Two-Stage Deep Learning Pipeline for Prostate and Lesion Segmentation in MRI Scans

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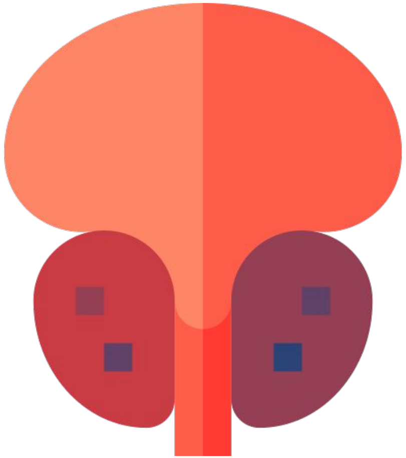
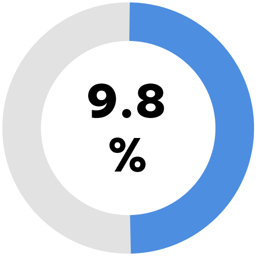
Table of Contents



Prostate Cancer Segmentation

1 in 44

Death among American men, the 2nd leading causing death



Brachytherapy-treated men had secondary malignancies, risk of missing cancerous regions

Prostate Cancer Segmentation

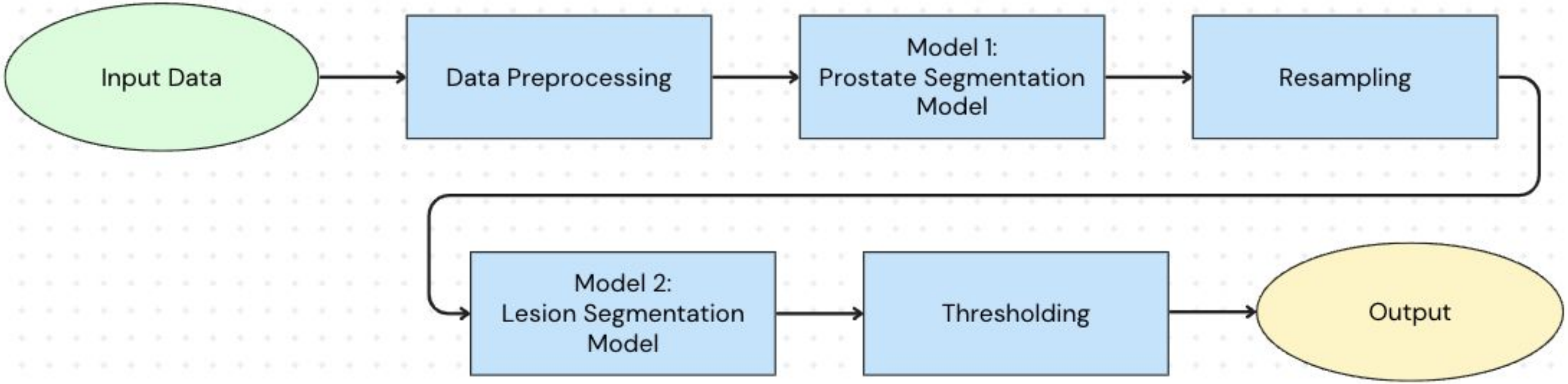
- ## Challenges

- **Variability** in prostate shapes, sizes
- **Low contrast** between the prostate legions and surrounding tissues

- ## Importance

- Improves **surgical precision** and **radiation therapy** outcomes
- Reduces the **risk of recurrence** by targeting cancerous tissues

