

Data management tools and strategy for responsible imaging AI

Beebe Symposium March 13, 2025

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Disclosures

This work was supported in part by funding from the National Institutes of Health:

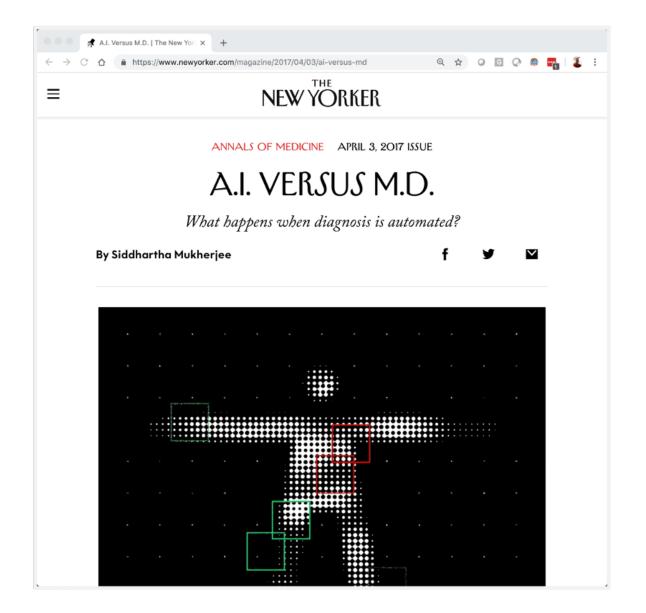
Ro1EB009352, U24CA258483, U24CA253531

I have an ownership interest and may financially benefit if the company is successful in marketing its products that are related to this research:

White Rabbit, Embark Labs, and Sora

Neuroscience

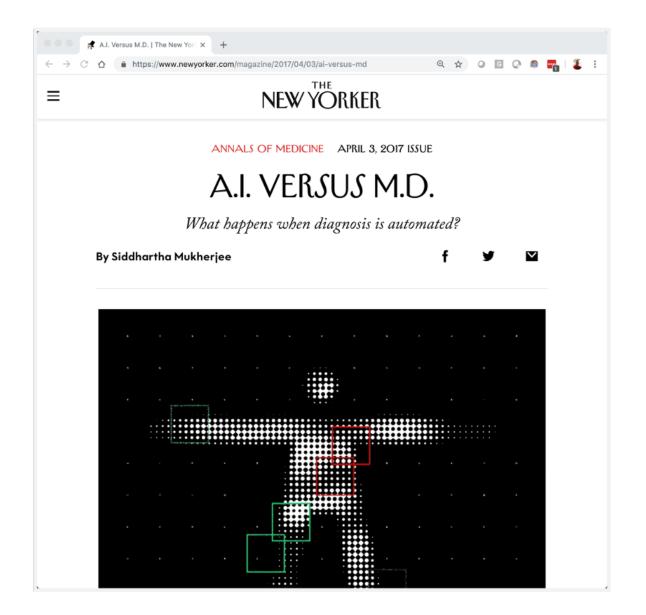
Is imaging AI ready for clinical use?



"I think that if you work as a radiologist you are like Wile E. Coyote in the cartoon. You're already over the edge of the cliff, but you haven't yet looked down. There's no ground underneath. It's just completely obvious that in five years deep learning is going to do better than radiologists. It might be ten They should stop training vears. radiologists now."

— Geoffrey Hinton, 2017

Is imaging AI ready for clinical use?



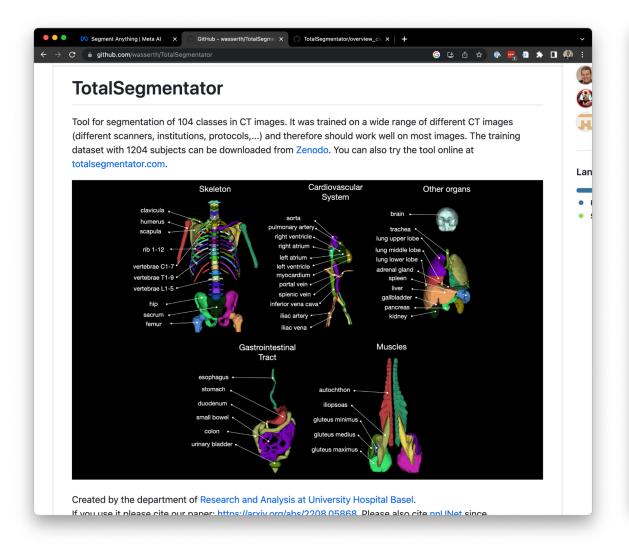
"Deep-learning platform detects malignant nodules on x-ray, beating radiologists"

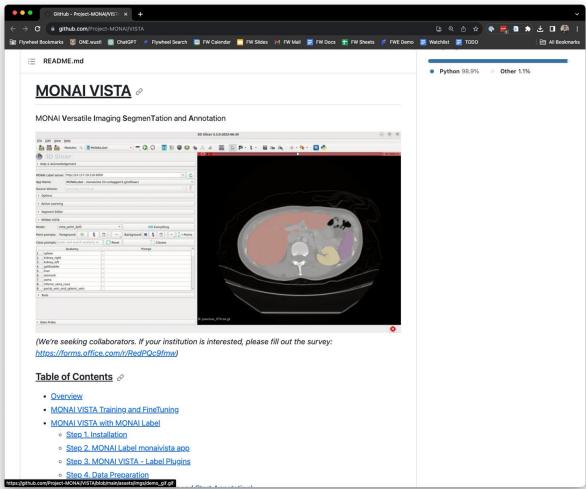
"Chinese Al Beats Doctors in Diagnosing Brain Tumors"

"Deep learning beats radiologists at fibrotic lung disease classification"

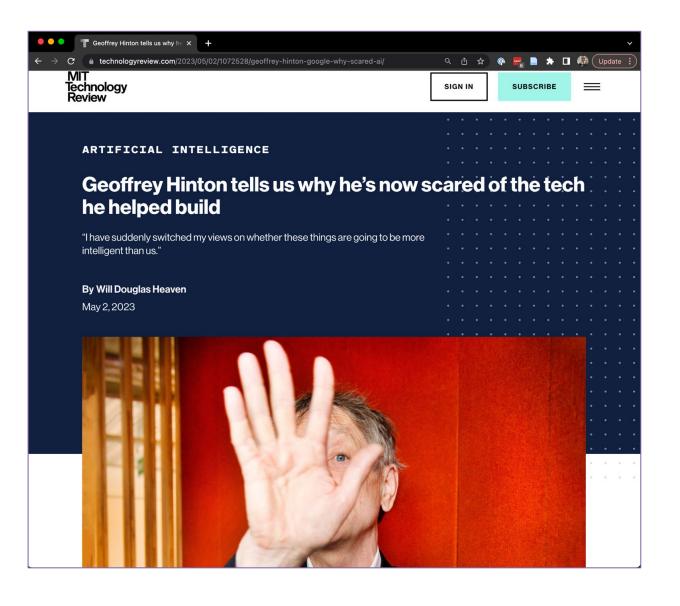
"Al system beats team of 15 doctors in competition"

It is getting pretty good





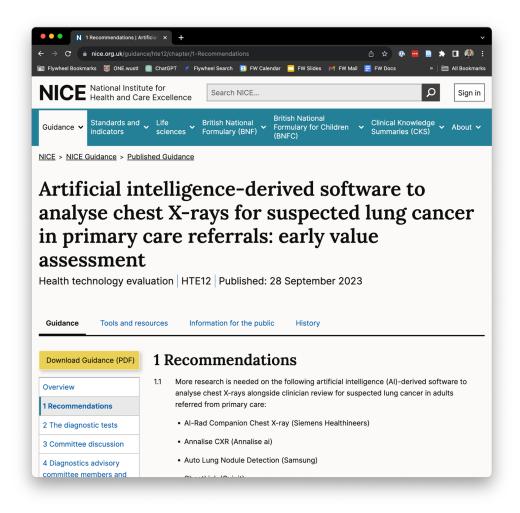
Any thoughts Geoff?



"I have suddenly switched my views on whether these things are going to be more intelligent than us. I think they're very close to it now and they will be much more intelligent than us in the future. How do we survive that?"

Geoffrey Hinton, May, 2023, upon resigning as head of AI at Google

Even though imaging AI is good... we've got issues



"More research is needed on the AI-derived software to analyse chest X-rays alongside clinician review."

