

A Novel Approach to Brain Tumour Detection

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Abstract - The detection of brain tumour is one of the most challenging tasks in the field of medical image processing, since brain images are very complicated and tumours can be analyzed efficiently only by the expert radiologists. Therefore, there is a significant need to automate this process. Segmentation of human brain from MRI scan slices without human intervention has become one of the most active research areas in the field of medical image processing. Brain segmentation has various important applications in diagnosing a number of disorders. The main aim of this research work is to recognize a tumour and its quantifications from a specific MRI scan of a brain image thereby obtaining the quantitative analysis of MRI brain tumour which allows useful key indicators of disease progression. Thresholding approach segment scalar images by generating a binary partitioning of the image intensities. Otsu's technique is used to automatically carry out histogram shape-based image thresholding. Then, compute the area of the tumour by fully automated process and its symmetry analysis. Segmentation is done on basis of a threshold, due to which whole image is converted into binary image. Finally SVM is used to carry out the actual classification.

Keywords—Graphical User Interfacing (GUI), brain tumour, Magnetic resonance imaging, Otsu thresholding, Tumour segmentation, Magnetic resonance imaging, SVM Classifier, MATLAB.

I. INTRODUCTION

Human brain is the first and foremost controller that controls the sympathetic and para-sympathetic activities. Our human brain is responsible for awareness about the environment, control of the movement of muscles and maintaining the internal temperature. Brain tumor is unwanted growth of diseased/abnormal cell in brain in an uncoordinated fashion. Brain Tumor increases the intracranial pressure within the skull which affect the region of cerebrospinal fluid (CSF), gray matter (GM), white matter (WM). Tumor can affect any part of brain and its severity depends on tumor size, type and location. Tumor cells grow in an uncontrolled manner, and like the normal old cells of body, they don't die. The tumor continues to grow as the number of cells are accumulated and formation of cyst occurs. There are two types of tumor:

- 1) Benign,
- 2) Malignant.

Benign tumour are non-cancerous cells, which do not invade surrounding healthy tissues. Malignant tumour are cancerous cells, which invades surrounding healthy tissues and spread to other part of brain or spine. This chapter discusses about following topics: human brain, brain

tumour, types of tumour, image segmentation and image processing using MATLAB toolbox. Human brain is the CPU of world's most complicated bio-computing machinery, coordination of muscular movements from sense organ (pain, taste, sight, hear, touch) etc. After this various examination and test has been performed by doctor for the diagnosing the problem, a suitable medication/remove the problem. Brain tumour detection is one of serious issue in imaging science. For the tumour detection, image processing toolbox has been used in MATLAB software.

II. PROPOSED METHOD

Introduction

Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics. Here we are using two different Image segmentation algorithms are: OTSU, SVM.

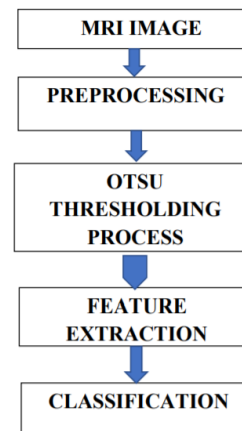


Fig. 1: Proposed methodology flow

MRI Input Image

MRI of the brain is given as the input. It has the RGB (Red Green Blue) mixing present in it. It is the basic colour used in computers, television, graphics etc.

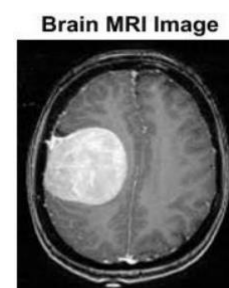


Fig 2: Brain MRI Image

Preprocessing:

Pre-processing is an important and required task has to be done in tumour recognition system. Pre-processing consists of two steps, Segmentation and Morphological filtering. Segmentation is done to convert gray scale image into binary image so that we can have only two areas in image one is foreground and other is background. Multiple Otsu algorithms is used for segmentation purpose where real brain MRI images are converted into binary image. After converting gray scale image into binary image it must be ensure that there is no noise and undesired elements in image so for that morphological filtering technique has been used. Morphological techniques consists operations like dilation and erosion.

