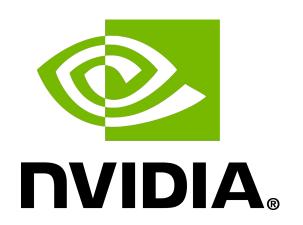


MONAI Label

https://github.com/Project-MONAI/MONAILabel







AGENDA

What is MONAI Label? Why use MONAI Label? How to create a MONAI Label App? Scribbles in MONAI Label Active Learning Strategies

- An intelligent open source image labeling and learning tool that enables users to create annotated datasets and build AI annotation models for clinical evaluation
- Framework for developing and deploying MONAI Label Apps to train and do inference using Deep Learning models
- MONAI Label includes Active learning strategies to improve model performance.
- It is all Python and can be installed with simple "pip install monailabel"
- Supported viewers:

For radiology app: 3D Slicer and Open Health Imaging Foundation (OHIF)

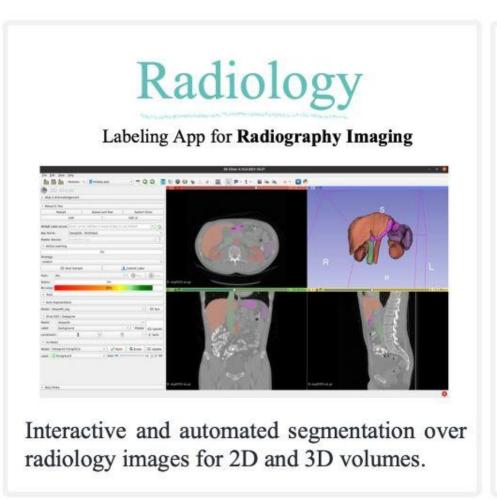
For pathology app: Digital Slide Archive (DSA) and QuPath

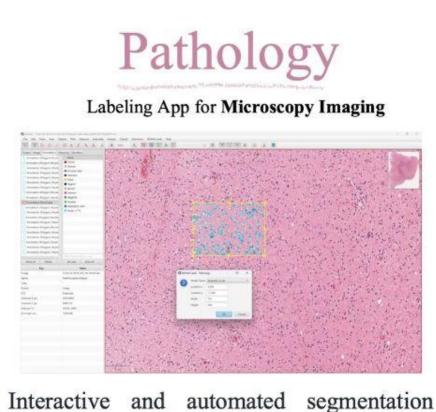
For endoscopy app: CVAT

Continuous development since we started in Feb 2021

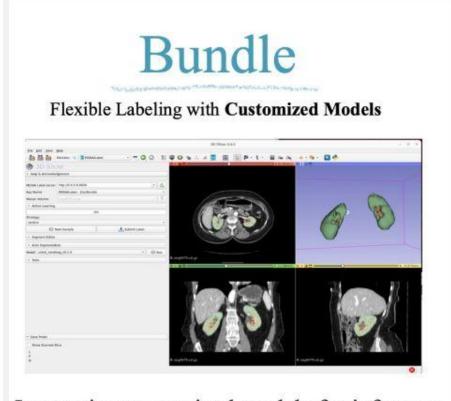


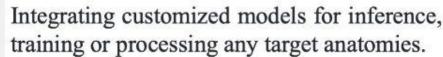
Sample Apps

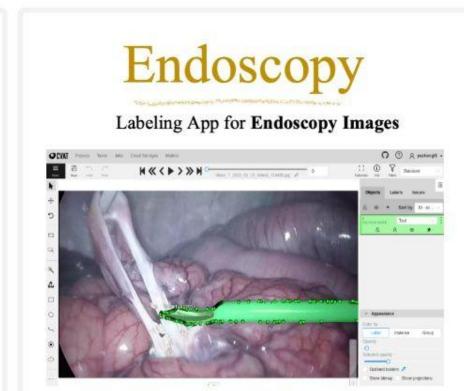




over pathology whole-slide images (WSI).







Interactive/automated segmentation, detection, classification for endoscopy images.

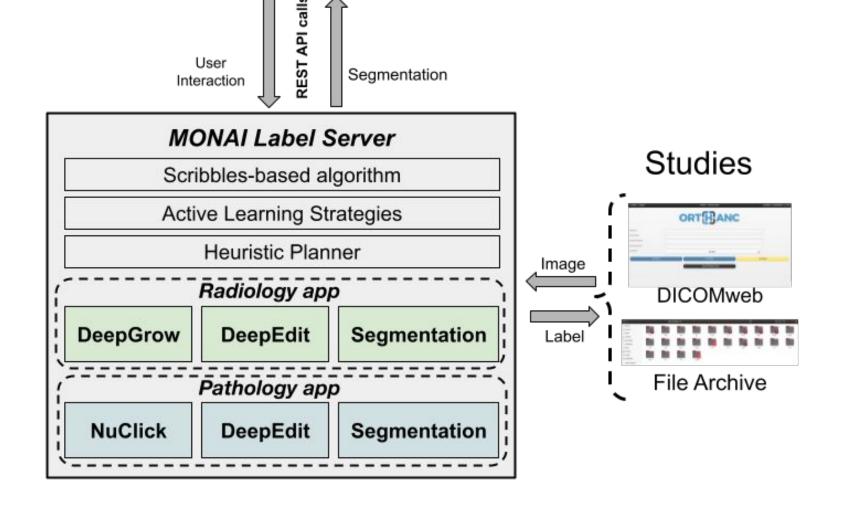
MONAI Label Infrastructure: server-client system

Plugins/Clients/GUIs



Three main parts:

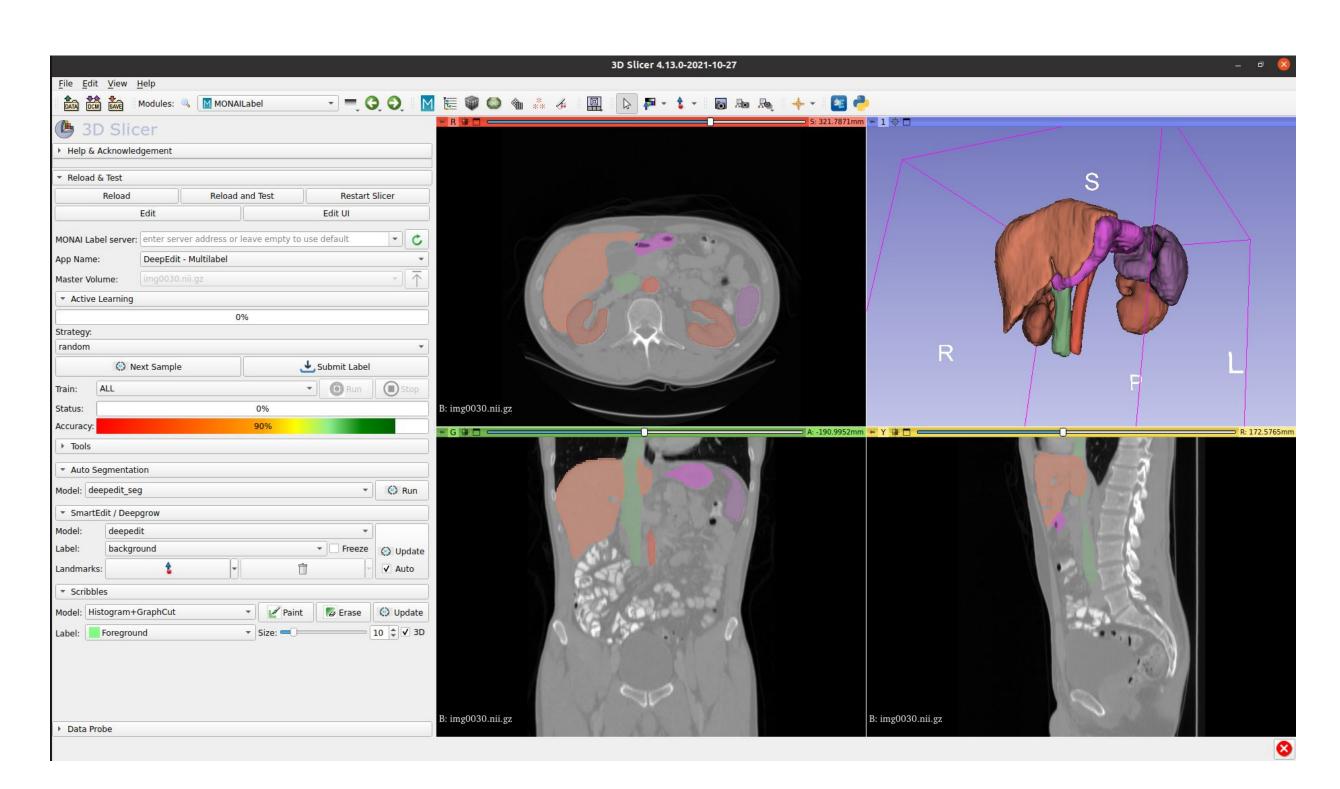
- MONAI Label server
- Datastore
- Clients/GUIs





Client - 3D Slicer

- Supportive community
- User-friendly
- Easy to customise
- Many manual annotation tools
- Image Registration