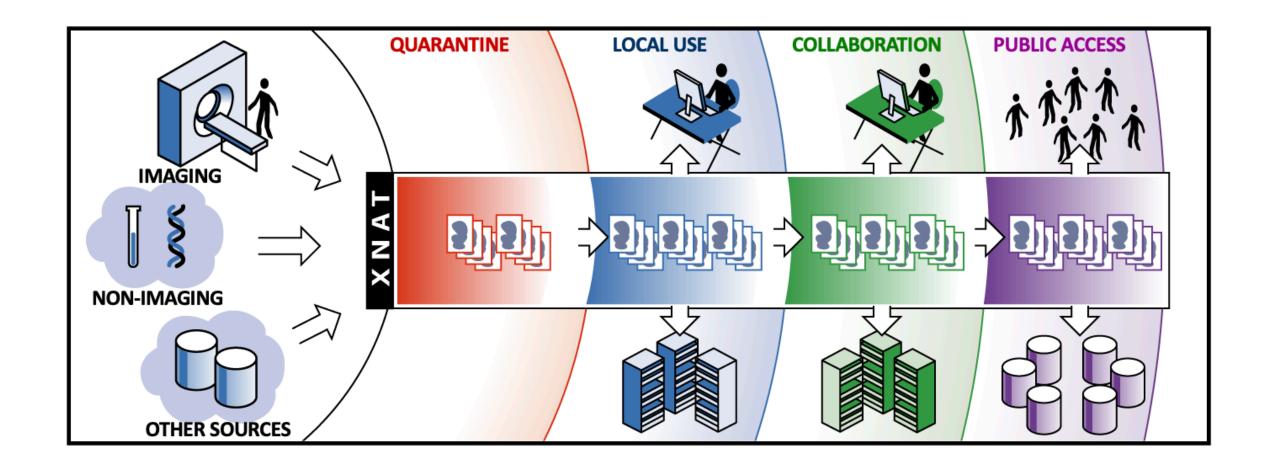
"With the available evidence, it is not possible to assess the clinical and cost benefits or risks of using the technology in the NHS. So, Al-derived software should not be used for clinical decision making in the NHS until more evidence is available."

"There is no evidence to show how accurate softwareassisted clinician review will be at identifying lung abnormalities... Using this software could lead to lung cancer being missed."

Even though imaging AI is good... we've got issues

- Insufficient evidence of effectiveness and reliability.
- Insidious bias in algorithms.
- Unknown performance in local context (i.e. generalizability).
- Questionable impact on radiologist behavior and workflows.
- How can imaging informatics help address these issues?
 - Plumbing
 - Data

XNAT



XNAT is...

...a feature rich...

Archive, manage, process, view, and share imaging and related data.

...open...

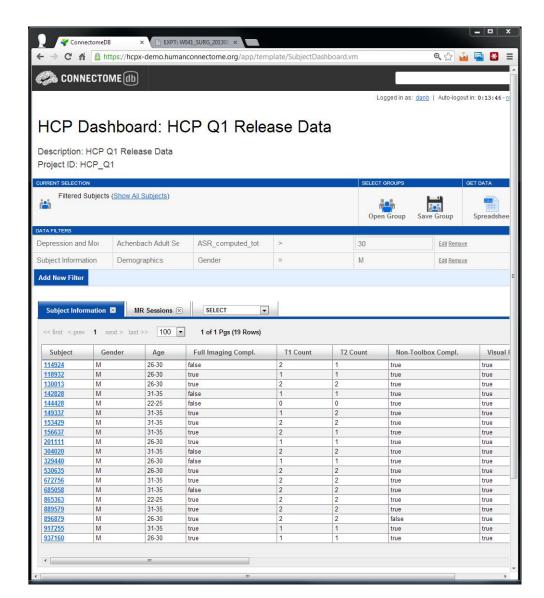
Open source Open API Free (though commercial support is available) Used by organizations around the world

...platform.

Clinical/translational research Institutional repositories Multi-center studies Data sharing

Primary Funding:

NIBIB R01 (Year 16) NCI ITCR U24 (Year 8) Commercial open source software

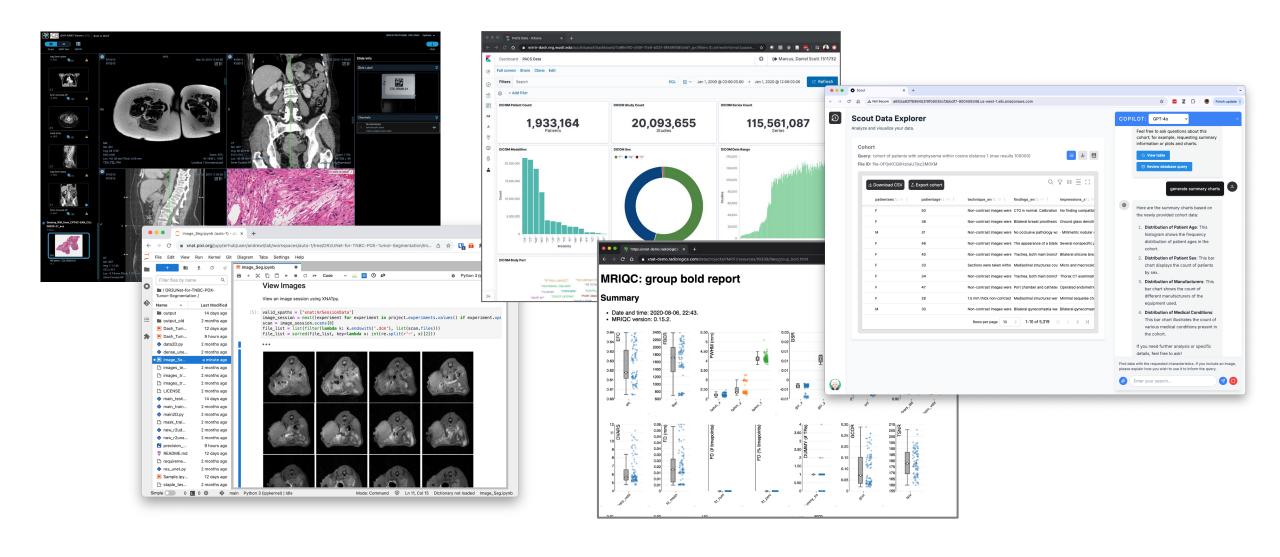


I3CR: XNAT for cancer research



INGEST CURATE **ANNOTATE COMPUTE ANALYZE PUBLISH** DICOM send from scanner Automated image QC OHIF integration Docker Container Service Standalone Jupyter Data sharing across projects • DICOM retrieve from PACS · Manual image review • Manual annotation tools • HPC integration (Slurm, integration • Data sharing across nodes • Pre-archive data staging • CLARA-based ML service • Federated datasets across Web-based upload (ROI, angles, lines, etc.) Torque, PBS, etc.) Metadata anonymization Scan type harmonization Al-assisted annotation Batch processing dashboard • Scriptable data sets for instances · Live Tensorboard and Automated export to public Pixel anonymization Group-level image statistics Templatized assessment training, test, validation Face scrubbing • Linked clinical, genetic, and stdout/stderr monitoring • Scriptable analysis with data repositories (e.g. TCIA) forms Support for all imaging other non-imaging data • Rapid reader module · Event-based container Python and Groovy Automated export to cloud modalities. Automated format · Blinded reader mode • Integrations with common automation storage • Export models to clinical • Support for all file formats Radreport.org integration analysis tools (3D Slicer, conversion (DICOM, NIFTI, TIFF, etc.) application hosts (e.g. Sectra MITK, CapTk, etc.) Amplifier)

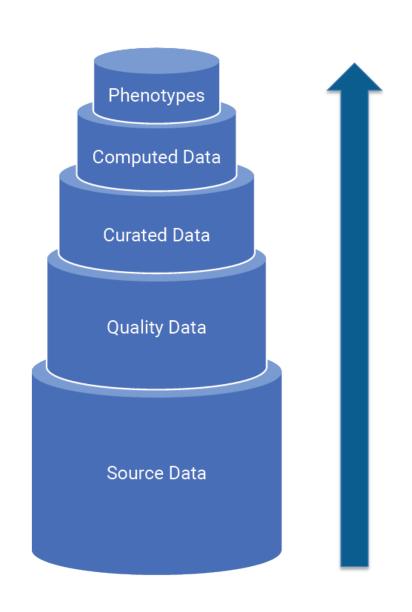
I3CR: XNAT for cancer research



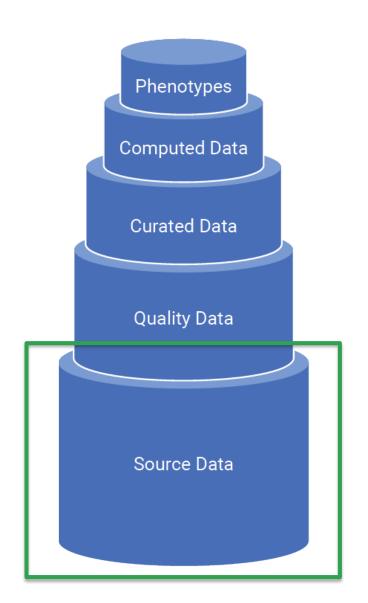
The Feature Stack



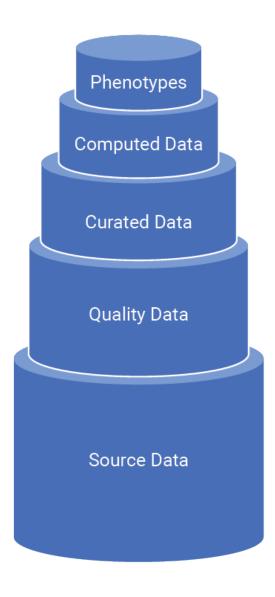
The Feature Stack



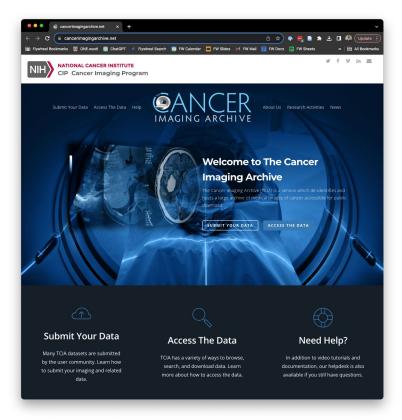
Al enables us to move up the stack to characterize patients in more detail and produce more meaningful & clinically reliable outcomes.



