Comprehensive study of good model training for prostate segmentation in volumetric MRI

Carlos Nácher Collado
August 30, 2022

Abstract

Prostate cancer was the third most common cancer in 2020 internationally, coming after breast cancer and lung cancer. Furthermore, in recent years prostate cancer has shown an increasing trend. According to clinical experience, if this problem is detected and treated early, there can be a high chance of survival for the patient. One task that helps diagnose prostate cancer is prostate segmentation from magnetic resonance imaging. Manual segmentation performed by clinical experts has its drawbacks such as: the high time and concentration required from observers; and inter- and intra-observer variability. This is why in recent years automatic approaches to segment a prostate based on convolutional neural networks have emerged. Many of them have novel proposed architectures. In this paper I make an exhaustive study of several deep learning models by adjusting them to the task of prostate prediction. I do not use novel architectures, but focus my work more on how to train the networks. My approach is based on a ResNext101 3D encoder and a Unet3D decoder. I provide a study of the importance of resolutions in resampling data, something that no one else has done before.

1 Introduction

According to the following study by the International Agency for Research on Cancer [SFS⁺21], in 2020 there were, globally, 1 414 259 new cases of prostate cancer, being the third most common cancer (7.3%) after breast cancer (11.7%) and lung cancer (11.3%); referring these percentages to the total number of new cases of any cancer in 2020 internationally, about 19.3 million; producing 375 304 (3.8%) deaths in that year. Clinical experience shows that if prostate cancer is detected early there is a high chance of survival for the patient. For this and other applications, automatic MRI prostate segmentation is useful for clinical support. In this paper I propose a comprehensive study of the training of several Deep Learning models.

Automatic prostate segmentation in magnetic resonance imaging (MRI) with Deep Learning has been based since its inception on Convolutional Neural Networks (CNN) first proposed by [Fuk75] and later improved upon by [LBBH98]. The best known CNN for medical image segmentation is the U-Net [RFB15]. Since the PROMISE12 competition started in 2012, there have been several proposals for improvements: Haozhe Jia et al. [JXS⁺18] proposed to do Transfer Learning [Boz20] of the VGG-19 [SZ15] network by separating the data according to whether the patient has endorectal coil or not; their coarse-to-fine strategy is based on atlas-based segmentation [BCDT15]. In 2018 Haozhe Jia et al. [JSZ⁺18] propose an improvement their previous contribution; they change the VGG-19 backbone [SZ15] to ResNet-50 [HZRS15] in 3D; they propose the use of GCB blocks [PZY⁺17] and RRB; furthermore, they propose the use of a Generative Adversarial Network (GAN) [GPAM⁺14] to discriminate the classification of each voxel and refine the results of the encoder-decoder. In January 2019, Isensee et al. [IKW⁺18] present a paper in which they claim that a well-trained basic U-Net network can achieve great results. They start from the 3D U-Net [RFB15] [ÇAL⁺16] and say that instead of focusing on the architecture of the network and adding complex layers such as a gan, they focus on the correct training of the network; this premise of Isensee et al. is the inspiration for my work. In August 2019, Zhu et al. [ZDY19] propose an adaptation of the data domain with a GAN-like discriminator. In July 2019, Haozhe Jia et al. [JXS⁺20] modify their GCBs and RRBs by Py-Conv and As-Conv, to account for the anisotropy of MRI data as well as extract features at various levels
of resolution; they also introduce CABs (attention modules) and a specialised prostate edge decoder. In 2019, Xiangxiang Qin \textit{HJIA3dapa} proposes a structure called PAM that combines the PyConv and the CABs of \textit{HJIA3dapa} into a single module; it also proposes a decoder specialising in the edges, but in 3D. In June 2022, and \textbf{being the state of the art as of today}, Haozhe Jia \textit{et al.} \cite{JCHX22} again propose an improvement to their previous contributions \cite{JXS+18}, \cite{JSZ+18}, \cite{JXS+20}; they change the ResNet backbone \cite{HZRS15} to Res2Net \cite{GCZ+19}.

State of the art proposals, in due course, have introduced new concepts such as: the use of GANs \cite{GPAM+14} \cite{JSZ+18} \cite{JXS+20}; the use of convolutions at different scales \cite{JXS+20} \cite{JSH+19} \cite{Qin19} \cite{JCHX22}; the use of anisotropic convolutions \cite{JSZ+18} \cite{JXS+20} \cite{JXS+20} \cite{JSH+19} \cite{Qin19} \cite{JCHX22}; the use of attention modules \cite{JSH+19} \cite{Qin19} \cite{JCHX22}; the use of a specialised decoder at prostate edges \cite{JSH+19} \cite{JCHX22}.