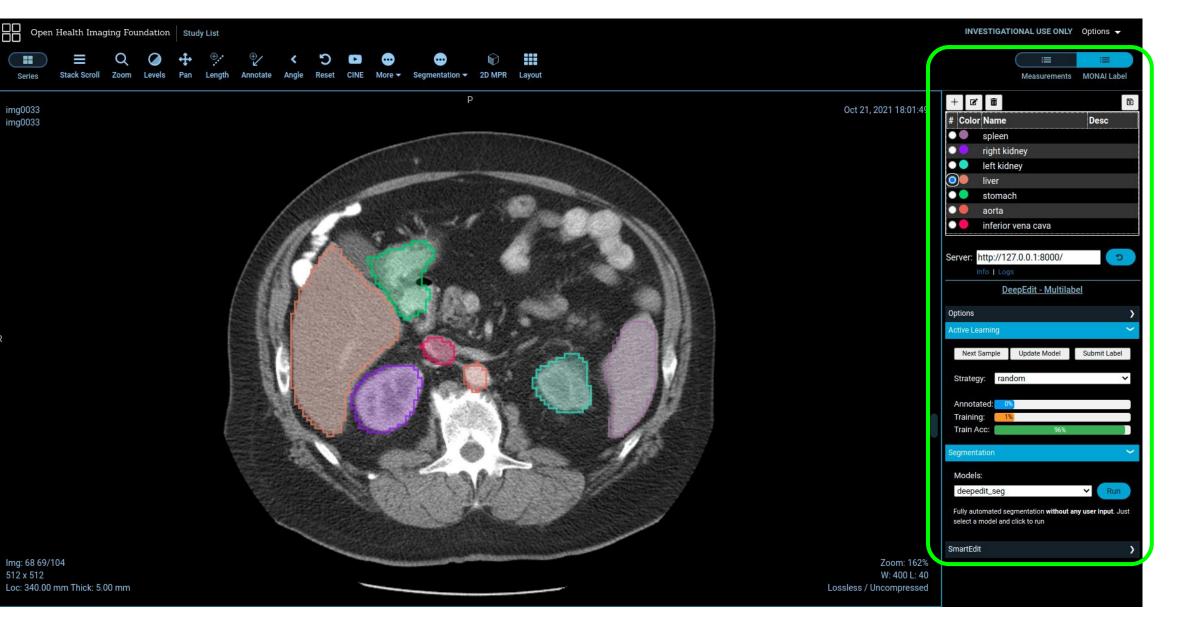




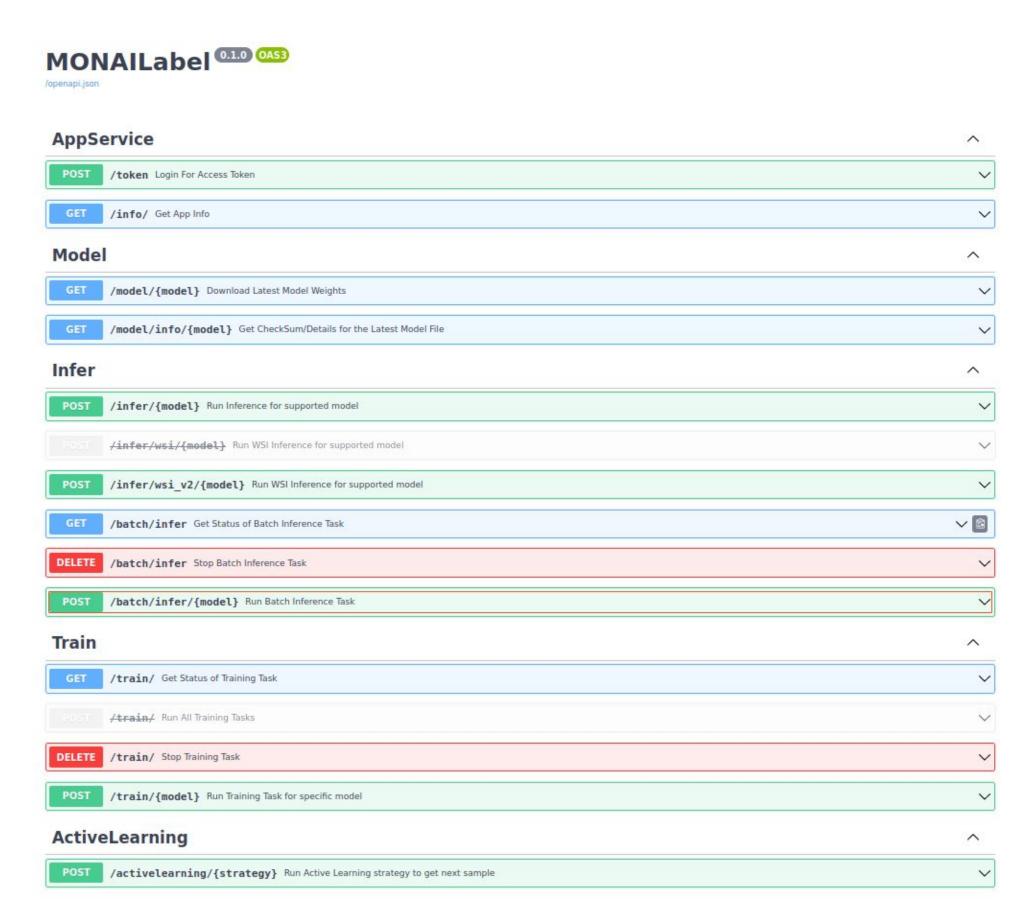
Client - OHIF

MONAI Label

- Works out-of-the-box with Image Archives that support DICOMWeb.
- http://127.0.0.1:8000/ohif
- Web-based viewer.
- Beautiful user interface (UI) designed with extensibility in mind.



Client - REST API





REST API at http://127.0.0.1:8000/







Researcher Perspective: MONAI Label allows researchers to

Create new annotation methods
Rapid App prototyping
Implement active learning techniques
Verify their effectiveness in real-world scenarios
Make incremental improvements
Readily deploy labeling apps to wider audiences

 Clinician user in a research setting perspective: MONAI Label reduces the time and effort of annotating new datasets

Ready-to-use viewers:

Radiology: 3D Slicer, OHIF Viewer

Pathology: DSA and QuPath

Endoscopy: CVAT





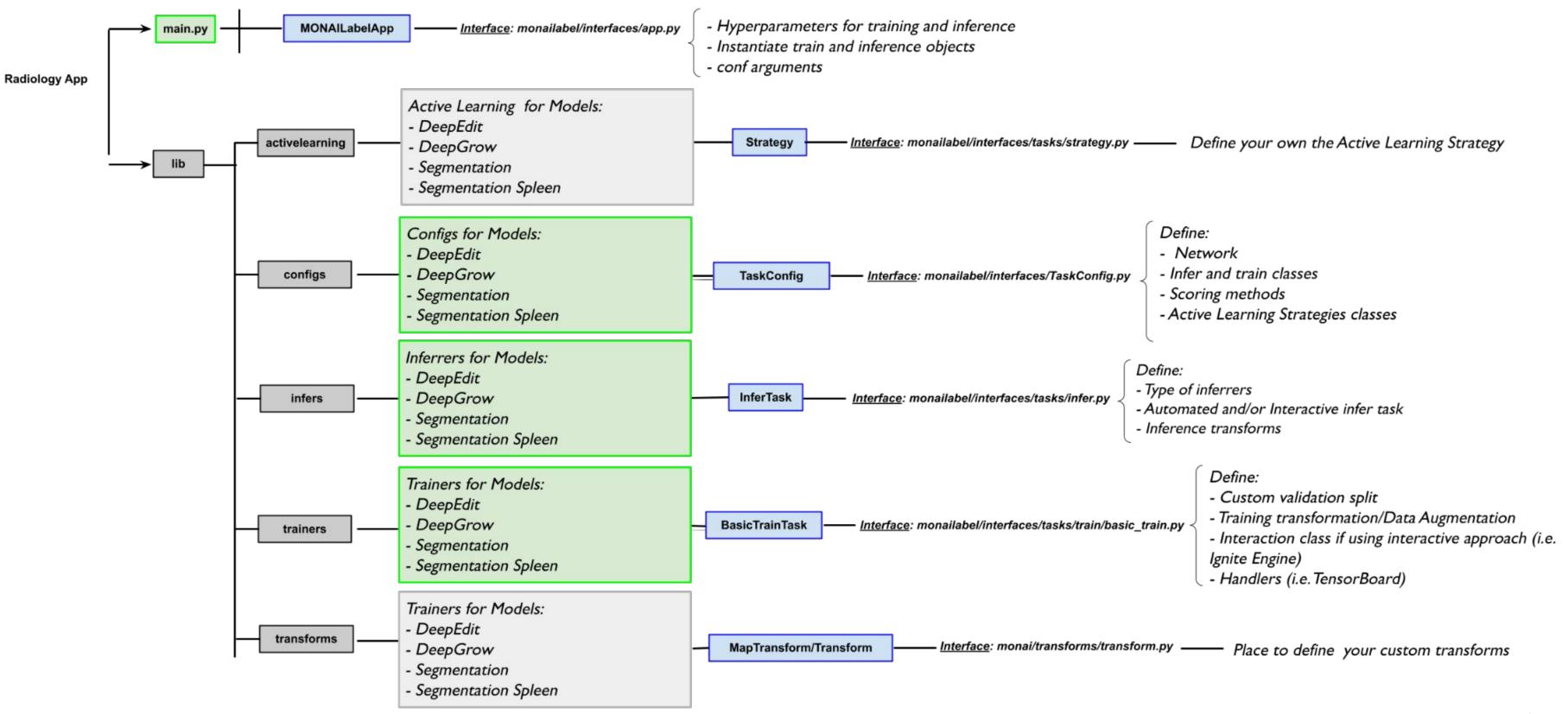
- Select an app (i.e. radiology, pathology or endoscopy) and model to use (i.e. deepedit, segmentation, nuclick)
- Prepare the dataset Labels with the same name as images
- Define the label names and label numbering in configs file accordingly

