BOOSTING 3D LIVER SHAPE DATASETS WITH DIFFUSION MODELS AND IMPLICIT NEURAL REPRESENTATIONS

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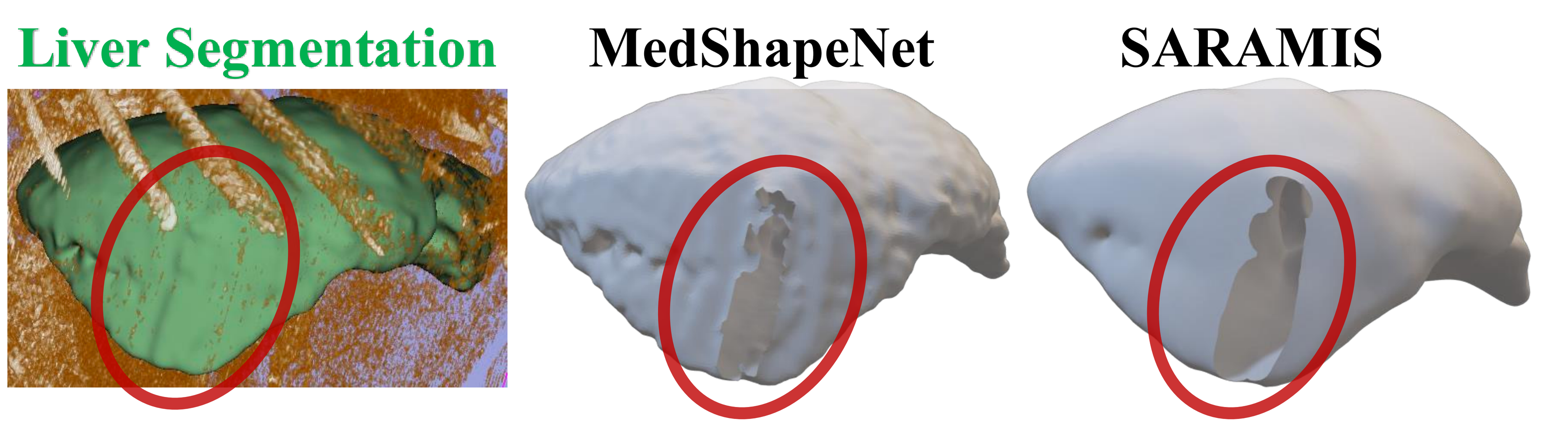
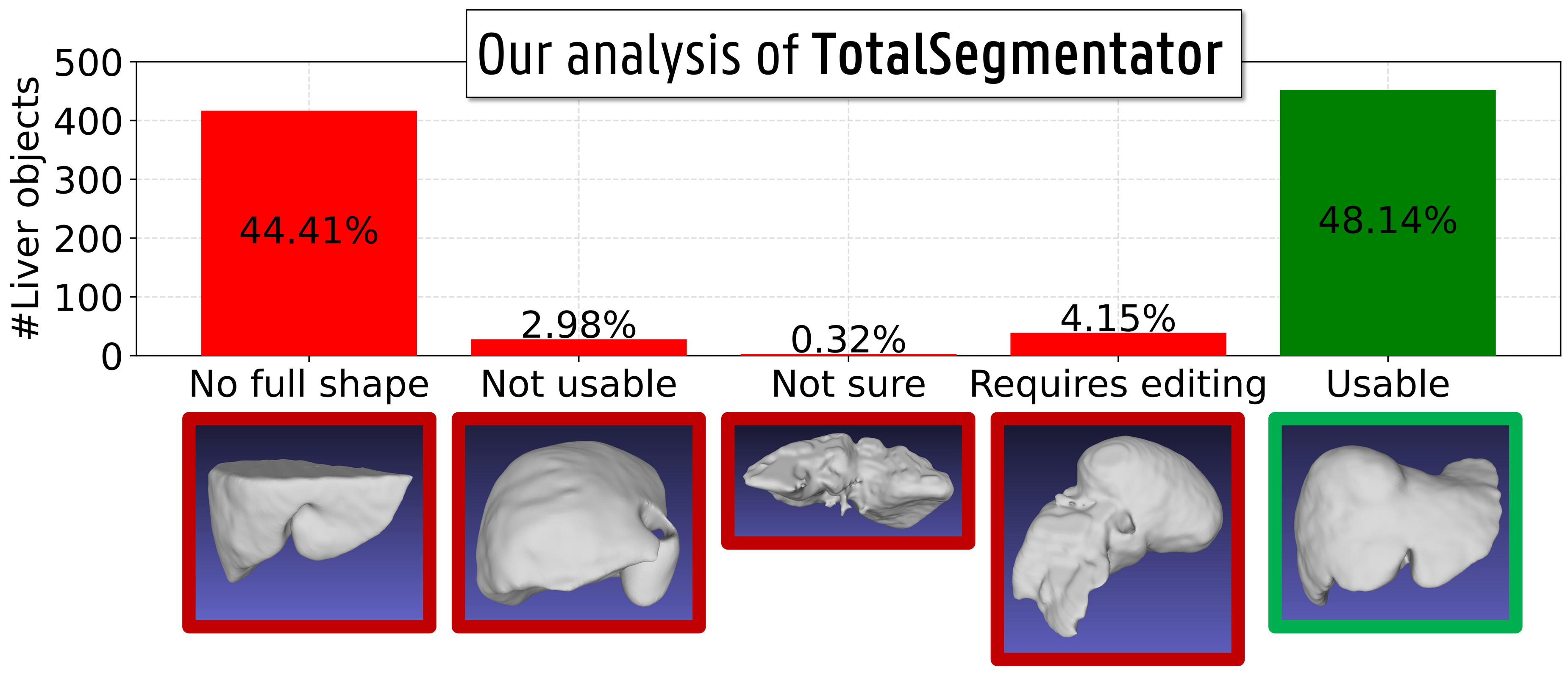
Introduction: 3D Shape Dataset Problem

