Automated Brain Tumor Detection Using Discriminative Clustering Based MRI Segmentation

Abhilash Panda, Tusar Kanti Mishra and Vishnu Ganesh Phaniharam

1 Introduction

The human body is made up of numerous kinds of cells and every cell is having a unique set of functionalities. Eminently, all the cells in the body performs cell division to sustain their normal growth, this keeps human body in good condition [1]. During this process of this growth, rarely cells drain their capability leading to abnormal growth of the cells. The mass of tissue caused due to abnormal growth of extra cells is called a “Tumor”. Tumor can be classified as three types, i.e., Benign tumor, Pre-malignant, and Malignant tumors. Benign tumor is a tumor where it does not enlarge in a brusque way and it does not cause any health issues. Moles are the best examples for the benign tumor [2]. Pre-malignant tumor can be considered as pre-cancer stage; if it is not medicated can lead to cancer. Malignant tumor is a tumor with abnormal growth of cells and can be considered as cancer stage, often leading to the death of a person. AQ1

In recent years, one of the main reasons for rising level of morality i.e., reduction in the lifespan of the adolescents is suffering from the brain tumor disease. It has been observed from contemporary studies that the enumeration of the people vanishing due to the brain tumor has risen to 300% [2]. So, brain tumor detection is an urgent need for today’s smart world as radiation growing into a dangerous case of causing sudden deaths of birds. Brain tumor detection has lot of applications such as clinical

A. Panda
Gandhi Engineering College, Bhubaneswar, Odisha, India
e-mail: inc.abhilash@gmail.com

T. K. Mishra · V. G. Phaniharam (✉)
Anil Neerukonda Institute of Technology and Sciences, Vizag, India
e-mail: vishnuganesh93@gmail.com

T. K. Mishra
e-mail: tusar.k.mishra@gmail.com

S. Tiwari et al. (eds.), *Smart Innovations in Communication and Computational Sciences*, Advances in Intelligent Systems and Computing 851,
https://doi.org/10.1007/978-981-13-2414-7_12

outlining and medication devising [3]. Brain tumor detection faces a lot challenges as tumors in the brain are size variant, shape variant, shape variant, location variant and image intensity variant.

1.1 Scopes and Challenges

Automated Brain Tumor Detection has evolved into an eminent research oriented field in the area of image processing and medicinal pathological research. Image processing is a sub discipline of signal processing, where useful information is being extracted by applying computing algorithms. Brain MRI segmentation plays a prominent role in brain tumor detection, where segmentation can be explained as dividing an image in different parts based on feature homogeneity. MRI technique is used in bio-medical analysis to visualize the cryptic elements of the imbricated regions of brain. When compared to the computed tomography, MRI is a far better technique to uncover the heterogeneities in the tissues. This quality makes MRI a special choice for segmentation of brain internal tissues and detecting a likely tumor in the brain. MRI aligns nuclear magnetization by using magnetic field whereas CT uses ionizing radiation. The scanner detects the change in the alignment of magnetization caused by radio frequencies and this signal is processed further to get internal structure details of the brain. Analyzing MR images manually is very difficult because of its large amount of data in it. So, automatic segmentation has become mandatory for brain tumor detection and clinical diagnostics. MRI segmentation has its own challenges namely acquisition noise, partial volume effect and bias effect. Acquisition noise arises because ideal conditions are never expected. Bias field, also known as intensity heterogeneity arises due to non-magnetic field thereby increasing the heterogeneity. Partial volume effect arises when different types of tissues occur in single voxel. To overcome these challenges, this method uses superpixel level zoning and discriminative clustering (Fig. 1). AQ2

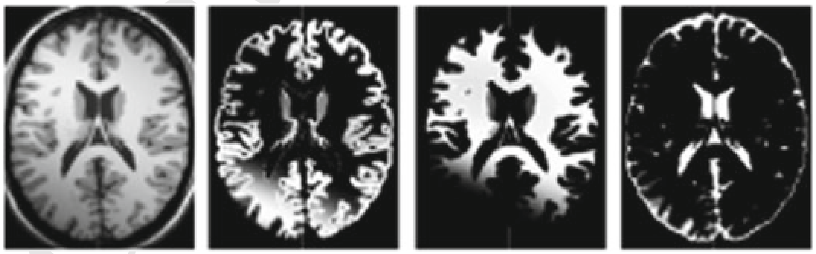


Fig. 1 Challenges faced during brain MRI segmentation

1.2 Paper Organization

The remaining section of this paper is systemized as follows. A literature review of the various previously proposed brain tumor detection algorithms is described in Sect. 2. Our automated brain tumor detection method which is proposed in this paper is explained in Sect. 3. Simulation and experimental results of the proposed method are being discussed in Sect. 4. In the last Sect. 5, conclusion and future work of our paper is being presented.

