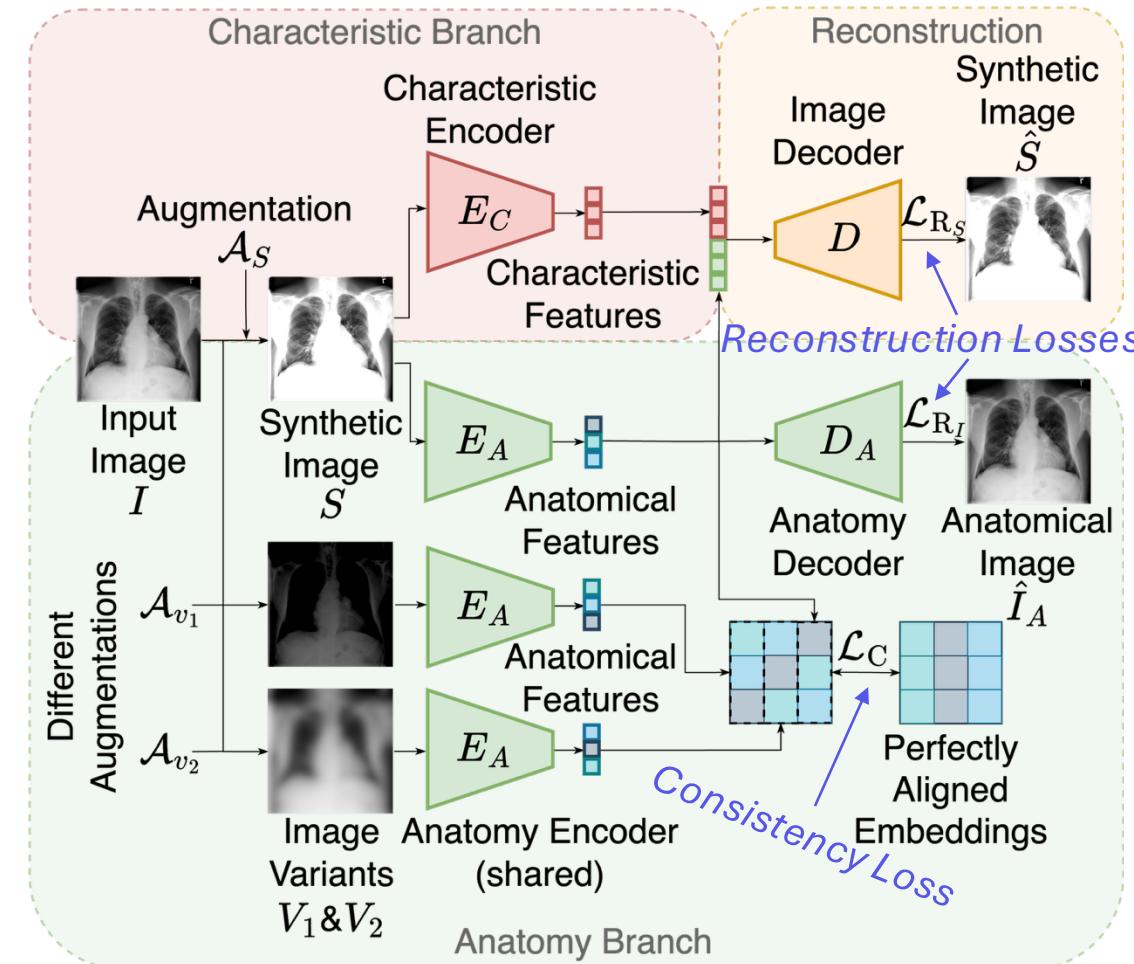
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Enforcing robust representations via  
strict disentangling of anatomy and  
image characteristic (style) features



