# AN EARLY BRAIN TUMOR DETECTION USING IMAGE PROCESSING TECHNIQUES

[1]Vikrant Sharma, [2]Sandeep Singh, [3]Neha Sehrawat

[1]Student, [2]Assistant Professor, [3]Assistant Professor
[1]Faculty of Engineering & Technology,
[1]SGT University, Gurugram, India

***Abstract :*** Brain tumor detection and classification is that the most troublesome and tedious task within the space of medicative image getting ready. Magnetic resonance imaging (MR imaging) is a medical procedure that is commonly used by doctors to visualise the inner structure of the body without the need for surgery. Magnetic resonance imaging (MRI) provides detailed information about human soft tissue, which aids in the diagnosis of brain tumors. For the diagnosis of a brain tumor using a laptop-based clinical device, precise segmentation of the magnetic resonance imaging image is required. This paper is focused on finding the best and most correct approach for detecting neoplasm from brain magnetic resonance imaging scans, and if it confirms the presence of a tumor, it's then focused on determining its stage, i.e., benign or malignant.

***IndexTerms* – Image Segmentation, Support Vector Machine, Self-Organized Mapping, MRI**

## I. INTRODUCTION

Medical field has many types of imaging methods, such as Computed Tomography Scans (CT Scans), X-Rays, Magnetic Resonance Imaging (MRI), etc. These technologies enable us to identify even the slightest flaws in the human body. A brain tumor is defined as abnormal development of tissues in the brain that interferes with normal brain processes. The primary objective of medical image processing is to extract accurate and useful information from pictures with as little error as possible.The majority of existing conventional diagnosis procedures rely on human experience in reading MRI-scans for judgement, which raises the risk of false brain tumor detection and identification. Digital image processing, on the other hand, ensures that the tumor is detected quickly and precisely. The segmentation procedure is one of the most successful approaches for extracting information from complex medical images and has a wide range of applications in the medical industry. The primary goal of image segmentation is to divide an image into mutually exclusive and exhausted sections, with each region of interest being spatially contiguous and the pixels within each region being homogeneous according to a preset criterion. Intensity, texture, colour, range, surface normal, and surface curvatures are all common
homogeneity requirements. Colour-based segmentation with K-means clustering for brain tumor diagnosis has been proposed, with the created algorithm achieving better results than other edge detection algorithms. In pathological circumstances, a modified method was presented that includes symmetry analysis and any significant prior knowledge of the region of interest, as well as region area and edge information in the tumor site.

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|---|---|
| Brain Tumor Classification [21] | Primary<br>1. Stem in Brain Cells<br>2. May Prolifate other parts of brain and stem<br>3.Rarely Spread to other organs |
| | Secondary<br>1. Stem in other parts of the body<br>2. Named by Location where it stems<br>3. Treated on the place of thier origin.<br>4. More comman than primary brain tumor |

Fig 1 :- Brain tumor classification on the basis of Primary & Secondary

| | |
|---|---|
| Brain tumor classification [21] | Benign<br>1. Not cancerous<br>2. Slow growing cells<br>3. Marked with clear borders<br>4. Do not spread to other tissues<br>5. Least Destructive<br>6. Can be surgically cured<br>7. Do not revert back once cured |
| | Malignant<br>1. Cancerous<br>2. Rapid growing cells<br>3. Not Marked with clear borders<br>4. Can spread to entire brain and spine<br>5. Life threating<br>6. Can be cured with radiation and chemotherapy<br>7. May revert back after the treatment |

Fig 2:- Brain Tumor classification in the basis of Benign & Malignant tumor.

## II. Segmentation Techniques

The process of separating an image into mutually exclusive and exhaustive sectors that are homogenous and adhere to a predefined standard is referred to as image segmentation. In the context of a brain tumor, segmentation entails identifying aberrant from normal brain tissues [18].