2 Literature Survey

This section of paper consists of review on previously contemplated automatic brain tumor detection algorithms. Radhakrishna Achanta et al. proposed a new brain MRI segmentation method which uses superpixels generated by clustering in the image plane space and color in five-dimensional space [4]. The simplicity and efficiency of this algorithm [4] are its advantages over advanced methods. Rajeev Ratan et al. proposed a Brain tumor detection method which uses multiple parameters to analyze the image and this method which uses watershed segmentation [1]. Of all these parameters, intensity is taken into consideration to for MR image segmentation. This method can detect the tumor in both 2D and 3D, which can be considered as fringe benefit [1]. Anam Mustaqeem et al. [2] used morphological operators for detecting a tumor from a brain MR image using Watershed and Thresholding Based Segmentation [2]. Prastawa et al. [3] considered T2 MR Image channel as an input to segmentation so as to propose a segmentation of brain using outlier detection. This method is used for diagnosis, planning, and treatment of brain tumor as it reveals the extent of edema. Dahab et al. [5] made use of neural network to propose an automatic detection of brain tumor from an MRI scanned image. The aforementioned works are proposed using several segmentation methods such as k-means and SVM method, neural network, fuzzy methods etc. Although these methods have produced desirable results, they are complex and high computational overhead. So, in this proposed methods we have used discriminative clustering which gives better variance in tissues of brain MR image and AdaBoost is pretty simple for classifying an image into normal or abnormal.

465550_1_En_12_Chapter ☑ TYPESET ☐ DISK ☐ LE ☑ CP Disp.:5/9/2018 Pages: 11 Layout: T1-Standard

