An Introduction to MONAI

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MONAI: Medical Open Network for AI

A Collaborative and Community-driven Effort

*Project MONAI is a **collaborative open-source initiative** built by **academic & industry leaders** to establish and standardize the **best practices for deep learning in healthcare imaging** to accelerate the pace of innovation"*

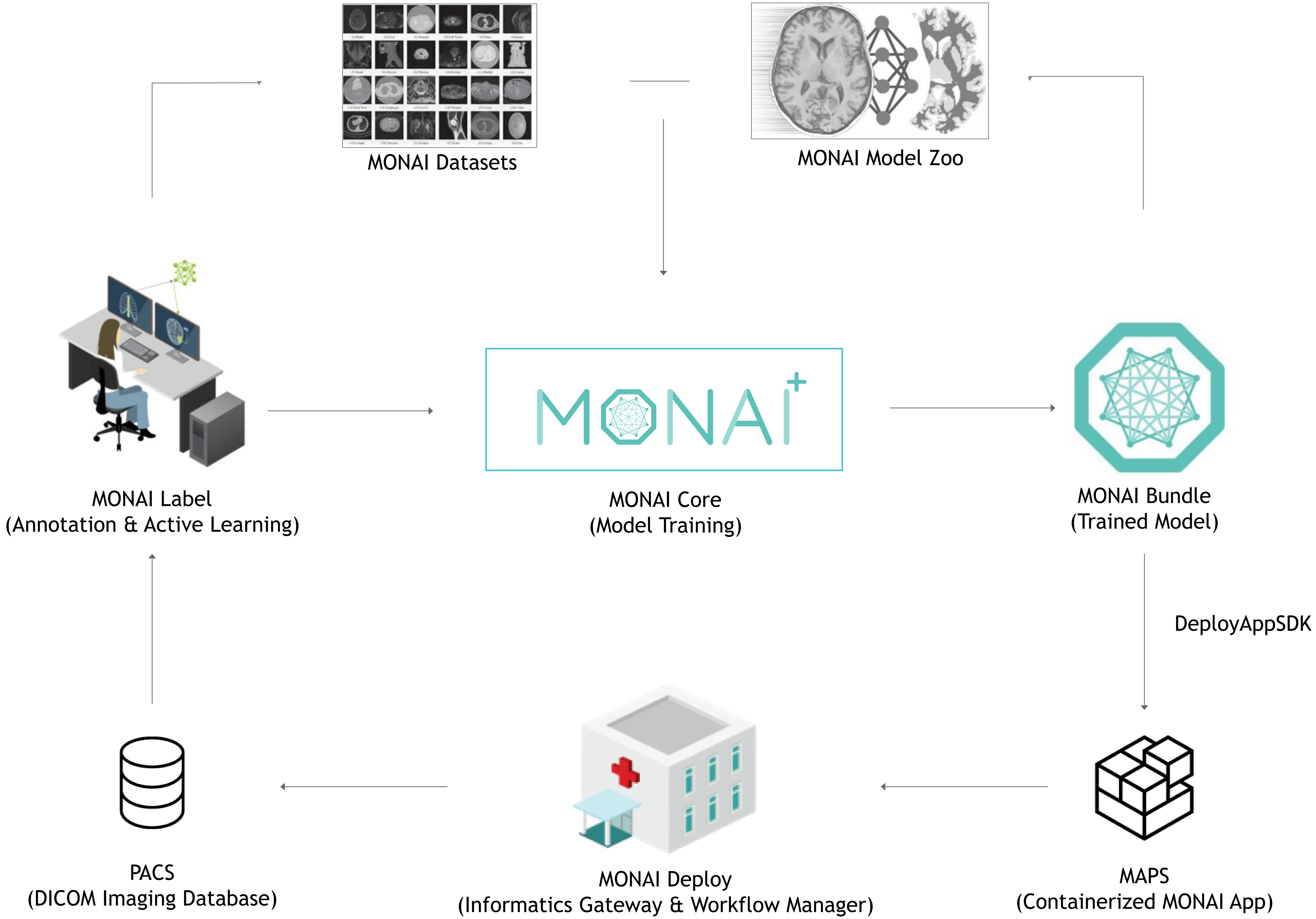
Founding Members: King's College London, NVIDIA

MGH & BWH Center for Clinical Data Science, Stanford University, Technische Universität München, dkfz. German Cancer Research Center in the Helmholtz Association, Charité Universitätsmedizin Berlin, Mayo Clinic, Frederick National Laboratory for Cancer Research, Kitware, Warwick The University of Warwick, Vanderbilt University, NIH, NHS

gsk, AstraZeneca, GE, Intuitive Surgical, Bayer, Philips, Tencent, Siemens, Canon

Project MONAI Advisory Board
Chair: Dr Stephen Aylward

MONAI: The Essential Framework for the Medical AI Ecosystem



MONAI Impact

Standard for Imaging Research and Clinical Deployment

600K Total Downloads

50K Download per Month

450+ Github Projects

150+ Papers Published

2019
MONAI Inception
MICCAI Shenzhen

NVIDIA and KCL initiate MONAI community

2020
MONAI Core 0.1
Domain specific training library

4 publications

550 Bootcamp registrants

2021
MONAI Label, MONAI Deploy
Expansion of imaging AI workflow

Won 5 challenges
709 Bootcamp registrants

2022
MONAI 1.0
Model Zoo, Active Learning, Auto3D

Won 6 challenges

MONAI Tutorial, MICCAI (Sept 22)

MONAI-Core

MONAI-Core: Covering all Pillars of Medical Image Analysis

Classification | Detection/ Segmentation | Registration | Generation | Reconstruction | Multi-Omics

MONAI-Core Building Blocks: PyTorch for Medical Data

Built to be customizable & easy to integrate

MONAI RESEARCH: Implementations of state-of-the-art research publications

Self Supervised Learning
UNETR based

AutoML
Model Parallelism/Neural Archi. Search

Vision Transformers 3D
UNETR | TransUNET

Segmentation, Classification, Registration
Medical/Pathology Imaging tasks

MONAI EXAMPLES: Rich set of examples & demo notebooks to demonstrate the capabilities and integration with OSS packages

Segmentation

Classification

Registration & Detection

Federated Learning

Get Started Notebooks

MONAI WORKFLOWS: Users can interface with MONAI workflows for ease of robust training & evaluation of Research Experiments

Engines
SupervisedTrainer
SupervisedEvaluator

Event Handlers
Checkpoint Loader; ValidationHandler; ClassificationSaver; CheckpointSaver;
LrSchedulerHandler; StatsHandler; TensorBoardHandlers; SegmentationSaver; MetricLogger

Metrics
MeanDice
ROCAUC

FOUNDATIONAL COMPONENTS: Users can integrate Independent domain specialized components into PyTorch Programs

Data
Multi modal
WSI Image loader
CacheDataset
PersistentDataset
ZipDataset
ArrayDataset
GridDataset
EnhancedDataLoader

Savers & Writers
Nifty, PNG & CSV

Inferers
SimpleInferer, Slidingwindow

Losses
DiceLoss & Extensions, FocalLoss, TverskyLoss

Visualize
Plot 3D/2D images,
Plot statistics curve

Networks
UNET (2D & 3D); DynUNET Layers & blocks; UNETR; DenseNet(2D & 3D)

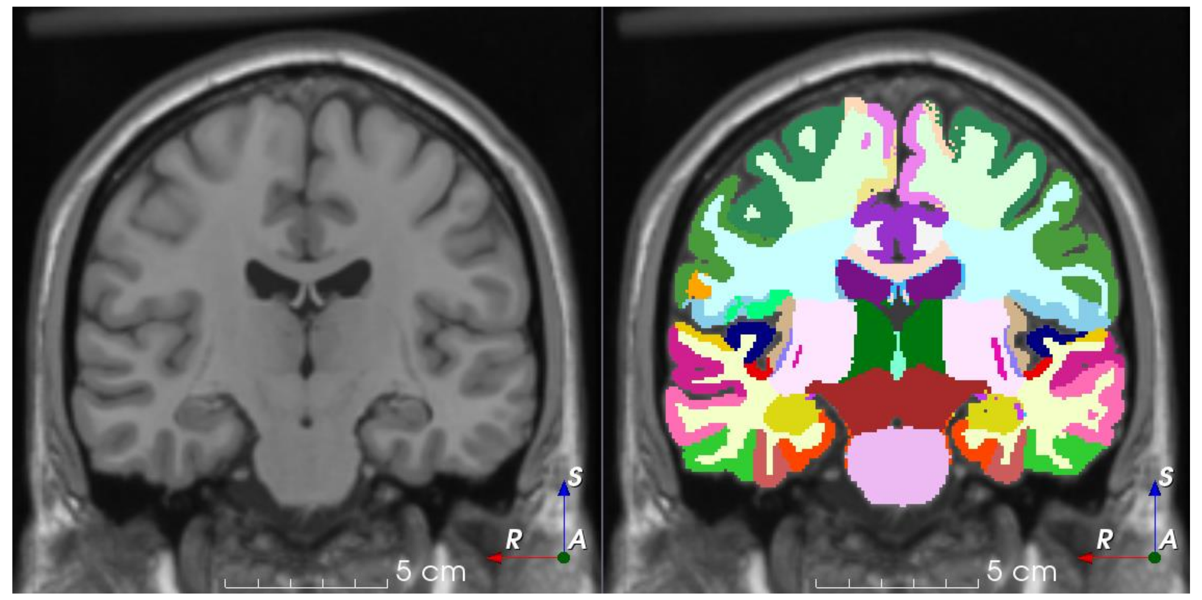
Metrics
MeanDice, ROCAUC

Transforms
Inverse, GPU accelerated
Spatial, Intensity
IO, Utility
Post, Compose
3rd Part adapter
BatchGenerator,
Rising,TorchI/O
....

MONAI-Core: Domain-specific deep learning tools

Integrating domain-specific (random) transforms for augmentation

Original volume



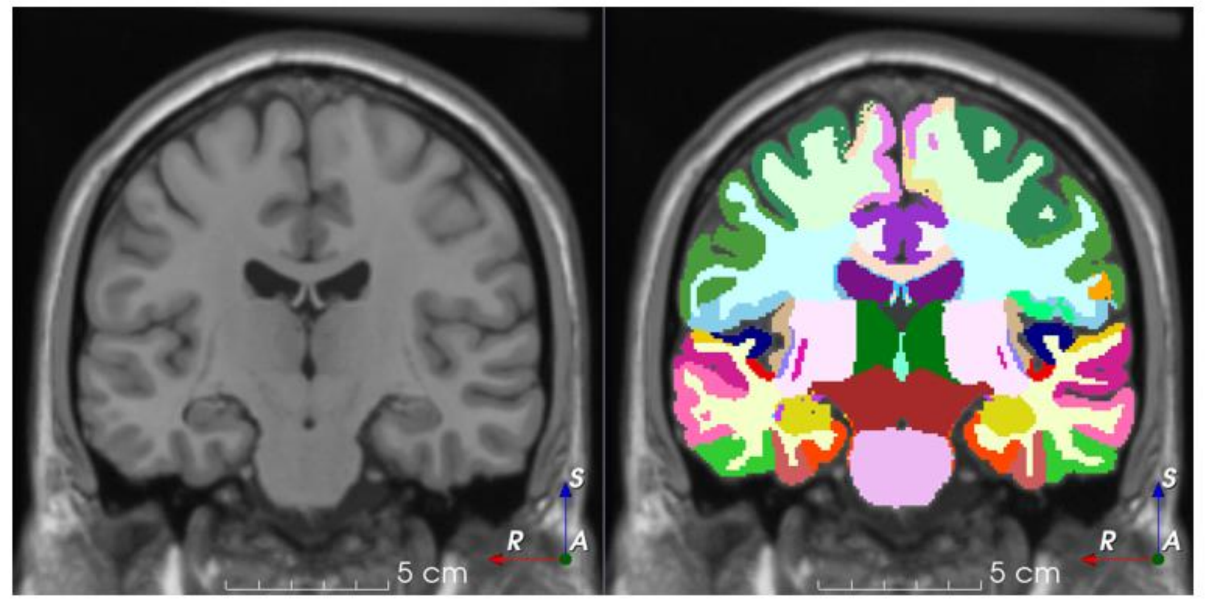
Single-line integration of transforms e.g. from:

TorchIO

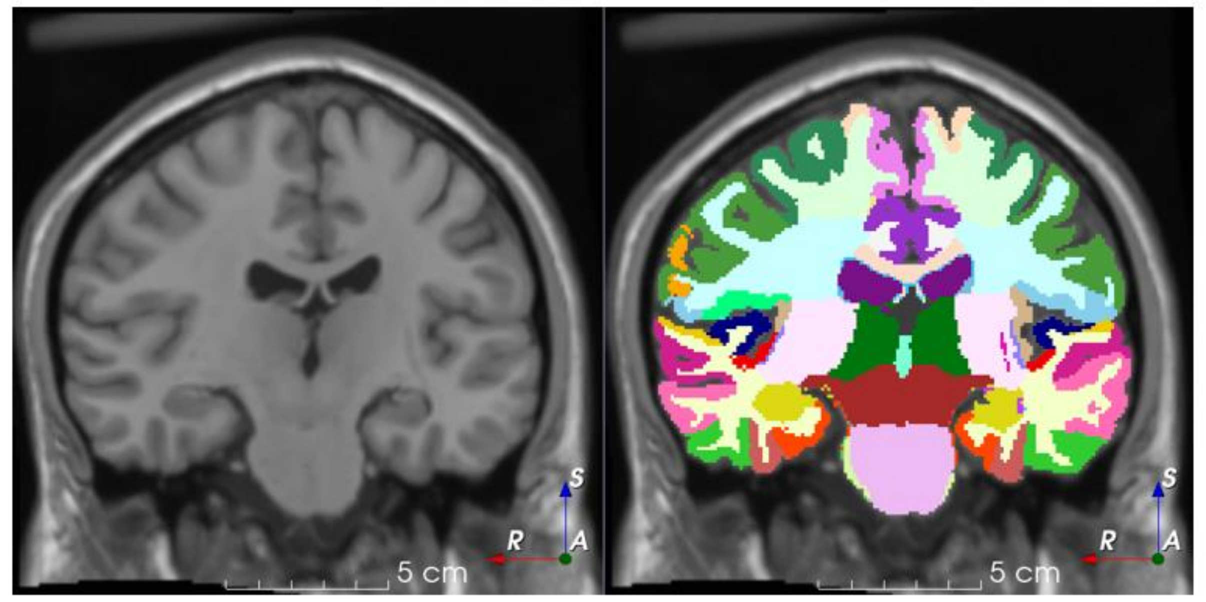
https://github.com/fepegar/torchio

Spatial

Flipping

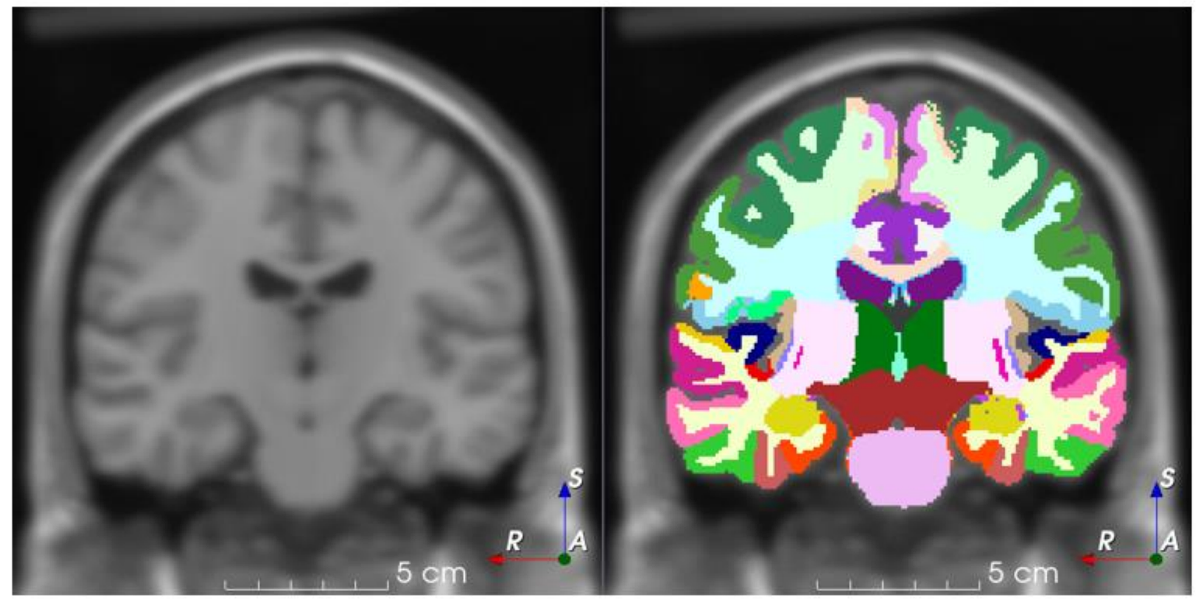


Affine/deformable

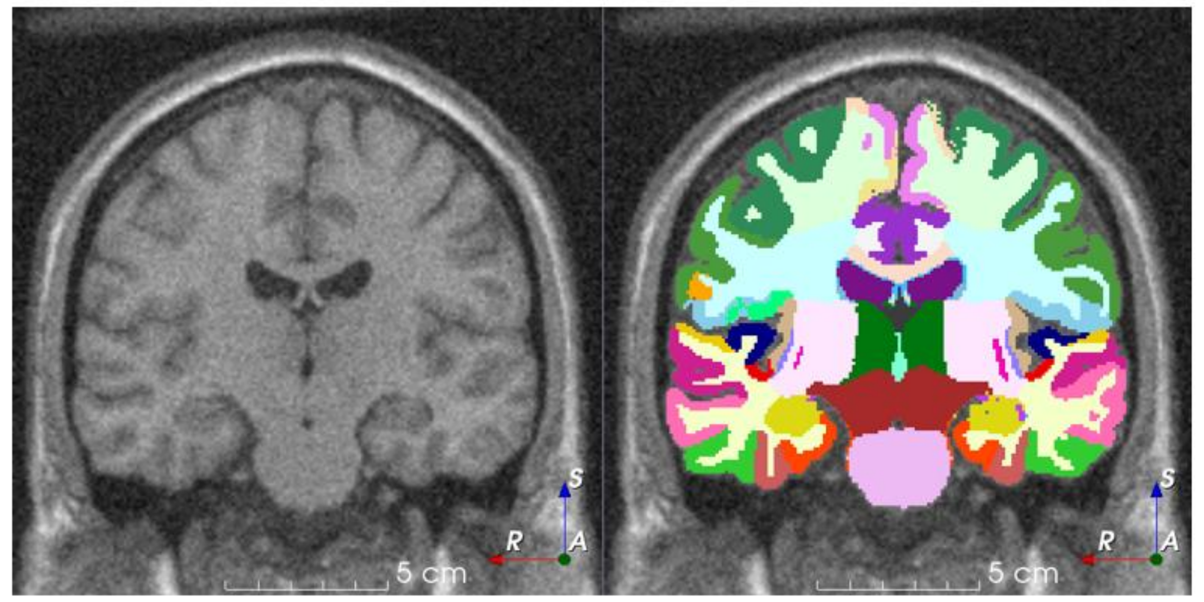


Intensity

Blurring

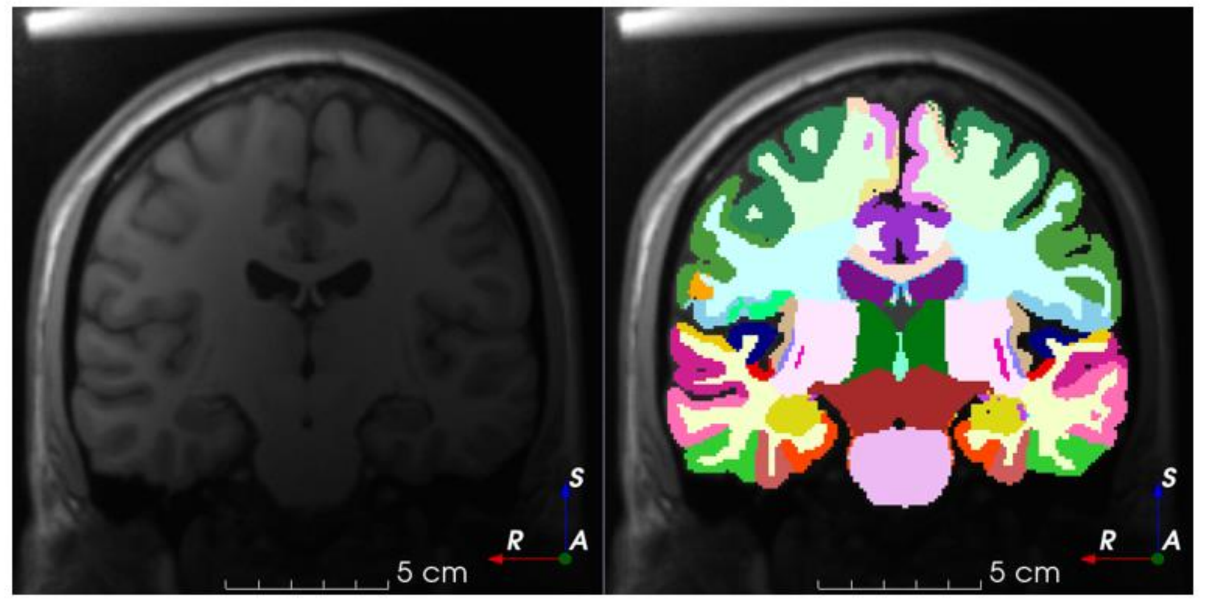


Sensor Noise

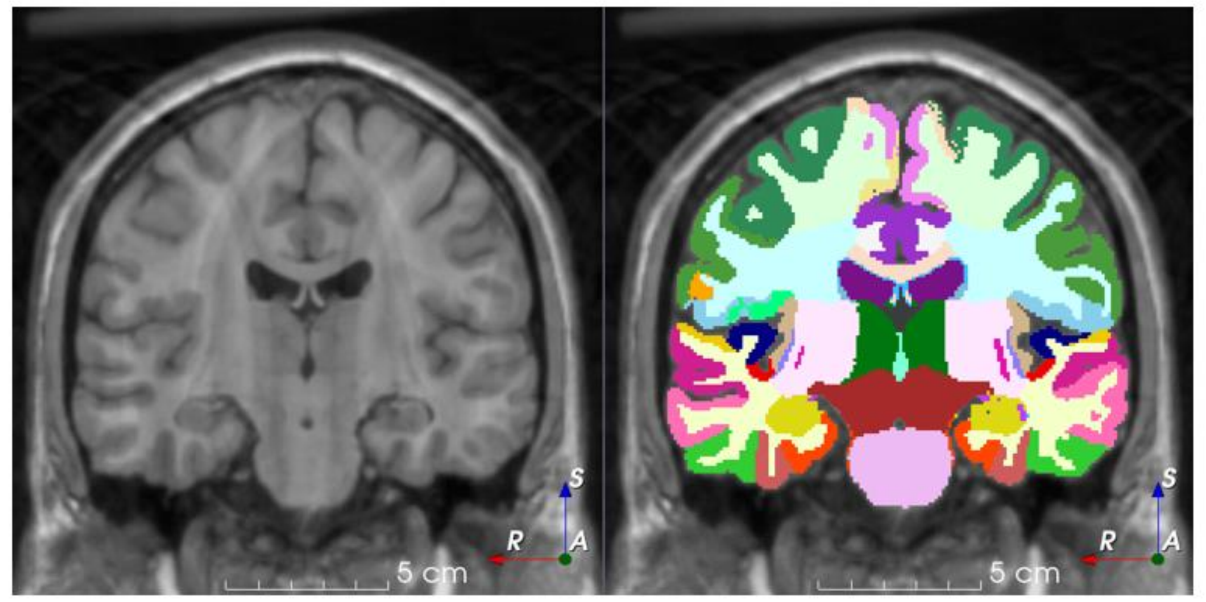


MRI artifacts

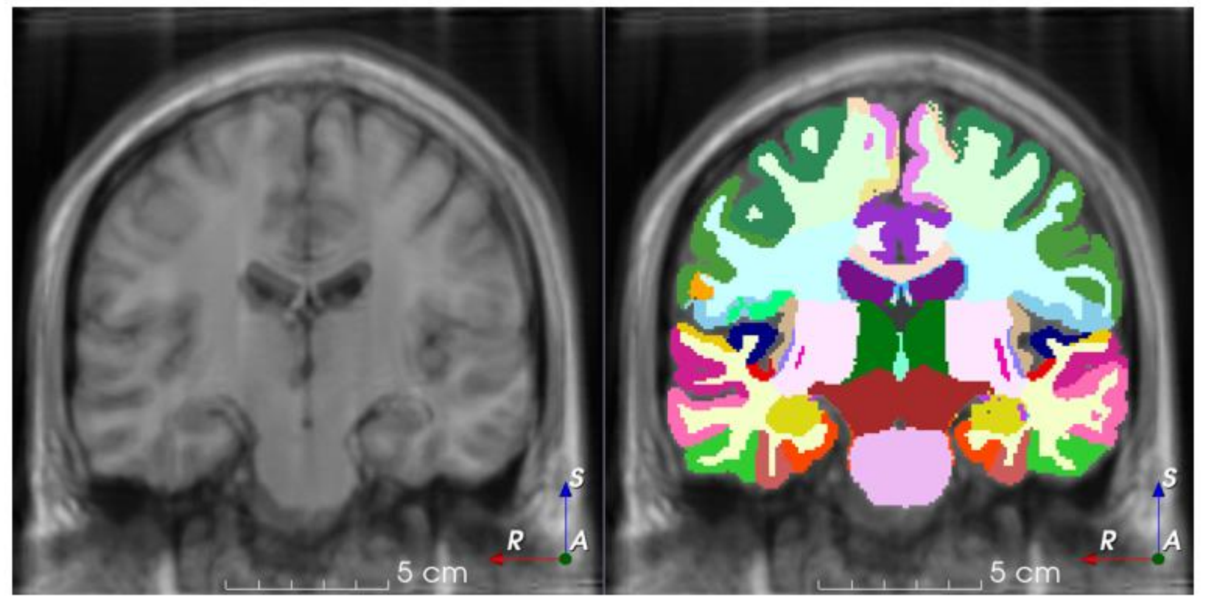
Bias field artifacts



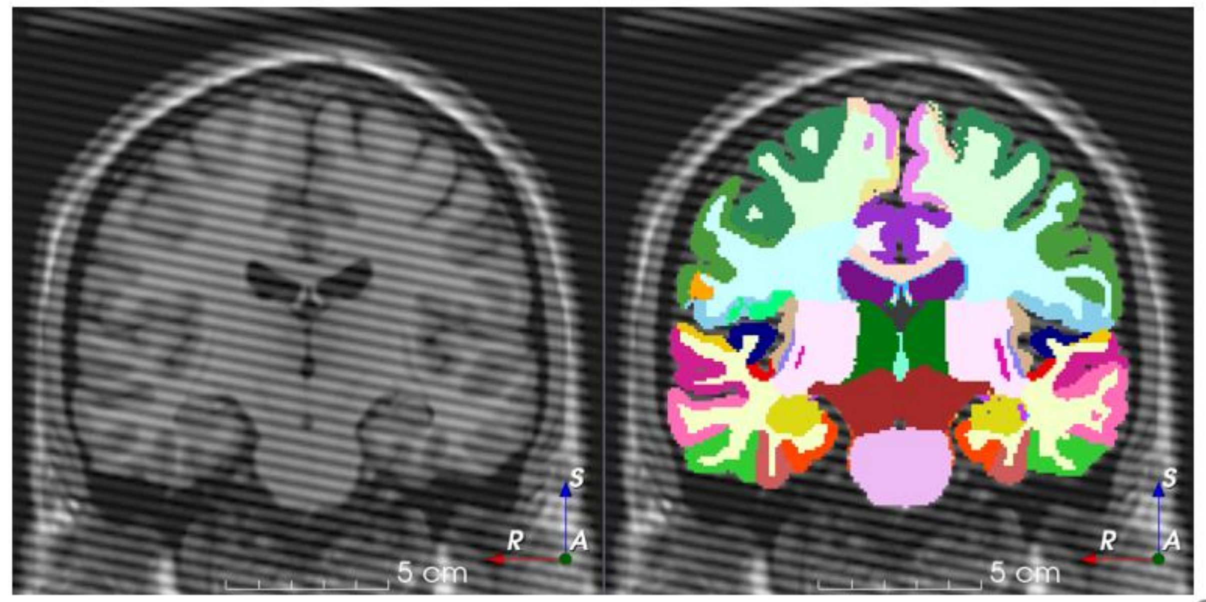
Ghosting artifacts



Patient motion artifacts



Spike artifacts



All augmentation visualizations from TorchIO: https://github.com/fepegar/torchio

MONAI BUNDLE

Open standard for Model definition & Package

Execute training:

```
python -m monai.bundle run training \
    --meta_file configs/metadata.json \
    --config_file configs/train.json \
    --logging_file configs/logging.conf
```

