AI Generated Segmentations in Medicine

FINAL PRESENTATION

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CS 608: ALGORITHMS & COMPUTING THEORY

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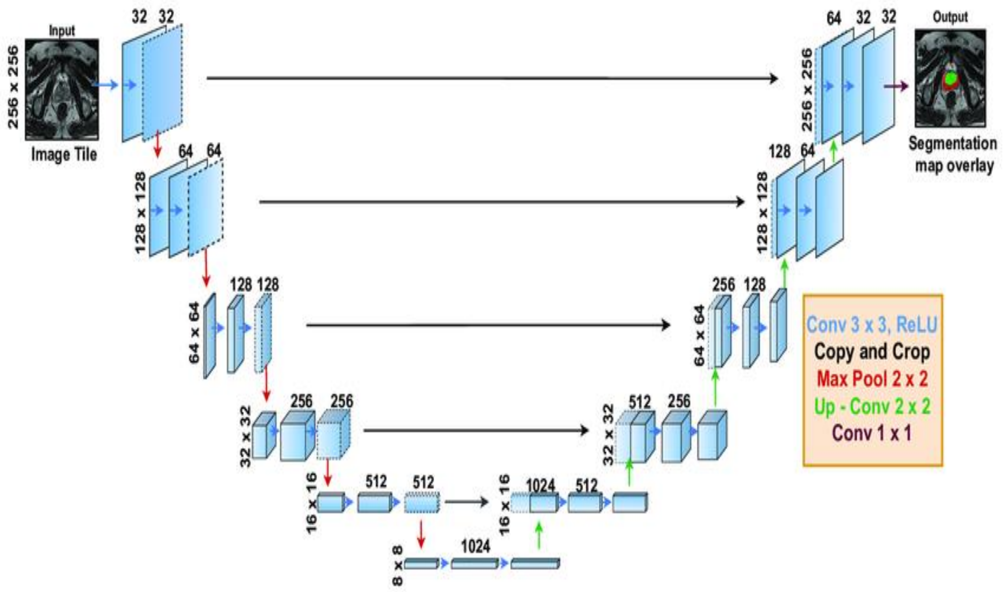
Research Objective

ANALYZE HOW AI IS USED IN MEDICAL SETTINGS

EXPLORE HOW IT IS USED TO CREATE MORE ACCURATE DIAGNOSES

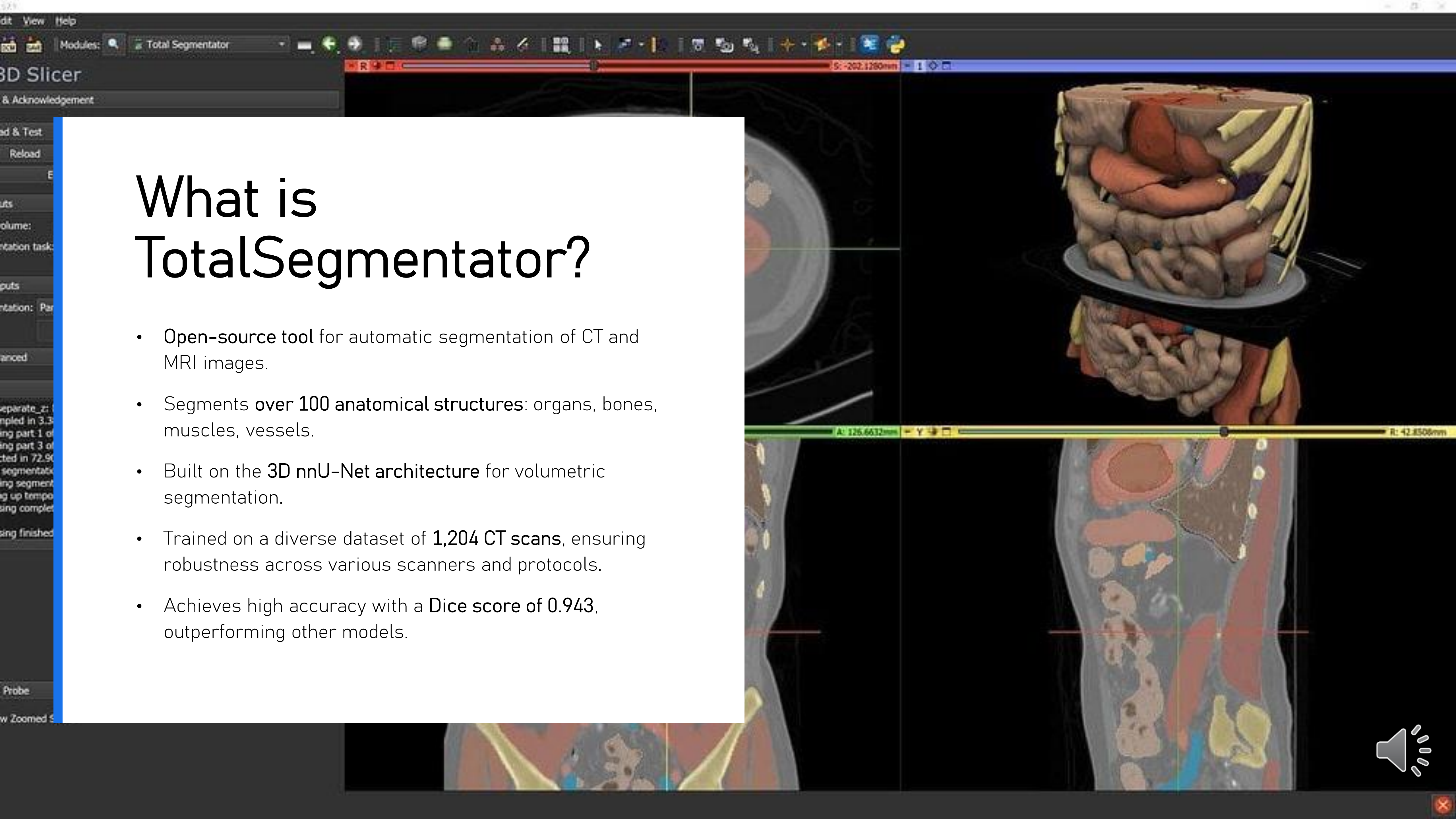
What is U-Net? A Foundational Architecture for Medical Image Segmentation



- **U-Net** is a convolutional neural network (CNN) architecture designed for **semantic segmentation**, especially in **biomedical imaging**.
- Originally introduced in 2015 for segmenting cells in microscopy images.
- It uses a **symmetric encoder-decoder structure**:
- **Encoder (Contracting Path):** Captures context using **convolutions + max pooling**.
- **Decoder (Expanding Path):** Recovers spatial resolution using **upsampling + concatenation** with earlier layers (skip connections).
- U-Net combines classical algorithmic concepts:
  - **Divide and conquer**: Splits image features into hierarchical representations.
  - **Dynamic programming-like reuse**: Uses skip connections to retain earlier computations.
  - Optimizes for both **local detail** and **global context**, balancing space and time complexity during training.