# unORANIC

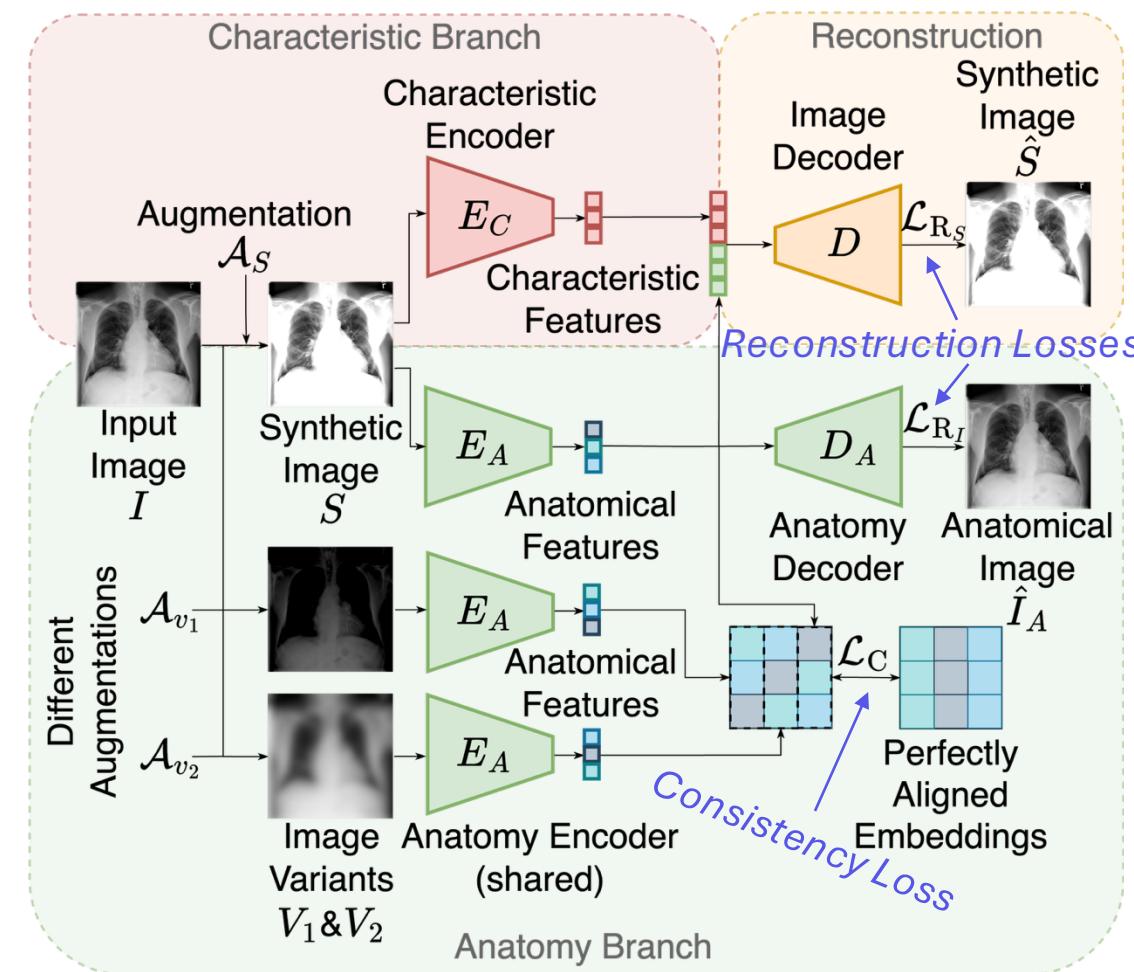
*Unsupervised  
Orthogonalization  
of Anatomy and  
Image  
Characteristic  
Features*



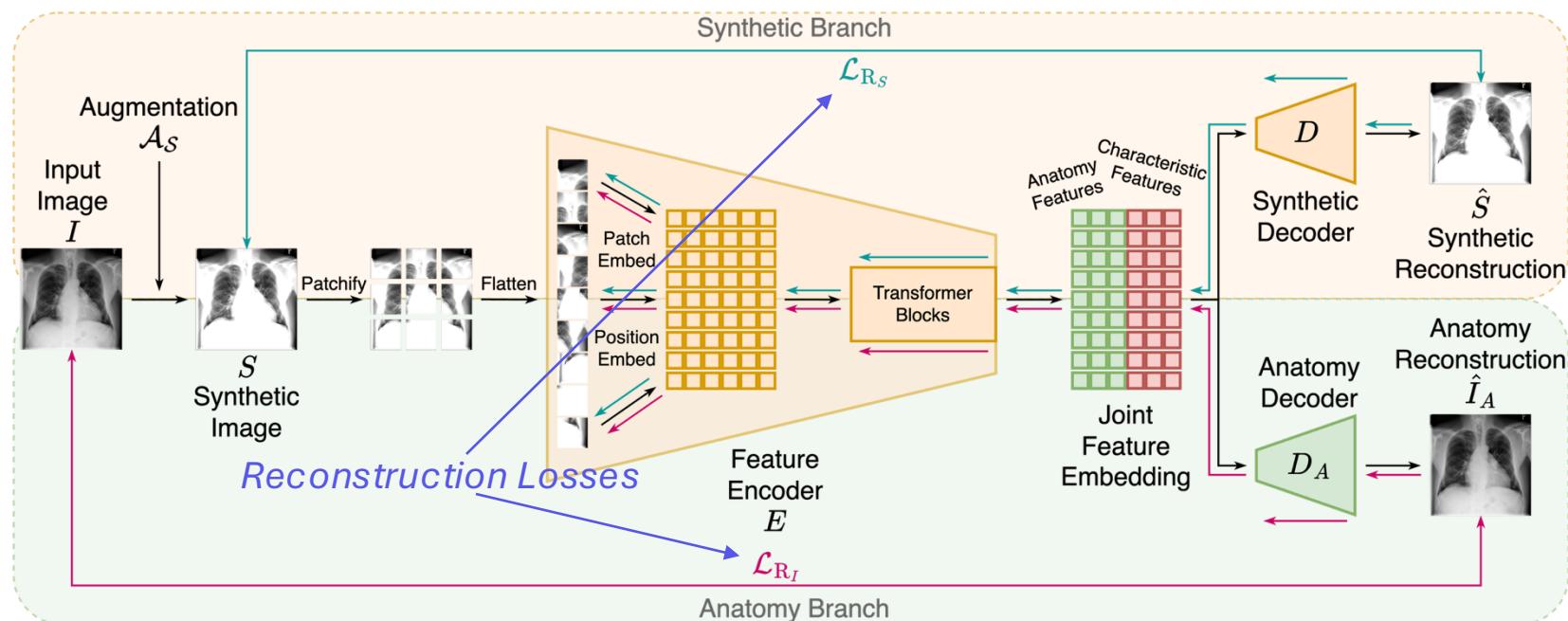
Doerrich et al. (2023) MLMI @ MICCAI. 62-71

