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Hybrid Segmentation Approach for Enhanced Brain Tumor Detection in Medical Imaging

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Abstract: - A brain tumor is a collection of tissues in the brain produced due to the continuous growth of tissues. The growing procedure of tumors is uneven, and thus, it affects the brain-controlling system. The symptoms of having a tumor in the brain are headache, dizziness, fainting attacks, paralysis, etc. If the mass of the cells can overgrow, it will hamper the proper working of the brain, and most of the time, humans will not recognize that they will suffer from any disease. If the growth of the cells is not controlled over time, it will lead to the person's death. Therefore, to find these cells accurately, magnetic resonance imaging is best suited, due to its high-resolution images, which are helpful in proper segmentation and early detection of tumors. In terms of brain tumors, it is a difficult task to exactly identify and segment the brain tumor from the brain, due to their appearance, size, and irregular shapes. Segmentation of brain tumors is a difficult task with medical imaging systems. In this paper, a brief discussion of the segmentation techniques is done. From the literature survey, we conclude that none of the single segmentation techniques can cover all the limitations. This paper proposes a new method called WCCA, which combines three segmentation algorithms (Watershed, Contourlet, Clustering Algorithm) and compares them with other previous hybrid segmentation techniques, on F1 score, precision, accuracy & sensitivity.

Keywords: Brain tumor, MRI Images, Pre-processing, Image segmentation

I. INTRODUCTION

According to facts and expert analysis, in a year around 40 to 50 thousand persons are diagnosed with brain tumors in India. Out of this data, almost 20 percent are less than 14 years of age. Almost a year ago, statistics were near about 5 percent. With growth in the brain-related disorders in the world, every year over 2,500 of children suffer from high-grade brain tumors, a kind of pediatric malignant primary brain tumor [2]. The medical experts suggested that if the cases are diagnosed and detected early with efficient computer-aided diagnostic methods, then 90 percent of the medulloblastoma (high-grade brain tumor) cases are treatable, provided the treatment procedure is followed correctly.

According to the Brain Tumor Foundation of India, brain tumor is the next most common cancer among children after leukemia. The medical practitioners have also declared that if the treatment starts within time, the patient can extend their life up to 20 to 30 years without any difficulty. According to the statistical data, just six percent of the children suffering from brain tumors can get the appropriate treatment [1]. Early and efficient diagnosis through computing algorithms is the prerequisite for the treatment.

Due to the abnormal color and shape of the tumor region, the challenge of detecting a tumor is high. With upgrading technologies and rapid development in different kinds of highly equipped medical instruments and increase in use of such abnormal images, interpreting and inferring correct diagnosis becomes more difficult [3]. In such dense images due to factors like eye fatigue etc. radiologist can make a human error and may not be able to interpret the irregularity in an image. So to fulfil the need of an hour that is early and correct interpretation of data with more accuracy a robust method is required. Processing of medical images increases the strength of diagnostic Accuracy.

Role of Image Processing in Medical Research:

In Last few years researchers observed a swift and a wide area of applications that involves field of image processing. In recent era of digitization, capturing, storing and processing of medical image had been digitized.

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Such tremendous growth in imaging technologies now consistently allows living organs and organisms to be explored non- invasively. To visualize the human body's structural arrangements, imaging has become an essential aspect of medical diagnosis and treatment, including guided surgery, surgical simulation, nano-science studies and therapy assessment. In medical imaging, images are obtained easily using Magnetic Resonance Images (MRI), X-Ray imaging, Ultrasound and Computed Tomography (CT) imaging techniques etc.

For medical imaging, MRI imaging is the most effective imaging system. One can easily adjust acquisition parameters for high contrast image in MR imaging using number of grey levels in different cases of brain ailments. Therefore, MRI image segmentation stands in the upcoming research limelight in medical imaging arena.

Magnetic resonance imaging has many advantages which make it possible to link it with digital image processing tools. To improve the accuracy of MR image interpretation various image processing methods have been proposed. Number of researchers have investigated various approaches to develop an improved image segmenting algorithm to detect the tumor region in MR images.

Digital image segmentation is demonstrated with the splitting or separation of the image into different sub-regions of alike features by various techniques. In this chapter, it is discussed that there are number of methodologies which show improvements in segmentation performance by combining two or more methods of segmentation or hybrid segmentation methods from different categories.

Image segmentations can be broadly classified under three categories:

Segmentation based on area are categorized as Local segmentation and Global segmentation, Local segmentation involves the segmentation of desired region of image and Global segmentation involves the segmentation of whole image, comprising of large number of pixels.

Segmentation based on properties are categorized as Detection based on discontinuity and Detection based on similarity. In discontinuity-based detection, segmentation is based on discontinuity in edges due to intensity variation. In similarity-based detection, segmentation is done on the basis of a similar set of pixels. The Hybrid Segmentation method involves a combination of two or more segmentation methods together for the more accurate and fine results. In the Literature review section we broadly discuss about all the segmentation-based methods that are discussed above. In the methodology part, the comparative method of three techniques is mentioned and in the result section the comparative study results are shown.

II. LITERATURE REVIEW

The segmentation method based on discontinuity are as follows:

Line detection: Based on the discontinuity of an intensity level in an image, line detection is used. Siva Kumar has presented a survey in which a 3 x 3 mask operation is done. The mask points ith, jth are associated with the mask line i direction. One-pixel thick lines and lines with linear orientations are easily detected [7].

Point detection: Siva Kumar et al. have presented that to find discontinuities based on intensity in an image is to run (i x i) mask over every point in a greyscale image. The mask has been made at the center position where the point (x, y) is located. This formula is able to calculate the weighted differences between the center coordinate and its neighbors [7].

Edge detection: Sivakumar et.al. have presented that in grey-level discontinuity segmentation, isolated points in lines with unitary pixel thickness are random in nature and edge detection can be used. Discontinuity in the image can be detected when the image changes from dark to white or vice versa.

First-order derivatives are used to detect discontinuity in intensity level. The method considers the leading edge as positive and the trailing edge as negative [7].

Table 1 Comparison between Edges based segmentation

S.No	Grey histogram	Gradient-based	Laplacian

1.	It is an intensity distribution function.	It is based on the first derivative	It is based on the second derivative
2.	Can be evaluated for limited data	It is easier to calculate large numbers of data	This can be applied to a large number of data
3.	Less Accurate	Accurate	Less Accurate

Segmentation Methods Based on Similarity:

Several authors suggested various algorithms for segmentation. A review survey on these methods is done to gain the knowledge and depth of research in this area.