We found that many 3D liver shape datasets are unfortunately disorganized and contain artifacts.

Artifacts from Segmentation-to-3D conversion



Our analysis of **TotalSegmentator**

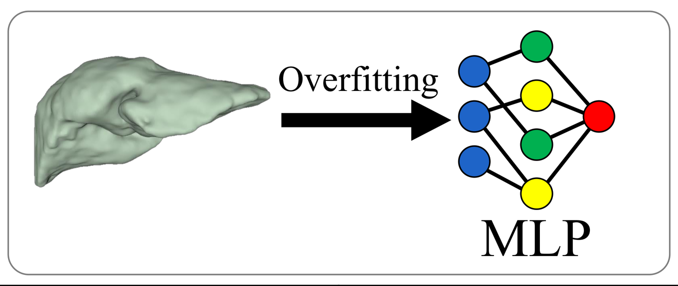


452 usable liver objects are too few → we generate synthetic data with HyperDiffusion

Method: 3D Liver HyperDiffusion

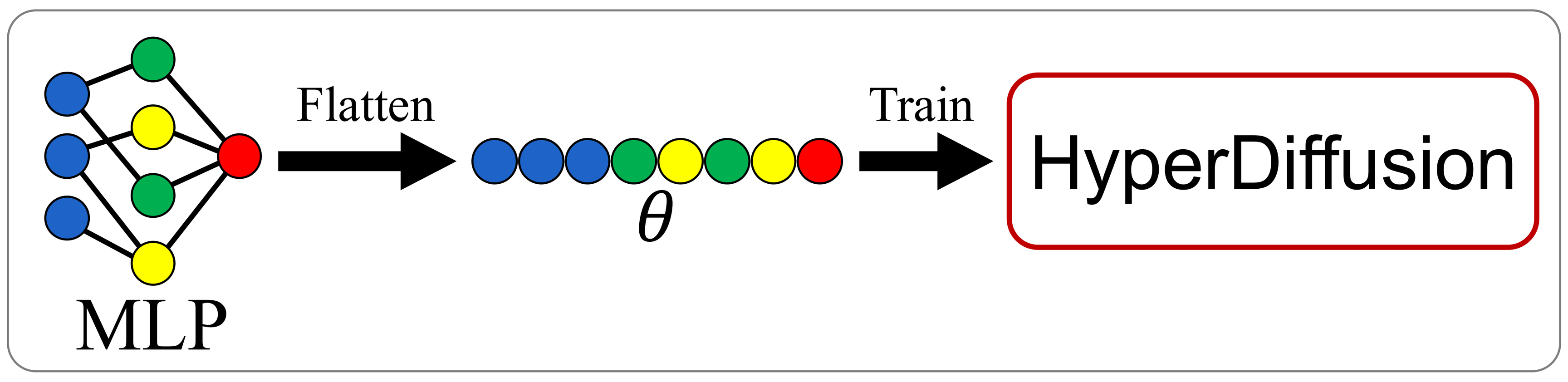
Our framework consists of two training stages:

(1) training MLPs to represent each 3D liver



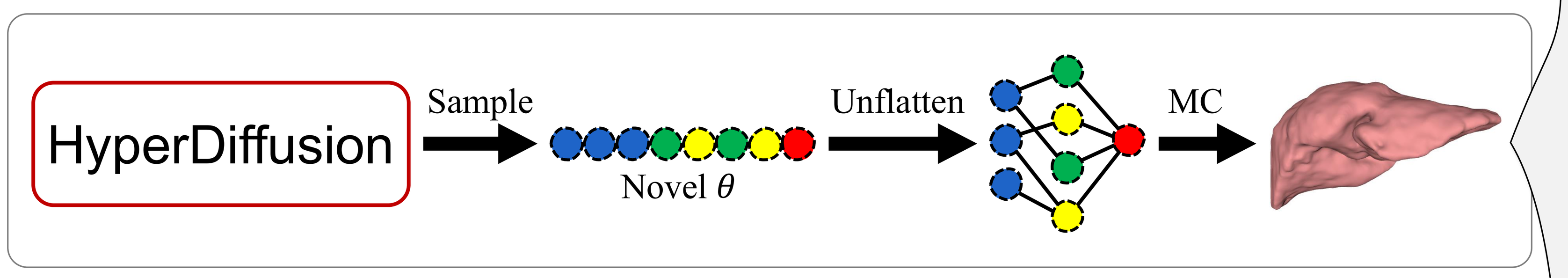
VIoU ↑	Chamfer-L_1 ↓	NC ↑	F-Score ↑
0.9747 ± 0.0043	0.0028 ± 0.0003	0.9780 ± 0.0053	1.0000 ± 0.0000

