University Medicine Essen
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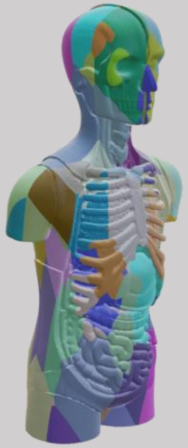

MedShapeNet - A Large-Scale Dataset of 3D Medical Shapes for Computer Vision

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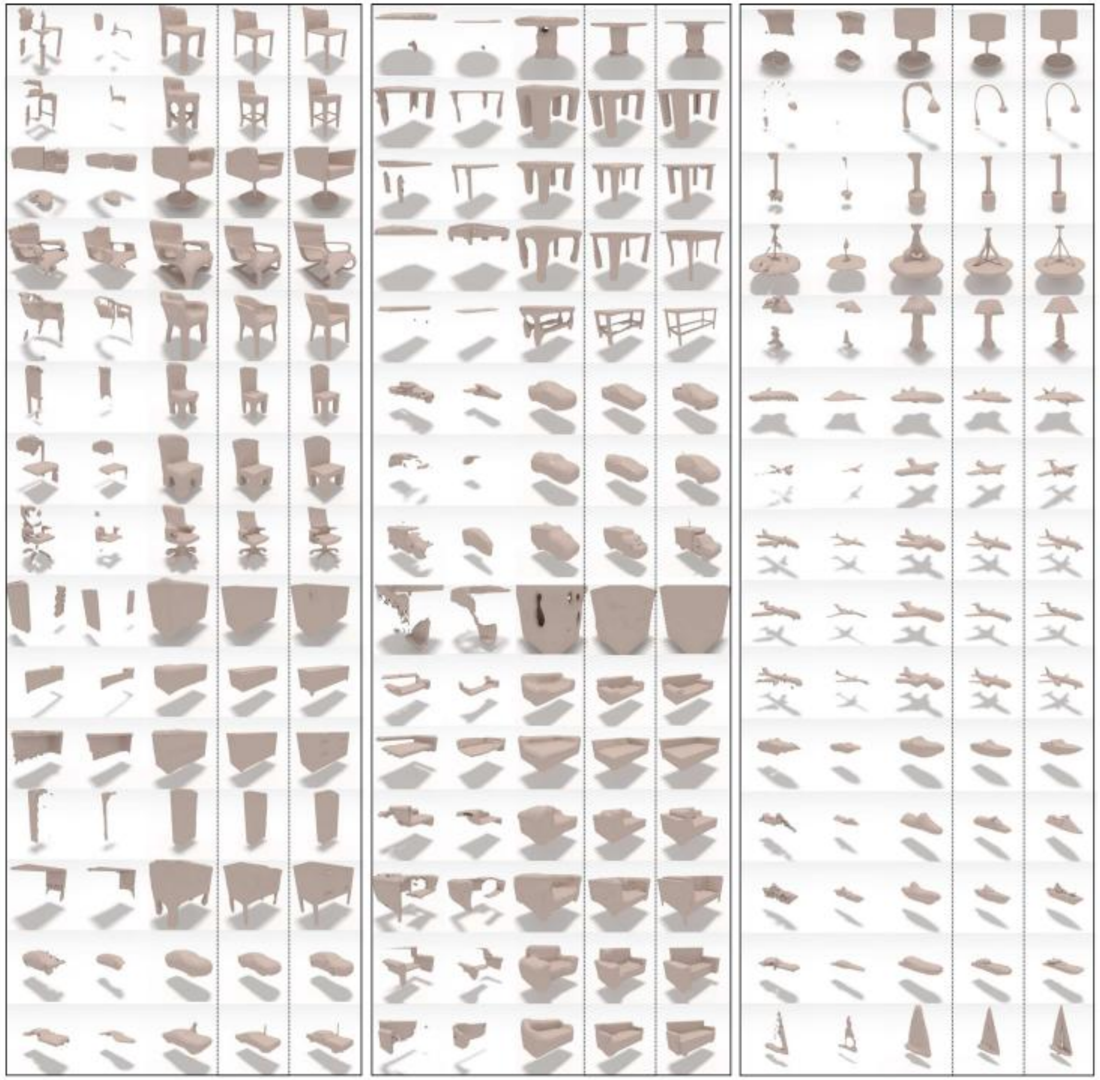
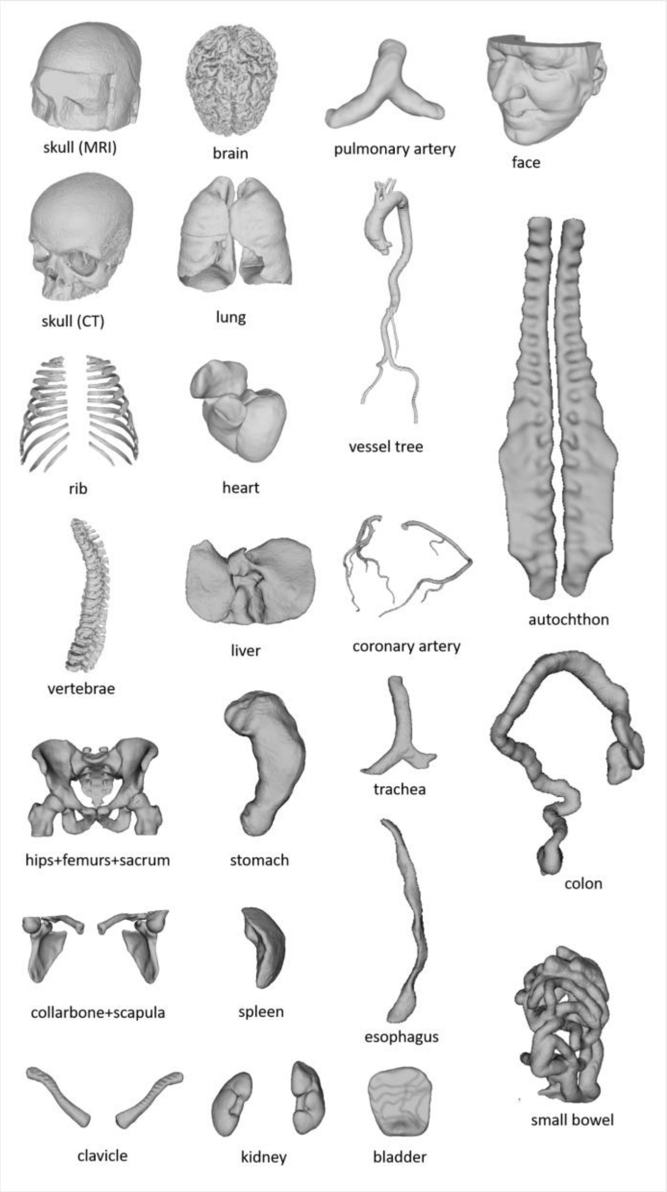
What's MedShapeNet?

MedShapeNet: (1) A medical version of ***ShapeNet.*** (2) A repository of 3D models of **real human anatomies**: heart, lung, liver, kidney… (3) extracted from imaging data of real patients

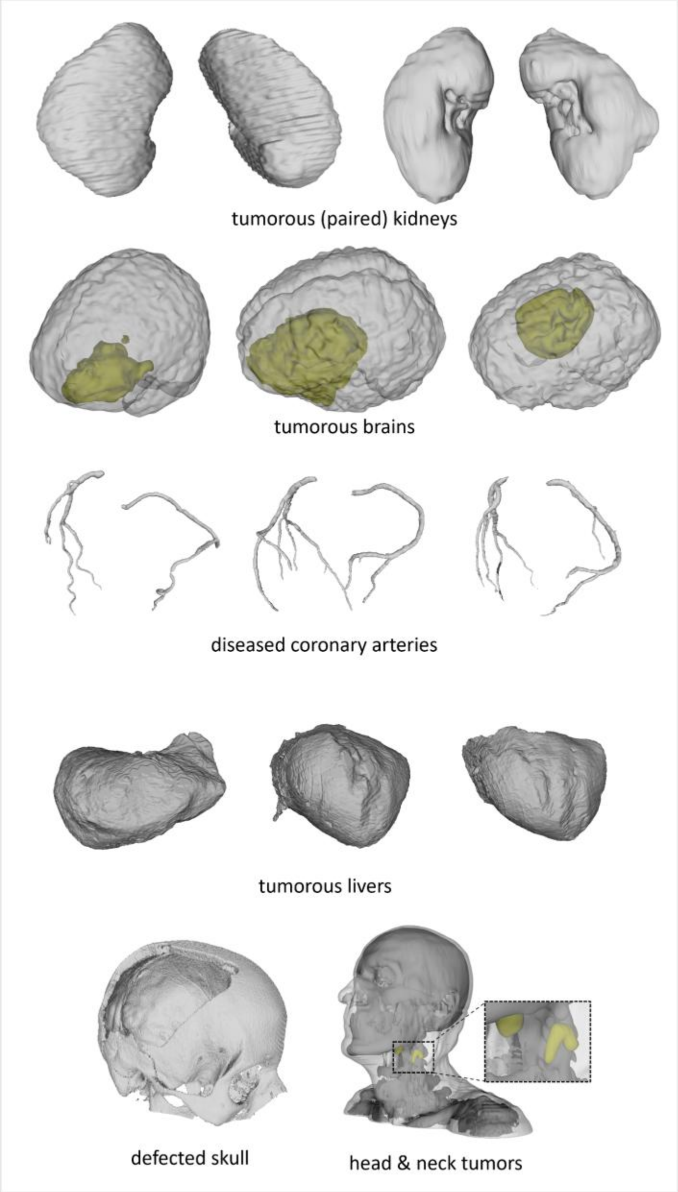
ShapeNet: 3D **CAD models** of **real-world objects**: chair, desk, car, airplane…



de-facto benckmark dataset: shape completion, retrieval/classification, 3D shape reconstruction…



