DETECTING TUMOURS IN BRAIN IMAGES

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ABSTRACT

A brain tumour is an uncontrollable growth of abnormal cells in the brain. As the brain is enclosed by the skull, it presses onto areas of the brain and would stop the function of that part of the brain when the tumour grows. Finding a proper cure for brain tumours is one of the most important goals of the medical industries and the early detection of such tumours allows a much higher success rate in treatment.

The purpose of the project is to detect the presence of a tumour from a brain MRI image through image processing methods with the use of MATLAB. The algorithm takes a raw MRI image as input and pre-processes it by enhancement as well as noise removal before segmenting the tumour area of the image with various segmentation techniques. Other post-processing works include morphological operations and feature extraction before classifying the MRI images into tumour or non-tumour. The work done demonstrates that generating the results of an MRI image can be automated and completed through a short amount of time.

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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. Aims & Objectives

This project aims to benefit the medical industry and attempts to solve the common issues regarding brain tumour detection by using modern image processing techniques.

Segmentation, detection, and extraction of a brain tumour from a MRI image are time consuming tasks performed by experts in the field, and deciphering the MRI image 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.

This project records different algorithms that apply varying methodologies and uses the results to achieve a higher level of accuracy and precision. The algorithm takes 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-means 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: METHODOLOGY & IMPLEMENTATION

3.1. Methodology

Pre-processing Algorithms – Smoothing and Image Enhancement

For pre-processing, the image is first converted to grayscale if it is in *rgb* format.

The image requires smoothing as it contains noise. Median filtering is used 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 the image is passed into a median filter, the size of the neighbourhood can be adjusted into the parameters, but for the purpose of this project, a 3 * 3 neighbourhood is sufficient as any unnecessary loss of information can be prevented.

Following that, blobs with centroids which are within 10% of the edge are removed as they are taken as noise. This is due to the fact that some images have text or other noise at the edge of the images.

A high pass filter is used to sharpen the details of the image by using a filter function after smoothing the image. This function utilizes a kernel to convulate the image, where the kernel is a fixed 3x3 sharpening kernel, [0 -1 0; -1 5 -1; 0 -1 0] (Powell n.d.). Adaptive histogram equalisation is then applied on the image.

After smoothing and enhancing, connected regions and morphological operations are used 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. The lower the threshold, the greater the area will be as more pixels will have a value greater than the threshold. Shijin Kumar and Dharun (2016) attained the best results by using a threshold value of 40. To select a suitable threshold automatically, the following algorithm has been implemented:

1. Using a low threshold luminance value, convert the image into binary. The resulting image has most non-zero valued pixels assigned to 1, including those of the skull. Calculate the bounding box of the whole skull using the binary image.
2. Increment the threshold luminance value and convert the image into a new binary image. Perform opening on the binary image to remove any thin connections between the skull and the brain parts.
3. Use connected regions labelling to find the largest connected region. Calculate the bounding box of this largest region.
4. Repeat steps 2 and 3 until the bounding box of the region is smaller than the bounding box of the whole skull to a certain extent. If the area is too small after step 2 and 3, then stop repeating. This is to prevent over-stripping of the brain parts.

The largest region that has a bounding box smaller than the original bounding box is taken as the region that contains only brain parts. Perform dilation on the complement of this 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 brain 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, a hybrid method with multiple techniques is used to yield multiple results from each technique. These results will then be collated to obtain a final result, which the benefits of each technique are expected to be drawn, 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 have been used are Otsu’s thresholding method, Fuzzy C-means algorithm and Watershed algorithm.

For Otsu’s thresholding, a threshold is chosen to convert the image into a binary image. Instead of only one threshold, multiple thresholds were computed as some brain images have no clear distinction of intensity values between those of the tumour part and those of other parts of the brain, resulting in bad choice of threshold to be used. As proposed by Kapoor and Thakur (2017), the threshold that minimises the intra-class variance of intensity values in the foreground as well as the background is chosen. A penalty is also applied to the variance if the area of the foreground is greater than the background, as the tumour is assumed to span a smaller area compared to normal parts of the brain.

To implement the Fuzzy C-means algorithm, the pixels are classified into four clusters according to their largest membership value. The region with the highest mean intensity is extracted. The image is converted into a binary image based on the clusters.