Why U-Net Works for Medical Segmentation

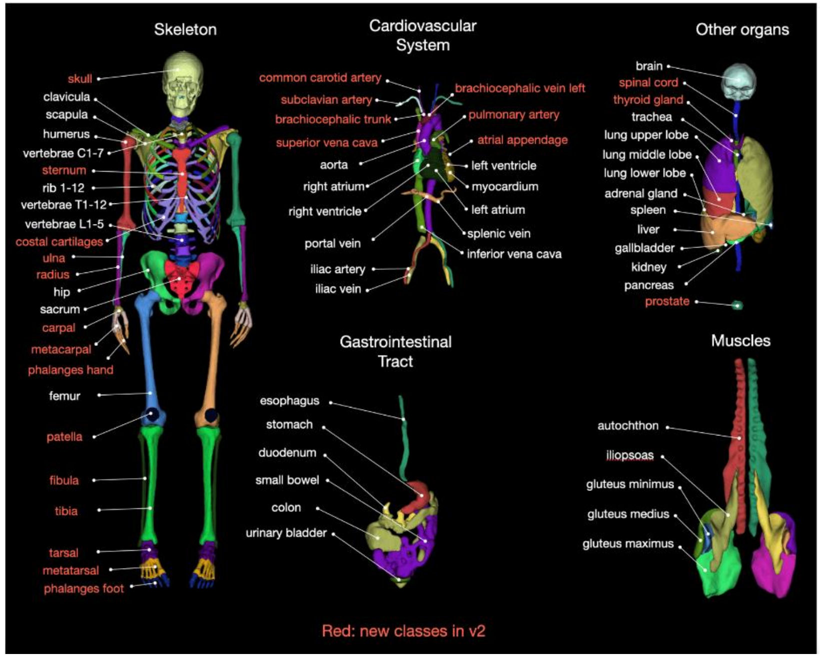
- **Precise Localization:** Skip connections help preserve fine-grained information (vital for medical applications like organ/tumor boundaries).
- **Efficient Computation:** Uses a **fixed-size receptive field** and padding to maintain spatial dimensions — important for consistency across scans.
- **Generalization:** Trained on small datasets using techniques like **data augmentation** — aligning with **algorithmic design principles** that emphasize robustness.
- **Connection to TotalSegmentator:**
  - TotalSegmentator uses **a modified 3D U-Net** to segment over **100 anatomical structures** from CT scans.
  - Extends U-Net's principles to 3D data: a **volumetric adaptation** of the same core algorithmic strategy.



What is TotalSegmentator?

- **Open-source tool** for automatic segmentation of CT and MRI images.
- Segments **over 100 anatomical structures**: organs, bones, muscles, vessels.
- Built on the **3D nnU-Net architecture** for volumetric segmentation.
- Trained on a diverse dataset of **1,204 CT scans**, ensuring robustness across various scanners and protocols.
- Achieves high accuracy with a **Dice score of 0.943**, outperforming other models.

Why TotalSegmentator



Medical imaging uses 3D models generated from CT, MRI, and other radiology technologies

Previously, radiologists had to manually identify organs and abnormalities

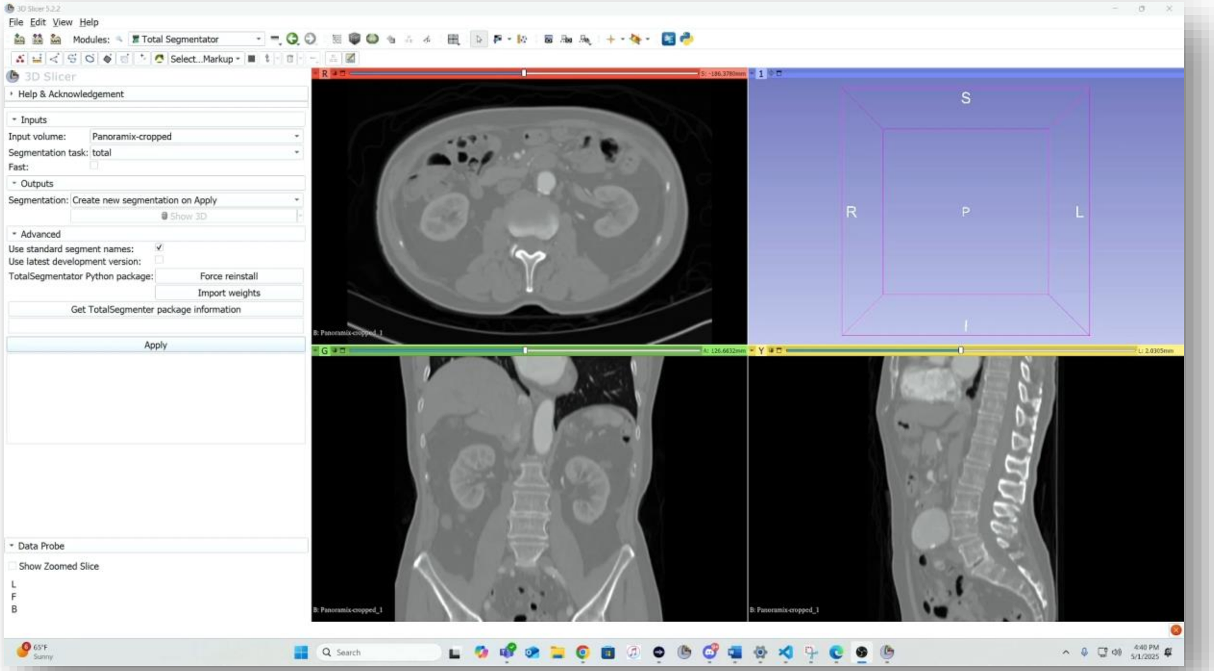
Using computational learning models, it has become possible to automatically identify the desired elements much faster

