# Brain Tumor Segmentation Techniques on Medical Images - A Review

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**Abstract**— Medical Image is one of the most imperative field in Image Processing. Working on this field is an ambitious task as well as challenging and tumor segmentation from a medical image is the tenacious task. Over the decades researchers went through considerable development to segment the tumor. Researchers developed various methods to articulate the carcinoma. Numerous segmentation techniques such as threshold based, region based, clustering based segmentation etc. have been applied for this purpose. Perceiving the current prominence in this terrain, we glean all the analytical information in addition to a brief analysis. In this paper, we entailed various image segmentation techniques, different types of existing algorithms based on some aspects of brain MRI images and at last we ended with a brief discussion of a few challenges for our future work.

**Keywords**— Carcinoma, Clustering, Edge, Histogram, Layer, Neural Network, Region, Terrain, Threshold, Segmentation.

## 1 Introduction

From the inception of Image processing, Medical Image is the preeminent and undoubtedly one of the most decisive sector where researchers are opting for. Health is a main concern of a human being to sustain in this thoroughly competitive world. Cancer is the most precarious and life threatening concern in terms of health discourse. Brain, Bladder, Colorectal, Leukemia, Breast, Kidney, Lung, prostate etc. are the most fatal as well as alarming for both children and adults and leukemia, brain tumors and lymphomas are the three most common childhood cancers [1]. Based on a graphic created by Cancer Research UK and THE BRAIN TUMOR CHARITY, the biggest cancer killer of children and adults under 40 are the Brain tumors. As a result of one of the most decisive cancer we took an approach to accomplish a work which is pertinent to the Brain.

Over the decades researchers are trying to find the reason behind the unfolding of the brain tumor characteristics and how to overcome the disease. Insufficient measure, data, record and treatment are the main apprehension behind calling brain cancer one of the most precarious one. Antiquated, non-automated, manual, lengthy, stagnant and tedious system of tumor detection are the accountable subjects. Researchers from all over the world are trying to convert this manual system to automate one, so that people can take proper measure and get the best treatment to defeat this life threatening challenge.

From the initiation of image processing techniques and further network based techniques, researchers are giving their utmost effort to detect the absolute brain tumor without any sort of flaw. In this paper, our main purpose is gleaning all the information and reviewing the segmentation techniques in terms of proposed model. Tables represent the information along with the methodology. We first introduced the basics of image processing, and then further we tried to depict the stats comprehensively. We tried to review most popular methods of brain MRI segmentation.

The most imperative and challenging task to change the existing system into an automated one is Brain tumor segmentation. Segmentation is the paramount task to detect the presence of tumor. Segmentation is considered to be the most critical task in medical image processing because of different types of complexities and abnormalities. Moreover, brain MRI images mostly contain noise, deviation etc. Hence, accurate segmentation of brain MRI images has become an assiduous task.

Working on a total of 52 research articles entitled from 2007 to 2018 and based on the information we break down the total process of segmentation along with respective figures. We try to select the articles based on various perspective such as- citation, year, dataset etc. but mostly focused on segmentation technique. Imparting the single and mixed segmentation technique, we further go through the articles which adopted the Neural Network.

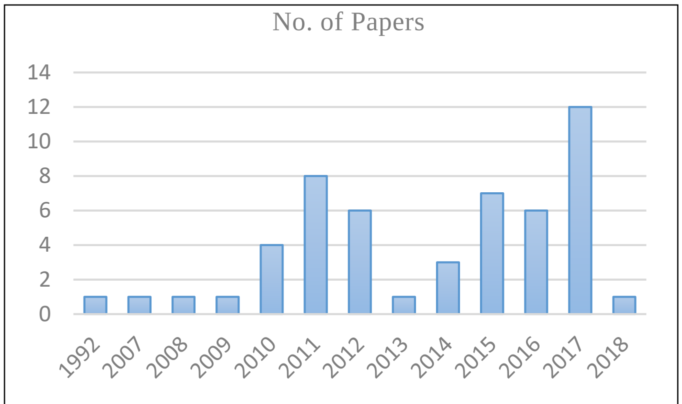


Fig. 1. Year-wise distribution of the articles

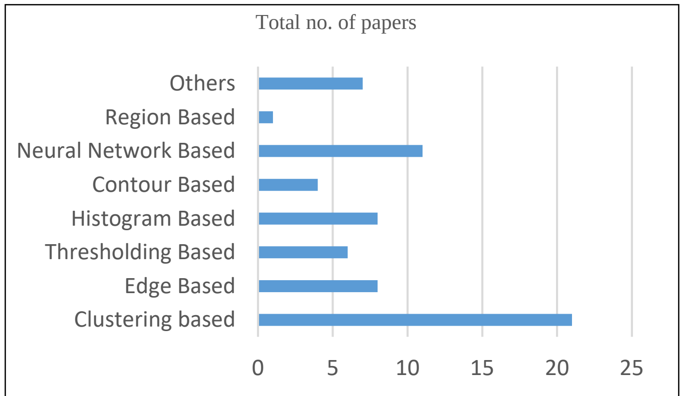


Fig. 2. Distribution of segmentation techniques used in the articles.

In figure 1 and 2, statistics of the articles according to years and based on segmentation types is being represented with all the accessible information. Further, in figure 3, categorizing the articles based on the number of citation is described. A total of 42 papers where the segmentation technique belongs to the primitive image processing techniques. In figure 4, the papers appertain to Neural Network based segmentation and the statistics represent the information about these papers citation.

