RESEARCH ARTICLE

An Efficient Method for Brain Tumor Detection Using Texture Features and SVM Classifier in MR Images

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Abstract

Objective: Detection and classification of abnormalities in Magnetic Resonance (MR) brain images in medical field is very much needed. The proposed brain tumor classification system composed of denoising, feature extraction and classification. Noise is one of the major problems in the medical image and due to that retrieval of useful information from the image is difficult. The proposed method for denoising an image is PURE-LET transform. **Methods:** This method preserves the diagnostic property of the images. In feature extraction, combination of Modified Multi-Texton Histogram (MMTH) and Multi-Texton Microstructure Descriptor (MTMD) is used and then Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM)are used to extract the feature from the image to compare performance. In classification, classifiers like Support Vector Machine (SVM), K Nearest Neighbors (KNN) and Extreme Learning Machine (ELM)are trained by the extracted features and are used to classify the images. **Result:** The performance of feature extraction methods with three different classifiers are compared in terms of the performance metrics like sensitivity, specificity, and accuracy. **Conclusion:** The result shows that the combination of MMTH and MTMD with SVM shows the highest accuracy of 95%.

Keywords: Denoising- PURE-LET- Feature extraction- MMTH- MTMD- GLCM- GLRLM- SVM- KNN- ELM

Introduction

A brain tumor occurs as a result of an abnormal growth of cells that have proliferated in an uncontrolled manner (Abbasi and Tajeripour, 2017). For easy disease diagnosis Magnetic resonance (MR) images are mostly used to help doctors and technicians, because this imaging technique produces clearer soft tissue details without causing disturbances to the patient's tissues (Deepa and Arunadevi, 2013).

MRI of brain image is an invasive method which produces detailed images of the brain and the brain stem. Without moving and causing any effect to the patient, MRI produces sectional images of equivalent resolution in each projection. We can get entirely automatic classification of magnetic resonance images as normal and tumor (El-Dahshan et al ., 2010).

Materials and Methods

Existing Method

In the existing method of denoising, various noise removal approaches for MRI images are available. Noisy MRI image is denoised by various transform method. This approach not only lessens the noise but also preserves the edges. In the same way various Feature extraction method

based on shape, texture, color and shape are available (Ain et al., 2014).The extracted feature is given as input to various classifiers like support vector machine, ELM, naïve bayes to classify brain image as normal or abnormal.

Proposed Method

Our proposed method consists of four phases namely, collection MRI images, denoising by applying PURE-LET transform and the feature is extracted from training dataset of 90 normal and abnormal brain MR images using combination of MMTH and MMTD and for comparison another two feature extraction methods known as GLCM, GLRLM are used and these feature vectors are used to train SVM, KNN, ELM classifier (Geethu Mohan and Monica Subashini, 2018). To test the classifier 44 brain MR images (normal and abnormal) are used and performance is evaluated.

A. Collection of data

The image data set for experiment contains 67 normal MR brain image and 67 MR brain tumor image and set of CT images from Brainweb database and the same number of images collected from Jansons MRI scan center Erode, Tamil Nadu, India. In the proposed method the brain image dataset is collected from Brainweb online website and Johnson Scan Centre, Erode. The collected images are

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used for training and testing. The training dataset is used for training the classifier and testing data set is used to evaluate the performance of proposed system.

B. Denoising
PURE-LET Transform

PURE (Poisson unbiased risk estimator) is defined as an unbiased estimate, of the mean-squared error between the original image and the estimated image defined in the Haar wavelet domain. By minimizing PURE, PURE-LET tries to evaluate the true image from the noisy image (Luisier et al ., 2010). PURE-LET associates inversion of a small size matrix.

In PURE has the following property: In the normalized Haar wavelet domain, the approximation coefficients of a Poisson image are also Poisson distributed and differences of Poisson random variables contributes to detail coefficients. The overall denoising procedure is expressed as a linear combination K elementary denoising procedures, i.e., a linear expansion of thresholds (LET) to minimize PURE. Then with respect to this linear representation coefficients PURE can be minimized. Computationally efficient and robust denoising algorithm PURE-LET can be developed by reducing the overall procedure to inverting a K × K matrix (K may be as small as six).