The following approaches are classified as segmentation techniques. [20]: • Thresholding technique

- Region growing technique
- Edge based technique
- Clustering technique
- Watershed technique
- Deformable model-based technique

2.1. Thresholding Techniques

Thresholding is the most often used segmentation technique. Based on the threshold value, the picture is split into two groups: one with pixel values more than or equal to the threshold value, and the other with pixel values less than the threshold value. Local, global, and adaptive thresholding approaches are the three categories. Local thresholding selects the threshold value based on local variables such as standard deviation or local mean value of various picture regions. The histogram of the image is used to pick a single threshold value for the entire image in global thresholding.

The threshold value has a significant impact on the segmentation outcome. Incorrect segmentation occurs when the threshold value is chosen incorrectly. Various approaches, such as Otsu's thresholding, have been presented to automate the threshold selection process. Noise sensitivity is caused by thresholding approaches that ignore the spatial features of the image [19].

2.2 Region Growing Techniques

By arranging the nearest pixel of comparable type, the pictures are partitioned using the region expanding segmentation method (homogeneity, texture, intensity levels and sharpness). This method begins with the selection of an initial seed point according to a set of rules. As a consequence, based on homogeneity criteria, neighbouring pixels are gradually added to the seed. [19].

This approach is simple, and it successfully divides picture pixels of equivalent quality into large pieces. When compared to the histogram thresholding approach [19], this technique is less noise sensitive and produces superior segmentation since it takes into account the image's spatial features.

This technique appropriately segments geographically separated areas and regions with comparable characteristics. This method can also result in linked areas [20].

The primary disadvantage of this approach is that it might result in a hole and unconnected parts in the specified form. [19].

2.3. Edge Based Techniques

In an image, the boundary or edge is the intensity gradient of a particular pixel or collection of pixels. [20]. Edge-based approaches identify the image pixels that match to the image's visible object's edges. As a consequence, a binary image with the location of the edge pixels is produced. This method employs a variety of edge operators, including Laplacian, Sobel, Canny, Prewitt, and others. Edge-based approaches are appropriate for images that are basic and noise-free. These approaches can result in additional or missing edges in noisy images [22]. These algorithms are computationally efficient, and they don't require any prior knowledge of the image's content. The primary issue with these approaches is that the boundaries do not completely enclose the object [20].

2.4. Clustering Techniques

Clustering is a segmentation method that divides data into groups based on traits, features, and characteristics. As a result, a cluster is made up of groupings of data that are comparable. These are unsupervised strategies that do not necessitate data learning. Clustering-based algorithms use less time to generate segmented data. K-means and Fuzzy C Means (FCM) clustering are two well-known clustering methods. [19].

2.5. Watershed Techniques

Image morphology is used in this technique. In this scenario, each item must have at least one marker or seed point. [20]. This approach divides image pixels into groups based on their brightness. Pixels with similar brightness are grouped together. The watershed technique has been used in two ways: first, the calculated loca1 minimum of the image gradient has been used as a marker, and then merging is performed; second, the calculated loca1 minimum of the image gradient has been used as a marker, and then merging is conducted. Watershed transformation was carried out in the second approach, which employs the clearly indicated marker placements. This method's primary drawback has been that it suffers from excess and under segmentation. [23].

2.6. Deformable Model Based Techniques

In these approaches, the segmentation issue was handled as an optimization job, with an appropriate energy function optimised to reach the segmentation boundary. [14]. The two forms of deformable model or snake model-based methods were free form models and shape models. A parameterized pattern of a given structure is often used in shape models to store past global structural information. Previous information in free form models, such as snakes, was generally made up of local continuity and smoothness restrictions, resulting in no discernible global structures. [24]. Deformable model-based segmentation techniques include random field methods, Active Contour Models (ACM), and level set approaches. [14]. The deformable or snake models were best for recovering items with anonymous topologies. Deformable models' mathematical structure makes it super easy to integrate picture input, knowledge-based restrictions, and necessary contour characteristics in a single extraction procedure [24]. The ability of these models to handle just simple topological objects is their primary limitation. Another disadvantage has been the snake's sensitivity to

initial circumstances, which would be due to the non-convex shape of the energy function and the contraction force generated by the internal energy term. [24].

