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PYTHON BASED BRAIN TUMOR DETECTION USING MACHINE LEARNING

[1] **Dr.K.N.S Lakshmi,** [2] **Menda Devi**

[1] Associate Professor &HOD, [2] MCA 2ND year
[1]Master of Computer Applications,
[1]Sanketika Vidhya Parishad Engineering College, Visakhapatnam, India

Abstract : The detection of brain tumours using magnetic resonance images is a difficulty for modern medical imaging studies. (MRI). Experts typically use MRI images to create images of the soft tissues in the human body. In place of surgery, it is utilised to analyse human organs. Image segmentation is necessary for the detection of brain tumours. The brain is divided into two separate regions for this reason. This is regarded as one of the most crucial but challenging steps in the process of finding a brain tumour. Therefore, it is crucial to precisely segment the MRI pictures before asking a computer to make the correct diagnosis. Previously, a variety of algorithms were created for the segmentation of MRI images utilising various instruments and methods. The methodologies and procedures utilised to identify brain tumours using MRI image segmentation are, however, thoroughly reviewed in this work. Finally, the report offers a path for the future trend of more sophisticated research investigations on brain picture segmentation and tumour identification in a succinct discussion at the end.

***IndexTerms* - Brain tumors, Magnetic resonance images(MRI), Medical imaging, Image segmentation, soft tissues, Surgery, Human organs, Algorithms, Methods, Research investigations**

I.INTRODUCTION

One of the most prevalent brain disorders, brain tumor, has impacted and ruined many lives. The International Agency for Research on Cancer (IARC)[1] estimates that each year, more than 126000 persons worldwide receive a diagnosis of a brain tumor, with a mortality rate of more than 97000. Statistics still demonstrate that people with brain tumours have a poor prognosis despite ongoing efforts to address the issue. Recently, researchers have employed a multidisciplinary approach to better understand the disease and discover more efficient treatment options. This strategy draws on information from the fields of health, mathematics, and computer science.The two most frequent exams used to determine the presence of a brain tumour and its location for a few specialised treatment options are magnetic resonance imaging (MR)[2]and computer tomography (CT)[3]scanning of the brain. For brain tumors, there are currently a variety of therapy options. Surgery, radiation treatment, and chemotherapy are some of the alternatives. Depending on the size, nature, and grade of the tumor, many treatment methods are available. It also depends on whether the tumour is pressing against critical regions of the brain. When choosing a course of treatment, it's crucial to take into account the extent of the tumour's spread across the central nervous system (CNS)[5] or the body as well as any potential negative consequences on the patient's general wellbeing and treatment preferences.To reduce diagnostic errors, precise diagnosis of the type of brain dysfunction is crucial for treatment planning. Utilizing computer-aided diagnostic (CAD)[4] technologies can increase accuracy. The fundamental idea behind CAD is to offer a computer output as a second opinion to aid radiologists in their image interpretation and to shorten the reading time for images. This enhances the consistency and accuracy of radiological diagnosis. However, it is quite challenging to segment the image of a brain tumour. First off, there is a broad category of tumour forms with a range in size and shape Another element that makes automated brain tumour picture recognition and segmentation problematic is the appearance of brain tumours at various sites in the brain with varying image intensities.The methodologies and procedures utilised to identify brain tumours using MRI image segmentation are reviewed in this research. The discussion of potential directions for further development of brain segmentation research finishes the paper.