Gray Scale Image:

It is the second step of the pre-processing stage. Since MRI input image contains some RGB mixing in it, we cannot get a clear expected output. Hence the input image is converted to gray scale image which is the black and white image. This image ranges from 0 to 255. The range 0 defines the black colour and the range 255 defines the white colour. As the name indicates image may also contain the shades of grey.

Binary Scale Image:

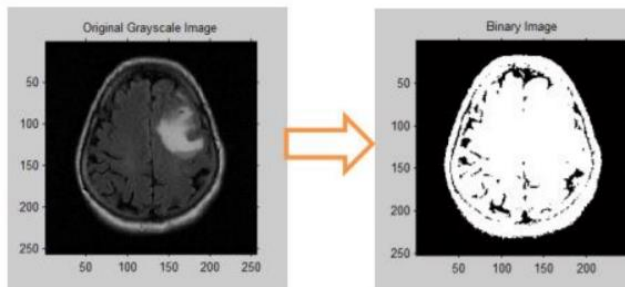


Fig 3: Convert the gray scale image to binary image

A binary image is a digital image that has only two possible values for each pixel. Typically, the two colours used for a binary image are black and white. The colour used for the object(s) in the image is the foreground colour while the rest of the image is the background colour. Binary images are also called bi-level or two-level. This means that each pixel is stored as a single bit— i.e., a 0 or 1.

OTSU Algorithm

In computer vision and image processing, Otsu's method, named after Nobuyuki Otsu, is used to automatically perform clustering-based image thresholding or the reduction of a gray level image to a binary image. The algorithm assumes that the image contains two classes of pixels following bi- 8 modal histogram, it then calculates the optimum threshold separating the two classes so that their combined spread (intra-class variance) is minimal, or equivalently (because the sum of pairwise squared distances is constant), so that their inter-class variance is maximal. Figure 4 and Figure 5 are the input and its respective output for Otsu Algorithm. The detection is done to get the row and column values from which the tumour starts and ends. After all the required operation only the tumour part is left, so only the tumour part is enhanced and rest part of the image is zero or black, from the row where the tumour starts is

considered to be minimum row, and where it ends is considered as maximum row. The same is followed for column operation. Below S_i is summation taken for row, it gives the number of minimum and maximum row of tumour.

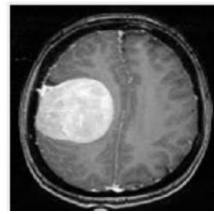


Fig 4: Original Image



Fig 5: Output Image

Otsu's method performs the clustering-based image thresholding, which is the conversion of a gray level image to a binary image with the help of the following techniques:

- $\sigma_w^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t)$
- $\omega_0(t) = \sum_{i=0}^{t-1} p(i)$
- $\omega_1(t) = \sum_{i=t}^{L-1} p(i)$
- $\sigma_b^2(t) = \sigma_t^2 - \sigma_w^2(t) = \omega_0(\mu_0 - \mu_t)^2 + \omega_1(\mu_1 - \mu_t)^2 = \omega_0(t)\omega_1(t)[(\mu_0(t) - \mu_1(t))]^2$
- $\mu_0(t) = \frac{\sum_{i=0}^{t-1} ip(i)}{\omega_0(t)}$
- $\mu_1(t) = \frac{\sum_{i=t}^{L-1} ip(i)}{\omega_1(t)}$
- $\mu_T(t) = \sum_{i=0}^{L-1} ip(i)$

Feature Extraction

Feature extraction starts from an initial set of measured data and builds derived values (features) intended to be informative and non-redundant, facilitating the subsequent learning and generalization steps, and in some cases leading to better human interpretations. Feature extraction is related to dimensionality reduction. When the input data to an algorithm is too large to be processed and it is suspected to be redundant (e.g. the same measurement in both feet and meter, or the repetitiveness of images presented as pixels), then it can be transformed into a reduced set of features (also named a feature vector). Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data, so that the desired task can be performed by using this reduced representation instead of the complete initial data. Feature extraction involves reducing the amount of resources required to describe a large set of data. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power, also it may cause a classification algorithm to over fit to training samples and generalize poorly to new samples.

