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# Tumorous Slices Classification from MRI Brain Volumes using Block based Features Extraction and Random Forest Classifier

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***Abstract***— The proposed work presents a fully automatic computer-aided diagnosis (CAD) system for magnetic resonance images (MRI) of brain tumor classification. Tumorous slices classification is one of the preprocess steps for brain tumor segmentation and visualization. The proposed work classifies each scan image of MRI volumes into normal or tumorous using block based feature extraction and random forest (RF) classifier. The given image has divided into $8 \times 8$ non overlapping blocks and extracted three Haralick features such as Energy, inverse difference moment (IDM) and directional moment (DM) from each block. These three extracted features of training blocks are helped to train the RF classifier. The MRI materials used are gathered from multimodal brain tumor segmentation (BraTS 2015) training dataset comprises 274 multisequence MR scans of glioma patients. The experimental results of proposed technique are validated using the measures sensitivity, specificity, accuracy, missed alarm (MA) and false alarm (FA). The average results of the proposed method reached upto 94% of sensitivity, 94% of specificity and 95% of accuracy in BraTS 2015. The error rates measures 1% of slices were missed to identify as tumor and 3% of slices spuriously detected as tumor. The performance of the proposed work was compared with eight existing methods. In summary, the results showed that the proposed method using RF classifier given effective classification for separating normal and tumorous slices from MR brain volumes.

***Keywords***— Tumor detection, Random forest, Feature extraction, Classification, BraTS dataset.

## I. Introduction

Brain tumor is uncontrolled growth of abnormal cells development in brain tissues. Brain tumors have irregular shape, size and presence in any location [1]. Brain tumors classified into two types: primary, secondary brain tumor. Primary brain tumor starts and spread into brain itself whereas secondary tumor's initial origin maybe anywhere in the body and starts to spread inside the brain. Brain tumor symptoms are headache, vomiting, vision problems and mental changes and these may vary based on the tumor location.

In recent years, brain tumor diagnosis and treatment planning significantly improved by medical imaging modalities [2]. They are X-rays, computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound imaging. Among them, MRI is a non-invasive technique to early detection of tumor and thus increases survival rate of the patient. MRI provides soft tissue characteristics of brain parts using radio frequency waves and powerful magnetic field. The MR images give high level information about normal and tumorous parts of the brain and thus improve the medical diagnosis process.

Manual diagnosis of MR images is a time consuming and painstaking task to the clinician due to large number of stack of 2D slices produced by scanner with partial volume effect (PVE) and intensity non uniformity (INU) artifacts [3]. Recent technologies overcome these difficulties and help to accelerate the diagnosis process along with the modern computers with accurate and quick results. Past few decades, several automatic methods have been developed for MR image classification to assist the clinician in diagnosis process [4].

MR image classification is always demand in the field of clinical and research studies due to its nature of large number of slices per patient with varied modalities and image types. Each abnormal volume, for example tumor affected patient volume contains both normal and tumorous slices. Hence MR image classification techniques help to focus only with the tumorous slices and thus quicken the medical expert's diagnosis procedures. Several classifiers are available at machine learning scenario. They are artificial neural networks (ANN), support vector machine (SVM), k-nearest neighbor (KNN), random forest (RF), and deep leaning neural network (DNN) [5 – 9]. The proposed work uses the RF classifier to classify the MR image of tumor volume into normal or tumorous images.

Feature extraction is generally combined with machine learning algorithms for object detection, content based image retrieval, and texture and image classification. Feature extraction is one of the dimensionality reduction processes to represent the part of the data using feature vectors [10]. Numerous features are possible and they are generally categorized into texture and statistical features. Feature extraction may depend on applications and they are used to train the classifier.

Several automatic methods have been proposed in recent time for MR image classifications using feature extraction. Nayak et al., developed a automatic method for brain MR image classification [11]. They extracting features from input image using two-dimensional discrete wavelet transform (DWT). Principal component analysis (PCA) helps to reduce the dimension of the features and applied to RF classifier. DWT features with RF classifier yielded the results upto 99% of accuracy for classification. Gupta et al., proposed a method for MR image classification and segmentation [12]. They used DWT for feature extraction and SVM, RF for classification. The method reported 90% sensitivity, 100% specificity and 95% accuracy. El-Dahshan et al., developed a hybrid technique for MR image classification. Feature extraction and reduction done by DWT and PCA respectively [13]. Feed forward back-propagation artificial neural network (FP-ANN) and k-nearest neighbor (KNN) techniques used to develop a hybrid classification. The results reached upto 97% for FP-ANN and 98% for k-NN respectively.