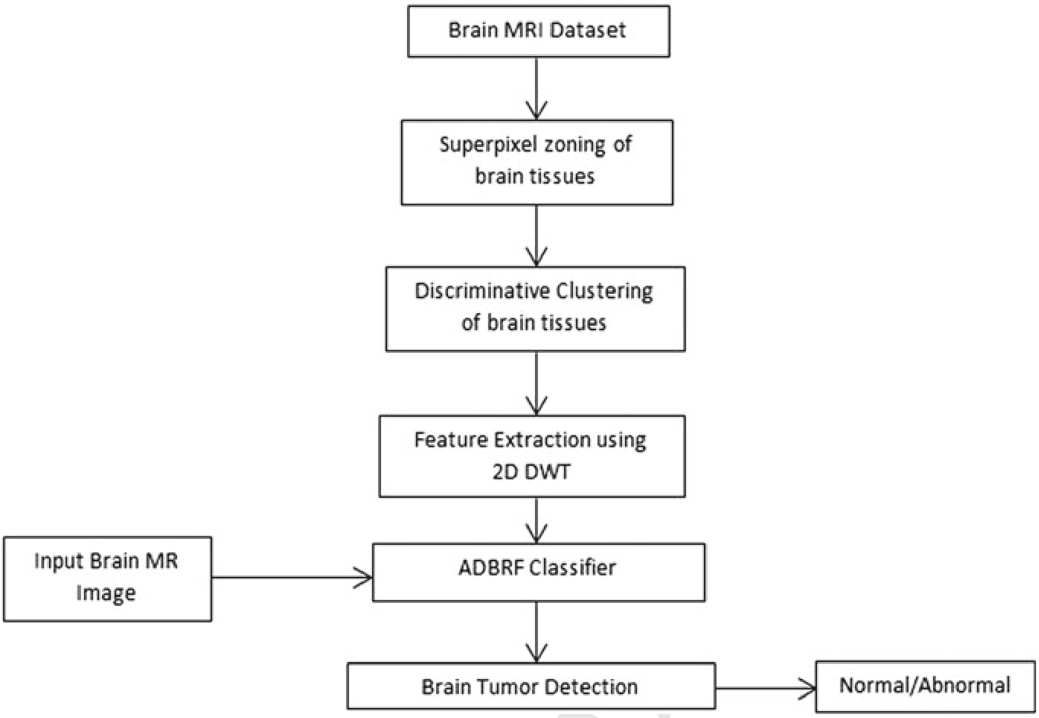


Fig. 2 Proposed system architecture

3 Proposed Model

3.1 System Architecture

Automated brain tumor detection using discriminative clustering based brain MRI segmentation architecture comprises of three stages especially, superpixel zoning, discriminative clustering, feature extraction using discrete wavelet transform (DWT) and classification using AdaBoost with random forests (ADBRF) algorithm. Here, Superpixel zoning is used as initial segmentation and discriminative clustering as secondary segmentation. These first two steps removes tissue heterogeneity in a single superpixel thereby increasing the clarity and correctness of brain MR image which helps in analysis of the image. First, a brain MRI dataset is inputted into the superpixel level feature zoning and the superpixel patches divided by taking cluster center as its lone parameter. These zones are clustered by using discriminative clustering, where these clusters are formed using the homogenous features in the brain tissues. These clustered MR image dataset performs feature extraction using level-3 2-D DWT forming the trained classifier. Using ADBRF as its base classifier, the feature vector can be classified as normal/abnormal, the system classifies it as normal, if it does not contain tumor and abnormal, if it contains tumor (Fig. 2).

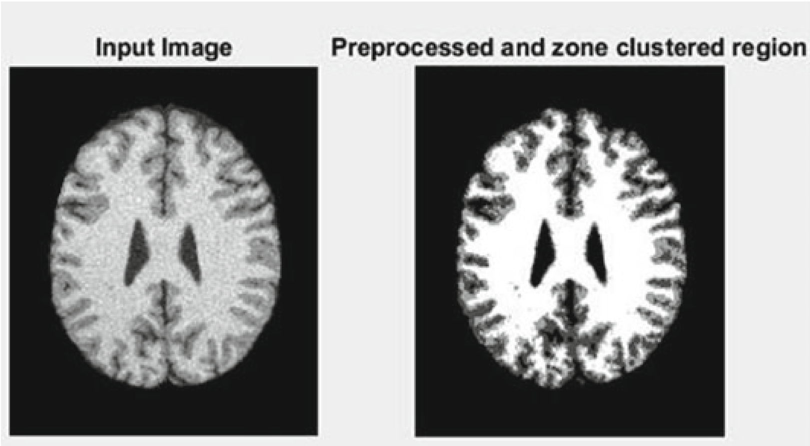


Fig. 3 Sample superpixel level zoning

3.2 Superpixel Level Zoning

Superpixels are becoming highly popular in medical image analysis applications; superpixels provide us ability to capture local image features and capture redundancy there by reducing computational complexity. Although they are popular, they face challenges such as high computational cost, poor quality segmentation, inconsistent size, and shape [4]. Superpixels are used in applications such as depth estimation [6], image segmentation [7, 8], skeletonization [9], body model estimation [10], and object localization [11]. Superpixel can be defined as group of image pixels which has homogenous pixel intensities. Pixels in the superpixels show same properties. If you consider an image grid of same intensity values and also neighborhood values which together grouped to form a superpixel. Let us assume a pixel intensity value of 1 and if we consider all the intensity values of neighboring pixels forming an edge of same values. We group these pixels to form a superpixel. Superpixels extract homogenous features so they account for bias field. In this paper, we have used the simple linear iterative clustering (SLIC) method to generate 2D superpixels for the inputted brain MR Image. This SLIC method uses consider a pixel as its center and initialize with "n" number of centers. It then calculates the Euclidean distance with nearer neighboring pixels and the pixels with same intensity values are grouped as matching pixels. This process is stopped when the distance is greater than threshold value. Figure 3 shows the brain MR image which is segmented using superpixel zoning.

