CENTER FOR VIRTUAL IMAGING TRIALS

Virtual vs. Reality: External Validation of COVID-19 Classifiers using XCAT Phantoms for Chest Computed Tomography

Fakrul Islam Tushar, Ehsan Abadi, Saman Sotoudeh-Paima, Rafael B.Fricks, Maciej A. Mazurowski, W. Paul Segars, Ehsan Samei, Joseph Y. Lo

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SPIE Medical Imaging, Session # 4 (COVID-19), paper #12033-9, Feb 21, 2022.

Duke Radiology

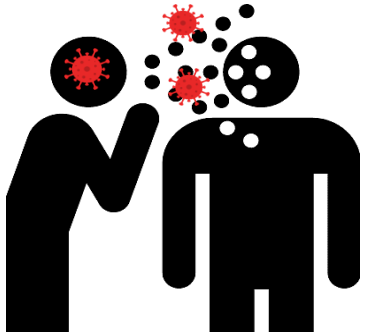
DUKE UNIVERSITY MEDICAL PHYSICS GRADUATE PROGRAM

Duke Clinical Imaging Physics Group

Duke UNIVERSITY | PRATT SCHOOL of ENGINEERING

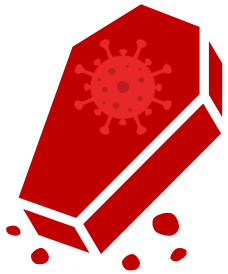
Overview| COVID-19

Cases



414.16 M

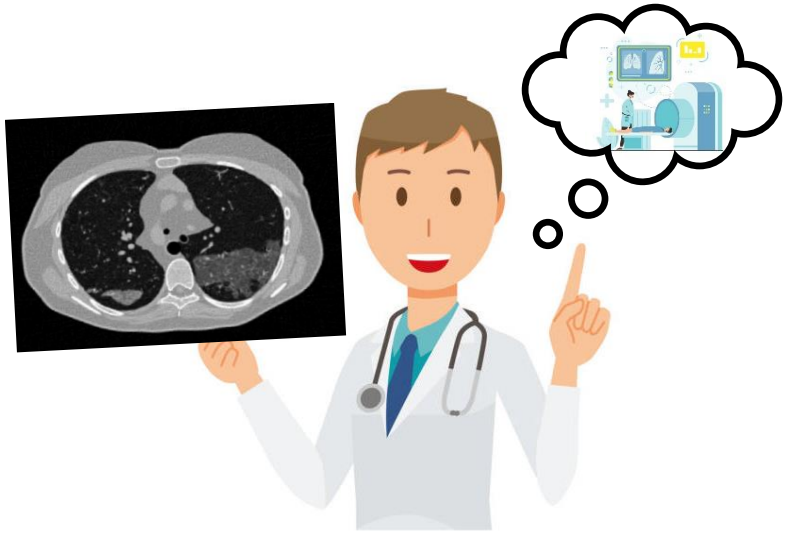
Deaths



5.84 M

Infection statistics world-wide

Chest Computed Tomography (CT)



Effectively determine lung involvement

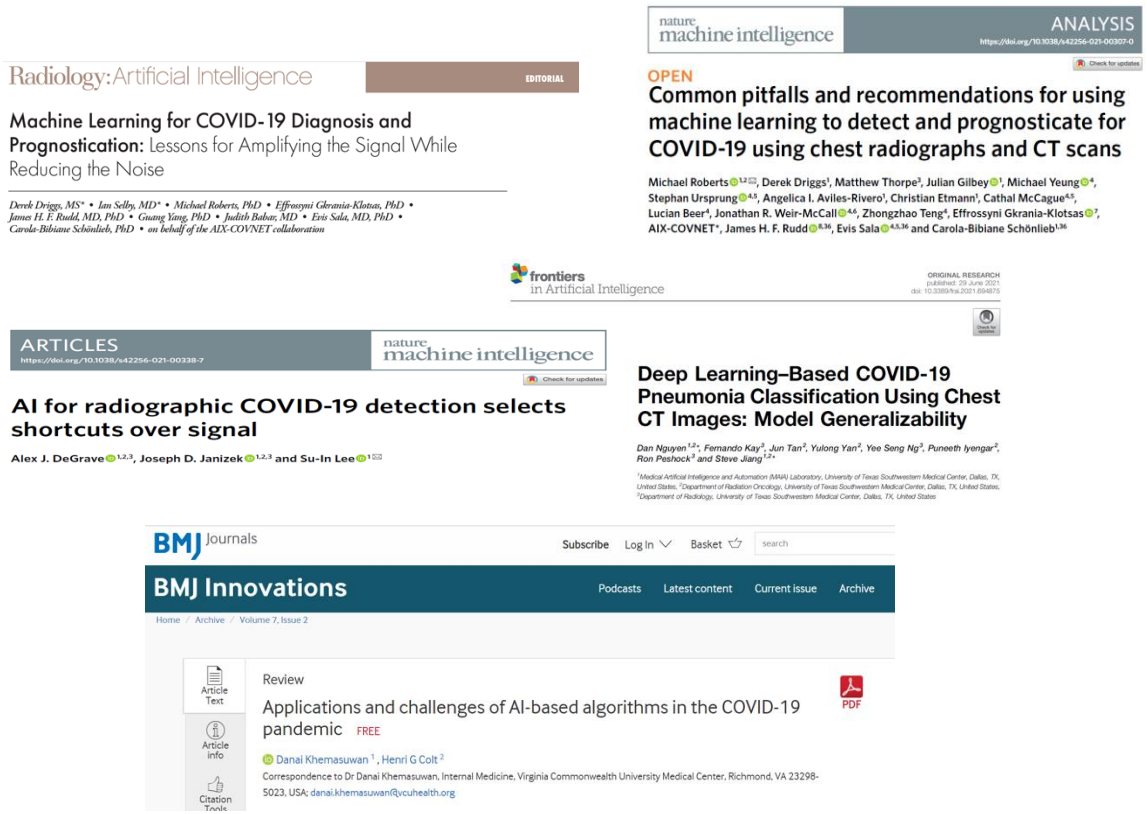
Overview| COVID-19

Google Scholar

91,400 results

Associated to COVID-19, Machine-learning, and Deep-learning.