C.Feature Extraction
1. Combination of MMTH and MTMD

The merits of co-occurrence matrix and histogram are integrated which forms a feature extractor and descriptor known as MTH to extract texture feature from image (Jayachandran and Dhanasekaran, 2013). Additionally, statistical parameters like mean and variance are used for interchanging the pixel value according to the threshold to improve texture feature extraction process, where the pixel variation is modified in accordance with the mean and variance by setting the threshold value. By this process, feature extraction performances improved while preserving the texture features even if the image has noisy pixels. The resultant image from MMTH is applied to MTMD to calculate feature vector.

i. Modified MTH

The modified multi-texton histogram feature extraction contains following steps:

Gridding: The given MRI brain image is partitioned into many small grids which is of size 3.

Interchanging: After the gridding process is completed, the interchanging process is done for every grid (Jayachandran and Dhanasekaran, 2014). For every grid, threshold is calculated based on mean (u) and variance (σ). If the mean and variance for a grid is u and σ then the threshold is $\{u+\sigma', u-\sigma'\}$. The threshold is computed as per equation (1)

$$T = \{u+\sigma', u-\sigma'\} \tag{1}$$

For every grid, if the center pixel of a grid lies in between the interval $\{u+\sigma', u-\sigma'\}$, then the center pixel is replaced with mean value. Otherwise the center pixel of

a grid is kept unchanged. The same procedure is applied for all grids. In modified MTH a 3x3 grid is chosen from the original image with u=20 and σ=5. The center pixel is checked and it is replaced with u value since it lies between threshold value. The same procedure is applied to all grids of original image. The resultant image from modified MTH is applied to MTMD to calculate feature vector (Zhu et al., 2005).

ii. MTMD

The MTMD consists of computation of following four features (Jayachandran and Sundararaj, 2015):

• Feature vector related to original image F(V1)
• Feature vector related to orientation image F(V2)
• Feature vector related to multi-texton image F(V3)
• Feature vector related to texton structure image F(V4)

Finally these four features are concatenated to form single feature vector of an image.

a) Computation of F(V1)

For calculating F(V1), the original image is divided into grids of size 4, 18 and 24 which are usually square in shape. The block count value is calculated For each intensity value the block count value is stored in a vector and it is termed as F(V1) (Liu et al., 2015).

b) Computation of F(V2)

In human perception texture orientation of images is of great influence in the texture of image. It is also used to estimate the shape of the textured images. Object boundaries and texture structures provide orientation mapto provides most of the information in the image (Jayachandran and Dhanasekaran, 2013). The gradient in x-axis and y-axis is calculated. Let Ix and Iy be the images after applying gradient in the x-axis and y-axis. After taking the gradient, both the values Ix and Iy are combined as in equation (2) and matrix g formed (Liu et al., 2010).This matrix g obtained by orienting each pixel. After orientation process the orientation image is divided into grids of size 4, 18 and 24. After gridding, for each intensity value the block count value is obtained. The vector resulted from this process is called F(V2).

$$G = \frac{1}{I_x{}^2 + I_y{}^2} \tag{2}$$

I_x – gradient in x axis

I_y – gradient in y axis

c) Computation of F(V3)

Textons refer to essential micro-structures in natural images and are considered as the atoms of preattentive human visual perception (Tang, 1998). Texton reduces information redundancy by decomposing an image into its constituent components which leads to lower dimensional representations.

Consider a 2x2 matrix with four pixels P1, P2, P3 and P4 in the image. The possible four textons denoted by T1, T2, T3 and T4 are formed with different combinations

of pixels with equivalent intensity values . The intensity values of original image, the two detected textons using four texton templates which slide over the entire image from top to bottom and left to right, the two categories of textons and multi-texton image formed from two textons (Liu et al., 2010). Then multi-texton image is divided into grids of size 4, 18 and 24. Once gridding is done, for each intensity range from 1 to 255 of the multi-texton image, the block count is computed. The vector resulted from this process is called F(V3).

d) Computation of F(V4)

In order to find the micro-structures, the original image is segregated into grid of size 5x5, 3x3, 2x2 and so on. In the proposed work, 3x3 blocks is used for micro-structure analysis. The 3x3 block is slide over the image from right to left and bottom to top throughout image. In the 3x3 block, The eight neighbors pixels nearer to center pixel is compared. When it is same value as center pixel then is is unchanged otherwise make it empty. Micro-structure is formed when the whole matrix becomes empty (Jayachandran and Sundararaj, 2015). This is fundamental micro-structure.

