Brain tumor detections and segmentation using improved thresholding-based algorithm

Jogendra Haobam
Electronics and communication Department
National Institute of Technology,Nagaland
Chumukeidma Dimapur, Nagaland 797103
Dimapur, India
jogenhaobam@gmail.com

Dr. Palungbam Roji Chanu
Electronics and communication Department
National Institute of Technology,Nagaland
Chumukeidma Dimapur, Nagaland 797103
Dimapur, India
rojichanu@gmail.com

***Abstract*- Brain tumor segmentation is the most crucial function in medical image analysis and processing as it helps in the diagnosis and treatment planning of brain tumors. In clinics or hospitals MRI or Magnetic Resonance Imaging is commonly used to assess these tumors, but the amount of data generated by the MRI prevents manual segmentations so in this paper we propose a novel approach for brain tumor segmentation using the improved thresholding-based segmentation algorithm which include filtering and using morphological operations. The performance of the proposed algorithm is compared with the normal thresholding segmentation algorithm using Jaccard Coefficient and Dice similarity coefficient and it shows an improvement in the results.**

***Keywords*-MRI or Magnetic Resonance Imaging, thresholding, Jaccard Coefficient, and Dice similarity coefficient.**

I. INTRODUCTION

Over the past decade, brain tumor segmentation has received significant interest [1]-[7] and the risk of malignant(cancer) cells in human organs is rising rapidly, especially among the elderly population in comparison to younger generations. According to National Cancer Institute figures, the general population's cancer incidence has increased by over 10%. Tumors are aberrant malignant cells that may cause damage to healthy tissue. If the segmentation is done manually there are many disadvantages. Tumors are aberrant malignant cells that may cause damage to healthy tissue. In clinical settings, conducting manual assessments of pathogenic changes is exhausting and vulnerable to human error. Automated tools for assessing lesions are urgently needed.

Image segmentation separates an image into distinct regions or objects. Segmenting the image into distinct areas is the main goal of image segmentation. There are two categories for tumors. Benign or malignant tumors are both possible. Benign tumors are benign and do not contain malignant cells. These tumors can grow larger in the same location, but they are not transmissible to different areas of the body. However, tumors can also be malignant(cancerous), which poses a serious risk to life. As these tumors have the potential to spread to other bodily parts, it is imperative that they are removed as soon as feasible. According to Balkrishna B. Y., the survival period following a brain tumor diagnosis may vary as brief as nine months [8]. Effective therapy and prompt diagnosis could increase survival and lower morbidity.

Magnetic resonance imaging or MRI is a popular and effective medical imaging technology. One benefit of MRI, or magnetic resonance imaging, is its non-invasiveness and ability to offer soft tissue contrast. An unmatched perspective within the body of an individual is offered by MRI. When we compare this amount of information to that of any other imaging method, it is astounding. According to Carl H [9] and Jacobs AH *et* *al*. [10], Magnetic Resonance Imaging or MRI is the gold standard for diagnosing brain tumors. Its excellent specificity and sensitivity have significant therapeutic implications.

Tumor identification at the brain tumor diagnostic facility is still done by hand. The radiologist claims that it takes a long time to find tumors in MRI reports, approximately between ten to fifteen minutes to diagnose a single report. Additionally, different professionals identify tumors in different ways. Thus, in this situation, computer-aided systems are beneficial. A computerized tumor identification system ought to be quicker and more accurate in identifying cancers from normal MR images. It needs to be dependable and give radiologists access to an intuitive, self-explanatory system.

II. RELATED WORKS

According to Pradeep Singh Yadav *et al*. [11], the normal tissue appears as low-intensity pixels in MRI reports while the cancer-affected area has high intensity pixels. Thresholding is a technique for segmenting data based solely on intensity. The basic form of segmentation classifies tumors depending on their gray level. Our suggested method uses fundamental morphological commands like imerode and imdilate to remove tumors, but also detects regions of interest and extracts specific tumor traits.

Dalila Cherif *et al.* [12] created the Expectation Maximization algorithm, which is an ongoing procedure for determining the greatest probability values of parameters in statistical models. It estimates parameters for several image classes. To classify tissue types as normal or abnormal, other criteria like mean, variance, and weight are used. Parameters are extracted using the maximum likelihood concept. This algorithm is really sophisticated. Using the intensity as a parameter, Morphometric operators can extract more visual characteristics with lower complexity, such as tumors.

