Threshold-Based Segmentation and Processing of Brain MRI Images

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Abstract

This report presents an extensive image processing pipeline for the analysis and segmentation of brain Magnetic Resonance Imaging (MRI) data. The workflow is based on classical image processing techniques and includes preprocessing, intensity normalization, histogram analysis, global and local threshold-based segmentation, multi-class segmentation, region splitting, and morphological post-processing. Both two-dimensional slice-based analysis and three-dimensional volumetric processing are investigated. The aim of this project is to study the theoretical foundations and practical behavior of threshold-based segmentation methods when applied to medical imaging data.

Contents

1 Introduction

Brain MRI is one of the most widely used imaging modalities for the visualization of anatomical brain structures due to its high soft-tissue contrast and non-invasive nature. Accurate segmentation of MRI data is a fundamental step for tasks such as tissue classification, disease analysis, and quantitative measurements. However, MRI images are often affected by noise, intensity inhomogeneity, and partial volume effects, which make segmentation a challenging problem.

This project focuses on classical image processing techniques, with particular emphasis on threshold-based segmentation methods. Although modern approaches often rely on machine learning and deep learning, thresholding techniques remain important for educational purposes, exploratory analysis, and as preprocessing steps in more complex pipelines.

2 Dataset Description

The dataset used in this project consists of a three-dimensional brain MRI volume stored in NIfTI (`.nii`) format. The volume represents a T1-weighted MRI acquisition, which is commonly used for anatomical studies due to its ability to clearly differentiate between gray matter, white matter, and cerebrospinal fluid (CSF).

Table 1: MRI Dataset Characteristics

Property	**Description**
Modality	T1-weighted MRI
File Format	NIfTI (.nii)
Dimensionality	3D Volume
Intensity Type	Grayscale
Analysis Type	2D and 3D

3 Methodology

3.1 Data Loading and Visualization

The MRI volume is loaded using the `nibabel` library, which provides tools for handling medical imaging formats such as NIfTI. Visual inspection of the data is a crucial first step to understand image orientation, intensity distribution, and anatomical content. Orthogonal views (axial, sagittal, and coronal) are used to explore the volume. For 2D analysis, a central axial slice is selected, as it typically contains representative anatomical structures.

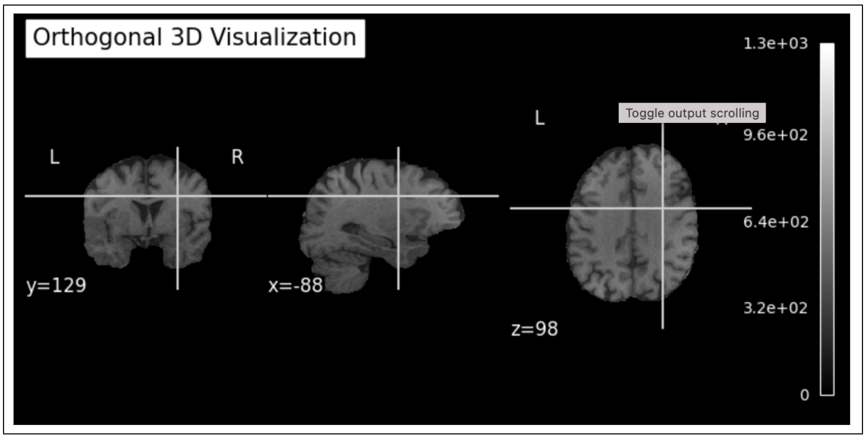

Figure 1: Orthogonal visualization of the 3D MRI volume.

3.2 Preprocessing

Preprocessing aims to improve image quality and reduce artifacts before segmentation. In this project, two main preprocessing operations are applied:

Intensity Normalization MRI intensity values are not standardized and may vary significantly across acquisitions. Min-max normalization rescales the image intensities to a fixed range, typically $[0, 1]$, improving numerical stability and allowing fair comparison between different processing steps.

Gaussian Smoothing Gaussian filtering is used to suppress high-frequency noise while preserving the overall structure of the image. This operation reduces small intensity fluctuations that could negatively affect threshold-based segmentation methods.

