

Medical Imaging with Deep Learning in MATLAB Advanced Techniques for Classification and Segmentation

Dr Paolo Panarese, Math PhD EDU Customer Success Engineer Academia Team, MathWorks 8 November 2024









MATLAB is used in many different industries



Aerospace and Defense



Automotive



Biological Sciences



Biotech and Pharmaceutical



Communications



Electronics



Energy Production





Financial Services







Medical Devices



Metals, Materials, Mining

Neuroscience

Railway Systems

Semiconductors

Software and Internet

3



Medical imaging a core part of several workflows





Radiotherapy Planning



Ophthalmology/OCT



Endoscopy



Radiology (MRI, US, X-ray, CT)



Intravascular Imaging



Medical Imaging Toolbox



Medical Imaging Toolbox provides apps, functions, and workflows for designing and testing diagnostic imaging applications. You can perform 3D rendering and visualization, multimodal registration, and segmentation and labeling of radiology images. The toolbox also lets you train predefined deep learning networks (with Deep Learning Toolbox).

You can import, preprocess, and analyze radiology images from various imaging modalities, including projected X-ray imaging, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound (US), and nuclear medicine (PET, SPECT). The Medical Image Labeler app lets you semi-automate 2D and 3D labeling for use in AI workflows. You can perform multimodal registration of medical images, including 2D images, 3D surfaces, and 3D volumes. The toolbox provides an integrated environment for end-to-end computer-aided diagnosis and medical image analysis.



What Is Medical Imaging Toolbox?

https://www.mathworks.com/products/medical-imaging.html





We are going to learn about ...

MATLAB makes Medical Imaging easier

- Interactive apps for Registration, Image Labeling
- Integration of medical models for Image segmentation

Examples:

- 1. Classification of Tumors using Radiomics features
- 2. Segmentation of Brain MRI using a MONAI model
- 3. Segmentation of CT scans using different models of MONAI
- 4. Segmentation of heart ROI using MedSAM







Flexible medical imaging workflow





+ Human Validation = Ground Truth

Dedicated functions to load medical images

```
medImage = medicalImage("forearmXrayImage1.dcm")
medImage =
  medicalImage with properties:
         Pixels: [1540x1250 uint16]
       Colormap: [] SpatialUnits: "mm"
       FrameTime: []
      NumFrames: 1
   PixelSpacing: [0.1390 0.1390]
       Modality: 'DX'
   WindowCenter: 2048
    WindowWidth: 4096
imshow(medImage.Pixels,[])
```



Note: you can create a medical image object from an image datastore dicomds = imageDatastore(dataFolder, FileExtensions=".dcm",ReadFcn=@(x) dicomread(x)); medImage = medicalImage(dicomds) MathWorks[®]

Import

Dedicated functions to load medical volumes

```
medVolMRI = medicalVolume("brainSegData anat.nii.gz")
medVolMRI =
  medicalVolume with properties:
                 Voxels: [256×256×128 int16]
         VolumeGeometry: [1×1 medicalref3d]
           SpatialUnits: "mm"
            Orientation: "coronal"
           VoxelSpacing: [0.9375 0.9375 1.5000]
           NormalVector: [0 -1 0]
       NumCoronalSlices: 128
      NumSagittalSlices: 256
    NumTransverseSlices: 256
                                      "transverse"
                                                        "coronal"]
           PlaneMapping: ["sagittal"
               Modality: "unknown"
          WindowCenters: 0
           WindowWidths: 0
volshow(medVol)
```

volshow(medVolMRI,RenderingStyle="SlicePlanes")

Import

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Dedicated functions to connect with PACS servers (Picture Archiving and Communication System)



- testConnection
- dicomstore
- dicomquery
- dicomget

- Test PACS server connection
- store DICOM images to PACS server
- Query attributes of DICOM images
- Retrieve DICOM images from PACS server



https://www.mathworks.com/help/medical-imaging/ug/working-with-pacs-server-for-dicom-image-retrieval.html

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Import

TensorFlow & PyTorch Interoperability

NEW



Import and export from deep learning frameworks

MathWorks[®]

Interoperate

Visualize 2d, 2d+time, and 3d multimodal medical image data

Visualize

MathWorks[®]



imshow
volshow
implay
montage
volumeViewer
medicalImageLabeler ...





