

My Thesis

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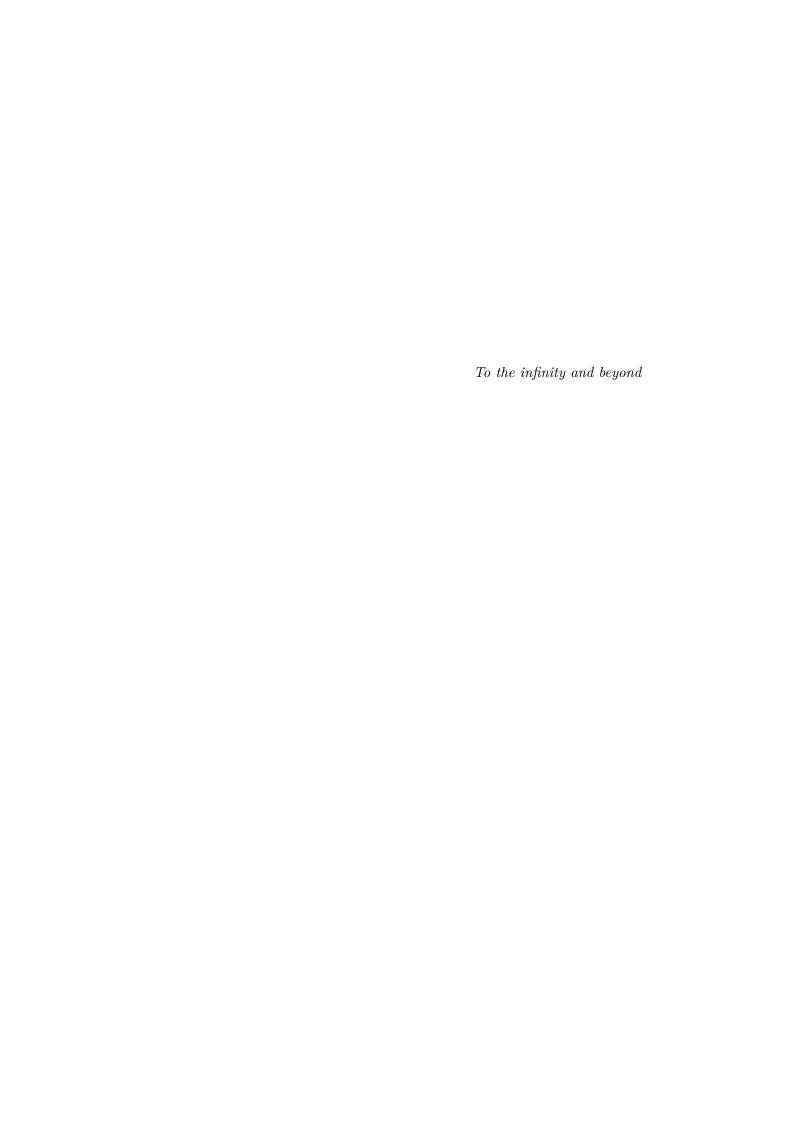
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Abstract

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Introduction

Image segmentation is a critical task in medical image analysis: it is often the first step to transform raw biomedical image into structured, valuable, information ready to be used both for scientific discoveries and clinical applications including early diagnosis during preclinical phase, therapy planning, intraoperative assistance and tumor growth monitoring. Brain tumor segmentation is the process of isolating the tumor from healthy brain tissue; however, it is still a challenging task due to the irregular form and confusing boundaries of tumors.

Simply put, one major challenge is the lack of open datasets for designing and testing new algorithms, while private datasets may differ for so many aspects that comparing the result obtained by different solutions has no relevance and it's often inconclusive. Whereas instead there is a common dataset (as in public challenges hosted by conferences focused on medical images), a new trend in medical image segmentation sprung after the advent of Vision Transformer (ViT): with abundance of available data the proposed algorithms have become more complex both in term of capacity (estimated in number of parameters) and model ensembling, sometimes neglecting simpler, yet promising solutions even developed for similar vision tasks.

Being conscious of my hardware limitations, the impracticability of training very large models and even the difficulties of making continuous training sessions, I had to devise a clever way to train a "good enough model" in the most stable, reproducible way, while keep tracking of the training processes in a fashion s.t. results of different experiments were easily comparable. For this reason I leveraged deep learning frameworks for professional AI researchers for both code refactoring/automation/organization and accelerating research and clinical collaboration in Medical Imaging, creating a personal baseline to confront to and flexibly adapt new part to my solution. Many official guides, as well as papers and tutorials present long training sessions (from hundreds to thousands epochs) and the few that show how the training process evolved, share the fact that the learning curves are very noisy for most of the time and only at the very end their models reach a convergence point. The only exception seems to be the ViT based architectures, but they incur more easily to overfitting. What I tried to obtain was a flexible, relatively small, model capable of learning without overfitting even with little data and in few epochs, so to have as quickly as possible a considerable amount of different "prototypes" to refine.

2 1. Introduction

The work is organized as follow: \dots

The Challenge

Related Works

SOTA Architectures and Procedures

The Data

Experimental Design and Result

Conclusions and Future Work