According to Eddins (2002), the Watershed algorithm can be implemented in a few steps. First, the gradient at each pixel is found. The gradient image is modified by using H-minima transform to remove minima that are too shallow to prevent over-segmentation. Only then the Watershed algorithm is performed on the processed image.

As the watershed algorithm only divides the brain into numerous regions based on the watershed lines, one possible region that corresponds to the tumour area has to be selected. To identify the tumour area, the segmentation results from Otsu's thresholding and Fuzzy C-means algorithm can be used as a mask to remove some parts from the watershed regions.

To select a suitable height threshold value for H-minima transform, different threshold values are used in attempting to find regions that fulfill the following conditions:

1. The centroid of the region is deviated from the center of the brain by a certain degree. More specifically, the centroid must not be in the 40% of the width and height of the brain. The lateral ventricles are at the center of the brain, which usually have higher intensity values than the rest of the brain, sometimes even the tumour. They might have been included in the segmentation results by Fuzzy C-means and Otsu's thresholding, which segments the image by their intensity values. Therefore, this condition is crucial to prevent the wrong selection of regions that are in the lateral ventricles region of the MRI brain image.
2. The major axis length of the region must not differ too much from the minor axis length of the region. More specifically, the minor axis length must be at least half of the value of the major axis length. The assumption that resulted in this condition is that all tumours have an elliptical shape.
3. The real diameter of the region must be smaller than the diameter of the brain by 70%.

Three different segmentation results from three different segmentation algorithms have now been obtained. There are many possible ways of combining multiple results. The results obtained from Otsu's thresholding and Watershed's algorithm are combined with an AND operation, as the results tend to be similar as they are both segmenting the image with intensity values. Two inputs now have to be combined. A concept similar to hysteresis thresholding is used to combine the results:

1. Mark pixels that are segmented as tumour pixels in both inputs above to be strong pixels. Mark pixels that are segmented as tumour pixels in only one to be weak pixels. Erosion is performed to the weak pixels so that weak pixels which are not strongly connected to the strong pixels will not be extracted in the following steps.
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.
4. The output from hysteresis is dilated to undo the erosion performed in step 1, and holes in the binary image are filled. Blobs with areas too small or not enough circularity are removed to prevent extracting non-tumour parts.

Morphological Operation Algorithm

Morphological operations are performed after obtaining the results from image segmentation. A structuring element is first created before performing dilation and erosion. After performing dilation and erosion, the tumour part of the image is separated. The area of the tumour in the brain image can now be identified.

Feature Extraction Algorithm

To detect and classify the brain images into tumours and non-tumours, feature extraction using the GLCM technique is performed. The GLCM of the post-processed brain image is first created. The features important to the system which includes the contrast, correlation, entropy and standard deviation of the images are then calculated from the GLCM of the image.

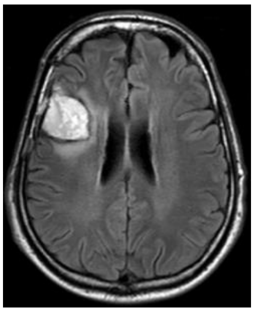
The important features of each image are stored in a table. A decision tree is then trained using these attributes to predict the presence of tumours in the brain images. The brain images can then be classified into tumours and non-tumours.

Final Output

Combining the results of classification and segmentation, the final output inclusive of the presence of tumours in the MRI image, the number and area of any existing tumour can be produced.

3.2. Implementation

Original Input

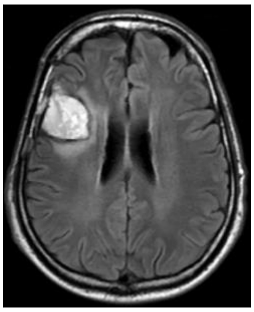


Original Input

Pre-processing Algorithms

The image will first be converted to grayscale using *rgb2gray* if necessary.

Smoothing



Apply smoothing

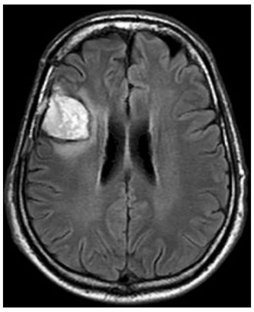
1. Remove noise in the image using *medfilt2*.