II. BRAIN ANATOMY OVERVIEW:

The human brain, which serves as the control centre for all of the body's organs, is a highly specialised organ that enables a person to adapt to and withstand a variety of environmental situations. The human brain gives a person the ability to express themselves in words, carry out actions, and share thoughts and feelings. To comprehend the goal of this study, the tissue structure and anatomical components of the brain are described in this section. The grey matter (GM) and white matter (WM) tissues make up the brain. (WM). The basal nuclei, which are the grey matter nuclei situated deep inside the white matter, are composed of neuronal and glial cells, also known as neuroglia or glia, that regulate brain activity. The caudate nucleus, putamen, pallidum, and claustrum are among the basal nuclei. The cerebral cortex is connected to other brain regions through white matter fibers, which are made up of many elinated axons. The corpus callosum, a wide band of white matter fibers, connects the left and right hemispheres of the brain. Cerebrospinal fluid (CSF)[6], which surrounds the brain and spinal cord through ventricles and is made up of glucose, salts, enzymes, and white blood cells, is also found in the brain and serves as an additional layer of protection against damage.

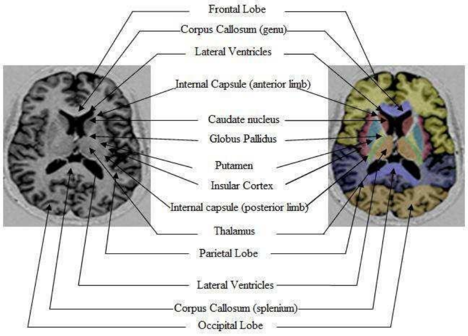


Figure 1: Shows The Human Brain's General Structure On The Left Side In An Axial Slice MR Image And On The Right Side In A Colour-Coded Version.

Figure 2 depicts the brain's anatomy. The brain stem and cerebrum make up its structure. The greatest portion of the brain is the cerebrum. It has a connection to conscious movement, ideas, and experiences. Additionally, it is divided into two half, the right and left hemispheres. The opposite side of the body is controlled by each. The frontal, temporal, parietal, and occipital lobes are the four lobes that make up each hemisphere. The cerebellum, the second-largest component of the brain, is. It has to do with managing bodily motor activities like walking, balance, posture, and general motor coordination. It is connected to the brain stems and is located towards the back of the brain. Both the cerebellum and the cerebrum have small but deeply positioned amounts of grey matter, internal white matter, and a very thin outer cortex of grey matter. The brainstem is joined to the spinal cord. It is situated near the brain's base. The brainstem regulates numerous essential bodily processes, including reflexes, cardiac, sensory, and motor pathways. The medulla oblongata, pons, and midbrain are its three structural components.

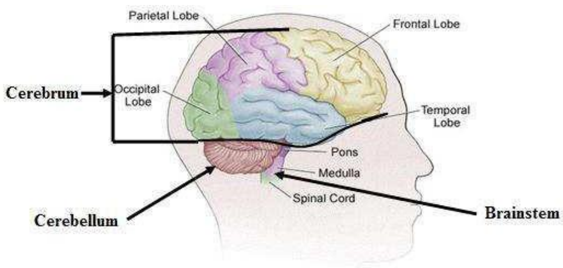


Figure 2: The Major Subdivision Of Human Brain

II.A) BRAIN TUMORS:

Under some circumstances, brain cells proliferate and multiply uncontrollably because the system that controls the growth of normal cells is unable to control the growth of the brain cells for a variety of reasons. The brain tumour is an abnormal mass of brain tissue that takes up space in the skull, interferes with normal brain activities, and puts pressure on the brain. Some brain tissues are moved, pushed up against the skull, or are to blame for nerve damage in other healthy brain tissues as a result of increased pressure on the brain. Scientists have classified brain tumour according to the location of the tumor, type of tissue involved, whether they are noncancerous or cancerous. The site of the origin (primary of secondary) and other factors involved. World Health Organization (WHO) classified brain tumour into 120 types. This classification is done on the basis of the cell origin and the behaviour of the cell from less aggressive to more aggressive behaviour. Even, some tumour types are graded ranging from grade I (less malignant) to grade IV (more malignant). This signifies the rate of the growth despite of variations in grading systems which depends on the type of the tumour Primary brain tumours are those that started in the brain and get their names from the cell types that gave rise to them. They might be malignant (cancerous) or benign (non-cancerous). (cancerous). Slow-growing benign tumours do not metastasize or spread to neighbouring tissues. Even a less aggressive tumour can exert significant pressure on the brain and cause malfunction because it only takes up a little amount of space. On the other hand, aggressive tumours may develop more quickly and invade additional areas. These tumours each have distinctive biochemical, radiological, and clinical traits Secondary brain tumours have their origins elsewhere in the body. These tumours are made up of cancer cells that have spread or metastasized to the brain from another part of the body. Lung cancer, breast cancer, melanoma, kidney cancer, bladder cancer, certain sarcomas, testicular and germ cell tumours are the most frequent causes of secondary brain tumours.

