

# GAN ALGORITHM USING IMAGE SEGMENTATION OF BRAIN CANCER OF MRI IMAGES USING GLCM FEATURES

<sup>1</sup>V.PAVANI, <sup>2</sup>T.JYOTHI KUMARI, <sup>3</sup>P.ROHIT

<sup>1</sup>Associate Professor, <sup>2,3</sup>Assistant Professor  
Department of Electronics & Communication Engineering  
Chaitanya College of Engineering  
JNTU-GV University  
Vishakhapatnam, India.

**Abstract-** The main motive of this paper is to detect tumor from MRI images with the interface of Gray Level Co-Occurrence Matrix (GLCM) methods using Matlab. Our goal is to apply semantic segmentation of brain tumours from MRI Images using a Generative Adversarial Network (GAN). In daily life, computational applications are becoming increasingly important. More research has been done on the use of computer-aided systems for computational biomedical applications. The most frequent cause of death in the current state of the medical community is the discovery of a brain tumor. One of the specialized medical image analysis techniques is the automated diagnosis of brain disorders using MR images. The primary topics of this research are the identification and segmentation of the brain tumor region. We are able to identify the cancer location early on by using a variety of approaches, including water segmentation, segmentation, filtering, and thresholding. Compared to the previous methods, this method yields a very accurate cancer zone with well-defined boundaries. This technological development is beneficial to radio surgery specialists. Therefore, by employing this technique, a physician may precisely distinguish the tumor area, shielding the unaffected tumor area from radiological exposure.

**Keywords:** Gray Level Co-Occurrence Matrix (GLCM), Segmentation, Generative Adversarial Network (GAN).

## I. INTRODUCTION

The brain is the central nervous system. A brain's structure is incredibly intricate. The brain is a spongy, fragile, irreplaceable mass of tissue. Patterns can enter and stabilize in this stable environment. The shielding skull keeps the brain out of sight. In addition to providing protection from harm, this skull obstructs research into how the brain functions in both health and sickness. A tumor is a clump of tissue that grows uncontrollably beyond the range of normal growth-regulating forces. A collection of aberrant cells that develops inside or outside the brain is called a brain tumor. All healthy brain cells can be directly destroyed by tumours. By compressing other areas of the brain, inducing inflammation, cerebral edema, and pressure inside the skull, it can also indirectly harm healthy cells. Tumor does not equal Primary brain tumors occur in 11–12 cases per 100,000 persons annually; primary malignant brain tumors occur in 6–7 cases per 100,000 people. Physicians and researchers can examine the brain non-invasively using two imaging modalities: magnetic resonance imaging and computed tomography.



**Figure 1:** Brain Tumour

## II. LITERATURE SURVEY

**B.Devkota, et.al [1]**, has outlined a computer-aided detection method called Mathematical Morphological Reconstruction (MMR) that can be used to identify brain tumors in their early stages. After pre-processing the image to eliminate artifacts and noise, it is segmented to identify areas of interest that may contain tumors.

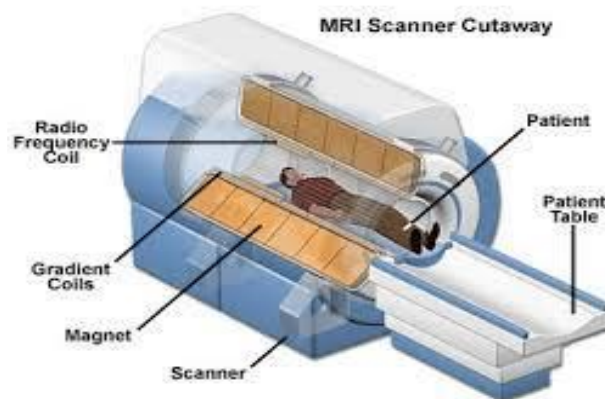
**A.Aslam, et.al [2]**, has talked about a brain tumor segmentation technique called Improved Edge Detection. On Sobel edge detection, it is based. It employs a closed contour approach to identify distinct regions and combines the Sobel method with an image-dependent thresholding technique. Ultimately, the intensity data contained in the closed outlines is used to extract malignancies from the picture.