The main objective of this work is to propose a MR image classification using block based feature extraction and RF classifier. The proposed method includes both training and testing process. The input image has divided into 8 × 8 non overlapping blocks for feature extraction such as energy, inverse difference moment (IDM) and directional moment (DM). Experimental tests were done on BraTS 2015 dataset with 274 subjects of multisequence tumor volumes. Promising results were obtained using BraTS dataset. The rest of the paper is organized as follows; Section II describes the materials and metrics used for the experiment; Section III presents the proposed methodology for tumor detection; Section IV reports the results and discussion; finally, section V concludes the paper.

## II. MATERIALS AND METRICS

The materials used for this work is obtained from multimodal brain tumor segmentation (BraTS 2015) training datasets comprises 274 multisequence MR scans of glioma patients. Each datasets has four modalities: $T_1$, $T_1$c, $T_2$, method has both training and testing phases with same processes such as block splitting and feature extraction.

FLAIR with the dimension of 240 × 240 × 155 voxels. All images are skull stripped and resampled to isotropic 1mm × 1mm × 1mm resolution and registered with the $T_1$c modality. The 274 datasets classified into 220 high and 54 low grade gliomas (HGGs and LGGs). BraTS 2013 training set is a subset of BraTS 2015 which contains 20 HGGs and 10 LGGs also used for this experiment.

Some of the validation metrics were used for analyzing the classification efficiency of proposed method. They are sensitivity, specificity, accuracy, missed alarm (MA) and false alarm (FA). The precision of the classification each measured using sensitivity, specificity and accuracy as given in Eq. (1) to Eq. (3). Sensitivity calculates number of tumorous slices correctly detected out of total number of tumorous slice. Specificity calculates number of normal slices correctly classified out of total number of normal slice. Accuracy calculates total number of normal and tumorous slices correctly identified. The classification error rates measured in terms of either fail to detect the tumorous slice (missed alarm) or identify the tumorous slice which is not present (false alarm) as given in Eq. (4) and Eq. (5).

$$Sensitivity\,\% = \frac{TP}{TP+FN} \times 100 \tag{1}$$

$$Specificity\,\% = \frac{TN}{TP+FP} \times 100 \tag{2}$$

$$Accuracy\,\% = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{3}$$

$$MA\,\% = \frac{FP}{Total\ Slices} \times 100 \tag{4}$$

$$FA\,\% = \frac{FN}{Total\ Slices} \times 100 \tag{5}$$

where, true positive (TP) is number of tumorous slices correctly identified. True negative (TN) is number of normal slice detected correctly. False positive (FP) is number of tumorous slice incorrectly identified. False negative (FN) is number of normal slice incorrectly classified.

## III. PROPOSED METHODOLOGY

Block diagram of the proposed method is shown in Fig. 1. From the multisequence MRI dataset, the method taking FLAIR images as input because of FLAIR suppresses the CSF signal due to long inversion time ($T_1$) and improves the visibility of tumor than $T_1$ and $T_2$ scans [14]. Normal and tumorous MR images are shown in Fig. 2. The proposed

In training and testing phases, MR FLAIR image splits into 8 × 8 non overlapping blocks as shown in Fig. 3. Block size of

$8 \times 8$ yields optimal results than various block size ranging from $4 \times 4$ to $16 \times 16$ pixels. Three optimal features such as energy, inverse difference moment (IDM) and directional moment (DM) are chosen from Haralick [15]. This features are extracted from each block as defined in Eq. (6) - Eq. (8). Energy measures the intensity uniformity, IDM computes local homogeneity and directional moment measures the intensity alignment of an image.

$$Energy = \sqrt{\sum_{i=1}^{8}\sum_{j-1}^{8} M^2(i,j)} \tag{6}$$

$$IDM = \sum_{i=1}^{8}\sum_{j-1}^{8} \frac{M(i,j)}{1+(i-j)^2} \tag{7}$$

$$DM = \sum_{i=1}^{8}\sum_{j-1}^{8} M(i,j)\,|\,i-j\,| \tag{8}$$

where, M denotes $8 \times 8$ block. Table 1 reports features value for non-tumorous and tumorous blocks. The table showed a linear difference occurred between non-tumorous and tumorous blocks. Tumorous blocks were given high values for all features than non-tumorous blocks.