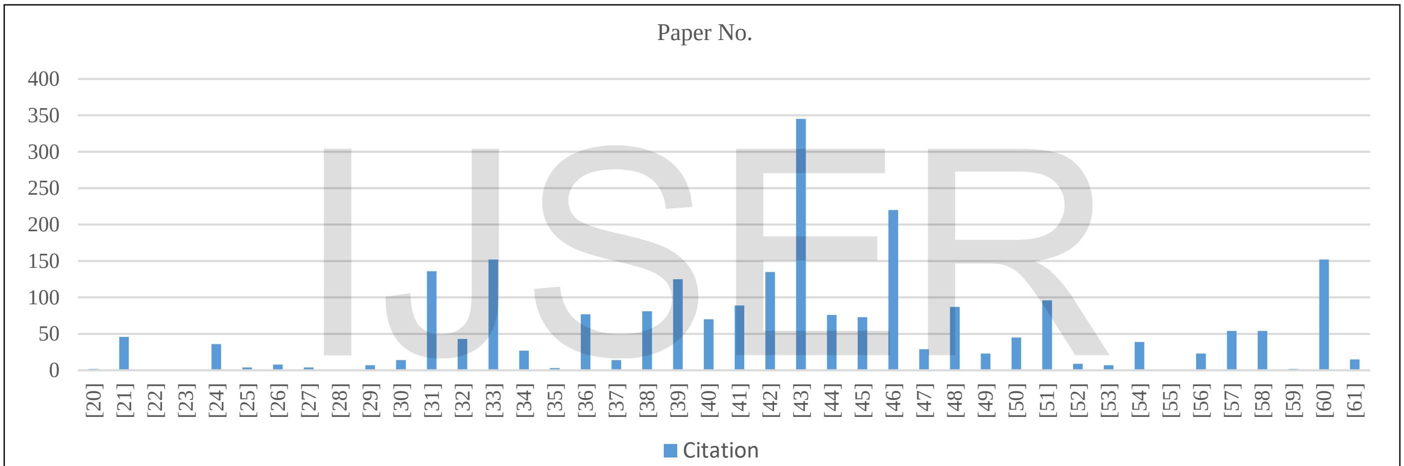



Fig. 3. Citation-wise distribution of the articles

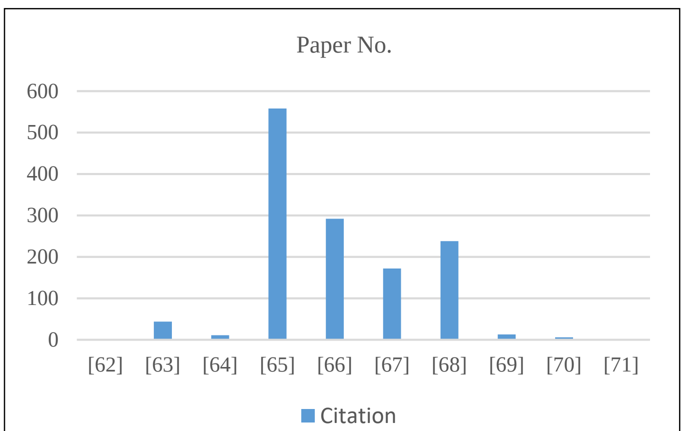


Fig. 4. Citation wise distribution of Neural Network based segmentation technique used in the articles

## 2. Analysis of Brain Image Segmentation

Segmenting a region of interest from a medical image is a challenging task which researchers are dealing with almost for decades. Several types of segmentation which is related to the abstract is enlisted and described in details. Firstly, we organize the segmentation according to their types. Hence the various methods along with their types is being described.

### 2.1 Segmentation based on types

Three types of brain tumor segmentation- Fully-Automatic, Semi-Automatic and Manual segmentation, by which we can disclose about the presence of a tumor.

#### 2.1.1 Fully Automatic Segmentation

A Fully Automatic segmentation is the process where the segmented edge or boundaries are assigned automatically by a programming schedule.

An automatic procedure carry out the complete segmentation so it's more accurate if the method is well trained to identify any abnormal cell. In fully automatic segmentation methods no user interaction is required, artificial intelligence and prior knowledge are combined to solve the segmentation problem [2]. Automatic brain tumor segmentation methods can be classified into two kinds- discriminative and generative methods where the detailed reviews of these methods were previously presented [3, 4, 5, 6].

### 2.1.2 Semi Automatic Segmentation

In a semi-automatic segmentation, automatic segmentation is followed by manual checking and editing of the segment boundaries. The user outlines the ROI (Region of interest) and algorithms are applied so that the path that best fits the boundaries of the image is demonstrated. In addition to initialization, automated algorithms can be driven towards a desired outcome during the process by receiving feedbacks and providing adjustments in response [2].