Removing edge blobs

1. Find a low threshold using *mode* to ensure non-black pixels are included.
2. Obtain a label matrix of the connected components in the image using *bwlabel*.

3. Pass the label matrix to *regionprops* with parameter '*Centroids'* to measure the set of properties for each connected component.
4. Concatenate the properties obtained using *cat*.
5. With the concatenated properties, find the centre blob using *find* and form a mask using *ismember*.
6. The mask is then passed through the original image to return a MRI brain image with edge blobs removed.

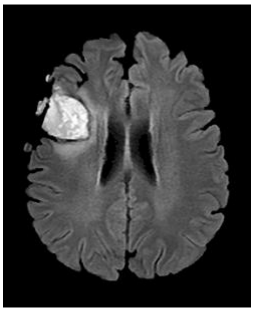
Image Enhancement



Apply image enhancement

1. Create a kernel [0 -1 0; -1 5 -1; 0 -1 0].
2. Use the kernel above with the function *imfilter*.

Skull Stripping



Apply skull stripping

1. Convert the image into a binary image with *imbinarize.*
2. Create a structuring element with shape '*disk*' and size 5 using *strel* and pass the image through *imopen*.
3. Find the connected components of the image using *bwlabel*.
4. The largest component contains only the brain area. Pass the previous output through *regionprops* and find the index of the largest connected component by finding the index with the highest frequency using *sort*.
5. Fill the largest connected region using *imfill* and create a mask after dilating the connected region using *imdilate* with structuring element of shape '*square'* and size 3.
6. The mask is now a binary image containing only the brain area of the MRI image, which is multiplied with the original image to extract the skull from the brain image.

Image Segmentation Algorithms

The preprocessed image is used as the input to all three segmentation algorithms.

Otsu's Thresholding

Apply Otsu's Thresholding

1. Compute multiple thresholds automatically using *multithresh*. A vector containing multiple thresholds is returned.
2. The second smallest threshold is used to binarize the image by using a logical operator.
3. Calculate the variance of the intensity values of the foreground pixels, *m*, and of the background pixels, *n*, using *var*.
4. Obtain the area of the segmented part using *regionprops*.
5. Calculate the area of the foreground and background using *regionprops*, and calculate the penalty as:

   penalty, p = area of foreground - area of background
6. Calculate the total score as m + n - p.
7. Select the number of levels and its respective threshold value which yields the smallest score.

Levels = 2

Levels = 3

The results of using different levels of thresholds are shown in the images above. The greater the levels of thresholds, the larger the segmented area.

Fuzzy C-Means Algorithm

Apply Fuzzy C-Means

1. Classify the pixels of the brain image into 4 clusters using *fcm*.
2. Calculate the mean intensity of each clusters using *regionprops*, so that the cluster with the highest mean intensity can be extracted.

Clusters = 4

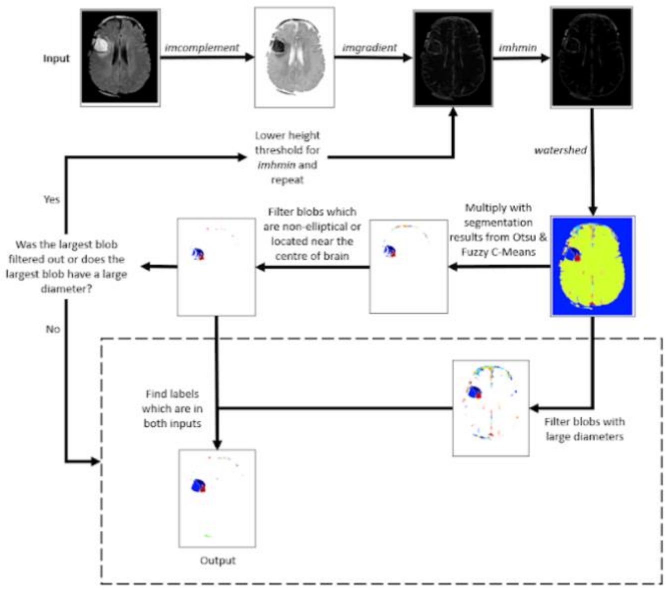
Clusters = 8

The results of segmenting the image into different numbers of clusters are shown in the images above. The greater the number of clusters, the smaller the segmented area.