Override the `train` config to execute multi-GPU training:

```
torchrun --standalone --nnodes=1 --nproc_per_node=2 -m monai.bundle run training \
    --meta_file configs/metadata.json \
    --config_file "['configs/train.json','configs/multi_gpu_train.json']" \
    --logging_file configs/logging.conf
```

Override the `train` config to execute evaluation with the trained model:

```
python -m monai.bundle run evaluating \
    --meta_file configs/metadata.json \
    --config_file "['configs/train.json','configs/evaluate.json']" \
    --logging_file configs/logging.conf
```

Execute inference:

```
python -m monai.bundle run evaluating \
    --meta_file configs/metadata.json \
    --config_file configs/inference.json \
    --logging_file configs/logging.conf
```

Verify the metadata format:

```
python -m monai.bundle verify_metadata --meta_file configs/metadata.json --filepath eval/schema.json
```

Verify the data shape of network:

```
python -m monai.bundle verify_net_in_out network_def --meta_file configs/metadata.json --config_file configs/inference.jsc
```

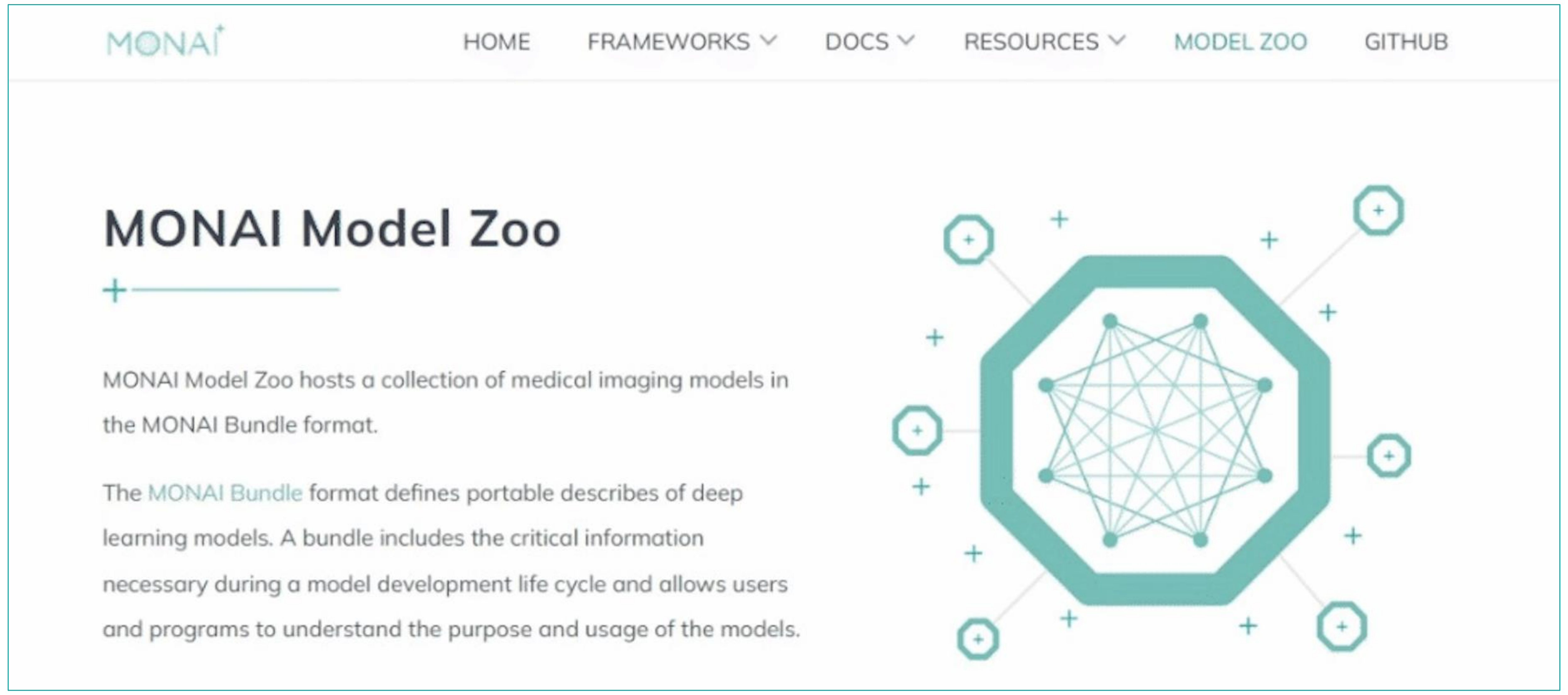
Export checkpoint to TorchScript file:

```
python -m monai.bundle ckpt_export network_def \
    --filepath models/model.ts \
    --ckpt_file models/model.pt \
    --meta_file configs/metadata.json \
    --config_file configs/inference.json
```

- MONAI Bundle is a self-contained model package with pre-trained weights and all meta data
- Build python workflows via structured configs
- Develop once and deploy anywhere
- Ease of use & flexibility to override & customize configs
- Hybrid programming with support for config to python conversion

MONAI MODEL ZOO

A Hub for Pre-Trained Imaging AI Models



Features	Benefits
15 and growing pre-trained models across CT, MR, Pathology, Endoscopy.	Jumpstart training workflows
Packaged as MONAI Bundle for publication to Model Zoo for 1-click	Establish common standard for reproducible research & collaboration
	Broaden reach and impact of research
	Leverage the SOTA pre-trained models for downstream clinical tasks

MONAI Model Zoo Browser

https://monai.io/model-zoo.html

All Models

Brats mri segmentation
MONAI team
A pre-trained model for volumetric (3D) segmentation of brain tumor subregions from multimodal MRIs based on BraTS 2018 data
Model Details

Endoscopic inbody classification
NVIDIA DLMED team
A pre-trained binary classification model for endoscopic inbody classification task
Model Details

Endoscopic tool segmentation
NVIDIA DLMED team
A pre-trained binary segmentation model for endoscopic tool segmentation
Model Details

Lung nodule ct detection
MONAI team
A pre-trained model for volumetric (3D) detection of the lung lesion from CT image on LUNA16 dataset
Model Details

Mednist gan
MONAI Team
This example of a GAN generator produces hand xray images like those in the MedNIST dataset
Model Details

Pancreas ct dints segmentation
MONAI team
Searched architectures for volumetric (3D) segmentation of the pancreas from CT image
Model Details

Pathology tumor detection
MONAI team
A pre-trained model for metastasis detection on Camelyon 16 dataset.
Model Details

Prostate mri anatomy
Keno Bressem
A pre-trained model for volumetric (3D) segmentation of the prostate from MRI images
Model Details

Renalstructures unest segmentation
Vanderbilt University + MONAI team
A transformer-based model for renal segmentation from CT image
Model Details

Spleen ct segmentation
MONAI team
A pre-trained model for volumetric (3D) segmentation of the spleen from CT image
Model Details

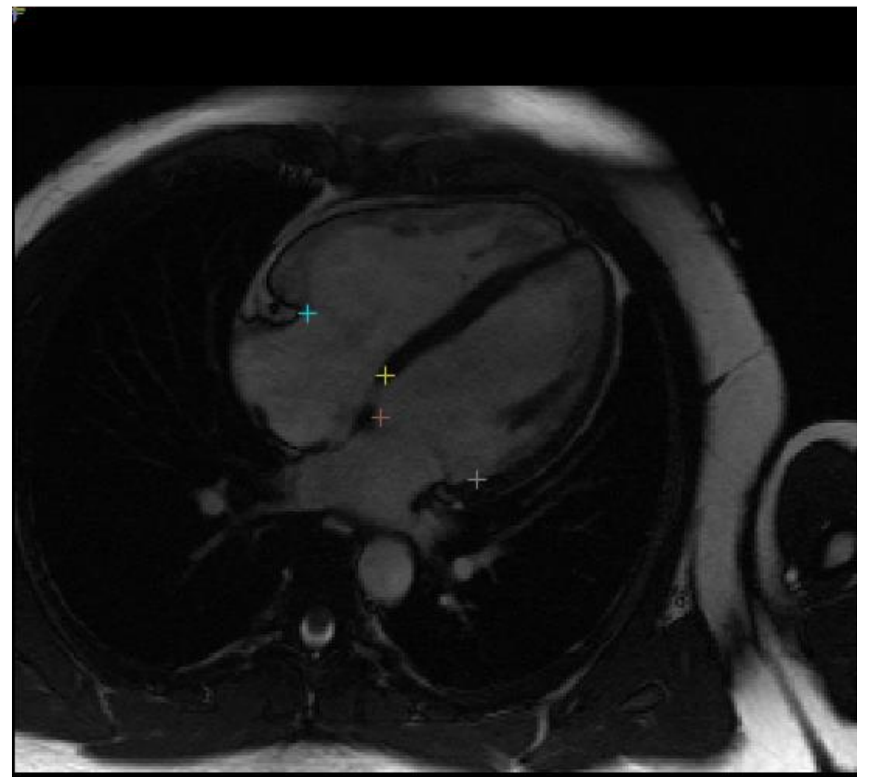
Spleen deepedit annotation
MONAI team
This is a pre-trained model for 3D segmentation of the spleen organ from CT images using DeepEdit.
Model Details

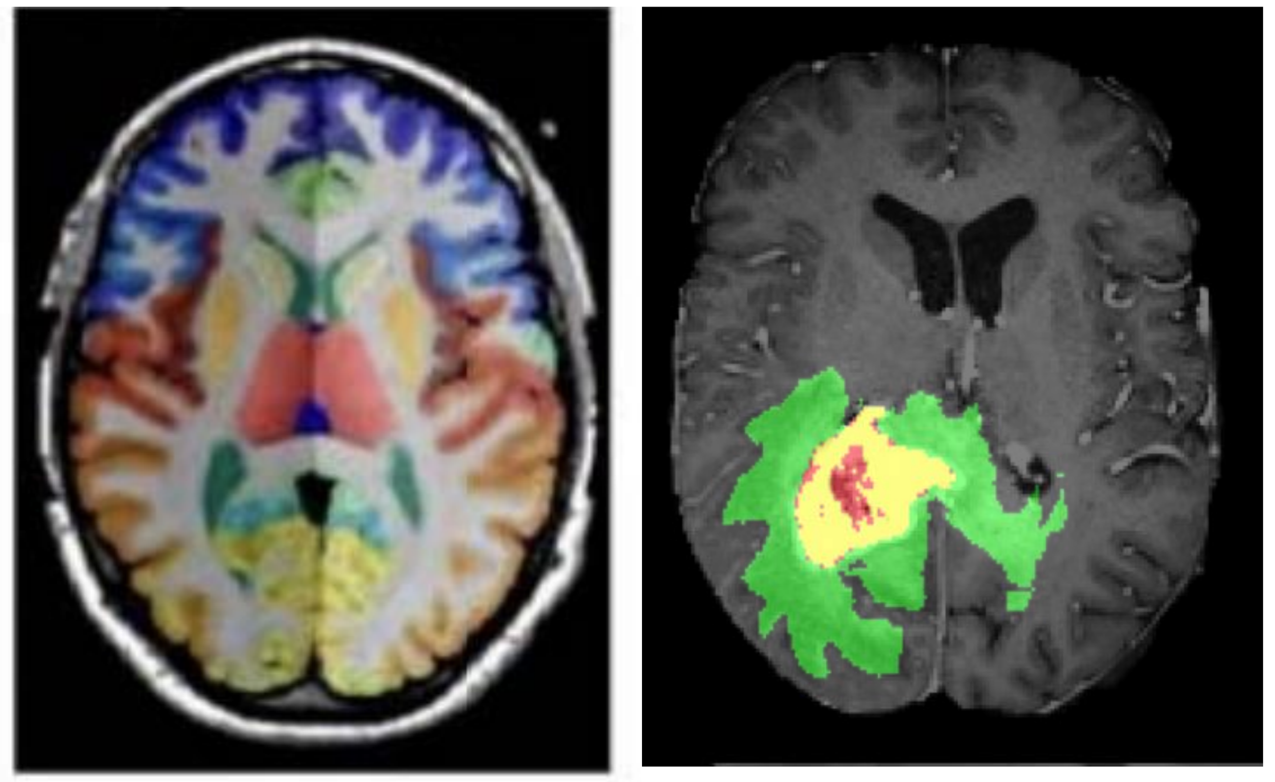
Swin unetr btcv segmentation
MONAI team
A pre-trained model for volumetric (3D) multi-organ segmentation from CT image
Model Details

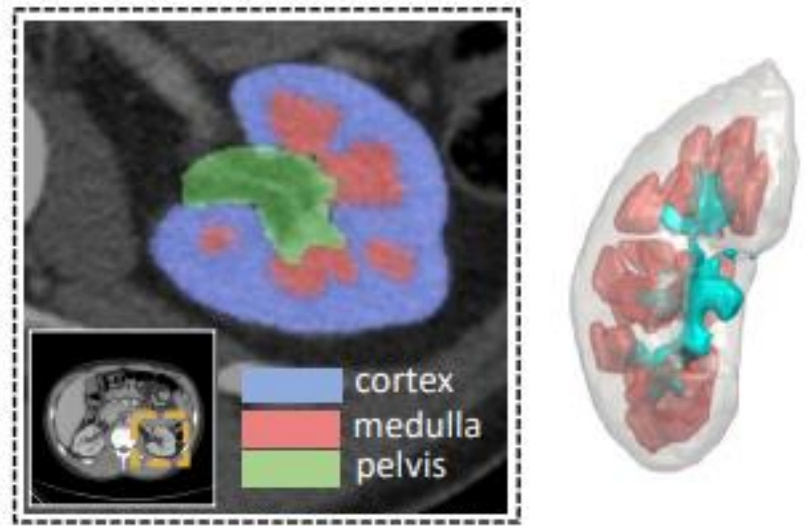
Valve landmarks
Eric Kerfoot
This network is used to find where valves attach to heart to help construct 3D FEM models for computation. The output is an array of 10 2D coordinates.
Model Details

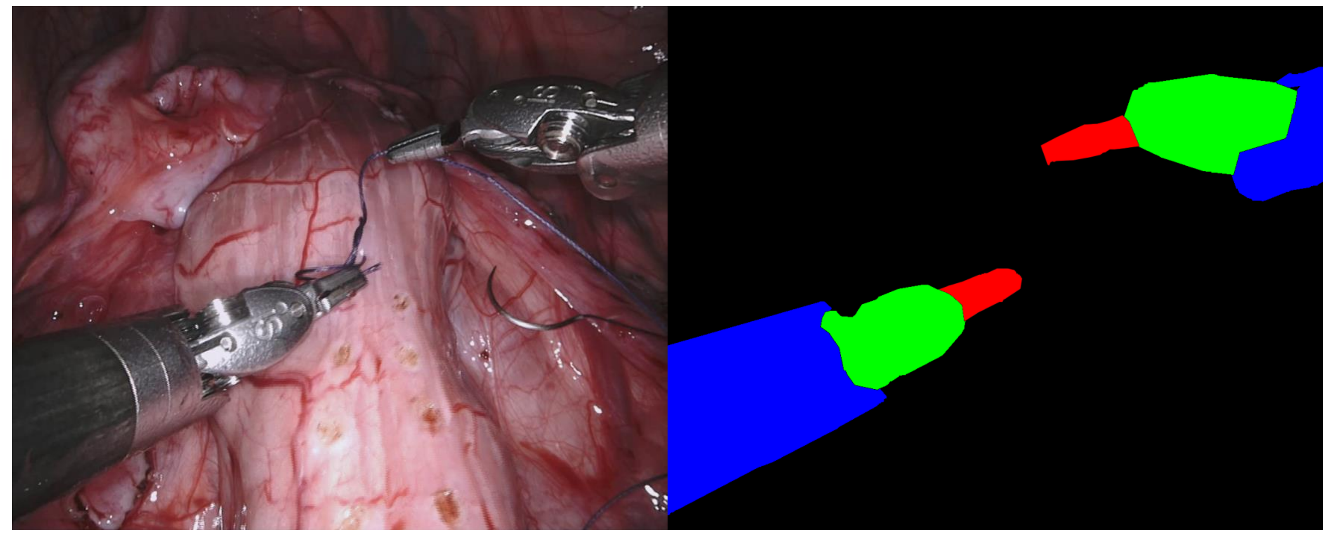
Ventricular short axis 3label
Eric Kerfoot
This network segments full cycle short axis images of the ventricles, labelling LV pool separate from myocardium and RV pool
Model Details

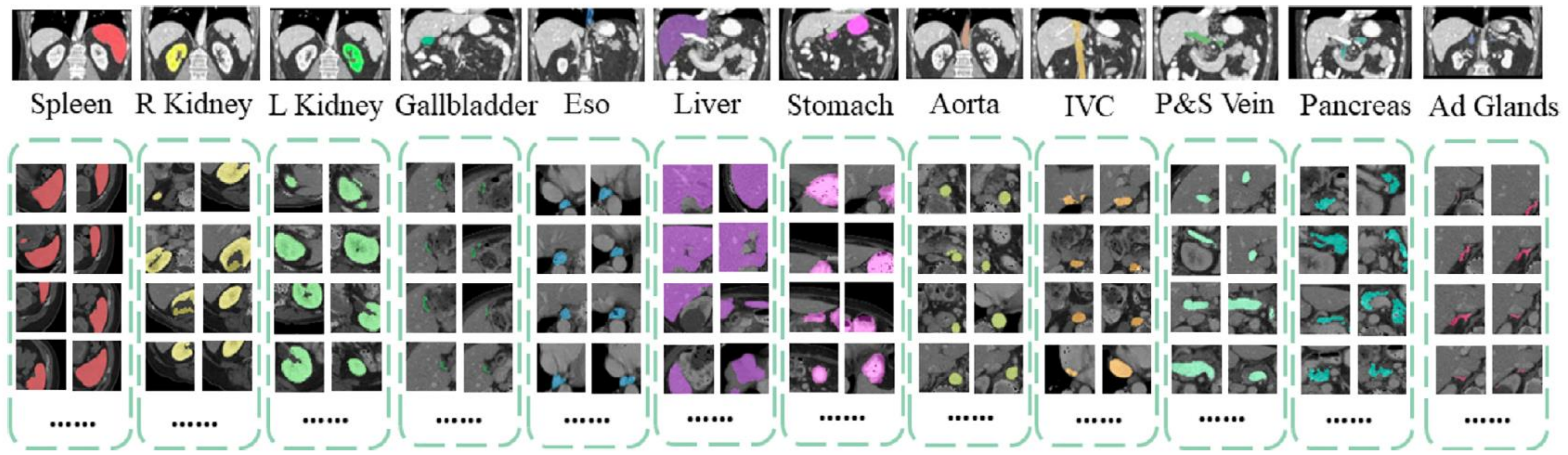
Wholebrainseg large unest segmentation
Vanderbilt University + MONAI team
A 3D transformer-based model for whole brain segmentation from T1W MRI image
Model Details