• The raw data on which all subsequent work is done.



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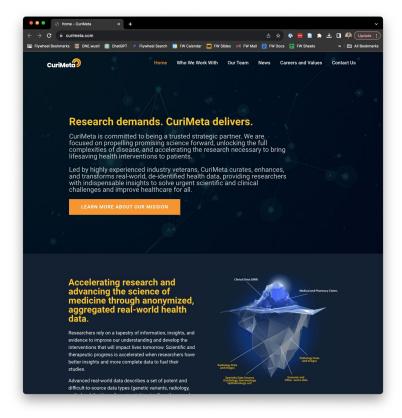


Open Data Resources

- TCIA, MIDRC, Hugging Face, etc.
- Free! (Usually.)
- Regularly used for challenges, can serve as common reference points.
- Limited outcomes and other related metadata.
- Limited novelty and specificity.

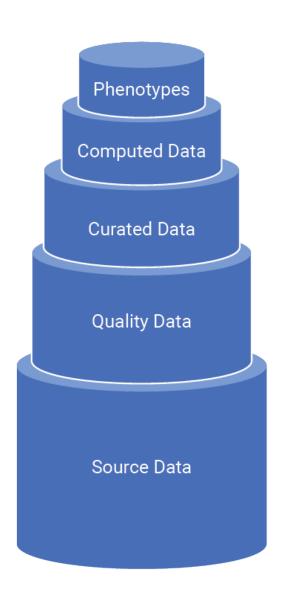


The raw data on which all subsequent work is done.

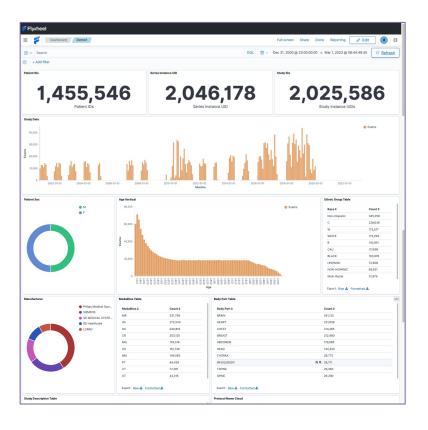


Commercial Data

- Gradient Health, CuriMeta, etc.
- Costly! (Always.)
- Tuned to needs of project
- Typically well validated and well characterized.
- Time to access ranges from instantaneous to protracted.



• The raw data on which all subsequent work is done.

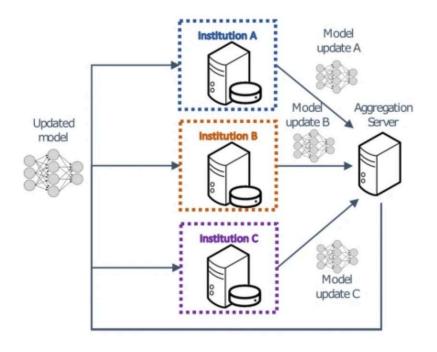


Institutional Data

- Clinical PACS, research data sets
- Low cost! (If you're lucky enough to be in clinical research setting.)
- Scale to fit project
- Cohort identification is up to researcher
- Time to access depends on institution

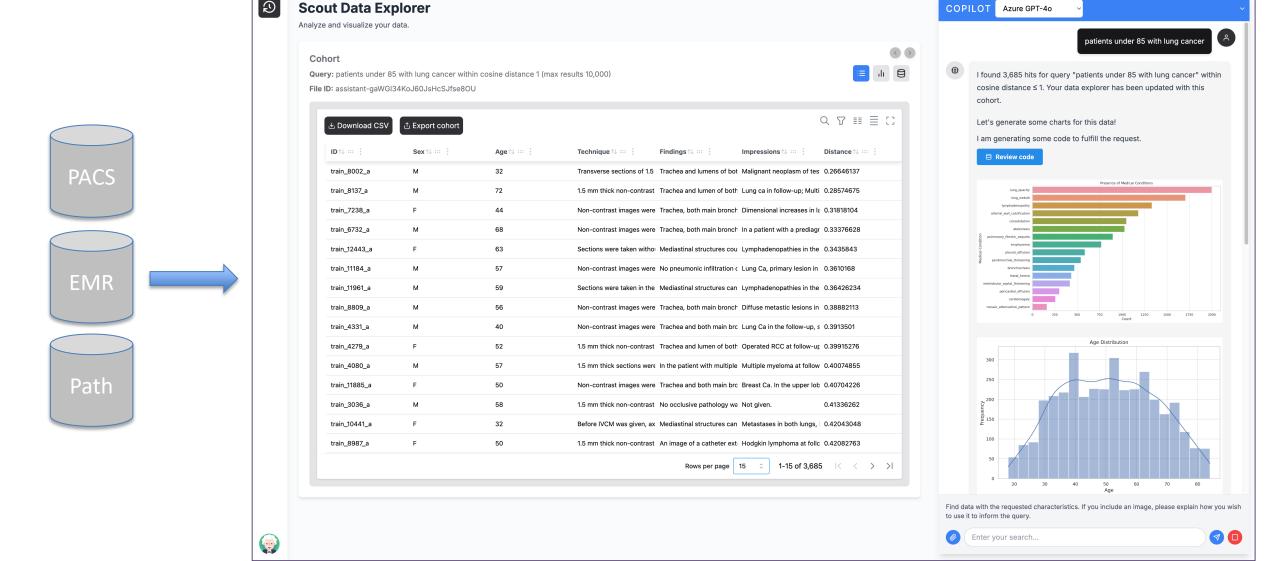


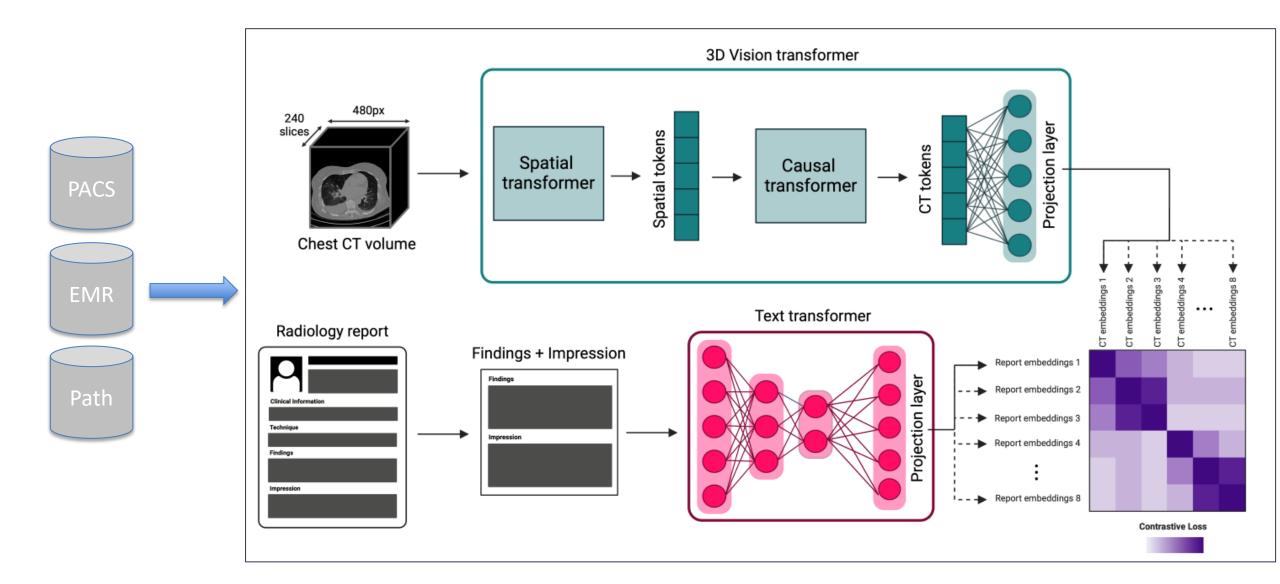
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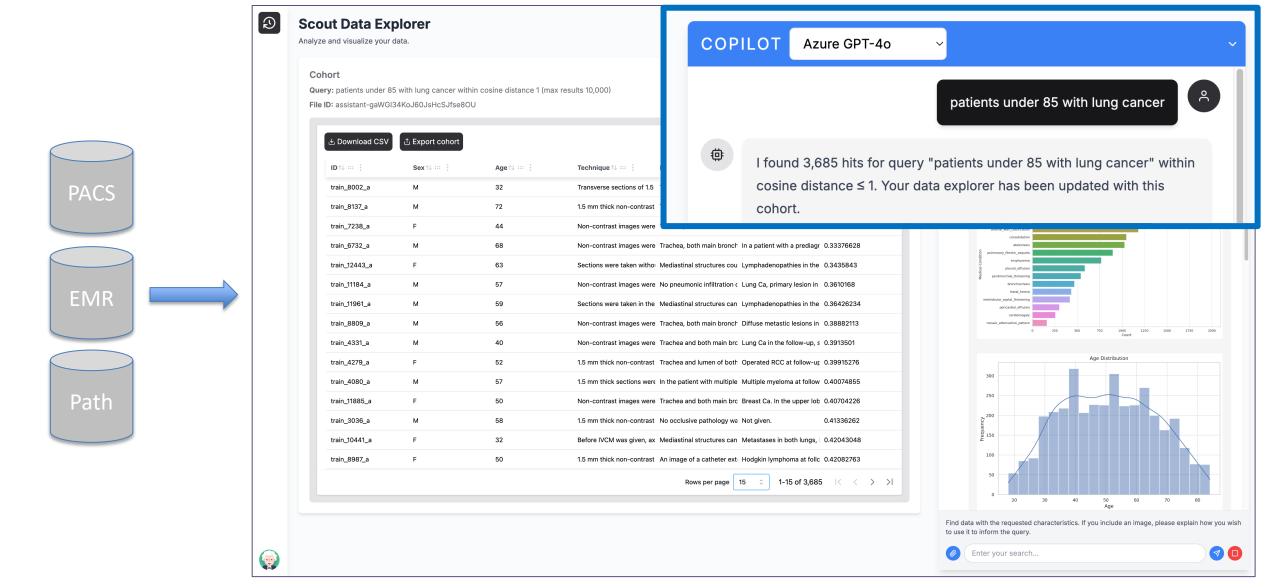