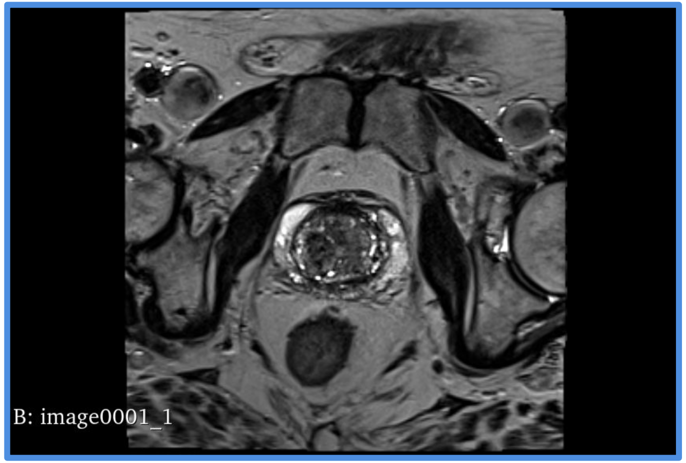
Objective



A pipeline of **data processing** and two **U-Net transformer models** that can output **prostate and legion segmentations**

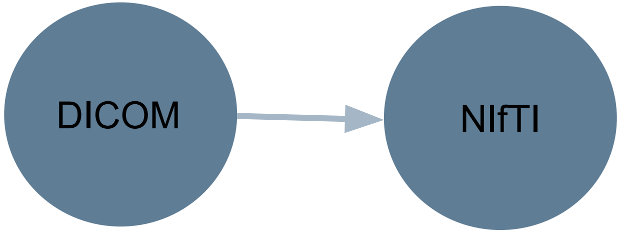
Data Preprocessing: Input Data

- **MRI scans of 1,152 patients** with prostate cancer from *The Cancer Imaging Archive (TCIA)*
- Downloaded corresponding Digital Imaging and Communications in Medicine (DICOM) annotations



Example MRI Scan Downloaded from TCIA

Data Preprocessing: Conversion to NIfTI

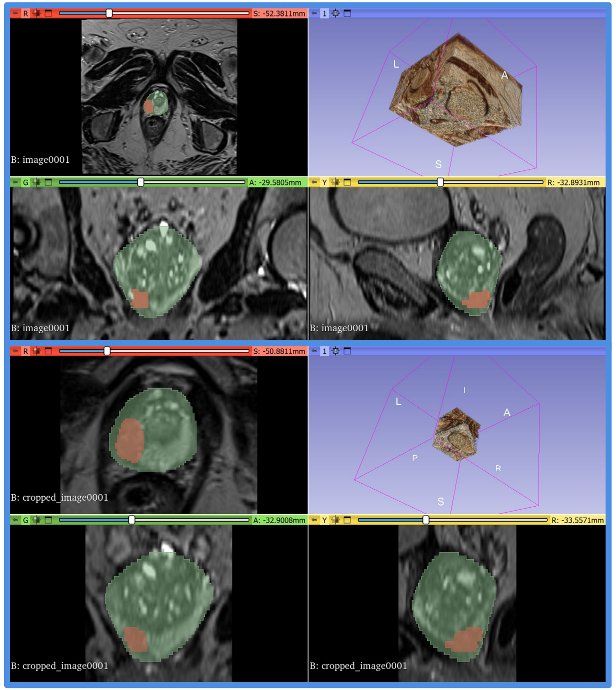


Used **NiBabel** and **Slicer Python packages**

- Easier integration of images and annotations with PyTorch training loops
- Facilitates handling of 3D slice information, affine transformations, and headers

Data Preprocessing: Bounding Boxes

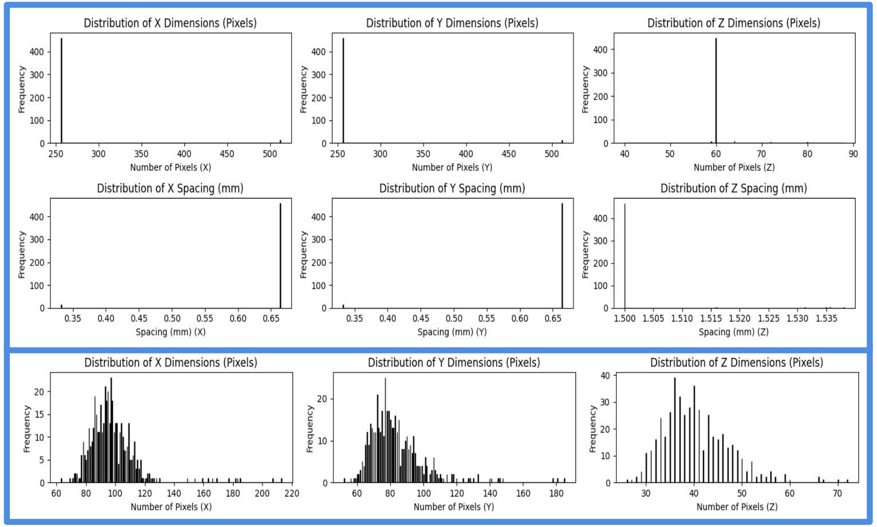
- Calculated minimum and maximum indices by converting original indices into **world coordinates** for consistency
- **Cropped** original image and segmentations according to **min/max indices** while **adding padding**