Thresholding segmentation:

Bezdek et al. [2] have presented a programmed image segmentation method that used a thresholding technique. The research depicts that segmentation is based on the assumption that neighboring pixels whose value (grey level, color value, texture, etc.) lies within a specified range are categorized in a similar class and thus, segmentation of images which includes only two differing components can only be obtained.

Jaskirat Kaur et al. [8] have presented thresholding segmentation with edge detection as an important feature of image segmentation. It has been notified that these features must be considered before the process of feature extraction and image recognition system for analyses of images. It also aids in finding the shape and structure of an image, but this method also overlooks the minute unnecessary details.

Zhang et al. have discussed a methodology related to histogram thresholding [10]. The researchers followed a concept where, on a uniform background, matters are unevenly placed which makes histogram equalization method as a prime objective for matter delineation and to find a suitable threshold between matter and background. Zhang has also discussed the analysis as well as the differences of these evaluation methods.

Region-based segmentation:

Pohle et.al. [12] have presented a fully automatic and complete segmentation method based on a region-growing algorithm with an assumption of homogeneity in simple shape properties of the desired region. The method is tested for segmentation on sample images. The only drawback of this method is that depends on the structural properties of an image.

Fan et al. [5] have proposed region-based techniques in remote sensing image segmentation with a clustering algorithm. The only limitation is that an assumption is made where adjacent pixels within the same region have alike graphic features such as grey level, color value, or texture. Based on the homogeneity criterion, split and merge methods are also used.

R. Adams et al. proposed a method in which regions are formed and then these regions in the image are segmented. The two techniques that incorporate this method are manual seed growing and automated procedures. This method is limited to number of seeds required in any form of individual pixels or different regions [11].

Clustering based methods:

Li –Hong Juang et al. [9] gave designing method for the detection of colored MR images. MRI brain tumor image detection is dependent on color and is further converted in accordance with K means clustering segmentation. The work done by them suggests results of tumor objects in brain images by tracking method. They used color conversion segmentation along with K means clustering method. This method is limited to solving only contoured tumor regions.

Watershed segmentation:

Seal et al. have presented a study based on watershed segmentation. The theory of water drop is illustrated and concluded the path to finally exit a local minima. The watershed segmentation in image processing depends on watershed lines exhibiting the properties of nodes, and their edges [13].

J.M.Gauch has presented a classification of image features by relative scales. Learning about the intensity maxima value, intensity ridges, and binary level values of watershed regions is discussed. Based on gradient properties, the gradient value of the original images is obtained. Relative scale analysis in terms of intensity gives a method based on scale order on watershed region. This method is limited to images with intensity variations that can be treated in terms of relative scale [14].

Dhage et al. have discussed the importance of watershed segmentation in biomedical image processing. For accurate detection in the case of irregular and difficult assessed features. It has been concluded that watershed segmentation is the most suited segmentation algorithm to use in the case of separating the clustered tissue from the normal in terms of simplicity and efficiency [15].

Safonov et.al. [17] have studied and overviewed to amount the expanded calculative features of watershed segmentation algorithms. Watershed segmentation has computational power for handling of numerous 2D or 3D images. The purpose of the segmentation algorithm shows a substantial importance as every pixel of the image is handled with limited computational resources.

Learning-based segmentation methods.

Sourav Ganguly et al. [18] have discussed several approaches in face recognition. For the improvement of the Principal component, Independent component linear discriminant analysis, and Evolutionary pursuit in images large number of experimental data is tested and implemented. A number of methods like the Kernel method, trace transform, and Active appearance 3D model are evaluated with a large number of data.

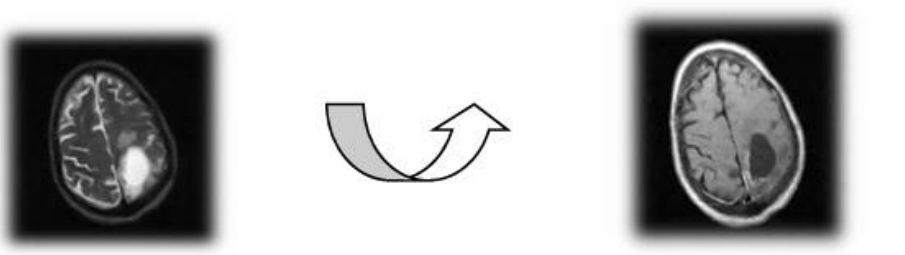


Fig.1: Segmentation through thresholding

Tabb and Ahuja [20], have presented research that addresses the problem of classification while detecting low-level structure in MR images. This problem includes the identification of local areas in an image that are homogeneous and different from other spatial adjacent regions.

Dass. [21], have described the various segmentation techniques implemented in the area of ultrasound imaging and SAR Image Processing. The research involved here examines and assembles a few technologies and basic tendencies in image segmentation.

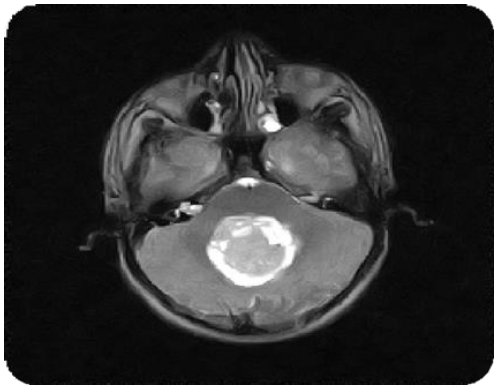


Fig.2: Brain Tumor View Inside Brain

N. Senthilkumaran et al. [16] have presented a study that shows Genetic Algorithms perform efficiently for edge detection in definite anatomical structures, but for all anatomic structures, they cannot be considered. Genetic algorithms form a robust framework; they are not exaggerated by unauthentic local optima in the finding solution.

Gudmundsson et al. [2] have proposed a theory for finding thin edges in medical images that is based on edge optimization that differentiates well-localized, fragmented boundaries, and fine edges using a genetic algorithm (GA). Various enhancement techniques were also added for the improvisation of the performance of the existing algorithm over a traditional Genetic Algorithm.

L. Prince et al. [19] have represented a model based on soft computing for machine learning and useful for image segmentation. They presented this model for medical imaging using a classifier, where weights are calculated with data training and then neural network algorithms segment the data in an image.

Literature Survey on Hybrid Segmentation Methods:

D. Anithadevi et al. have presented a hybrid approach based segmentation where features of single seed region growing and threshold segmentation technique are used. The results of region growth are improved. The gap in this research no filtering technique is discussed as pre-processing [22].