# unORANIC

*Unsupervised  
Orthogonalization  
of Anatomy and  
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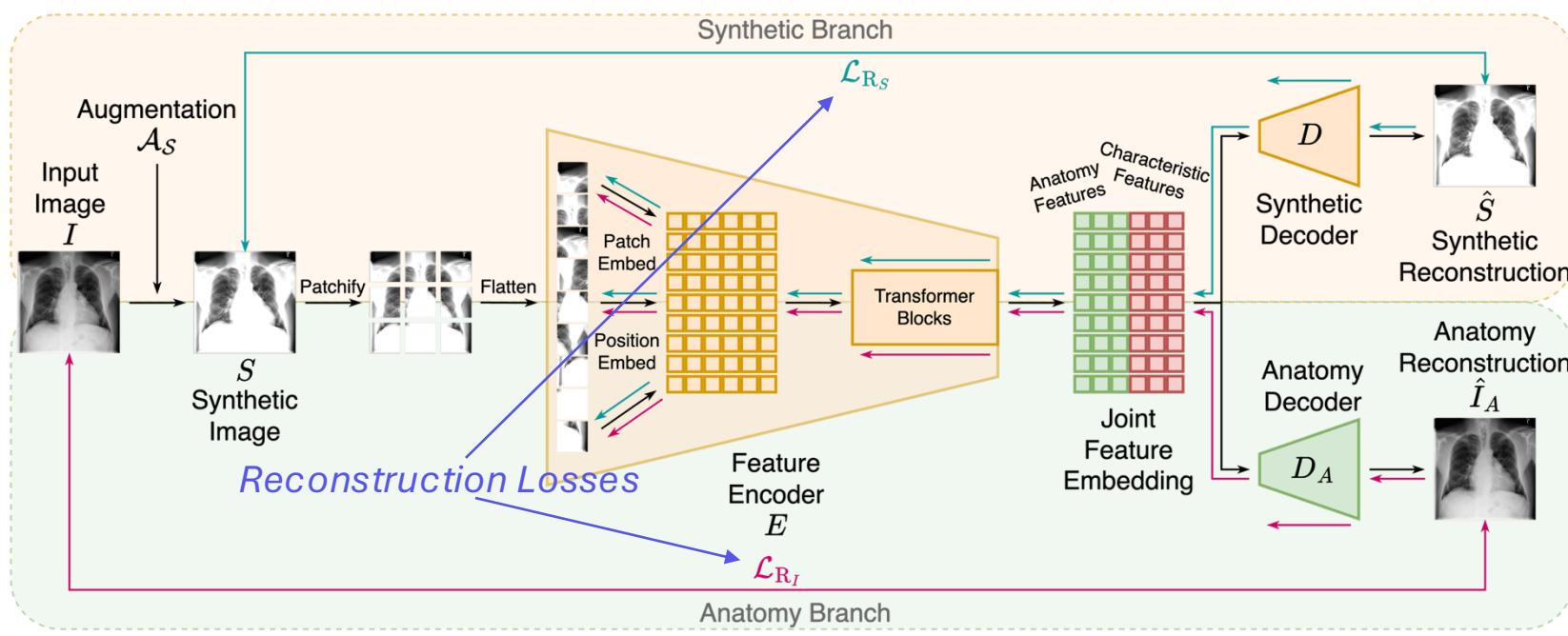