(2) training a HyperDiffusion model on the MLP weights

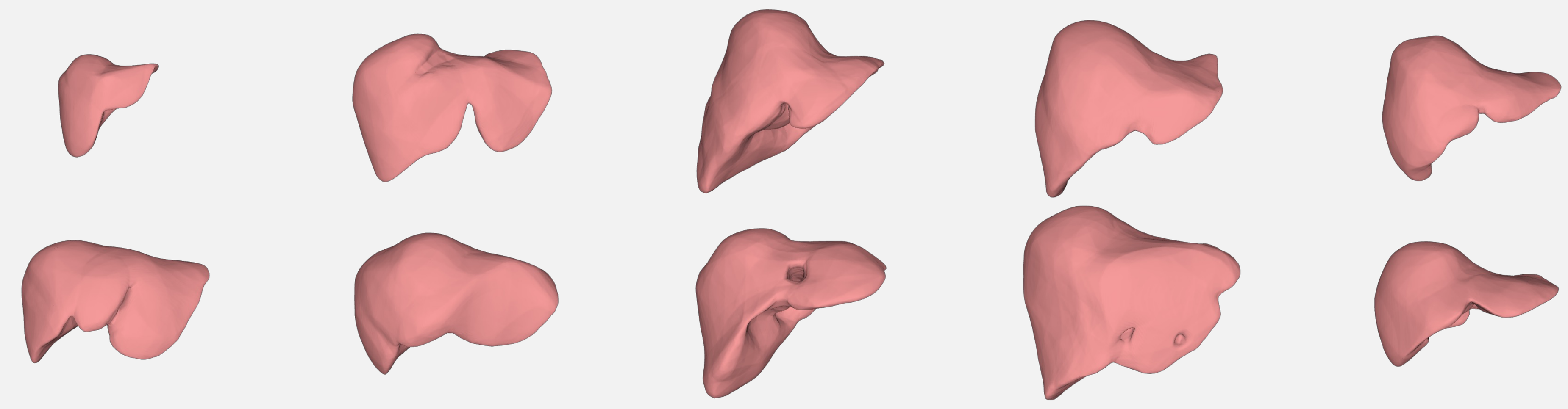


Results: Synthetic Dataset Generation

We sample new MLPs and reconstruct 3D liver objects.

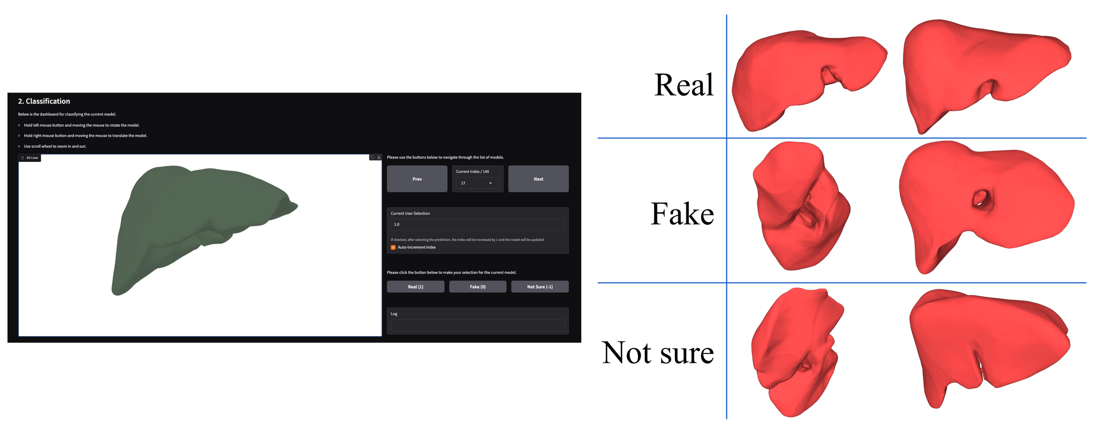


Visualization and metrics of synthesized 3D liver objects



Model Type	MMD ↓	COV (%) ↑	1-NNA (%) ↓	FPD ↓
Transformer	**0.24**	**55.88**	**53.68**	**2.27**
1D UNet	0.25	42.65	68.38	6.41

Our surgical team conducted an additional survey to classify 75 real and 75 synthesized 3D liver objects. Based on the results, the synthesized objects appear realistic, as most were classified as real.



Discussion and Future work

- We addressed the shortage of high-quality 3D medical data by using HyperDiffusion to synthesize livers that resemble real structures
- Our current work is limited to the liver, but future work will extend to other human organs
- Additionally, future work includes adding conditional generation to HyperDiffusion (text-to-3D, image-to-3D)
- Finally, since expert evaluation is time-consuming and labor-intensive, we will develop supportive evaluation methods to accelerate this process

Scan for the Code

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