DETECTING TUMOURS IN BRAIN IMAGES

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CHAPTER 1: INTRODUCTION

1.1. Background

A brain tumour is an uncontrollable growth of abnormal cells in the brain. As the brain is enclosed by the skull, when the tumour grows, it presses onto areas of the brain and would stop the function of that part of the brain.

Magnetic Resonance Imaging, or MRI for short, is a type of scan that uses strong magnetic fields and radio waves to produce detailed images of the body. MRI scans can be used to examine almost any part of the body and helps to locate the tumour, as well as check whether the tumour cells have spread.

According to an article (World Cancer Research Fund, 2018), approximately 300,000 people were diagnosed with brain cancer in 2018 alone. Malignant brain tumour patients have an average of 35.1% survival rate (National Brain tumour Society, 2019).

Nonetheless, brain tumours are also defined by their grade, which determines the severity of the tumour. The grade will range from Grade I to IV, where it increases based on its spread, growth rate and incurability. Grade I tumours are removable by surgery while tumours of grade III and IV are cancerous and will look abnormal ("Brain cancer grades" n.d.). As the size, appearance and location of the tumour can determine the grade, it will help if the tumour can be detected early before it worsens to seek the proper treatment for it.

1.2. Motivation

The segmentation, detection, and extraction of a brain tumour from a MRI scan are time consuming tasks performed by experts in the field, and deciphering the scan will be based on their experience in handling brain tumours. To add on to that, early stages of the brain tumour will be much harder to detect as it will look similar to the normal cells and tissues, and while tumours of late stages will be obvious, it might be too late to seek treatment.

A MRI scan is also prone to missing out on a tumour as a non-enhanced MRI scan lacks details and has troubles differentiating cancerous tissues with cysts (fluid sacs) or other non-cancerous tissues ("Are MRIs Accurate In Diagnosing Cancer" n.d.). There are cases where only partial tumour is detected and treated, missing out tumours in other locations of the brain that start growing and spreading uncontrollably. In an article by Boodman, a doctor misread a MRI scan for blood clots when the patient in fact had a brain tumour.

With the help of image processing techniques, we can instead process the image through segmentation and enhancement to produce results based on the existence and severity of a brain tumour. There exists many different image processing methodologies to detect brain tumours, but as of writing this, there is no one conclusive approach to the problem. The project will determine the better of the said methodologies in terms of its accuracy and precision, and the success of the project can help improve the efficiency of the medical industry along with further improvements of detections of brain tumours, enabling a more suitable treatment for the patients.

1.3. Aims & Objectives

The purpose of this project is to record different algorithms that apply varying methodologies and use the results to achieve a higher level of accuracy and precision. The algorithm would take an untouched brain MRI scan, pre-process it by smoothing and enhancing methods, segment it with various techniques such as thresholding and clustering, and finally post-process the image with morphological operations and classify them through feature extraction. The results would give us information regarding the tumour's presence, size and location.

CHAPTER 2: LITERATURE REVIEW

2.1. Pre-processing

Image pre-processing is the first step towards any digital image processing projects. Images obtained through any methods are bound to come with errors or imperfections in them, making it difficult to apply advanced image processing techniques (Gamage, 2017). In this phase, the original image is converted to a grayscale image before smoothing is applied to remove noise from the image, followed by image enhancement to improve the finer details of the image (Tulo, Nayak, Kumar & Khushboo, 2017).

The most popular technique used for noise elimination is the median filter which is especially effective on salt & pepper noise from grayscale images. It works by replacing each pixel with the median of its neighbouring pixels.

Other common noise removal techniques include the mean filter and the Wiener filter. The mean filter is similar to the median filter in practice while the Wiener filter is a de-noising filter based on inverse filtering in the frequency domain (Gamage, 2017).

After smoothing the image and eliminating noise, image enhancement is used to improve the details of the image through contrast adjustment, brightness adjustments or image sharpening. Through image sharpening, important details such as edges are enhanced to enable further analysis to be more accurate.

A popular image enhancement method for MRI scans is by using the high pass filter. It is able to increase contrast of an image by removing or minimising low frequency data and only retaining the high frequency data (Tripathi & Chaudhary 2018).

Another known method of image enhancement is the histogram equalization technique. It sharpens images by spreading the histogram of the grayscale frequencies of the image, resulting in the global change of contrast of an image.

