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CAD Scheme Based Brain Lesion Segmentation and Classification Approach

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Abstract

Segmentation is a key process in most imaging and classification analysis for Computer-Aided Diagnostic or radiological evaluation (CAD). The pixel based method is a key technique in k-means clustering, as this method is simple and computational complexity is low compared to other region-based or border-based methods. In addition, segmentation of biomedical images using the clustering concept as the number of clusters is known from images of particular regions of human anatomy. The K-means clustering technique is used to track tumor objects in Magnetic Resonance Imaging (MRI). The key concept of the segmentation algorithm is to convert an MR input image into a gradient image and then separate the tumor location in the MR image through the K-media pool. These methods can obtain segmentation of brain images to detect the size and region of the lesion. Therefore, the average k cluster can obtain a robust, effective and accurate segmentation of brain lesions in MRI images automatically and the run time for segmentation of a single lesion is 0.021106. The detection of the tumor and the removal of the magnetic resonance of the brain are performed using the MATLAB software. The automatic instrument is designed to quantify brain tumors using magnetic resonance sets is the main focus of the work. The different methods used for this concept in the content-based recovery system are precision, memory and precision value for visual words, descriptive color and border descriptors, diffused histogram of color and structure. It is expected that the experimental results of the proposed system will produce better results than other existing systems. Total accuracy of 95.6% is obtained using GLCM functions in MATLAB software.

Index Terms: *Magnetic resonance (MR), Brain lesion segmentation, Region growing, toboggan, Clustering Concept, Supervised Classification, Unsupervised technique.*

INTRODUCTION

Segmentation is a key process in most analyzes and classification of medical image for radiological evaluation or computerized diagnosis [3]. In essence, the image segmentation method can be categorized into three types: edge-based methods, region-based methods [6], and pixel-based methods. K-means clustering is a key technique in pixel-based methods. Since K-based pixel-based methods are simple and the concept of computational complexity of clustering is relatively low compared to other region-based or border-based methods.

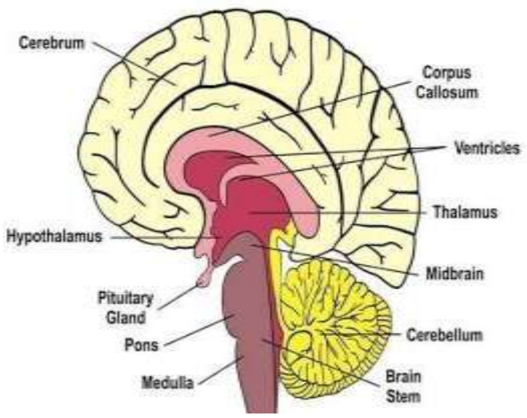

Fig: 1. *Structure of human brain*

The automated classification and detection of indifferent medical images of tumors is motivated by the need for high precision when it comes to human life. In addition, IT assistance is required by medical institutions in that it could improve man's results in a domain where false negative cases should be at a very low level. It has been shown that double reading of medical images could lead to better detection of tumors. The implicit cost of Butte's dual reading is very high and for this reason good software to help humans in medical institutions is of great interest today. Conventional methods of surveillance and diagnosis of diseases are based on the detection of the presence of particular features by a human observer [4]. Due to the high number of patients in intensive care units and the need to constantly observe these conditions, several automated diagnostic techniques have been developed in recent years to try and solve this problem. These techniques work by transforming the most qualitative diagnostic criteria into a more objective quantitative classification problem in this project. We propose the automated classification of magnetic resonance imaging using some prior knowledge such as pixel intensity and some anatomical features. There are currently no widely accepted methods, so automatic and reliable methods for tumor detection are of great need and interest. The PNN application in the classification of MR image data is not yet fully utilized. These include grouping and classification techniques especially for MR image problems with large data and power consumption and power times manually. Therefore, comprehensive understanding of recognition, classification or grouping techniques is essential for the development of neural network systems, particularly in medical problems. The segmentation of brain tissue in gray matter, white matter, and cancer in medical images is not only of great interest for the serial follow-up of the "load of disease" in oncological imaging, but also in popularity with the advancement of approaches surgical guided by the image. The representation of the contours of brain tumors is an important step in the design of localized radiotherapy locally, which is usually performed manually in weighted T1-resonance imaging (MRI) contrasted in current clinical practice. In the MR images of T1 acquired after the administration of a contrast agent (gadolinium), blood vessels and parts of the tumor where the contrast can pass blood-borne barrier are considered areas of hyperintensity. There are several attempts to segment brain tumors in literature that use one mode, combine multiple modes and use a priori obtained from the atlases of the population. Segmentation problems are the bottleneck to get the object extraction, object-specific measurements and quick rendering of objects from multidimensional image data. Simple segmentation techniques are based on the local classification of pixel-quarters. Such methods, however, fail to reach global objects rather than local appearances and often require intensive operator support. The reason is that the "logic" of an object does not necessarily follow its local image representation. Local properties, such as texture, clutter and ugliness, etc. they do not always represent the related features of a given object. The technology growing region marks image pixels that belong to an object in the regions. Segmentation is based on predefined criteria. Two pixels can be grouped if they have the same intensity characteristics or if they are close to each other. It is assumed that the pixels that are closed between them and have similar intensity values are likely to belong to the same object. The simplest form of segmentation can be achieved by determining and encoding the components. Another method is to find the boundaries of the region using edge detection.

