SESSION 6: NEW APPLICATIONS

ASSESSING UTILITY AND BUILDING INDUSTRY TRUST FOR IMAGING DATA IN HEALTHCARE

uOttawa

Replica Analytics
AN AETION COMPANY

Presented by:

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RYVER AI

Making Radiology AI more robust
with diverse synthetic training data

Our diverse founder team combines deep technological capabilities and experience in strategy and venture capital

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MSc. Robotics, Systems & Control

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Tech
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MSc. Management & Technology

HOLTZBRINCK DIGITAL accenture
SIEMENS

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Generative AI understands the characteristics of medical imaging data and creates fictional datasets that mimic the real world

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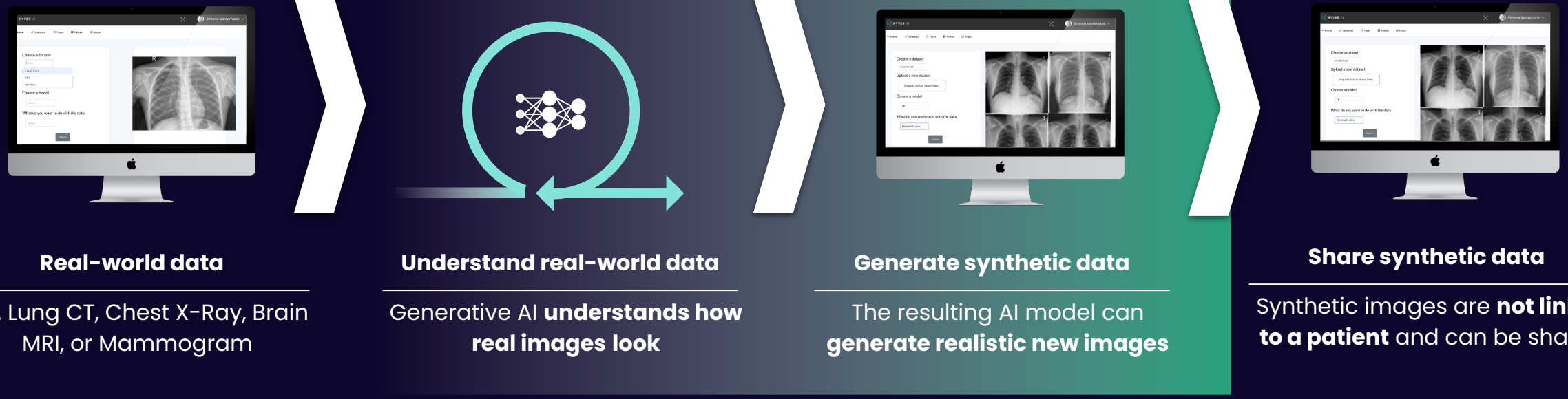


Real-world data

E.g. Lung CT, Chest X-Ray, Brain MRI, or Mammogram

Understand real-world data

Generative AI **understands how real images look**

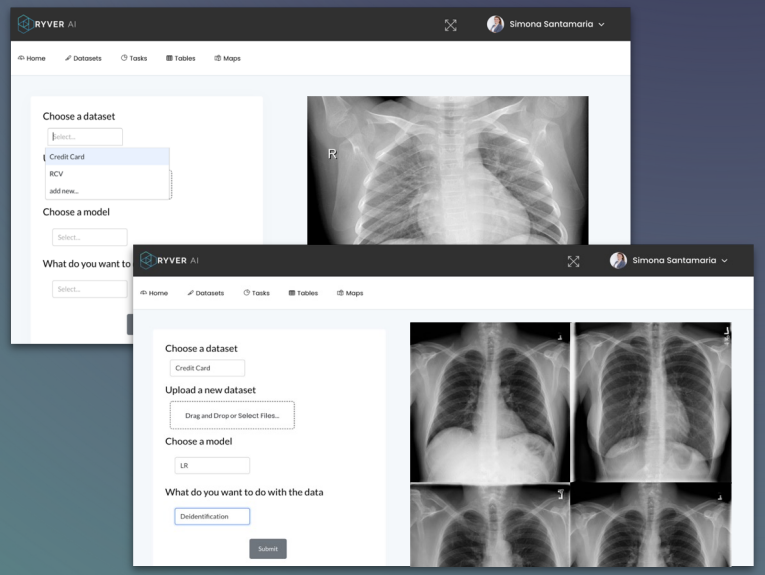
Generate synthetic data

The resulting AI model can **generate realistic new images**

Share synthetic data

Synthetic images are **not linked to a patient** and can be shared

Fuel imaging AI research and make radiology AI more robust without compromising privacy of real-world patients