Advanced changes:

- Select the spatial/intensity transforms to preprocess images for training and inference
- Define the active learning technique use in the labeling app
- Define neural network architecture
- *Upgrade interactions:* Preprocess ROI, closed curve, or any input sent to the MONAI Label server through the REST API

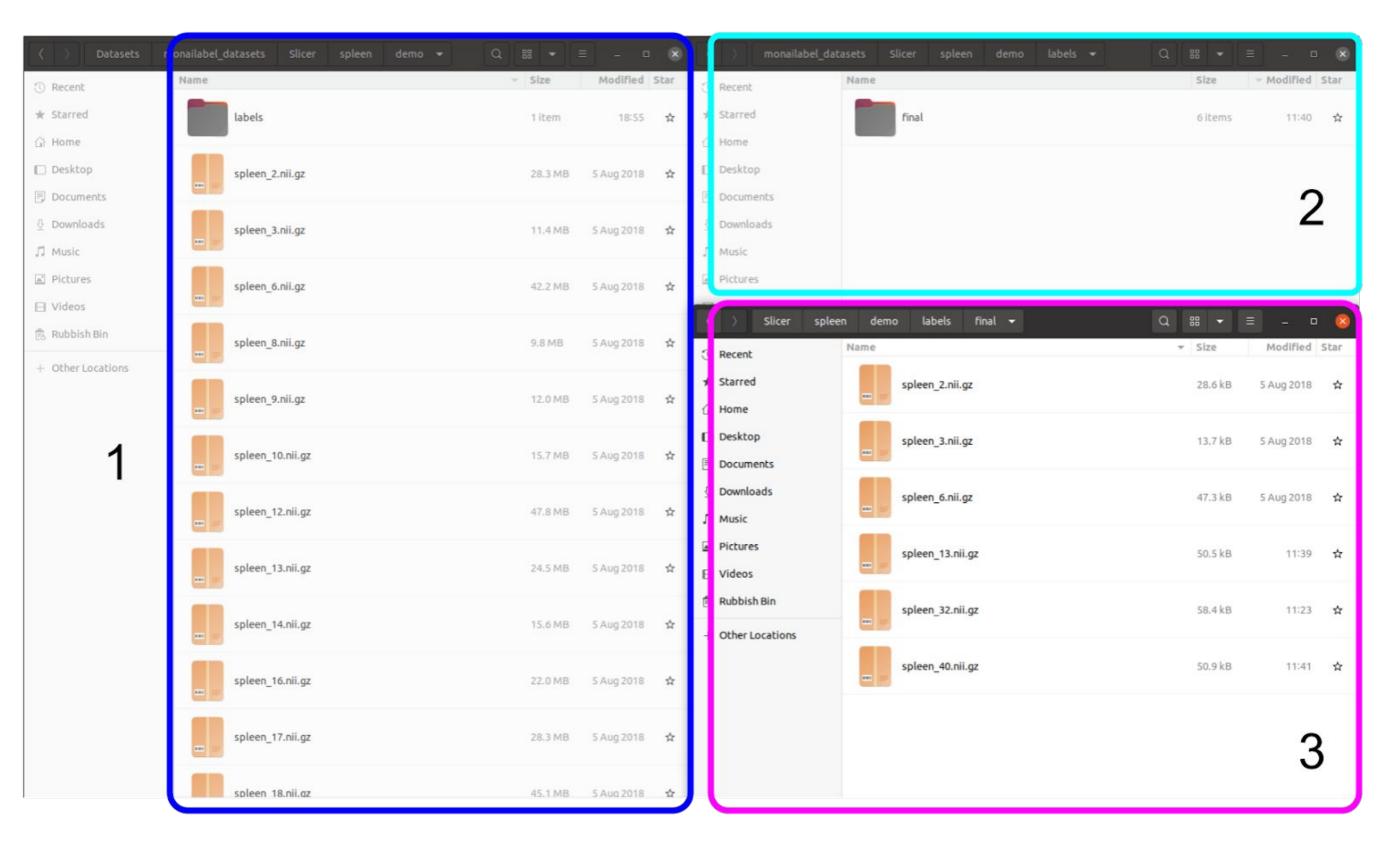
Users can directly use <u>samples models</u> (i.e. DeepGrow, DeepEdit and Segmentation) to jumpstart the development of their own custom labeling apps