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Researchers have proposed related research in clustering K-mean clustering [1, 5]. In this document, we carefully select the appropriate brain image features such as clustering characteristics to achieve good segmentation results, while maintaining the computational low aspect of the segmentation algorithm [1, 5].

Since the color space transformation function in our proposed method is a fundamental operation for most image processing systems, the color space translation does not cause an additional overhead in the proposed scheme. Therefore, using color segmentation with K-means clustering on brain magnetic resonance tumors (MR), the proposed image tracing method maintains efficiency. The experimental results also confirm that the proposed method helps pathologists to distinguish exact dimensions and injury regions.

REVIEW OF EXISTING ALGORITHM

The toboggan algorithm is an important tool for segmentation of images, the result of segmentation of images depends on how to calculate the degraded image greatly if you apply the toboggan to it. We propose a morphological gradient of the multiscale slide algorithm to get the gradient image. Excessive segmentation of the slide is reduced by a region fusion method. A test result shows that the algorithm is valid and more accurate than any conventional algorithm in segmentation of images; in particular it has a wide scope of application due to the selective flexibility of the structural element, such as shape and size.

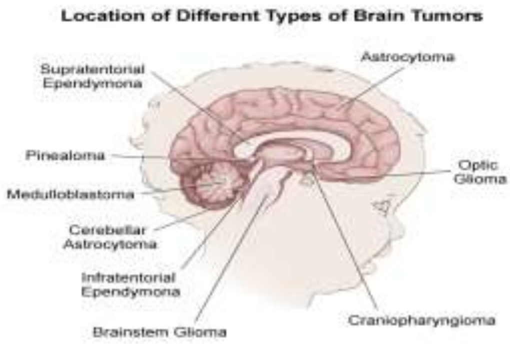


Fig.2. *Brain tumors location*

The precise segmentation of Magnetic Resonance Imaging (MRI) is an important problem in medical and computer communities. The intrinsic complexity of images and their relative systematic lack have led to the development of different approaches to segment the various parts of the human head. PCA is a mathematical procedure that uses a orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly related variables called major components. The number of main components is less than or equal to the number of original variables. This transformation is defined so that the first major component has the largest possible variation (that is, represents most of the variability of the possible data) and each subsequent component has the maximum possible variance under the constraint to be orthogonal to (i.e. unrelated to) the above components. Primary components are guaranteed to be independent only if the data set is distributed in a normal way. PCA is sensitive to the relative scale of the original variables. Depending on the scope, it is also called discrete Karhunen-Loève Transformation (KLT), Hotelling transform or Proper Orthogonal Decomposition (POD).

Table I: *Survey of different methods performance advised for brain cancer diagnosis*

Sr. No	Author	Methodology	Remarks
1	Dubey, R. B., Hanmandlu, M., Gupta, S. K., & Gupta, S. K. [13]	Probability level set evolution	• The automatic method has a lower level ofagreement with the human expertscompared to the semi-automatic method. • Only two MR images samples are used fortesting and evaluate.
2	Singh, Laxman, R. B. Dubey, Z. A. Jaffery, and Z. aheeruddin.[14]	Marker ControlledWatershed	• Different values of threshold are selectedfor creating the Marker ControlledWatershed. • Threshold values are highly dependent onshape and size of tumor and also on theview points (axial, coronal) of images.
3	Amruta, A., AbhijeetGole, and Yogesh Karunakar.[15]	OTSUs Threshold	• Tumor contrast suffusion high quality MRIscans with resolution and contrast for automated volume measurement anddisplay.
4	Somasundaram, K., and T. Kalaiselvi[16]	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
5	Iftekharuddin, Khan M., Jing Zheng, Mohammad A. Islam, and Robert J. Ogg.[17]	Fractal wavelet texture features	• There is no availability of multimodality MR image data. • The researchers haveconsidered onlythe clearly visible tumor in pediatricbrain MR image.
6	Park, Jong Geun, and Chulhee Lee.[18]	Histogram analysis 2D region Growing	• The proposed algorithm showed areliable performance against differentartifacts such as noise.