Fuel imaging AI research with high-quality data
providing quick access to diverse synthetic data samples

Improve robustness of diagnostic AI models
by generating synthetic outliers and diversifying training data

Eliminate privacy risk of data sharing
by never sharing information of actual patients

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Assessing Utility and Building Industry Trust for Imaging Data in Healthcare

Image utility focuses on the outcome of the downstream task and other metrics cover the image parameters

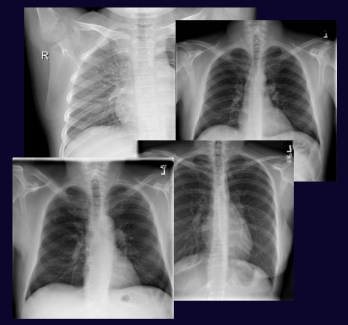
Privacy

?

real patient vs. synthetic

is the privacy of individual patients protected?

Variety



is the synthetic data diverse?

Fidelity

original

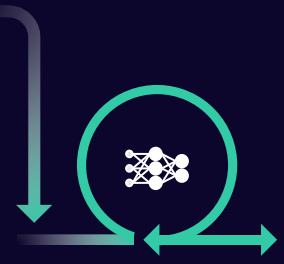
synthetic

is it similar to original images?

Utility

synthetic

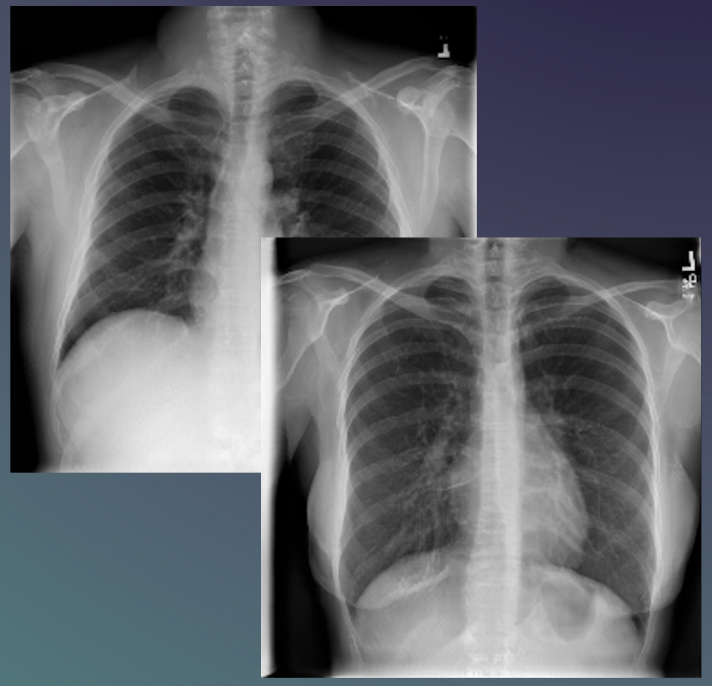
original



is it helpful for the downstream task?

Chen, Richard J., et al. "Synthetic Data in Machine Learning for Medicine and Healthcare." *Nature Biomedical Engineering*, vol. 5, no. 6, June 2021, pp. 493–497.
Xing, Xiaodan, et al. "You Don't Have to Be Perfect to Be Amazing: Unveil the Utility of Synthetic Images." *Lecture Notes in Computer Science*, 1 Jan. 2023, pp. 13–22, https://doi.org/10.1007/978-3-031-43904-9_2. Accessed 16 Nov. 2023.