Overview| **Concerns**



Radiology: Artificial Intelligence — EDITORIAL

Machine Learning for COVID-19 Diagnosis and Prognostication: Lessons for Amplifying the Signal While Reducing the Noise

Derek Driggs, MS • Ian Selby, MD* • Michael Roberts, PhD • Effrosyni Gkrania-Klotsas, PhD • James H. F. Rudd, MD, PhD • Guang Yang, PhD • Judith Babar, MD • Evis Sala, MD, PhD • Carola-Bibiane Schönlieb, PhD • on behalf of the AIX-COVNET collaboration*

nature machine intelligence — ANALYSIS

OPEN

Common pitfalls and recommendations for using machine learning to detect and prognosticate for COVID-19 using chest radiographs and CT scans

Michael Roberts, Derek Driggs, Matthew Thorpe, Julian Gilbey, Michael Yeung, Stephan Ursprung, Angelica I. Aviles-Rivero, Christian Etmann, Cathal McCague, Lucian Beer, Jonathan R. Weir-McCall, Zhongzhao Teng, Effrossyni Gkrania-Klotsas, AIX-COVNET, James H. F. Rudd, Evis Sala and Carola-Bibiane Schönlieb

frontiers in Artificial Intelligence — ORIGINAL RESEARCH

Deep Learning–Based COVID-19 Pneumonia Classification Using Chest CT Images: Model Generalizability

Dan Nguyen, Fernando Kay, Jun Tan, Yulong Yan, Yee Seng Ng, Puneeth Iyengar, Ron Peshock and Steve Jiang

ARTICLES — nature machine intelligence

AI for radiographic COVID-19 detection selects shortcuts over signal

Alex J. DeGrave, Joseph D. Janizek and Su-In Lee

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Review

Applications and challenges of AI-based algorithms in the COVID-19 pandemic FREE

Danai Khemasuwan, Henri G Colt

Correspondence to Dr Danai Khemasuwan, Internal Medicine, Virginia Commonwealth University Medical Center, Richmond, VA 23298-5023, USA; danai.khemasuwan@vcuhealth.org

- Near perfect diagnostic performance
- Internal and external variability in performance
- Underlying data biases
- performance can vary depending on data population, image quality, image acquisition protocols, dose differences, and disease appearance.

Objective | Primary Objective

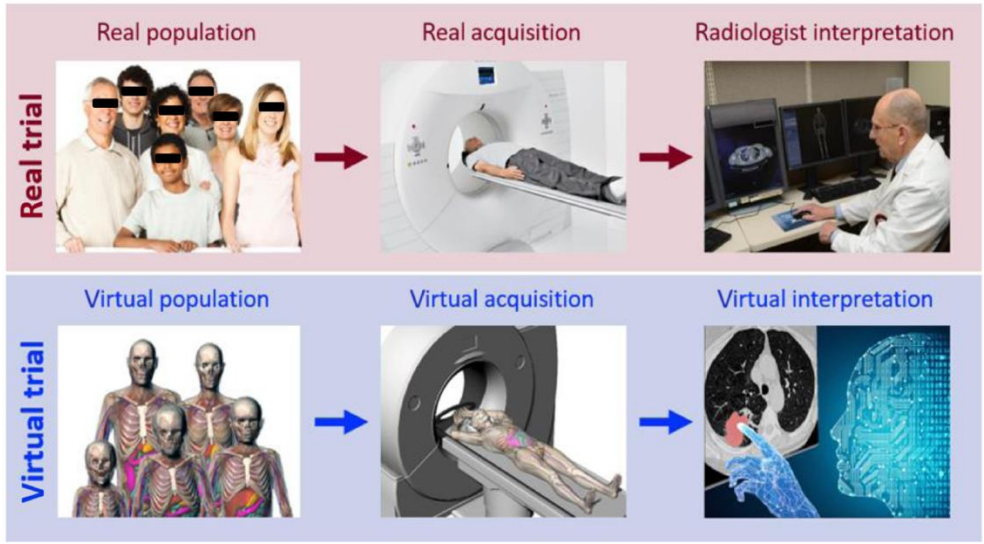
Investigating variability of diagnostic performance based on disease appearance and imaging properties.

Objective | **Challenges**

— Challenging in real clinical setup

— Health concerns- Ionizing radiation

Probable solution -Virtual Imaging Trials (VITs)

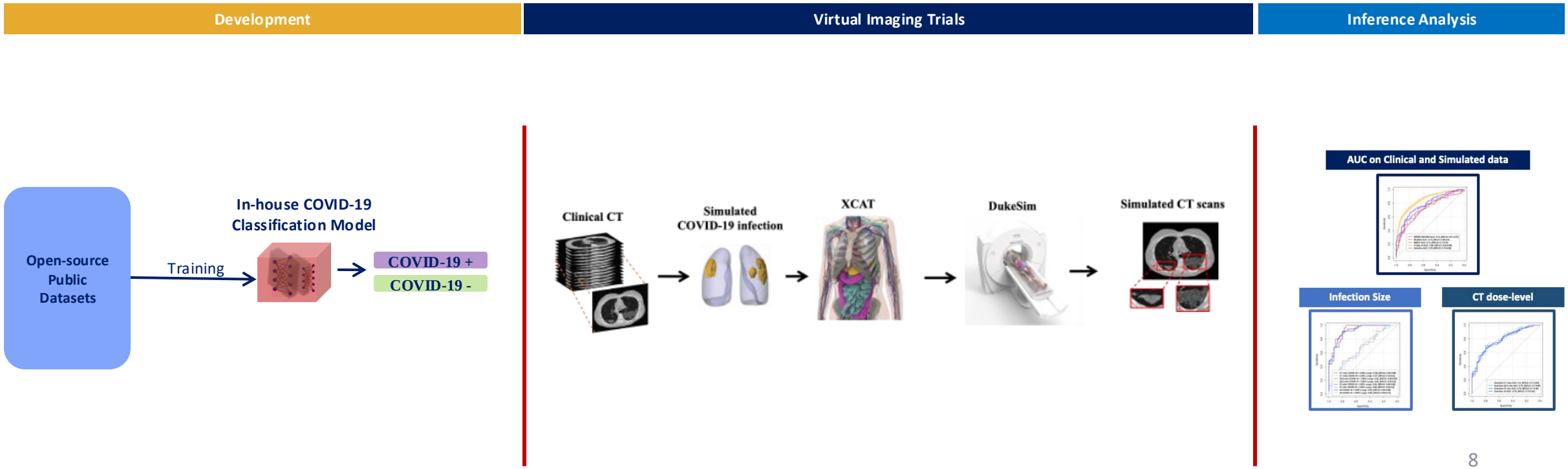


— **Virtual imaging trial** (VIT) is a process of simulating imaging evaluations with varying factors such as **computational human phantoms** (CPs), **imaging scanner systems**, and **virtual readers** .

—**AI** model belongs in the **virtual reader** category.

