# Automatic image segmentation in Radiation Oncology

# The radiation therapy workflow

The radiation therapy workflow can be broken down into five main stages: patient evaluation and development of the clinical plan, preparation of the treatment (including segmentation or contouring targets and organ at risk, and dose planning), treatment setup and delivery, and completion.

A picture containing timeline

Description automatically generated

**Figure 1 : Radiation therapy workflow[1]**

Currently, manual segmentation of the primary tumour and organs at risk is one of the most time-consuming but crucial tasks performed by the radiation oncologist .

The accuracy of tumour segmentation can directly affect outcomes: an incorrectly delineated tumour can lead to underdosing or overdosing, resulting in a decrease in the likelihood of tumour control or an increased risk of toxicities, respectively and tumour segmentation is subject to inter-observer variation, even among expert radiation oncologists which can lead to differences in the quality of treatment plans, with consequent effects on survival outcomes.

So, to overcome these problems let’s talk about Automated tumour and organ segmentation:

The main goal of an automated segmentation is to have a delineation or a segmentation similar to an expert.

But what is a semantic segmentation??

Diagram

Description automatically generated

**Figure 3 :Visual recognition tasks: segmentation and detection[3]**

Figure 3 shows different tasks of computer vision, the most classic task in computer Vision is the image classification problem where given an image, we expect the computer to output a discrete label. In image segmentation the goal is to label each **pixel**of an image with a corresponding **label** of what is being represented.

But unlike the previous tasks, the expected output in semantic segmentation are not just labels. The output itself is a high resolution image (typically of the same size as input image) in which each pixel is classified to a particular class.

So if we go back to our image of a CT or MRI scan, the input will be the image, and the output Is another image with only background and the prostate.

|  |  |
| --- | --- |
| A picture containing sitting, laying, bed, small  Description automatically generated  Inpu**t** | A star in the background  Description automatically generated  Output |

**Figure 4:example of input/output in prostate segmentation[5]**

There are different ways of doing image segmentation:

**Region-based Segmentation:** One simple way to segment different objects could be to use their pixel values.

**Edge Detection Segmentation:** There is always an edge between two adjacent regions with different pixel values.

**Image Segmentation based on Clustering**: we use clustering techniques to divide images into segments

**Image Segmentation with deep learning:** The most popular architecture for image segmentation is U-net. The [UNET](https://arxiv.org/abs/1505.04597)was developed by Olaf Ronneberger et al.[3] for Bio Medical Image Segmentation. The architecture contains two paths. First path is the encoder path which is used to capture the context in the image. The encoder is just a traditional stack of convolutional neural network. The second path is the decoder path which is used to enable precise localization using transposed convolutions.

Chart, box and whisker chart

Description automatically generated

**Figure 5: UNET Architecture**

# End Notes

This article is just the beginning of our journey to learn all about image segmentation. In the [next article of this series](https://www.analyticsvidhya.com/blog/2019/07/computer-vision-implementing-mask-r-cnn-image-segmentation/?utm_source=blog&utm_medium=introduction-image-segmentation-techniques-python), we will deep dive into the implementation of U-NET. So stay tuned!

Reference:

[1]: **images: <https://www.philips.co.uk/>**

[2]: <https://radiologykey.com/segmentation-of-pelvic-structures-from-ct-scans-for-planning-in-prostate-cancer-radiotherapy/>

[3] Chen et al. 2016. <https://arxiv.org/pdf/1604.02677.pdf>

[4] Olaf Ronneberger et al <https://arxiv.org/pdf/1505.04597.pdf>

[5] <https://vitalab.github.io/article/2019/02/07/prostate-seg-two-nets.html>