

# A MULTI-STAGE HYBRID CAD APPROACH FOR MRI BRAIN TUMOR RECOGNITION AND CLASSIFICATION

Aju\*and Rajkumar

School of Computing Science and Engineering, VIT University, Vellore, TN, INDIA

## ABSTRACT

Brain tumor is one of the acute diseases that happen to humans and it is the major reasons of death amid all other types of the cancers. Appropriate and timely diagnosis can prolong the death of a person to some extent. Therefore, an automated and reliable computer-aided diagnostic system for diagnosing and classifying the brain tumor has been proposed. The proposed method is a multi-stage diagnostic system that recognizes and classifies the brain tumor effectively. First, a pre-processing step is performed for both T1-weighted and T2-weighted MR images. The T1-weighted image is sharpened for improving the brightness of its edges. Subsequently, the T2-weighted image is filtered for noise removal and edge retention using trilateral filtering. The sharpened T1-weighted image and the filtered T2-weighted image are blended together to obtain a single improved MR image. Secondly, the improved MR image is segmented using a hybrid segmentation process of skull stripping and enhanced watershed segmentation for extracting the tumor regions. Finally, the extracted tumor is classified using support vector machine to determine whether the tumor is benign or malignant. The results of the proposed system is promising and shows that the extracted brain tumor is better than the ground truth images in most of the cases. Also, the proposed system was able to achieve an accuracy of 94% in classifying the extracted tumor. Hence, the proposed computer-aided diagnostic system can effectively enhance the diagnostic capabilities of physicians with reduced time.

Received on: 2<sup>nd</sup>-Oct-2015

Revised on: 13<sup>th</sup>-Nov-2015

Accepted on: 18<sup>th</sup>-Nov-2015

Published on: 10<sup>th</sup>-Jan-2016

### KEY WORDS

CAD, Enhanced Watershed Segmentation, Support Vector Machine, Skull-Stripping.

\*Corresponding author: Email: [daju@vit.ac.in](mailto:daju@vit.ac.in) Tel: +91-9042250288

## INTRODUCTION

Brain tumor is one of the most common and major source of death around the world. Always, early detection of brain tumor is a very hectic and challenging task. Brain tumor may appear clear in Magnetic Resonance Imaging than the other types of imaging. The MRI provides better information on soft tissues and significantly improves the understanding of the normal and the diseased anatomy of the brain. Image contrast is the main purpose of all imaging methods and it allows us to differentiate the brain structures. It also determines which brain structures are normal and which structures are abnormal.

MRI structural contrast is superior to the structural contrast present in other imaging modalities. In MRI, tissue relaxation properties greatly influence image contrast. The two relaxation properties in MR imaging is T1 relaxation and T2 relaxation. The T1-weighted imaging is used to discern the structures based on the T1 values and the T2-weighted imaging discerns the structures based on the T2 values. Tissues with high fat content appear bright and the partitions filled with water appears dark in T1-weighted image. And in T2-weighted images, the partitions filled with water will appear bright and the tissues with high fat content will appear dark. The developed CAD system exploits both these weighted images to segment the tumor and classify whether it is benign or malignant. Further, image processing techniques applied to MRI can cater greater help in probing and diagnosing the brain tumor.

## RELATED WORKS

A comprehensive overview and comparison of brain tumors in MR imaging [1], [2] is provided and the pre-processing operations and a futuristic method for brain tumor segmentation is introduced. Also, the evaluation and the validation of the obtained segmented results are presented based upon its efficiency. Various clustering techniques [3] were utilized and implemented to extract and specify the tumor area in a MR image. The classification in the executed methodology confirms whether the tumor is benign or malignant. A three stage approach [4] for diagnosing the brain tumor identifies and segregates the tumor and is invariant in terms of size,

shape and intensity of the tumor. The histogram equalization and morphological processing based CAD system [5] is described. Experimentation is carried out with the help of 125 MR images from 8 persons having tumor and 3 persons without tumors. Six classification algorithms are compared to each other for its efficiency and the authors claim that particle swarm optimization SVM with KNN delivers 100% attainment with their developed system.

Detection and analysis of brain tumor [6] by a novel multi-stage method deals with three brain tumor types such as HG gliomas, metastases and meningioma's. The developed method is experimented for segmenting and accessing the brain tumor with FLAIR, T1-Weighted, Contrast Enhanced T1-Weighted and Perfusion Weighted Image modalities. A brain tumor extraction method [7] reduces the noise and retains the edges in the MRI T2-weighted images. Morphological operations are utilized and manipulated with four different methodologies for extracting and calculating the area of the mass of tissue region.

A fully automated brain tumor detection system [8] aims to determine whether the given T2-weighted MR image has tumor or not and localize it. The developed system was experimented with 131 healthy and 72 tumor affected brain images of T2-weighted MRI modality. The system was able to register an efficiency rate of 95.83 % of correct anomaly detection and 87 % of correct tumor location. A segmentation and automatic tumor class identification methodology [9] is proposed based on a statistical approach assisted by probability maps. The developed system is compared and evaluated with the BRATS (BRAIn Tumor Segmentation) and Leaderboard dataset which encouragingly gave improved results. It is interestingly found that the (GHMRF) Gaussian Hidden Markov Random Field approach attained first in the overall test ranking.

A statistical approach algorithm [10-12] is designed for analyzing the MRI brain images that extracts the data related to brain tumor and locates the tumor. The segmented images are made use of for constructing a 3D model of the tumor region. Various texture features are extracted from the T1-weighted and T2-weighted MR image and classified to find the pathological deficiency in the image. A novel technique for Glioblastoma feature extraction [13] extracts the Gaussian mixture model (GMM) features utilizing the T1-weighted, T2-weighted and Fluid-Attenuated Inversion Recovery (FLAIR) MR images and yields 97.05 % of high accuracy with the classification. A classification system [14] classifies the brain cancer using Principal Component Analysis (PCA) and Back Propagation Neural Network (BPNN) influencing the Gray Level Co-occurrence matrix features. A spatial fuzzy clustering method segments and analyses [15] the structure of MRI brain for segregating the normal tissues and the abnormal tissues of the brain by the enhanced image fusion technique through fuzzy c-means algorithm.