After smoothing and image enhancement, skull stripping can be performed. Skull stripping is the process of removing the non-brain parts in a scanned image, and it can effectively reduce misclassification as well as improve segmentation results (Shijin Kumar & Dharun, 2016).

According to Bahadure, Ray and Thethi (2017), there are several ways where we can perform skull stripping – namely segmentation and morphological operation, histogram analysis, using image contour, thresholding and connected regions. Shijin Kumar and Dharun (2016) also mentioned the use of region growing techniques for skull stripping.

2.2. Image Segmentation

Image segmentation is the process of splitting the images into several segments. It is a process used for object detection or edge detection. In this case, image segmentation is done to separate the brain tumour area from brain images, so that further medical decisions can be made based on the result of segmentation. There are a lot of ways and methods used to determine the tumour area in a scanned brain image.

The most common way to segment the image is by using fixed thresholding. A fixed threshold is used to convert the pre-processed brain images into a binary image, where pixels with gray-level values greater than the threshold have a value of 1, while pixels with gray-level values smaller than the threshold have a value of 0. Automatic thresholding methods such as histogram thresholding and Otsu thresholding are also used to segment images.

According to Gamage (2017), histogram thresholding uses the gradient magnitude to determine the possible edges and compute an optimal thresholding value to use. Otsu thresholding on the other hand, does not have a fixed threshold value. It optimises the separation of foreground and background by minimising the intra-class variance of pixel values (Kapoor & Thakur, 2017).

Besides using thresholding methods, another well-known technique in brain tumour segmentation is the Watershed Segmentation technique, which is based on the similarities of neighbouring pixels in regions (Kapoor & Thakur, 2017).

Clustering pixels into tumour regions and non-tumour regions is also a popular segmentation method. Hard clustering, which classifies pixels into one and only one cluster (tumour area or non-tumour area in this case), is widely used. The most common hard clustering method is the K-means clustering method. On the other hand, soft clustering, such as the Fuzzy C-mean clustering method, assigns a probability value of pixels being in the two clusters. The pixels can then be classified by taking the cluster which has the highest possibility.

Another common method in identifying tumour areas is by using region based methods, which include techniques such as contour and shape based methods, region growing (RG), region based level (RBL) and graph based method. These methods make use of the texture, intensity or shape features of a local region to segment an image.

Other less common methods include Genetic Algorithm and edge detection. Genetic Algorithm uses evolutionary techniques and natural selection to segment an image (Kapoor & Thakur, 2017). Edge detection is the identification of edges in an image by selecting the pixels where a fast rate of change of intensity is observed.

2.3. Morphological Operation

Morphological operation is the processing of images based on the structure of the object. Due to the noise caused during thresholding, defects tend to exist in binary images (Gamage, 2017). Thus, morphological operations seek to remove these defects considering the shape and structure of the object in the image.

Based on our literature review, the only techniques used for morphological operation are dilation and erosion, which are the most basic operations. Dilation operations are used to add pixels to the boundary region of the image while erosion operations are used to eliminate the pixels from the boundary region of the image. Both operations are based on the structuring element of the image.

2.4. Feature Extraction

Feature extraction is the process of gathering necessary information from an image to reduce the dimensions of image data. Extraction of relevant features is an important step due to the complicated structure of various tissues such as white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) in the brain MRI images (Bahadure, Ray & Thethi, 2017). Feature extraction can directly be applied on pre-processed images for tumour detection.

A popular feature extraction method in literature is the Gray Level Co-occurrence Matrix (GLCM) which is a popular method for texture analysis. A GLCM gives tabulated information about the positions of pixels with similar gray level values in an image while textural properties are calculated based on the GLCM. This technique observes texture which takes into account the spatial association of pixels, also known as the gray-level dependence matrix (Rao & Dharmar, 2018).

Gamage (2017) also mentioned the use of “Histogram of Oriented Gradients” for feature extraction, which takes into account the gradient orientation of pixels. The image is divided into regions called cells, where the histogram of gradient orientation for the pixels in the cells are computed.

Other feature extraction methods include the Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA). The DWT technique is a time-frequency analysis method while the PCA technique is more commonly used in image compression.

