Brain Tumor Detection Deep learning

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Abstract

The perilous disease in the worldwide now a days is brain tumor. Tumor affects the brain by damaging healthy tissues or intensifying intra cranial pressure. Hence, rapid growth in tumor cells may lead to death. Therefore, early brain tumor diagnosis is a more momentous task that can save patient from adverse effects. In the proposed work, the otsu method is applied for accurate segmentation of actual lesion symptoms while Transfer learning model visual geometry group (VGG-19) is fine-tuned to acquire the features which are then concatenated with hand crafted (shape and texture) features through serial based method. These features are optimized through entropy for accurate and fast classification and fused vector is supplied to classifiers. The presented model is tested on top medical image computing and computer-assisted intervention (MICCAI) challenge databases including multimodal brain tumor segmentation (BRATS) 2015, 2016, and 2017 respectively. The testing results with dice similarity coefficient (DSC) achieve 0.99 on BRATS 2015, 1.00 on BRATS 2015 and 0.99 on BRATS 2017 respectively.

Keywords:

Tumors

Classification

Brain image

Contourlet

1. Introduction

The morphology behavior of the cells in brain isaffected by improper mitosis process. This leads to theformation of tumor cells in brain region. These tumor cell sare having different morphological properties such as size and intensity. Most of the tumor cells in brain region are low contrast with respect to the other surrounding cells. These abnormalities in brain image are identified bys canning the brain regions using Magnetic Resonance Imaging (MRI) technique [12]. The detection and segmentation of intratumor region in brain MRI image is a challenging task due to the low intensity variation between tumor cells and its surrounding cells in brain image. In current medical scanning methods, MRI scanning procedure is superior to Computer Tomography (CT) due to its high sensitivity and high contrast with respect to various intensity tissues in brain image. The brain tumorsare categorized into Glioma and Glioblastoma [10]. The Gliomatumors are high pixel intensity cells and irregular boundary regions (Bandhyopadhyay et al. [3]). Glioblastomatumors are low pixel intensity cells and it can be detected by many conventional methods with high level of accuracy. The detection and segmentation of Glioma brain tumors in brain MRI image is a challenging task due to its irregular boundary regions (Funmilola et al. [7]). In common, the Gliomatumor images are categorized into low grade Gliomatumors and high-grade Gliomatumors based on its severity level. In this paper, ANFIS classification approach-based Glioma brain tumor detection and segmentation methodology is proposed in an automated manner. The main purpose of this paper is to develop an efficient system which localizes the tumor boundary with high level of accuracy. Fig. 1 shows the Glioma brain MRI image which clearly represents the irregular boundary region of tumor cells. This paper is structured as, section 2 states various conventional methodologies for Glioma brain tumor detection, section 3 proposes an efficient methodology for brain tumor detection and segmentation using ANFIS classification approach, Section 4 discusses the simulation results of the proposed Gliomatumor Segmentation method with respect to other state-of-arts methods and Section 5 concludes the paper by stating its advantages and future developments.

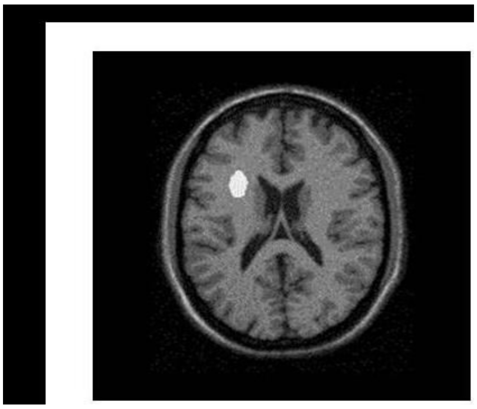

Fig 1. Glioma brain MRI image.