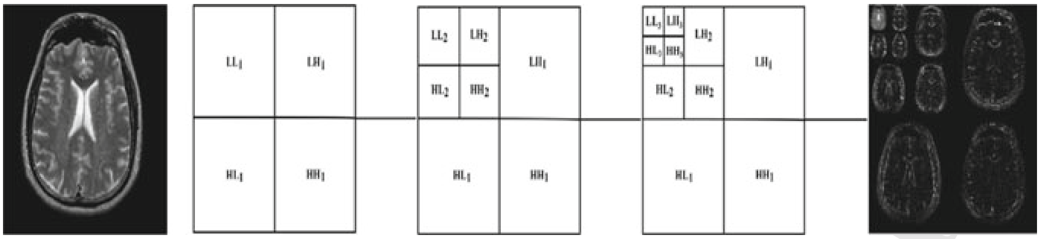


Fig. 4 Decomposition using Haar wavelet

3.3 Feature Extraction Using Haar Wavelet Transform

The Haar Wavelet Transform is an effective method for feature extraction [12]. It has many applications in image processing and signal processing as it considers local features of images. Haar wavelet transform is simple and computationally efficient. It offers decomposition of MR images using time scale representation, which is very useful in classification scenarios [13]. DWT is accepted as new compression standard JPEG2000. At level zero, This wavelet transform has two filters to pass through the image i.e., low pass filter and high pass filter. The input signal is sent into low pass filter where a low resolution signal is extracted whereas when the input signal is sent into high pass filter it extracts a difference signal. At level 1, the output signals of the high pass filters are applied by another pair of filters [13]. This process repeats until the level 3 is completed. It is the best suitable dwt for the classification process as it is very fast, symmetric and orthogonal in nature, it also used to extract structural information from the images and performs well in the presence of noise. DWT is decomposed in this process up to three levels. Firstly, a brain MR image of size M $\times$ M is segregated to (M/2) $\times$ (M/2) of four sub bands namely, LL (low-low), LH (low-high), HL (high-low) and HH (high-high). The LH, HL and HH are the sub-band images that contain the edges in the vertical, horizontal and diagonal directions respectively. The low-low sub-band image contains maximum information and it can also be treated as output of high filters and sent into next level for decomposition. This low-low sub-band image is also called approximation image (Fig. 4).

Algorithm: Superpixel level Discriminative Segmentation based brain tumor detection.

Input: Brain MR Image dataset (D) with each sample (di), with dimension M x M.

Output: Feature Matrix (f).

Step 1: Initialize $f \rightarrow \phi$

Step 2: Repeat for each image (I).

Step 3: Put X superpixel seed points.

Step 4: Label each pixels using

$D(x, l) = I(x, l) + C(x, l)$

Step 5: Update seed points.

Step 6: Update each pixel label using

$D(x, l) = wb \times B(x, l) + wi \times I(x, l)$

Step 7: Repeat step5-6 until pixel label is optimized.

Step 8: Connect the neighboring pixel surroundings the seed pointers.

Step 9: Apply discriminative clustering to the zones obtained above.

Step 10: Generate final segmented image Iseg with distinct colors for each segment.

Step 11: Apply Level3 2D-DWT to I_{seg} and the feature to f.

$f \leftarrow f \cup fi$, Where fi is feature set from I_{seg}

Step 12: final feature set F is given to ADBRF classifier.

3.4 *Classification Using ADBRF*

ADBRF is an acronym for AdaBoost with random forests algorithm. In this method, AdaBoost is combined with random forests algorithm to build a classifier, which is used to categorize the regions of brain by using the features extracted by haar wavelet transform. It is used to better the results of the accuracy and stability of the any learning algorithm. When we consider several weak classifiers of high error rates and to make them useful, ADB combines them and generate a classifier with a small training error rate [14, 15]. ADB is easy to implement, fast and simple. This algorithm can be integrated with other classifiers as it is non-parametric in nature [16]. RF is a machine learning algorithm which is simple, effectively estimates the missing data, robust to outliers and noise [12]. It can run efficiently on large datasets, estimates important features for classification. Here, we use this algorithm for binary

