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Assessment on Brain Tumor Detection Techniques in Hyperintense Mr Images

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Abstract: ***Brain tumors have different characteristics such as shape, size, location, and image intensities. Magnetic-resonance images (MRIs) typically have a degree of noise and randomness associated with the natural random nature of brain structure. MRI is a profoundly created medical imaging strategy giving a range of data about the individual's delicate tissue structure. Even though it gives a rich data, the complex dynamics of the tumor evolution cannot be captured perfectly because of the uncertainty in the tumor segmentations. Different methods are available to identify and segment a brain tumor. Stages of medical image processing in brain tumor detection are discussed in this paper and overview of the analogous papers is quoted by analyzing several research papers. This paper provides delving of technologies which can be used to prognosticate brain tumor.***

Keywords **:** ***Brain tumor, Classification Techniques, Feature extraction, MRI, Noise, Segmentation, tissue structure.***

I. INTRODUCTION

A brain tumor is developed when weird cells are formed within the brain. There are two main categories in tumors: Malignant and Benign tumors. The origin of the malignant or cancerous tumor is from the brain itself then it is said to be primary tumor and the tumors spread from somewhere else is said to be secondary tumor or brain metastasis tumors. Symptoms of the brain tumor will change depending on the region of the brain involved. The Primary tumors that commonly affect the adults are meningiomas (benign), and astocytomas such as glioblastomas. The most common type of tumor that usually affects the children is a malignant medullo blastoma. Diagnosis is usually done by medical examination with supporting machines like Computed Tomograpy (CT) or Magnetic Resonance Imaging. MR images can be processed in various stages like enhancement, segmentation, feature extraction and classification to predict and classify brain tumors. Each stages uses various technologies and algorithms to make the diagnosis automotive which could be the alternative for biopsy.

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A. Human Brain Anatomy

The human brain anatomy shown in Fig-1 has three main parts:

- ***Cerebrum:*** It is responsible for the activities like Contact, vision and hearing, in addition to speech, reasoning, emotions, gaining knowledge of, and motion.
- ***Cerebellum:*** The characteristic of cerebellum is to preserve posture, coordinate muscle movements, and stability.

Brainstem: It connects the cerebrum and cerebellum to the spinal cord. It controls sports like respiratory, heart fee, frame temperature, sleep and wakeup cycles, and digestion, vomiting, sneezing, and coughing.

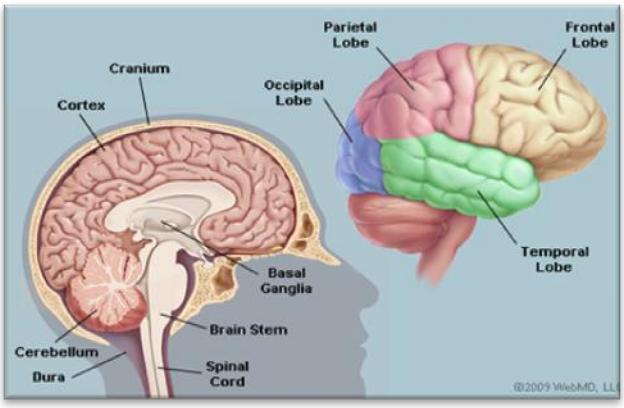


Fig-1 Human Brain anatomy
Courtesy:
https://www.webmd.com/brain/picture-of-the-brain#1

The Cerebrum is divided into four lobes:

Frontal lobe: It is involved in speak me, muscle moves and making judgments.

Parietal lobe: This gets sensory enter for touch and frame function. It also interprets signals from vision, hearing, motor, sensory and memory.

Occipital lobe: This receives facts from the visible (vision processing).

*Temporal lobe***:** This includes the auditory regions (Hearing), Memory and so forth.

B. Brain tumor types

Primary brain tumors can be benign or malignant:

- ***Benign brain tumors do not have cancer cells:*** Benign brain tumors usually have some sort of border or edge.

In rare case only, the benign tumors cells invade tissues around them. They don't unfold to different elements of the body. However, benign tumors can reason severe fitness troubles when they press on sensitive regions of the mind. Benign brain tumors may flip in to malignant.

- **Malignant brain tumors (brain cancer) consist of cancer cells**: Malignant brain tumors are considered to be very serious and are often a threat to life. They have a rapid growth and accumulate or invade the neighboring healthy brain tissue. Cancer cells may break away and spread to other portion of the brain or to the spinal cord. The spreading of cancer cells to other parts of the body is very rare. Cancerous tumors that starts with in the brain is said to be primary tumor and that have spread from somewhere else, known as secondary tumor or brain metastasis tumors.

C. Diagnosis of brain Tumor

- **A Physical examination**: A Physical exam can be completed that includes checking coordination, vision, balance, listening to, energy and reflexes. Problem in these regions can also provide some indication approximately the part of the mind that might be stricken by a brain tumor.
- **Diagnosis by Imaging Technique**: MRI is a very effective imaging technique used to help in diagnosing brain tumors as shown in Fig-2. In some cases a dye may be injected through a vein in the arm during the MRI study.
- **MRI scan components**: It includes functional MRI, perfusion MRI and magnetic resonance spectroscopy that evaluates tumor and plan the treatment. In some cases other imaging tests are recommended, including computerized tomography (CT). Positron emission tomography (PET) is generally not as useful for creating images of brain cancer as it is meant for other types of cancer.

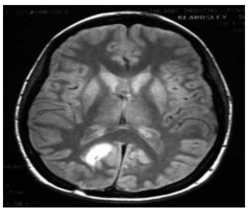


Fig-2 MRI Image of Brain Tumor

Courtesy:

http://papersim.com/wp-content/uploads/2018/03/Image_Processing__Clustering_Algorithms_MR_Images_2011.pdf

Benign brain tumors appear as hypodense (darker than brain tissue) on CT scans and they seems to be either hypodense or isointense (same as the intensity of brain tissue) on T1-weighted MRI scans, or hyperintense (brighter than brain tissue) on T2-weighted MRI.

T_1-weighted (T1W) images: Cerebrospinal fluid (CSF) is dark. T_1-weighted images are useful for visualizing normal anatomy.

T_2-weighted (T2W) images: CSF is light or bright, but fat (and thus white imatter) is darker than with T_1. T_2-weighted images are useful for visualizing pathology.

The magnetic resonance imaging sequence is represented in Fig.4 and Fig.5. Shows T1 weighted and T2 weighted brain images.

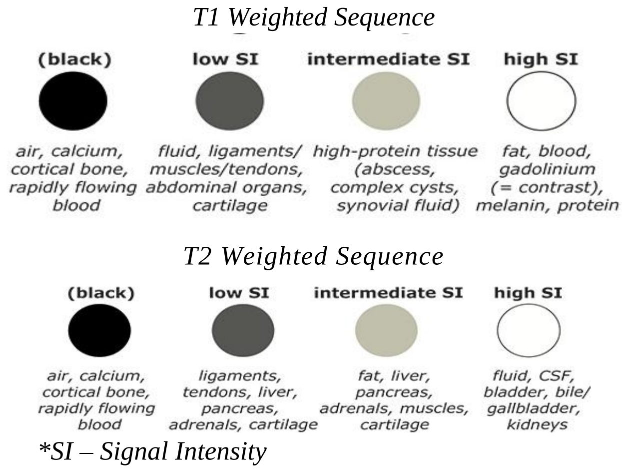


Fig-3 Magnetic resonance imaging sequence

Courtesy:

http://www.startradiology.com/the-basics/mri-technique/

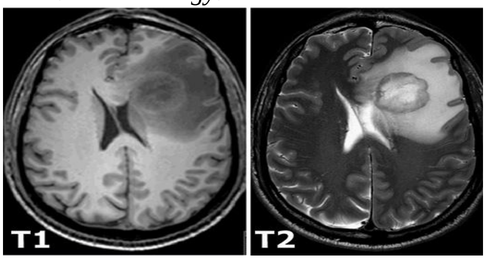


Fig-4 T1 weighted and T2 weighted

Courtesy:

http://www.startradiology.com/the-basics/mri-technique/

- *Invasive Biopsy or Surgical Biopsy:* A sample of the tissue is taken from the affected part of brain to study the abnormality exist in the brain. A surgical biopsy can be performed using a needle.

II. STEPS INVOLVED IN BRAIN TUMOR DETECTION

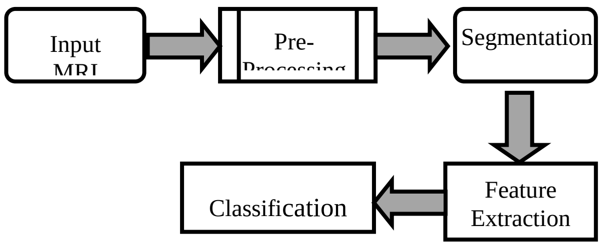


Fig-6 Steps Involved in Brain Tumor Detection

Steps involved within the detection of brain tumor are depicted in fig 5. In this first the samples are collected and store it in a database. After that the enter photograph is preprocessed for segmentation process. After segmentation the functions are extracted and trained. Feature extraction includes extraction of intensity histogram, form and texture features from capabilities. Then it will likely be categorised and provides a end result as benign or malignant.