<u>Watershed Algorithm</u>

Apply Watershed

1. Find the complement of the brain image using *imcomplement* so that the dark pixels are perceived as peaks and bright pixels are perceived as valleys.
2. Find the gradient magnitudes of the image using *imgradient*.
3. Perform H-minima transform on the gradient image by using *imhmin* with an arbitrary height threshold.
4. Calculate different features of the segmented areas such as the 'EquivDiameter', 'MajorAxisLength', 'MinorAxisLength' and 'Centroid' using *regionprops*. These values are then compared against thresholds using logical operations.
5. If no region fulfils the conditions as shown in the flowchart below or as described in the methodology, decrease the height threshold and repeat steps 2 – 4.



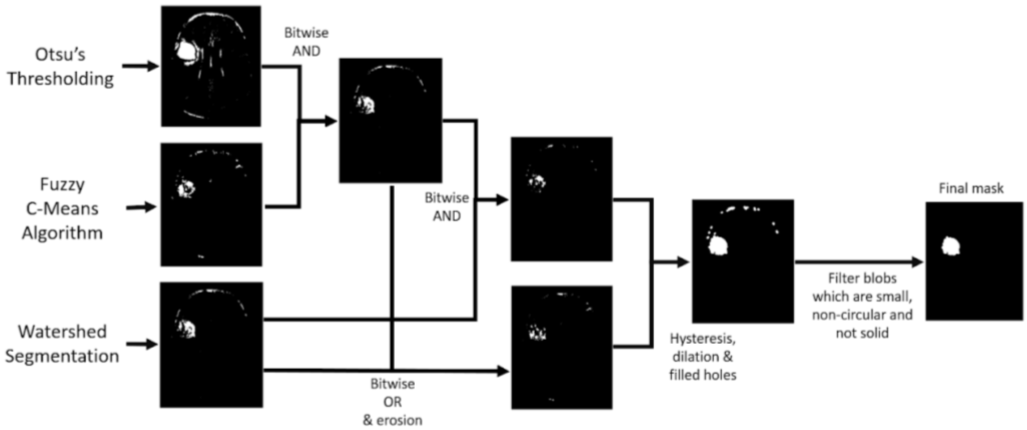
Flow chart of automatic algorithm to select a suitable threshold for Watershed algorithm

Height = 4

Height = 8

The results of segmentation by using different height thresholds in step 2 are shown in the images above. The greater the threshold, the greater the amount of shallow minima removed. Hence, the segmented areas appear to be larger.

Combination of Results



Flow chart of algorithm to combine results

1. Combine the results of Otsu's Thresholding and Fuzzy C-Means algorithm using *bitand*.
2. Combine the result of step 1 with the result of watershed segmentation with "and" operation (&) as well as "or" operation (|) to produce the strong pixels and weak pixels respectively.
3. Erode the weak pixels using *imerode* with a 'disk' shaped structuring element of radius 1.
4. Implement the function *hysteresis* to find pixels which are either strong pixels or weak pixels that are connected to a strong pixel by a path of non-background pixels. In short, this is done by finding all connected regions, then extracting connected regions which contain a strong pixel.
5. Fill any holes in the result using *imdilate* with a structuring element of shape '*disk'* and radius 4.
6. Find the '*Circularity'* and '*Solidity'* of the extracted regions using *regionprops*, then filter regions which are too small, non-circular and not solid.

Morphological Operation Algorithm

Apply dilation and erosion

1. Create a structuring element with shape '*square*' and size 3 using *strel.*
2. Perform dilation followed by erosion using *imclose*.

Feature Extraction Algorithm

1. Create the GLCM of the image using *graycomatrix.*
2. Calculate contrast, correlation, energy and homogeneity of image using *graycoprops.*
3. Calculate entropy of image using *entropy*.
4. Calculate standard deviation of image using *std2*.