Comparison between original image and prostate/legion segmentations (top) and cropped image and prostate/legion segmentations (bottom)

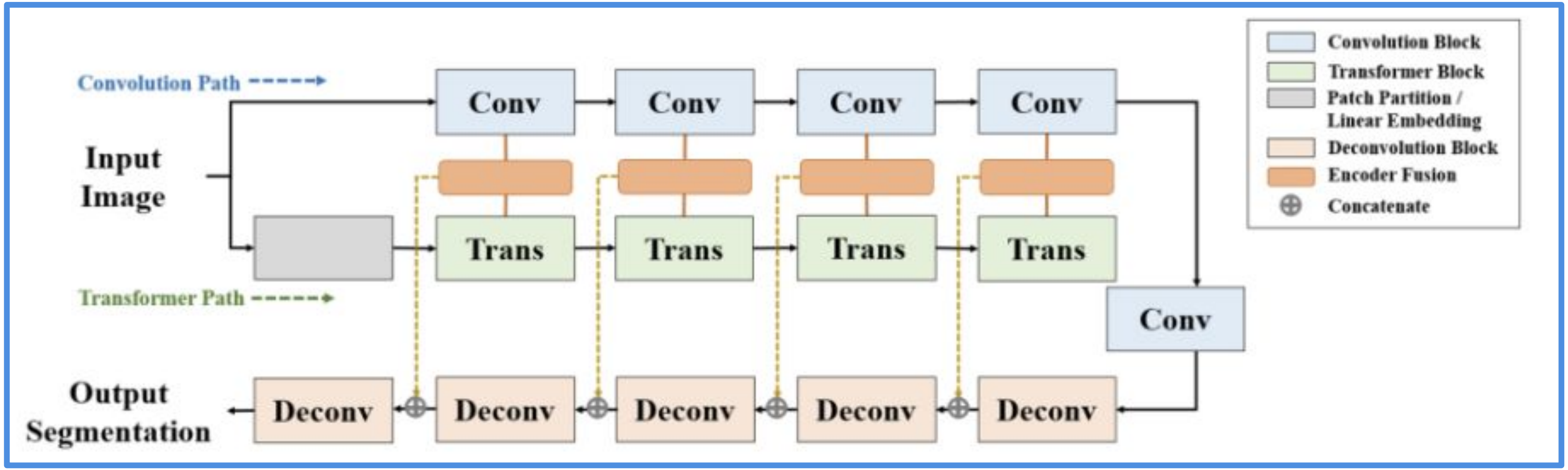
Data Preprocessing: Transformers

- Orient all input MRI images in the **same orientation** as CNNs are not rotationally invariant
- **Normalize intensity** within all input MRI data
- **Standardize size and spacing** for input data that goes into Model 1 and Model 2

