Apply super pixel-based segmentation techniques to brain tumor segmentation
Final Project Report

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1 Abstract

Our main objective in this project is to segment brain metastasis using MRI. Brain metastasis can be split into three distinct areas : the NCR (Necrotic non-enhancing tumor), the ET (Enhancing Tumor) and the ED (The surrounding Oedema), from interior to exterior. We used contrast-enhanced MRI channel ($T1ce$) to segment all together these three regions.
In the first step, we've explored different filters and considered different intensity-based and positional features. In the second step, we've created three different types of training sets : A training set consisting of Super pixels form the same image we're trying to segment, a training set consisting of super pixels from different frames of the same MRI, and a training set consisting of super pixels from different MRIs. We used SLIC algorithm to perform the super-pixel segmentation and finally, we applied several classification techniques to segment the MRI based on the mean and variance of features of the pixels consisting a super pixel .

2 Introduction

The management of brain metastasis has evolved over the last fifteen years and involves a variety of strategies including more or less aggressive treatments, sometimes combined, resulting in longer survival and improved quality of life for patients. Radiotherapy techniques are very effective but establishing a diagnosis between radio-necrosis and recurrence remains difficult mainly because MRI currently does not allow differentiation of tumor progression from the effects induced by treatment. However, the ability to clearly differentiate a tumor among non-tumor tissues is crucial to ensure appropriate patient management.

In order to ease the work of specialists, we want to develop a new way to segment the area of interest (tumor or radio-necrosis). Indeed with a fine segmentation, doctors will gain a huge amount of time to directly focus on the classification task that is deciding whether we are facing an enhancing tumor or just radio necrosis induced by the treatment.

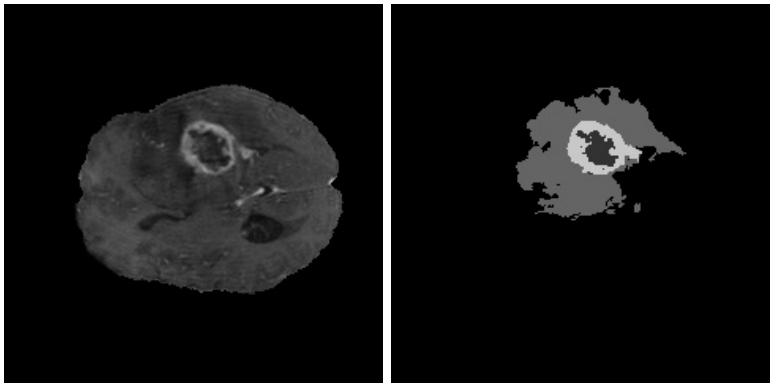

FIGURE 1 – MRI slice of patient with brain metastasis. **Left** MRI slice. **Right** Segmentation mask annotated by expert

3 Problem definition

In this project we will try to isolate the metastasis from MRI of patient that have brain tumors. We divided the problem into three parts : In the first part we've applied different filters on MRI pictures to later decide which features to use for classification purposes, in the second part we segment the image into super-pixels and we retrieve interesting features for each one of them. The final part consists of classifying these super-pixels in order to identify the region of interest.

3.1 Feature extraction using filters :

The difficulty of the classification task in hand, is that there isn't a well defined shape or size of the different parts of the metastasis, thus we cannot simply look for certain key points that indicate presence of the cancer, however we can segment the different parts of the cancer using a succession of filters (see Figure 2)