normal

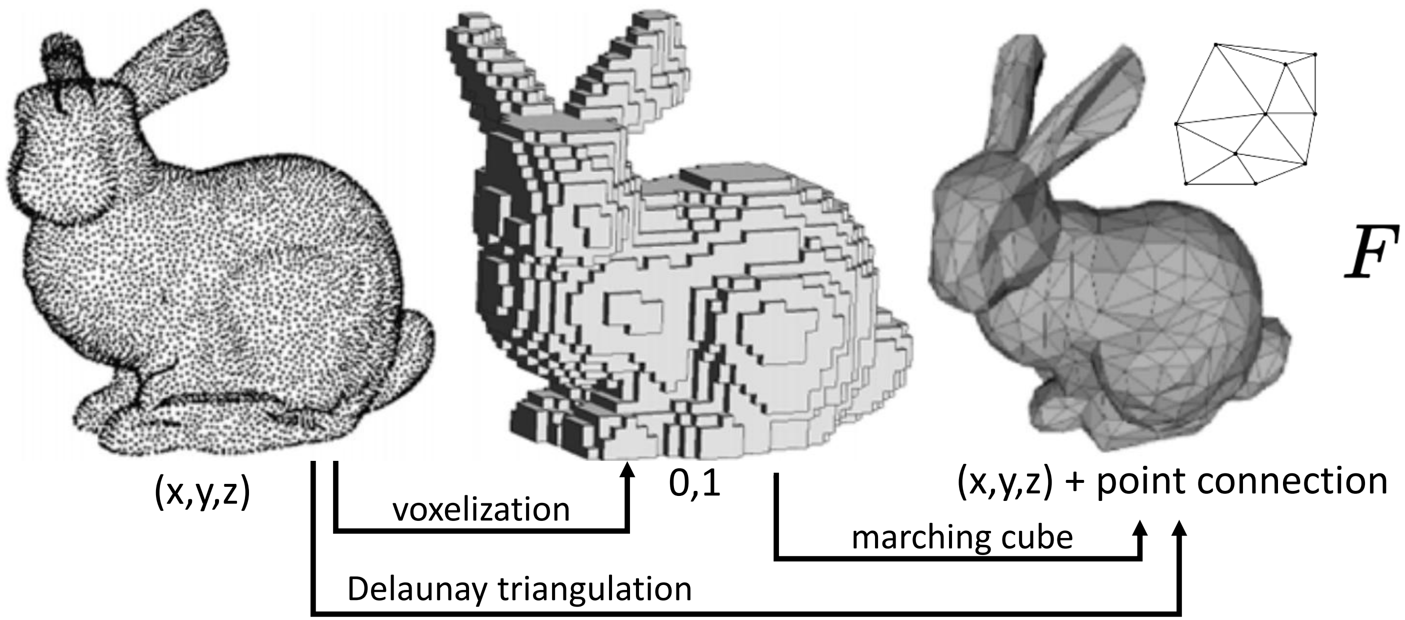


pathological

https://shapenet.org/

https://medshapenet.ikim.nrw/

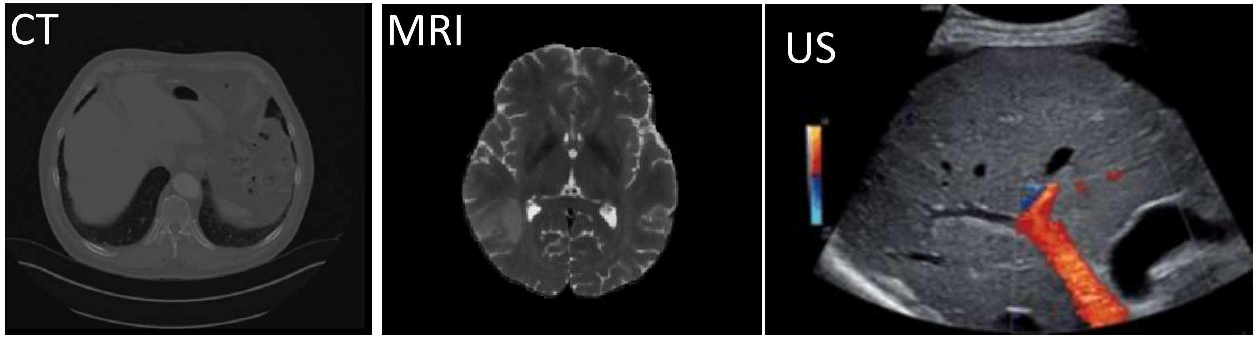
3D Shape Representations



$$F(x, y, z) = 0$$

implicit surfaces

from left: the Stanford bunny model represented as ***point clouds***, ***voxel occupancy grids,*** **meshes** (image from [1])



gray-scale 2D/3D medical images

- different **data structures**
- different processing **algorithms**
- **convertible** to each other

[1] Hoang, L., et. al., **A deep learning method for 3D object classification using the wave kernel signature and a center point of the 3D-triangle mesh**. In *Electronics* (2019)

Agenda

I. Shape acquisition

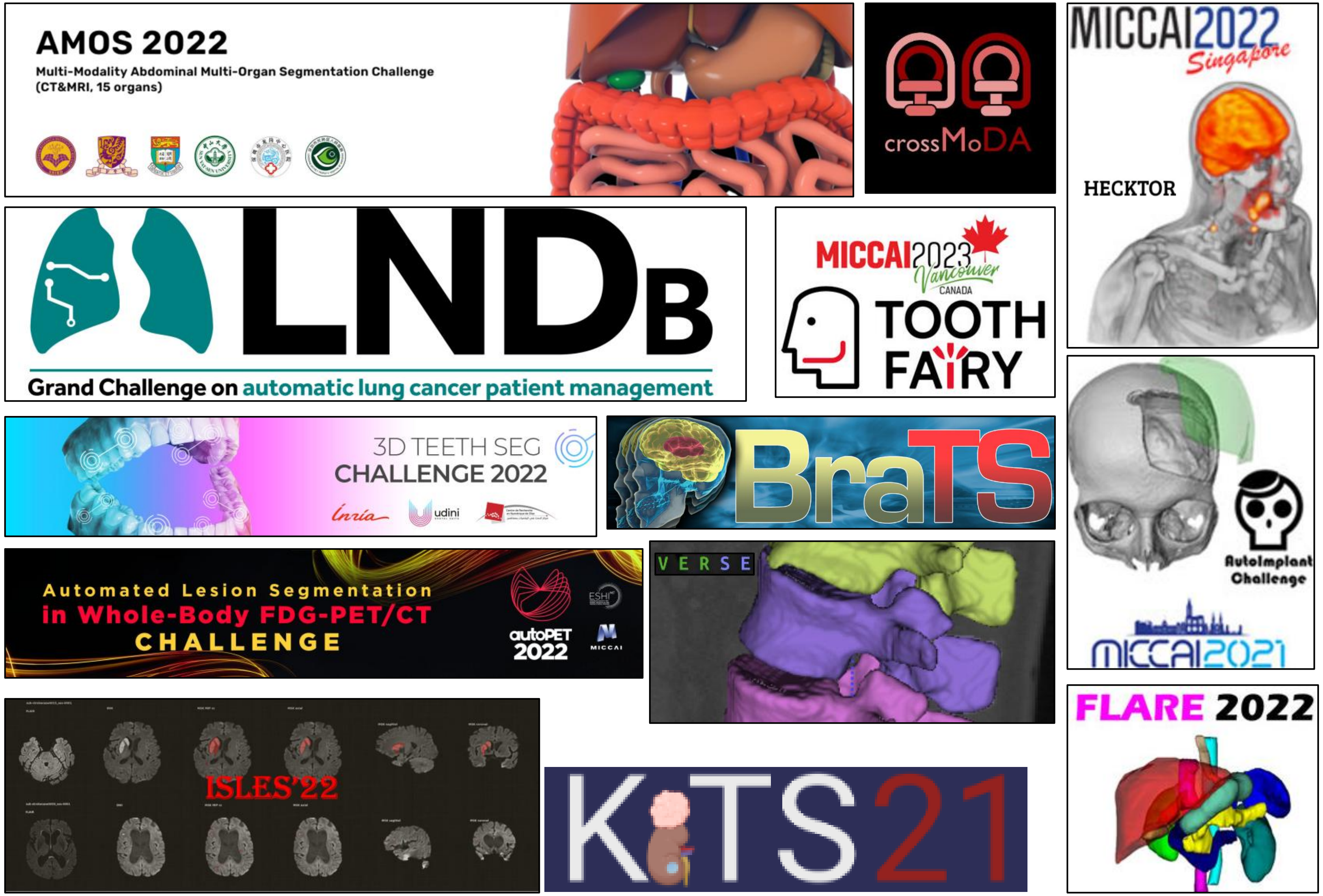
II. Shape annotation

III. A web interface to browse and access the shape data

IV. Existing use cases of *MedShapeNet*

V. Limitations and future plans

I. Shape Acquisition: Public Challenges and Datasets

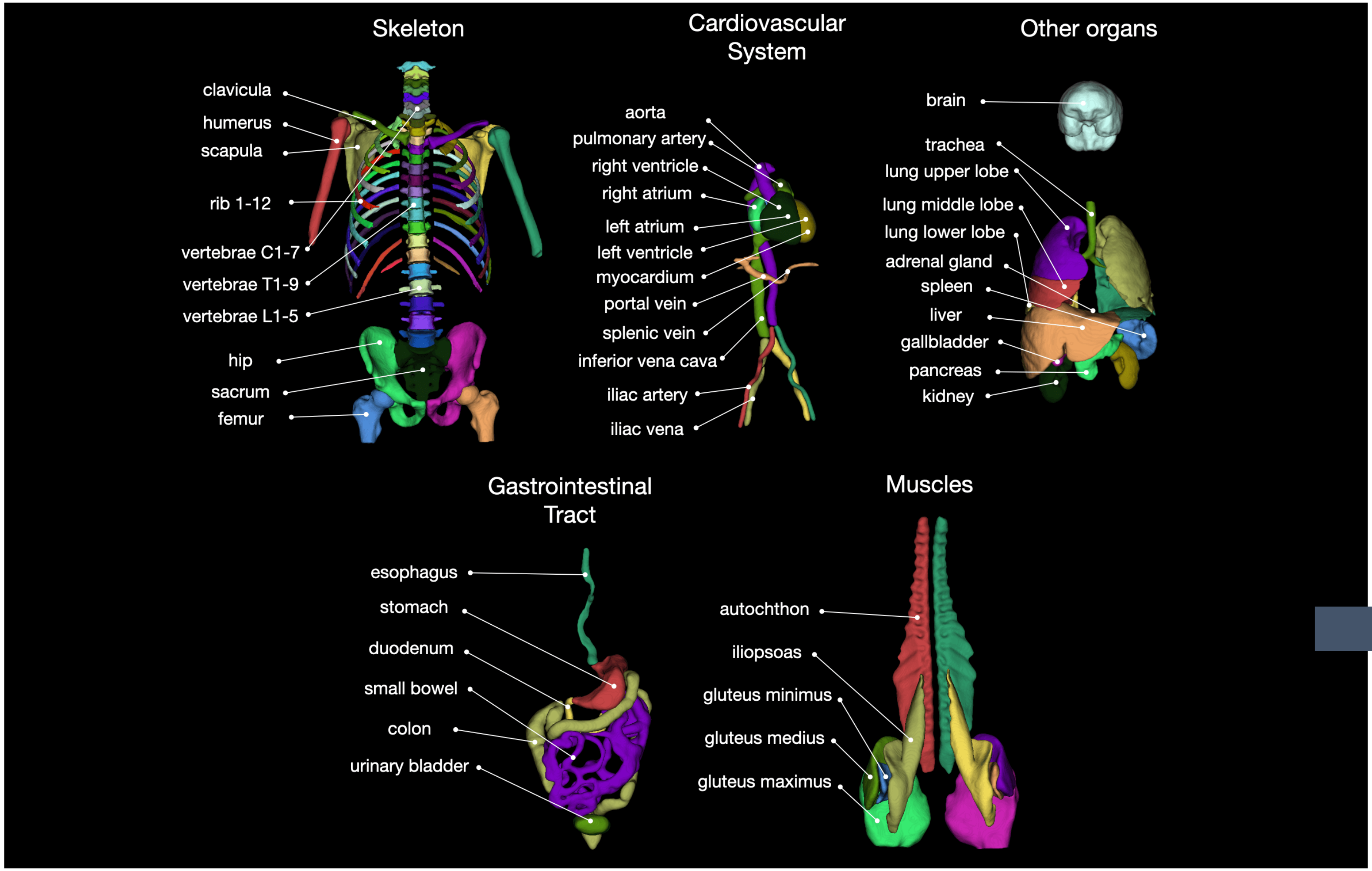


- Biomedical image segmentation challenges (MICCAI, ISBI)
- Publicly available datasets (e.g., TCIA, Scientific Data)
- Quality-assured ground truth segmentations, and are naturally represented as binary voxel occupancy grids

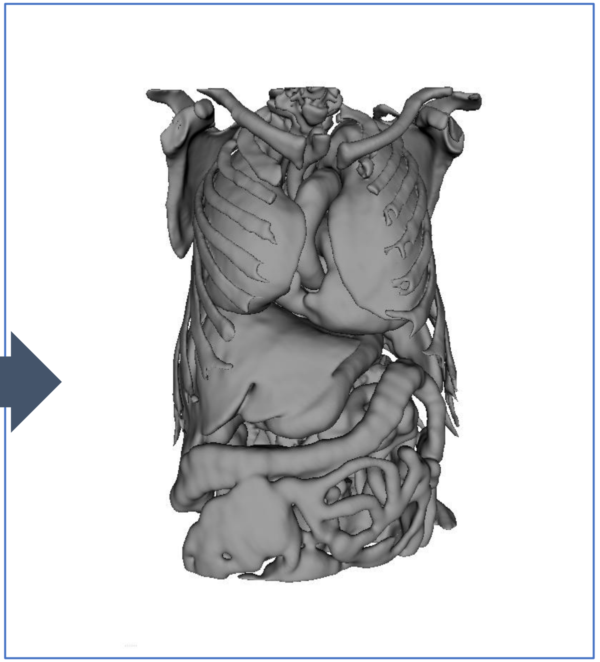
MedShapeNet - A Large-Scale Dataset of 3D Medical Shapes for Computer Vision