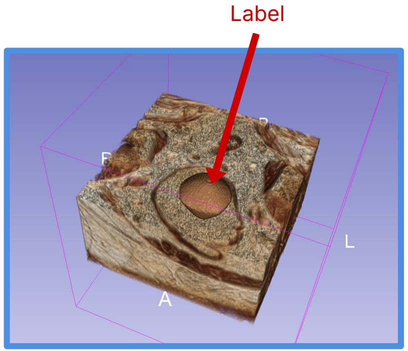


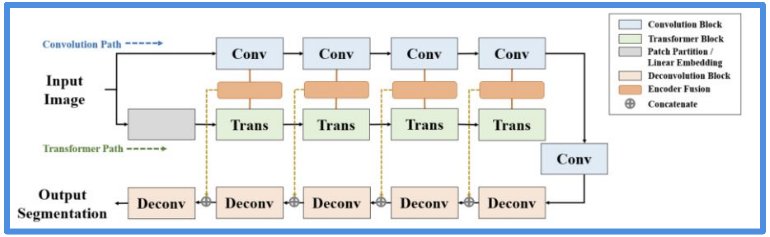
Distribution of image shapes (top), spacing (middle), and prostate shapes (bottom)

U-Net Transformer Model



Model 1: Prostate Segmentation Model





Output Prostate Segmentation

Input MRI Image

U-Net Transformer

Conv

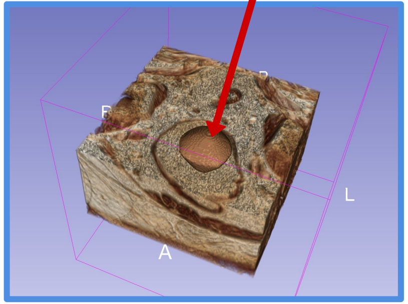
- Two sequential 3×3×3 convolutions
- Dropout Probability = 0.2
- Parametric ReLU Activation

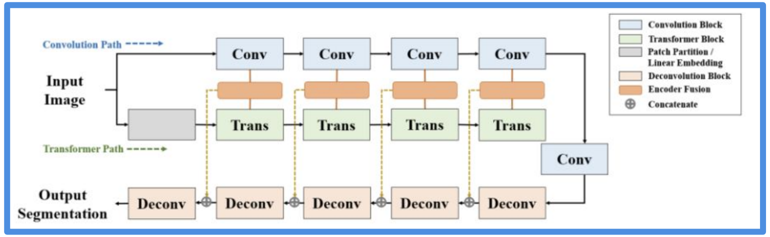
Trans

- 3D Tokenization and Windowed Self-Attention
- Global Context Learning
- Multi-Head Self-Attention and Multi-Layer Perceptron