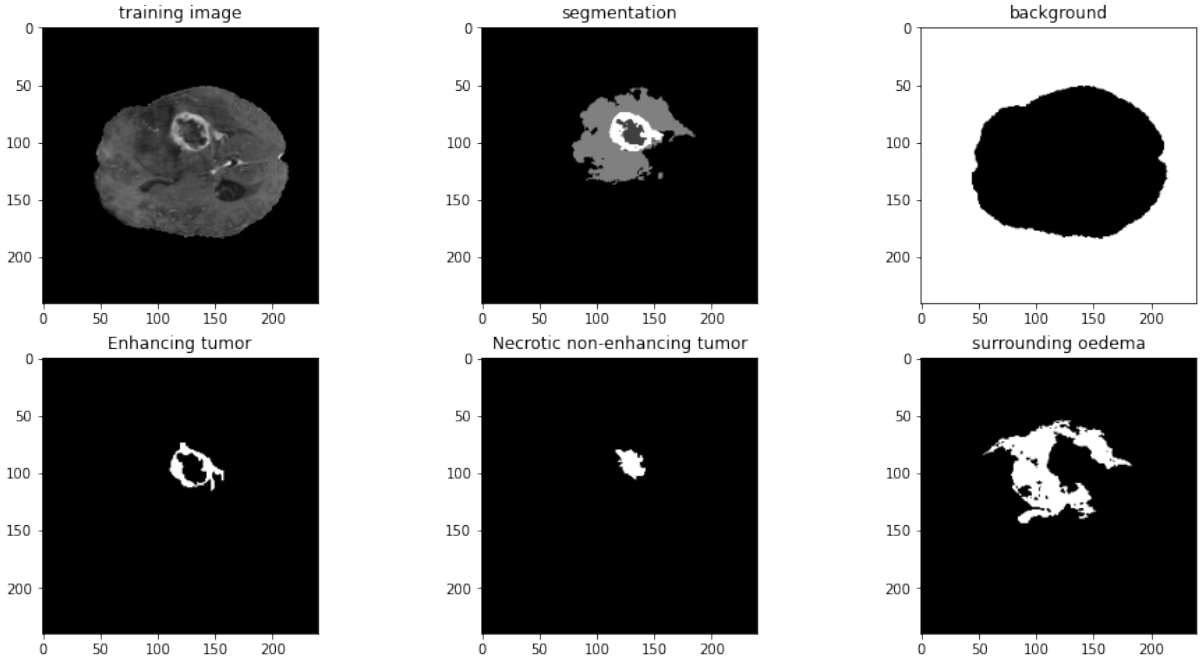

FIGURE 2 – Segmentation of the metastasis as result of a succession of thresholding algorithms

However, one can't expect that the same thresholds would apply to all MRIs, and thus the need to apply a more complex model : one that requires segmenting an image into super-pixels then classifying features from several filters .

3.2 Super-pixels segmentation

Super-pixels are segmentation techniques that group pixels together based on a "similarity" measure. For example one can chose to group pixels based on their color and there position in the image. In the end, we end up with a lower resolution image where each super pixel keeps the mean information of the pixels it is composed of.

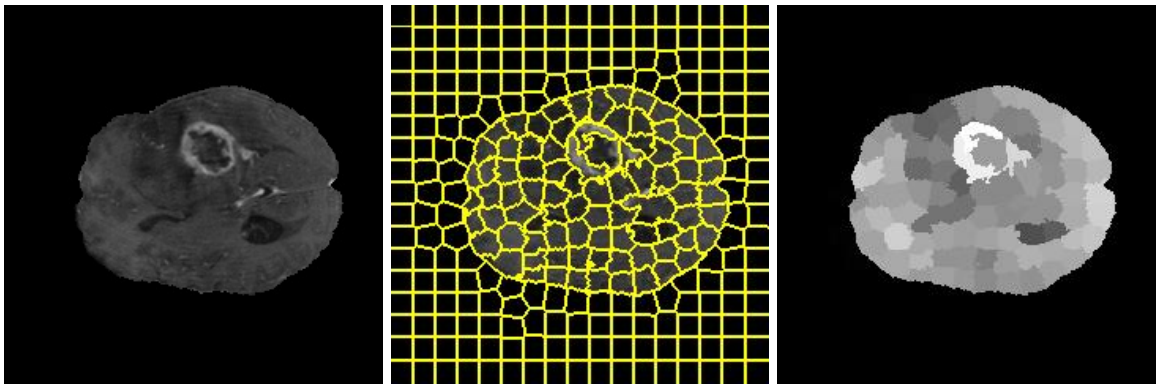

FIGURE 3 – MRI slice of patient with brain metastasis. **Left** MRI slice. **Right** Segmentation mask annotated by expert

3.3 Classification of super-pixels

In our application, Super-pixels classification can be a difficult task. Indeed we are working with MRI that are gray scale images and color variations are quite smooth. Only the active part of the tumor is clearly delimited as it is enhanced by the contrast product (it is the white contour we can observe on the MRI). Predicting the full damaged area, meaning also segmenting the oedema area seems to be a difficult task as even for a human eye, it is difficult to distinguish it from the rest of the brain. Fortunately detecting the oedema is not really interesting for expert radiologist and if the prediction over the oedema is not entirely correct, it should not affect the work of a radiologist.

4 Related Work

Image segmentation is an active field of research and especially in the medical imaging field. The recent development of deep learning based segmentation algorithms recently opened a new horizon for high performance models.

Super-pixels Super-pixels are widely use when it comes to image segmentation. In many recent papers, researcher used super-pixel segmentation to perform image segmentation. It is used in many fields where image segmentation can be applied such as building modeling [4], image classification [7] and it is widely used in the medical imaging sector [5] [1] [3].

Deep learning In the medical sector, image segmentation is one of the main subject of study. Indeed, today's specialists spend a consequent amount of time identifying and segmenting regions of interest. With the rise of deep learning, many sophisticated and highly performing models have been developed. Among them U-Net architecture models [8] have been developed for medical imaging segmentation in the first place and widely adapted to various segmentation tasks.

5 Methodology

5.1 Feature extraction using filters

We accord to each super pixel a vector of features : consisting of barycenter of the super pixel to account for the spatial dependency, the mean and variance of the intensity of the pixels that constitute a super pixel, as well as the mean and variance of the intensity of images that are result of contrast enhancing, sharpening and thresholding filters.