## III. LITERATURE SURVEY

Various researchers have put forth a lot of effort to partially or totally automate the task of brain tumor segmentation and detection. The following is a summary of the findings of the numerous studies:

Shivhare Sharma [15] demonstrated a completely automated methodology for segmenting brain tumors based on the parameter-free K-means clustering algorithm and mathematical morphological operations such as dilation and holefilling. On the Brats 2015 training dataset, the proposed algorithm has been tested. The dataset's ground truth result is associated with the tumor segmented using the provided approach. The produced findings have a Dice Similarity Coefficient (DSC) of 75% when compared to the given ground truth.

Jagan[1] demonstrated an unique tumor segmentation method in which the obtained picture is pre-processed with an anisotropic filter. To achieve initial segmentation, the FCM and enhanced Expectation Maximization (EM) approaches are used. The suggested methodology is then used to accomplish superior segmentation. In terms of segmentation accuracy, the proposed technique's work is associated with the FCM clustering strategy and the enhanced EM approach. Over ten patients, the suggested method achieved an average segmentation accuracy of 97.98 percent, outperforming FCM clustering and enhanced EM techniques.

Dandu et al.[16] proposed a classification-based method for pancreatic and brain tumor segmentation using Statistical Region Merging (SRM) and Back Propagation Neural Network (BPNN). The picture is first pre-processed utilising the Decision Based Couple Window Median Filter (DBCWMF) method in this manner. After that, SRM is used to segment the data. Then, utilising Cat Swarm Optimization (CSO) and Scale Invariant Feature Transform (SIFT) approaches, features are retrieved. The BPNN classifier is then used to classify the data. DBCWMF outperforms the median and PGPD filters in the suggested technique, while the BPNN classifier outperforms the Artificial Neural Network (ANN) and AdaBoost classifier.

Filho[2] demonstrated an adaptive and parameter-free medical picture segmentation system based on Optimum Path Snakes (OPS). Pre-processing was done to extract characteristics such as texture using HU moments, Gray Level Co occurrence Matrix (GLCM), Human Density Analyzer (HDA), and statistical moments. The data was subsequently segmented using the OPS method.

Suneetha and Rani[3] proposed a novel method for early diagnosis of brain tumors. The suggested method pre-processes collected brain MRI images using the Optimized Kernel Possibilistic C-means Method (OKPCM). The picture would then be enhanced using an adaptive Double Window Modified Trimmed Mean Filter (DW-MTMF). Finally, picture segmentation was finished using the region expanding approach. The suggested OKPCM methodology was compared to K means, CLOPE, and FCM methods in terms of processing time and accuracy. When compared to existing approaches, the suggested OKPCM yields higher accuracy. However, the K-means algorithm is faster in terms of processing time.

Zhang[4] demonstrated a method for detecting diseased brain using a Multilayer Perceptron (MLP). The first phase includes obtaining 12 Fractional Fourier Entropy (FRFE) characteristics. In the following stage, the MLP algorithm is presented to categorise the data. Using the pruning procedure, the optimal number of hidden neurons is identified. Three pruning techniques are compared: the Kappa Coefficient (KC), Bayesian Detection Boundaries (BDB), and Dynamic Pruning (DP). Adaptive Real-Coded Biogeography Based Optimization (ARBO) has been used to train the weights and biases (ARCBBO). According to the statistics, combining FRFE, KC, MLP, and ARCBBO resulted in a better average accuracy of 99.53 percent.

## COMPARISON TABLE

| S.no | Author | Total Images/Patients | Result(Accuracy) |
|---|---|---|---|
| 1 | Jagan[1] | 10 | 97.98% |
| 2 | Shivhare Sharma[15] | 2015 | 75.06% |
| 3 | Dandu et al [16] | 27 | 95.56% |
| 4 | Filho[2] | 24 | 94% |
| 5 | Suneetha & Rani[3] | 457 | 78.9% |
| 6 | Amin et al[7] | 521 | 98.9% |
| 7 | Raju & Suresh[8] | 18 | 93% |
| 8 | Emmanuel & Deepa[17] | 81 | 99.84% |
| 9 | Lim &Mandava[11] | 30 | 70% |
| 10 | K.T and S[5] | 67 | 95% |
| 11 | Nanda [6] | 45 | 67.82% |
| 12 | Zhang[4] | 55 | 99.53% |
| 13 | V.Hanan[10] | 38 | 97% |