Jianning Li, Antonio Pepe, Christina Gsaxner, Gijs Luijten, Yuan Jin, Narmada Ambigapathy, Enrico Nasca, Naida Solak, Gian Marco Melito, Viet Duc Vu, Afaque R. Memon, Xiaojun Chen, Jan Stefan Kirschke, Ezequiel de la Rosa, Patrick Ferdinand Christ, Hongwei Bran Li, David G. Ellis, Michele R. Aizenberg, Sergios Gatidis, Thomas Küstner, Nadya Shusharina, Nicholas Heller, Vincent Andrearczyk, Adrien Depeursinge, Mathieu Hatt, Anjany Sekuboyina, Maximilian Löffler, Hans Liebl, Reuben Dorent, Tom Vercauteren, Jonathan Shapey, Aaron Kujawa, Stefan Cornelissen, Patrick Langenhuizen, Achraf Ben-Hamadou, Ahmed Rekik, Sergi Pujades, Edmond Boyer, Federico Bolelli, Costantino Grana, Luca Lumetti, Hamidreza Salehi, Jun Ma, Yao Zhang, Ramtin Gharleghi, Susann Beier, Arcot Sowmya, Eduardo A. Garza-Villarreal, Thania Balducci, Diego Angeles-Valdez, Roberto Souza, Leticia Rittner, Richard Frayne, Yuanfeng Ji, Soumick Chatterjee, Florian Dubost, Stefanie Schreiber, Hendrik Mattern, Oliver Speck, Daniel Haehn, Christoph John, Andreas Nürnberger, João Pedrosa, Carlos Ferreira, Guilherme Aresta, António Cunha, Aurélio Campilho, Yannick Suter, Jose Garcia, Alain Lalande, Emmanuel Audenaert, Claudia Krebs, Timo Van Leeuwen, Evie Vereecke, Rainer Röhrig, Frank Hölzle, Vahid Badeli, Kathrin Krieger, Matthias Gunzer, Jianxu Chen, Amin Dada, Miriam Balzer, Jana Fragemann, Frederic Jonske, Moritz Rempe, Stanislav Malorodov, Fin H. Bahnsen, Constantin Seibold, Alexander Jaus, Ana Sofia Santos, Mariana Lindo, André Ferreira, Victor Alves, Michael Kamp, Amr Abourayya, Felix Nensa, Fabian Hörst, Alexander Brehmer, Lukas Heine, Lars E. Podleska, Matthias A. Fink, Julius Keyl, Konstantinos Tserpes, Moon-Sung Kim, Shireen Elhabian, Hans Lamecker, Dženan Zukić, Beatriz Paniagua, Christian Wachinger, Martin Urschler, Luc Duong, Jakob Wasserthal, Peter F. Hoyer, Oliver Basu, Thomas Maal, Max J. H. Witjes, Ti-chiun Chang, Seyed-Ahmad Ahmadi, Ping Luo, Bjoern Menze, Mauricio Reyes, Christos Davatzikos, Behrus Puladi, Jens Kleesiek, Jan Egger

I. Shape Acquisition: Whole-body Segmentations



segmentations (voxel occupancy grids)

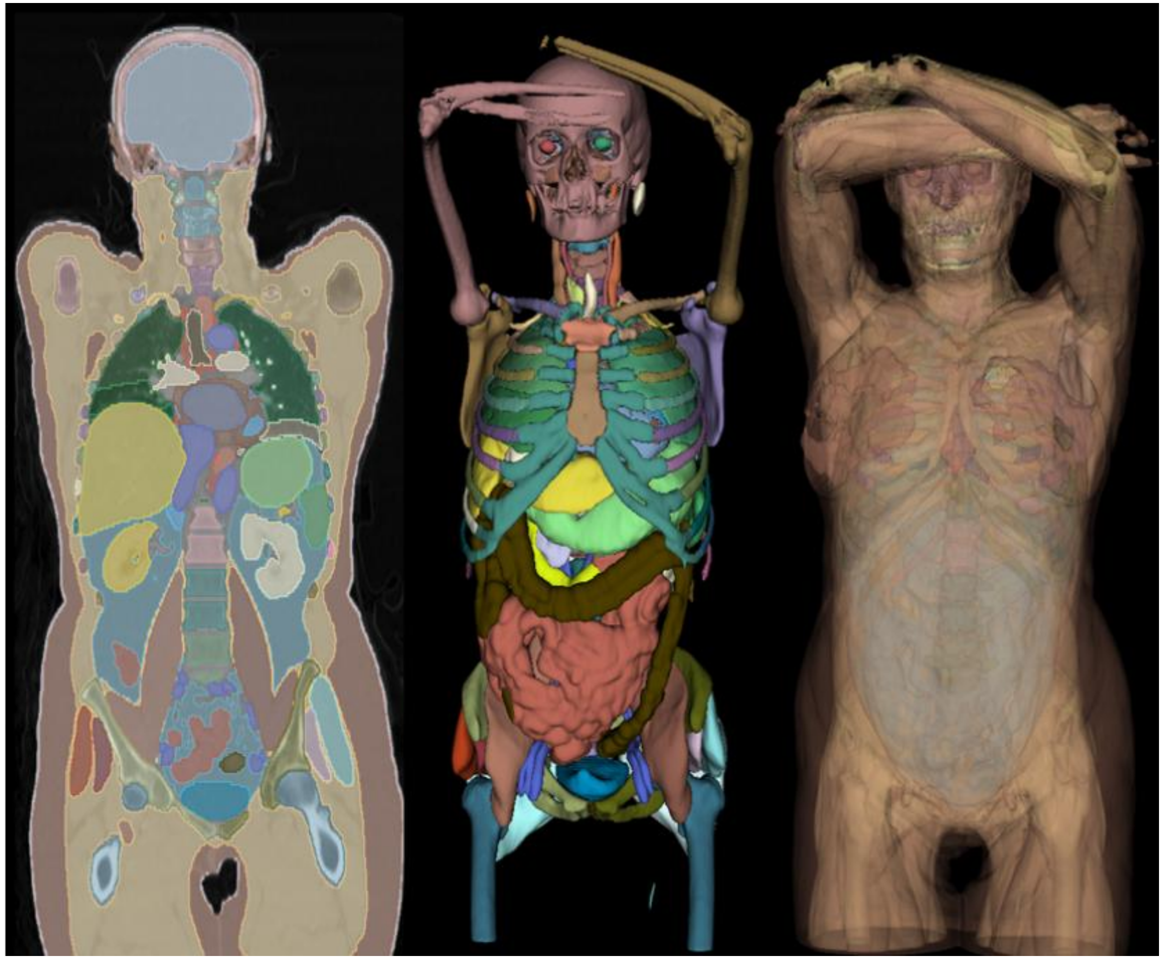


3D models

- Totalsegmentor [1]
- 1204 whole-body CT scans (90% training, 5% validaiton, 5% test)
- Each scan provides annotations for 104 anatomies
- Manual annotation is labor-intensive and impractical
- nnU-Net automatic segmentation + manual refinement, iteratively increase te number of CT scans
- Not all segmentations are quality-checked
- Public access: https://zenodo.org/record/6802614

[1] Wasserthal, J., et al., **TotalSegmentator: robust segmentation of 104 anatomical structures in CT images**. arXiv preprint arXiv:2208.05868 (2022).

I. Shape Acquisition: Whole-body Segmentations

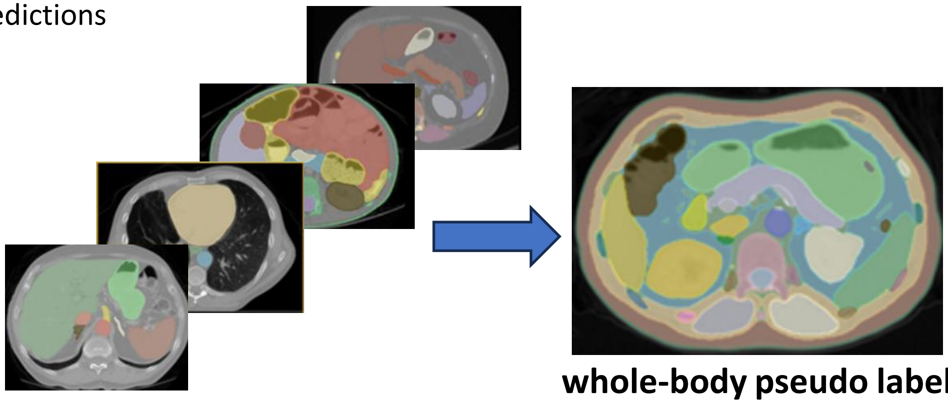


- 533 whole-body CT scans from the **autoPET challenge**
- each scan provides annotations for 142 anatomies

(1) fully automatic, nnU-Net-based **pseudo-labeling method** [1]:

- Publicly-available datasets with annotations of different anatomies
- Private dataset with privately trained models
- Train a series of nn-unet on these datasets
- Anatomical rule-based refinement

(2) **label Aggregation**: the trained models are applied on the autoPET dataset to generate labels of different anatomies, which are aggregated by taking the union of the respective predictions



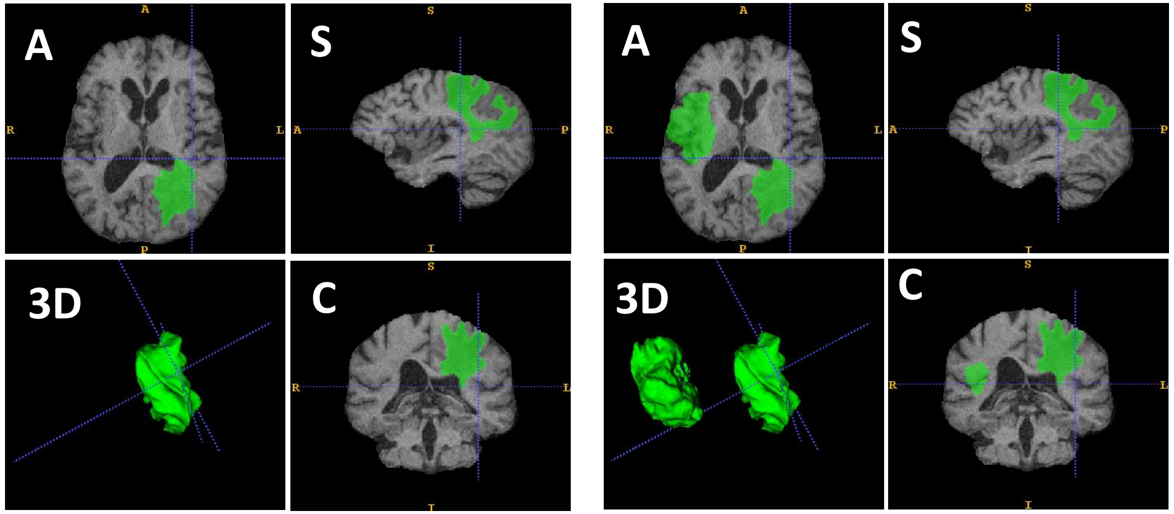
(3) train another nnU-Net using the aggregated whole-body pseudo labels, and apply the trained model on the autoPET dataset again to generate uniform whole-body annotations.

acknowledgement: Constantin Seibold

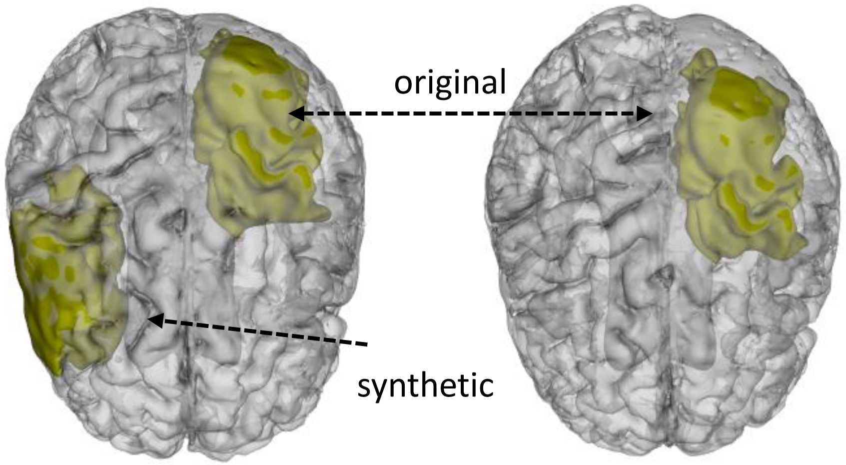
[1] Jaus, A., Seibold, C., et al. "**Towards unifying anatomy segmentation: Automated generation of a full-body ct dataset via knowledge aggregation and anatomical guidelines**." arXiv:2307.13375(2023)