Model 1: Prostate Segmentation Model

Label





Output Prostate Segmentation

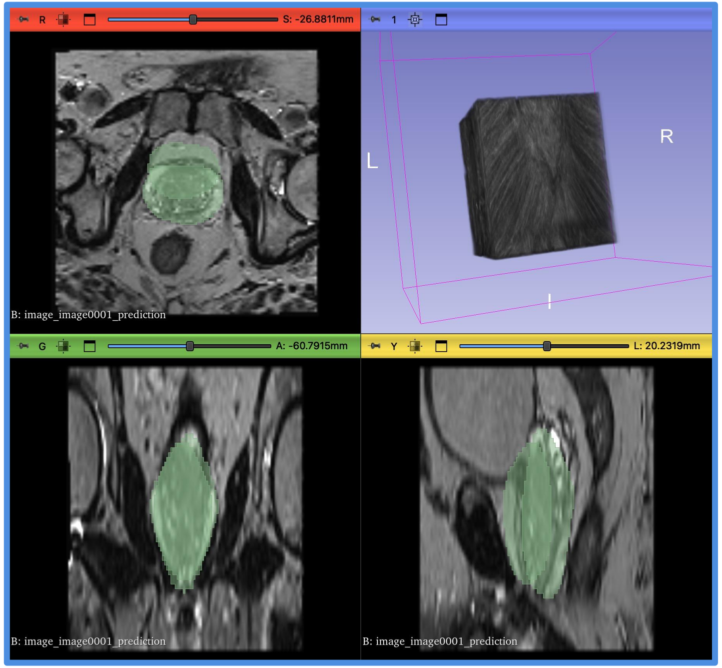
Input MRI Image

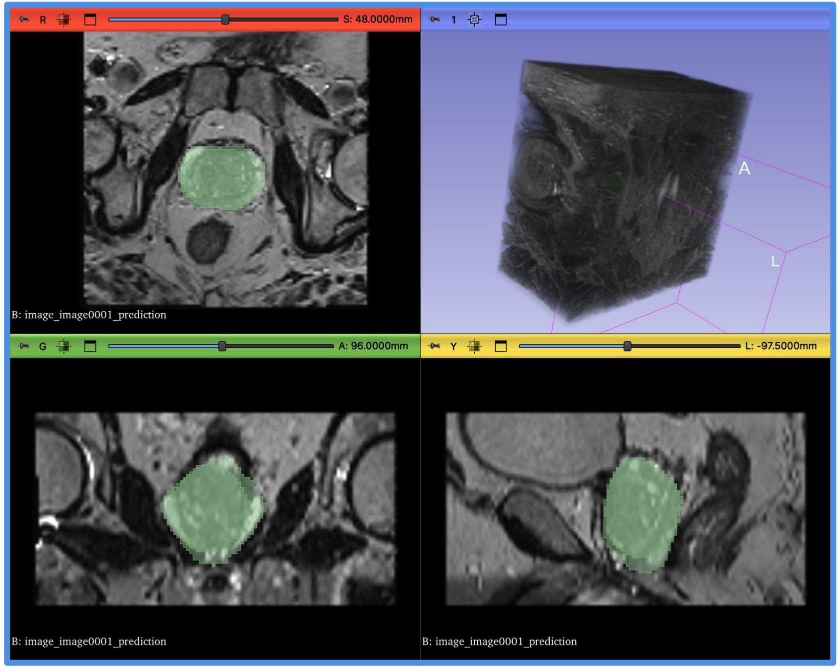
U-Net Transformer

Deconv

- Downsampling in Encoder layers lose spatial information
- Deconv upsamples the feature maps back to the original image size
- Segmentation output must match the spatial resolution of the input

Model 1: Prostate Segmentation Model





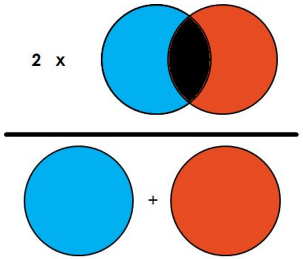
Unaligned Orientations of the Segmented Prostate Region Generated from the Prostate Segmentation Model

Aligned Orientations of the Segmented Prostate Region Generated from the Prostate Segmentation Model

Model 1: Prostate Segmentation Model

- **Dice Score**

$$\frac{2 \cdot |A \cap B|}{|A| + |B|} = \frac{2 \cdot \mathrm{TP}}{2 \cdot \mathrm{TP} + \mathrm{FP} + \mathrm{FN}}$$



- **Hausdorff Distance**

$$H(A,B) = \max\left(\sup_{a \in A} \inf_{b \in B} d(a,b), \sup_{b \in B} \inf_{a \in A} d(a,b)\right)$$

- Measures the largest distance from any point in A to its closest point in B
- Measures the largest distance from any point in B to its closest point in A
- Takes the maximum of the two distances

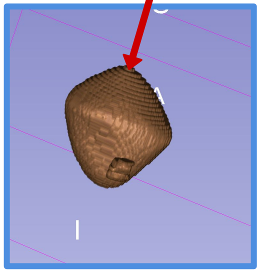
Model 1: Prostate Segmentation Model

- **Dice Metric:**
  - Score: 0.61
  - Standard Deviation: 0.22

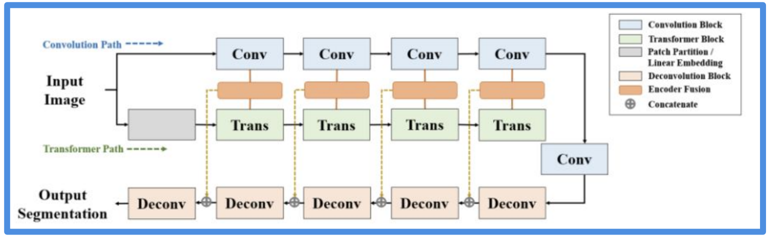
- **Hausdorff Distance (95th Percentile):**
  - Mean: 9.44
  - Standard Deviation: 6.09