D. Jayadevappa et al. have proposed a hybrid segmentation technique that deals with CT and MR images. The combined method involves Geometric vector flow and watershed segmentation that improves the concave localization of the desired region but noise ratio is not considered [3].

Wang et al. have also proposed a hybrid segmentation technique that works for multivariate time series analysis for non-varying common factor series to adjust the methods for segmentation. In this hybrid method, binary segmentation, and neighborhood segmentation were applied to predict the change points [23].

Despotovic et al. [24] have proposed a hybrid technique to segment the brain volume from newborn MR images that aids in evaluating the development and growth of the brain, in the detection of early complexities in the brain, and reconstruction of three-dimensional volume structures. Various segmentation techniques are also compared with existing manual segmentation techniques. This method focuses mainly on newborn infants of 39-41 weeks. This method can be further extended to different age groups of a child with some refinement in algorithms.

Jhanavi et al. [25] have proposed a system that involves a hybrid technique, a combination of the SVM algorithm with clustering techniques k means clustering and FCM methods to trace the brain tumor. These hybrid techniques involve the enhancement of images using contrast upgrading and average value extension and are proved as more accurate techniques than other algorithms.

Choplin et al. [26] proposed a new hybrid segmentation that involves a pre-segmented image and earns a more precise segmentation that exactly gives sharp desired features. The outcome of this approach is matched with the existing techniques using three error metrics. On using various methods like erosion, dilation, contour smoother, window size, Gaussian smoother, and shakes parameters better results are attained. Through machine learning algorithms number of parameters required can be considerably reduced.

It can be seen from the literature survey some important inferences may be drawn. Although a lot of research has been conducted in the domain of Brain tumor detection using MR images there is still scope for exploring better and more effective techniques of detection. Digital Image processing has been explored as an effective tool for brain tumor detection and segmentation in MR images. The approach may be different with the implementation of hybrid segmentation that gives more accurate results with noisy images.

Comparative study of segmentation techniques:

Image Segmentation plays a vital role in the extraction of tumors from Brain MR Images. It is a computer-aided technique. The results of the segmentation of an image depend on the accuracy of the desired parameter measurement.

Using a single type of segmentation may work well in some cases with simple images. But to segment complex images with varying grey intensities and blur boundaries, more than one segmentation technique needs to be employed. To overcome such limitations, hybrid segmentation techniques need to be employed. In the methodology part we discuss the three hybrid techniques used for segmentation.

III. METHODOLOGY

In the present work, MR images from the dataset are taken and the following segmentation techniques are applied:

Hybrid segmentation of threshold segmentation & watershed segmentation geometric transform invariant. Hybrid segmentation of watershed segmentation contourlet transform and fuzzy C-means based clustering algorithm or WCCA segmentation The methodology adopted for the above-mentioned segmentation techniques is briefly shown in Figure 3.

As described earlier pre-processing is a pre-requisite step in MR image processing. It helps in developing the finer details of the image and removes areas which not much of interest. It includes Brain Surface Extraction (BSE) using a Morphological Operator.

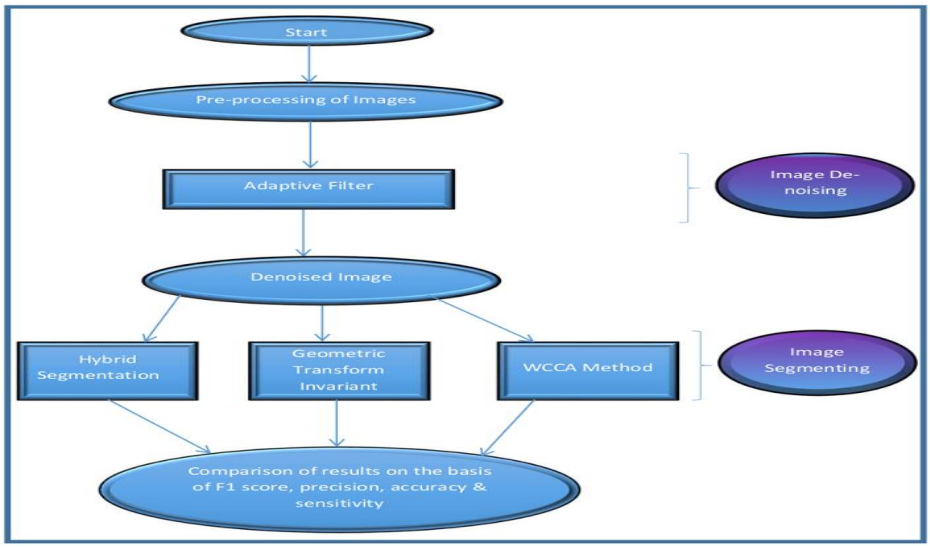


Fig.3: Steps of the methodology adopted

Pre-processing is common for all segmentation techniques. The results shown above are applied to the three proposed segmentation techniques and further processing and post-processing are performed separately on the results obtained from pre-processing.

*A. **First Method**: Hybrid segmentation of Threshold segmentation and Watershed segmentation:*

MR imaging scans of brain tumors were segmented along with edge detection together to extract the tumor's exact edges, its types, its shape, its anatomic functional positioning as well as its effect on other brain areas. To segment the brain MR image, the steps as mentioned below are followed:

Pre-processing:

Pre-processing on the MR images is performed as described in above and further processing is performed on the resultant images.

Processing:

After the removal of the Brain surface from the MR image, the image is further processed for the removal of noise by using an Adaptive de-noising filter.

Post Processing:

Post-processing is performed on the MR image after pre-processing and processing by applying the following segmentation techniques as below:

Threshold Segmentation:

Threshold segmentation categorizes every pixel of an image in expressions of intensity values and that intensity value is compared with a predefined threshold value. Pixels having lower intensity than threshold value "x" are converted into black and pixels having higher intensity than "x" are converted into white. Thus, the resulting image is converted into a pure black-and-white image. Considering the threshold value of 16, the MR image is segmented.