### 2.1.3 Manual Segmentation

In medical image, the segmentation requires the radiologist to use the multi-modality information presented by the MRI images with their respective expertise and the use of a human transcriber assures that the segment boundaries and labels are intuitively valid. It's a time consuming task, manual segmentation is also expert dependent and segmentation consequences are also subject to large intra and inter rater variability [7]. After fully automatic and semi-automatic segmentation, manual segmentation is needed to appraise and evaluate the results. Figure 5 illustrates the types of segmentation -

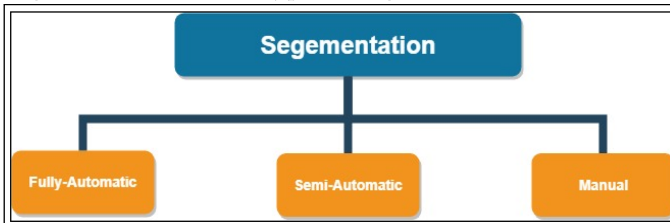


Fig. 5. Types of Segmentation

## 2.2 Single and Mixed Segmentation

In our exercised articles, we can break-down the techniques based on the number of segmentation used in their methodology- Single and Mixed. Single segmentation means the model is built up using a unit technique and mixed segmentation stands for two or more algorithm.

There are 25 and 17 articles in which single and mixed segmentation model respectively was applied. Table I shows the distribution of papers according to single segmentation and mixed segmentation techniques.

TABLE 1
SEGMENTATION TECHNIQUE TYPE WISE PAPER DISTRIBUTION

| Segmentation Technique Type | Total no. of paper | Reference |
|---|---|---|
| **Single** | 25 | (Nooshin et al., 2017)[26], (Yantao et al., 2016)[27], (Pei et al., 2017)[28], (Rao et al., 2017)[29], (Swapnil et al., 2016)[30], (Wankai et al., 2010)[32], (Parveen et al., 2015)[34], (Mariam et al., 2017)[35], (Dina et al., 2012)[36], (Karthik et al., 2015)[37], (Othman et al., 2011)[38], (Zexuan et al., 2012)[41], (Bing et al., 2011)[43], (Logeswari et al., 2010)[44], (Huang et al., 2014)[45], (Angel et al., 2011)[47], (Gordillo et al., 2010)[49], (Akram et al., 2011)[50], (Jainy et al., 2012)[51], (Nilesh et al., 2017)[54], (R. Ayachi, 2009)[56], (Demirhan et al., 2015)[57], (Vijay et al., 2013)[58], (Dawood et al., 2016)[60], (Pranita et al., 2015)[61] |
| **Mixed** | 17 | (B. Devkota, 2017)[20], (A. Rajendran, 2011)[21], (K. Rajesh Babu, 2017)[22], (Malathi, 2014)[23], (Debnath Bhattacharyya, 2011)[24], (Umit Ilhan, 2017)[25], (Eman Abdel-Maksoud, 2015)[31], (Anam Mustaqeem,2012)[33], (Ming-Ni Wu, 2007)[39], (Ehab F. Badran, 2017)[40], (J.selvakumar, 2012)[42], (Bauer S., 2011)[46], (N. Nandha Gopal, 2010)[48], (Jianwei Liu, 2015)[52], (Chaiyanan Sompong, 2016)[53], (Kirti Mittal, 2017)[55], (Elisabetta Binaghi, 2014)[59] |

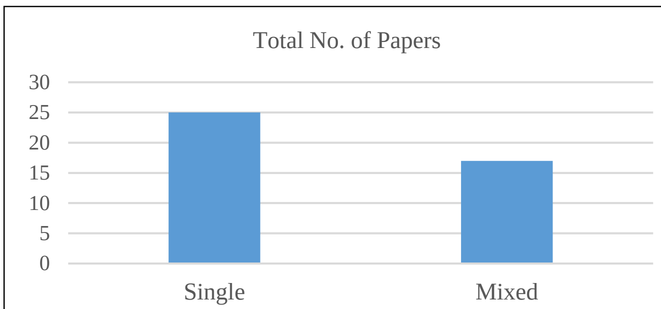


Fig. 6. Paper-wise distribution of segmentation technique

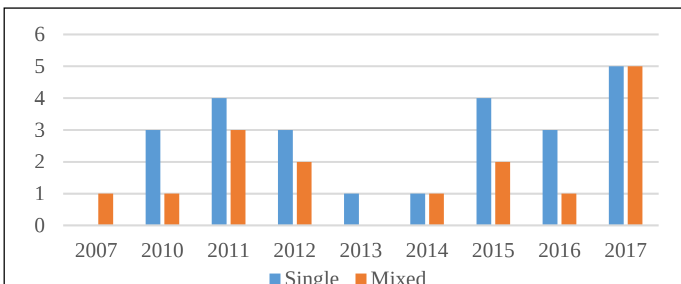


Fig. 7. Year-wise distribution of single & mixed segmentation technique

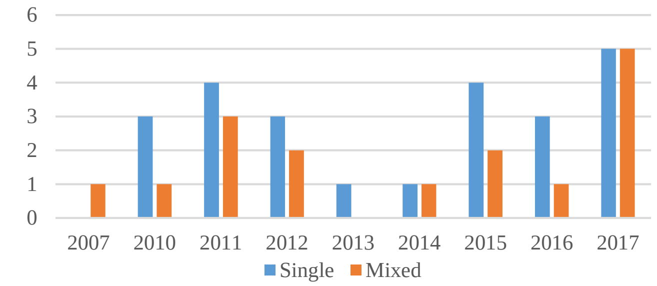


Fig. 7. Year-wise distribution of single & mixed segmentation technique

Figure 6 demonstrates the total number of single and mixed segmentation techniques used in our selected papers. In figure 7, an enumeration year-wise representation of the articles based on single and mixed segmentation technique is depicted.