However, there is one particular paper, \textit{No-New Net}, by Isensee \textit{et al.} \cite{IKW+18}(more extended in Isensee \textit{et al.} \cite{IPK+19}), which hypothesises that a "basic" network for 3D segmentation, such as the 3D-Unet \cite{CAL+16}, may be sufficient to achieve state-of-the-art results. He focuses his research on how to train the neural network, and not on the architecture itself. He has proven to be among the top performers on several occasions with his work Isensee \textit{et al.} \cite{IKW+18} and is currently ranked fourth on PROMISE12.

Based on this work, I propose an intensive study of the training of a basic network (3D-Unet \cite{CAL+16}), with different tests on: the choice of the backbone used; the optimiser used and its hyperparameters; the Data Augmentation techniques used. In addition, I propose a study on the way of resampling the data and the choice of the common output resolution, \textit{which no one else has proposed in their work, with which I show that there is room for improvement in other aspects of the task of training an Artificial Intelligence model, other than the choice of the architecture itself.}

2 Method

2.1 Implementation

I use the 50 training cases provided by the contest. As preprocessing I do MCLAHE \cite{SBE+19}. As data augmentation I do flips in the x,y,z axis; rotations from -15 to 15 degrees in the z axis; scaling between 0.75 and 1.5; and BSpline deformations. All these transformations are applied online to random patches of 192x192x32.

The loss function used was Dice 1 + BinaryFocalCrossentropy 2. The optimizer used was Adam with initial learning rate of 0.006, with decay when validation loss stopped improving and epsilon = 0.001.

All training was run on a 16GB Tesla P100 GPU graphics card.

2.2 Comprehensive study of training

The first thing I propose is a metric called Reconstruction Dice (rDSC). Basically this means, resampling a segmentation to a particular resolution different from its original resolution, resampling it, and then calculating the Dice coefficient between the original segmentation and the reconstructed segmentation. I do this to study the resampling of the training data to the optimal resolution. The resolutions I propose for the 50 training cases are:

- Half of the resolution of each particular segmentation.
- Twice the resolution.
- The median of the resolutions in the training set (0.625x0.625x3.6).
- The resolution (0.625x0.625x1.5) as this is the resolution used by most of the PROMISE12 papers.
- A proposal (0.3125x0.3125x1.5).
The proposed resolution \((0.3125\times0.3125\times1.5)\) was proposed because it was observed that decreasing the resolution of a piece of data (i.e. making its spacing larger) resulted in a worse rDSC than increasing the resolution (i.e. making its spacing smaller). This is because reducing the resolution often discards information that, when you want to return to the original resolution, is not available because it was lost in the first resampling. On the other hand, when the resolution is increased, new values are “invented” (interpolated), and then it is easier to return to the original image with fewer losses.

I tested all five strategies with the 50 training cases. The results can be seen in figure 1. With a p-value \(<\ 0.05\), the proposed \((0.3125\times0.3125\times1.5)\) achieves better rDSC than \((0.625\times0.625\times1.5)\). Later on, I try to train the best of my models for data with both resolutions, and show that the one using data with resolutions \((0.3125\times0.3125\times1.5)\) obtains better validation metrics. (See 7)

![Figure 1: Comparison of the different resolutions in terms of rDSC.](image)

Then, with the resolution \((0.3125\times0.3125\times1.5)\) chosen, I make some intensive tests to choose the data augmentation to use, the cost function, the backbone and the decoder model, among others.

In terms of cost function, I tried 5:

- Dice
- BinaryFocalCrossEntropy
- Tversky
- Dice+ BinaryFocalCrossEntropy
- Tversky + BinaryFocalCrossEntropy

The best one turns out to be Dice+ BinaryFocalCrossEntropy, so it is the one I choose to train the models.

\[
\text{Dice} = \frac{2|A \cap B|}{|A| + |B|} \tag{1}
\]

\[
CE = -\frac{1}{n} \sum_{j=1}^{n} \sum_{i=1}^{c} [y_i \log (p_i) + (1 - y_i) \log (1 - p_i)] \tag{2}
\]

\[
TI = \frac{TP}{TP + \alpha FN + \beta FP} \tag{3}
\]

As backbones try several (freezing weights vs. non-freezing):

- ResNet18 \([HZRS15]\)
- ResNet50 [HZRS15]
- ResNext 101 [GCZ⁺19]

A comparison of the tested backbones can be seen in figure 2. The results are somewhat noisy, but according to the T-test, ResNext 101 is better with p-value $< 0.05$. The general architecture of ResNext can be seen in figure 3, and a comparison between ResNet and ResNext blocks (the latter being equivalent but more efficient) in figure 4.