Watershed Segmentation:

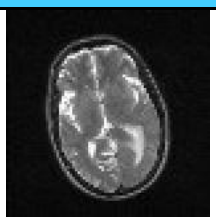
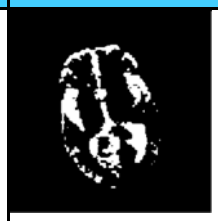
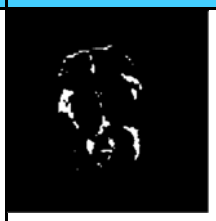
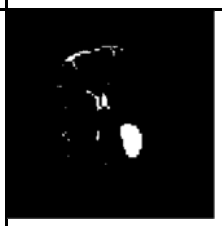
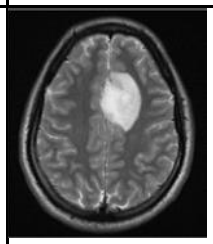
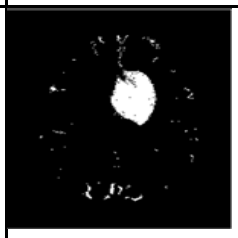
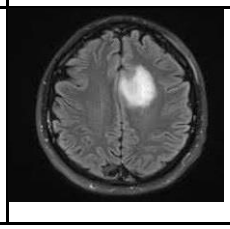
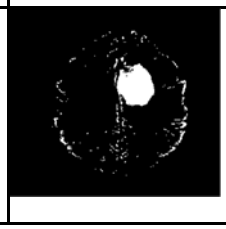
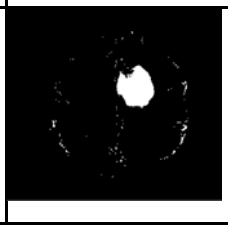
Watershed segmentation is based on the principle of local minima in terms of pixel intensity. The tropical gradient approach is combined with watershed segmentation. It helps in the calculation of Catchment basins with watershed rigid lines. An input image is considered here as a base. Watershed segmentation is used here to avoid over-segmentation to give the best and most accurate results.

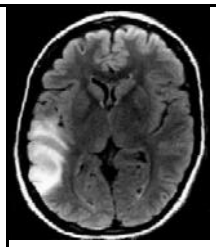
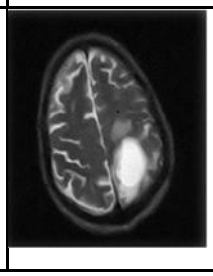
Results of the first method:

After, morphological operators, the de-noising filter is applied to the pre-processed image, which contains brain tumor. Threshold segmentation is applied to the resultant image. A white spot is visible after threshold segmentation as shown in Table 2 second column as thresholded segmented output. This is the region with the intensity values greater than the defined threshold value. High-intensity areas mostly consist of tumors. So through threshold segmentation, the location of the tumor is specified in terms of pixels [30].

Further watershed segmentation is applied to the resultant image. Only the portion that contains the tumor is highlighted now as shown in Table 2. The white portion is marked by using the watershed segmentation method. The tumor is tinted white after removing the areas that are not significant.

Table 2: Results of Hybrid segmentation - Threshold segmentation and Watershed segmentation

Sr. No.	Original MR	Threshold segmentation	Watershed segmentation
1.			
2.			
3.			
4.			

5.			
6.			

B. Second Method: Geometric Transform Invariant

In the second method, the image is partitioned into smaller quadrant sub-images for approximating the region of interest. Each sub-image is subjected to a simpler Geometric Transformation and then the transformed sub-image is estimated using pairs of corresponding pixels. GT is then performed on each sub-image [28]. The flow diagram of this method is given in Fig. 4.

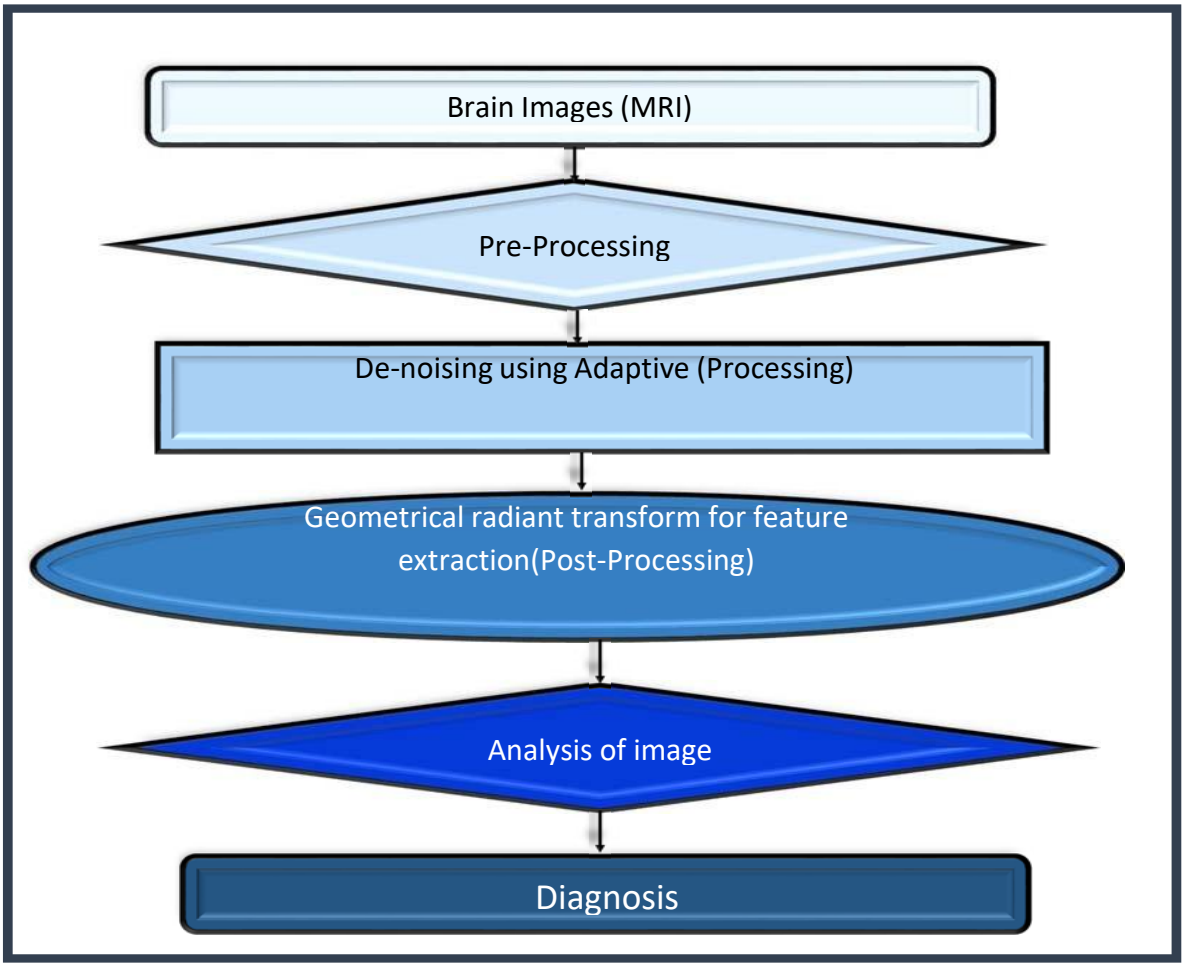


Figure 4: Flowchart of the steps involved processing in geometric transform invariant

To segment the brain MR image, the steps mentioned below are followed:

Pre-processing: Pre-processing on the MR images is performed as described above and further processing is performed on the resultant images.

