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Brain Tumor Detection using Fuzzy Support Vector Machine Classification based on a Texton Co-occurrence Matrix

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Abstract. *Segmentation of tumors in medical images is not only of high interest in serial treatment monitoring of "disease burden" in oncologic imaging, but is also gaining popularity with the advance of image guided surgical approaches. Magnetic resonance images are widely used in the diagnosis of brain tumors. In this article, an automatic tumor detection and classification system is presented, which focuses on the structural study on both tumorous and normal tissue. The proposed system consists of the following steps: (i) pre-processing, (ii) feature extraction using an enhanced texton co-occurrence matrix and (iii) classification. In classification, a fuzzy logic based support vector machine is used to classify the experimental images into normal and abnormal. The obtained experimental results show that the proposed brain tumor detection approach is more robust than other neural network based classifiers, feed forward neural network and radial basis function, in terms of sensitivity, specificity and accuracy.*

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INTRODUCTION

A brain tumor is a cluster of abnormal cells growing in the brain. Its effects may not be the same for each person, and they may even change from one treatment session to the next. It can appear at any location, shape, size and with different image intensities. Brain tumors can be benign or malignant. Low grade gliomas and meningiomas[1] are benign tumors, and glioblastoma multiform is a malignant tumor and represents the most common primary brain neoplasm. Benign brain tumors have a homogeneous structure and do not contain cancer cells. They may either simply be monitored radiologically or surgically eradicated, and they seldom grow back. Malignant brain tumors have a heterogeneous structure and contain cancer cells. They can be treated by radiotherapy, chemotherapy or a combination of these, and they are life threatening. Therefore, diagnosis of brain tumors in an appropriate time is essential for further treatment. In recent years, neurology and basic neuroscience have been significantly advanced by imaging tools that enable *in vivo* monitoring of the brain.[2]

Magnetic resonance image (MRI) segmentation is used to create different categories of volumetric data into gray matter (GM), white matter (WM), and cerebro-spinal fluid (CSF) tissue types. It support many medical image applications such as radiotherapy planning, clinical diagnosis, treatment planning and Alzheimer's disease. MRI provides more perfect information for medical examination than that of other medical images such as ultrasonic, CT images and X-ray. MRI gives better results than computed tomography (CT) because it provides greater contrast between different soft tissues of the human body.[3] In particular, secondary tumors can be composed of an enormous variety of tissue types depending on the primary tumor site. Its application to several datasets with different tumor sizes, intensities and locations shows that it can automatically detect and segment very different types of brain tumors with a good quality. The quantitative analysis of MRI brain tumor allows useful key indicators of disease progression to be obtained.[4–6]

In the bioinformatics system various supervised and unsupervised based classification methods are proposed. However, most of the methods produce poor results when the data are non-linearly separable. But SVM (support vector machine) is one of the suitable classification methods for both linear and non-linear data. It is usually adopted for non-linear classification function and density estimation. It produces successful classification results in several application domains, for, e.g., medical diagnosis.[7,8] SVM follows the structural risk minimization principle from the statistical learning theory. Its kernel is to control the practical risk and classification capacity in order to broaden the margin between the classes and reduce the true costs.[9] A support vector machine searches an optimal separating hyperplane between members and non-members of a given class in a high dimension feature space.[10] To capture the visual content of an image, feature extraction is used as one of the most important methods. To facilitate decision making such as pattern classification, feature extraction is used as the process to represent the raw image in its reduced form. Various methods such as multi texton histogram (MTH), principal component analysis (PCA), linear discriminant analysis (LDA) and semantic structure feature are used to reduce the number of features. In semantic structure feature, the algorithm uses a hypothesis in line with the Gestalt laws of proximity for human vision that, in an image, basic semantic structures are formed by line segments

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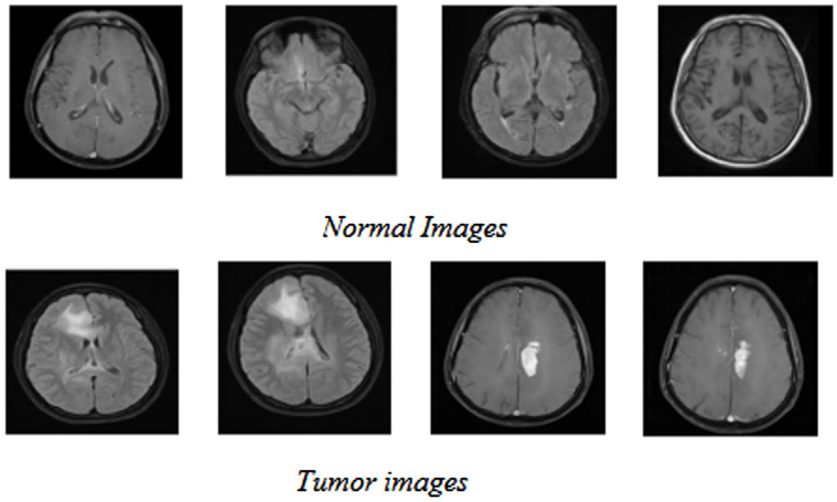