I. Shape Acquisition: Synthetic Anatomy Generation with GANs

A: axial, S: sagittal, C: coronal



original augmented

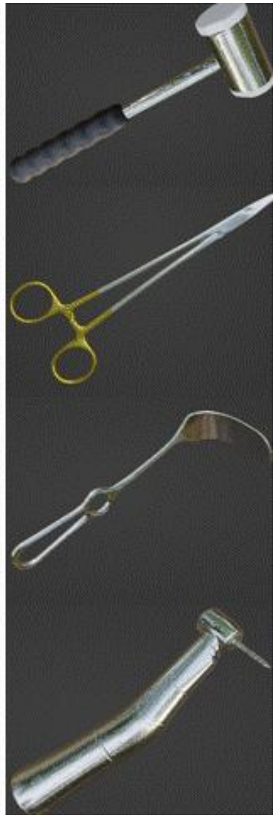


- Synthetic data: widely used for **data augmentation** in data-driven research.
- Generate synthetic brain tumors for 27390 brains extracted from the **Brats challenge** dataset, using Generative Adversarial Networks (**GANs**).
- Future work: include the synthetic shapes of **other anatomies** in *MedShapeNet*.

acknowledgement: Andre Ferreira

I. Shape Acquisition: 3D Scanning & Surgical Instruments

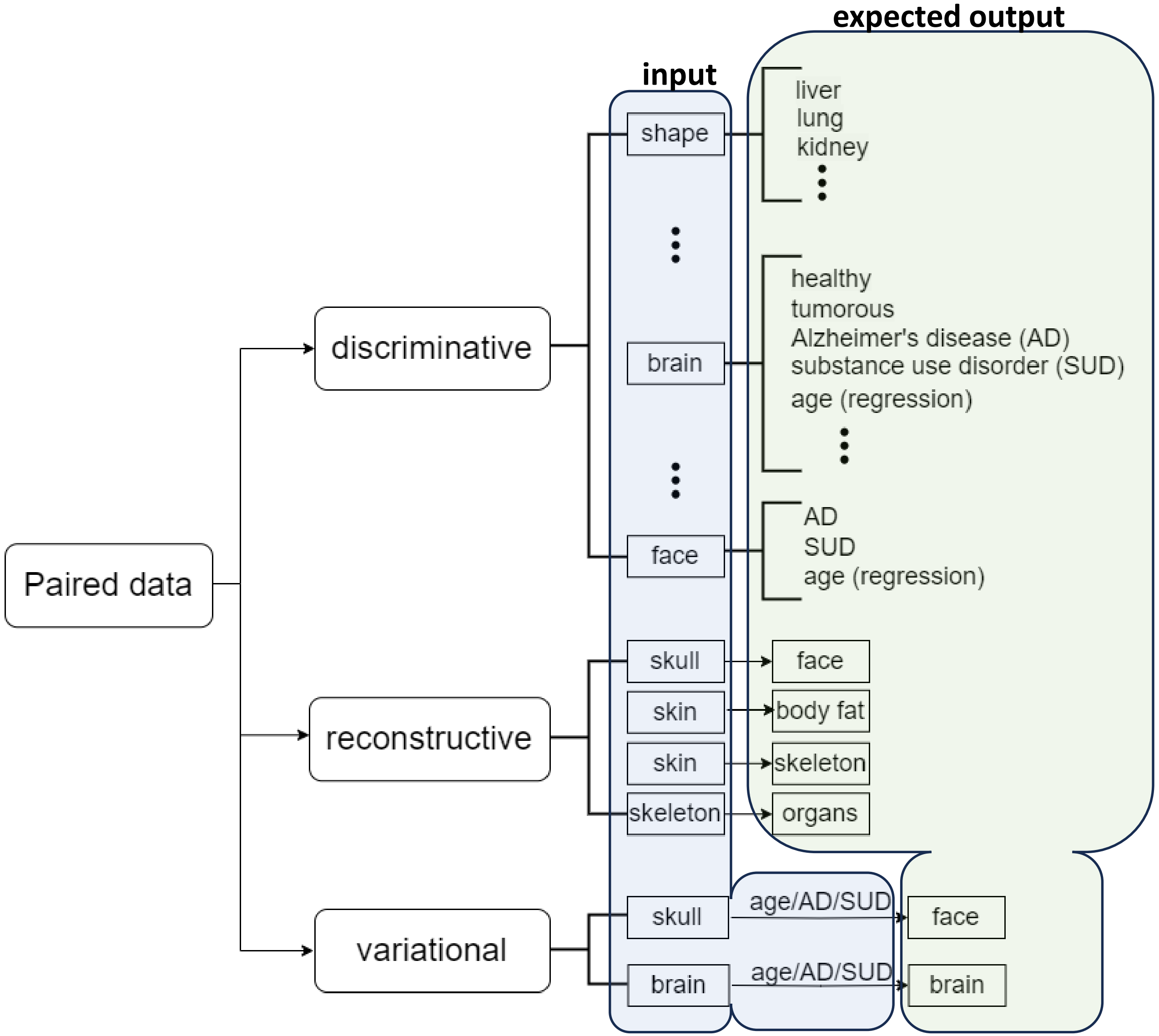
3D scanners



- use structured light **3D scanners** to scan (digitalize) **surgical instruments,** and create 3D instrument models
- structured light 3D scanners can also be used to scan humans (future work: build a databse of **3D digital human models**)
- more details about 3D scanning: https://xrlab.ikim.nrw/

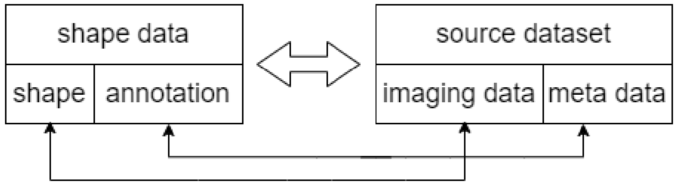
acknowledgement: Gijs Luijten

II. How Are These Shapes Annotated?

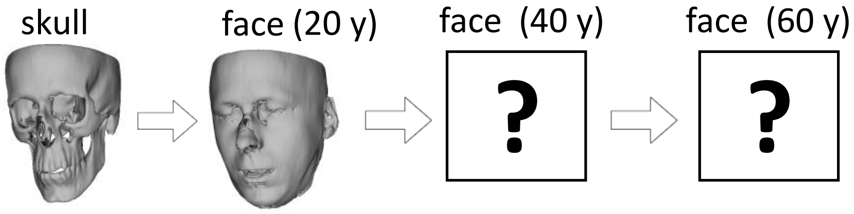


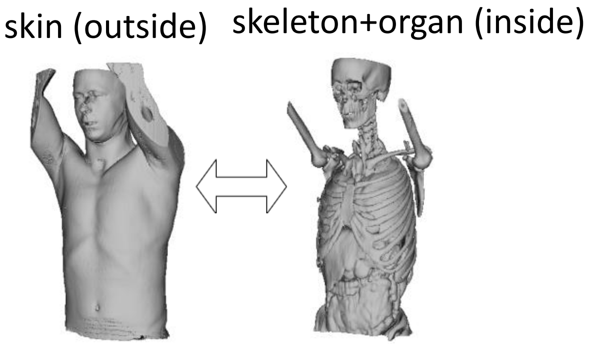
use paired data to train supervised learning algorithms

- Annotations: expected output of a learning algorithm w.r.t a specific input (paired data)
- Two types of data: shape data and patients' meta data (pathology, age, gender, etc.)
  - **Discriminative:** shape classification (anatomy category, pathological condition)
  - **Reconstructive:** shape reconstruction
  - **Variational:** conditional shape reconstruction (conditioned on age or a pathology)

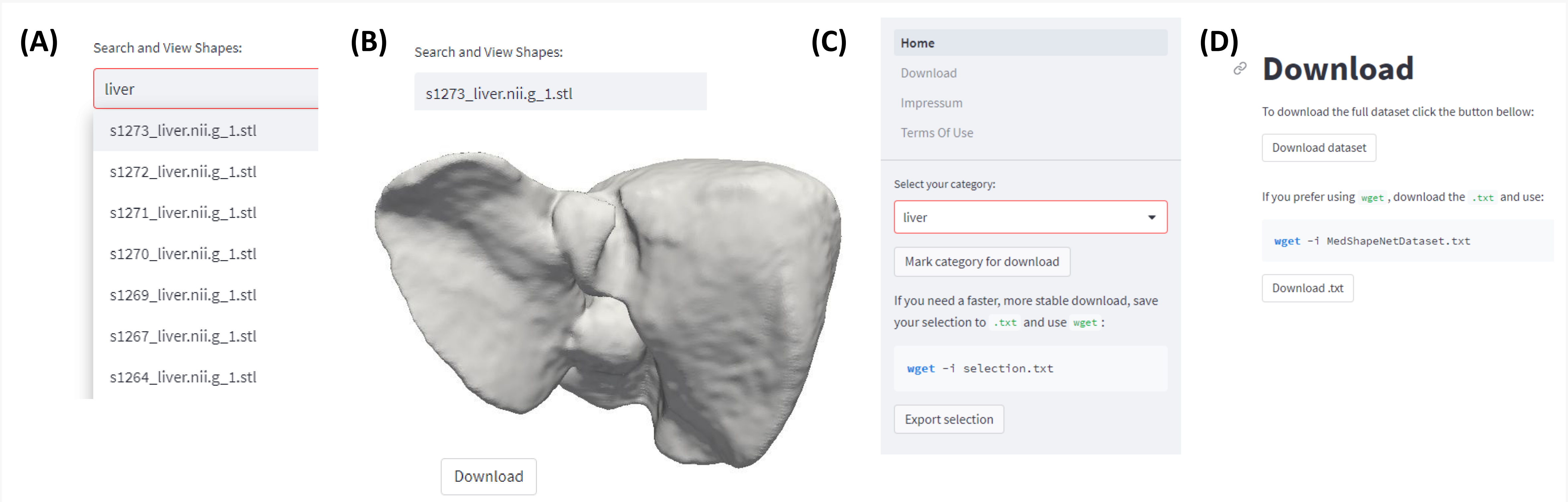


- Future work: provide more annotations by extracting more meta information from the source imaging datasets





III. Online Interface: Shape Search, Visualization and Download



permanent url: https://medshapenet.ikim.nrw/, temporary url: https://medshapenet-ikim.streamlit.app/

- *MedShapeNet* has over 100K shapes, occupying around **2TB** of storage
- Online interface:
  - **(A)** a search box to find individual shape **by name** (e.g., instrument, liver, brain, kidney) or **by pathology** (e.g., tumor)
  - **(B)** display a selected shape in 3D, and download it
  - **(C)** download all the shapes belonging to the same anatomy category (e.g., liver) at once
  - **(D)** download the entire database (~2TB, a lot more to be uploaded)
- Separate shape storage (**sciebo**, ~2TB) from website server (free **streamlit** server, 1GB RAM)
- Disclaimer: due to **space limitation**, not all shape data described in the *MedShapeNet* paper are available for search & download on the interface