Video Viewer

Volume Viewer



Medical Apps facilitate registration and segmentation



Preprocess Segment

📣 MathWorks

Visualize

Medical Registration Estimator app



Example 1: Classification of Breast Tumors using radiomics features



Goal: classify Benign vs Malignant Tumors from Ultrasound images

Ultrasound Image with Benign Tumor

437 scans with benign tumors (with corresponding mask)

Ultrasound Image with Malignant Tumor



210 scans with malignant tumors (with corresponding mask)

Split the data into 70% training data and 30% test data



Compute Radiomics features for the training set

- Radiomics is a technique that extracts shape, intensity and texture features from a specified region of interest (ROI)
- Reduces subjectivity in data analysis because it uses the same radiomics features for any medical imaging modality: MRI, CT or ultrasound

```
radiomicsFeaturesTrain = table;
for each image i-th in the training set
  image → DATA (medicalVolume)
  mask → roiDATA (medicalVolume)
```

```
R = radiomics(DATA, roiDATA);
S = shapeFeatures(R, SubType="2D");
radiomicsFeaturesTrain(i-th,:) = S;
end
```



Methods of <u>radiomics</u> object: <u>shapeFeatures</u> <u>intensityFeatures</u> textureFeatures

The image biomarker standardisation initiative (IBSI) provides standardized nomenclature and definitions for radiomics features and reporting guidelines



Train a classification neural network using radiomics features

Remove redundant radiomics features (i.e. with correlation >=0.95)





Evaluate performance and accuracy

False negatives can be more undesirable than false positives in automated medical diagnosis.
 falseNegativeCost = 8;

model.Cost = [0 1;falseNegativeCost 0];

predictedLabelsTest = predict(model, radiomicsFeaturesTest);

confusionchart(labelsTest, predictedLabelsTest, Normalization="total-normalized")



Accuracy = 97%



Example 2 Segmentation of Brain MRI scans using a MONAI model



Step 1: Medical Registration

- <u>Medical image registration</u> is the process of <u>aligning multiple medical images</u>, volumes, to a common coordinate system. You may need to compare scans of multiple patients or scans of the same patient taken in different sessions under different conditions.
- Types of registration: translation, rigid, similarity, affine, non-rigid/deformable
- In this example, before segmentation, we need to **register the brain MRI data to the MNI305 atlas**, a standardized brain atlas commonly used in neuroimaging analysis.



resample imregtform (returns T) imwarp (to apply T) imregicp imregmoment imregdemons imregdeform

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Preprocess



Step 1 bis: use Medical Registration Estimator App





Step 2: import registered image into Medical Image Labeler App



>> medicalImageLabeler





Step 3a: Use MONAI from Medical Image Labeler app

 First, install <u>Medical Imaging Toolbox™ Interface for MONAI Label Library</u> <u>support package</u>



- Use MONAI Label within the Medical Image Labeler app
- Start a MONAI Label server containing the deep learning models





The MONAI Label platform provides fully automated and interactive deep learning models for segmenting radiology images

https://monai.io/index.html

Note: for local machine, a CUDA-enabled GPU is required, otherwise you get an error





Step 3b: choose MONAI models for segmentation

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Models for one organ:

- segmentation spleen ٠
- pancreas ct dints segmentation •
- localization spine ٠
- localization vertebra ٠
- wholeBrainSeg Large UNEST ٠ segmentation

Models for multiple organs:

- wholeBody ct segmentation ٠
- segmentation ٠

- deepedit (interactive) ٠
- deepgrow 3d (interactive) ٠

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



Step 3c: Run the MONAI model





Step 4: analyze the segmentation results

• Overlay of the MONAI labels on the registered volume



 Calculate the volume of different brain structures and the overall brain volume

Name	Volume (voxels)	Volume (<u>ccm</u>)
	1000	4 4077
"x3rd_ventricle"	1280	1.6875
"x4th_ventricle"	1935	2.551
"right_accumbens_area"	340	0.44824
"left_accumbens_area"	522	0.68818
"right_amygdala"	925	1.2195
"left_amygdala"	959	1.2643
"brain_stem"	14316	18.874

The total brain volume is about 1446 cubic cm
totalBrainVol = sum(volume)
totalBrainVol =
 1.4462e+03



Example 3: Segment CT scans using different MONAI models and refining labels



Step 1: import CT scans in the Medical Image Labeler app

 Dataset: 1228 CT images, including abdominal and whole-body scans, with segmentation labels for up to 117 anatomical structures per scan.





