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# Detection and Segmentation of Meningioma Brain Tumors in MRI brain Images using Curvelet Transform and ANFIS

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**ABSTRACT-** The detection of abnormal tumor region brain Magnetic Resonance Images (MRI) is complex task due to its similar structures between tumor and its surrounding regions. In this paper, Adaptive Neuro Fuzzy Inference System (ANFIS) classification method-based meningioma brain tumor detection is proposed. The proposed method consists of the following stages as preprocessing, transformation, feature extraction and classifications. The brain MR images are enhanced in preprocessing stage and this spatial domain image is converted into multi resolution image using Curvelet transform. The texture and statistical features are extracted from the transformed coefficients. These features are trained and classified by ANFIS classifier and further morphological operations are applied on the classified brain image to segment the tumor regions. This proposed meningioma tumor detection approach is analyzed in terms of sensitivity, specificity, Jaccard Similarity Index (JSI), Dice Similarity Index DSI) and accuracy. The reported results showed that an accuracy of 98.5%, sensitivity 91.5% and specificity 98.6 %was achieved from the finely Curvelet Transform and ANFIS Model.

**Keywords:** Brain Tumor, MR Images, Preprocessing, Feature extraction, Meningioma.

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## 1. INTRODUCTION

The abnormal development of cells in brain regions is the main reason for tumor formation. The abnormalities in brain are categorized into benign and malignant. The benign tumor region has no active abnormal cells and it does not spread to other regions of the brain. The malignant tumor has more active abnormal cells and it spreads to the other regions of the brain. Hence, the detection and segmentation of malignant tumor is having high significant than the detection process of benign. Further, the malignant tumors are categorized into Glioma and Meningioma. Among them, meningioma tumors are visualized larger size when compared with other tumor categories. In accordance with the report of World Health Organization (WHO), the grading system is used to classify the severity of the tumor. Generally, the grading system provides grade 1 and 2 for benign tumors and grade 3 and 4 for malignant tumors. *Figure 1* shows the meningioma brain MRI from open access dataset.

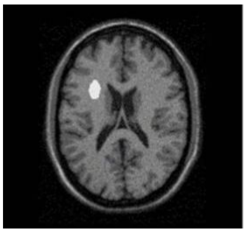

**Figure 1:** Meningioma brain MRI

The non-invasive image scanning methods plays an important role in the process of capturing the human brain regions. Computer Tomography (CT) and MRI is the primary non-invasive image scanning techniques. When compared with CT scanning method, MRI image provides clear pictorial view of the internal structure if the brain. In this paper, MRI brain images are used to detect the tumor regions. Segmentation plays an important role in segmenting the tumor regions in brain MRI images based on its textures, pattern shapes and sizes. In this paper, Morphological operations based ANFIS classification method is used to detect and segment the tumor regions in brain MR images. This manuscript is structured into five sections. *Section 1* introduces the brain tumor types and its scanning methods. *Section 2* describes the conventional methods used to detect and segment the tumor regions in brain MRI images and *section 3* discusses the proposed method. *Section 4* discusses the results and *section 5* concludes the paper by highlighting main findings in this work.

## 2. LITERATURE SURVEY

The K-means classification approach applied in the process for the detection of brain tumors. The features as solidity, area and perimeter were extracted from the source brain MR image and the brain MR image was classified into either normal case or abnormal case based on the response from this K-means classification approach [1]. Further, authors used threshold technique on classified brain image in order to segment the tumor regions.

Feed forward back propagation neural network classification approach is used for detecting and segmenting the brain tumor regions [2]. The authors obtained 90.1% of sensitivity, 95.2% of specificity and 94.5% of accuracy on the brain MR images which were available from Brain Web dataset.

Fuzzy clustering algorithm based implementation is developed for automatic detection of meningioma brain tumors in brain MR images. According to Fuzzy clustering the brain MR images into either normal or meningioma brain images [3]. This clustering algorithm produced two classes as response which was categorized as class high for normal and as class low for abnormal.

Support Vector Machine (SVM) other classification approach for detecting the abnormal regions in brain MR images. The authors tested their proposed feature extraction-based brain tumor detection system with respect to supervised and non-supervised SVM classification approach in order to improve the tumor classification accuracy [4]. The authors obtained 89.5% of sensitivity, 94.2% of specificity and 96.5% of accuracy on the brain MR images which were available from BrainWeb dataset.

Convolutional Neural Networks (CNN) is another approach for detecting and classifying the brain MR images. The authors designed CNN using 3*3 convolution layers and max pooling algorithm [10] for reducing the computational complexity. The feed forward neural network layer was implemented with max pooling algorithm for brain tumor classifications. The authors tested their proposed method on both BRATS 2013 and BRATS 2015 dataset.

