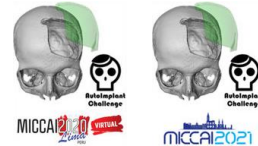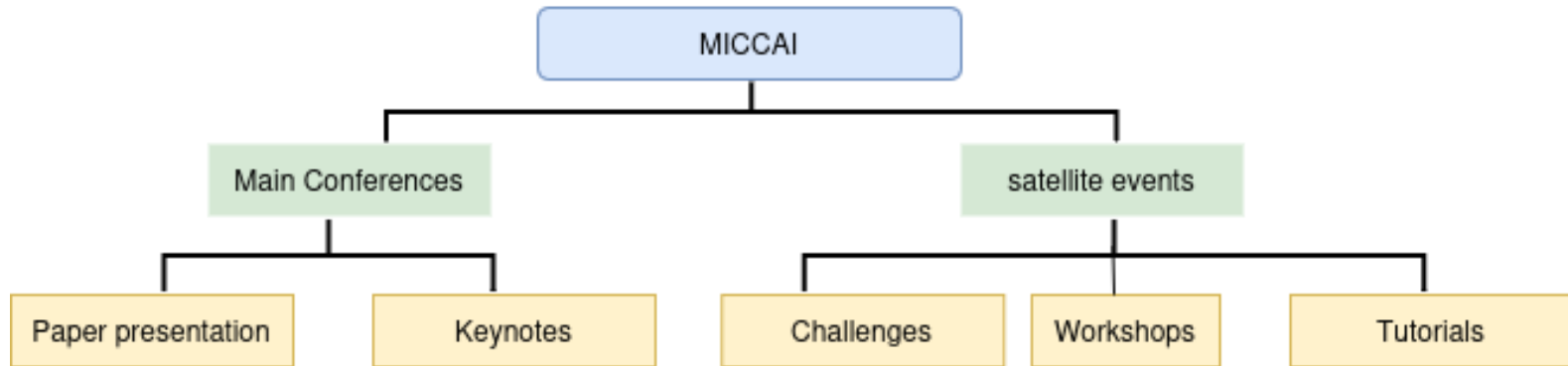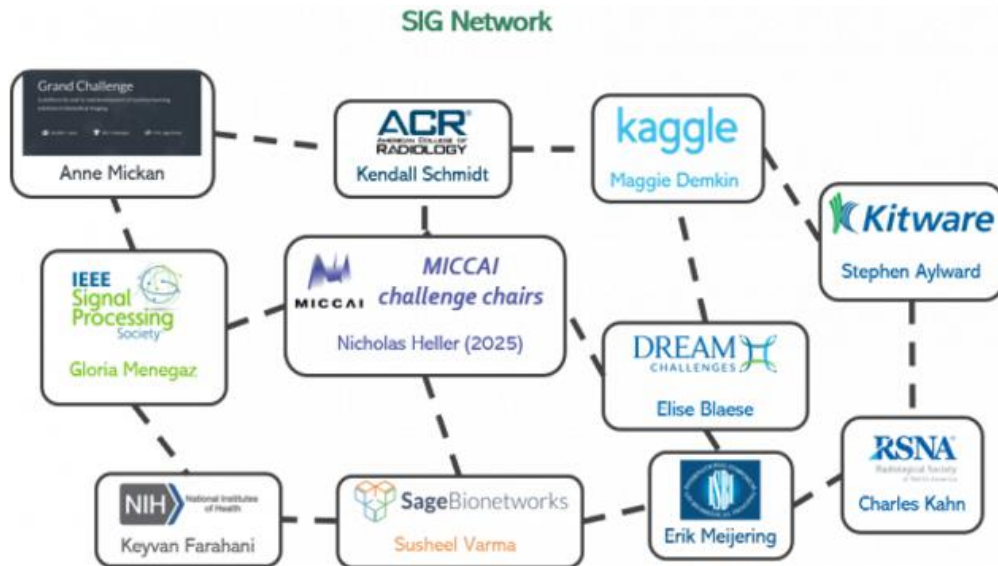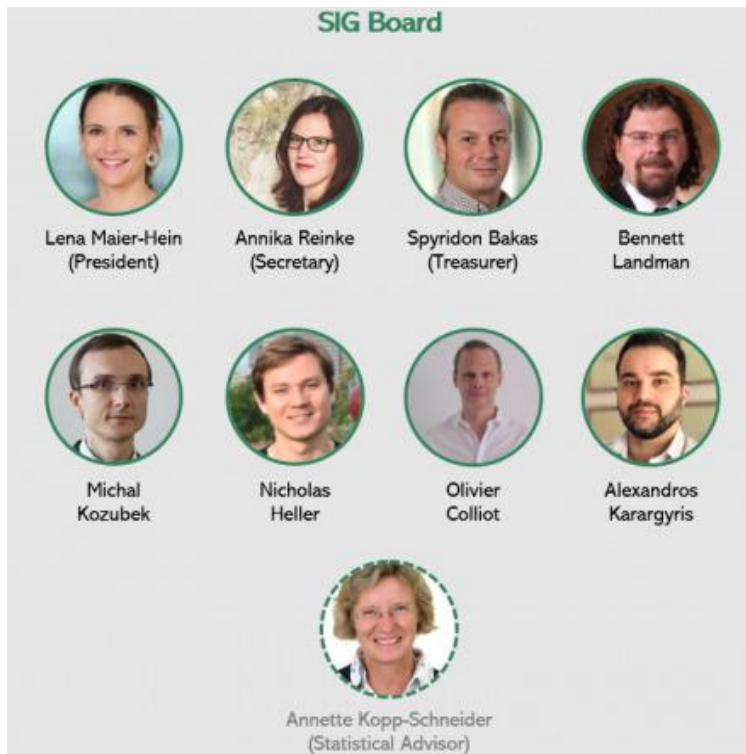# Deep Learning for Cranial Implant Design: Insights from Two Years' MICCAI Challenges

Department Meeting Talk 2025-03-25
Jianning Li, Zuse Institute Berlin

MICCAI Challenge
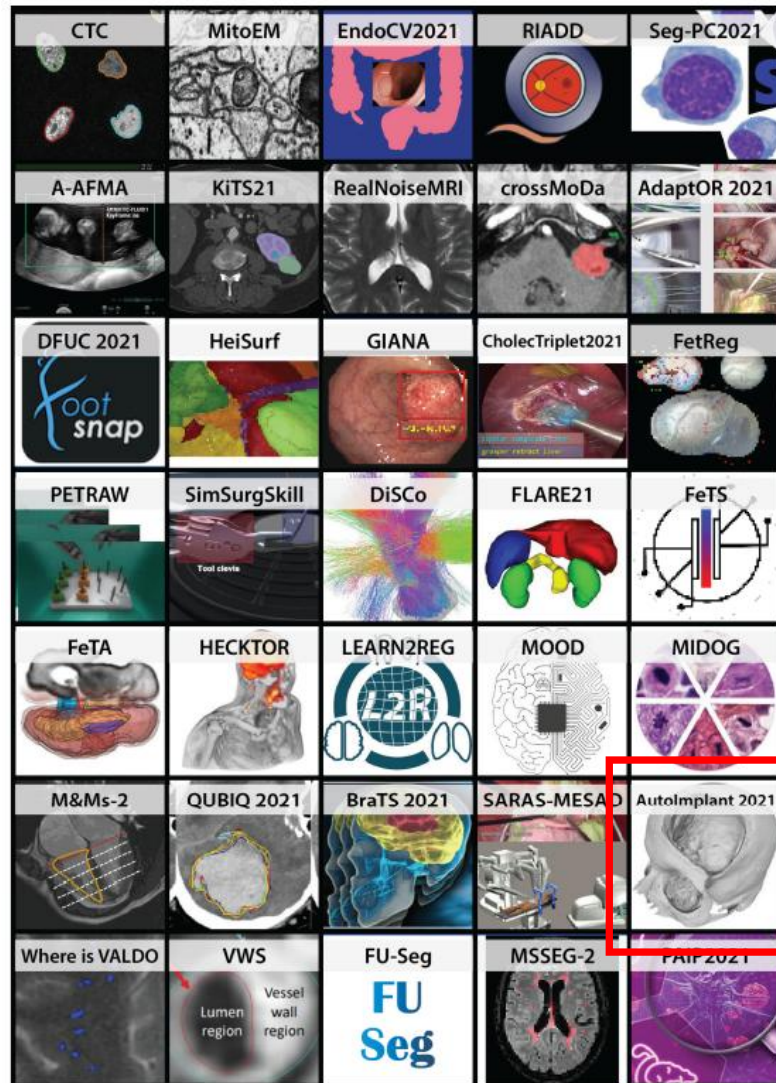
MICCAI Challenge: Special Interest Group (SIG)

SIG Board

Lena Maier-Hein (President)
Annika Reinke (Secretary)
Spyridon Bakas (Treasurer)
Bennett Landman
Michal Kozubek
Nicholas Heller
Olivier Colliot
Alexandros Karargyris
Annette Kopp-Schneider (Statistical Advisor)

SIG Network

Grand Challenge — Anne Mickan
ACR American College of Radiology — Kendall Schmidt
kaggle — Maggie Demkin
Kitware — Stephen Aylward
IEEE Signal Processing Society — Gloria Menegaz
MICCAI challenge chairs — Nicholas Heller (2025)
DREAM CHALLENGES — Elise Blaese
NIH National Institutes of Health — Keyvan Farahani
SageBionetworks — Susheel Varma
Erik Meijering
RSNA Radiological Society of North America — Charles Kahn