PROPOSED METHOD

METHOD 1:HBBAS

Learn without supervision, we have only a set of comments and there is no label information for each sample. Usually these observations or features are caused by a set of unobserved or latent variables. The primary purpose of unattended learning is to discover the relationship between samples or to reveal latent variables behind the observations. Undeveloped learning examples include clustering, density estimation, and the separation of blind sources. In our proposed method, two pixel-based segmentation methods are applied. One is histogram statistic and the other is K-means clustering. The histogram method defines single or multiple thresholds to classify a pixel image. A simple approximation to determine the gray value threshold T is by analyzing the peak value histogram and finding the lowest point, typically localized between two consecutive peak values of the histogram. If a histogram is clearly bimodal, the histogram statistics method can provide good results.Natural data generally shows pooling properties: Samples belonging to the same group are more similar, or have a closer distance, in certain metrics than with samples from different groups. Analyzing data pooling properties will help us understand the nature of data and possible real applications. It has extensive radiology applications such as segmentation and diagnosis of medical images. Famous cluster algorithms include k-means clustering, hierarchical clustering, DBSCAN standardized cut and Gaussian blends. The basic idea of clustering k is to assign each sample or point to the cluster with the nearest center (also called centroid, the average of all the clusters belonging to this cluster). Grouping optimization is done by reiterating iterative tags (cluster markers) and recalculating the centroid. K-means clustering has the advantage of simplicity and speed, but is subject to local minima, as there is no guarantee of a global minimum of intra cluster variations. The k-means group assigns a hard tag to each sample. The cluster is the most important learning problem without supervision, as all other problems of this type are to find a structure in a data collection that is not labeled. K-means algorithm is a process of technical iteration and is used for MRI partition in group K. The combination of binder histogram and centroid based clustering provides better results than the existing method.