2. Gray Level Co-occurrence Matrix

Texture is one of the most valuable designating appearances of an image. It is distinguished by the spatial allotment of gray levels in a community (Ivan Cabria and Iker Gondra, 2017). The most popular mathematical representation of texture is co-occurrence Matrix. A co-occurrence matrix is characterized for an image by the method of partitioning of co-occurring ideals at a given offset (Zhu et al., 2005). In the Gray Level Co-occurrence Matrix (GLCM), the spatial relationship of pixels is considered to examine the texture by using statistical method. The main purpose of gray level co-occurrence matrix is to measure the texture of the image. GLCM is created by calculating how repeatedly a pixel with gray level value i horizontally occurs adjacent to a pixel with the value j.

i. Contrast

In the gray level co-occurrence matrix, texture of shadow depth and local variations are measured using contrast and it is used to return the measure of the contrast intensity between a pixel and its neighbor over the whole image.

$$I = \sum_{i,j} |i - j| * |i - j| \, p(i, j) \qquad (3)$$

ii. Correlation

Correlation is used to measure the degree to which activities of two variables is associated. It returns a measure of how a pixel is correlated with its neighbor over the whole image. The range is (-1 1). -1 denotes negative correlation value, and +1 denotes positive correlation value.

$$J = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j) p(i, j)}{\sigma_i \sigma_j} \qquad (4)$$

iii. Energy

Energy is used to calculate the sum of squared elements in the GLCM. The energy value range lies in between 0 and 1.

$$E = \sum_{i,j} p(i, j) * p(i, j) \qquad (5)$$

iv Homogeneity

It returns the measure of closeness of distribution of GLCM elements to the GLCM diagonal. The range is (0 1) and for diagonal GLCM its value is 1.

$$H = \sum_{i,j} \frac{p(i, j)}{1 + |i - j|} \qquad (6)$$

3. Gray Level Run Length Matrix

Texture is one of the main features utilized in image processing and pattern recognition used to characterize the surface of a given object or region. Gray Level Run Length Matrix (GLRLM) characterizes texture images based on run lengths of image gray levels. A set of consecutive and collinear pixels with the same gray level value is termed as gray level run (MeghaKadam and Avinash Dhole, 2017). The number of pixels in the run is defined as length of the run. The element (i, j) in matrix denotes number of times the image contains a run of length j, consisting of pixels having gray level i. For example the entry (1, 1) in matrix is filled by the number of times gray value 0 occurs in the 4x4 image having run length 1 by checking all rows of the image. Similarly all entries in the matrix are filled according to the run length and gray values (Tang, 1998).

D. Classification
1. Support Vector Machine

SVM is a binary classifier which is based on supervised learning. The key concept of SVM is to use the hyperplane to define decision boundaries for separating between data points of different classes. The basic idea of SVM is to classify data between two classes by constructing a hyperplane in high dimensional feature space (Kumar and Vijayakumar, 2015).

Consider a training set,

$$\{(x_i, y_i), i = 1, 2, ..., n; x_i \varepsilon R^d; y_i \varepsilon \{+1, -1\}; \} \qquad (7)$$

where $x_i \, \varepsilon R^d$ is input vectors and $y_i \varepsilon \{+1, -1\}$ is class labels of MRI brain image.

SVM maps the d-dimensional input vectors from input space to high dimensional feature space using non linear function $\Phi(x)$. The separating hyper plane is defined as $w^T \Phi(x) + b = 0$, with w as weight vector having dimension equal to $\Phi(x)$ and b is bias (Alfonse and Salem, 2016).

The separating hyper plane can be defined in many ways when the data are linearly separable. However, SVM is based on the maximum margin principle in which the aim is to construct a hyper plane by satisfying maximal distance between the two classes.