2. Literature Survey

. Differentiated the normal brain MRI image from abnormal MRI brain image using Convolutional Neural Network (CNN) approach. The authors used Maxpool methodology in CNN architecture in order to improve the classification accuracy of the brain tumor detection system. The authors achieved 88.8% of sensitivity, 91.6% of specificity and 92.1% of accuracy on Leader Board data subset of BRATS dataset. The authors achieved 91.2% of sensitivity, 93.4% of specificity and 93.3% of accuracy on Challenge data subset of BRATS dataset. Rao et al. [13] used conditional random field technique to detect and segment the abnormal tissues region in brain MR images. The authors applied morphological based segmentation methodology in order to segment the abnormal tumor regions in brain MR images. Pereira et al. [12] applied Convolutional neural network classification algorithm on source brain MRI images in order to identify the abnormal patterns. The authors achieved 94.2% of sensitivity, 94.4% of specificity and 94.6% of accuracy on the brain MRI images available from LeaderBoard dataset and the authors achieved 87.1% of sensitivity, 89.1% of specificity and 92.8% of accuracy on the brain MRI images available from Challenge dataset. Proposed features based brain tumor detection and segmentation methodology using SVM classification approach. The features which were extracted from both normal and abnormal brain images were trained and tested by Support Vector Machine (SVM) classification approach. The authors achieved 76.1% of sensitivity, 92.8% of specificity and 93.1% of tumor segmentation accuracy with respect to ground truth images. Vinotha [15] used fuzzy logic based brain tumor detection and segmentation using SVM classification approach. Initially, the source brain MRI images with low resolution format was enhanced using histogram equalization technique and then this enhanced brain MRI image was used to identify the abnormal patterns in histogram equalized brain image. Then, the authors extracted texture features and these texture features were used by SVM classification algorithm in order to differentiate the normal brain image from abnormal brain image. El-Melegy et al. [5] detected tumor region in brain MR images using fuzzy logic based tumor segmentation method. The authors constricted fuzzy rules for detecting the boundary of the tumor pixels in brain MR images. Eltaher Mohamed Hussein et al. [6] applied feed forward back propagation neural network classification approach to differentiate the normal brain image from abnormal brain image. The authors tested their proposed methodology on different brain image dataset with respect to low and high resolution images. The following points are observed from conventional methods of Gliomatumor detection.

- The metric values of performance evaluation are low and not suitable for further tumor diagnosis.
- The conventional methods did not support low resolution brain MRI images for accurate tumorregion segmentation.
- The classification accuracy of the most conventional methods was low.
- The conventional methods required high level of feature extraction from brain MRI images.
- Most of the conventional brain tumor detection process was carried out in spatial domain format.

3. Methods

This paper proposes an image fusion based Gliomabrain tumor detection and segmentation methodology using ANFIS classification approach. Fig. 2 shows the proposed brain MR image fusion using NSCT transform coefficients.

It fuses low frequency and high frequency coefficients and inverse NSCT transform is applied over these fused coefficients in order to obtain fused brain MR image.

3.1. Brain MR image fusion using NSCT transforms

In this paper, contourlet transform is used to fuse thebrain images of the same patient in order to enhance the abnormal regions in brain MRI image. The contourlettransform has two types as Sub sampled ContourletTransform (SCT) and NSCT.

This paper uses NSCT transform due to its reconstruction property. This NSCT transform has been constructed by Pyramid Filter Banks (PFB) and Directional Filter Banks (DFB). The Pyramid and directional filter banks decomposes the brain image into low and high frequency sub bands.

The low frequency sub band is obtained when PFB is applied on the spatial domain MR image and high frequency sub bands are obtained when DFB are applied on spatial domain MR image.

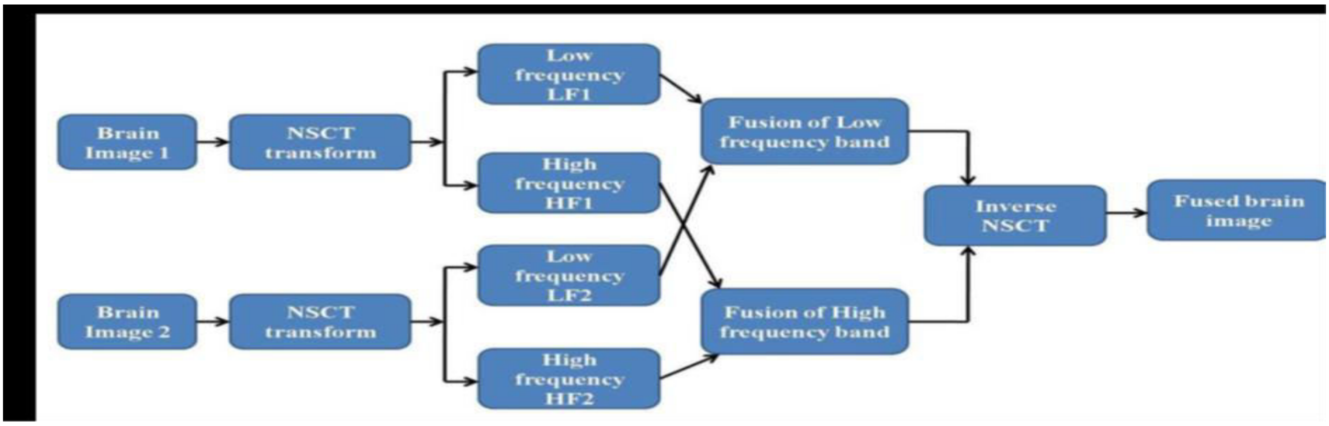

Fig 2.Brain image fusion usingNSCT transform.