The work carried out by all the aforementioned authors were unique in their own way and they were able to achieve better results. Even though few authors were able to work with different modalities of imaging, none of them were able to capitalize by manipulating the T1-weighted and T2-weighted MR images. Evidently, the proposed system uses and manipulates both the T1-weighted and T2-weighted MR images which helps in segmenting and diagnosing the tumor in an efficient manner. Moreover, an enhanced watershed segmentation algorithm is utilized in the proposed system to extract the brain tumor in an effective way.

The main goal of this work is to design, implement and evaluate a CAD system for early diagnosis of brain tumor in MR Images. The CAD system is designed and developed utilizing the image processing techniques such as, pre-processing, segmentation, feature extraction and classification.

## PROPOSED MULTI-STAGE CAD APPROACH

### The proposed approach consists of the following steps

Pre-processing for noise removal and image enhancement, Hybrid enhanced segmentation process for skull removal and tumor region extraction, Feature extraction from the extracted tumor region using statistical texture features and Classification using support vector machine. The proposed system is shown in [Figure-1](#).

In this proposed system, T1-weighted and T2-weighted MR images are considered and given as input to the CAD system. Both the T1-weighted and the T2-weighted MR images are processed separately and combined later for obtaining better results. The T1-weighted MR images are enhanced by sharpening the edges of the image. The T2-weighted MR images are filtered by trilateral filtering where it removes the noise and retains the structural details of the image. Now the processed images of both T1-weighted and T2-weighted are added together to obtain an improved MR image where it is segmented subsequently. In the segmentation process, first the unwanted skull area is removed by applying the skull stripping method. Further, for segregating

the tumor region, an enhanced watershed image segmentation method is applied to the improved MR image. Once the appropriate tumor is extracted, it is classified using support vector machine. The classification method classifies the extracted tumor either as benign or malignant.

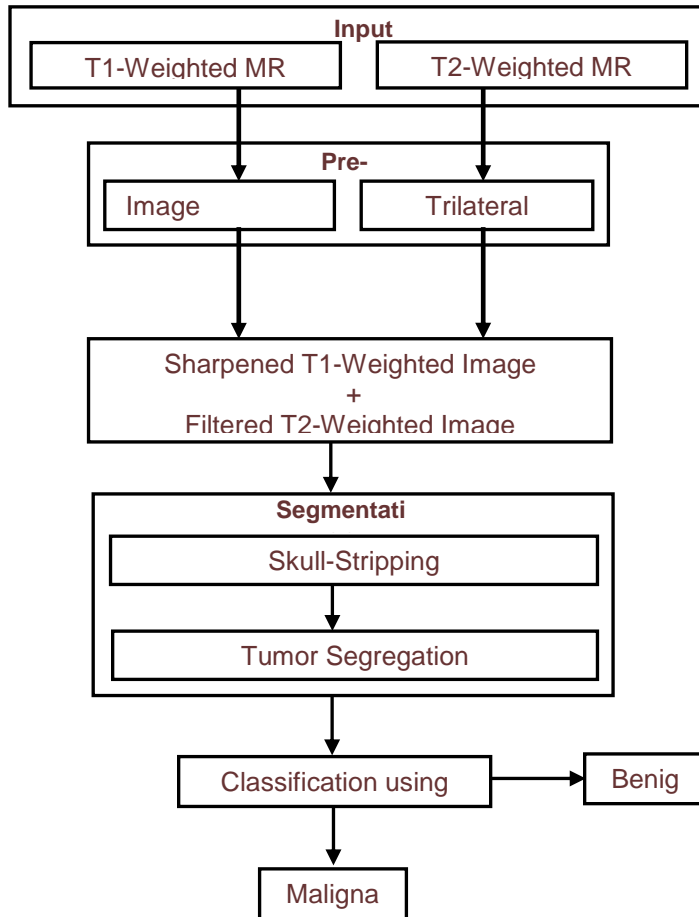


Fig: 1. Overall architecture of the CAD system

### MR image pre-processing

The fundamental objective of medical image enhancement is to process the given input image so that the resultant image is more pertinent than the original image for the specific application. The focus of the enhancement is to accentuate or sharpen the image features such as the edges, boundaries or the contrast in order to visualize and for further analysis. The T1-weighted and T2-weighted MR images are considered for the pre-processing procedure. Both the MR images are manipulated and gone through the sharpening and filtering process.

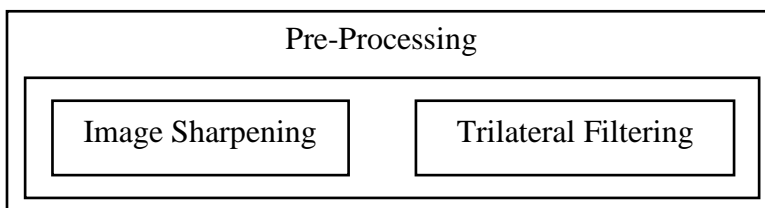


Fig: 2. Pre-processing

## Image sharpening

Sharpness describes the clarity of a digital image and the unsharp masks are probably the most common type of sharpening. An unsharp mask cannot generate additional information, but it can significantly improve the edge details. Here, an unsharp mask of the original T1-weighted image is added to the original T1-weighted image to get the sharpened image.