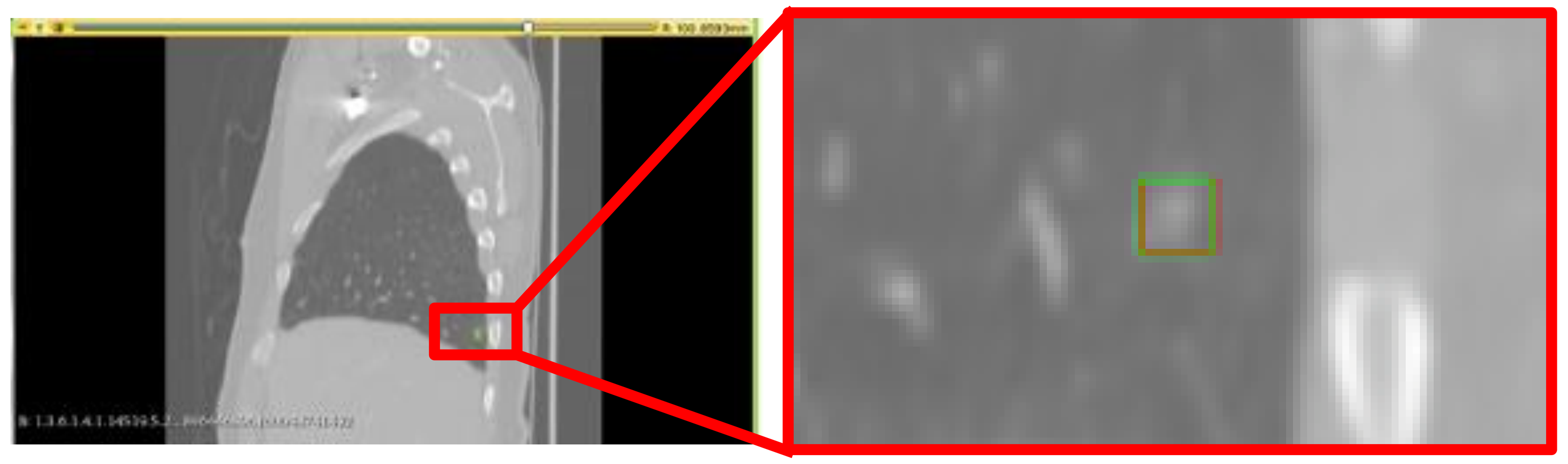


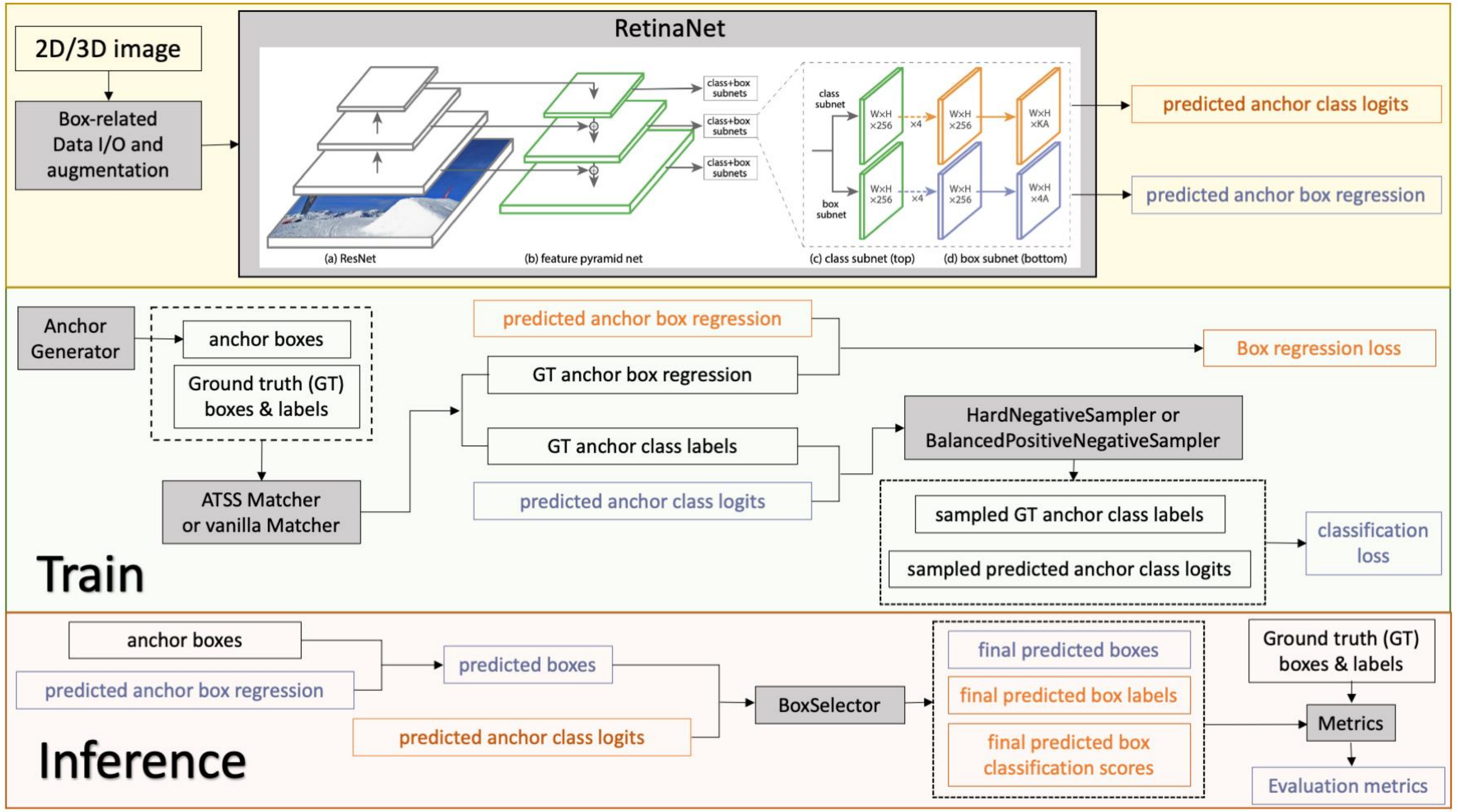


MONAI Core v1.0.0

Object detection in medical images

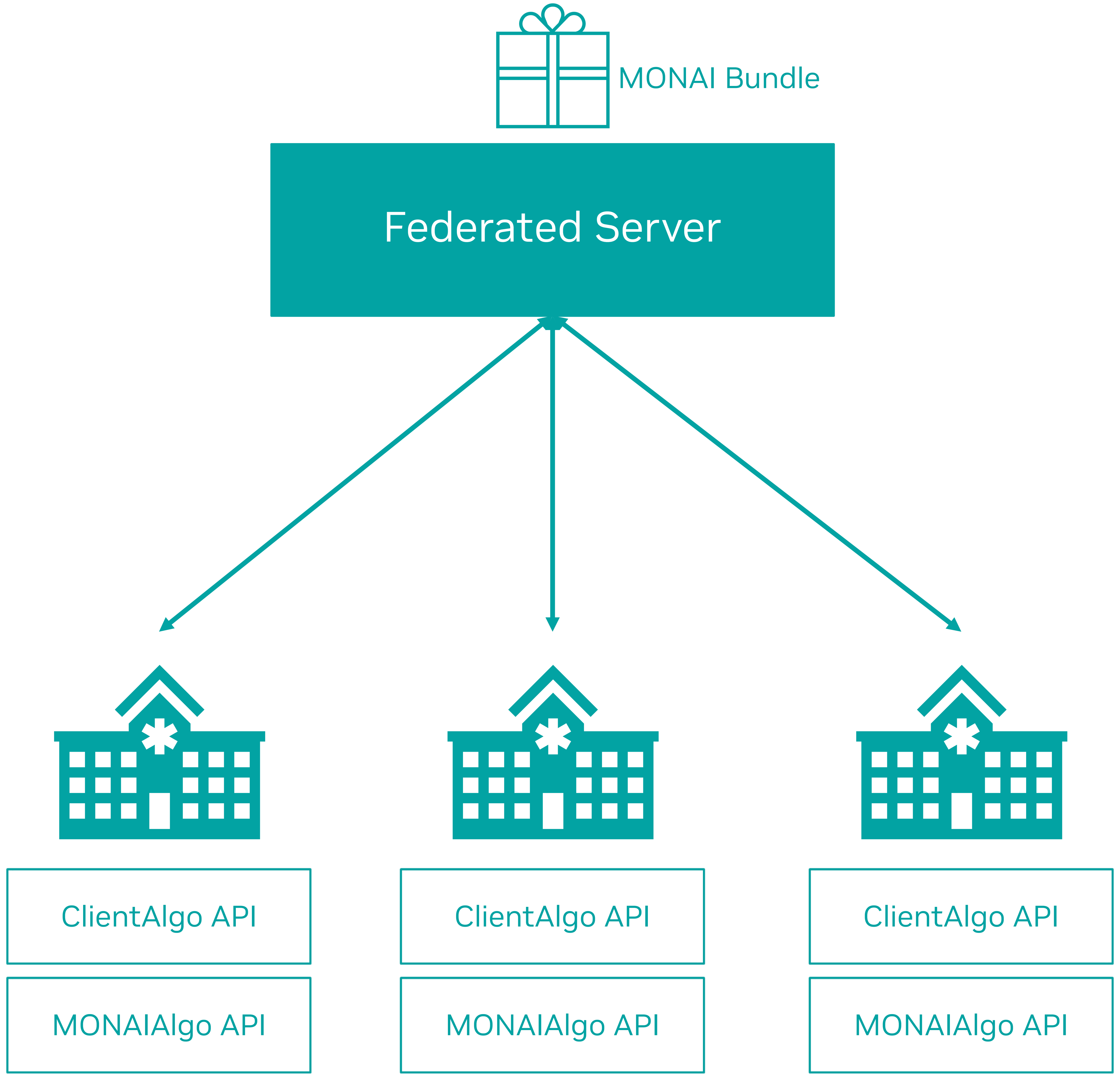
- MONAI Core includes essential components for object localization and categorization workflows.
- Includes 2D and 3D bounding box handling, network blocks and architectures of RetinaNet
- Common utility modules such as coordinate-based preprocessing, hard negative sampler.
- The application specific modules are made available at monai.apps.detection.





MONAI Core v1.0.0

Federated Learning Client integrated with NVFlare



monai.fl

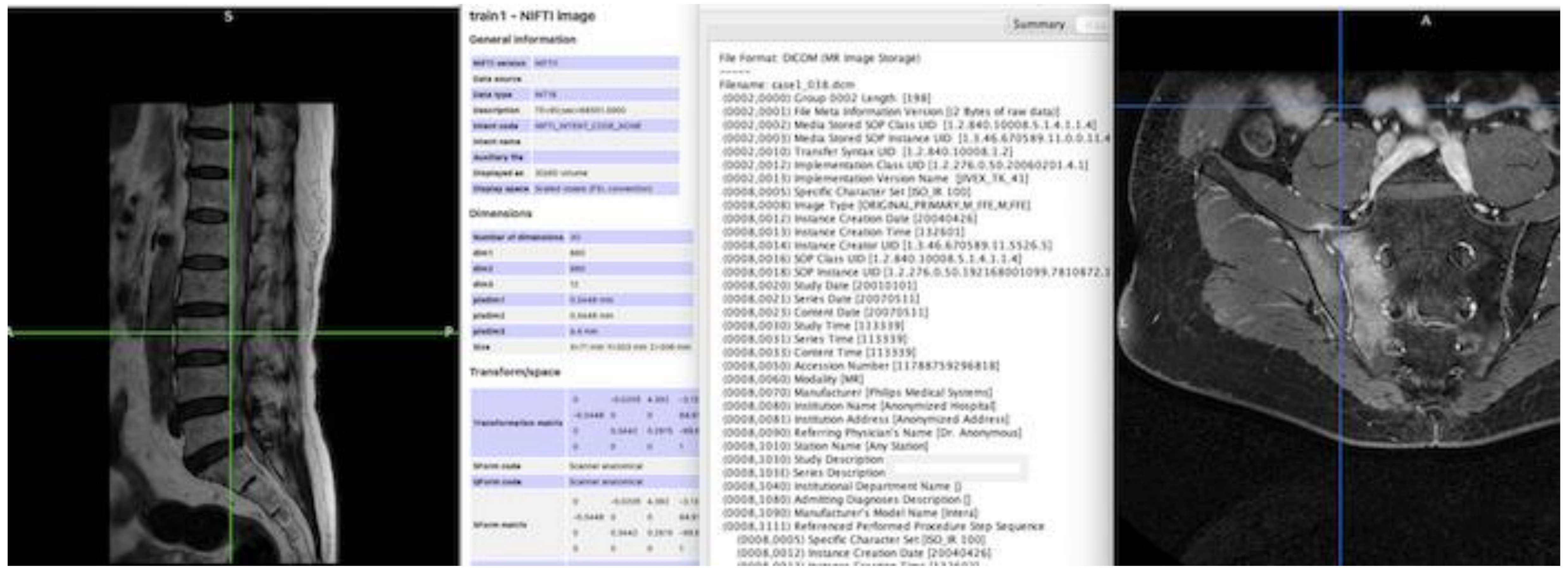
Low Code Framework for high quality 3D Segmentation Models

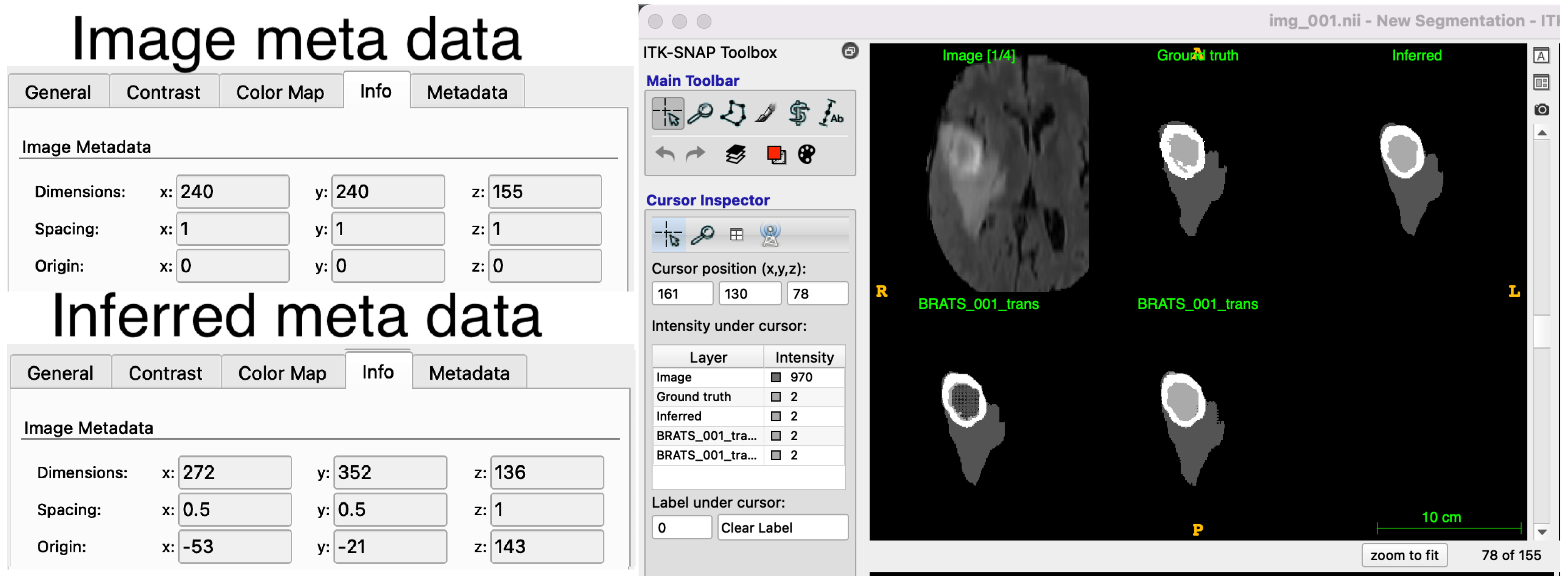
Features	Benefits
Federated Learning Client Algo APIs	Ability to defining a MONAI client app that can run on any FL platform. Enabler for FL Toolkits interoperability.
NVIDIA FLARE Integration	NVIDIA FLARE, the federated platform developed by NVIDIA, already integrated with MONAI FL Client APIs
MONAI Bundle compatibility	Allow for seamlessly extending any bundle from MONAI zoo to a federated paradigm

MONAI Core v1.0.0

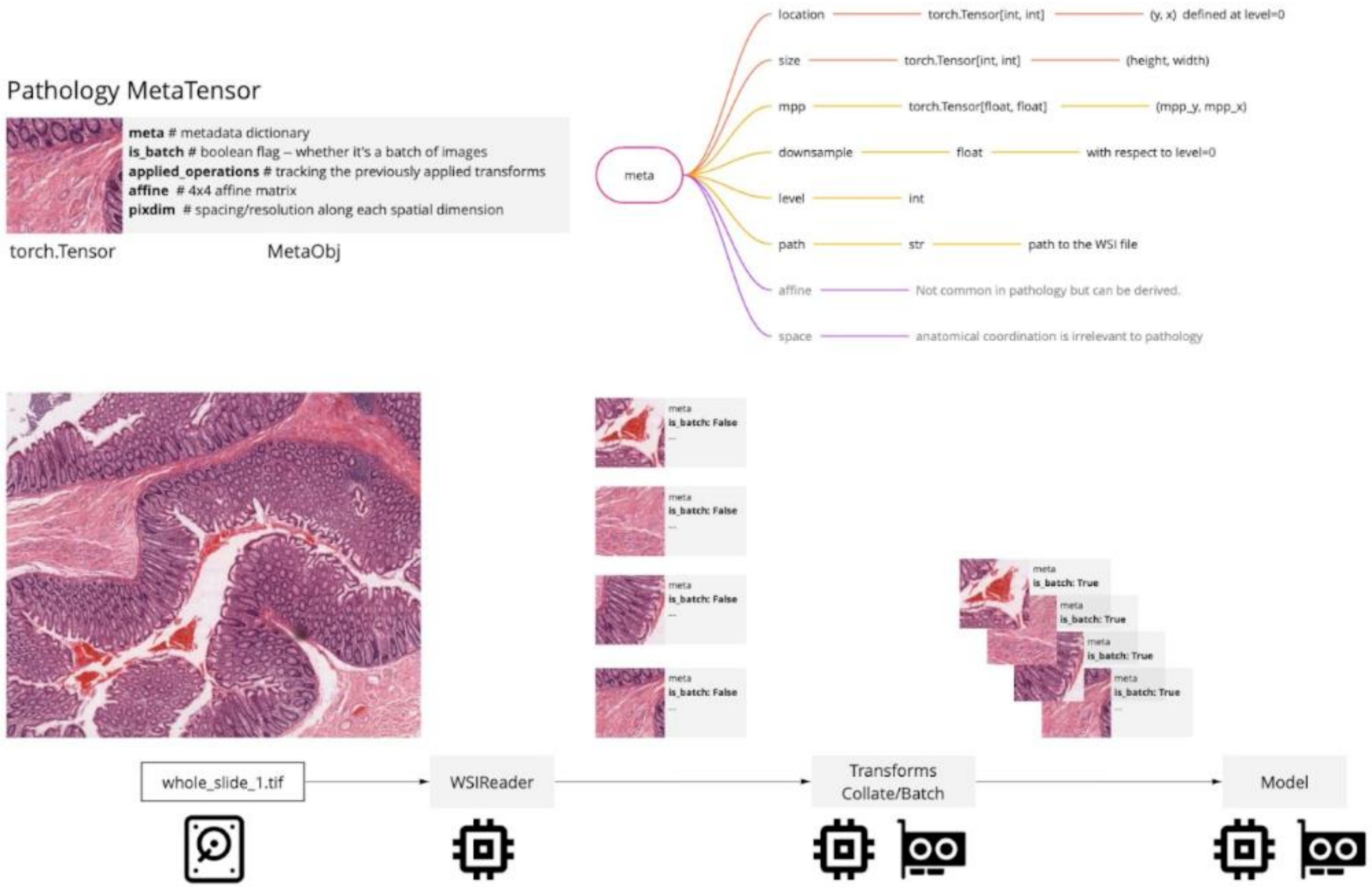
MetaTensor Support for Radiology and Digital Pathology Workflows

Radiology





Digital Pathology



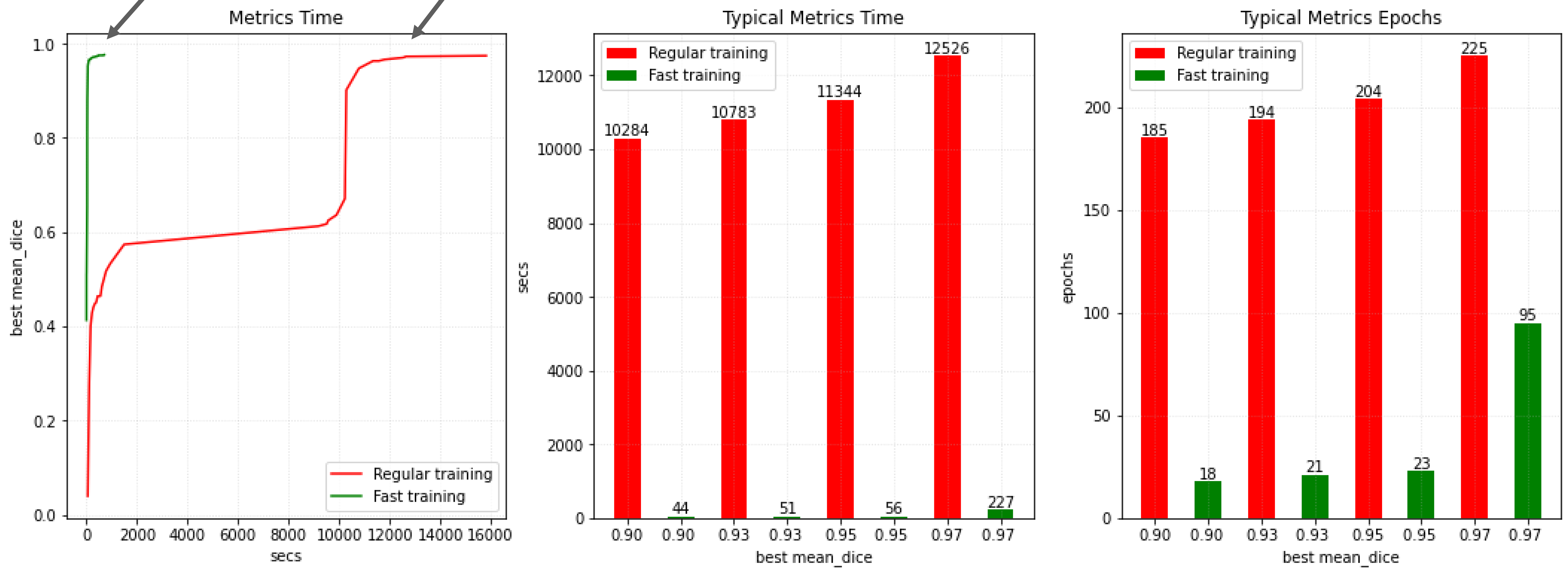
[MetaTensor developer tutorial and migration guide: Jupyter Notebook]()

MONAI NVIDIA

MONAI-Core: GPU-optimized Implementations

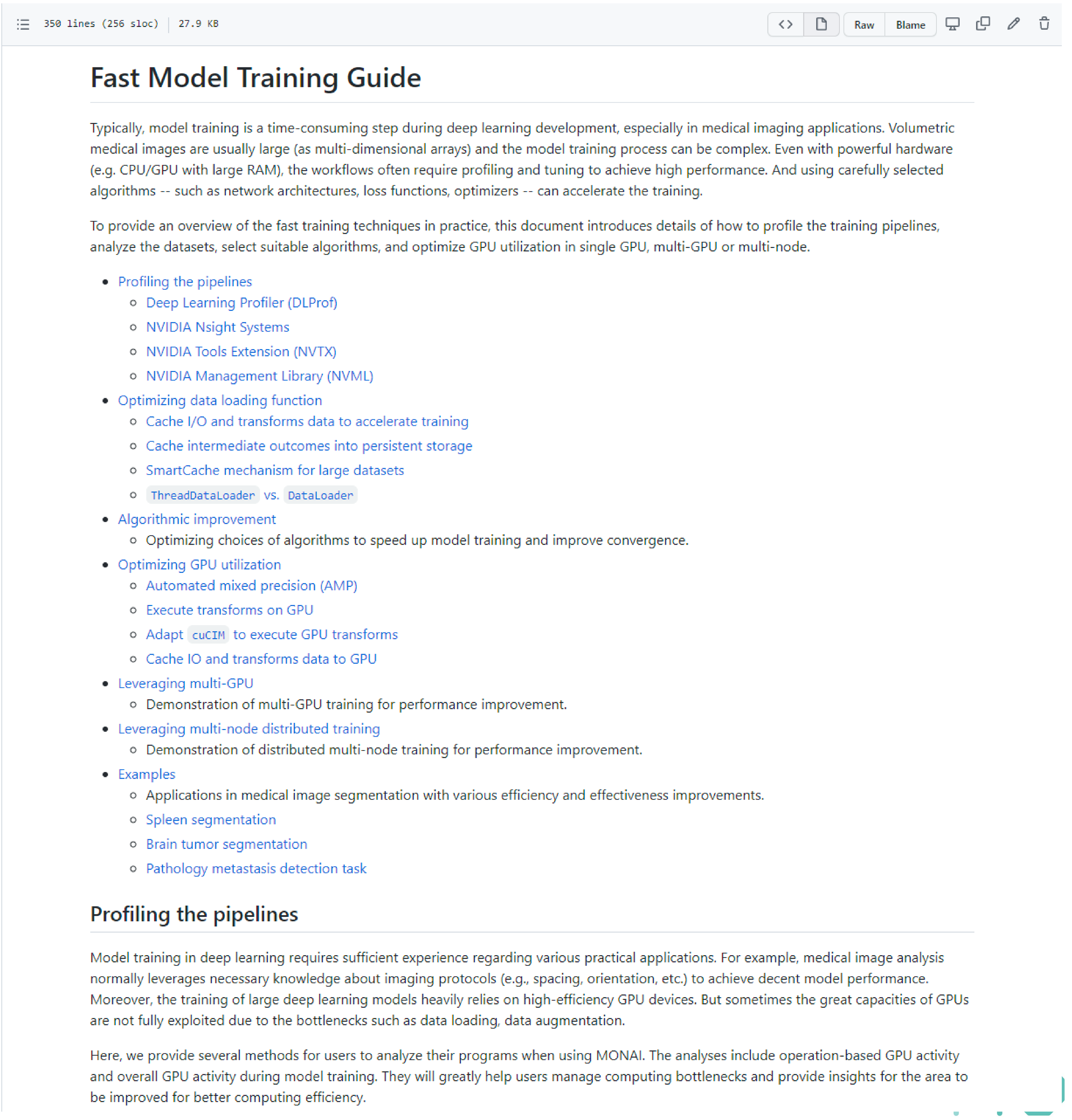
Fast Training Recipes, Beginner-friendly tutorials, Bootcamps and Workshops

- Spleen segmentation fast training tutorial with MONAI:
  - 20x faster epoch duration
  - **>200x faster** convergence to target Dice (56 seconds vs 3.6 hours!)



- MONAI's Fast Model Training Guide:

https://github.com/Project-MONAI/tutorials/blob/master/acceleration/fast_model_training_guide.md



350 lines (256 sloc) | 27.9 KB

Raw Blame

Fast Model Training Guide

Typically, model training is a time-consuming step during deep learning development, especially in medical imaging applications. Volumetric medical images are usually large (as multi-dimensional arrays) and the model training process can be complex. Even with powerful hardware (e.g. CPU/GPU with large RAM), the workflows often require profiling and tuning to achieve high performance. And using carefully selected algorithms -- such as network architectures, loss functions, optimizers -- can accelerate the training.

To provide an overview of the fast training techniques in practice, this document introduces details of how to profile the training pipelines, analyze the datasets, select suitable algorithms, and optimize GPU utilization in single GPU, multi-GPU or multi-node.

- Profiling the pipelines
  - Deep Learning Profiler (DLProf)
  - NVIDIA Nsight Systems
  - NVIDIA Tools Extension (NVTX)
  - NVIDIA Management Library (NVML)
- Optimizing data loading function
  - Cache I/O and transforms data to accelerate training
  - Cache intermediate outcomes into persistent storage
  - SmartCache mechanism for large datasets
  - `ThreadDataLoader` vs. `DataLoader`
- Algorithmic improvement
  - Optimizing choices of algorithms to speed up model training and improve convergence.
- Optimizing GPU utilization
  - Automated mixed precision (AMP)
  - Execute transforms on GPU
  - Adapt `cuCIM` to execute GPU transforms
  - Cache IO and transforms data to GPU
- Leveraging multi-GPU
  - Demonstration of multi-GPU training for performance improvement.
- Leveraging multi-node distributed training
  - Demonstration of distributed multi-node training for performance improvement.
- Examples
  - Applications in medical image segmentation with various efficiency and effectiveness improvements.
  - Spleen segmentation
  - Brain tumor segmentation
  - Pathology metastasis detection task

Profiling the pipelines

Model training in deep learning requires sufficient experience regarding various practical applications. For example, medical image analysis normally leverages necessary knowledge about imaging protocols (e.g., spacing, orientation, etc.) to achieve decent model performance. Moreover, the training of large deep learning models heavily relies on high-efficiency GPU devices. But sometimes the great capacities of GPUs are not fully exploited due to the bottlenecks such as data loading, data augmentation.

Here, we provide several methods for users to analyze their programs when using MONAI. The analyses include operation-based GPU activity and overall GPU activity during model training. They will greatly help users manage computing bottlenecks and provide insights for the area to be improved for better computing efficiency.

