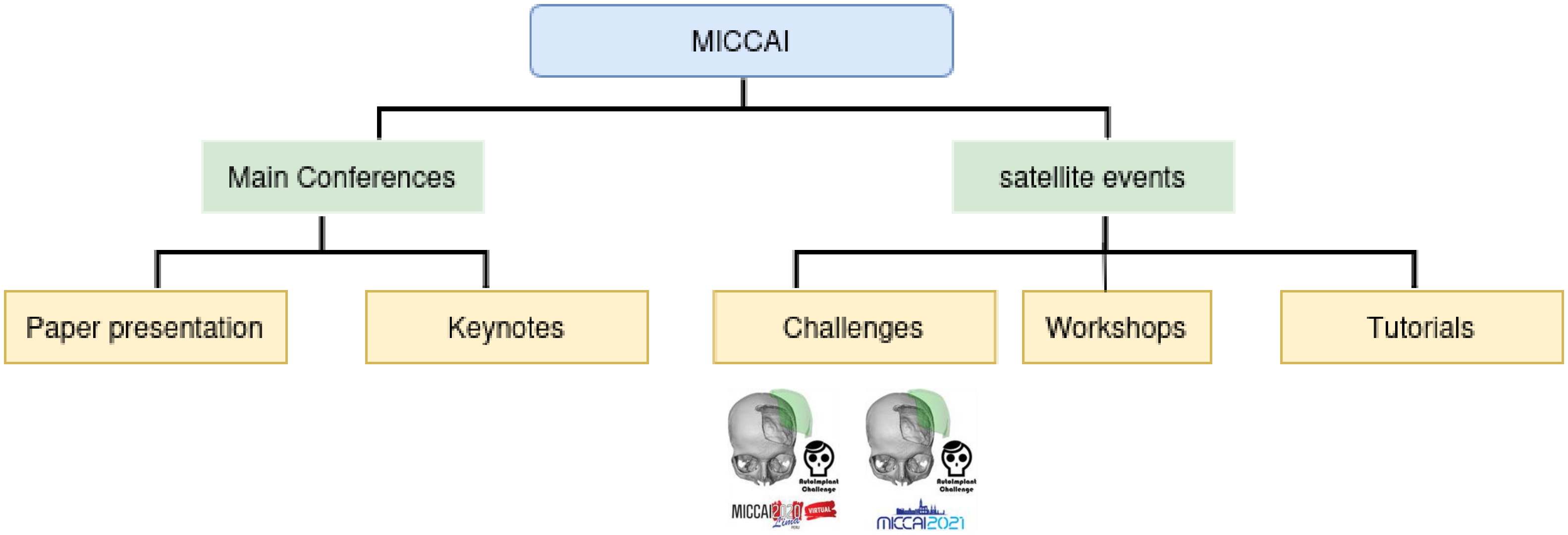
# Deep Learning for Cranial Implant Design: Insights from Two Years' MICCAI Challenges

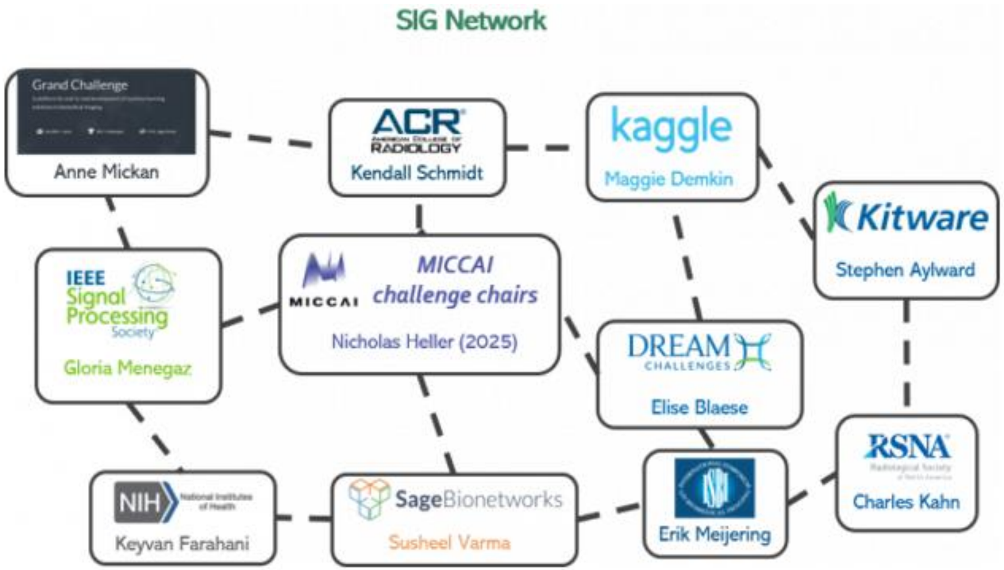
Department Meeting Talk 2025-03-25

Jianning Li, Zuse Institute Berlin

# MICCAI Challenge



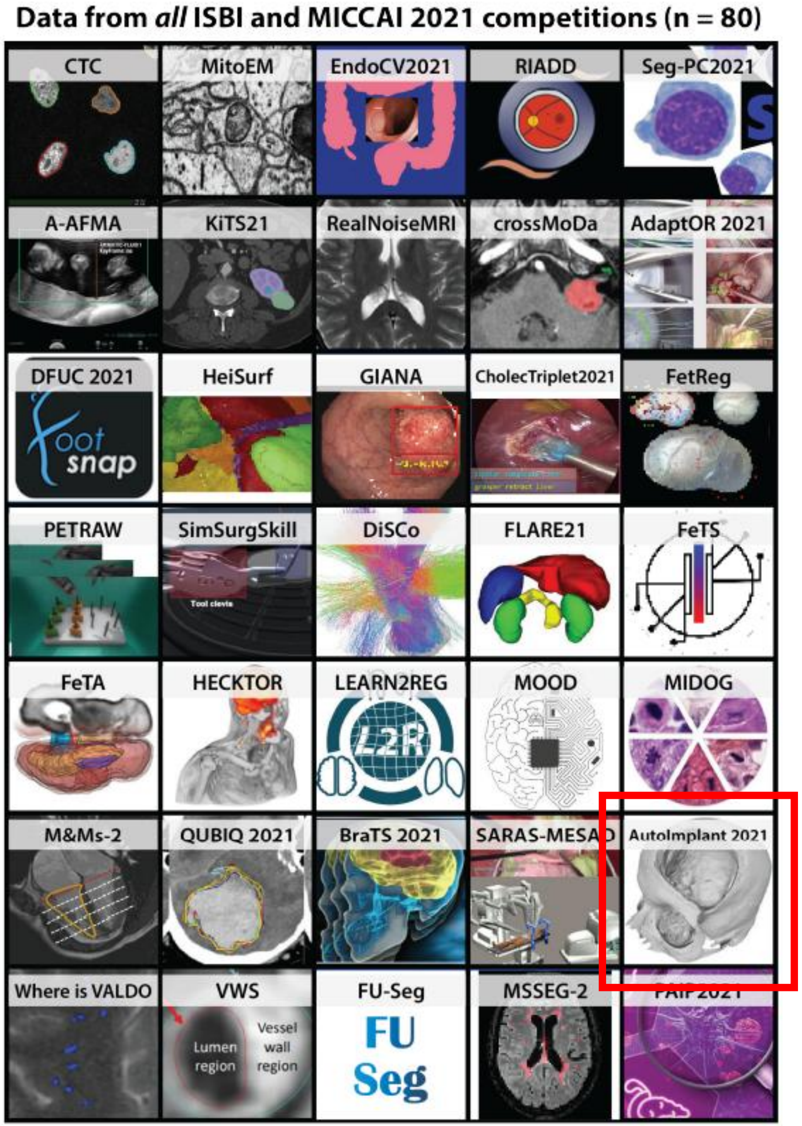
# MICCAI Challenge: Special Interest Group (SIG)