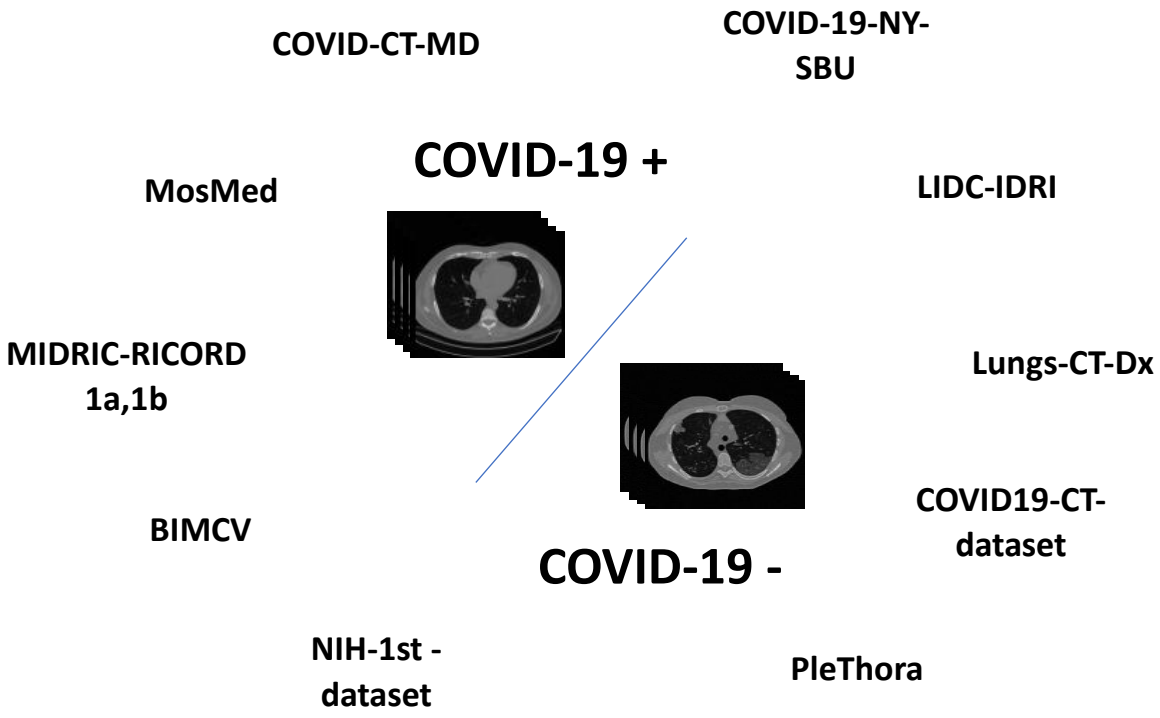
Method| Study Design

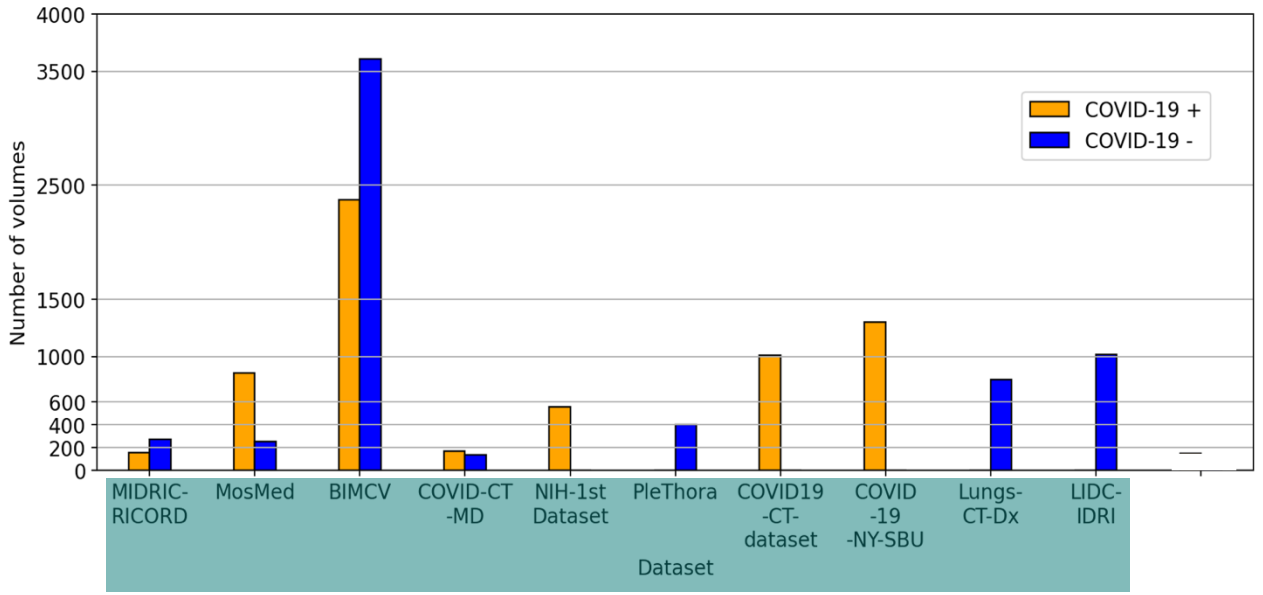
- Open-Source clinical data for model development.
- Generating Simulated CT scans utilizing VITs platform.
- Clinical Vs . Virtual performance analysis.



Method| Open-source Datasets

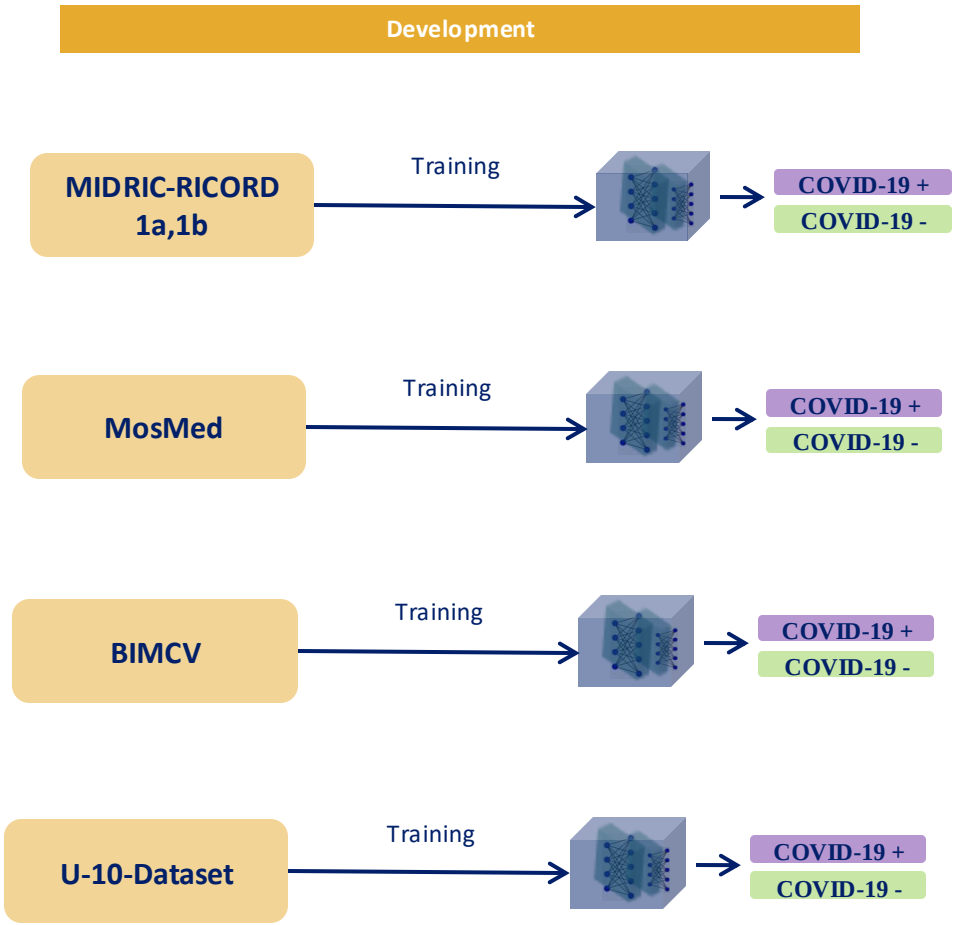
12,000+ open-source clinical CT scans from 6,847 patients.