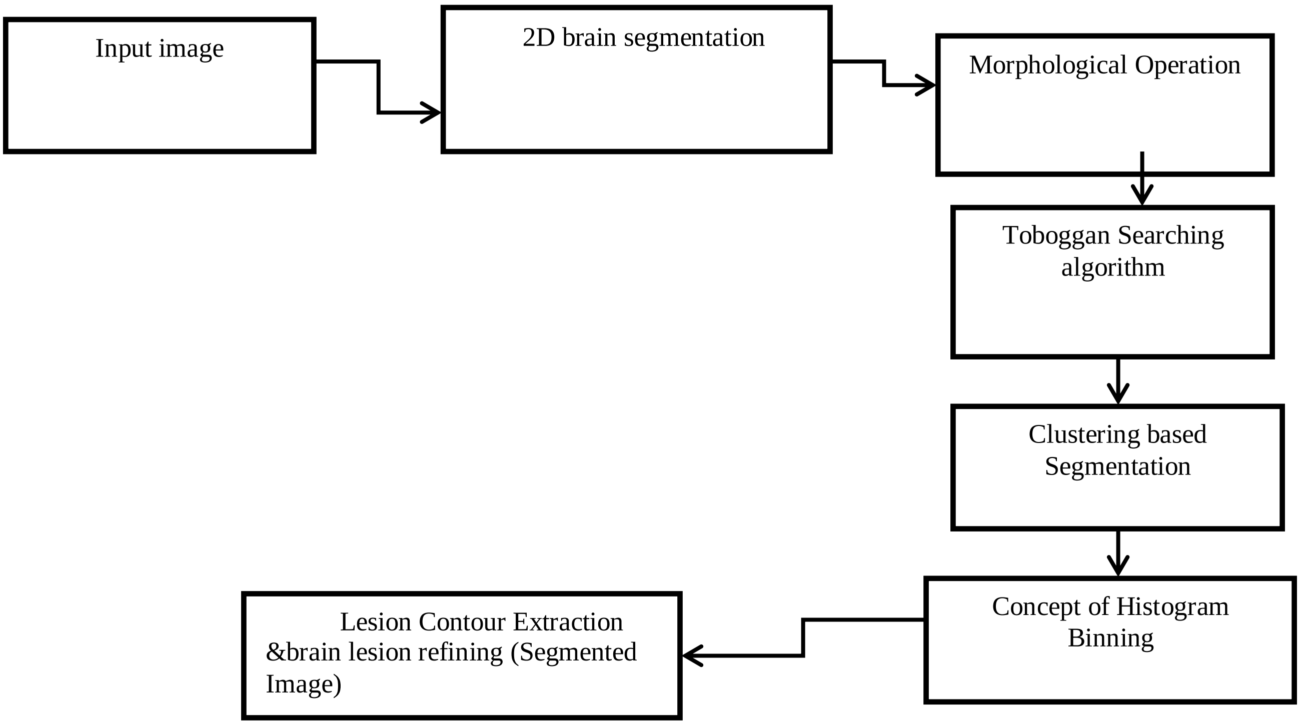


Fig: 3. *Proposed Histogram Binning Based Automatic Segmentation (HBBAS) method Block diagram*

RESULTS

An input image taken here is RIDER Neuro MRI database image, MRI is the imaging technique that has most benefited from technological innovation. The many advances have led to improvements in quality and acquisition speed. In proposed clustering based automatic Segmentation approach consist totally eight steps. In first step is MR image is given as an input, next step is 2D brain segmentation here the input image is convert in to a gradient image then third step is preprocessing here noise in the image are removed from brain field. Then toboggan search algorithm is used to select a seed lesion in the brain image. After select the seed point grouping of similar pixel is done by using k-means clustering. Then histogram binning concept is used here the range interval of image pixel value, then contour of lesion region is extracted. Final output of an proposed algorithm is an segmented image.

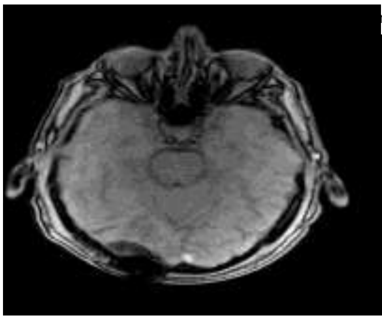
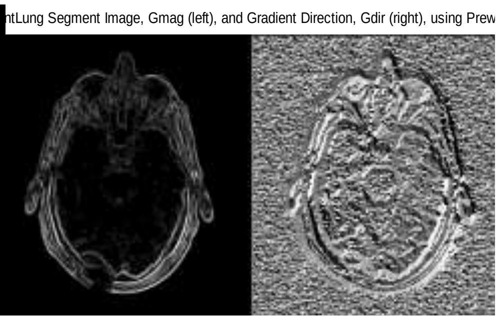
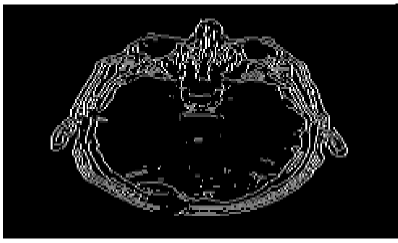



Fig.4. *Input MR brain image* ***Fig.5.****2D gradient brain segmentation*



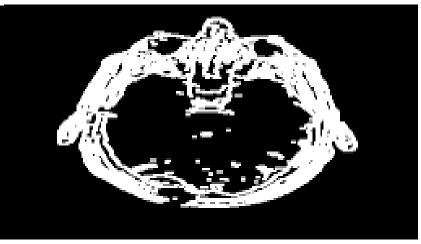


Fig.6. *Binary gradient mask* ***Fig.7.****Dilated gradient mask*

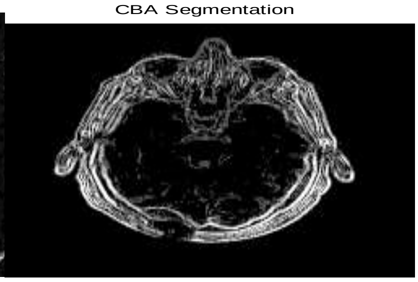


Fig.8. *Toboggan search image* ***Fig.9.****Clusteringbased automatic segmentation*

