



**Medical Open Network for AI**

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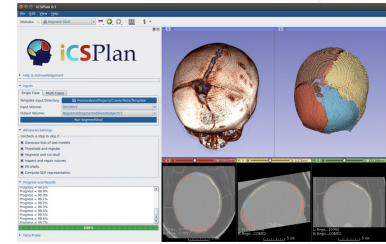
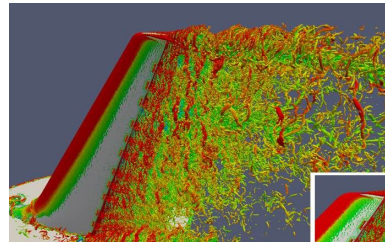
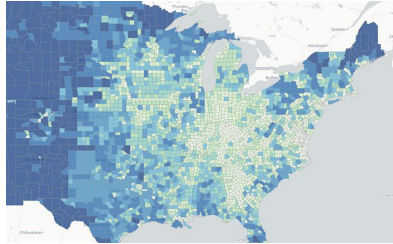
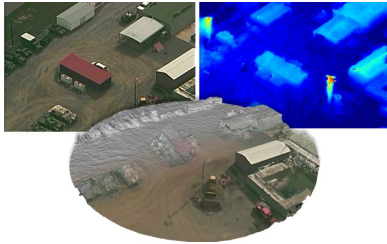
25/04/2025 - DLMI 2025

## A word about me

- 3 years R&D Engineer at Kitware EU in medical image processing and machine learning
- Trainer for ITK, 3D Slicer and MONAI
- [roman.fenioux@kitware.com](mailto:roman.fenioux@kitware.com)



# Kitware - Areas of expertise / Built on open source



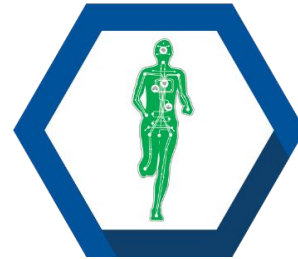
Computer  
Vision



Data and  
Analytics



Scientific  
Computing



Medical  
Computing



Software  
Solutions

# Kitware - Services



TRAINING



SUPPORT



DEVELOPMENT



GRANT  
COLLABORATION

# Introduction



PyTorch based, open-source framework for deep learning in medical imaging

Goal: Accelerate the pace of research and development by providing a common software foundation and a vibrant community for medical imaging deep learning

# Medical Open Network for A. I. (MONAI)

- **Began as a collaboration between Nvidia and King's College London**
  - Prerna Dogra (Nvidia) and Jorge Cardoso (KCL)
- **Open Source: freely available and community-supported**
- **Part of the PyTorch ecosystem**
- **Optimized for medical imaging**
- **Prioritizes reproducibility**

# Why is MONAI Needed?

- Biomedical applications have specific requirements
  - Image modalities require specific processing methods: MRI, CT, etc.
  - Image formats require special support: DICOM, NIfTI, etc.
  - Image meta-data must be considered: voxel spacing, HU, etc.
- Certain network architectures are designed for, or are highly suitable for, biomedical applications
- Prioritization of capabilities is domain specific: sample size limitations, annotation uncertainties, ... reproducibility



# Why does MONAI emphasize reproducibility?

## ◆ MONAI's focus on reproducibility

- Reduces code re-implementation (time and errors)
- Provides baseline implementations (education and startup)
- Demonstrates best practices for DL in medical image computing and computer-assisted interventions (quality)
- Enables Open Science in DL for medicine (dissemination and impact)

# What is MONAI?

## MONAI Working Groups.



### Imaging I/O

**Focus:** define how data is read into and written out from memory in MONAI.



### Data

**Focus:** Defining support for bioinformatics, biomarkers, and metadata that are in scope for MONAI.



### Transformations

**Focus:** Topics related to data preprocessing and augmentation modules in MONAI.



### Federated Learning

**Focus:** Unify the disparate methods of Federated Learning in a common MONAI framework.



### Evaluation, Reproducibility, and Benchmarking

**Focus:** Provide the infrastructure and tools for quality-controlled validation and benchmarking of medical image analytics methods.



### Research

**Focus:** Establish MONAI as a catalyst for scientific progress and real-life impact.



### Community Development

**Focus:** Establish MONAI as a common software foundation that the medical imaging research and development community can build upon.



### Deploy

**Focus:** Close the existing gap from research and development to clinical production environments by bringing AI models into the medical workflow.