Processing:

Noise plays an important role in degrading the quality of the image. It diminishes the features, attributes, the parameters that can be extracted for the processing of an image.

After removal of Brain surface from MR image, the image is further processed for removal of noise by using Adaptive de-noising filter.

Post Processing:

Geometric transform invariant:

Geometric transform is a function that reorients a position of a pixel to a new position through mathematical equations. These equations can be determined based on the original image and deformed image or an image can be processed by applying transformation function.

Following steps are involved in a geometric transform:

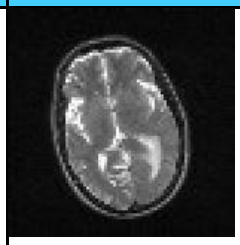
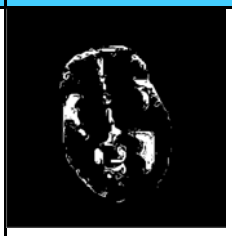
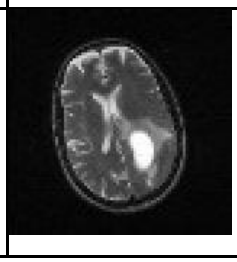
Deriving the transformation function for pixel co-ordinate i.e. formulation of mapping the co-ordinates of the input image to the output image.

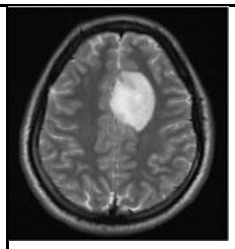
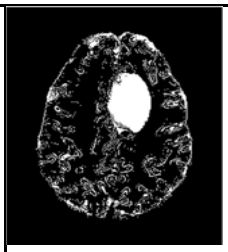
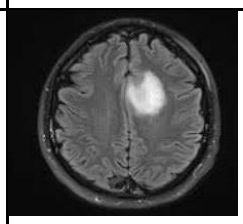
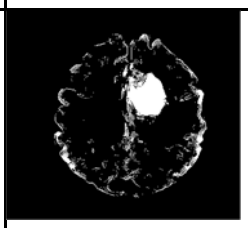
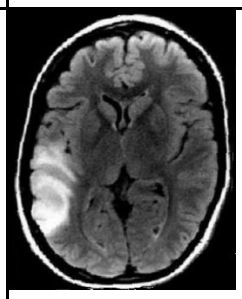
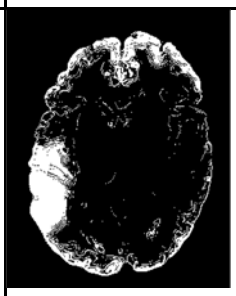
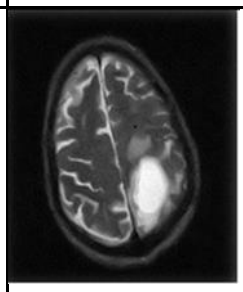
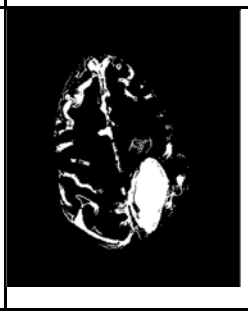
Matching of the points in original image to transformed image and assigning it the brightness calculated using interpolated brightness of neighboring pixels.

Results of second method:

This method is used to get a noise free and enhanced image using morphological operators along with segmentation techniques using geometric transform invariant to get binary decoded image. The result shown in Table 3 depicts that the image is filtered and subjected to geometric transform invariant and decoded binary image is retrieved.

Table 3: Results of the Geometric transform invariant method

Sr. No.	Original MR	Geometric Transform Invariant
1.		
2.		

3.		
4.		
5.		
6.		

C. Third Method: Proposed Method "WCCA" (Watershed, Contourlet, Clustering Algorithm)

This image segmentation method is also divided in pre-processing, processing and post processing stages. First, in the preprocessing the brain surface is extracted using BSE algorithm to extract the important features and attributes from brain surface area and then de-noising is performed using adaptive filtering technique and termed as processing of an image. Later, in post processing Fuzzy C Means Clustering and Contourlet transforms are applied one after the other [29]. In the third stage, tumor is extracted using watershed segmentation.

Flowchart of WCCA method is given in Fig 5.

