Informatics

3D CT Proximal Femora Segmentation Using Optimized nnU-Net

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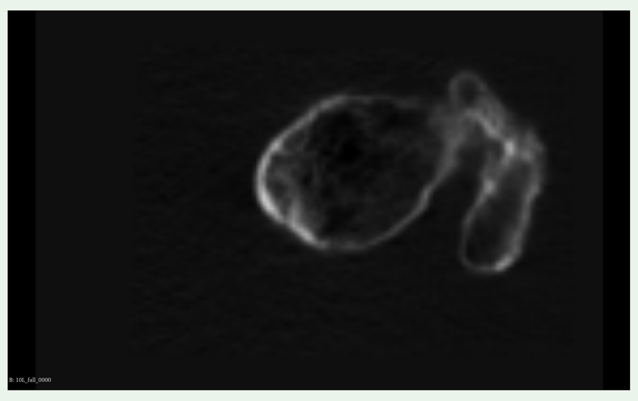
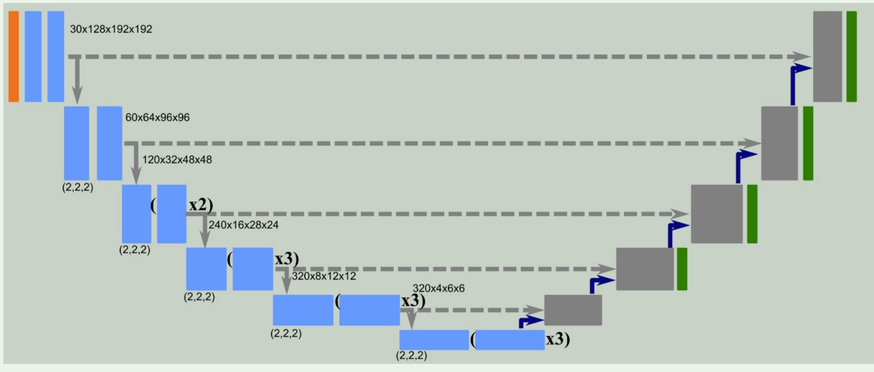
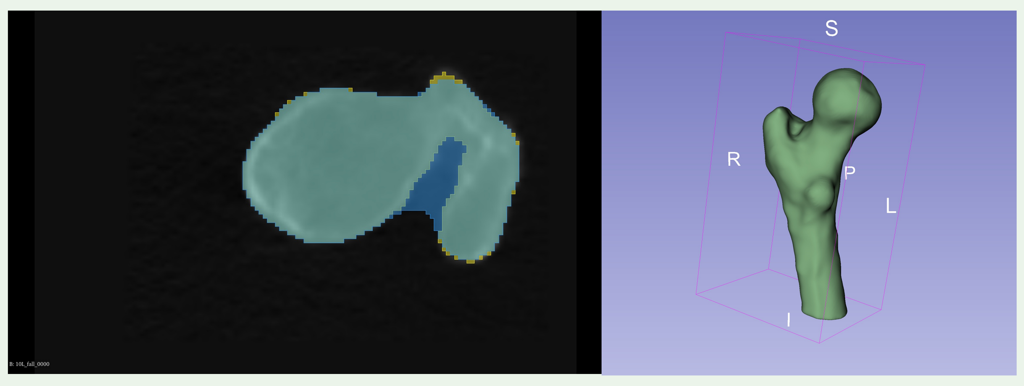
Main Objective



Raw 3D CT femur images



Train U-Net based segmentation model on ground truth labels



Automatically generate accurate segmentations, needed for simulation in biomechanics

Problem Definition

Accurate segmentation of bones from CT images is crucial for biomechanical modeling and medical planning. Manual segmentation is time-consuming and introduces human error, underlining the need for automated deep learning models. Classical algorithms using morphological operations often struggle with complex geometries, while deep learning models promise to have better local context. Despite the relatively recent introduction of larger transformer models, older U-Net-based models like the self-adapting nnU-Net continue to compete effectively. However, the optimal U-Net configurations, especially when comparing 2D slice-wise approaches to full 3D approaches, remain unclear. This project focuses on implementing and optimizing both 2D and 3D nnU-Net models for femur 3D CT images and analyzing their performance.

Results

Model	Dice	Sensitivity	Specificity	Avg. Surface Distance
3D corrected	0.9895	0.9914	0.9981	0.1246
2D corrected	0.9879	0.9895	0.9979	0.1424
3D original	0.9923	0.9909	0.9990	0.0922
2D original	0.9892	0.9876	0.9985	0.1308

Model	Training Time [s]	Training VRAM [MiB]	Inference Time [s]	Inference VRAM [MiB]
3D	7343.8	4830	1.68	2000
2D	14017.2	9456	6.00	408

The parameter search only yielded slightly better performance for the 2D network. High performance scores were obtained on the test set for both the 2D and 3D models. In all cases the 3D model outperformed the 2D model in all performance metrics. The results for the models trained and tested on the original, not corrected labels were slightly better. The inference and training times for the 3D model was faster, while the VRAM usages were higher than the 2D model.