5.1.1 Denoising the image

This step precedes feature extraction as in we don't use the result of noise reduction filters for feature step but as a pre-step for other filters that we will use for feature extraction, we've applied different type of algorithms and we deduced that the best filter to use in this case is the Bilateral filter because it helps us distinguish between the different parts of the metastasis. Figure 4 shows the result several noise reduction algorithms :

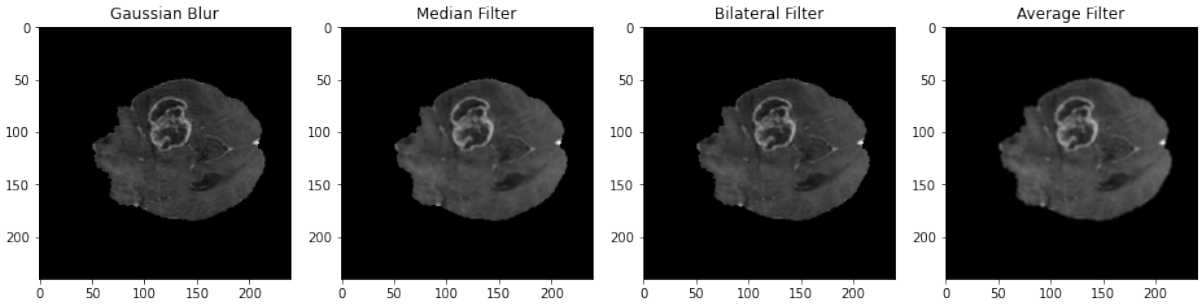

FIGURE 4 – Noise reduction using several denoising algorithms

5.1.2 Enhancing contrast

We use enhancing contrast to exaggerate the difference between adjacent structures, this type of filters is particularly interesting here because it helps distinguish between the different parts of the metastasis. We've tried three different algorithms :

- Histogram equalization : The histogram equalization improves contrast in images by effectively stretching out the intensity range of the image. This method usually increases the global contrast of images when its usable data is represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast.

- Contrast-limited adaptive histogram equalization (CLAHE) : CLAHE is a variant of Adaptive histogram equalization (AHE) which takes care of over-amplification of the contrast. CLAHE operates on small regions in the image, called tiles, rather than the entire image. The neighboring tiles are then combined using bilinear interpolation to remove the artificial boundaries.

- Contrast using sigmoid function : Each pixel's value intensity value in the output image is equal to its intensity value added to the value of the sigmoid mask.

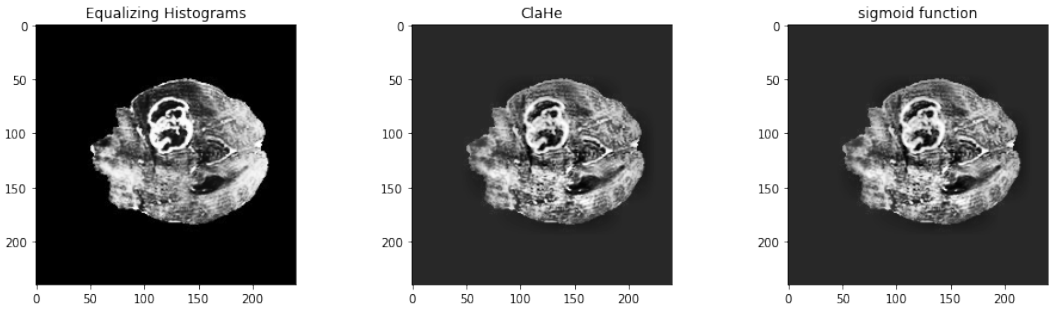

FIGURE 5 – Contrast enhancement, using Histogram equalization ,claHe and applying Sigmoid function

5.1.3 Sharpening the image

Image sharpening is an effect applied to digital images to give them a sharper appearance. It helps embolden the edges in the image. Famous sharpening algorithms are the high pass filter, the laplacian filter and the Sobel

filter. We've tried less common sharpening algorithms like the Prewitt filter and the Scharr filter.

- Prewitt Filter : The Prewitt operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical directions.
- Scharr Filter : This is a filtering method used to identify and highlight gradient edges/features using the 1st derivative. Typically used to identify gradients along the x-axis and y-axis independently.