II.B) MRI BRAIN IMAGING AND CHARACTERISTICS OF BRAIN TUMORS:

Several imaging methods, including magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET)[7] single photon emission computer tomography (SPECT)[8], and cerebral angiography, are used to analyse brain tumours. Due to their broad availability and capacity to provide high resolution images of both diseased tissues and normal anatomical structures, CT and MR imaging are currently the most popular procedures. Because of the following factors, magnetic resonance imaging (MRI), a technique used to see diseased or other physiological changes in living tissues, is frequently utilised for brain tumour imaging. Unlike CT, SPECT, and PET, it does not employ ionising radiation. Compared to the other methods listed above, its contrast resolution is better. Because MRI machines can provide 3D space images, they are better equipped to locate tumours because they can simultaneously gather functional and anatomical data about the tumour.It is vital to explain the MR imaging process before going into detail about the characteristics of brain tumours' MR images. Protons in the body's water molecules align in either a parallel (low energy) or anti-parallel (high energy) orientation with the magnetic field when the patient is exposed to a strong magnetic field during MR imaging. The spinning protons are then forced to leave their equilibrium state by the introduction of a radiofrequency pulse. Protons return to equilibrium once a radio frequency pulse is interrupted, and this causes them to create a sinusoidal signal at a frequency that depends on the local magnetic field. The image is then produced by the scanner's radio frequency coils or resonators, which have detected the signal.

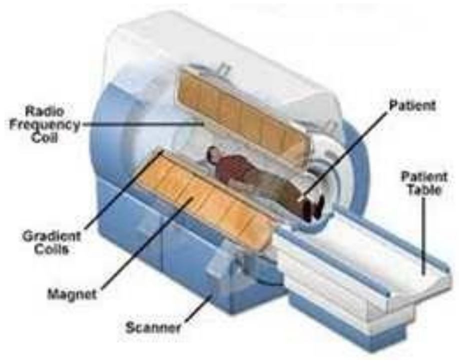


Figure 3: Mri Scanner Cutaway

II.C)MR IMAGING (MRI):

Signal processing in MRI takes signal emissions into account. These are distinguished by the weighting of different magnetic signals with specific values for the echo time (Tg) and repetition time (Tr). Three alternative images produced by the signal processing are possible from the same body: T1-weighted, T2-weighted, and proton density (PD)-weighted images.

Figure 4 (a) demonstrates how the coronal plane, sagittal plane, and plane are used to evaluate the patient's head while making a clinical diagnosis.

Figure 4(b), (c), and (d) also display T1-weighted brain MR images from various planes.

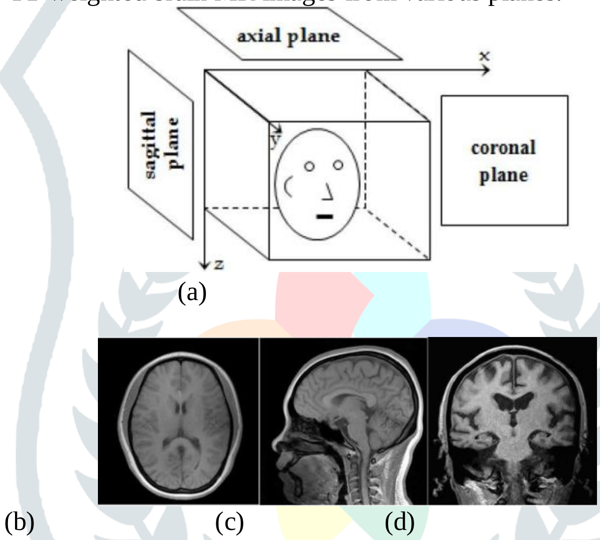


Figure 4: Brain MR Images From (B) Axial Plane, (C)Sagittal Plane And (D) Coronal Plane