## 3. Overview of Segmentation Techniques on Medical Images

Segmentation subdivides an image into its constituent regions or objects based on some concurrent characteristics where the objects which are depicted are strongly related to the regions. The level of details to which the subdivision is carried depends on the problem being solved, that is, segmentation should stop when the objects or regions of interest in an application have been detected such as- for distinction of the tumor interests lied on separating the abnormal tissues.

### 3.1 Layer Based Segmentation

Articulating an ROI and extracting decisive features, Layer Based segmentation techniques are the most indispensable one. In this segmentation process, three layers are generated from an image entitled as mask, graphics and text layer. JBIG (Joint Bi-level Image Experts Group) algorithm is used to losslessly compress the mask layer, text layer is compressed using token based order [7], and graphics layer are compressed using the JPEG coder.

A layered model is used for object detection and image segmentation that composites the result of a bank of object detectors defining shape masks and explaining the appearance, depth ordering, and that evaluates both class and instance segmentation [8].

### 3.2 Region Based Segmentation

Deng et al. [32] proposed an adaptive region growing method based on the two preeminent subjects which cover variances and gradients along and inside of the boundary curve in order to overcome the difficulty of manual threshold selection. There are significant region-based segmentation methods which we can accomplish our approach-

#### 3.2.1 Region Growing

Region growing is the simplest and straightforward region based segmentation that groups' pixels or sub-regions into larger regions based on some pre-defined criteria. The common procedure is to differentiate one pixel with its neighbors [33]. There are two types of region growing method-

**3.2.1.1 Seeded Region Growing Method:** Along with the image, seeds are being taken as input and marking each of the objects that are to be segmented. The regions are iteratively grown by comparison of all unallocated neighboring pixels to the regions [10].

**3.2.1.2 Unseeded Region Growing Method:** It does not require the seed point and begins with a single region. At each iteration, it works as considering the adjacent pixels in the same way as seeded region growing.

#### 3.2.2 Clustering

In region-based segmentation, Determination of the data set that belongs together and is known as clustering. Clustering can be done in two ways- Partitioning (carve up the data set according to some notion of the association between items inside the set) and grouping (wish to collect sets of data items that are relevant to the respective model) [12]. Over the decades, multiple clustering based segmentation techniques have been developed and researchers administered these techniques in their model-

**3.2.2.1 K-Means Clustering:** When it comes to vector quantization and signal processing, K-Means clustering algorithm is one of the most dynamic and compelling algorithms. The edema and tumor tissues were distinguished in the abnormal regions based on the contrast enhancement T1 modality by k-means method [8]. In several other respective research articles, K-means clustering and histogram clustering is applied after the initial image converted to color space and then CIELab color model [20]. Applying K-Means segmentation technique after pre-processing and skull masking [30].

**3.2.2.2 Fuzzy C-Means Clustering:** One piece of data belongs to two or more clusters. Developed by Dunn in 1973 [13] and improved by Bezdek in 1981 [14], is frequently used in Image Segmentation. Use of FCM algorithm on intensity features where FCM segments image into a pre-specified number of clusters (K), FCM gives a fuzzy membership (U) to describe the degree of similarity of one pixel to each cluster [32, 38, 48, 49].

**3.2.2.3 Spatial Fuzzy C-Means Clustering:** This algorithm utilizes the local spatial information which is convenient in reducing noise distortion and intensity inhomogeneity in the segmentation [15]. Segmentation was done by spatial FCM.

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An extension of PNN, called WPNN, which uses anisotropic Gaussians rather than the isotropic Gaussians used by PNN was used for classification [50]. Figure 8 shows the depiction of the above information and figure 8 depicts the information about the total number of papers which used clustering according to years-

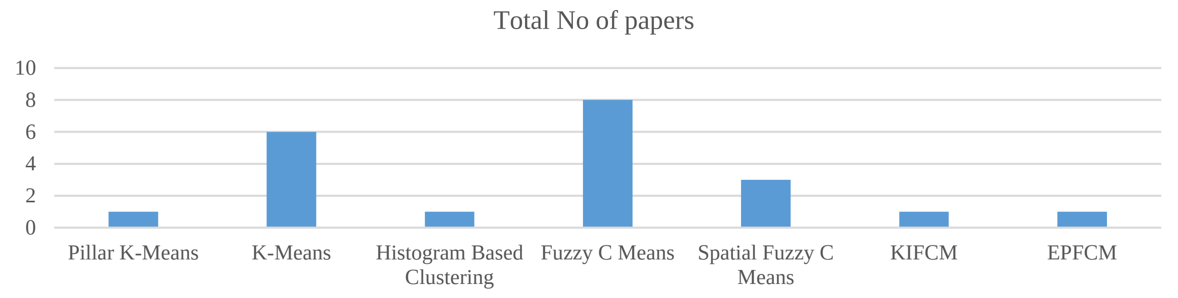



Fig. 8. Number wise distribution of clustering techniques used in articles.