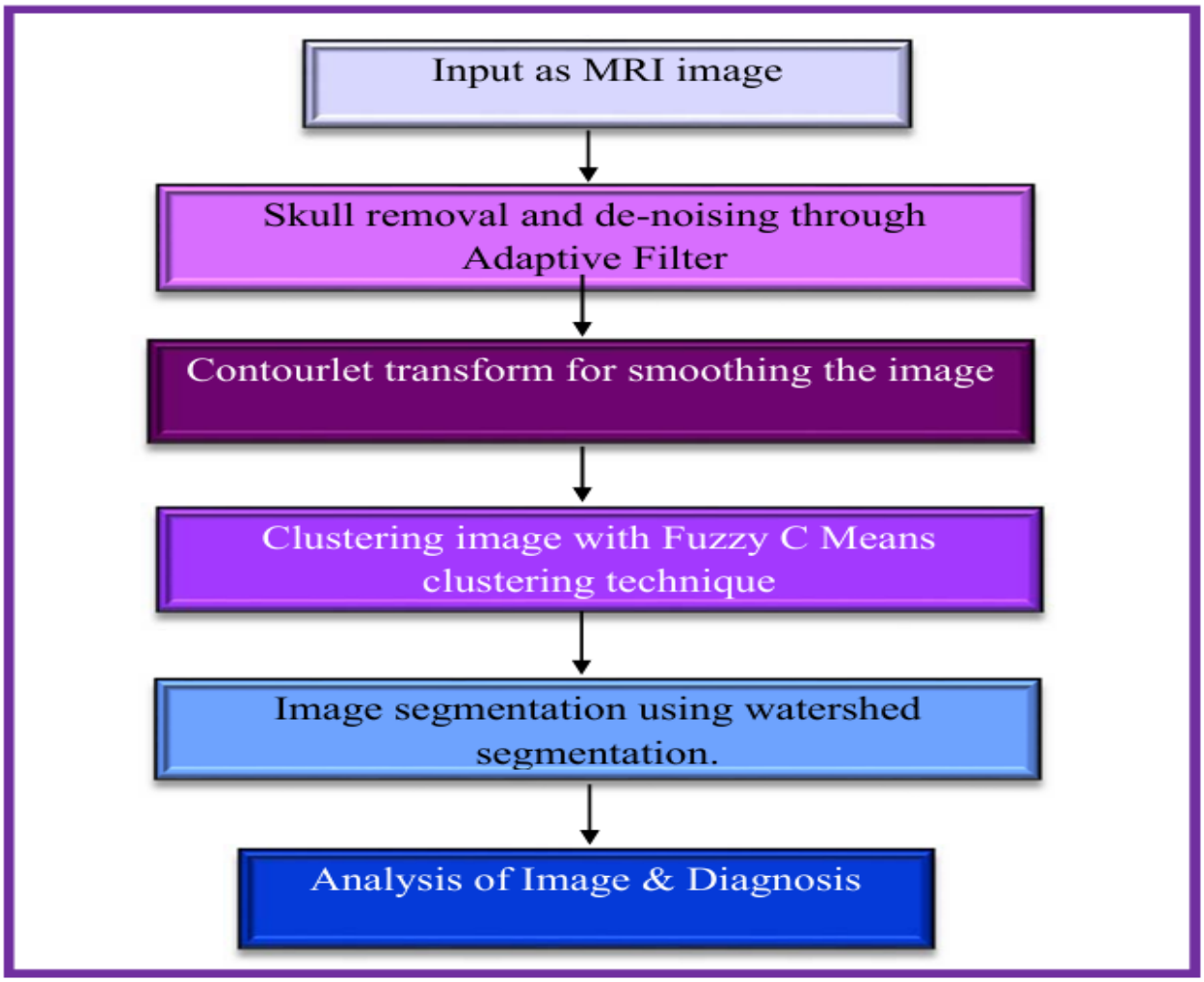


Figure 5: Flowchart for the segmentation techniques proposed

Pre-processing stage:

Pre-processing on the MR images is performed as described above and further processing is performed on the resultant images.

Processing:

After removal of Brain surface from MR image, the image is further processed for removal of noise by using Adaptive de-noising filter.

Post Processing:

Contourlet transforms:

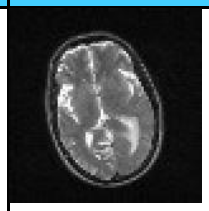
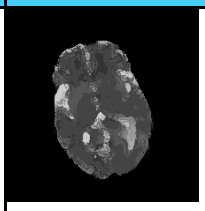
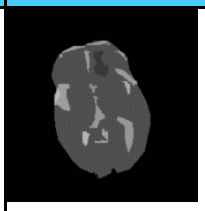
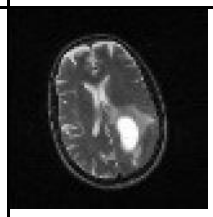
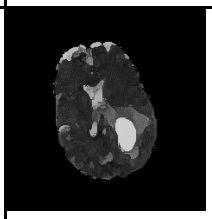
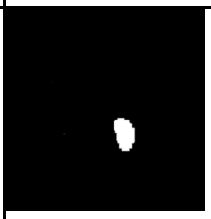
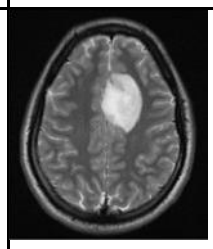
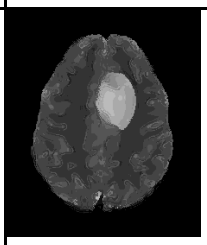
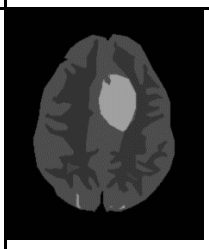
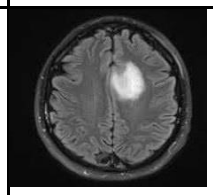
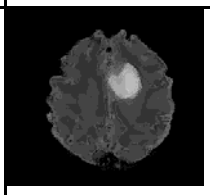
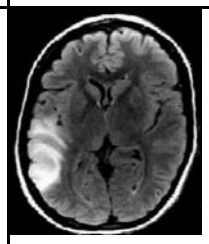
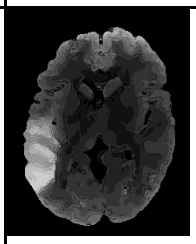
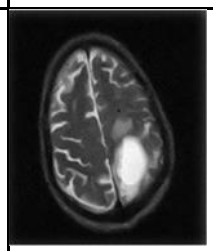
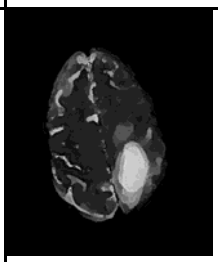
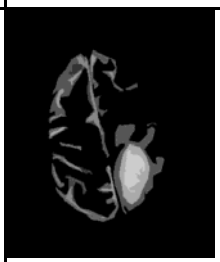
Contourlet transform is used for image smoothening. The basic purpose of using active contourlet transforms is to combine the advantages of both edge and region approaches. A curve well described in an image that can modify its coordinates and locations and its shape to satisfy the pre-specified conditions which makes segmentation easier for region of interest. The benefit of using active contour model is that it is immune to noise, boundaries and gaps present in an image [29].

The advantage of using contourlet transform here is it is a simple method to represent a 2D image and an efficient technique that captures the internal geometrical structure of an image. It also helps in the compression of an MR image by capturing the singularity points of the structural edges first and then in accordance to the information singularity points of pixels comes together to make a contour section.

Clustering:

Clustering is the method of consolidating data with same properties into larger units for analysis. Clustering techniques are utilized for complex pathology. In the third technique, Fuzzy C means algorithms are used for clustering.

Table 4: Results of the WCCA method

Sr. No.	Original MR	Contourlet transforms	Fuzzy C Means clustering Algorithm	Watershed Segmentation
1.				
2.				
3.				
4.				
5.				
6.				

Flow diagram of Fuzzy C mean clustering is shown in Fig 6. For simple, efficient technique many iterated filter banks are used here.