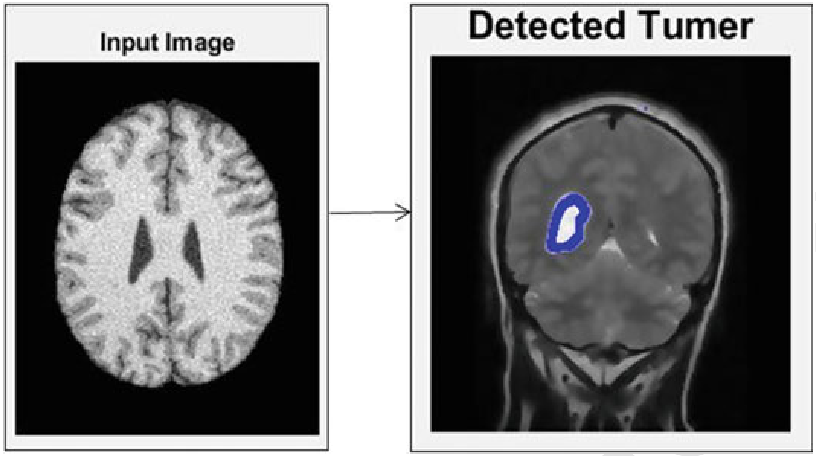


Fig. 5 Sample input and output

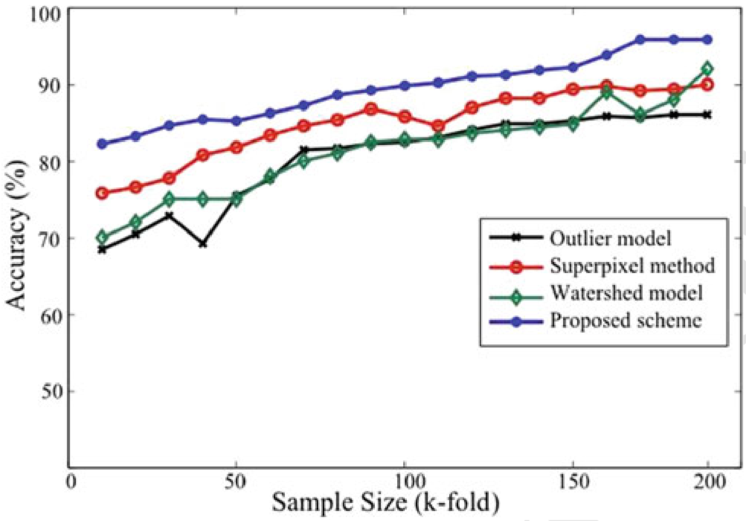
classification; it results in two class labels 0 and 1. The class label 0 denotes the normal class whereas the class label 1 denotes the abnormal class (Fig. 5).

4 Simulation Results

Simulation is carried using MATLAB codes and the output figures are attached with each section separately for better understanding. Its performance is being evaluated on the BrainWeb dataset where it acquired 100% accuracy. BrainWeb database is a brain MRI database with several parameters and the images provided with tissue label for each brain tissue voxel, with a size of 181 × 217 pixels which can be retrieved from http://brainweb.bic.mni.mcgill.ca/brainweb/. In this dataset, the echo time and the repetition time have been set to 10 ms and 18 ms respectively. A total of 200 samples are analyzed for the purpose. For computing the accuracy the k-fold (k = 5) cross-validation strategy has been adopted. Overall accuracy rate of 96% has been reported for the proposed scheme on the said dataset. This is quite satisfactory.

A comparative analysis is also performed with other proposed algorithms on same problem statement. The proposed scheme outperforms the rest of the state of the art methods as shown in below figure.

465550_1_En_12_Chapter ☑ TYPESET ☐ DISK ☐ LE ☑ CP Disp.:5/9/2018 Pages: 11 Layout: T1-Standard



5 Conclusion and Future Work

In this paper, a method for detecting a tumor from a brain MR Image is proposed. This method uses superpixel level zoning of the brain MR Image and performs clustering using the discriminative clustering. These clusters divide the scanned image of brain into different brain tissues into White Matter, Gray Matter, and Cerebro Spinal Fluid. Extraction of features from the structures of brain is carried out by Haar Wavelet Transform. ADBRF is used as a base classifier where it classifies a brain MR Image into normal or abnormal. This method achieves 100% of accuracy on BrainWeb MRI dataset. How to extend our proposed method by integrating with deep learning algorithms and to use in real-world applications constitutes our future work. AQ3