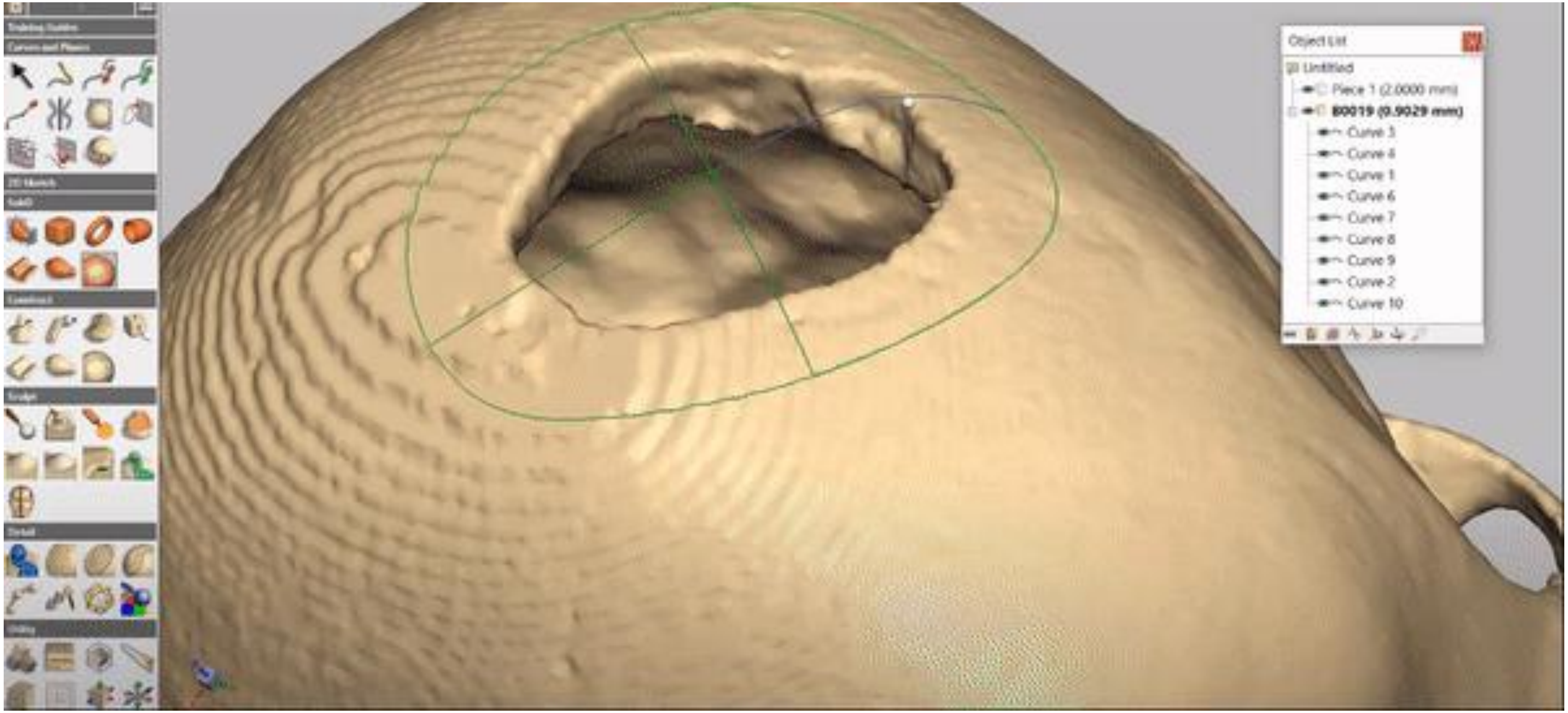
MICCAI Challenge

# Why is the winner the best?

CVPR 2023

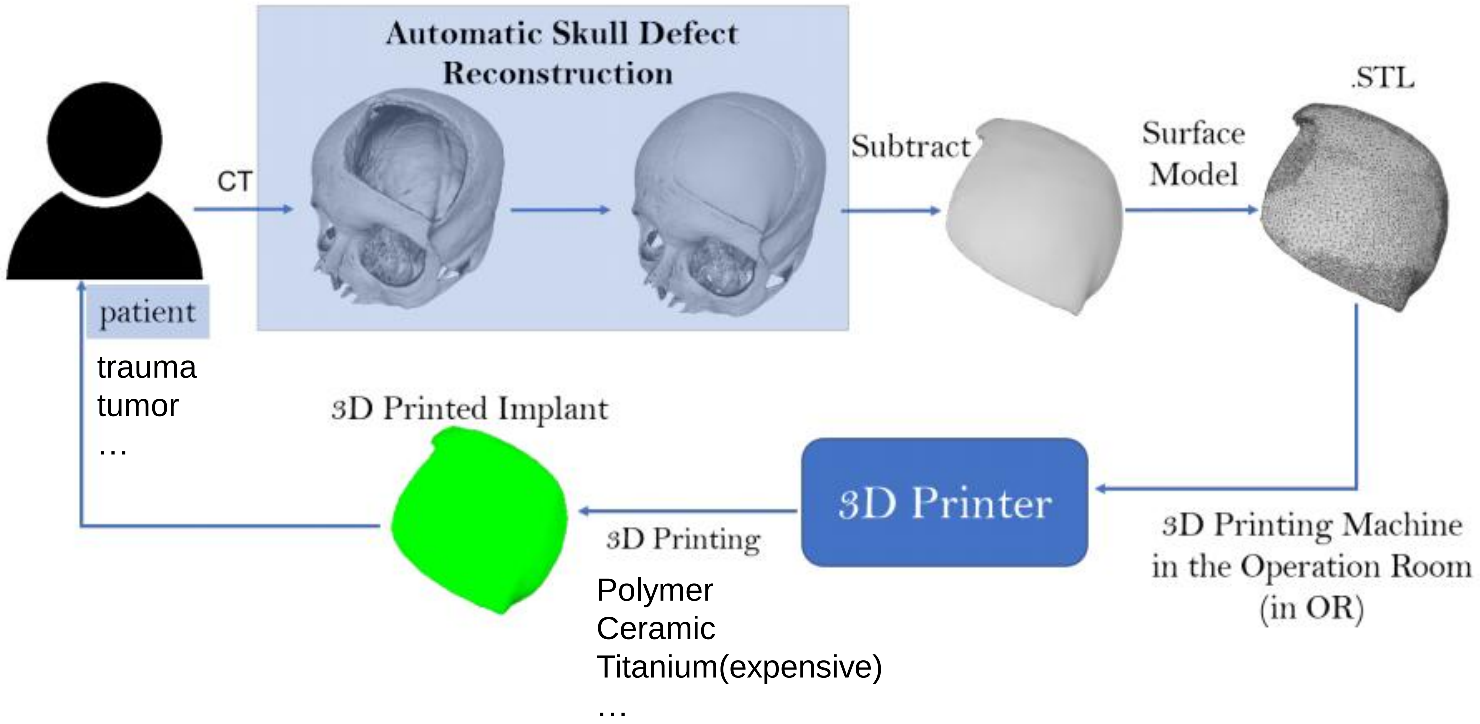


# Cranial Implant Design: Manual Design

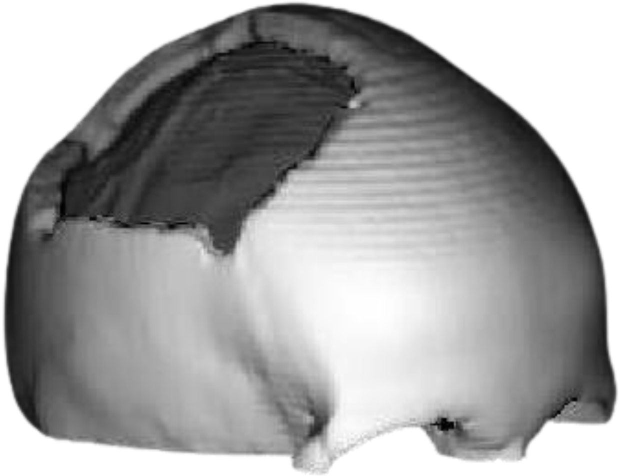


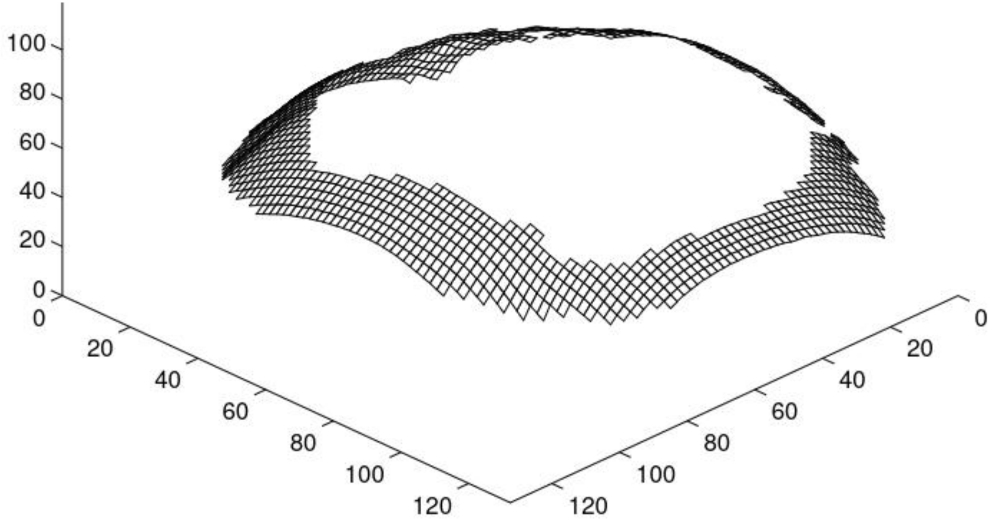
# Cranial Implant Design: 3D Printing

# Cranial Implant Design



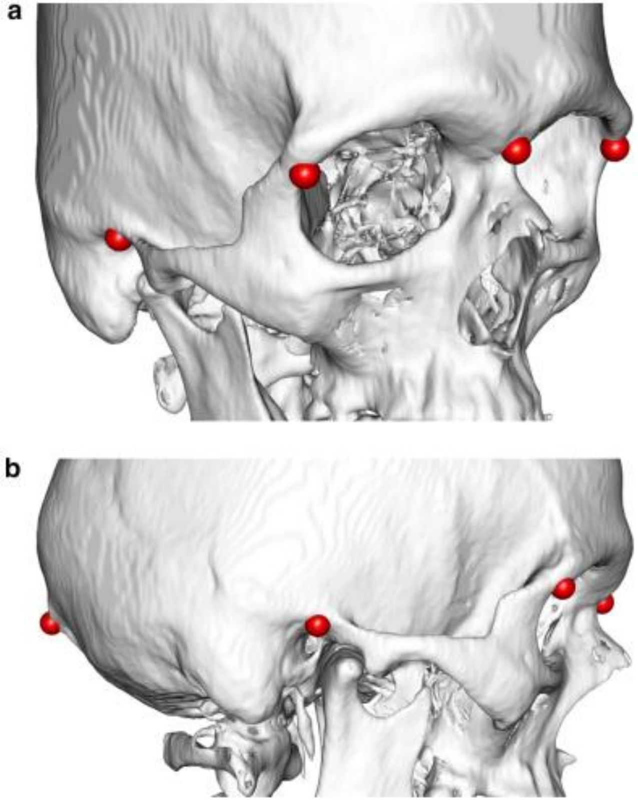
# Cranial Implant Design: Surface interpolation using RBF



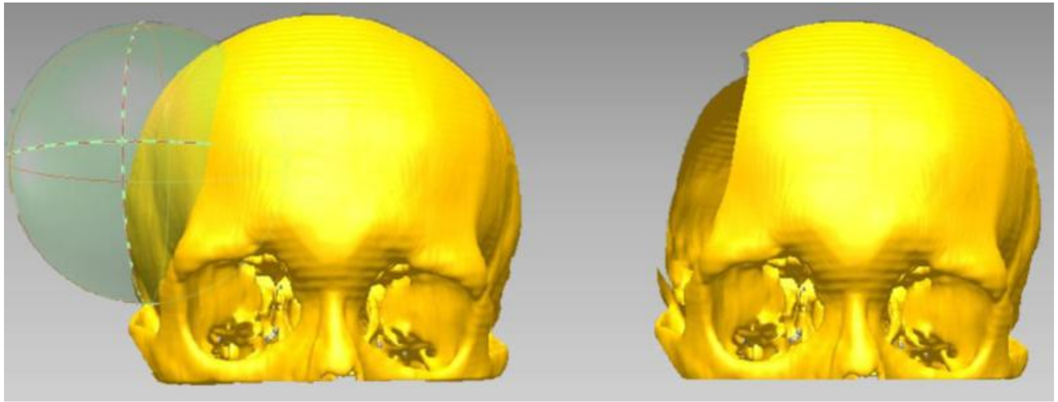



[Carr, J.C., 1997, IEEE TMI]