## Trilateral filtering

This module has been designed for enhancing the quality of MRI by reducing the noise in the image. Sharp ridges and gutters are commonly found in biomedical images, such as folded gray and white matters in brain MR imaging. Therefore, a narrow spatial window, say, 3 pixels in each dimension, should be used in order to avoid over smoothing structures of sizes comparable to the image resolutions. This leads to the necessity of performing more iterations in the filtering process. In this paper, a trilateral filtering method is used for enhancing the MR images and for noise removal, which works along the same lines as the bilateral filtering. It takes not only the geometric and photometric similarities into account, but also, the local structural similarity to smooth the images with a narrow spatial window while preserving the edges. Local structural information is used to determine inhomogeneity in the images. On one hand, low-pass filtering is performed in the homogeneous regions. On the other hand, smoothing along edges is achieved by considering the geometric, photometric and local structural orientation similarities between neighboring pixels in the inhomogeneous regions. This trilateral approach provides greater noise reduction than bilateral filtering with a 3- pixel-width spatial window. The trilateral filtering is expressed as given in equation (1).

$$MRI^{t+1}(x) = \frac{1}{I(x)} \sum_{\xi \in M_x} MRI^t \cdot w(\xi, x, t) \text{----- (1)}$$

where t is a time variable.

Both T1-weighted and T2-weighted MR images give different levels of contrast. The knowledge about these different contrast levels are exploited for achieving better pre-processing of the given images. The signal in the MRI is murky or bright, depending upon the pulse sequence used and the type of tissue in the image region of interest. The edema and the tumor part is murky in T1-weighted and bright in T2-weighted image. This interesting evidence is well made use of and both T1-weighted and T2-weighted MR images are merged together. The outcome of these combined images yields favorable results where the image edges are highlighted and the structural information is retained. The obtained result aids in segmenting the image in a superior manner.

## Skull stripping for removal of skull

An important procedure in brain image analysis is the skull stripping [10] which involves the removal of the scalp, skull and dura matter. Removal of non-brain tissues, particularly dura, is essential in facilitating accurate measurement of brain structures. Inclusion of non-brain structures can result in mistaken interpretation which makes the detection and analysis very difficult and cumbersome. Another concern in skull stripping is the segregation of non-cerebral and the intracranial tissue due to their homogeneous qualities in their intensities. The process of skull stripping is given below,

- Step 1: Apply local threshold to the trilateral filtered image.
- Step 2: Dilate the threshold image using a structuring element of disc.
- Step 3: Apply masking
- Step 4: Normalize the image for easy extraction of tumor region.

## Enhanced watershed segmentation

Watershed segmentation is a predominant segmentation scheme with several advantages. It ensures the closed region boundaries and gives solid results. It is a way of automatically separating or making the regions distinct without touching. The watershed algorithm uses concepts from mathematical morphological operations to partition images into homogeneous regions.

Start

- Step 1: Read the input images,  $Im_{t1}$  and  $Im_{t2}$ .
- Step 2: Compute  $IM_{b_{t1,t2}}(f) = imfuse(Im_{t1}, Im_{t2})$
- Step 3: Compute multiscale gradient,  
 $MS_{\sigma_{r_{t1,t2}}}(f) = \frac{1}{N} \sum_{i=1}^N [Er(Di(IM_{b_{t1,t2}}(f), SE_i) - Er(IM_{b_{t1,t2}}(f), SE_i), SE_{i-1}))]$
- Step 4: Compute  $Op_{t1,t2} = in_r \int \|\nabla f(y(s))\| ds$
- Step 4: Compute  $MSRec_{\sigma_{r_{t1,t2}}}(f) = (MS_{\sigma_{r_{t1,t2}}}(f) \oplus SE + Op_{t1,t2}, MS_{\sigma_{r_{t1,t2}}}(f))$
- Step 5: Create Internal Markers and External Markers.
- Step 6: Apply the created markers to  $MSRec_{\sigma_{r_{t1,t2}}}(f)$
- Step 7: Create final Gradient Image,  $FG_{im_p}(f)$
- Step 8: Apply watershed  $\rightarrow FG_{im_p}(f)$

End

A gradient helps detecting ramp edges and avoids thickening and merging of edges. The local gray level variation in the image can very well be given by the morphological gradient. The gradient image,  $G(f)$  is morphologically obtained by subtracting the eroded image,  $Er(f)$  from its dilated version,  $Di(f)$ . The morphological gradient of  $f$  is given by

$$G(f) = Di(f) - Er(f) = f \oplus b - f \ominus b \quad (2)$$

where  $\oplus$  and  $\ominus$  represents the dilation and the erosion respectively.

A multiscale gradient,  $IM_{b_i}(f)$  is the average of morphological gradients of the structuring element,  $B_i$  with different scales. The multiscale gradient is given by

$$MS_{grad}(f) = \frac{1}{N} \sum_{i=1}^N [Er(Di(IM_{b_i}(f), SE_i)) - Er(IM_{b_i}(f), SE_i), SE_{i-1})] \quad (3)$$

where  $IM_{b_i}(f)$  is the fused T1-weighted image and T2-weighted image,  $SE$  is the structuring element.

When the computed multiscale gradient is subjected to watershed segmentation process, over-segmentation happens due to the occurrence of trivial minima in the resulting gradient. In order to eliminate this inappropriate minima, the multiscale gradient,  $MS_{grad}(f)$  is dilated with a structuring element. This structuring element,  $SE$  should be smaller than that of the  $SE$  that is applied earlier to the multiscale gradient. An optimal threshold,  $Op_{th}$  is calculated and added to the dilated  $MS_{grad}(f)$  to discard the local minima with low contrast.

The optimal threshold value is computed using minimal projection distance. Assume that the image  $f$  is an element of the space  $K(D)$  of a connected domain  $D$  then the topographical distance between points  $m$  and  $n$  in  $D$  is given in equation (4).

$$Op_{th}(m, n) = in_y \int \|\nabla f(y(s))\| ds \quad (4)$$

where,  $in_y$  is over all paths (smooth curve) inside  $D$ , defines the watershed as follows. Let  $f \in K(D)$  have a minima,  $\{m_k\}_{k \in I}$  for some index set  $I$ . The catchment basin  $KB(m_i)$  of a minimum  $m_i$  is defined as the set of points  $K \in D$ , which are topographically closer to  $m_i$  than to any other regional minimum  $m_j$ . The reconstructed gradient image,  $MSRec_{grad}(f)$  is obtained by the reconstruction of the multiscale gradient image,  $MS_{grad}(f)$  with its dilated image.