The algorithms used to identify elements have known shortcomings

Improving the learning algorithm is a continuing research area

Applications and Impact

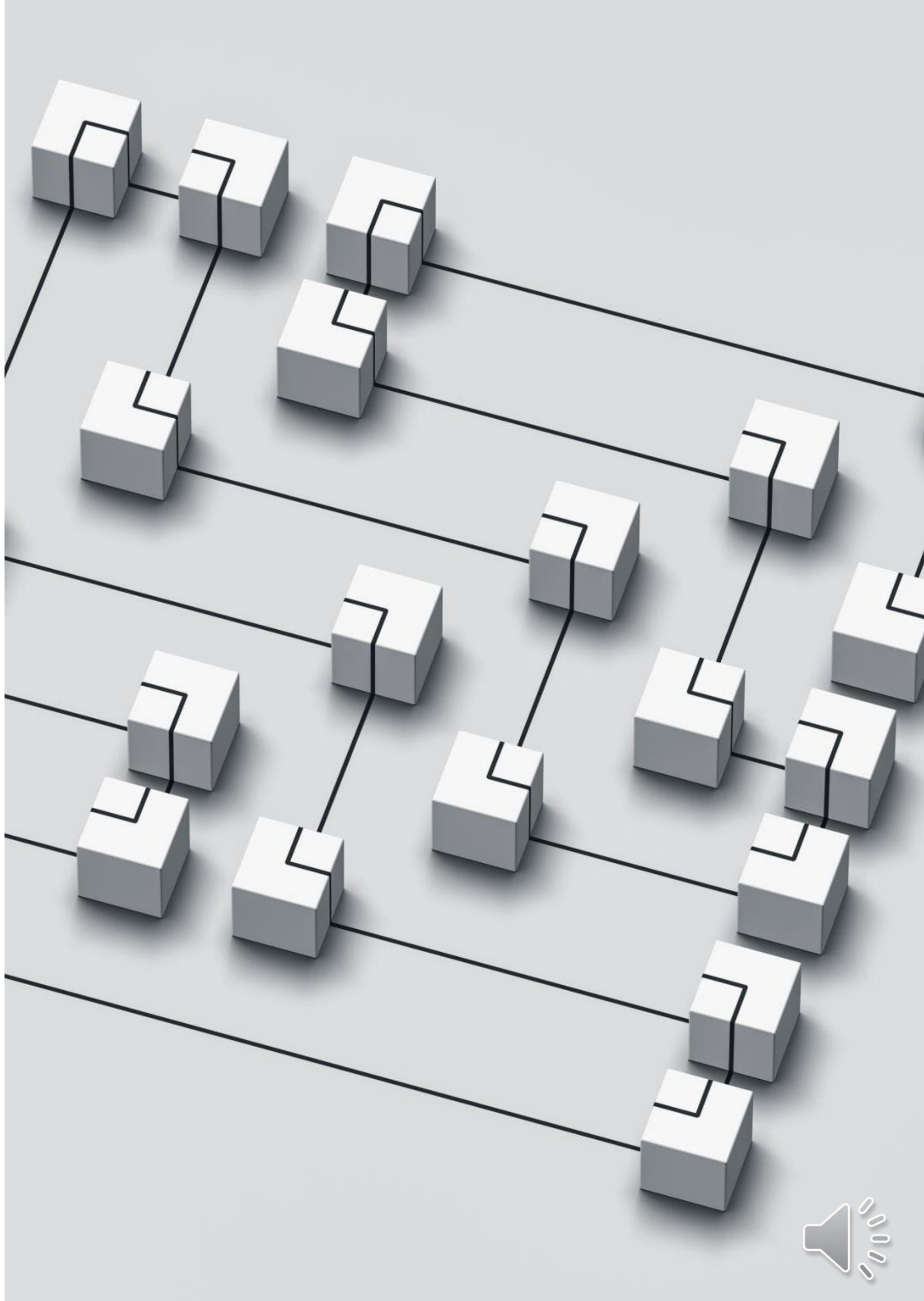
TotalSegmentator Demo Video: HIT PLAY!



- Clinical Use Cases:
  - Organ volumetry for treatment planning.
  - Disease characterization and monitoring.
  - Surgical and radiation therapy planning.
- Research Applications:
  - Large-scale anatomical studies.
  - Training data generation for other AI models.
- Integration:
  - Available as a 3D Slicer extension.
  - Online demo accessible at totalsegmentator.com.

Data Sets

- We used data from multiple published papers that analyze the utilization of a U-Net network in automatic segmentation generation
- Data used volume comparison and DICE scores for accuracy
- This is a retrospective study with no data cleaning required as previous studies have already performed this step



Initial Analysis

The TotalSegmentator software suite depends heavily on the data it is given to generate the 3D models and labels.

The algorithms in the software are very accurate in creating models and identifying organs, based on the available public datasets.

Identifying and highlighting abnormalities is also quite accurate.

Challenges Encountered

- The available public data sets are limited, thus not making it difficult to test the 3D modeling algorithms thoroughly.
- Abnormal anatomy can also give the algorithm issues, causing it to misidentify organs.
- Low quality data also causes problems, probably due to the low contrast blurring the edges of organs.
- Certain anatomical structures consisting of rare or small organs, may be underrepresented within the dataset(s); resulting in poor segmentation accuracy for these specific structures.
- Varying CT scan protocols used at different medical facilities can result in inconsistent image quality and data distribution.
- Sometimes, liver bleedings are mislabeled, resulting in a significantly lower reliability in liver bleeding detection.

Potential Adjustments

Access to more data sets would help identify where the algorithm fails to properly model the anatomy.

Modify pre-trained models from similar tasks (e.g., brain tumor or skin lesion segmentation) to improve TotalSegmentator's performance and accuracy.