The number of sub bands (N) in NSCT transform isgiven in the following equation.

$$N = 2p + 1 \quad (1)$$

Whereas, the multi level decomposition stages is represented by ‘p’.

In this paper, the multi level decomposition stage is set to 2, which produces five sub bands. The first sub band is low frequency sub band and the remaining sub bands (four) are belonging to high frequency sub bands. The NSCT is applied on brain MRI images of the same patient at different orientation. The low frequency sub bands and high frequency sub bands are fused individually in order to produce the fused low and high frequency sub bands. The fusion logic used in this paper is shown in following steps.

Step1: Select scaling factor (S) from histogram count method using the following equation,

S= Max (histogram) (2) This scaling factor of the particular image

Step 2: Apply the following arithmetic fusion rule on both low and high frequency sub bands, respectively.

LF=LF1+S*LF2; (3)

HF=HF1+S*HF2; (4)

Step 3: Apply inverse NSCT on both LF and HF sub bands, respectively in order to obtain fused image.

3.2. Glioma brain tumorclassifications and segmentation

The features are extracted from the fused brain MRimage and then these extracted features are trained and classified into non-Glioma or Glioma brain MR image using ANFIS classification approach. Then, the tumors in Glioma brain MR image is detected and segmented using morphological operations. Fig. 3 shows the proposed Glioma brain tumor detection and segmentation methodology using ANFIS classification approach.

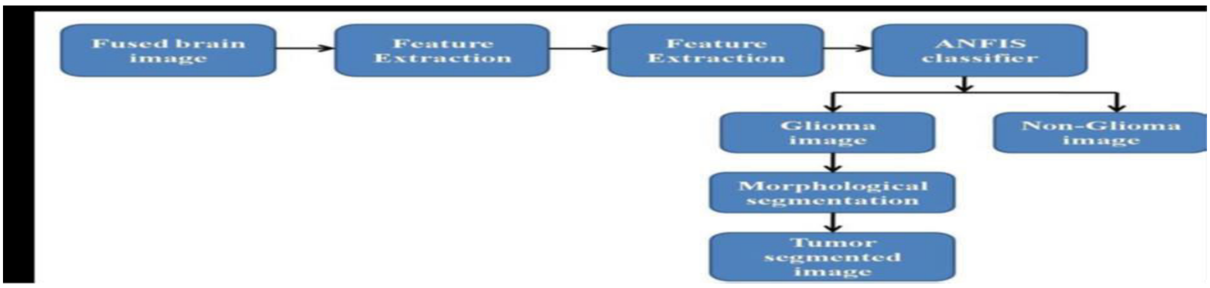

Fig. 3 Proposed Glioma brain tumor detection and segmentation methodology using ANFIS approac

3.3. GLCM features

The relation between each pixel in preprocessed brain MRI image is extracted using GLCM features. In this paper, GLCM matrix is constructed using the number of repeated pixels in a preprocessed image at different orientations as 00,450,900 and 1350. From GLCM matrix, the following GLCM features as Contrast,Energy, Homogeneity and Correlation are extracted.

Contrast =(|i-j| *p(i,j)) (5)

Energy = p(i,j) (6)

Where, p(i,j) is the elements in GLCM matrix, is mean of GLCM matrix and is standard deviation.

Table 1 shows the extracted GLCM values for both normal and abnormal brain MRI images. These extracted values are fed to the input of the classification algorithm.

Table 1

Extracted GLCM values for normal and abnormal images

Parameters	Normal Image	Glioma
Contract	1.2*10	1.8*10
Energy	1.0035	3.8267
Correlation	0.0023	0.1029

3.4. Law's Energy Texture Features

The statistical energy features are represented byLaw's texture features. Texture classification refers to the process of grouping test samples of texture into classes, where each resulting class contains similar samplesaccording to some similarity criterion. If the classes have not been defined a priori, the task is referred to as unsupervised classification. Alternatively, if the classes have already been defined (normally through the use of training sets of sample textures) then the process is referred to as supervised classification.

Laws developed a coherent set of 'texture energy'masks derived from three simple one-dimensional nonrecursivefilters. These may be convolved with each other to give a variety of one and two-dimensional filters. The outputs from these masks are passed to texture energy filters consisting of a moving window calculation of variance. Thus, the texture energy images are obtained and can be used as feature images for segmentation and classification.

In order to obtain macro-texture features (f'k), each ofthe micro-texture images (fk) is transformed into antexture energy image by moving macro-texture window.

Where, w is the size of a macro-window.

