BENCHMARKING MEDICAL SEGMENTATION MODELS WITH LIMITED TRAINING SETS

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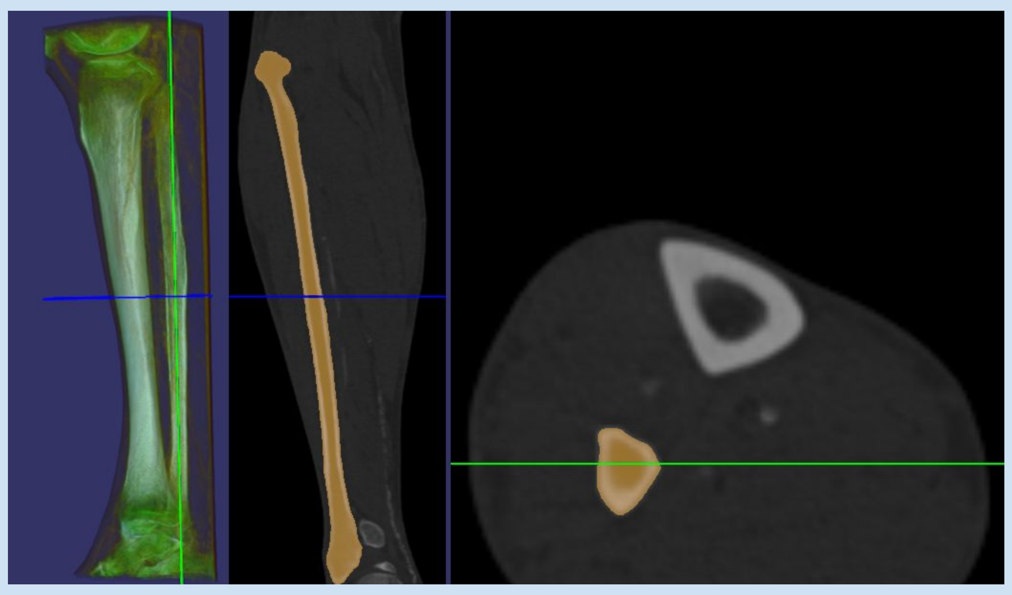
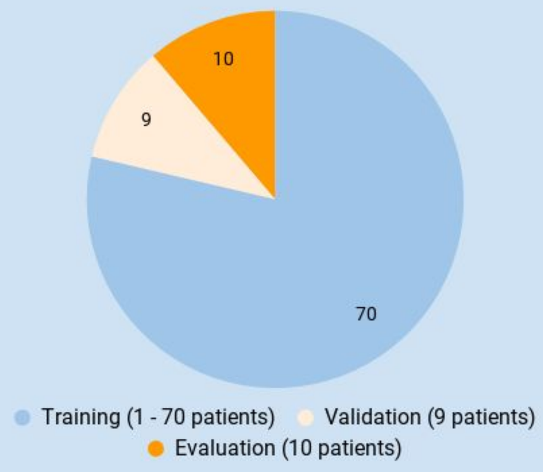
What is it about?

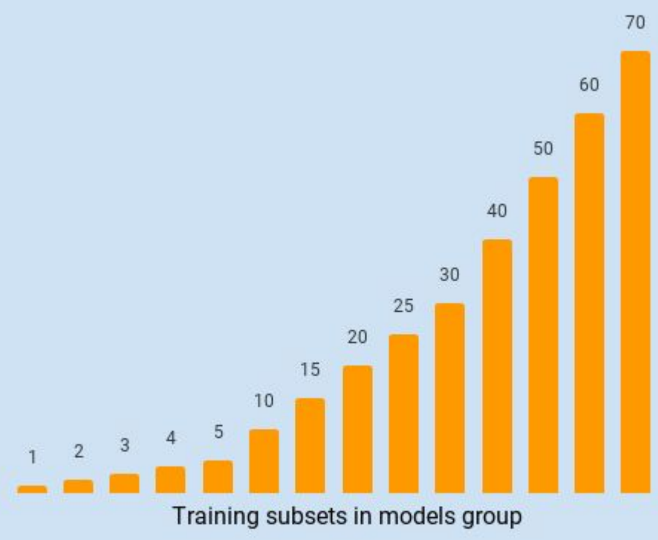
Obtaining the sufficient amount of training data for deep learning based segmentation might be an issue, especially in the medical field. In this work, we focus on the task of longitudinal bone segmentation in human body CT scans. We designed three groups of segmentation models with varying amount of training data to examine the impact of two possible means of battling the lack of data problem.