Trustworthy experiments focusing on the downstream task help advance industry trust



Design trustworthy experiments

Take all metrics into account

Put special focus on utility and privacy

Due to complex representation and subjectivity it is hard to determine image quality

Complexity in Data Representation

In images **information displays** in **various unstructured forms** making it **hard to extract certain information** and measure their quality

Subjectivity in Interpretation

Even when **checked with experts** like physicians there is often **not a clear answer or uniform opinion** about one image/patient

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Image Utility can me measured using **metrics, expert opinions or test** the effect of synthetic data on **the downstream task**

Metrics

FID, Inception Score, Recall etc. are all **metrics to analyse images** and **measure** rather **image fidelity** than utility

Expert Opinion

Performing a **turing test with physicians** can indicate whether **synthetic images are realistic to the human eye**

Test Downstream Task

Adding synthetic images to train e.g. a classifier can show if the synthetic images **are useful for the downstream task**

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High fidelity could also indicate for a major privacy breach

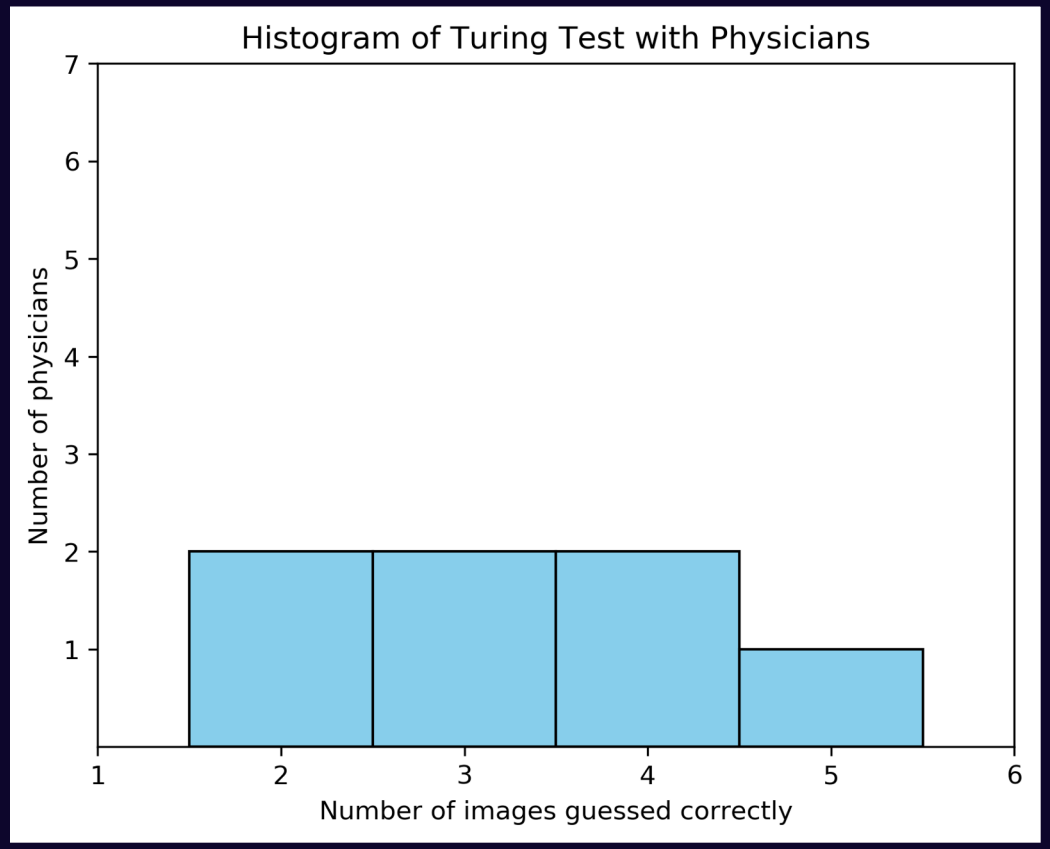
Synthetic data being **really similar to real world data**

