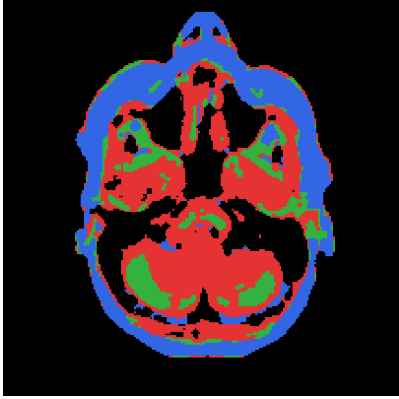
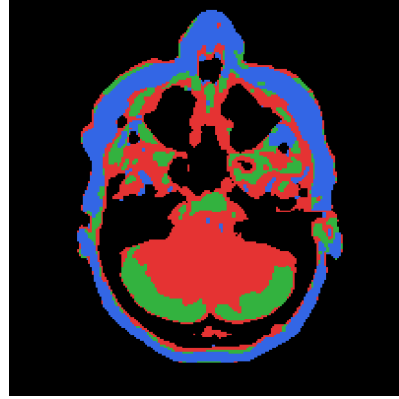


# HMRF-EM segmentation (WM=red, GM=green, CSF=blue)

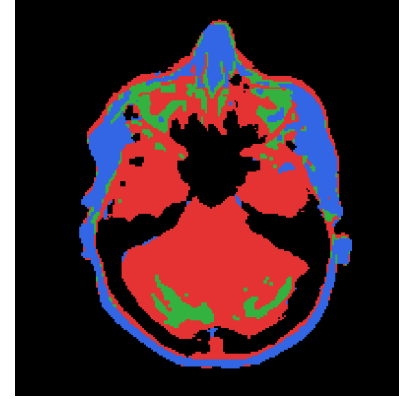
slice 7/64



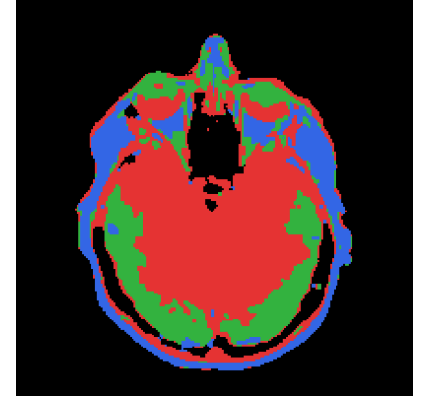
slice 11/64



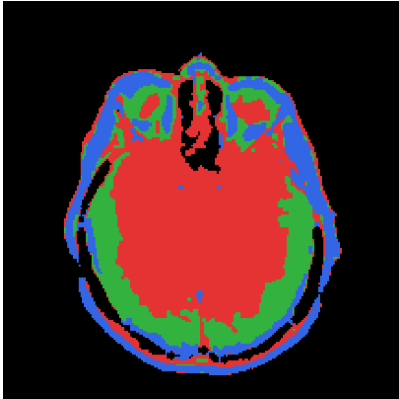
slice 16/64



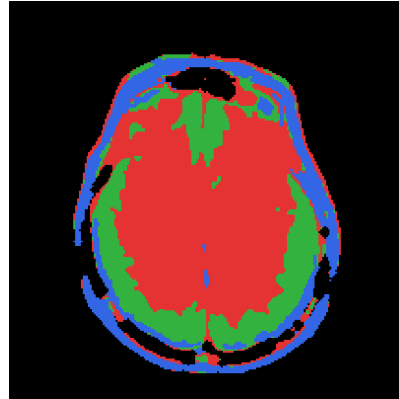
slice 20/64



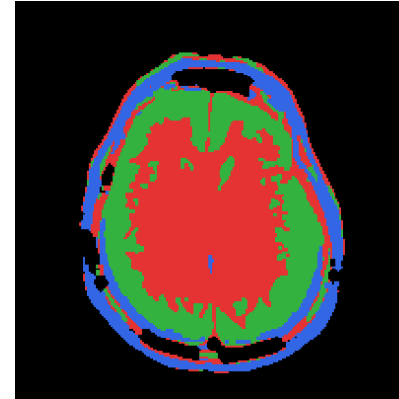
slice 25/64



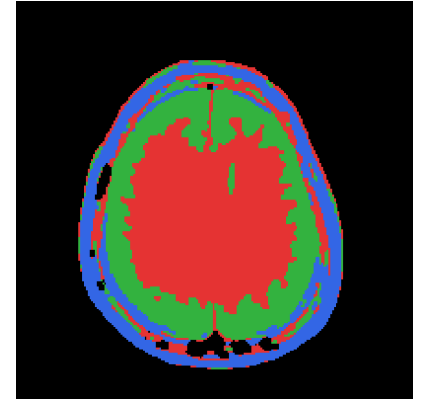
slice 30/64



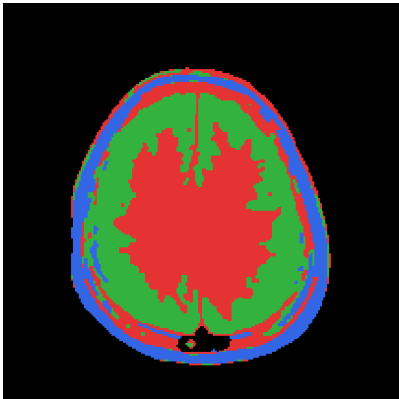
slice 34/64



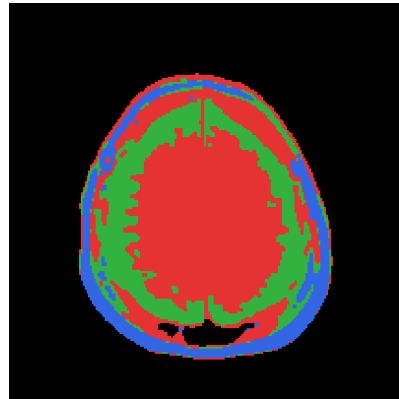