The SVM start with following formulations
for $y_i = +1$

$$w^T \Phi(x_i) + b \geq +1 \qquad (8)$$

$$yi = -1 \quad \text{for} \quad w^T \Phi(x_i) + b \leq -1 \qquad (9)$$

equivalent to

$$y_i(w^T \Phi(x_i) + b) \geq 1, \qquad i = 1,2,...,n \qquad (10)$$

The classifier is defined as

$$f(x) = sign(w^T \Phi(x) + b) \qquad (11)$$

An example of SVM classification with an optimal hyperplane that minimizes the separating margin between the two classes is illustrated by points noted by 'o' s and 'Δ's is shown in Figure 1 . Support vectors are elements of the training dataset that lie on the boundary of hyperplanes of the two different classes.

2. K Nearest Neighbor

K Nearest Neighbor method is mostly used method for classification of image. An object is classified based on the distance from its neighbors. If k = 1, then the object is classified simply as the class of its nearest neighbor. The K Nearest Neighbors classification method is based on nearest distance of neighbor classes. Based upon the distance, the K Nearest Neighbors selects only k-nearest neighbor classes. Finally the majority vote is then taken to predict the class for an object (Damodharan and Raghavan, 2015). The most common method used in k-nearest-neighbor for measuring distance is Euclidean. The Euclidean distance is used to measure the distance between the test data and train data. Then based on the distance measure the object is classified to one of the predefined classes. This same procedure is followed for classification of MR brain image as normal and tumor.

3. Extreme Learning Machine

In machine learning field to create pattern classification model for the purpose of identifying tissue abnormalities in brain histology using MRI, Extreme Learning machine (ELM) is widely used. Extreme Learning Machine (ELM) is a Single hidden Layer Feed forward Neural Network (SLFNN) in which input weights and hidden neuron biases are selected randomly without training. To determine output weights, the norm least-square solution and Moore-Penrose inverse of a general linear system is used which allows significant reduction of time in training. Among the various activation functions (like sine, gaussian, sigmoidal, radial basis) any one can be chosen for hidden neuron layer and linear activation function are chosen for the output neurons.

Let the training set given be $N = \{(x_i, t_i)\}$, where $x_i = [x_{i1}, x_{i2}, ..., x_{in}]$ denotes training samples and $t_i = [t_{i1}, t_{i2}, ..., t_{in}]$ denotes corresponding target value. With 'N' hidden neurons and activation function $f(x)$ SLFNN is mathematically modeled as:

$$\sum_{i=1}^{N} \beta_i f(w_i.x_j + b_j) = t_{j,j} = 1,2,...N \qquad (12)$$

Where $b_i = [b_{i1}, b_{i2}, ..., b_{in}]$ denotes the weight vector

used to connect the input neurons and i^{th} hidden neuron, bias of ith hidden neuron is b_i . $\beta_i = [\beta_{i1}, \beta_{i2}, ..., \beta_{in}]$ is the weight vector used to connect the ith hidden neuron and the output neurons. The inner product of w_i and x_i is denoted by $w_i. x_i.$

Training and Testing Process: The entire process of classifying MRI brain image is divided into two phases namely training and testing. From the image database, set of images are chosen for training the classifiers and another set of images are chosen to test the performance of classifiers. For training, proposed method for feature extraction, Gray Level Co-occurrence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM) are used.

In testing process, the values of trained images are used for classification purpose. From the image database, another set of images is chosen for testing purpose. Using the above mentioned three feature extraction methods, features are extracted for the testing images. From the set of trained and test features, the classifiers SVM, ELM and KNN are then used for classification purpose which classifies the MR brain image as normal or abnormal.

Results

In this section, the experimental results of the proposed method using MR brain images is explained. The implemented is done in MATLAB 2014a.

1. Performance assessment of proposed technique

The MR brain image is given as input to the PURE-LET transform method. Noise free MRI brain image is shown in Figure 2.

