Research Article

Performance Analysis of Brain Tumor Detection and Diagnosis based on Optimized Features and SVM Classifier

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ABSTRACT

Magnetic Resonance Images (MRI) are widely used in the diagnosis of brain tumor because of its faster processing, avoiding malfunctions and suitability with physician and radiologist. This paper proposes a new approach to automated detection of brain tumor. This proposed work consists of various stages in their diagnosis processing such as preprocessing, image fusion, feature extraction and classification. The local binary pattern and wavelet features are extracted and these features are trained and classified using Support vector machine classifier. The achieved results and quantitatively evaluated and compared with various ground truth images. The proposed method gives fast and better segmentation and classification rate by yielding 97.25% of sensitivity, 99.99% of specificity and 99.91% of overall accuracy

KEYWORDS

MRI, Tumor, Classifiers, Ground Truth Image, Sensitivity, Specificity

1. INTRODUCTION

Brain tumor is one of the most dangerous diseases which require early and accurately detection methods, current used detection and diagnosis methods for image evaluation depend on decision of neuro-specialists, and radiologist which possible to human errors. Manual classification of brain tumor is time consuming. This paper describes the processes and techniques used in detecting brain tumor from magnetic resonance imaging (MRI) and ANN techniques, which are of the most application of artificial intelligent that used in biomedical image classification and recognition. There are more than 100 types of brain and spinal cord tumors (also called central nervous system or CNS tumors). They are usually named after the cell type they started in [2] but there are two basic kinds of brain tumors; primary brain tumors and metastatic brain tumors. Malignant tumors are primary tumors that usually grow rapidly and spread within the brain and spinal cord. Malignant brain tumors can also be life-threatening. About 40% of brain and spinal cord tumors are malignant [1]. Benign tumors are also primary tumors that are typically surrounded by an outer surface (fibrous sheath of connective tissue) or remain with the epithelium [2].Benign tumors usually have slow-growing cells and clear borders (margins), and they rarely spread. Whereas, Cancer cells that begin growing elsewhere in the body and then travel to the brain form metastatic brain tumors. For example, cancers of the lung, breast, colon and skin (melanoma) frequently spread to the brain via the bloodstream or a magnetic-like attraction to other organs of the body. All metastatic brain tumors are, by definition, malignant, and can truly be called "brain cancer" [3].

Imaging techniques are now a days most accurate abnormality detection methodologies as Magnetic Resonance Imaging (MRI) and Computer Tomography (CT). In this paper, MRI scanning techniques are used for brain abnormality detection in human brain due to its high visibility of abnormal patterns.

The grade of a tumor refers to the way the cells look under a microscope [4]:

Grade I: The tissue is benign. The cells look nearly like normal brain cells, and they grow slowly.

Grade II: The tissue is malignant. The cells look less like normal cells than do the cells in a Grade I tumor.

Grade III: The malignant tissue has cells that look very different from normal cells. The abnormal cells are actively growing (anaplastic).

Grade IV: The malignant tissue has cells that look most abnormal and tend to grow quickly.

In this paper, a computer aided automatic brain tumor detection and diagnosis technique is proposed using genetic algorithm based SVM classifier. Section 2 discusses various conventional methods for brain tumor detection; Section 3 proposes the brain tumor detection and diagnosis methods. The experimental results of our proposed method are detailed in Section 4. Finally, Section 5 concludes the paper

2. MATERIALS AND METHODS:

2.1 Materials:

BRATS dataset (2019) is used in this paper and it consists of 300 numbers of high and low grade brain tumor images. These dataset is created and maintained through Cancer Imaging Archive programme. The brain images in this dataset are interpolated to 1mm3 voxel resolution. The ground truth images are also available in this dataset which are obtained from expert radiologist. In this paper, 100 brain normal images and 100 brain abnormal images are used.

2.2 Methodology:

The source brain images are denoised using SEPD technique and then they are fused using pixel level image fusion technique. The features from fused image are extracted and these extracted features are optimized using genetic algorithm. The optimized features are trained and classified using SVM classifier. The tumor region is segmented using morphological operations and then the segmented tumor is diagnosed into either early or advanced based on the count of tumor pixels. The proposed flow of tumor detection and diagnosis methodology is illustrated in Fig. 1.