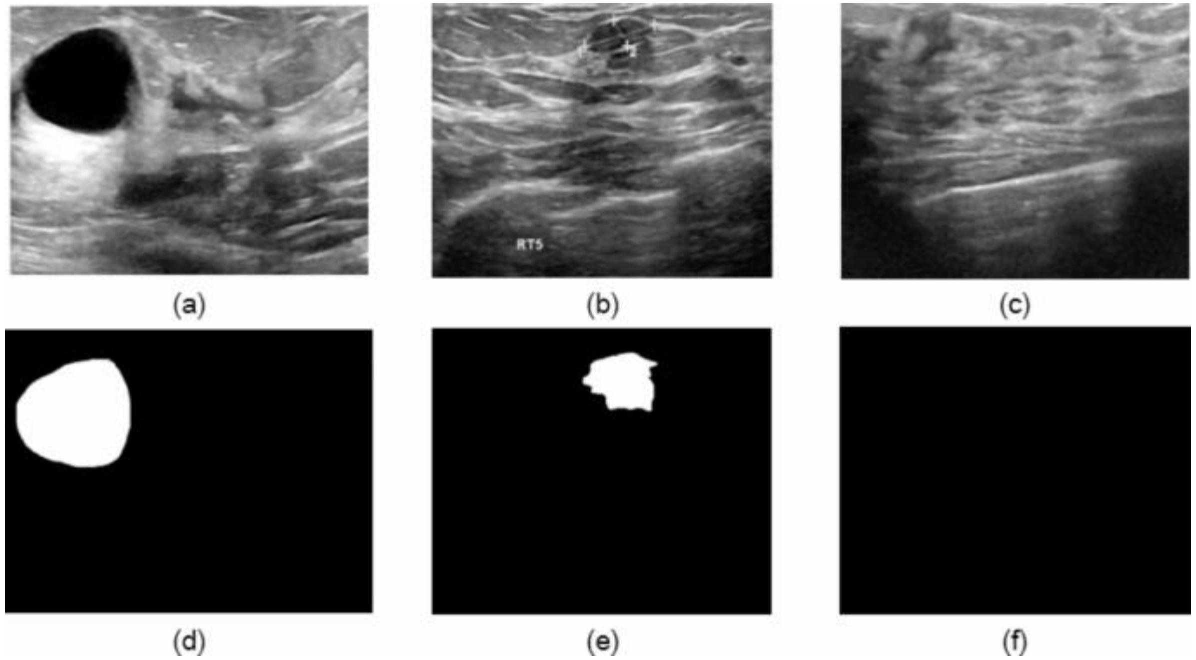
Final Analysis

- Image segmentation quality heavily depends on the quality of contrast.
- Better contrast results in more distinct boundaries between structures, leading to better segmentation.

- CT scans enhanced with IV contrast produce clearer images for robust segmentation, especially for organs like the kidneys.

- **Challenges in small bowel and colon segmentation:**
  - High anatomical variability.
  - Low contrast between structures.
  - Motion artifacts due to peristalsis.
  - Variability in contents (air, fluid, feces).

The Importance of Accurate Organ Segmentation



Dataset samples (a) benign, (b) malignant, (c) normal image without tumor, (d) benign mask, (e) malignant mask, (f) normal mask without any tumor.

- Supports clinical workflows in several fields
  - Ex., Diagnostic Interventions, Treatment planning, surgical therapy
- Mislabeled areas can delay critical diagnosis and interventions.
- Precise segmentation helps radiologists and pathologists detecting and identifying diverse locales.

What Didn’t Work and Why

- High Anatomical Variability:
  - The small bowel and colon vary greatly in shape, size, and position across patients.
  - Small bowel is highly convoluted, with loops overlapping and twisting.
  - Within a single scan, its appearance can change across slices, complicating segmentation.
- Low Contrast Between Structures:
  - Without contrast, the boundaries between bowel loops and adjacent organs are often subtle or missing, making segmentation difficult.
- Peristalsis and Motion Artifacts:
  - Constant motion of the bowel due to peristalsis leads to blurring or inconsistent appearance, complicating segmentation.
- Presence of Variable Contents:
  - The bowel’s contents (air, fluid, feces, contrast) change its appearance, adding intra- and inter-patient variability.

Changes and Reasoning

- No major changes yet, as this remains an active research area.
- Challenges like anatomical variability, motion artifacts, and low contrast continue to hinder segmentation accuracy.
- Ongoing research focuses on addressing these issues through improved algorithms and advanced imaging techniques.

Reproducibility Check

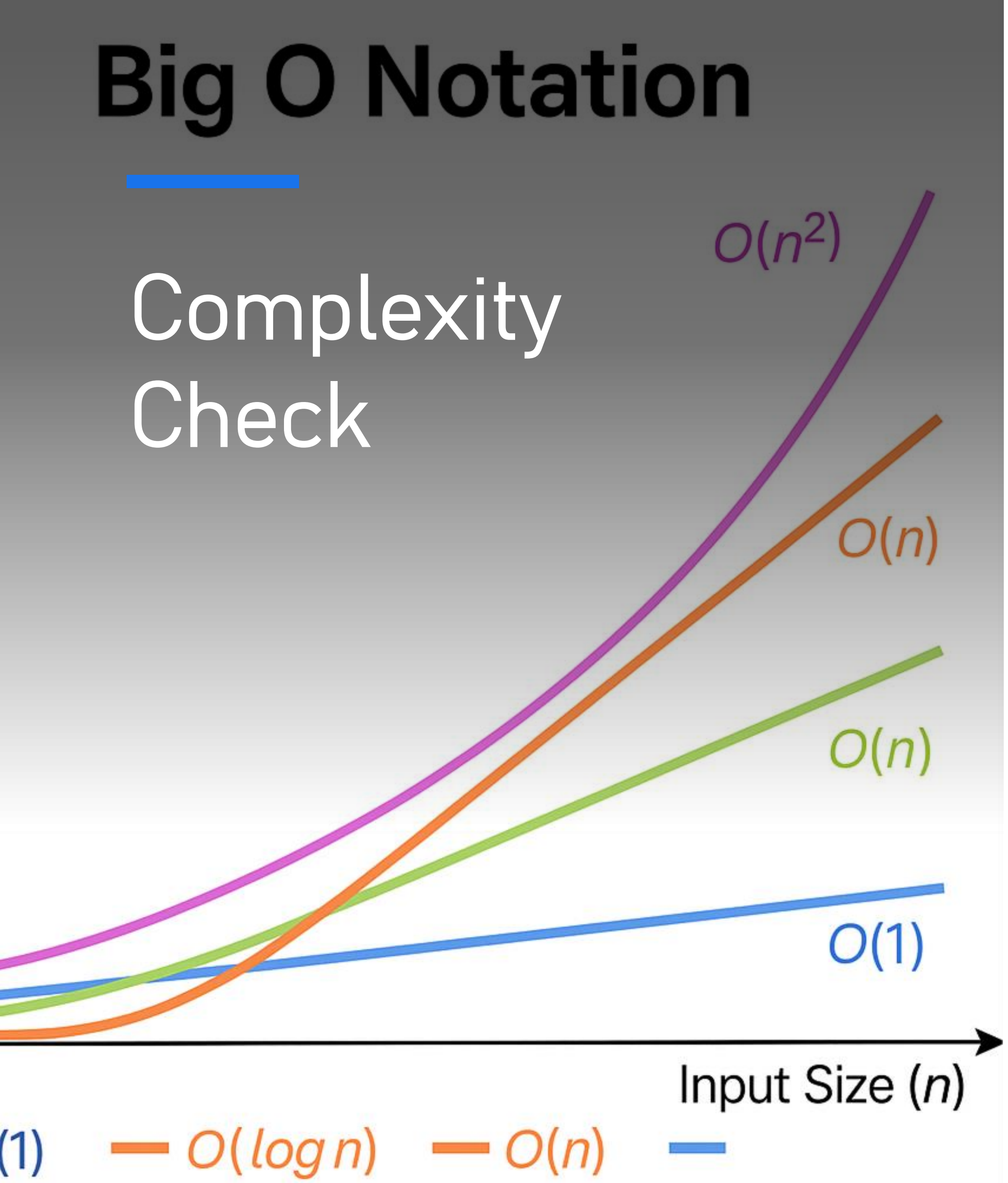
Does your algorithm give the same output every time for the same input?