According to Ali Gooya *et al.* [13], combining the Expectation Maximization algorithm with Atlas Registration yields better results than using the approach alone. This sort of segmentation is known as hybrid segmentation. The technique is advanced and requires a prior brain atlas for optimal tumor extraction, which can be an exhausting process. To address this limitation, we can extract tumors using intensity and morphology operator without requiring atlas registration, resulting in identical efficiency.

III. ANISOTROPIC DIFFUSION FILTERING

Using isotropic diffusion filtering, it is possible to reduce noise while preserving its edges at the same time. It is especially beneficial in situations when typical linear filters can distort edges or features in the image. Anisotropic diffusion filtering works by diffusing picture intensities in a way that retains edges while leveling out regions of uniform intensity. This is accomplished by modifying the diffusion process in response to the amplitude of the local gradient. Anisotropic diffusion involves convolving the picture with a diffusion kernel that varies according to the size of the local gradient. High gradient regions (edges) endure less diffusion, allowing edges to remain sharp while lower gradient regions or homogeneous areas experience more diffusion which results in smoothing. The diffusion equation determines how an image changes over time. It is commonly described as a partial differential equation or PDE. In anisotropic diffusion filtering, a typical diffusion equation is

$$\frac{\partial I}{\partial t} = \nabla . (c(\| \nabla \mathrm{I} \|)\nabla \mathrm{I}) \qquad (1)$$

I represent the intensity of the image, t represents the time, ∇ represents the gradient operator, $\| \nabla \mathrm{I} \|$ represents the gradient magnitude and $c(\| \nabla \mathrm{I} \|)$ represents the diffusion coefficient which determines which is the function of the gradient magnitude.

IV. THRESHOLDING

Thresholding is considered one of the simplest, most extensively used, and quickest segmentation procedures. The image is separated into areas based on the value of intensity or the value's attributes. It attempts to differentiate the two sections of the image's background and foreground. This thresholding-based segmentation assumes that an image consists of many grey level zones. Despite its simplicity and speed, it ignores an image's spatial properties. The thresholding technique converts the multilevel image into a binary image to select an appropriate threshold 'T' and to separate objects from the backdrop or background by dividing the image pixel into various areas or regions. This threshold 'T' can be defined as the lowest point between two peaks in a bimodal histogram. Let's take any pixel F (x, y). When F (x, y) > T, meaning the pixel intensity is greater than or equal to the threshold, the picture is in the forefront (F), otherwise it is in the background (B).

V.PROPOSED ALGORITHM

The proposed algorithm consists of anisotropic diffusion filtering, thresholding, and morphological operations. Most of the medical photos utilized for segmentation are low contrast. We used the anisotropic diffusion filter to reduce the noise while keeping the edges of the images. After applying the anisotropic diffusion filter, we used the thresholding algorithm then we performed the morphological operations where the solidity and the area are calculated. The proposed algorithm is as below.

1. Load the image to be segmented.
2. Apply the anisotropic diffusion filter.
3. Apply the thresholding algorithm to segment the image into binary regions and pixels above a certain threshold value are identified tumors while the pixels below are classified as background.
4. Morphological operation is applied to the binary image to distinguish the tumor regions. In the operations solidity and area is calculated where the largest area is identified as tumor. The threshold (Th) value is set at 200.
5. Subsequently, we perform an erosion operation surrounding the identified tumor, subtracting the erosion zone from the initial binary picture while retaining the tumor's contour.