Table 2: Preprocessing Operations

Step	**Technique**	**Purpose**
Normalization	Min-Max Scaling	Intensity standardization
Smoothing	Gaussian Filter	Noise reduction

3.3 Histogram Analysis

The intensity histogram of an MRI slice provides a global description of the distribution of gray-level values. Peaks in the histogram often correspond to different tissue types, while valleys may indicate suitable threshold locations. Histogram analysis is therefore a fundamental tool for understanding image contrast and guiding threshold selection.

3.4 Global Thresholding Using Otsu's Method

Otsu's method is a global, unsupervised thresholding technique that automatically selects an optimal threshold by maximizing the between-class variance of pixel intensities. The underlying assumption is that the image can be divided into two classes (foreground and background) with distinct intensity distributions.

In the context of brain MRI, Otsu's method is commonly used to separate brain tissue from background or to obtain a coarse tissue segmentation. While simple and computationally efficient, global thresholding may struggle in the presence of intensity inhomogeneities.

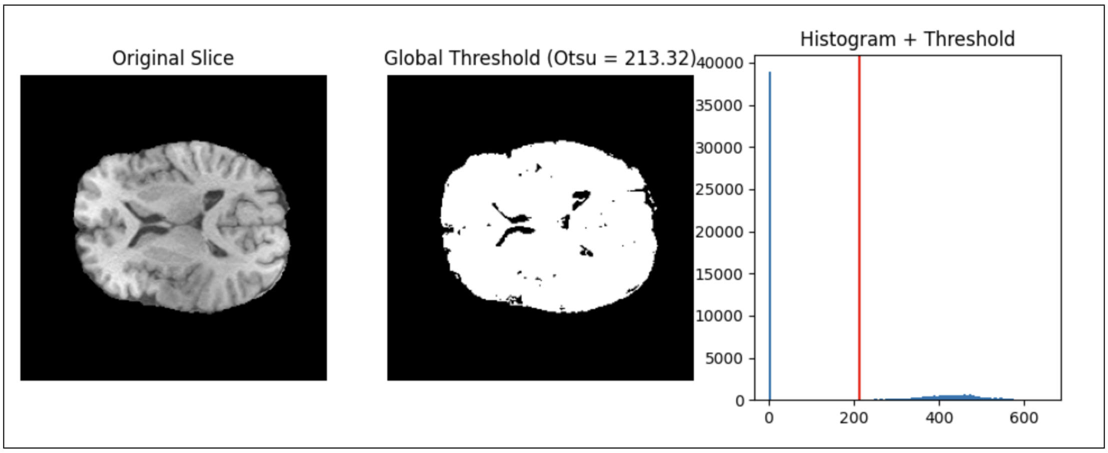

Figure 2: Original slice, Otsu binary mask, and intensity histogram with threshold.

3.5 Multi-Level Thresholding (Multi-Otsu)

Multi-level Otsu thresholding is an extension of the original Otsu method that allows the segmentation of an image into more than two classes. Instead of a single threshold, multiple thresholds are computed to partition the intensity histogram into several regions.

This approach is particularly useful for brain MRI, as different tissue types (CSF, gray matter, white matter) often occupy distinct intensity ranges. Multi-Otsu segmentation provides a coarse tissue classification based purely on intensity information.

Table 3: Multi-Otsu Segmentation Classes

Class	**Description**
Class 1	Low-intensity regions (e.g., CSF or background)
Class 2	Medium-low intensity regions
Class 3	Medium-high intensity regions
Class 4	High-intensity regions (e.g., white matter)