The algorithm consistently produces the same output for identical input data.

- Same contour is produced every time.
- Excluding or adding an organ doesn't alter contour results
  - Ex. Adding a liver segmentation doesn't change the boundaries of other previously included organs like the kidneys
  - Ex. Adding spinal cord segmentation doesn't alter previous contours for bones or nearby soft tissues

Output variations occur only if we modify the lift of target organs for segmentation, while the general annotations remain the same.

Complexity Check



Does the runtime match what you expect based on your complexity analysis?

Traditional Big-O notation isn't typically used for deep learning models like TotalSegmentator, however, if we still want to approximate it in terms of complexity, the inference time complexity is roughly:

O(V), where V = D × H × W (the volume of the input 3D scan)

This means TotalSegmentator's runtime scales *linearly* with the number of voxels in the CT image being processed.

Performance is dependent on a combination of:

- Input image size
- Number of organs/tissues segmented
- GPU hardware and batch size

Invariant Check

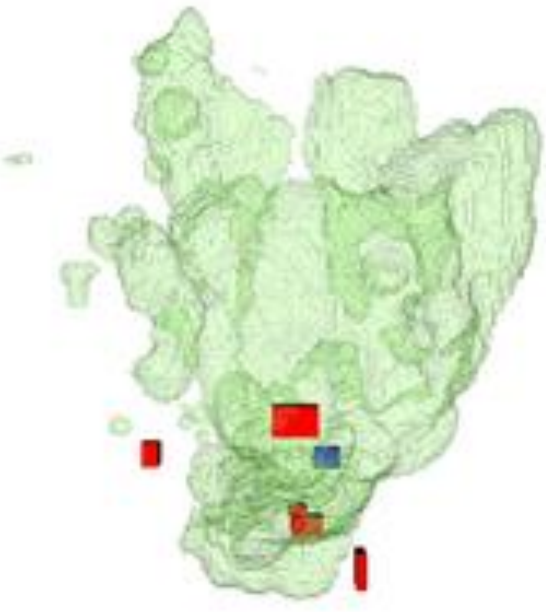
Does your algorithm maintain key rules or patterns while it runs?

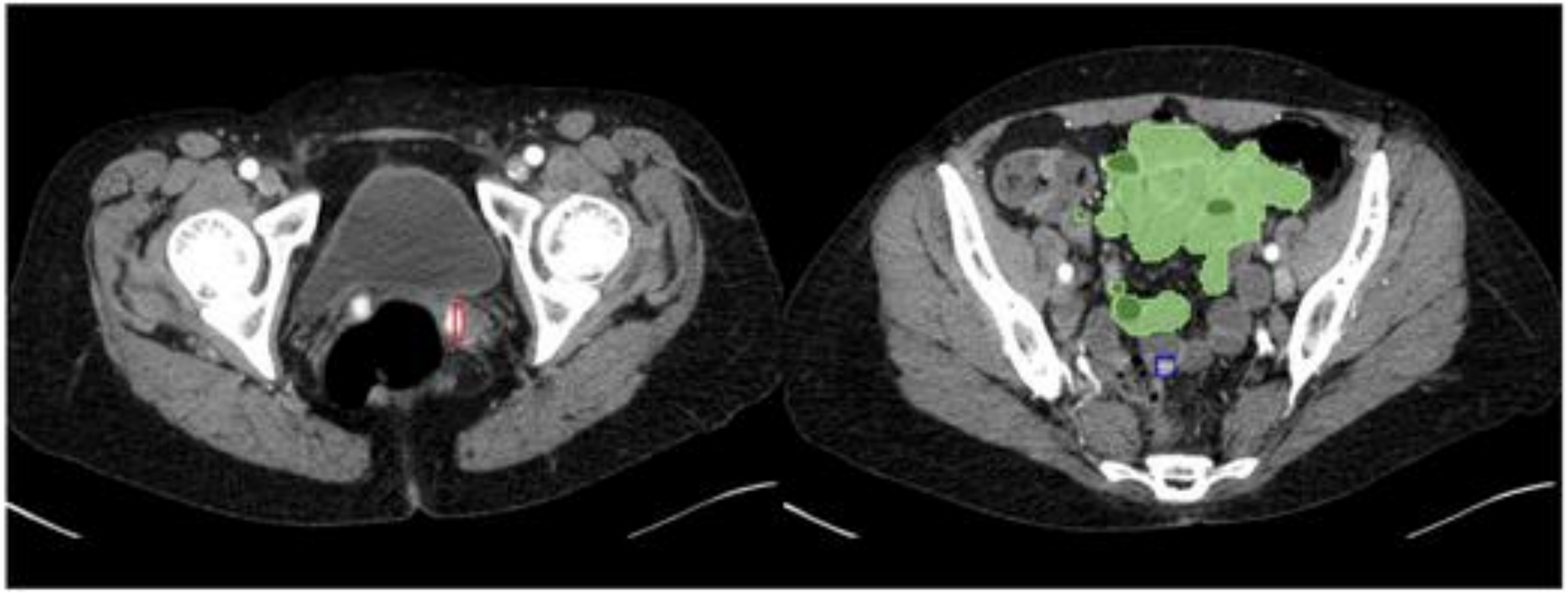
Yes, the TotalSegmentator algorithm maintains key rules and patterns during execution.

Important Invariants

- **Each voxel in the image is assigned to only one anatomical label at a time**—this ensures that the segmentation map remains valid throughout processing.
- Maintains the **dimensionality and spatial alignment** of the segmentation output with the input 3D image.
- These invariants are preserved from the beginning of the segmentation process through to the final output, ensuring anatomical accuracy and usability within tools like 3D Slicer.