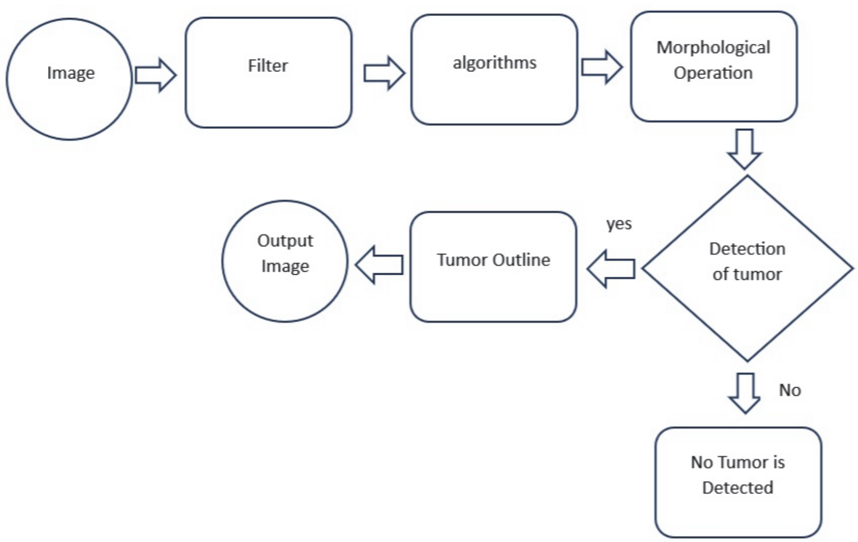
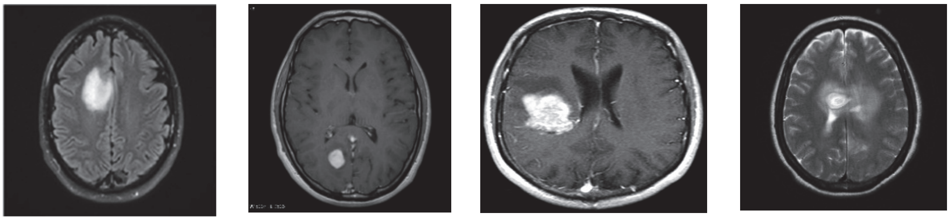


Fig. 1. A flow diagram illustrating the proposed method

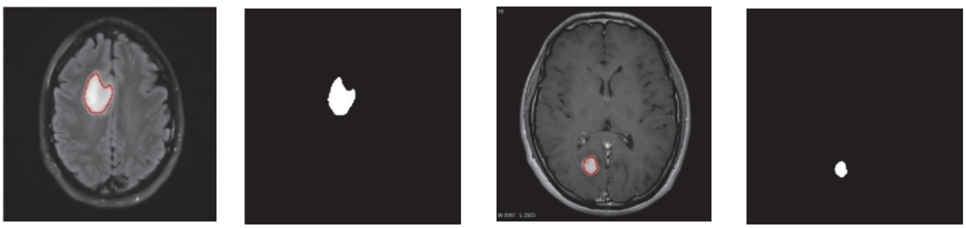
VI. RESULTS

We used many kinds of medical photos for the analysis, to be precise we used 256 images. Medical image analysis typically separates diseased patches from the backdrop. We used MRI images of brain which have tumor in it. MATLAB is used to implement the proposed algorithm.

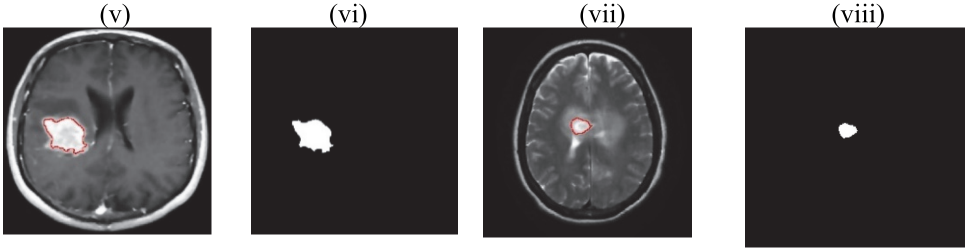


(i) (ii) (iii) (iv)

Fig. 2. (i), (ii), (iii) and (iv) are the original image which have tumor inside it.