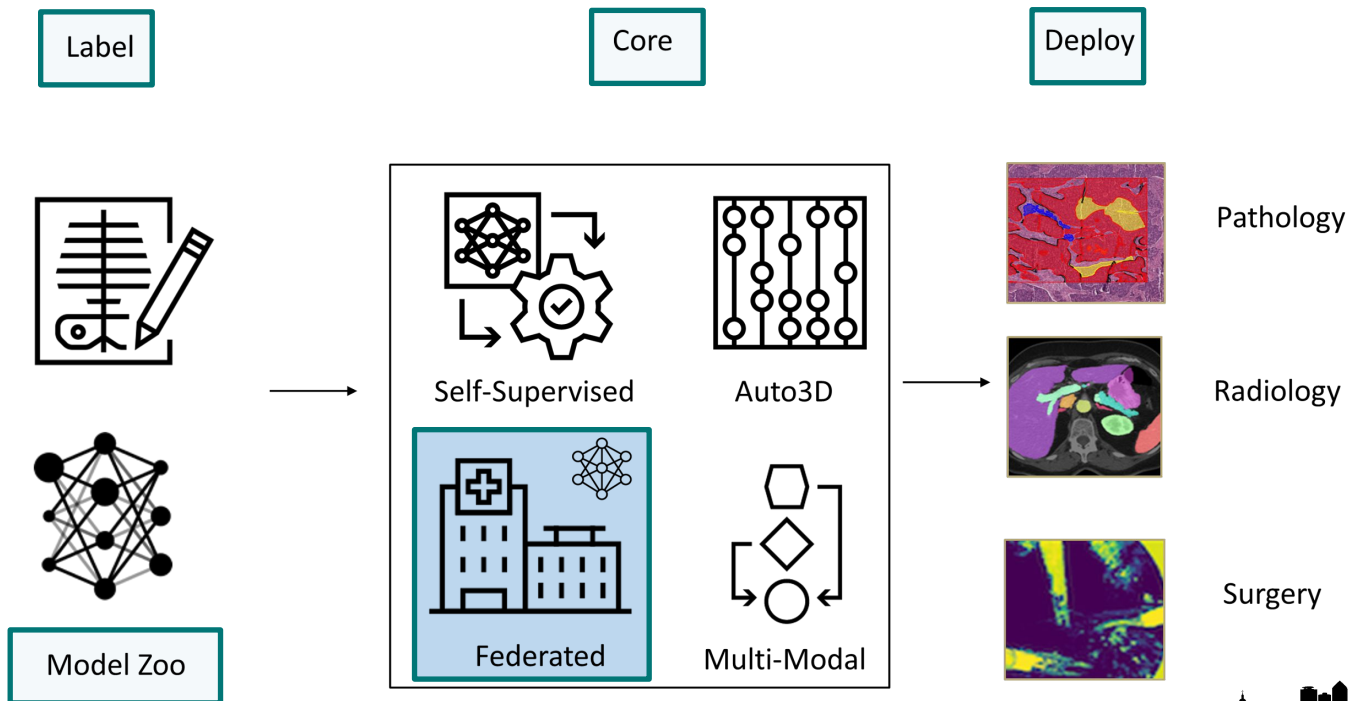


### Digital Pathology

**Focus:** Creating a standard pipeline for preprocessing, analysis, and visualization of pathology images.



# What is MONAI?



# What is MONAI Core?



# MONAI Core - Built for customization and reproducibility

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

Multi-modality Support  
Radiogenomics

Unconstrained and Optimized Models  
Model Parallelism/Neural Archi. Search

End-to-end research lifecycle  
DICOM/HL7 FHIR/Model Exchange & Deploy

Comprehensive Decision-making  
COVID-19

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

Segmentation

Classification

GANs & AutoEncoder

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

CacheDataset  
PersistentDataset  
ZipDataset  
ArrayDataset  
GridDataset  
EnhancedDataLoader

Savers & Writers

Nifty, PNG & CSV

Losses

DicesLoss & Extensions, FocalLoss,  
TverskyLoss

Networks

UNET (2D & 3D); Layers & blocks;  
DenseNet(2D & 3D)

Transforms

Spatial, Intensity  
IO, Utility  
Post, Compose  
3<sup>rd</sup> Part adapter  
BatchGenerator,  
Rising, TorchIO