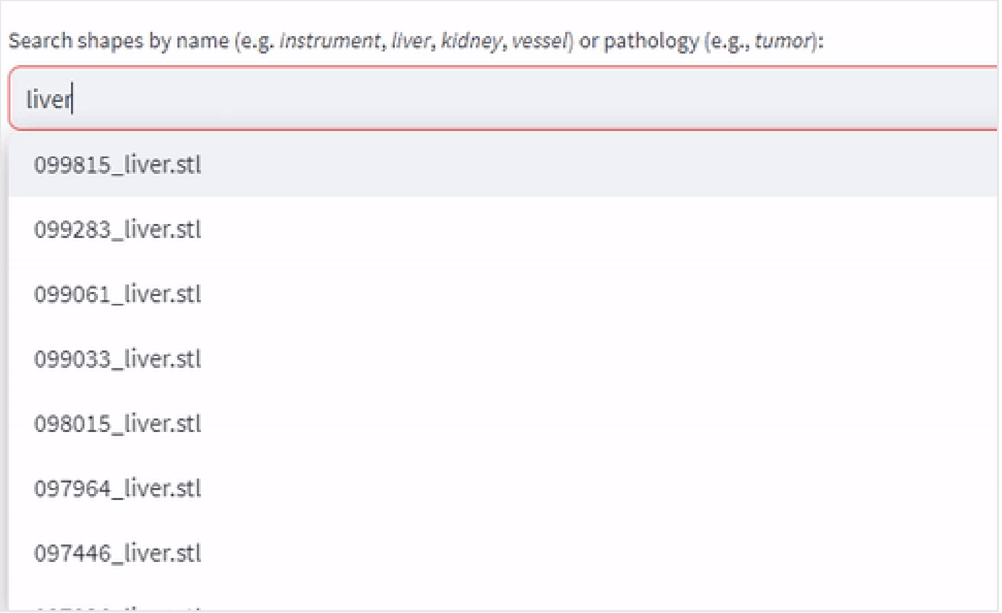
acknowledgement: Alexander Brehmer, Lukas Heine, Jianning Li, Enrico Nasca

III. Online Interface: search queries

.html file to view the 3D model locally

a non-inclusive list of single-word search queries

CT	mri	brain	skull	brain	vertebrae	stomach
bladder	bowel	rib	sacrum	bowel	scapula	lung
heart	ventricle	atrium	kidney	iliopsoas	iliac	artery
gland	gluteus	femur	esophagus	autochthon	colon	aorta
trachea	hip	pancreas	vein	bowel	clavicula	myocardium
humerus	vena_cava	duodenum	face	vessel_tree	glioblastoma	cranial_defect



limitation: allow only one key-word (liver, heart, stomach, kidney...)

Agenda

I. Shape acquisition

II. Shape annotation

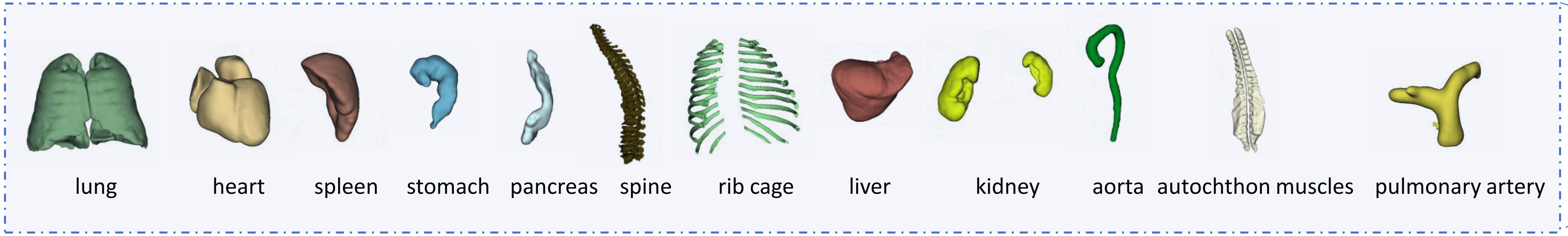
III. A web interface to browse and access the data

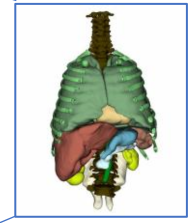
IV. Medically-oriented use cases of *MedShapeNet*

- Multi-class anatomy completion (*shape completion / inpainting*)
- Forensic facial reconstruction (*shape completion / inpainting*)
- Skull reconstruction (*shape completion / inpainting*)
- Brain tumor screening (*shape classification*)
- Anatomy education in augmented reality (AR)

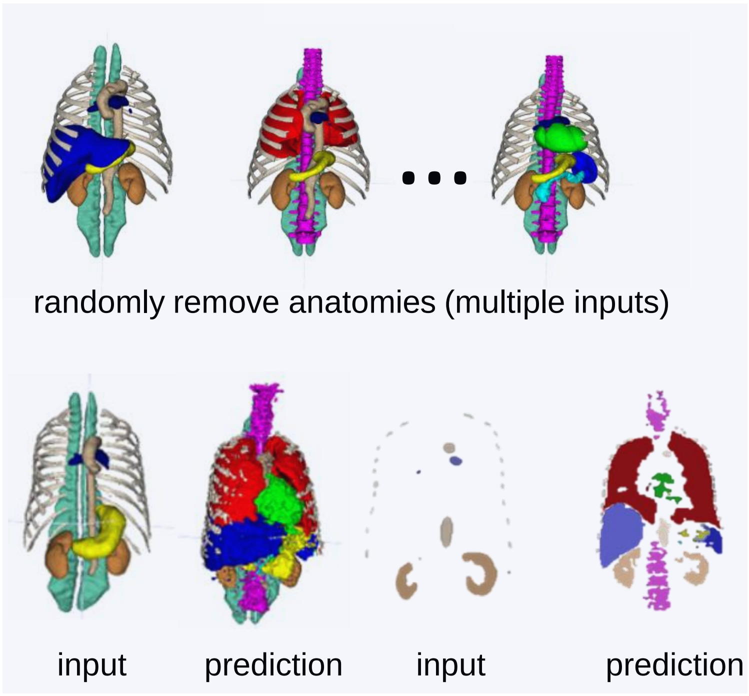
V. Limitations and future plans

IV. Use Cases 1: Multi-class Anatomy Completion

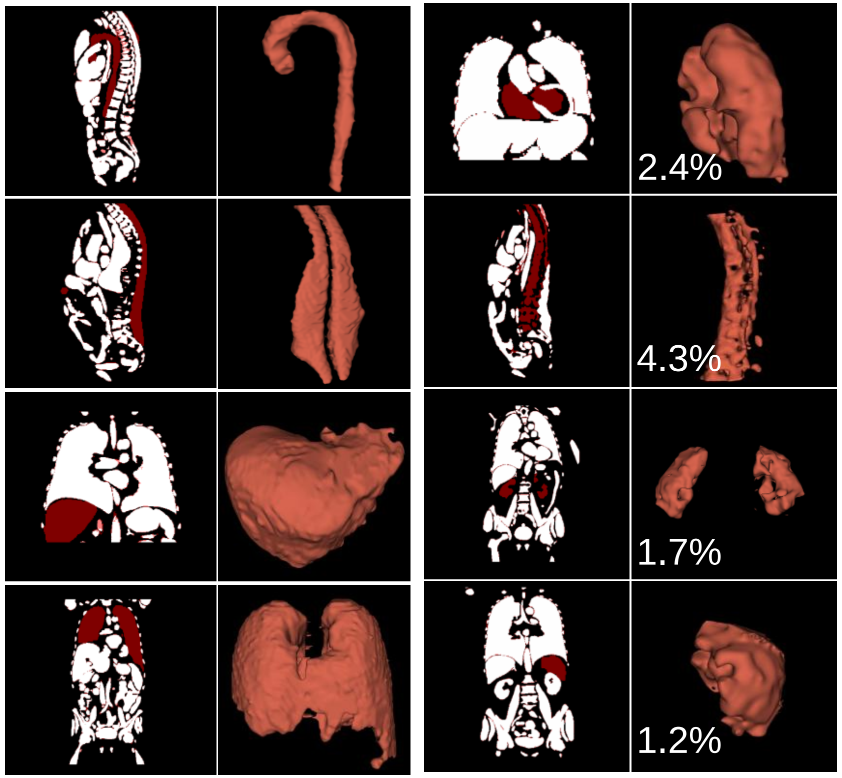




combined



several random anatomies are missing



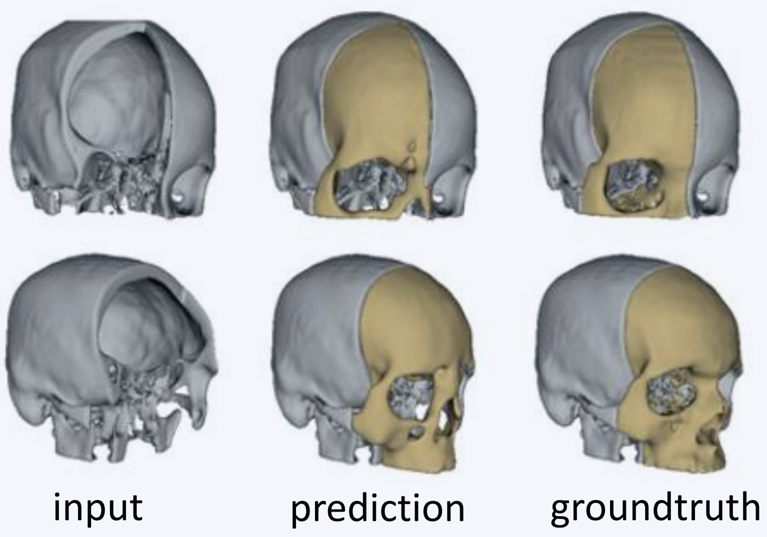
one specific anatomy is missing

- 12 anatomies (12 classes): lung, heart, spleen ...
- Learn a many-to-one mapping (3D auto-encoder)
- Reconstruct several missing anatomies, or a specific one
- Applications:
  - generate pseudo labels for whole-body segmentation
  - automatic 3D organ modeling
- More details: [1]
- MICCAI workshop: October 8th, 2023, Vancouver, Canada

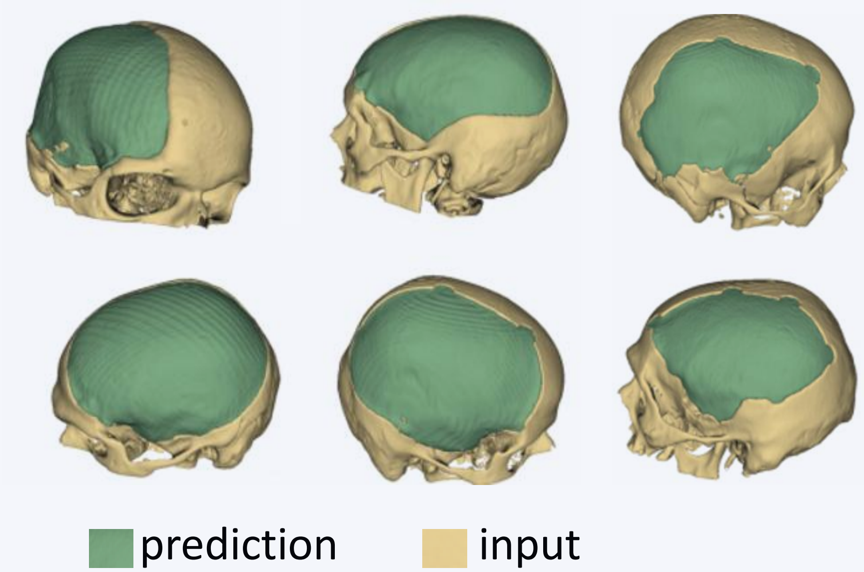
[1] Li, J., et al., **Anatomy Completor: A Multi-class Completion Framework for 3D Anatomy Reconstruction.** arXiv preprint arXiv:2309.04956 (2023)