# unORANIC+



Doerrich et al. (2023) RROW@BMVC

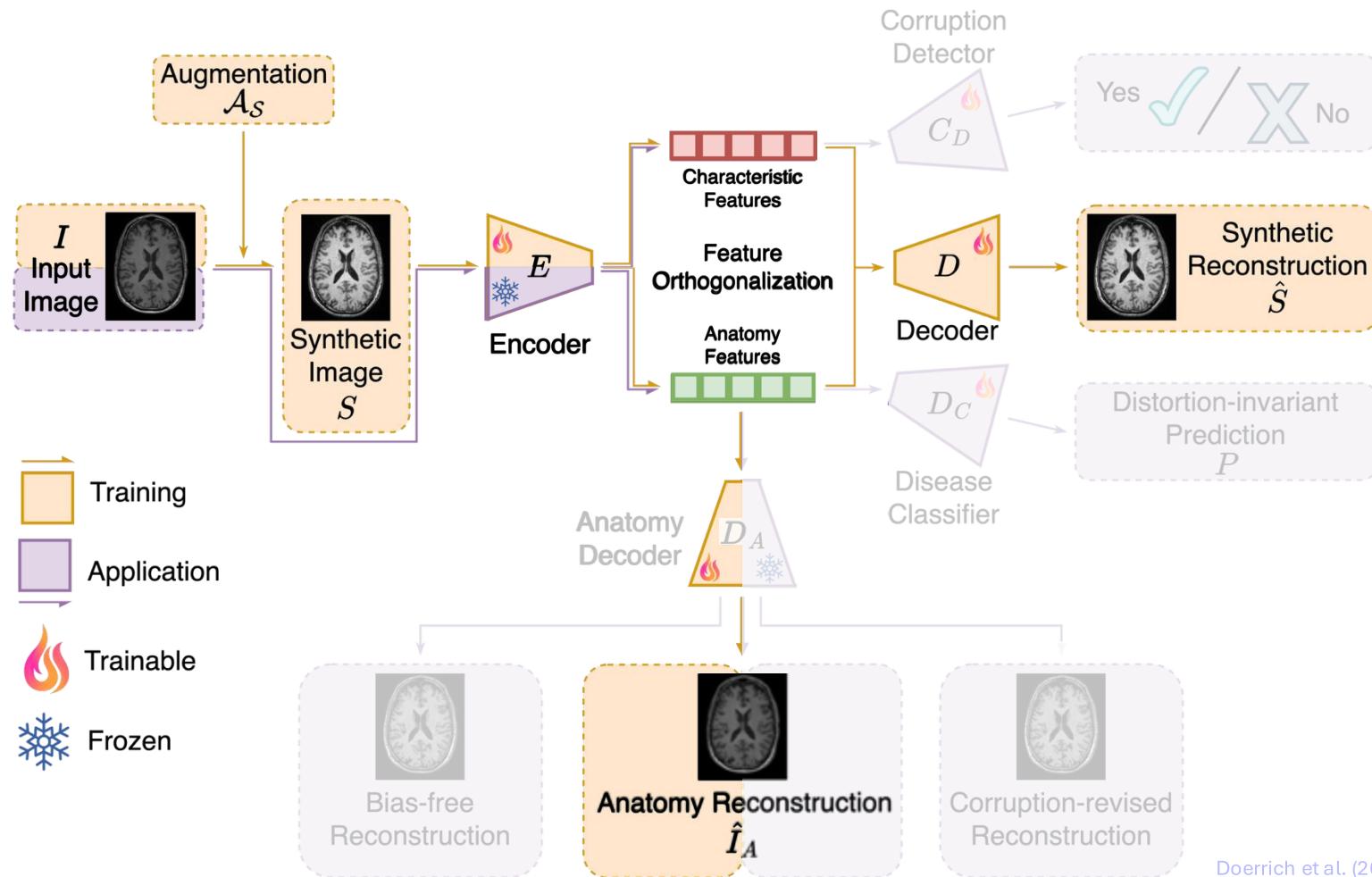
# unORANIC+



Doerrich et al. (2023) RROW@BMVC

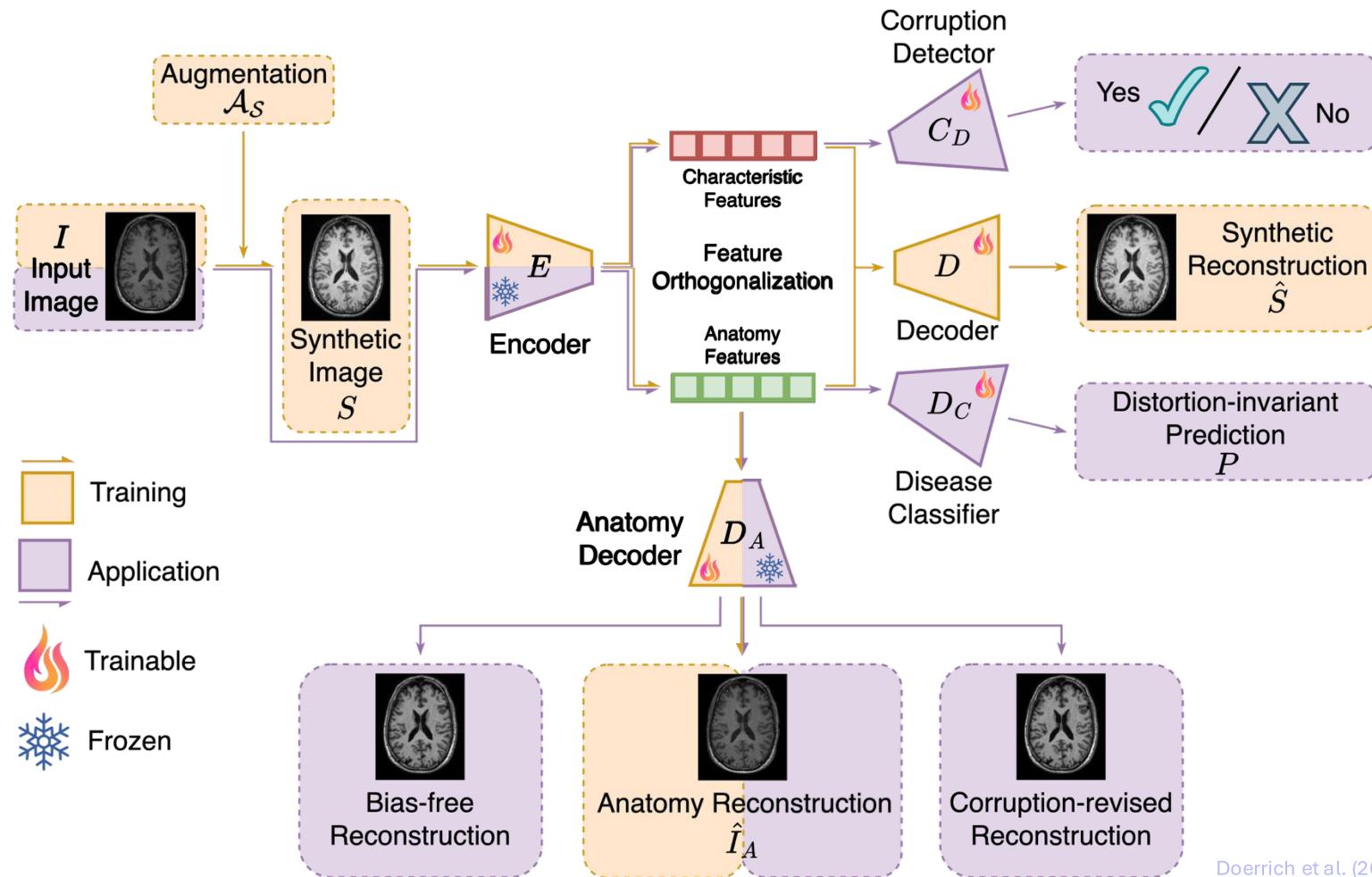
- ↗ Robustness
- ↗ Generalizability
- ✗ Domain knowledge
- ✗ Paired data
- ✗ Labels
  