K-Nearest Neighbor (KNN) is the method that is used to classify brain MR images as either meningioma or non-meningioma [11]. The authors tested their proposed brain tumor detection algorithm on both low and high resolution brain MR images.

Convoluted Gaussian Filtering (CGF) is another approach to detect and reduce the artifact components in an image and then authors used Sparse Space Segmentation (SSS) methodology to split the entire artifact removed brain image into various non-overlapping regions for segmenting the abnormal pixels in an images. Finally, the authors applied Deep Recurrent Long Short-Term Memory (DRLSTM) technique to classify the various region of pixels in an image for detecting the abnormal portion of pixels in a brain MRI image [16]. The authors compared the results of their proposed brain tumor detection method with other existing methods with respect to number of variables and parameters to validate the proposed work. This work resulted 98.8% for benign image classifications and also obtained 98.9% for malignant image classifications. Developing an automated brain tumor diagnosis system is a highly challenging task in current days, due to the complex structure of nervous system. The Magnetic Resonance Imaging (MRIs) are extensively used by the medical experts for earlier disease identification and diagnosis.

Fuzzy imposed logic is other approach for detecting and segmenting the abnormal tumor regions in brain MRI image. The authors initially segmented the abnormal region in brain image using fuzzy logic after constructed fuzzy rules which were related with the image regions of pixels [17]. Then, the intensity normalization method was used in this work to segment the tumor region of pixels in a brain image. The experimental results of this method were significantly compared with various state of art models in this work.

The MRI images of the patient's brain analyzed using different soft computing methods. The authors used machine learning and deep learning classification models for the classification of the brain MRI images. The authors compared these classification models-based brain tumor detection methods with respect to various imaging modalities [18] in this paper. This proposed method was well applied and analyzed for the various dataset brain images.

## 3. PROPOSED METHODOLOGY

This paper proposes meningioma brain tumor detection and segmentation method using Curvelet transform based ANFIS classification approach. This method consists of preprocessing stage, transformation stage, feature extraction stage, classification and segmentation stages as depicted in *Figure 2*.

### 3.1 Preprocessing

In order to improve the image quality for further processing of tumor detection, preprocessing is applied on source brain MR image. In this paper, Adaptive local histogram equalization method is applied on the source brain MR image to obtain the enhanced image. In this method, the brain MR image is split into non-overlapping 3*3 masks. Then, histogram count of each mask is computed and the intensity of the center pixel in 3*3 masks is replaced by its histogram. The same procedure is followed for all the masks in source image which produces the enhanced brain MR image.

### 3.2 Curvelet transform

The spatial format brain MR image is now converted into multi resolution format image with different scales and orientation. In conventional method, Gabor transform was used by many researchers in medical image analysis. The main limitation of this transform is that its poor scaling redundancy. This scaling redundancy was reduced in Curvelet transform which is suitable for medical image analysis. The Curvelet transform decomposes the preprocessed brain MR image into dyadic sub bands in the form of coefficients.

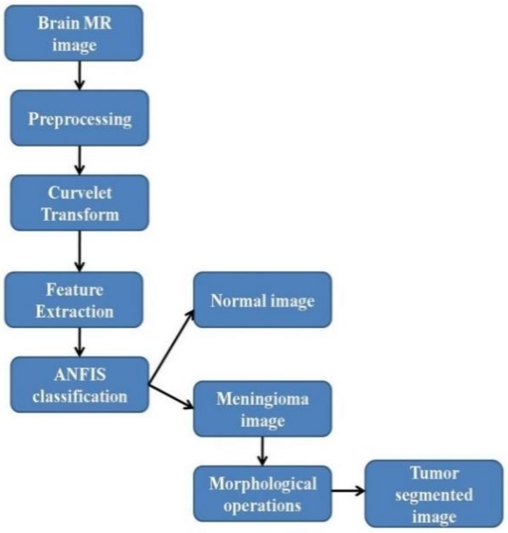


**Figure 2:** Proposed meningioma brain tumor detection method

The Curvelet transform have a set of filter banks with dyadic scales as represented by,

$\{P_0 f, \Lambda_1 f, \Lambda_2 f, \Lambda_3 f, \ldots\}$ (1)

Whereas, $P_0$ is dyadic scale and $\Lambda_s$ is the pass band filter in the frequency range of $2^{2s}$ to $2^{2s+2}$. The number of decomposition levels is denoted by s.

The pass band filter in the frequency range is defined as,

$\Lambda_s = \psi_s * f$ (2)

The decomposition procedure for Curvelet transform is given the following steps.