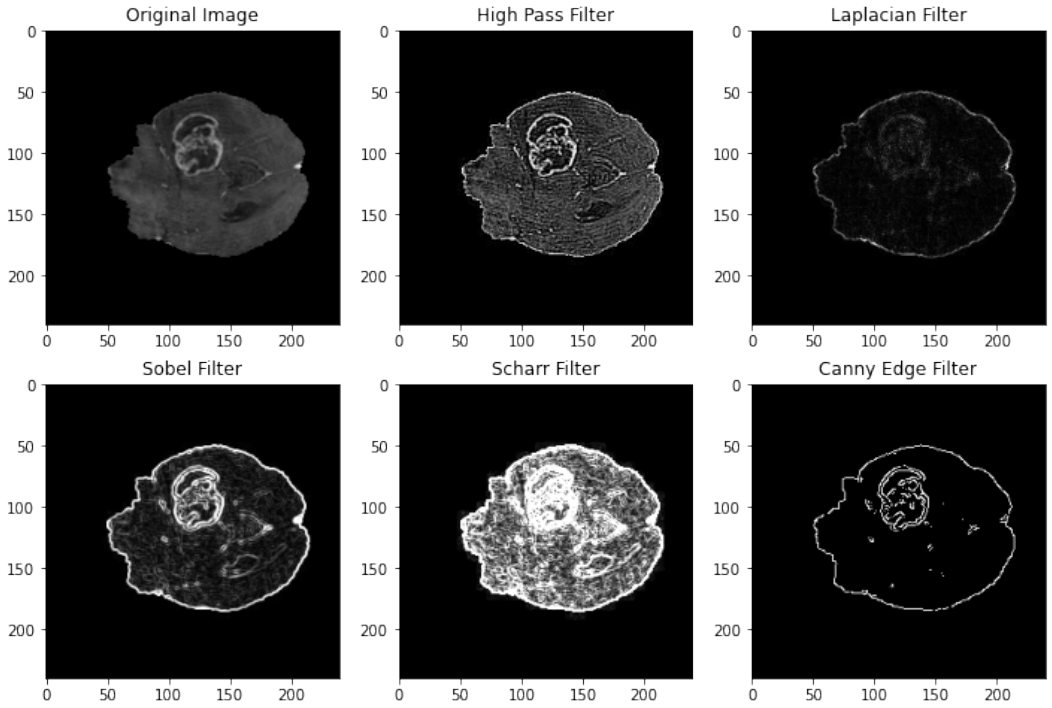

FIGURE 6 – Contrast enhancement, using Histogram equalization ,claHe and applying Sigmoid function

5.1.4 Thresholding image

Thresholding is the simplest method to segment images, we've implemented different threshold techniques for different purposes :

- Li threshold : We've used the Li threshold algorithm to separate the foreground from the background by minimizing the cross entropy.

- Otsu threshold : Otsu's thresholding method involves iterating through all the possible threshold values and calculating a measure of spread for the pixel levels each side of the threshold, i.e. the pixels that either fall in foreground or background. The aim is to find the threshold value where the sum of foreground and background spreads is at its minimum

- multi-otsu threshold : Multi-Otsu calculates several thresholds, determined by the number of desired classes. The default number of classes is 3 : for obtaining three classes, the algorithm returns two threshold values.

- Binary threshold : the most basic threshold : creates a binary image based on setting a threshold value on the pixel intensity of the original image.

- Binary inverse pixel : its just the opposite of the binary threshold.

- adaptative mean threshold : the threshold is found by dividing an image into an array of overlapping subimages and then find the optimum threshold for each subimage by investigating its histogram. The threshold for each single pixel is found by interpolating the results of the subimages.

– Adaptative gaussian threshold : the threshold value is the weighted sum of neighbourhood values where weights are a gaussian window