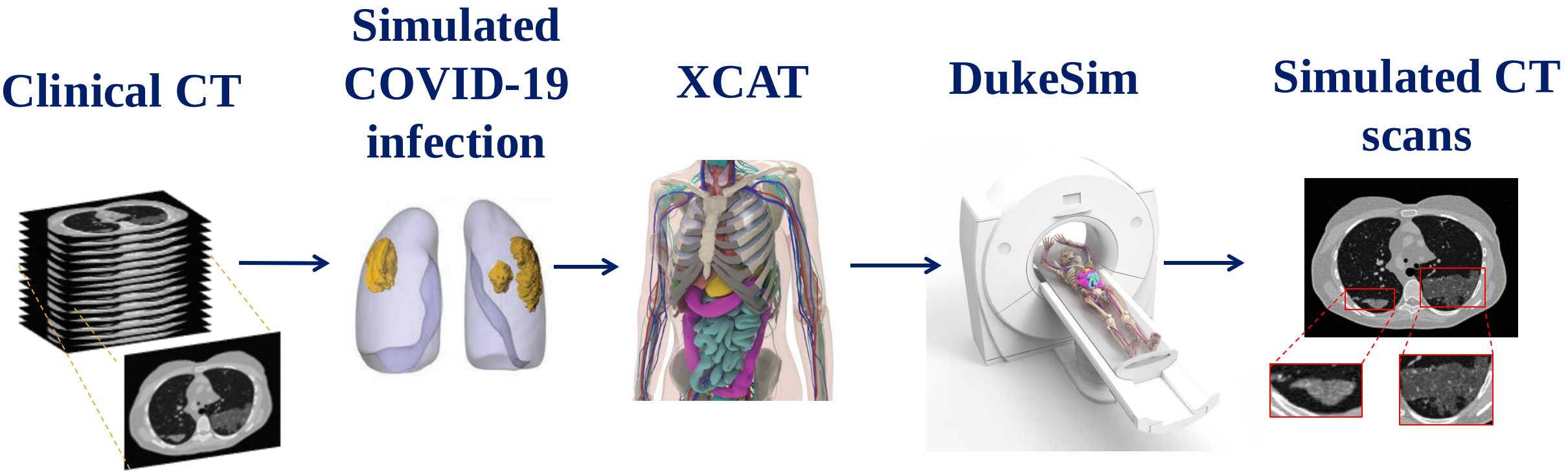


U-10 Dataset

Method| Model Development



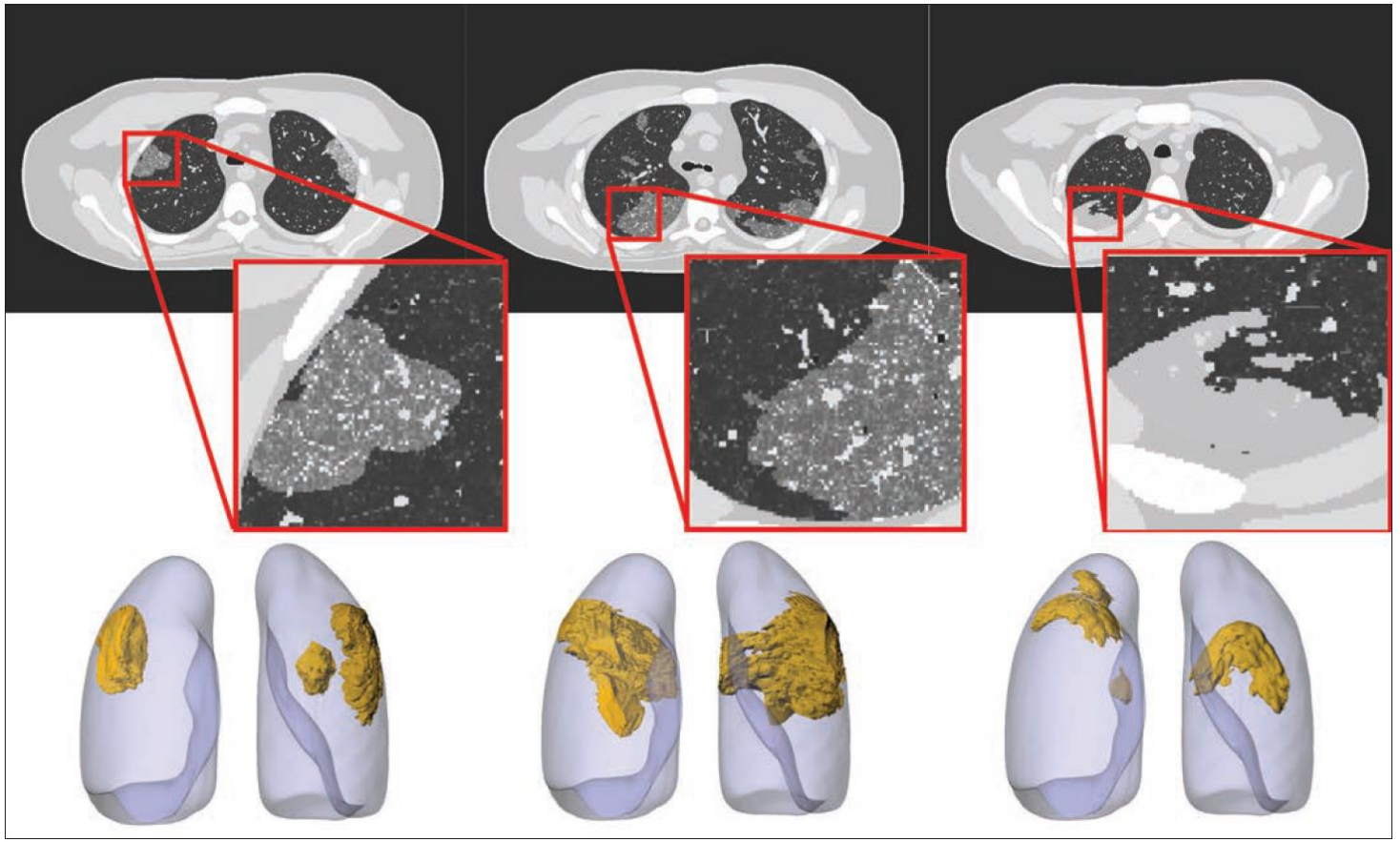
Method| Virtual Imaging Trials (VITs)



E. Abadi, W. Paul Segars, H. Chalian, and E. Samei, "**Virtual Imaging Trials for Coronavirus Disease (COVID-19)**," AJR Am J Roentgenol, vol. 216, no. 2, pp. 362-368, Feb 2021, doi: 10.2214/AJR.20.23429.