Depending on the kind of echo recorded, there are two primary groups of MR imaging sequences: spin echo sequences and gradient echo sequences. The typical MRI pulse sequences for anatomical and pathological details have been the spin echo (SE)[9] sequence and its variation fast spin echo (FSE)[10] sequence.MRI scans of the brain might produce normal or abnormal results. Grey matter (GM), white matter (WM), and cerebrospinal fluid (CSF) components make up the typical brain. Along with normal brain tissues, the aberrant brain frequently has active tumour, necrosis, and edoema. Edoema is seen close to the boundaries of active tumours, whereas necrosis is a dead cell found inside an active tumour. Edoemas[11], which are caused by local blood-brain barrier disruption, frequently overlap with normal tissues and are challenging to differentiate from the other tissues.The grey level intensity values in the pixel spaces make up an MRI scan image. The cell density in the volume being scanned determines the grey level intensity values. An anomaly[12] is present when a region is darker.

The image intensity level for brain tissues increases in normal brain MR pictures.

brightness in the T1-weighted (T1-w) image is from CSF, GM, to WM, and in the T2-weighted (T2-w) image is from WM, GM, to CSF. Figure 5 gives an illustration of this.

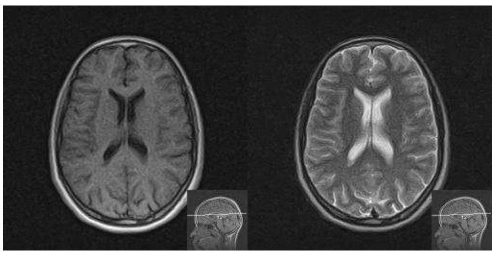
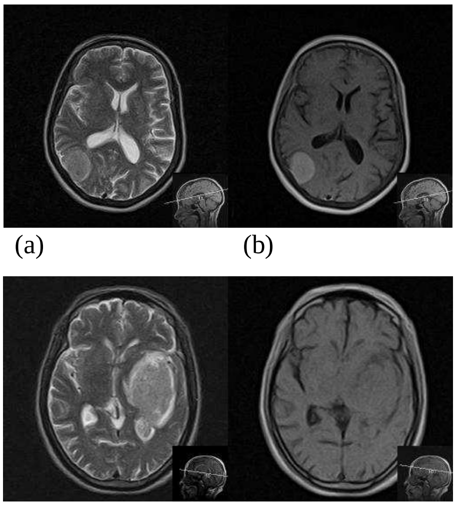


Figure 5: Original Raw MRI Data From Pioneer Diagnostic Canter. (A) T1-W Axial Scan Image, (B) T2-Waxial Scan Image

Depending on the type of tumour, the intensity level of tumorous tissues on T1-w and T2-w MR images differs in a tumorous brain. On T1-w, the majority of tumours show low or intermediate signal intensity, however for some tumours, such as glioblastoma multiforme, this is not the case. The majority of tumours on T2-w have dazzling intensity, while some have low intensity; lymphoma tumours being the classic examples. Examples of MRI tumour intensity level features are shown in Figure 6.