Inferers

SimpleInferer, Slidingwindow

Visualize

Plot 3D/2D images,  
Plot statistics curve

Metrics

MeanDice, ROCAUC

# Data Augmentation and Pre-processing

## Medical domain specific

- LoadImage
- Spacing
- Orientation
- Ultrasound Linearization

## Image transforms

- Blur
- AddNoise
- ITK Filters
- Numpy Filters
- ...

```
[ ] train_transforms = Compose([
    LoadPNG(image_only=True),
    AddChannel(),
    ScaleIntensity(),
    RandRotate(range_x=15, prob=0.5, keep_size=True),
    RandFlip(spatial_axis=0, prob=0.5),
    RandZoom(min_zoom=0.9, max_zoom=1.1, prob=0.5, keep_size=True),
    ToTensor()
])

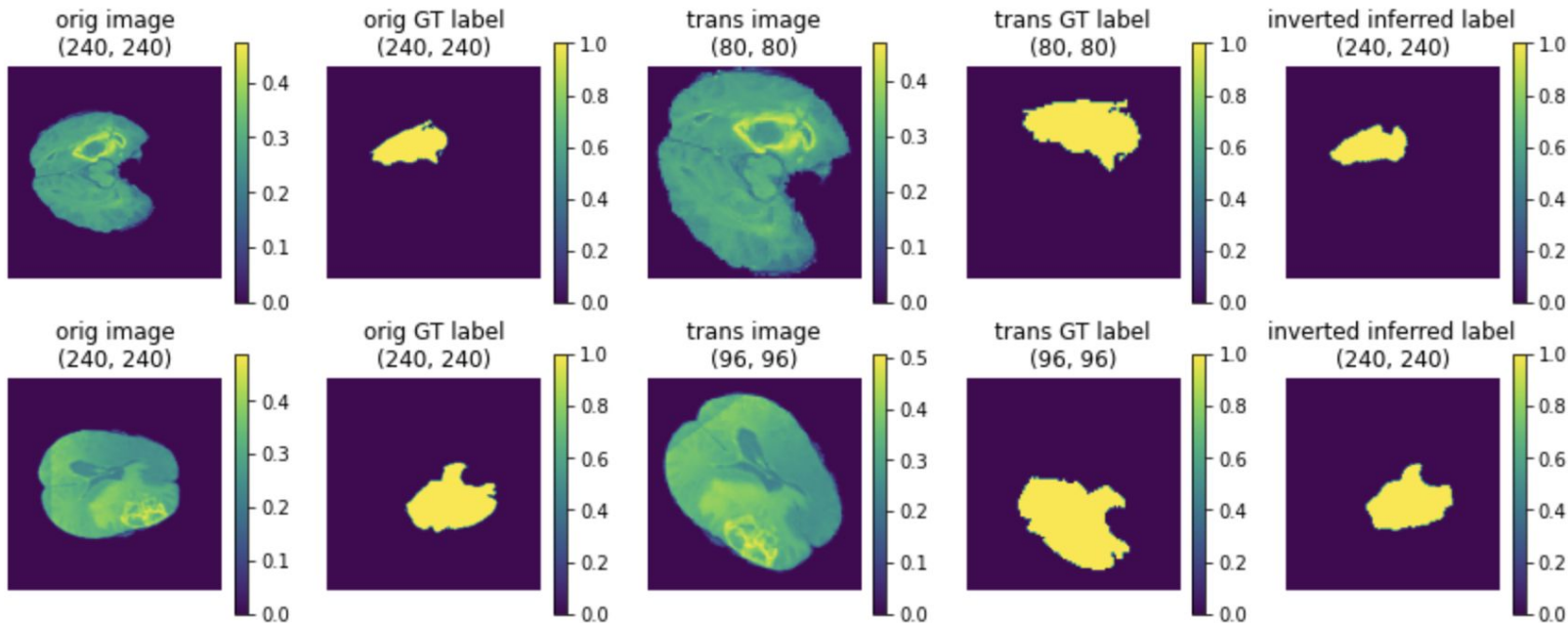
val_transforms = Compose([
    LoadPNG(image_only=True),
    AddChannel(),
    ScaleIntensity(),
    ToTensor()
])
```

# Invertible Transforms

## Why Invertible Transforms?

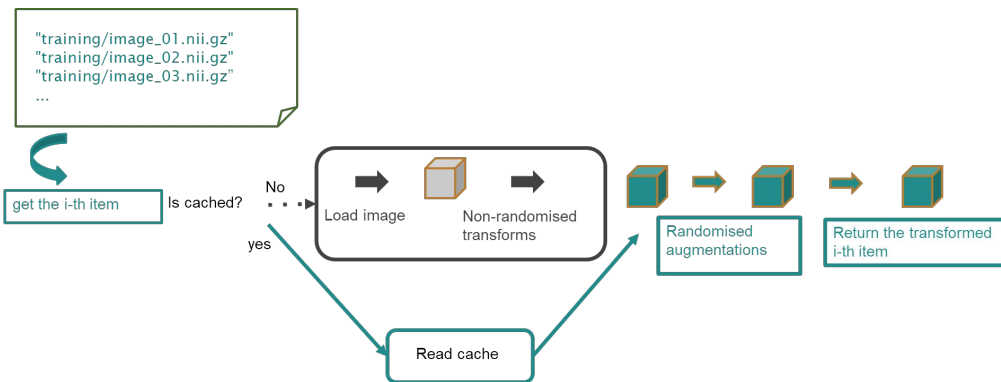
- ◆ Randomly augment the test case
- ◆ Track the transform parameters
- ◆ Run model inferences (segmentation)
- ◆ Resume to the original image space
- ◆ Compute ensemble/uncertainties