Method | Virtual Imaging Trials (VITs)

Ground Truth 4D **XCAT COVID-19 phantoms**



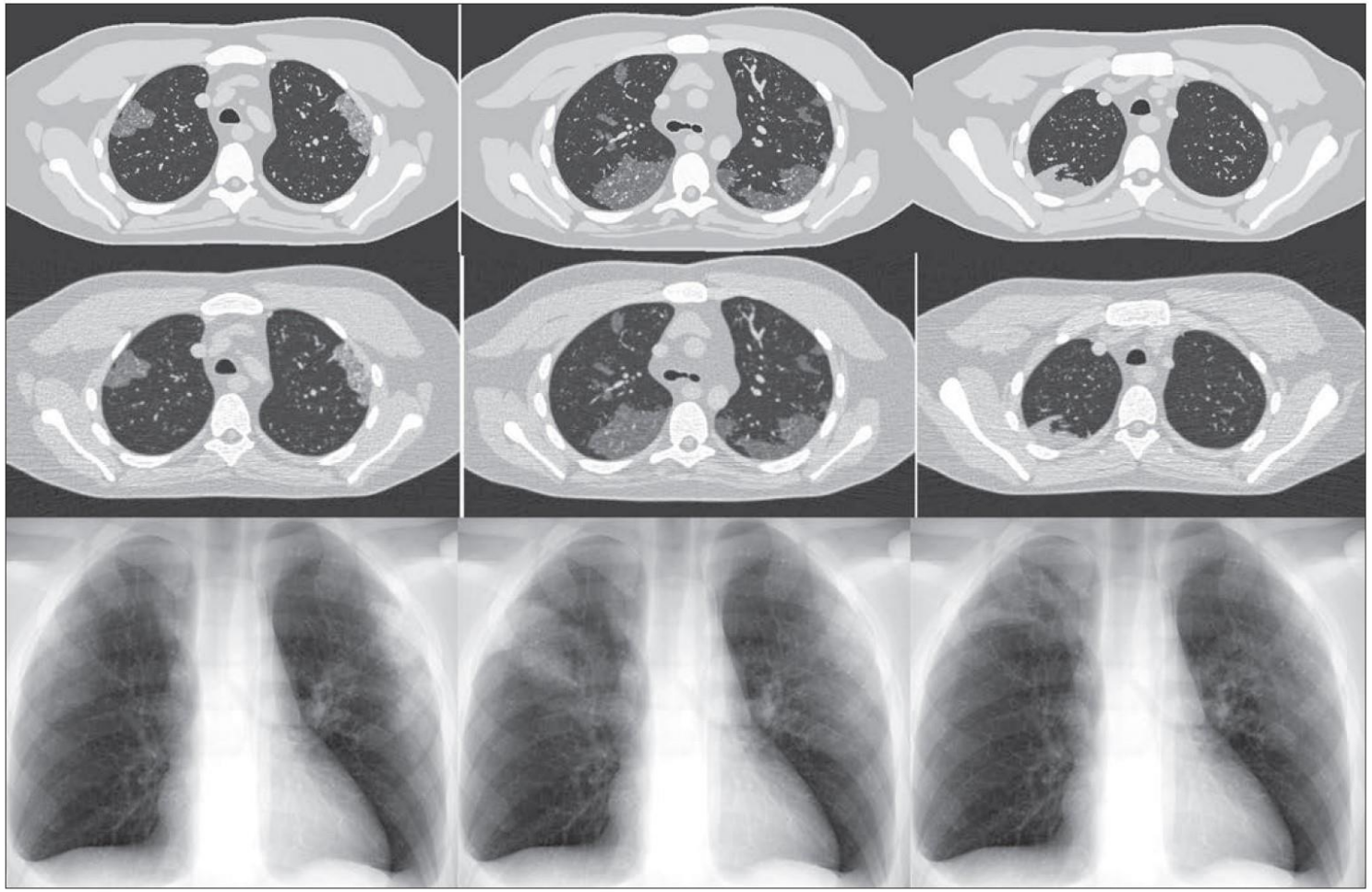
E. Abadi et al. (2021).

Method | Virtual Imaging Trials (VITs)

4D **XCAT phantom** developed at Duke University

Simulated CT

Simulated Xray



E. Abadi et al. (2021).

Method | Virtual Imaging Trials (VITs)

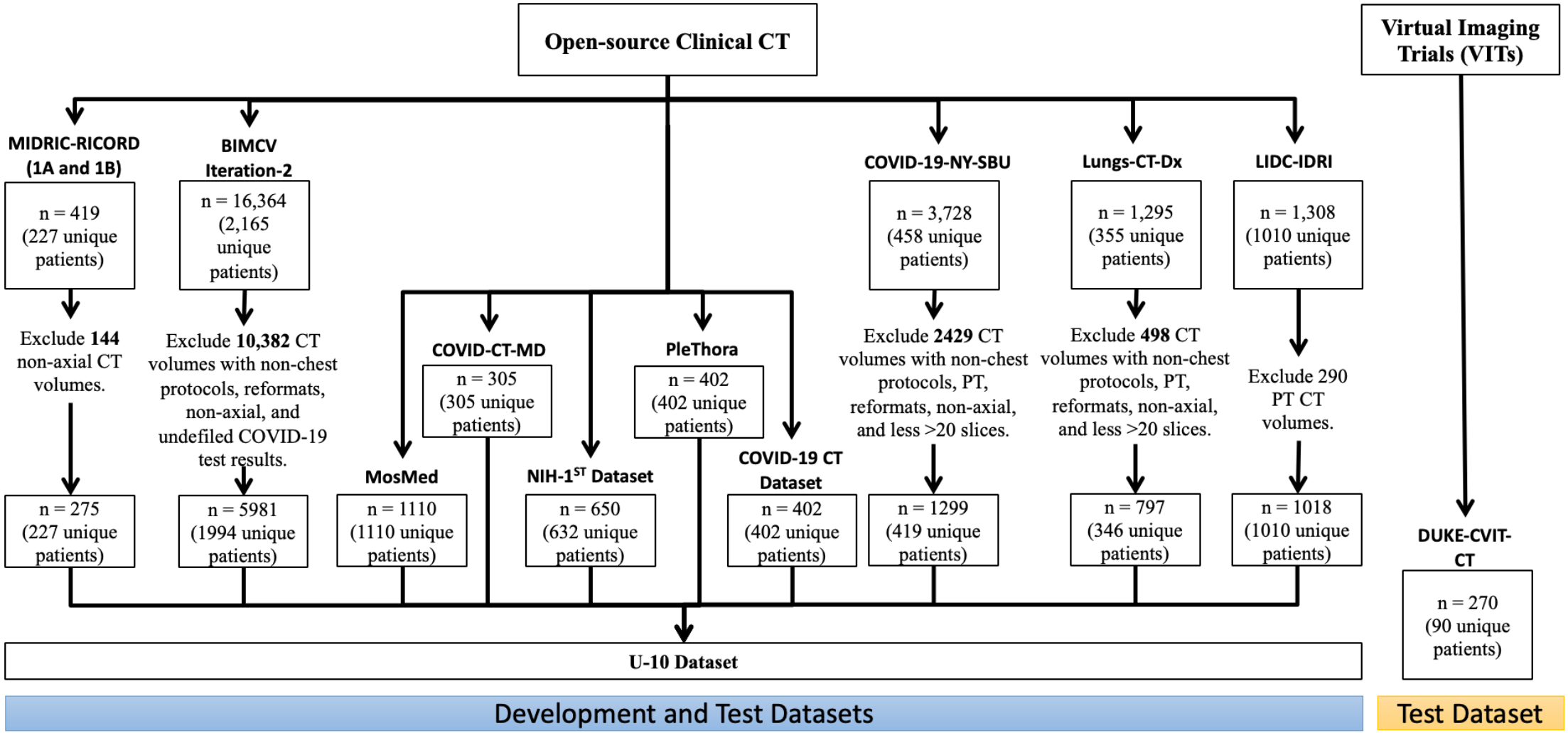
Duke-CVIT-CT / DukeSim Dataset

Dose Level (mAs)	Number of Volume	
	COVID-19	Normal
5.7	50	40
28.5	50	40
57	50	40
Total	**150**	**120**