MICCAI Challenge

Why is the winner the best?
CVPR 2023

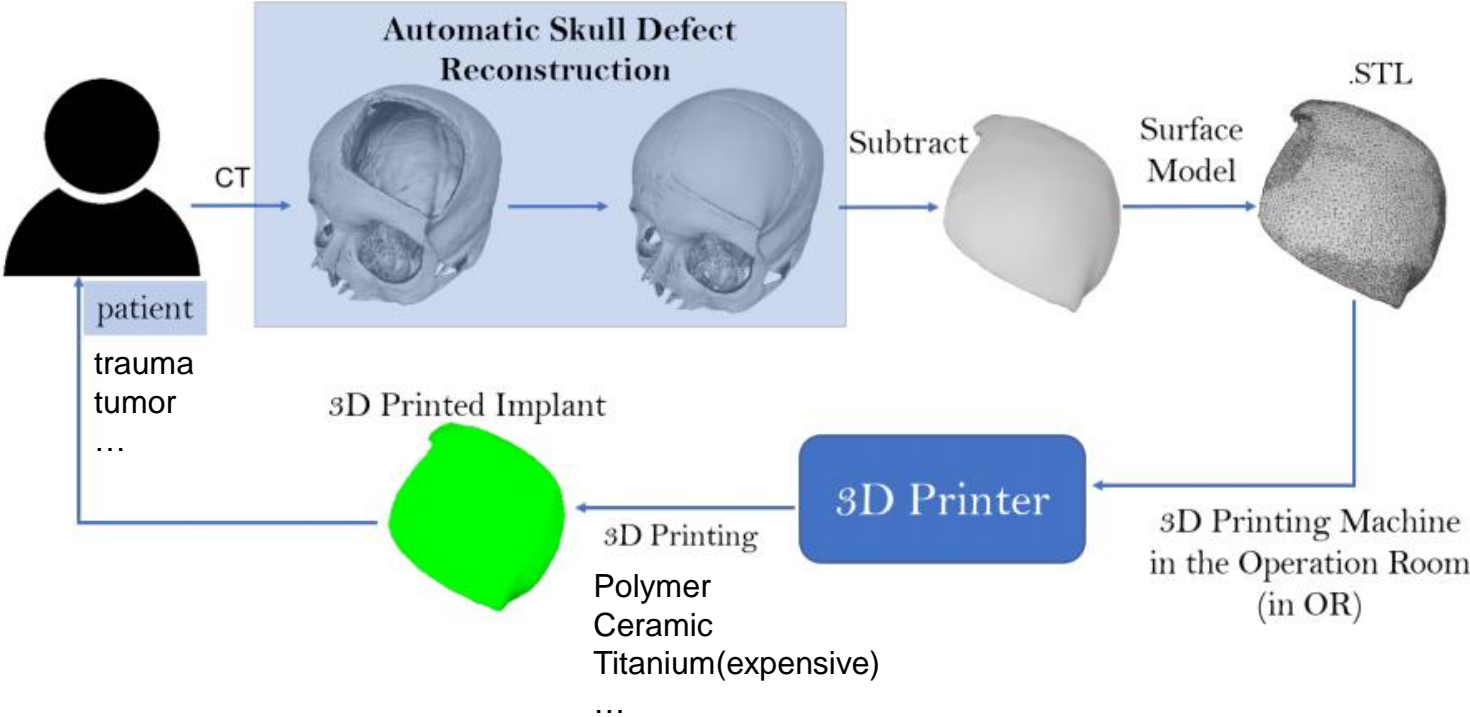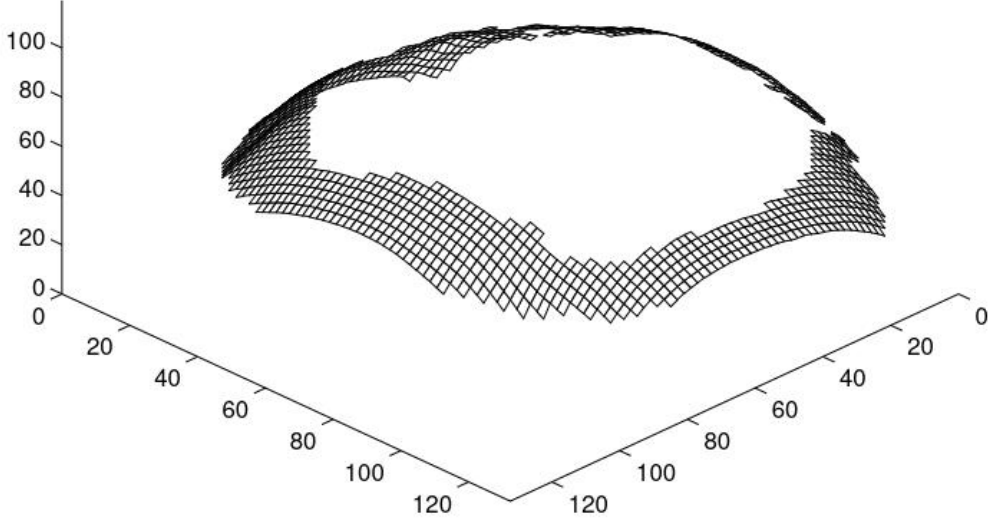Data from *all* ISBI and MICCAI 2021 competitions (n = 80)

Cranial Implant Design: Manual Design
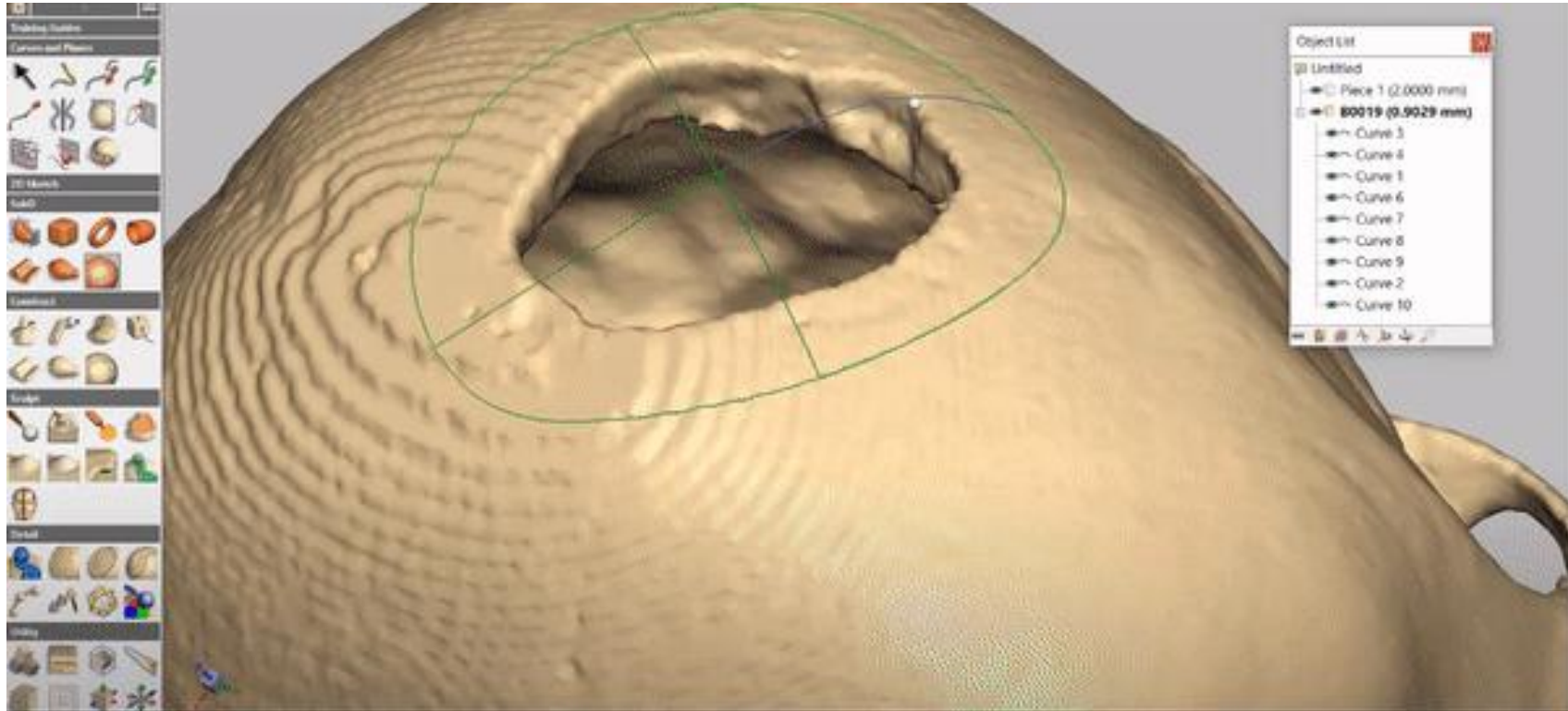
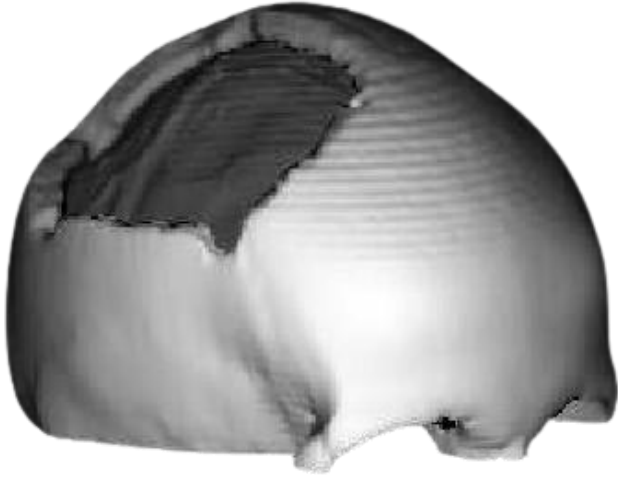# Cranial Implant Design: 3D Printing

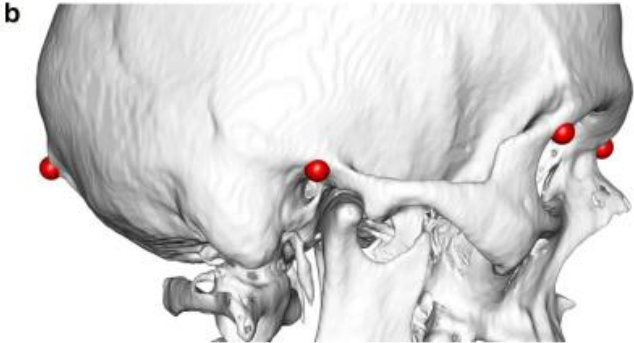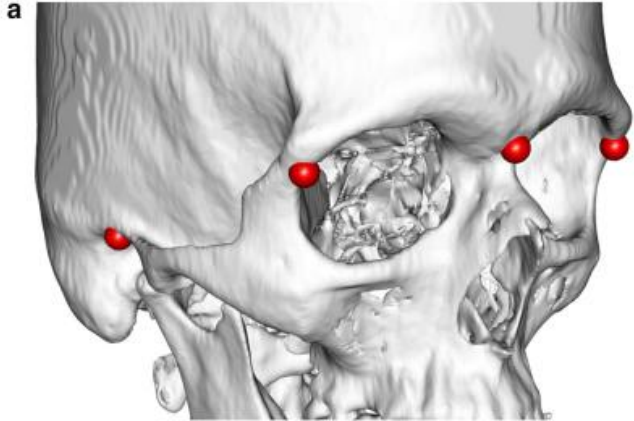# Cranial Implant Design

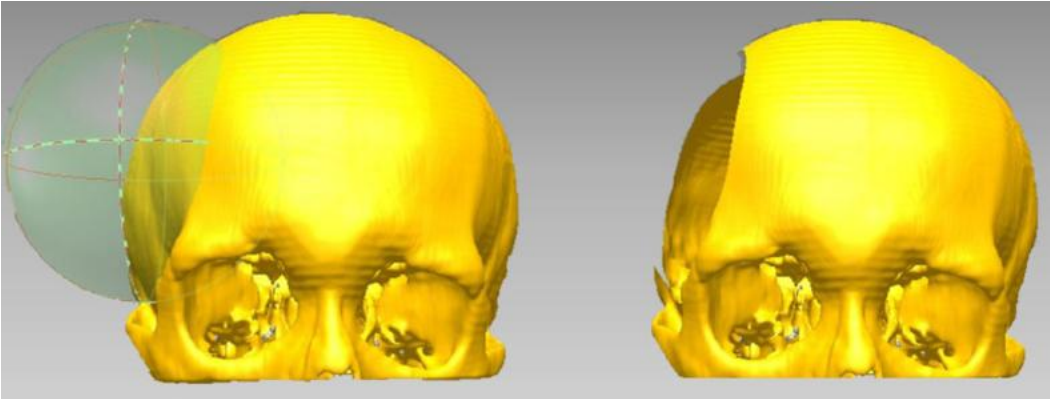# Cranial Implant Design: Surface interpolation using RBF

[Carr, J.C., **1997**, IEEE TMI]

Cranial Implant Design: Statistical shape model
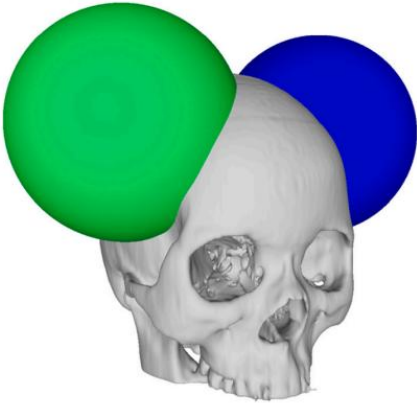