2.5. Critical Analysis of the Literature Review Conducted

To detect tumour areas in brain MRI images, multiple methods and techniques used. Some methods are used together to yield better results. Each of the methods are discussed below to evaluate their advantages and downsides.

For smoothing, median filter has the ability to reduce noise from an image while preserving the edges and boundaries (Gamage, 2017), which can improve the results of the following processes such as image segmentation and morphological operations. MRI scans have a simple and consistent layout to it and does not carry much external information. Through the median filter process, loss of crucial information can be prevented, making it a suitable smoothing technique to be used.

As for mean filtering, although it can run faster, mean filtering tends to distort boundaries and edges of an image. Preserving edges is an important part in detecting tumors in an image and thus, mean filtering is ineffective in this scenario. Wiener filters can also denoise an image in the form of blur, but it tends to run slower as it works on the frequency domain of an image and may add unnecessary complexity to our algorithm.

For image enhancement, the high pass filter method is preferred over the histogram equalization technique as the latter tends to brighten unnecessary parts of the image and may cause a loss in detail or important parts of the image such as the tumour, or makes it harder to segment tumours from an image due to its surrounding getting brighter.

A high pass filter is usually a filter kernel that has a positive value in the center of a matrix and negative values as its neighbours. It will then pass the kernel by convolution to enhance the original image. A high pass filter retains the high frequency information within an image while reducing the low frequency information (Tripathi & Charles, 2017). This results in a high quality contrast image.

The most common method for skull stripping is using connected regions, which accurately and efficiently removes non-brain tissues from brain images. It is recommended by both Bahadure, Ray and Thethi (2017), as well as Shijin Kumar and Dharun (2016) in their articles.

In their article about skull-stripping, Shijin Kumar and Dharun (2016) also stated that the seed region growing method requires human supervision for manual seed selection, and so is thresholding for threshold selection. Double thresholding is an improvement to the robustness of producing good results for various images.

The usage of morphological operation requires the image to be a binary image, so some process to convert the input image to a binary image must be done, usually by segmentation or thresholding. As such, morphological operation is also suitable to be used after any skull-stripping techniques that produce a binary image to further increase the accuracy of the output.

For image segmentation, fixed thresholding is simple and often yields satisfactory results after pre-processing of images. However, the choice of a suitable threshold is a problem in using this method. Therefore, automatic thresholding methods are sometimes more preferred because of their automatic selection of a threshold.

Based on the segmentation results by Gamage (2017), histogram thresholding yielded less accurate results than fixed thresholding. The performance of Otsu's thresholding is unknown as its accuracy is not discussed. However, according to Kapoor and Thakur (2017), it is simple, straightforward, and works well with high contrast images.

Watershed algorithm is widely used to detect brain tumours because of its basis on grouping pixels with similar intensities together, whose results are not largely affected by the fact that different patients often produce different intensities and contrast in their brain images. According to Kapoor and Thakur (2017), it is preferred because of its good extraction results, although it can be highly affected by noise.

Clustering methods are used because they have a more local segmentation effect compared to thresholding methods (Tulo, Nayak & Khushboo, 2017). Fuzzy C-mean clustering method is time consuming but more preferred than K-means clustering method because of its more accurate results compared to hard clustering methods (Rao G & Dharmar, 2018). Suhag and Saini (2015) recommended the use of Fuzzy C-means as it is least affected by blocking tissues that appear to be dark in a brain image.

On the other hand, region based methods are useful to deal with spatial information and features (Rao G & Dharmar, 2018), but each technique has their own drawbacks which may affect the accuracy of the results. They are less popular to segment tumour areas in brain MRI images compared to other methods. Edge detection is also not a well-received tumour detection method as the boundaries in the original image are often unclear or distorted due to other tissues in the brain.

As for morphological operations, the techniques used in literature only include dilation and erosion. Dilation can help to enhance the visibility of an object by filling in small holes in the object, while erosion has the ability to remove small objects so that only concrete objects remain. These two processes can help to enhance the shape of the tumour. However, as morphological operation is the rearranging of the relative order of pixel values and not of mathematical values, it is only suitable for processing binary images (Bahadure, Ray & Thethi, 2017).