The internal markers and the external markers are extracted to prevent over-segmentation. Both the markers created are applied to the reconstructed gradient image,  $MSRec_{grad}(f)$ . Markers are created to identify and distinguish the inner structure of the objects that are to be segmented. Finally, the watershed algorithm [17] is applied to the final gradient image,  $FG_{msd}(f)$  where a stable and robust object segmentation is obtained.

## Feature extraction

Features are extracted from the segmented image using GLCM techniques. Features are the characteristics of the objects of interest. It is the illustrative of the maximum pertinent facts that the image has to offer for a comprehensive characterization of a lesion. Feature extraction methods analyze the various objects in the image and the image itself to extract the most prominent features to classify the objects. The first order image features such as mean, variance, standard deviation, skewness and kurtosis are considered and extracted. Also, the second order image features such as contrast, correlation, energy, homogeneity, smoothness and eccentricity are extracted for this empirical research.

### First order features

#### Mean

Mean is an average value that measures the general illumination of the image. The formula for calculating the mean is given by

$$Int_{mean} = \frac{\sum_{i=1}^{N-1} I(i, j)}{N-1} \quad (5)$$

#### Variance

The variance is calculated as the average squared deviation of each number from its mean. It tells us how far a set of numbers are spread out from the mean.

$$Int_{var} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i - \mu)^2 I(i, j) \quad (6)$$

#### Standard deviation

The standard deviation,  $\sigma$  is a measure that is used to quantify the amount of scattering of a set of pixel values. It is the square root of variance which is given by the formula

$$Int_{sd} = \sqrt{Int_{var}} \quad (7)$$

### Skewness

Skewness is defined as a measure of the asymmetry of the probability distribution. It is used to find out whether a wider range of either darker or lighter pixels are present. If the amount of the scattering is intense towards left it is a positive skew. If the amount of the scattering is intense towards right, it is a negative skew.

$$Int_{skew} = \left( \frac{1}{Int_{var}} \right) \sum_{i=1}^N \sum_{j=1}^N (f(i,j) - Int_{mean})^3 \dots\dots\dots (8)$$

### Kurtosis

Kurtosis measures the peak of the probability distribution of a variable. A high kurtosis spreading will have a sharper peak and a flattened tails. A low kurtosis spreading will have a rounded peak with wider shoulder.

$$Int_{kurtosis} = \left( \frac{1}{Int_{var}} \right) \sum_{i=1}^N \sum_{j=1}^N (f(i,j) - Int_{mean})^4 \dots\dots\dots (9)$$

### Second order features

#### Contrast

Contrast is a measure of intensity juxtapose between a pixel and its neighbouring pixels. Contrast will be 0 for a constant image. It can be calculated by the formula.

$$Tex_{con} = \sum_{i,j=0}^{N-1} |i - j|^2 I(i,j) \dots\dots\dots (10)$$

#### Correlation

The gray level linear dependence between the pixels at the specified positions relative to each other is measured by calculating the correlation. Correlation will be +1 or -1 for an accurate positive or negative related image.

$$Tex_{correlation} = \sum_{i=0}^{M-1} \sum_{j=0}^{M-1} \frac{[i \times j] \times I(i,j) - [\mu_x \times \mu_y]}{\sigma_x \times \sigma_y} \dots\dots\dots (11)$$

#### Energy

Energy is also known as uniformity or angular second moment. It returns the sum of squared elements in the gray level co-occurrence matrix. Energy will be 1 for a constant image and is calculated by

$$Tex_{energy} = \sum_{i,j=0}^{N-1} P(i,j)^2 \dots\dots\dots (12)$$

#### Homogeneity

Homogeneity returns a value that measures the closeness of the spreading of elements in the GLCM to the GLCM diagonal. The range of the homogeneity ranges from 0 to 1. It is 1 for a diagonal GLCM. Homogeneity can be measured by

$$Tex_{homog} = \sum_{i,j} \frac{I(i,j)}{1 + |i - j|} \dots\dots\dots (13)$$

#### Smoothness

Smoothness measures the relative softness of the intensity in a region. It is defined as

$$Tex_{smooth} = 1 - \frac{1}{1 + \sigma^2} \dots\dots\dots (14)$$

### Eccentricity

Eccentricity is the ratio of the distance between the centre of the ellipse and its major axis length. The values of eccentricity will be between 0 and 1. An ellipse whose eccentricity is 0, is actually a circle. An ellipse whose eccentricity is 1 will be a line segment. The eccentricity can be measured by

$$Tex_{eccen} = \frac{c}{a} \dots\dots\dots (15)$$

where c is the distance from the centre to the focus of the ellipse and a is the distance from the centre to a vertex

### Classification using support vector machine

Classification of the extracted features is performed using Support vector machine (SVM). It is a powerful supervised classifier and an accurate statistical learning theory technique [16] that works on the basis of structural risk minimization principle. The basic purpose of SVM classifier is to choose the appropriate margins between two classes during the training. The kernel in the classifier controls the empirical risk and the categorization competence with the aim of maximizing the margin between the classes and minimize the true costs [1]. In the higher dimension feature space, an optimal separating hyperplane is explored between the members and non-members of the given class. The graphic representation of feature vectors in the input space and in the feature space is represented in Figure- 3.