- ↘ Complexity
- ↘ Training difficulty
- ↘ Room for improvement

# Possibilities



Doerrich et al. (2023) RROW @ BMVC

# Possibilities



Doerrich et al. (2023) RROW @ BMVC

# Experiments & Results

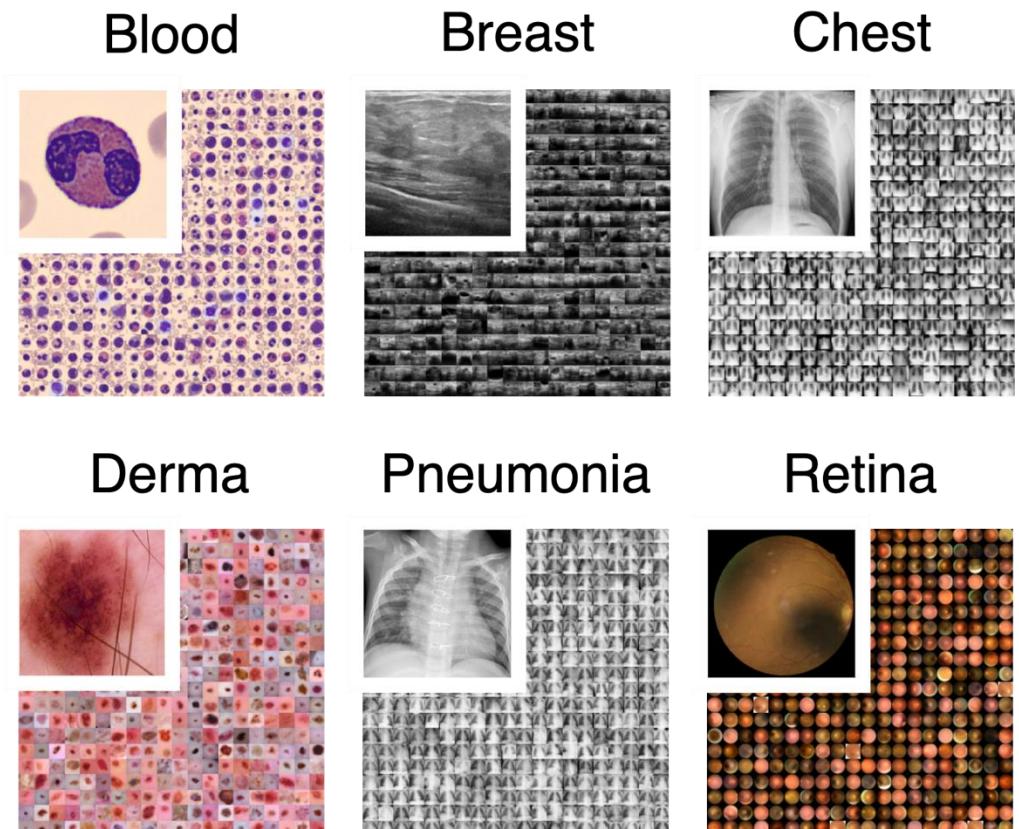
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# Datasets