(a) (b)

(c) (d)

Figure 6: Tumor Region Intensity Characteristics, Original Raw MRI Data From Pioneer Diagnostic Center.
(A) And (C) T2-W Images, (B) And (D) T1-W Images. Tumor Region In A) Low Intensity, B) High Intensity, C) High Intensity And D) Low Intensity

III. LITERATURE REVIEW:

III.A) IMAGE SEGMENTATION:

By drawing borders between the healthy brain and the malignant and tumorous brain, segmentation serves the function of dividing picture information into distinct, relevant sections. Regions of the image must not overlap during segmentation. Therefore, segmentation can be formally defined as follows:

If F is the set of all pixels and P( ) is a homogeneity predicate[13] defined on groups of connected pixels, then segmentation is a partitioning of the set F into a set of connected subsets or regions (S1, S2, …, Sn) such that:

$$\bigcup_{i=1}^{n} s_i = F \quad \text{With } S_i \cap S_j = \emptyset \qquad i \neq j$$

Typically, homogeneity predicates P() are based on the brightness, colour, texture, etc. of the image. Image segmentation[14] can be divided into three groups, according to Harlick and Shapiro: spatial clustering split and merge techniques, and region growth schemes.

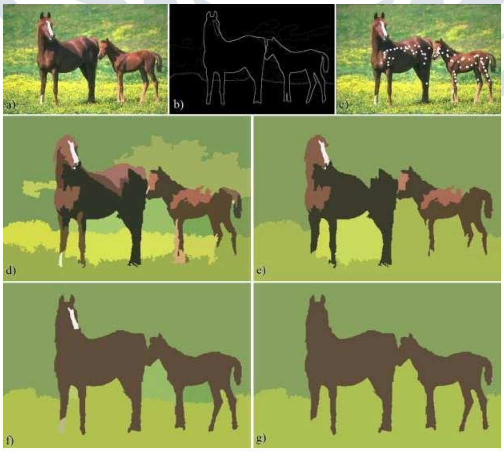


Figure 7: (A) Original Image. (B) Ground Truth-Based BorderImage. (C) Seeded Image. (D), (E) Segmentation Results Using The RGB As Color Space Presenting Their Best Rand Index And Best BGM, Respectively. (F) And (G) Segmentation Results Using The Adaptive Discrimination Function Generated By The Seed Points Inpresenting, Respectively, The Results With Best Rand Index AndBest BGM Index

III.B)SPATIAL CLUSTERING

Picture segmentation and picture clustering are not the same thing. Image segmentation is the grouping of images in the spatial domain. Image clustering involves grouping in the measurement space. Clustering might result in overlapping zones. Segmentation does not allow for the creation of overlapping zones. Spatial clustering combines histogram approaches with spatial linking techniques for improved results. If the homogeneity criteria is not met, the split method begins with the complete image and repeatedly divides each segment into quarters. These splits can sometimes separate parts of the same entity. The merge method connects adjacent object pieces. It is critical to designate separate regions for intensity-based segmentation so that over- and under-segmentation of regions can be distinguished. This type of task can be completed utilising split segmentation[15] or merge segmentation[16]. If a region is not properly segmented, it can be corrected by adding boundaries to or breaking certain regions that contain pieces of different items. If a region has been segmented more than necessary, it can be corrected by removing false boundaries and merging adjacent sections that belong to the same item or feature.

III.C)REGION GROWING

Growing an area joins neighbouring points to form a larger region. Certain conditions associated with the selection of a threshold value govern the process of region growth. Growing a seeded region begins with one or more seed points and then expands within the region to generate a bigger region that meets some homogeneity criteria[17]. The homogeneity of a region in an image can be determined by any attribute of the region, such as texture, colour, or average intensity.

IV)THRESHOLDING BASED METHODS

Image segmentation in the thresholding approach is based on the grey level intensity value of pixels. A thresholding technique aims to find an intensity value, known as the threshold, that distinguishes the intended groups. The segmentation is then accomplished by categorising all pixels with intensities greater than the threshold as one class and all other pixels as another. However, thresholding is frequently used as the first step in an image segmentation process. Its biggest shortcoming is that it generates only two classes and does not operate when confronted with structures that lack defined borders.