IV. Use Cases 3: Skull Reconstruction

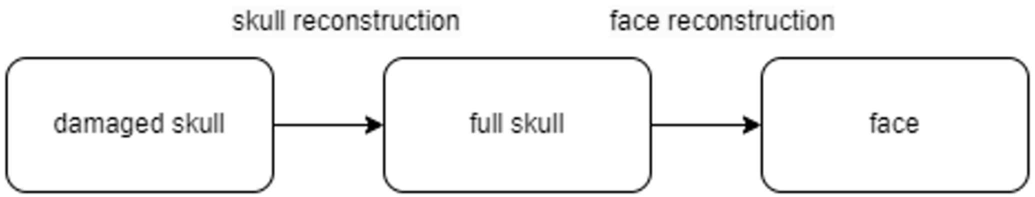
facial bone reconstruction

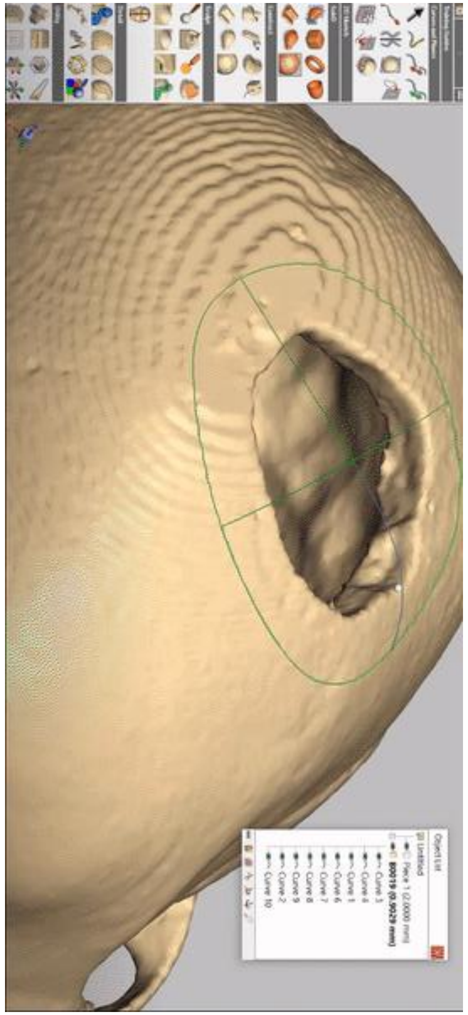


cranium bone reconstruction



automatic skull repair: fast and data-driven (aesthetic)





manual skull repair (cranial implant design)

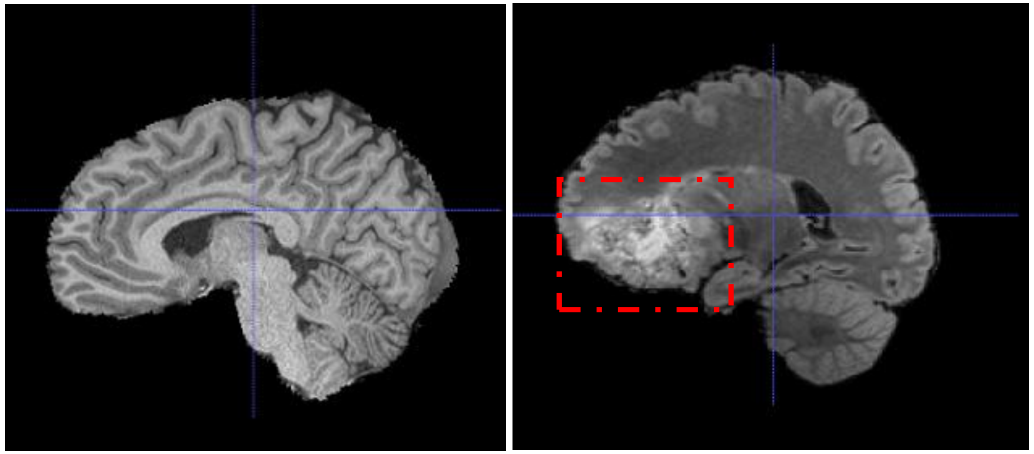
- ***highly subjective***
- ***requires costly 3D software***
- ***time-consuming***

[1] Li, J., et al., **AutoImplant 2020-first MICCAI challenge on automatic cranial implant design**. IEEE TMI (2021)

[2] Li, J., et al., **Towards clinical applicability and computational efficiency in automatic cranial implant design: An overview of the AutoImplant 2021 cranial implant design challenge**. Medical Image Analysis (2023)

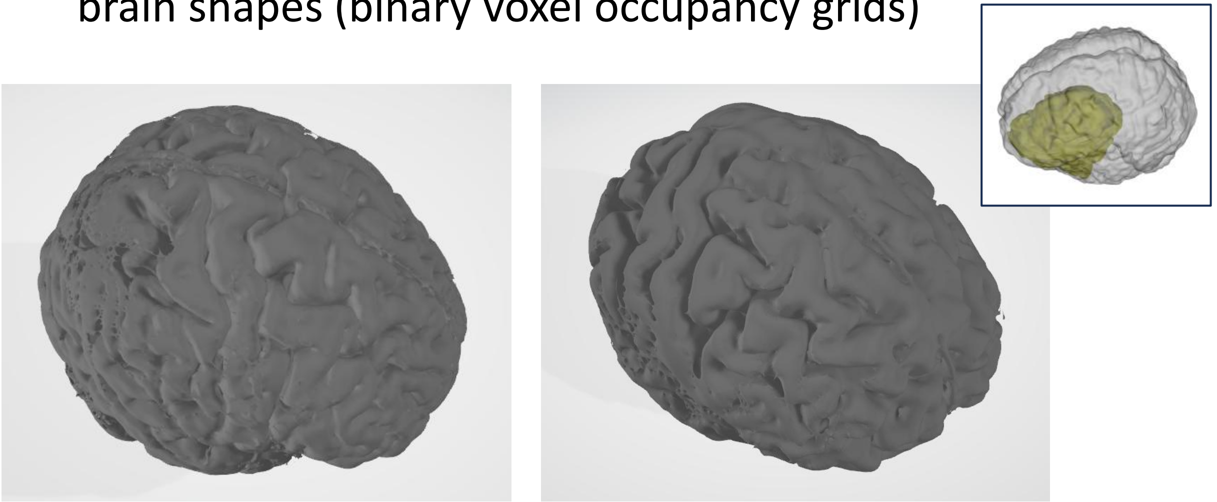
IV. Use Cases 4: Brain Tumor Screening

gray-scale (skull-stripped) brain MRIs



healthy tumorous

brain shapes (binary voxel occupancy grids)

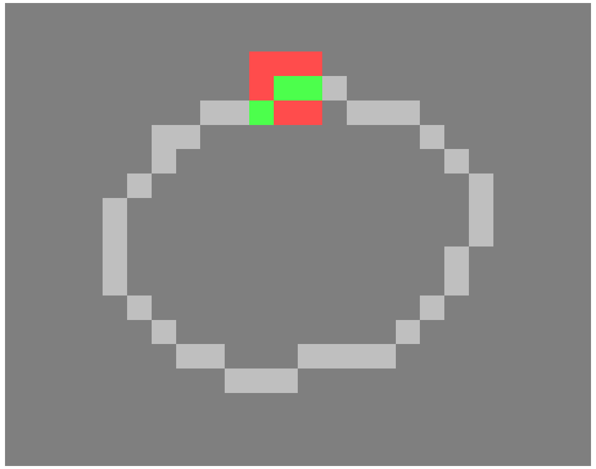


healthy tumorous

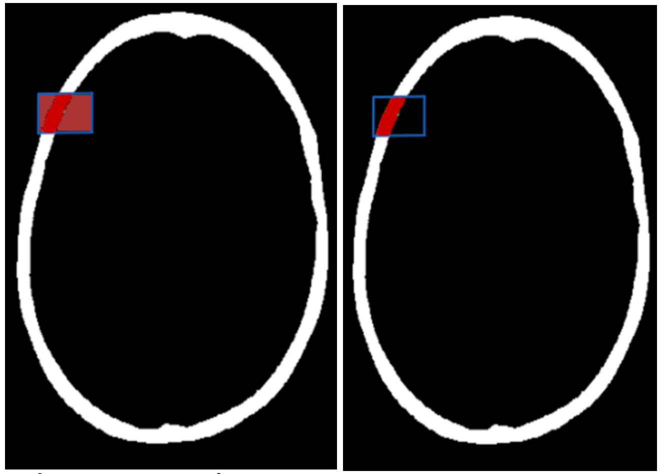
- It is possible to distinguish between healthy and tumorous brains **without voxel information**
- Tumors can induce changes of some **shape features** of the brains
- Healthy versus tumorous brains (**volume differences are statistically significant**)
- Male versus female brains (**volume differences are statistically significant**)

Benefits of using shape data over imaging data: computational efficiency

spatial sparsity of manifold/shape data



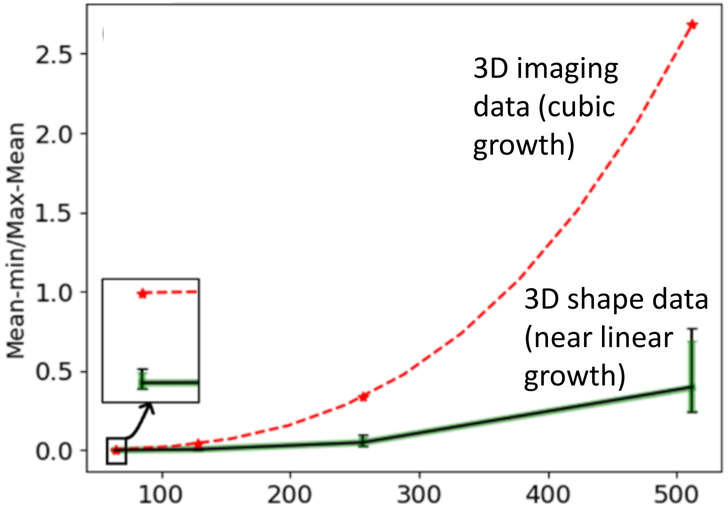
sparse convolutions [1]



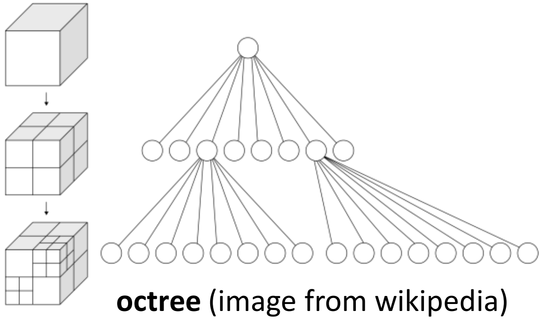
dense convolution   sparse convolution

axial view of a skull (most voxels are empty)

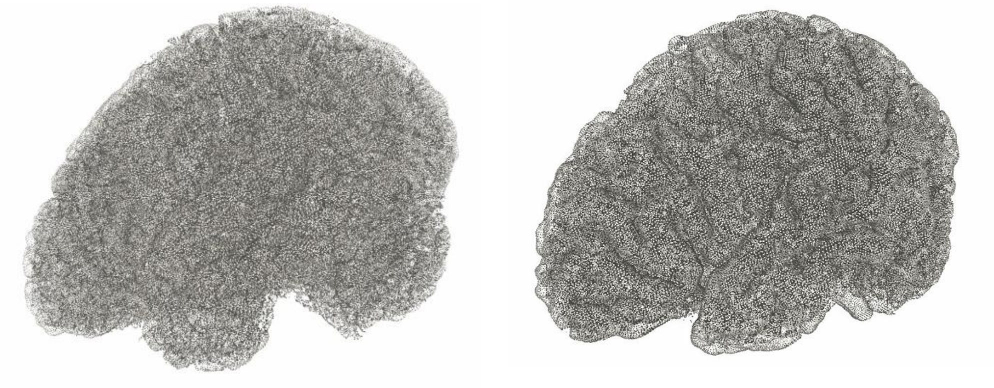
memory occupancy (y-axis) w.r.t. **resolution** (x-axis) [2]