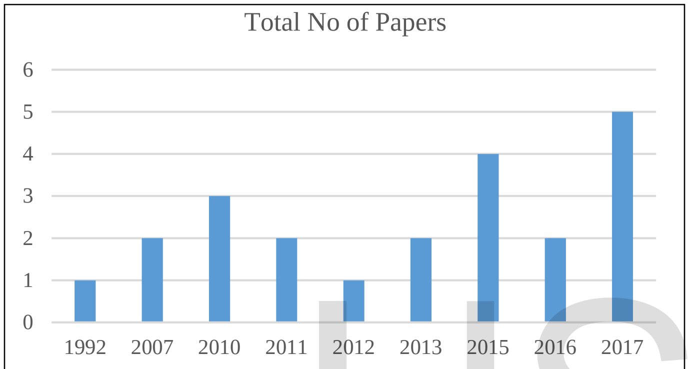



Fig. 9. Year wise distribution of clustering techniques used according to years

### 3.3 Edge Based Segmentation

Segmentation of the image by identifying the edges of the Region of Interests. Edges can be connected and disconnected according to the data or methodology, one needs region boundaries which are closed and the desired edges are the boundaries between such objects or spatial-taxon [71].

#### 3.3.1 Edge Detection

Working with their developed thresholding and edge detection technique Debnath et al. [24] identified the tumor successfully but the computation time, as well as the classifier and efficiency, is below average in contrast with the others work.

#### 3.3.2 Canny edge Detection

By optimizing canny edge detection model and GA for canny edge detection. Malathi et al. [23] improved the efficiency used closed contour segmentation. Badran et al. [40] used two sets of a neural network in their work. For the first set, they used canny edge detection.

#### 3.3.3 Watershed Segmentation

Mustaqeem et al. [33], applied thresholding segmentation and watershed segmentation, followed by morphological operations. Karthik et al. [37] used the watershed transform-based segmentation process to extract the necessary region of interest from the skull stripped MRI images.

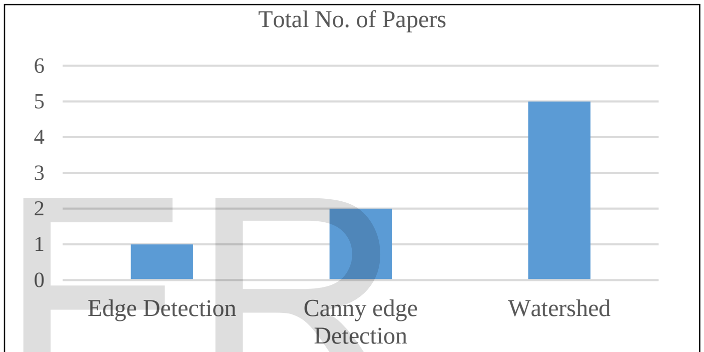



Fig. 10. Number wise distribution of edge detection techniques used in articles

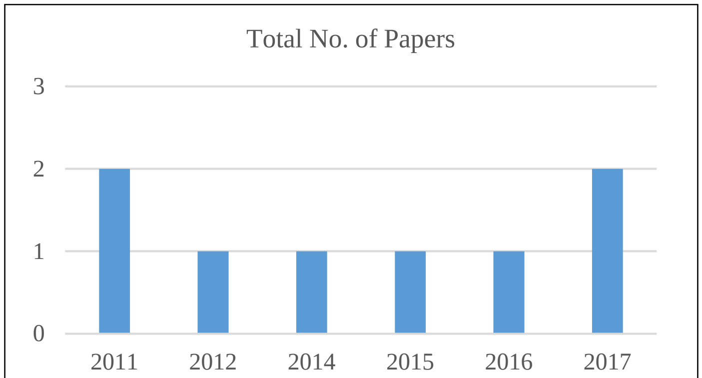



Fig. 11. Year wise distribution of edge detection techniques used in articles.

### 3.4 Thresholding Based Segmentation

Thresholding is based on a threshold-value or clip-level to convert a gray-scale image into a binary image and segments the region of interests.

#### 3.4.1 Binary Thresholding

Debnath et al. [24] presented their algorithm which includes thresholding for tumor segmentation. Converting 24-Bit Color Images to 256 Gray Color Images and Calculating histograms the resulting images were converted to a binary thresholded image, histograms were calculated and at last edge detection algorithm was used [25].

#### 3.4.2 Adaptive or Dynamic Thresholding

Different thresholds for different regions of the same image is calculated in this approach [16]. Badran et al. [40] tried two different segmentation techniques in their work and among them, one is adaptive thresholding.

#### 3.4.3 Otsu Thresholding

This algorithm presumes that the image encompasses two classes of pixels following bi-modal histogram [17]. Mittal et al. [55] used Otsu Thresholding segmentation along with watershed technique, asserting that Otsu's thresholding chooses the threshold for minimizing the intra-class variance of the thresholded black and white pixels.

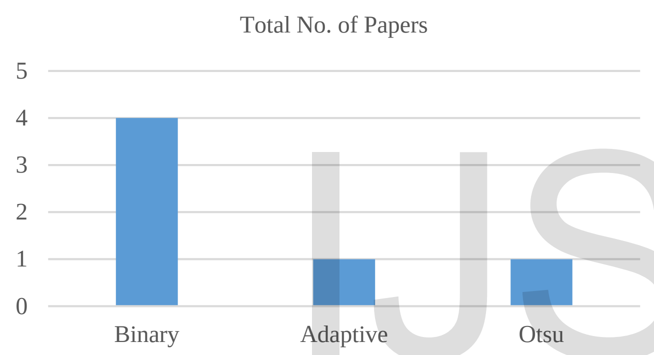



Fig. 12. Type wise distribution of thresholding techniques used in the articles

### 3.5 Histogram-Based Segmentation

Peaks and valleys in the histogram are used to discover the clusters of an image using a histogram which is computed from all the pixels in the image [18]. Working with their developed thresholding and edge detection technique they identified the tumor successfully but the computation time, as well as the classifier and efficiency is below average in contrast with the others work [20, 26, 39].