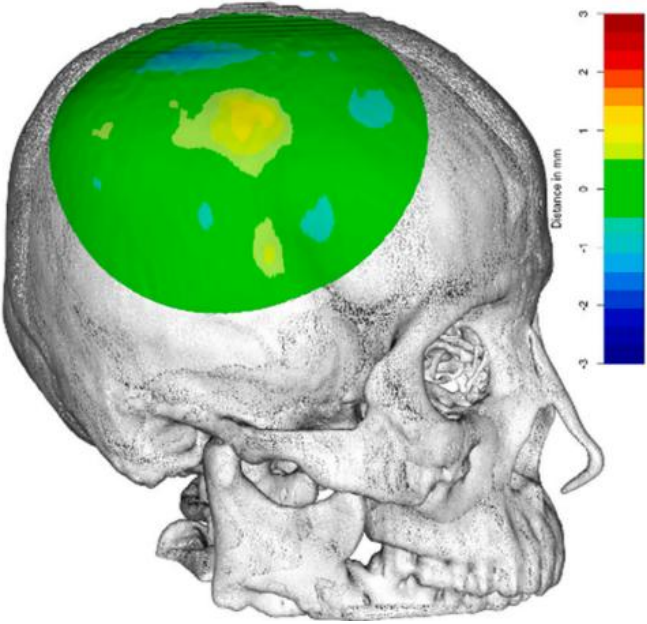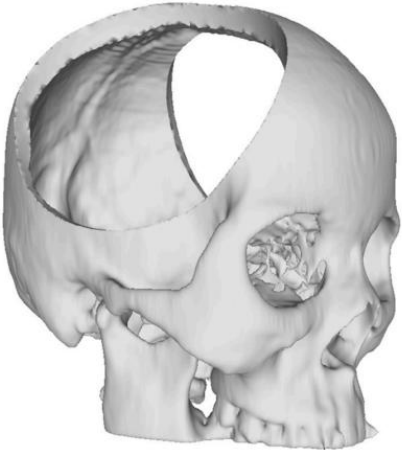manual landmarks

virtual defects

[Fuessinger, M.A., **2018**, IJCARS]

Cranial Implant Design: Statistical shape model

European statistical shape on Chinese dataset

virtual defects

Chinese reconstruction: distance map

[Fuessinger, M.A., 2022]

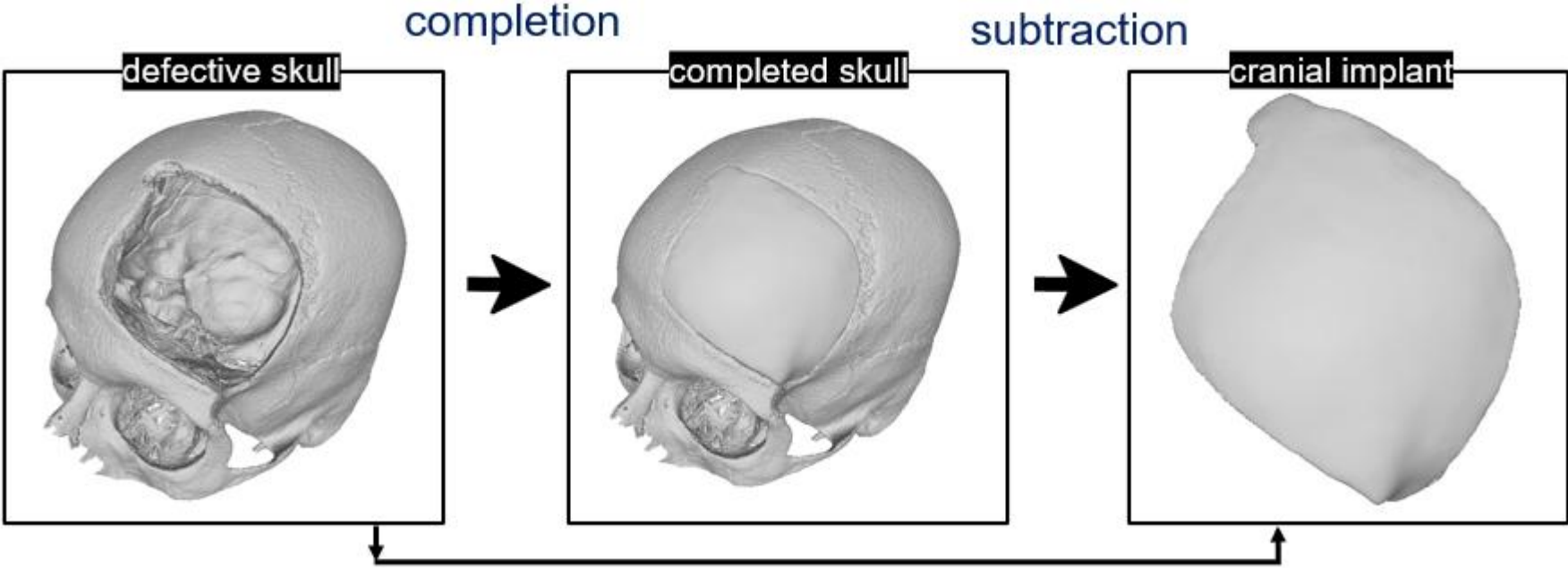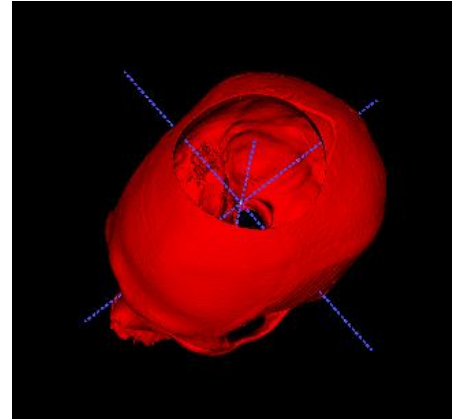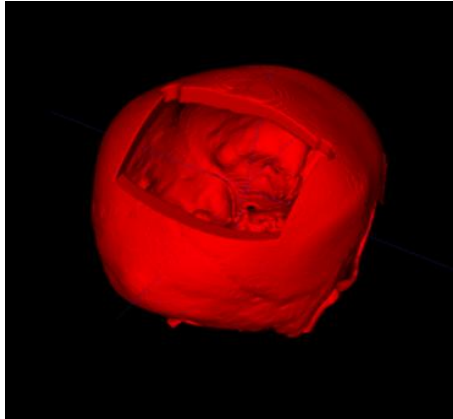# MICCAI Cranial Implant Design Challenge: Deep Learning Solutions

AutoImplant II

AutoImplant I

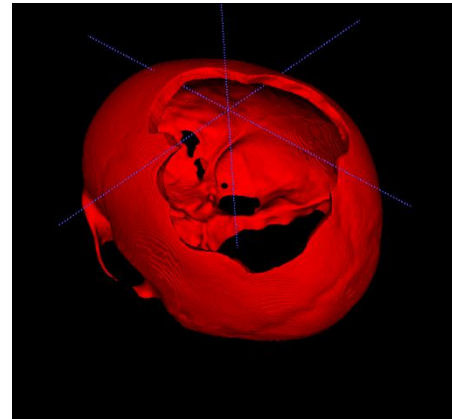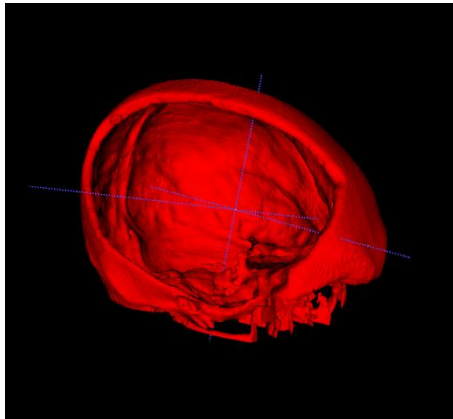# Cranial Implant Design: Learning-based Solutions

Learning-based 3D (skull) **shape completion/inpainting**

Dataset

AutoImplant I

AutoImplant II

Evaluation Metrics and Ranking

AutoImplant I: DSC, HD
AutoImplant II: DSC, hd95, border DSC, neurosurgeons' scores

Methods Overview

AutoImplant I

○ V-Net
○ U-Net
○ ED + Squeeze-and-Excitation block (cvpr 2018)
○ ED + Residual blocks (ResNet, cvpr 2016)
○ U-Net + Residual blocks (1st place submission)
○ Residual Dense U-Net (DenseNet, cvpr 2017)

AutoImplant II

○ ED
○ U-Net
○ LSTM (2D)
○ U-Net+ Residual block (1st place submission)

Notes:
ED: Encoder-Decoder

Methods Overview

"Details in method configuration have more impact on performance than do architectural variations"

nnU-Net. Isensee et al. (2021). *Nature Methods*

Pre-processing/ data augmentation/ method configurations contribute the most to the ranking

- Preprocessing
- Data augmentation
- Training strategies

Methods Overview

Ferreira, A., Solak, N., Li, J., Dammann, P., Kleesiek, J., Alves, V. and Egger, J., 2024. *How we won brats 2023 adult glioma challenge? just faking it! enhanced synthetic data augmentation and model ensemble for brain tumour segmentation*. arXiv preprint arXiv:2402.17317.
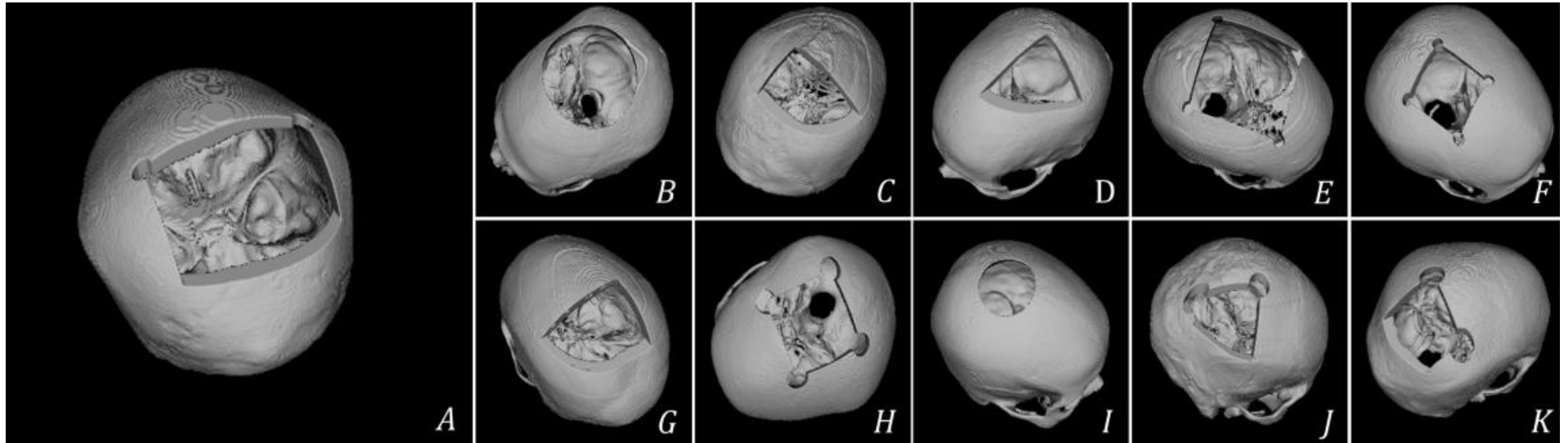
Technical Challenges

- o Generalization
- o High memory footprint
- o Clinical feasibility

Technical Challenges

- **Generalization**
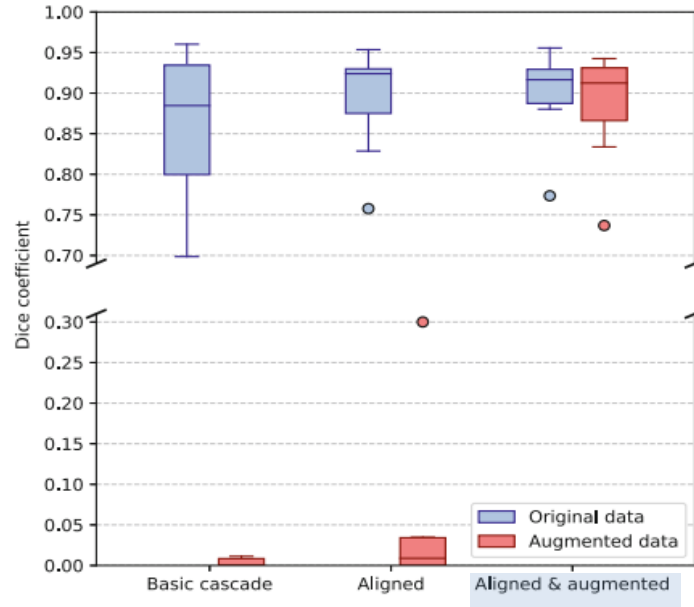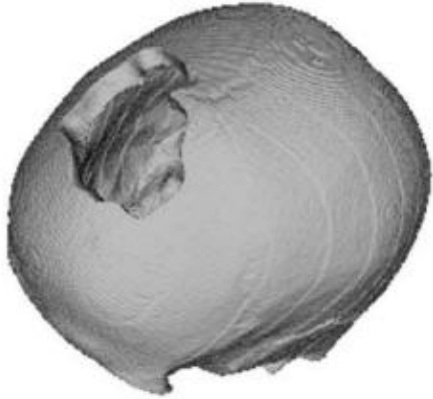- High memory footprint
- Clinical feasibility

Generalization

AutoImplant I: 5 out of 11 submissions failed on the 10 out-of-distribution cases.
AutoImplant II: only 3 teams attempted clinical cases with irregularly shaped defects.