# Cranial Implant Design: Statistical shape model




manual landmarks

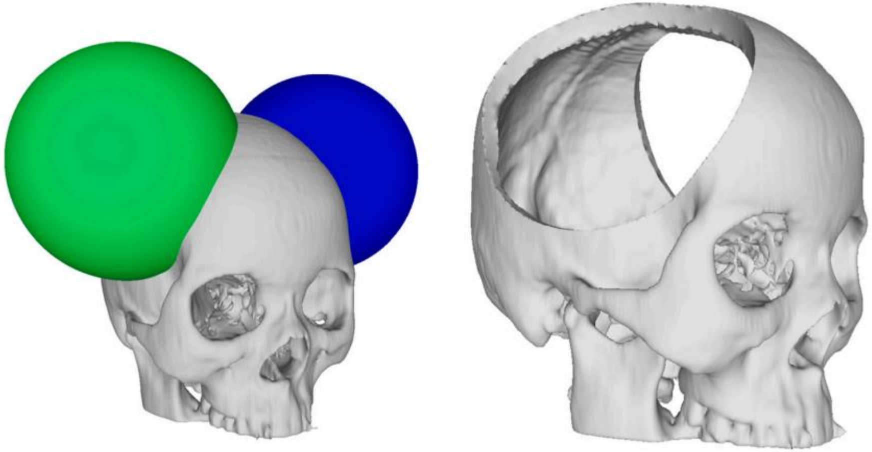


virtual defects

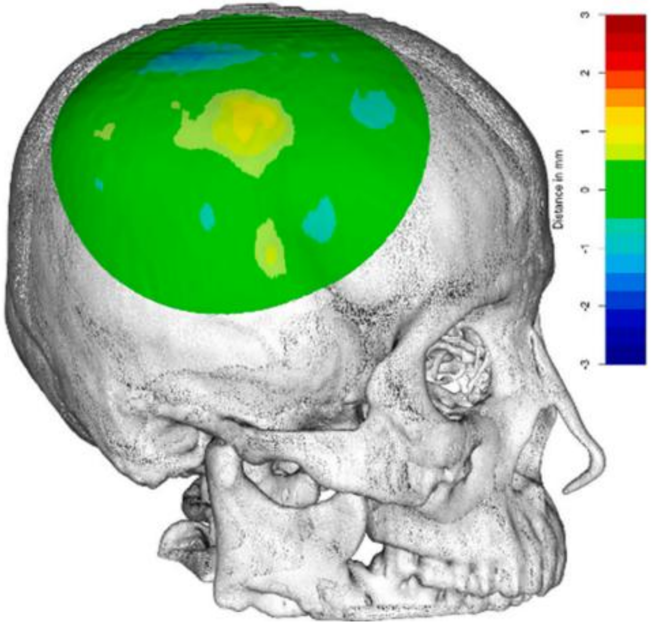
[Fuessinger, M.A., **2018**, IJCARS]

# 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 Challenge

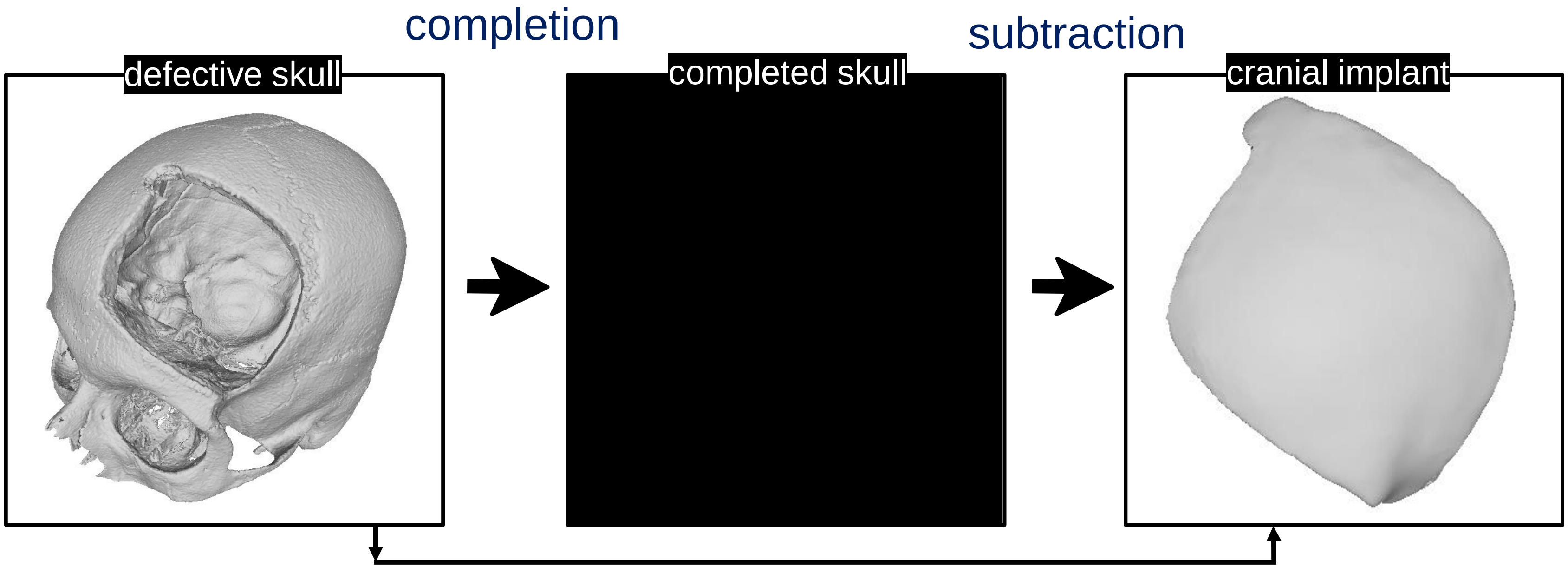
MICCAI 2021

*AutoImplant II*

MICCAI 2020 Lima PERU VIRTUAL

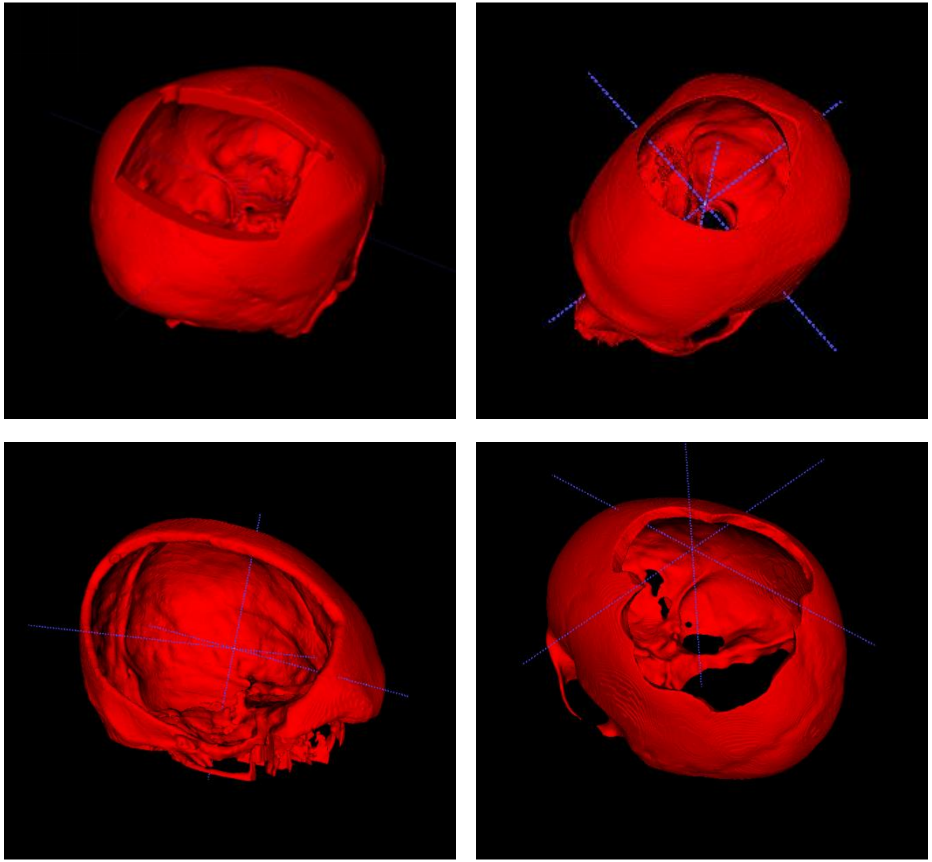
*AutoImplant I*

# 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, <u>border DSC</u>, <u>neurosurgeons' scores</u>

# 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 ($1^{st}$ 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*.

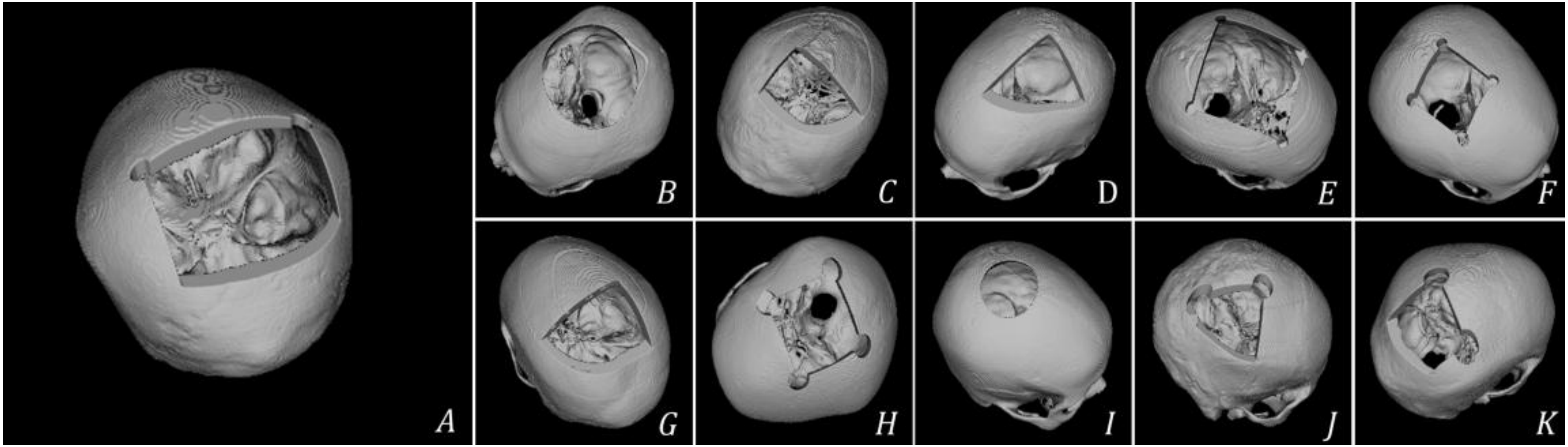
# Technical Challenges

- Generalization
- High memory footprint
- Clinical feasibility

# Technical Challenges

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

## Generalization

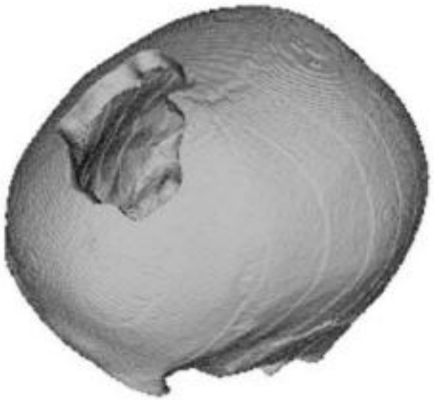


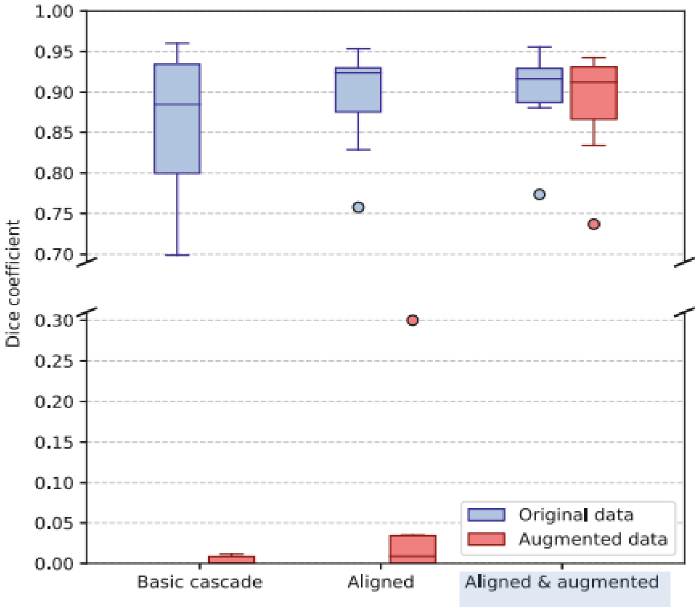

**AutoImplant I:** 5 out of 11 submissions failed on the 10 out-of-distribution cases.
**AutoImplant II:** only 3 teams attempted clinical cases with irregularly shaped defects.