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- 6 diverse datasets from the MedMNIST+ dataset collection (*blood, breast, ..., retina*)
- 5 different modalities (*cell microscopy, ..., fundus camera*)
- 2 distinct image resolutions (*28 x 28 and 224 x 224 pixels*)
- Disparate dataset scales (*546 up to 78,468 samples*)
- Various classification tasks (from 2 up to 8 classes)
- Grayscale and RGB images



Doerrich et al. (2023) RROW @ BMVC

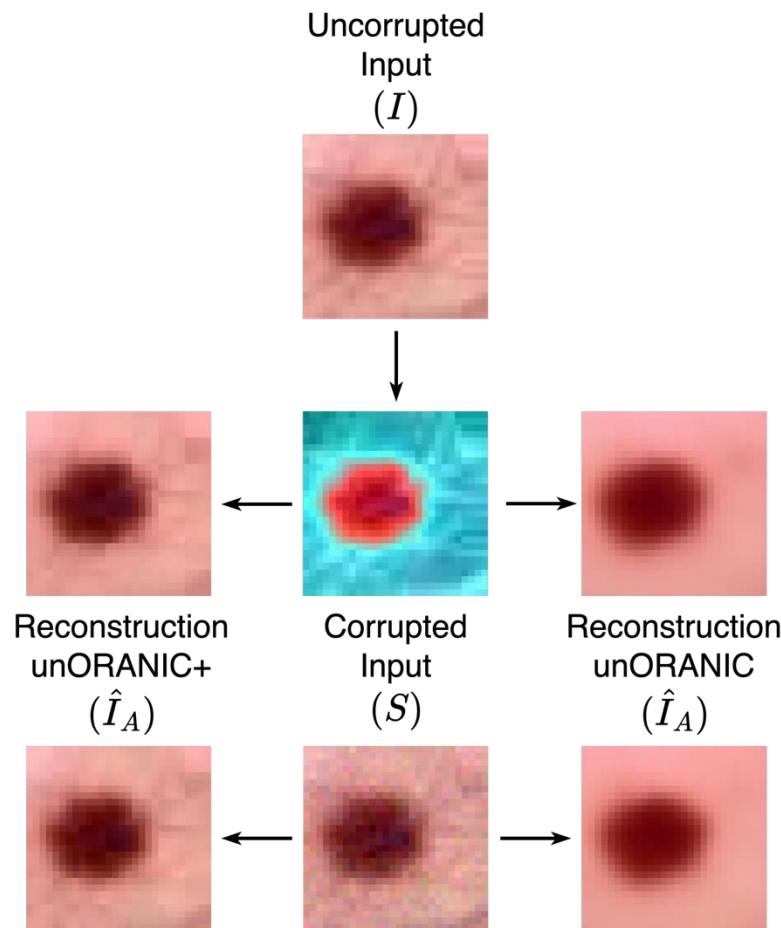
# Reconstruction and Corruption Revision

Dataset	Peak Signal-to-Noise Ratio				Structural Similarity Index			
	PSNR		SSIM		PSNR		SSIM	
	$\hat{I}_A$	$\hat{I}$	$\hat{I}_A$	$\hat{I}$	$\hat{I}_A$	$\hat{I}$	$\hat{I}_A$	$\hat{I}$
Blood	27.06	31.70	<b>35.88</b>	<b>49.15</b>	0.877	0.943	<b>0.987</b>	<b>0.999</b>
Breast	19.48	29.39	<b>26.21</b>	<b>33.55</b>	0.526	0.816	<b>0.889</b>	<b>0.957</b>
Chest	27.93	33.73	<b>35.30</b>	<b>56.02</b>	0.956	0.983	<b>0.995</b>	<b>0.999</b>
Derma	23.73	38.57	<b>30.07</b>	<b>45.09</b>	0.864	0.970	<b>0.971</b>	<b>0.995</b>
Pneumonia	24.00	36.04	<b>28.96</b>	<b>44.80</b>	0.901	0.977	<b>0.977</b>	<b>0.997</b>
Retina	27.50	36.31	<b>30.39</b>	<b>37.71</b>	0.888	0.954	<b>0.936</b>	<b>0.978</b>

*28 x 28*

Anatomical Reconstructions						Input Reconstructions						
Input Reconstruction ( $\hat{I}$ ) [PSNR]						Anatomical Reconstruction ( $\hat{I}_A$ ) [PSNR]						
Blood	Breast	Chest	Derma	Pneumonia	Retina	Blood	Breast	Chest	Derma	Pneumonia	Retina	
unORANIC	26.66	20.28	28.33	27.55	27.21	31.25	24.57	17.62	26.02	23.10	21.61	25.64
unORANIC+	<b>44.63</b>	<b>27.80</b>	<b>42.23</b>	<b>33.22</b>	<b>34.97</b>	<b>35.37</b>	<b>38.23</b>	<b>24.94</b>	<b>32.35</b>	<b>26.91</b>	<b>26.86</b>	<b>31.41</b>