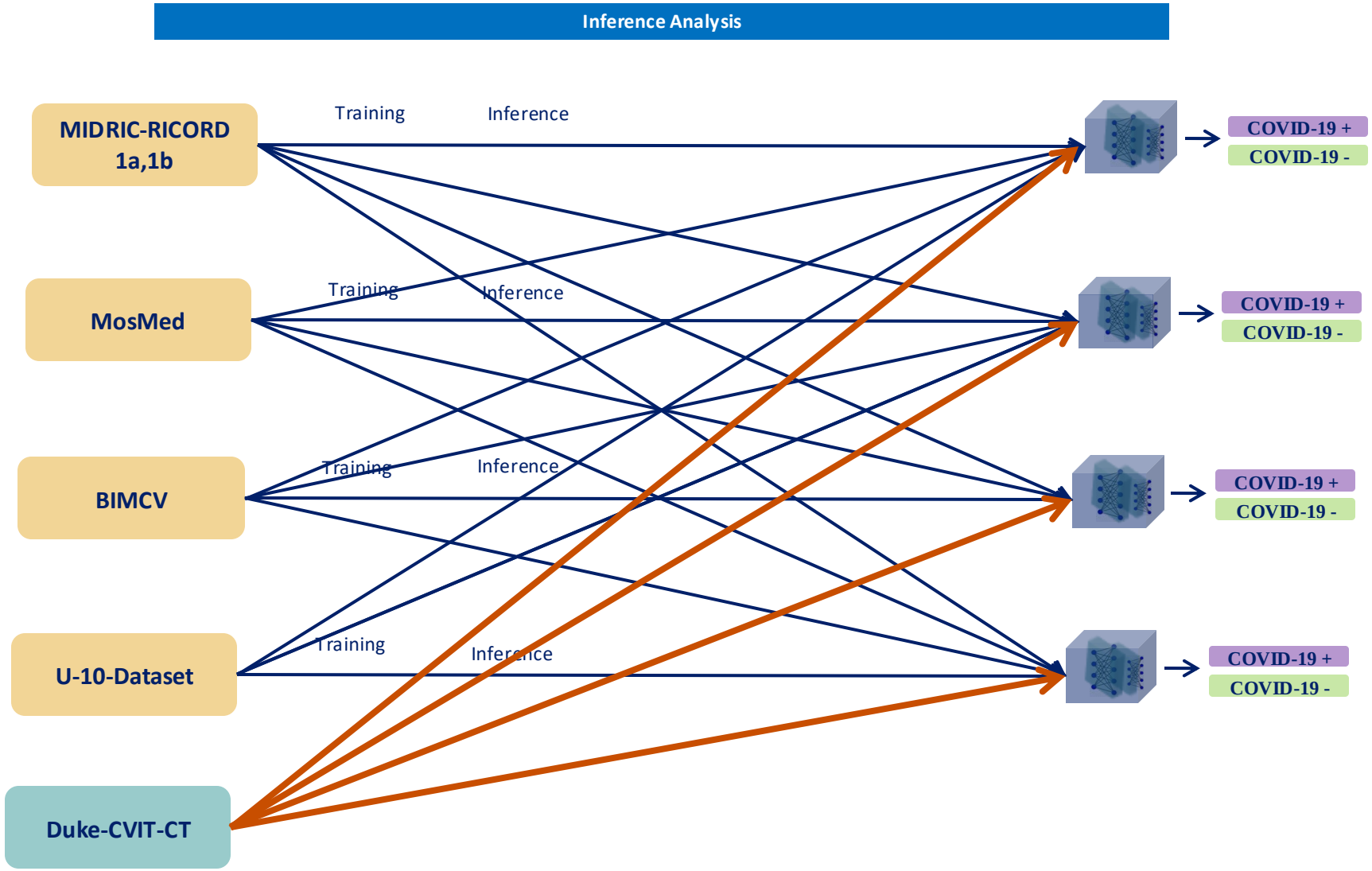
Method | Clinical Vs Virtual Data

Datasets	Class Type		Label Level			Same CT scan with multiple dose levels
	COVID-19 positive	COVID-19 negative	Patient-level	Slice-level	Pixel-level	
MIDRIC-RICORD						

Method | Inclusion and Exclusion



Method| Inference



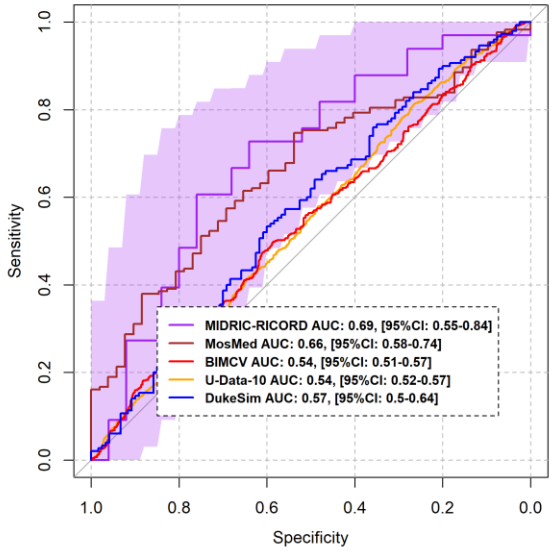
Results | Clinical and Virtual Data

Test (COVID+/-) / Training (COVID+/-)	MIDRIC-RICORD *(33/25)	MosMed (174/52)	BIMCV-V2 (470/823)	U-10-Dataset (1159/1201)	Duke-CVIT-CT (150/120)
MIDRIC-RICORD (90/72)	**0.69** [0.55,0.84]	0.66 [0.58,0.74]	0.54 [0.51,57]	0.54 [0.52-0.57]	0.57 [0.50,0.64]
MosMed (512/152)	0.76 [0.64,0.88]	**0.87** [0.81,0.92]	0.63 [0.60,0.66]	0.68 [0.66,0.70]	0.69 [0.63,0.76]
BIMCV-V2 (1421/2077)	0.64 [0.49,0.78]	0.58 [0.50,0.67]	**0.77** [0.74,0.79]	0.68 [0.66,0.70]	0.68 [0.62,0.75]
U-10-Dataset (3926/3768)	0.74 [0.61,0.87]	0.73 [0.66,0.80]	0.73 [0.70,0.76]	**0.85** [0.84,0.86]	0.79 [0.73,0.84]

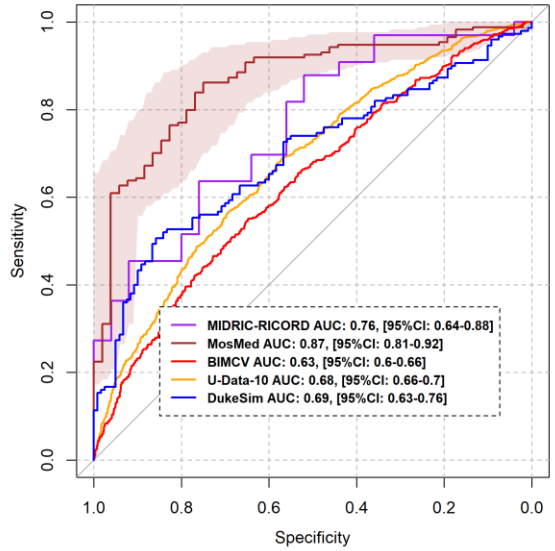
Results | Clinical and Virtual Data

Performance dropped due to domain-shift, simulated data consistent with multiple clinical test set.