![Figure 2: Comparison of backbones. The losses are a bit noisy because they are the first epochs.](image)

| stage | output | ResNet50 | ResNet50 (32 x 4d) |
|-------|--------|----------|-------------------|
| conv1 | 112 x 112 | 7 x 7, 64, stride 2 | 7 x 7, 64, stride 2 |
| | | 3 x 3 max pool, stride 2 | 3 x 3 max pool, stride 2 |
| conv2 | 56 x 56 | 1 x 1, 64 | 1 x 1, 128 |
| | | 3 x 3, 64 | 3 x 3, 128, C=32 |
| | | 1 x 1, 256 | 1 x 1, 256 |
| conv3 | 28 x 28 | 1 x 1, 128 | 1 x 1, 256 |
| | | 3 x 3, 128 | 3 x 3, 256, C=32 |
| | | 1 x 1, 512 | 1 x 1, 512 |
| conv4 | 14 x 14 | 1 x 1, 256 | 1 x 1, 512 |
| | | 3 x 3, 256 | 3 x 3, 512, C=32 |
| | | 1 x 1, 1024 | 1 x 1, 1024 |
| conv5 | 7 x 7 | 1 x 1, 512 | 1 x 1, 1024 |
| | | 3 x 3, 512 | 3 x 3, 1024, C=32 |
| | | 1 x 1, 2048 | 1 x 1, 2048 |
| | 1 x 1 | global average pool | global average pool |
| | | 1000-d fc, softmax | 1000-d fc, softmax |
| # params. | $25.5 \times 10^6$ | $25.0 \times 10^6$ |
| FLOPs | $4.1 \times 10^9$ | $4.2 \times 10^9$ |

![Figure 3: ResNet and ResNext architectures and shapes.](image)

As decoder models I test: the U-Net 3D [RFB15] [ÇAL⁺16], the LinkNet 3D [CC17] (which is identical to the U-Net with the difference of adding instead of concatenating) and the PSP-Net [ZSQ⁺17]. The schematic of the three architectures is shown in figure 5. The U-Net 3D gave me the best results.
Tras esta y otras muchas pruebas que no incluyo en este paper, consigo el mejor modelo, cuyo Dice de validación muestro en la figura 6.

For predictions I use the Sliding Windows technique with windows of size 192x192x32 and fixed stride of 48x48x8, which gives me better results than using stride of 96x96x16.
3 Ablation experiments

Once I got the best model for the resolution (0.3125x0.3125x1.5), I resampled the data again, this time to 0.625x0.625x1.5mm, and trained the best model but now with the new data (keeping all the hyperparameters like the batch size the same, also to occupy the same physical space I took the random patches of size 96x96x32). In figure 7 you can see how the proposed strategy improves the validation Dice by up to one point.

Figure 7: Comparison of training the same models with data in resolution (0.625x0.625x1.5mm) vs (0.3125x0.3125x1.5mm).

4 Conclusions

I have shown that good training of a basic network can contribute sufficiently good results compared to other complex methods, just as Isensee et al. demonstrate with [IKW+18].

I have shown that there is room for improvement of the algorithms if we focus on the way the data is handled and not only on the architecture. Demonstrating how the resampling resolution of the data can improve Dice by up to 1 point.

I am waiting for the test results at the hands of the PROMISE12 competition.