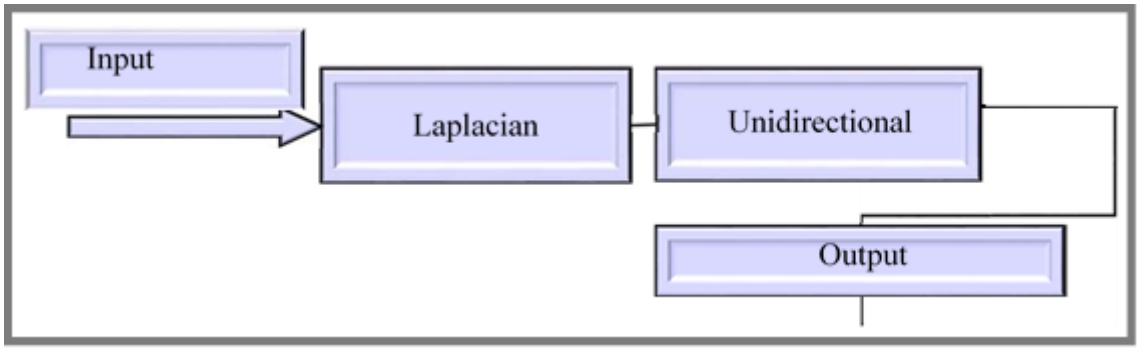


Fig.6: Fuzzy C-Means clustering technique

In figure 6 Input MR Image is fed to a laplacian pyramid and then to Unidirectional Filter to obtain the clustered image.

The significance of Fuzzy C means clustering technique used here is that it allows single value of data to be grouped into two or more clusters if required. It is a soft classification method based on fuzzy set theory. In the case of brain tissue segmentation which is classified as a soft segmentation, separation of tumours pixels is done due to homogeneity in pixel intensity with the assistance of fuzzy C means clustering. As in this method pixels can be clustered in more than one cluster gives more accurate results. It is a generalised method of k- means clustering which permits every single pixel that belongs to multiple classes giving to a certain or fixed relationship k value. This Fuzzy C means clustering technique is the best approach in order to minimize the objective function.

$$O = \sum_{k=1}^{m} \quad \sum_{l=1}^{m} mod(a_l k \quad - c_k)2$$

k = count of clusters, l = count of cases and c is the centroid for a cluster.

The advantage of using fuzzy c means clustering is this that the objective function can be modified to compensate or correct intensity homogeneity. Similar result can be obtained on every iteration through this method and resultant clusters depends on primary assignments of centroid which makes it more accurate.

Watershed Segmentation:

Watershed segmentation is created on the principle of local minima in terms of pixel intensity. Tropical gradient approach is combined with watershed segmentation. Watershed segmentation is used here to avoid an over segmentation and to give best and accurate results.

Watershed segmentation has many advantages over others as it provides closure contouring in less computational time, which makes it fast and simple. It provides total division of the image in separated regions. Contouring and clustering aids the better extraction of results as in watershed segmentation it may fragments the cells of interest that is tumor cells during over segmentation which shows that the area of interest may get omitted that can be preserved by contouring and clustering technique.

Results of third method:

Table 5 indicates the resultant images after applying filtering, clustering and segmentation techniques and tumor images are very clearly identifiable through visual inspection.

The method used in the third method, is found efficient for the datasets considered. It works efficiently for the images of malignant brain tumor and provides maximum information of the input image to be processed. WCCA, the third method is most accurate algorithm that can be implemented for drawing out the brain tumor in MR image

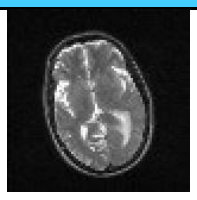
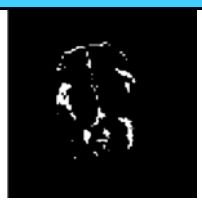
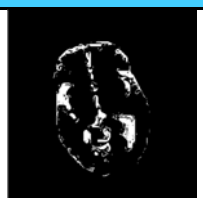
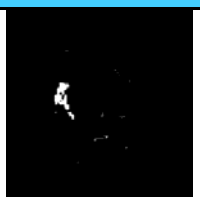
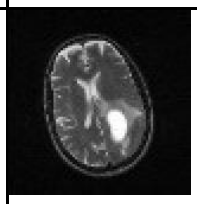
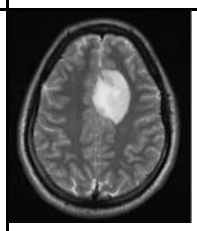
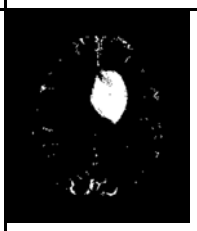
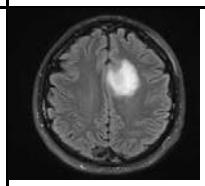
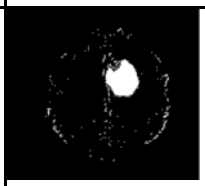
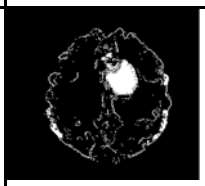
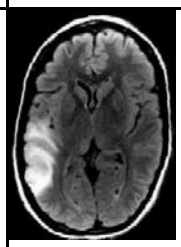
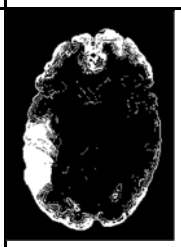
and it is clearly evident from the outcomes as the edges of the desired region are preserved using contourlet transform and clustering validates the pixels of homogeneity that is tumor cells in one cluster. The first method may not preserve the edges of the desired area in every case as it has the fixed threshold value and can give inaccurate results for another diffused tissues area near the tumour in an image. The second method does not establish a generalized algorithm due to the variation of noise in an image and is less accurate.

IV. RESULTS

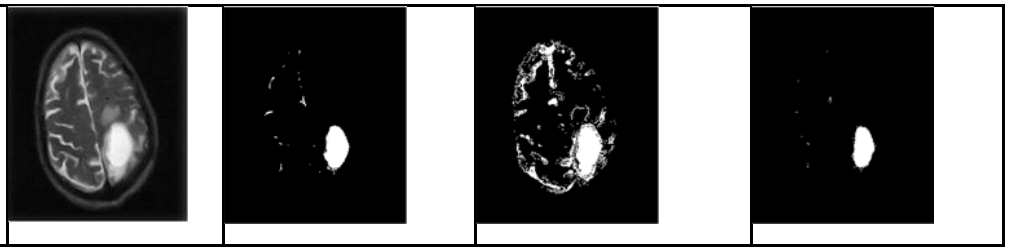
Comparative performance of Segmentation techniques:

To demonstrate and qualitative analyze the performance of the three segmentation techniques, statistical parameters are used viz. accuracy, sensitivity and specificity, precision and F1-score [84]. These parameters are calculated and the results of the three methods are compared and analyzed. On the basis of the results, the third method, the proposed method WCCA is considered as the most efficient method.