# Invertible transforms

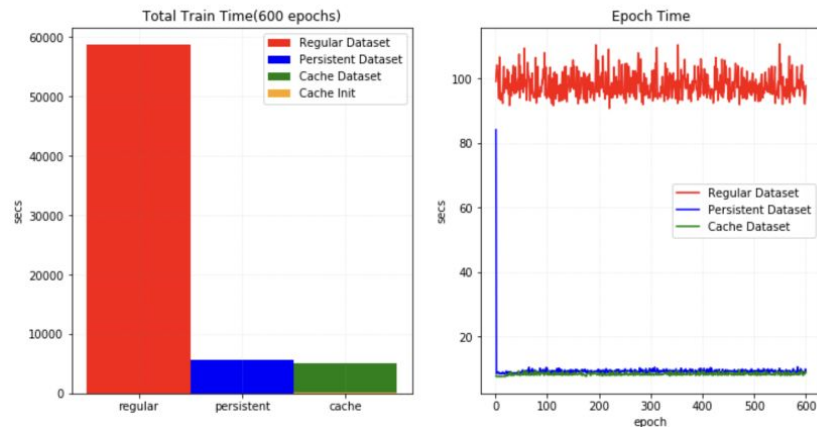




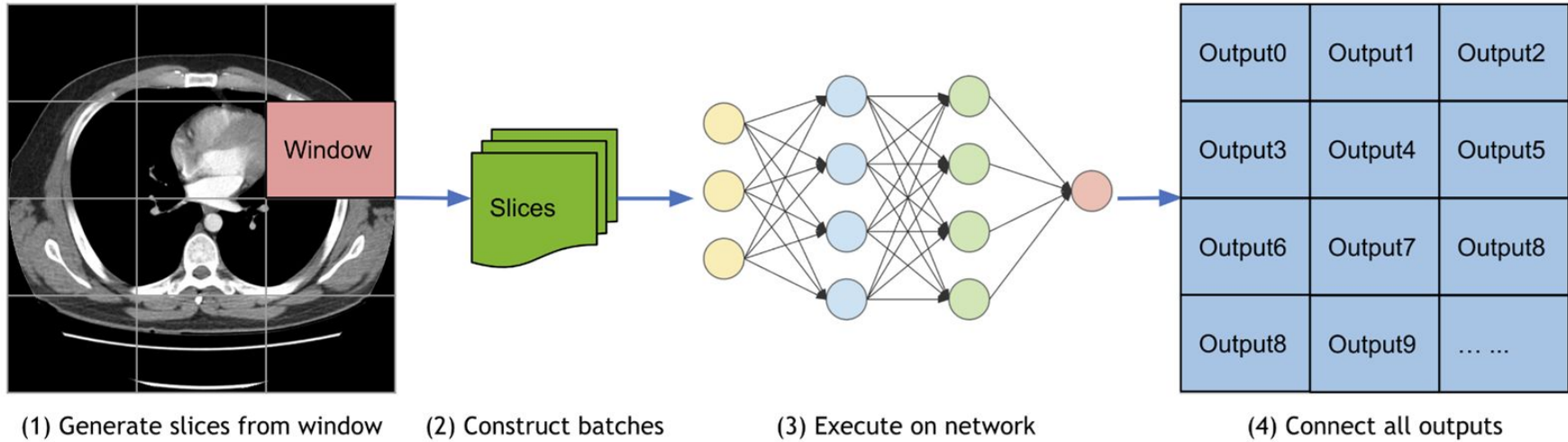
# Dataset and Caching APIs.



## Caching Performance



# Sliding Window Inference and Evaluation



# Metrics and Metrics APIs

## Metrics

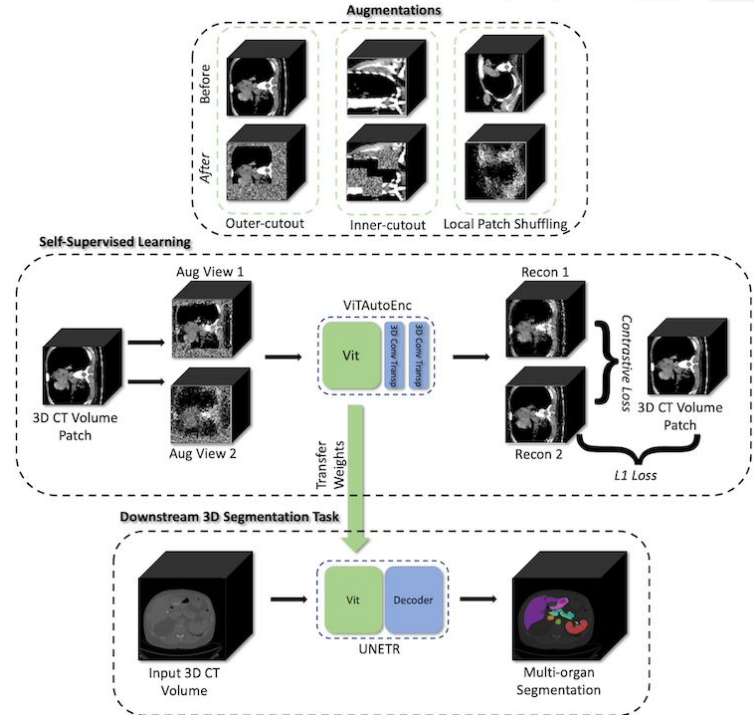
- ◆ Mean Dice
- ◆ Area under the ROC curve
- ◆ Confusion matrix
- ◆ Hausdorff distance
- ◆ Average surface distance
- ◆ Peak signal to noise ratio
- ◆ ...

## Metrics APIs

- ◆ Iterative Metric
- ◆ Cumulative
- ◆ Cumulative Average
- ◆ ...

# Network Architecture and Building Blocks

- Predefined Layers and Blocks
- Implementation of generic 2D and 3D networks
- Network adapter to finetune final layers
- State of the Art Architectures like: DiNTS, SSL, and Swin UNETR