**Sahil J Prajapati, et.al [3]**, has talked about Non Negative Matrix Factorization and Different Image Segmentation Techniques for Brain Tumor Detection. One of the most promising methods for reducing the dimensionality of the data is nonnegative matrix factorization. Finding two non-negative matrices whose product closely resembles the original matrix is the goal of NMF. The NMF results indicate no cancellations, linear superposition alone, and significant sparsity. The NMF contains all matrices to contain only non-negative entries.

**P.Natarajan, et.al [4]**, has talked about a method for effectively identifying a brain tumor on MRI brain scans. The steps in the methodology are as follows: thresholding is used for picture segmentation, histogram equalization is used for image enhancement, and median and sharpening filters are used for preprocessing. Next, this method is followed by additional morphological processes.

## III. Various Diagnosing Techniques Magnetic Resonance Imaging

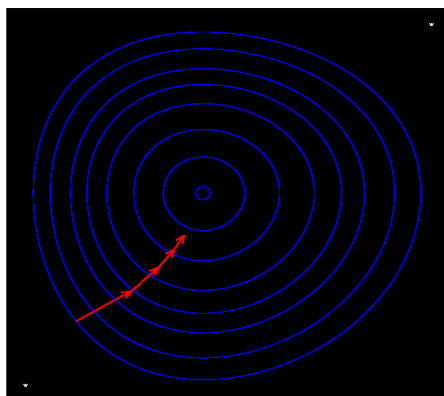
A medical imaging method called magnetic resonance imaging (MRI) is utilized in radiology to see inside body structures in great detail. MRI uses the nuclear magnetic resonance (NMR) property to view the body's atomic nuclei. In an MRI scanner, the patient lies inside a sizable, strong magnet. Radiofrequency magnetic fields are then delivered to systematically change the alignment of the magnetization, which is created by aligning certain atomic nuclei in the body through magnetic fields. When compared to other medical imaging methods like computed tomography (CT) or X-rays, magnetic resonance imaging (MRI) is particularly helpful in examining the brain, muscles, heart, and malignancies because it offers strong contrast between the various soft tissues of the body. The fact that an MRI scan is safe for patients is one of its key benefits.



**Figure 2:** Magnetic Resonance Imaging (MRI) Scanner

### Gradient based Method

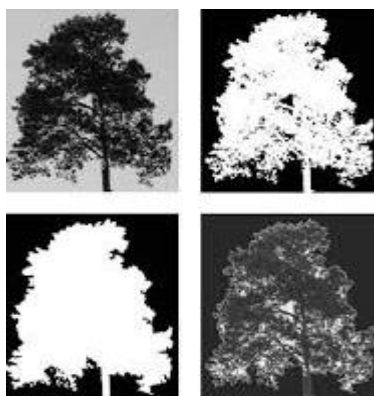
An algorithm for first-order optimization is gradient descent. Gradient descent is a technique for finding a function's local minimum in steps proportional to the function's gradient at the current location. Gradient ascent is the process of approaching a local maximum of that function by taking steps that are proportionate to the gradient's positive value. Steepest descent, or the steepest descent method, is another name for gradient descent. Gradient descent, when referred to as the latter, is not to be mistaken with the steepest descent approach when it comes to approximating integrals.



**Figure 3:** Gradient based method

### Thresholding

The thresholding approach is the most basic technique for segmenting images. This technique converts a grayscale image to a binary image at the clip-level. Choosing the threshold value is the crucial step in this process.



**Figure 4:** Thresholding

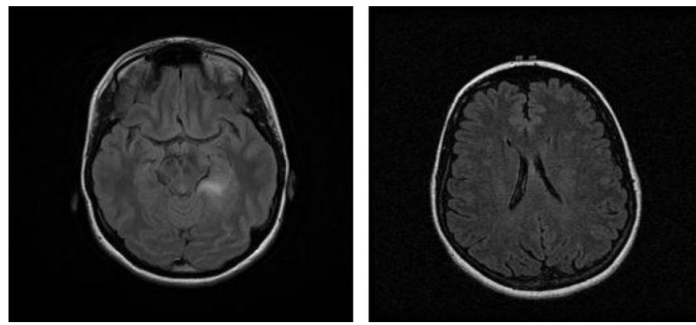
The primary shortcomings of these current methods include their increased resilience to noise and decreased effectiveness, as well as the imprecise definition of tumor boundaries. In order to address the shortcomings of the current procedure, a process that yields precise results must be developed. As a result, we have decided to use neural networks for classification and cellular automata for segmentation.