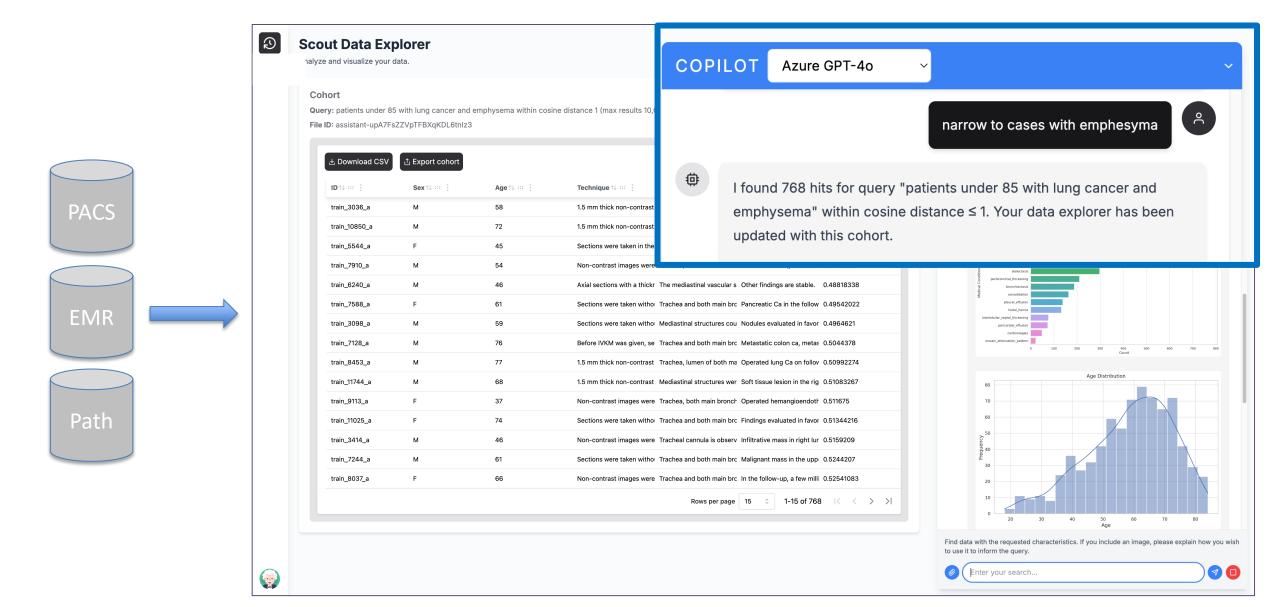
Federated Data

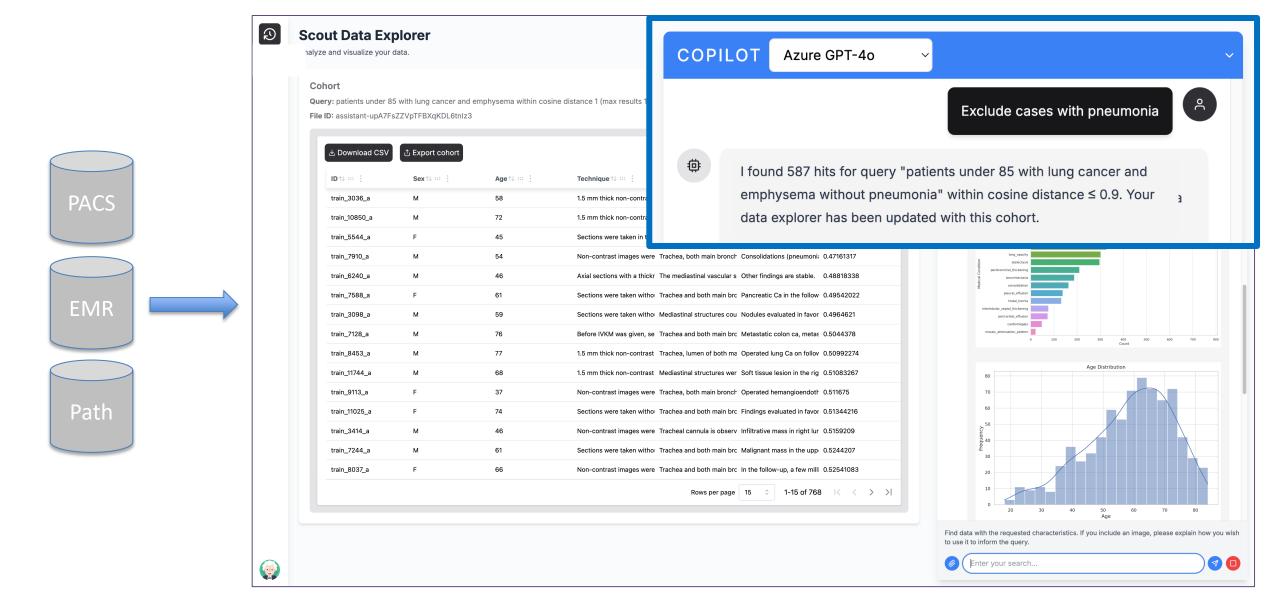
- Localized data aggregated at the time of training/analysis.
- Supports more diverse data sets.
- Manages data privacy concerns.
- Introduces new challenges in model development, validation, maintenance.