# Generalization

Data augmentation:

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





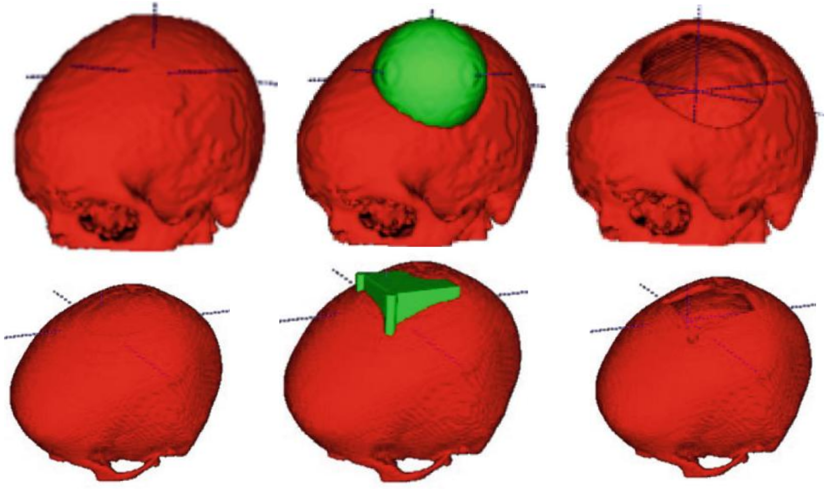

| | Test case (100) | Test case (10) | Overall (110) |
|---|---|---|---|
| Mean DSC | 0.920 | 0.910 | 0.919 |
| Mean HD | 4.137 | 4.707 | 4.189 |

[Kodym, O et al]

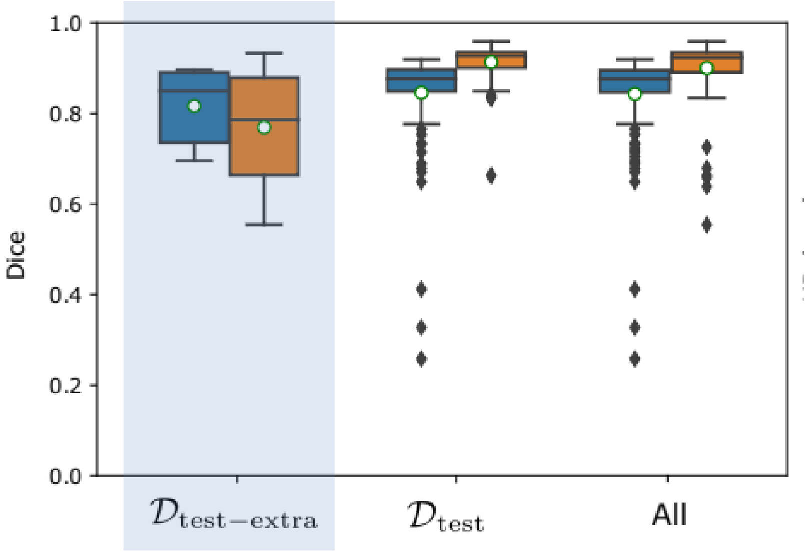
# Generalization

Data augmentation:

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



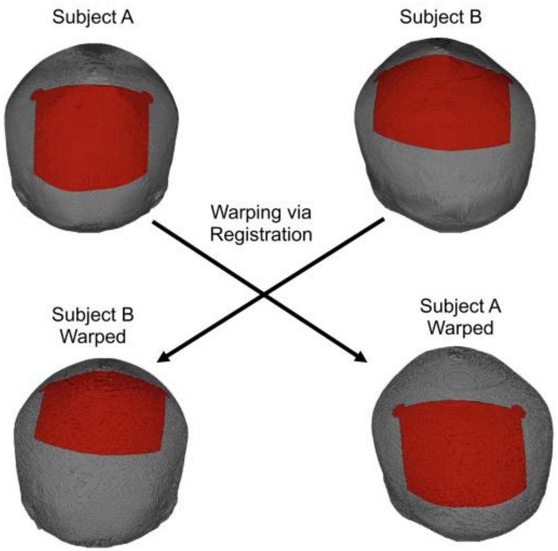
[Matzkin, F et al]

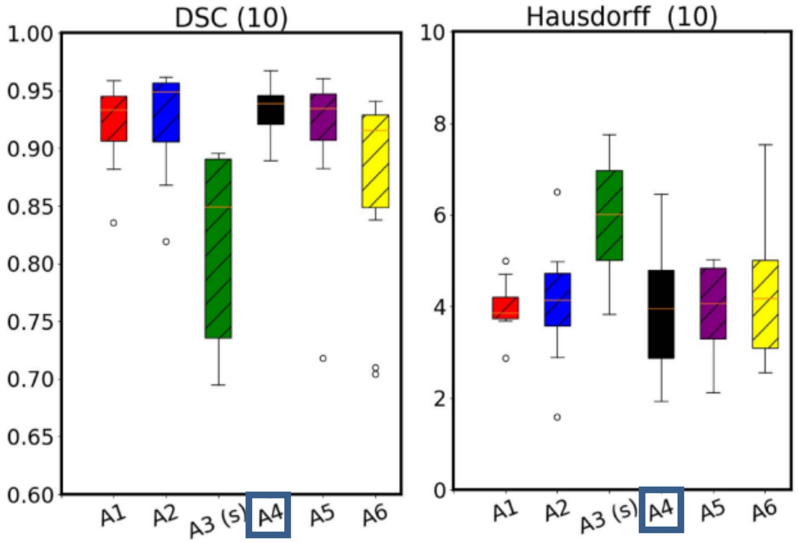


# Generalization

Data augmentation:

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



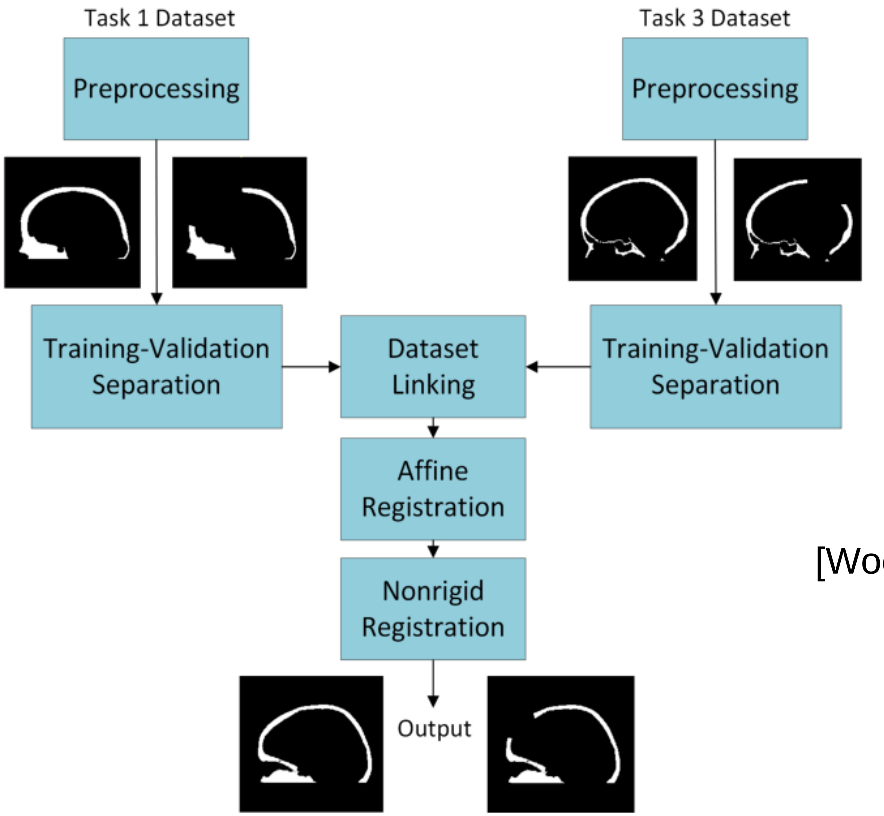




[Ellis, D.G. et al]

# Generalization

Data augmentation:

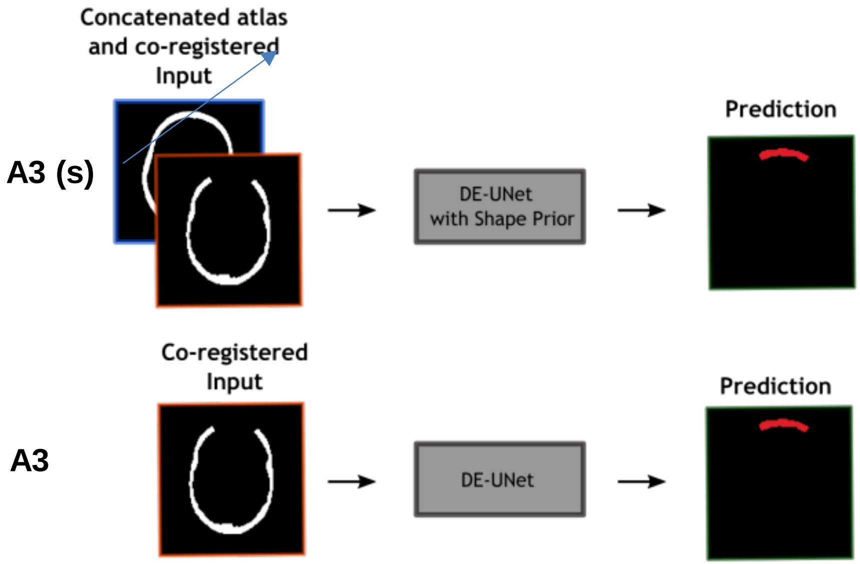
- intensive augmentation + dataset linking (**1st place, AutoImplant II**)