### IV. Proposed Method

Three steps can be used to summarize the proposed system. Pre-processing is the first step, which improves the brain MRI image and makes it easier to evaluate. Morphological processes, pixel subtraction, and image filtering are used to create enhanced images. The second stage, known as intensity adjustment based segmentation, divides the tumor's area from the improved image. Pixel addition, the third stage, displays the tumor's position on the original image.

#### Database

Digital magnetic resonance imaging (MRI) is used in this paper. The Cancer Imaging Archive website is where the database can be found. Every image has 256 by 256 pixels and is grayscale (8 bits). The database contains 100 images total, of which 70 are aberrant and 30 are normal (tumor-free) brain MRI scans. The initial data was saved in a dicom file. To use the photos in the MATLAB environment, they must be converted to raw format. The brain MRI image examples are displayed in Figure 5.

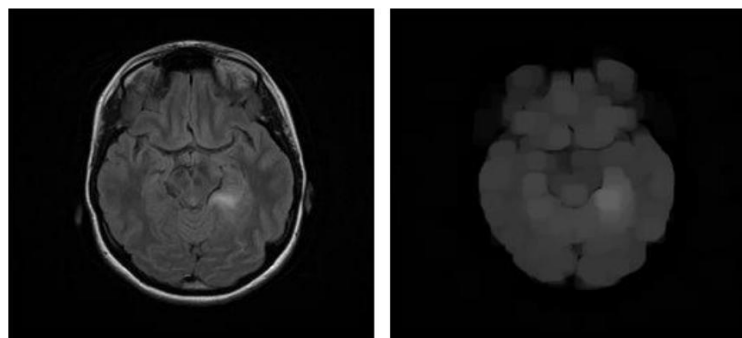


a) Abnormal image                      b) Normal image

**Figure 5:** Brain MRI images

### Morphological Operations

A small shape or template known as a structural element is produced on a picture by morphological procedures. Using the structure element "disk" and radius "7," a morphological operation is used to extract the image's background. Dilation and erosion are the two morphological processes that occur most frequently. One morphological operation that can be used on binary and grayscale images is dilation. Dilation enlarges the borders, which makes objects grow. Similar to dilation, erosion is a morphological technique that can be applied to binary and grayscale images. Examining object dimensions is a result of erosion. The morphological process known as image opening facilitates the extraction of the backdrop. The morphological process that results in the picture opening uses the same structural element for both erosion and dilation. The application of the background extraction technique is seen in Figure 6.