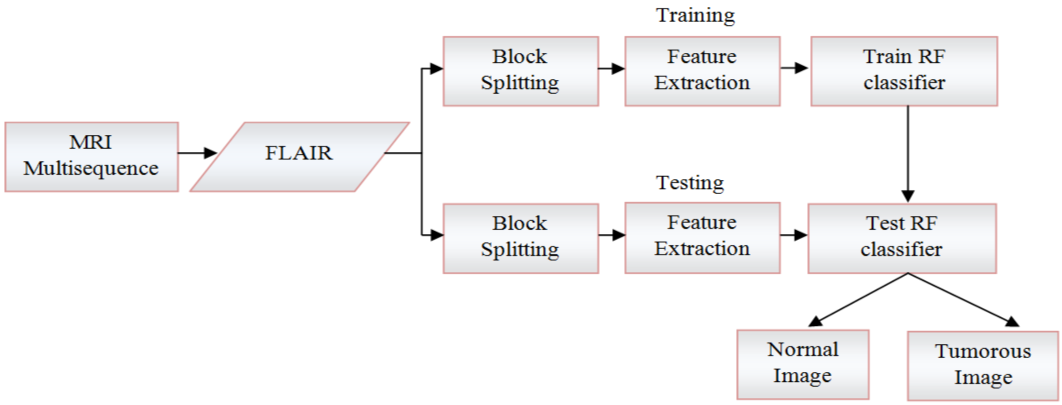



Figure 1. Block diagram of the proposed method

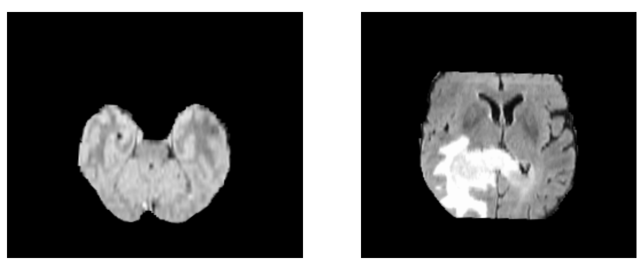


Figure 2. Normal and Tumorous FLAIR images

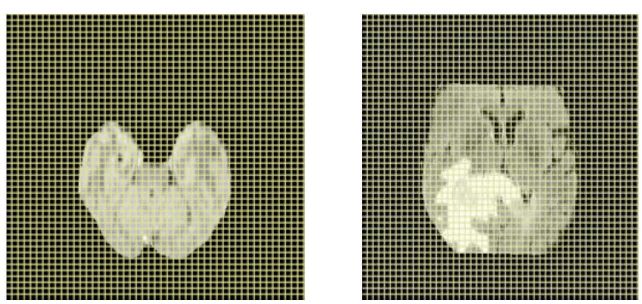


Figure 3. Normal and Tumorous FLAIR image with $8 \times 8$ blocks

Table 1. Feature extraction results for normal and Tumorous blocks

| Block Category | Energy | Homogeneity | Directional Moment |
|---|---|---|---|
| Non-tumorous | 759.51 | 1493.05 | 12271 |
| Non-tumorous | 950.47 | 1778.05 | 15551 |
| Non-tumorous | 1224.23 | 2888.25 | 26120 |
| Non-tumorous | 549.56 | 880.84 | 6588 |
| Tumorous | 2032.67 | 4889.36 | 42672 |
| Tumorous | 2026.03 | 4874.52 | 42512 |
| Tumorous | 1931.24 | 4731.74 | 39574 |
| Tumorous | 1910.02 | 4464.41 | 40749 |

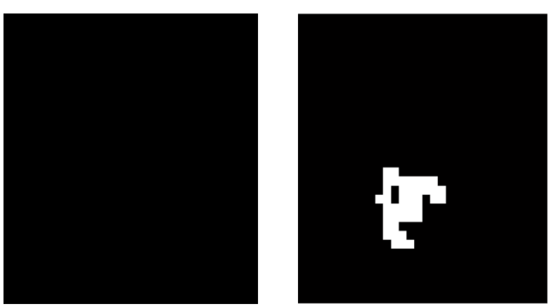
RF is a supervised machine learning algorithm working with the concept of decision tree and each tree grown using randomization principles [16]. RF classifier helps to classify the given MR images into normal or tumorous. RF classifier classifies the image based on the training features using weighted voting technique. The weight updating computation defined as