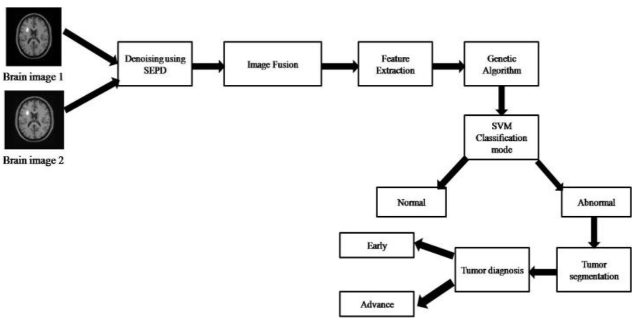


Fig. 1 Proposed tumor detection system

3. DENOISING:

In this paper, Source Edge Pixel Denoising (SEPD) algorithm is proposed to denoise the source brain MRI image.

Step 1: The source brain MRI image is divided into number of sub blocks and each sub block contains group of pixels which consist of 81 pixels per sub block.

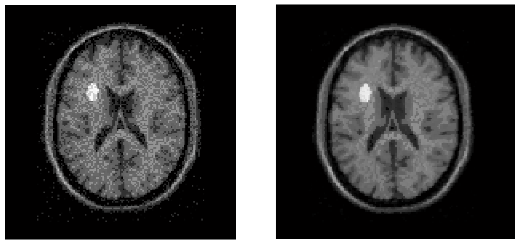
Step 2: Each sub block is split into four directional patterns. The pixel under denoising is removed from each directional pattern.

Step 3: Next, the elements in each directional pattern are ordered in ascending and then the first and final elements are removed.

Step 4: The elements in the vector are sorted in ascending manner. The elements that have high and low values are excluded from the vector list. This will form the new vector list.

Step 5: Standard deviation for each element in new vector list is computed and the minimum standard deviation is selected for best directional representation.

Step 6: The matching factor is computed between each element in the best directional representation and the center pixel which is under testing for noise. Then, the computed matching factor is compared with threshold value. The center pixel is considered as noisy if the matching factor lies below the threshold value. The center pixel is considered as noise free if the matching factor lies above the threshold value. Finally, mean filter is used to remove the noise from the center pixel if it is noisy.



(a) (b)

Fig. 2 (a) Source brain MRI image (b) Noise suppresed brain MRI image

Fig.2 (a) shows the source brain MRI image with noise and Fig.2 (b) shows the noise removed brain MRI image using proposed noise removal algorithm in this paper

4. IMAGE FUSION

Pixel-level image fusion is used in this paper to integrate the information from multiple brain MRI images of one scene to get an informative image which is more suitable for human visual perception or further image processing. In this proposed system, we fuse two brain images of the same patient taken at different angles, in order to improve the image quality and also obtain the detailed information from the fused (enhanced) brain image.

A typical pixel level fusion system consists of six sub-systems: imaging, registration, pre-processing, fusion, post-processing and displaying. Various pixel level fusion algorithms have been proposed. We employ the simplest pixel level fusion method, namely the weighted averaging (WA) fusion. The simplest image fusion based on weighted averaging is by taking the average of the source image pixel by pixel, such as:

$$C(m,n) = \alpha A(x,y) + \beta B(x,y) \quad (1)$$

Where, α and β are the scalar weights. The WA method is simple and fast to implement. This method also reduces the noise present in the source image. Fig. 3 represents the brain image after image fusion process.

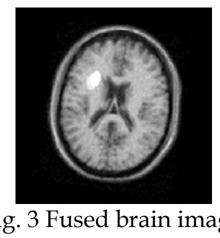


Fig. 3 Fused brain image

5. FEATURE EXTRACTION:

Features play an important role in classifying the brain image into either normal or abnormal. In this paper, LBP, DWT and Gabor features are used for differentiating the normal from abnormal brain MRI image.

5.1 Local Binary Pattern Features:

The local binary pattern (LBP) operator is an efficient texture based image operator which transforms an image into an array or image of integer labels representing the small-scale appearance of the image. The MRI image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as an image feature descriptor. It operates by labeling the pixels of an image by thresholding the neighborhood of every pixel and saves the result as a binary number. These labels are most commonly then used for further image analysis. The LBP operator is a simple computation methodology which makes it possible to implement in real-time applications to analyze the brain MRI images.

The LBP operators describe a 2-D pattern using local spatial patterns and grey scale contrast. The LBP operator generates a label for each pixel of the image using threshold functioning of the 3×3 adjacent pixels with the centre value and the resulting binary value is stored. The unsupervised LBP methodology performs better when combined with a local contrast measure.

The LBP operator can be defined by, $LBP_{(J,K)}^{u}$ where, (J,K) denotes the LBP operator used in a (J,K) neighborhood, 'u' represents the uniform patterns being used. On obtaining the LBP labeled image fl(u,v), the LBP histogram Hi is given by,,

$$H_i = \sum_{u,v} I\{ f_l(u,v) = i \} \quad i = 0,1,\dots,n-1 \qquad (2)$$

Where, 'n' is the number of LBP labels and I{F} is 1 if F is true and 0 if F is false. The LBP feature extracted image is shown in Fig. 4.