Table 5: Comparison of MR images on the basis of three segmenting methods

S.No.	Original Image	Image after Hybrid Segmentation [First Method]	Image after Geometric Transform Invariant. [Second Method]	Image after WCCA [Proposed method]
1.				
2.				
3				
4				
5				

6



The final segmented images after three segmentation techniques are shown in Table 5 in the subsequent sheet.

Results of Hybrid segmentation of threshold segmentation & watershed segmentation technique are presented in Table 6. It can be seen that accuracy and sensitivities are in the range of 87% to 96% while average accuracy and sensitivity are 91.7% for all datasets. F1 score is also in the range of 93% to 98% and the average F1 score across all datasets is 95.6%.

Table 6: Error metrics of Hybrid Segmentation of Threshold Segmentation & Watershed Segmentation

Datasets	TP	TN	FP	FN	Accuracy	Sensitivity	F1 Score
DB1	82.94	4.37	2.03	10.67	87.30	88.60	92.89
DB2	84.96	4.94	1.82	8.28	89.90	91.12	94.39
DB3	90.33	5.77	0.66	3.24	96.10	96.54	97.89
DB4	87.80	5.50	1.01	5.70	93.30	93.91	96.32
AVG.	87.85	3.85	1.49	6.81	91.70	92.81	95.49

The results of the geometric transform invariant technique are indicated in Table 7. It can be seen that accuracy and sensitivities are in the range of 79% to 94% while average accuracy and sensitivity are 86.4% for all datasets. F1 score is also in the range of 88% to 97% and the average F1 score across all datasets is 92.7%.

Table 7: Error metrics of Geometric Transform Invariant

Datasets	TP	TN	FP	FN	Accuracy	Sensitivity	F1 Score
DB1	75.43	3.97	3.30	17.30	79.40	81.34	87.99
DB2	78.91	4.59	2.97	13.53	83.50	85.36	90.53
DB3	87.98	5.62	1.09	5.31	93.60	94.31	96.49
DB4	83.94	5.26	1.62	9.18	89.20	90.14	93.96
AVG.	82.77	3.63	2.45	11.15	86.40	88.13	92.41

Results of watershed segmentation, contourlet transform and fuzzy C-means based clustering algorithm (WCCA) technique are indicated in Table 8. It can be seen that test that accuracy and sensitivities are in the range of 90% to 100% while average accuracy and sensitivity being 94.6% for all datasets. F1 score is also in the range of 95% to 100% and average F1 score across all datasets is 97.2%.

Table 8: Error metrics of Watershed Segmentation, Contourlet Transform and Fuzzy C-Means Based Clustering Algorithm or WCCA

Datasets	TP	TN	FP	FN	Accuracy	Sensitivity	F1 Score
DB1	93.96	4.95	0.18	0.92	98.90	99.03	99.42
DB2	92.80	5.40	0.32	1.48	98.20	98.43	99.04

DB3	94.00	6.00	0.00	0.00	100.00	100.00	100.00
DB4	93.63	5.87	0.08	0.43	99.50	99.55	99.73
AVG.	95.03	4.17	0.14	0.66	99.20	99.31	99.58

From the tables above, it is evident that Hybrid segmentation of Threshold segmentation and Watershed segmentation performs well with the given datasets whereas Geometric transform invariant is relatively inconsistent. The results of Watershed segmentation, Contourlet transform and Fuzzy C-means based clustering algorithm or WCCA are better among all segmentation techniques. Table 9 shows the comparison of all these three methods.

Table 9 Statistical measures to compare the three methods

Statistical Measures	Hybrid Segmentation (First Method)	Geometric transform invariant (Second Method)	WCCA (Proposed method)
F1 score	95.49	92.41	99.58
Sensitivity	92.81	88.13	99.31
Accuracy	91.70	86.40	99.20

The graphical comparison of the three segmentation techniques discussed above with respect to various performance parameters is shown in Figure 7 and is illustrated below in the form of graphical data to visualize the comparison.

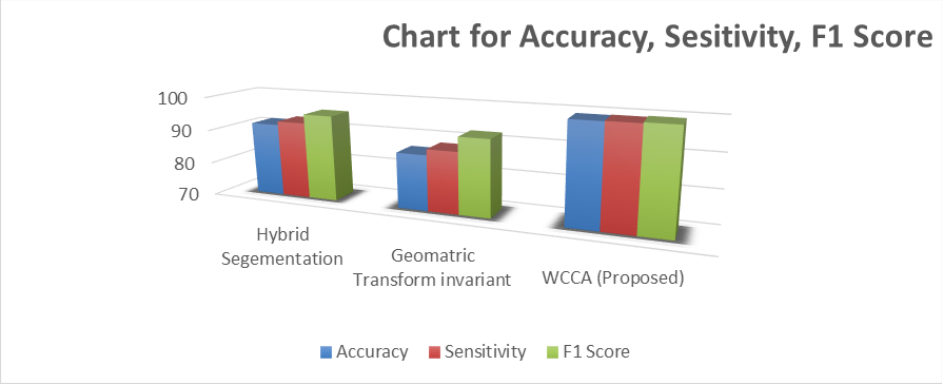


Fig.7: Comparison of Accuracy, Sensitivity, F1

After obtaining the results of the three methods, results are compared on the basis of image processing tools and on the basis of statistical parameters and it has been found that the third method “WCCA” shows more accurate and efficient results.

V. CONCLUSION

In this study, we conducted a comparative analysis of two image processing methods and one proposed method for segmenting brain tumors from MRI images. Through this comparison, we found that the third method, Weighted Clustering and Component Analysis (WCCA), consistently delivered more accurate and efficient results compared to the other techniques. WCCA demonstrated superior performance in accurately identifying and segmenting tumor regions, highlighting its potential for clinical applications in tumor diagnosis and treatment planning.

However, despite the promising results of WCCA, we recognize that the field of image processing continues to evolve, and there are limitations in our method that future research could address. New segmentation techniques and advancements in image processing technologies are expected to emerge, offering opportunities to overcome the challenges not fully addressed by our approach. Moving forward, one of the key areas for improvement lies in the enhancement of the quality and performance of the filters used in image processing. By refining these filters, we can improve the clarity, accuracy, and precision of tumor segmentation, paving the way for even more reliable medical imaging techniques.

Ultimately, our work contributes to ongoing research efforts in brain tumor segmentation and lays the foundation for future innovations in this critical area of medical image analysis.

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