### 3.6 Neural Network

In the recent years, Neural Network marked its steps through its highly adaptive system. Researchers are opting for this method and trying to accomplish their respective projects. A computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs [19]. Probabilistic Neural Network model based on Learning Vector Quantization [62]. In [66], describing a 2-phase training procedure that apprehends the imbalance of tumor labels and pursued a cascade artifice exercising the output as an additional source of knowledge for a posterior CNN.

## 4. Statistical Information of All the Summarized Papers

Working on a total of 52 papers in which 10 of them used neural network based segmentation and the rest of them worked on various traditional segmentation. Gleaning all the essential and statistical information, we compose a table which reflects the bottom line of the articles about their performance and relative work.

Distribution of Skull Stripping techniques based on uses are represented through Figure 14 and 15. Summarizing all the information through necessary figures and tables are given below -

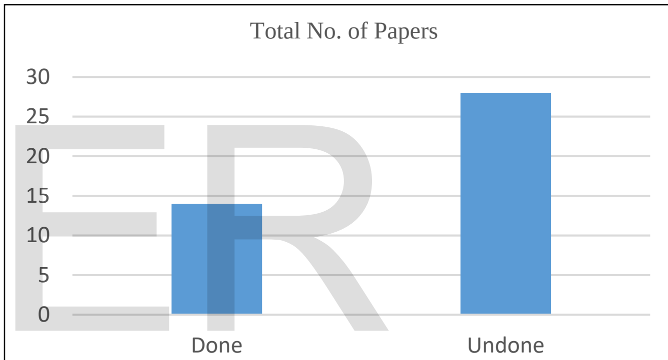



Fig. 13. Number of papers according to Skull Stripping technique

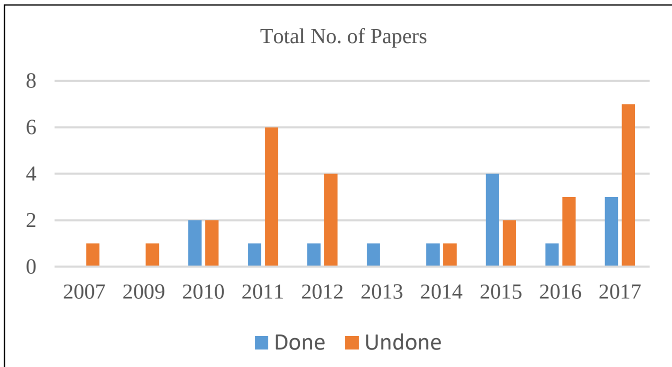



Fig. 14. Distribution of Skull stripping technique based on years

TABLE 2
Result-wise distribution of Clustering-based segmentation technique

| Technique | Authors & Year | No of Images used | Citation | Result | Total |
|---|---|---|---|---|---|
| **Pillar K-Means** | (Rajesh et al., 2017)[22] | Unspecified | 0 | Computational Time: 0.7020 (for k=3), 0.5304 sec (for k=4) | 1 |
| **K-Means** | (Song et al., 2016)[27] | 125 | 4 | Dice: 80.7±3.9, Sensitivity: 95.2±1.2 | 7 |
| | (Telrandhe et al., 2016)[30] | Unspecified | 14 | Momentum factor is 0.9 and total numbers of epochs are 500 | |
| | (Wu et al., 2007)[39] | Unspecified | 125 | Separation of the lesion and detection of the tumor using the features derived from CIELab color model | |
| | (Selvakumar et al., 2012)[42] | Unspecified | 135 | Find the stage of the tumor by Area Calculation | |
| | (Liu et al., 2015)[52] | Unspecified | 9 | Jaccard Similarity Coefficient: 0.8702, 0.7619, 0.7300 for WM, GM, CSF. | |
| | (Vijay et al., 2013)[58] | 100 | 54 | Accuracy: 95% | |
| | (Rajesh et al., 2017)[22] | Unspecified | 0 | Computational Time: 1.2636 (for k=3), 1.1232 sec (for k=4) | |
| **Histogram Based Clustering** | (Wu et al., 2007)[39] | Unspecified | 125 | Separation of the lesion and detection of the tumor using the features derived from CIELab color model | 1 |
| **Fuzzy C Means** | (Rajesh et al., 2017)[22] | Unspecified | 0 | Computational Time: 6.9732 (for k=3), 11.8561 sec (for k=4) | 8 |
| | (Rao et al., 2017)[29] | 200 | 7 | Dice Co-efficient: 79% (avg.), 88% (max.) | |
| | (Parveen et al., 2015)[34] | 120 | 27 | Accuracy: 91.66% for linear kernel; 83.33% for quadratic kernel, 87.50% for polynomial kernel | |
| | (Logeswari et al., 2010)[44] | Unspecified | 76 | Execution Time: 28.364 for 11X11 pixel window | |
| | (Nandha et al., 2010)[48] | 120 | 87 | Accuracy: 92.3% | |
| | (Gordillo et al., 2010)[49] | 20 | 23 | Jaccard Similarity Measure: 71% (lowest), 93% (highest) | |
| | (Sompong et al., 2013)[53] | Unspecified | 7 | Dice co-efficient: 84% | |
| | (Lawrence et al., 1992) [65] | 12 | 338 | False Negative: 20% for FCM/AFCM to 35% for FFCC. | |
| **Spatial fuzzy C means** | (Devkota et al., 2017)[20] | 19 | 2 | Accuracy 92% | 3 |
| | (Bing et al., 2011)[43] | 3 | 345 | Level set evolution stabilizes automatically once it approaches the genuine boundaries, suppressing boundary leakage and alleviates manual intervention | |
| | (Kanade et al., 2015)[61] | 15 | 15 | Low error rates | |
| **KIFCM** | (Abdel-Maksoud et al.,2015) [31] | 204 | 136 | Accuracy on Dataset1: 90.5%, Dataset 2: 100%, Dataset 3: 100% | 1 |
| **Enhanced Possibilistic Fuzzy C-Means (EPFCM)** | (Rajendran et al., 2011) [21] | 15 | 46 | Average similarity metrics: 95.3%, Jaccard index: 82.1% | 1 |