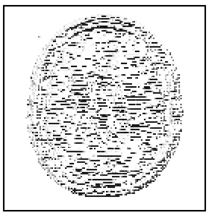
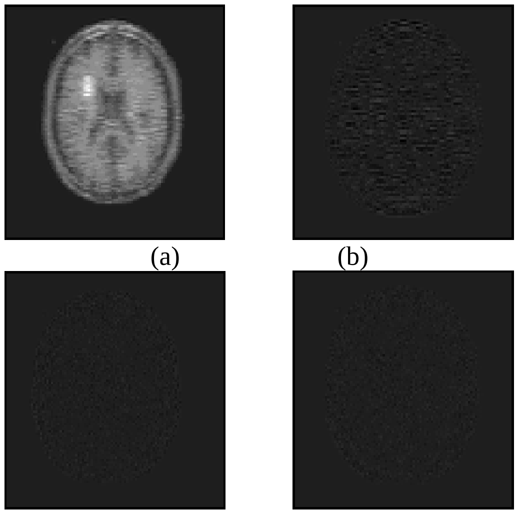


Fig. 4 LBP image

5.2 DWT features

Discrete Wavelet Transform (DWT) is used to transform the spatial domain brain MRI image into multi resolution brain image by decomposing the source image with different decomposition scales. Each decomposition produces four equal sub bands as Approximate; Horizontal, Vertical and diagonal sub bands, respectively. The low frequency details are represented by Approximate sub band and high frequency details are represented by other sub bands, respectively. The coefficients in these sub bands are used as feature set for the brain image classifications. In this paper, single decomposition level is used for the brain image decomposition. The discrete wavelet decomposed images of source brain image as approximate sub band (Fig.5a), Horizontal sub band (Fig.5b), Vertical sub band (Fig.5c) and Diagonal sub band (Fig.5d) are shown in Fig. 5.



(a) (b)

(c) (d)

Fig. 5 (a) Approximate band image; (b) Horizontal band image; (c) Vertical band image; (d) Diagonal band image

5.3 Gabor features

Gabor transform features are used in this paper for brain tumor classifications, which transforms the spatial domain brain MRI image into image which contains time, frequency and phase components. It can be operated in different scales and orientations. In this paper, four scales f={1,2,3,4} and five orientations θ= { 00, 450,900, 1350,1800}. Each scale produces five orientation images and totally 20 orientation images are obtained in this paper. The orientation image constitutes real and imaginary values. Hence, magnitude image is constructed by eliminating the imaginary terms in 20 orientation images. The maximum pixel in 20 magnitude images is obtained which produces single Gabor transformed brain image. The coefficients in this Gabor transformed brain image are used as Gabor features for brain image classifications.

5.4 Genetic Algorithm

Optimization algorithms are used as feature selection process, which optimize the extracted features for obtaining best classification rate. Particle Swarm Optimization (PSO) algorithm and Genetic Algorithm (GA) are the optimization algorithms. The internal architecture of PSO algorithm is complex and it is not suitable for Gabor based feature selection. Hence, this paper uses GA algorithm for optimization process. GA algorithm is based on the functions of genes as it is composed of selection, cross over, mutation and fitness. The selection of genes for bset classification is achieved by selection of features. Cross over exchanges the feature set in the selection feature list between chromosome lists where as mutation exchanges the feature set with in the same chromosome list. Finaly, fitness is used to select the best feature set in the mutation list.

5.5 SVM Classifier

Classification process is used to classify the source brain MRI image into either normal or abnormal based on the features received from GA process. Conventional classification algorithms such as Neural Networks (NN) and Random forest classifiers used complex internal architecture for the classification. The classification accuracy of these classifiers is low due to its difficult traing methodology. In order to overcome such limitations of the conventional classifiers, SVM classifier is used in this paper to classify the source brain image into either normal or abnormal. This SVM classifier can be operated in two modes as learning and classification. The learning mode of this classifier trains the features of both normal and abnormal brain images. The classification mode of this classifier classifies the source test brain MRI image based on the features set obtained from learning mode. It produces binary output, which indicates low for normal brain image and high for abnormal brain image.