Model 2: Lesion Segmentation Model

Identified Prostate



Input MRI Image

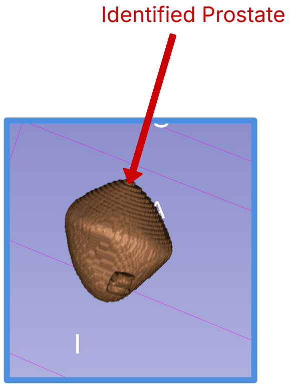


U-Net Transformer

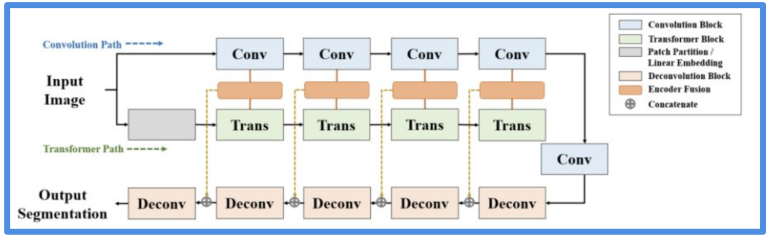
Output Cancer Lesion Segmentation

- Utilizes same model that we implemented for Model 1 except with different transforms that we calculated during the training loop.
- Transform for Model 2 is of higher resolution to segment smaller legions

Model 2: Lesion Segmentation Model



Input MRI Image



U-Net Transformer

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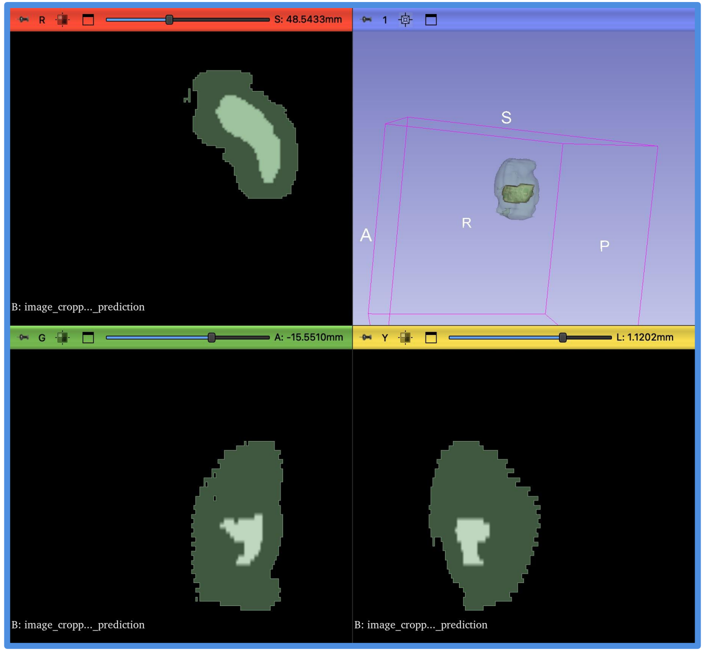
Model 2: Lesion Segmentation Model



Unaligned Orientations of the Segmented Prostate Region Generated from the Prostate Segmentation Model

Model 2: Lesion Segmentation Model

- **Dice Metric:**
  - Score: 0.04
  - Standard Deviation: 0.08

- **Hausdorff Distance (95th Percentile):**
  - Mean: 43.26
  - Standard Deviation: 20.21

Conclusion

- ## Summary

  Developed two **Transformer-U-Net models** for accurate **prostate and lesion segmentation**

- ## Implications of Our Results/Models

  Enables **faster, more accurate prostate cancer detection** to support **diagnosis and treatment** for clinicians

- ## Future Work

- **Explore using the first model's predicted prostate region** for training the second model to compare it with our current second model
- Research ways to **invert transforms** given cropped and padded date
- Apply our models to **other organs** in the human body as it can be indicative of potential diseases

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