- **Skull reconstruction**: sparse convolutional neural networks (SCNN) [2]
- **Forensice facial reconstruction:** SCNN
- **Brain shape classification:** SCNN, PointNet, PointCNN
- **Other computationally efficient algorithms:** O-CNN [3], OctNet [4]



octree (image from wikipedia)



brain point clouds

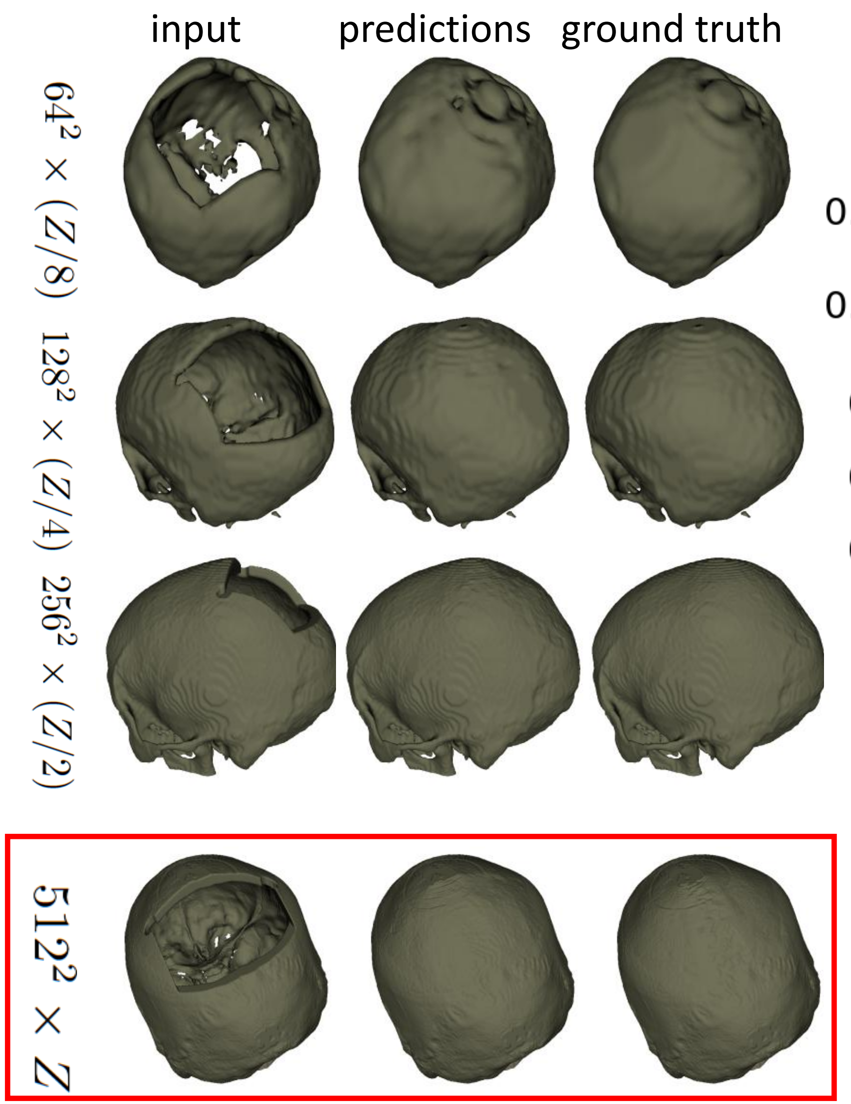
[1] Graham, B. and Van der Maaten, L., 2017. **Submanifold sparse convolutional networks**. arXiv preprint arXiv:1706.01307.

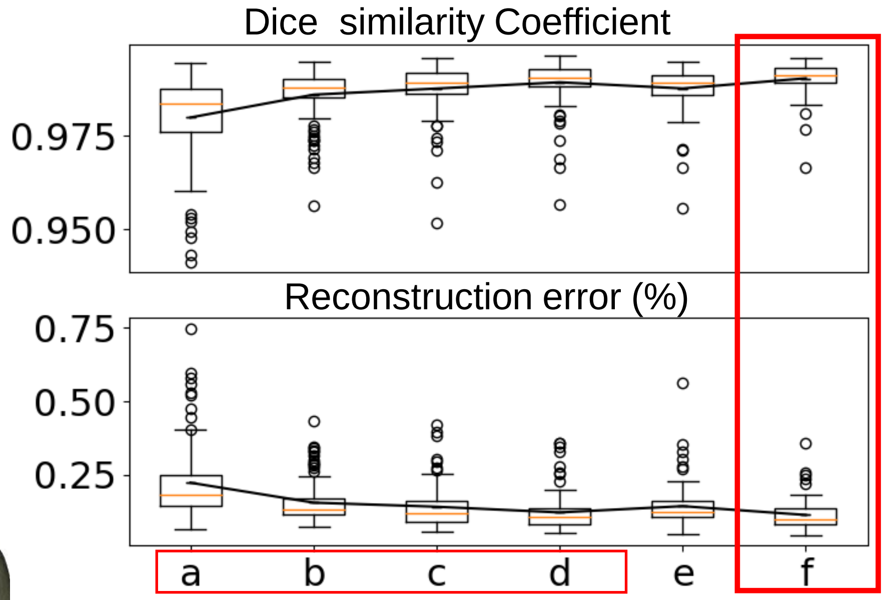
[2] Li, J., Gsaxner, C., Pepe, A., Schmalstieg, D., Kleesiek, J. and Egger, J., 2022. **Sparse Convolutional Neural Networks for Medical Image Analysis**. TechRixv techrxiv.19137518.

[3] Wang, P.S., Liu, Y., Guo, Y.X., Sun, C.Y. and Tong, X., 2017**. O-cnn: Octree-based convolutional neural networks for 3d shape analysis**. ACM Transactions On Graphics (TOG)

[4] Riegler, G., Osman Ulusoy, A. and Geiger, A., 2017. **Octnet: Learning deep 3d representations at high resolutions**. In Proceedings of the IEEE conference on computer vision and pattern recognition

Sparse CNN - 3D skull shape reconstruction (shape completion)





voxel grid resolutions (Z: axial dimension**):**

(a) 64^2x(Z/8) (model1)
(b) 64^2x(Z/8) (model2)
(c) 128^2x(Z/4) (model1)
(d) 128^2x(Z/4) (model2)
(e) 256^2x(Z/2)
(f) 512^2xZ

model1 (0.435M params)
model2 (18.14M params)

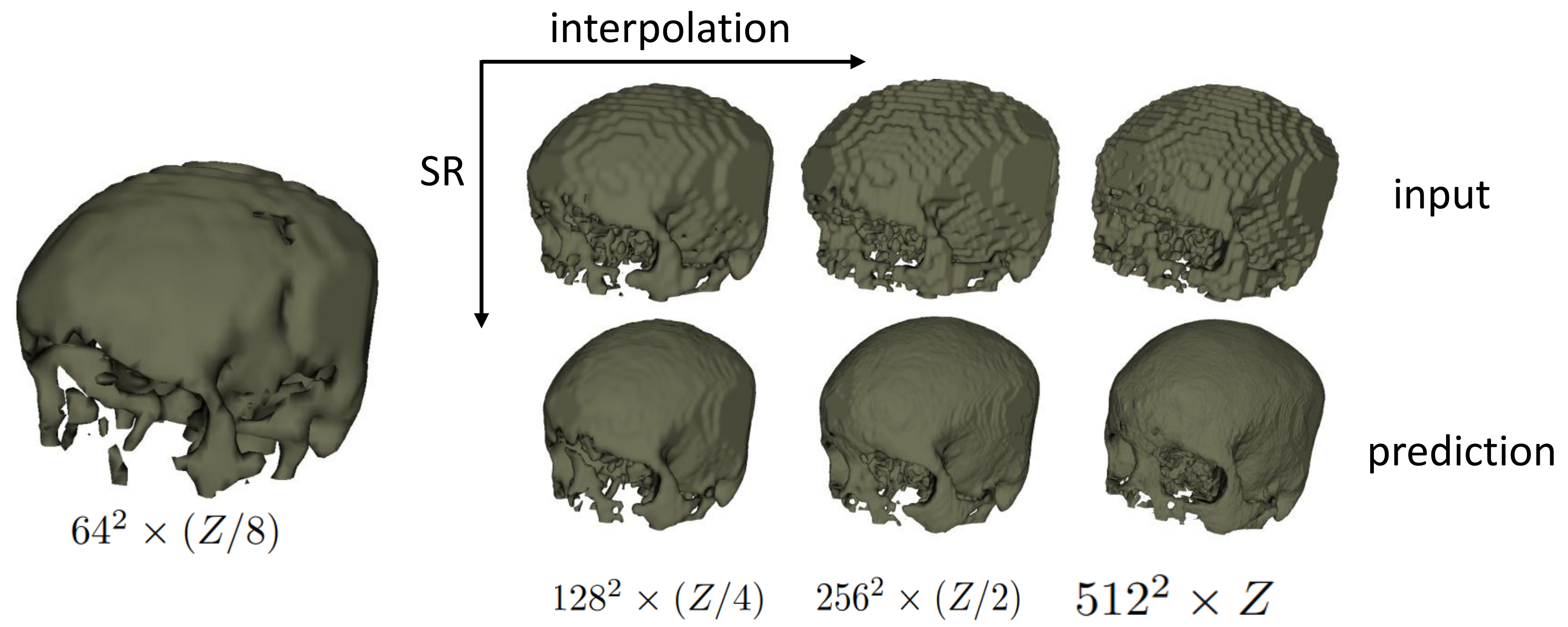
comparison: memory usage wrt. resolution

cat. \ I_s	64	128	256	512
sparse train	1.5119	1.6256	2.7341	11.3049
sparse test	1.4519	1.5097	1.8905	2.7993
dense train	1.6543	1.9043	4.8145	-
dense test	1.6699	1.8184	2.6934	-

Hardware: standard desktop GPU with 24GB RAM

Li, J., Gsaxner, C., Pepe, A., Schmalstieg, D., Kleesiek, J. and Egger, J., 2022. **Sparse Convolutional Neural Networks for Medical Image Analysis**. TechRixv techrxiv.19137518.

Sparse CNN - 3D shape super-resolution (SR)



	$64 \rightarrow 128$	$64 \Rightarrow 128$	$64 \rightarrow 256$	$64 \Rightarrow 256$	$64 \rightarrow 512$	$64 \Rightarrow 512$	$128 \rightarrow 256$	$128 \Rightarrow 256$
DSC	0.8750	0.8359	0.8779	0.8359	0.6640	0.6402	0.9372	0.9146
reconstruction error (%)	1.3821	1.8685	1.3589	1.8942	3.7850	4.2358	0.7187	0.9867

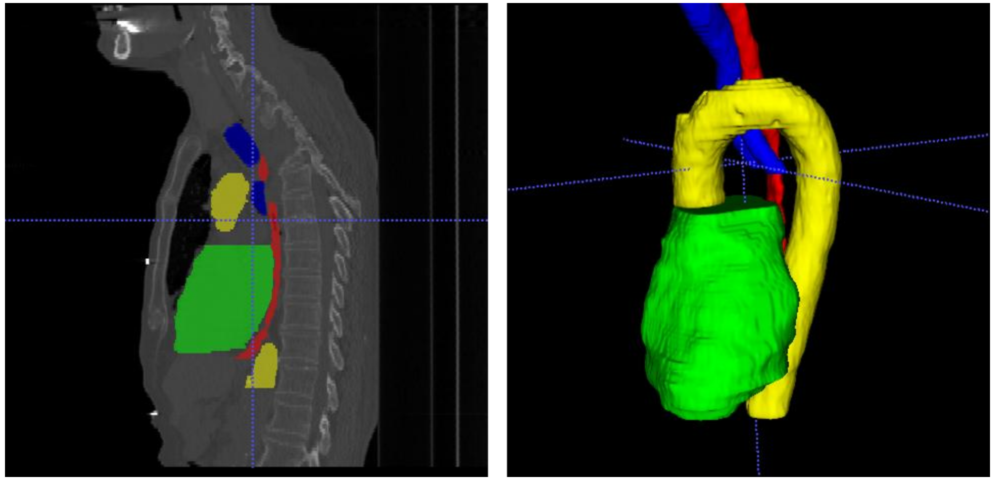
$\rightarrow$ SR
$\Rightarrow$ interpolation

- increase the resolution of the low-resolution shapes
- train a sparse-CNN based SR network to learn a mapping between low- and high-quality skull shapes
- the reconstruction quality can be substantially improved with an additional SR step after interpolation

Li, J., Gsaxner, C., Pepe, A., Schmalstieg, D., Kleesiek, J. and Egger, J., 2022. **Sparse Convolutional Neural Networks for Medical Image Analysis**. TechRixv techrxiv.19137518.

