Hippocampus Segmentation

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April 2025

1 Introduction

The hippocampus, a seahorse-shaped structure in the medial temporal lobe, is crucial for memory formation and spatial navigation. Divided into anterior (emotion regulation) and posterior (spatial memory) regions, it plays a significant role in disorders like Alzheimer's and epilepsy.

Accurate segmentation of the hippocampus from magnetic resonance imaging (MRI) scans is essential for both clinical and research applications. Segmentation involves delineating the hippocampus's boundaries in 3D MRI data to isolate it from surrounding brain structures, enabling precise quantitative analysis. This process allows for volumetric measurements, which are critical for assessing structural changes associated with disease progression. For instance, in Alzheimer's disease, volumetric reduction in the hippocampus correlates with cognitive decline, serving as a biomarker for early diagnosis and monitoring therapeutic interventions. Similarly, in epilepsy, segmentation aids in identifying hippocampal abnormalities, such as sclerosis, to guide surgical planning for seizure control.

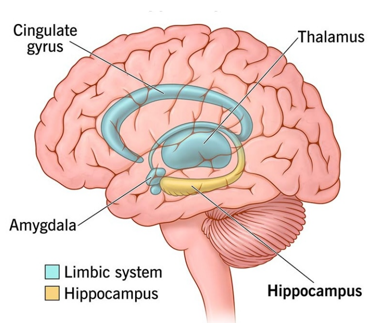

Figure 1: Hippocampus location in the brain.

2 Related Works

Hippocampus segmentation has progressed from atlas-based methods to deep learning. Below is an overview of key approaches, datasets, and metrics. Early methods, limited by generalization, used atlases or gradient-based techniques. Patch-based and ensemble methods improved robustness. Now, CNNs and U-Net variants have set new standards. Table 1 summarizes these approaches, datasets, and performance metrics, illustrating the progression from atlas-based to deep learning methods and their respective strengths. The table highlights the dominance of U-Net-based models in recent years, driven by their ability to handle complex 3D MRI data with high accuracy.

Table 1: Overview of Hippocampus Segmentation Methods

Authors and Articles	Year	Datasets	Algorithms	Performance
Somasundaram et al. [1]	2015	NITRC	Atlas-based	Dice: 0.82
Tang et al. [2]	2012	NA	LDDMM	Kappa: 0.76
Hao et al. [3]	2014	ADNI	Local Label Learning (LLL)	Dice: 0.83
Zhu et al. [4]	2016	ADNI	Multi-atlas based	Dice: 0.88
Zarpalas et al. [5]	2013	IBSR	Gradient-based	Dice: 0.84
Manjon et al. [6]	2017	NITRC	Patch-Based Boosted Ensemble	Dice: 0.87
Coupe et al. [7]	2011	ICBM	Patch-based	Kappa: 0.92
van der Lijn et al. [8]	2008	NA	Atlas registration based	Accuracy: 85%
Goubran et al. [9]	2020	SDS, ADNI, UPenn	3D CNN based	Dice: 0.89
Hansch et al. [10]	2020	NA	CNN-based	Dice: 0.76
Ataloglu et al. [11]	2019	MICCAI, ADNI	Deep Convolutional Neural Network Ensembles	Dice: 0.89
Safavian et al. [12]	2019	ADNI	Level set based	Dice: 0.847
Chupin et al. [13]	2009	ADNI	Simultaneous region deformation approach	Accuracy: 73z%
Isensee et al. [14]	2021	Medical Segmentation Decathlon	nnU-Net	Dice: 0.94 (0.9 for hippocampus only)
Modified U-Net (2D) [15]	2023	ADNI	U-Net based	Dice: 0.97

3 Project Description

This project develops a 3D Attention U-Net model for segmenting the anterior and posterior hippocampus from T1-weighted MRI scans, enabling precise analysis of hippocampal subregions for neurological research.

3.1 Dataset

The **Medical Segmentation Decathlon (MSD) Hippocampus Dataset** includes 390 T1-weighted MRI scans with expert-annotated masks for:

- Label 1: Anterior hippocampus
- Label 2: Posterior hippocampus

The images are pre-processed to an isotropic resolution $1\,\text{mm}^3$, with skull splinters, and intensity normalized. The dataset is split as follows:

- Training: 208 images (80 %)
- Validation: 52 images (20 %)
- Test: 130 images

3.2 Preprocessing

Pre-processing steps ensure data consistency:

- Conversion of masks to `uint8` format.
- Z-score normalization: $I_{\text{norm}} = \frac{I-\mu}{\sigma}$.
- Resizing to 64x64x64 voxels using SimpleITK (linear interpolation for images, nearest-neighbor for masks).

4 Model Architecture and Training

The **3D Attention U-Net**, implemented in MONAI, uses an encoder-decoder architecture with attention gates to prioritize relevant regions. Specifications:

- Input: 1 channel (grayscale MRI)
- Output: 3 channels (background, anterior, posterior hippocampus)
- Feature channels: (32, 64, 128, 256)
- Dropout: 0.1

Training parameters:

- Optimizer: Adam (lr $= 10^{-3}$, weight decay 10^{-5})
- Loss: DiceCELoss (Dice + Cross-Entropy)
- Batch size: 8
- Epochs: 50, with early stopping (patience 10) and `ReduceLROnPlateau` scheduling

Mixed-precision training and TensorBoard monitoring were employed.