Methodology

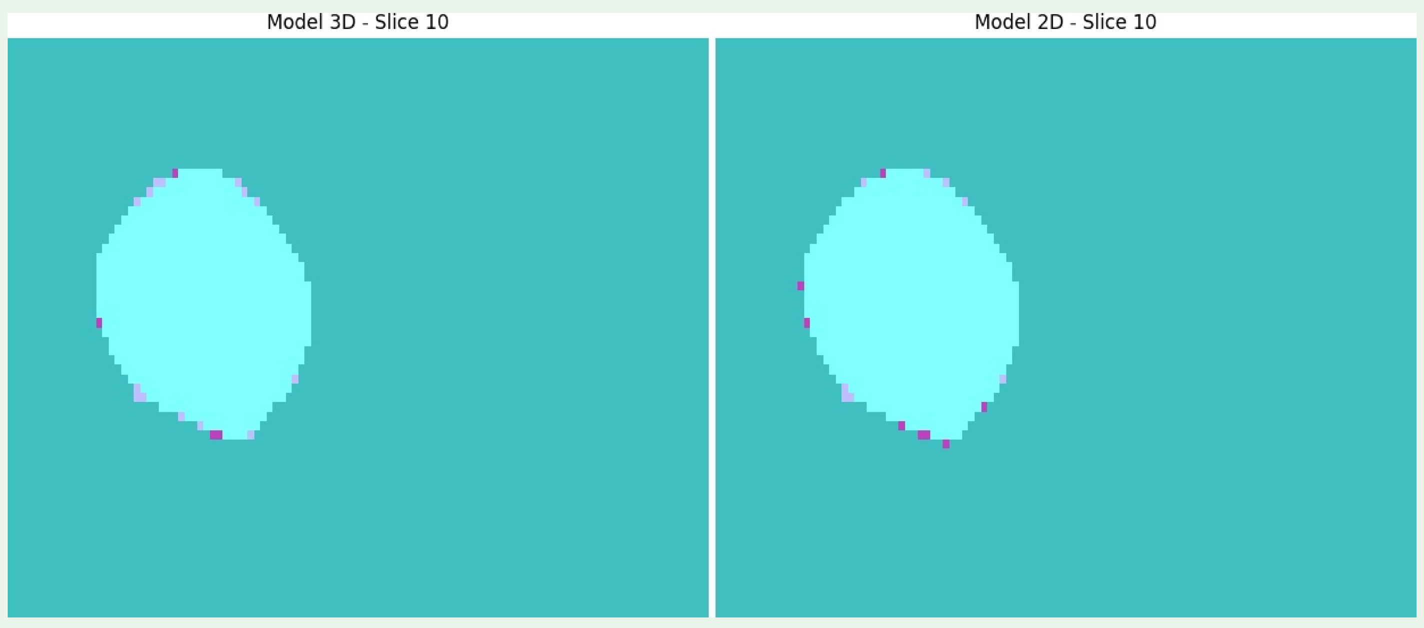
Parameter Search

Various nnU-Net configurations were explored by tuning key hyperparameters like batch size, use of residual encoders, and data augmentation (DA5). Grid search was conducted on the chosen parameters on a separate validation split.

The best performing 2D and 3D configurations were selected for further training and evaluation on the test set.

- Preprocess Data / Manual Corrections in 3D Slicer
- Configure 2D / 3D architectures
- Optimize Hyperparameters
- Evaluation in Validation Split
- Prediction on Test Split
- Analysis of model performance
- Publish on Github to ensure reproducibility

Visualizations



Interactive visualizations, such as an error map, were created to compare model predictions with actual labels. These make it easier to explore differences in segmentation across CT slices and between different models, giving a clearer view of where predictions differ.

Conclusion

This project successfully implemented both 2D and 3D nnU-Net models for femur segmentation in 3D CT images. The 3D model outperformed the 2D model across all performance metrics, including sensitivity, specificity, and average surface distance (ASD), while also providing faster inference times although higher resource requirements. The parameter search revealed that the default nnU-Net settings already performed well . Additionally, as the model trained and tested on the original labels performed better, it is indicated that more consistent while realistic labeling could further improve model performance.

nnU-Net Code Repository

Fabian Isensee et al., nnU-Net: Self-adapting Framework for U-Net-Based Medical Image Segmentation, 2020, https://github.com/MIC-DKFZ/nnUNet

Project Code Repository

Jeremias Lang, 3D CT Proximal Femora Segmentation Using Optimized nnU-Net, 2024, https://github.com/jereOG/femur_nnUNet