Powering Digital Pathology

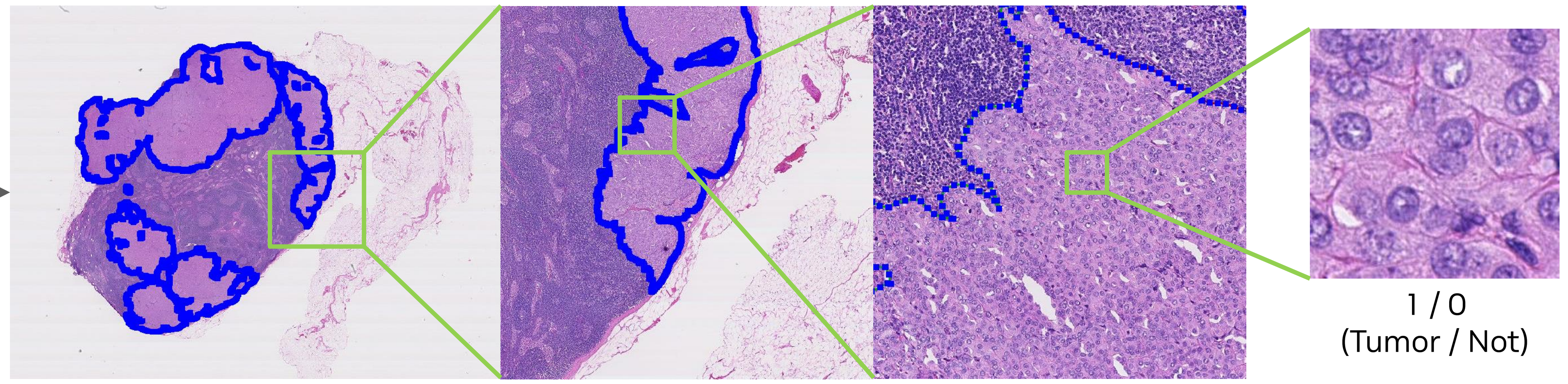
Open source MONAI implementation & Clara MMAR

rapidsai/**cucim**

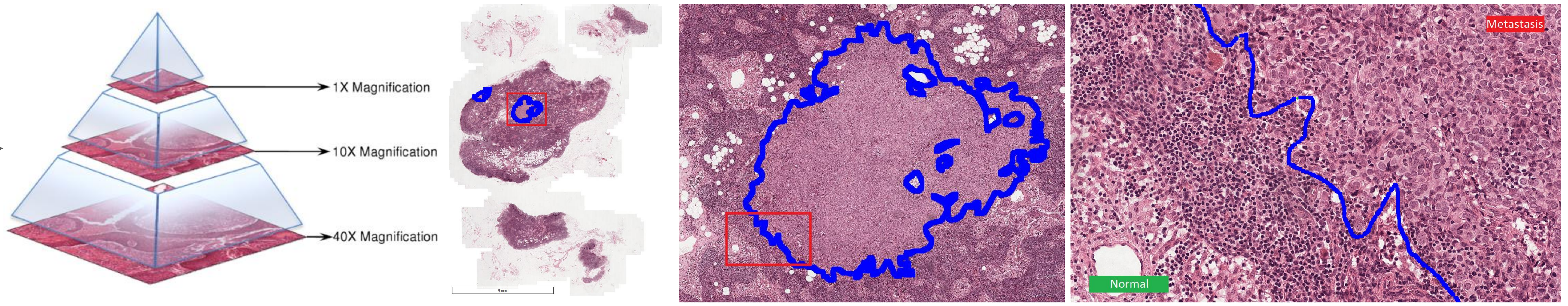
Tutorials for pathology imaging:
https://github.com/Project-MONAI/tutorials/tree/main/pathology

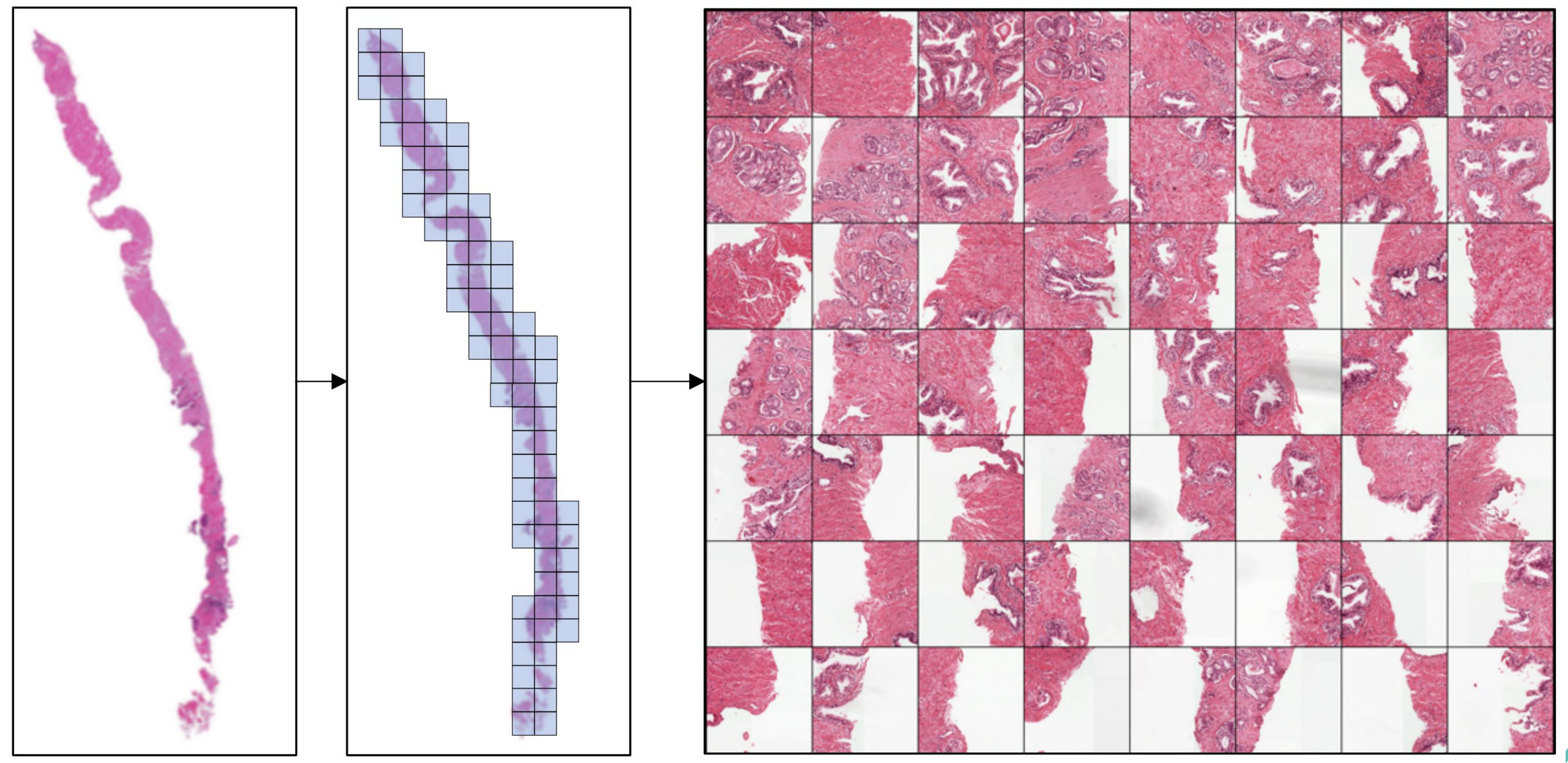
Metastasis Detection in Whole Slide Images

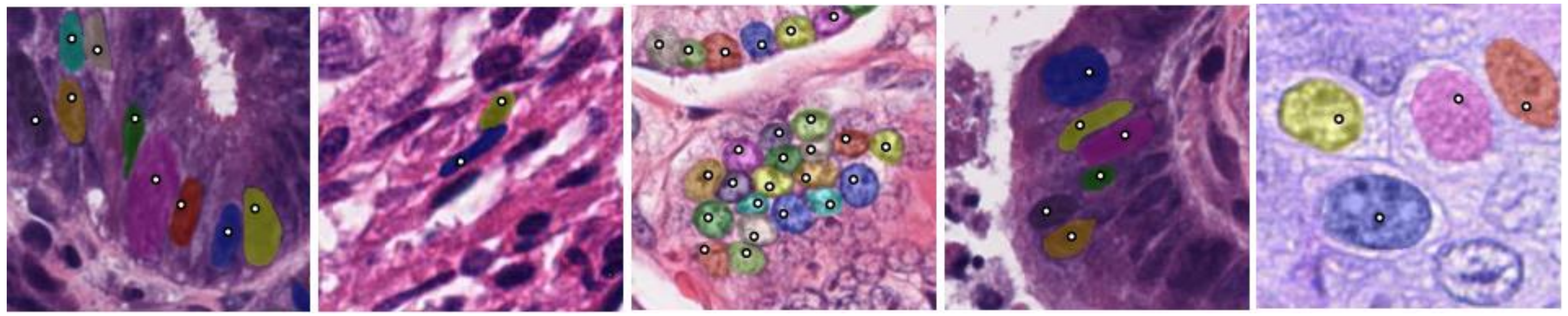
- Domain Optimized Training Pipeline for Pathology
  - Giant Images – 100~1000x Larger than CT/MR.
  - Efficient WSI IO with RAPIDS CuCIM
- Optimized End-to-End – Up to 10x Faster Training
- Prepared Pathology Pipelines
  - Metastasis Detection Task
  - Whole-slide image classification (MIL)
- Collaboration with reference centers and domain experts
  - Birmingham Children's Hospital / PathLake consortium
  - NuClick single-click cell segmentation



Detection of metastasis in whole-slide histopathology images.







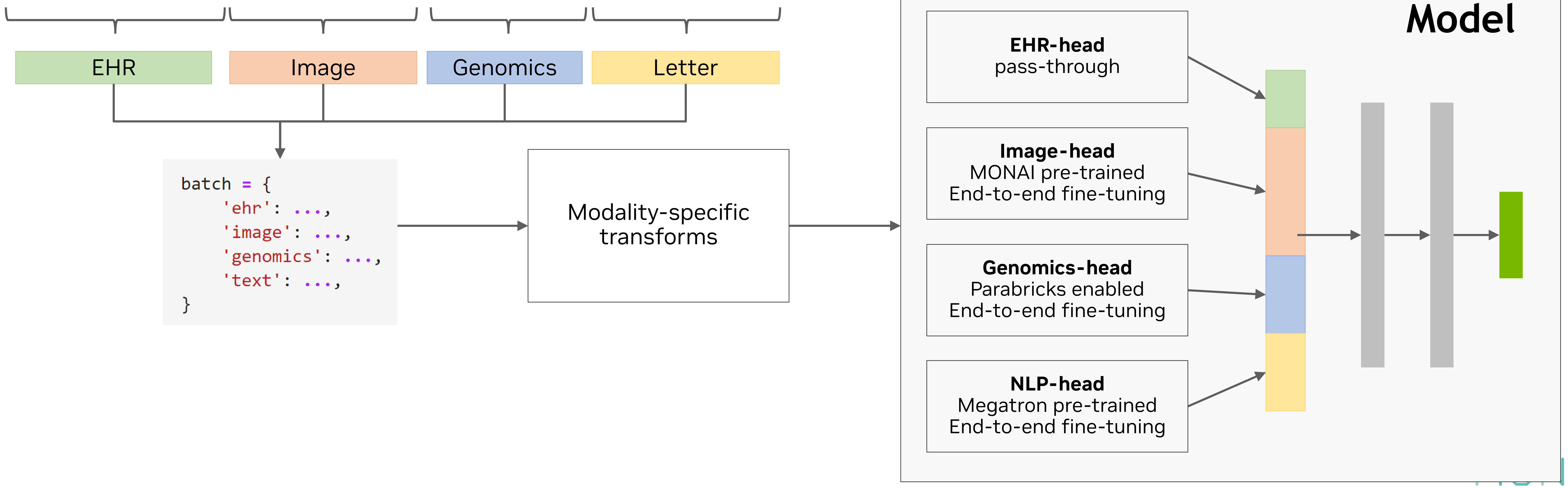
MONAI NVIDIA

MONAI Multi-Omics

Multimodal data from tabular patient representations

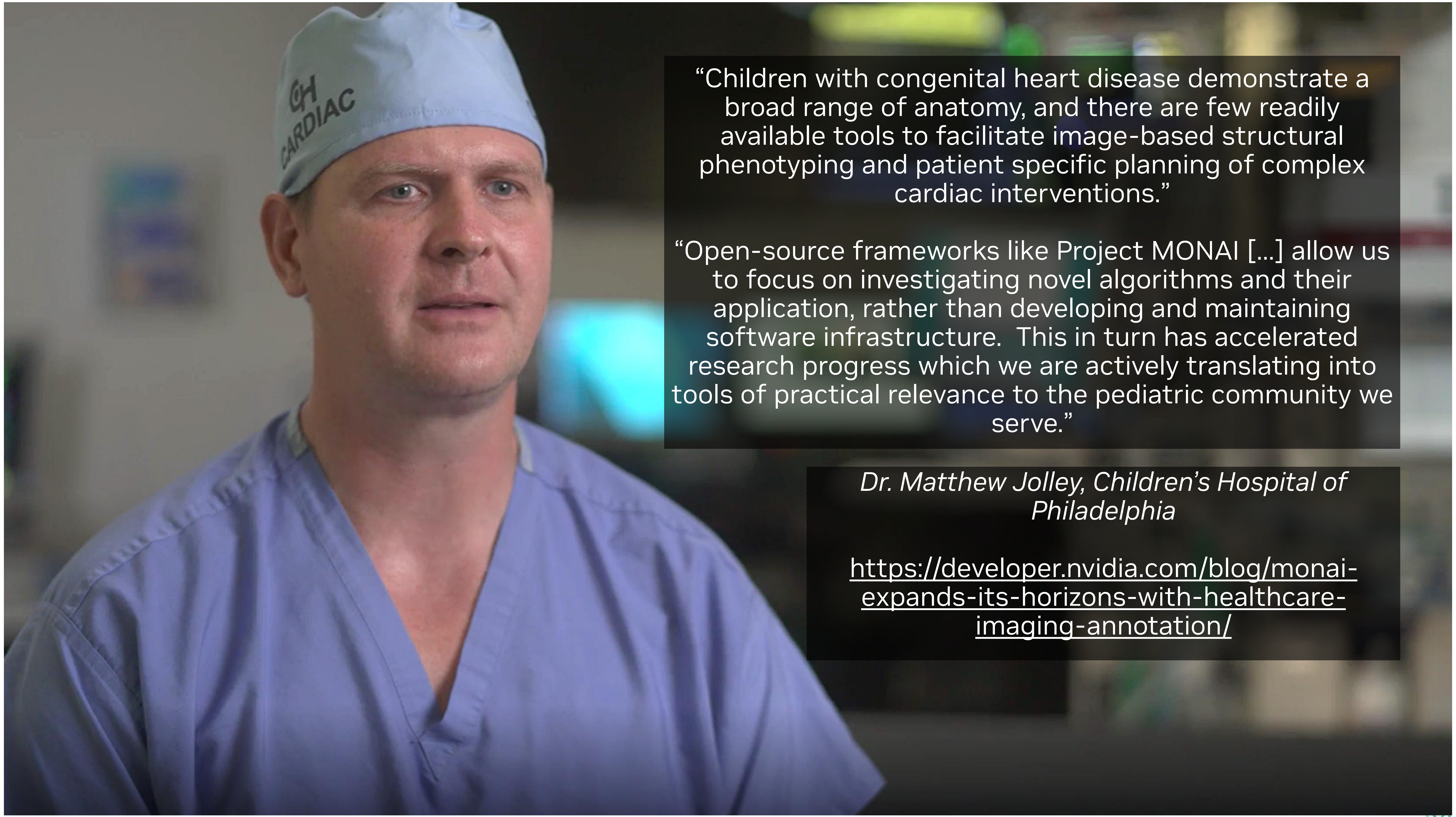
```python
class CSVDataset(Dataset):
    """
    Dataset to load data from CSV files and generate a list of dictionaries,
    every dictionary maps to a row of the CSV file, and the keys of dictionary
    map to the column names of the CSV file.
```

patient_id	age	sex	kg	image	genomics	text
Subject_01	34	M	75	./imgs/01.nii.gz	./genx/01.csv	./letters/01.doc
Subject_02	62	F	84	./imgs/02.nii.gz	./genx/02.csv	./letters/02.doc
Subject_03	57	M	112	./imgs/03.nii.gz	./genx/03.csv	./letters/03.doc
...						



MONAI-Core

Accelerating the transition of data science into the clinic



"Children with congenital heart disease demonstrate a broad range of anatomy, and there are few readily available tools to facilitate image-based structural phenotyping and patient specific planning of complex cardiac interventions."

"Open-source frameworks like Project MONAI [...] allow us to focus on investigating novel algorithms and their application, rather than developing and maintaining software infrastructure. This in turn has accelerated research progress which we are actively translating into tools of practical relevance to the pediatric community we serve."

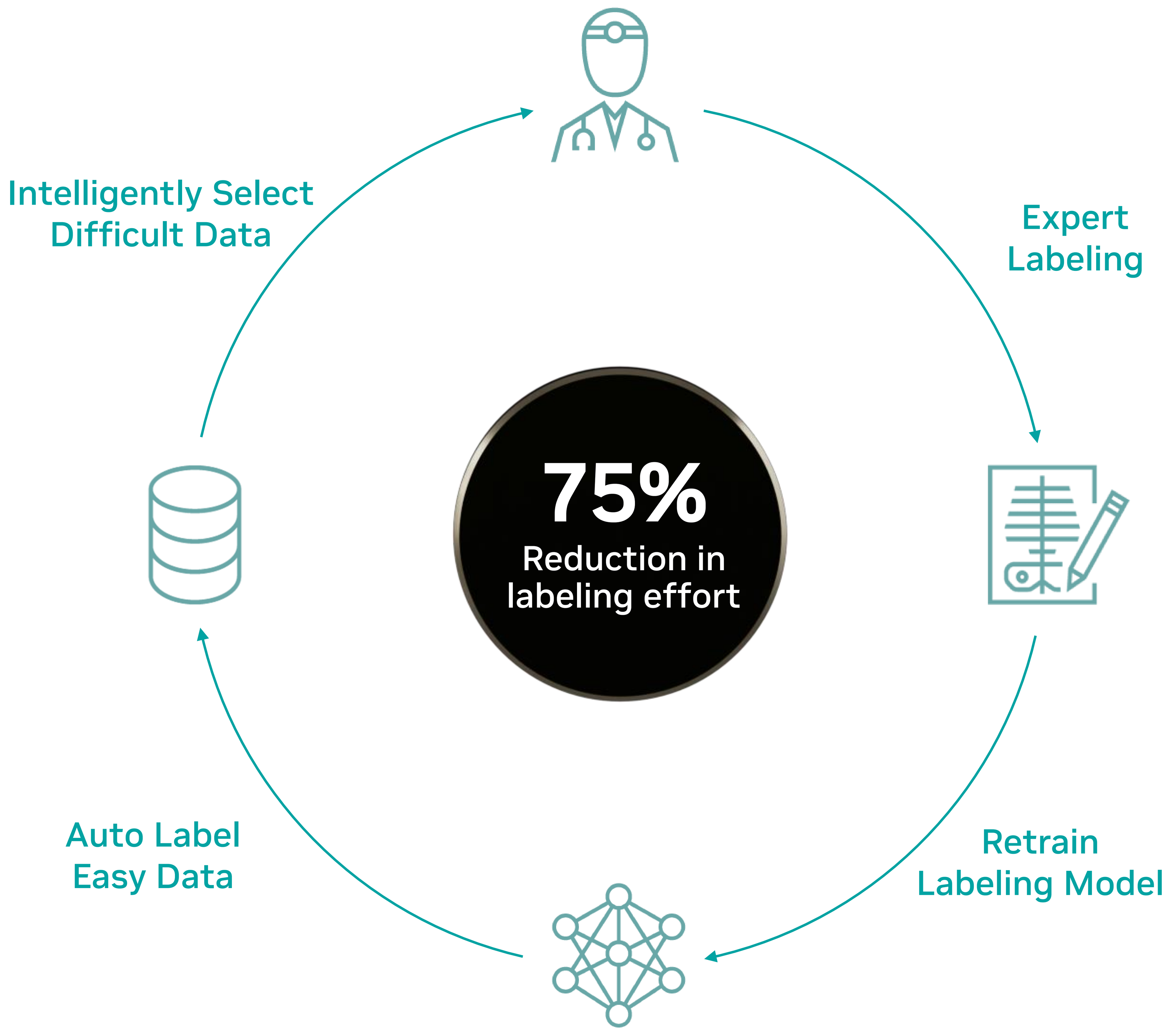
Dr. Matthew Jolley, Children's Hospital of Philadelphia

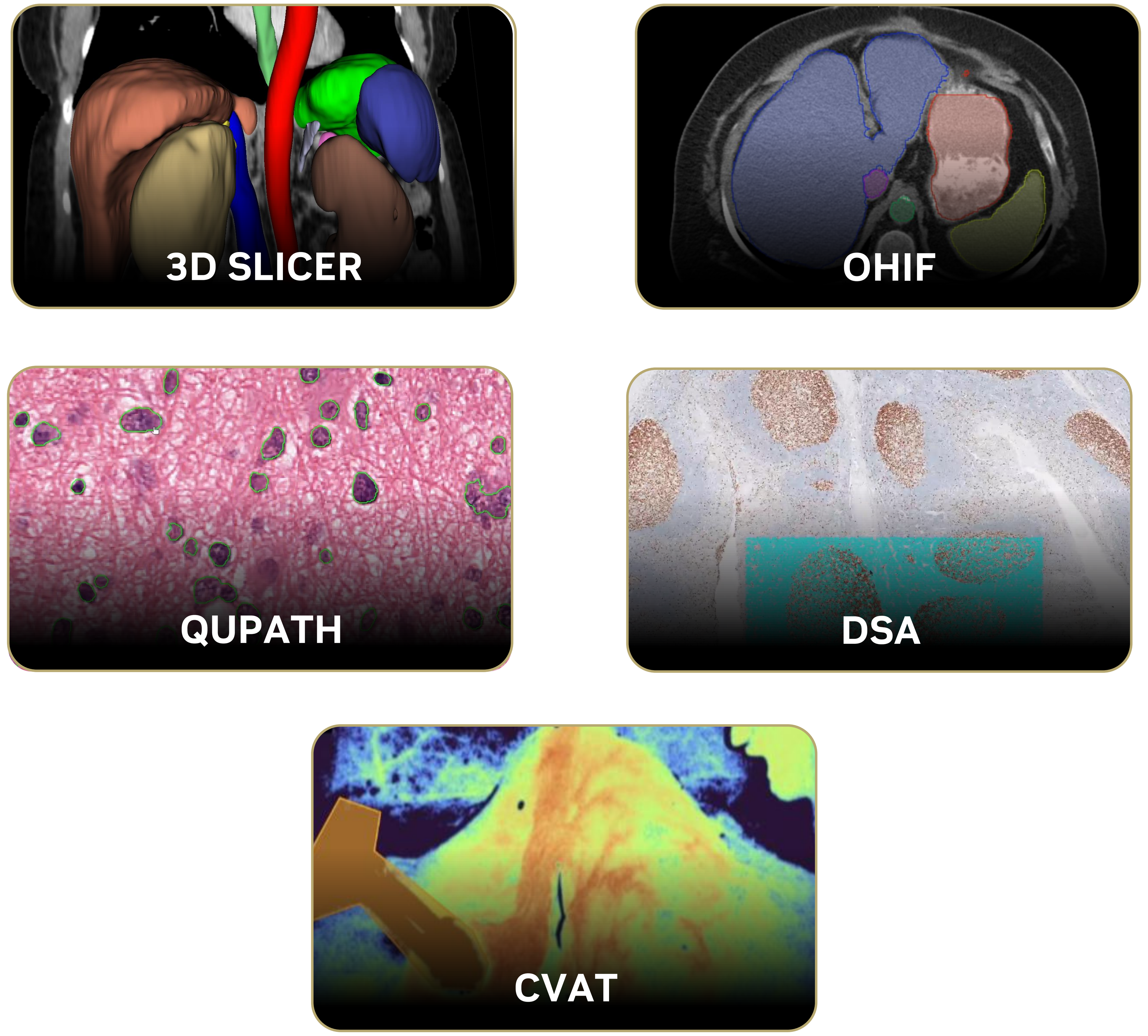
https://developer.nvidia.com/blog/monai-expands-its-horizons-with-healthcare-imaging-annotation/