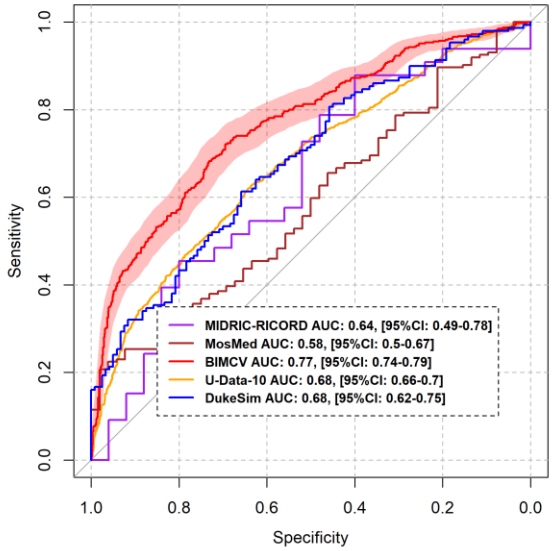
Model MIDRIC-RICORD



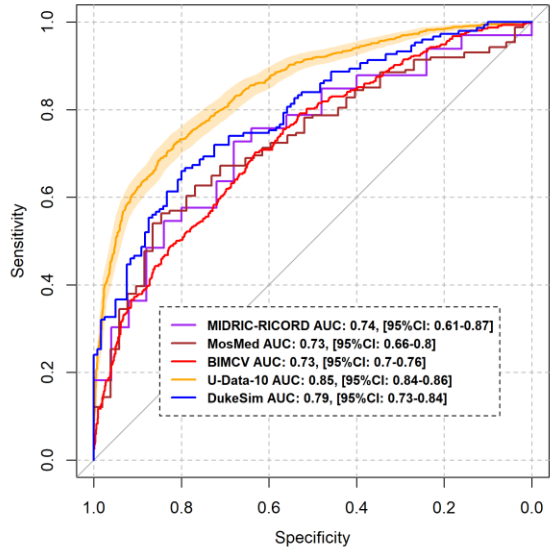
Model MosMed



Model BIMCV

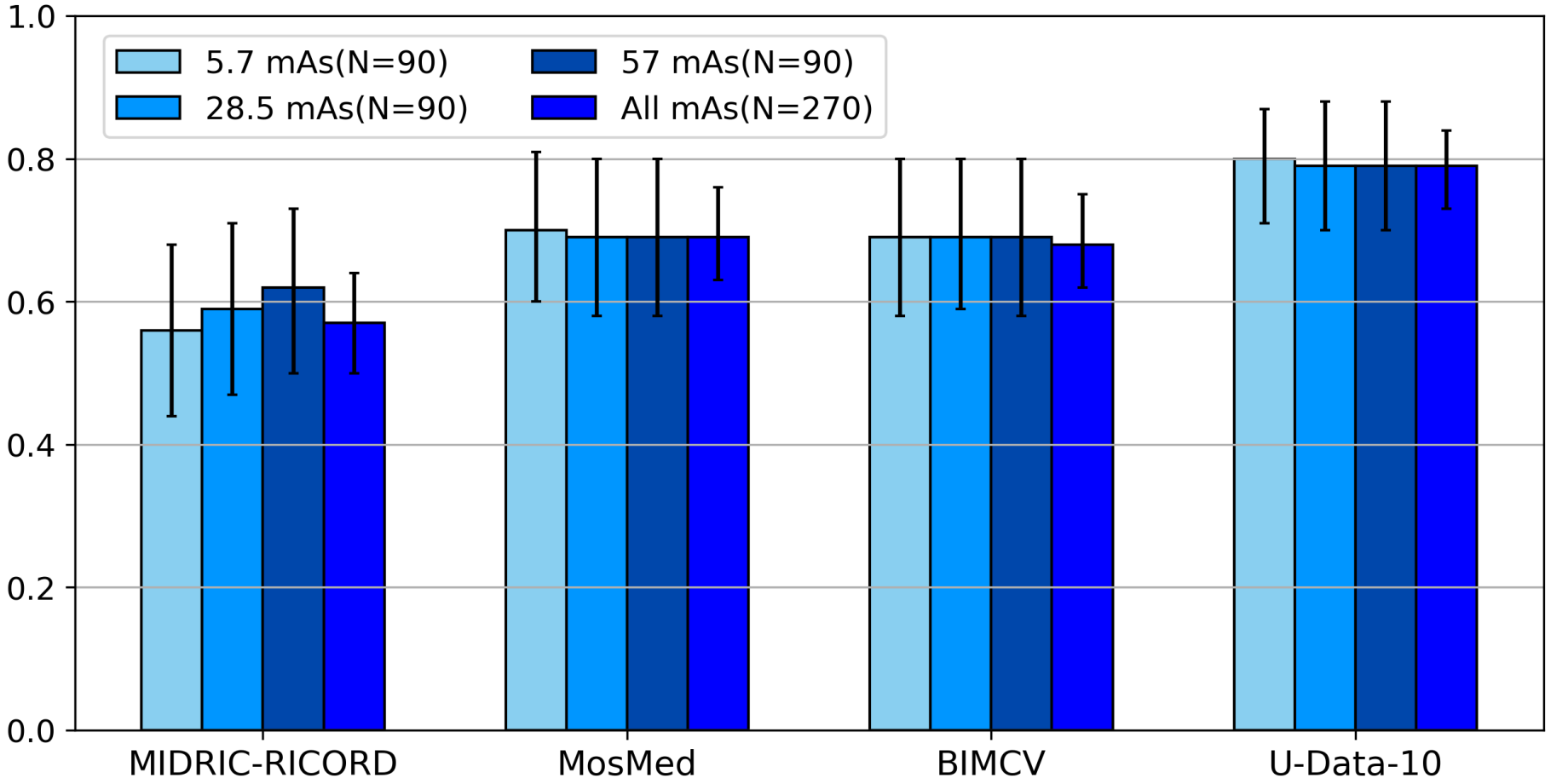


Model U-DATA-10

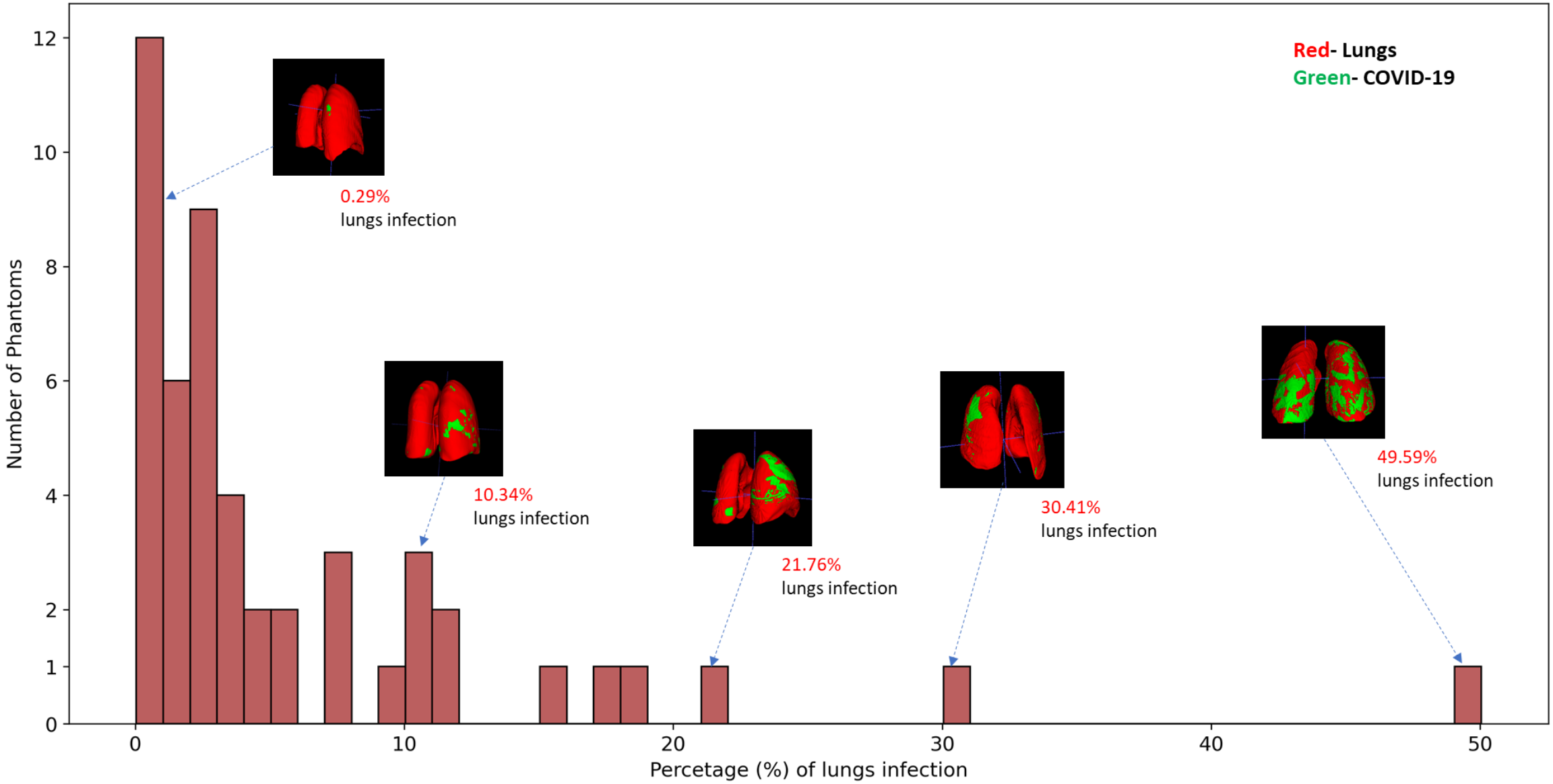


Results | Dose-level Analysis

No dose dependence for all models tested on simulated data



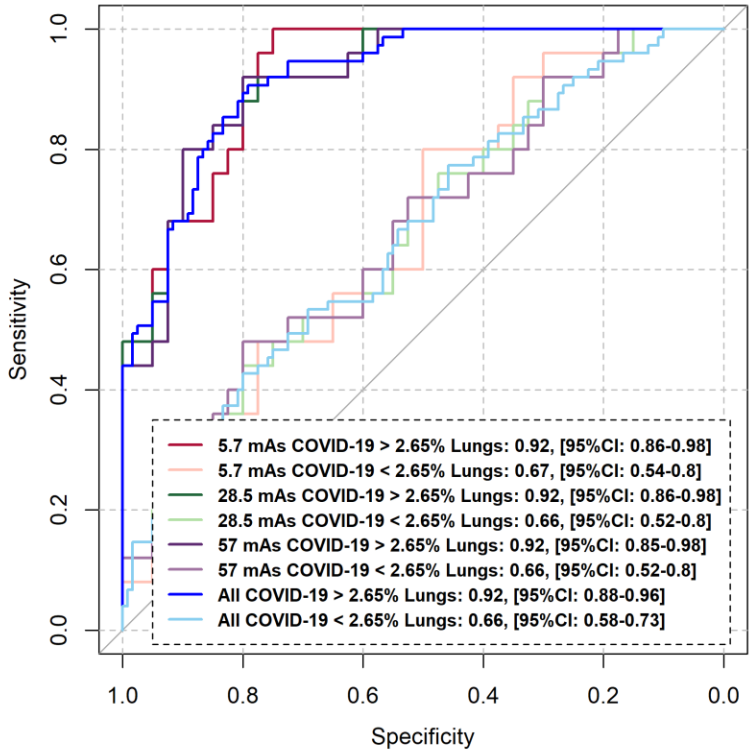
Results | COVID-19 Infection Size



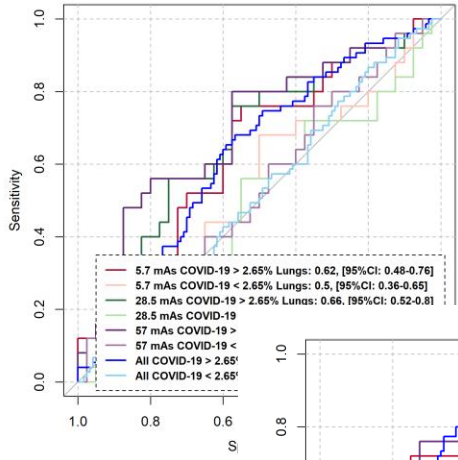
Results | COVID-19 Infection Size

Infection volume strongly affects performances across all models and doses