$$W_i = W_i^0 - \frac{1}{S}\sum_{j=1}^{S} | p_i^{\hat{c}_j}(j) - p_i^{c_j}(j) | \tag{9}$$

where, $W_i^0$ is initial weight, $s$ is feature set from training process, random index *(i)* varies from 1 to total number of trees (T) and the class label $c_j$ is defined as:

$$c_j = \underset{c}{\arg\max} \sum_{i=1}^{T} W_i \, p_i^c(j) \tag{10}$$

In training, five thousand number of non-tumorous and tumorous blocks are used to train the RF classifier. Trained RF classifier makes the effective classification using these three features in testing process. Fig. 4 shows that the resultant images of proposed method on normal and tumorous images of Fig. 3 using RF classifier. The classifier gives binary classification results. It may be either zero or one to each block. Block with zero represents non- tumorous block and one represents tumorous block. RF Classifier classifies any tumorous blocks in the image considered as tumorous image. Fig 4 (a) shows results of all blocks are zero and classified as normal image. The classifier is given the results in white as shown in Fig. 4 (b) are considered to be tumorous image.



(a) (b)

Figure 4. Classification results of proposed method on Fig. 3 (a) and (b).

(a) Normal image (b) Tumorous image

## IV. RESULTS AND DISCUSSION

The experimental setup is equipped with Intel I5 M560 @ 2.67GHz, 4 processors with 4 GB RAM. Classification performance of the proposed method compared with corresponding gold standard image given by the medical experts for BraTS dataset. Table 2 reports the quantitative validation for tumorous slice detection in BraTS 2013. Five metrics are used to report the efficiency of the classification. In general, error rate should be minimum (MA and FA) and prediction rate should be maximum (sensitivity, specificity and accuracy). Three features based RF classifier achieved the results with 96.21% sensitivity, 96.53% specificity, 96.15% accuracy and error rates with 1.56% MA, 2.27% FA for BraTS 2013.

Table 2. Quantitative results for tumorous slice classification in BraTS 2013

| Volume | Sensitivity% | Specificity% | Accuracy% | MA% | FA % |
|---|---|---|---|---|---|
| HG01 | 97.10 | 100.0 | 98.70 | 1.29 | 0 |
| HG02 | 100.0 | 93.81 | 96.12 | 0 | 3.87 |
| HG03 | 88.15 | 100.0 | 94.19 | 5.80 | 0 |
| HG04 | 97.01 | 100.0 | 98.70 | 1.29 | 0 |
| HG05 | 98.61 | 98.79 | 98.70 | 0.64 | 0.64 |
| HG06 | 91.25 | 100.0 | 95.48 | 4.51 | 0 |
| HG07 | 98.21 | 93.93 | 95.48 | 0.64 | 3.87 |
| HG08 | 93.15 | 100.0 | 96.77 | 3.22 | 0 |
| HG09 | 93.055 | 92.77 | 92.90 | 3.22 | 3.87 |
| HG10 | 100.0 | 93.27 | 94.83 | 0 | 5.16 |
| HG11 | 95.23 | 100.0 | 98.06 | 1.93 | 0 |
| HG12 | 87.80 | 100.0 | 96.77 | 3.22 | 0 |
| HG13 | 86.20 | 100.0 | 97.41 | 2.58 | 0 |
| HG14 | 93.42 | 100.0 | 96.77 | 3.22 | 0 |
| HG15 | 98.71 | 96.10 | 97.41 | 0.64 | 1.93 |
| HG22 | 92.95 | 100.0 | 96.77 | 3.22 | 0 |
| HG24 | 100.0 | 100.0 | 100.0 | 0 | 0 |
| HG25 | 100.0 | 88.09 | 93.54 | 0 | 6.45 |
| HG26 | 92.30 | 100.0 | 95.48 | 4.51 | 0 |
| HG27 | 89.47 | 100.0 | 94.83 | 5.16 | 0 |
| LG01 | 93.61 | 93.51 | 93.54 | 1.93 | 4.51 |
| LG02 | 100.0 | 100.0 | 100.0 | 0 | 0 |
| LG04 | 100.0 | 95.00 | 96.77 | 0 | 3.22 |
| LG06 | 100.0 | 92.24 | 94.19 | 0 | 5.80 |
| LG08 | 100.0 | 97.56 | 98.06 | 0 | 1.93 |
| LG11 | 100.0 | 89.00 | 92.90 | 0 | 7.09 |
| LG12 | 100.0 | 87.03 | 90.96 | 0 | 9.03 |
| LG13 | 100.0 | 92.15 | 94.83 | 0 | 5.16 |
| LG14 | 100.0 | 94.65 | 95.48 | 0 | 4.51 |
| LG15 | 100.0 | 98.23 | 98.70 | 0 | 1.29 |
| | **96.21** | **96.53** | **96.15** | **1.56** | **2.27** |