MONAI-Label

MONAI LABEL: Active Learning

Reduce the cost of labeling imaging data



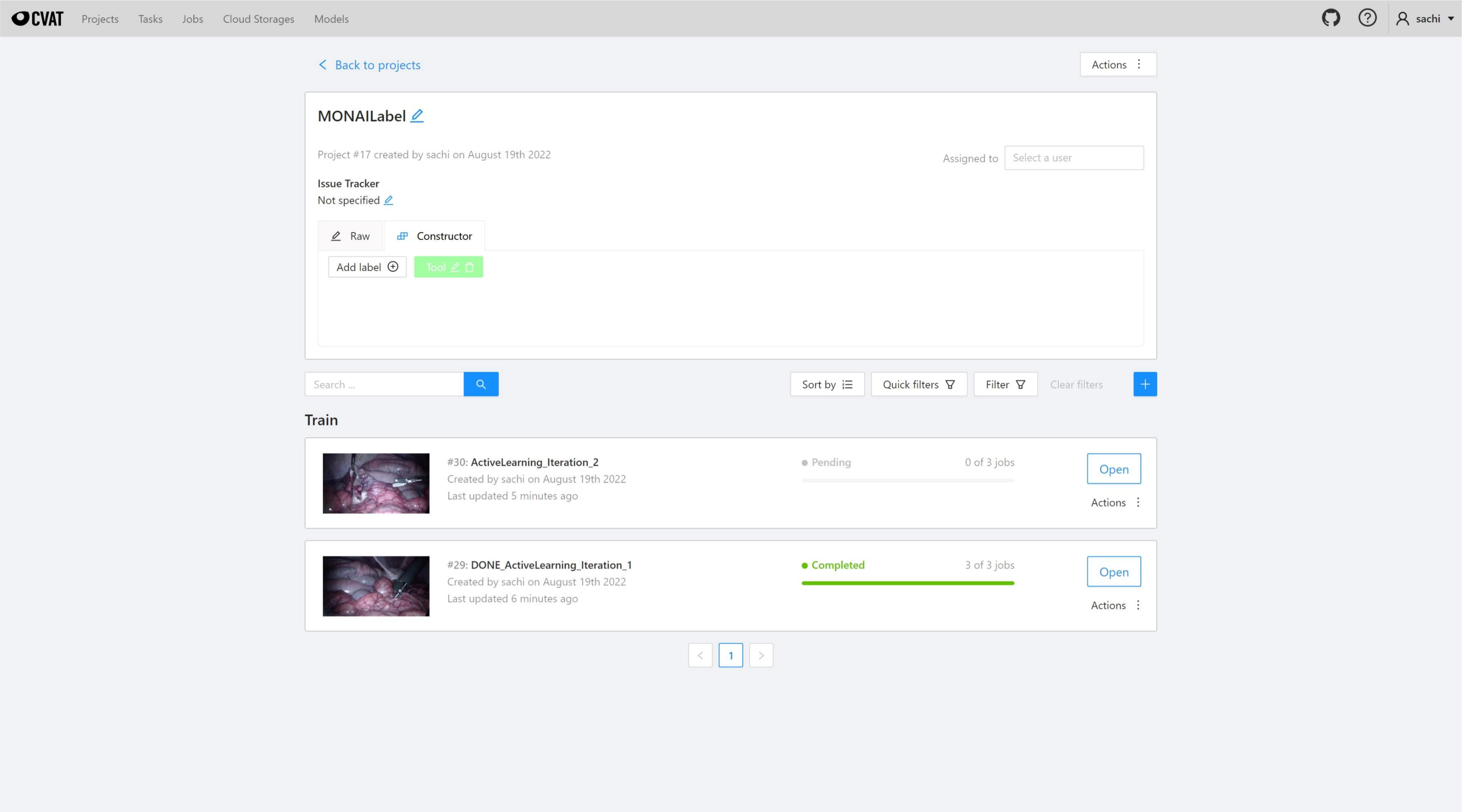


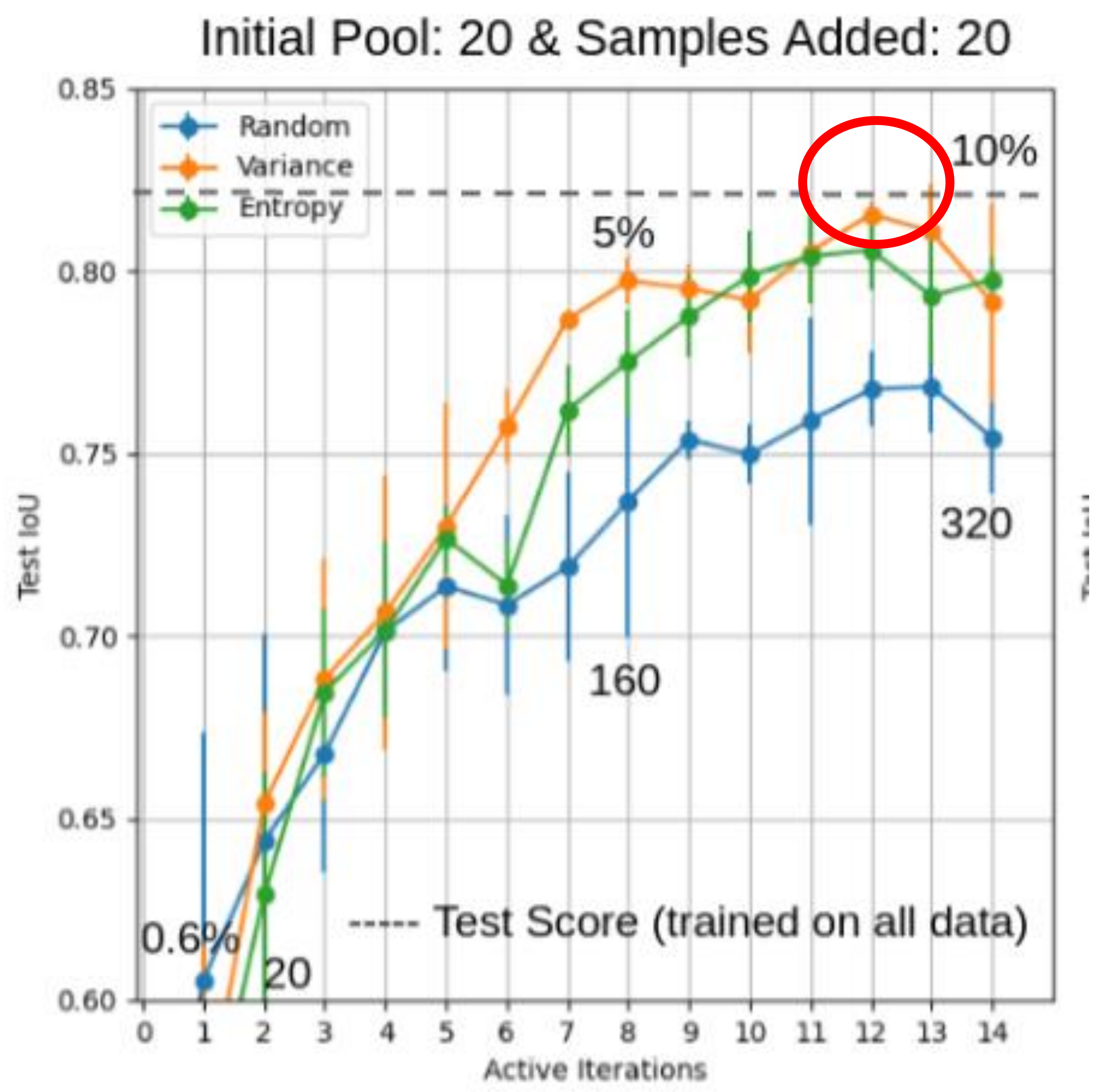
MONAI Label v0.5.1

Endoscopy Sample Application

Endoscopy Active Learning using CVAT client UI

- Segmentation model for surgical tool tracking
- InBody vs OutBody classification model
- Nearly reaching full-train data test score with active learning on <10% of data



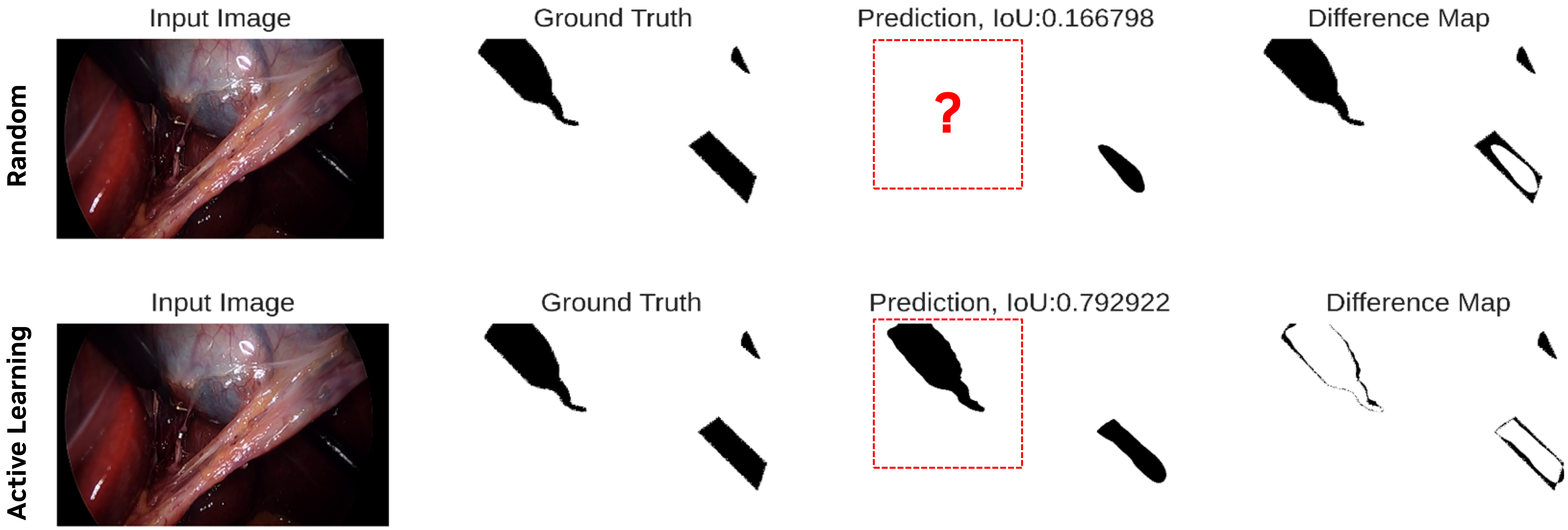


https://github.com/Project-MONAI/MONAILabel/tree/main/sample-apps/endoscopy

MONAI Label v0.5.1

Endoscopy Sample Application

- **Further evidence for the value of Active Learning:** Good Segmentation by AL where Random strategy fails



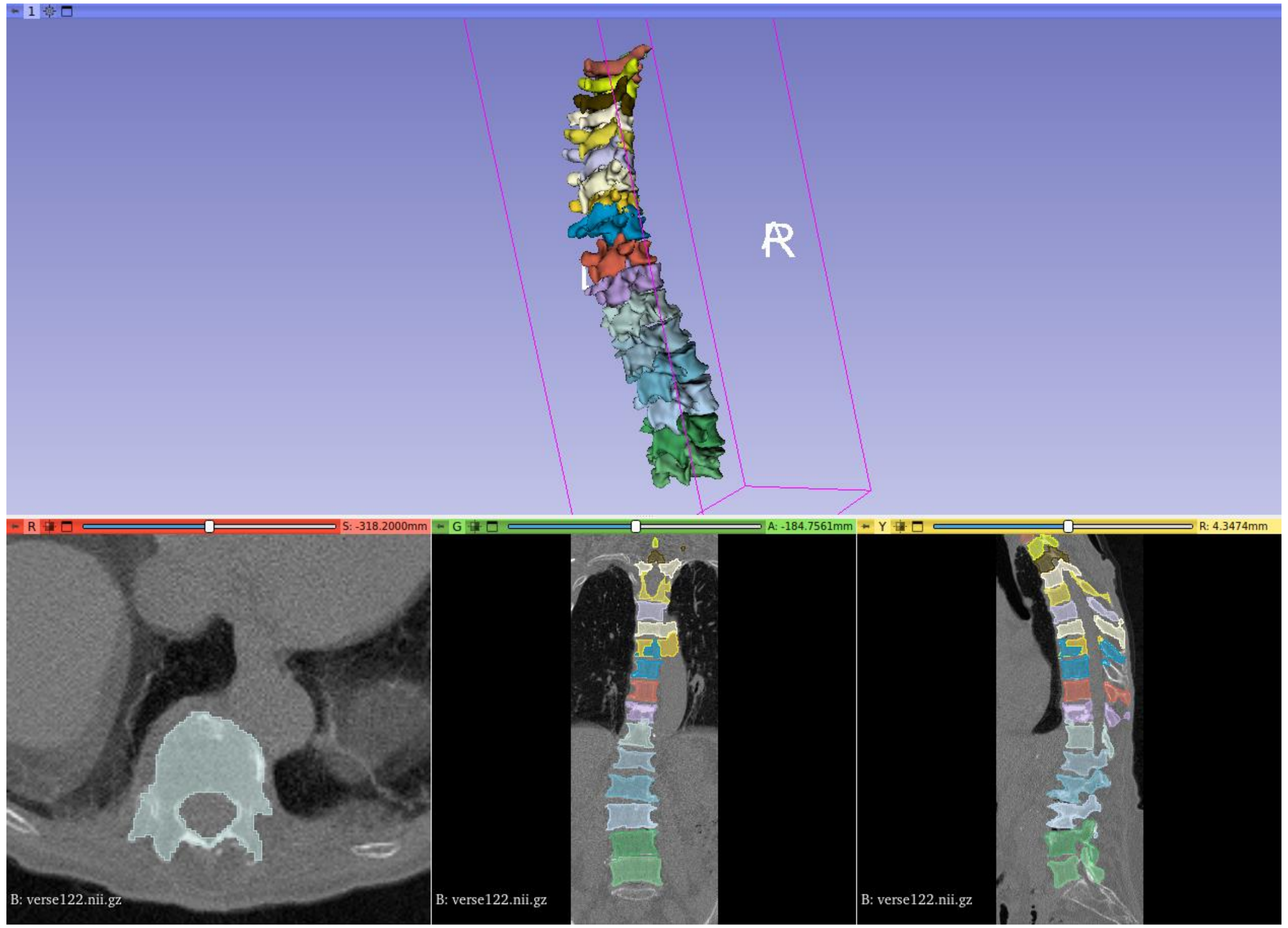
https://github.com/Project-MONAI/MONAILabel/tree/main/sample-apps/endoscopy

MONAI Label v0.5.1

Multistage Vertebra Segmentation

Model 1: spine localization

Model 2: vertebra segmentation



- Labels:


```
{
        "C1": 1,
        "C2": 2,
        "C3": 3,
        "C4": 4,
        "C5": 5,
        "C6": 6,
        "C7": 7,
        "Th1": 8,
        "Th2": 9,
        "Th3": 10,
        "Th4": 11,
        "Th5": 12,
        "Th6": 13,
        "Th7": 14,
        "Th8": 15,
        "Th9": 16,
        "Th10": 17,
        "Th11": 18,
        "Th12": 19,
        "L1": 20,
        "L2": 21,
        "L3": 22,
        "L4": 23,
        "L5": 24
}
```


https://github.com/Project-MONAI/MONAILabel/tree/main/sample-apps/radiology

MONAI Label v0.5.1

MONAI Bundle application

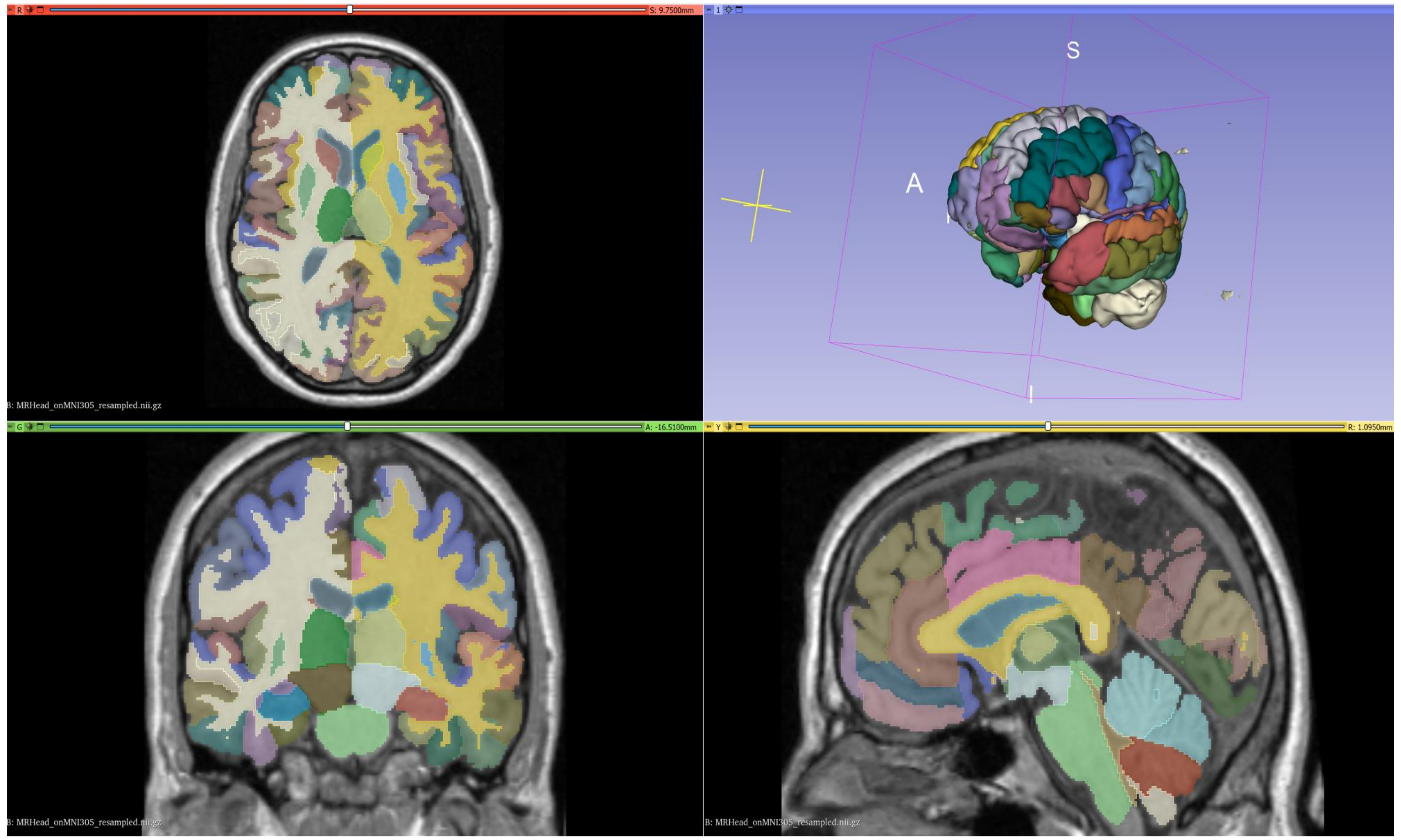
- Most model bundles from Model Zoo can be used in MONAI-Label's Bundle Application
- Prepared configs for training and inference
- Finetune pre-trained model weights for various anatomies and modalities

```
# skip if "monaibundle" app was already downloaded
cd /path/to/monailabel/apps/

monailabel apps --download --name monaibundle --output ./

# Add additional paths for python scripts (part of the MONAI-Bundle)

export
PYTHONPATH=$PYTHONPATH:/path/to/apps/monaibundle/model/wholeBrainSeg
_Large_UNEST_segmentation_v0.2.0

export
PYTHONPATH=$PYTHONPATH:/path/to/apps/monaibundle/model/wholeBrainSeg
_Large_UNEST_segmentation_v0.2.0/scripts

# Run server with the whole brain seg model

monailabel start_server \
  --app /path/to/apps/monaibundle \
  --studies /path/to/data/WholeBrainSegT1w \
  --conf models wholeBrainSeg_Large_UNEST_segmentation_v0.2.0 \
  --conf multi_gpu true
```

Supported Models

The Bundle App supports most labeling models in the Model Zoo, please see the table for labeling tasks.

Bundle	Model	Objects	Modality	Note
spleen_ct_segmentation	UNet	Spleen	CT	A model for (3D) segmentation of the spleen
swin_unetr_btcv_segmentation	SwinUNETR	Multi-Organ	CT	A model for (3D) multi-organ segmentation
prostate_mri_anatomy	UNet	Prostate	MRI	A model for (3D) prostate segmentation from MRI image
pancreas_ct_dints_segmentation	DiNTS	Pancreas/Tumor	CT	An automl method for (3D) pancreas/tumor segmentation
renalStructures_UNEST_segmentation	UNesT	Kidney Substructure	CT	A pre-trained for inference (3D) kidney cortex/medulla/pelvis segmentation
wholeBrainSeg_UNEST_segmentation	UNesT	Whole Brain	MRI T1	A pre-trained for inference (3D) 133 whole brain structures segmentation
brats_mri_segmentation	SegResNet	Brain Tumor	MRI	A pre-trained for brain tumor subregions segmentation
spleen_deepedit_annotation	DeepEdit	Spleen	CT	An interactive method for 3D spleen Segmentation



https://github.com/Project-MONAI/MONAILabel/tree/main/sample-apps/monaibundle

MONAI-Label: AI-Assisted Annotation

Example AIAA Workflow: Cold Start Prediction

MONAI-Label: AI-Assisted Annotation

Example AIAA Workflow: 1st Manual annotation

MONAI-Label: AI-Assisted Annotation

Example AIAA Workflow: Prediction after training on 1 annotation

MONAI-Label: AI-Assisted Annotation

Example AIAA Workflow: Prediction after training on 2 annotations

MONAI-Label: AI-Assisted Annotation

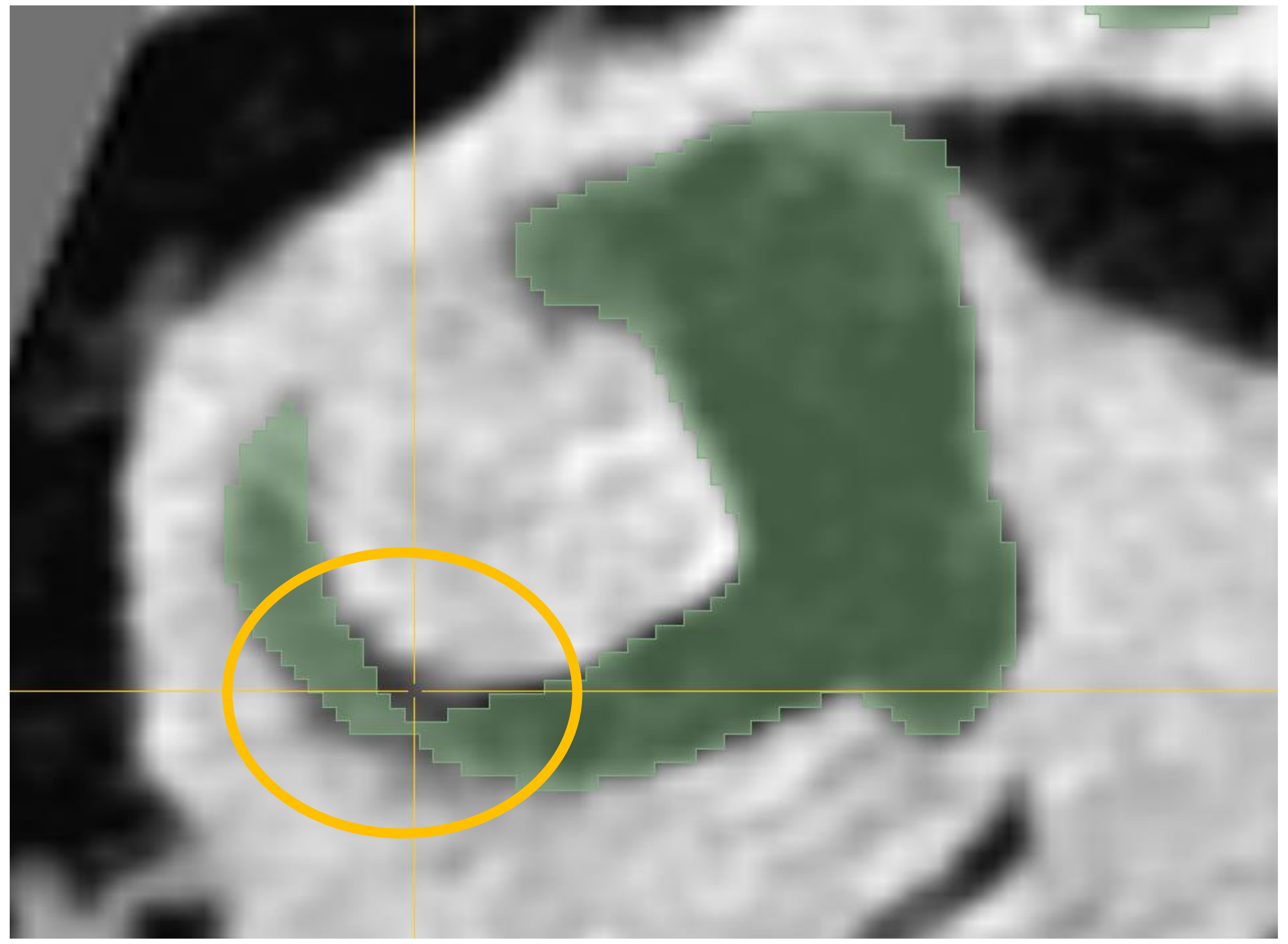
Example AIAA Workflow: Prediction after training on 3 annotations