TABLE 3
Result-wise distribution of Edge-based segmentation technique

| Technique | Authors & Year | No of Images used | Citation | Result | Total |
|---|---|---|---|---|---|
| **Edge Detection** | (Debnath et al., 2011)[24] | 12 | 36 | Mean, Median, Std. Dev. And number of white pixels measured to detect the tumor | 1 |
| **Canny Edge Detection** | (Malathi, 2014)[23] | Unspecified | 0 | Dice: 90.13% - 93.26% | 2 |
| | (Badran et al., 2017)[40] | 102 | 70 | False Positive: 18.75% | |
| **Watershed** | (Mustaqeem et al., 2012)[33] | 60 | 152 | Hybrid Segmentation technique is used | 5 |
| | (Karthik et al., 2015)[37] | Unspecified | 14 | Accuracy: 90% | |
| | (Viji et al., 2011)[47] | Unspecified | 29 | App Volume of 4075.65 $mm^3$ and 1072.60 $mm^3$ respectively | |

| | | | | | |
|---|---|---|---|---|---|
| | (Mittal et al., 2017)[55] | Unspecified | 0 | Correctly locate the tumor based on intensity | |
| | (Dilber et al., 2016)[60] | 2 | 152 | Percentage of successfully pixel count: 86.25% - 93.21% | |

TABLE 4
Result-wise distribution of Thresholding-based segmentation technique

| Technique | Authors & Year | No of Images used | Citation | Result | Total |
|---|---|---|---|---|---|
| **Binary Thresholding** | (Debnath et al., 2011)[24 ] | 12 | 36 | Mean, Median, Std. Dev. And number of white pixels measured to detect the tumor | 4 |
| | (Ilhan et al., 2017)[25] | 100 | 4 | Accuracy: 96% | |
| | (Mustaqeem et al., 2012)[33] | Unspecified | 152 | Hybrid Segmentation technique is used | |
| | (Akram et al., 2011)[50] | 100 | 45 | Accuracy: 97% | |
| **Adaptive Thresholding** | (Badran et al., 2017)[40] | 102 | 70 | False Positive: 18.75% | 1 |
| **Otsu Thresholding** | (Mittal et al., 2017)[55] | Unspecified | 0 | Correctly locate the tumor based on intensity | 1 |

TABLE 5
Result-wise distribution of Histogram-based segmentation technique

| Authors & Year | No of Images used | Citation | Result | Total |
|---|---|---|---|---|
| **(Devkota et al., 2017)[20]** | 19 | 2 | Accuracy 92% | 8 |
| **(Debnath et al., 2011)[24]** | 12 | 36 | Mean, Median, Std. Dev. And number of white pixels measured to detect the tumor | |
| **(Nabizadeh et al., 2017)[26]** | Unspecified | 8 | Execution Time: 140ms | |
| **(Song et al., 2016)[27]** | 125 | 4 | Dice: 80.7±3.9, Sensitivity: 95.2±1.2 | |
| **(Wu et al., 2007 )[39]** | Unspecified | 125 | Separation of the lesion and detection of the tumor using the features derived from CIELab color model | |
| **(Logeswari et al., 2010)[44]** | Unspecified | 76 | Execution Time: 28.364 for 11X11 pixel window | |
| **(Bauer et al., 2011)[46]** | 10 | 220 | DSC: 0.84 (intrapatient case), 0.77 (interpatient leave-one-out case) | |
| **(Viji et al., 2011)[47]** | Unspecified | 29 | App Volume of 4075.65 $mm^3$ $and$ 1072.60 $mm^3$ respectively | |