3.5. ANFIS Classifier design

The extracted features are used to differentiate thenormal brain MRI image from Glioma brain image. These features are grouped into feature vector with N number of features from both normal and Glioma brain MRI images.This feature vector is fed to the classification chosen for obtaining high level of Gliomatumor classification accuracy. Many conventional methods used SVM and Neural Network (NN) for Glioma image classification. These conventional approaches failed to classify the low intensity Glioma brain MRI images which produced low classification accuracy. Hence, ANFIS classification approach is used in this paper which works on both low and high intensity Glioma brain MRI images. The ANFIS classification architecture used in this paper have a single input and output layer with five intermediate hidden layers. The neurons in input layer are equal to the number of features in extracted feature vector. Each hidden layer has 10 neurons and they are fixed after several iterations in order to obtain high level of Glioma classification accuracy. The output layer has single neuron which produces binary low and high based on the extracted feature vector from source brain MRI image. The designed ANFIS architecture in this paper turn out binary low value when the classified image is non-Glioma image and it turn out binary high value when the classified image is Glioma image Table 2 shows the impact of extracted features on the classifications of brain MRI images for tumor detection process. The proposed method incorporated only GLCM features achieved 89.1% of classification accuracy, Law's texture features alone achieved 92.7% of classification accuracy and the proposed method incorporated GLCM and Law's texture features achieved 98.5% of classification accuracy.

Table 2

Impact of extracted features on classifications

Features	Classification accuracy(%)
GLCM only	89.1
Law texture	92.7
GLCM	98.5

The boundary of the tumor region in classified Glioma brain MRI image is segmented usingmorphological functions (Wang et al. [16]). The dilatedclassified image is subtracted from eroded classified brainimage in order to spot out the pixels in tumor boundaries.Fig. 4(a) shows the source brain MR images which areobtained from open access dataset, Fig. 4(b) shows thetumor segmented brain MR images by proposed methodstated in this paper and Fig. 4(c) shows the tumorsegmented brain MR images by radiologist or Groud truth image.

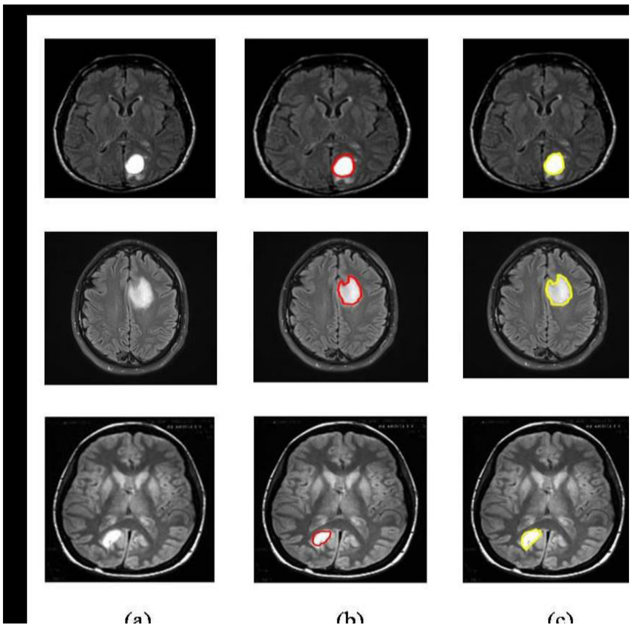

Fig. 4. (a) Source brain MRI image (b) Tumor segmented brain image by proposed method (c) Tumor segmented brain image by radiologist (Ground truth image).

4. Results and Discussions

In this paper, the proposed brain tumor detection methodology is applied on the MRI brain images which are accessed from publicly open access dataset BRATS 201516. The proposed algorithm is simulated using MATLAB R2014b version with 3.1 GHz GPU Processor and 4GB internal RAM as hardware devices. This open access BRATS 2015 dataset [4] consists of three different brain MRI image sub datasets as Training, Leaderboard and Challenge. The training sub dataset consists of 20 High Grade Tumor (HGT) images and 10 Low Grade Tumor (LGT) images. These HGT and LGT brain MRI images are also having ground truth images from different expert radiologist. The Leaderboard sub dataset consists of 21 HGT images and 4 LGT images with its individual ground truth images. The challenge sub dataset consist of 10 HGT images alone with its corresponding ground truth

images. The ground truth images are not publicly available. But they are available in online mode forevaluating the performance of the proposed brain tumor segmentation methodology stated by various authors. The brain MRI images in Training sub dataset of BRATS 2015 dataset are used for training the classification approach it training mode alone. The proposed brain tumor detection and segmentation methodology is tested on the brain MRI images from Leaderboard and Challenge sub datasets

only.