NVIDIA

MONAI-Label: Interactive Annotation

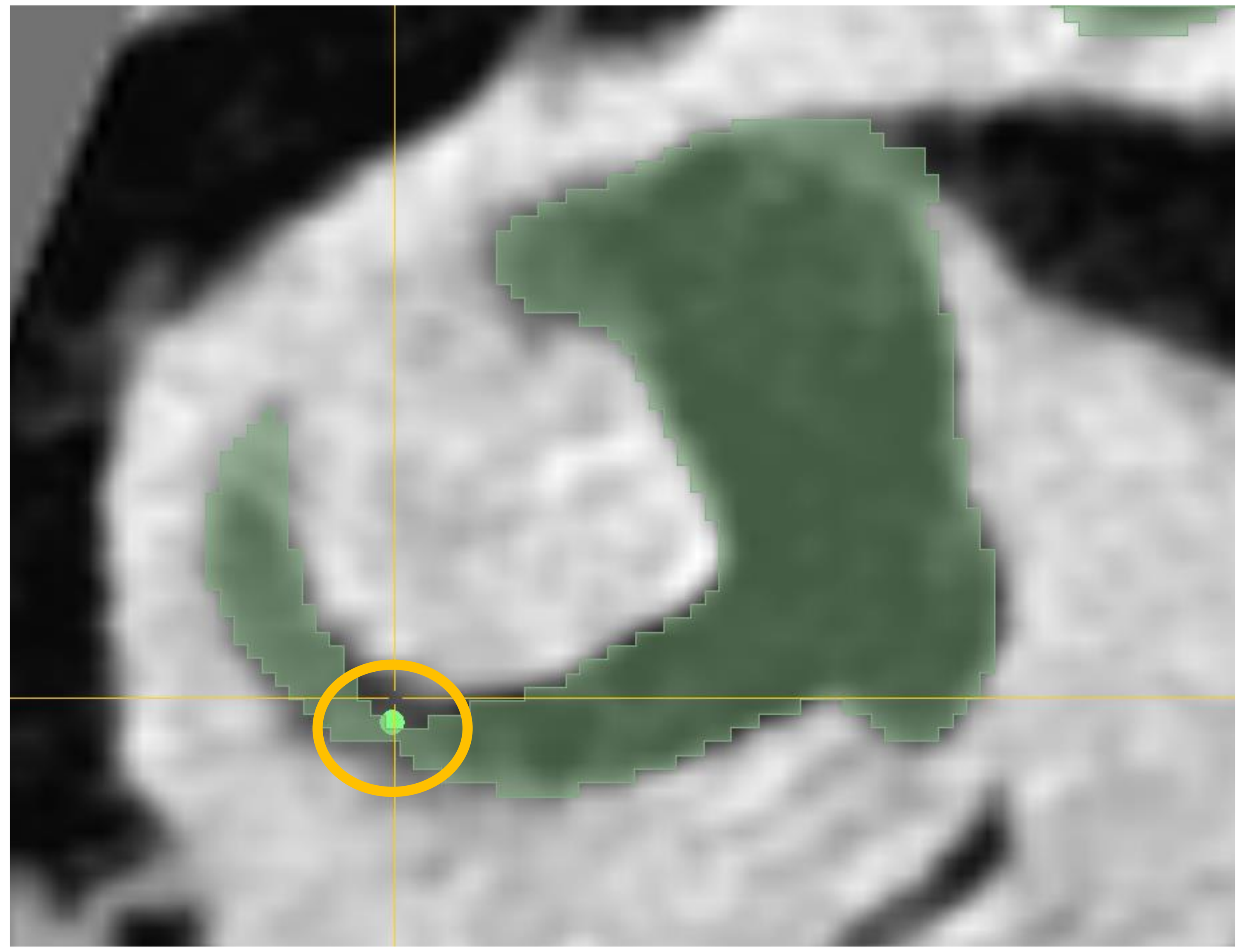
Annotation speedups from click-based refinement

Model prediction after training on 3 annotations



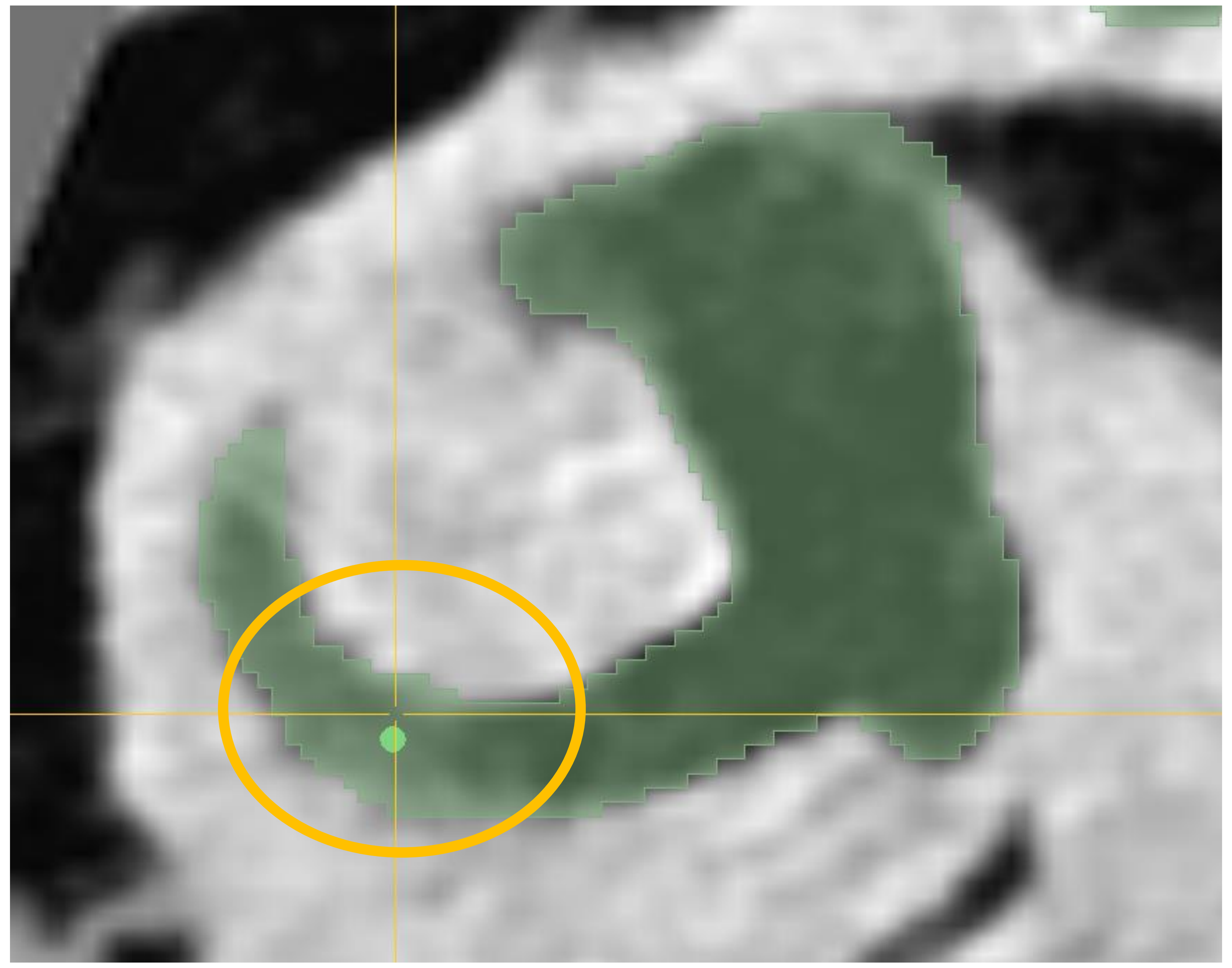
Under-segmentation

Correction via clicks



Manual refinement

Improved prediction

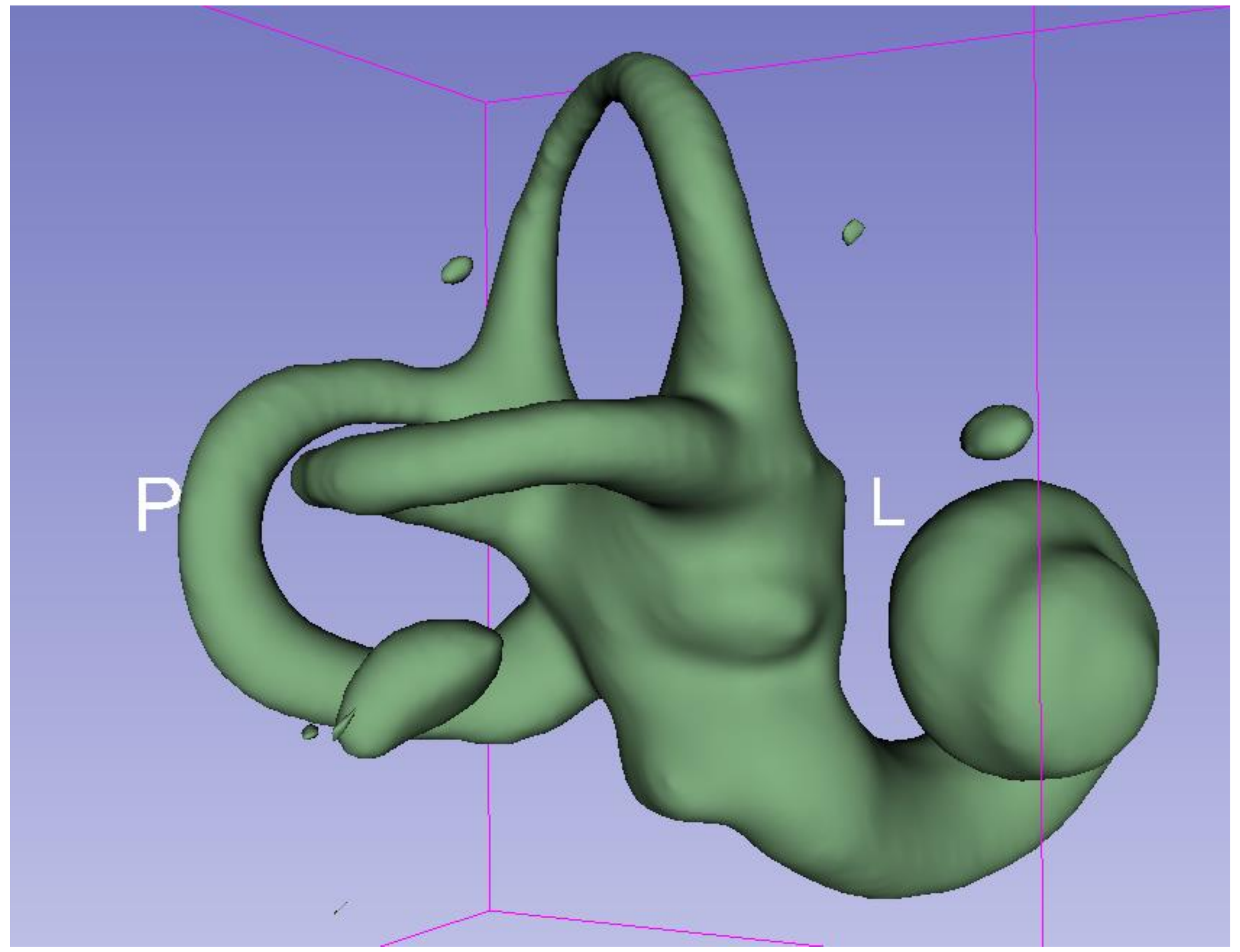


Local improvements

MONAI-Label: AI-Assisted Annotation

Annotation speedups from Active Learning

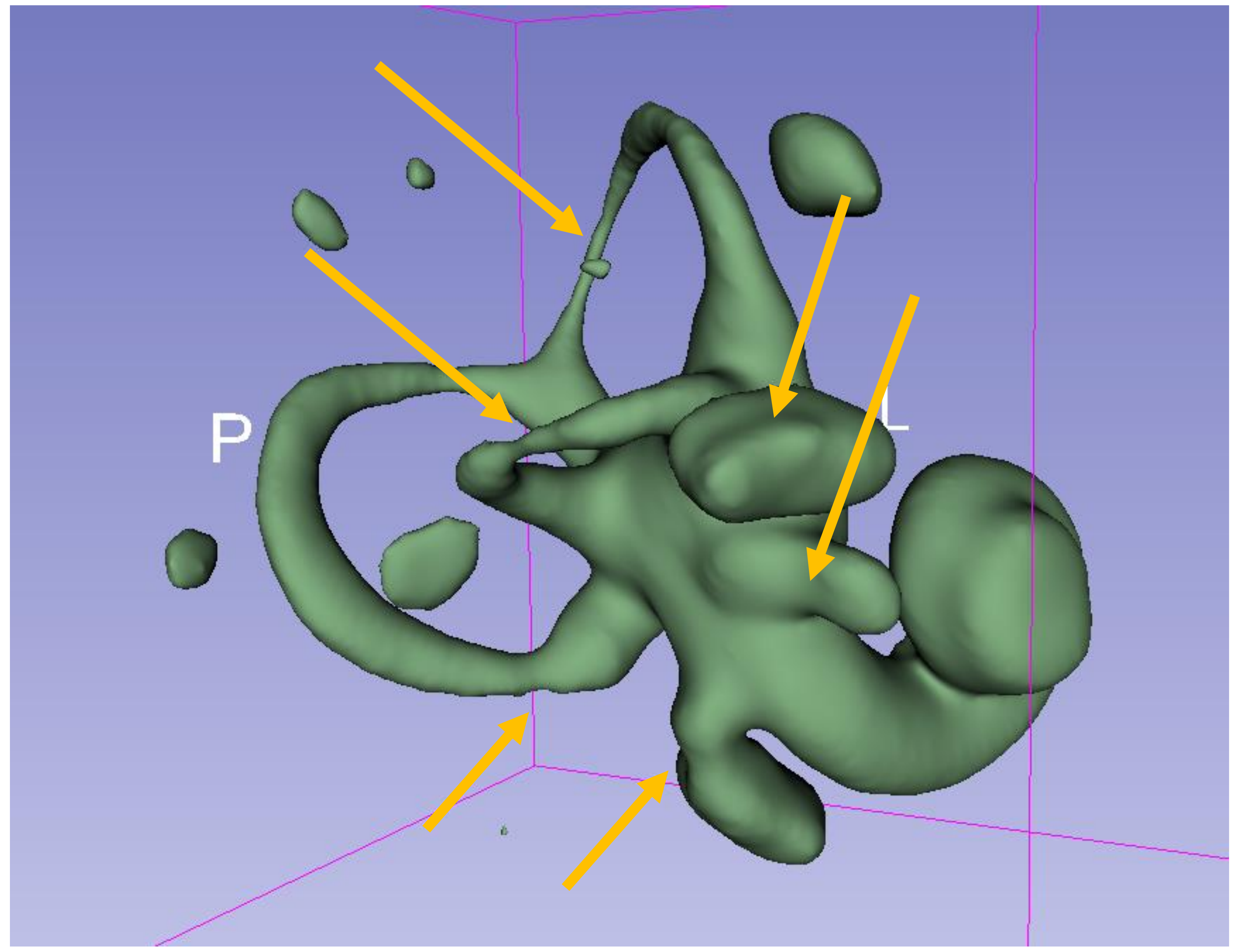
Next sample:
Without Active Learning



Next sample strategy:
Random Sampling

“With Active Learning, annotation time is time spent well.”

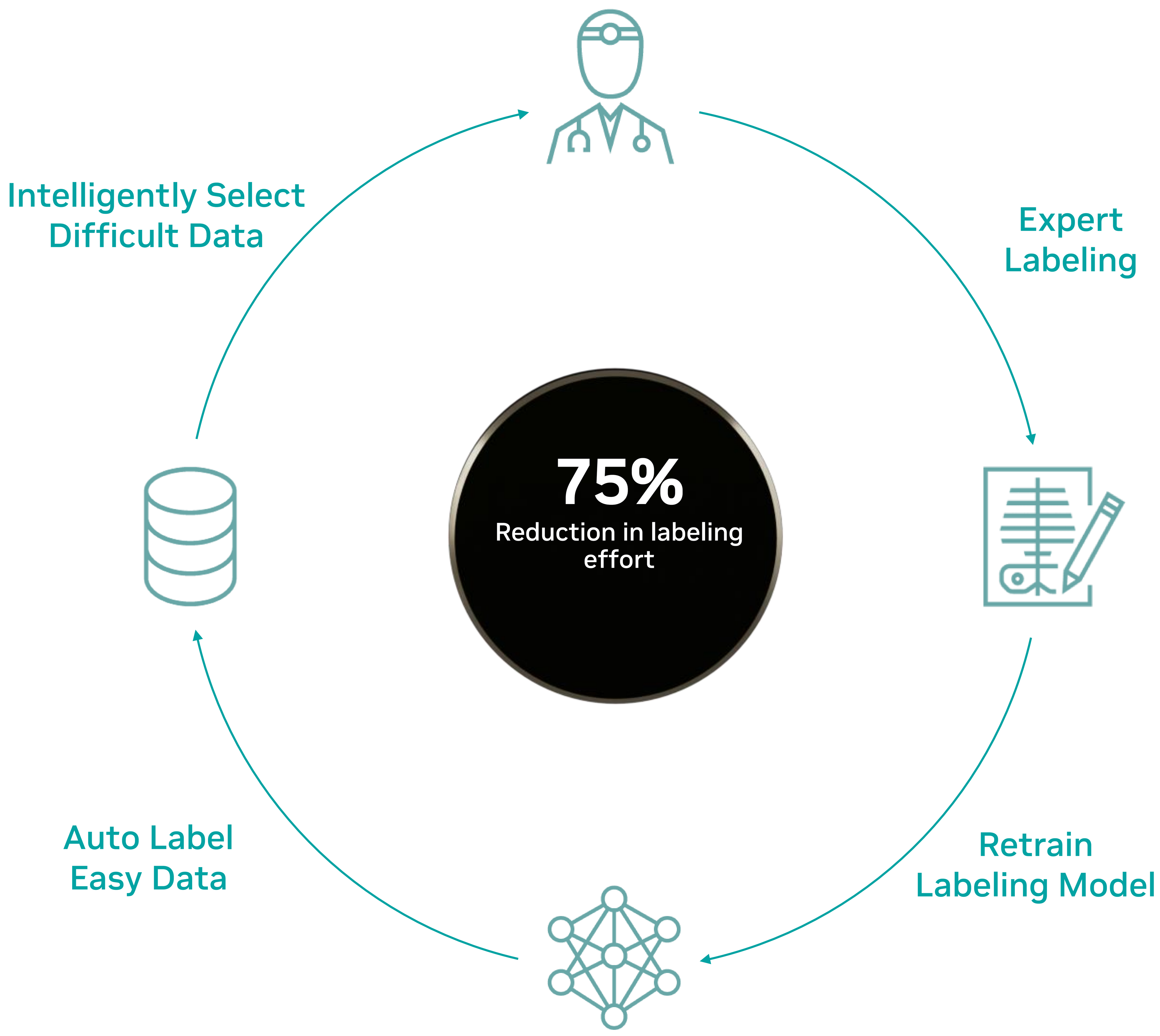
Next sample:
With Active Learning



Next sample strategy:
Aleatoric Uncertainty

MONAI-Label: AI-Assisted Annotation

End-to-end / zero-code entry point into the MONAI ecosystem



Dr. Keno Bressem
Charité University Medicine Berlin

- MONAI Label's Active Learning helped annotators review and label 50-100 images a day
- Interactive Labeling allowed for continuously visible progress
- Used Epistemic image selection algorithm to intelligently select highest value images to be annotated

"MONAI Label reduced our overall labeling effort by 50%."

MONAI-Deploy

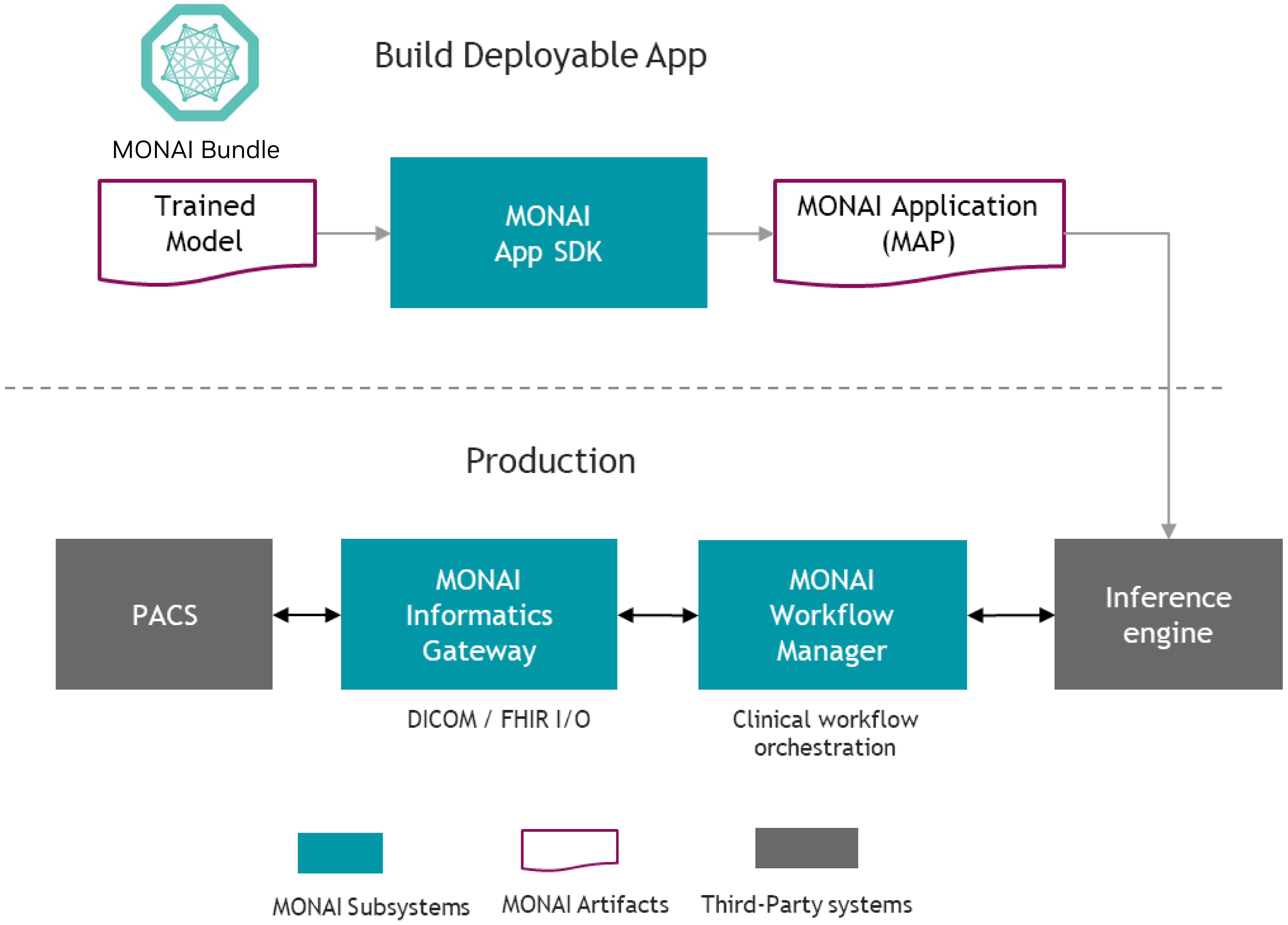
What is MONAI Deploy?

Bridging the gap from research to clinical production
The de-facto standard for developing, packaging, testing, deploying, and running medical AI applications in production

For Researchers and Developers
Build MONAI Applications (MAPs) from trained models in <20 minutes and a few Python LoC

For Hospital Operations

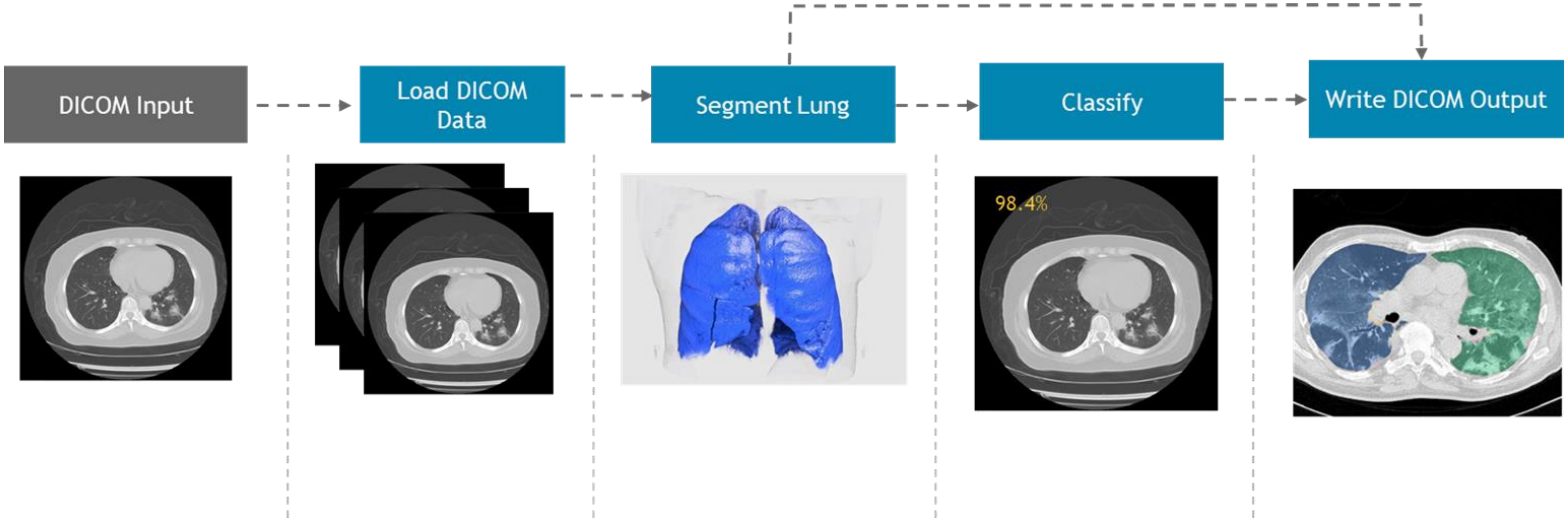
- Define what a clinical infrastructure to run AI should look like
- Provide building blocks to create a clinical inference processing pipeline, integrated with hospital systems over standards like DICOM, FHIR, and HL7



MONAI Deploy App SDK?