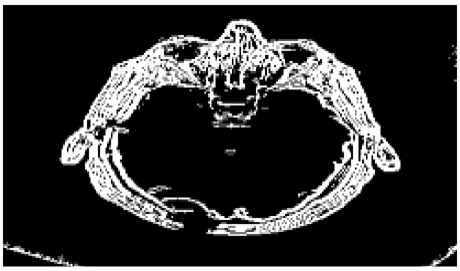


Fig.10. *Histogram binning image*

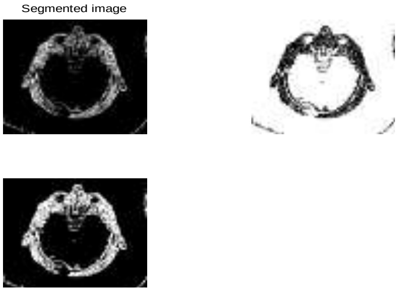


Fig.11.*Segmented image*

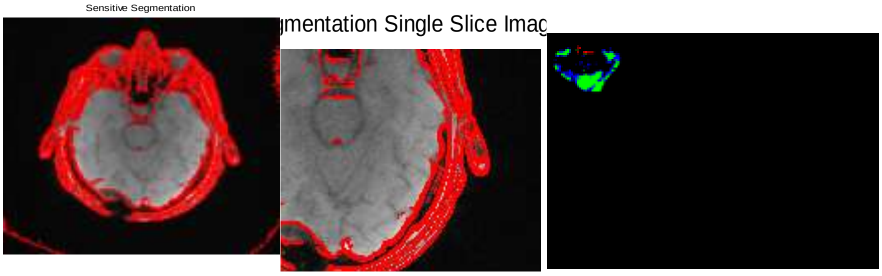


Fig.12. Sensitive Segmentation image

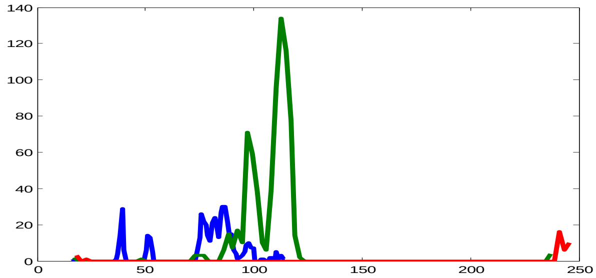


Fig.13. *Different types of brain lesions(Traumatic (blue color plot), neurofibromatosis (green color plot), glioma (red color plot))*

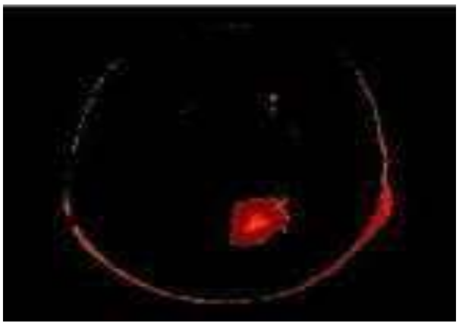


Fig.14. *Cavity extracted tumor region*

METHOD 2: SVM-VW with Median Filter Method

The supervised learning algorithm analyzes training data and produces a deduced function that can be used to map new examples. The main purpose of this method is to detect and classify brain tumor time is a tumor affected or not using the BOVW (Visual Words) classifier. It improves the accuracy of brain classification and also finds border errors. So actions are analysis based on the output of the classifiers.

The algorithm of the visual word has several steps. They are given a magnetic resonance imaging image as input, converted to grayscale image, median filter for noise elimination is applied, the median filter is applied to improve image quality, calculate grouping, morphological calculations, and extraction of shape image features,Calculate the classifier, and finally the output will be a tumor region.

Brain tumors may also spread from cancers primarily located in other organs. A tumor can cause damage by increasing pressure in the brain, by shifting the brain or pushing against the skull, and by invading and damaging nerves and healthy brain tissue.

Contrast enhancement technique is used for enhance the MRI image.

- Read the input brain MRI image.

- Remove the color components by changing the image mode to gray-scale.
- Make the edges in the image clear and crisp by sharpening the components.
- Enhance the quality of the image by applying a median filter.
- Plot the histogram to study and analyze the intensity distribution of the pixels.