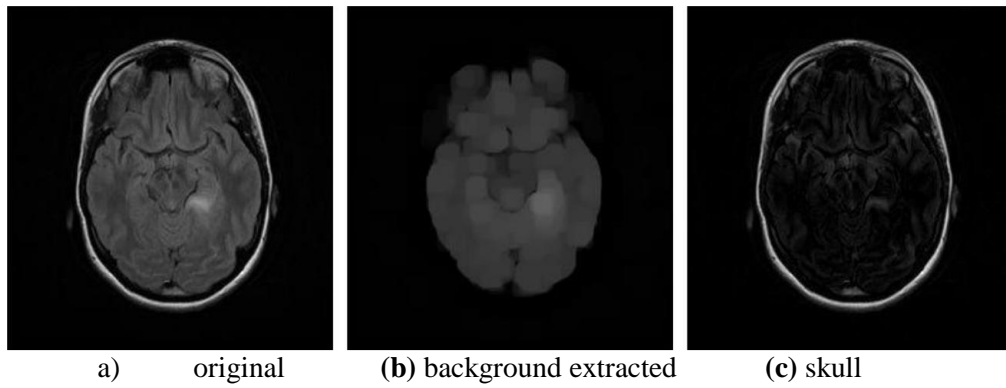


(a) original                      (b) background extracted

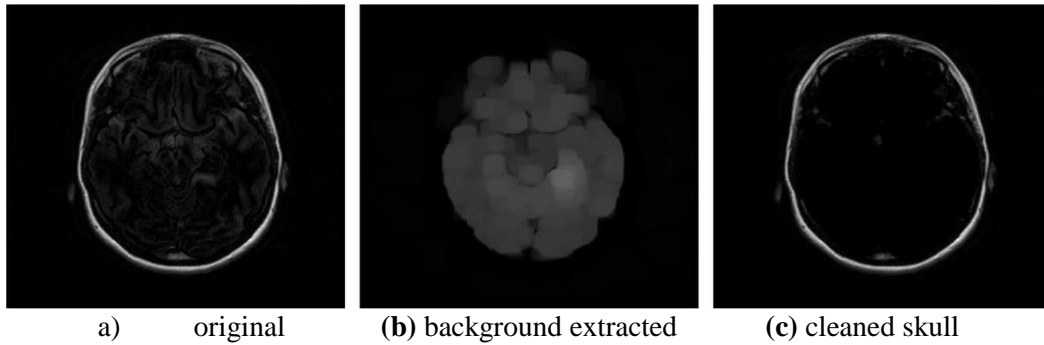
**Figure 6:** Images before and after background extraction

### Pixel Subtraction

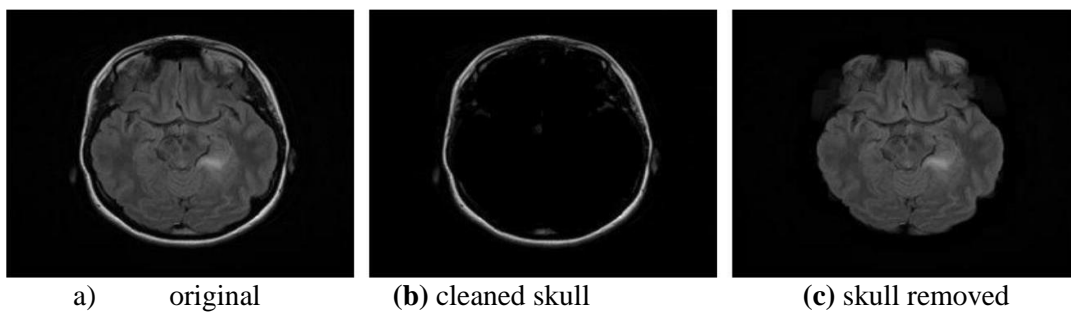
The pixel subtraction operation accepts two identically sized pictures as input. After deducting the pixel values from the second image from the corresponding pixel values in the first image, a third image is produced. Another frequent procedure is to take an image as input and subtract a predetermined value from each pixel. The subsequent operations for pixel subtraction are carried out. To separate the skull from the original image, first the image generated via background extraction is removed from the original image. The outcome of the skull extraction procedure is displayed in Figure 7. The unwanted gray pixels in the skull image are then eliminated by subtracting the background extraction image from the original image. The outcome of the skull cleaning procedure is displayed in Figure 8. Finally, the original image is removed from the cleaned skull image. This provides us with a picture of the brain devoid of the skull. The outcome of the skull removal procedure is depicted in Figure 9.