**Step 1:** The preprocessed image is decomposed into sub bands as depicted in equation (1).

**Step 2:** The sub bands are now partitioned with respect to scale $2^{-s}$.

**Step 3**: Normalization is applied on each sub bands in order to obtain coefficients with respect to scale function.

### 3.3Feature Extraction

In this paper, first order statistical features and second order texture features are extracted from the coefficients of Curvelet transform. The decomposed coefficients from Curvelet transform is grouped into matrix (S) and indexed by its row (i) and column (j). The first order statistical features Skewness and Kurtosis are given in the following equations as stated below.

$$\text{Skewness} = \frac{1}{P\times Q}\cdot\frac{\sum[S(i,j)-M]^3}{\sigma^3} \quad (3)$$

Whereas, the width and height of the decomposed coefficient matrix are represented as 'P' and 'Q'. The mean value is depicted as 'M' and standard deviation is denoted as 'σ'.

$$\text{Kurtosis} = \frac{1}{P\times Q}\cdot\frac{\sum[S(i,j)-M]^4}{\sigma^4} \quad (4)$$

The mean (M) is defined in the following equation,

$$\text{Mean (M)} = \frac{1}{P\times Q}\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1} S(i,j) \quad (5)$$

The standard deviation (σ) is defined in the following equation,

$$\sigma = \sqrt{\frac{1}{P\times Q}\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1}[S(i,j)-M]^2} \quad (6)$$

The second order texture features Coarseness (C) and Optimality (O) are given in the following equations as stated below.

$$\text{Coarseness} = \frac{1}{2^{P+Q}}\sum_{i=1}^{P}\sum_{j=1}^{Q} S(i,j) \quad (7)$$

$$\text{Optimality} = \exp[S(i,j)-M]^2 \quad (8)$$

These extracted features are fed into input of the ANFIS classifier for the classifications of meningioma.

### 3.4 Classifications

The meningioma tumor affected brain MR image is differentiated from normal brain MR image using classification process based on the extracted features from the Curvelet transformation coefficients. In this paper, ANFIS classification approach is used to differentiate the normal brain MR image from abnormal brain MR image. This classification architecture has five layers with number of neurons in each layer. For ANFIS architecture construction, two fuzzy rules are adopted as stated below.

**Rule 1:** If X is L1 and Y is K1, then R=f1(X, Y)
**Rule 2:** If X is L2 and Y is K2, then R=f2(X, Y)
The layer 1 is constructed with the following design equations using mean function of the extracted input features as stated below.

$$\text{Res(Layer1)} = \begin{cases}\mu_{Li}(x), & i = 1,2\\ \mu_{K_{i-2}}(y), & i = 3,4\end{cases} \quad (9)$$

Layer 2 performs multiplication function between membership function of X and Y and the response of this layer is noted as weighting function. The process of this layer is stated as,

$$\text{Res(Layer2)} = \omega_i = \mu_{Li}(x)\times\mu_{K_j}(y) \quad (10)$$

Layer 3 perform normalization process between weighting functions of the individual node to the total weight of all nodes present in this layer as stated as,

$$\text{Res(Layer3)} = \frac{\omega_i}{\sum_{i=1}^{N}\omega_i} \quad (11)$$

Whereas, N is the number of neurons in layer 3.

Layer 4 performs accumulation function as stated below.

$$\text{Res(Layer4)} = \omega_i\,.\,f(x,y) \quad (12)$$

Layer 5 is called as summation layer and produces output as stated below.

$$\text{Res(Layer5)} = \frac{\sum_{i=1}^{N}\omega_i\,.\,f(x,y)}{\sum_{i=1}^{N}\omega_i} \quad (13)$$

The response from layer 5 is binary value which may be either 0 or 1. The '0' response is produced for normal brain MR image and '1' response is produced for abnormal meningioma brain MR image.

### 3.5 Segmentation

It is the process of segment the tumor region in classified meningioma brain MR image. In this paper, morphological

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operations are applied on classified meningioma image for segmenting the tumor regions. The process of tumor region segmentation is given in the following steps.