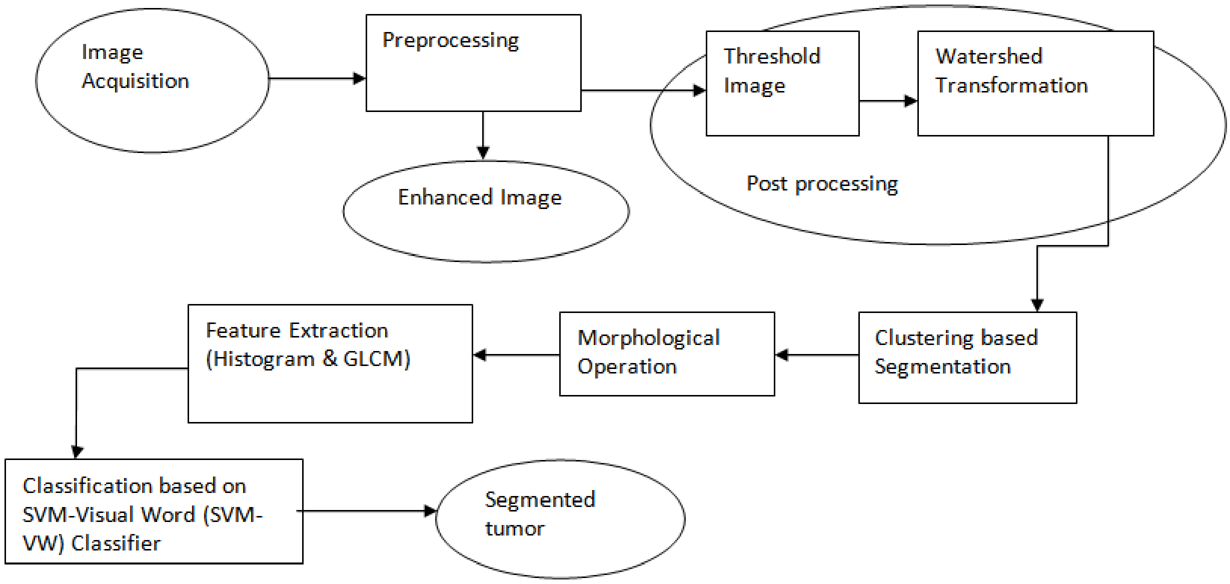


Fig.15. *Proposed SVM Visual Words (SVM-VW) Classification Method Block Diagram*

Gray-Level Co-occurrence Matrix (GLCM):

For extracting second order texture information from different images, GLCM is a robust statistical tool. The spatial distribution of gray level in an image is characterized by this matrix. At a distance d and direction θ, a GLCM indicates the probability of gray-level 'i' occurring in the neighbourhood of gray-level j. Using different values of d and θ, Gray-Level Co-occurrence Matrix of an imageis calculated from texture images and also the co-occurrence matrix G(i,j|d,θ) is created by these probability values. GLCM is additionally known because of the gray-level spatial dependence matrix. The GLCM function characterizes the texture of an image creating a Gray-Level Co-occurrence Matrix and then extracts statistical measures by using this GLCM matrix. The most important steps in this process are (a) Creating a Gray-Level Co-Occurrence Matrix, (b) Specifying the Offsets and (c) Deriving Statistics from a GLCM.

1	1	5	6	8
2	3	5	7	1
4	5	7	1	2
8	5	1	2	5

Fig. 16: *Pixels of input image*

	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

Fig. 17: *GLCM for input image*

In fig(17), element (1,1) contains the value 1 because there is only one instance in the input image where two horizontally neighbouring pixels have the values 1 and 1, respectively. GLCM(1,2) contains the value 2 because there are two instances where two horizontally neighbouring pixels have the values 1 and 2.

The Statistics derived are:

i. Contrast = $\sum_{i=0}^{N_p-1}\sum_{j=0}^{N_p-1}(i-j)^2 p(i,j)$(1)

ii. Cor= $\sum_{i=0}^{N_p-1}\sum_{j=0}^{N_p-1}\frac{(i-\mu)(j-\mu)p(i,j)}{\sigma_i\sigma_j}$

(2)iii. Energy =$\sum_{i=0}^{N_p-1}\sum_{j=0}^{N_p-1}p^2(i,j)$

(3)iv. Homogeneity = $\sum_{i=0}^{N_p-1}\sum_{j=0}^{N_p-1}\frac{p(i,j)}{1+|i-j|}$

(4)

The intensity histogram shows how individual brightness levels are occupied in an image; the image contrast is measured by the range of brightness levels. The histogram plots the number of pixels with a particular brightness level against the brightness level.

Mean, standard deviation, Skewness, kurtosis, and entropy are called as a color feature. Entropy gives the quantity of information of the image that is desired for image compression. These features are extracted using Color Moment (CM) descriptor. Statistical features equations are given as

Mean is defined as

Mean :$\mu_i=\frac{1}{N}\sum_{j-1}^{N} f_{ij}$ (5)

Standard deviation defines

SD : $\sigma_i=\left(\frac{1}{N}\sum_{j-1}^{N}\left(f_{ij}-\mu_i\right)^2\right)^{\frac{1}{2}}$ (6)

Skewness defines

Skewness: $\gamma_i=\left(\frac{1}{N}\sum_{N}^{1}\left(f_{ij}-\mu_i\right)^3\right)^{\frac{1}{3}}$ (7)

Entropy defines

Entropy: $\varepsilon_i=-\sum_{j-1}^{N}\left(f_{ij} * \log f_{ij}\right)$ (8)

Where

N is the total number of pixels in the image

The BoVW model is one of the most widely used ways that represents images as a collection of local features. For this reason, some researchers tend to name it as a bag of features. These local features are typically grouped of local descriptors. The total number of local descriptors that is extracted for each image may be colossal. In addition, searching nearest neighbors for each local descriptor in the image query consumes a long time. Therefore, BoVW was proposed as an approach to tackling this issue by quantizing descriptors into “visual words,” which decreases the descriptors’ sum drastically.