Dataset and the training subsets

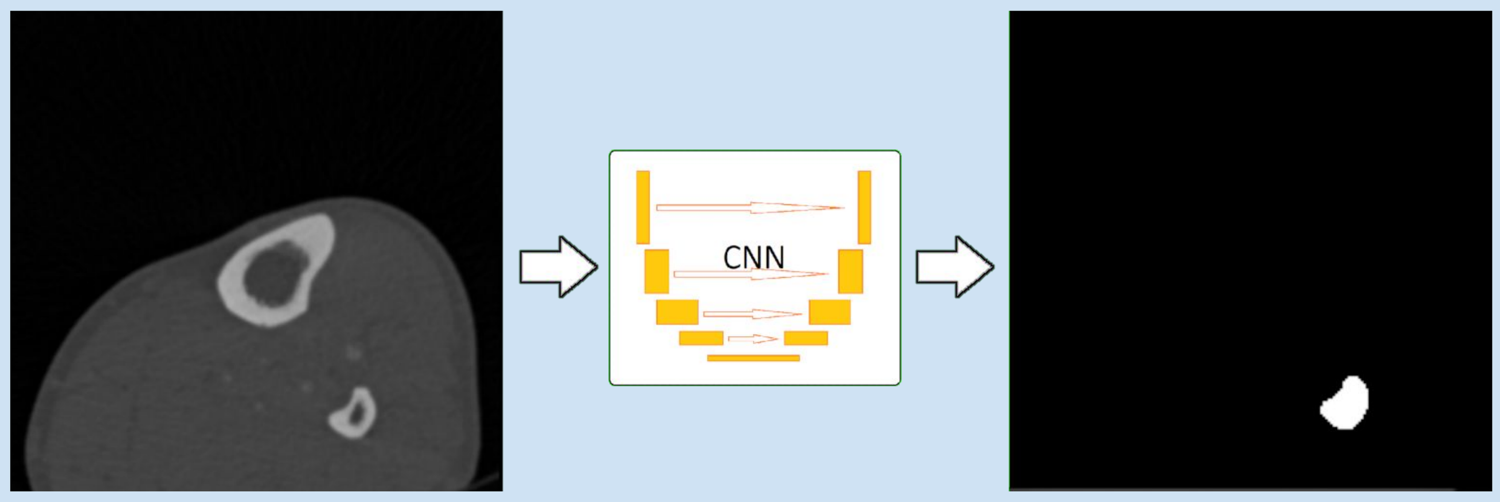
- Benchmarking of the segmentation methods on Fibula bone dataset.
- 3 groups of models, each containing 14 models which are trained on variably sized subsets.





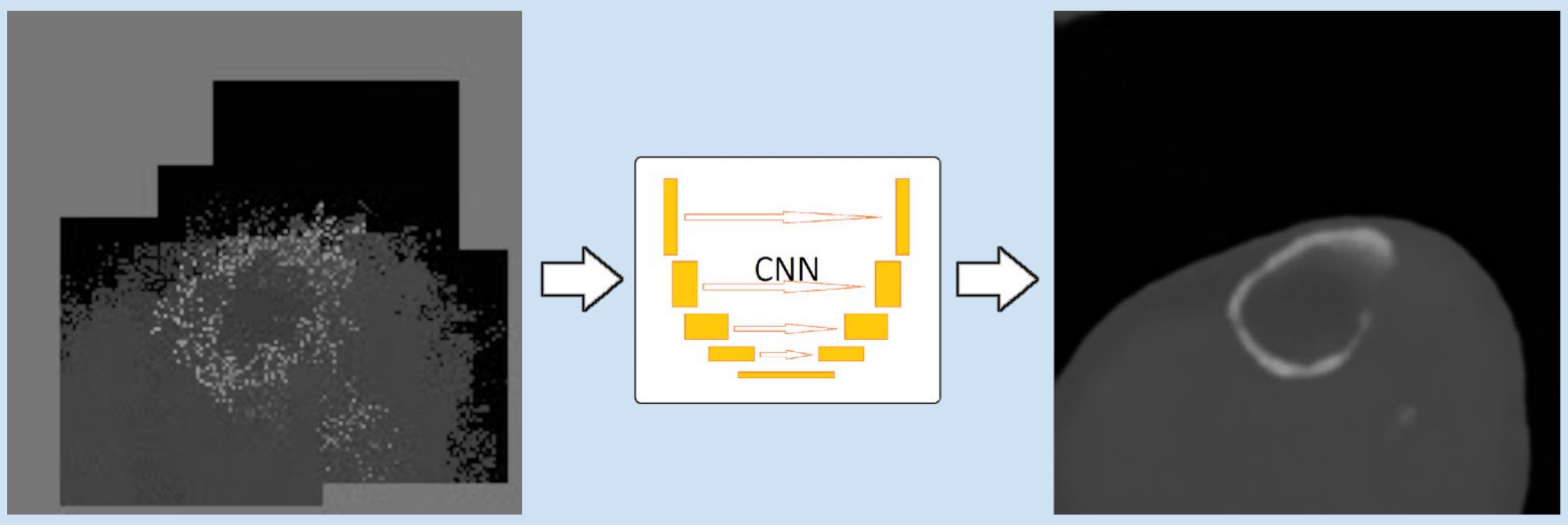
Baseline models group (Seg)