## CONCLUSION

A brain tumor is an unwelcome mass of flesh in which cells multiply and develop uncontrollably. These days, it's a very prevalent and devastating problem. Because of the tumor's complicated structure in terms of size, form, and existence, a proper diagnosis of a brain tumor is challenging. Radiologists' manual identification of brain tumors may be imprecise, and results may differ from one radiologist to the next, therefore a correct diagnosis is not always guaranteed. To properly detect brain tumors, some form of automation is essential. When it comes to analysing medical photos, image processing is crucial. The procedure of separating normal brain tissues from malignant tumor tissues is known as brain tumor segmentation. Various segmentation approaches have been addressed, as well as their benefits and drawbacks. A comprehensive assessment of the researchers' work in the field of brain tumor detection and segmentation is provided. A segmentation methodology's clinical acceptability is decided by its simplicity and degree of human engagement. This study focuses on the future advances of medical image processing in healthcare and medicine, specifically on the timely identification of brain tumors for accurate diagnosis. Existing brain tumor detection methods that employ pre-processing and segmentation stages are unable to distinguish between normal and abnormal segmented regions. Existing work that incorporates additional methods like feature extraction and classification may classify the extracted region as normal or abnormal, but with less certainty. As a consequence, this activity will be expanded to develop improved ways for automating the job of identifying brain tumors, which will provide better results than current systems.

## REFERENCES


**[1]** A. Jagan. (2019) "A Contemporary Framework and Novel Method for Segmentation of Brain MRI," in Proceedings of the International Conference on ISMAC in Computational Vision and Bio-Engineering 2018 (ISMAC-CVB) 30: 739–747.

**[2]** P. P. R. Filho, A. C. da Silva Barros, J. S. Almeida, J. P. C. Rodrigues, and V. H. C. de Albuquerque. (2019) "A New Effective and Powerful Medical Image Segmentation Algorithm Based on Optimum Path Snakes." Applied Soft Computing Journal 76: 649–670

**[3]** B. Suneetha and A. J. Rani. (2018) "Brain Tumor Detection in MR Imaging Using DW-MTM Filter and Region-Growing Segmentation Approach." in R. S. Bapi, K. S. Rao, and M. V. N. K. Prasad (eds) First International Conference on Artificial Intelligence and Cognitive Computing: AICC 2018. Advances in Intelligent Systems and Computing, Springer Singapore: 549–560.

**[4]** Y. Zhang, Y. Sun, P. Phillips, G. Liu, X. Zhou, and S. Wang. "A Multilayer Perceptron Based Smart Pathological Brain Detection System by Fractional Fourier Entropy." Journal of Medical Systems 40(7).

**[5]** K. K. K, M. D. T, and M. S. (2018) "An Efficient Method for Brain Tumor Detection Using Texture Features and SVM Classifier in MR Images." Asian Pacific Journal of Cancer Prevention 19(10): 2789–2794.

[**6**] S. J. Nanda, I. Gulati, R. Chauhan, R. Modi, and U. Dhaked. (2018) "A K-Means-Galactic Swarm Optimization-Based Clustering Algorithm with Otsu's Entropy for Brain Tumor Detection." Applied Artificial Intelligence: 1–19.

**[7]** J. Amin, M. Sharif, M. Raza, and M. Yasmin. (2018) "Detection of Brain Tumor Based on Features Fusion and Machine Learning." Journal of Ambient Intelligence and Humanized Computing: 1–17.

**[8]** A. R. Raju, P. Suresh, and R. R. Rao. (2018) "Bayesian HCS-based Multi-SVNN: A Classification Approach for Brain Tumor Segmentation and Classification Uing Bayesian Fuzzy Clustering." Biocybernetics and Biomedical Engineering 38(3): 646–660.

**[9]** Lukas L. et Al. Brain Tumor Classification Based On Long Echo Proton Mrs Signals. Artificial Intelligence In Medicine, 31:73–89, 2004.