**Figure 7:** Images of skull extraction process



**Figure 8:** Images of skull cleaning process

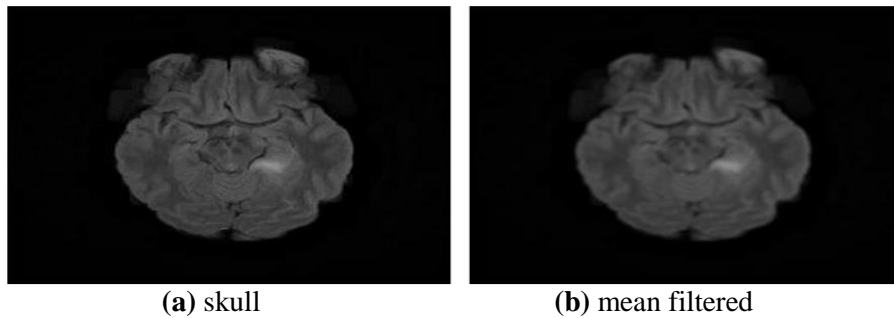


**Figure 9:** Images of skull removal process

### Image Filtering

Image filtering is used to take out noise from digital photographs. One of the most popular techniques for raising the quality of images is image filtering. The quality of an image is crucial for human vision. In image processing, noise in the image is frequently present and difficult to eliminate. The image quality is significantly impacted by the noise. The noise in the image can be removed in a variety of methods. The mean (average) filter is one of the most often used image filtering techniques. The mean filter is a linear filter that is simple to use and intuitive for filtering photos. Typically, noise in an image is removed using the mean filter. The mean filter's basic method is to replace each pixel's value in the image with an average value that takes into account both the pixel and its neighbors. This procedure eliminates from the image any pixel values that do not accurately depict the surrounding area. Most people consider the average filter to be the convolution filter. Its foundation, like that of other convolution filters, is a kernel that symbolizes the size and form of the neighborhood that must be ascertained in order to calculate the mean. An explanation of the mean filter operator is presented in Figure 10.

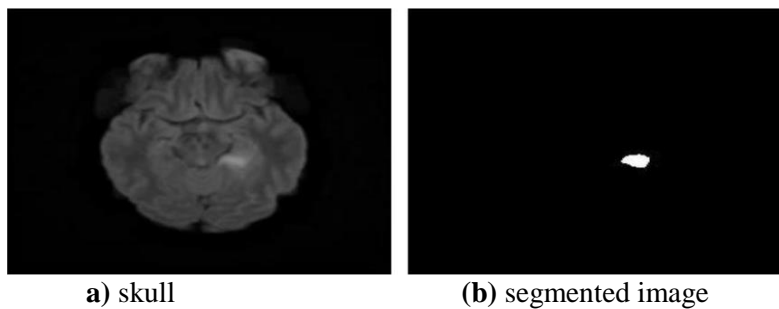




(a) skull (b) mean filtered  
**Figure 10:** Images before and after noise removal

**Intensity Adjustment**

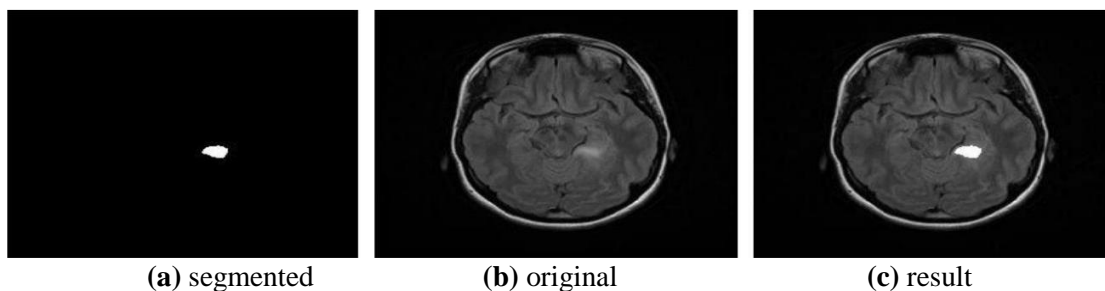
Grayscale photographs are subjected to the intensity adjustment procedure. This method shows pixel values as black for values below a given threshold and white for values above that threshold. The pixel colors that fall between these two values are grayscale. To put it briefly, this method involves adjusting the high and low intensity levels to enhance the image. The mean filtered image is subjected to intensity modification. The tumor area has the highest intensity pixel following the removal of the skull. A few changes had to be made to the image in order to segment the tumor. The values for high and low intensity are respectively set at 0.42 and 0.41. Pixel values exceeding high intensity are set to 1, while those below low intensity are set to 0. A database sample is used to determine the high intensity value. This figure is computed as the mean value of all the columns in the sample photos that contain the tumor's greatest intensity pixel averaged overall. Through this process, the tumor is separated from the image and gray pixels are eliminated. The outcome of the tumor segmentation is displayed in Figure 11.