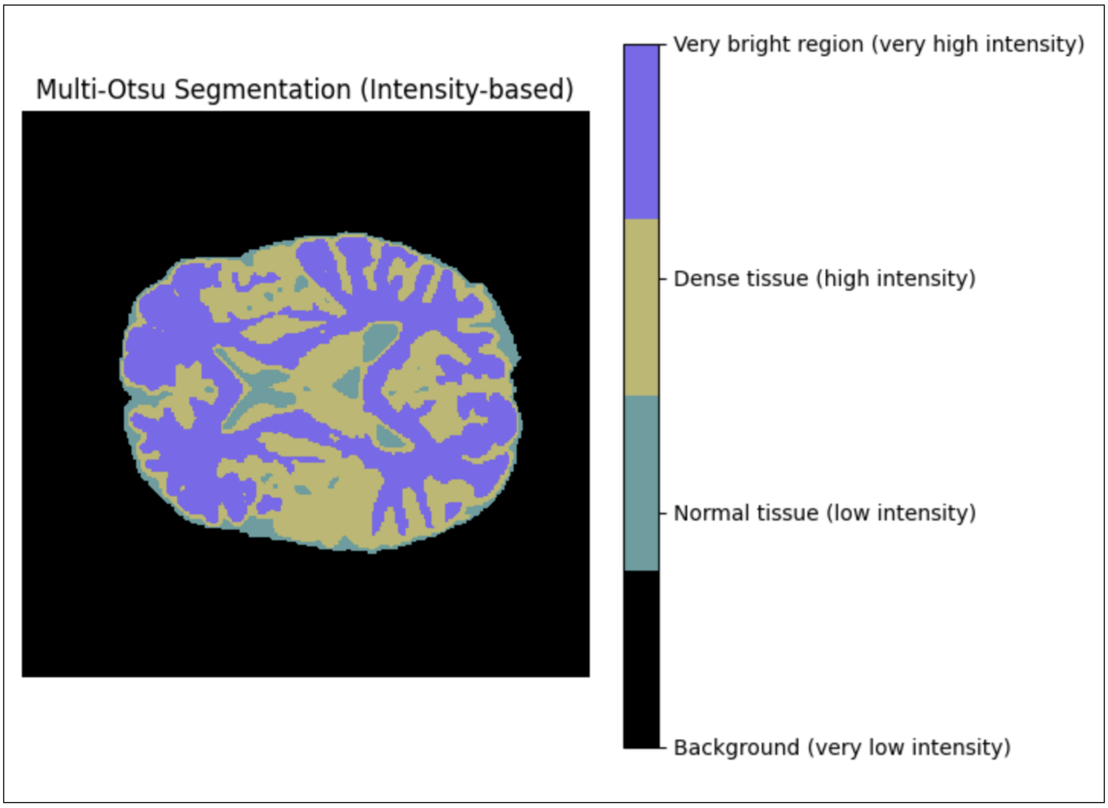

Figure 3: Multi-Otsu segmentation result on a central MRI slice.

3.6 Adaptive (Local) Thresholding

Adaptive thresholding computes a different threshold for each local neighborhood of the image, rather than using a single global value. This technique is particularly effective when the image exhibits spatial intensity variations caused by bias fields or illumination non-uniformities.

In this project, adaptive thresholding improves segmentation performance in regions where global methods fail, at the cost of increased computational complexity.

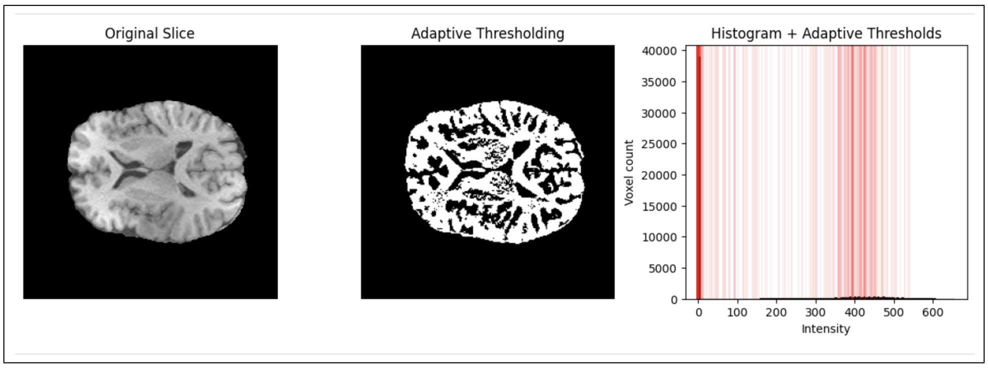

Figure 4: Adaptive thresholding result on the central MRI slice.