Step 2: choose multi-organ model and select the labels you want

LABELER	DRAW	AUTOMATE			MONAI LABEL
Start MONAI Label 👻	 Disconnect Server Server Info 	localization spine	localization vertebra	segmentati.	segmentati spleen
MONAI	LABEL SERVER		DEE	P LEARNIN SE	egmentation - A pr
Data Browser		Tra	insverse		

- 1. Choose the model based on the labels you want to predict
- Select the labels you want to predict:
 spleen, kidneys, all lobes of lungs,...
- 3. Run the model
- Adjust contrast and brightness changing window level/width parameters

📣 Label Mapping

For each label you want MONAI to predict, select the check box and choose a label definition for the app. You can create a new label definition or map the MONAI label to an existing label definition

×

Predict?	MONAI Label Name	Label Definition in App	
~	spleen	<create new=""></create>	,
✓	kidney_right	<create new=""></create>	,
~	kidney_left	<create new=""></create>	,
	gallbladder	<create new=""></create>	
\checkmark	liver	<create new=""></create>	,
	stomach	<create new=""></create>	
	aorta	<create new=""></create>	
	inferior_vena_cava	<create new=""></create>	
	portal_vein_and_splenic_vein	<create new=""></create>	
	pancreas	<create new=""></create>	
	adrenal_gland_right	<create new=""></create>	
	adrenal_gland_left	<create new=""></create>	
	lung upper lobe left	<create new=""></create>	







Step 3: combine labels using Label Mapping

		1		
Lab	Label Definitions			
ł	Create Label Definition	L		
\odot	spleen	н.		
\odot	kidney_right	н.		
\odot	kidney_left	н.		
\odot	liver	н.		
\odot	lung_left	1.		
Ó	lung_right			
		н.		
		н.		
14		1		

Predict?	MONAI Label Name	Label Definition in App	
	pancreas	<create new=""></create>	^
	adrenal_gland_right	<create new=""></create>	
	adrenal_gland_left	<create new=""></create>	
~	lung_upper_lobe_left	lung_left	*
✓	lung_lower_lobe_left	lung_left	
✓	lung_upper_lobe_right	lung_right	*
\checkmark	lung_middle_lobe_right	lung_right	
✓	lung_lower_lobe_right	lung_right	-
	esophagus	<create new=""></create>	
	trachea	<create new=""></create>	
	heart_myocardium	<create new=""></create>	
	heart_atrium_left	<create new=""></create>	
	heart_ventricle_left	<create new=""></create>	-

- 1. Delete labels for lung lobes and create 2 new labels: lung_left and lung_right
- 2. Remap labels
- 3. Rerun the same model: each lung label contains all of the corresponding lobes.

LABELER	DRAW	AUTOMATE	VOLUME RENDERIN	G MONAI LABEL					्र त ?
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Iung_right			R			L 99/311			
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									Yolume Session (



Step 4: refine labels by choosing a specific model



📣 Label Mapping	_		×
For each label you want MONAI to predict, select the check box and choose a label	definitior	n for the a	app.

You can create a new label definition or map the MONAI label to an existing label definition

Predict?	MONAI Label Name	Label Definition in App	
~	spleen	spleen	*
	2		
Select	All		

- 1. a few areas of the spleen label may need refinement
- 2. In the Label Mapping, select the spleen label
- 3. Select the segmentation spleen model
- 4. Run the model and visually assess whether the segmentation improved





Step 5: refine labels using interactive models

redict?	MONAI Label Name	Label Definition in App	
	spleen	spleen	
\checkmark	rightKidney	<create new=""></create>	*
	leftKidney	<create new=""></create>	
	liver	spleen	
	stomach	kidney_right	N
	aorta	kidney_left	3
	inferiorVenaCava	liver	
	background	lung_left	
		lung_right	
Selec			



- 1. Select deepedit interactive model (requires foreground/background markers)
- 2. select the rightKidney label and map it to the o the existing kidney_right label definition.
- 3. To draw foreground markers (GREEN): select Mark Foreground and drag INSIDE the kidney.
- 4. To draw background markers (RED): select Mark Background and drag OUTSIDE the kidney
- 5. Run to run the model. Visually inspect the updated kidney_right label to assess whether the segmentation has improved.