VISUALS





Small bowel segmentation is displayed in green, with the red and blue rectangular boxes representing the predicted bounding boxes. Red indicates false positive detections, and blue indicates true positive detections within the CT scan.

- Low contrast and overlapping anatomy in pre-segmentation CT images
  - Hard to distinguish between loops of the small bowel and colon.
  - Post-segmentation shows improvement, despite the colon segments still overlapping with the small bowel
    - *Complicates clear separation*
- Misclassification of some colon regions as surrounding tissues
- Unclear Small bowel Segmentation
  - *Poorly defined boundaries*
  - *Disorganized appearance*
  - *Highlights the complexity of accurate bowel segmentation*

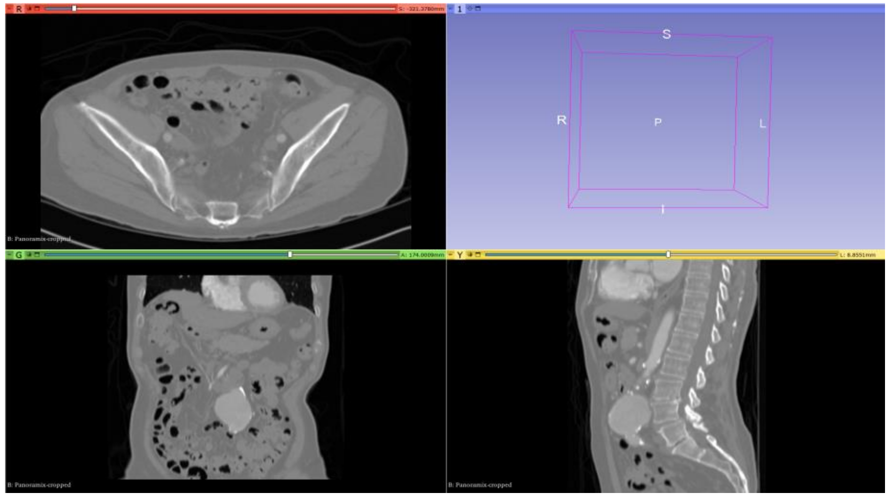


Figure 1: Abdomen CT pre-automatic segmentation
Source: *3D Slicer*. Image generated using a sample CT scan provided by 3D Slicer.