**Step 1:**
Apply erosion function between the classified meningioma brain MR image (I) and structuring element 'S'. In this paper, disc shaped structuring element having radius 1 is used in this paper. This process is illustrated in the following equation.

$$I \ominus S = \{z|(S) \subseteq I\} \tag{14}$$

**Step 2:**
Apply dilation function between the classified meningioma brain MR image and structuring element 'S'. This process is illustrated in the following equation with respect to the closed function 'z'.

$$I \oplus S = \{z|(S) \cap I\} \tag{15}$$

**Step 3:**
The morphological opening image is obtained using eroded image and its structuring element as stated below.

$$\mu_{opening} = (I \ominus S) \oplus S \tag{16}$$

**Step 4:**
The morphological closing image is obtained using dilated image and its structuring element as stated below.

$$\mu_{closing} = (I \oplus S) \ominus S \tag{17}$$

**Step 5:**
Perform absolute subtraction between morphological opening and closing image in order to segment the tumor regions. Figure 3(a) shows the source brain MR image, Figure 3(b) shows the absolutely subtracted image and Figure 3(c) shows the tumor segmented image.

(a) (b) (c)

**Figure 3**: (a) Source brain MR image (b) Absolutely subtracted image (c) Tumor segmented image

## 4. RESULTS AND DISCUSSION

The proposed meningioma tumor detection and segmentation approach is applied on the brain MR images available in BRATS 2015 dataset. The performance of this proposed meningioma tumor detection approach is analyzed in terms of sensitivity, specificity, Jaccard Similarity Index (JSI), Dice Similarity Index (DSI) and accuracy. This performance analysis is made with respect to gold standard images which are available in open access dataset. The performance evaluation parameters are given as,

$$\text{Sensitivity (Se)} = TP/(TP + FN) \tag{18}$$

$$\text{Specificity (Sp)} = TN/(TN + FP) \tag{19}$$

$$\text{Accuracy (Acc)} = (TP + TN)/(TP + FN + TN + FP) \tag{20}$$

$$\text{Dice Similarity Index (DSC)} = TP/(TP + 0.5 * FN + 0.5 * FP) \tag{21}$$

$$\text{JaccardSimilarity Index (JSC)} = TP/(TP + FP + FN) \tag{22}$$

*Table 1* shows the performance analysis of proposed brain tumor detection and segmentation methodology using ANFIS method on the brain MR images in Brain Web dataset. This proposed method obtained 91.5% of Se, 98.6% of Sp, 98.5% of Acc, 93.1% of DSI and 92.0% of JSI with respect to gold standard images available in Brain Web dataset.

**Table 1.Performance analysis of proposed brain tumor detection and segmentation methodology on Brain Web dataset**

| Image Sequences | Se (%) | Sp (%) | Acc (%) | DCS (%) | JSI (%) |
|---|---|---|---|---|---|
| 1 | 91.8 | 98.1 | 99.1 | 89.7 | 91.8 |
| 2 | 90.7 | 99.7 | 98.7 | 92.1 | 93.1 |
| 3 | 89.8 | 97.8 | 98.4 | 91.9 | 92.7 |
| 4 | 92.9 | 98.9 | 99.1 | 92.7 | 91.6 |
| 5 | 91.6 | 98.4 | 98.4 | 94.8 | 92.1 |
| 6 | 91.5 | 99.1 | 98.6 | 96.2 | 92.7 |
| 7 | 90.9 | 98.8 | 97.9 | 95.1 | 91.5 |
| 8 | 92.7 | 98.4 | 98.1 | 94.2 | 90.9 |
| 9 | 91.9 | 98.6 | 98.8 | 91.9 | 91.7 |
| 10 | 92.1 | 99.1 | 98.6 | 92.8 | 92.1 |
| **Average** | **91.5** | **98.6** | **98.5** | **93.1** | **92.0** |

*Table 2* shows the performance analysis of proposed brain tumor detection and segmentation methodology using ANFIS method on the brain MR images in BRATS 2013 dataset. This proposed method obtained 91.8% of Se, 98.2% of Sp, 98.4% of Acc, 92.1% of DSI and 91.7% of JSI with respect to gold standard images available in Brain Web dataset.

**Table 2. Performance analysis of proposed brain tumor detection and segmentation methodology on BRATS 2013 dataset**

| Image Sequences | Se (%) | Sp (%) | Acc (%) | DCS (%) | JSI (%) |
|---|---|---|---|---|---|
| 1 | 92.1 | 97.9 | 97.1 | 89.5 | 91.7 |
| 2 | 91.9 | 98.1 | 98.5 | 88.9 | 90.3 |
| 3 | 92.8 | 99.6 | 99.1 | 92.1 | 92.8 |
| 4 | 90.6 | 93.8 | 98.6 | 96.1 | 91.3 |
| 5 | 91.7 | 98.1 | 99.8 | 92.6 | 91.7 |
| 6 | 90.9 | 99.6 | 96.9 | 91.7 | 92.8 |
| 7 | 92.7 | 98.5 | 98.7 | 94.7 | 92.7 |
| 8 | 91.8 | 98.4 | 98.9 | 93.2 | 91.8 |
| 9 | 90.8 | 99.2 | 97.6 | 90.1 | 90.6 |
| 10 | 92.7 | 99.1 | 98.9 | 92.8 | 91.6 |
| **Average** | **91.8** | **98.2** | **98.4** | **92.1** | **91.7** |

*Table 3* compares of proposed brain tumor detection and segmentation methodology on BrainWeb and BRATS 2013 dataset using ANFIS method with respect to gold standard images. From Table 3, the proposed brain tumor detection and segmentation methodology achieved high performance on the

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brain images available in BrainWeb dataset when compared with BRATS 2013 dataset.