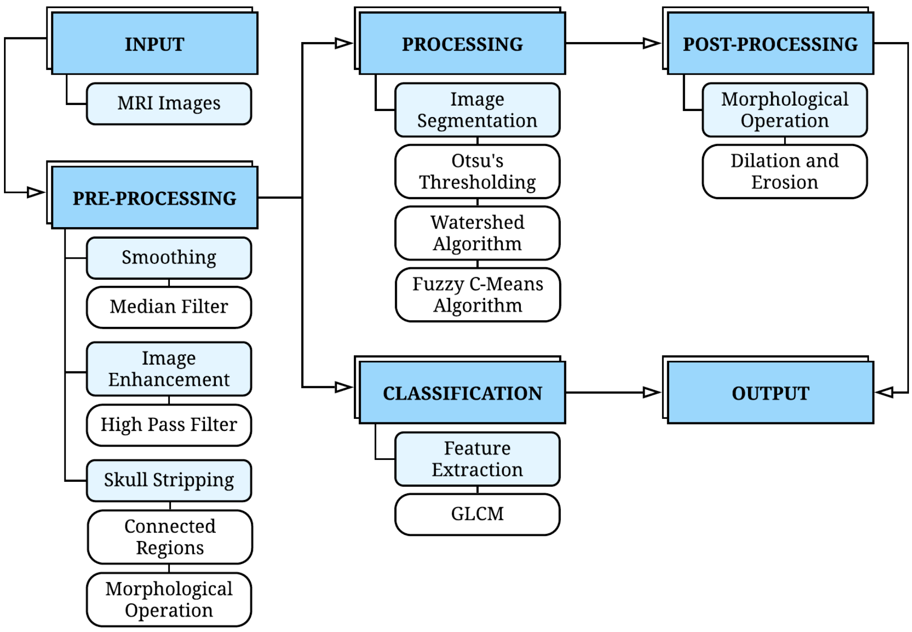
For feature extraction, the GLCM technique has the advantage of being able to extract important features of the image by allowing the calculation of textural properties. Features which are important for the detection of brain tumours such as contrast, correlation, dissimilarity, energy, entropy, homogeneity, mean, variance and standard deviation (Zulpe & Pawar, 2012) can easily be calculated using the GLCM technique.

Based on this advantage, the other methods used in literature such as the Histogram of Oriented Gradients, DWT and PCA techniques would be inferior to the GLCM technique as the features calculated from the GLCM can directly detect and classify the brain images into tumours and non-tumours.

All in all, different methods have their own advantages and drawbacks. There is not an indubitable method that is clearly dominant and favoured over other methods after analysing numerous research papers. The broad differences between approaches and standpoints used by researchers are even more bewildering.

CHAPTER 3: TENTATIVE METHODOLOGY & IMPLEMENTATION PLAN

3.1. Overall System Architecture



3.2. Methodology

Pre-processing Algorithms – Smoothing and Image Enhancement

For pre-processing, we must first convert the image to grayscale if it is in rgb format, by using the function *rgb2gray*.

The image requires smoothing as it contains noise. We propose to use median filtering to remove noise from the image as it preserves edges and boundaries well. The median filter will replace each pixel with the median of its neighbouring pixels. As we pass the image into *medfilt2*, the size of the neighbourhood can be adjusted into the parameters, with the default value being a [3 3] neighbourhood.

We propose to use a high pass filter to sharpen the details of the image by using *imfilter* after smoothing the image. This function requires a kernel to convulate the image, where the kernel will be a 3x3 sharpening kernel, [0 -1 0; -1 5 -1; 0 -1 0] (Powell n.d.).

After smoothing and enhancing, we propose to use connected regions and morphological operation to perform skull stripping, as suggested by Shijin Kumar and Dharun (2016).

The image is first converted to a binary image with a selected threshold. Shijin Kumar and Dharun (2016) attained the best results by using a threshold value of 40, but trial and error can be done during implementation to obtain a threshold that may be more robust. Then, use connected regions labelling to find the largest connected region. Perform dilation on the complement of the largest connected region to fill any holes within the region, and the result is inverted again to produce the mask required to perform skull stripping. The enhanced scanned image is then multiplied with the mask pixel-wise.

The output image will contain sharpened details such as edges or tumours, with minimal noise and non-brain tissues removed to ensure better results for the following image processing algorithms.