3.7 Histogram Equalization and Thresholding Comparison

In addition to previous steps, a central MRI slice is enhanced using histogram equalization, followed by global (Otsu) and adaptive thresholding.

Histogram equalization redistributes image intensities to produce a more uniform histogram, thereby enhancing global contrast. This process amplifies underrepresented intensity ranges, making anatomical structures more distinguishable and potentially improving the performance of threshold-based segmentation methods. This enables a direct comparison between original, equalized, and thresholded slices, as well as their corresponding histograms.

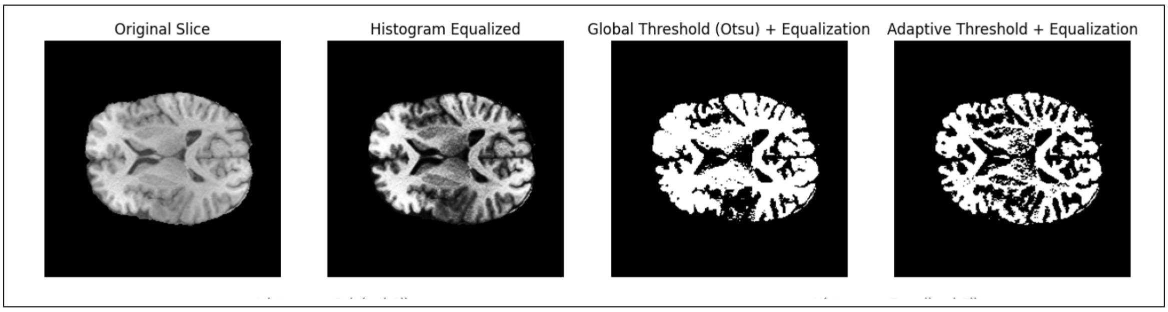

Figure 5: Comparison of original slice, histogram-equalized slice, global threshold after equalization, and adaptive threshold after equalization.

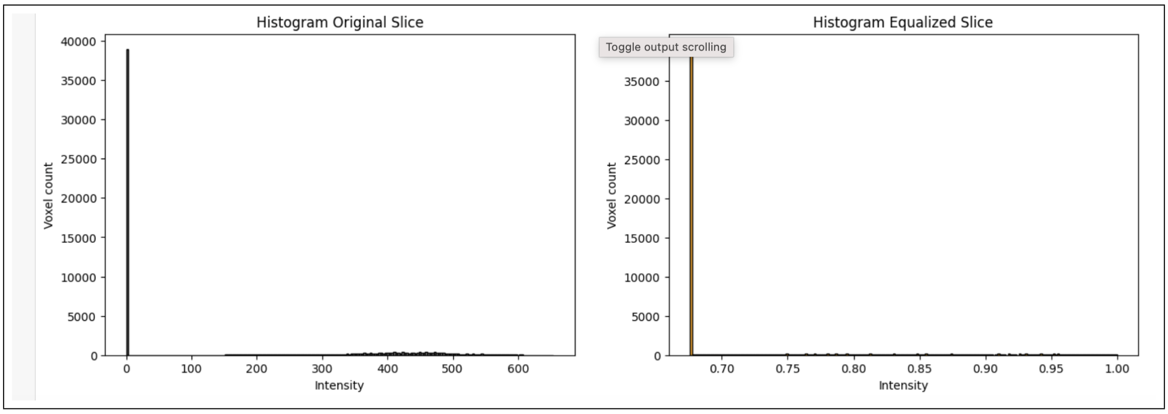

Figure 6: Histograms of original and histogram-equalized slices.

3.8 Region Splitting and Merging

Region splitting divides the image into multiple regions based on predefined intensity thresholds, while region merging combines adjacent regions with similar properties. This strategy allows for a more structured segmentation and helps reduce over-segmentation.