# MONAI Core Installation (Python)

```
> pip install monai
```

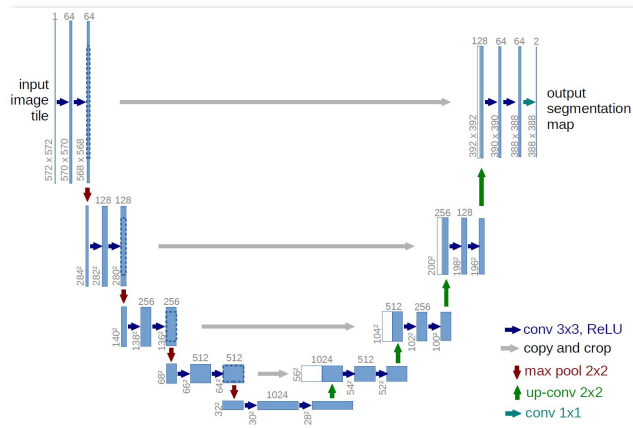
```
import monai
monai.config.print_config()

MONAI version: 0.3.0
Python version: 3.6.9 (default, Oct 8 2020, 12:12:24) [GCC 8.4.0]
OS version: Linux (4.19.112+)
Numpy version: 1.18.5
Pytorch version: 1.7.0+cu101
MONAI flags: HAS_EXT = False, USE_COMPILED = False

Optional dependencies:
Pytorch Ignite version: 0.4.2
Nibabel version: 3.0.2
scikit-image version: 0.16.2
Pillow version: 7.0.0
Tensorboard version: 2.3.0
gdown version: 3.6.4
TorchVision version: 0.8.1+cu101
ITK version: 5.1.1
tqdm version: 4.51.0
```

# Ease-of-use Example

```
net = monai.networks.nets.UNet(  
    spatial_dims=2, # 2 or 3 for a 2D or 3D network  
    in_channels=1, # number of input channels  
    out_channels=1, # number of output channels  
    channels=[8, 16, 32], # channel counts for layers  
    strides=[2, 2] # strides for mid layers  
)
```



# Access Medical Data

- **Goal: Harmonize and simplify open data and biomedical challenges**
  - Participate in / use public challenges
  - Define “challenges” (custom datasets) within your lab
- **Thin layer on top of PyTorch `torch.data.utils.Dataset` construct**
  - Automated (verified) download and unzip
  - Caching of data as well as intermediate results of preprocessing
  - Random splits of training, validation, and test

# Access Medical Data

```
from monai.apps import DecathlonDataset
```

```
dataset = DecathlonDataset(root_dir="./", task="Task05_Prostate", section="training", transform=None, download=True)  
print(f"\nnumber of subjects: {len(dataset)}.\nThe first element in the dataset is {dataset[0]}.")
```

```
Task05_Prostate.tar: 100%|██████████| 229M/229M [03:15<00:00, 1.22MB/s]
```

```
Verified 'Task05_Prostate.tar.part', md5: 35138f08b1efaef89d7424d2bcc928db.
```

```
Verified 'Task05_Prostate.tar', md5: 35138f08b1efaef89d7424d2bcc928db.
```

```
Verified 'Task05_Prostate.tar', md5: 35138f08b1efaef89d7424d2bcc928db.
```

```
Load and cache transformed data: 100%|██████████| 26/26 [00:00<00:00, 196489.92it/s]
```

```
number of subjects: 26.
```

```
The first element in the dataset is {'image': 'Task05_Prostate/imagesTr/prostate_46.nii.gz', 'label': 'Task05_Prostate/label'}
```



# Transforms for training and validation

```
[ ] train_transforms = Compose([
    LoadPNG(image_only=True),
    AddChannel(),
    ScaleIntensity(),
    RandRotate(range_x=15, prob=0.5, keep_size=True),
    RandFlip(spatial_axis=0, prob=0.5),
    RandZoom(min_zoom=0.9, max_zoom=1.1, prob=0.5, keep_size=True),
    ToTensor()
])

val_transforms = Compose([
    LoadPNG(image_only=True),
    AddChannel(),
    ScaleIntensity(),
    ToTensor()
])
```

Random yet reproducible:

```
set_determinism(seed=XXXXXX)
```

```
from monai.apps import DecathlonDataset

dataset = DecathlonDataset(root_dir=".", task="Task05_Prostate", section="training", transform=None, download=True)
print(f"number of subjects: {len(dataset)}. The first element in the dataset is {dataset[0]}")

Task05_Prostate.tar: 100% |██████████| 229M/229M [03:15<00:00, 1.22MB/s]
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Load and cache transformed data: 100% |██████████| 26/26 [00:00<00:00, 196489.92it/s]
number of subjects: 26.
The first element in the dataset is {'image': 'Task05_Prostate/imagesTr/prostate_46.nii.gz', 'label': 'Task05_Prostate/label'}
```