**[10]** A. Vishnuvarthanan, M. P. Rajasekaran, V. Govindaraj, Y. Zhang, and A. Thiyagarajan. (2017) "An Automated Hybrid Approach Using Clustering and Nature Inspired Optimization Technique for Improved Tumor and Tissue Segmentation in Magnetic Resonance Brain Images." Applied Soft Computing 57: 399–426.

**[11]** K. Y. Lim and R. Mandava. (2018) "A Multi-phase Semi-automatic Approach for Multisequence Brain Tumor Image Segmentation." Expert Systems with Applications 112: 288– 300.

**[12]** S. J. Nanda, I. Gulati, R. Chauhan, R. Modi, and U. Dhaked. (2018) "A K-Means-Galactic Swarm Optimization-Based Clustering Algorithm with Otsu's Entropy for Brain Tumor Detection." Applied Artificial Intelligence: 1–19.

**[13]** C. Sompong and S. Wongthanavasu. (2017) "An Efficient Brain Tumor Segmentation Based on Cellular Automata and Improved Tumorcut Algorithm." Expert Systems with Applications 72: 231–244.

**[14]** V. G. Kanas, E. I. Zacharaki, C. Davatzikos, K. N. Sgarbas, and V. Megalooikonomou. (2015) "A Low Cost Approach for Brain Tumor Segmentation Based on Intensity Modeling and 3D Random Walker." Biomedical Signal Processing and Control 22: 19–30.

**[15]** S. N. Shivhare, S. Sharma, and N. Singh. (2019) "An Efficient Brain Tumor Detection and Segmentation in MRI Using Parameter-Free Clustering," in M. Tanveer and R. B. Pachori (eds) Machine Intelligence and Signal Analysis. Advances in Intelligent Systems and Computing 748, Springer Singapore: 485–495.

**[16]** J. R. Dandu, A. P. Thiyagarajan, P. R. Murugan, and V. Govindaraj. (2019) "Brain and Pancreatic Tumor Segmentation Using SRM and BPNN Classification," Health and Technology (Berl).

**[17]** A. R. Deepa and W. R. Sam Emmanuel. (2018) "An Efficient Detection of Brain Tumor Using Fused Feature Adaptive Firefly Backpropagation Neural Network." Multimedia Tools and Applications: 1–16.

**[18]** N. Gordillo, E. Montseny, and P. Sobrevilla. (2013) "State of the Art Survey on MRI Brain Tumor Segmentation." Magnetic Resonance Imaging 31(8): 1426–1438.

**[19]** A. Altameem et al.. (2014) "Medical Image Segmentation Methods , Algorithms , and Applications." IETE Technical Review 31(3): 199– 213.

**[20]** J. Rogowska. (2009) "Overview and Fundamentals of Medical Image Segmentation." in Handbook of Medical Image Processing and Analysis, San Diego, USA: Academic Press: 73–90.

**[21]** "Brain Tumors - Classifications, Symptoms, Diagnosis and Treatments." [Online]. Available: https://www.aans.org/Patients/Neurosurgical-Conditions-and-Treatments/Brain Tumors. [Accessed: 25-Feb-2019].

**[22]** S. Sapna Varshney, N. Rajpal, and R. Purwar. (2009) "Comparative Study of Image Segmentation Techniques and Object Matching Using Segmentation." in 2009 Proceeding of International Conference on Methods and Models in Computer Science (ICM2CS): 1–6.

**[23]** A. Mustaqeem, A. Javed, and T. Fatima. (2012) "An Efficient Brain Tumor Detection Algorithm Using Watershed & Thresholding Based Segmentation." International Journal Image, Graphics and Signal Processing 10: 34–39.

**[24]** G. A. Giraldi, P. S. Rodrigues, L. S. Marturelli, and R. L. S. Silva. (2005) "Improving the Initialization, Convergence, and Memory Utilization for Deformable Models," in J. Suri, D. Wilson, and S. Laxminarayan (eds) Handbook of Biomedical Image Analysis. Volume I: Segmentation Models Part A, New York: Kluwer Academic / Plenum Publishers: 359–414.