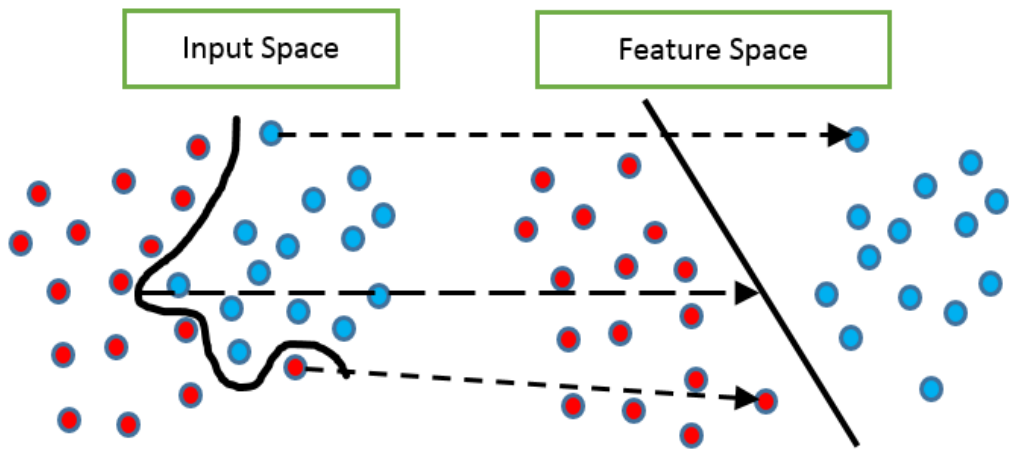


Fig: 3. Representation of feature vectors both in the input space and the feature space

Hyperplane can be defined by H such that

$$x_i \cdot w + b \geq +1 \text{ when } y_i = +1 \dots\dots\dots (16)$$

and

$$x_i \cdot w + b \leq -1 \text{ when } y_i = -1 \dots\dots\dots (17)$$

Here H1 and H2 are termed as two planes and are given by

$$H1: x_i \cdot w + b = +1 \dots\dots\dots (18)$$

$$H2: x_i \cdot w + b = -1 \dots\dots\dots (19)$$

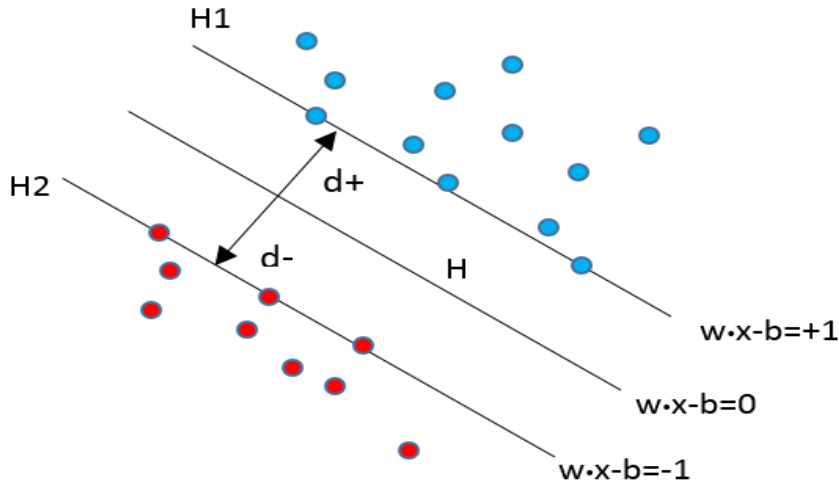


Fig: 4. Selection of the decision boundary between different classes

The points on these planes H1 and H2 are the support vectors. The distance  $d+$  is the shortest distance to the closest positive point in the hyperplane. The distance  $d-$  is the shortest distance to the closest negative point. The selection of the decision boundary between different classes in the support vector machine is shown in Figure– 4.

The inputs to the SVM algorithm are the gray level co-occurrence matrix (GLCM) features subset extracted from the MR images. The classification procedure separates the input features dataset in the feature space into benign tumors and malignant tumors.

Let us consider that the  $n$ -dimensional input  $x_i$  ( $i = 1, \dots, N$ ) belong either to the benign class or the malignant class. Let the associated labels be  $l_i = +1$  for benign tumor and  $l_i = -1$  for malignant tumor. The decision function for the SVM is given by

$$des(x) = w \cdot x + b \text{ ----- (20)}$$

where  $w$  is an  $n$ -dimensional vector,  $b$  is a scalar, and  $y_i = des(x_i) \geq 1$  for  $i=1, \dots, N$ .

A margin is defined as the distance between the separating hyper plane and the training data set nearest to the hyperplane. When the hyperplane decision function,  $des(x_i) = 0$  with the maximum margin, an optimal separating hyperplane is achieved.

### Quality metrics

Image quality is a basic characteristic of an image that determines the degradation of the observed image compared to a ground truth image. Here, the quality metric parameters such as PSNR, Structural Similarity, Normalized Cross-Correlation and Normalized Absolute Error are computed for its efficiency.

#### Peak-Signal-to-Noise-Ratio (PSNR)

PSNR is expressed as the ratio between the maximum possible value of a signal and the value of distorting noise that affects the quality of the image. It is inversely proportional to the mean squared error and is measured in decibels. PSNR can be calculated by

$$Met_{psnr} = 10 \log_{10} \frac{(x^m - 1)^2}{MSE} \text{ ----- (21)}$$

$$\text{where, } MSE = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (x(i,j) - y(i,j))^2 \text{ ----- (22)}$$

Here,  $x(i,j)$  is the original reference image and  $y(i,j)$  is the modified image.  $i$  and  $j$  are the pixel position of the  $M \times N$  image. MSE will be 0 when  $x(i,j) = y(i,j)$ .



### Structural similarity

Structural similarity measures the similarity between two images. It can be measured by the equation

$$Met_{SS} = \frac{\sum_{i=1}^M \sum_{j=1}^N (x(i,j) \cdot y(i,j))^2}{\sum_{i=1}^M \sum_{j=1}^N (x(i,j))^2} \quad (23)$$

where  $x(i,j)$  is the original image and  $y(i,j)$  is the modified image.