Image segmentation with threshold holding is said to be a simple and effective method for segmenting photographs with luminous objects on dark backgrounds. Threshholding is a strategy that is based on image space area, or picture properties. It is used to convert a multilayer image to a binary image. For example, it chooses a suitable threshold to divide image pixels into several regions and spate objects to form the background. Any pixel (x, y) is considered to be part of the object if its intensity is greater than or equal to the threshold value. There are two sorts of thresholding values based on thresholding value: global and local thresholding. When T is fixed or constant, the method is known as global thresholding. Otherwise, it is referred to as local thresholding. The global thresholding is likely to fail if the background light is uneven. Multiple thresholds are used in local thresholding to compensate for uneven illumination. In most cases, the threshold is chosen interactively. However, automatic threshold algorithms can be derived. The threshold approach has the constraint of producing only two classifications. As a result, it cannot be used in multicultural imagery. Furthermore, because thresholding does not take into account an image's spatial characteristics, it is susceptible to noise. Both of these artefacts thus distort the image's histogram, making separation more intricate and challenging.

a) Threshold and outlier detection and Gaussian models:

The edema region may require secondary analysis followed by treatment after the primary focus on the tumor region .The detecting technique uses a concept to detect difference between normal andabnormal space. Intensity features are used in this Technique

b) Probability level set evolution:

The automatic method has a lower level ofagreement with the human experts compared to the semi automatic method. Only two MR images samples are used fortesting and evaluate

c) Marker Controlled Watershed:

Different values of threshold are selected for creating the Marker Controlled Watershed. Threshold values are highly dependent on shape and size of tumor and also on the view points (axial, coronal) of images

d) OTSUs Threshold:

Tumor contrast suffusion high quality MRIscans with resolution and contrast for automated volume measurement andDisplay

e) Threshold maxima:

An automatic image based method todetect tumors in 2D MRI head scans.Inter-hemisphere fissure(IHF) andsymmetrical nature threshold of the brainare used in the tumor detection

V)REGION GROWING BASED METHODS:

Region growing is a technique to extract a regionof the image based on predefined criteria. In its simplest form, region growing requires a seed pointthat is manually selected by an operator, and extracts all pixels connected to the initial seed withthe same intensity value. To eliminate the dependency on initial seeds and to make the methodautomatic statistical information and a priori knowledge can be incorporated in the algorithm. Region growing can be so sensitive to noise, that itmay cause extracted regions to have holes or even is disconnected. Conversely, overlapping gray value distribution in MR images can cause separate regions to become connected .Region growing is not often used alone because itis not sufficient to segment brain structuresaccurately and robustly. Pohle suggested that regiongrowing can be an integrated technique using multi-level sets of boundary information. In the algorithm, region growing is used as a propagationforce and boundary information is used as a stopping criteria. Pohle successfully applied this technique to a total of 246 slices containing imagesof axial tumor obtained from 10 patients. However, this method is semi-automatic as it relieson manual input seed region for region growing. A more accurate method needs precise anatomical information to locate initial seed pixels for each anatomical region and together with their associatedhomogeneity. Its reliability depends on accuracy ofthe model assumption on homogeneity and region characteristics. As compared to edge detection method, segmentation algorithms based on region aresimpler and have strongly immune to noise. Edge method divide an image based on frequent changes in intensity near the edges, while, region method divide an image into regions which are similar as per a set of predetermined criteria. Segmentation algorithms based on region consist of the following methods:

V.A)Region Growing:

This is a method that divides pixels in a picture into sub-areas or huge regions depending on a specified criterion. The region growing process is divided into four steps:

a. Choosing a collection of seed pixels from an original image.

b. Choosing a set of identical criteria, such as grey level intensity or hue, and developing a stopping rule.

c. To grow areas, attach neighbouring pixels with predefined attributes identical to seed pixels to each seed.

d. To control the expanding region when it is discovered that no more pixels fulfil the condition for inclusion in that region, such as (size, similarity between a prospective pixel and the pixel grown thus far, or form of the already grown region).