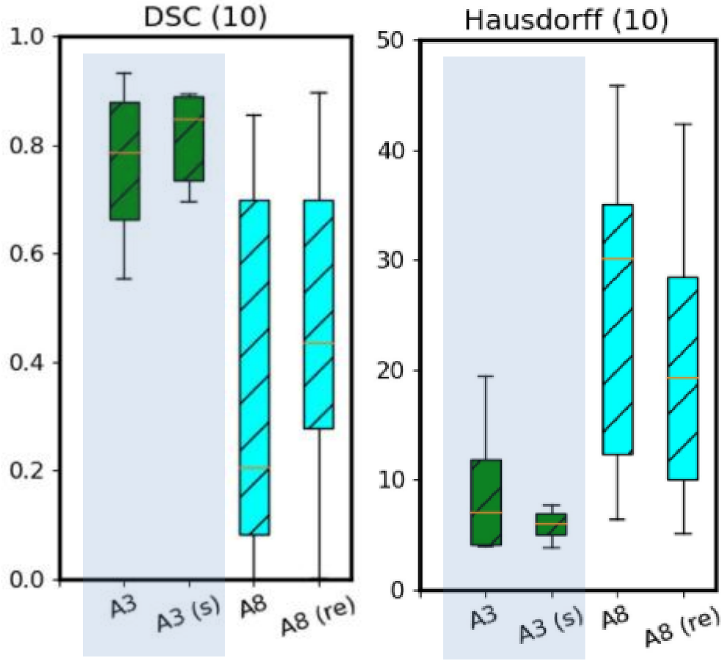



[Wodzinski, M et al]

# Generalization

Use a shape prior (average shape of healthy skulls)



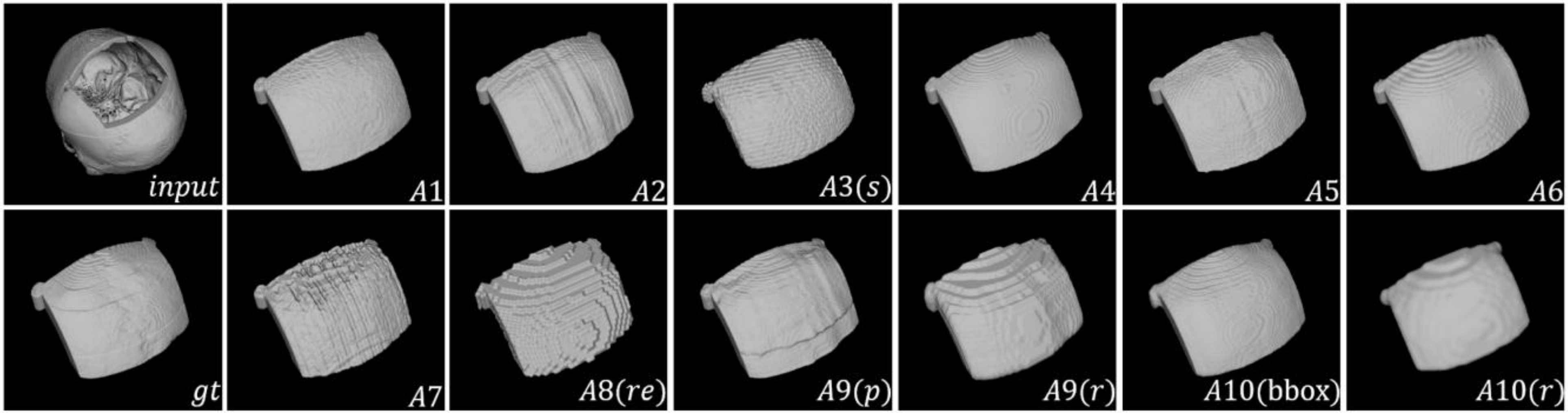




[Matzkin, F et al]

## Technical Challenges

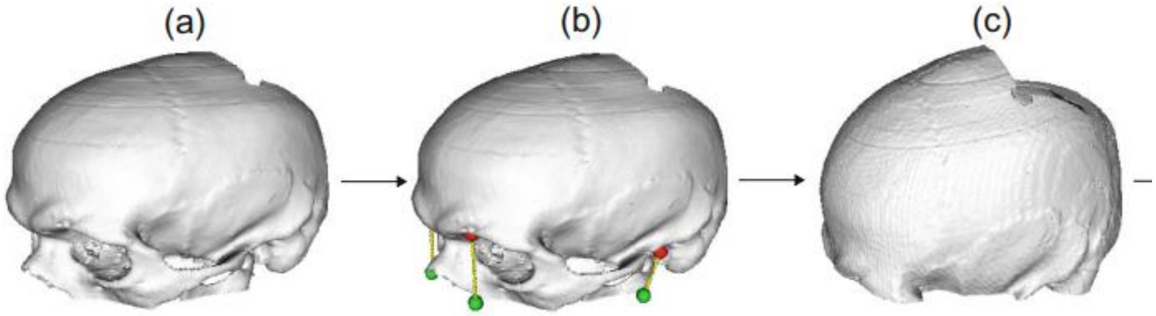
- Generalization
- **High memory footprint**
- Clinical feasibility

# High Memory Footprint

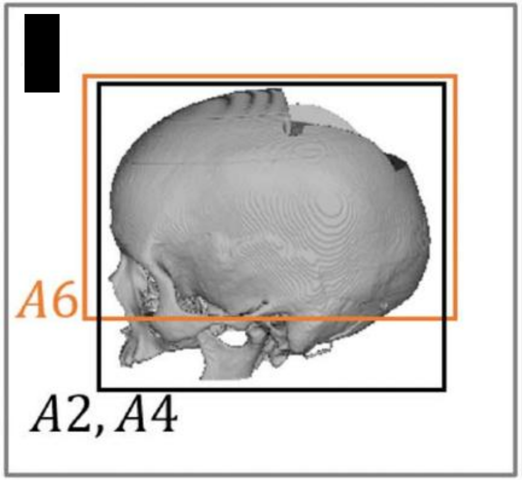


# High Memory Footprint

Cropping:
- Keep only the ROI



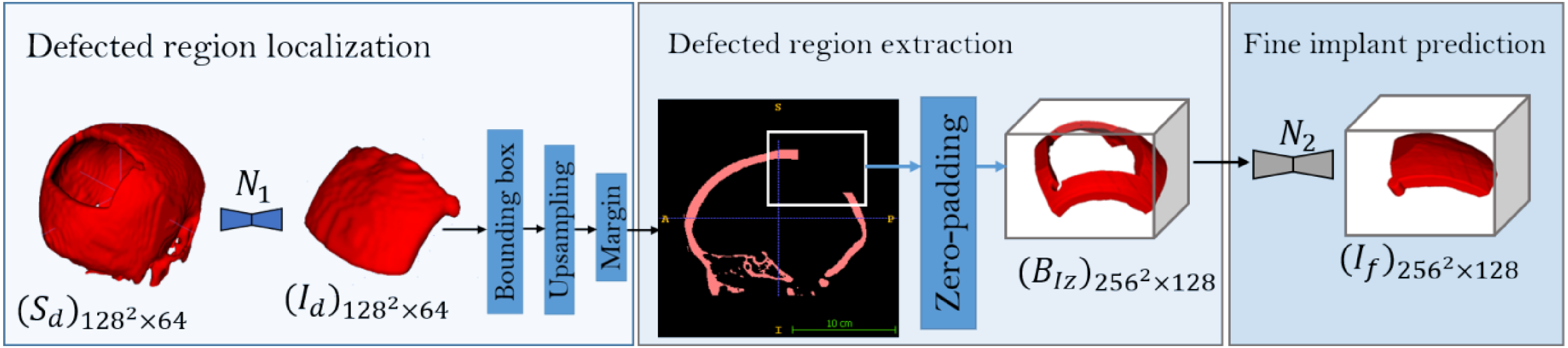

[Kodym, O et al]



# High Memory Footprint

Core-to-fine:

- Use two networks

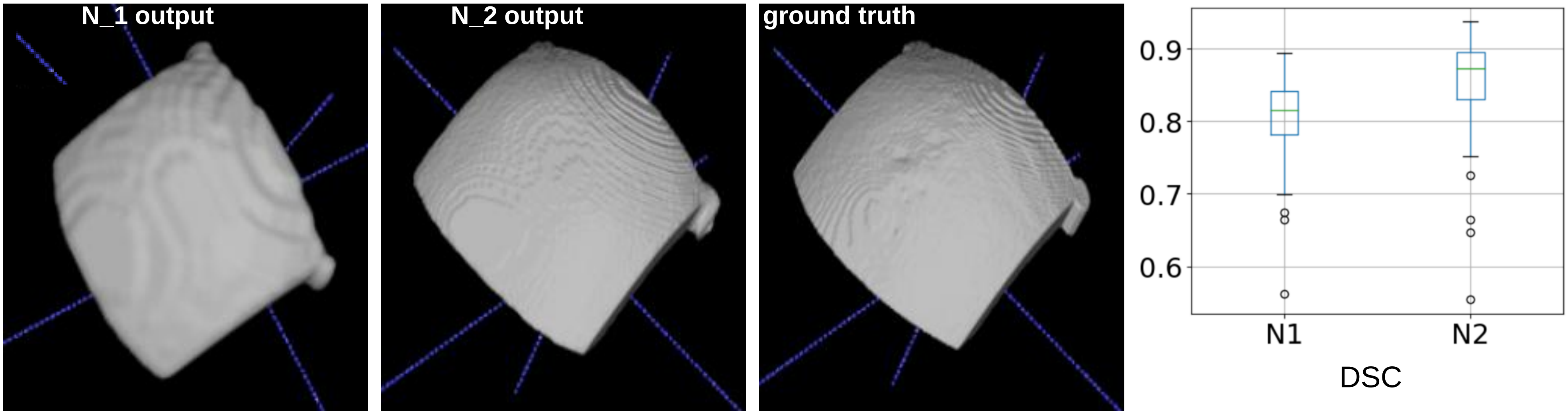



[Li, J .et al]

# High Memory Footprint

Core-to-fine:

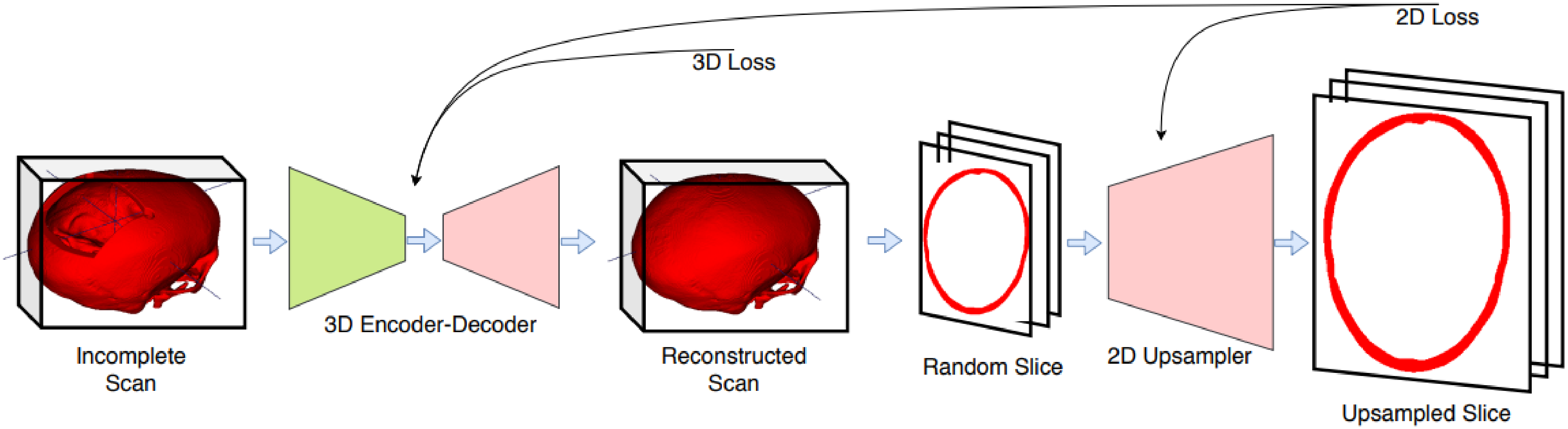
- Use two networks




[Li, J .et al]

# High Memory Footprint

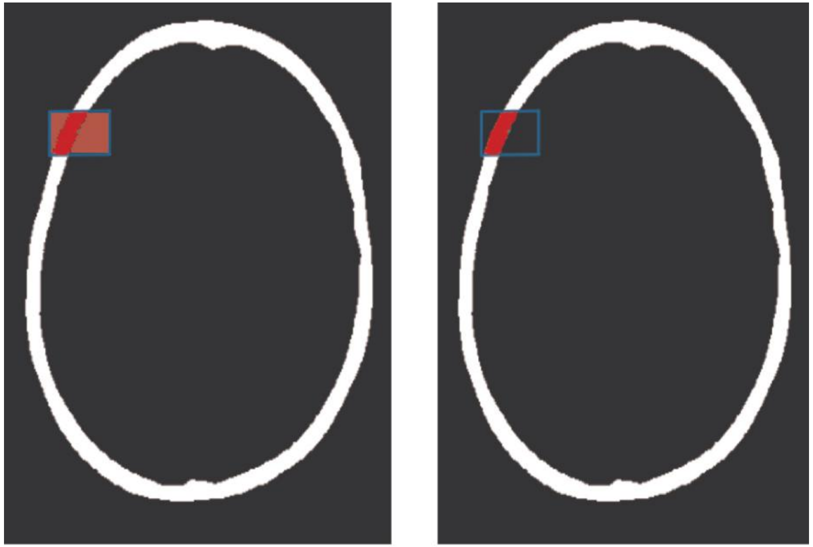
Core-to-fine:
- Use two networks




[Bayat, A et al]

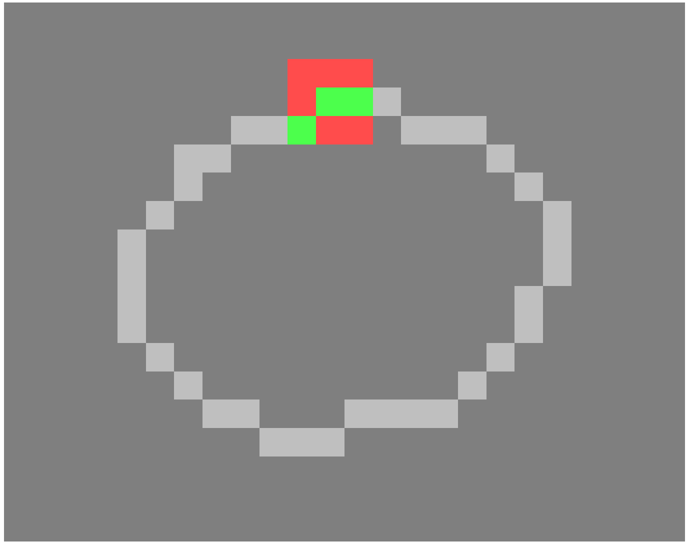
# High Memory Footprint

Use sparse convolutions



*(a) Traditional convolution*

*(b) Sparse convolution*

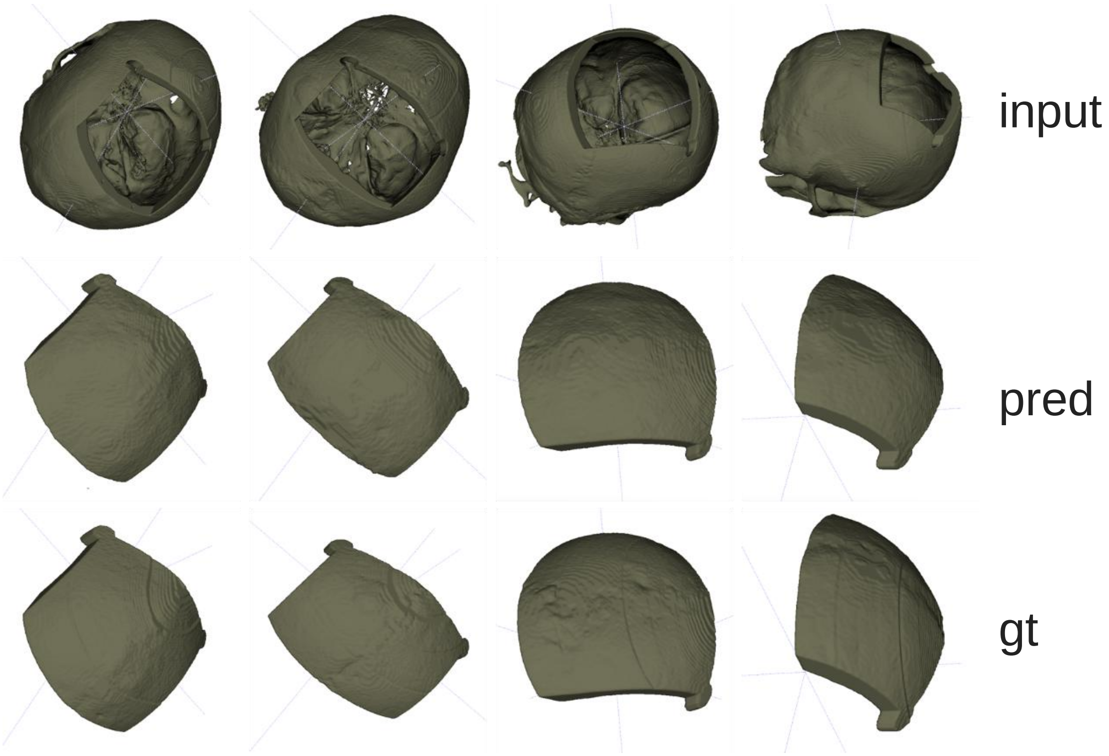


[Graham, B et al]

[Li, J .et al]

# High Memory Footprint

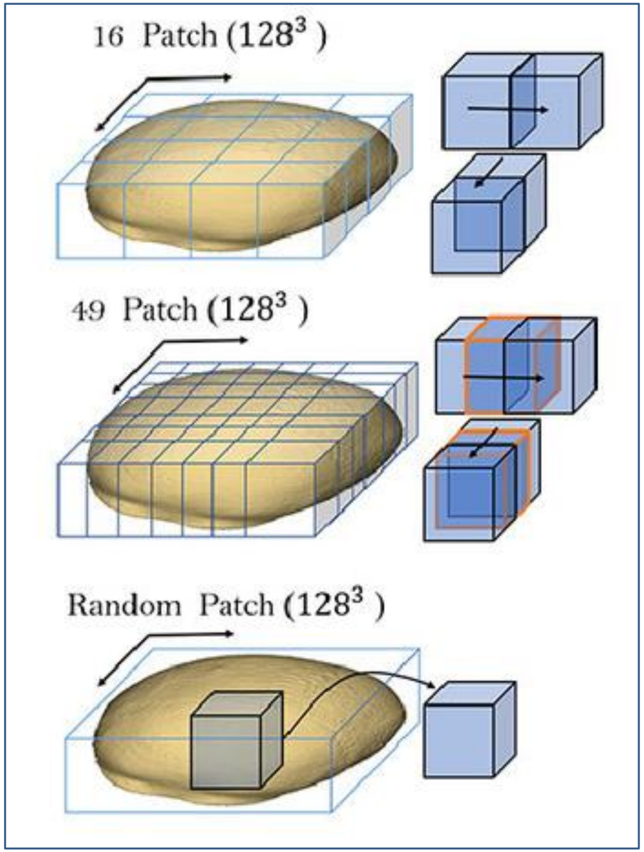
Use sparse convolutions: implant generationa **at full resolution 512x512xZ**




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

# High Memory Footprint

Patch-wise training



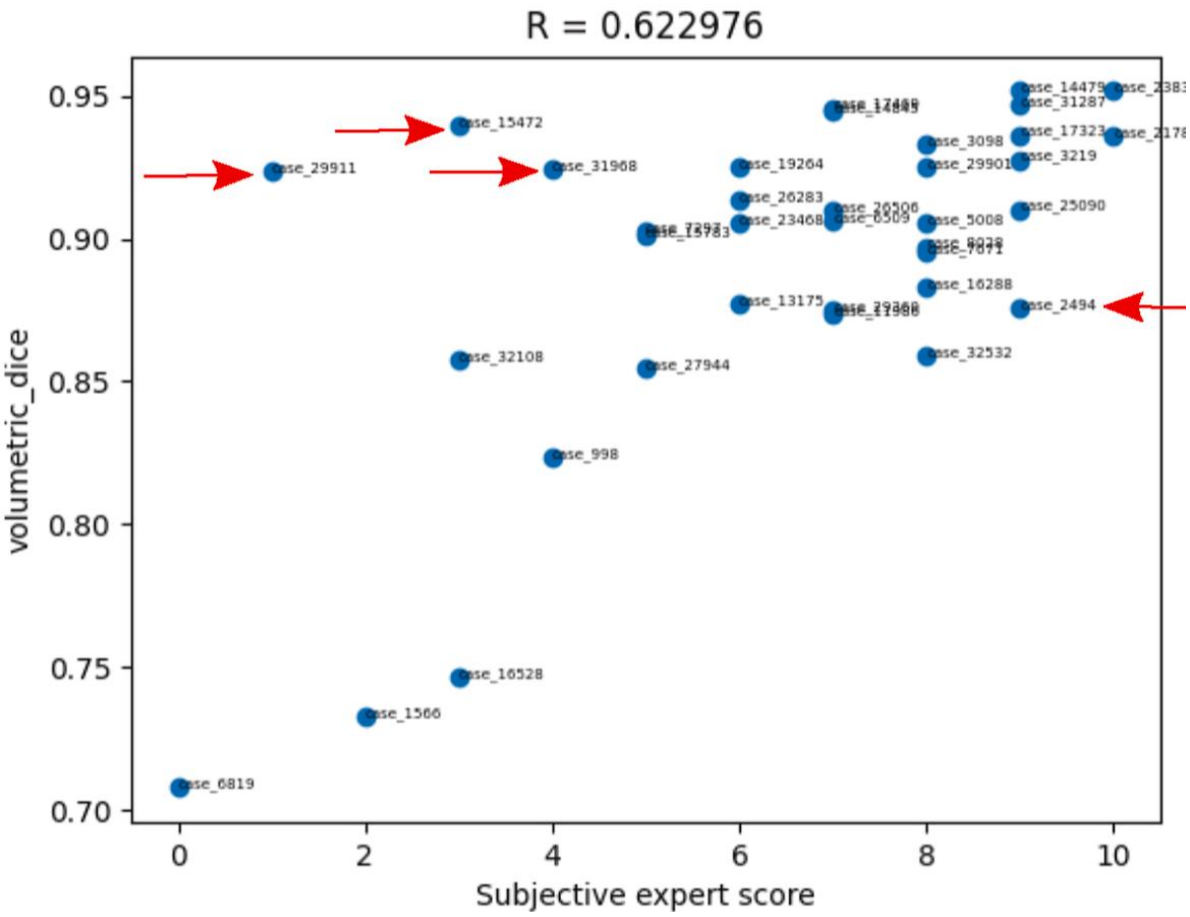

[Li, J .et al]