To analyze the performance of the proposed tumor segmentation methodology, the tumor segmentation results are compared with ground truth images which are available in open access BRATS dataset. The ground truth images are created by two and more expert

medical radiologist. The performance of the proposed brain tumor segmentation methodology is analyzed using the following parameters.

- Sensitivity (Se = TP/(TP + FN))
- Specificity (Sp = TN / (TN + FP))
- Positive predictive value(PPV = TP/(TP+FP)
- Negative predictive value(NPV=TN/(TN+FN))

The correctly segmented tumor pixel in brain MRIimage is noted as True Positive (TP) and correctly segmented non-tumor pixel in brain MRI image is noted as True Negative (TN). The wrongly segmented tumorpixel in brain MRI image is noted as False Positive (FP) and wrongly segmented non-tumor pixel in brain MRI image is noted as False Negative (FN). These parameters are computed from tumor region segmented brain images with respect to ground truth images. The value of the parameters Se, Sp, PPV, NPV, ACC and Pr varies between 0 and 100. The performance evaluation parameter PPV is the determination of FP and TP. The parameter NPV is the determination of the metrics TN and FN. The proposed tumor segmentation accuracy is low when these parameters have low metric value and the proposed tumorsegmentation accuracy is high when these parameters have high metric value. The value of the parameters FPR, FNR, LPR and LNR varies between 0 and 1. The proposed tumor segmentation accuracy is low when these parameters have low metric value and the proposed tumorsegmentation accuracy is high when these parameters have high metric value. Table 3 shows the proposed brain tumor segmentation methodology on BRATS 2015 dataset [4] with respect to ground truth images**.**

Table 4

Compares the proposed brain tumor segmentation results with other state-of-arts methods on LeaderBoard dataset. The proposed method achieves 92.8% and 91.9% of sensitivity for LGT and HGT images, respectively, achieves 96.9% and 95.6% of specificity for LGT and HGT images, respectively and achieves 96.1% and 95.8% of accuracy for LGT and HGT images, respectively. As an average, the proposed brain tumor segmentation methodology achieves 92.3% of sensitivity, 96.2% of specificity and 95.9% of accuracy. The conventional method Anitha et al. [2] achieved 88.8%, 91.6% and 92.1% of sensitivity, specificity and accuracy,

respectively. Pereira et al. [12] achieved 87.1%, 89.1% and 92.8% of sensitivity, specificity and accuracy, respectively. Urban et al. [14] achieved 89.3%, 91.1% and 92.1% of sensitivity, specificity and accuracy, respectively. Islam et al. [8] achieved 90.9%, 91.5% and 93.4% of sensitivity, specificity and accuracy,respectively.

Table 5

Compares the proposed brain tumorsegmentation results with other state-of-the-arts methods on Challenge dataset. The proposed method achieves 96.8% and 95.7% of sensitivity for LGT and HGT images, respectively, achieves 95.9% and 94.3% of specificity for LGT and HGT images,

respectivelyand achieves 96.7% and 96.1% of accuracy for LGT and HGT images, respectively. As an average, the proposed brain tumor segmentation methodology achieves 96.2% of sensitivity, 95.1% of specificity and 96.4% of accuracy.

Authors	Methodology	Grades	Se(%)	Sp(%)	Acc(%)
Proposed work	ANFIS classification algorithm	LGT HGT Average LGT	92.8 91.9 92.3 99.1	96.9 95.6 96.2 91.0	96.1 95.8 95.9 92.7
Anitha et al.(2017)	CNN classification algorithm	HGT Average LGT	88.5 88.8 87.9	91.5 91.6 89.7	91.6 92.1 92.2
Pereira et al.(2016)	CNN classification algorithm	HGT Average LGT	86.1 87.5 89.8	80.1 82.1 83.3	83.2 84.4 82.4
Urban et al.(2014)	Deep CNN classification algorithm	HGT Average LGT	80.3 82.1 81.2	87.3 91.3 82.3	84.1 83.2 83.3

Islam et al.(2013)	Modified Ada Boost algorithm	HGT Average LGT	90.1 90.3 93.4	83.1 83.8 90.3	82.1 72.1 82.1

5. Conclusions

This paper proposes a methodology to detect and segment the Gliomatumors in brain MR image. The method uses fusion technique based on NSCT transform. The enhanced image by fusion technique is applied to the feature extraction process. The extracted texture features are classified using ANFIS classifier. The proposed methodology is applied on both low grade and high grade Gliomatumor MR images in BRATS open access dataset. The results obtained from the proposed methodology are compared with various state-of-the-arts methods in term of performance evaluation parameters.

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