(v) (vi) (vii) (viii)



(ix) (x) (xi) (xii)

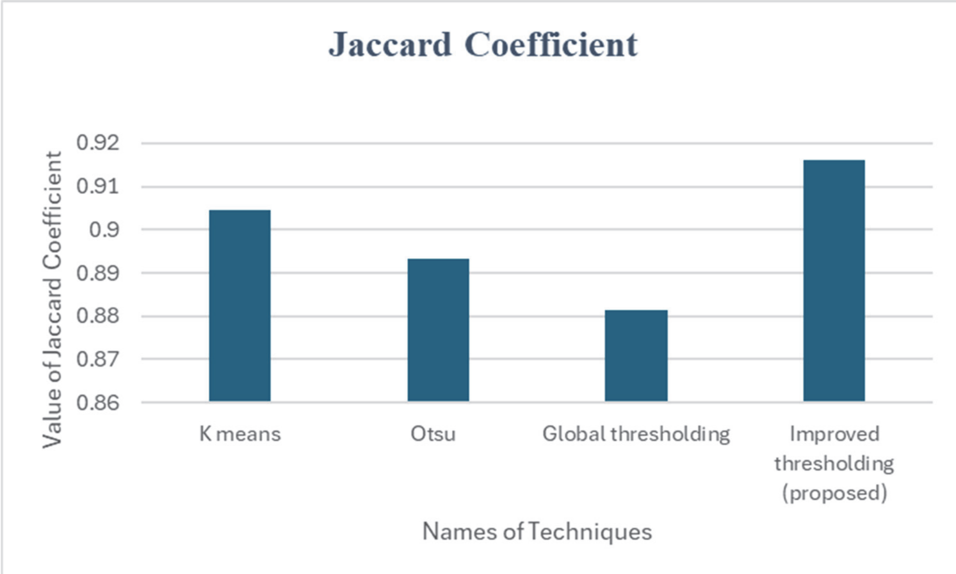
Fig. 3. (v) and (vi), (vii) and (viii), (ix) and (x), (xi) and (xii), are the detected tumor and the tumor alone of (i), (ii), (iii) and (iv) respectively.

. We compare the results using Jaccard Coefficient and Dice similarity coefficient.

- Jaccard Coefficient: Using segmented pixels as a basis for an evaluation of the similarity between a segmentation (A) and a reference segmentation (B), the Jaccard index, also known as the Jaccard Similarity Coefficient or JSC, calculates the similarity between two segments.

$$JCS = \frac{(A \cap B)}{(A \cup B)} \qquad (2)$$

ISBN : 978-81-978522-2-0



6. Fig. 4. Chart comparison using Jaccard Coefficient with different techniques.

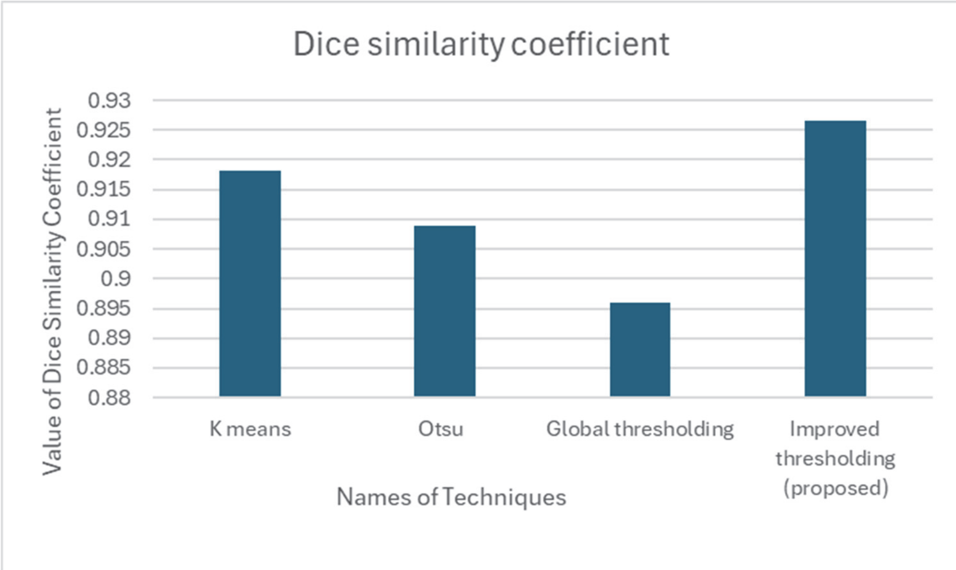
- The Dice similarity coefficient: Several similarities are observed between the Dice similarity coefficient and the Jaccard index. A DSC is an intersection between two sections that takes place when their sum is higher than their intersection. The coefficient DSC between regions A and B can be represented as follows:

$$DCS = \frac{2(A \cap B)}{(A+B)} \tag{3}$$

Indeed, the higher values of the Dice similarity and Jaccard coefficients can be interpreted as better performance.