The classifiers are trained with training dataset (46 normal and 44 tumor) images and the classification accuracy is calculated with the testing (21 normal and 23 tumor) images. The testing is done using testing data. The obtained result of classifier without and with tumor is
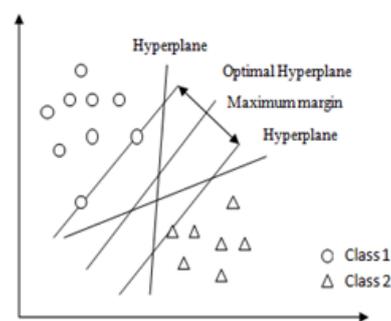

Figure 1. Illustration of SVM

Table 1. Performance Analysis

Image	Parameters	Curvelet Transform	Pure-Let Transform
Set I	MSE	21.56	15.99
Set II	PSNR	30.63	37.51
Set III	SSIM	0.74	0.988
Set IV	UQI	0.26	0.987

Table 2. Performance Analysis of Various Classifiers

Classifier	Feature extraction	Sensitivity (%)	Specificity (%)	Accuracy (%)
KNN (k=5)	MTMD	86	70	77
	Modified MTH with MTMD	90	70	80
	GLCM	81	74	77
	GLRLM	67	83	75
ELM	MTMD	86	83	84
	Modified MTH with MTMD	81	100	91
	GLCM	81	65	73
	GLRLM	90	78	84
SVM	MTMD	100	74	86
	Modified MTH with MTMD	100	91	95
	GLCM	100	52.17	75
	GLRLM	90	96	93

Sl. No	Image Set	Noisy Image	Curvelet Transform	Purelet Transform
Set I				
Set II				
Set III				
Set IV				

Figure 2. Comparison of Purelet and Curelet Transform

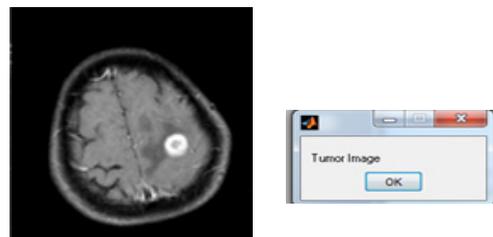Figure 3. MRI Brain Image and Classified Output

Figure 4. MRI Brain Tumor Image and Classified Output

shown in Figure 3 and Figure 4 which classified the MR image as normal and tumor image respectively.

2. Performance analysis of proposed technique
   The obtained classified output from SVM and KNN classifier is resolved through performance metrics likespecificity, sensitivity, and accuracy .

$$Specificity = \frac{t_n}{t_n + t_p}$$

$$Sensitivity = \frac{t_p}{t_p + t_n}$$

$$Accuracy = \frac{t_p + t_n}{t_n + t_p + f_p + f_n}$$

True positive (t_p): Tumor people correctly identified as having the condition
   False positive (f_p): Normal (healthy) people incorrectly

identified as tumor

True negative (t$_n$): Normal (healthy) people correctly identified as healthy

False negative (f$_n$): Tumor people incorrectly identified as normal (healthy)

The performance metrics sensitivity, specificity, and accuracy of SVM classifier KNN classifier with three feature extraction methods is shown in Table 2.

3. Comparative analysis

As shown in above table 2, we have compared our proposed method of feature extraction which is by combining MTMD and MMTH with GLCM, GLRLM using three classifiers. The accuracy of proposed method with SVM classifier is 95%, with KNN classifier 80% and with ELM classifier 91%.

Discussion

In the proposed method, brain tumor classification system consists of two stages: Feature extraction and classification and in each stage different methods are used to classify Magnetic Resonance (MR) brain image as normal or abnormal. The proposed feature extraction method which is the combination of Modified Multi-Texton Histogram (MMTH) and Multi-Texton Microstructure Descriptor (MTMD).It is compared with other feature extraction methods known as Gray Level Co-occurence Matrix (GLCM) and Gray Level Run Length Matrix (GLRLM) and MTMD. Three classifiers Support Vector Machine (SVM), K Nearest Neighbors (KNN) and Extreme Learning Machine (ELM) are used for classifying the image. The result of classification is evaluated using sensitivity, specificity and accuracy. KNN with combination of MMTH and MTMD shows 80% accuracy compared to other feature extraction methods. Similarly ELM and SVM with combination of MMTH and MTMD shows accuracy of 91% and 95%. From the comparison result, SVM with combination of MMTH and MTMD shows high accuracy of compared to other two classifiers.

Statement conflict of Interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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