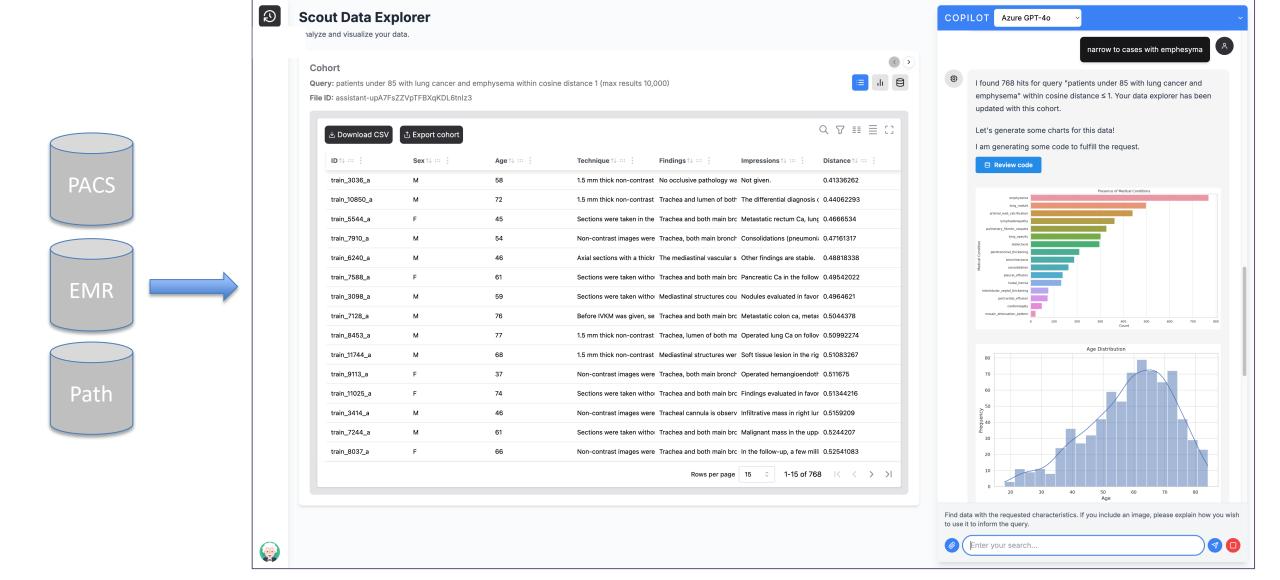


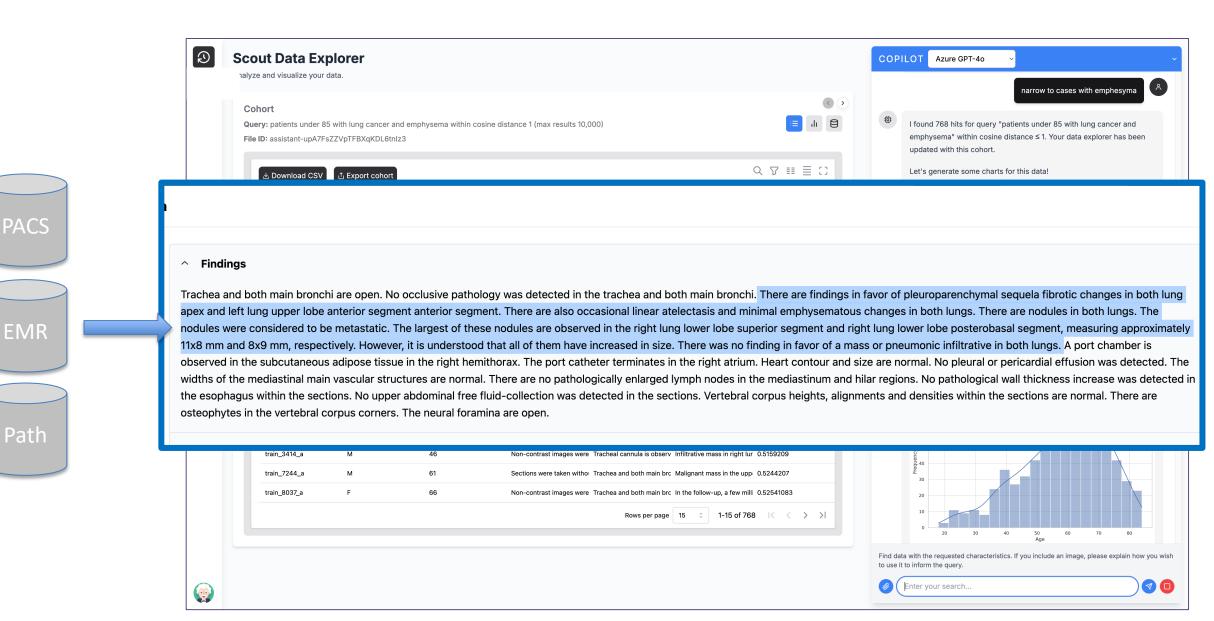


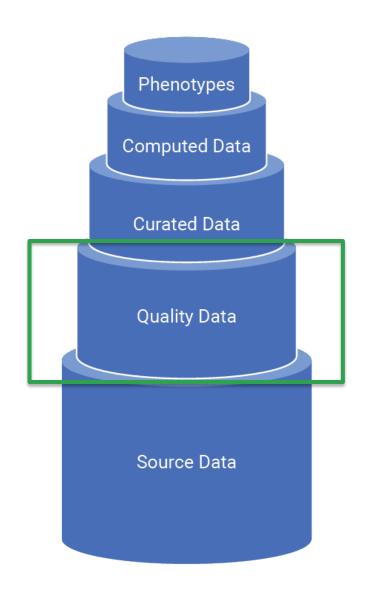




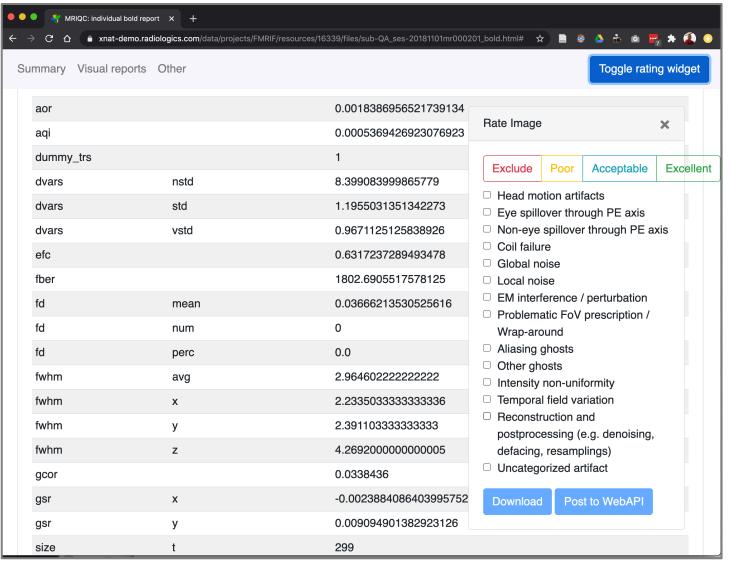




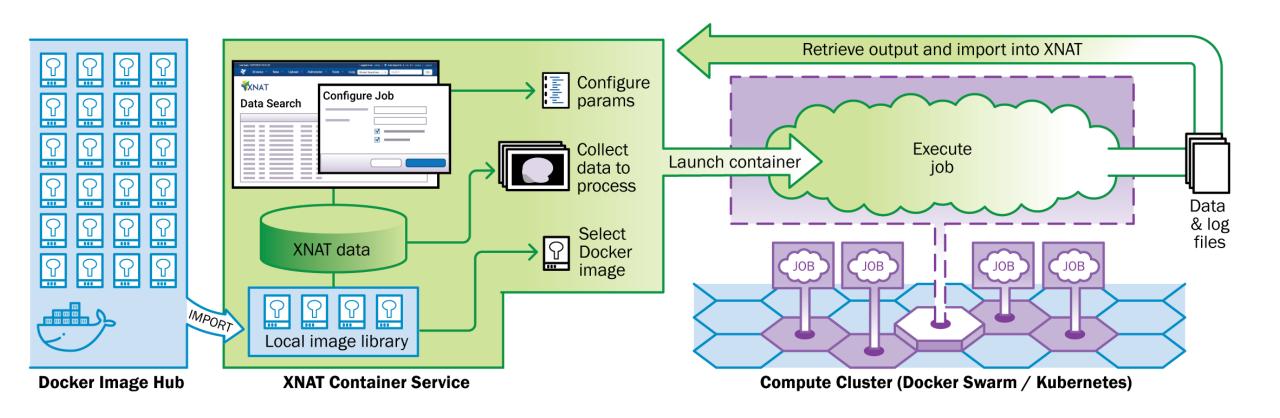


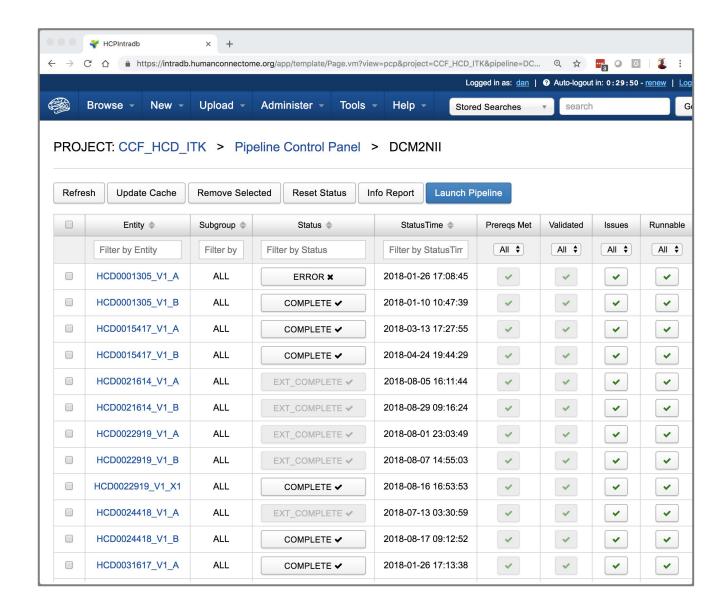


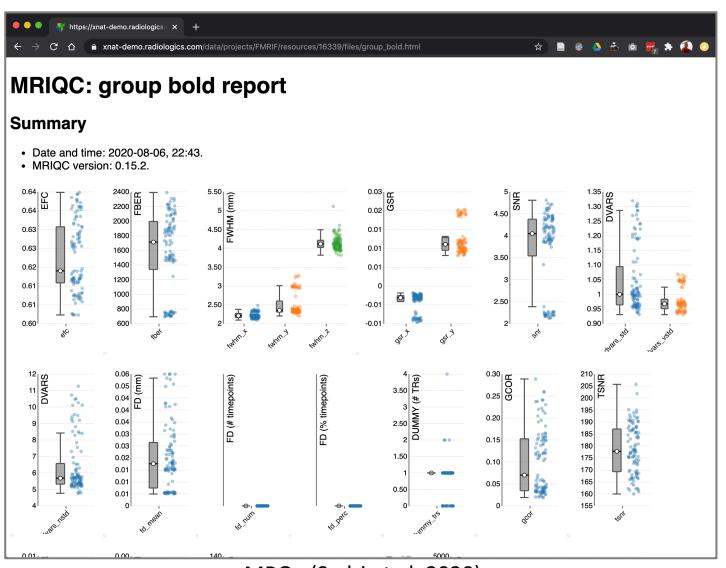
- Data on which quality metrics have been obtained systematically to drive subsequent decisions.
- Quality is always an issue, but it's potentially a bigger issue with quantification.
- "Low" quality isn't necessarily bad, but it needs to be understood.
- E.g. if quality is different by site, geography, demographics, etc, you need to ensure that measurements aren't biased.