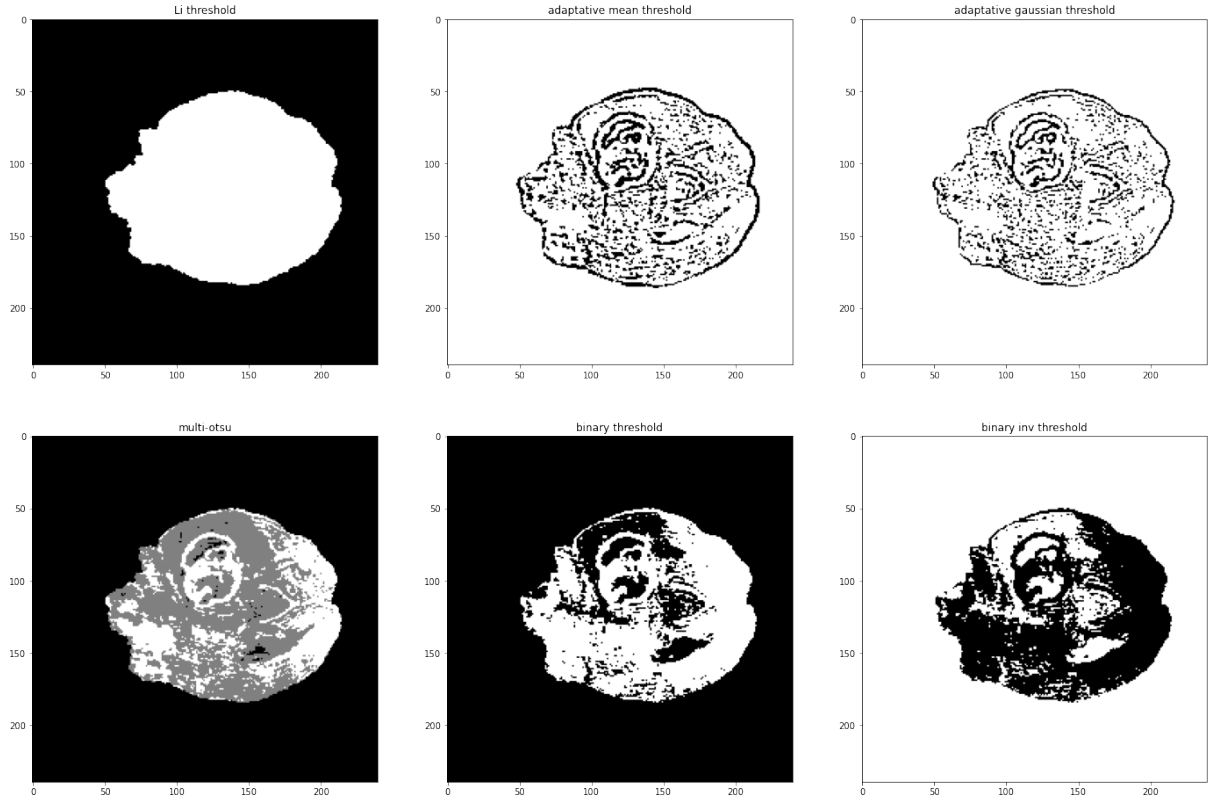

FIGURE 7 – Threshold filters

5.2 Super-pixels segmentation

In this project we used SLIC algorithm to create super-pixels. Within a super-pixel create by SLIC, pixels have similar colors (level of gray in our case), textures, and intensities. SLIC [**slic**] is a fast and effective method to generate super-pixels. SLIC is nothing else than a K-means algorithm that uses intensity, color and space criterion. The algorithm works as follow :

Initialization Initialization of seed points. Given K the number of super-pixels, the points are equally distributed on the image each super-pixel containing $\frac{N}{K}$ pixels where N is the total number of pixels in the image.

Assignment Each pixel of the image is attributed to the closest center cluster based on its parameters (I, c, x, y) where I denotes the intensity, c the color, x and y the pixel location. The center of the cluster is then adjusted.

To compute the distance between two pixels, we need to normalize color proximity and spacial proximity :

$$d_{color} = \sqrt{(l_i - l_j)^2 + (c_i - c_j)^2} \tag{1}$$

$$d_{spacial} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{2}$$

$$D = \sqrt{\left(\frac{d_{color}}{m}\right)^2 + \left(\frac{d_{spacial}}{S}\right)^2} \tag{3}$$

where S represents the interval between grids, and m is a parameter to balance the proportions of color information and spatial information in this distance.

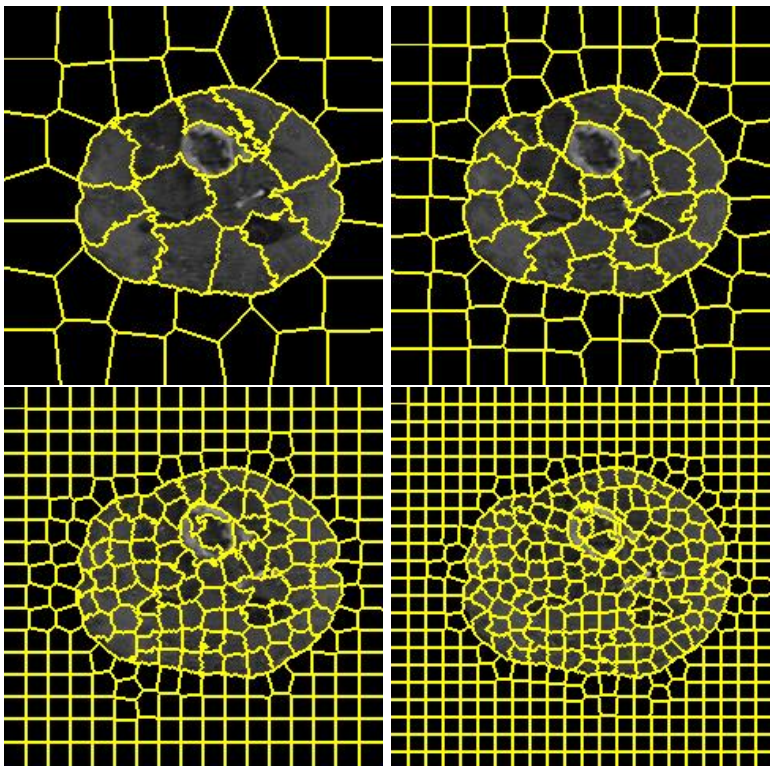

FIGURE 8 – Brain MRI slice super-pixel segmentation for different values of K (number of super-pixels). **Top-left** 50. **Top-right** 100. **Bottom-left** 300. **Bottom-right** 500

5.3 Creating Training Dataset

Now after the super pixels segmentation is done, and that we've defined a vector of features consisting of the coordinates of the barycenter of the superpixel, and thr mean and variance of intensity and other transformations of pixels that constitute the superpixel, we need to create a training set. We've considered three different types of datasets :

5.3.1 Training set within the image to segment :

We can create a small training set from the image we want to segment,

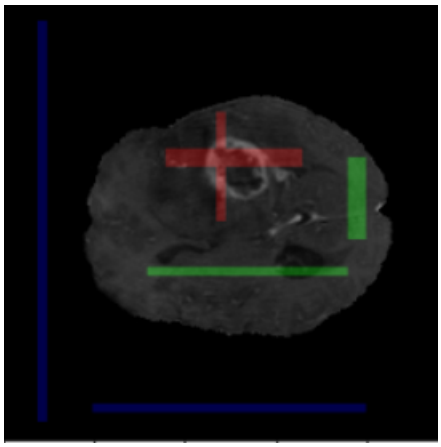

FIGURE 9 – Annotated MRI to train classification model. **Blue** background. **Greed** brain. **Red** tumor and oedema

Since we manually annotate the super-pixels, we'll only consider three classes : background, normal cells and tumor cells. The disadvantage of such a method is that we will have to annotate every MRI and train a new model for each of them. Indeed the feature space for each super-pixel not only depends on color but also highly depends on the localization features x and y. From one MRI to another, the tumor can be localized in a completely different region, therefore the model we trained no longer works on a new MRI.