V.B)Neural networks based methods

Artificial neural network computational models comprised of processing elements (called neurons) and weighed connections between them are used in neural network-based segmentation approaches. At the connections, the weights (coefficients) act as multipliers. To achieve the coefficient values, training is required. Various forms of neural networks have been developed and applied in medical picture segmentation and other domains. Some of the techniques used in segmentation are multilayer perceptrons, back-propagation learning algorithms (MLP), Hopfield neural networks (HNN)[18], and self-organizing maps (SOM)[19] neural networks. A comprehensive treatment of neural networks can be found in. The ability of neural networks to learn segmentation procedures through some type of learning process has attracted more image segmentation researchers than other image processing techniques. One of the earliest uses of MLP in brain tumour segmentation was by , who trained the neural networks using a known diagnostic picture. The information gathered during the training procedure was used to build an MLP model. For adaptive systems, subsequent image information was used to generate the next training data set, which was then used to segment the subsequent image. Iteratively, the complete image data set was segmented. The proposed method is semi-automatic and requires constant engagement with the user. Tumour segmentation accuracy is assessed using Jaccard's similarity measure between areas designated as tumours by human experts and the suggested automatic approaches, yielding a similarity index ranging from 0.6 to 0.8. Self-organizing maps (SOM), a sort of unsupervised learning artificial neural network, can be used to detect and visualise brain tumours. Logeswari and Karnan employed a modified version of SOM termed hierarchical self-organizing map (HSOM)[20] to perform detection and visualisation. Their system is divided into two stages. The MRI brain picture is preprocessed to reduce artefacts in the first phase before being segmented using HSOM. The number of neural units in the competitive layer in conventional SOM must be about equal to the number of regions needed in the segmented image. Unfortunately, determining the correct number of areas in the segmented image is difficult or impossible a priori. HSOM solves this problem by running a process that takes into account weight vectors, execution time, and tumour pixels discovered. However, the accuracy of the results obtained by Loges Wari and Karnan Karnan cannot be quantified and failed to distinguish the outer layer of the brain as seen in MR brain images.

V.C)Fuzzy based methods

Fuzzy logic is a set of mathematical principles for knowledge representation based on degrees of membership rather than on crisp membership of classical binary logic. In brain tumor segmentation fuzzy systems allow for the development of methods and algorithms to perform the tasks relatedto intelligent human behaviours gordillo used a fuzzy logic system to segment and detect tumours by combining expert knowledge and MR image data to create fuzzy rules. This system is completely automated and uses unsupervised learning. Knowledge extraction was accomplished as a novel technique to create membership functions for MRI data using intensity histogram analysis. With trials done on two forms of brain tumours, glioblastoma and meningioma multiform, the detection and segmentation results were found to be good, with the lowest score of 71% and the best score of 93%. Despite the fact that the experiment is limited to two types of brain tumours, glioblastoma and meningioma multiforme. Dunn proposed utilising the fuzzy c-means (FCM)[21] clustering technique for picture segmentation. Several studies have used FCM and its improved versions to segment brain tumours from brain MR images. Rajendran presented fuzzy logic processing on MRI for brain tumour segmentation using c-means clustering. The fuzzy clustering tumour class output was utilised to initialise the region-based approach, which iteratively progresses towards the final tumour border. This method was tested to determine its efficiency for 15 MR images where manual segmentation ground truth is provided. The obtained results are good, with a Jaccard coefficient average value of 83.19% and sensitivity of 96.37%. Glioblastoma-multiform (GBM)[22] brain tumours were segmented using the FCM clustering technique. Although the FCM approach is simple, fast, and unsupervised, the susceptibility of FCM to noise and initialization parameters resulted in error in tumour segmentation. Hsieh used the percent match and correspondence ratio to assess the system's accuracy and efficiency. The suggested system's total percent match value was 72.80% 36.20%, and the correspondence ratio value was 0.43% 0.86%. However, if there are any visible edoema tissues[23] in the image, the system's overall performance will suffer. Indah Soesanti proposed the FCM algorithm, which includes information about the membership function summation in the vicinity of each pixel under consideration into the membership function for clustering. Indah Soesanti proposed the FCM algorithm for clustering, which includes information about the sum of the membership function in the neighbourhood of each pixel under consideration into the membership function. They compared this system to different methods of measuring thethe method's effectiveness for noisy MRI brain pictures and discovered that it is successful for somewhat large tumour sizes ranging from 9.65 to 27.71 cm2. Jaffar proposed FCM with a curvelet transform to eliminate noise. Although Jaffar described his FCM process in detail, he did not provide the results of segmentation or the qualitative performance and effectiveness of his system in tumour detection.