III. PRE-PROCESSING

Pre-processing of MRI images is the foremost step in image analysis where improvement of the image and noise reduction methodologies is utilized for the enhancement of the image quality. Image is refined in such a way that the minute details are enhanced so that the image is free of noise. Image enhancement and noise reduction techniques are implemented in the detection of brain tumor to provide optimum results. Through enhancement more prominent edges are received and a very sharp image like tumor is obtained. Image enhancement and filtering techniques is utilized in Noise discount that enables in decreasing the blurring impact from the image.

A. Removing Bias field using N4ITK

Bias discipline is a low frequency and very easy signal that corrupts MRI images which includes precious facts. Image turns into blur due to bias subject. The bias field is produced because of magnetic in homogeneity in intensities. N4ITK algorithm [1] is used to remove the bias field

Wei Chen in his paper named "Automatic Brain Tumor Segmentation based on Features of separated Local Square" [2] used N4ITK algorithm to eliminate the bias field. Then histogram matching algorithm [3] is used to transform each image to a specified histogram to make sure that all the images have equal gray level ranges.

Michael Goetz, Christian Weber [4] implemented N4 bias field correction algorithm in the preprocessing step of "Extremely randomized trees based brain tumor Segmentation" to correct nonuniformity within each MRI followed by histogram normalization. If the shapes are too different then the histograms that are normalized to compare with a template histogram for the existence of a match, as done by the piece-wise linear normalization may lead to an incorrect result. To overcome these problems a simple normalization to the image mode was used. This was carried out by subtracting the mode from each gray-value and then normalizing the standard derivation to 1.

To minimize the intensity bias of the MR image, S. Reza and K. M. Iftekharuddin in his paper "Multi-fractal Texture Features For Brain Tumor and Edema Segmentation" [5], carried out intensity normalization as pre–processing step. N4ITK MRI bias correction tool is used for bias correction. A two- step normalization method [3] is implemented, where the image histograms are modified so that the image histograms match with the mean histogram obtained using the training data. After normalization the intensity values for the same tissue in different MR images fall into a very narrow range (a single value).

B. Skull Stripping

Skull stripping is not anything however disposing of non-Brain tissues from MRI Images. The MRI Brain pix must be skull-stripped earlier than applying other photo processing algorithms. The brain extraction set of rules is used to take away the skull from an picture, leaving best the place occupied by using actual mind tissue. These algorithms separates these through using the dark space between the cranium and brain, occupied with the aid of the CSF(cerebrospinal fluid).

A novel method for the preprocessing of MR brain images based on mathematical morphology operations was introduced by Benson C.C [6]. They proposed an efficient method for the skull stripping based on mathematical morphology. One of the main disadvantages of MRI method is its low contrast. So an algorithm is implemented to enhance the contrast of MR brain images by employing morphological operations. Mathematical morphology is a shape based tool which is useful in extracting the components of image used in the representation and description of shape, region, boundaries and convex hull [7]. Mathematical morphology is developed on the basis of set theory. The two basic operations in mathematical morphology are Erosion and dilation[8].

Kavitha Srinivasan, Nanditha NM [8] dealt with an intelligent skull stripping algorithm for MRI image sequences. They used mathematical morphology in their algorithms. The Skull stripping process, which separates brain tissue and non-brain tissue, is one of the important preprocessing steps. Brain segmentation is complicated and time consuming and it can only be done with good accuracy by experienced radiologist with proper training or clinical expert. Computer aided diagnosis is needed to overcome these limitations. The method was validated on the international database collected from whole brain Atlas. The metrics such as Dice Similarity Coefficient (DSC), Jacquard Similarity Coefficient (JSC), False Positive Rate (FPR), False Negative Rate (FNR), sensitivity, specificity and accuracy are used to evaluate the performance.

An improved Skull Stripping Algorithm of MRI Brain Images Based on Fuzzy Morphological Operation was proposed by Shaima Abd El-Kader, Mohamed Morse [9]. The proposed skull stripping algorithm consists of continuous steps: Nonsensical Filter, Binarization by Otsu's threshold, Largest Connected Component Selection, Fuzzy Morphological Operators and Region-Based Binary Mask Extraction.

Skull stripping based on Image Contour [10], labeling and morphological erosion has been proposed by Somasundaram.K and Kalavathi in "Automatic Skull Stripping of Magnetic Resonance Images (MRI) of Human Head Scans Using Image Contour". The algorithm first pre-processes the image by removing noise and blurs to obtain a rough image contour.

The rough image contour is further processed to produce brain mask.

C. Noise Reduction

Priyanka Balwinder Singh [11] made a proposal for Median Filter technique for de-noising the salt & pepper noise and poisson noise from the images. A median filter functions in a way that, the output intensity value of the pixel being processed is obtained by sliding a window along the image and the median intensity value of the pixels within the window is set as the output intensity. Median filter maintains edges in an image also with a reduction in random noise. Every pixel's value is set to median value of the pixels in the vicinity of the corresponding input pixels. This filter is then utilized for the removal of these noises and then the bounding box technique is employed to detect the position of the tumor.

Researchers Nobi and Yousuf, have been involved in the development of Order statistics filters [12] which allow for a simple and effective methodology to eliminate noise from the medical images. This technique employs the combination of both median filtering and mean filtering to decide on the pixel value in the no-noise image. It is also for the elimination of the Rician noise affecting the images.

Weighted median filters [13] are used by Jaya, Thanushkodi, Karman. High frequency components are eliminated by the application of De-noising using weighted median filter and also salt and pepper noise from images are also removed without any disturbance towards the edges. Its application is also for the extraction of each pixel of a 3x3, 5x5, 7x7, 9x9, 11x11 windows of neighborhood pixels and analysis of the mean value of background, mean grey value of foreground, and contrast value.

A Gaussian filter [14] is a smoothing filter, defined by the Gaussian kernel. This filter shows lower blurring effects compared to simpler averaging filter. The key point of Gaussian filter is that it not only corrects the spectral coefficients of interest, but also all the amplitude spectrum coefficients that lies within the filter window. Gaussian lowpass filters generally compute a weighted average of pixel values in the neighborhood, in which the weights decrease with distance from the neighborhood centre.

IV. SEGMENTATION TECHNIQUES USED IN BRAIN TUMOR SEGMENTATION

The primary step and complicated task of image analysis of an brain MRI is the Image segmentation. Its aim is that of separating a tumor area from an MR image. There are many techniques to build computer aided diagnosis to help medical experts in recognizing and diagnosing brain tumor. However, proper segmentation is not easy because of the great verities of the lesion shapes, colors, and sizes along with various skin types and textures. A brief survey of segmentation techniques used so-far for segmenting brain tumor i.e. Watershed Method and Morphology Based Segmentation, Level Set Based Segmantation, Combination of Watershed and Level Set Segmentation, Region Growing Based Segmentation, Thresholding based Segmentation, K-nearest neighbor (KNN) are analyzed here.

Shunmuga Sundaram.R.S and Sridhar [15] attempt to find out the severity of the cells that causes cancer by segmenting the images. Probablistic Boundary Edge Map Technique algorithm is used to segment the image with a pixel estimate and the edges are detected. The Segmentation is carried out again and again until the threshold estimate is greater than the original estimate

Watershed segmentation [16] is one of the high-quality techniques to group pixels of an photo primarily based on their intensities. Watershed algorithm is based totally mostly on morphological procedure notwithstanding the fact that it could be blended up with aspect primarily based segmentation to yield a hybrid technique. Usually, photos obtained by means of diverse techniques that uses electromagnetic spectrum, possesses a massive no of discontinuities within the intensity and these in the end give rise to over segmentation whilst morphological segmentations like watersheds are achieved. Pixels falling beneath similar intensities are grouped collectively [17] [18]. Watershed is an effective approach for segmenting an picture and to split a tumor from the picture.

Watershed Techniques have the capacity to detect the non-stop boundary of the region of hobby; it could be exceptional suitable for the ones kinds of programs wherein high accuracy and precision is wanted. The place of most cancers research is the nice desirable place of application wherein watershed segmentation can be applied efficaciously. Watershed is stated to be a gradient-based segmentation method wherein unique gradient values are considered as special heights. A hollow is made in every nearby minimum and immersed in water; the water will upward thrust until neighborhood maximums. When two frame of water meet, a dam is constructed among them. The water rises progressively until all factors in the map are immersed. The photo receives segmented through the dams. The dams are called watersheds and the segmented areas are known as catchments basins [19].

The number one problem of watershed rework is its sensitivity to intensity variations, ensuing in over segmentation, which takes place whilst the photograph is segmented into an unnecessarily large range of areas. The over segmentation problem is decreased by Padmakant Dhage [20]. His work represent CCL (Connected Component Labeling) based totally Watershed set of rules to identify and phase the mind tumors efficaciously. When compared to location growing set of rules, it requires much less processing time and the over segmentation hassle is decreased up to a large quantity.

Dawood Dilber and Jasleen [21] attempted to segment the brain tumor using Watershed algorithm by assigning different values to some operators for different input images, because the tumor is not always at the same part or location. For different people, tumor may be at different places, or it may or may not be deep inside the brain (as it depends on the level of the tumor).