Figure 1. Samples of T1-weighted tumor and normal MR images.

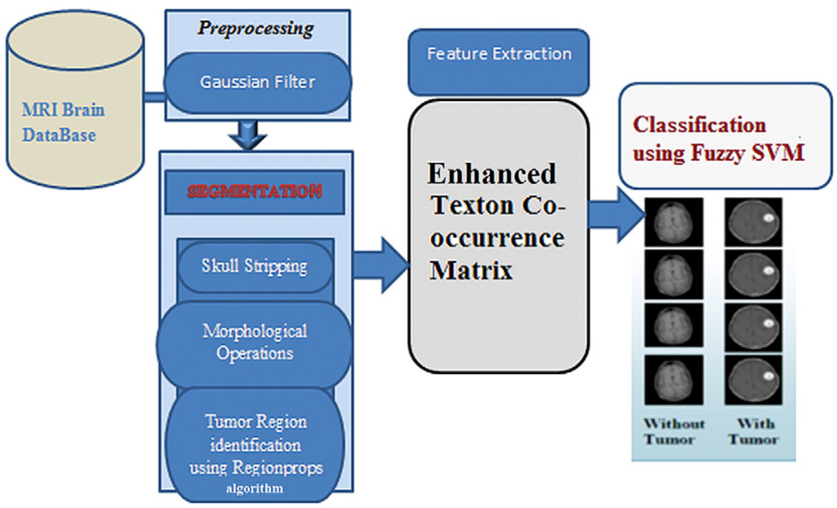

Figure 2. Overall block diagram of the proposed system.

that are in close proximity to each other. Further, these basic semantic structures are hierarchically combined (by the brain) until a point where a semantic meaning of the structure can be extracted.[11] The MTH is a feature extractor and a descriptor to retrieve images which integrates the advantages of representing the attribute of the co-occurrence matrix using histograms.[12] The rest of the article is organized as follows. The MRI data set description and methods for feature extraction as well as for classification are presented in the next section. The detailed experimental results and discussion are then given in the third section while the conclusion is summarized in the fourth section.

DATASET DESCRIPTION AND METHODS

Input data set

For our proposed method, the experimental image dataset contains 80 brain MR images. Of these, a total of 60 T1-weighted gadolinium enhanced MR images are tumorous, and the other 20 images are non-tumorous. These 3D DICOM real images were obtained from the Government Medical College Hospital, Tirunelveli, Tamilnadu, India, using a Siemens 1.5 Tesla MR unit. In each case, only T1-weighted post-contrast (gadolinium) images, spin-echo (SE) sequence (TR = 480 ms, TE = 8.7 ms), with matrix size of 256 × 256 and slice thickness of 1 mm are used for analysis. Sample T1-weighted contrast enhanced MR images are shown in Figure 1.

Methods

In this article, we propose a novel method using texture features as input to a fuzzy support vector machine (FSVM) for classification of magnetic resonance (MR) images of the human brain. The proposed method classifies MR brain images as either normal or abnormal. Initially, the input image passes through a Gaussian filter to eliminate the noise and enhance the image for further processing. Subsequently, the pre-processed image is segmented using a thresholding technique, then tumor regions are identified using the regionprops algorithm. After the segmentation process, the features are extracted from the regions using an enhanced texton co-occurrence matrix and are given to the fuzzy support vector machine for training. In the final stage, the image is classified as tumorous or normal with the help of the trained FSVM. The overall block diagram of the proposed technique is shown schematically in Figure 2.