a) skull (b) segmented image  
**Figure 11:** Images before and after noise segmentation

**Pixel Addition**

Two identically sized images are supplied into the pixel addition operator. By adding the pixel values from the first image to the corresponding pixels from the second image, this operator creates a third image. It can be applied to several images in a subsequent phase by following the same protocol. Another popular approach is to take a picture as input and add a fixed value to every pixel. The medical professionals can examine the image and make decisions by adding the segmented image to the original. Figure 12 displays the tumor's clarity.



(a) segmented (b) original (c) result  
**Figure 12:** Images of clarification of the tumor

V. RESULTS

STAGE-1: Output of the Brain Tumor Stage Classification



Figure 13 (a) MRI of human brain b) Segmented image c) contrast output after filtering

STAGE-2: To remove color components from the input image, convert RGB to grayscale.

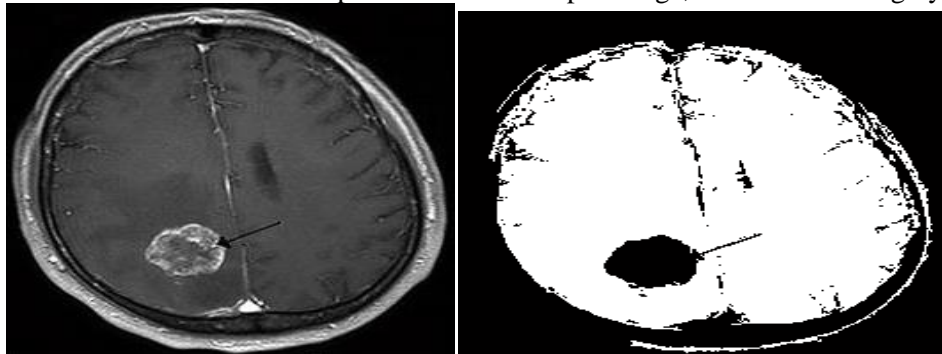


Figure 14 (a): MRI of human brain

Figure 14 (b): Tumour region is obtained



Figure 14 (c): Output after morphological operations

Figure 14 (d): Output after filter

STAGE-3: This is resizing the input image to 256 by 256 pixels. It's also being turned into a grayscale image.

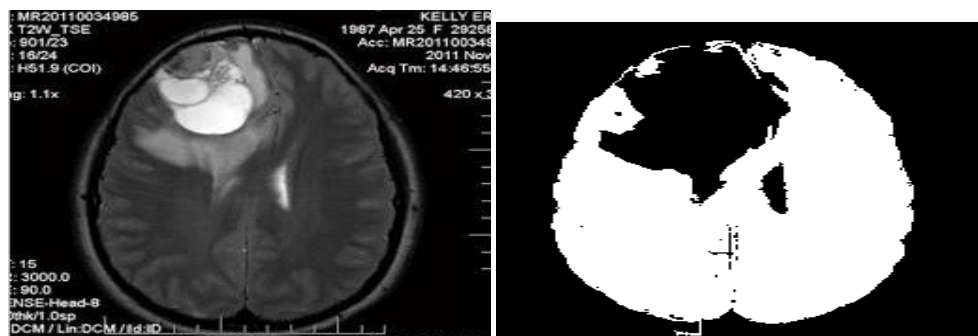


Figure 15 (a): MRI of human brain

Figure 15 (b): Tumour region is obtained



**Figure 15 (c):** Output after morphological operations      **Figure 15 (d):** Output after filter

## VI. CONCLUSION

This Paper implies a tool to help doctors use MRI pictures to diagnose brain cancer. To distinguish between images with and without tumors, the system performs morphological operations, pixel subtraction, mean filtering, intensity adjustment based segmentation, and pixel addition. The photos that are utilized are from The Cancer Imaging Archive (TCIA). The presented method provides a 100% recognition rate on tumor-free photos and a 94.29% recognition rate on tumor-filled images. The total success rate is 96%, which is higher than the performance of our approaches in comparison. My system still needs to be enhanced in two areas. One is the tumor-classified photos that are incorrectly identified. Perhaps in this case, it would be best to try various categorization techniques like Support Vector Machine or Neuro Fuzzy. The second is that the suggested approach isn't a robotic process. It is possible to combine the many technologies into a single processing environment.