### Normalized cross-correlation (NCC)

NCC measures the similarity between two images. The proximity between these two images can be computed in terms of the correlation function. The NCC is given by the equation

$$Met_{NCC} = \frac{\sum_{i=1}^M \sum_{j=1}^N (x(i,j) \cdot y(i,j))}{\sum_{i=1}^M \sum_{j=1}^N (x(i,j))^2} \quad (24)$$


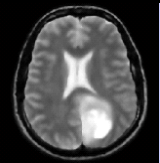
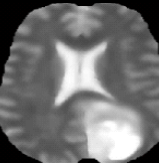

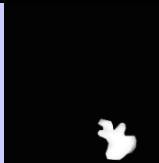
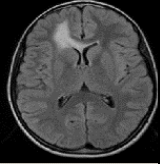
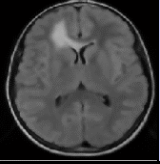
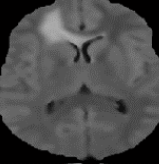

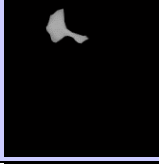
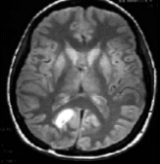
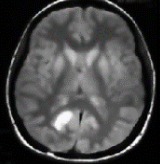
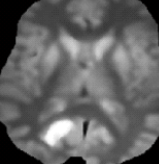



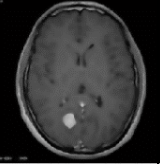
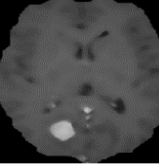
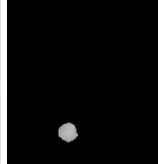
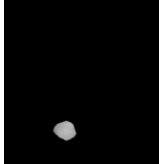
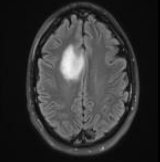
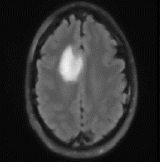
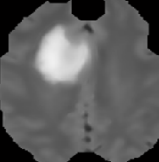
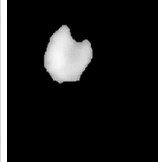
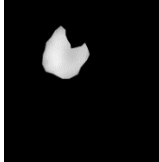
### Normalized absolute error (NAE)

NAE is the average of absolute difference between the reference image and the modified image. It is calculated by

$$Met_{NAE} = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N |x(i,j) - y(i,j)| \quad (25)$$

## RESULTS AND DISCUSSIONS

Table: 1. Output obtained from various stages of the CAD system

Sl. No	Input Image	Pre-processed Image	Skull Stripped Image	Ground Truth Image	Segmented Image
1					
2					
3					
4					
5					

**Table-1** shows five sample image dataset which is processed and manipulated with the developed CAD system. The output obtained in each stage is tabulated in the above table. Only a negligent disparity is observed between the ground truth images and the obtained segmented images which provides higher rate of efficiency.

### MRI brain image features and quality assessment

The features of the MR images are of immense importance for better classification. Here, the intensity features and the texture features are extracted effectively from the processed MR images and are tabulated. Moreover, the quality metrics are computed for its efficiency.

### GLCM features and quality assessment of the ground truth data

**Table: 2. Intensity features obtained from the ground truth images.**

Intensity Features					
Image	Mean	Variance	SD	Skewness	Kurtosis
1	0.0227	0.022	0.1491	6.4036	42.0065
2	0.0313	0.0303	0.174	5.3867	30.0162
3	0.0135	0.0133	0.1152	8.4449	72.3164
4	0.012	0.0119	0.1091	8.9484	81.0731
5	0.0723	0.0671	0.259	3.3021	11.9039

**Table: 3. Texture features obtained from the ground truth images.**

Texture Features						
Images	Contrast	Correlation	Energy	Homogeneity	Smoothness	Eccentricity
1	170.5	0.2335	6.7114	0.0305	0.0217	0.7009
2	170.59	0.4631	4.8804	0.0364	0.0294	0.81
3	128.13	0.6005	0.0011	0.0091	0.0131	0.878
4	122.7	0.0714	0.0013	0.0091	0.0118	0.5186
5	808.63	0.0336	2.1097	0.085	0.0629	0.2811

**Table: 4. Quality assessment of the ground truth images using the quality metrics**

Quality Assessment				
Images	PSNR	Normalized Cross-Correlation	Structural Content	Normalized Absolute Error
1	17.9215	0.9464	0.992	0.2475
2	27.9011	0.9706	1.0434	0.0981
3	23.3358	0.9543	1.0578	0.1318
4	24.6374	0.9468	1.0567	0.1407
5	25.3106	0.98	0.9972	0.1458

Extracted GLCM features and quality achieved through the CAD system

Table: 5. Intensity features extracted from the input image data

Intensity Features					
Images	Mean	Variance	SD	Skewness	Kurtosis
1	0.0215	0.019	0.1485	6.1932	42.1034
2	0.0311	0.0281	0.169	5.2145	30.1145
3	0.013	0.0132	0.115	8.3023	72.3172
4	0.11	0.0116	0.1089	8.5621	80.9852
5	0.0752	0.0686	0.263	3.4211	12.0121

Table: 6. Texture features extracted from the input image data

Texture Features						
Images	Contrast	Correlation	Energy	Homogeneity	Smoothness	Eccentricity
1	169.8	0.2532	6.5612	0.2991	0.0201	0.8211
2	170.5	0.3932	4.7991	0.0297	0.0281	0.887
3	128.11	0.5908	0.0012	0.009	0.0099	0.898
4	122.2	0.0911	0.0122	0.0089	0.0101	0.5821
5	808.86	0.0412	2.1727	0.09	0.0871	0.2744

Table: 7. Quality metrics computed from the output image

Quality Assessment				
Image	PSNR	Normalized	Structural Content	Normalized Absolute
		Cross-Correlation		Error
1	18.8762	0.9243	0.7712	0.2354
2	25.6754	0.9611	0.9987	0.0972
3	23.4575	0.9367	1.0321	0.1317
4	25.8751	0.9485	0.9989	0.1205
5	27.2136	0.979	0.9811	0.1332