5 Evaluation

The model achieved the following on the validation set:

- Validation Loss: 0.1565
- Mean Dice Score: 0.8729

Per-class metrics are presented in Table 2.

Table 2: Per-class segmentation metrics on the validation set.

Class	Dice	Sensitivity	Specificity	Precision	Jaccard
Anterior Hippocampus	0.8740	0.8845	0.9962	0.8680	0.7783
Posterior Hippocampus	0.8551	0.8542	0.9964	0.8591	0.7488

6 Visualizations

ITK-SNAP visualizations compare ground truth and predictions for three validation samples (random, best Dice, worst Dice). Overlays use:

- **Anterior Hippocampus**: Green (correct), Red (extra), Blue (missed)
- **Posterior Hippocampus**: Yellow (correct), Magenta (extra), Cyan (missed)

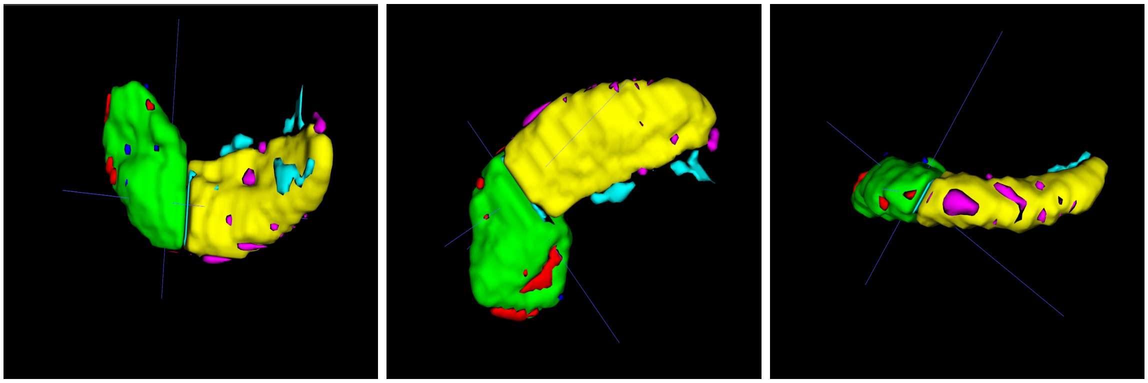

Figure 2: Random Sample

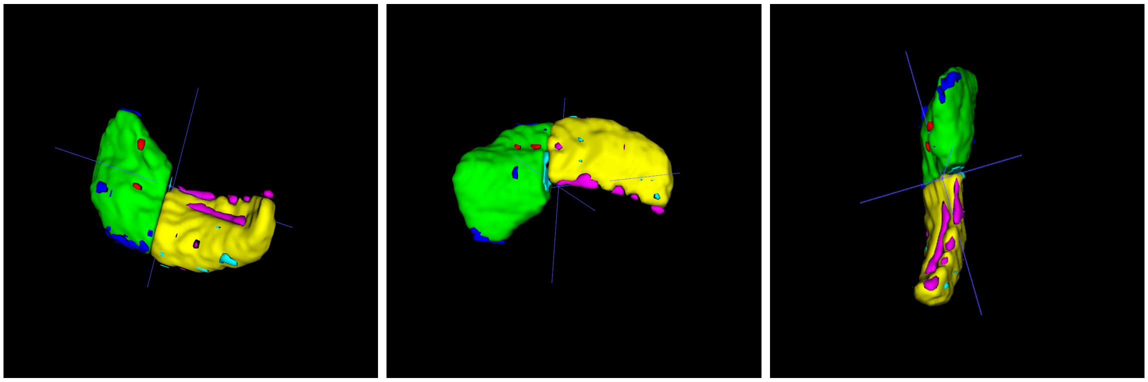

Figure 3: Best Sample

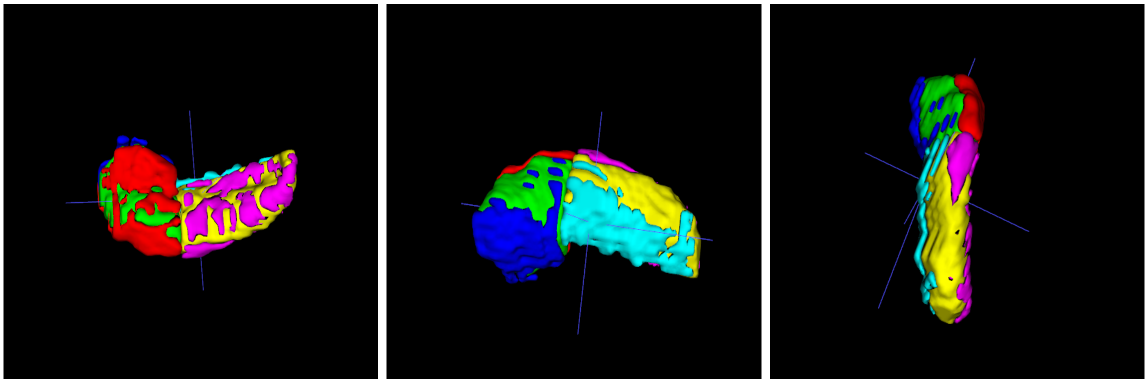

Figure 4: Worst Sample

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