# MONAI:End-End Training Workflow in ~10 Lines of Code

```
from monai.application import MedNISTDataset
from monai.data import DataLoader
from monai.transforms import LoadPNGd, AddChanneld, ScaleIntensityd, ToTensord, Compose
from monai.networks.nets import densenet121
from monai.inferers import SimpleInferer
from monai.engines import SupervisedTrainer

transform = Compose(
    [
        LoadPNGd(keys="image"),
        AddChanneld(keys="image"),
        ScaleIntensityd(keys="image"),
        ToTensord(keys=["image", "label"])
    ]
)

dataset = MedNISTDataset(root_dir="./", transform=transform, section="training", download=True)

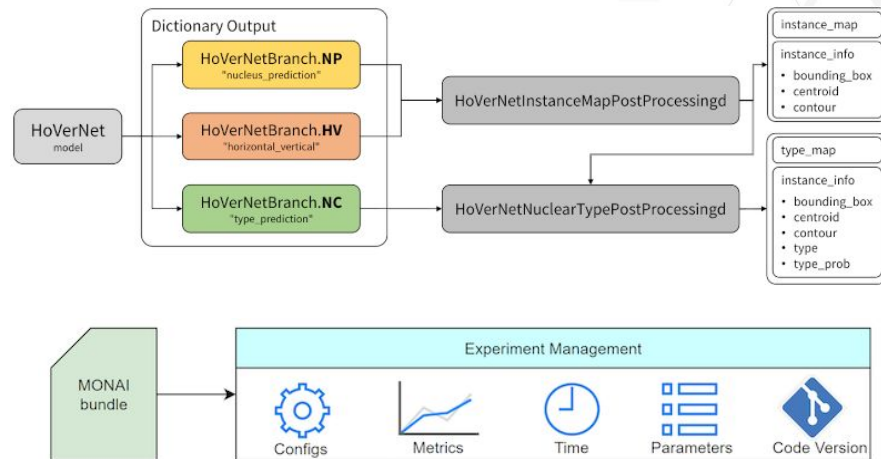
trainer = SupervisedTrainer(
    max_epochs=5,
    train_data_loader=DataLoader(dataset, batch_size=2, shuffle=True, num_workers=4),
    network=densenet121(spatial_dims=2, in_channels=1, out_channels=6),
    optimizer=torch.optim.Adam(model.parameters(), lr=1e-5),
    loss_function=torch.nn.CrossEntropyLoss(),
    inferer=SimpleInferer()
)

trainer.run()
```

# MONAI Core v1.4

Latest Release

- MAISI 3D Latent Diffusion Model
- VISTA-3D foundation model for human anatomy segmentation
- VISTA-2D for cell segmentation
- Easy TensorRT export
- Geometric Data Support



Surgical Tool Localization in endoscopic videos

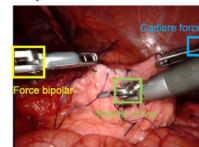
Train only using tool presence labels



Tools present: [Force bipolar, Needle driver, Cadere forceps]



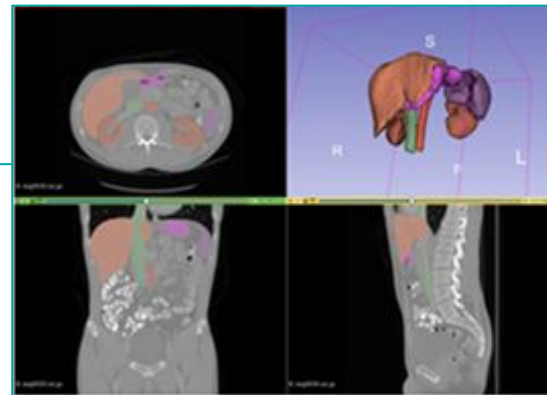
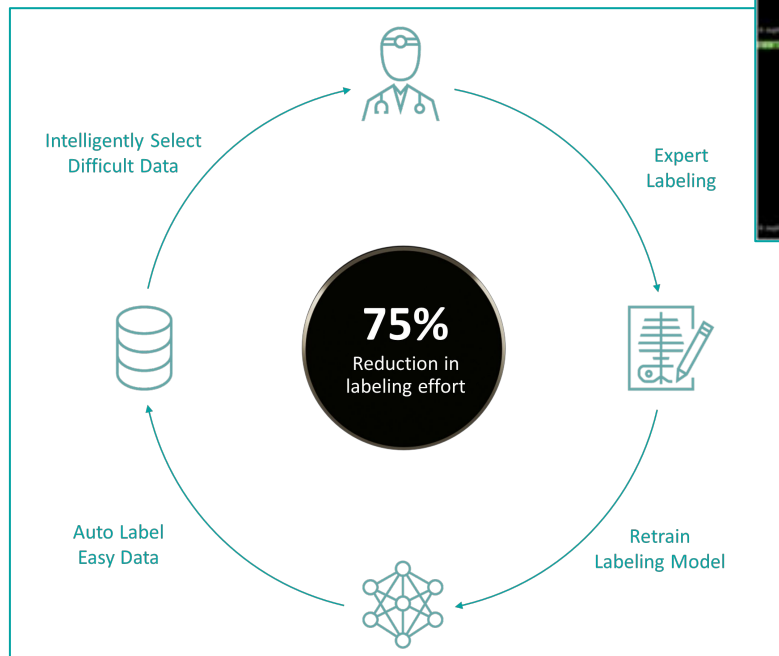
Classify and localize tools in test images



