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nnU-Net for the Automatic Knee Segmentation from CT Images: A Comparative Study with a Conventional U-Net Model

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Abstract

This study aims at comparing the nnU-Net, an open-source deep learning framework, with a previous customized U-Net model that we developed for the automatic segmentation of tibial and femoral bones from CT scans. The main purpose of our work is to develop a segmentation module that could be integrated into a surgical planning software for the design of customized Total Knee Prosthesis. The nnU-Net framework was chosen for its user-friendly design and features developed for medical imaging.
The same dataset of 112 CT scans of lower limbs from 63 patients was used to train and test both our customized U-Net model and the nnU-Net model. All these data were manually annotated. The evaluation was done by computing the Average Symetric Surface Distance, the Dice Coefficient, the Hausdorff Distance, the precision, the recall and the Jaccard Index. Both models yielded similar results on these metrics, but the nnU-Net model is easier to setup.
The performances of both models are also consistent with the literature, however, further tests on pathological data will be needed.

1 Introduction

The objective of this work is to assess the effectiveness of the nnU-Net [1], an open-source deep learning framework, for the automatic segmentation of both the tibial and femoral bones from CT scans. The mid-term goal is to incorporate this segmentation module into a surgical planning software for the design of customized Total Knee Prosthesis. The nnU-Net is a user-friendly framework designed for medical image segmentation that offers several advantages over a conventional U-Net, including the elimination of manual parameter tuning and the addition of advanced features such as handling multiple image sizes, resolutions and types, and robustness to variations in data.

In a previous work [2], we have created a U-Net network [3] with an architecture which has proven to be fast and efficient for segmenting CT-Scans. We are now interested in comparing the performance of our model with a ready-made solution such as nnU-Net.

Recently, the TotalSegmentator software [4], which uses the nnU-Net framework, has been developed for segmenting bones, soft tissues, and tumors in CT scans of the full body, except for the lower limbs. The present study aims to build on this previous work by focusing specifically on segmenting the tibial and femoral bones in lower limb CT scans.

TotalSegmentator has shown particularly good dice scores on bones despite the challenge of having to deal with a complex task (104 different classes). Therefore, given the limited scope of our task (CT scans segmentation of the tibia and femur bones), and the availability of a large dataset of manually annotated lower limb images, we assume that the nnU-Net will yield substantial improvements to our workflow.

2 Material and Methods

2.1 Data

112 CT scans of lower limbs (right and/or left) from 63 patients were collected to train the deep learning models. The images were obtained from 3 different machines (Toshiba® Aquilon One, Siemens® Somatom Edge Plus, Siemens® Somatom Definition Edge) from the Brest University Hospital between 2020 and 2021. The volumes were manually segmented and then split into training (80 scans from 45 patients) and test sets (32 scans from 18 other patients).

Both the ready-made nnU-Net and our custom implementation of U-Net were trained and tested on the exact same datasets.

2.2 Models

In order to develop the segmentation method based on nnU-Net, we adopted the methodology proposed by the MIC-DKFZ/nnUNet GitHub repository [5] to train a customized 2D model, without making any modifications to the code, like enforcing architecture or hyperparameters choice, as nnU-Net is designed to make such decisions automatically.

Our 2D U-Net model has slightly changed since our previous publication [2], as the encoder now integrates a ResNet50V2 backbone pre-trained on ImageNet. However, the overall architecture and the fundamental outlines remain unchanged.

2.3 Setup

Both models where trained on a GPU Nvidia® Titan RTX 24 Go Ram GDDR6, 4608 cores 1350-1770 MHz, 576 Tensor cores, BP Memory 672 GB/s.
Due to integration requirements, performances are evaluated on CPU; therefore, inference was carried out on a CPU Intel® Core™ i7-7820HQ, 2.90GHz.

3 Results

In order to compare both models, we selected the best performing nnU-Net model among the five ones given by the nnU-Net algorithm, based on the highest validation accuracy, and we used it for further inferences and comparisons.