Morphological picture processing [22] well-knownshows quite a number image processing strategies that deal with the form of features in an picture and normally morphological operations are applied to eliminate imperfections added at some stage in segmentation, and so it operates on binary pictures [23]. Morphological operations may be done in boundary extraction, Region filling, extraction of related additives, thinning/thickening, skeletonisation [24]. Most of the morphological processing operations are based totally on Fit and Hit. Fit approach the structuring detail suits inside the neighbouhood and Hit means intersects the community [25].

A morphological image segmentation technique based on the watershed algorithm is proposed by Md. Shakowat, Tan Wooi and Rajasvaran [26]. Morphological based pre and post-processing techniques were introduced to reduce over-segmentation by means of merging and removing duplicate segments. In preprocessing trivial regions and background noise are removed by first make the image to undergo morphological smoothing before it is convolved with a Gaussian kernel. Then it is followed by a global intensity thresholding with a low intensity value. This is used to filter the background intensities in the image. In post-processing a more concise region representation of the watershed-segmented image is produced, in that a region adjacency list (RAL) is built for the region merging process. A similarity function is defined to control the merging, from where the most similar neighboring regions are merged.

Level Set Based Segmentation: The level set method for capturing dynamic interfaces and shapes was firstly introduced by Osher and Sethian [27]. The primary idea of the level set method is to represent contours as a zero level set of an implicit function defined in a higher dimension, normally referred to as the level set function and to derive the level set function according to a partial differential equation (PDE) [28]. For medical processing purpose, it is been linked to computer applications. In computer vision applications and image processing, the level set method was introduced independently in the context of active contour (or snake) models for MR image segmentation [29-31]. There are still key challenges in this area and there is no wellknown degree set technique that works for all applications.

Pan Lin, Chongxun Zheng [32] have proposed a new speed function for level set framework. The new method integrates the image region statistical information and image boundary statistical information instead of the conventional method that uses spatial image gradient information.

The new models modify the level set speed function utilizing region intensity information and gradient information. The scheme here proposed is particularly well adapted to situations where edges are weak and overlap, and images are noisy.

Medical images can also be segmented using Level set without re-initialization [33] approach applied with certain specific shape based model. The advantage of Level set without re-initialization is the possibility of large time steps which speeds up the process of curve evolution. The disadvantage of this method is that it is not able to work with signed distance function and also not able to work with some shapes.

Combination of Watershed and Level Set Segmentation: The combinational technique profits the advantages of both the watershed and stage set methods. First the watershed segmentation is done which turns as an initialization of the extent set method. Watershed rework reduce the blindness of segmentation [34] and improves the accuracy of segmentation. The very last segmentation is achieved the use of degree set approach. This aggregate offers particularly correct segmentations of topologically and geometrically complex systems with a great deal decreased time.

Segmentation of bright field cell images [35] is difficult because the contrast between cells and the background is low and the Cells are usually surrounded by “halo", an optical artifact common in bright field images. Shutong Tsea, Laura Bradburya [35] introduced a Combined Watershed and Level Set segmentation method for bright field images. In standard level set segmentation, only one level set function is used. But here multiple level set functions are used to capture the different intensity levels in a cell image. The cell interior also shows high intensity variation but low contrast compared with the background. This method combines the advantages of the level set and watershed segmentation algorithms. By assigning initial markers at the appropriate locations, it is able to resolve the low contrast and cell division problems [36].

An accurate segmentation using Gradient Based watershed transform in level set method for a medical diagnosis system was proposed by Khushboo Mantri, Dr. Shiv Kumar [37]. In contrast to the standard level set methods, the tumor and non-tumor region information is embedded within the level set speed function to automatically extract the tumor surface. The primary approach known as the block 1 process uses the level set segmentation as a deformable model and defines its speed function based on intensity thresholding inorder that no explicit knowledge about the density functions of the tumor and non-tumor regions are required. The threshold is updated iteratively all through the level set growing process. The next approach which is called as block 2 consists of two level gradient based watershed segmentation. Some morphological operators are also used along with watershed transform in order to extract a sharp segmented region. This hybrid approach is better for the cases where the intensity level difference amongst the tumor and non-tumor regions is higher. It can also segment non homogenous tumors provided that the non-homogeneity is within the tumor section.

Nguyen Mong Hien and Nguyen Thanh Binh [38] proposed a method using Region-Growing Combined with Level Set for the detection and segmentation of brain tumor in MR image. In this method the MR image contrast is enhanced by the use of histogram equalization and the region of tumor is labeled using region growing technique.

The exact boundary of the tumor region which is labeled in the previous stage is created using level set method.

The region developing based totally segmentation strategies segments the image based totally on the developing of seeds (preliminary pixels). These seeds can be selected manually [39] (based totally on previous expertise) or routinely (primarily based on precise software). Then the developing of seeds is controlled by means of connectivity between pixels and with the assist of the previous information of trouble, this may be stopped. It is a method for extracting an picture area in which those regions are connected primarily based on a few predefined criterion. These criteria can be based on depth statistics or barriers inside the image. The possible criterion might be to develop the location [40] till a boundary in the photograph is met. In case if adjacent areas are observed, then a region-merging algorithm is used in which dangerous edges are dissolved and robust and prominent edges are left intact. The manual attempt to gain the seed point is the splendid disadvantage for this place developing.

An automatic seed point selection [41] for region growing is proposed by Archana Chaudhari, Vaidarbhi Choudhari using fuzzy C means algorithm. Experiments for tumor segmentation are conducted on Flair images from publically available BRATS database. Fuzzy c-means is one among the method of clustering which allows one piece of data to belong to two or more cluster.

According to this algorithm, assigning membership to each data point corresponding to each cluster center is carried out on the basis of distance between the center of cluster and the data point. More the data is near to the cluster center more is its membership towards the particular cluster center.

A combination of local search procedure with thresholding region growing [42] is used by A. Afifi and S. Ghoniemy to achieve better generic seeds and optimal thresholds for region growing method. A procedure is used to detect the best possible seeds from a set of data distributed all over the image as a high accumulator of the histogram. The output seeds are fed to the local search algorithm to extract the best seeds around initial seeds. Optimal thresholds are used to overcome the limitations of region growing algorithm and to select the pixels sequentially in a random walk starting at the seed point.N. Mohd Saad, S.A.R. Abu-Bakar [43] developed an automatic region growing algorithm that can accurately segment brain lesions in diffusion-weighted magnetic resonance imaging (DW-MRI or DWI). Diffusion-weighted image (DWI) is first preprocessed for normalization, background removal and enhancement. Region splitting and merging is applied to produce blocky segmented region before region growing process is started. Simple statistical features based on histogram, mean of region and number of region pixels are used as homogeneity criteria to produce the segmentation.

Thresholding [44] [45] is the simplest method of image segmentation. From a gray scale image, thresholding can be used to create binary images. Segmentation is the process of assigning each pixel in the source image to two or more classes. If there are more than two classes then the usual result is several binary images. In image processing, thresholding is used to split an image into smaller segments, or junks, using at least one color or gray scale value to define their boundary. Umit Ilhana and Ahmet Ilhana [46] proposed Brain tumor segmentation technique primarily based on a brand new threshold method. In this approach, sum of unique pixel values excluding zeros (black pixels) are divided through the count of unique pixel values. By this operation, the average gray value (threshold cost) is calculated to transform the grayscale photograph to binary photograph.

An automatic histogram threshold technique based totally on a fuzziness degree is presented by means of Nuno Vieira Lopes and Pedro Couto [47]. This is an improvement of an current technique. Using fuzzy logic concepts, the issues worried in locating the minimal of a criterion characteristic are avoided. Similarity between grey stages is the key to find an optimal threshold. Two preliminary regions of grey ranges, positioned on the barriers of the histogram, are defined. Then, using an index of fuzziness, a similarity method is started to discover the threshold factor. A sizeable evaluation between objects and history is assumed. This technique overcomes some obstacles of an current method regarding the definition of the initial seed periods. Method convergence relies upon on the right initialization of those preliminary durations. After calculating the preliminary seeds a similarity system is started to find the threshold factor. This assets of similarity is acquired with the aid of calculating an index of fuzziness.

By combining different techniques with Thresholding, accuracy of detecting the tumor portion can be increased. Sarika Tale and Chaitra G [48] introduced a new method by applying K-means combined with thresholding technique and bounding box method to segment brain tumor in T1-weighted MRI images. The segmented tumor from the K-means method contains not only the tumor portion but also some misclassified healthy tissues. These cells are eliminated by applying the threshold technique that is increasing the threshold value until the misclassified tissues are eliminated to obtain fine tumor. Then finally result is evaluated with bounding box method. The features such as centroid, area, perimeter, solidity, extent and segmented area are extracted from the detected tumor.