Bridging Deploy-ready AI Applications (MAPs)

- Include one or more trained models and the necessary interoperability, pre and post-processing to do clinical inference in a single container.
- Build once, deploy anywhere
- DICOM data loaders with series selection and series to volume and writers for DICOM Seg, STL, etc.
- Create new data loaders and writers to include other modalities (Pathology), data formats (WSI) or even training frameworks (TensorFlow)
- Reuse predefined operators, or create your own, and link them in a flow to compose an application in < 20 minutes
- MONAI Bundle to MAP inference operator for automated integration with MONAI trained models



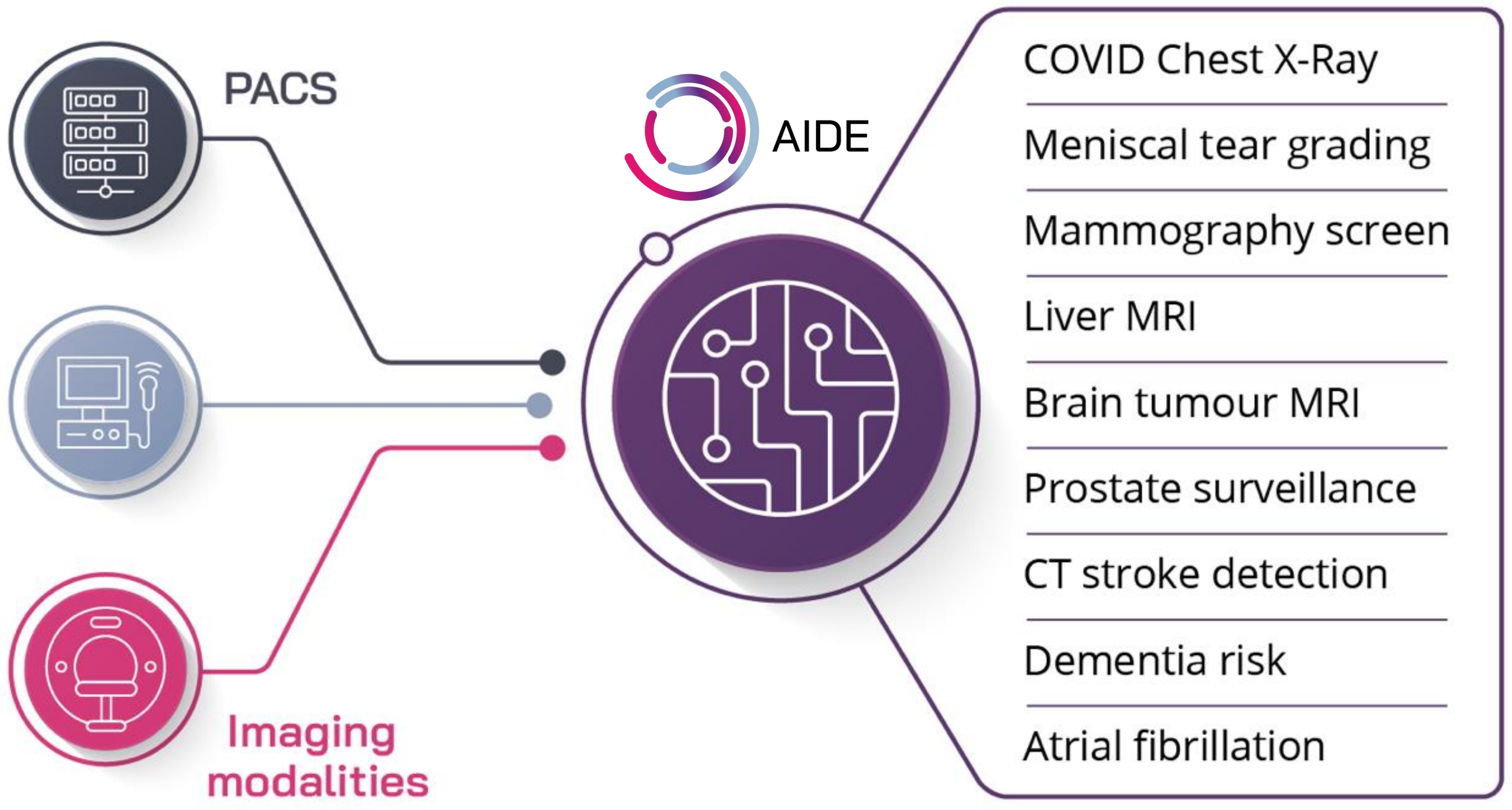
AIDE

AI Deployment Engine

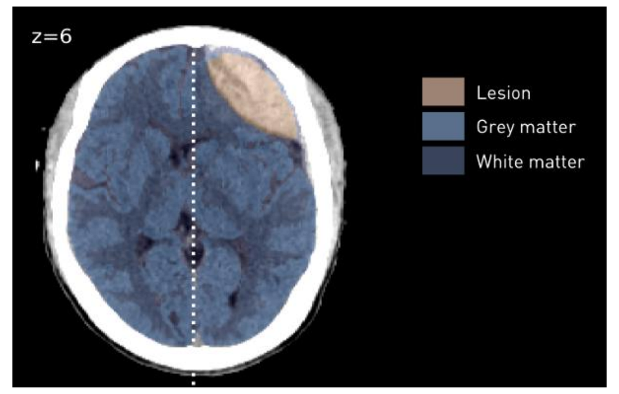
AI CENTRE for Value Based Healthcare

- Integrates with clinical information systems (DICOM, FHIR, HL7)
- Enterprise platform for the management and deployment of AI.
- AIDE App Store to share and distribute AI applications.
- Help manage technical, clinical and regulatory risks around AI deployment.
- 2022-23: deployment at 10 NHS Trusts

Targets: 10 Trusts | ~20M people | ~20 Apps

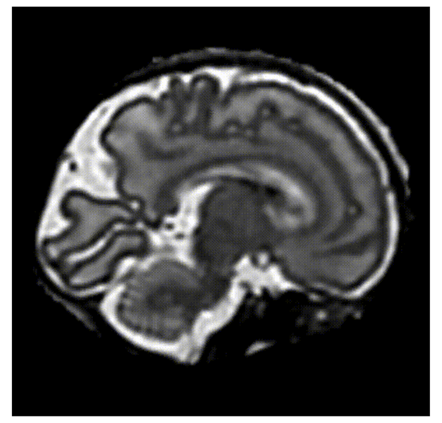


UCL | King's College London



AI automated stroke CT analysis

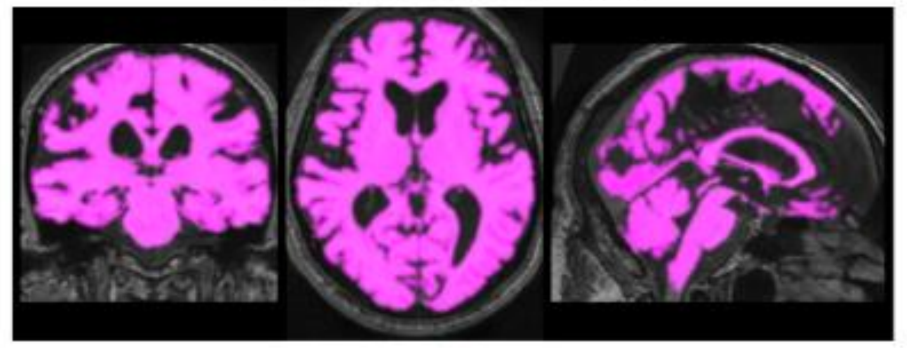
King's College London



AI-driven motion-corrected 3D fetal MRI

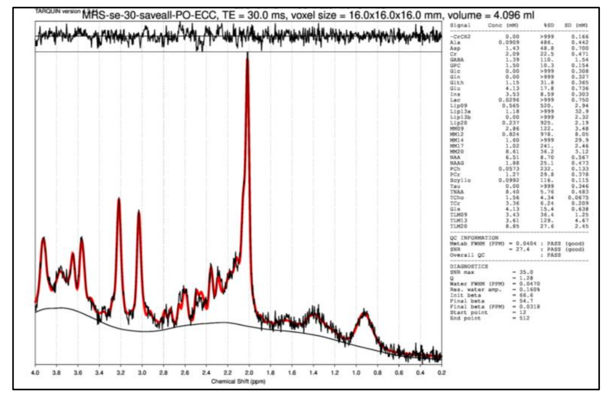
brainminer

Brain Volume Fraction



AI automated brain MRI analysis

NHS Guy's and St Thomas' NHS Foundation Trust



MR Spectroscopy modelling

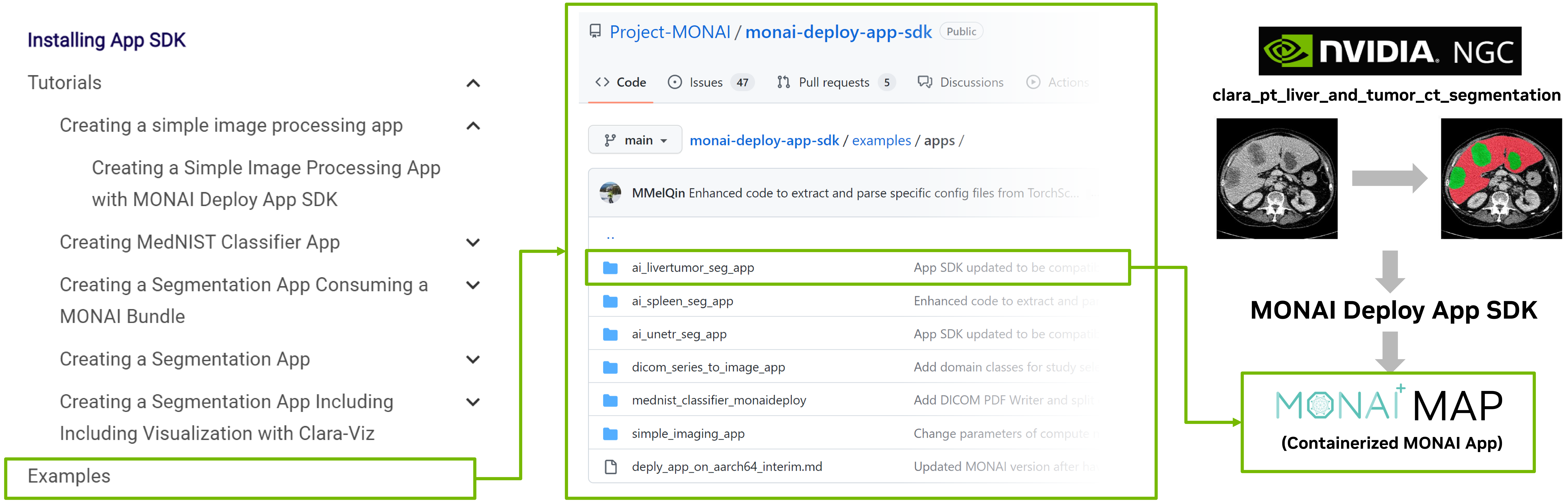
Industry partner

AI head CT

MONAI Deploy App SDK v0.5.0

Design, develop and verify AI-driven MONAI Applications (MAPs)

- Enhanced DICOM support:
  - DICOM Encapsulated PDF Writer
  - DICOM Segmentation Writer with highdicom back end
  - Generated DICOM instance file names now based on SOP instance UID
  - Support DICOM instance level attribute matching in the DICOM Series Selection Operator
- Tutorials and Jupyter notebooks, are enhanced, re-organized and updated:

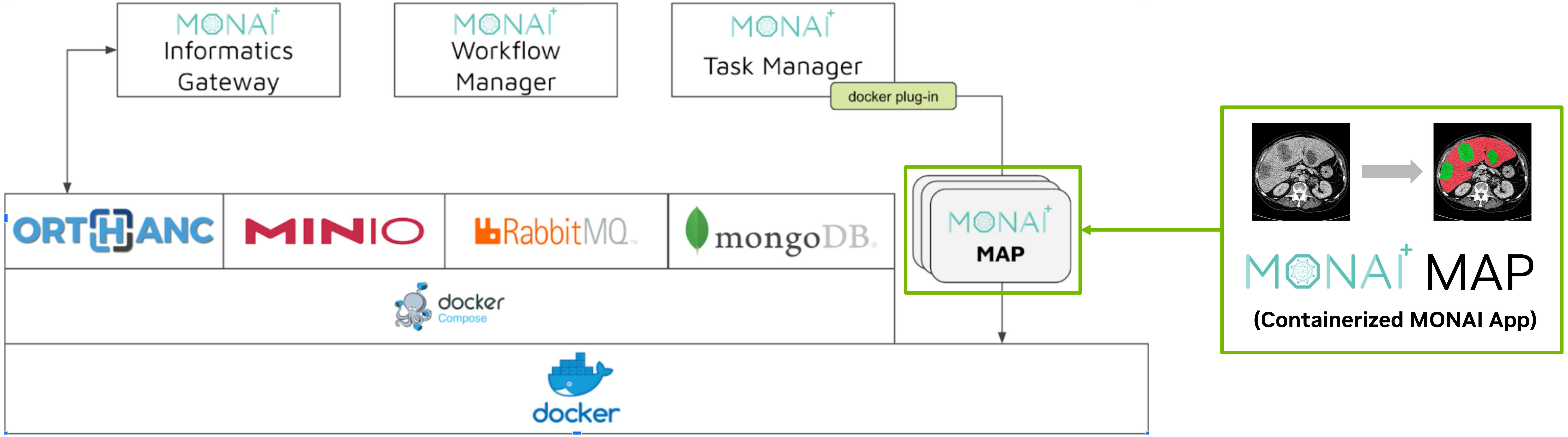


https://docs.monai.io/projects/monai-deploy-app-sdk/en/latest/getting_started/index.html

MONAI Deploy Express

Facilitate testing and validation of MAPs

- The journey from development to production usually requires multiple steps across different environments, operated by different teams and with different requirements.
- MONAI Deploy Express is designed to facilitate the testing and validation of MAPs in the early stages of this pipeline (i.e. workstation environment), where ease of use and time to get started are most important.
- Users of MONAI Deploy Express will be able to run their MAPs, connected to a test PACS, or their own test/research PACS, for further validation, confidently taking steps towards production.
- Reusing the same essential core services for DICOM I/O and AI workflow orchestration provides the same functionality and consistent experience independently of where and how the applications are run, with minimal changes for the end user.



https://github.com/Project-MONAI/monai-deploy/tree/main/deploy/monai-deploy-express

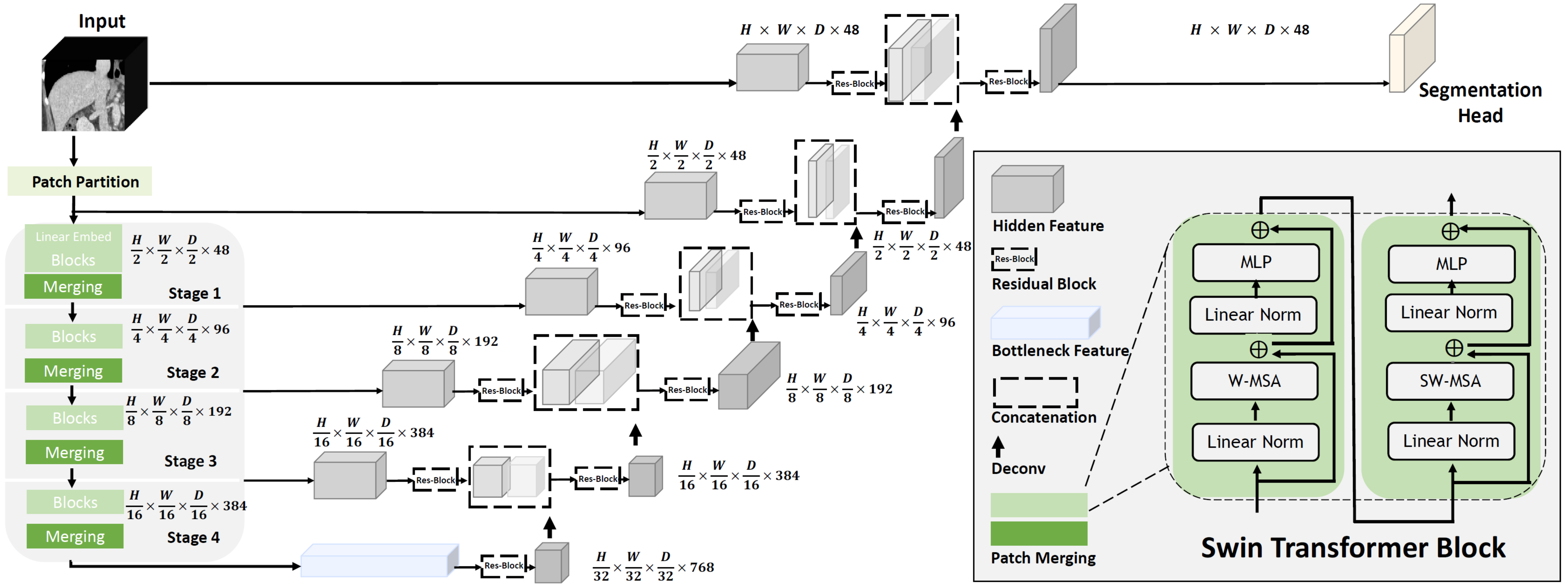
State-of-the-Art Research

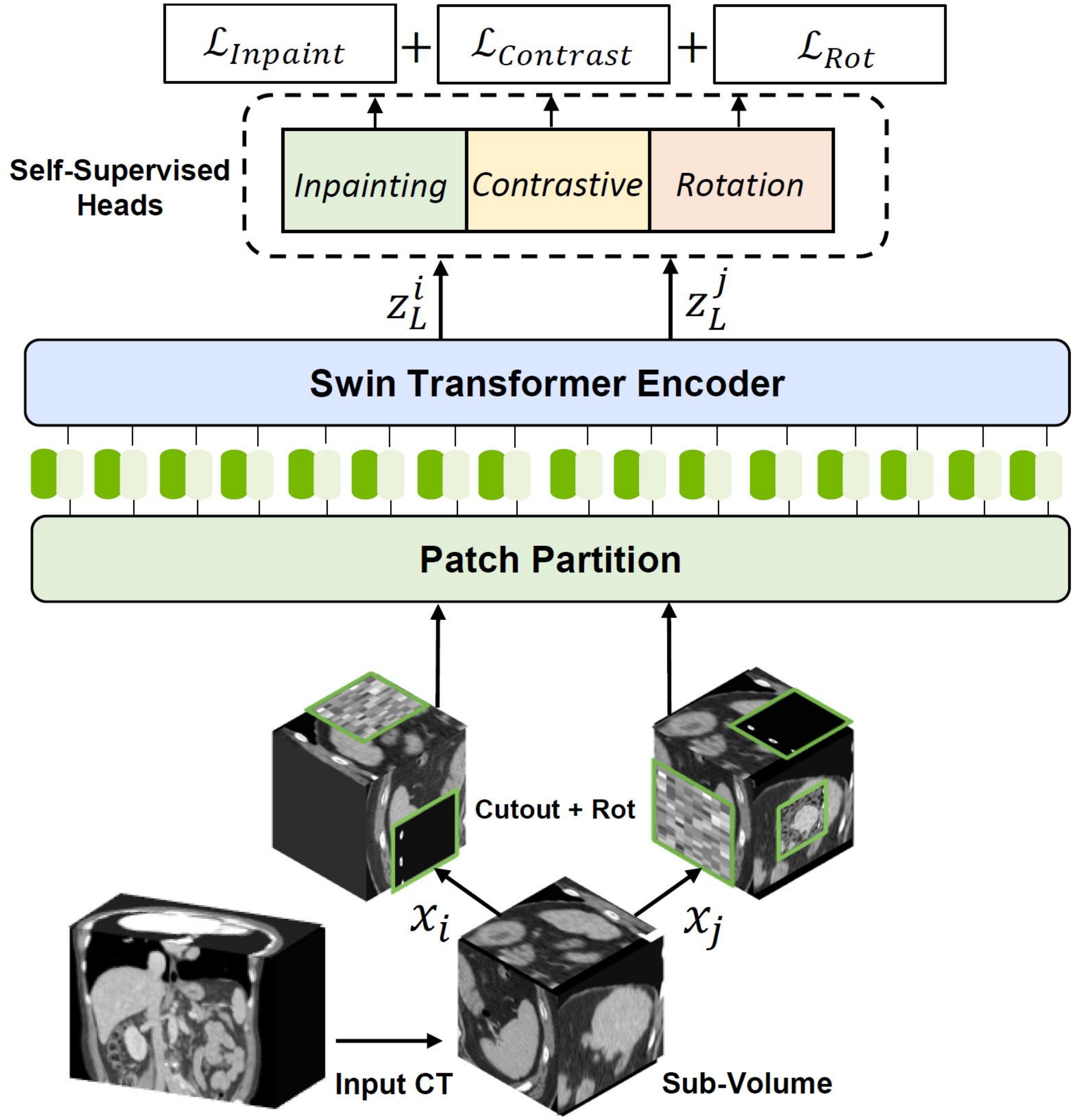
- Vision Transformers
- Self-supervised pre-training
- Auto3DSeg

3D Swin-UNETR

Self-supervised pre-training

- Utilize Terabytes of unlabeled archived radiology/pathology manner
- Pre-training of imaging models in a label-free manner via self-supervision
- Fine-tuning on various down-stream tasks with only few labels (segmentation, classification, localization)
- Achieved SOTA on “Beyond the Cranial Vault” (BTCV) and “Medical Segmentation Decathlon” (MSD) challenge datasets

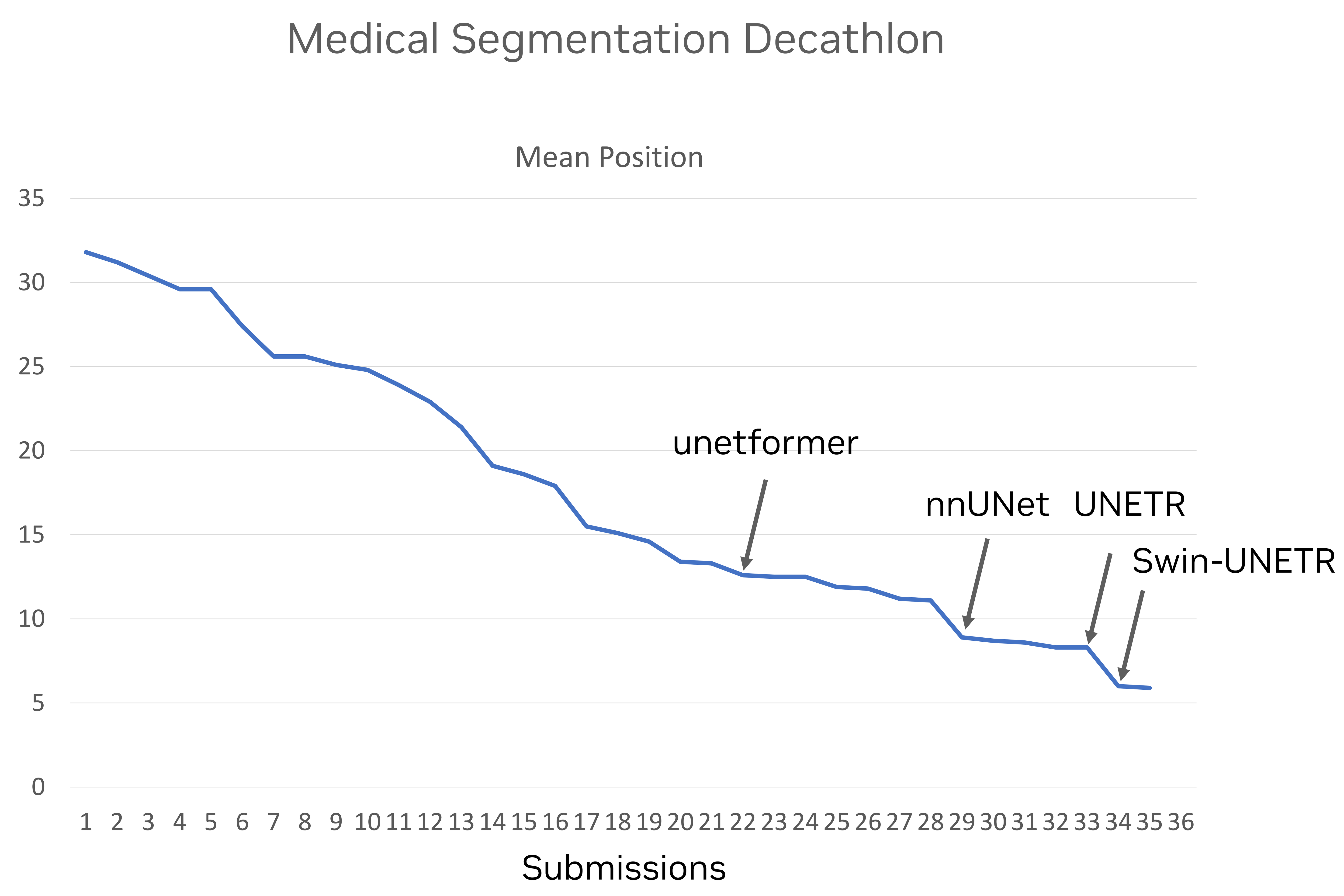




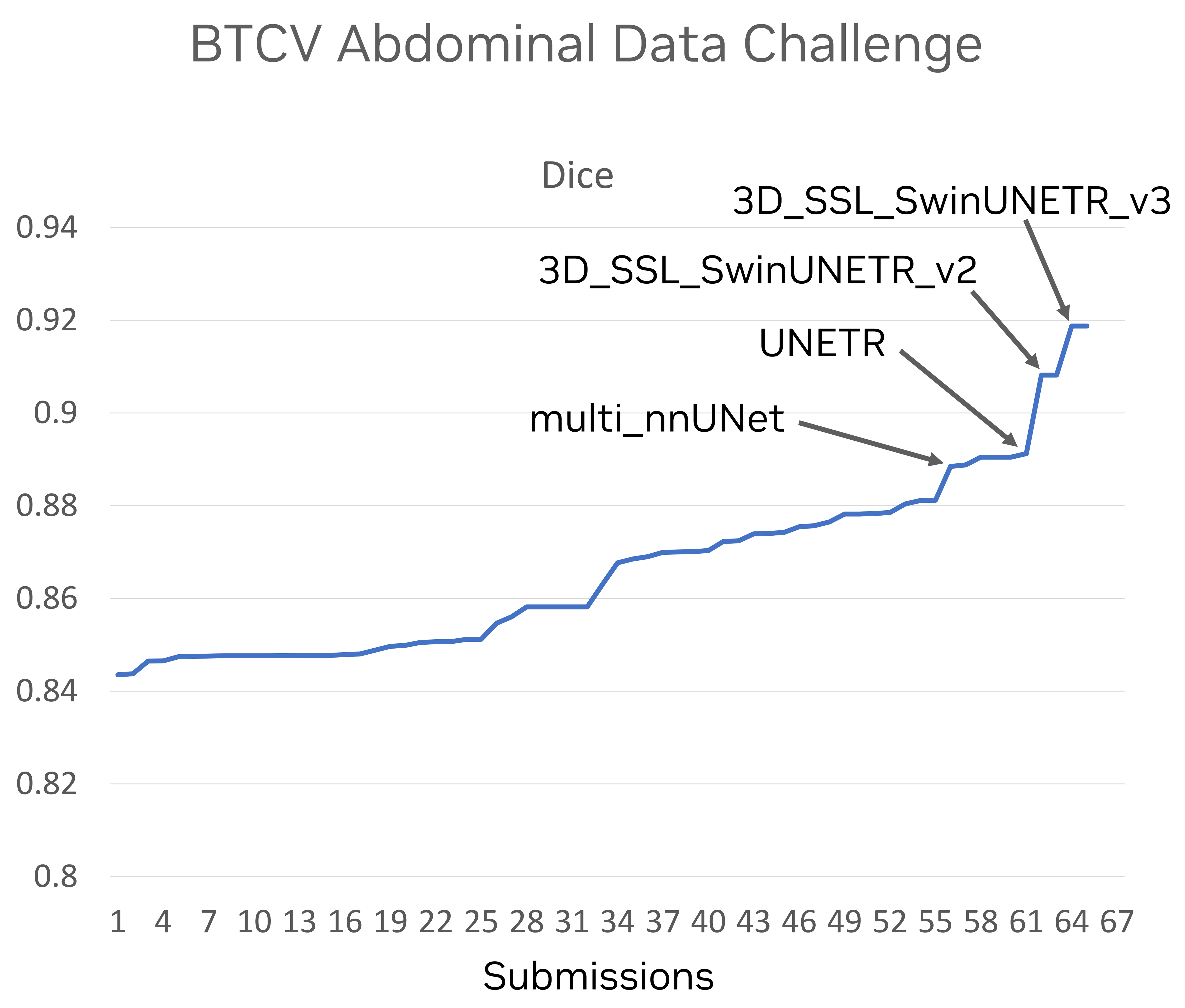
https://github.com/Project-MONAI/research-contributions/tree/main/SwinUNETR