Segmentation: In medical image processing, segmentation is an important and challenging factor. It is classically used to detect object contours in an image and to extract the object from the image.[13] In this article a thresholding method is used for segmentation. Pre-processing and the segmentation process are the steps in the tumor region identification stage. In pre-processing, the input image is passed through a filter which diminishes the noise and enhances the image quality. In this article, a Gaussian filter is used for reducing image noise without removing significant parts of the image content, particularly the edges, lines or other details that are important for the interpretation of the image.[14] Generally, skull stripping is a major segmentation step for the analysis of medical images of the brain region. The main purpose of skull stripping is removal of the scalp, skull and dura parts of the brain.[15] The different steps of the segmentation process are given below.

(i) Transformation of the MRI image into a binary image by thresholding.
(ii) Sharpening of the region using morphological operations.
(iii) Tumor region identification.

Binarization via thresholding: Initially, the MRI image is transformed into a binary image. An image of up to 256 gray levels is translated to a black and white image using a threshold value. The gray level value of every pixel in the improved image is considered at this stage. All the pixels with values above the threshold are set as white and the remaining pixels are set as black in the image during the binarization process.

$$B_{\mathrm{Binary}}(i,j) = \begin{cases} 0, & \text{if } B_{\mathrm{gray}}(i,j) \le \text{Threshold}, \\ 1, & \text{Otherwise}. \end{cases} \tag{1}$$

The threshold calculation process is as follows.

i. Select an initial estimate of the threshold T. A good initial value is the average intensity of the image.
ii. Calculate the mean gray values μ_1 and μ_2 of the partitions, $R1$ and $R2$.
iii. Partition the image into two groups, $R1$ and $R2$, using the threshold T.
iv. Select a new threshold: $T = \frac{1}{2}(\mu_1 + \mu_2)$.
v. Repeat steps ii to iv until the mean values μ_1 and μ_2 in successive iterations do not change.

Morphological operation: This is used as an image processing tool to sharpen the regions and fill the gaps for binarized image. After segmenting the brain MR image, morphological operations are applied to the image to clearly locate the tumor part in the brain. The basic purpose of the operations are to show only that part of the image that has the tumor, which is the part of the image having more intensity and more area. Morphological operators such as opening, closing, erosion and dilation are applied to the segmented brain MR image with a 3 × 3 structuring element using Eqs. (2) and (3).

$$A \Theta B = \{z/(B)_z \subseteq A\}, \tag{2}$$

$$A \oplus B = \{z/(\overline{B})_z \cap A \neq \varphi\}. \tag{3}$$

Tumor area identification: After the erosion process, the tumor area is identified using the regionprops algorithm and the tumor location area is marked based on the area properties. The properties of image areas are calculated by the regionprops function. It measures a set of properties for each connected component in the binary image. Using the definite number of pixels in the region, the tumor region's area is segmented. This value is somewhat different from the value returned by bwarea. The bwarea function returns the area of a binary image. The area is a measure of the size of the foreground of the image. It does not simply count the number of pixels set to on, however. Rather, bwarea weights different pixel patterns unequally when computing the area. This weighting compensates for the distortion that is inherent in representing a continuous image with discrete pixels by weighting varied patterns of pixels in an unusual way. By measuring the space between each neighboring pair of pixels around the border of the region regionprops calculates the area.

Enhanced texton co-occurrence matrix: In our proposed method, the feature extraction process is done with the help of an enhanced texton co-occurrence matrix. In this method, both a histogram and a texton co-occurrence matrix are used for the feature extraction process. Here, the information on spatial correlation between neighboring pixels is extracted using a texton co-occurrence matrix and spatial information on the pixels is extracted using a histogram. The concept of the texton was developed by Julesz et al.[16] It is a very useful tool for analyzing texture features of the image. It has a set of emergent patterns sharing a common property all over the image. It analyzes the spatial correlation between neighboring pixel color and edge orientation based on four special texton types. These four different types of texton are described in Figure 3.

The histogram technique is simple to compute but has high indexing performance. In this article a histogram based texton co-occurrence matrix method is used for feature extraction. Using a histogram the texton co-occurrence matrix attributes are described with respect to the characteristic relationship between neighboring pixels. Here, image features are represented using a co-occurrence matrix. If

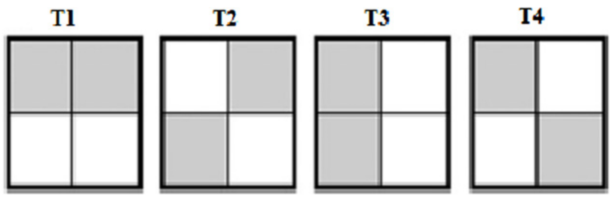

Figure 3. The four special texton types for a 2×2 grid.