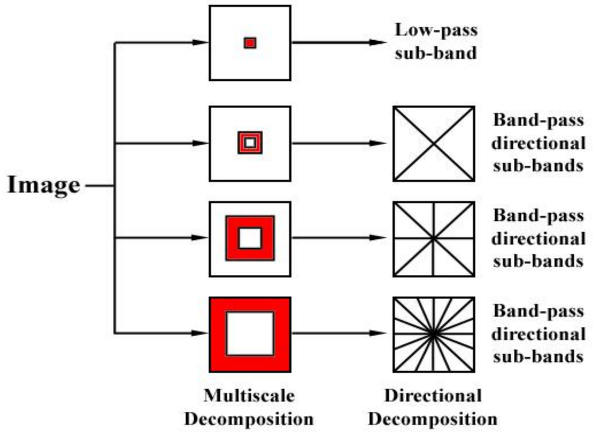
Otsu technique proposed by means of Nobuyuki Otsu is a international thresholding technique. In this approach [49][50], the grey level is selected in this type of manner that the between-magnificence variance is most or inside magnificence variance is minimal[51]. This algorithm does not work nicely for all type of mind MRI. This is due to big depth version of the foreground and background picture depth. It is clear that Otsu strategies is much less suitable for mind tumor segmentation and quantification as it binarize entire photo and bring some unnecessary element which is not significant.

Segmentation Methods	Ref	Advantages	Disadvantages
Watershed	[16-21]	1. Detect the non-stop boundary of the area of hobby. 2. Large number of segmented region in edges is reduced by marker controlled watershed algorithm.	Sensitivity to intensity variation resulting to over segmentation.
Morphological based segmentation	[22-26]	1. Reduce the over segmentation problem. 2.Good accuracy and less processing speed is obtained.	Need to undergo repeated steps for segmentation.
Level Set based segmentation	[27-33]	1. Well suited for the image where edges are weak and overlapped. 2. Levelset with reinitialization results in large time steps which speed up the process of curve evaluation.	1. It is not able to work with signed distance function and not able to work with some shapes. 2. Low contrast problem. Computational complexity is high.
Combination of watershed and Level set method.	[34-38]	1. Gives fairly accurate segmentations of topologically and geometrically complex systems. 2. It is able to resolve low contrast and cell division problem. Segment non- homogeneous tumors provided that the non-homogeneity is within the tumor section.	If the nonhomogeneity is out of the tumor section, the accuracy of segmentaion will be reduced
Region growing based segmentation	[39-43]	1. Overcome over and under segmentation. 2. The borders of regions found by region growing are perfectly thin and connected. 3. The algorithm is also very stable with respect to noise.	1. This method may not distinguish the shading of the real images. 2. Selection of seed point is difficult. The Execution time is high. 3. They fail for complex images consisting of complex regions.
Threshold based segmentation	[44-46]	1. Does not require prior information of the image Computationally inexpensive. 2. Work well for homogeneous image	1. It doesn't work well for an image with broad and flat valleys or without any peak. 2. Spatial information of an image is neglected, cannot guarantee that the segmented regions are contiguous. 3. Selection of optimal threshold is difficult, wrong choice may result into over or under segmentation.
K-means method	[48]	1. For small values of k, k-means is computationally faster. 2. Eliminates noisy spots. More homogeneous regions are obtained.	1. Difficult to predict k with fixed number of clusters. 2. Sensitive to initialization condition of cluster number and centre. 3. Doesn't works well with non globular clusters.
Otsu method	[49-51]	Easy to execute	Does no longer paintings well for all type MRI of mind photograph, this is because of large intensity version of the foreground and historical past photo intensity.

V. FEATURE EXTRACTION TECHNIQUES USED IN BRAIN TUMOR CLASSIFICATION

The main objective of the feature extraction is to facilitate the task of the classifiers. In figuring out the brain tumor, the methods like NSCT, GLCM, Feature reduction the use of PCA, Gabour wavelet transform(GWT) are used to extract the features of mind tissue. These extracted features are used to distinguish the ordinary and obnormal tissue.

DaCunha, Zhou and Do proposed one of the moset prominent variations of the contourlet transform [52] . The nonsubsampled contourlet transform (NSCT) was developed mainly due to the fact that the contourlet transformation is not shift invariant [52]. A nonsubsampled pyramid structure is replaced instead of the Laplacian Pyramid to retain the multiscale property [53], and a nonsubsampled directional filter bank for directionality. The first major noticeable difference is that the removal of upsampling and downsampling from both processes. Instead the filters are upsampled in both the Laplacian Pyramid [54] and the directional filter banks (DFB).



Nonsubsampled contuorlet transform

Courtesy: https://en.wikipedia.org/wiki/Contourlet

Chandan Saha and Md. Foisal Hossain extracted seven features[55] : Entropy, contrast, Energy, Variance, Skewness, Kurtosis, and Standard Deviation using NSCT . It is carried out to the segmented photograph for extracting functions from the low and high frequency subband coefficients. The seven capabilities which might be obtained from the subband coefficients of NSCT [55] are used to teach the help vector system (SVM) for the category of MRI brain snap shots.

J.S. Leena Jasmine, Dr.s.Baskaran [56] used Nonsubsampled contourlet transform(NSCT) for the classification of microcalcification in digital mammograms with the help of support vector machine (SVM). The classification is achived by extracting the microcalcification features using NSCT with different scales. A bank of filters is used here that splits the 2D frequency plane in the sub bands. This transform can be divided into two shift-invariant parts: a Nonsubsampled pyramid structure that ensures the multi scale property and a Nonsubsampled DFB structure that gives directionality. The multi scale property of the NSCT is obtained from a shift-invariant filtering structure that achieves sub band decomposition similar to that of the Laplacian pyramid.

Gray-level Co-occurrence Matrix (GLCM) [57] is the statistical method in which the textures are examined by considering the spatial relationship of the pixels. The GLCM functions characterize an image texture by calculating how often pixel pairs with specific values occur in an image and in a specified spatial relationship, creating a GLCM, and then extracting statistical measurements from that matrix.

Haralick et. al. [58] suggested a set of 14 textural features which can be extracted from the co-occurrence matrix, and which contain information about image textural characteristics[57][59] such as Homogeneity (Angular Second Moment), Contrast, Inverse Difference Moment, Entropy, Correlation, Variance, Sum Average, Sum Entropy, Difference Entropy, Cluster Shade, Cluster Prominence and Inertia.

GLCM can only extract the textures under single scale and single direction. He Xiaolan and Wu Yili projected a kind of texture feature extraction method combining nonsubsampled contour transformation (NSCT) and GLCM [60], so as to achieve the extraction of texture features under multi-scale and multi-direction.In this method, the extracted grey values and grey variances are taken as the grey features, the multi-feature fusion strategy (namely combining texture feature and gray features) is used.

A.Harshavardhan and Dr.Suresh Babu made an evaluation on the Feature Extraction methods for the Classification and Detection of Brain Tumour [61]. They analysed Histogram, GLCM and GLRM methods and also proposed to mix histogram, GLCM and GLRLM as a way to examine the performance of the aggregate of techniques. The effect of combined features used for the classification of Brain tumor are also analyzed. Various statistical parameters such as sensitivity, specificity and accuracy are used to evaluate the performances of classifiers for texture analysis methods. The combination of histogram features, GLRLM features and GLCM features outperformed well in discriminating between malignant and benign on Brain tumor images.

Reema Mathew A and Babu Anto P made an attempt to extract the features using DWT, Gabour wavelet and GLCM [62] . Initially they use Otsu's Thresholding for preprocessing and K-Means clustering for segmentation. Principal component analysis (PCA) is applied for feature set reduction. Since the feature vector obtained is a large vector, it is reduced with the help of PCA.

The most successful techniques that have been used in image recognition and compression is the Principal Component Analysis (PCA) [63] and it is used to reduce the large dimensionality of the data. Sonali B. Gaikwad and Madhuri S. Joshi[64] used PCA algorithm as a dimensionality reduction technique which transforms the pixel vector $\Phi 1$ to a vector $\omega 1$ which has a dimensionality d where $d << M \times N$. For each training image Ωi, these feature vectors ωi are calculated and stored.

Gabor wavelet evaluation [65] consequences in the extraction of the texture functions of MRI tumor images that helps to distinguish between primary important frightened gadget lymphoma (PCNSL) and glioblastoma multiforme (GBM) [66]. The discriminant functions which include tumor shape records are extracted from T1-weithted MR pix by using acting eight orientations and various frequencies with Gabor wavelet remodel. Yi -hui Liu and Manita Muftah[66] done texture analysis and extract texture features primarily based on Gabor wavelets to improve the diagnostic accuracy of differentiating PCNSL from glioblastoma multiform (GBM). Discriminant information is extracted from MR photographs to construct a class version.Gabor wavelets with exclusive guidelines and frequencies can discover the moderate differences among numerous sorts of tumor.