References

1. Ratan, R., Sharma, S., Sharma, S.K.: Brain tumor detection based on multi- parameter MRI image analysis. ICGST-GVIP J. **9**(III) (2009). ISSN 1687-398X
2. Mustaqeem, A., Javed, A., Fatima, T.: An efficient brain tumor detection algorithm using watershed & thresholding based segmentation. Int. J. Image Graph. Signal Process. **10**, 34–39 (2012) (Published Online September 2012 in MECS). http://www.mecs-press.org/. https://doi.org/10.5815/ijigsp.2012.10.05
3. Prastawa, M., Bullitt, E., Ho, S., Gerig, G.: A brain tumor segmentation framework based on outlier detection. Med. Image Anal. **8**, 275–283 (2004)
4. Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., Susstrunk, S.: SLIC Superpixels, EPFL Technical Report 149300, June 2010
5. Dahab, D.A., Ghoniemy, S.S., Selim, G.M.: Automated brain tumor detection and identification using image processing and probabilistic neural network techniques. Int. J. Image Process. Vis. Commun. **1**(2) (2012). ISSN 2319-1724

6. Hoiem, D., Efros, A., Hebert, M.: Automatic photo pop-up. SIGGRAPH (2005)
7. Li, Y., Sun, J., Tang, C.K., Shum, H.Y.: Lazy snapping. SIGGRAPH 303–308 (2004)
8. He, X., Zemel, R., Ray, D.: Learning and incorporating top-down Cues in image segmentation. ECCV 338–351 (2006)
9. Levinshtein, A., Sminchisescu, C., Dickinson, S.: Multiscale symmetric part detection and grouping. ICCV (2009)
10. Mori, G.: Guiding model search using segmentation. In: ICCV 1417–1423 (2005)
11. Fulkerson, B., Vedaldi, A., Soatto, S.: Class segmentation and object localizationwith superpixel neighborhoods. In: ICCV (2009)
12. Nayak, D.R., Dash, R., Majhi, B.: Brain MR image classification using two-dimensional discrete wavelet transform and AdaBoost with random forests. Neurocomputing **177** 188–197 (2016)
13. Kour, P.: Image processing using discrete wavelet transform. IPASJ Int. J. Electron. Commun. (IIJEC) **3**(1) (2015). ISSN 2321-5984
14. Freund, Y., Schapire, R.E.: Experiments with a new boosting algorithm. In: International Conference on Machine Learning, vol. 96, pp. 148–156 (1996)
15. Duda, R.O., Hart, P.E., Stork, D.G.: Pattern Classification. Wiley, New York (2012)
16. Schapire, R.E.: A brief introduction to boosting. In: International Joint Conference on Artificial Intelligence, vol. 99, pp. 1401–1406 (1999)
17. Achanta, R., Shaji, A., Smith, K., Lucchi, A., Fua, P., Susstrunk, S.: Slic superpixels compared to state-of-the-art superpixel methods. IEEE Trans. Patt. Anal. Mach. Intell. **34**(11), 2274–2282 (2012)
18. Breiman, L.: Random forests. Mach. Learn. **45**(1), 5–32 (2001)
19. Kapoor, L., et al.: A survey on brain tumor detection using image processing techniques. In: 2017 7th International Conference on Cloud Computing, Data Science & Engineering—Confluence. https://doi.org/10.1109/confluence.2017.7943218
20. Rao, H., et al.: Brain tumor detection and segmentation using conditional random field. In: 2017 IEEE 7th International Advance Computing Conference (IACC). https://doi.org/10.1109/iacc.2017.0166
21. Santosh, S., et al.: Implementation of image processing for detection of brain tumors. In: 2017 International Conference on Computing Methodologies and Communication (ICCMC). https://doi.org/10.1109/iccmc.2017.8282559
22. Somwanshi, D., et al.: An efficient brain tumor detection from MRI images using entropy measures. In: 2016 International Conference on Recent Advances and Innovations in Engineering (ICRAIE). https://doi.org/10.1109/icraie.2016.7939554
23. Singh, B., et al.: Detection of brain tumor using modified mean-shift based fuzzy c-mean segmentation from MRI Images. In: 2017 8th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON). https://doi.org/10.1109/iemcon.2017.8117123
24. Krishnamurthy, T.D., et al.: Automatic segmentation of brain MRI images and tumor detection using morphological techniques. In: 2016 International Conference on Electrical, Electronics, Communication, Computer and Optimization Techniques (ICEECCOT). https://doi.org/10.1109/iceeccot.2016.7955176
25. Nanda Gopal, N., et al.: Diagnose brain tumor through MRI using image processing clustering algorithms such as Fuzzy C Means along with intelligent optimization techniques. In: 2010 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC). https://doi.org/10.1109/iccic.2010.5705890