Generalization

Data augmentation:
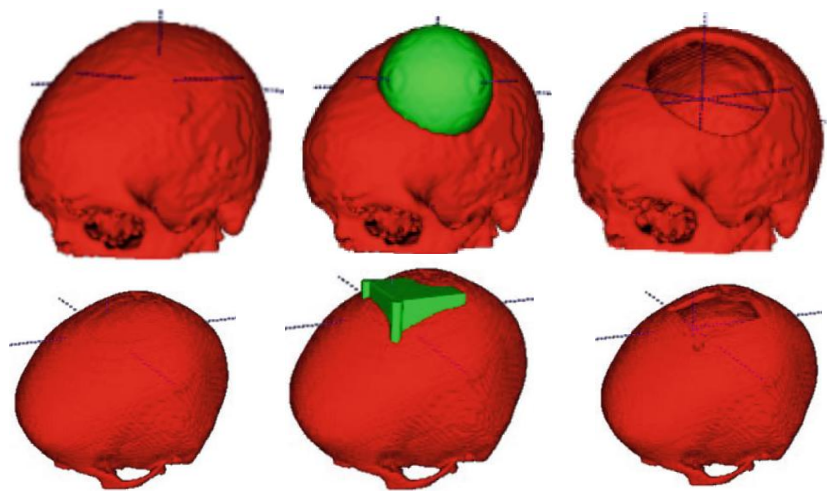- created additional 5 **random virtual defects** for each healthy skull in the training set.

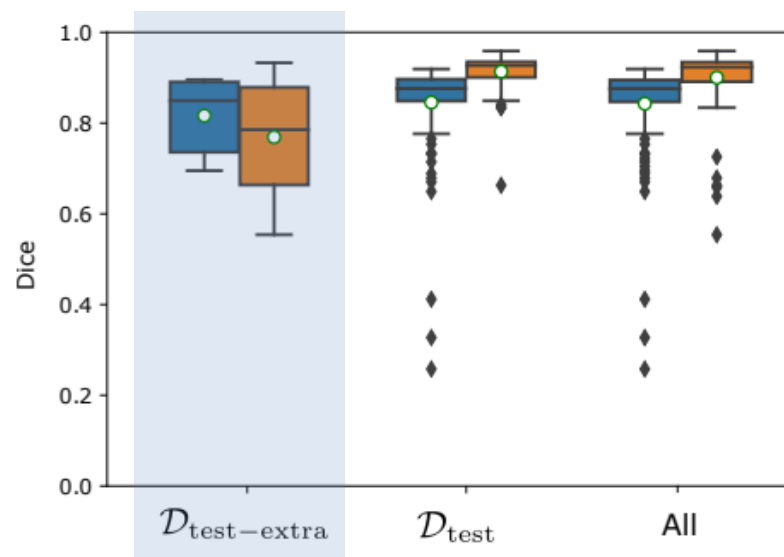|	Test case (100)	Test case (10)	Overall (110)
Mean DSC	0.920	0.910	0.919
Mean HD	4.137	4.707	4.189

[Kodym, O et al]

Generalization

Data augmentation:
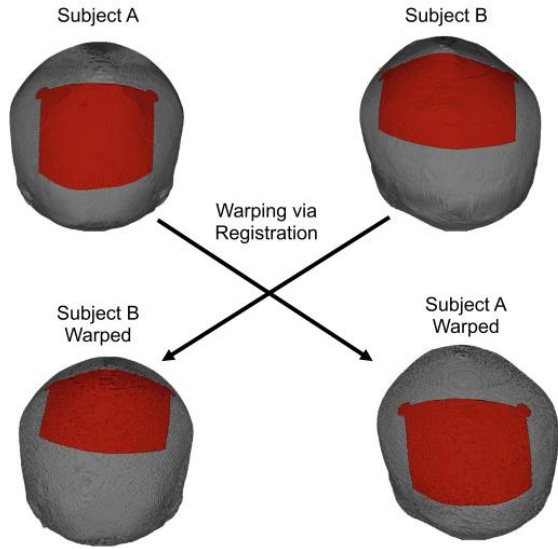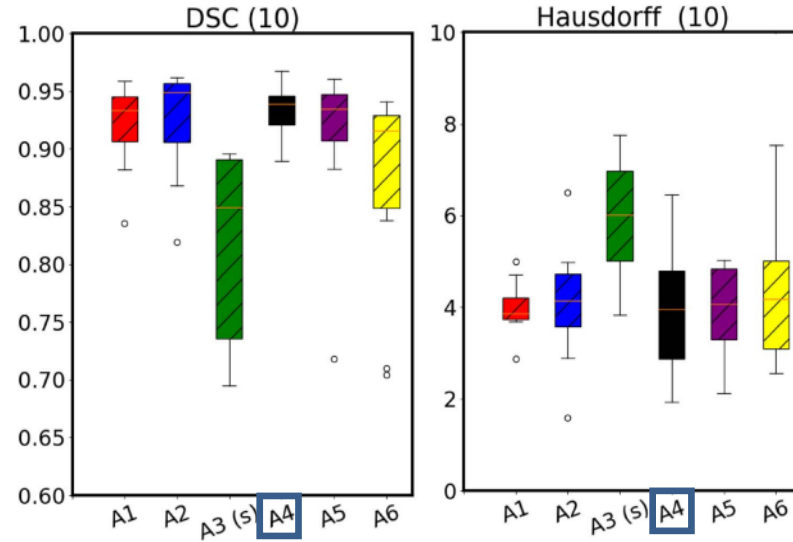- create defects **similar to the out-of-distribution test cases**

[Matzkin, F et al]

Generalization

Data augmentation:
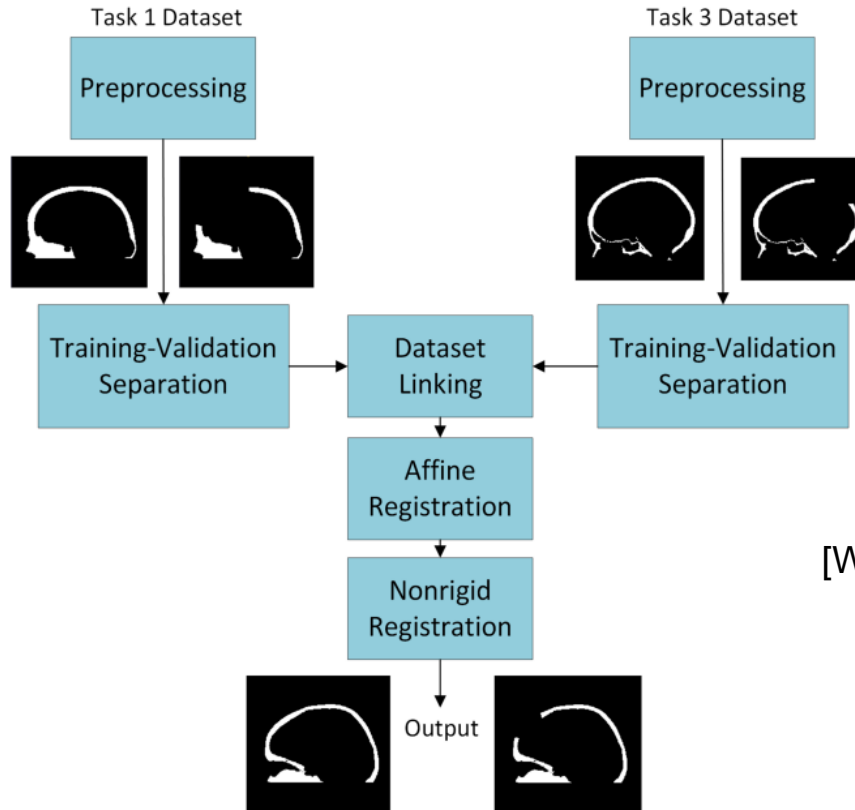- 100 training samples augmented to 99*100+100=10000 samples **(1st place)**

[Ellis, D.G. et al]

Generalization

Data augmentation:
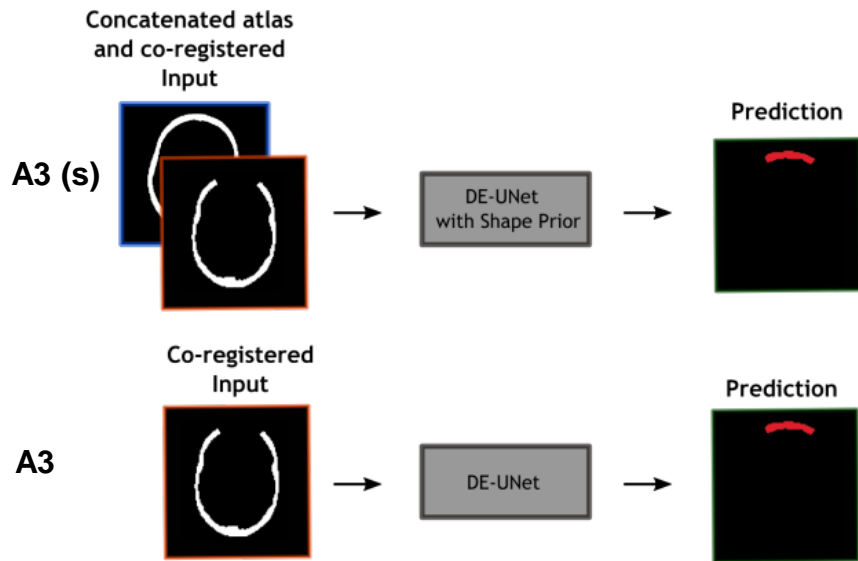- intensive augmentation + dataset linking (**1st place, AutoImplant II**)
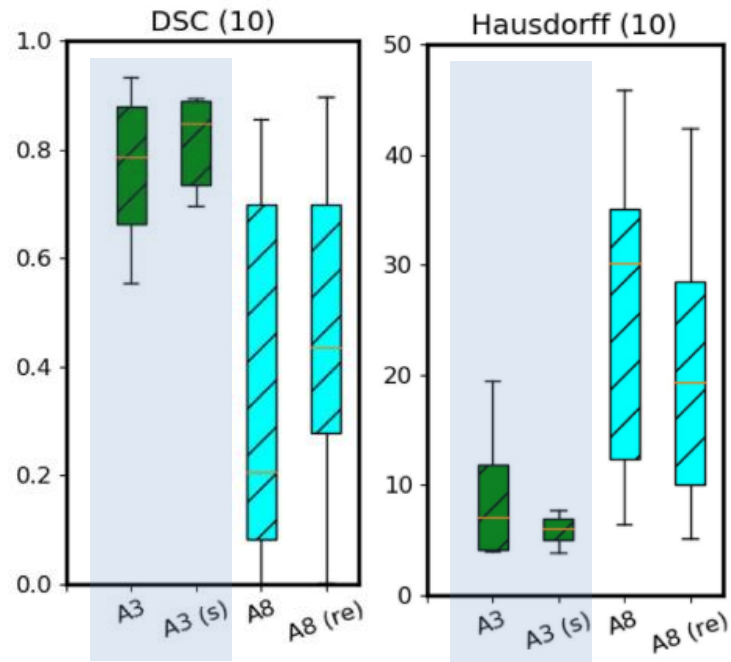