- *Mean (M):*

The mean of an image is calculated by adding all the pixel values of an image divided by the total number of pixels in an image.

$$M = \frac{1}{m \times n} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y)$$

- *Standard Deviation (SD):*

The standard deviation is the second central moment describing probability distribution of an observed population and can serve as a measure of inhomogeneity. A higher value indicates better intensity level and high contrast of edges of an image.

$$SD = \sqrt{\left(\frac{1}{m*n}\right) \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (f(x,y) - M)^2}$$

- *Entropy(E):*

Entropy is calculated to characterize the randomness of the textural image and is defined as

$$E = -\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x,y) \log_2 f(x,y)$$

- *Skewness(S_k):*

Skewness is a measure of symmetry or the lack of symmetry. The skewness of a random variable is defined as

$$S_k = \left(\frac{1}{m*n}\right) \frac{\sum (f(x,y) - M)^3}{SD^3}$$

- *Kurtosis(K_{urt}):*

The shape of a random variable's probability distribution is described by the parameter called Kurtosis. The Kurtosis is defined as

$$K_{urt} = \left(\frac{1}{m*n}\right) \frac{\sum (f(x,y) - M)^4}{SD^4}$$

- *Energy(En):*

Quantifiable amount of pixel pair repetitions to measure similarity of an image

$$En = \sqrt{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f^2(x,y)}$$

- *Contrast(C_{on}):*

To Measure intensity of a pixel and its neighbour over image.

$$C_{on} = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f^2(x,y)$$

- *Inverse Difference Moment(IDM):*

Inverse Difference Moment is a measure of the local homogeneity of an image. IDM may have a single or a range of values so as to determine whether the image is textured or nontextured.

$$IDM = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} \frac{1}{1+(x-y)^2} f(x,y)$$

- *Homogeneity (or) Directional Moment (DM):*

It is textural property of image calculated by considering the alignment of the image in terms of angle.

$$DM = \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x,y) |x - y|$$

- *Correlation (C_{orr}):*

Describes the spatial dependencies between pixels

$$C_{orr} = \frac{\sum_{x=0}^{m-1} \sum_{y=0}^{n-1} (x,y) f(x,y) - M_x M_y}{\sigma_x \sigma_y}$$

SVM Algorithm:

SVM is a classification algorithm for high-dimensional data analysis which is proposed by Vapnik to solve the classification problems of two issues. SVM has been widely used in the fields of medical image processing, text analysis, image retrieval and so on. SVM is based on the principle that the data in the original input space can be linear separable in a higher-dimensional feature space after a certain mapping. The feature space after mapping is a complete Hilbert space, in which the inner product of data can be calculated as the equivalent function value of the input vectors by introducing the corresponding kernel function. The inner product is the measurement of the distance, which can be expressed as the degree of similarity between two vectors in a certain extent. In general, the closer the distance between two vectors is, the higher the similarity of them is. Due to the kernel function, the computation of distance in the feature space is transformed to the input space without the need to solve the mapping of spatial transformation, therefore, it reduces the computational difficulty to a certain extent. SVM has many extensions, such as one-classification SVM, in which all the interested data will be considered as one class and all the other data as the other 24 class. In the classification, the training is only fulfilled on the data of the first class. This is a simple application of two-class SVM classification. Another important application of SVM is the multi-kernel SVM. It is especially suitable for dealing with high-dimensional data of different sources and different types. The classification algorithm does not use a uniform kernel function in order to be able to dig the implicit information in the data and to take full use of the characteristics in the data.

In general, the multi-kernel SVM has two typical forms:

1. For different types of input data from different sources, use different kernel functions or different parameters with a same kernel function to design different classifiers for each input respectively, select the optimal parameters to classify each input one by one to obtain the optimal results. The final result is the integration of all the optimal results of the input data
2. First, some strategy is adopted to fuse all the input data, and then use different kernel functions or different parameters of a same kernel function to carry out the classification; finally using the selected fusion strategy to obtain the integrated results.