The statistical measures are sensitivity, specificity ,accuracy, precision, similarity, and border error

Sensitivity: It shows the percentage of the actual lesion that has been truly detected by the automated method.

Sensitivity defines as

$$Sensitivity=\frac{TP}{TP+FN}\times 100\% \quad (9)$$

Specificity: It shows the percentage of the actual background brain tumor that has been truly detected by the automated method.

Specificity defines as

$$Specificity=\frac{TN}{TN+FP}\times 100\% \quad (10)$$

Accuracy: It takes into account both lesion pixels and background pixels that have been truly detected by the automated method.

Accuracy defines as

$$Accuracy=\frac{TP+TN}{TP+FP+FN+TN}\times 100\% \quad (11)$$

Precision: It shows what percentage of the detected border is the true lesion

Precision defines as

$$Precision=\frac{TP}{TP+FP}\times 100\% \quad (12)$$

Similarity: It exhibits the degree of agreement between the automatic borders produced by an automated method.

Similarity defines as

$$Similarity=\frac{2TP}{2TP+FN+FP}\times 100\% \quad (13)$$

Border Error: It measures the discrepancy between these two borders.

Border defines as

$$BorderError=\frac{FP+FN}{TP+FN}\times 100\% \quad (14)$$

Where

TP is True positive

FP is false positive

FN is false negative

Performance evolution of SVM-VW classifiers

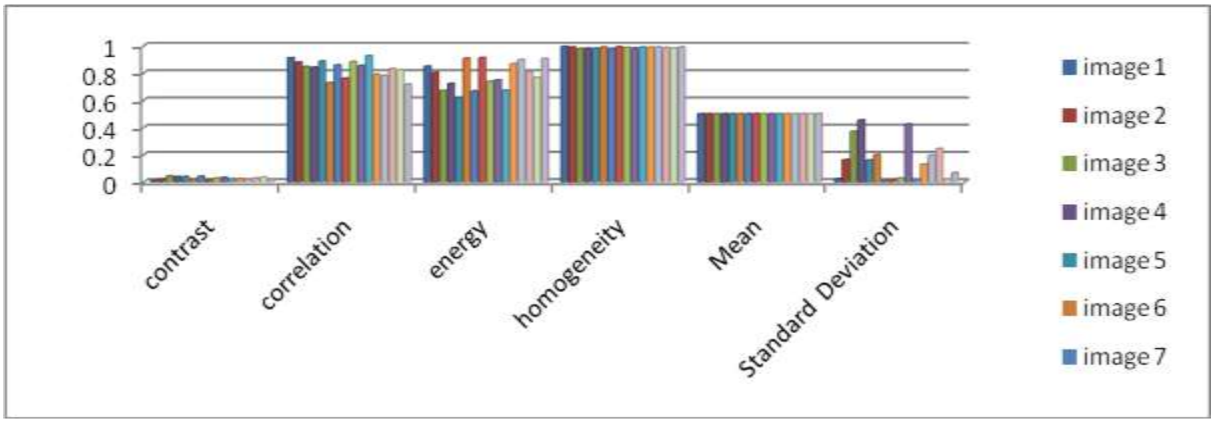
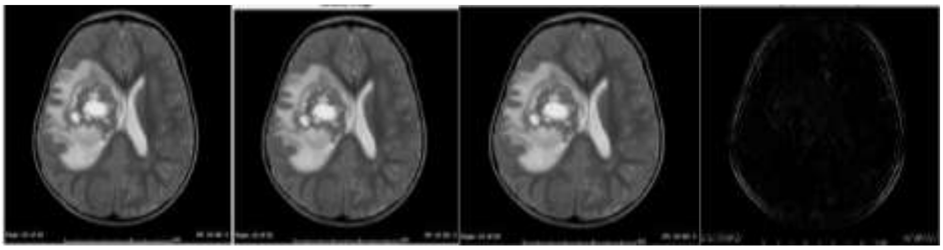