*224 x 224*



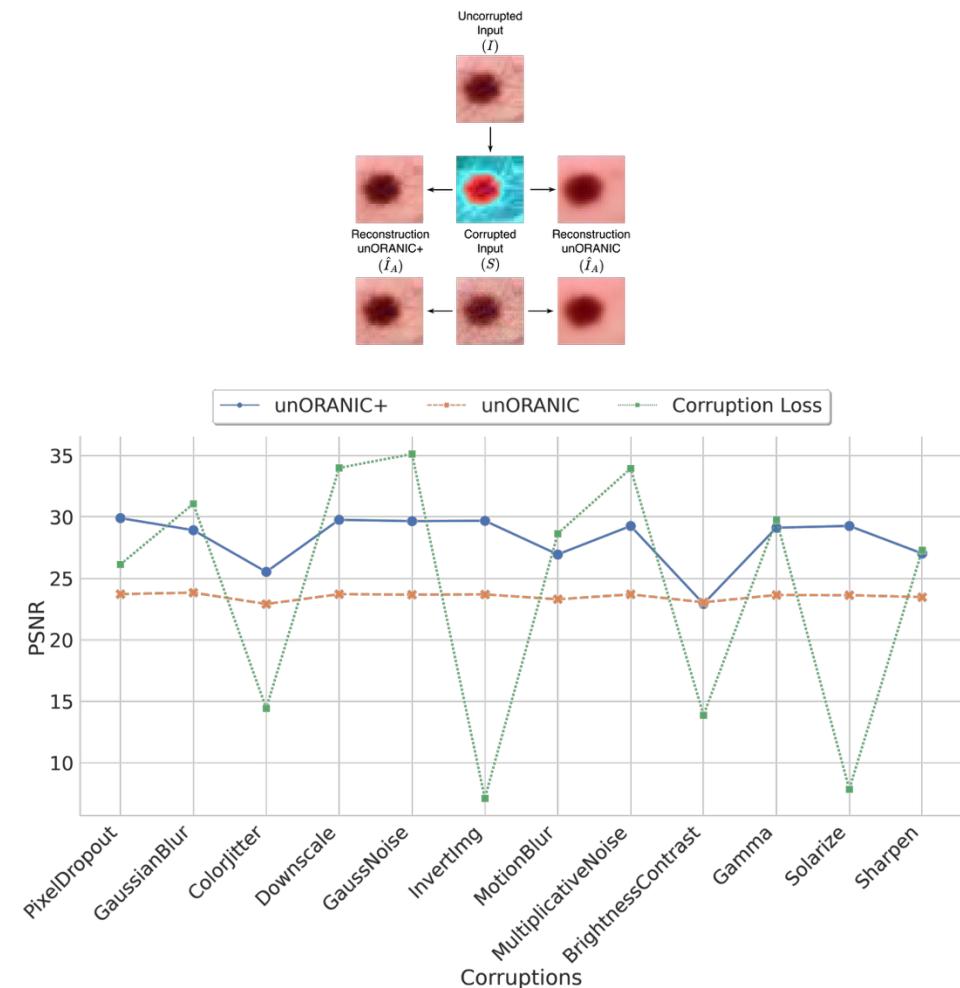
# Reconstruction and Corruption Revision

Dataset	Peak Signal-to-Noise Ratio				Structural Similarity Index			
	unORANIC		unORANIC+		unORANIC		unORANIC+	
	$\hat{I}_A$	$\hat{I}$	$\hat{I}_A$	$\hat{I}$	$\hat{I}_A$	$\hat{I}$	$\hat{I}_A$	$\hat{I}$
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**28 x 28**

Anatomical Reconstructions						Input Reconstructions						
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Blood	Breast	Chest	Derma	Pneumonia	Retina	Blood	Breast	Chest	Derma	Pneumonia	Retina	
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**224 x 224**



# Disease Classification and Corruption Detection

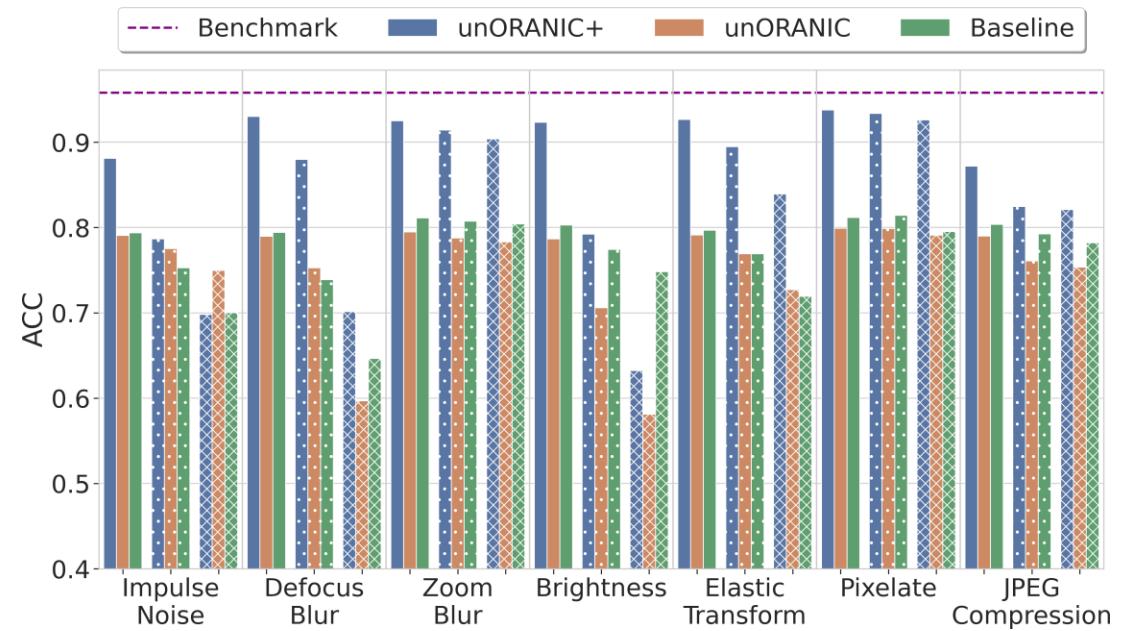
Methods	Disease Classification		Corruption Detection	
	ACC	AUC	ACC	AUC
ResNet-18 <sup>†</sup>	0.958	0.998	0.973	0.998
ViT <sup>†</sup>	0.930	0.992	0.914	0.926
unORANIC	0.800	0.952	0.962	0.976
unORANIC+	<b>0.935</b>	<b>0.994</b>	<b>0.970</b>	<b>0.980</b>