MONAI Label App Structure



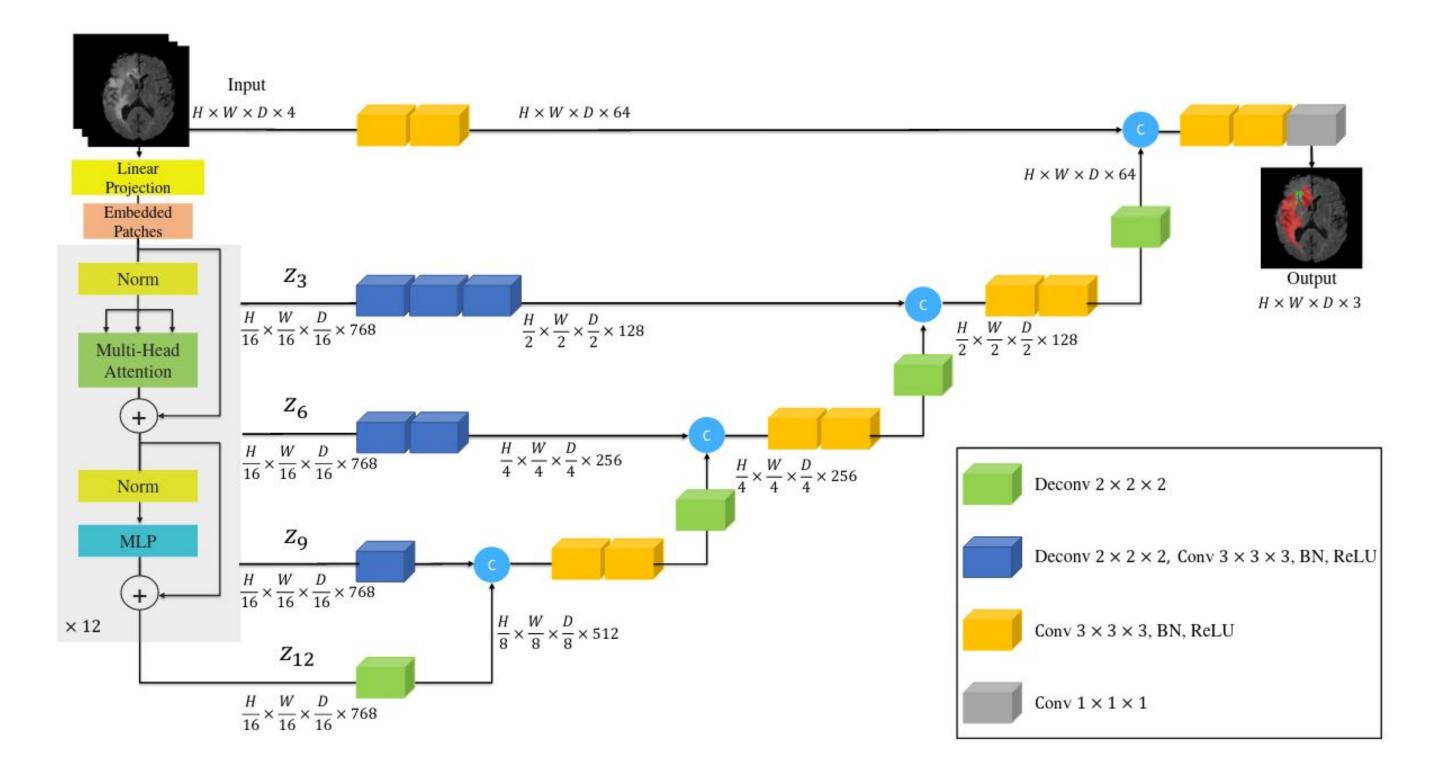
Datastore in file archive





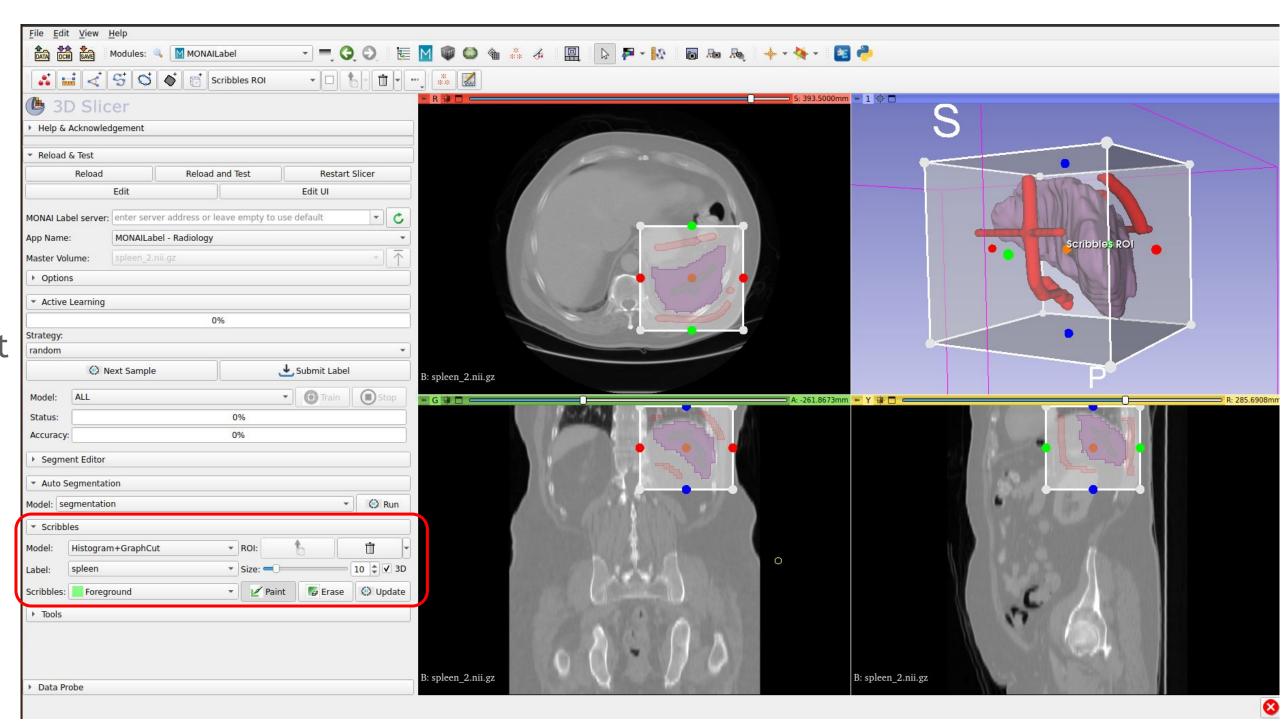
Possible backbones

- UNET
- UNETR
- DynUNet
- Any PyTorch CNN



Create your customised Slicer Module

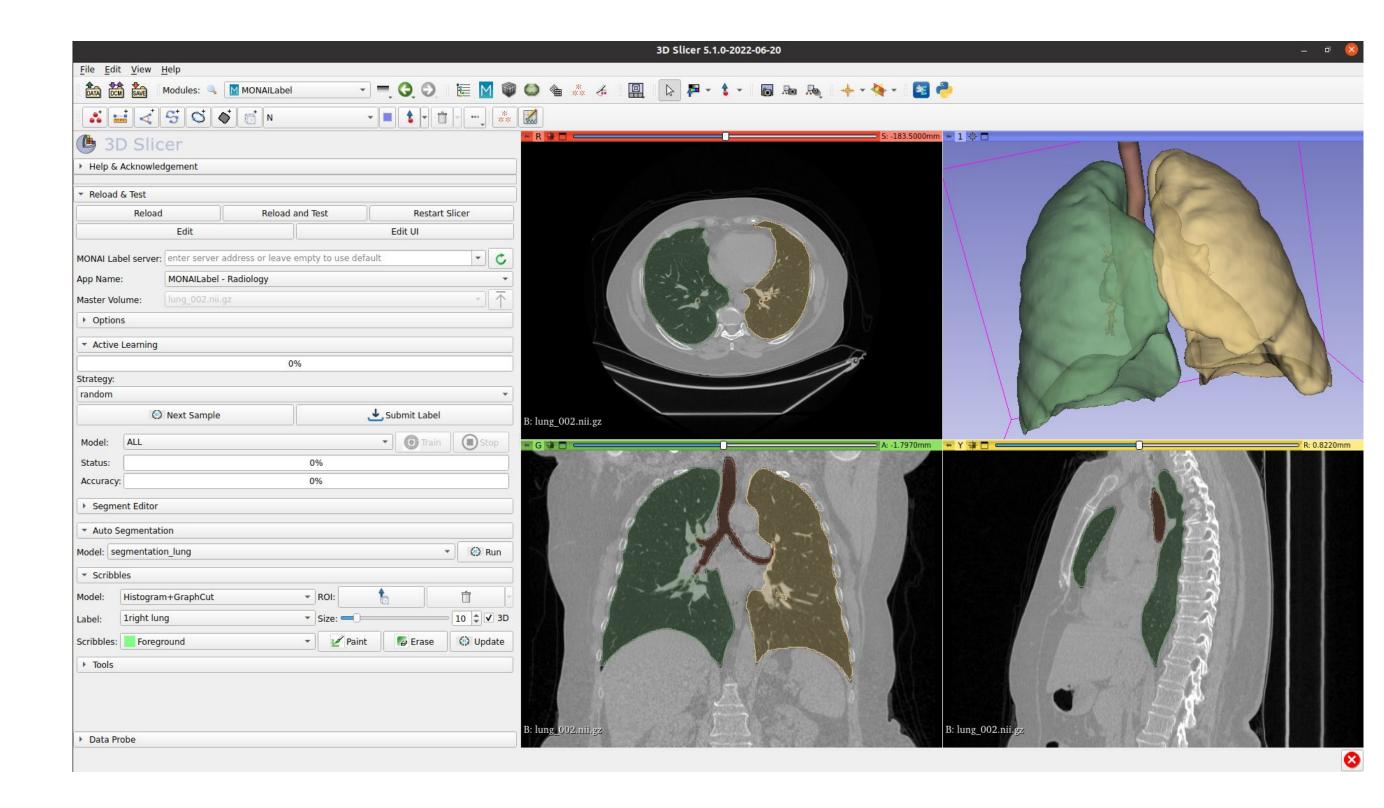
- More dynamic extensions! Support different types of interactions such as closed curves.