We compared the automatic segmented images and the corresponding manually-segmented ones (considered as the reference) in terms of six metrics: Average Symmetric Surface Distance (ASSM), the Dice Coefficient (DC), the Hausdorff Distance (HD), the precision, the recall and the Jaccard Index (JI). Table 1 and Table 2 reported some of the metrics obtained on the test dataset to compare our both models between them and with the state-of-the art methods [6].

On average, the computational time required to process a knee CT volume using the nnU-Net is 1 minute and 10 seconds, which is equivalent to the 1 minute and 5 seconds taken by our specifically designed workflow.

	DC (%)		HD (mm)		ASSD (mm)	
Femur Custom U-Net	98.86 ± 0.45	min. 97.78 max. 99.44	**3.46** ± 1.62	min. 1.40 max. 10.32	0.21 ± 0.08	min. 0.11 max. 0.39
Femur nnU-Net	**99.17** ± 0.75	min. 95.26 max. 99.56	9.90 ± 23.46	min. 1.63 max. 126.34	**0.17** ± 0.21	min. 0.08 max. 1.27
Tibia Custom U-Net	98.61 ± 0.60	min. 96.34 max. 99.25	**4.06** ± 1.77	min. 1.89 max. 11.62	0.22 ± 0.08	min. 0.13 max. 0.44
Tibia nnU-Net	**99.18** ± 0.21	min. 98.61 max. 99.49	15.6 ± 28.67	min. 1.89 max. 113.77	**0.20** ± 0.20	min. 0.08 max. 0.94

Table 1: Comparative results on the test dataset of 32 CT volumes. ASSD : Average Symetric surface Distance, DC : Dice Coefficient, HD : Hausdorff Distance.

FEMUR	Precision		Recall		Jaccard Index	
custom Unet	0.99	(0.98-0.99)	**0.99**	**(0.99-1.0)**	0.98	(0.97-0.98)
nnUNet	**0.99**	**(0.99-0.99)**	0.99	(0.99-0.99)	**0.99**	**(0.98-0.99)**
CEL-Unet [6]	0.98	(0.98-0.99)	**0.99**	**(0.99-1.0)**	0.98	(0.97-0.98)

TIBIA	Precision		Recall		Jaccard Index	
custom Unet	0.99	(0.98-0.99)	0.99	(0.98-0.99)	0.98	(0.97-0.98)
nnUNet	**0.99**	**(0.99-0.99)**	**0.99**	**(0.99-0.99)**	**0.98**	**(0.98-0.99)**
CEL-Unet [6]	0.98	(0.98-0.99)	0.99	(0.98-0.99)	0.97	(0.97-0.98)

Table 2: Comparison of both networks with the results of the literature as median and inter-quartile range.

4 Discussion

The accuracy of the segmentation is comparable for both frameworks. Our U-Net model performed better regarding the Hausdorff distance and the nnU-Net model showed slight improvements in terms of ASSD and Dice coefficient. The inference times are also equivalent.
In terms of training time, while the duration required to train the U-Net model itself is shorter,

an extensive development effort is required to design the U-Net architecture, implement its pre- and post-processing steps and fine-tune the hyperparameters. Eventually, it entailed significant resource consumption and required more time than using the pre-defined nnU-Net framework.

Previous studies such as [7] and [6] effectively employed U-Net-derived methods for knee bone segmentation. A comparison of our results with theirs suggests that the automatically defined nnU-Net model may perform better. However, it is important to note that the dataset used in our study contains limited instances of severe osteoarthritis, whereas the datasets used in the aforementioned studies were specifically built from patients undergoing total knee arthroplasty. Therefore, further evaluations of both models on severe osteoarthritis cases are necessary to establish their applicability in the context of surgical planning.

In conclusion, the nnU-Net framework presents itself as a highly viable option for the automatic segmentation of the bones of the knee joint from CT images. The results demonstrate comparable performance with our conventional approach, with a lower development cost. However, further tests on datasets with higher prevalence of severe osteoarthritis are required to fully assess the suitability of such a model in a surgical planning software.

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