## Technical Challenges

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

# Clinical Feasibility

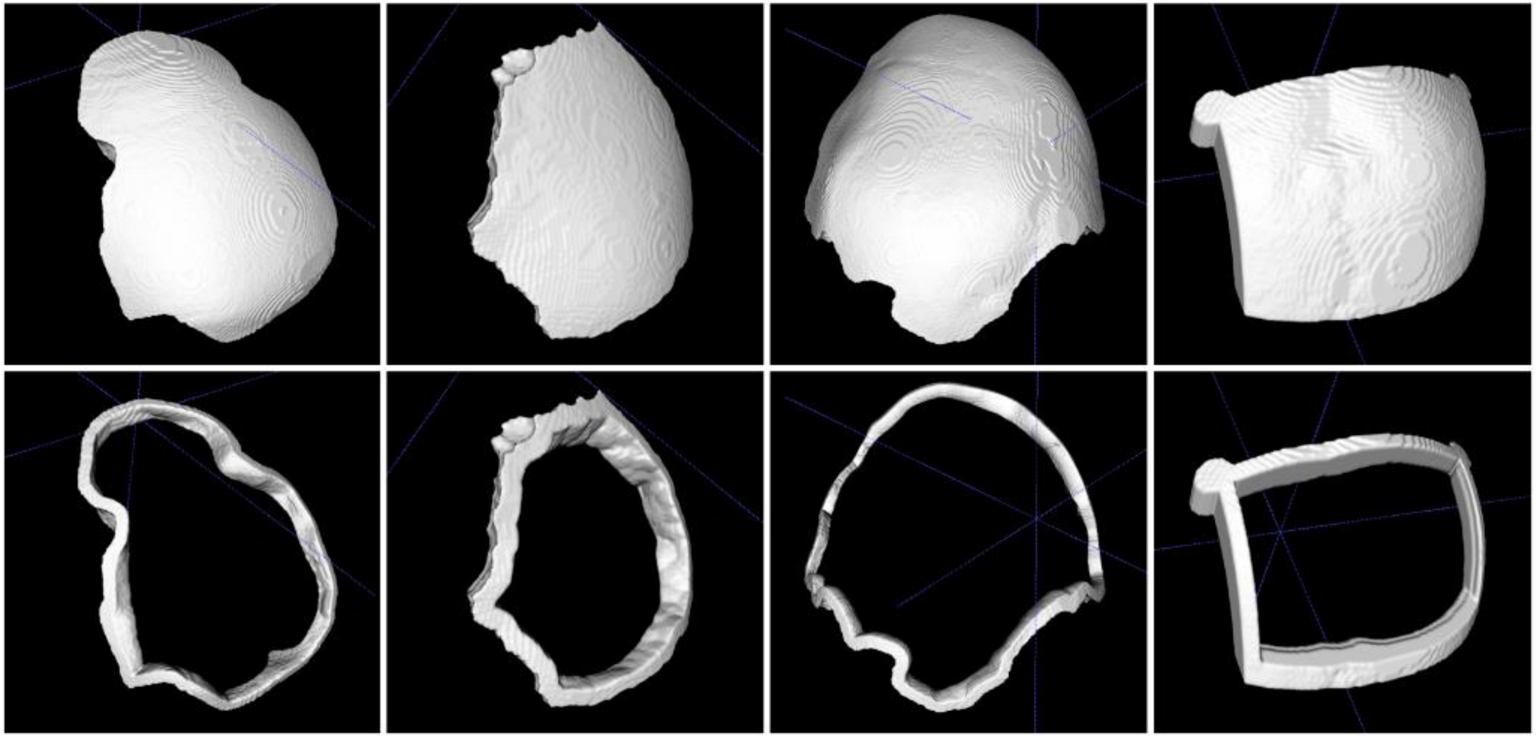
Correlation between **quantitative score** (Dice) and **experts‘ evaluation (gold standard)**




[Kodym, O et al]

# Clinical Feasibility

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]

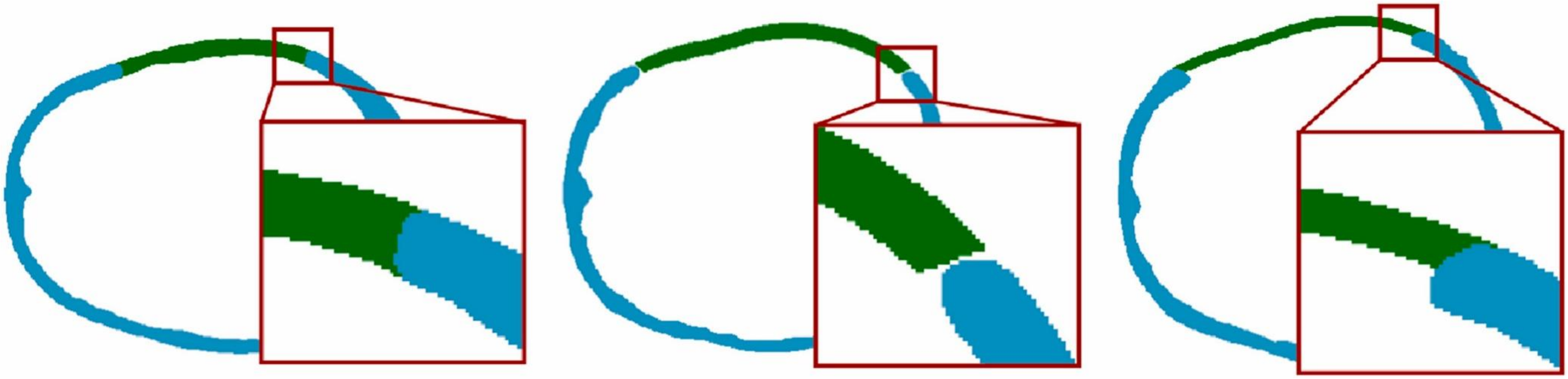
# Clinical Feasibility

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

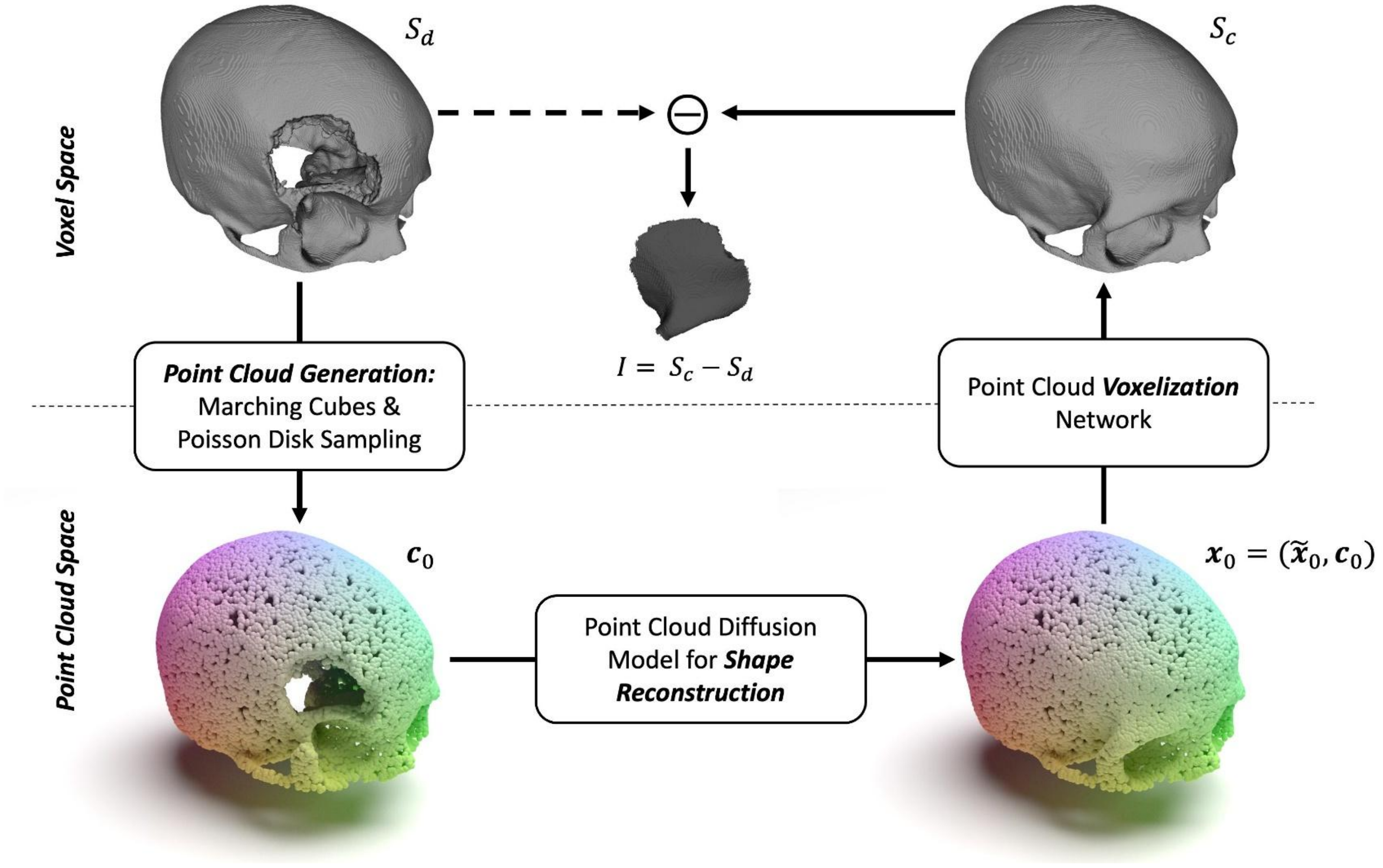
Li, J., et al., 2021. ***AutoImplant 2020-first MICCAI challenge on automatic cranial implant design***. *IEEE transactions on medical imaging*, *40*(9), pp.2329-2342.