Gabor wavelets [65] [67] are often used to extract the texture features due to its being a mathematical approximation to the spatial receptive field [68] of a simple cell in the V1 area of human brain. The problem with these Gabor texture measures is the high computational cost involved in the convolution in the feature extraction process. To partially solve this problem, X.L. Wang, X. Wang and L. Hu [69] studied the behaviors of the Gabor wavelets used to form the texture features and find out that only a small subset of the filters have important contributions to the identification process. Finaly they concluded that , by removing redundant filters, better performance can be achieved in a much shorter time. Sanjay Shingade and Pritesh Jain [70] proposed a process for automatic brain tumor diagnostic system with Gabor Wavelets techniques. This method includes three phases to detect a brain tumor. First, preprocessing the photograph observed by way of the Image texture features extracted by way of convolving the picture with Gabor filters. And the segmentation is performed the use of threshold technique. A summary of the survey of feature extraction techniques used in Brain tumor classification:

Technique	Extracted features	Remarks	Ref.
NSCT	Entropy, Contrast, Energy, Variance, Standard Deviation, Skewness, Kurtosis.	1. Outstanding features of NSCT like multiscale, multidirection, shift invariance and better frequency selectivity and regularity than CT. 2. Ensure multiscale and Directionality features.	[55, 56]
GLCM	Homogeneity(Angular Second Moment), Contrast, Entropy Correlation, Inverse Difference Moment, Variance, Sum Average, Sum Entropy, Difference Entropy, Inertia, Cluster shade and Cluster Prominence	1. The spatial relationship of the pixels are considered. 2. Extracted textural features. 3. Used to train the feed forward neural network.	[57, 58]
DWT	Energy, Entopy, Homogenity, Dissimilarity And Contrast	1. Extract features from a MRI via successive excessive pass and occasional pass filtering on various scales. 2. Provide localized frequency statistics approximately a function of a signal.	[62]
PCA	Extract the principal components that will explain largest amount of variation in the data. Covariance is a measure to find the relationship between the dimensions among the datasets.	1. Principal components can be identified by calculating the eigenvectors and eigen values of the data covariance matrix. 2. The main Advantage is that the patterns found in the data can be compressed by reducing the number of dimensions without loss of information.	[63, 64]
GABOR	When a function is convolved with the Gabor wavelet, the frequency information near the center of the Gaussian is captured. Gabor wavelets are described by parameters that control orientation, frequency, phase, size, and aspect ratio and can take a variety of different forms.	1. Its main use is to extract the texture features. 2. The problem with these Gabor texture measures is the high computational cost consumed in the convolution calculation of the feature extraction process. 3. Only a small subset of the filters has important contributions to the identification process.	[65-70]

VI. SURVEY ON CLASSIFICATION TECHNIQUES USED IN BRAIN TUMOR DETECTION

Classification [71] is slightly differ from segmentation in such a way that Segmentation means to divide the image into a patchwork of regions, each of which is "homogeneous", that is, the "same" in some sense – Intensity, texture, color etc.. And Classification means to assign to each point in the image a tissue class, where the classes are agreed in advance– Grey matter (GM), White matter (WM), cerebrospinal fluid (CSF), air, etc. in the case of the brain. ie.

A classifier implicitly segments an image, and a segmentation implies a classification. Different classification techniques such as KNN, SVM, Naïve Bayesian, SOM, Decision Tree, Neural Network, and Genetic Algorithm are reviewed in this section.

KNN classifier [72, 73] is a simple classifier, where each pixel or voxel is classified in the same class as the training data with the closest intensity. The K-Nearest Neighbor classifier is a non-parametric classifier because it makes no implicit assumption about the statistical structure of the statistics. The k-NN need an integer ok set of labeled examples (education information) and a metric to measure closeness through Euclidean distance [74]. K-NN is very easy to understand and simple to implement. Sunitha Singh [75] deals with new approach for brain Tumor detection using K-NN Algorithm as a classifier and K- means clustering as segmentation. Abnormality of the brain based on symmetry analysis of image gray levels is analysed. Here K-NN classification is divided into five major steps: K value determination [76], Finding Distance (Euclidean distance) [74, 77] between the query instance and the training samples, Sortation of distance based on the kth minimum distance, Assignment of majority class and Determination of class. For cases where the tumor intensity distribution is strongly homogeneous, this algorithm fails and shows large spectral overlap with brain tissue.

Classification is in general relying on the characteristic of the picture and so the accuracy relies upon only at the function extraction technique. Nikita V. Chavan and B.D. Jadhav [78] extracted the features of the photo using GLCM. These features are used to classify the tumor as normal and abnormal and got overall recognition rate or classification accuracy up to 96.15%. Bharanidharan N and Harikumar Rajaguru [79] Perform an Analysis of KNN Classifier with and Without GLCM Features In Brain Tumor Detection and found that KNN classifier perform well along with GLCM.

Support Vector Machine (SVM) is a category algorithm used for each linear and non-linear information class. The base of this classifier is the statistical getting to know principle [80] given by way of Vipnik in 1999. SVM classifier works through locating out the hyper-plane[81] with largest margin or maximal marginal hyper-plane. In case of the facts which isn't always linearly separable [82], it transforms the authentic training statistics into a better measurement with the aid of doing non-linear mapping. By remodeling it into high dimensional space, it searches for linear foremost isolating hyper-plane. This transformation technique into high dimension always helps in attempting to find an top-quality hyper-plane the usage of help vectors and margins.

Amruta Hebli, Dr. Sudha Gupta [83] developed a novel methodology to distinguish between benign and malignant tumors from brain MRI. Feature extraction is done using DWT followed by Principal component analysis (PCA). The proposed system segmented tumors accurately and classified them as benign and malignant. In this work for training and testing kernel based SVM is used with Linear, Polynomial, RBF kernels (radial basis function kernels).

In MR images, localizing a mass of abnormal cells using SVM classifier and segmentation of tumor cells are carried out by T. Sathies Kumar and K. Rashmi [84] to know about the size of the tumor present in the segmented area. The classification is done by building a hyper plane based on a kernel function (K). The extracted features of the segmented portion will be trained using ANN to display the type of the tumor. The classification linear app is used to compare the efficiency of SVM with various classifiers.

SVM classifiers also use Lagrangian multiplier [85, 86] to solve the optimal hyperplane for linearly separable patterns. Xiaowu Sun and Lizhen Liu [87] mainly focus on building a hyperplane as the decision surface with the help of SVM. The Lagrange multiplier is transformed into its dual problem in order to solve the optimal hyperplane for separable patterns. Support vector machines present excellent features not only in regression problem but also in image classification. The eigen values [88] of the image gray information extracted using Principal Component Analysis are the input data through which the support vector machine can perfectly solve the problem of classification.

A naive Bayes classifier (NBC) is an algorithm that uses Bayes theorem to categorise items. Naive Bayes classifiers count on that the data point attributes are strongly or naively unbiased. Therefore every pair of features being classified is independent of each other [89]. It has two main disadvantages: (i) its classification accuracy decreases when the attributes are not independent, and (ii) it cannot deal with nonparametric continuous attributes. Miriam Martinez-Arroyo proposed a method that deals with both problems, and learns an optimal naïve Bayes classifier. The method consists of two phases, discretization and structural improvement, which are repeated alternately until the accuracy of classification cannot be improved. Minimum description length principle is the base for Discretization. Structural improvement method is used to deal with dependent and irrelevant attributes, which eliminates and/or joins attributes based on mutual and conditional information measures.

Weighted Naïve Bayesian Classifier (WNBC) is a brand new sort of Bayesian classifier that uses the Weighting scheme. Hamad Alhammady [90] applies the idea of weighted training at the NB classifier. The weighting scheme proposed is based on Emerging Patterns (EPs) [91]. They are described as object sets whose helps growth appreciably from one elegance to any other. The discriminating strength of EPs may be measured through their increase quotes. An EP's growth fee is the ratio of its assist in a sure magnificence over that in another class. Usually the EP's discriminating strength is proportional to its increase price.

The tumors in the temporal lobe are very hard to detect. Naïve Bayes classification [92] is utilized by Hein Tun Zaw and Noppadol Maneerat to detect tumor region that with all spreading cancerous tissues.

The main advantage is that it can precisely detect the tumor in all possible region including the temporal lobe (which align with the eye level). Detecting the tumors in that area is difficult as the thresholding and clustering approach usually detect the eyes as tumors, which is wrong. To overcome this error, the segmented tumor images are trained and tested with Naïve Bayes classifier to find out whether it is a tumor or not. This prediction can properly detect the tumor located in all regions of the brain with high accuracy of 94%.

An efficient method for brain tumor prediction is Decision Tree algorithm [93] which is more accurate than Naïve Bayes classification. Danda Shashank Reddy [94] showed that the prediction using the decision tree algorithm is simple, easy and accurate than the Naïve Bayes' algorithm. Decision tree is the learning algorithms that construct a classification tree to classify the data and it represents the visual picturization of a problem. Greedy approach [95] [96] is used to form a decision tree. Greedy Approach is purely grounded on the heuristic Problem Solving concept by making optimal local choice at each and every node. By doing this we get the approximate optimal solution universally.

The probabilistic neural network was developed by Donald Specht [97]. PNN affords a ordinary way to pattern type troubles with the aid of following a statistical approach known as Bayesian classifiers [97, 98]. Mohd Fauzi Othman uses a stage hierarchical choice tree that segregate the metastatic mind tumor cases from the gliomas and meningiomas (primary brain tumor) cases. Here, class changed into accomplished the usage of special LSFT-PNN classifier [99] (Least Square Features Transformation). Then LSFT-PNN is in comparison with the help Vector Machines with Radial Basis Function (SVM-RBF) and the Artificial Neural Network (ANN) classifiers. The training velocity of PNN is much faster than a BP network. PNN can technique a Bayes gold standard end result below certain easily met conditions [100]. Advance hybrid PNN completed by using Georgiadis ET all [101] aimed to improve brain tumor class on MR Images through the usage of PNN and non-linear transformation of textured functions.