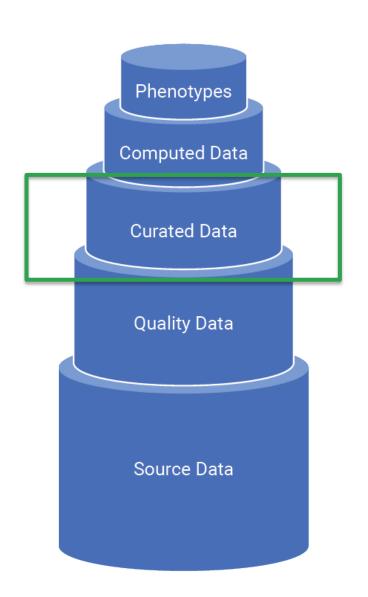
MRQy (Sadri et al, 2020)



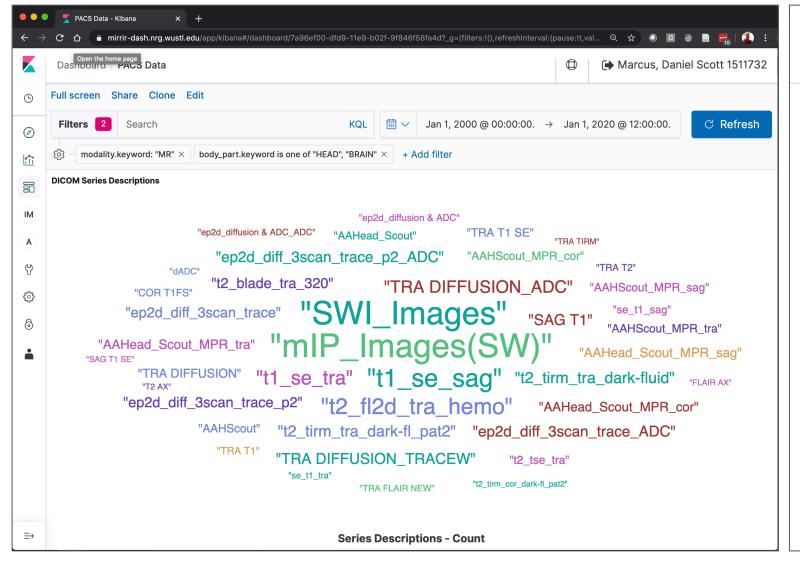




MRQy (Sadri et al, 2020)



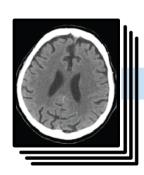
- Data curation tasks include harmonization, labelling, annotating, sorting, and organizing.
- Curation is traditionally manual, time consuming and error prone.
- All is really good at handling disparate data, so it's particularly suitable for automating curation tasks.



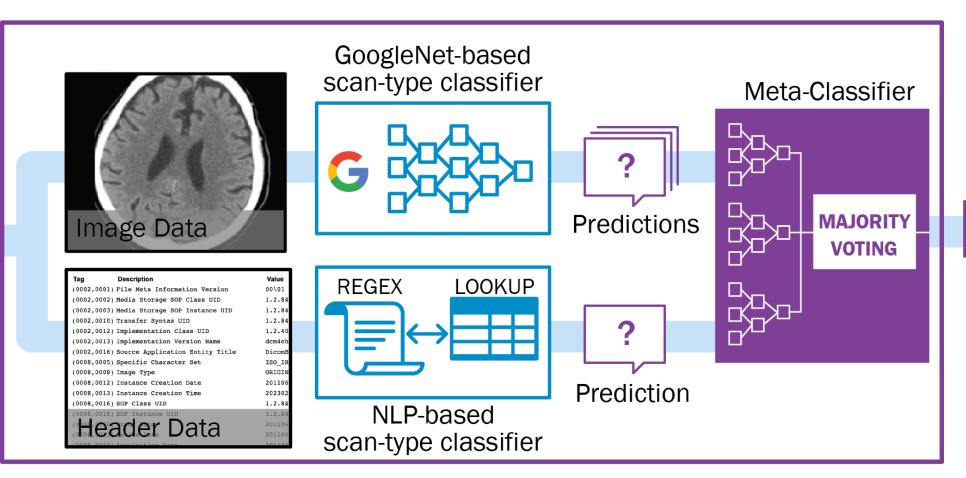
DICOM Series Descriptions

Series Descriptions	Count
"mIP_Images(SW)"	67,135
"SWI_Images"	67,053
"t1_se_sag"	50,716
"t2_fl2d_tra_hemo"	43,570
"t1_se_tra"	37,099
"TRA DIFFUSION_ADC"	31,353
"t2_tirm_tra_dark-fl_pat2"	28,995
"t2_tirm_tra_dark-fluid"	28,657
"ep2d_diff_3scan_trace_p2_ADC"	27,426
"TRA DIFFUSION_TRACEW"	27,009
"SAG T1"	26,830
"ep2d_diff_3scan_trace_ADC" \oplus \bigcirc	26,259
"ep2d_diff_3scan_trace"	26,011
	25.222