Self-supervised Pre-training in Challenges

3D Swin-UNETR + SSL performance in MSD and BTCV

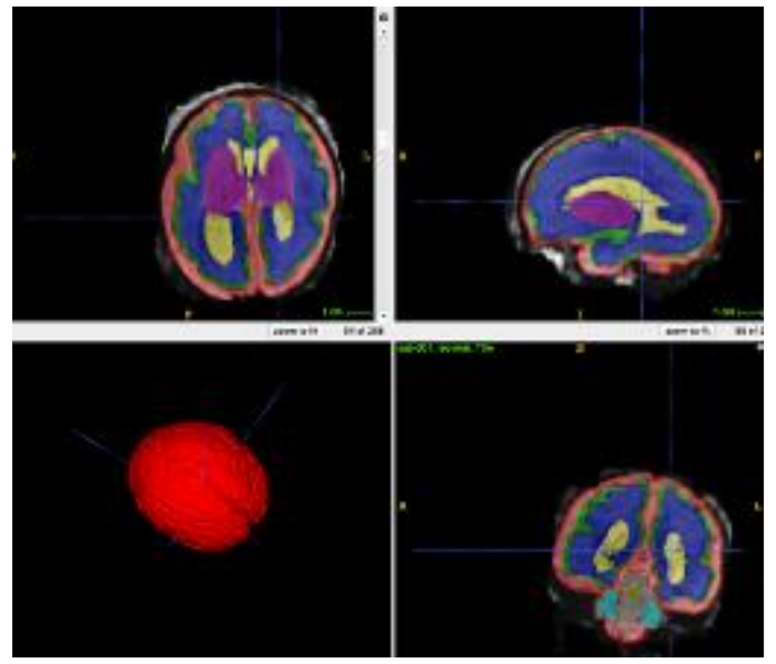


https://decathlon-10.grand-challenge.org/evaluation/challenge/leaderboard/
Leaderboard snapshot from: 25. April 2022



https://www.synapse.org/#!Synapse:syn3193805/wiki/217785
Leaderboard snapshot from: 25. April 2022

https://github.com/Project-MONAI/research-contributions/tree/main/SwinUNETR



Auto3DSeg

AutoML Segmentation Pipeline End-to-End

For each algorithm (MONAI Bundle)

Start → Data Analysis → Algorithm Selection → Bundle Config Generation → Model Training and HPO → Ranking, Ensemble, Post-Proc. → End

Input
Image directory
+ Data list

Data Analysis
Input:
File-list
Modality
Output:
Data statistics
saved as configuration file (*.yaml)

Algorithm Selection
Input:
Data statistics, list of available algos (SegResNet, DynUNet, Swin-UNETR, DiNTS, U-Net)
Output:
Selected algos

Bundle Config Generation
Input:
Params so far
Output:
MONAI Bundles
Yaml config files (train/val/test)
+ Python code

Model Training and HPO
Input:
MONAI Bundles
Output:
*.pth files
Metric logs
Tensorboards
progress.yaml

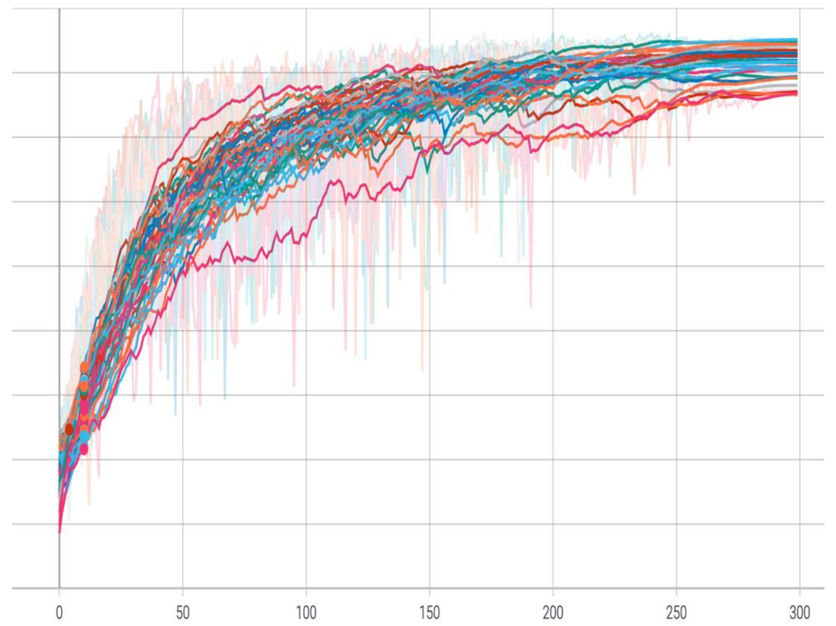
Ranking, Ensemble, Post-Proc.
Input:
Trained models
Output:
Ensembling on the fly
Log of selected models and selected postproc algorithms

Output
Optional:
Inference on the hidden test data
Performance results (if ground truth is available)

tasks > Task04_Hippocampus > ! datastats.yaml


```yaml
stats_summary:
  image_stats:
    shape:
      max:
      - [43, 59, 47]
      mean:
      - [35.3769, 49.9808, 35.6538]
      median:
```

```yaml
stats_summary:
  image_stats:
    cropped_shape:
      max: [256, 256, 236]
      mean: [256.0000, 195.1125, 169.2125]
      median: [256.0000, 197.0000, 168.0000]
      min: [256, 129, 111]
      percentile_00_5: [256.0000, 129.0000,
      percentile_99_5: [256.0000, 256.0000,
      stdev: [0.0000, 31.0077, 24.9212]
    shape:
      max: [256, 256, 256]
      mean: [256.0000, 256.0000, 256.0000]
```

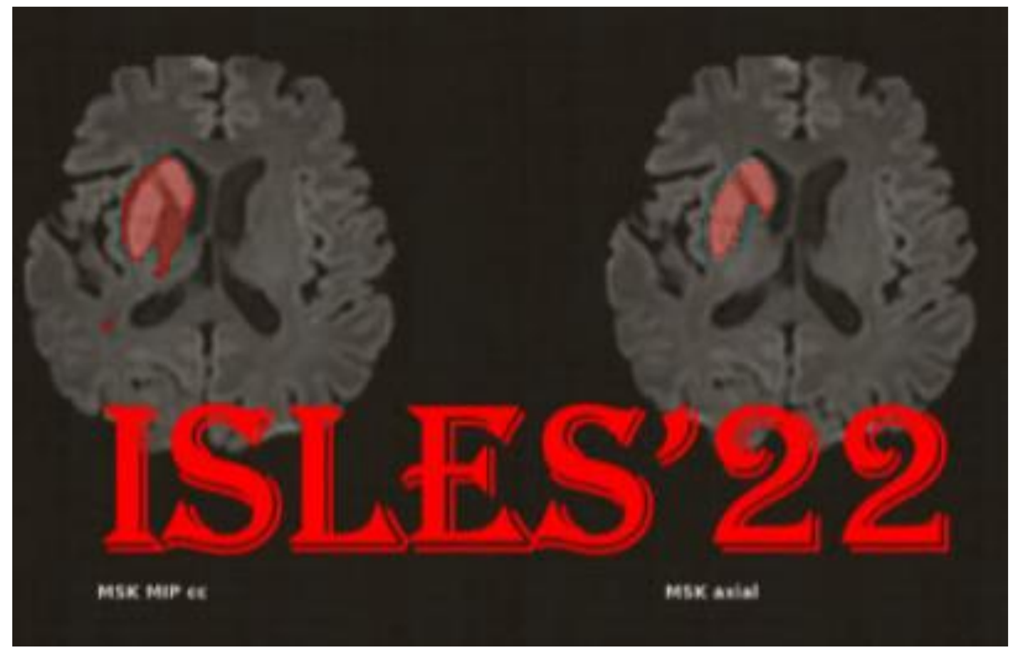



MONAI NVIDIA

Auto3DSeg

MICCAI 2022 Challenge Results

- HECKTOR challenge: final rank #1
    - Task: Head and neck tumors and lymph nodes segmentation from 3D PET and CT
- ISLES22 challenge: final rank #2 (and best Dice)
    - Task: Ischemic strong segmentation form 3D MRIs (DWI, ADC, FLAIR)
- INSTANCE22 challenge: final rank #2 (and best Dice)
    - Task: Intracranial Hemorrhage Segmentation from 3D CT
- FETA22 challenge: final rank #4
    - Task: Fetal brain segmentation (7 classes) from 3D MRI
- KIPA22 challenge: final rank #6
    - Task: Kidney, tumor, artery, vein segmentation from 3D CT
- Preliminary takeaways
    - Ensemble selected models are a mix of CNN and transformers. Neither CNN nor transformers are all you need.
    - Auto3DSeg creates a very strong baseline, but domain knowledge is still needed for cutting edge.



https://github.com/Project-MONAI/tutorials/tree/main/auto3dseg

MONAI @ Kaggle 2022 GI Tract Segmentation

https://www.kaggle.com/competitions/uw-madison-gi-tract-image-segmentation

- 1565 registered teams @ Kaggle GI Tract Segmentation Challenge
- MONAI was adopted by many participants, including several gold medal winners (#1, #2, #5, #11), and silver/bronze medal winners (#15, #17, #41, #82, #90)
  - KGMON team gold medalist (#5): Used MONAI 3D augmentations for all 3D models (even non-MONAI models)
  - NVIDIA DLMed team silver medalist (#41): Used DiNTS approach for differentiable AutoML
- Among the top 20 teams, 9 published solutions as open-source, of which 6 were based on MONAI
- The top 4 of 5 highest scored open-source codes were based on MONAI

MONAI NVIDIA

Start-up Use Cases

Start-up Use Cases

Joseph Peterson
Co-founder
SimBioSys

- Building clinical support tools for patient centric precision medicine for **breast and lung cancers**
- **MONAI Core** reduced prototyping time from months to days
- **MONAI Label** allows clinicians to be part of the AI process, from labeling to how it is deployed and used for patient care

Why MONAI:

- Open, standardized, inclusive, interoperable, scalable
- End-to-end suite: annotation / training / deployment
- Foundational models in Model Zoo

Jorrit Glastra
Chief Technology Officer (CTO)
Quantib

- Building MRI analysis applications for prostate cancer diagnosis and brain tissue quantification
- **MONAI Core:** Accelerated imaging AI workflow, image segmentation
- **MONAI Label:** Accelerated annotation/labeling of data

Why MONAI:

- Team shifting from Tensor Flow to PyTorch, transition made easy by MONAI
- Advisory Board / Thought leadership behind MONAI helped them to adopt
- SOTA: Rapid availability of new published approaches for fast iteration and innovation

Sasank Chilamkurthy
Chief Technology Officer and Co-Founder
Qure.ai

- Qure.ai technology analyzes and prioritizes medical imaging scans for teleradiologists
- Custom built platform that needs integration support to deployment in 600 + hospitals
- **MONAI Deploy:** Removes barrier from R&D to the clinical impact

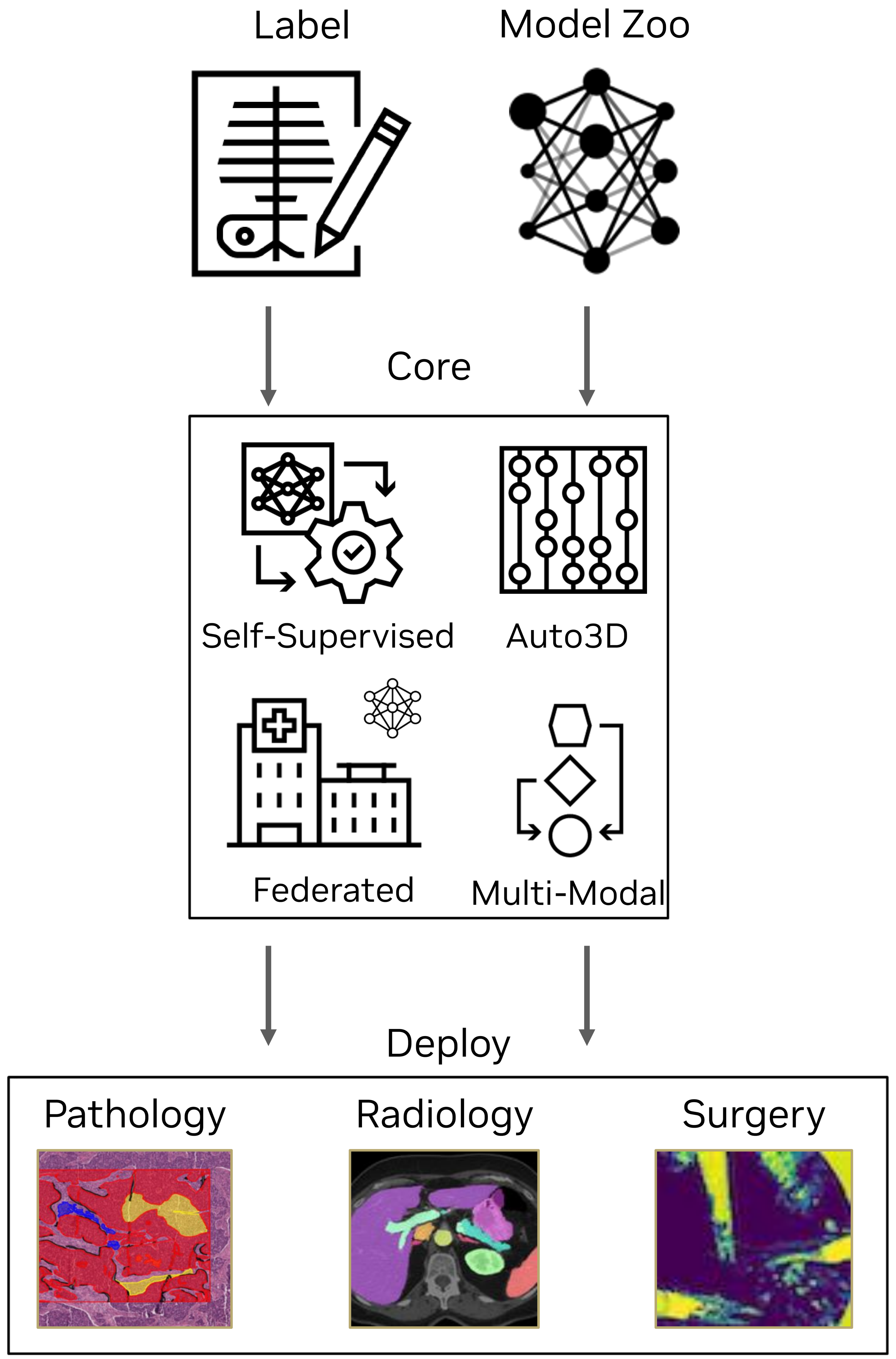
Why MONAI:

- Ease of installation to integrate with Healthcare IT
- Already leverages **MONAI Core** for training and interested in Deploy for standardization and support

Summary and Outlook

Summary

- MONAI Label v0.5.1
  - Endoscopy Sample App
  - Multi-stage workflows, e.g. for vertebra segmentation
  - Improvements in epistemic uncertainty estimation Active Learning
  - Support for MONAI Bundles and pre-trained models from Model Zoo
- MONAI Core v1.0.0
  - MONAI Bundles and Model Zoo: Reproducibility, Acceleration, Exchange
  - Auto3DSeg: Challenge-winning AutoML segmentation pipeline
  - Federated Learning Client
  - Self-supervised pre-training with vision transformers
- MONAI Deploy | App SDK v0.5.0
  - Deploy App SDK: Enhanced DICOM support
  - Deploy App SDK: Enhanced / updated / re-organized tutorials
  - MONAI Deploy Express for hosting MAPs in development environments



Getting Started

Get Started with MONAI

Use MONAI everywhere

- From edge to datacenter to cloud
  - Local pip install
  - Dockerhub containers based on NGC-Torch
- AWS / GCP / Azure
- LaunchPad

  https://www.nvidia.com/en-us/launchpad/ai/annotate-adapt-medical-imaging-with-monai/

Community channels

- Webpage / GitHub / Slack

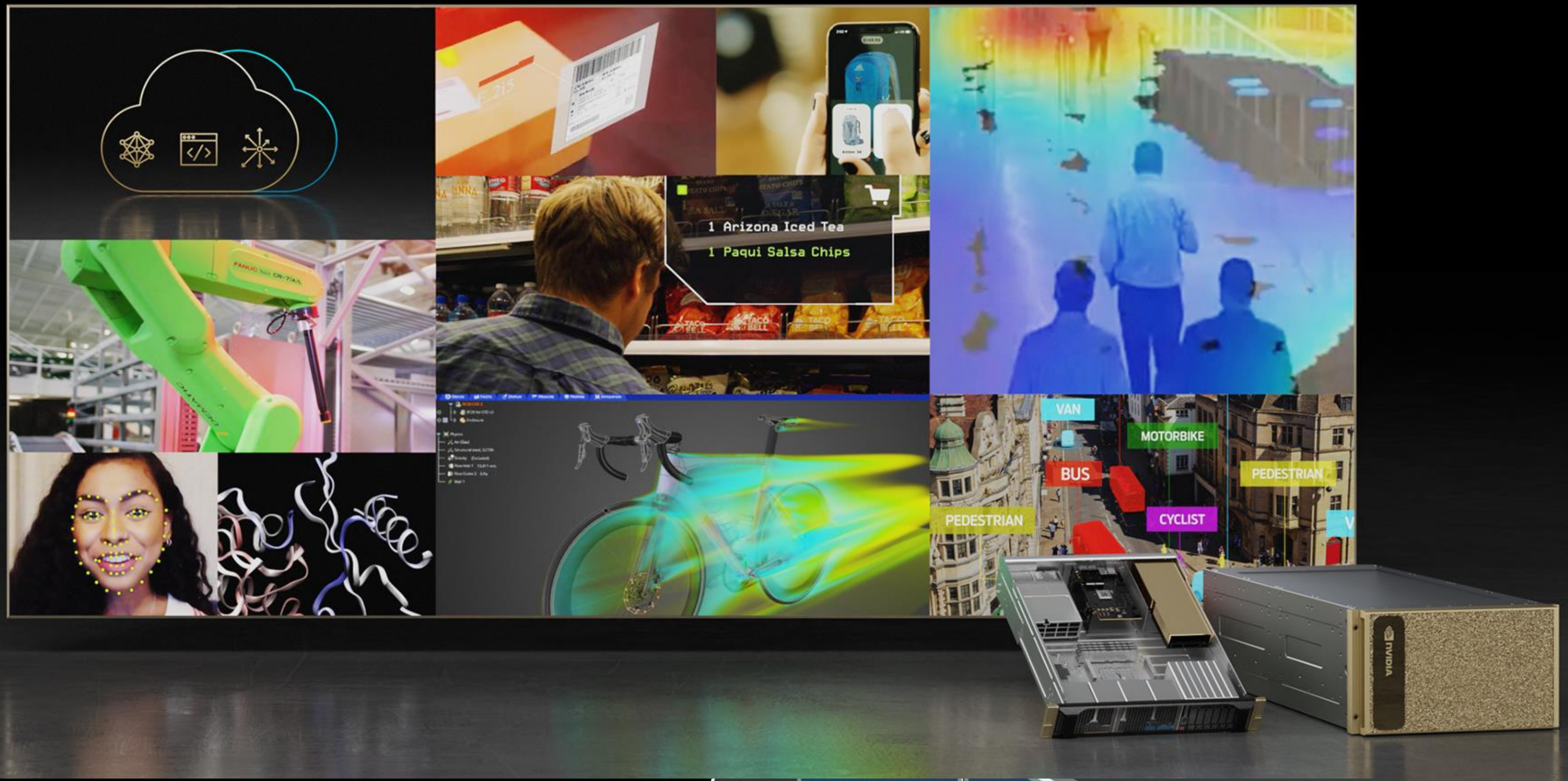
Tutorials

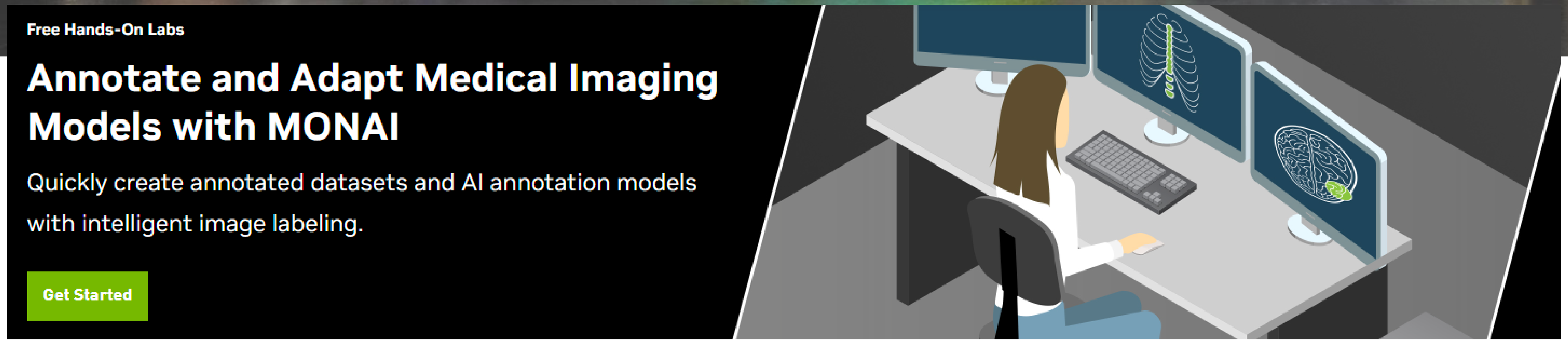
- Available on Github
- Covering all major scenarios for deep learning in medical imaging and multi-omics, including accelerated training

MONAI Bootcamp

- 3-day in-depth tutorials, end-to-end
- Available on Github / YouTube

MONAI is now available on LaunchPad





MONAI Enables the Medical Imaging Community

From surgeons and radiologists, to hospital systems nationwide

Dr. Matthew Jolley
Pediatric Cardiologist and Anesthesiologist
Children's Hospital of Philadelphia

- Provided the boiler plates to build, scale and deploy AI faster for clinical applications
- Open-source community to share ideas, labels, code and implementation
- Extensible MONAI framework that integrates into image viewers like 3D slicer

"What used to take us years has been accelerated to days."

Dr. Keno Bressem
Charite University Medicine Berlin

- MONAI Label's Active Learning helped annotators review and label 50-100 images a day
- Interactive Labeling allowed for continuously visible progress
- Used Epistemic image selection algorithm to intelligently select highest value images to be annotated

"MONAI Label reduced our overall labeling effort by 50%."

Haris Shuab
Medical Physicist
Guy's and St. Thomas's NHS Foundation Trust

- Open, standardized, inclusive, interoperable, scalable, improves accessibility – across every patient pathway worldwide
- MONAI helps not have to reinvent the wheel
- Foundational, pre-trained models in Model Zoo that can be used off the shelf and finetuned for specific applications

"MONAI scales AI across the entire medical record and patient pathway."

MONAI Outlook

High-Level Roadmap 2022-2023

July 2022

MIDL Conference

MONAI Plug and Play Models &
MONAI Open Datasets

- MONAI Bundles std model spec that connects to every part of workflow: Label->Core->Deploy
- MONAI for Pathology (Label & Train)
- MONAI dataset public integrations

Sept 2022

GTC/MICCAI Conferences

MONAI Model Zoo

- MONAI Zoo with world class imaging bundles
- App Framework for Auto3D Seg
- MONAI Deploy uses Triton

Nov 2022

RSNA Conference

MONAI Further Enhancements

- Labeling w/ Active Learning
- Model & Experiment Management
- Bundle Pruning & TRT Optimized

March 2023

GTC/MICCAI Conferences

MONAI for CAI

- Experiments Management
- Robotics, navigation, tracking, registration
- "SOTARR" State-of-the-art Reproducible Research Framework

NVIDIA