**Table 3. Performance comparisons of proposed brain tumor detection and segmentation methodology on BrainWeb and BRATS 2013 dataset**

| Image Sequences | Dataset | |
|---|---|---|
| | Brain Web | BRATS 2013 |
| Se | 91.5 | 91.8 |
| Sp | 98.6 | 98.2 |
| Acc | 98.5 | 98.4 |
| DSI | 93.1 | 92.1 |
| JSI | 92.0 | 91.7 |

*Table 4* compares the proposed methodology for brain tumor detection and segmentation with other conventional methods on BRATS 2013 dataset in terms of sensitivity, specificity and accuracy. The conventional method [6] Kamnitsas et al. (2017) used CNN classification algorithm and obtained 90.6% of Se, 93.2% of Sp and 92.6% of Acc. [4] Havaei et al. (2016) used deep neural network classification approach for brain tumor detection and obtained 90.8% of Se, 94.1% of Sp and 93.7% of Acc. [5] Hsieh et al. (2011) used Fuzzy clustering approach for brain tumor detection and obtained 89.4% of Se, 96.3% of Sp and 95.1% of Acc.

**Table 4. Performance comparisons of proposed methodology with other conventional methods on BRATS 2013 dataset**

| Authors | Methods | Se (%) | Sp (%) | Acc (%) |
|---|---|---|---|---|
| **Proposed** (in this paper) | ANFIS | **91.8** | **98.2** | **98.4** |
| [6] Kamnitsas et al. (2017) | CNN | 90.6 | 93.2 | 92.6 |
| [4] Havaei et al. (2016) | Deep Neural Networks | 90.8 | 94.1 | 93.7 |
| [5] Hsieh et al. (2011) | Fuzzy clustering approach | 89.4 | 96.3 | 95.1 |

*Table 5* compares the proposed methodology for brain tumor detection and segmentation with other conventional methods on BrainWeb dataset in terms of sensitivity, specificity and accuracy. The conventional method [9] Nilesh Bhaskarrao Bahadure et al. (2017) used SVM classification algorithm and obtained 89.5% of Se, 94.2% of Sp and 96.5% of Acc. [2] Demirhan et al. (2015) used neural network classification approach for brain tumor detection and obtained 90.1% of Se, 95.2% of Sp and 94.5% of Acc. [7] Kong et al. (2015) used Discriminative clustering Algorithm for brain tumor detection and obtained 91.1% of Se, 93.7% of Sp and 92.8% of Acc. [3] El-Melegy et al. (2014) used Fuzzy logic Approach for brain tumor detection and obtained 89.4% of Se, 95.8% of Sp and 94.1% of Acc.

**Table 5. Performance comparisons of proposed methodology with other conventional methods on BrainWeb dataset**

| Authors | Methods | Se (%) | Sp (%) | Acc (%) |
|---|---|---|---|---|
| **Proposed** | ANFIS | **91.5** | **98.6** | **98.5** |
| [9] Nilesh Bhaskarrao Bahadure et al. (2017) | SVM | 89.5 | 94.2 | 96.5 |
| [2] Demirhan et al. (2015) | NN | 90.1 | 95.2 | 94.5 |
| [7] Kong et al. (2015) | Discriminative clustering Algorithm | 91.1 | 93.7 | 92.8 |
| [3] El-Melegy et al. (2014) | Fuzzy logic Approach | 89.4 | 95.8 | 94.1 |

## 5. CONCLUSIONS

This paper proposes meningioma brain tumor detection and segmentation method using Curvelet transform based ANFIS classification approach. This method consists of preprocessing stage, transformation stage, feature extraction stage, classification and segmentation stages. The first order statistical features and second order texture features are extracted from the coefficients of Curvelet transform. The meningioma tumor affected brain MR image is differentiated from normal brain MR image using classification process based on the extracted features from the Curvelet transformation coefficients. This proposed method is validates on the brain MR images available from BRATS 2013 and Brain Web dataset.

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