5.3.2 Training set consisting of other slices from the same MRI :

In this second type of training sets, in order to segment the slice 62 from the first MRI, we've trained the model on slices 65 to 70 from the same MRI :

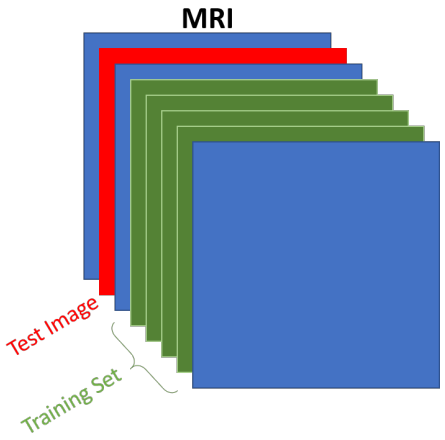

FIGURE 10 – Training set from the same MRI

5.3.3 Training set consisting of slices from different MRIs :

In this third type of training sets, in order to segment the slice 62 from the first MRI, we've trained the model on slices 55 to 65 from MRIs 2, 3 and 4 :

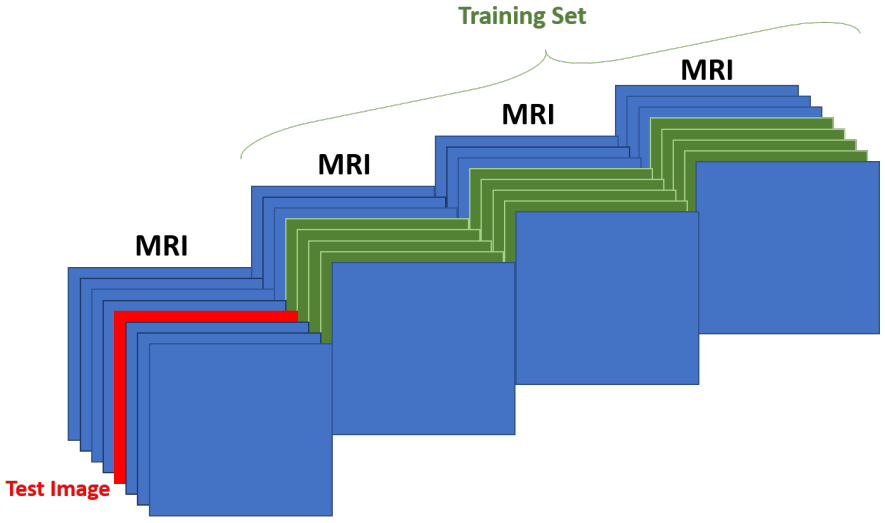

FIGURE 11 – Training set from different MRIs

5.4 Super-pixels classification

Once the super-pixels segmentation is done we need to classify them into distinct classes. In our case we have 3 evident distinct classes : *background, brain, tumor*. We selected three different algorithm and compared their results.

5.4.1 SVM

SVM (support vector machine) is a type of classifier that perform well on the task we are trying to solve. Indeed the objective of the SVM is to find an optimal solution (the optimial hyper-plane) that separates the super-pixels into three classes. The solution is optimal in the sens that SVM algorithm will try to maximise the margin between the data and the hyper-plane which is important in our case as separation between two classes may sometime be difficult to identify.

5.4.2 Gradient Boosting

Gradient Boosting consists in assembling several "weak learners" to make a "strong learner", i.e. assembling several low-performance algorithms to create a much more efficient and satisfying one.

In Gradient Boosting, each predictor tries to improve on its predecessor by reducing the errors. Instead of fitting a predictor on the data at each iteration, it fits a new predictor on the residual errors made by the previous predictor.

6 Evaluation

The dataset we used for this project is the dataset provided by the BraTS Challenge [6] which is a challenge dedicated to the task we are addressing. The dataset is composed of 369 MRI files and their ground truth segmentation. This ground truth segmentation was established by expert radiologists and contains fine segmentation of the $NCR(Necrotiquenon - enhancingtumor)$, the $ET(EnhancingTumor)$ and the $ED(Oedema)$ parts of the tumor.

To evaluate the performance of our model we used the Dice coefficient metric [2] (or Sørensen index [9]) which is a famous metric to measure the similarity of two samples. If we denote X and Y two binary samples and $|X|$ and $|Y|$ their cardinalities, then the dice coefficient is defined as :

$$Dice = 2 * \frac{|X \cap Y|}{|X| + |Y|} \tag{4}$$

The Dice coefficient equals twice the number of elements common to both sets divided by the sum of the number of elements in each set. It ranges from 0 (if X and Y are disjoint) to 1 (if X and Y are equal).