[Wodzinski, M et al]

Generalization

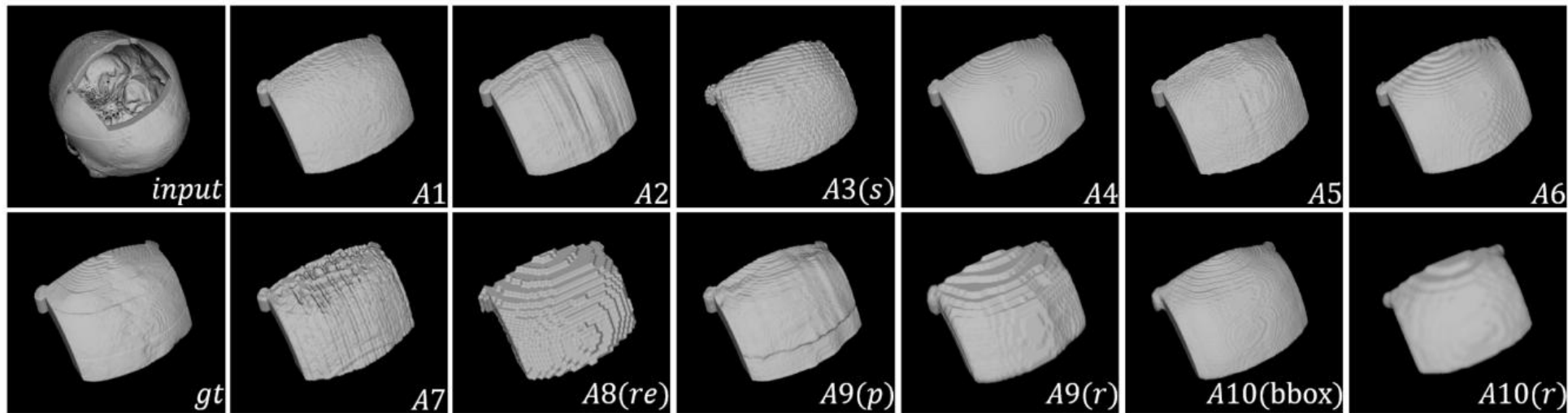Use a shape prior (average shape of healthy skulls)

[Matzkin, F et al]

Technical Challenges

o Generalization

o **High memory footprint**
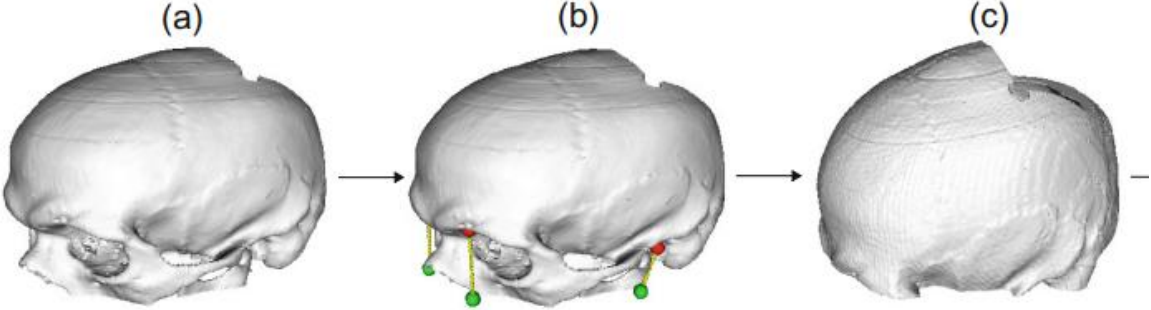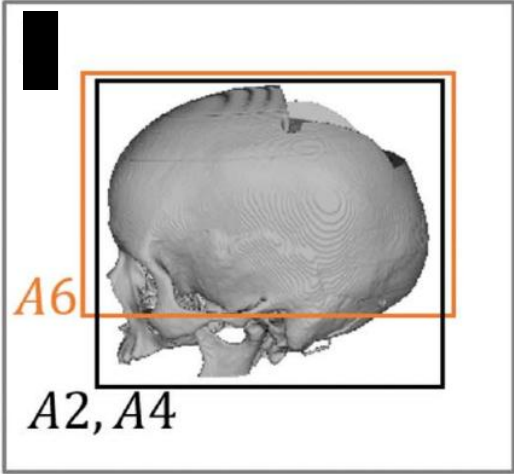
o Clinical feasibility

High Memory Footprint

High Memory Footprint

Cropping:
- Keep only the ROI

[Kodym, O et al]

High Memory Footprint

Core-to-fine:
- Use two networks

Defected region localization

$(S_d)_{128^2 \times 64}$ N_1 $(I_d)_{128^2 \times 64}$ Bounding box   Upsampling   Margin

Defected region extraction

Zero-padding $(B_{Iz})_{256^2 \times 128}$

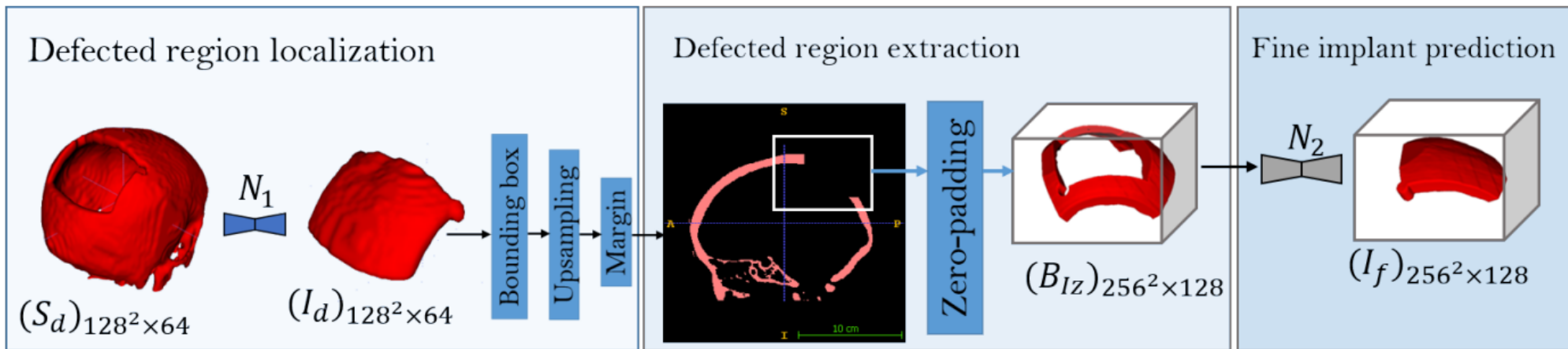Fine implant prediction
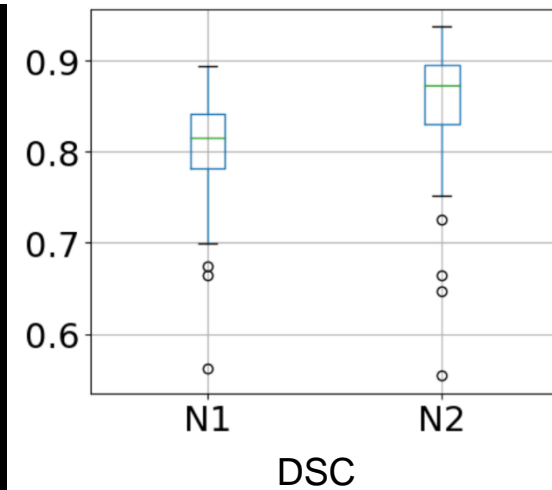
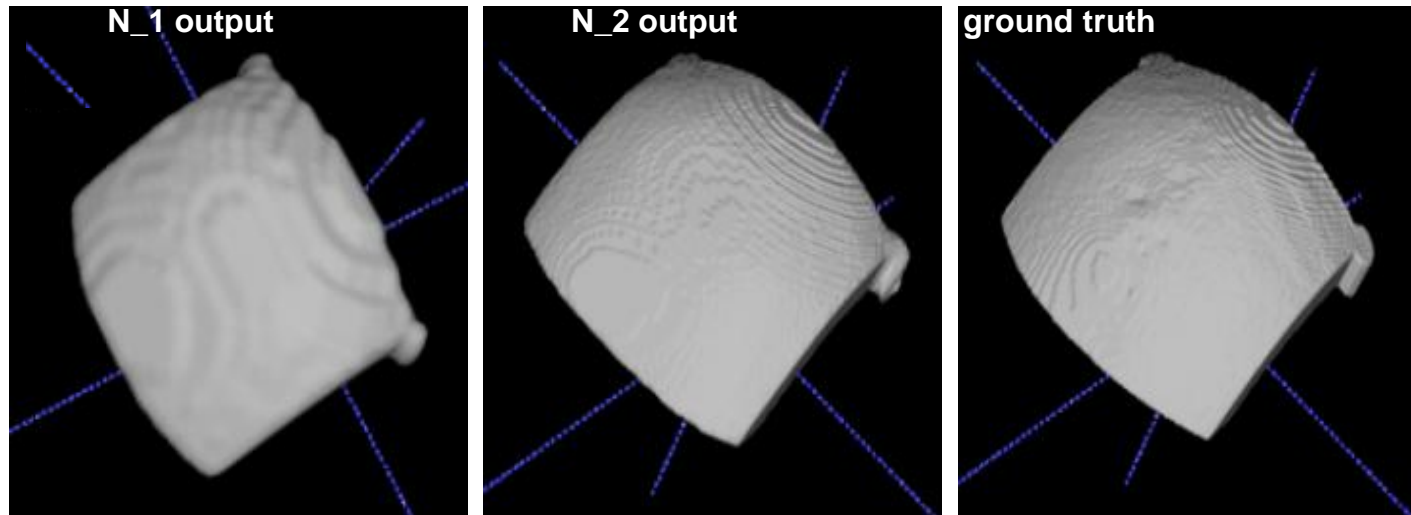N_2 $(I_f)_{256^2 \times 128}$

[Li, J .et al]

High Memory Footprint
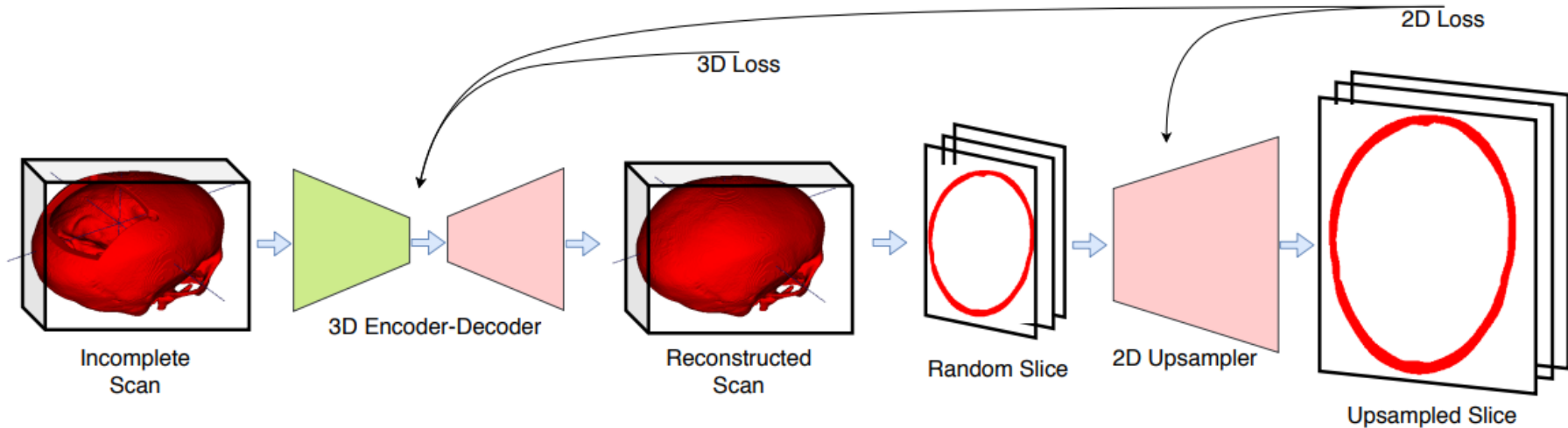
Core-to-fine:
- Use two networks