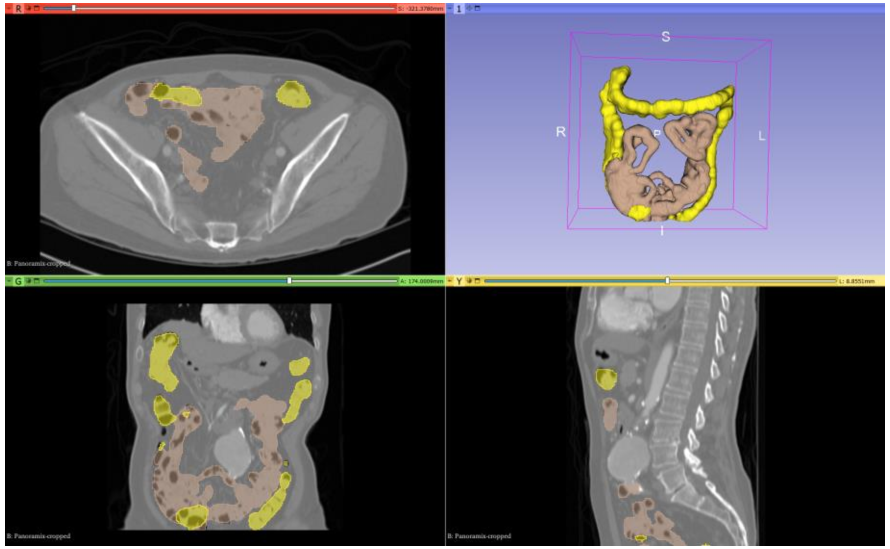
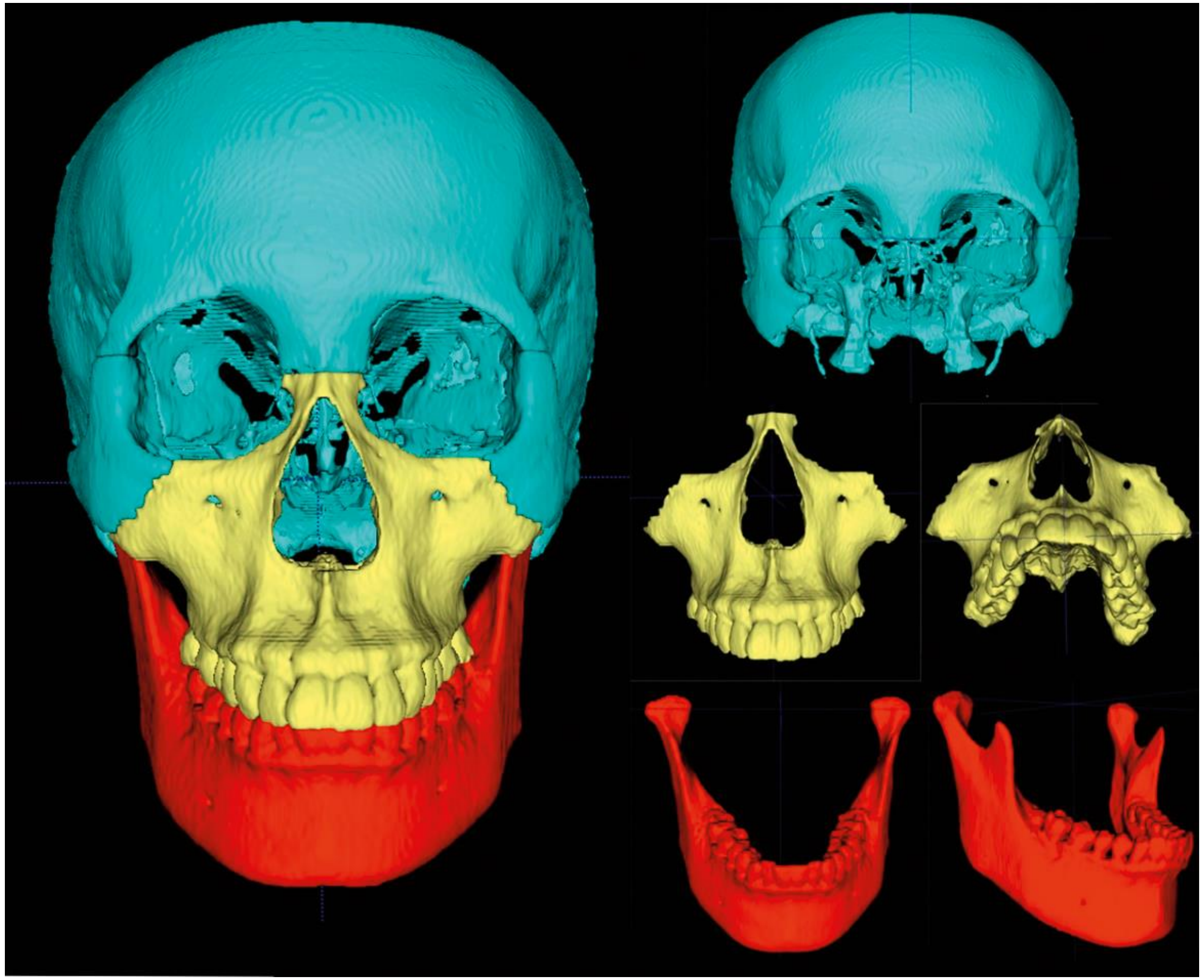
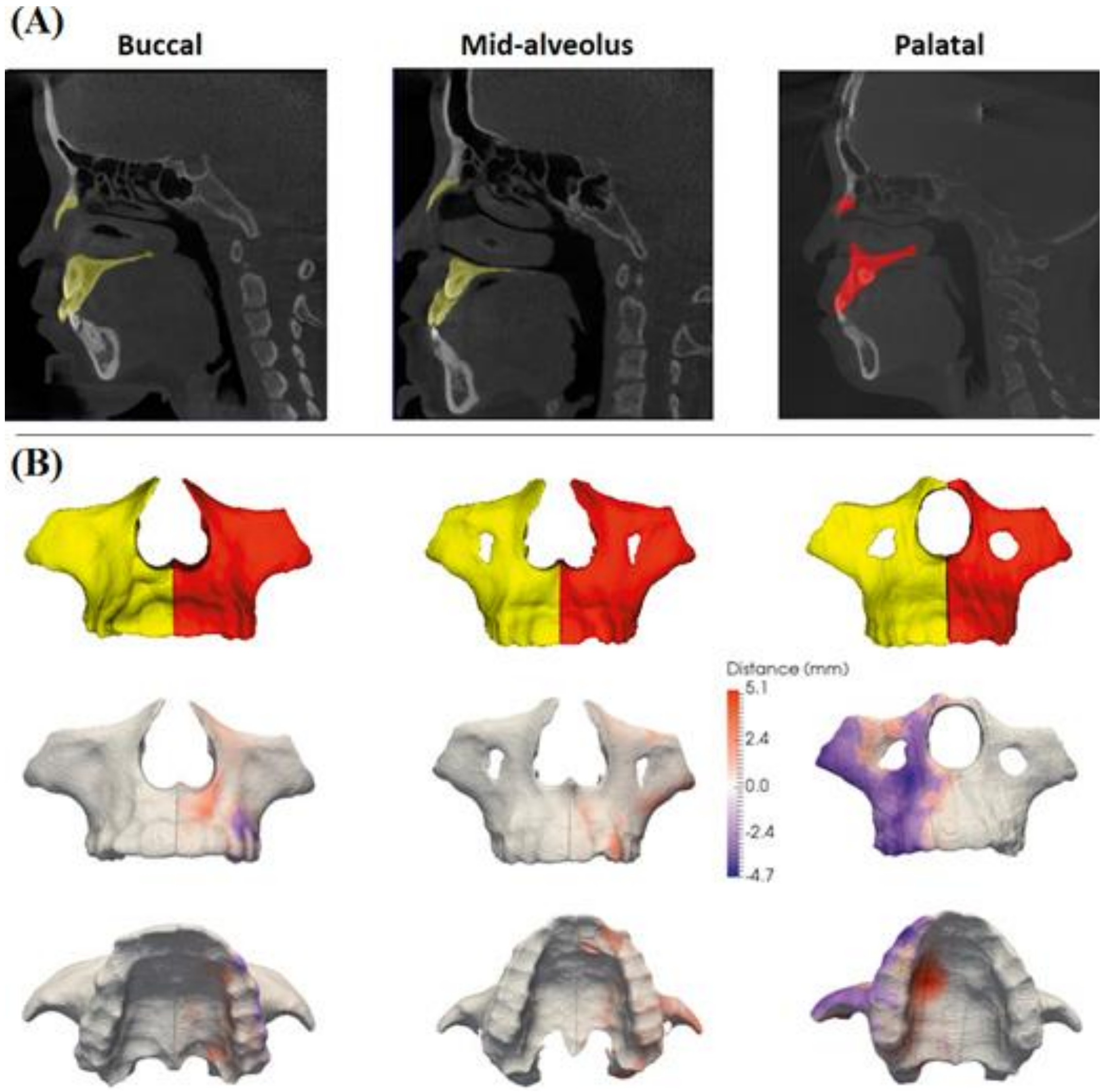