slice 39/64



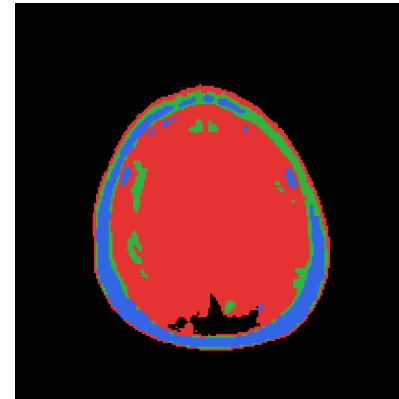
slice 44/64



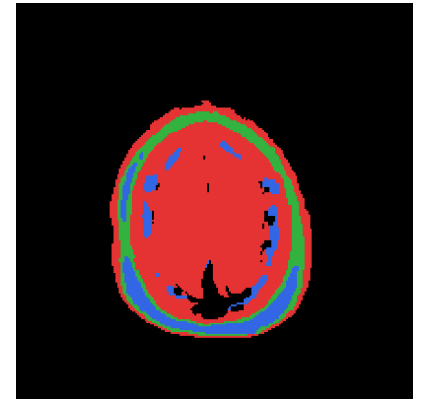
slice 48/64



slice 53/64



slice 58/64

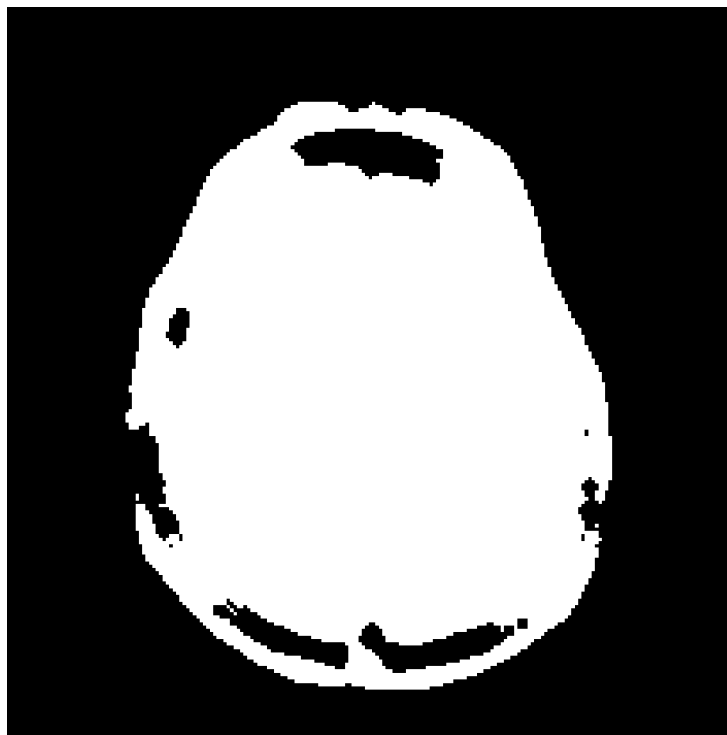


## Mid-slice + stats

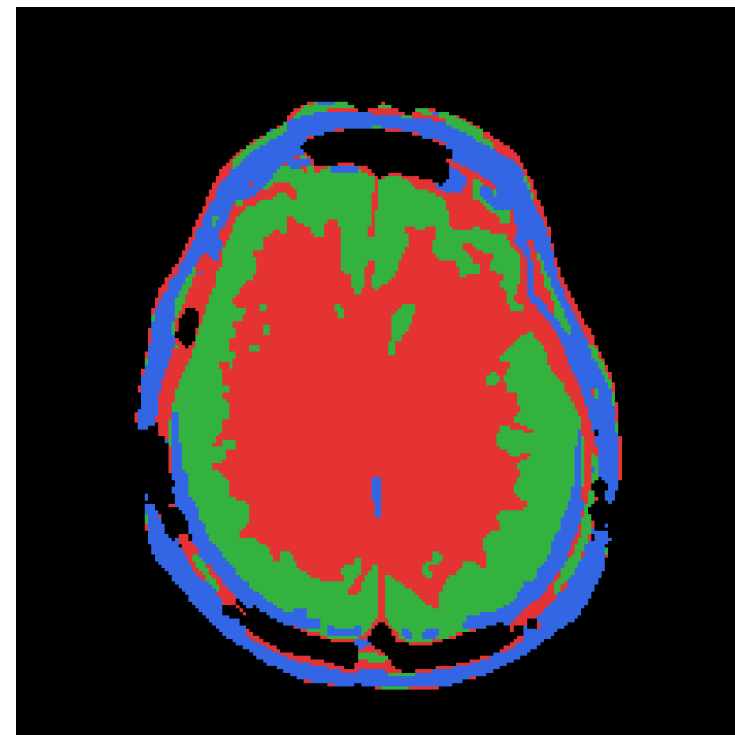
Brain mask (no BG saved)



Mask



Labels overlay — slice 33/64



Class means (sorted T2): WM=0.3427, GM=0.4625, CSF=0.7019

Voxel counts: WM=513,390 (54.8%), GM=228,111 (24.4%), CSF=194,539 (20.8%)

# Run Settings & Key Points

## Pre-processing

- Normalize intensities (2–98%).
- Denoise: Gaussian  $\sigma = 1.0$ .
- Bias-field correction (homomorphic).
- Skull-strip + morphological cleanup.

## Model

- HMRF-EM with Potts prior ( $\beta = 1.6$ ).
- Neighborhood: in-plane 4-connected.
- ICM sweeps: 2
- EM iterations: 8

## Emissions & Colors

- Gaussian per class (learned  $\mu$ ,  $\sigma^2$ ).
- Colors: WM = red, GM = green, CSF = blue.

## Why it works

- $\beta$  encourages smooth, contiguous labels.
- Less speckle than plain GMM/k-means.

## Deliverables

- segmentation\_labels.npy
- brain\_mask.npy
- class\_means.npy, class\_vars.npy
- (optional) NIfTI + QA PNGs