Step 6: refine labels manually (without MONAI)







Paint by Superpixels



Example 4: Segment Heart ROI using MedSAM



MedSAM (Medical Segment Anything Model)



nature communications



Received: 24 October 2023	Jun Ma ^{1,2,3} , Yuting He ⁴ , Feifei Li ^{®1} , Lin Han ⁵ , Chenyu You ^{®6} &
Accepted: 5 January 2024	Bo Wang @ Wash >> 🖂

In MATLAB install this support package

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File Autori II mio File	Exchange - Pubblica Informazioni	Software di prova
	Medical Imaging Toolbox Model for Medical Segment Anything Model ds MathWorks Medical Imaging Team STAFE Pre-trained Medical Segment Anything Model (MedSAM) for medical image segmentation	Aggiornato 11 set 2024
		< Condividi Scarica

MedSAM is a state of the art, **zero-shot**, **foundational**, **medical image segmentation model**. MedSAM is adapted from SAM to perform segmentation **specifically for medical images** from different modalities including CT, MRI, Endoscopy, X-ray, Ultrasound, Pathology etc. The zero-shot capabilities of MedSAM enable to use this model for image segmentation without the need for re-training or transfer learning

https://www.nature.com/articles/s41467-024-44824-z



Segment image using medSAM in MATLAB



Note: image taken from 45 cine-MRI images, DICOm format, acquired from multiple patients with various cardiac pathologies (healthy, hypertrophy, heart failure with infarction and heart failure without infarction).



Interactive setup to recompute segmentation for moving roi



addlistener(roi, "ROIMoved",

@(src,evt) ...
segmentAndAnalyzeROI(evt.CurrentPosition,med
sam,embeddings,img,dispIm,t));

function segmentAndAnalyzeROI (callback)
 apply decoder segmentObjectsFromEmbeddings
 Fill the region with insertObjectMask
 Compute radiomics features
 Visualize radiomics features in yellow
end



Conclusions

We have learnt ...

MATLAB makes Medical Imaging easier

- Interactive apps for Registration, Image Labeling
- Integration of medical models for Image segmentation

Examples:

- 1. Classification of Tumors using Radiomics features
- 2. Segmentation of Brain MRI using a MONAI model
- 3. Segmentation of CT scans using different models of MONAI
- 4. Segmentation of heart ROI using MedSAM







References

- Medical Imaging Toolbox
- <u>Medical Imaging Toolbox™ Interface for MONAI Label Library support package</u>
- Medical Imaging Toolbox Model for Medical Segment Anything Model
- Example: <u>Classify Breast Tumors from Ultrasound Images using Radiomics features</u>
- Example: Segment and Analyse Brain MRI scan using AI
- Example: <u>Segment CT scan using MONAI Label</u>
- Example: Interactively Segment and analyze ROI using MedSAM and Radiomics
- <u>Get Started with Radiomics</u>.
- Get Started with MONAI Label in Medical Image Labeler.
- Get Started with Medical Segment Anything Model for Medical Image Segmentation.
- MATLAB Portal for University of Parma

For any technical question: please

- contact MathWorks Tech Support
- write to Paolo Panarese: <u>ppanares@mathworks.com</u>



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AI, Machine Learning, and Deep Learning

Self-Paced Courses

Getting Started (22)

MATLAB (6)

Simulink (10)

Al, Machine Learning, and Deep Learning (6)

Physical Modeling (5) Math and Optimization (7)

Image and Signal Processing (6)

System Engineering (1)

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Machine Learning with MATLAB 6 modules | 12 hours | Languages Explore data and build predictive models.

Machine Learning Onramp

6 modules 2 hours Languages

Deep Learning Onramp 5 modules | 2 hours | Languages Get started quickly using deep learning methods to perform image recognition.



Deep Learning with MATLAB

11 modules | 7 hours | Languages

Learn the theory and practice of building deep neural networks with real-life image and sequence data.

Learn the basics of practical machine learning methods for classification problems.