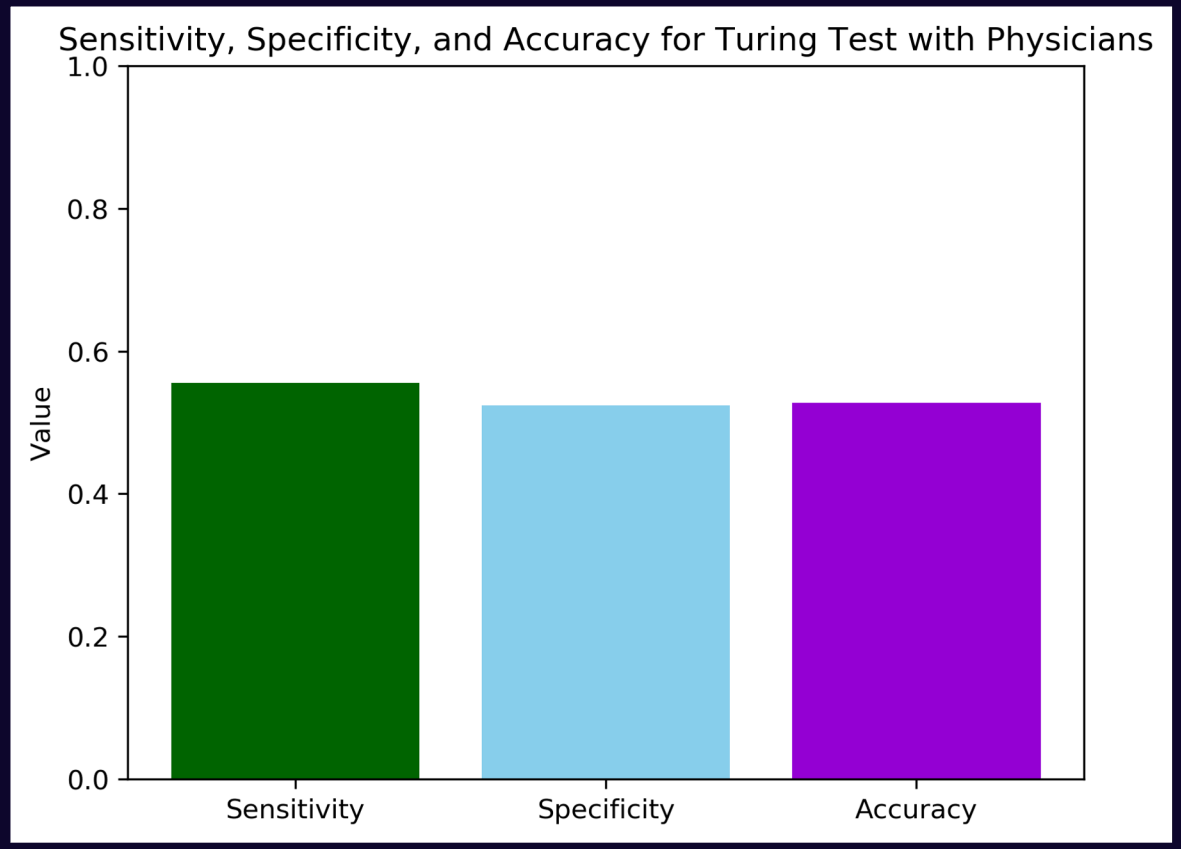
VS.

Synthetic model just **reproducing the real world data**

Our X-Ray experiments show that an evaluation of the images by experts might not be enough to determine utility

Expert Opinion: Physicians could not determine a clear difference between synthetic and real images





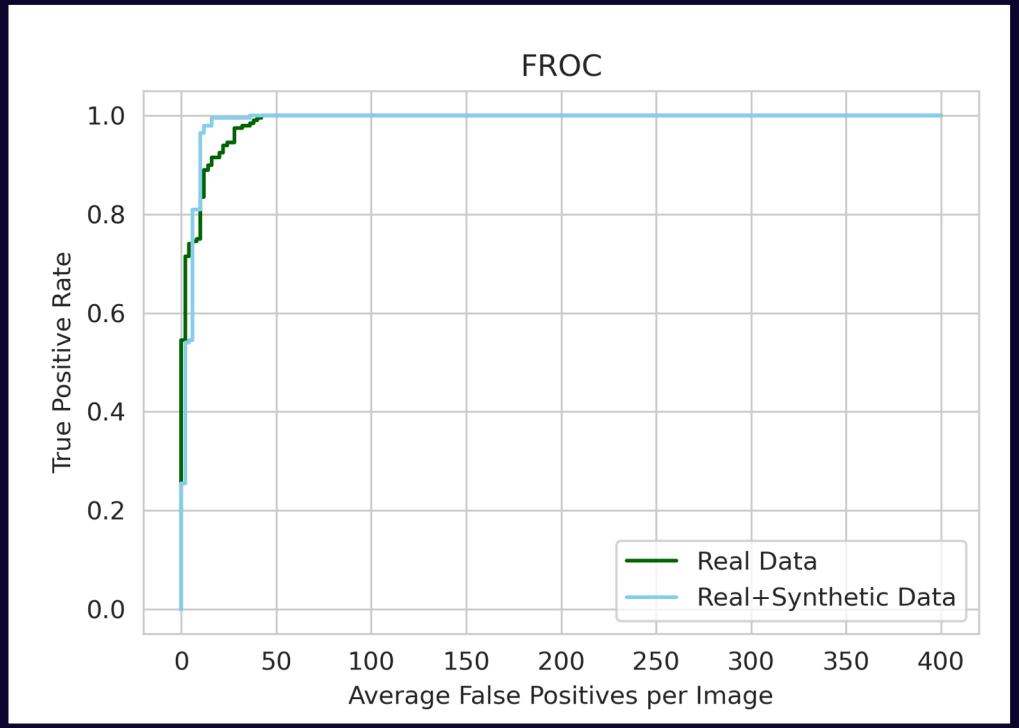
Our X-Ray experiments show that an evaluation of the images by experts might not be enough to determine utility