28 x 28

*Fully supervised model trained end-to-end*

	Disease Classification [AUC]					Corruption Detection [AUC]						
	Blood	Breast	Chest	Derma	Pneumonia	Retina	Blood	Breast	Chest	Derma	Pneumonia	Retina
ResNet-18 <sup>†</sup>	0.840	0.794	0.518	0.608	0.917	0.684	0.910	0.833	0.876	0.842	0.867	0.869
ViT <sup>†</sup>	0.891	0.580	0.535	0.501	0.810	0.647	0.791	0.663	0.820	0.660	0.639	0.700
unORANIC	0.930	0.774	0.528	0.717	0.913	0.681	0.744	0.586	0.635	0.625	0.639	0.644
unORANIC+	<b>0.997</b>	0.757	<b>0.563</b>	0.563	<b>0.945</b>	0.675	<b>0.754</b>	<b>0.616</b>	<b>0.892</b>	<b>0.690</b>	<b>0.694</b>	<b>0.783</b>

224 x 224



*Resilience to unseen corruptions during training*

# Take-Home Message

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# Take-Home Message

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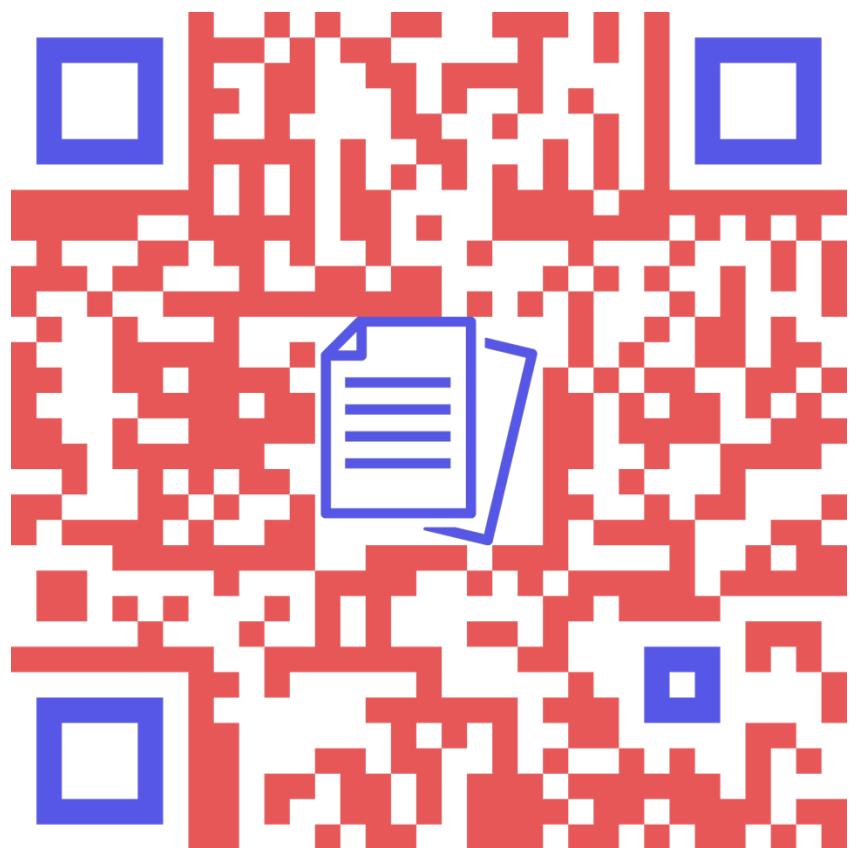


*Self-supervised **orthogonalization of** anatomical  
and image-characteristic **information** in images  
**enables** the generation of **robust** latent  
representations even **in the presence of** data  
**inhomogeneities** and **domain shifts.***



*Thank you for your attention!*

Paper



Code



# References

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# References

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