- MONAI Label backend APIs can support those interactions (i.e. text input, binary input)





Lung & Airway Segmentation

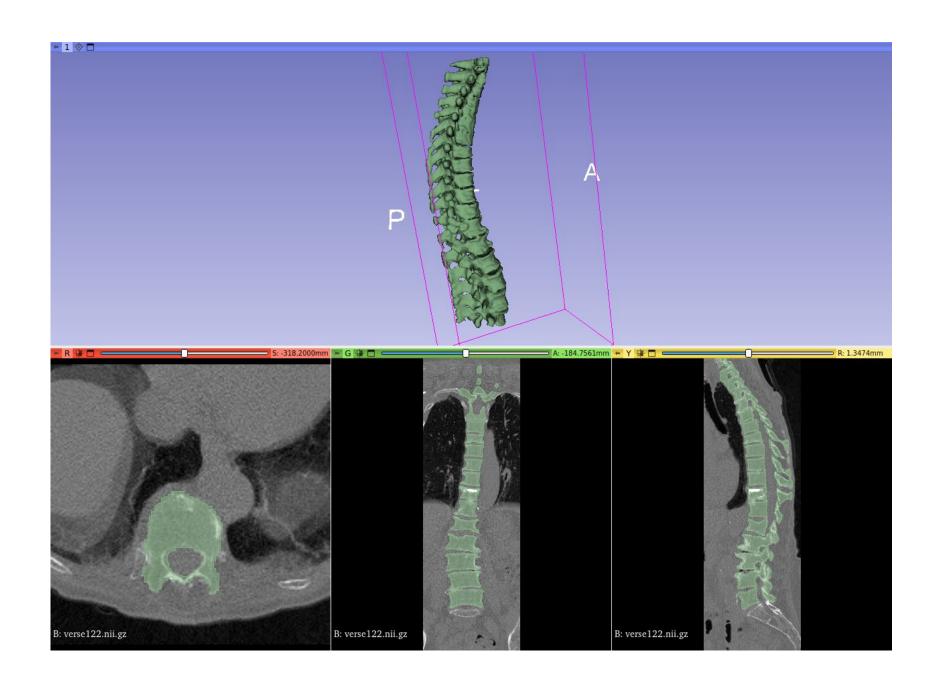
Results obtained after training on Task06_Lung dataset from the Medical Segmentation Decathlon (http://medicaldecathlon.com/).