TABLE FOR THE PROPOSED SYSTEM OF DETECTION OF BRAIN TUMORS:

Proposed Technique	Remarks
Fuzzy models Image Fusion	The proposed algorithm consists of: the registration of multispectral MR images,the creation of fuzzy models describing the characteristics of tumor, the fusion based on fuzzy fusion operators and the adjustment by fuzzy region growing basedon fuzzy connecting. Using linear image registration tool[24] for evaluate the proposed method.

Histogram-based	The FSL library tool based software was compared with the performance of the proposed algorithm. It is considered to be a good candidate for fully automatic MRI analysis systems
Fuzzy c- mean smoothen the boundaries	Because of the fully automated nature of the algorithm with no human intervention, along with lesser number of iterations taken
Fuzzy C- Means	Generalized spatial fuzzy c-means (CSFCM) algorithm which possesses both pixel attributes and spatial local information that is weighted in correspondence with neighbor elements based on their distance attributes. This has the potentiality to improve the segmentation performance tremendously. This improve the segmentation performance dramatically. Poor contrast, noise and non-uniform intensity variation can affect the results
Fuzzy possibilistic c-means	The paper announce the developed a hybrid segmentation method that uses both region and boundary information of the image to segment the tumor. Compare a fuzzy classification method and a symmetry analysis method for detecting the tumors. Evaluate the proposed method by testing 2 images provide by IBSR data
Aggravation of filtering method Fuzzy expert[25]	Feature Extraction is done by thresholding method. And, they develop Approximate Reasoning method to recognize the tumor grade in brain MRI. More than 26.3% of tested image gives not correct answer using both proposed algorithm type I and typeII

VI)CONCLUSION:

A good segmentation method for MR images is necessary for accurate diagnosis of brain tumour patients in order to carry out an improved diagnosis and therapy. Currently, many images from various slices provide the information needed for accurate diagnosis, planning, and treatment. To inform decision-making, the volume of available information necessitates computation processing. Researchers no longer have to worry about calculation speed. As a result, the emphasis is on improving information from pictures gained from slice orientation and optimising the segmentation procedure to provide an accurate picture of the brain tumour. We try to discuss some of the important recent research works on brain tumour identification and segmentation in this study. We discovered through a review of the literature that automation of brain tumour detection and segmentation from brain MR images is one of the most active study fields, with substantial research done in this area over the previous many years. However, there is currently no clinically acknowledged automated approach.

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Dr.K.N.S Lakshmi Currently working as Professor from Department of Computer Science and Engineering at Sanketika Vidya Parishad Engineering College, affiliated to Andhra University, accredited by NAAC. Madam is currently working as Head of The Department , Published Papers in Various National & International Journals.her Subjects of interests are Machine Learning, Data Mining & Warehousing

Menda Devi is studying his 2nd year Master of Computer Applications in Sanketika Vidya Parishad Engineering College, Visakhapatnam, A.P With his interest in Python, machine Learning and as a part of academic project she chose brain tumor detection using Python. The article have been evolved from an idea to understand the flaws in conventional reporting and keeping time consistency, quality report generation inbrain tumor detection. A full fledged project along with code has been submitted for Andhra University as an Academic Project