We ran several experiments using different classification methods and different number of super-pixels, and different training sets :

6.1 SVM

We ran our SVM classifier on a segmented image with 1000 super-pixels and the results are shown in figure 12.

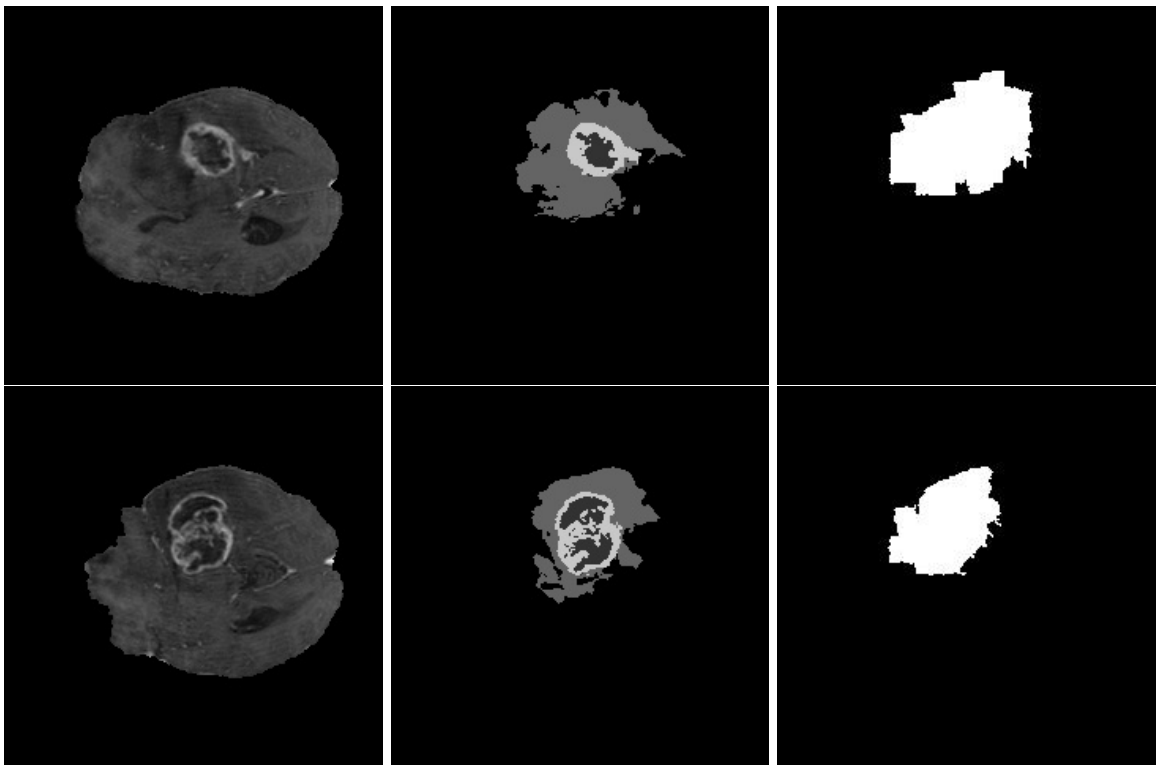

FIGURE 12 – SVM predictions using 1000 super-pixels. **Left** MRI slice. **Middle** Segmentation mask annotated by expert. **Right** Predicted mask

6.2 Gradient Boosting

As for the Gradient Boosting, we've experimented a bit more because its much more flexible than SVM, let's present the results for the three types of training sets :

- for the training set of the first type, we've used as features the mean of the intensity, the mean of the image obtained by applying a binary filter and the positional features :

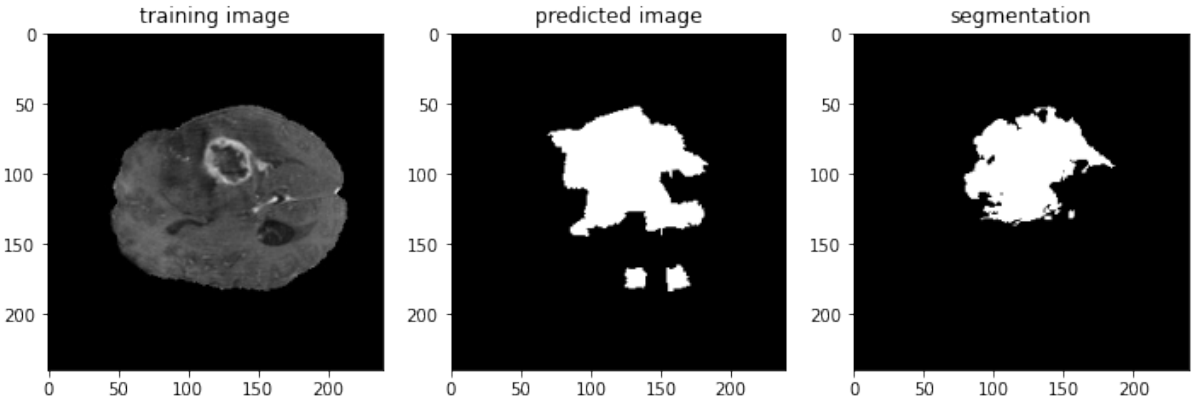

FIGURE 13 – predicted image after training the model on a training set of type 1

the dice coefficient is : 0.775

- For the training set of the second type, we've used as features the mean and variance of several sharpening filters, the result is :
  The dice coefficient is : 0.784