- Training pair consisting of 2D input patch and corresponding manual segmentation patch.
- U-net CNN architecture (shared among all 3 groups).
- Automatic approach with no other extensions.



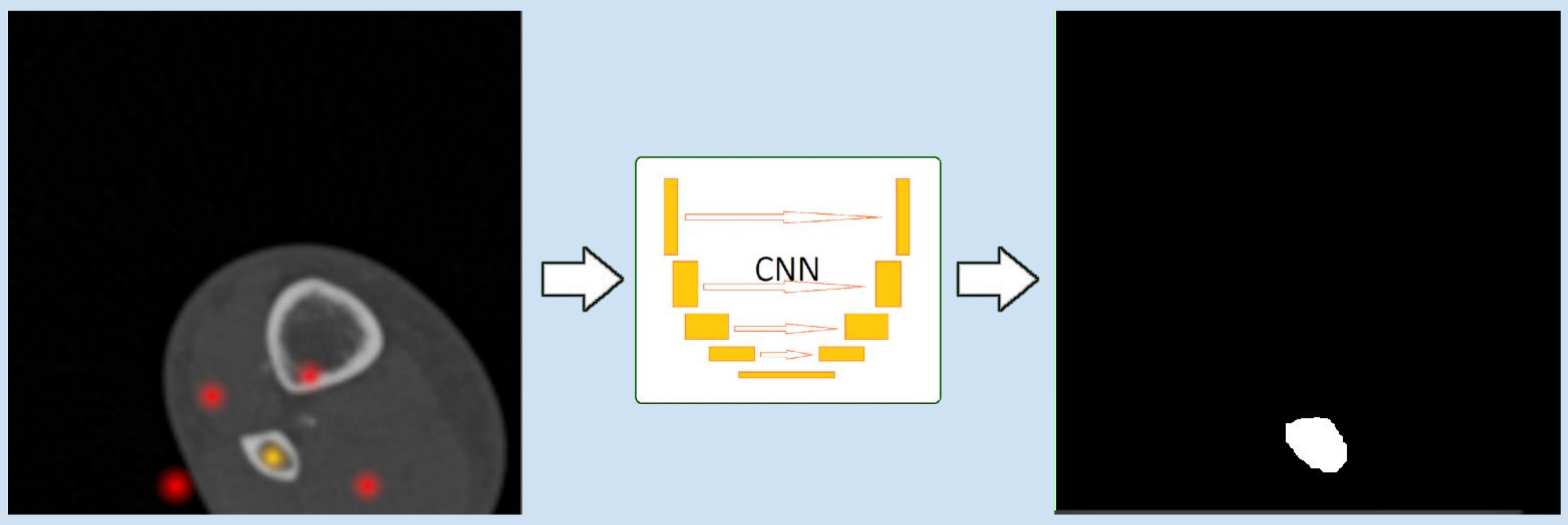
Unsupervised pretraining (SegPretrained)

- Inspired by Models Genesis **[1]**.
- Pretrain without manual annotations on image restoration.
- Finetune to the segmentation task.
- Improvement from **0.749** (baseline model) to **0.830** Dice score when trained on two patients.