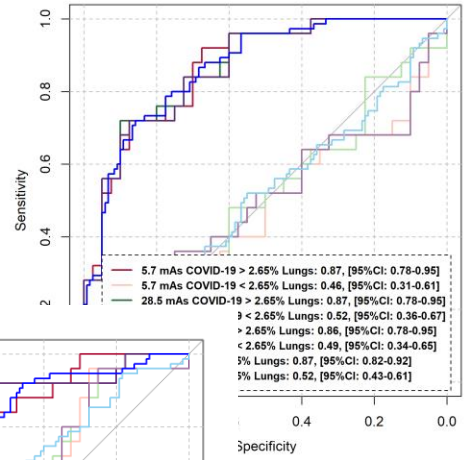
Model U-DATA-10



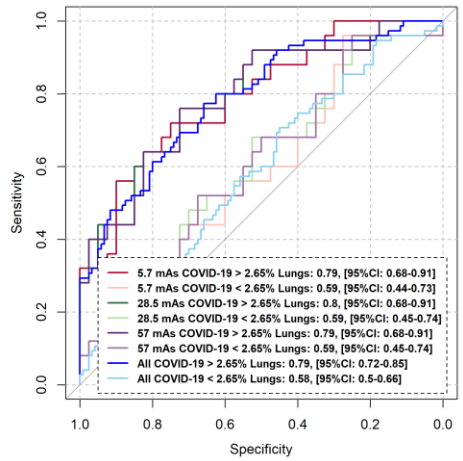
Model MIDRIC-RICORD



Model MosMed



Model BIMCV



Conclusion

- Performance dropped due to domain-shift, simulated data consistent with multiple clinical test set.
- No dose dependence for all models tested on simulated data.
- Infection volume strongly affects performances across all models and doses
- Virtual Imaging Trials make it possible to answer clinically relevant questions.

CVIT: A growing community…

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