# What is MONAI Label?



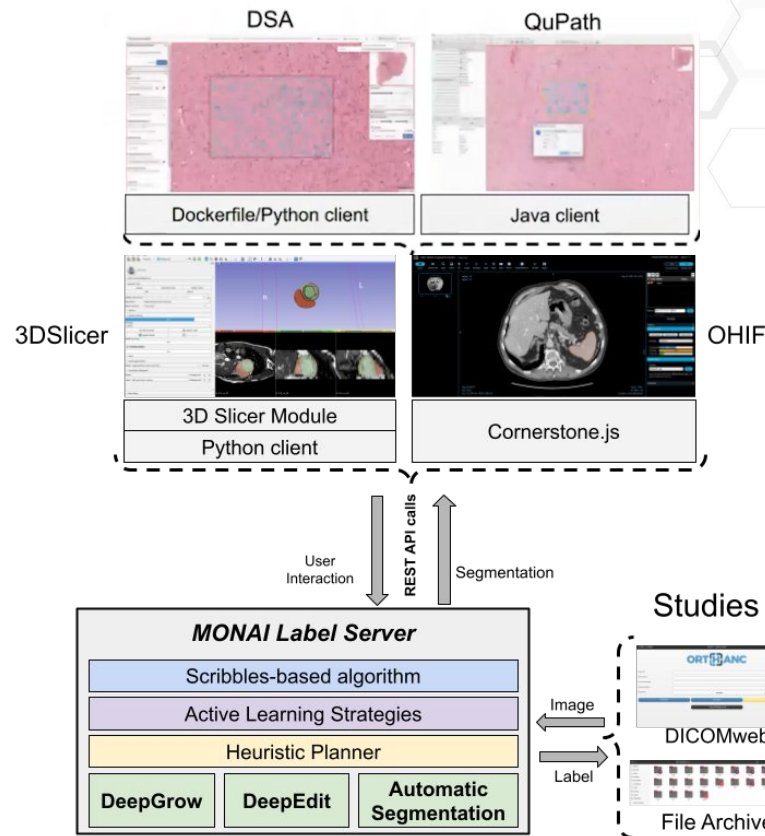
# MONAI Label - AI-Assisted Annotation (AIAA)



# MONAI Label Infrastructure.

## Three Main Parts: server-client system

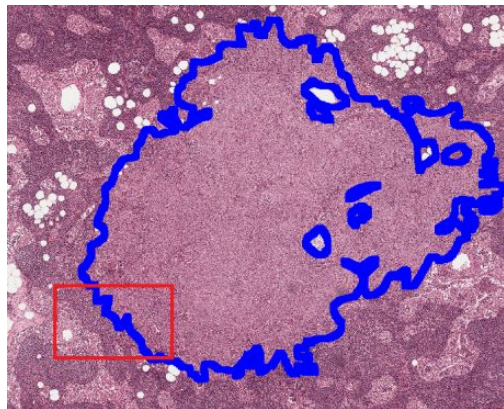
- MONAI Label Server
- Client / GUIs
- Datastore



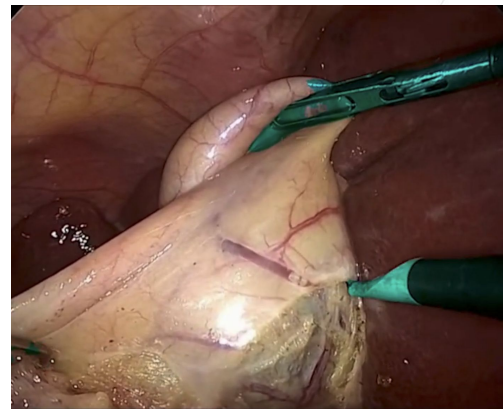
# MONAI Label Applications



Radiology



Pathology



Endoscopy

**And more !**



# Why MONAI Label?

## For Clinician

Radiology: X-Ray, CT, and MRI  
Pathology: Whole Slide Images



### Viewer Integration

Existing viewer integration with common applications in both radiology and pathology workflow including 3D Slicer and DSA.



### Multiple Annotation Methods

Start by using traditional annotation methods like Scribbles or use an interactive algorithm like DeepEdit.



### Sample Apps and Pretrained Models

MONAI Label includes sample applications for both radiology and pathology. You can also use the our pretrained models or start from scratch.

## For Researcher and Data Scientists

Quickly get started with a common framework



### Rapid App Prototyping

Use a sample app to jumpstart the development of your own custom labeling app.



### Active Learning Techniques

Use existing Active Learning strategies or implement your own.