Table 4: Region Splitting Strategy

Region	**Intensity Range**	**Interpretation**
Region 1	Low	Background / CSF
Region 2	Medium-Low	Soft tissue
Region 3	Medium-High	Gray matter
Region 4	High	White matter

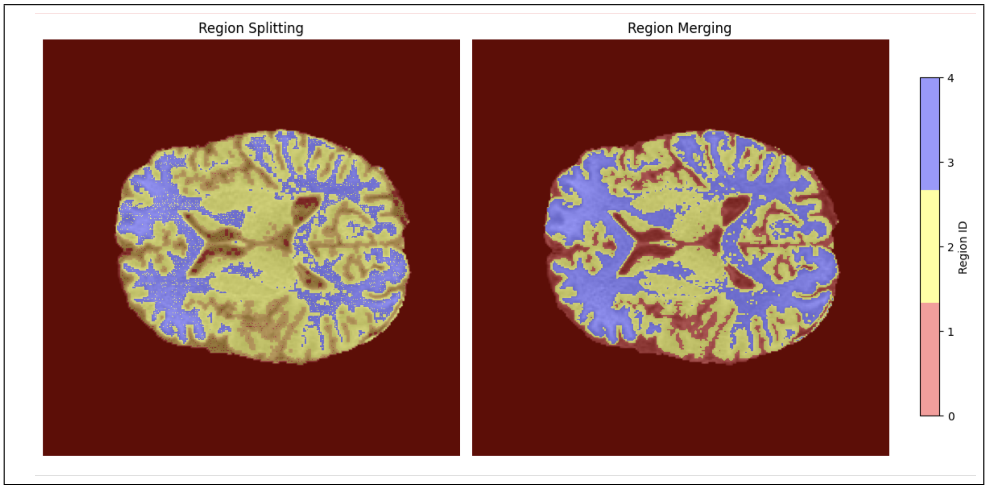

Figure 7: Overlay of segmented and merged regions on MRI slice.

4 Morphological Post-Processing

Morphological operations are applied to refine segmentation results and remove artifacts. Opening operations eliminate small isolated objects, while closing operations fill small holes within segmented regions. These steps improve spatial coherence and visual quality of the segmentation.

Table 5: Morphological Operations

Operation	**Structuring Element**	**Effect**
Opening	Disk	Noise removal
Closing	Disk	Hole filling
Object Removal	Area threshold	Artifact suppression