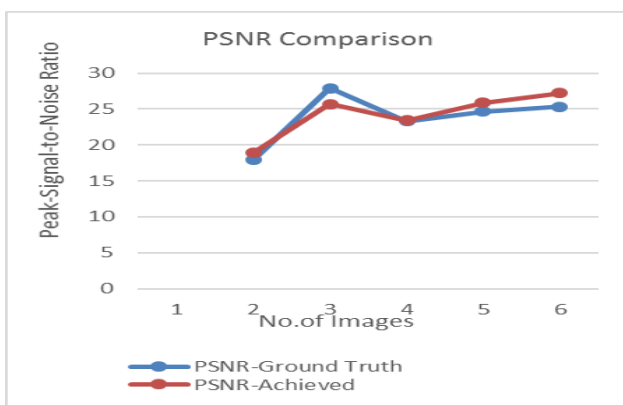


Fig: 5. PSNR: Ground Truth data Vs Achieved data

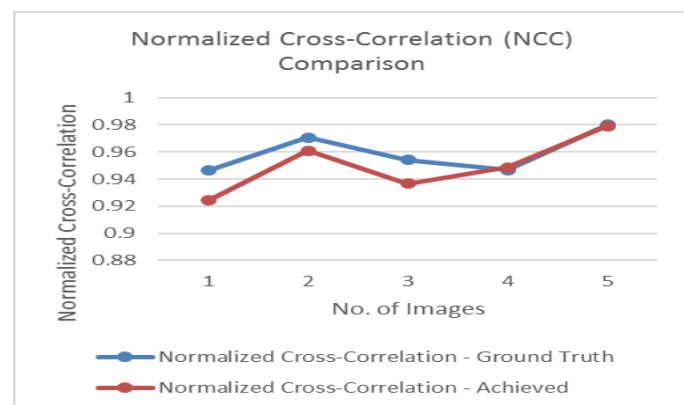


Fig: 6. NCC: Ground Truth data Vs Achieved data

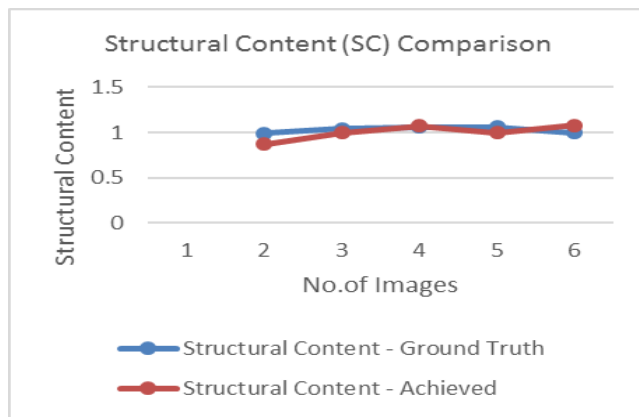


Fig: 7. SC: Ground Truth data Vs Achieved data

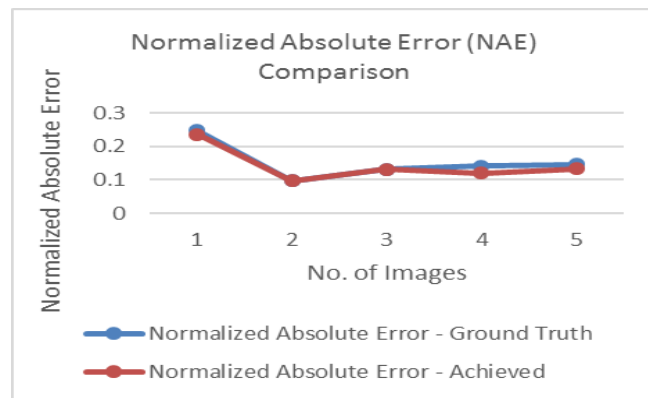


Fig: 8. NAE: Ground Truth data Vs Achieved data

The graphical representation shows the various comparison of the quality metrics for the ground truth image dataset and the actual achieved image dataset. **Figure- 5** shows that the PSNR value is higher for the obtained image compared to the ground truth image data. **Figure- 6** shows that the Normalized Cross-Correlation is lesser compared to the ground truth data. **Figure-7** shows that the structural content is higher in the achieved image data compared to the ground truth image data. And in **Figure- 8**, it is interestingly noted that the Normalized Absolute Error is lesser when compared to the available ground truth MR image data.

### Classification

Table: 8. Classification Rates

Methods	TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	Accuracy (%)
Morphology + SVM	20	12	10	8	71	54	64
Watershed + SVM	30	10	5	5	85	66	80
Enhanced Watershed +SVM (Proposed Method)	42	5	2	1	97	71	94

The classification efficiency rates for three different methods are performed and is tabulated in **Table- 8**. It is interesting to observe that the proposed system performed well compared to the other two methods.

**Figure-9** depicts the comparative analysis of the three different classification methodologies. The developed CAD system bestows 97 % of sensitivity, 71% of Specificity and were able to achieve 94 % of accuracy.

### CONCLUSION

A new and effective computer aided diagnostic (CAD) approach for identifying and classifying the brain tumor is proposed and developed. For this empirical research work, 116 MR images were utilized and employed to yield efficient results. Amongst the 116 MR images, 58 images were T1-weighted and another 58 images were T2-weighted MR images. All the MR images were obtained from Christian Medical College, Vellore, India and Devi Scans, Thiruvananthapuram, India.