TABLE 6
Result-wise distribution of Neural Network based segmentation technique

| Authors & Year | No of Images used | Citation | Result | Total |
|---|---|---|---|---|
| **(Sobhaninia et al., 2018) [62]** | 3064 | 0 | Dice Score: 0.73 (Single Network), 0.79 (Multiple Networks) | 10 |
| **(Pereira et al., 2016) [68]** | 392 | 238 | Accuracy-70% | |
| **(Havaei et al., 2017) [66]** | 65 | 292 | Dice Co-efficient varies from 0.80 -0 .88 | |
| **(Dina et al., 2012) [63]** | 82 | 44 | Accuracy-100% | |
| **(Othman et al., 2011) [64]** | 35 | 11 | Accuracy-98% | |
| **(Lawrence et al., 1992) [65]** | 12 | 338 | False Negative: 20% for FCM/AFCM to 35% for FFCC. | |
| **(Corso et al., 2008) [67]** | 20 | 172 | Accuracy: 70% | |
| **(Shenbagarajan, et al., 2016) [69]** | 80 | 13 | Accuracy-94% | |
| **(Elisee et al., 2017) [70]** | 613 | 6 | Accuracy-93.20% | |
| **(Shree et al., 2017) [71]** | 25 | 1 | Accuracy-95% | |

TABLE 7
Result-wise distribution of Contour-based segmentation technique

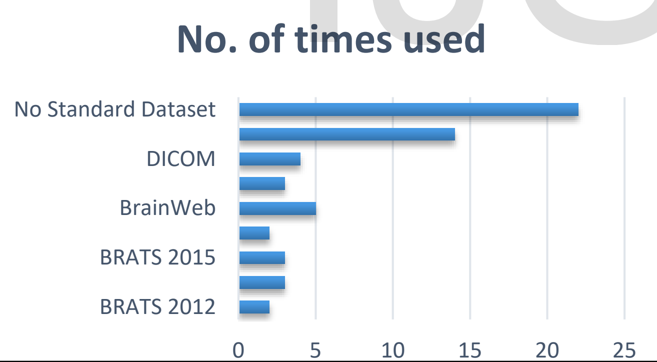
| Technique | Authors & Year | No of Images used | Citation | Result | Total |
|---|---|---|---|---|---|
| **Parametric deformable active contour model model with gradient vector field(GVF)** | (Rajendran et al., 2011) [21] | 15 | 46 | Average similarity metrics: 95.3%, average Jaccard index: 82.1% | 1 |
| **Content Based Active Contour Model** | (Jainy et al., 2012)[51] | 428 | 96 | Gives substantial results for homogeneous tumors against different and similar background | 1 |
| **Region Based Active Contour** | (Shenbagarajan, et al., 2016) [69] | 80 | 13 | Accuracy-94% | 1 |
| **Localized Region based active contour** | (Elisee et al., 2017) [70] | 613 | 6 | Accuracy-93.20% | 1 |

TABLE 8
Result-wise distribution of other segmentation technique

| Technique | Authors & Year | No of Images used | Citation | Result | Total |
|---|---|---|---|---|---|
| **Tumor Growth Model, Lattice-Boltzmann Method** | (Pei et al., 2017)[28] | 100 | 1 | Mean DSC with tumor cell density: 0.82122 (complete), 0.685811 (core), 0.812388 (enhancing) | 1 |
| **Masking based on Symmetric Property** | (Mariam et al., 2017)[35] | 40 | 3 | Accuracy: 95.5% | 1 |
| **Fuzzy Logic Gaussian Mixture Model** | (Ji et al, 2012)[41] | 80 | 89 | Jaccard Similarity: 0.8138 (for GM), 0.9339 (for WM) | 1 |
| **Local Independent Projection** | (Huang et al., 2014)[45] | 120 | 73 | Dice Similarity: 79.8 ± 17.0 for real high grade tumor | 1 |
| **Berkeley Wavelet Transformation** | (Bahadure et al., 2017)[54] | 201 | 39 | Accuracy: 96.51%, Specificity: 94.2%, Sensitivity: 97.72%, Dice co-efficient: 0.82 | 1 |
| **Self-Organizing Map** | (Demirhan et al., 2015)[57], | 63 | 54 | Average Dice for Tumor: 60.92% | 1 |
| **Graph Cut** | (Binaghi et al., 2014)[59] | Unspecified | 2 | Jaccard index: 0.867(for interpatient), 0.031 (for intrapatient) | 1 |



Fig. 15. Distribution of the datasets used in the articles




Several competition and resources from universities are open for all to work on those data. Focusing on the evaluation of state-of-the-art methods for segmentation of brain tumors in MRI scans BRATS dataset is available for all. Several sources of databases used in the papers. Figure 15 represent the datasets names used by the articles and distribution of the dataset based on their used respectively are given below-

## 5. Discussion, Future Work & Conclusion

Usage and purpose of different segmentation techniques intensify the range of brain tumor segmentation. Researchers can have a glimpse at a glance of the techniques and how they worked on a method. We tried to glean all of the possible information thoroughly. Distribution of the techniques like- year-wise, type-wise, citation-wise, acceptation-wise etc. extolled the spectrum of this area. We concealed disparate types of segmentation methods enlisted from 2007 to 2018 a total of 52 from discrete journals and conferences.

Elimination of redundant and irrelevant features for the training phase is a key factor for system performance. Consideration of feature selection will play a vital role in the classification techniques in future work. Segmentation is the preeminent subject of this article. Focus on the efficient methods with its analytical information has been deliberately highlighted. Enumeration of the data based on deep learning methods, addition of the statistics of tumor detection step with feature extraction and selection will augment and outright the Brain Tumor Segmentation techniques.

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