References

[BCDT15] M. Bach Cuadra, V. Duay, and J.-Ph. Thiran. Atlas-based Segmentation, pages 221–244. Springer US, Boston, MA, 2015.
[Boz20] Stevo Bozinovski. Reminder of the first paper on transfer learning in neural networks, 1976. Informatica, 44, 09 2020.
[ÇAL+16] Özgün Çiçek, Ahmed Abdulkadir, Soeren S. Lienkamp, Thomas Brox, and Olaf Ronneberger. 3d u-net: Learning dense volumetric segmentation from sparse annotation. CoRR, abs/1606.06650, 2016.
[CC17] Abhishek Chaurasia and Eugenio Culurciello. Linknet: Exploiting encoder representations for efficient semantic segmentation. 2017 IEEE Visual Communications and Image Processing (VCIP), pages 1–4, 2017.
[Fuk75] K Fukushima. Cognitron: a self-organizing multilayered neural network. Biol Cybern, 20(3-4):121–136, November 1975.
[GCZ+19] Shang-Hua Gao, Ming-Ming Cheng, Kai Zhao, Xin-Yu Zhang, Ming-Hsuan Yang, and Philip Torr. Res2net: A new multi-scale backbone architecture. IEEE transactions on pattern analysis and machine intelligence, 43(2):652–662, 2019.
[GPAM+14] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. Advances in neural information processing systems, 27, 2014.
[HZRS15] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. CoRR, abs/1512.03385, 2015.

[IKW+18] Fabian Isensee, Philipp Kickingereder, Wolfgang Wick, Martin Bendszus, and Klaus H. Maier-Hein. No new-net. CoRR, abs/1809.10483, 2018.

[IPK+19] Fabian Isensee, Jens Petersen, Simon A. A. Kohl, Paul F. Jäger, and Klaus Maier-Hein. mmu-net: Breaking the spell on successful medical image segmentation. ArXiv, abs/1904.08128, 2019.

[JCHX22] Haozhe Jia, Weidong Cai, Heng Huang, and Yong Xia. Learning multi-scale synergic discriminative features for prostate image segmentation. Pattern Recognition, 126:108556, 2022.

[JSH+19] Haozhe Jia, Yang Song, Heng Huang, Weidong (Tom) Cai, and Yong Xia. Hd-net: Hybrid discriminative network for prostate segmentation in mri images. In MICCAI, 2019.

[JSZ+18] Haozhe Jia, Yang Song, Donghao Zhang, Heng Huang, Dagan Feng, Michael J. Fulham, Yong Xia, and Weidong Cai. 3d global convolutional adversarial network for prostate MR volume segmentation. CoRR, abs/1807.06742, 2018.

[JXS+18] Haozhe Jia, Yong Xia, Yang Song, Weidong Cai, Michael Fulham, and David Dagan Feng. Atlas registration and ensemble deep convolutional neural network-based prostate segmentation using magnetic resonance imaging. Neurocomputing, 275:1358–1369, 2018.

[JXS+20] Haozhe Jia, Yong Xia, Yang Song, Donghao Zhang, Heng Huang, Yanning Zhang, and Weidong Cai. 3d apa-net: 3d adversarial pyramid anisotropic convolutional network for prostate segmentation in mri images. IEEE Transactions on Medical Imaging, 39(2):447–457, 2020.

[LBBH98] Y. Lecun, L. Bottou, Y. Bengio, and P. Haffner. Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11):2278–2324, 1998.

[PZY+17] Chao Peng, Xiangyu Zhang, Gang Yu, Guiming Luo, and Jian Sun. Large kernel matters - improve semantic segmentation by global convolutional network. CoRR, abs/1703.02719, 2017.

[Qin19] Xiangxiang Qin. Transfer learning with edge attention for prostate mri segmentation. ArXiv, abs/1912.09847, 2019.

[RFB15] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. CoRR, abs/1505.04597, 2015.

[SBE+19] Vincent Stimper, Stefan Bauer, Ralph Ernstorfer, Bernhard Schölkopf, and Rui Patrick Xian. Multidimensional contrast limited adaptive histogram equalization. IEEE Access, 7:165437–165447, 2019.

[SFS+21] Hyuna Sung, Jacques Ferlay, Rebecca L. Siegel, Mathieu Laversanne, Isabelle Soerjomataram, Ahmedin Jemal, and Freddie Bray. Global cancer statistics 2020: Globocan estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA: A Cancer Journal for Clinicians, 71:209 – 249, 2021.

[SZ15] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. CoRR, abs/1409.1556, 2015.

[ZDY19] Qikui Zhu, Bo Du, and Pingkun Yan. Boundary-weighted domain adaptive neural network for prostate MR image segmentation. CoRR, abs/1902.08128, 2019.

[ZSQ+17] Hengshuang Zhao, Jianping Shi, Xiaojuan Qi, Xiaogang Wang, and Jiaya Jia. Pyramid scene parsing network, 2017.