Classification Algorithm

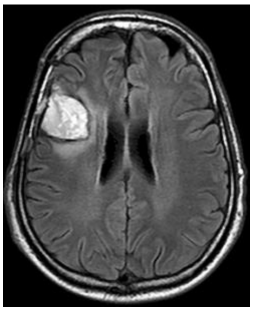
1. Fit a decision tree with the features extracted using *fitctree*.
2. Predict the class of the image (tumour or non-tumour) using *predict*.
3. Calculate the accuracy of the decision tree by computing a confusion matrix using *confusionmat*.

CHAPTER 4: RESULTS AND DISCUSSION

4.1. Results

The results shown below includes a successful classification case, failure classification case and average classification case.

Successful Classification Case



Original Input

Final Output

The images above show the original input and final output of a successful classification case. The tumour of the brain is perfectly segmented. The algorithm also successfully detected the MRI image to consist of one tumour with an area of 4225 pixels.

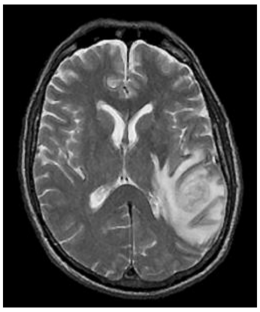
Failure Classification Case

Original Input *Final Output*

The images above show the original input and final output of a failure classification case. The MRI image actually does not consists of any tumours but the algorithm detected it as an image with two tumours, where the area of the first tumour is 723 pixels and the area of the second tumour is 1039 pixels.

Average Classification Case

Original Input *Final Output*

The images above show the original input and final output of an average classification case. The MRI image actually consists of only one tumour at the bottom right side of the brain but the algorithm detected it as an image with two tumours, where the area of the first tumour is 824 pixels and the area of the second tumour is 7085 pixels. Even though the algorithm classified the image correctly as an image with tumour, it detected the number of tumours wrongly. Thus, it is an average classification case.

4.2. Discussion

Pre-processing is completed by converting images to grayscale, using a median filter to remove noise and enhancing the image with a high pass filter. The functions do not require any particular adjustments as the default values worked fine. However, the skull stripping process may not provide optimal results every time.

In some MRI images, the brain appears to be closer to the skull or even in contact, which causes the skull stripping algorithm to consider that part of the skull to be a single object with the brain, causing the output image to contain an area of the skull. This leads to issues where the segmentation algorithm may fail and recognise the skull as a tumour as well due to the contrast and positioning of the skull, leading to the final output to either detect both the skull and the original tumour, or miss out on the tumour completely.

Nevertheless, the failure of the skull stripping algorithm is rare and will not always affect the segmentation results later on. However, if the skull stripping algorithm is excluded entirely, it will cause detection algorithm results to fail more often. Thus, the skull stripping algorithm is necessary for a higher success rate.

The segmentation results of Otsu’s Thresholding algorithm and Fuzzy C-Means algorithm seem to complement each other well. They either agree with each other by producing similar results, or the Fuzzy C-Means algorithm might extract smaller areas. This will lessen the effect on mis-segmentation of one of these algorithms, and by performing bitwise and operation, the possibility of choosing non-tumour parts can be reduced.

On the other hand, the results of watershed algorithm might segment a tumour into multiple regions as some watershed lines exist within the tumour area, which are hard to be removed by using H-minima transform. However, by imposing several conditions and filtering parts that should not contain tumours, the possibility of extracting non-tumour parts have been greatly reduced.

The combination of results have yielded results that takes into account the intensity, shape, location and change in intensity values across the edges of the tumour. This is in line with our initial hope that by collating results from three different algorithms, the results can be improved.

The intensity of the areas extracted is hyperintense to other parts of the brain, as is enforced by both the Otsu’s Thresholding and Fuzzy C-Means algorithm. It is ensured that the change in intensity values across the edges of the extracted area is large by using the Watershed algorithm, while other conditions such as shape and location are used to choose areas of interest.

Moving on to feature extraction, it is performed on both pre-processed images and post-processed images to identify the set of images that will yield a higher accuracy when detecting tumour in brain images. Several features which are calculated from the GLCM include contrast, correlation, energy, homogeneity, entropy and standard deviation.