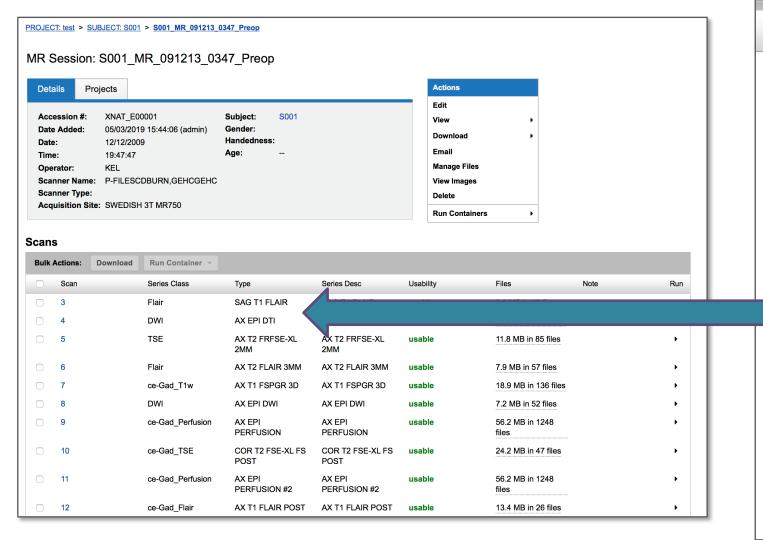


Brain CT Scan

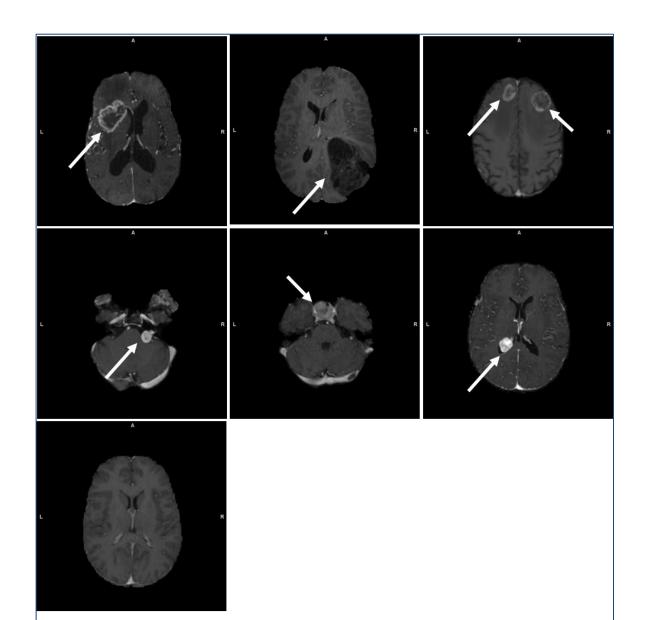


Scan

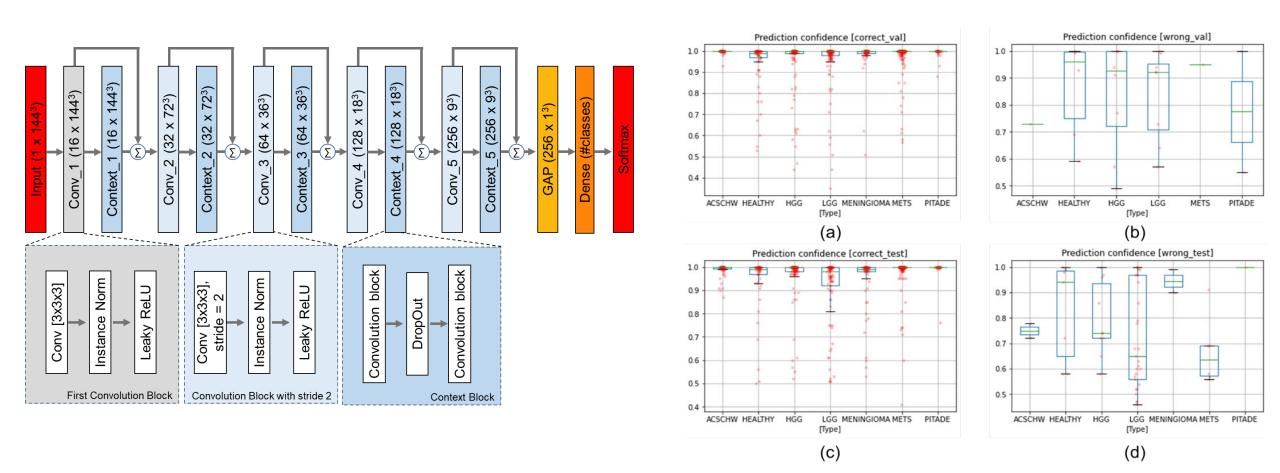
Label



Series Class	Туре
Flair	SAG T1 FLAIR
DWI	AX EPI DTI
TSE	AX T2 FRFSE-XL 2MM
Flair	AX T2 FLAIR 3MM
ce-Gad_T1w	AX T1 FSPGR 3D
DWI	AX EPI DWI
ce-Gad_Perfusion	AX EPI PERFUSION
ce-Gad_TSE	COR T2 FSE-XL FS POST
ce-Gad_Perfusion	AX EPI PERFUSION #2
ce-Gad_Flair	AX T1 FLAIR POST

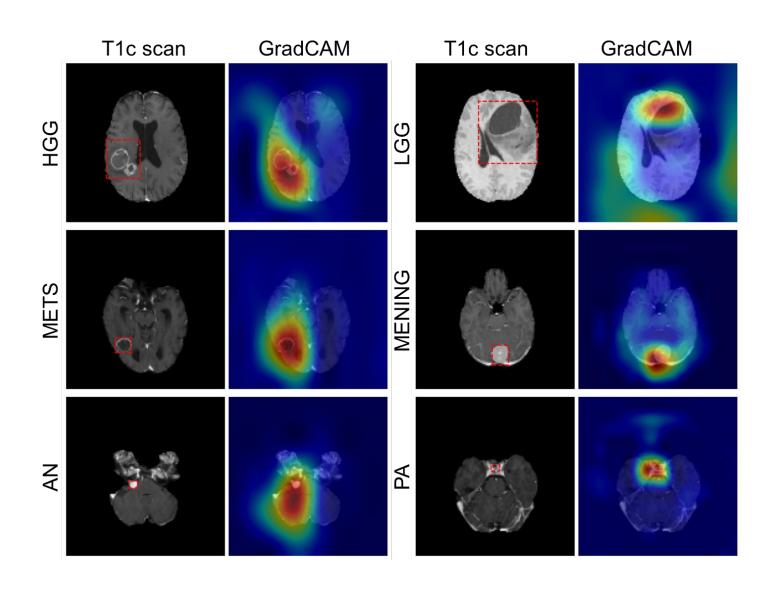


The Feature Stack: Curated Data

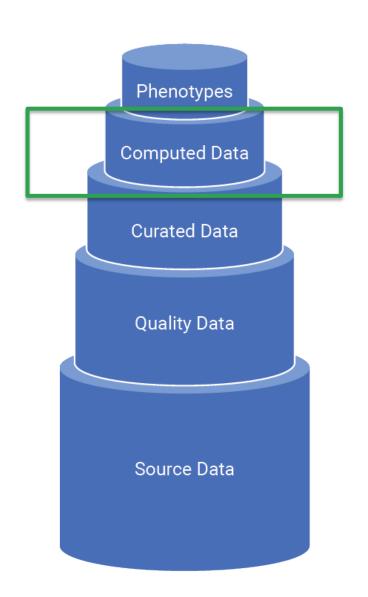


Chakrabarty et al, 2021

The Feature Stack: Curated Data



The Feature Stack: Computed Data



- Features extracted using computational methods including (but not limited to) AI.
- Computed features can be highly sensitive to underlying data distribution, so the preceding layers of the feature stack are critical.
- Computed features are analysis ready leaving image space and into numeric space.