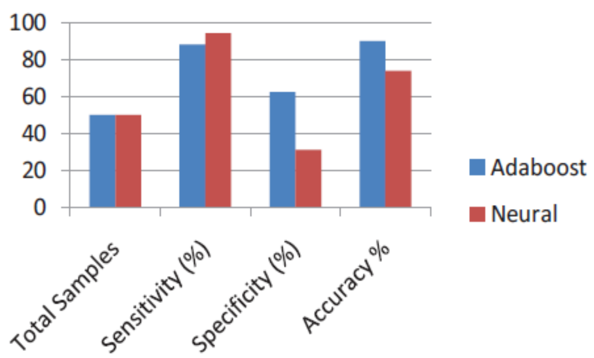
Rajeshwar Nalbalwar designed and developed system that works in two phases namely Learning Phase and Testing Phase [102]. In Learning/Training Phase the ANN is trained for recognition of different types of brain cancer. Here the textural features are extracted using Gray Level Co-occurrence Matrix. The extracted features are used in the Knowledge Base which helps to classify unknown images successfully. These features are given as input to ANN classifier after normalizing the features in the range -1 to 1.

The Adaboost algorithm [103], a boosting algorithm was introduced and developed by Freund and Schapire, in 1994 . Ravindra Sonavane and Poonam Sonar uses ensemble method in the Adaboost Classifier to boost the weak learners. [104]. Adaboost algorithm selects the extracted features and classifies malignant (tumor) and benign (non-tumor) structures. Adaboost classifier is most successful pattern in ensemble learning. Instead of single learner generated from the input training vectors, the ensemble method tries to generate sets of base learners and collect them. The ensemble is the process of boosting the weak learners to make a strong classifier. In the process, different distributions of sample sets should be used using weak classifier. In next training misclassified classifier will get large training. After several training they will get greatest weight. Comparision of Neural Network and Adabooster classifiers are done by Astina Minz and find that the find that the classification accuracy of Adabooster is 89.90% which is given in the following table [105]:

ANN'S are networks of interconnected nodes. The input of a specific node is the weighted sum of the output of all the nodes in which it is connected. A node's output value is generally a non-linear function (referred to as the activation function) of its input value. The multiplicative weighing factor between the input of node j and the output of node I is referred to as the weight w_{ji}. An artificial neural network is an adaptive, most nonlinear system that learns to perform a fuction (an input / output map) from data. Adaptive means the system parameters are changed during operation, normally called the Learning/Training phase. The artificial neural network parameters are fixed after the training phase and the system is used to solve the problem. The Artificial neural network is used to adjust the weights so that with each iteration the error decreases and the neural model becomes closer and closer to the desired output.

VII. RESULTS AND DISCUSSION

ML ALGORITHM	TOTAL SAMPLES	SENSITIVITY (%)	SPECIFICITY (%)	ACCURACY (%)
ADABOOST	50	88.23	62.5	89.90
NEURAL	50	94.18	31.25	74



MRI the use of category technique is an critical diagnostic device for the prediction of brain tumors.

The diagnosis of a patient can be medical and rational segmentation can do with new synthetic methodologies, the adaboost and neural community is a population-based totally stochastic search system to locate genuine answers to the optimization and seek issues. The ANN idea creates a sequence of populations for every successive technology with the aid of using a ramification mechanism and the operators consisting of selection, crossover, and mutation.

VIII. CONCLUSION

In this paper we made a survey of numerous preprocessing strategies to apply for MR mind image and a comparative examine of diverse segmentation techniques. Feature extraction methods and category techniques used by many researchers also are discussed. Even even though many segmentation algorithms are emerging these days, there is no universally widely wide-spread method for picture segmentation for the reason that end result of the segmentation is stricken by many factors like choppy form, length, and residences. Therefore we cannot recall a spinster method to be right. Each and each method has its personal gain that allows you to be equally exact for a particular type of photo. It is observed that the segmentation algorithms used for mind tumor detection may be multifarious and feature a couple of processes. It is realized that the accuracy of the detection relies upon on the extracted functions and so the combinational method is usually favored in which the capabilities like coloration and texture performs a completely important position as they've benefit of being awesome in nature. Detecting tumors in the temporal vicinity is tough as the thresholding and clustering technique generally wrongly detect eyes as tumors. In that case Naïve Bayes classifier suit ideal with accuracy of ninety four%. It is also located that KNN classifier plays well in conjunction with GLCM and were given an accuracy of ninety six.15%. Future studies may be targeting the combinational approach that mixes the advantages of two or more classifiers to supply the nice accuracy amongst others.

REFERENCES

1. Nicholas J. Tustison and James C. Gee , "N4ITK- Nick's N3 ITK Implementation For MRI" - April 30, 2009 Penn Image Computing and Science Laboratory University of Pennsylvania
2. W. Chen, X. Qiao, B. Liu, X.Qi, R.Wang and X.Wang, "Automatic brain tumor segmentation based on features of separated local square," *2017 Chinese Automation Congress (CAC)*, Jinan, 2017, pp. 6489-6493.
3. L. G. Nyul, J. K. Udupa and Xuan Zhang, "New variants of a method of MRI scale standardization," in *IEEE Transactions on Medical Imaging*, vol. 19, no. 2, pp. 143-150, Feb. 2000.doi: 10.1109/42.836373.
4. Michael Goetz,Christian Weber, "xtremely randomized trees based brain tumor segmentation", January 2014 , Medical and Biological Informatics, German Cancer Research Center (DKFZ), Heidelberg, Germany https://www.researchgate.net /publication/267762444
5. S. Reza and K. M. Iftekharuddin "Multi-fractal texture features for brain tumor and edema segmentation", Proc. SPIE 9035, Medical Imaging 2014: Computer-Aided Diagnosis, 903503 (18 March 2014);https://doi.org/10.1117/12.2044264
6. Benson C. C. and Lajish V. L.," A Novel Skull Stripping and Enhancement Algorithm for the Improved Brain Tumor Segmentation using Mathematical Morphology", *I.J. Image, Graphics and Signal Processing*, 2016, 7, 59-66 Published Online July 2016 in MECS (http://www.mecs-press.org/) DOI: 10.5815/ijigsp.2016.07.07.
7. R. C. Gonzales and R. E. Woods, ―Digital Image processing‖, Chapter 9, Third Edition, Prentice Hall, 2008.
8. Kavitha Srinivasan, Nanditha NM, "An intelligent skull stripping algorithm for MRI image sequences using mathematical morphology", Biomedical Research 2018; 29 (16): 3201-3206.
9. Shaima Abd El-Kader, Mohamed Morse, "Improvement Skull Stripping Algorithm of MRI Brain Images Based on Fuzzy Morphological Operation", International Journal of Science and Research (IJSR) ISSN (Online): 2319-7064.
10. K. Somasundaram and P. Kalavathi, Automatic Skull Stripping of Magnetic Resonance Images (MRI) of Human Head Scans Using Image Contour, Image Processing (NCIMP 2010)- http://ruraluniv.ac.in/papers/62.pdf.
11. Priyanka , Balwinder Singh, "An Improvement In Brain Tumor Detection Using Segmentation And Bounding Box", IJCSMC, Vol. 2, Issue. 11, November 2013, pg.239 – 246.
12. M. N. Nobi and M. A. Yousuf, "A New Method to Remove Noise in Magnetic Resonance and Ultrasound Images", Journal Of Scientific Research, 3 (1), 81-89 (2011).
13. J.Jaya1 , K.Thanushkodi 2 ,M.Karnan3, "Tracking Algorithm for De-Noising of MR Brain Images", IJCSNS International Journal of Computer Science and Network Security, VOL.9 No.11, November 2009.
14. Amrita Naik, Saaylee Diuker, "Comparison of Different Filters and Segmentation Techniques for Brain Tumor Detection Using Image Processing", International Journal of Research in Advent Technology, Vol.5, No.8, August 2017.
15. Shanmuga Sundaram R.S. and Sridhar T.M., Cancer Identification Using Probabilistic Boundary Value Edge Mapping. Aust. J. Basic & Appl. Sci., 8(1): 17-22, 2014
16. Padmakant Dhage, Prof. M. R. Phegade, "Watershed Segmentation Brain Tumor Detection", 2015 International Conference on Pervasive Computing (ICPC), 978-1-4799-6272-3/15/$31.00(c)2015 IEEE.
17. Joshua E. Cates, Ross T. Whitaker, Greg M. Jones, "Case Study: An Evaluation of User-Assisted Hierarchical Watershed Segmentation", Medical Image Analysis 9 (2005) 566–578.
18. Anam Mustaqeem, Ali Javed, Tehseen Fatima, "An Efficient Brain Tumor Detection Algorithm Using Watershed & Thresholding Based Segmentation", I.J. Image, Graphics and Signal Processing, 2012, 10, 34-39 Published Online September 2012 in MECS (http://www.mecs-press.org/) DOI: 10.5815/ijigsp.2012.10.05.
19. Pooja Thakur, Dr. Kuldip Pahwa, "Brain Tumor Detection, Segmentation Using Watershed Segmentation And Morphological Operation" International Journal of Advanced Research in Electronics and Communication Engineering (IJARECE) Volume4, Issue 6, June 2015.
20. Padmakant Dhage, Dr. S. K. Shah., "Watershed and Region Growing Segmentation Tumor Detection", International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181 IJERTV4IS031088 www.ijert.org -Vol. 4 Issue 03, March-2015.
21. Dawood Dilber, Jasleen, "Brain Tumor Detection using Watershed Algorithm", International Journal of Innovative Research in Science,Engineering and Technology- Vol. 5, Issue 3, March 2016, ISSN(Online) : 2319-8753-ISSN (Print) : 2347-6710.
22. Md. Shakowat Zaman Sarker, Tan Wooi Haw and Rajasvaran Logeswaran, "Morphological based technique for image segmentation", International Journal of Information Technology, Vol. 14 No. 1.
23. Luc Vincent, Edward R. Dougherty, "Morphological Segmentation for Textures and Particles", Published as Chapter 2 of Digital Image Processing Methods, E. Dougherty, Editor, Marcel-Dekker, New York, 1994, Pages 43--102.
24. J.Angulo, B.Schaack, "Morphological-Based Adaptive Segmentation And Quantification Of Cell Assays In High Content Screening", IEEE International Symposium on Biomedical Imaging · June 2008.
25. Dr. Raman Chadha, Shivani Thakur, "Brain Tumor Detection In Mri Using Morphological Operations Based Image Segmentation", international journal of engineering sciences & research technology-April, 2016.