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

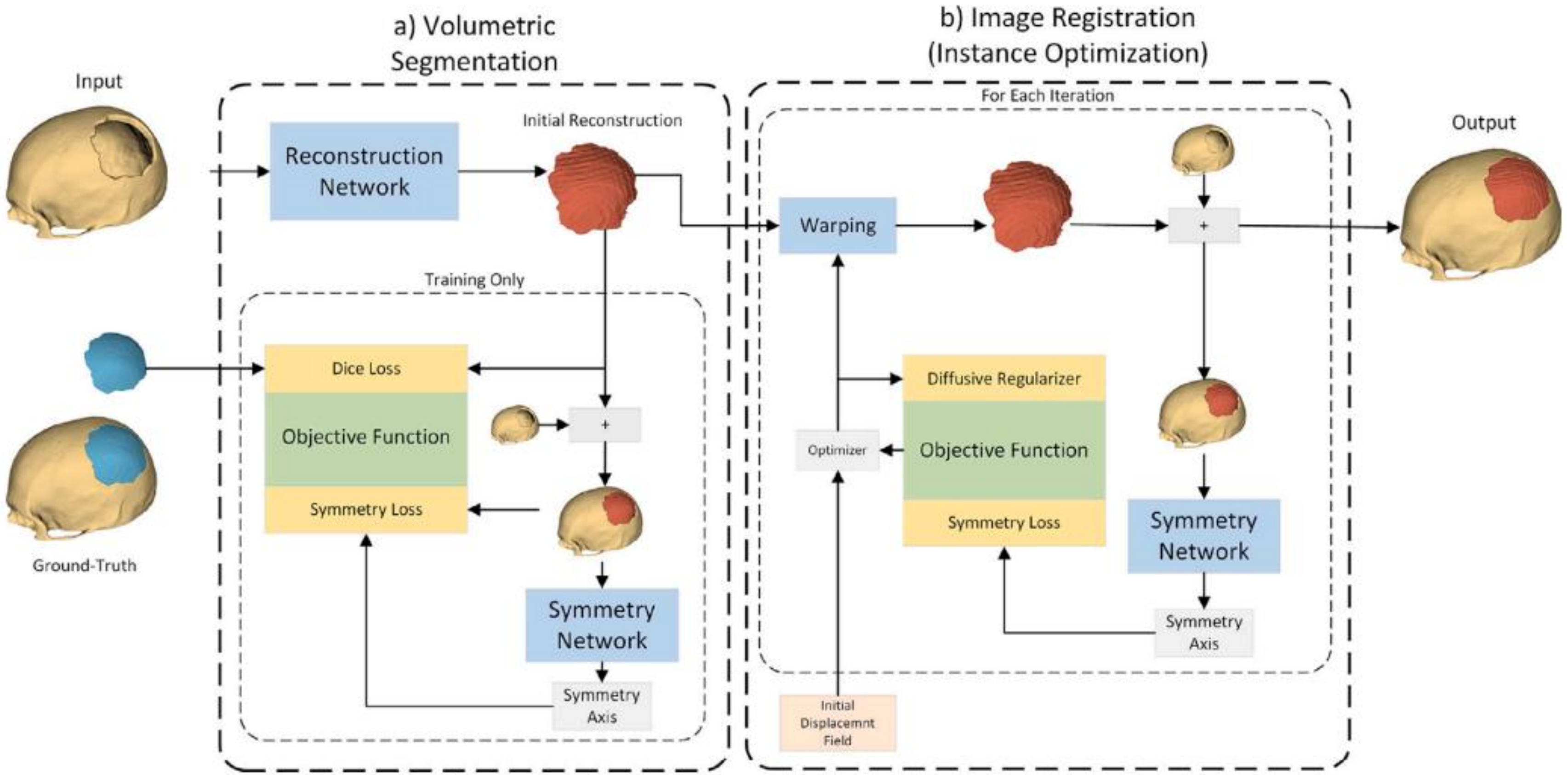
# Point Cloud Diffusion Models for Automatic Implant Generation

MICCAI **2023**, Paul Friedrich, University of Basel



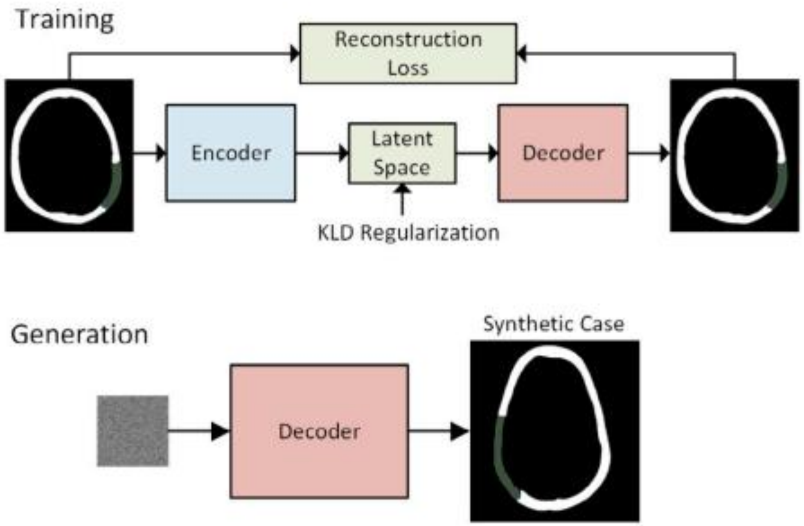
# Automatic skull reconstruction by deep learnable symmetry enforcement

Marek Wodzinski, CMPB **2025**

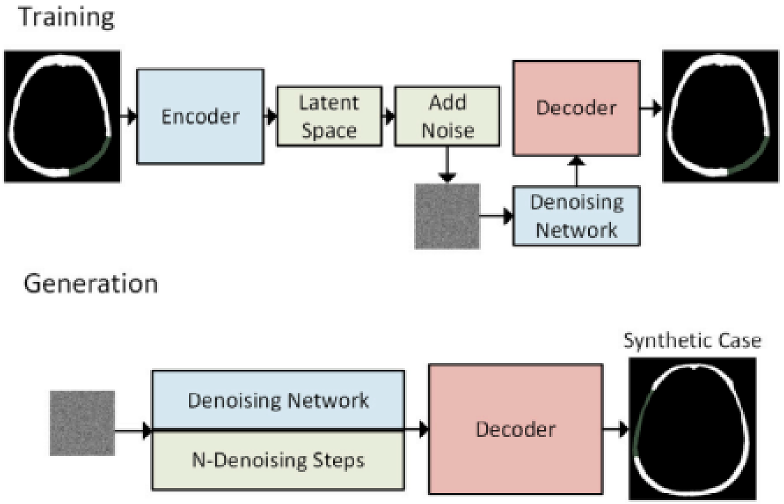


# Improving deep learning-based automatic cranial defect reconstruction by heavy data augmentation: From image registration to latent diffusion models

Marek Wodzinski, CBM **2024**




VAE

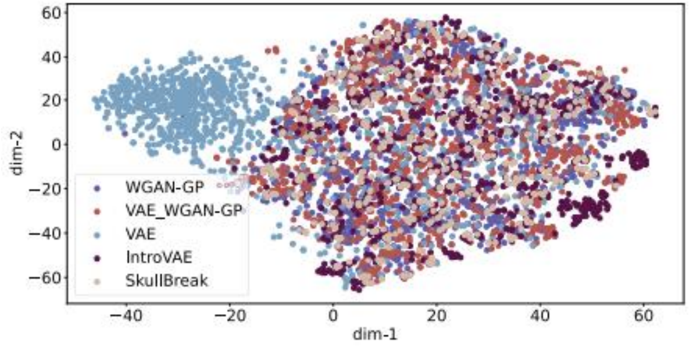



Diffusion model

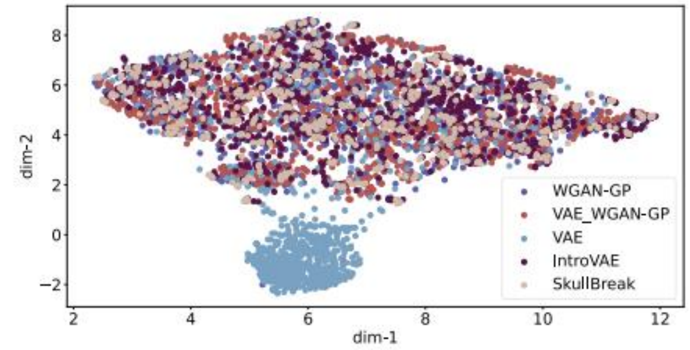
# Deep Generative Networks for Heterogeneous Augmentation of Cranial Defects

Kamil Kwarciak, Marek Wodzinski, ICCV **2023**

- WGAN-GP,
- VAE/WGAN-GP
- IntroVAE

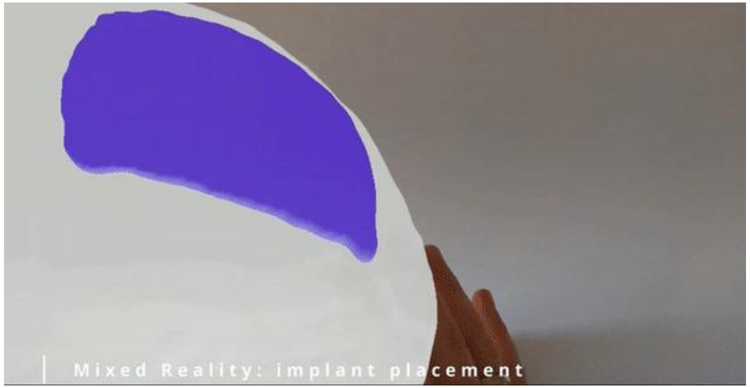



(a)

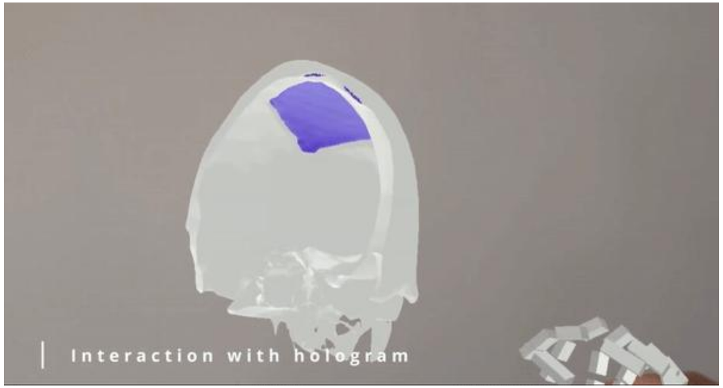


# Deep learning-based framework for automatic cranial defect reconstruction and implant modeling

Marek Wodzinsk  CMPB **2022**




virtual inspection




virtual interaction & see inside

# Thank you for your attention