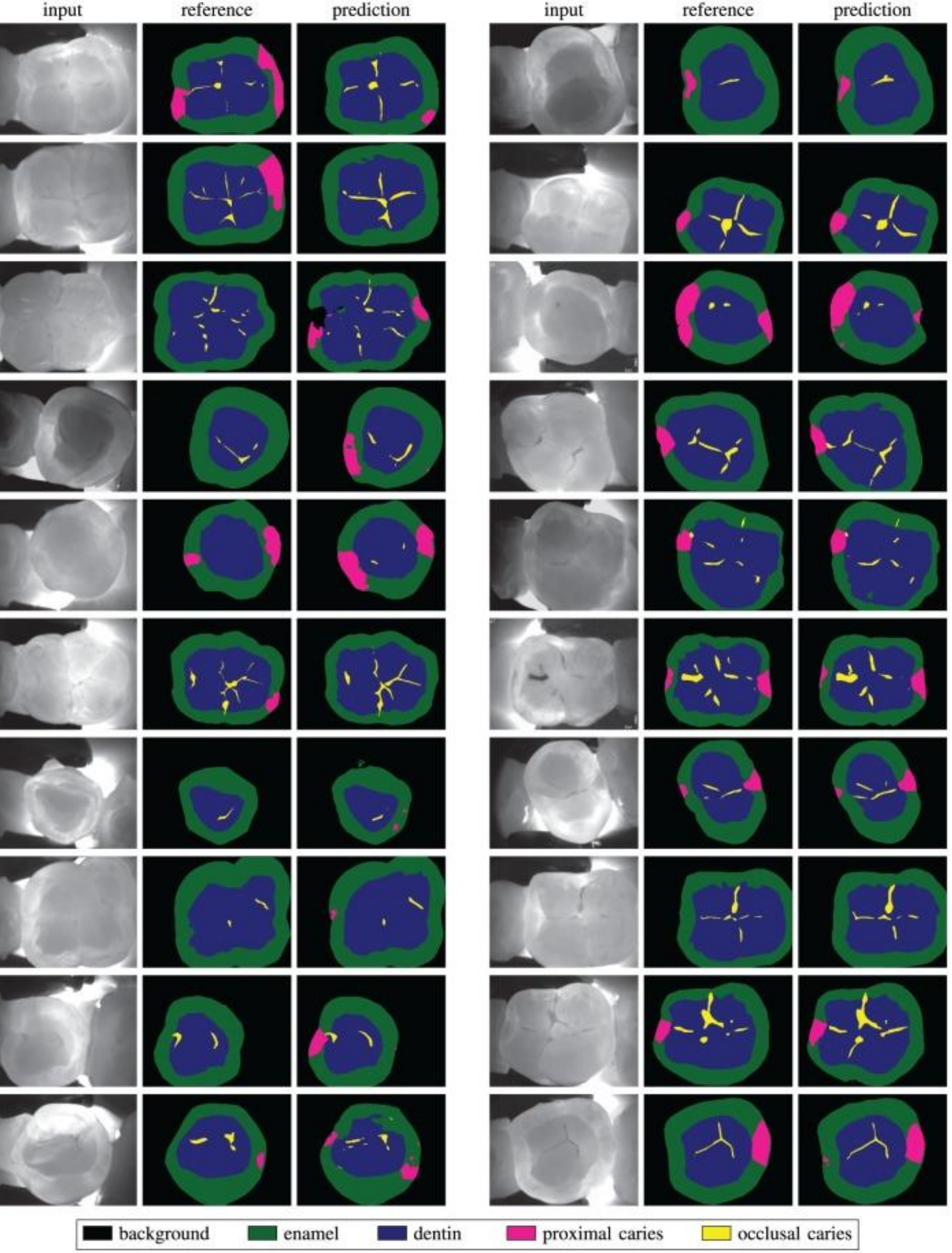
Figure 2: Automatic segmentation results of the small bowel and colon.
Source: *TotalSegmentator*, *3D Slicer*. Image generated using a sample CT scan provided by 3D Slicer.



Craniofacial Segmentation



Maxilla Segmentation



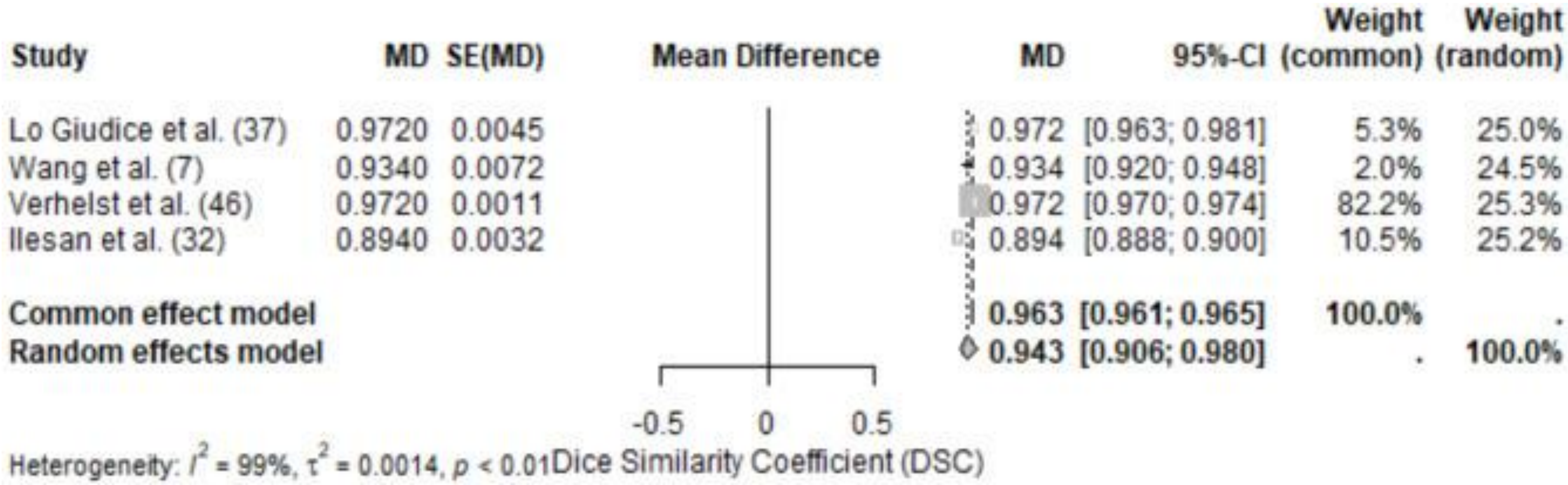
Dental Caries Segmentation

- Left: Increase in inconsistencies between reference and prediction
- Right: Decrease in inconsistencies between reference and prediction.

(a) (b) (c) (d)


(e)

Dice Similarity Coefficient (DSC) TABLE



Study	MD	SE(MD)	MD	95%-CI	Weight (common)	Weight (random)
Lo Giudice et al. (37)	0.9720	0.0045	0.972	[0.963; 0.981]	5.3%	25.0%
Wang et al. (7)	0.9340	0.0072	0.934	[0.920; 0.948]	2.0%	24.5%
Verhelst et al. (46)	0.9720	0.0011	0.972	[0.970; 0.974]	82.2%	25.3%
Ilesan et al. (32)	0.8940	0.0032	0.894	[0.888; 0.900]	10.5%	25.2%
Common effect model			**0.963**	**[0.961; 0.965]**	**100.0%**	**.**
Random effects model			**0.943**	**[0.906; 0.980]**	**.**	**100.0%**

Forest plot of DSC values for mandible segmentation

The Dice Similarity Coefficient (DSC) is a table used to display the DSC values for various segmented organs; evaluating and measuring segmentation accuracy.

Thank You