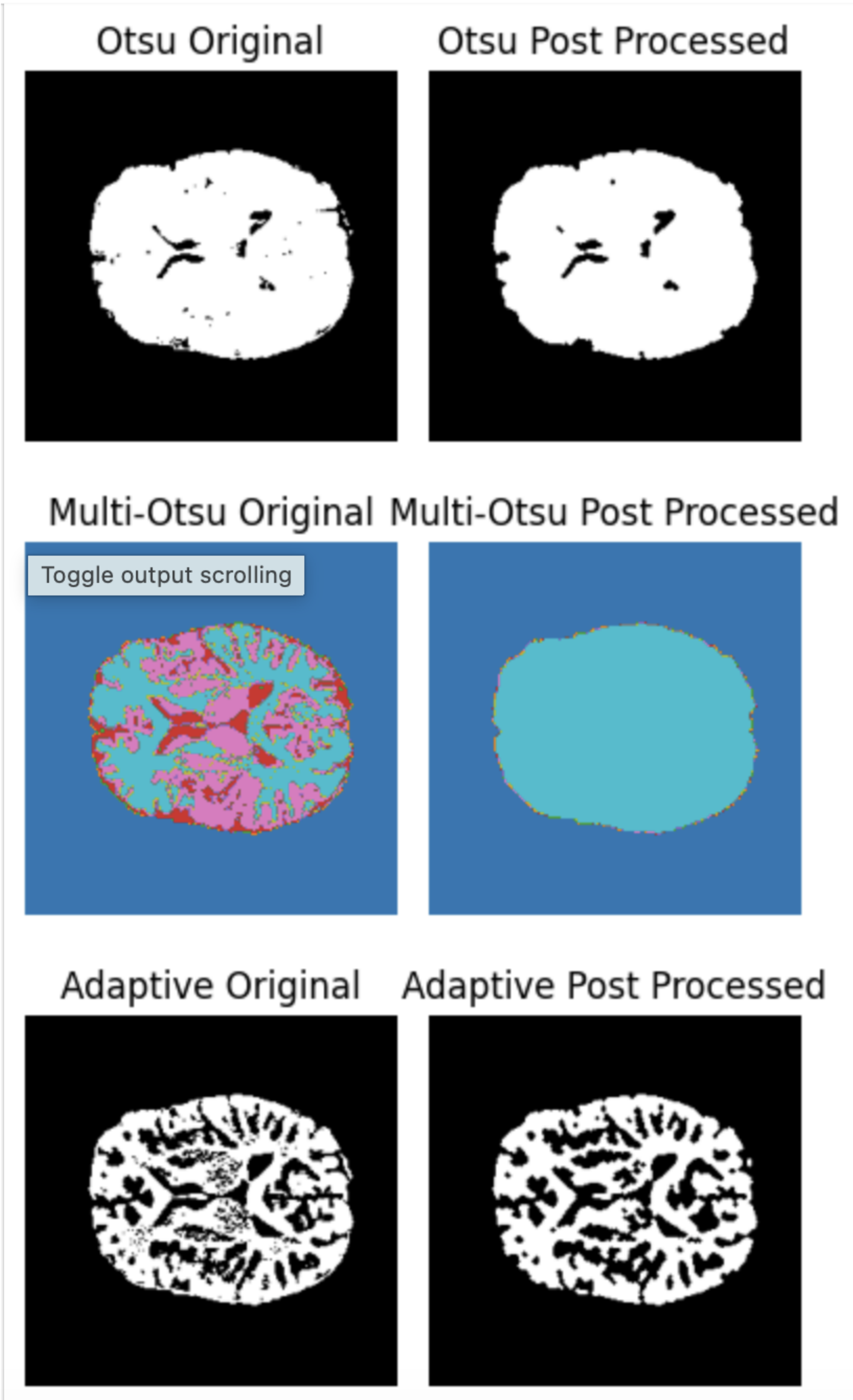

Figure 8: Comparison of segmentation results before and after morphological operations. Post-processing improves spatial coherence by removing small artifacts and filling holes.

5 Quantitative Analysis of Segmentation Methods

To provide a numerical assessment of segmentation performance, the following metrics are computed for different thresholding methods and preprocessing strategies. Metrics include the number of background (BG) and foreground (FG) voxels, the percentage of foreground voxels, and threshold values.

5.1 Global Otsu Thresholding

Table 6: Global Otsu Thresholding Results

Method	**BG Voxels**	**FG Voxels**	**% FG**	**Threshold**
Original Raw	39835	17765	30.84%	213.316
Original Cleaned	39848	17752	30.82%	213.316
Equalized Raw	45372	12228	21.23%	0.789
Equalized Cleaned	45503	12097	21.00%	0.789

5.2 Multi-Otsu Thresholding (4 classes)

Table 7: Multi-Otsu: Class Distributions and Foreground Voxels

Method	**Class0**	**Class1**	**Class2**	**Class3**	**FG Voxels**	**% FG**
Original Raw	38945	2582	8387	7686	18655	32.39%
Original Cleaned	0	18661	18661	18661	18661	32.40%
Equalized Raw	41686	5176	5136	5602	15914	27.63%
Equalized Cleaned	0	16132	16132	16132	16132	28.01%

Table 8: Multi-Otsu: Threshold Values per Method

Method	**Thresholds**
Original Raw	118.79, 312.95, 443.24
Original Cleaned	118.79, 312.95, 443.24
Equalized Raw	0.7245, 0.8157, 0.9056
Equalized Cleaned	0.7245, 0.8157, 0.9056

5.3 Adaptive Thresholding

Table 9: Adaptive Thresholding Results

Method	**BG Voxels**	**FG Voxels**	**% FG**
Original Raw	45242	12358	21.45%
Original Cleaned	45505	12095	21.00%
Equalized Raw	47189	10411	18.07%
Equalized Cleaned	47744	9856	17.11%

5.4 Discussion of Quantitative Results

From the tables above, several observations can be made:

- Histogram equalization generally reduces the percentage of foreground voxels, indicating that preprocessing modifies intensity distributions and segmentation sensitivity.
- Cleaned images (after Gaussian smoothing or noise removal) show minimal variation in voxel counts compared to raw images, suggesting that preprocessing improves spatial coherence without drastically altering the segmentation volume.
- Multi-Otsu segmentation provides more balanced class distributions but requires careful interpretation of threshold ranges.
- Adaptive thresholding is more sensitive to local intensity variations and yields lower FG percentages, particularly on equalized images.