The two forms of multi-kernel SVM have very different characteristics. The former takes full use of the properties of their own in different types of data, which are independent. The use of different kernel functions can mine a variety of important and implied characteristics of data and the ultimate classification result is the integration of all the optimal results. The latter fuses the data first to use the implicit information, characteristics or relationship in various data, although different kernel functions are applied to all the parts of the data. The more important point in this processing mode is to use the correlation and mutual influence of data to achieve the classification. In addition to adapt to multiple 25 types of input data, multi-kernel SVM can also extended to the multi-class classification problem. At present, the multi-class classification problems on brain tissues' detection mainly depends on the fuzzy theory or the probability models, both of which are not very accurate in general. Some algorithms can just segment edema and

normal tissues separately, which indicates the lack of ability to deal with brain tumors. There is no specific multi-class classification algorithm in traditional SVM. The existing multi-class classification strategies are the simple expansions of two class classification algorithms, such as a commonly used one versus all strategy, in which it is necessary to construct a two-class classifier for each classification of different data. The interested data will be considered as one class and all of the other data as the other class. Each class has its special classifier to make the margin between this class of samples and the other samples the largest. Then the multi-class classification can be achieved by determine each category one by one.

Output stages

It is the final stage and the most important stage because segmented image is shown as output image and the type of tumour is specified. It consists of two steps. They are

- SVM Classifier
- Output Image

SVM classifier

It is Support Vector Machine. It was first proposed by Vapnik. It is very easy method compared to other methods. It is used to classify the type of the tumour present in the segmented image whether it is malignant, benign or normal. We have many methods to perform this image segmentation process like fuzzy k, 26 fuzzy c means, neural networks, etc. But SVM classifier is the most efficient method to perform this because in this we can compare the input image parameters with the already trained SVM parameters to specify the type of brain tumour.

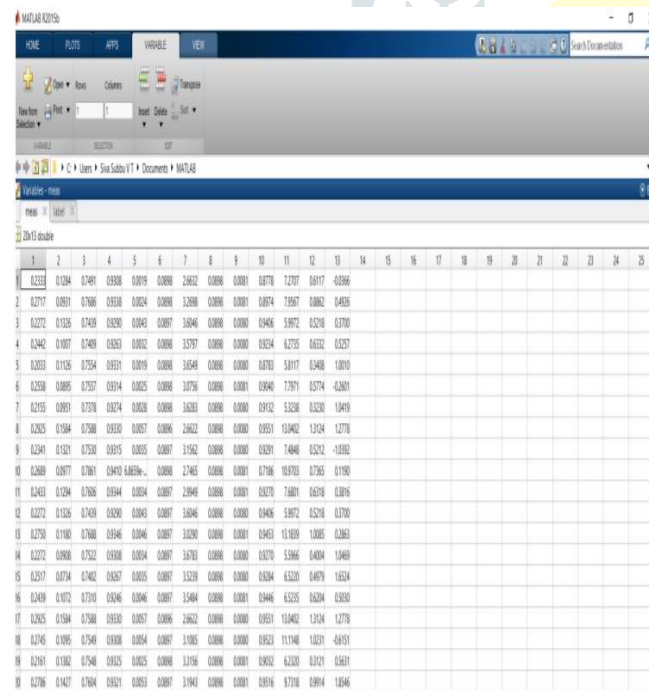


Fig 6: SVM Training set

Output Image: It is final step in output stage. It gives the final output from given MRI input. The tumour present in the brain is segmented and it is shown in the white colour segmented image. It also specifies the type of the tumour using SVM classifier.