Reinforcement Learning Onramp

5 modules | 2.5 hours | Languages

Master the basics of creating intelligent controllers that learn from experience.



Computer Vision Onramp

6 modules | 2 hours | Languages Learn the basics of computer vision to design an object detector and tracker

Self-Paced Courses

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MATLAB (6) Simulink (10) Al, Machine Learning, and Deep

Learning (6) Physical Modeling (5)

Math and Optimization (7)

Image and Signal Processing (6)

System Engineering (1)

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Image Processing Onramp 6 modules | 2 hours | Languages

Learn the basics of practical image processing techniques in MATLAB.



Image Processing with MATLAB 11 modules | 11 hours | Languages

Learn practical image processing workflows in MATLAB.



Computer Vision Onramp 6 modules | 2 hours | Languages





Signal Processing Onramp 7 modules | 1.5 hours | Languages An interactive introduction to signal processing methods for spectral analysis.



Signal Processing with MATLAB 8 modules | 7.5 hours | Languages Learn how to perform signal processing in MATLAB.



Wireless Communications Onramp 6 modules | 1 hour | Languages Learn the basics of simulating a wireless communications link in MATLAB.



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Given Imaging (Medtronic) Develops Camera-in-a-Capsule Using MATLAB to Improve the Diagnosis of Gastrointestinal Disorders

Challenge

Create an alternative to endoscopy and other invasive gastrointestinal imaging procedures

Solution

Use MATLAB and companion toolboxes to develop and implement a swallowable video capsule

Results

- Fast, efficient development
- Easy access to precise diagnostic information
- Improved patient care



The PillCam[®] SB 2 video capsule.

"With MATLAB, we simulated the intended system and finetuned it at the early stages of implementation, enabling us to develop critical engineering programs that met requirements on the first iteration." - Rafi Nave, Given Imaging



Philips Healthcare Develops Smart Digital RF Power Subsystem for MRI Systems

Challenge

Develop a novel digital RF power subsystem for use in MRI systems

Solution

Use Simulink to model, simulate, and verify the design, and use HDL Coder to generate consistent and predictable VHDL code for the FPGA implementation

Results

- Design issues resolved early in development
- Tradeoffs rapidly assessed and implemented
- Process consistency and predictability improved



Van Helvoort (left) and van Bakel with a Philips Healthcare MRI scanner.

"Simulink helps system architects and hardware designers communicate. It is like a shared language that enables us to exchange knowledge, ideas, and designs. Simulink and HDL Coder enable us to focus on developing our algorithms and refining our design via simulation, not on checking VHDL syntax and coding rules." - Juha Inberg, Ponsse



JUNIA Develops Autonomous Pediatric Exoskeleton for Children with Severe Neurological Disorders

Challenge

Develop an exoskeleton to be used as a physical therapy tool for children with cerebral palsy.

Solution

Use MATLAB, Simulink, and Simscape Multibody to model motor dynamics and design motor controllers. Conduct real-time testing of prototype hardware with Speedgoat.





"We found that Simulink Real-Time is the best choice because you can design whatever model you want, whatever control algorithm you want, and you can apply it quickly to your prototype." — Yang Zhang, postdoctoral researcher at JUNIA HEI

Model of the JUNIA exoskeleton. (Image credit: JUNIA HEI)



University of Twente Develops Software for Visualizing Reduced Blood Circulation with Augmented Reality and Deep Learning

Challenge

Enable clinicians and diabetic patients to visualize reduced blood circulation using an affordable, handheld imaging device

Solution

Use MATLAB to develop algorithms that construct a 3D representation of blood circulation and project that representation on the skin's surface

Results

- Data acquisition, localization, mapping, and AR projection algorithms run in real time
- Deep learning models trained to detect poor blood flow before it becomes visible
- Low-cost, fully functional prototype developed and tested



Augmented reality (AR) visualization of blood flow in the wrist and hand.

"One of the biggest advantages of using MATLAB in my research is the ability to use a single platform for all aspects of the project, including image processing and computer vision, SLAM, and deep learning." - Dr. Beril Sirmacek, University of Twente



Thank you!

Q&A



Accelerating the pace of engineering and science

For any technical question: please

- contact MathWorks Tech Support
- write to Paolo Panarese: ppanares@mathworks.com