After extracting features from both pre-processed images and post-processed images, three types of decision trees are trained to identify the tree with the best prediction accuracy:

1. Decision tree using features extracted from pre-processed images (tree A)
2. Decision tree using features extracted from post-processed images (tree B)
3. Decision tree using features extracted from both pre-processed and post-processed images (tree C)

70% of the data set will be used as the training set while the remaining 30% of the data set will be used as the test set. As the data set consists of 253 images, 177 images are used for training and 76 images are used for testing.

A few combinations of the features are fit to the decision trees to find the most suitable features which would yield the highest classification accuracy. A confusion matrix is computed for each of the decision trees when each combination of features is tested and the classification accuracy based on each tree is calculated. The table below shows the accuracy of each decision tree when each combination of features are used to train the decision tree.

Features	Tree A	Tree B	Tree C
Contrast, correlation, energy, homogeneity, entropy, standard deviation	0.71	0.67	0.66
Contrast, correlation, entropy, standard deviation	0.74	0.83	0.78
Contrast, entropy, standard deviation	0.76	0.79	0.75
Contrast, energy, entropy, standard deviation	0.78	0.76	0.66
Contrast, homogeneity, entropy, standard deviation	0.79	0.75	0.83

The final results show that contrast, correlation, entropy and standard deviation extracted from post-processed images as well as contrast, homogeneity, entropy and standard deviation extracted from both pre-processed and post-processed images will yield the highest classification accuracy when fit into the decision tree. As it is lesser work to extract features from only one set of (post-processed) images, future classifications will be based on a decision tree fitted on the features extracted from post-processed images.

As the feature extraction process is done using a loop for efficiency purposes, automatic threshold values have been used during image segmentation. With the implementation of sliders for users, the threshold values can be adjusted accordingly based on the MRI image. This will yield better segmentation results as well as values of features which are more accurate. Thus, the classification accuracy can be higher than 0.83.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1. Limitations

The 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).

3. Too many assumptions have been made during the computation of conditions while choosing suitable thresholds for different algorithms. **One of the assumptions that the algorithm heavily relies on is that the tumour is hyperintense, that is, the tumour has higher intensity values than other brain parts in a scanned brain image**. This assumption is only true for FLAIR, T2-, and proton-weighted MRI scans, while tumours in T1-weighted scans are usually hypointense (Jacobs, et al., 2005). These assumptions might be broken by individual brain images, resulting in undesired

segmentation results. Many of these assumptions were done without any expert's input, such that there may be discrepancy with general beliefs in the medical field.

4. The classification model trained can only decide if a brain image contains any tumour. It does not classify any existing tumour into different types of tumour.

5.2. Further Works

1. Further research can be conducted to choose a suitable slice as there is no method in the current algorithm which is capable of that.

2. As the current algorithm only works on 2D brain images, further research can also be conducted to enable it to directly work on 3D models.

3. To overcome the assumption that the algorithm heavily relies on hyperintense tumour, develop an algorithm for segmenting hypointense tumour, which can be done in a similar manner. Otherwise, ensure that the input brain image is not of type T1-weighted where the tumours are hypointense.

4. If the data set provided has already classified the tumours into their respective grades, features can be extracted from the images to train a decision tree which can identify the grade of the tumour. As the current data set does not classify the type of tumours in brain images, such a decision tree cannot be trained.

5.3. Conclusion

This project is aimed to help the medical industry with an algorithm that detects brain tumours from MRI images through image processing techniques with MATLAB. It enables medical professionals to detect the existence of a tumour with the algorithm instead of having it done manually, allowing the process to be sped up, leading to less resources wasted and also earlier treatment for the patient.

Various researches similar to our project have been conducted and were used as a reference for the project. They provided information regarding different algorithms used for different stages of processing and also included the results of their research. With the literature reviewed, by selecting the most appropriate techniques or by combining multiple methods suggested, we were able to write our own algorithm which would yield the best results for our given problem.

As a summary of our algorithm written to detect the brain tumour from MRI image, the grayscale image is first pre-processed with noise removal, blob removals, image enhancements, and skull stripping techniques.