Image Segmentation Algorithms

To detect the tumour area, we propose to use multiple techniques to yield multiple results from each technique. These results will then be collated to obtain a final result, which we expect to draw benefits of each technique, while lessening the effects of drawbacks of each technique.

The main reason for using various tumour-detection methods is because there is not an indubitable method that is clearly dominant and favoured over other methods after analysing numerous research papers. The algorithms that we propose to use are Otsu's thresholding method, Watershed algorithm and Fuzzy C-means algorithm.

For Otsu's thresholding, a threshold is first computed using *graythresh*, with the image being converted into a binary image using the threshold.

According to Eddins (2002), the Watershed algorithm can be implemented in a few steps. First, the image is modified to remove minima that are too shallow to prevent over-segmentation. Only then the Watershed algorithm is performed on the processed image using *watershed*.

Fuzzy C-means algorithm can then be done using the function *fcm*. Each pixel is classified into the cluster with the largest membership value. The image is converted into a binary image based on the clusters.

There are many possible ways of combining multiple results. We propose to use a concept similar to hysteresis thresholding to combine the results, whose performance is to be tested during implementation:

1. Mark pixels that are segmented as tumour pixels in all three algorithms above to be strong pixels. Mark pixels that are segmented as tumour pixels in less than three algorithms to be weak pixels.
2. Assign grayscale values to these pixels, for example 255 for strong pixels, 100 for weak pixels and 0 for non-tumour areas.
3. Apply hysteresis (as in Canny Algorithm) to obtain the final result. Use *hysthresh*, a function written by Fierro (2008) to apply hysteresis and obtain the final classification of pixels.

Morphological Operation Algorithm

After obtaining the results from image segmentation, dilation and erosion will be performed. A structuring element will first be created using *strel*. Depending on the condition of the image, dilation or/and erosion will be performed. Both dilation and erosion can also be performed in a single step using *imopen* (erosion followed by dilation) or *imclose* (dilation followed by erosion).

After performing dilation and/or erosion, the tumour part of the image will be separated. The tumour area of the image will be shown as white color as this area has the highest intensity compared to other regions of the image (Mustaqeem, Javed & Fatima, 2012).

After applying morphological operations to enhance the segmentation results, we can also calculate the number of tumours using connected component labelling and the area of each white region by counting the number of pixels spanned over each white region.

Feature Extraction Algorithm

To detect and classify the pre-processed brain images into tumours and non-tumours, the feature extraction method that we propose to use is the GLCM technique. Firstly, create the GLCM of the pre-processed brain image using *graycomatrix*. The features important to our system can then be calculated using built-in functions such as *graycoprops, entropy, mean2* and *std2* or by using formulas.

After completing this step, we can predict the existence of tumours in brain images by analysing the contrast, mean and standard deviation calculated through the GLCM technique.

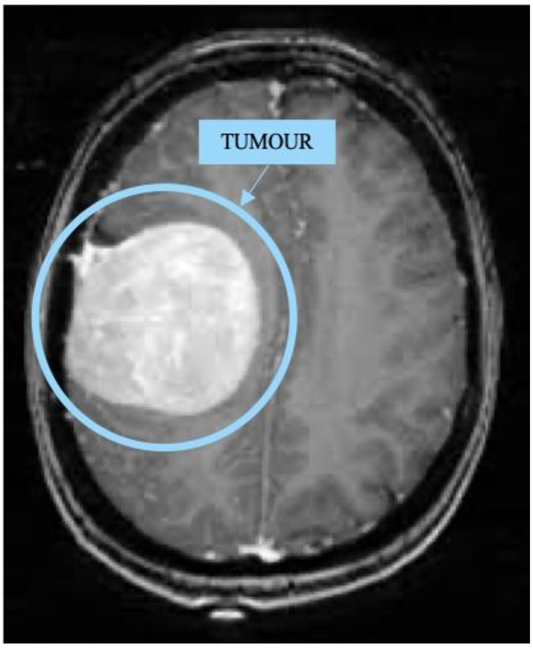
Final Output

Combining the results of classification and segmentation, we can produce the final output of whether there is a tumour in the brain MRI scan, along with the number, shape, location and area of any existing tumour.