[Li, J .et al]

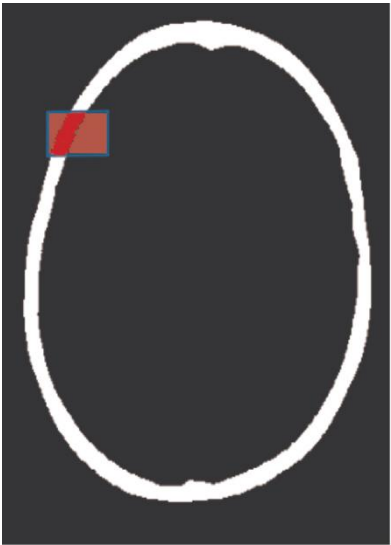# High Memory Footprint

Core-to-fine:

• Use two networks

[Bayat, A et al]

High Memory Footprint

Use sparse convolutions

(a) Traditional convolution
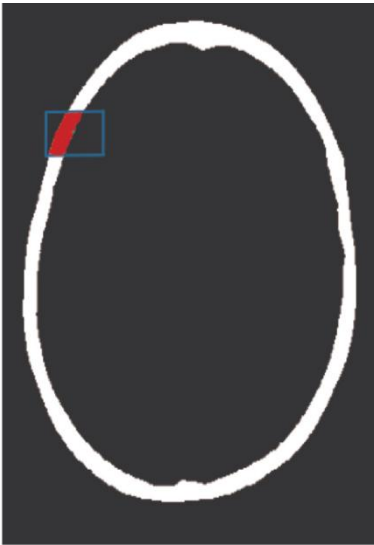
(b) Sparse convolution
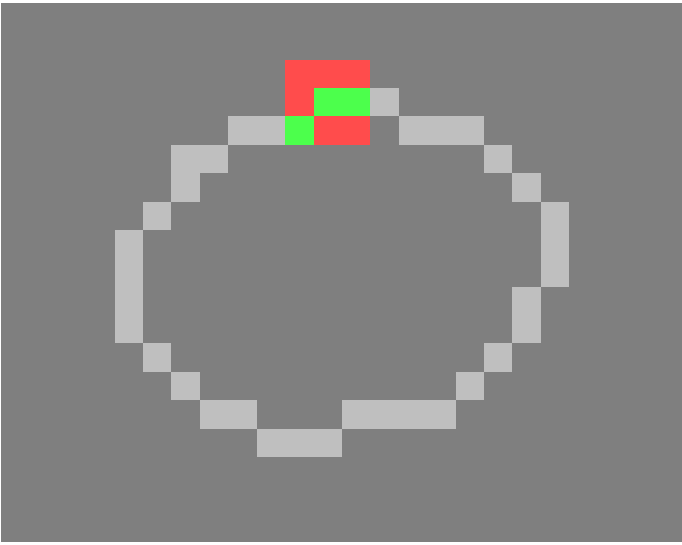
[Graham, B et al]

[Li, J .et al]

High Memory Footprint

Use sparse convolutions: implant generationa **at full resolution 512x512xZ**

input

pred

gt
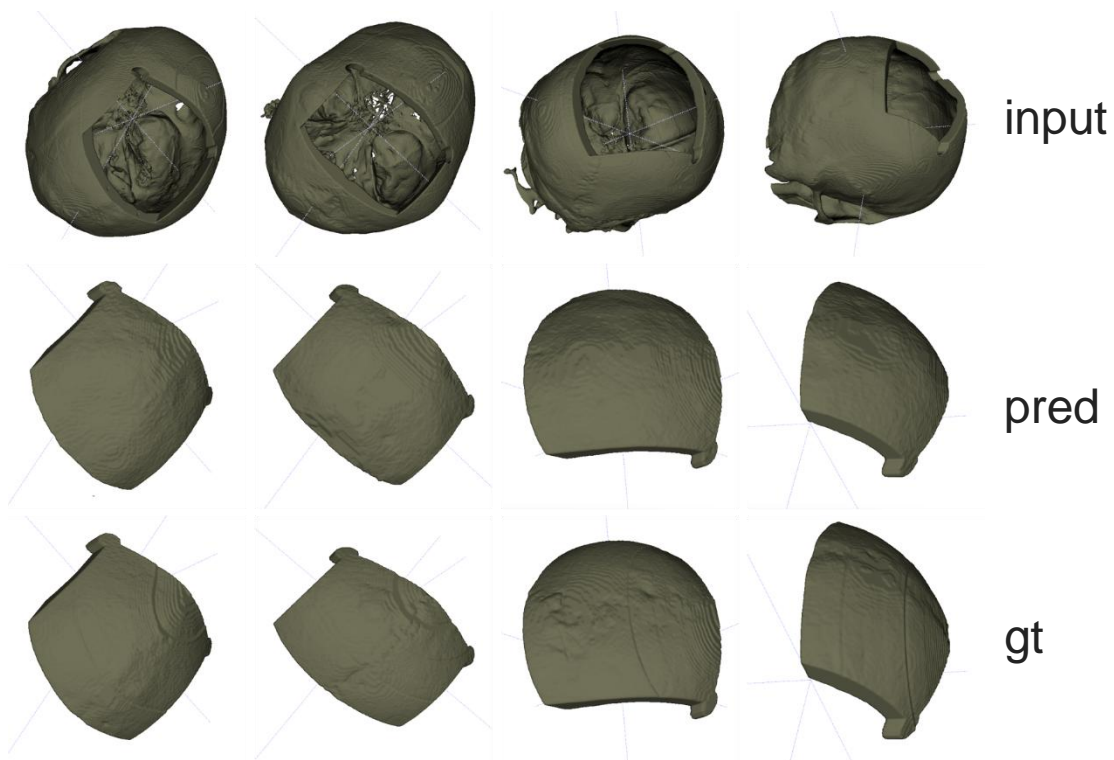
use about 11GB memory for training and 3GB for evaluation

High Memory Footprint

Patch-wise training

16 Patch (128^3)

49 Patch (128^3)

Random Patch (128^3)
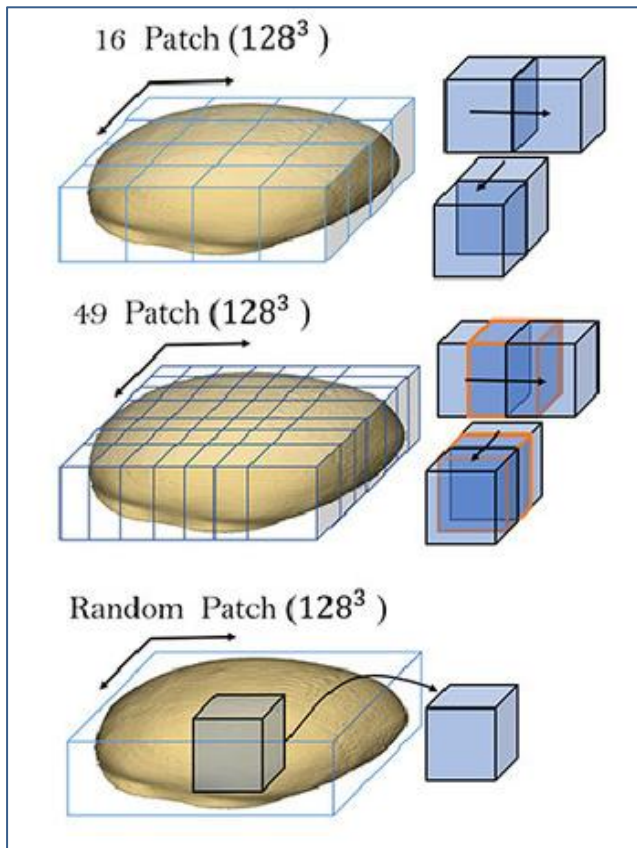
[Li, J .et al]

Technical Challenges

○ Generalization

○ High memory footprint

○ **Clinical feasibility**

Clinical Feasibility

Correlation between **quantitative score** (Dice) and **experts' evaluation (gold standard)**
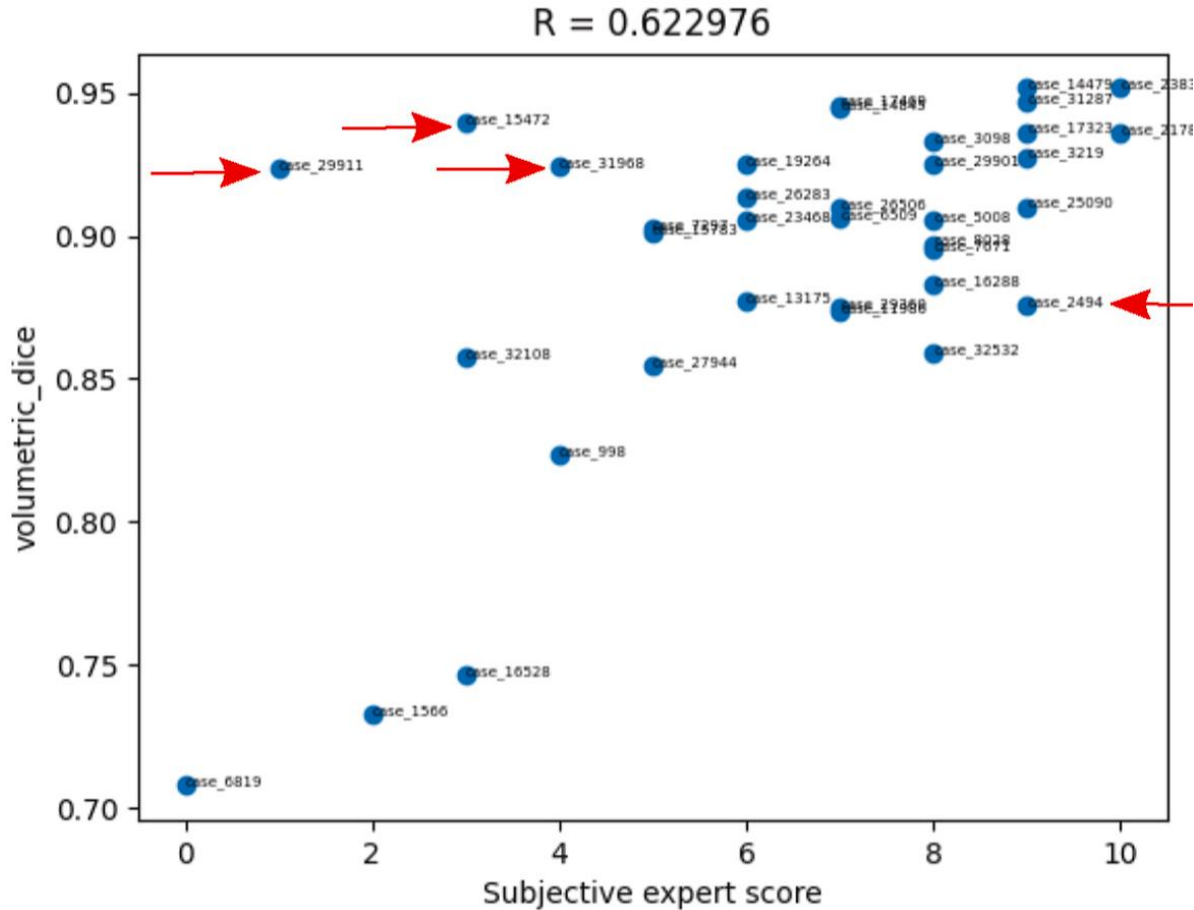
[Kodym, O et al]

Clinical Feasibility

Maier-Hein, L., Reinke, A., Godau, P., Tizabi, M.D., Buettner, F., Christodoulou, E., Glocker, B., Isensee, F., Kleesiek, J., Kozubek, M. and Reyes, M., 2024. *Metrics reloaded: recommendations for image analysis validation*. *Nature methods*, 21(2), pp.195-212.