5.6 Tumor Segmentation

Tumor region segmentation plays an important role in proposed method, which segments the abnormal region in classified source brain image. In this paper, morphological operations are used to detect and segment the tumor region in the classified brain MRI image. The four morphological operations are used in this paper for brain tumor segmentation and they are defined as follows:

Dilation:

$$(f \oplus h)\,(x,y) = \sup_{(r,a)\in H} \{x - r, y - s) + h(r,s)\} \qquad (7)$$

Erosion:

$$(f \ominus h)\,(x,y) = \inf_{(r,a)\in H} \{x + r, y + s) - h(r,s)\} \qquad (8)$$

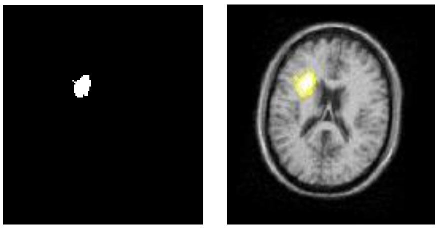
Opening:

$$f \circ h = (f \ominus h) \oplus h \qquad (9)$$

Closing:

$$f \bullet h = (f \oplus h) \ominus h \qquad (10)$$

Where, sup{} and inf{} denote the supremum and infirmum operation. Erosion and Dilation are merged to form a powerful operator called Opening, by which objects that are adjacent are spaced and objects that are adjoined are detached and the holes within the objects are enlarged. The eroded image is absolutely subtracted from the dilated image to detect the tumor pixels. Fig.7 (a) shows the absolute difference image and Fig.7 (b) shows the tumor segmented image.



(a) (b)

Fig. 7 Results of tumor segmentation: (a) Absolute difference image; (b) Tumor segmented image;

5.7 Tumor Diagnosis

The segmented tumor region is analyzed further for diagnosing into either early or advance. The total numbers of tumor pixels are counted for tumor diagnosing. The MRI brain images having tumor from the database is split into early and advance category. These images are trained by SVM classifier for diagnosing purpose. The number of tumor pixels is belonging to below the threshold value 50 for the case of early tumor and the number of tumor pixels is belonging to above the threshold 50 for the case of advance

6. RESULTS AND DISCUSSION

MATLAB R2019b is used in this paper to simulate the proposed system. The following parameters are used in this paper to evaluate and analyze the performance of the proposed tumor detection system using genetic algorithm based SVM classifier.

Sensitivity (Se) = TP/ (TP+FN) (11)

Specificity (Sp) = TN/ (TN +FP) (12)

Accuracy (Acc) = (TP+TN) / (TP+FN+TN+FP) (13)

Positive Predictive Value (PPV) = TP/ (TP+FP) (14)

Negative Predictive Value (NPV) = TN/ (TN+FN) (15)

Where, TP is the True Positive which is the total tumor pixel count as tumor pixels, TN is the True Negative which is the total background pixel count as background pixel, FP is the False Positive which is the total tumor pixel count as background pixels and FN the False Negative which is the total background pixel count as tumor pixels.

Table 1.1 Performance Analysis

Parameters	Resultsachieved (%)
Sensitivity (Se)	97.25
Specificity (Sp)	99.99
Positive Predictive Value (PPV)	99.78
Negative Predictive Value (NPV)	99.91
Accuracy (ACC)	99.91

This proposed brain tumor segmentation methodology achieves 97.25% sensitivity, 99.99% specificity, and 99.78% positive predictive value, 99.91% negative predictive value and 99.91% accuracy over the set of 100 brain tumor images in BRATS 2019 dataset, as shown in Table 1.

Methodology	Year	Se (%)	Sp (%)	Acc (%)
Proposed work	2022	97.25	99.99	99.91
Ursula Perez et al.	2020	92.18	96.27	-
Thirumurugan et al.	2019	96.17	97.51	99.80
Selvathi et al.	2018	92.16	98.56	-
Viswa Priya and Shobarani	2017	78.3	84.16	89.65

The proposed method provides better tumor segmentation accuracy when compared with other conventional methodologies for tumor region detection in brain MRI images. Table 2 shows the performance comparisons of the proposed method with conventional methodologies Classification accuracy is defined as the ratio between total number of images correctly classified as tumor images and the total number of images in the dataset. Table 3 illustrates the classification accuracy of the proposed system with respect to conventional methods.

7. CONCLUSION

In this paper, brain tumor detection is proposed using SEPD and SVM classifier. SEPD is used for denoising the brain tumor image and the fused brain image performance is analyzed. Features such as LBP, DWT and Gabor features are extracted from the fused image. The genetic algorithm finds the best features among the set of extracted features. These features are further trained and classified into normal or abnormal brain image using the classifier. The proposed system achieved a sensitivity rate of 97.25%, specificity rate of 99.99% and accuracy of 99.91%.

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