26. Md. Shakowat Zaman Sarker, Tan Wooi Haw and Rajasvaran Logeswaran, "Morphological based technique for image segmentation", International Journal of Information Technology, Vol. 14 No. 1.
27. R. Kimmel, Numerical Geometry of Images, Springer Science+Business Media New York 2004The Osher-Sethian Level Set Method.
28. Xin-Jiang, Renjie-Zhang, "Image Segmentation Based on Level Set Method", Published by Elsevier, 2012 International Conference on Medical Physics and Biomedical Engineering.
29. V. Caselles, F. Catte, T. Coll, and F. Dibos, "A geometric model for active contours in image processing", Numer. Math. 66, 1-31 (1993).
30. R. Malladi, J. A. Sethian, and B. C. Vemuri, "Shape modeling with front propagation: A level set approach," IEEE Trans. Pattern. Anal. Mach. Intell., vol. 17, no. 2, pp. 158–175, Feb. 1995.
31. M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," International Journal of Computer Vision,., vol. 1, no. 4, pp. 321–331, Jan. 1987.
32. Pan Lin, Chongxun Zheng," Medical Image Segmentation by Level Set Method Incorporating Region and Boundary Statistical Information", CIARP 2004, LNCS 3287, pp. 654–660, 2004 ,Springer-Verlag Berlin Heidelberg 2004.
33. Manish Khare, Rajneesh Kumar Srivastava, "Medical Image Segmentation using Level set Method without reinitialization", International Conference on Signal, Image and Video Processing (ICSIVP) 2012.
34. Veronica Mazza, Massimo Turatto, Carlo Umilta, "Foreground–background segmentation and attention: A change blindness study", Article in Psychological Research · February 2005 DOI: 10.1007/s00426-004-0174-9 ·
35. Shutong Tsea, Laura Bradburya, Justin W.L. Wana, "A Combined Watershed and Level Set Method for Segmentation of Bright field Cell Images", Proceedings of SPIE - The International Society for Optical Engineering · February 2009.
36. Christophe Zimmer, Bo Zhang, Alexandre Dufour, "On the Digital Trail of Mobile Cells", IEEE Signal Processing Magazine · June 2006.
37. Khushboo Mantri, Dr. Shiv Kumar, "MRI Image Segmentation Using Gradient Based Watershed Transform In Level Set Method for a Medical Diagnosis System", Int. Journal of Engineering Research and Application, ISSN : 2248-9622, Vol. 4, Issue 11(Version 1), November 2014, pp.27-36.
38. Nguyen Mong Hien and Nguyen Thanh Binh, "Efficient Brain Tumor Segmentation in Magnetic Resonance Image Using Region-Growing Combined with Level Set", ICST Institute for Computer Sciences,Social Informatics and Telecommunications Engineering 2016.
39. Dilpreet Kaur1, Yadwinder Kaur, "Various Image SegmentationTechniques: A Review", IJCSMC, Vol. 3, Issue. 5, May 2014, pg.809 – 814.
40. Shilpa Kamdi1, R.K.Krishna2, "Image Segmentation and Region Growing Algorithm", International Journal of Computer Technology and Electronics Engineering (IJCTEE) Volume 2, Issue 1.
41. Archana Chaudhari, Vaidarbhi Choudhari, "Automatic Brain Mr Image Tumor Detection Using Region Growing", Proceedings of SARC International Conference, 27th August, 2017, Nagpur, India, ISBN: 978-93-86831-47-7
42. A. Afifi and S. Ghoniemy, E.A. Zanaty and S. F. El-Zoghdy, "New Region Growing based on Thresholding Technique Applied to MRI Data", I. J. Computer Network and Information Security, 2015, Published Online June 2015 in MECS (http://www.mecs-press.org/) DOI: 10.5815/ijcnis.2015.07.08.
43. N. Mohd Saad, S.A.R. Abu-Bakar. "Fully Automated Region Growing Segmentation of Brain Lesion in Diffusion-weighted MRI", IAENG International Journal of Computer Science, 39:2, IJCS_39_2_03.
44. K. Bhargavi, S. Jyothi, "A Survey on Threshold Based Segmentation Technique in Image Processing", International Journal Of Innovative Research & Development, November, 2014, Vol 3 Issue 12.
45. G. Evelin Sujji, Y.V.S. Lakshmi, G. Wiselin Jiji, "MRI Brain Image Segmentation based on Thresholding", International Journal of Advanced Computer Research (ISSN (print): 2249-7277 ISSN (online): 2277-7970).
46. Umit Ilhana, Ahmet Ilhana, "Brain tumor segmentation based on a new threshold approach", ICSCCW 2017, 22-23 August 2017, Budapest, Hungary.
47. Lopes, Nuno & Couto, Pedro & Sola, Humberto & Melo-Pinto, Pedro. (2010). "Automatic Histogram Threshold Using Fuzzy Measures". Image Processing, IEEE Transactions on. 19. 199 - 204. 10.1109/TIP.2009.2032349.
48. Chaitra G., Sarika Tale, "Detection and Segmentation of Brain Tumor by Thresholding and Bounding-Box using K-Means as a Seed", International Journal of Computer Applications (0975 – 8887) Volume 173 – No.5, September 2017.
49. Nobuyuki Otsu, "A Tlreshold Selection Method from Gray-Level Histograms", IEEE Transactions On Systrems, Man, And Cybernetics, Vol. Smc-9, No. 1, January 1979.
50. Salem Saleh A-amri1, N.V. Kalyankar and Khamitkar, "Image Segmentation by Using Thershod Techniques ",Journal Of Computing, Volume 2, Issue 5, May 2010, Issn 2151-9617.
51. Patil Priyanka Vijay, Prof. N. C. Patil," Gray Scale Image Segmentation using OTSU Thresholding Optimal Approach", Journal for Research| Volume 02| Issue 05 | July 2016.
52. Arthur L. da Cunha, Jianping Zhou," The Nonsubsampled Contourlet Transform: Theory, Design, and Applications", IEEE Transactions On Image Processing, Vol. 15, No. 10, October 2006.
53. Y. Lu and M. N. Do, "A new contourlet transform with sharp frequency localization," IEEE Int. Conf. Image Processing, Atlanta, GA, Oct. 2006., pp. 1–4.
54. Kangkana Bora, Lipi B Mahanta, "Fuzzy NSCT based Feature Extraction Method for Automated Classification of Pap Smear images", International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 9 (2018) pp. 6709-6716.
55. Chandan Saha, Md. Foisal Hossain, "MRI Brain Tumor Images Classification Using KMeans Clustering, NSCT and SVM", 2017 4th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (UPCON).
56. J.S. Leena Jasmine, Dr.s.Baskaran, "Nonsubsampled Contourlet Transform Based Classification of Microcalcification in Digital Mammograms", International Conference on Modeling, Optimization and Computing-ICMOC-2012.
57. Nitish Zulpe,Vrushsen Pawar, "GLCM Textural Features for Brain Tumor Classification", IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 3, No 3, May 2012.
58. Haralick R. M., Shanmugam K., Dinstein I., "Textural Features for Image Classification", IEEE Trans. On Systems Man and Cybernetics, 1973, 3(6), p. 610-621.
59. SivaSankari.S, Sindhu.M, Sangeetha, "Feature Extraction of Brain Tumor Using MRI", IJIRSET, Vol. 3, Issue 3, March 2014.
60. He Xiaolan and Wu Yili, "Texture Feature Extraction Method Combining Nonsubsampled Contour Transformation with Gray Level Co-occurrence Matrix", Journal Of Multimedia, Vol. 8, No. 6, December 2013.
61. A.Harshavardhan, Dr. Suresh Babu, "Analysis of Feature Extraction Methods for the Classification of Brain Tumor Detection", International Journal of Pure and Applied Mathematics-Volume 117 No. 7 2017, 147-155.
62. Reema Mathew A, Dr. Babu Anto P, "Brain Tumor Segmentation And Classification using DWT,Gabour Wavelet And GLCM", IEEE Trans.- 2017 International Conference on Intelligent computing Instrumentation and Control Technologies (ICICICT).
63. Suganthy, M. and P. Ramamoorthy, "Principal Component Analysis Based Feature Extraction,Morphological Edge Detection and Localization for Fast Iris Recognition", Journal of Computer Science 8 (9): 1428-1433, 201-ISSN 1549-3636-2012.
64. Sonali B. Gaikwad, Madhuri S. Joshi, "Brain Tumor Classification using Principal Component Analysis and Probabilistic Neural Network" International Journal of Computer Applications (0975 – 8887)- Volume 120 – No.3, June 2015.
65. A. Ahmadian, A. Mostafa, "An Efficient Texture Classification Algorithm using Gabor Wavelet", Conference: Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE-2003.
66. Yi -hui Liu, Manita Muftah, Tilak Das, "Classification of MR Tumor Images Based on Gabor Wavelet Analysis", J. Med. Biol. Eng., Vol. 32. No. 1 2012.
67. Mr. Akshay M. Malviya, "Review on Automatic Brain Tumor Detection based on Gabor Wavelet", International Journal of Engineering Research & Technology (IJERT) - Vol. 3 Issue 1, January – 2014.
68. Darragh Smyth, Ben Willmore, "The Receptive-Field Organization of Simple Cells in Primary Visual Cortex of Ferrets under Natural Scene Stimulation", The Journal of Neuroscience, June 1, 2003.