Clinical Feasibility

Customized evaluation metrics: border DSC

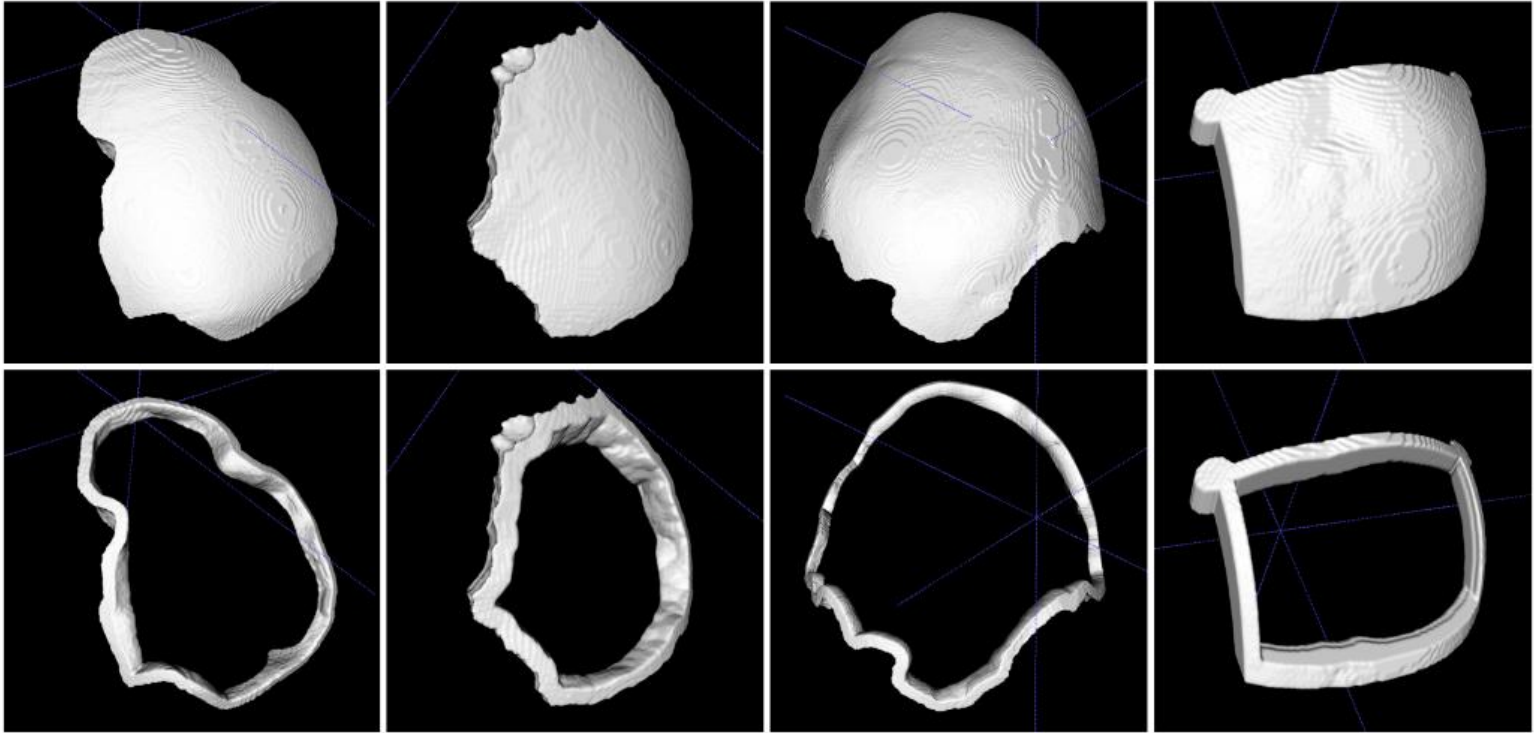# Clinical Feasibility

Quantifying neurosurgeons' manual evaluations

Table 2. Qualitative criteria for a feasible implant design.

| Criteria	Description
Complete	The implant should cover the whole defect area
No false positive area	The implant should not extend beyond the defect area
Implantable	The implant should be able to be placed into the defect area
Restores skull shape	The implant should restore the expected skull shape
Smooth transition with skull	The area of transition between the skull and implant should be smooth
Minimal thickness	The implant must be thin enough as not to overly compress underlying tissue. Ideally, the implant should be at least 50% thinner than the skull

[Ellis, D G et al]

Clinical Feasibility

The 1st place method (intensive data augmentation) ranked well for both metrics

Methods \ Scores	Comp	FPA	Fit	Feasibility
$\bar{S}$ (50)	0.89	0.73	0.64	0.62
M. Wodzinski. et al. [32]	0.93	0.57	0.55	0.42
L. Yu. et al. [35]	0.80	0.59	0.36	0.42
H. Mahdi. et al. [31]	0.76	0.43	0.45	0.33

Clinical Feasibility

Implant Thickness
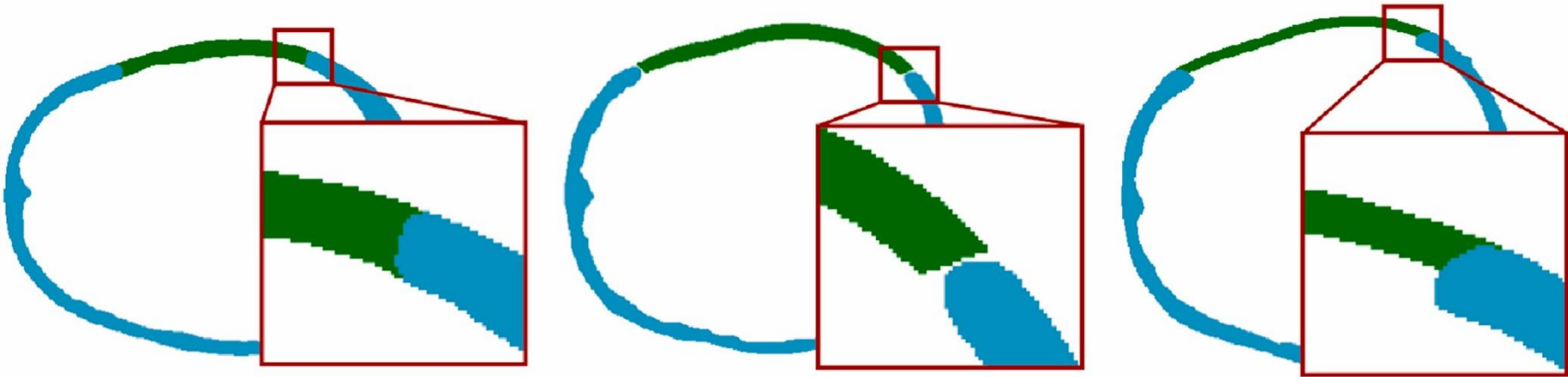
synthetic samples   clinical samples

[Kodym, O. et al]

Technical Challenges

- ○ **Generalization**
- ○ **High memory footprint**
- ○ **Clinical feasibility**

Recommended Reading

Li, J., et al., 2021. ***AutoImplant 2020-first MICCAI challenge on automatic cranial implant design***. *IEEE transactions on medical imaging, 40*(9), pp.2329-2342.

Li, J., et al., 2023. ***Towards clinical applicability and computational efficiency in automatic cranial implant design: An overview of the autoimplant 2021 cranial implant design challenge***. *Medical Image Analysis, 88*,p.102865.

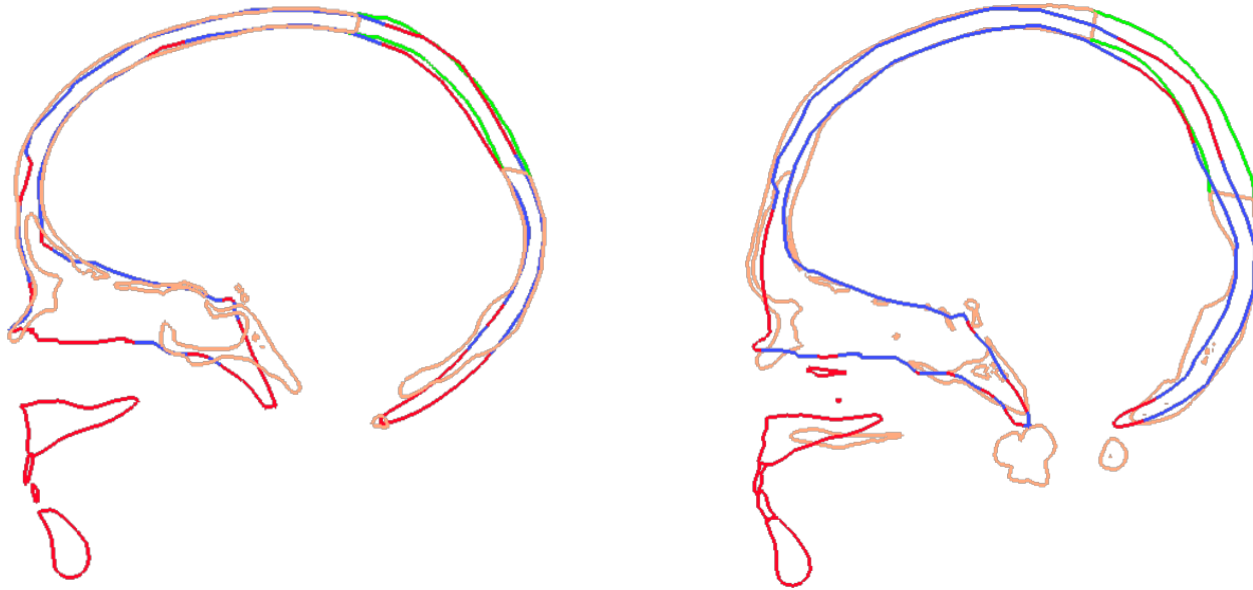# Learning-based Cranial Implant Design: Recent Development