Sparse CNN - 3D shape super-resolution (SR) in medical image segmentation

heart (green), aorta(yellow), trachea (blue) and esophagus (red) from the *SegTHOR* challenge. **CT scan resolution: 512x512xZ**



voxel occupancy rate (VOR) and the memory usage (in *GB*) during training and inference of a SR network

organ	train	test	VOR (%)
aorta	2.05	1.75	0.20
heart	2.46	2.38	0.79
trachea	1.73	1.64	0.04
esophagus	1.77	1.64	0.05

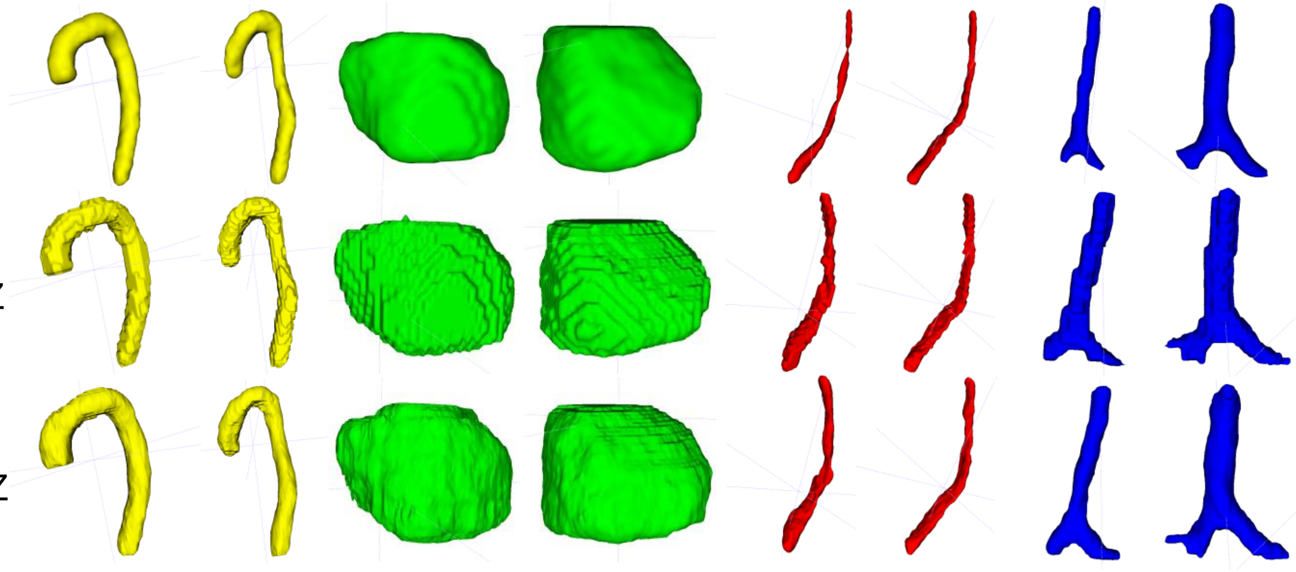
128^3

interpolation ⇓

512^2xZ

SR ↓

512^2xZ



output from a dense segmentation network

interpolation results (output of interpolation, input of SR network)

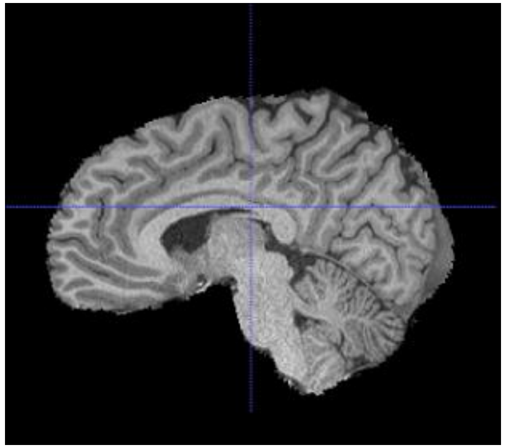
sparse cnn-based super-results (output of a SR network)

Li, J., Gsaxner, C., Pepe, A., Schmalstieg, D., Kleesiek, J. and Egger, J., 2022. **Sparse Convolutional Neural Networks for Medical Image Analysis**. TechRixv techrxiv.19137518.

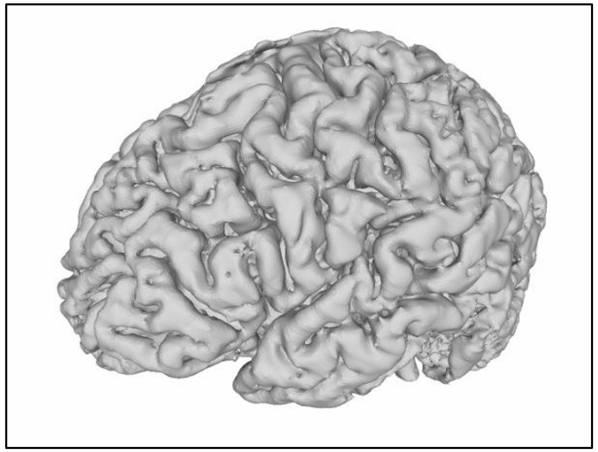
Shape/Geometric features and voxel features

Shape feature: jaggedness, volume, elongation, curvature, boundary, (surface, curve) continuities/smoothness, etc.
Voxel features: voxel intensity (gray-scale), etc

- **Gray-scale voxel features might be redundant for some applications:** (brain) tumor screening

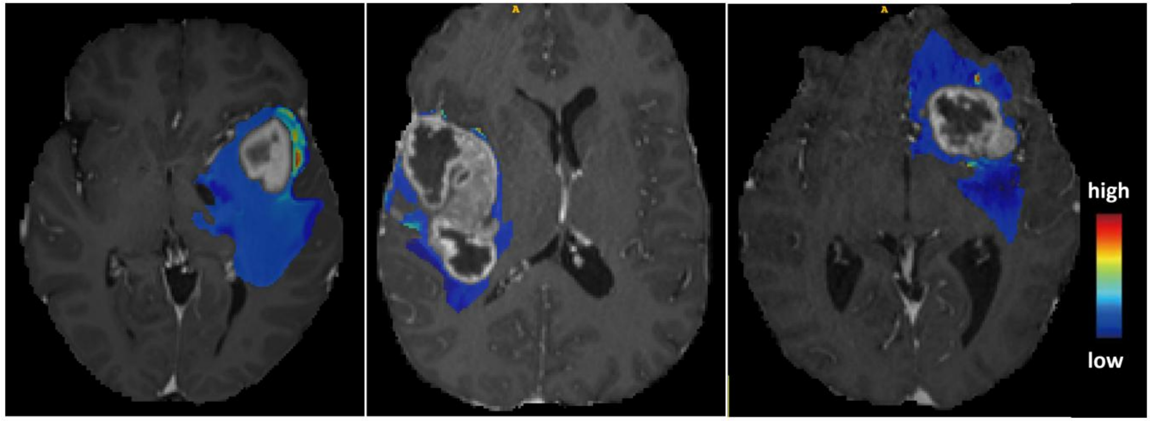


gray-scale brain voxels



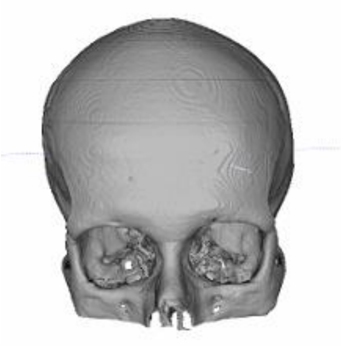
geometric shape of a brain

- Voxels features can be indispensable for some applications: **tumor infiltration maps**



predictive maps calculated over gray-scale MRIs, indicating probability of tumor infiltration

- **Some applications do not require gray-scale voxel information:** skull reconstruction, facial reconstruction



- The role voxel and shape features play remains to be investigated
  - **substance use disorder:** cocaine use disorder, alcohol use disorder
  - **cognitive impairment**: mild cognitive impairment, Alzheimer's disease
  - a combination of voxel and shape features?

IV. Use Cases 5: Anatomy Education in Augmented Reality (AR)

first-per

third-person (teachers‘) view

- Import whole-body anatomies (from a **whole-body segmentation**) into an augmented reality environment
- Anatomies can dissembled and reassembled (like a lego puzzle), by articulated **hand or hand rays**
- Multiuser mode: students (**first-person view**) and teachers (**third-person view**) can share the **same scene,** which makes the teaching experience more realistic
- More details about AR/VR: https://xrlab.ikim.nrw/

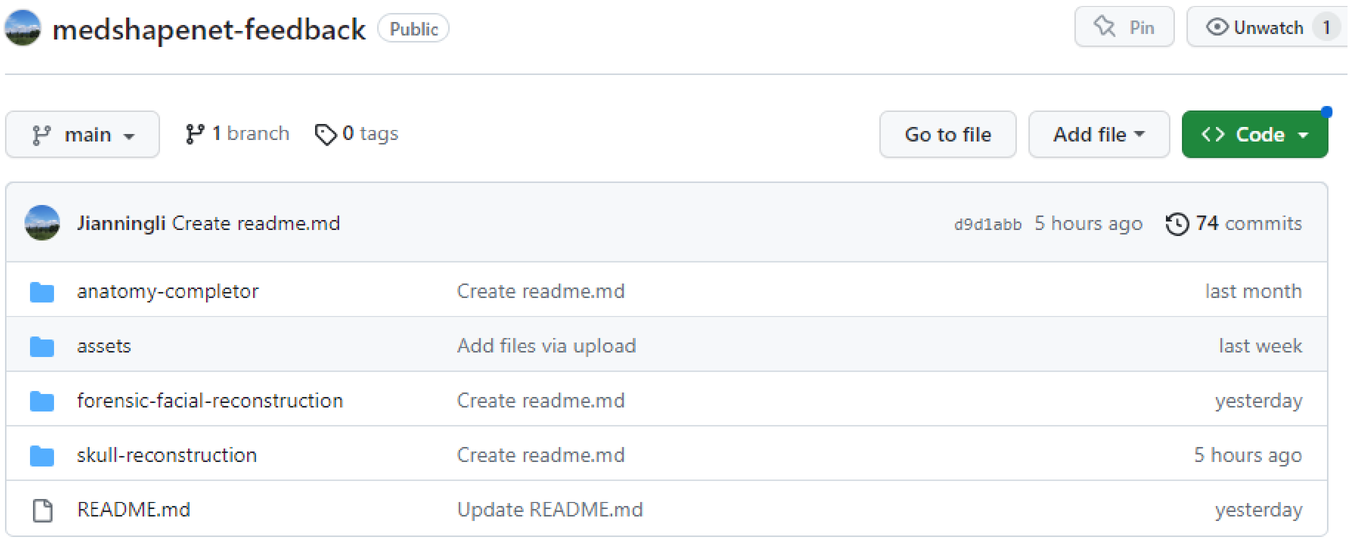
acknowledgement: Gijs Luijten, Christina Gsaxner, Kathrin Krieger

IV. Limitations and Future Plans

1. Shape acquisition & annotation
- Collect more shapes: quality-check of shape data
- Provide more annotations: consistency check
- Redesign the naming convention of the shape files: more compact, informative and descriptive

2. Hardware & online interface
- Increase storage to upload more shapes
- Upgrade the hosting server of the online interface to allow larger traffic
- Refine the shape search function: precise search with multiple key words, e.g., “male” + “brain” + “tumor ”
- Improve user interface: better appearance and more user-friendly

3. Usecases: Establish more use cases and benchmarks



https://github.com/Jianningli/medshapenet-feedback

Community involvement is vital:
- Report corrupted shape data for removal
- Contribute shapes
- Showcase your own research featuring *MedShapeNet*
- Request features of the online interface
- Codes and benchmark datasets of the previously mentioned use cases will be released on this Github repository

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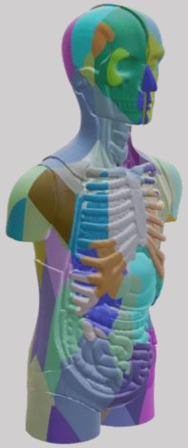

MedShapeNet - A Large-Scale Dataset of 3D Medical Shapes for Computer Vision

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