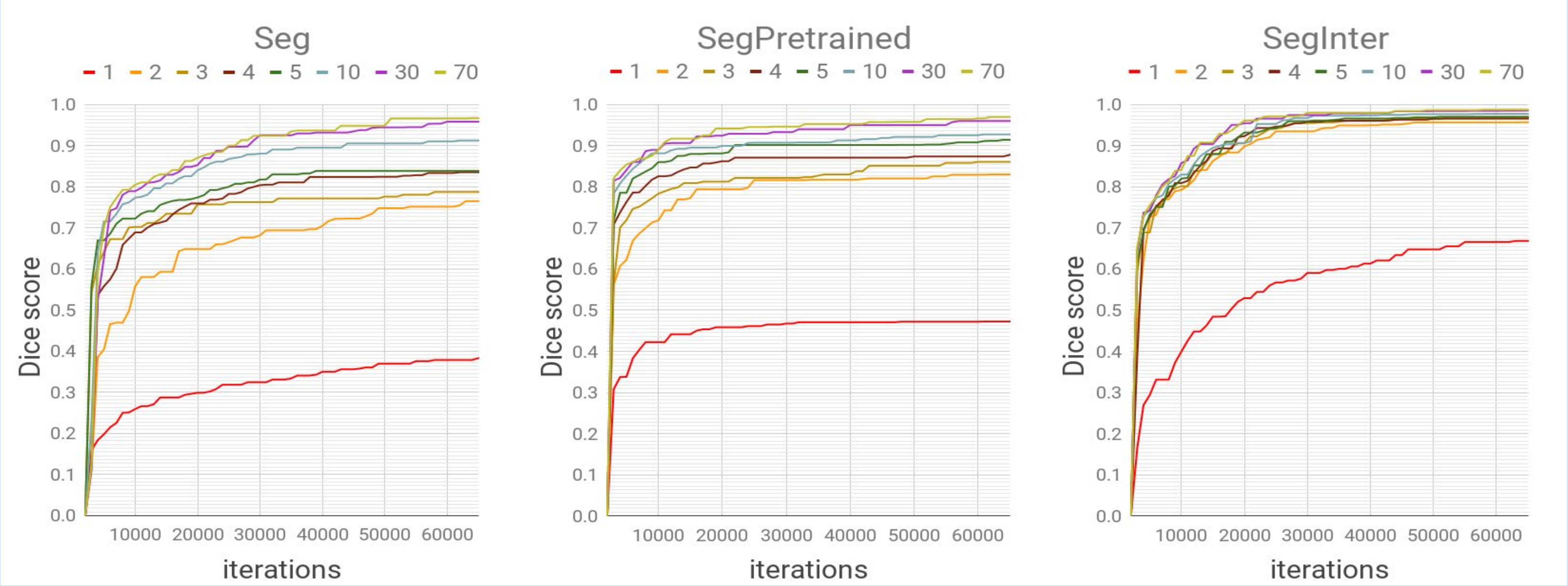
User interaction (SegInter)

- Based on interactive segmentation model **[2]**.
- Object and background clicks (2 additional channels).
- Better object localization than the baseline.
- Promising results - Dice score **0.929** with only two training patients.



The comparison of Dice score during training of different models

- Dice score is measured on the validation data during the training.
- In **Seg** group we can clearly see the tendency of quality loss with small amount of data.
- **SegPretrained** group is slightly better than the baseline, most visible on the 1 patient model. There is also visible speed up in the convergence.
- The most promising are the results of the **SegInter** group. This way we can obtain considerably good segmentation quality with as few as two training patients.
- **Practical use** of the interactive method (possibly combined with pretraining) lies in speeding up the creation of new segmentation datasets. We are able to update the training set with new data created by the model with human expert assistance. This can be done iteratively until the required segmentation quality is reached.



[1] ZHOU, Zongwei, Vatsal SODHA, Md Mahfuzur RAHMAN SIDDIQUEE, Ruibin FENG, Nima TAJBAKHSH, Michael B. GOTWAY a Jianming LIANG. Models Genesis: Generic Autodidactic Models for 3D Medical Image Analysis. *Medical Image Computing and Computer Assisted Intervention – MICCAI 2019*. Cham: Springer International Publishing, 2019, 2019-10-10, , 384-393. Lecture Notes in Computer Science. DOI: 10.1007/978-3-030-32251-9_42. ISBN 978-3-030-32250-2.
[2] SAKINIS, Tomas, Fausto MILLETARI a Holger ROTH. Interactive segmentation of medical images through fully convolutional neural networks. CoRR. 2019, (abs/1903.08205) .