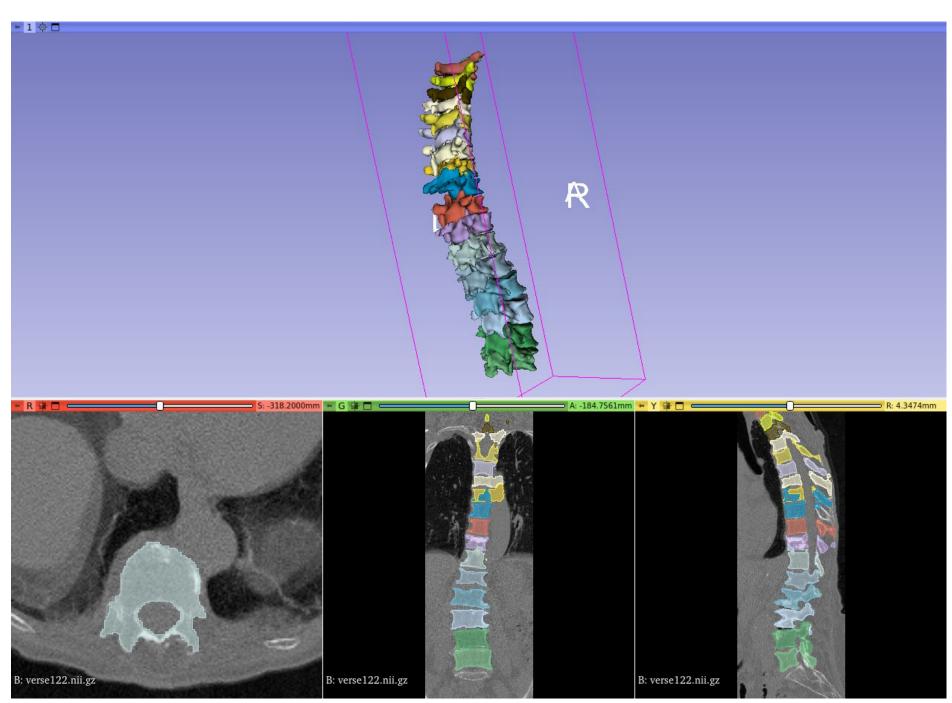


Spine & Vertebra Segmentation

Results obtained after training on **VerSe** dataset

(https://github.com/anjany/verse).



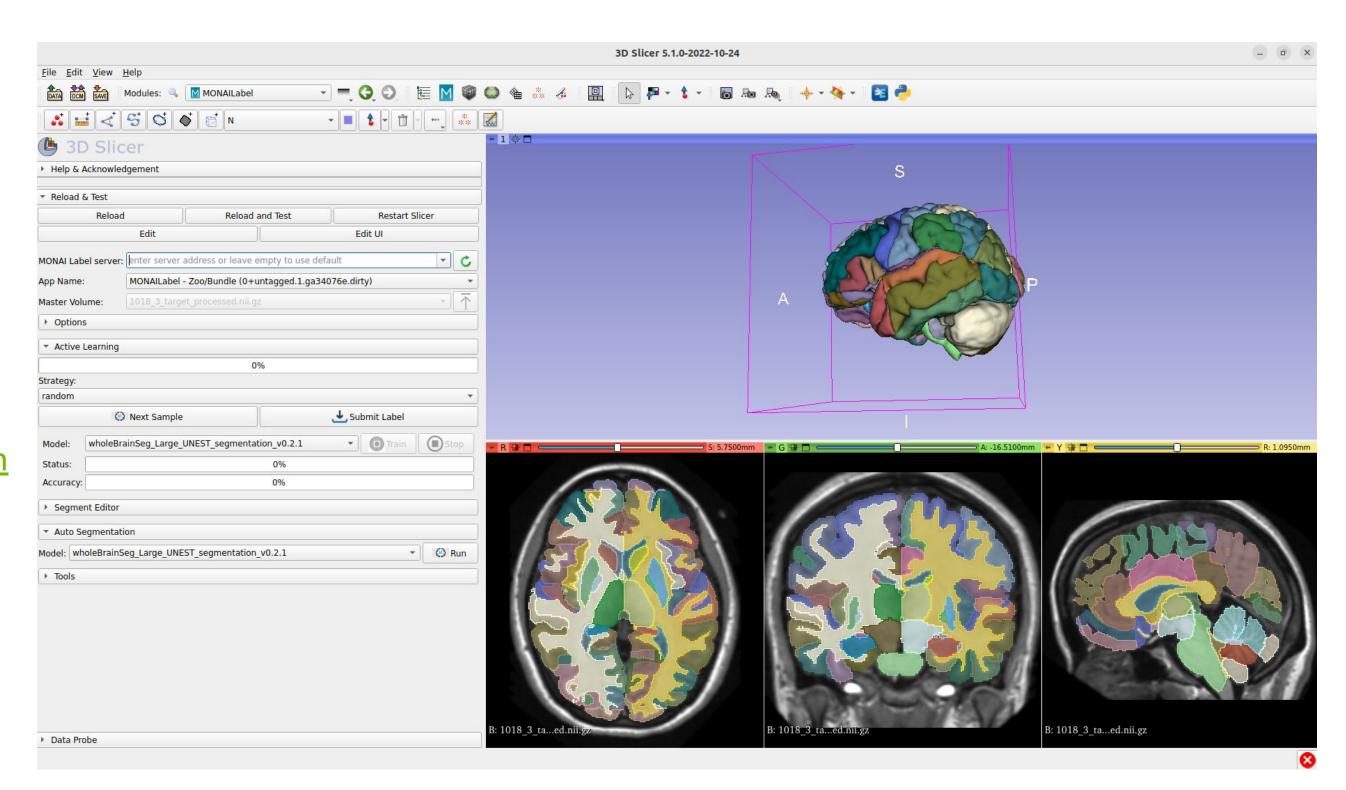


Whole brain Segmentation

Results obtained after training on OASIS and CANDI datsets.