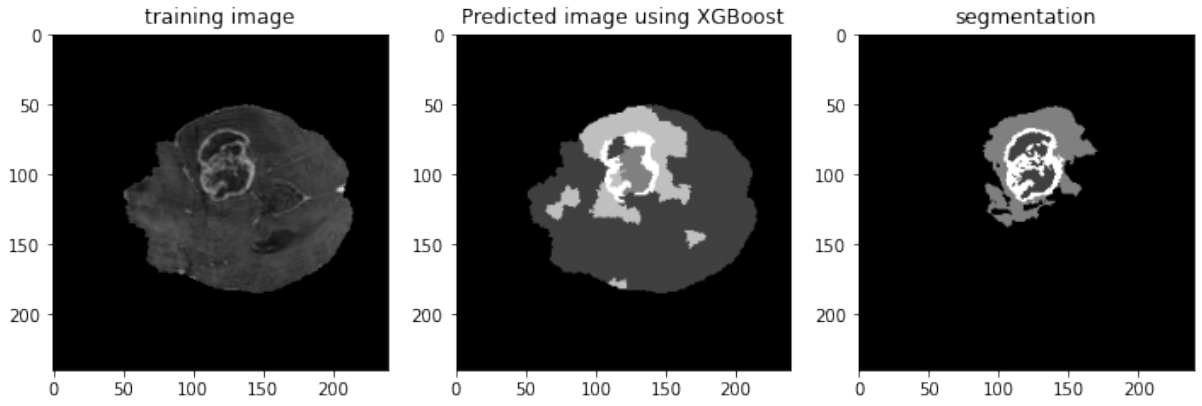

FIGURE 14 – predicted image after training the model on a training set of type 2

- For the training set of the third type, we've used as features the mean and variance of several sharpening filters, the result is :

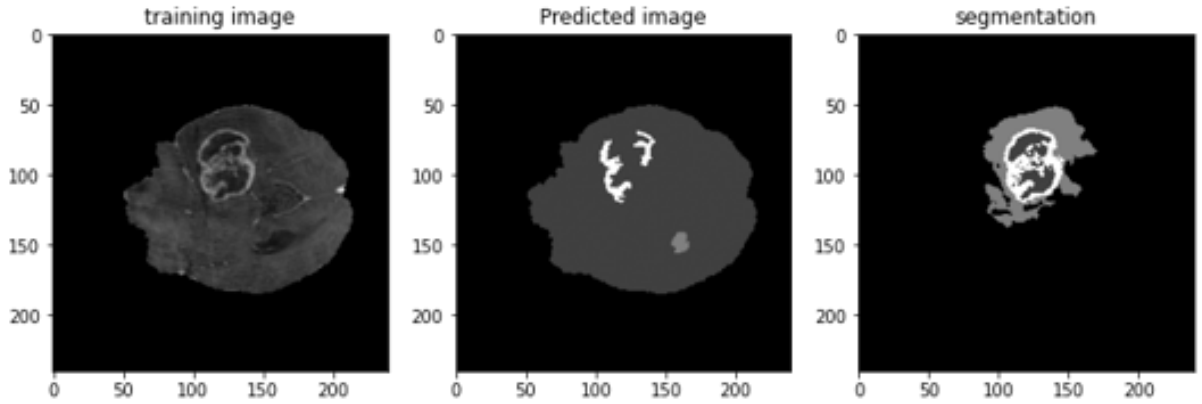

FIGURE 15 – predicted image after training the model on a training set of type 3

The dice coefficient is : 0.198

As we can see using this dataset manages to detect the enhancing tumor but fails to detect the other parts of the cancer.

7 Conclusion

In this project, We divided the problem into three parts : In the first part we've applied different filters on MRI pictures to later decide which features to use for classification purposes, in the second part we segment the image into super-pixels and we retrieve interesting features for each one of them. The final part consists of classifying these super-pixels in order to identify the metastasis. For the next steps, one can explore the Gabor filter ; a linear filter used for texture analysis which would be idea to detect the surrounding Oedema, the challenging part is to determine the hyperparameters of the Gabor filter :

$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2})exp(i(2\pi\frac{x'}{\lambda} + \psi))$$

$$x' = xcos\theta + ysin\theta$$

and :

$$y' = -xsin\theta + ycos\theta$$

The second step that we can do, is instead of using a hard assignment from the classifier, we keep the soft assignement, we first assign the background superpixels and the enhancing tumor, then we go back and take and

focus on the superpixels surrounding the enhancing tumor part : We look at the orientation of the gradient of these superpixels and their soft assignement and from this we decide which superpixels are necrotic tumor, which superpixels represent oedema, and which superpixels are normal cells

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