With the improved image, it is passed through different segmentation algorithms such as Otsu's Thresholding algorithm, Fuzzy C-Means algorithm and Watershed algorithm. The segmentation results are then combined to produce one final result. The usage of three algorithms have allowed us to segment the image using not only one property, such as the intensity or boundary; but by collating the results, both properties are taken into account.

The segmented image is then post-processed with morphological operations. Feature extraction is performed on the post-processed images where the important features of the images are calculated using the GLCM technique. The extracted features are used to train decision trees which will be used to classify whether an image has a brain tumour or not. The end result provides us with information on the tumour(s) in the brain images.

The algorithm developed has an accuracy of approximately 83%, which achieves the initial goal to allow medical professionals to accurately detect tumours at a faster pace, allowing them to make the final decision on the patient's treatment.

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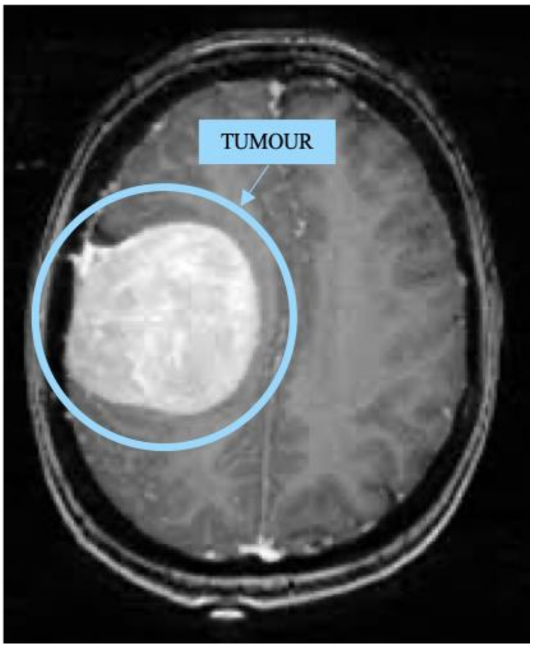
APPENDICES

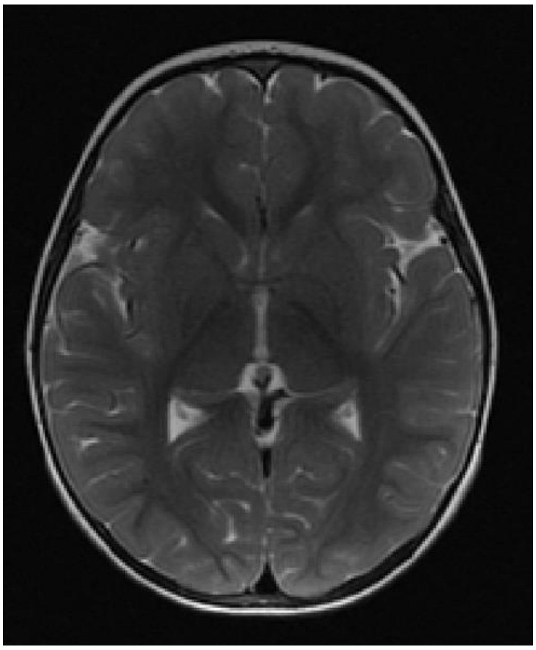
APPENDIX A: DATA SET

The data set that was used 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.

APPENDIX B: WORKLOAD DISTRIBUTION

<table>
<tr><th>Task</th><th>Person-in-Charge</th><th>Deadline</th></tr>
<tr><td>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
▪ GLCM
• Classification of Brain Images
▪ Decision Tree</td><td>
Gian Hao

Yuan Ai

Yuan Ai
Amber

Amber

Amber</td><td>
1/5/2020 (Friday)

8/5/2020 (Friday)

8/5/2020 (Friday)
15/5/2020 (Friday)

15/5/2020 (Friday)

15/5/2020 (Friday)</td></tr>
<tr><td>Review and testing of algorithm</td><td>All</td><td>22/5/2020 (Friday)</td></tr>
<tr><td>Report:
• presentation of findings with results
• improvements and suggestions for future work</td><td>All</td><td>5/6/2020 (Friday)</td></tr>
<tr><td>Final check on submission</td><td>All</td><td>12/6/2020 (Friday)</td></tr>
</table>