Table 3 Quantitative results for tumorous slice detection in BraTS 2015

| Volume (274) | Sensitivity % | Specificity % | Accuracy % | MA % | FA % |
|---|---|---|---|---|---|
| HGGs (220) | 97.10 | 93.93 | 95.39 | 1.09 | 3.52 |
| LGGs (54) | 90.73 | 94.07 | 95.15 | 1.30 | 3.31 |
| | **93.91** | **94.00** | **95.27** | **1.19** | **3.41** |

Table 3 describes the classification results for tumorous slice detection in BraTS 2015. The results tabulated in the form of HGGs followed by the LGGs dataset. The average results of the proposed method for BraTS 2015 are upto 94% of sensitivity, 94% of specificity and 95% of accuracy. The error rates are 1% of MA and 3% of FA. High contrast white matter tissues in the FLAIR images increase FA rate in the results.

Proposed results were compared with several existing methods on BraTS datasets [17 - 19] and are shown in Fig. 5. The results showed that the proposed method yielded comparable prediction with the existing methods. Average processing time taken by the tumorous slice detection process is 8.6 minutes per dataset.

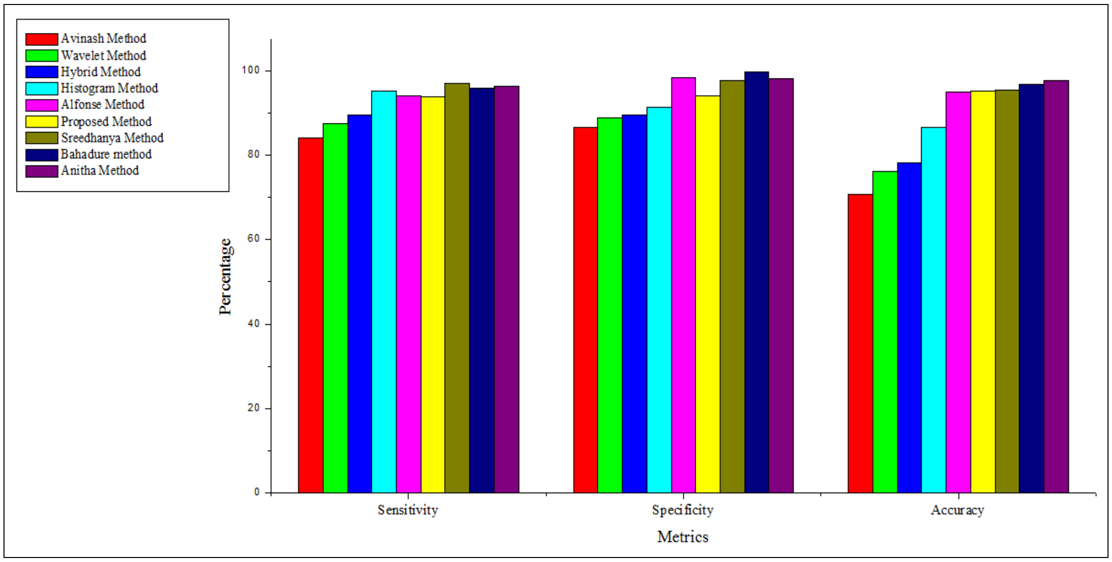



Figure 5. Comparison among proposed and existing methods for tumorous slice detection in BraTS

## V. CONCLUSION AND FUTURE SCOPE

The proposed work developed for classifying the MRI volume into normal and tumorous slices using block based three features RF classifier. Three feasible features were extracted from 8 × 8 non overlapped blocks of given image. The selected three features were given linear difference between normal and tumorous images using RF classifier. Overall classification results of the method achieved upto 94% sensitivity, 94% specificity, 95% accuracy and error rates upto 1% MA and 3% FA. In summary, proposed work was given high accuracy of tumorous slice classification from MR brain volumes using feature extraction and RF classifier. In future, processing time can be reduced using graphics processing unit (GPU) computation.

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