Point Cloud Diffusion Models for Automatic Implant Generation

MICCAI **2023**, Paul Friedrich, University of Basel
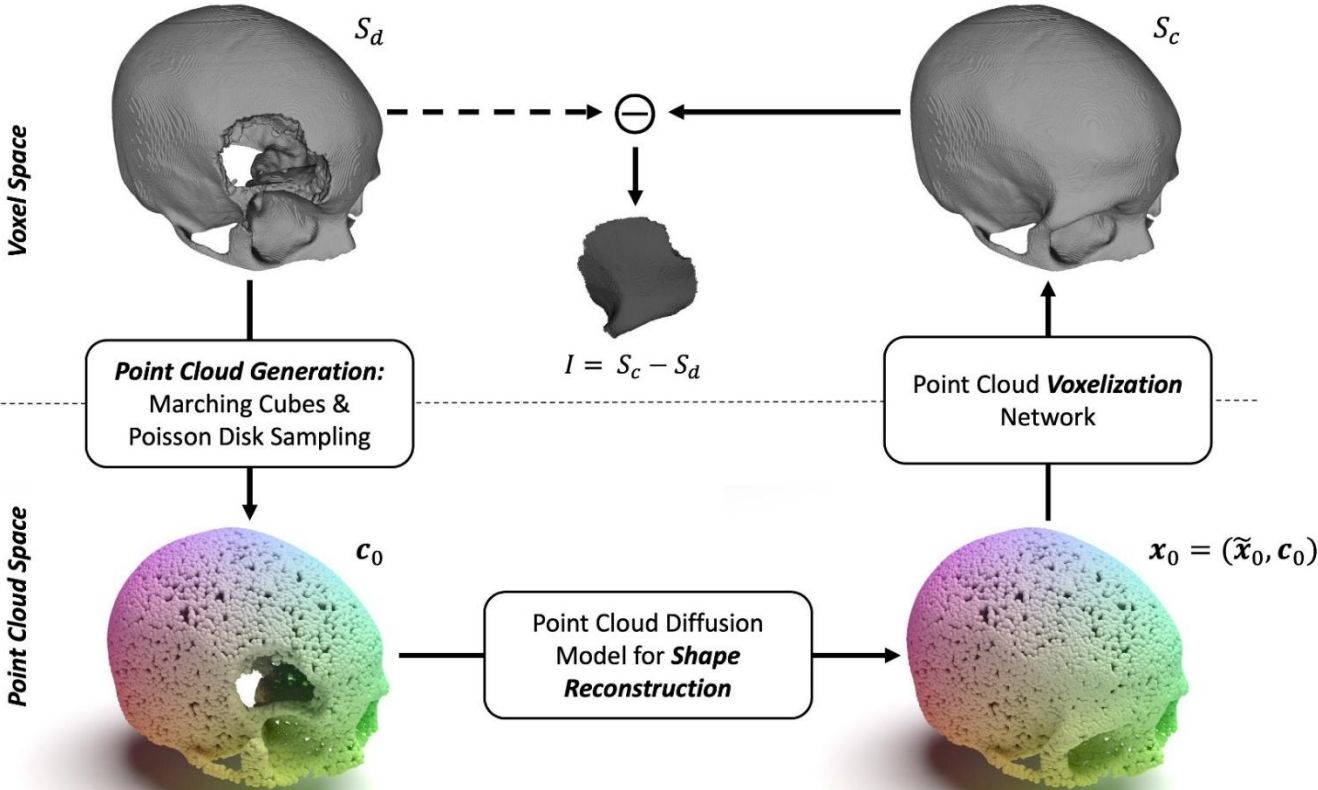
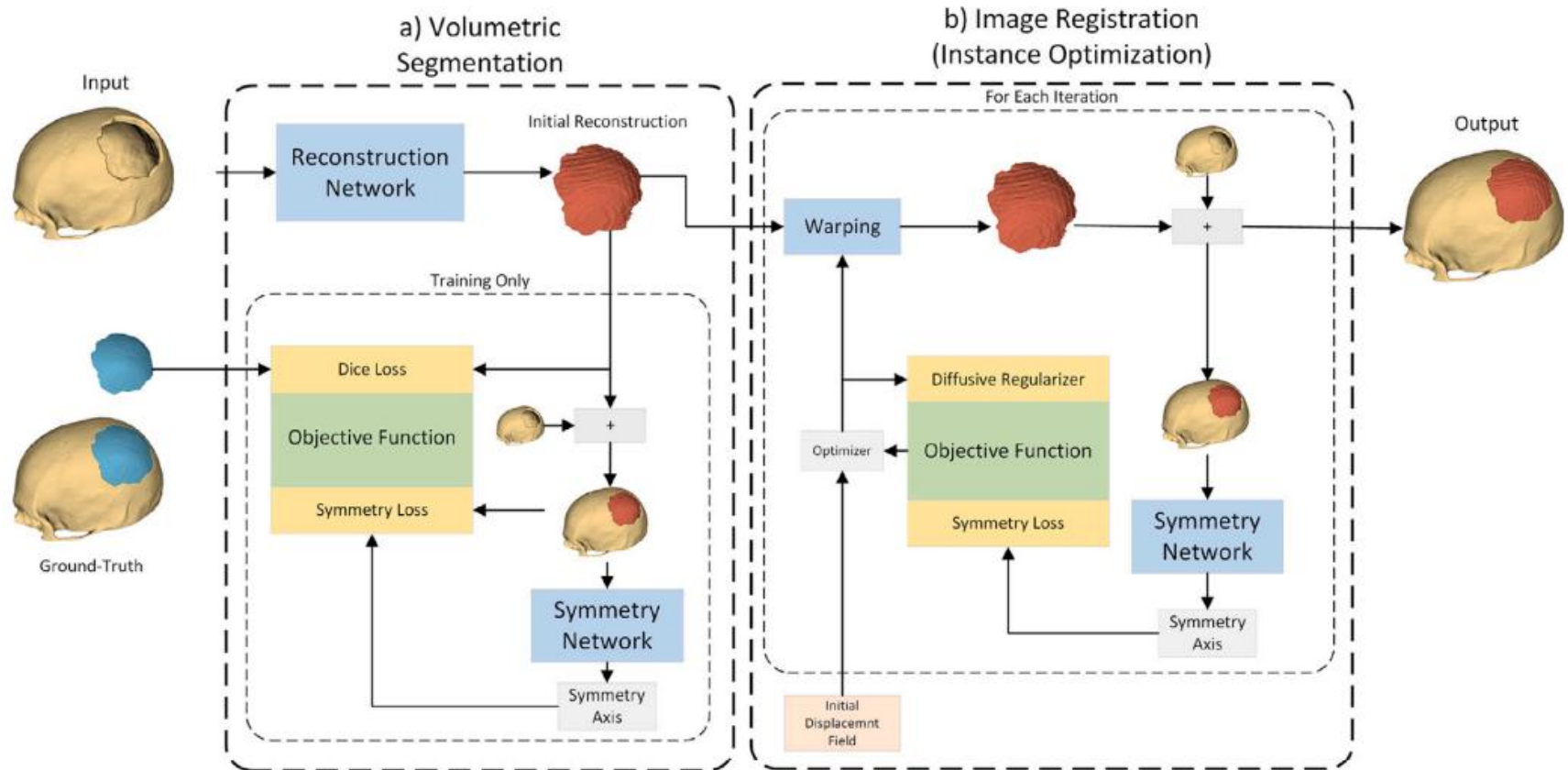# Outlier Detection for Shape Model Fitting

Dana Rahbani, 2022

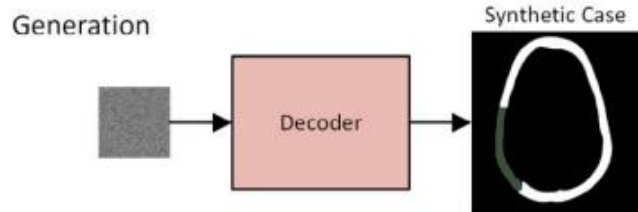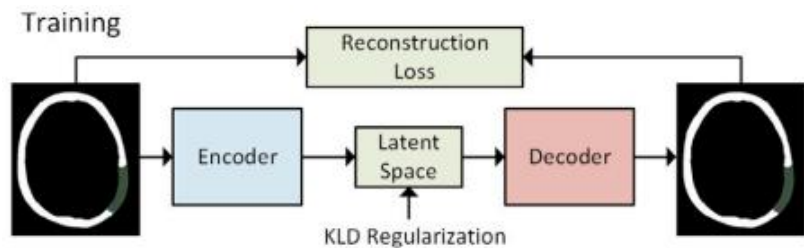Gaussian Process Morphable Model (**using AutoImplant I data**)

Automatic skull reconstruction by deep learnable symmetry enforcement
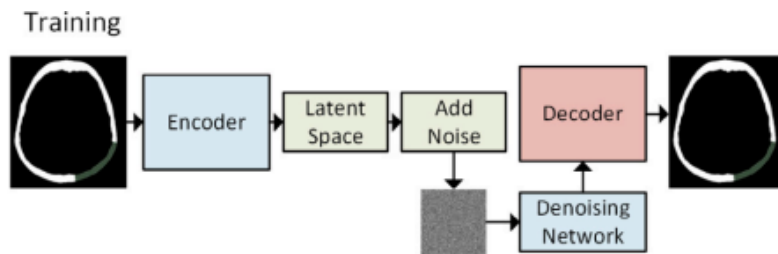
Marek Wodzinski, CMPB **2025**

Improving deep learning-based automatic cranial defect reconstruction by heavy data augmentation: From image registration to latent diffusion models
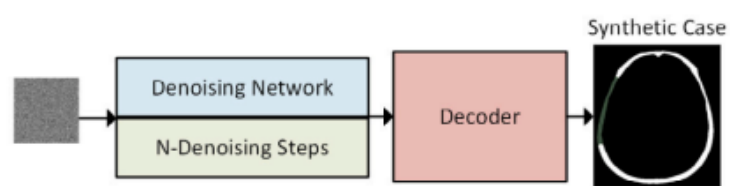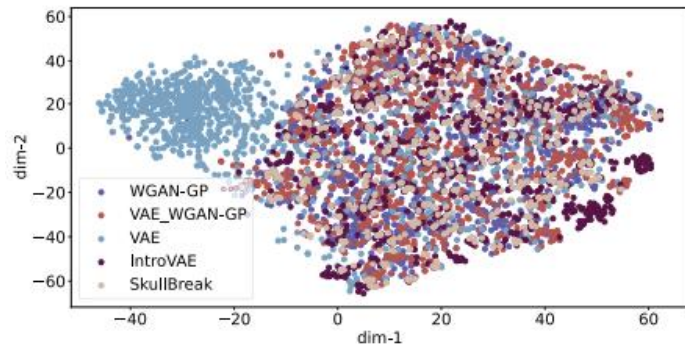
Marek Wodzinski, CBM **2024**
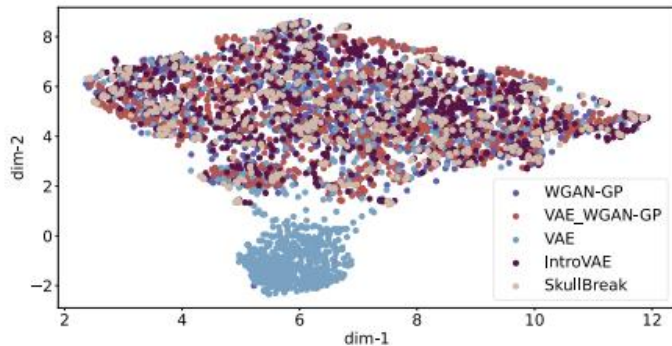

VAE

Diffusion model

Deep Generative Networks for Heterogeneous Augmentation of Cranial Defects

Kamil Kwarciak, Marek Wodzinski, ICCV **2023**
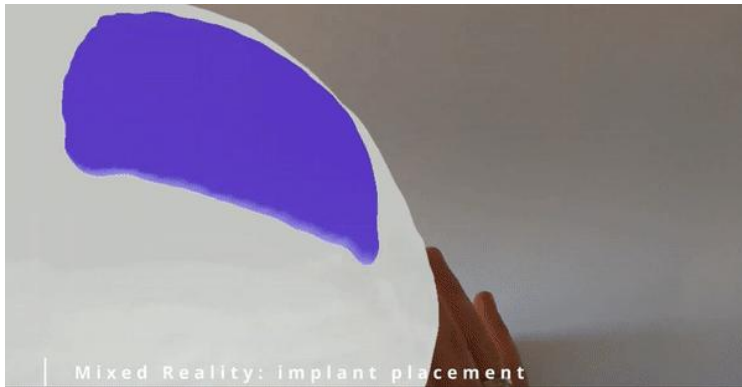
- WGAN-GP,
- VAE/WGAN-GP
- IntroVAE

Deep learning-based framework for automatic cranial defect reconstruction and implant modeling

Marek Wodzinsk CMPB **2022**

virtual inspection

virtual interaction & see inside

Thank you for your attention