69. X.L. Wang, X. Wang and L. Hu, "A Fast Texture Feature Extraction Method Based on Gabor Wavelets", Int'l Conf. IP, Comp. Vision, and Pattern Recognition | IPCV'16 |.
70. Sanjay Shingade, Pritesh Jain, "Identification of Brain Tumor using Gabor Wavelets Techniques", International Journal of Innovative Computer Science & Engineering- Volume 4 Issue 2; March-April-2017; Page No. 16-21.
71. Prof.Michael Brady, FRS, Fello of the Royal Academy of Engineering(FREng), "Image Segmentation and Classification" Lecture5- http://www.robots.ox.ac.uk/~jmb/lectures/ InformaticsLecture5.pdf
72. Shichao Zhang, Xuelong Li, "Efficient KNN Classification With Different Numbers of Nearest Neighbors", 2017 IEEE Transactions On Neural Networks And Learning Systems
73. P.A.Charde, S.D.Lokhande, "Classification Using K Nearest Neighbor for Brain Image Retrieval", International Journal of Scientific & Engineering Research, Volume 4, Issue 8, August-2013.
74. Shweta Taneja, Charu Gupta, "An Enhanced K-Nearest Neighbor Algorithm Using Information Gain and Clustering" , IEEE- 2014 Fourth International Conference on Advanced Computing & Communication Technologies.
75. Sunita Singh, "Using classification Of Human Brain Tumors From Mri Using K-Nn Algorithm K-Nn Algorithm", International Journal of Advances in Science Engineering and Technology, Volume- 3, Issue-1, Jan.-2015.
76. Jingwen Sun,Weixing Du, "A Survey of kNN Algorithm" - Information Engineering and Applied Computing (2018).
77. R. Ragupathy, B. Abirami, "FCM and KNN Based Automatic Brain Tumor Detection", Br J Med Health Res. 2017;4(5).
78. Nikita V. Chavan, B.D. Jadhav, "Detection and Classification of Brain Tumors", International Journal of Computer Applications- Volume 112 – No. 8, February 2015.
79. Bharanidharan N, Harikumar Rajaguru, "Performance Analysis of KNN Classifier with and Without GLCM Features In Brain Tumor Detection", IJITEE- Volume-8 Issue-2S2 December, 2018.
80. Vladimir N. Vapnik, "An Overview of Statistical Learning Theory", IEEE ransactions On Neural Networks, Vol. 10, No. 5, September 1999.
81. Bernhard, PChris,VladimirVapnik AT&T Bell Laboratories 101 Crawfords Corner Road,Holmdel NJ 07733,USA, "Extracting Support Data for a Given Task"- KDD-95 Proceedings. Copyright © 1995.
82. Chen Junli, Jiao Licheng, "Classification Mechanism of Support Vector Machines", 2000 IEEE -Proceedings of ICSP2000.
83. Amruta Hebli, Dr. Sudha Gupta, "Brain Tumor Prediction and Classification using Support Vector Machine", 2017 IEEE.
84. T.Sathies Kumar, K.Rashmi, "Brain Tumor Detection Using SVM Classifier-3rd International Conference on Sensing,Signal Processing and Security"(ICSSS)-2017 IEEE
85. Johan Suykens, "Support Vector Machines and Kernel based Learning" -IJCNN 2005 Tutorial - July 2005.
86. V. Panca and Z. Rustama, "Application of Machine Learning on Brain Cancer Multiclass Classification", International Symposium on Current Progress in Mathematics and Sciences- Published Online: 10 July 2017-https://doi.org/10.1063/1.4991237.
87. Xiaowu Su, Lizhen Liu, "Image Classification via Support Vector Machine", 2015 4th International Conference on Computer Science and Network Technology (ICCSNT 2015)- 2015 IEEE.
88. Vilas H. Gaidhane, Yogesh V. Hote, "A New Approach for Estimation of Eigenvalues of Images", International Journal of Computer Applications, Volume 26– No.9, July 2011.
89. Miriam Martinez-Arroyo,L. Enrique Sucar, "Learning an Optimal Naive Bayes Classifier"-The 18th International Conference on Pattern Recognition(ICPR'06)-2006 IEEE.
90. Hamad Alhammady, "Weighted Naive Bayesian Classifier", ACS International Conference on Computer Systems and Applications-2007 IEEE.
91. Hongjian Fan, Kotagiri Ramamohanarao "A Bayesian approach to use emerging patterns for classification", Proceedings of the 14th Australasian Database Conference, ADC 2003, February 2003.
92. Hein Tun Zaw, Noppado Maneerat, Khin Yadanar Win, "Brain tumor detection based on Naïve Bayes Classification", 2019 5th International Conference on Engineering, Applied Sciences and Technology (ICEAST)- 2019 IEEE.
93. Kalyani A. Bhawar, Prof. Ajay S. Chhajed, "Brain Tumor Classification Using Data Mining Algorithms", IJESRT- November, 2016.
94. Danda Shashank Reddy, Chinta Naga Harshitha, "Brain tumor prediction using naïve Bayes' classifier and decision tree algorithms", International Journal of Engineering &Technology, 7 (1.7) (2018) 137-141.
95. Cicalese F., Jacobs T., Laber E., Molinaro M.(2010), "On Greedy Algorithms for Decision Trees."- International Symposium on Algorithms and Computation.(ISAAC) - 2010. Lecture Notes in Computer Science, vol 6507. Springer, Berlin, Heidelberg.
96. Alkhalid A., Chikalov I., Moshkov M. (2013) "Comparison of Greedy Algorithms for Decision Tree Optimization",Rough Sets and Intelligent Systems - Professor Zdzisław Pawlak in Memoriam. Intelligent Systems Reference Library, vol 43. Springer, Berlin, Heidelberg.
97. D.F. Specht, "Probabilistic Neural Networks" Neural Networks, vol. 3, No.1, pp. 109-118, 1990.
98. D.F. Specht, "Probabilistic Neural Networks for Classification, mapping, or associative memory", Proceedings of IEEE International Conference on Neural Networks, Vol.1, IEEE Press, New York, pp. 525-532, June 1988.
99. Mohd Fauzi Othman and Mohd Ariffanan, "Probabilistic Neural Network For Brain Tumor Classification", Second International Conference on Intelligent Systems, Modelling and Simulation-2011 IEEE- DOI 10.1109/ISMS.2011.32.
100. V.M. Ramaa Priyaa, "Probabilistic Neural Network for Brain Tumor Classification", IJAREEIE, Vol. 2, Issue 5, May 2013.
101. Georgiadis.et all , " Improving brain tumor characterization on MRI by probabilistic neural networks and non-linear transformation of textural features",Computer Methods and program in biomedicine, vol 89, pp24-32, 2008.
102. Rajeshwar Nalbalwar,Umakant Majhi, "Detection of Brain Tumor by using ANN", International Journal of Research in Advent Technology, Vol.2, No.4, April 2014.
103. Yoav Freund, Robert E. Schapire, "A Short Introduction to Boosting", Journal of Japanese Society for Artificial Intelligence, 14(5):771-780, September, 1999.
104. Ravindra Sonavane, Poonam Sonar, "Classification and Segmentation of Brain Tumor Using Adaboost Classifier".,International Conference on Global Trends in Signal Processing, Information Computing and Communication-2016 IEEE.
105. Astina Minz, "MR Image classification using adaboost for brain tumor type", 2017 IEEE 7th International Advance Computing Conference (IACC).

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