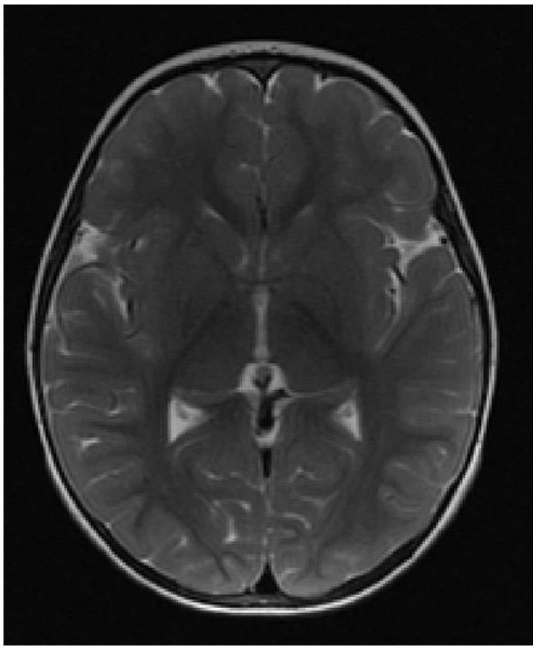
3.3. Data Set

The data set that we will be using is found on Kaggle at the URL https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection#18%20no.jpg.

The following is an example of MRI images with and without tumour from the data set above.



MRI image with tumour


MRI image without tumour

This data set was uploaded by Navoneel Chakrabarty on 14th April 2019. It consists of a total of 253 brain MRI images. The data set has already been categorised into brain images with and without tumours. Out of the 253 MRI images, 98 of them are healthy brain images and the remaining 155 brain images have tumours.

There are a lot of other data sets available online too. Some have classified images into more detailed groupings, which is not necessary for our algorithm; while others have more than one image slice for each brain, which would require us to implement some kind of slice choosing algorithm. Further discussions about this issue can be found under Chapter 4.

Therefore, we have chosen this data set as it is very clean and tidy compared to the other data sets that we found, where slices of brain images have already been classified clearly into two categories: with tumour or without tumour. Since we are not attempting to classify the type of tumour, this classification is substantial to test our algorithm. The memory size of the dataset is also not too massive, which is suitable to be processed smoothly using the available devices with limited computing capabilities.

3.4. Workload distribution among the group members

Task	Person-in-Charge	Deadline
Presentation slides	Gian Hao	27/4/2020 (Monday)
Presentation	All	4/5/2020 (Monday)

Implementing algorithm in MATLAB:
• Pre-processing:
  ▪ Median Filter
  ▪ High Pass Filter
  ▪ Skull Stripping
• Image segmentation:
  ▪ Otsu's Thresholding
  ▪ Watershed Algorithm
  ▪ Fuzzy C-means Algorithm
• Combination of results
• Morphological Operation
  ▪ Dilation and Erosion
• Feature Extraction and Classification of Brain Images
  ▪ GLCM
	
	Gian Hao
	
	Yuan Ai
	
	Yuan Ai
	Amber
	
	Amber
		
		1/5/2020 (Friday)
		
		8/5/2020 (Friday)
		
		8/5/2020 (Friday)
		15/5/2020 (Friday)
		
		15/5/2020 (Friday)

Review and testing of algorithm	All	22/5/2020 (Friday)
Report: • presentation of findings with results • improvements and suggestions for future work	All	5/6/2020 (Friday)
Final check on submission	All	12/6/2020 (Friday)

CHAPTER 4: Assumptions and limitations

The proposed algorithm works on individual pre-selected slices of brain images. Some limitations of the proposed algorithm include:

1. There is no method to choose which slices to detect the brain tumour. Therefore, the best way of using this algorithm is to classify each slice of brain images, then using the results of classification of neighbouring slices to compute a final result. There may be cases where one slice is classified as containing brain tumour while a neighbouring slice does not, which does not make sense if the tumour is thicker than the separation between slices. The algorithm does not take this into account, and therefore, may not be accurate compared to algorithms that do consider neighbouring slices.

2. The algorithm only works on 2D brain images. There are algorithms which are applied on 3D models. Apart from the limitation explained in the previous point, working on 2D images may also increase the chance of incorrectly classifying a tumour region and erroneous highlighting of small foreground regions, such as ending slices with small brain areas (Mitra, Banarjee, & Hayashi, 2017).

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