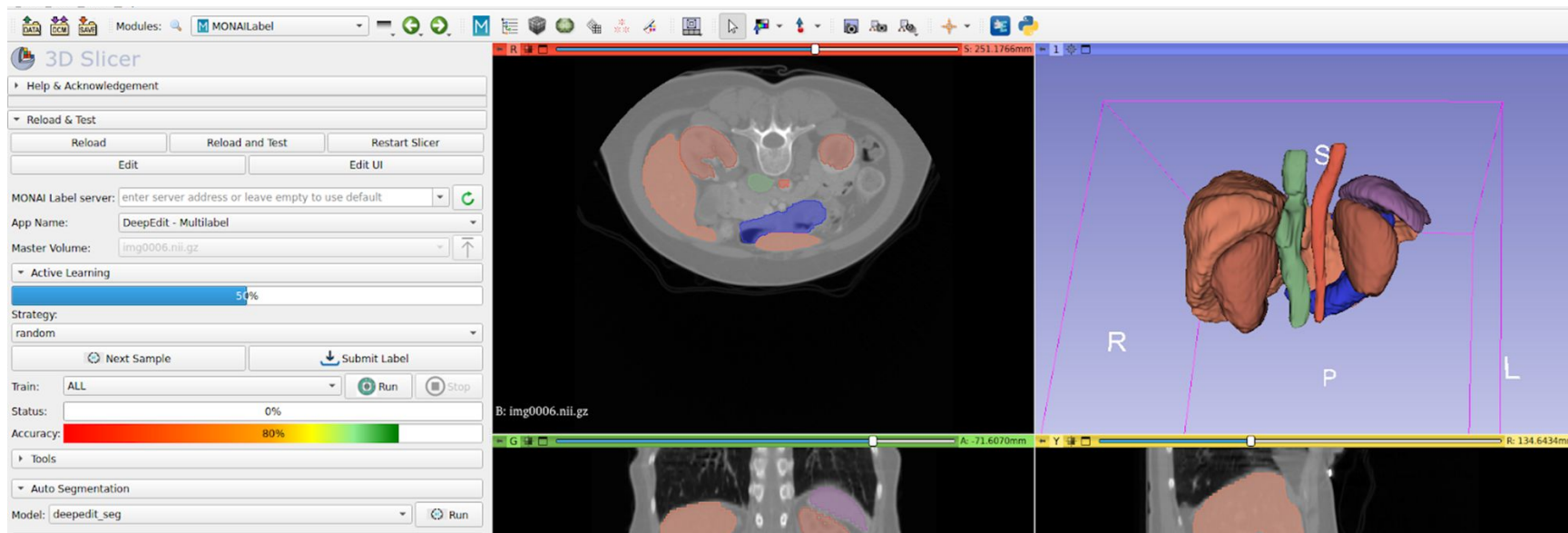


### Easy Integration

MONAI Label exposes a REST API that you can use to integrate in to your own viewer or workflow.



# MultiLabel DeepEdit



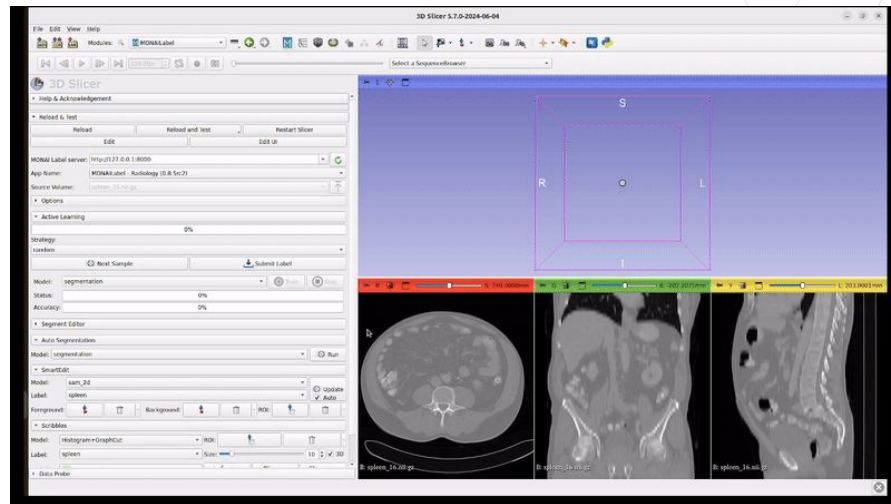
# MONAI Label Demo



# MONAI Label v0.8.5

Latest Release

- Add SAM2 model
- Support latest versions of OHIF and CVAT clients (including point prompts)



Segmentation using SAM2 in 3DSlicer

# What is MONAI Deploy?



# MONAI Deploy - Packaging and deployment



- **Aims to become the standard for packaging, testing, deploying and running medical AI applications in clinical production**
- **Creates a set of intermediate steps where researchers and physicians can build confidence in the techniques and approaches used with AI**

# Key features

- **MONAI Application Package (MAP)**
  - Self-descriptive, containerized application or service. Defines how applications can be packaged and distributed
- **MONAI Deploy App SDK**
  - Set of development tools to create MAPs out of MONAI / Pytorch models.
- **MONAI Deploy Informatics Gateway (MIG)**
  - I/O for DICOM and Fast Healthcare Interoperability Resources (FHIR)
- **MONAI Deploy Workflow Manager**
  - Orchestrates what has to be executed based on the clinical workflow specification and incoming requests.
- **MONAI Deploy Express**
  - End-to-end pipeline for testing and validation of MONAI Applications (MAPs).

# MONAI Deploy v0.6

Latest Release

- Upgrade of the underlying NVIDIA Holoscan SDK to version 0.6
- Update of tutorials and examples
- Support latest version of MONAI

# Walkthrough



<https://github.com/Project-MONAI/monai-bootcamp>



# MONAI Resources

MONAI Website: <https://monai.io/>

MONAI Slack: <https://forms.gle/QTxlq3hFictp31UM9>

MONAI Docs:

**MONAI Core:** <https://docs.monai.io/en/stable/>

**MONAI Label:** <https://docs.monai.io/projects/label/en/latest/index.html>

**MONAI Deploy App SDK:** <https://docs.monai.io/projects/monai-deploy-app-sdk/en/latest/>

MONAI Github: <https://github.com/Project-MONAI>

**MONAI Core:** <https://github.com/Project-MONAI/MONAI>

**MONAI Label:** <https://github.com/Project-MONAI/MONAIlabel>

**MONAI Deploy:** <https://github.com/Project-MONAI/monai-deploy>

MONAI YouTube: <https://www.youtube.com/c/Project-MONAI>

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# Questions ?