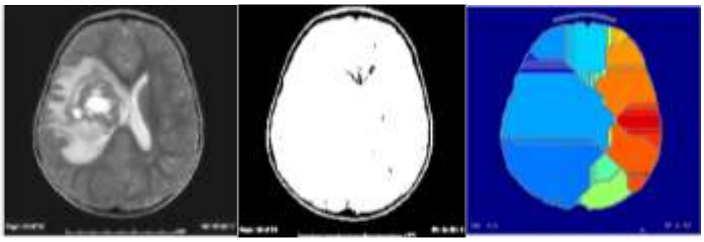
Fig.18. *Performance Evolution*

EXPERIMENTAL RESULTS

Stepwise results of the proposed method are shown in Fig. 1, it comprises of different images :1.Input image, 2. Resized image, 3. Grayscale image, 4. median filter image, 5. Enhanced MRI image, 6. Threshold image,7. Threshold image,8.Distance transform ,9.Watershed transformation ,10.Clustered image ,11.Segmented tumor , 12.Morphological operation . At the end of process, final output is obtained. The complete flow of the proposed approach is visualized from the figure

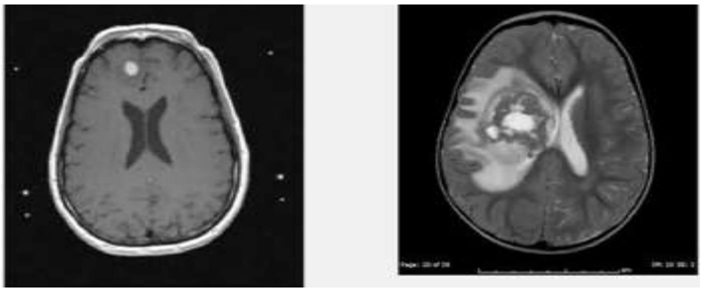


MRI image of tumor   Resized image   Grayscale image Median filter image

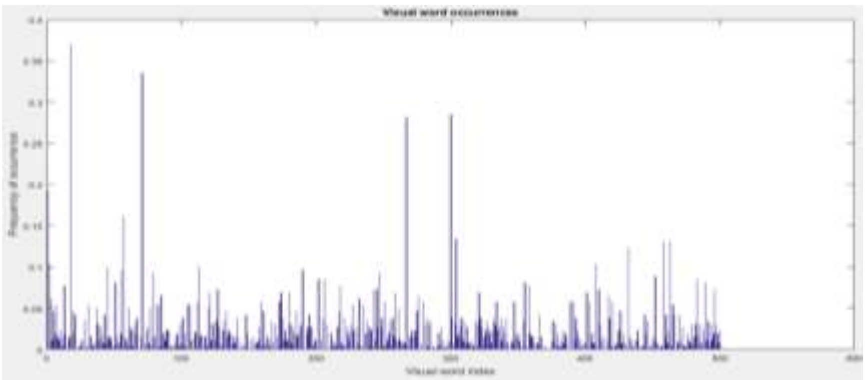


Enhanced MRI image Threshold image Watershed transformation

Clustered image Segmented tumor Morphological operation



MRI scan of benign and malignant brain tumor



Histogram of visual word occurrences

Fig: 19. Brain Tumor Images

SEGMENTATION RESULTS

Parameter	Value
Sensitivity	96.0%
Specificity	98.25%
Accuracy	95.0%

CONCLUSION

In this paper, segmentation method based on K-means clustering for detect and extract tumor in the MRI brain image is proposed. A preliminary experiment conducted on the MRI brain image demonstrates encouraging results. In addition, the proposed method simply combines K-means clustering and histogram-clustering, thus making it efficient and very easy to implement. The important component of this work is that it does not require any training datasets or human interactions for lesion seed point detection, while it could obtain more accurate segmentation results compared with other methods. Better performance was obtained with Execution time single lesion segmentation is 0.021106s by our method. The marked area is segmented and the assessment of this tool from the radiologist, whom the project is concerned with, is positive and this tool helps them in diagnosis, the treatment procedure and state of the tumor monitoring.

FUTURE WORK

As the new method has a variety of advantages for the segmentation of brain lesions and can also be applied as a reference for lesion segmentation in other tissues. In the future classification (Both Supervised and Unsupervised Classification) of the lesions into benign and malignant to be done and calculation of the area and the size of the lesions using simpler algorithms will be addressed. These can be improved by incorporating discrete and continuous-based segmentation methods. Computational effectiveness will be crucial in real-time processing applications. Segmentation methods have proved their utility in research areas and are now emphasizing increased use for automated diagnosis and radiotherapy. These will be particularly important in applications such as computer integrated surgery, where envision of the anatomy is a significant component.

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