Overall, these metrics provide a quantitative basis for comparing segmentation strategies and evaluating the effect of preprocessing steps.

6 Results and Discussion

The segmentation results demonstrate that threshold-based methods are effective for coarse separation of brain tissue from background, but each approach exhibits specific characteristics and limitations:

- **Global Otsu:** Provides a fast and simple binary segmentation. It reliably separates background from foreground, but it does not distinguish between different tissue types within the brain. Subtle intensity variations are lost, which limits its usefulness for detailed tissue analysis.
- **Multi-Otsu (4 classes):** Before post-processing, Multi-Otsu separates the slice into multiple intensity classes, corresponding roughly to different tissue types such as CSF, gray matter, and white matter. After morphological post-processing (opening, closing, and small object removal), however, the differences between classes within the brain are largely flattened, producing a nearly uniform foreground mask. While background remains well separated, the internal intensity distinctions are largely erased, demonstrating how post-processing can simplify complex segmentations.
- **Adaptive Thresholding:** Retains local sensitivity to intensity variations and captures fine details that global methods miss. Morphological operations improve spatial coherence without completely flattening intensity distinctions, but results depend on parameters such as the local block size. In some noisy regions, spurious foreground detections may occur if the block size is too small.
- **Preprocessing Effects:** The preprocessing steps applied in this pipeline include Gaussian smoothing and histogram equalization. Gaussian smoothing reduces high-frequency noise in the image, which can slightly alter intensity distributions and

remove small spurious variations. This affects threshold-based segmentation by stabilizing threshold computation and producing smoother masks. Histogram equalization, on the other hand, changes the overall intensity distribution more significantly, shifting threshold values for both global and multi-level methods. Cleaning operations such as small object removal primarily affect the spatial consistency of the masks but do not alter threshold computation. Together, these preprocessing and post-processing steps improve segmentation quality, but they can also homogenize regions and reduce the ability to distinguish subtle tissue differences, particularly in multi-class segmentations.

- **Overall Observations:** Threshold-based segmentation is highly dependent on intensity distributions, preprocessing, and parameter choices. Global methods are simple but coarse, multi-level methods can initially capture multiple tissues but may lose internal variation after post-processing, and adaptive methods are more robust to local variations but computationally more demanding. Morphological post-processing improves mask coherence but can also reduce the information available from intensity-based segmentation.

7 Conclusion

This project shows that classical image processing techniques can effectively be applied to brain MRI data for segmentation and analysis. Threshold-based methods, including global Otsu, multi-level Otsu, and adaptive local thresholding, provide a variety of approaches for distinguishing foreground from background and for separating different tissue types based on intensity.

Although these methods have limitations compared to modern learning-based approaches, such as reduced ability to capture subtle anatomical variations or to generalize across datasets with different acquisition conditions, they offer clear advantages in terms of simplicity, interpretability, and computational efficiency. The results also highlight the importance of preprocessing steps, such as Gaussian smoothing and histogram equalization, which improve segmentation quality and stability, as well as post-processing steps, such as morphological operations, which enhance spatial coherence and reduce artifacts.

Overall, this study demonstrates that classical threshold-based pipelines remain valuable educational and practical tools. They provide a solid foundation for understanding image characteristics, evaluating segmentation strategies, and serving as preprocessing or initialization steps for more advanced methods, including machine learning or deep learning approaches. These techniques also allow researchers and clinicians to perform rapid, interpretable analyses of MRI data, which can be particularly useful in exploratory studies or in environments where computational resources are limited.

References

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- Otsu, N. (1979). A Threshold Selection Method from Gray-Level Histograms. IEEE Transactions on Systems, Man, and Cybernetics.
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