TABLE 1. VALUES OF JACCARD COEFFICIENT AND DICE SIMILARITY COEFFICIENT

Techniques	**Jaccard Coefficient**	**Dice similarity coefficient**
K means	0.9046	0.9182
Otsu	0.8932	0.9089
Global thresholding	0.8814	0.8959
Improved thresholding (proposed)	0.9162	0.9266



7. Fig. 5. Chart comparison using Dice similarity coefficient with different techniques.

Interestingly, the higher the values of the Dice similarity and Jaccard coefficients, the better the performance of the system is believed to be.

ACKNOWLEDGEMENTS

I would like to express our deepest gratitude to Dr. Palungbam Roji Chanu for her invaluable guidance and support throughout this research. Her insights and expertise in the field of brain tumor segmentation have been instrumental in shaping the direction and outcomes of this work.

We are also grateful to the Electronics and Communication Department at the National Institute of Technology, Nagaland, for providing the necessary resources and a conducive environment for carrying out this research

REFERENCES

[1] Wu, M.N., Lin, C.C. and Chang, C.C., 2007, November. Brain tumor detection using color-based k-means clustering segmentation. In *Third international conference on intelligent information hiding and multimedia signal processing (IIH-MSP 2007)* (Vol. 2, pp. 245-250). IEEE.

[2] Wilson, B. and Dhas, J.P.M., 2014. An experimental analysis of Fuzzy C-means and K-means segmentation algorithm for iron detection in brain SWI using Matlab. *International Journal of Computer Applications*, *104*(15)

[3] Abdel-Maksoud, E., Elmogy, M. and Al-Awadi, R., 2015. Brain tumor segmentation based on a hybrid clustering technique. *Egyptian Informatics Journal*, *16*(1), pp.71-81.

[4] Sinha, K. and Sinha, G.R., 2014, March. Efficient segmentation methods for tumor detection in MRI images. In *2014 IEEE Students' Conference on Electrical, Electronics and Computer Science* (pp. 1-6). IEEE.

[5] Kumari, A. and Mehra, R., 2014. Design of hybrid method PSO and SVM for detection of brain neoplasm. *International Journal of Engineering and Advanced Technology*, *3*(4), pp.262-266.

[6] Vijay, V., Kavitha, A.R. and Rebecca, S.R., 2016. Automated brain tumor segmentation and detection in MRI using enhanced Darwinian particle swarm optimization (EDPSO). *Procedia Computer Science*, *92*, pp.475-480.

[7] Kumari, N. and Saxena, S., 2018, March. Review of brain tumor segmentation and classification. In *2018 International conference on current trends towards converging technologies (ICCTCT)* (pp. 1-6). IEEE.

[8] Kumari, N. and Saxena, S., 2018, March. Review of brain tumor segmentation and classification. In *2018 International conference on current trends towards converging technologies (ICCTCT)* (pp. 1-6). IEEE.

[9] Jacobs, A.H., Kracht, L.W., Gossmann, A., Rüger, M.A., Thomas, A.V., Thiel, A. and Herholz, K., 2005. Imaging in neurooncology. *NeuroRx*, *2*(2), pp.333-347.

[10] Murthy, T.D. and Sadashivappa, G., 2014, October. Brain tumor segmentation using thresholding, morphological operations and extraction of features of tumor. In *2014 international conference on advances in electronics computers and communications* (pp. 1-6). IEEE.

[11] Mohit, K. and Mishra, R., 2015. A morphological filtration approach towards brain tumor segmentation. *IJSRD*, *3*(8), pp.171-174.

[12] Cherifi, D., Doghmane, M.Z., Nait-Ali, A., Aici, Z. and Bouzelha, S., 2011, May. Abnormal tissus extraction in MRI brain medical images. In *International Workshop on Systems, Signal Processing and their Applications, WOSSPA* (pp. 357-360). IEEE.

[13] Gooya, A., Biros, G. and Davatzikos, C., 2010. Deformable registration of glioma images using EM algorithm and diffusion reaction modeling. *IEEE transactions on medical imaging*, *30*(2), pp.375-390.