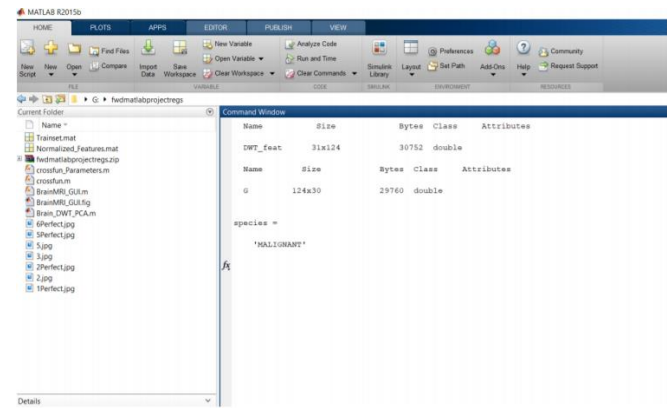


Fig 7: SVM classifier output

III. RESULTS AND DISCUSSION

Simulation Result

Figures given below shows the observed results after simulation of proposed work on MATLAB. These figures shows the original, segmented image or detected tumour image.

Input MRI image	OTSU thresholded image	Segmented tumour

Fig 8: Simulated result

Performance Evaluation:

True positive: Cases, the proposed system correctly calculates tumour and diagnosis without error.

True negative: Cases, the system properly detects absence of tumour.

False positive: Cases, the system indicates the presence of tumour, when there is actually no tumour.

False negative: Cases, the system wrongly suggests absence of tumour where tumour is actually present.

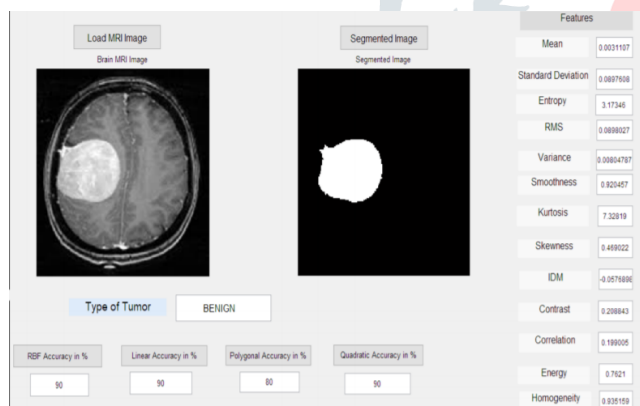
Table 1: Performance Evaluation by the Parameters

Parameters	K-means	Fuzzy-C	Adaptive-K	SVM
True Positive	8	10	12	13
True Negative	1	1	1	2
False Positive	4	2	2	NIL
False Negative	2	2	NIL	NIL
Accuracy	60%	73.33%	88.67	93.76%

$$\text{System Accuracy (\%)} = ((\text{TP}+\text{TN}) / (\text{TP}+\text{TN}+\text{FP}+\text{FN})) * 100$$

GUI developed in Matlab

In GUI database is taken first and then it takes the test image in which the tumour has to be recognized and when this test image is loaded, Thresholding and morphological filtering is performed on it. This processed image is then compared with the database templates. If the test image is matched with any of the images in database then there is no tumour in the test image and if the test image does not matched then there is a tumour in the test image.



IV. CONCLUSION AND FUTURE SCOPE

Conclusion

Magnetic resonance imaging (MRI) provides detailed information about brain tumour anatomy, cellular structure and vascular supply, making it an important tool for the effective diagnosis, treatment and monitoring of the disease. A segmentation approach is proposed in this research work that enables users to quickly and efficiently segment tumours in MRI of brain. This approach uses OTSU thresholding technique for better efficiency. The results show that Watershed Segmentation can successfully segment a tumour provided the parameters are set properly

in MATLAB environment. Finally, thus the tumour regions from the MRI brain image are segmented using threshold segmentation method and the type of brain tumour is specified using SVM classifier.

Future Work:

This proposed work finds its wide applications in the Medical Imaging Sciences and other related research areas. The Image segmentation has evolved as a basic technique for image processing and computer vision, however no unified algorithm that can be generalized over all types of images. Therefore, a universal and unique segmentation algorithm for researchers has vast future prospects. The remaining module of the proposed work which focusses on different type of tumour like CNS medullaoblastoma, glioblastoma multiform (GBM), meningioma and many others (by checking its level either it is benign or malignant).

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