Training and testing data are MRI T1-weighted (T1w)

https://github.com/Project-MONAI/m odel-zoo/tree/dev/models/wholeBrain Seg_Large_UNEST_segmentation





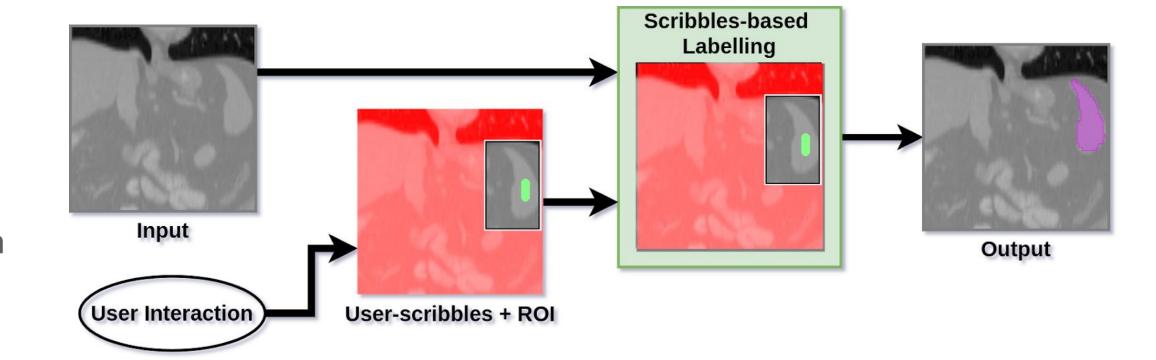
Scribbles in MONAI Label

Scribbles: free-hand line drawings for minimal interaction

MONAI Label provides two scribbles-based modes:

Scribbles-only: uses scribbles to generate segmentation labels (demo) [1, 2]

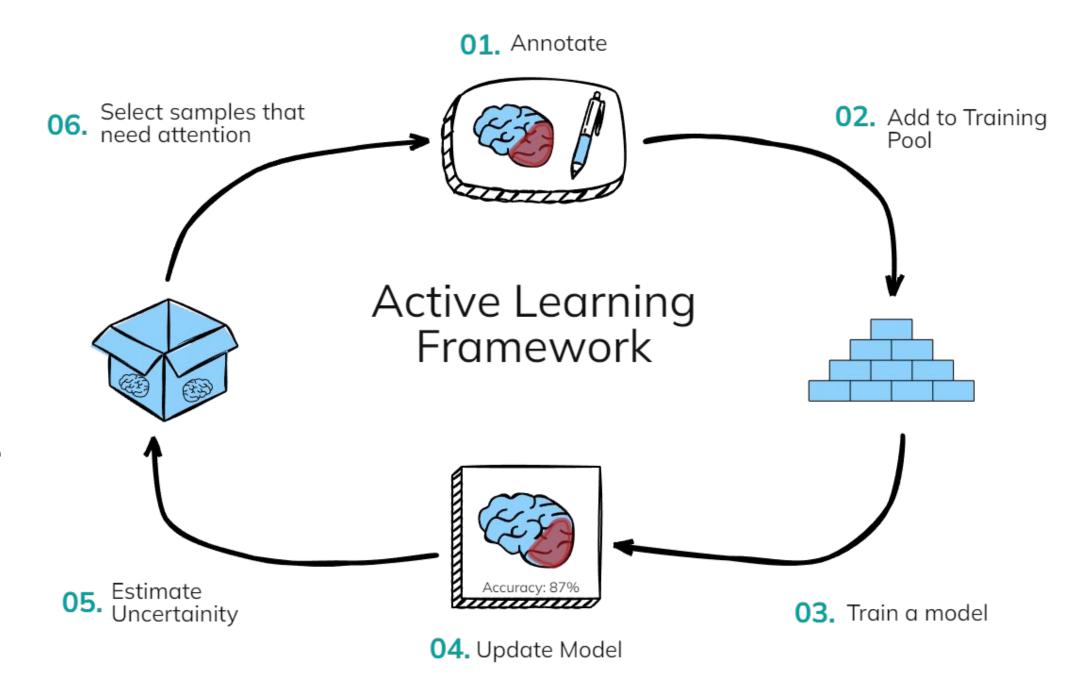
Scribbles-based refinement: refines labels from a deep learning model [2]





Active Learning Strategies

- Active learning is a semi-supervised machine learning approach where the algorithm can choose which data it wants to learn from
- Available in MONAI Label: Aleatoric (Test Time Augmentation) and Epistemic (using Dropout) Uncertainty
- After having a pretrained model, uncertainty of each image can be computed. Unlabeled samples that need more attention from the clinician will be selected
- Selection of harder samples or samples that need more attention





Conclusions and future work

Conclusion:

MONAI Label is a open source project that facilitates annotations of medical images.

It is one of the frameworks that uses Active learning strategies to segment medical images.

• Future Work:

Standalone version

"ImageNet" pretrained model for 3D medical image segmentation

Self-supervised learning or unsupervised learning algorithms to leverage unlabeled data for better performance.

Resources

- MONAI Label repo https://github.com/Project-MONAI/MONAILabel
- MONAI Label wiki https://github.com/Project-MONAI/MONAILabel/wiki
- MONAI Label Deep Dive series https://www.youtube.com/watch?v=8y10BQs2wis&list=PLtoSVSQ2XzyD4lc-lAac FBzOdv5Ou-9IA
- Quick start https://github.com/Project-MONAI/MONAILabel/blob/main/README.md
- MONAI Label + OHIF https://github.com/Project-MONAI/MONAILabel/tree/main/plugins/ohif
- Active Learning https://github.com/Project-MONAI/MONAILabel/wiki/Active-Learning
- FAQ https://github.com/Project-MONAI/MONAILabel/wiki/FAQ



DeepEdit

Andres Diaz-Pinto edited this page on 16 Sep 2021 · 20 revisions

DeepEdit is an algorithm that combines the power of two models in one single architecture. It allows the user to perform inference, as a standard segmentation method (i.e. UNet), and also to interactively segment part of an image using clicks (Sakinis et al.). DeepEdit aims to facilitate the user experience and at the same time the development of new active learning techniques.

Training schema:

The training process of a DeepEdit App involves a combination of simulated clicks and standard training. As shown in the next figure, the input of the network is a concatenation of three tensors: image, positive (foreground) and negative (background) points or clicks. This model has two types of training: For some iterations, tensors representing the foreground and background points are zeros and for other iterations, positive and negative clicks are simulated so the model can receive inputs for interactive segmentation. For the click simulation, users can take advantage of the already developed transforms and engines in MONAL