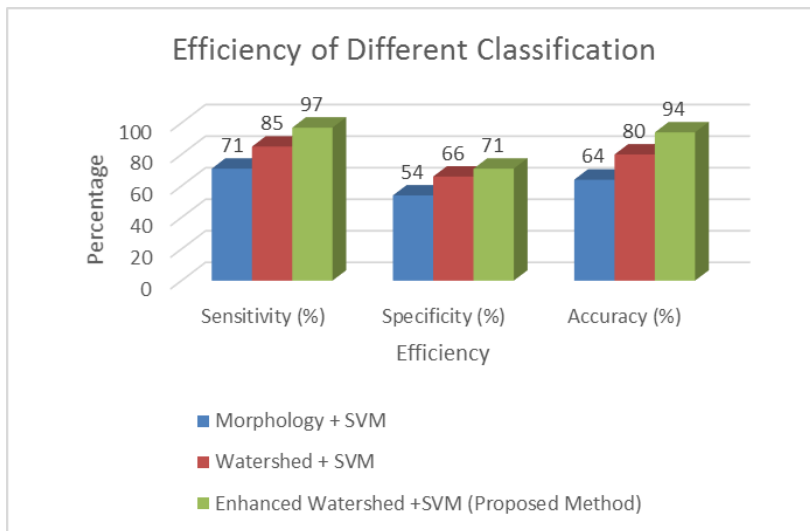


Fig: 9. The efficiency comparison of different classification methods

The developed system is a multi-stage diagnostic system that utilizes the image processing techniques to identify and classify the brain tumor. The proposed system capitalizes with both the T1-weighted and T2-weighted MR images by manipulating and blending it together to obtain an improved results. The enhanced watershed segmentation algorithm is designed and utilized for segmenting the tumor region in the brain effectively. Support vector machine is used to classify the extracted tumor and determine whether the tumor is benign or malignant. The intensity based features and texture based features were extracted by the developed system and is compared to the ground truth dataset. It is interesting to note that the obtained result from the developed system gave better results most of the time when compared to the ground truth dataset. A comparative analysis of two other hybrid classification methods such as Morphology + SVM and Watershed + SVM is performed along with the developed system. By comparing these three classification methods, a higher percentage of efficiency is achieved by the developed system for the brain tumor classification with an accuracy of 94%.

#### CONFLICT OF INTEREST

Authors declare no conflict of interest.

#### ACKNOWLEDGEMENT

None.

#### FINANCIAL DISCLOSURE

Authors have not received any financial support from any individual or organization to carry out this project.

#### REFERENCES

- [1] International Jin Liu, Min Li, Jianxin Wang, Fangxiang Wu, Tianming Liu, Yi Pan. [2014] A Survey of MRI-Based Brain Tumor Segmentation Methods, *Tsinghua Science and Technology*, 19(6):578–595.
- [2] Muhammed Anshad PY, SS Kumar. [2014] Recent Methods for the Detection of Tumor Using Computer Aided Diagnosis – A Review, International Conference on Control, Instrumentation, Communication and Computational Technologies, *IEEE*, pp: 1014-1019, doi: 978-1-4799-4190-2/14.
- [3] Ramish B. Kawadiwale, Milind E Rane. [2014] Clustering Techniques for Brain Tumor Detection", Proceedings of the Fifth International Conference on Recent Trends in Information, Telecommunication and Computing, *ACEEE*, pp: 299-305, doi: 02.ITC.2014.5.49.
- [4] Akram MU, Usman A. [2011] Computer Aided System for Brain Tumor Detection and Segmentation, 2011 International Conference on Computer Networks and Information

- Technology, *IEEE*, pp:299–302, doi:10.1109/ICC/NIT.2011.6020885.
- [5] Ulku EE, Camurcu AY. [2013] Computer Aided Brain Tumor Detection with Histogram Equalization and Morphological image processing techniques, International Conference on Electronics Computer and Computation, *IEEE*, 48–51.
- [6] Jacek Kawa, Marcin Rudzki, Ewa Pietka, Pawel Szwarc. [2015] Computer Aided Diagnosis Workstation for Brain Tumor Assessment, Proceedings of the 22nd International Conference on Mixed Design of Integrated Circuits and Systems, pp: 98–103.
- [7] SM Ali, Loay Kadom Abood, Rabab Saadoon Abdoon. [2013] Brain Tumor Extraction in MRI images using Clustering and Morphological Operations Techniques, *International Journal of Geographical Information System Applications and Remote Sensing*, 4 (1):1–14.
- [8] P Dvorák, WG Kropatsch, K Bartušek. [2013] Automatic Brain Tumor Detection in T2-weighted Magnetic Resonance Images, *Measurement Science Review*, Technische Universität Wien, 13(5): 223–230.
- [9] Javier Juan-Albarracín, Elies Fuster-Garcia, José V. Manjón, Montserrat Robles, F. Aparici, L. Martí-Bonmatí, Juan M. García-Gómez [2015] Automated Glioblastoma Segmentation Based on a Multiparametric Structured Unsupervised Classification, *PLOS ONE* 10(1):1-20, doi:10.1371/journal.pone.0125143
- [10] D Aju, R Rajkumar. [2015] Locale Detection, Identification and Significant Feature Extraction of brain Tumor Manipulating MR Images, *International Journal of Pharma and Bio Sciences*, 6(4): 291–304.
- [11] SM Ali, Loay Kadom Abood, Rabab Saloon Abdoon. [2014] Automatic Technique to Produce 3D Image for Brain Tumor of MRI Images, *Journal of Babylon University/Pure and Applied Sciences*, 22(7): 1896 – 1907.
- [12] Gaurav R Dandge, Karuna G Bagde. [2014] MRI Brain Images Segmentation & Classification using Texture Features, *International Journal of Computer, Information Technology & Bioinformatics*, 2(1):5–9.
- [13] Chaddad A. [2015] Automated Feature Extraction in Brain Tumor by Magnetic Resonance Imaging Using Gaussian Mixture Models, *International Journal of Biomedical Imaging, Hindawi Publishing Corporation*, 2015: 1-11, dx.doi.org/10.1155/2015/868031.
- [14] Nayak GR, Verma T. [2014] Brain Cancer Classification using Back Propagation Neural Network and Principle Component Analysis, *International Journal of Technical Research and Applications*, 2(4): 26–31.
- [15] Mohammed MR, Reddy ES. [2015] Enhanced Image Fusion Technique for Segmentation of Tumor Using Fuzzy C-Means Cluster Segmentation, *Global Journal of Computer Science and Technology: (F) Graphics & Vision, Global Journals Inc*, 15 (1): 1–4.
- [16] Zhang K., CAO HX, Yan H. [2006] Application of support vector machines on network abnormal intrusion detection, *Application Research of Computers*, 5: 98–100.
- [17] Ali Abdullah Yahya, Jieqing Tan, Min Hu. [2013] A Novel Model of Image Segmentation Based on Watershed Algorithm, *Advances in Multimedia, Hindawi Publishing Corporation*, 1–8.