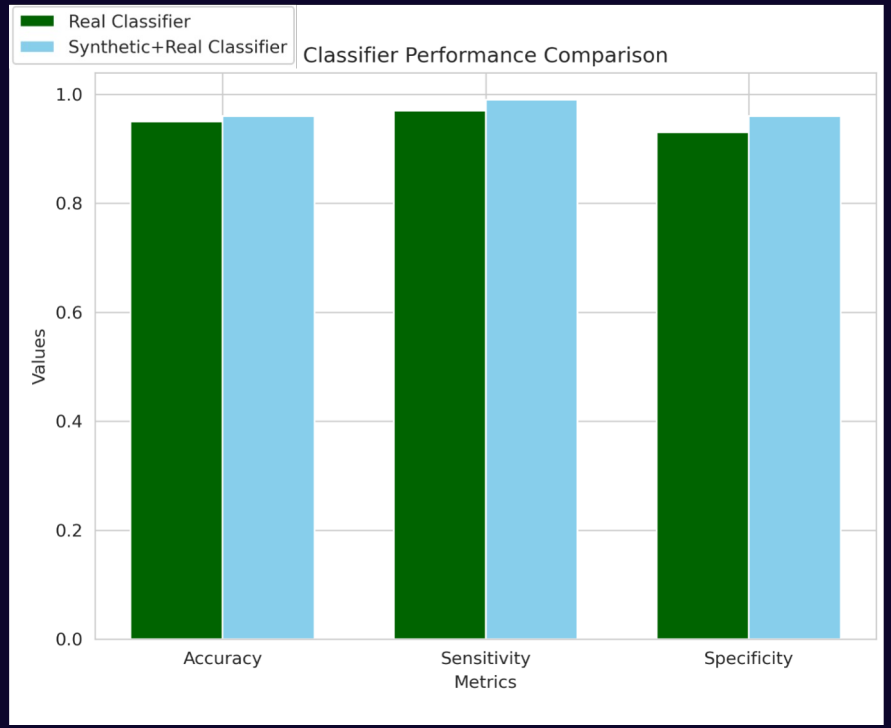
Test Downstream Task: The classifier could determine a difference between the real and synthetic images

	Real Only	1:1	1:2	1:3	1:4	1:5	1:6	1:7	1:8
	experimer	experimer	experimer	experimer	experimer	experimer	experimer	experimer	experimen
AUC	**0.91**	0.89	0.87	0.88	0.86	0.88	0.88	0.88	0.85
Sensitivity	0.90	0.87	0.92	0.93	**0.96**	0.94	0.84	0.82	0.77
Specificity	**0.77**	0.75	0.67	0.64	0.54	0.63	0.76	0.79	0.77
Accuracy	0.78	0.76	0.68	0.65	0.56	0.64	0.77	**0.79**	0.77
F1	**0.27**	0.25	0.21	0.20	0.17	0.20	0.25	0.27	0.24

Our CT experiments laid an emphasis on a realistic benchmark to proof the utility of the synthetic data

Test Downstream Task: The synthetic data improved the performance of the classifier





Focusing on privacy and utility can build industry trust and show a solid indication of the quality of the synthetic data

- Utility can be measured by focusing on the outcome of the downstream task
- Privacy should always be taken into consideration together with utility
- Focusing on both utility and privacy delivers strong proof points for industry players

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Let’s stay in touch