The Feature Stack: Computed Data

Intensity-Based Features

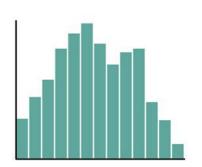
Histogram-Based Features

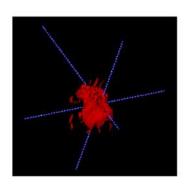
Volumetric & Morphologic Features

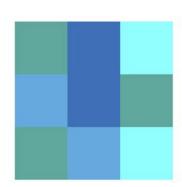
Textural Features

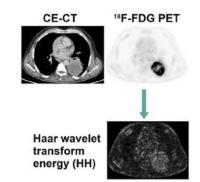
Higher Order Features



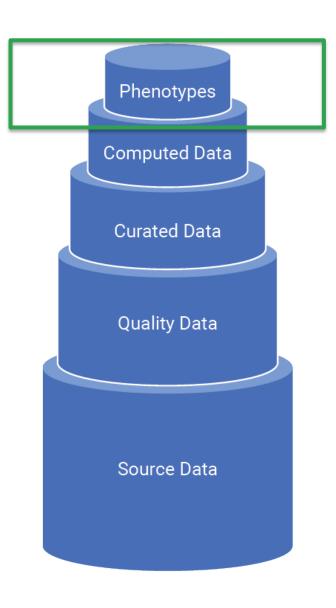






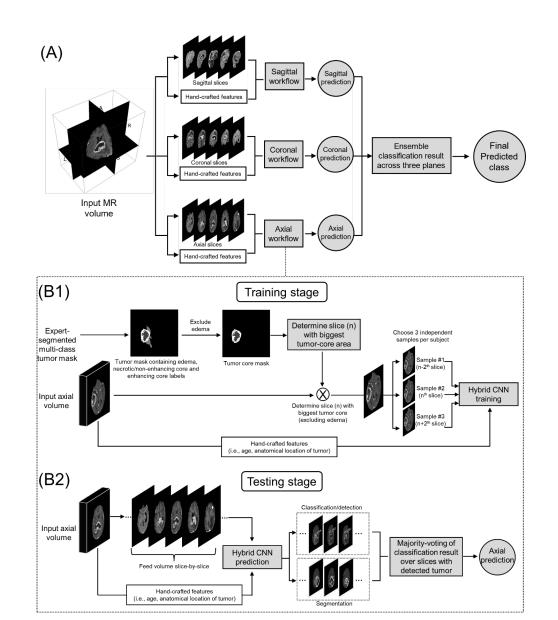


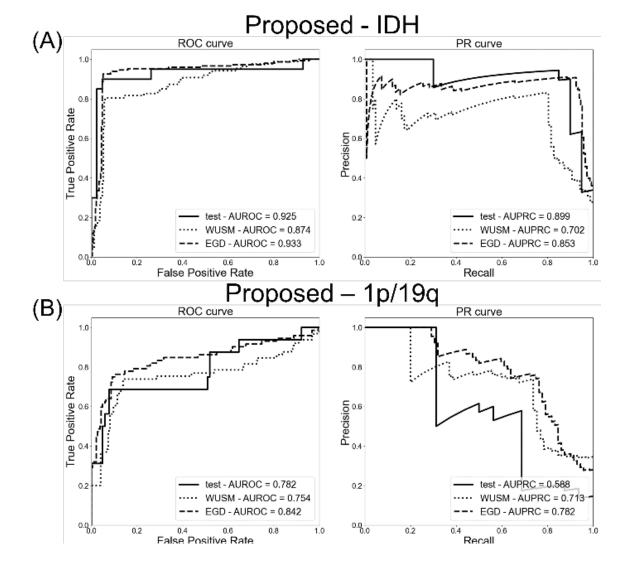
The Feature Stack: Phenotypes

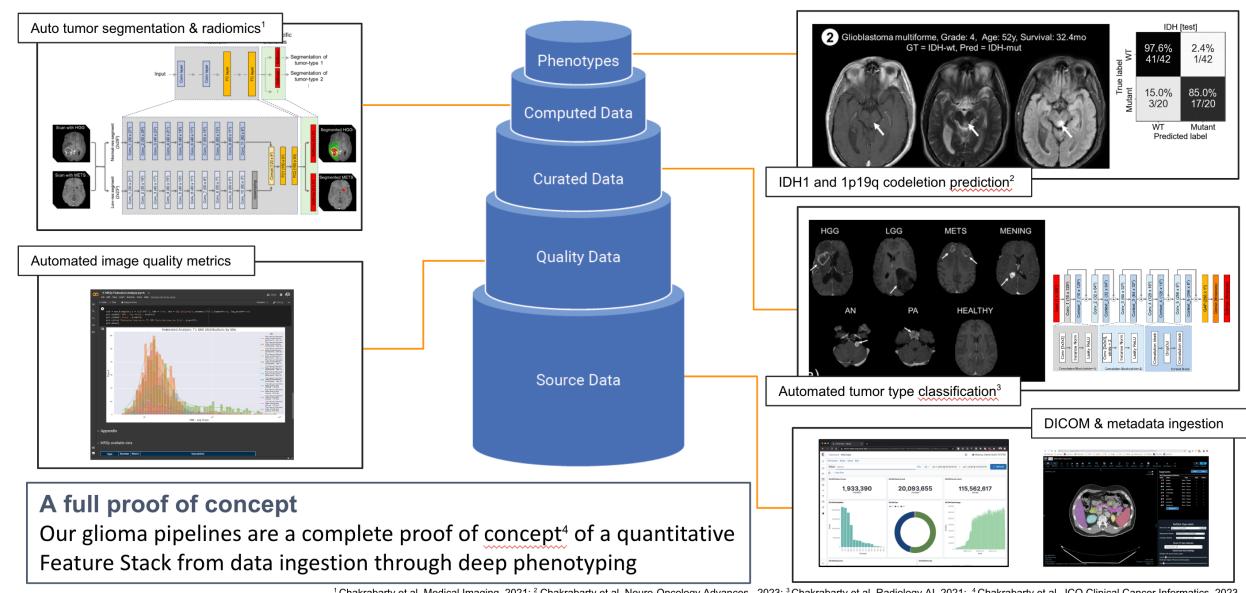


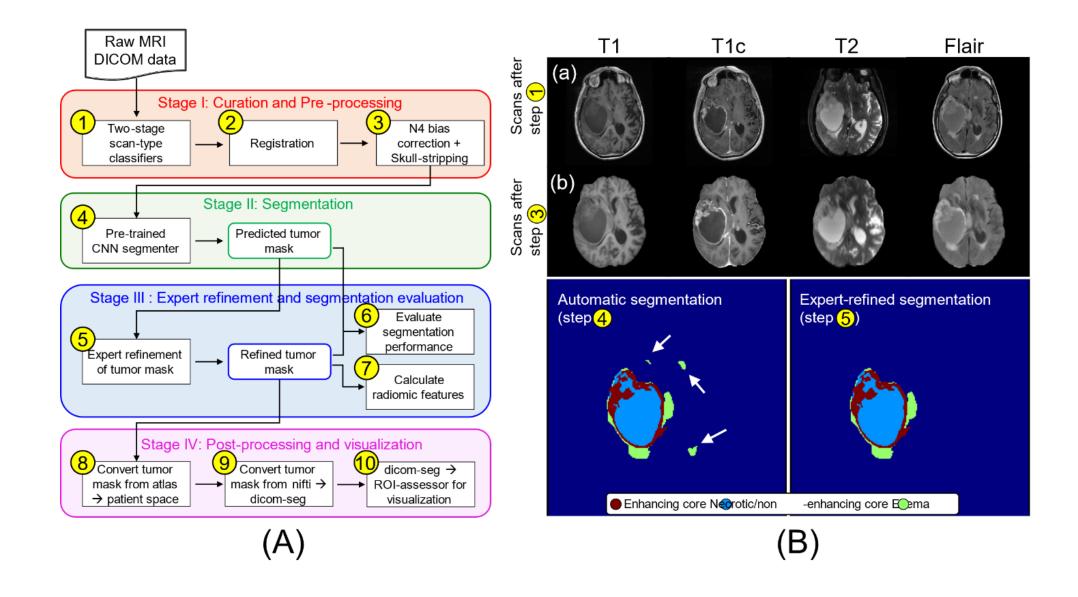
- Computed phenotypes align to known attributes of disease.
- Phenotypes may be alternatively obtainable through more invasive methods (e.g. biopsy).
- Useful phenotypes are predictive of outcomes.
- You might also call them biomarkers.

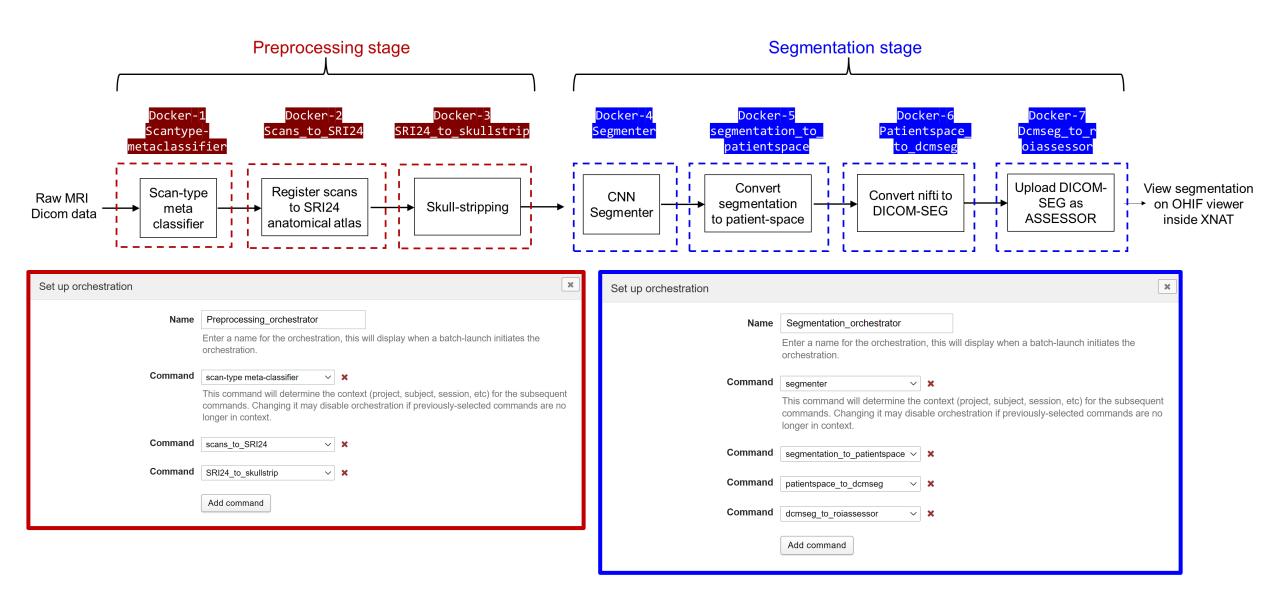
The Feature Stack: Phenotypes

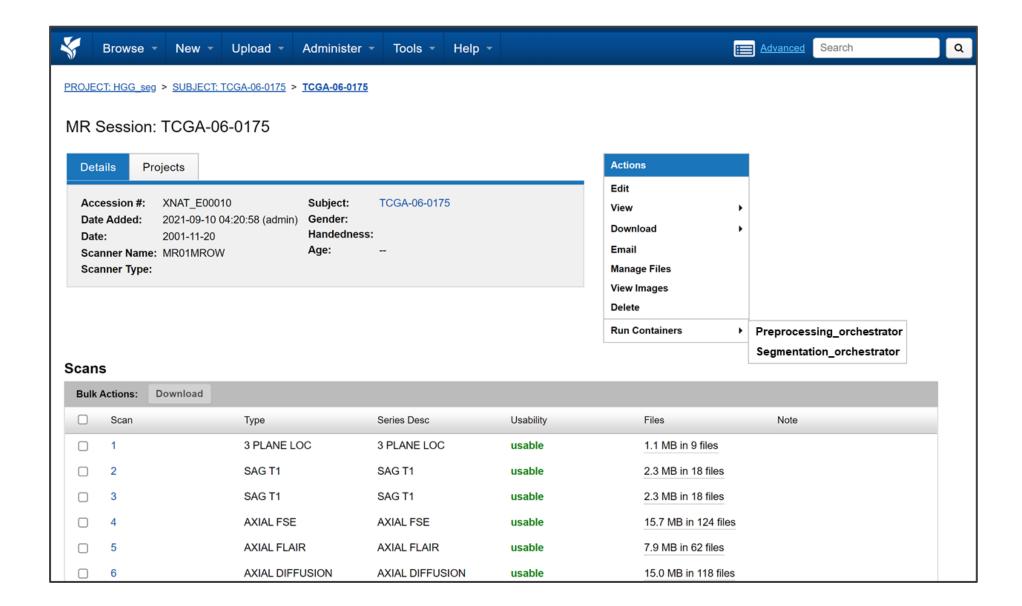




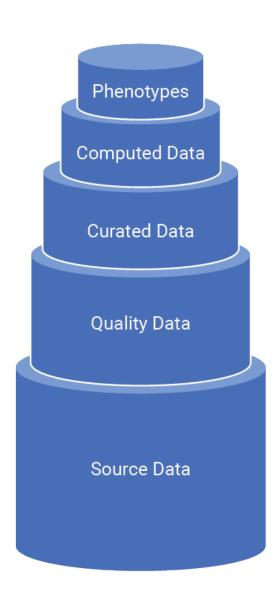








Conclusions



- Many relevant AI methods... transformers, classifiers, segmentation, clustering, etc.
- Attending to all levels of the feature stack supports reliable, trustworthy AI.
- Scalable informatics tools like XNAT enable development, validation, and deployment of Alpowered data pipelines.

Thank you