## REFERENCES:

1. B Devkota, Abeer Alsadoon, P.W.C. Prasad, A.K. Singh, A. Elchouemi, Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction, *Procedia Computer Science*, Volume 125, 2018, Pages 115-123, ISSN 1877-0509, <https://doi.org/10.1016/j.procs.2017.12.017>.
2. Aslam, Asra, Ekram Khan, and MM Sufyan Beg. "Improved edge detection algorithm for brain tumor segmentation." *Procedia Computer Science* 58 (2015): 430-437.
3. Prajapati, Sahil & Jadav, Kalpesh. (2015). Brain Tumor Detection By Various Image Segmentation Techniques With Introduction To Non Negative Matrix Factorization. *IJARCCCE*. 4. 599-603. 10.17148/IJARCCCE.2015.43144.
4. P. Natarajan, N. Krishnan, N. S. Kenkre, S. Nancy and B. P. Singh, "Tumor detection using threshold operation in MRI brain images," 2012 IEEE International Conference on Computational Intelligence and Computing Research, *Coimbatore, India, 2012*, pp. 1-4, doi: 10.1109/ICCIC.2012.6510299.
5. Rajesh C. Patil, Dr. A. S. Bhalchandra, "Brain Tumour Extraction from MRI Images", *International Journal of Electronics, Communication & Soft Computing Science and Engineering*, ISSN: 2277-9477, Volume 2, Issue 1, April 2012.
6. Dr. M. Karnan, K. Selvanayagi, "Improved Implementation of Brain MRI Image Segmentation Using Meta Heuristic Algorithms", *IEEE International Conference on Computational Intelligence and computing Research (ICCIC)*, pp: 1-4, 2010.
7. Ehab F. Badran, Esraa Galal Mahmoud, and Nadder Hamdy, "An Algorithm for Detecting Brain Tumors in MRI Images". *IEEE International Conference on Computer engineering and Systems (ICCES)*, pp: 368-373, 2010.
8. Ahmed kharrat, Mohamed ben messaoud, Nacera benemrane, Mohamed Abid, "Detection of Brain tumor in Medical Image", *International Conference on Signals, Circuits and Systems*, pp: 1-6, 2009.
9. Natarajan. P, Krishnan. N, "MRI Brain Image Edge Detection with Windowing and Morphological Erosion", *IEEE International Conference on Computational Intelligence and computing Research*, pp: 94-97, 2011.
10. R. Ratan and S. Sharma, "Brain Tumor Detection based on Multiparameter MRI Image Analysis", *ICGST-GVIP Journal ISSN 1687- 398X*, vol. 9, no. III, June 2009.
11. Mrigank Rajya, Sonal Rewri and Swati Sheoran, "Application Of Fuzzy System in Segmentation of MRI Brain Tumor", (*IJCSIS*) *International Journal of Computer Science and Information Security*, vol. 8, no. 1, April 2010.
12. T.W. Ridler and S. Calvard, "Picture Thresholding using an iterative selection method", *IEEE Trans. on Systems Man and Cybernetics*, vol. 8, no. 8, pp. 630-632, 1978.
13. Qurat-ul-Ain and Arfan M. Jaffar, "An Automated system for Brain Tumor Detection from MRI images", *First international e-health conference 2010*.



14. J. Canny, "A Computational Approach to Edge Detection", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 8, no. 6, pp. 679-698, 1986.
15. Tony Lindeberg, "Feature Detection with Automatic Scale Selection", *Int. J. of Computer Vision*, vol. 30, no. 2, pp. 77, 1998.