the dimension of the image feature set is high then the performance is decreased. The spatial information is lost when we use the histogram only for feature representation of the image. Hence, we combine the histogram and the co-occurrence matrix for feature extraction and representation. Let the pixel position be $P = (x, y)$. At the same position $P_i = (x_i, y_i)$, every component of the texton image has a pixel value, thus five components of a texton image have five pixel values. If those five pixel values are the same, the final texton image will keep its original value in the corresponding positions. If zero and nonzero values appear in those five pixels, the final texton image will be kept at the nonzero values. The texton image detection process is illustrated in Figure 4. The proposed feature extraction process is a four step process which consists of the following:

- Gridding,
- Block count value of the original image for each intensity (1–255),
- Block count value of the texton image for each intensity (1–255),
- Concatenation of the two vectors.

Gridding: Normally, gridding partitions the image into several smaller sub-images known as grid images. In this technique, the original image is divided into 4, 18 and 24 grid images. The grid images are normally square in shape. Gridding results in smaller grids, so that the analysis can be performed easily.

Block count value of the original image for each intensity (1–255): Normally, the intensity value range is from 0 to 255 for each block. After the gridding process, the block count value is calculated for each intensity value (1–255). Finally, the resultant vector $H(V_1)$ is obtained from the original gridding image.

Block count value of the texton image for each intensity (1–255): The values of a texton image T are denoted as $w \in \{0, \ldots, W-1\}$. Denote by $P_1 = (x_1, y_1)$ and $P_2 = (x_2, y_2)$ two neighboring pixels, and their values are $T(P_1) = w_1$ and $T(P_2) = w_2$. If the probability P_r of two values w_1 and w_2 co-occurring with two pixel positions related by D defines the cell entry (w_1, w_2) of the co-occurrence matrix $C_{D,\theta}$ and is defined as follows:

$$C_{D,\theta}(w_1, w_2) = 1 - p_r\{T(P_1) = w_1 \wedge T(P_2) = w_2 \|P_1 - P_2\| = D\}. \quad (4)$$

Then the block count value is calculated for each intensity value (1–255) of the Texton co-occurrence matrix with different angle and distance ($D = 1$). Finally, the result vector $H(v_2)$ is obtained from the texton gridding image.

Concatenation of the two vectors: Thus, the total TCM uses an $H(V) = H(V_1) + H(V_2)$ dimensional vector as the final image feature in image retrieval.

Classification: The SVM has been widely used in pattern recognition applications due to its computational efficiency and good generalization performance. It is widely used in object detection and recognition, content based image retrieval, text recognition, biometrics, speech recognition, etc. It creates a hyperplane that separates the data into two classes with the maximum margin. A support vector machine searches for an optimal separating hyperplane between members and non-members of a given class in a high dimensional feature space. In SVMs, the training process is very sensitive to those training data points that are away from their own class. In our proposed method a fuzzy logic based SVM (FSVM) is applied for classification. It is an effective supervised classifier and accurate learning technique, which was first proposed by Lin and Wang.[17] In the FSVM each data point is assigned a membership value according to its relative importance in the class. Since each data point x_i has an assigned membership value μ_i, the training set s_f is given by

$$s_f = \{x_i, y_i, \mu_i\}_{i=1}^{n}. \quad (5)$$

For positive class ($y_i = +1$), the set of membership values are denoted as μ_i^+, and they are denoted as μ_i^- for negative class ($y_i = -1$); they are assigned independently. The main process of the FSVM is to maximize the margin of separation and minimize the classification error.

The optimal hyperplane problem of the FSVM can be defined as the following problem:[15,16]

$$\min_{w,\varsigma} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} f_i \varepsilon_i, \quad (6)$$

$$\text{subject to} \quad \begin{array}{l} y_i(w.x_i + b) \geq 1 - \varepsilon_i, \\ \varepsilon_i \geq 0, \quad i = 1, \ldots, n, \end{array}$$

where f_i $(0 \leq f_i \leq 1)$ is the fuzzy membership function, $f_i\varepsilon_i$ is an error of different weights and C is a constant.

The input to the FSVM algorithm is the feature subset selected via the enhanced TCM. It follows the structural risk minimization principle from the statistical learning theory. Its kernel is to control the practical risk and classification capacity in order to broaden the margin between the classes and reduce the true costs. A fuzzy support vector machine searches an optimal separating hyperplane between members and non-members of a given class in a high dimension feature space.[18,19]

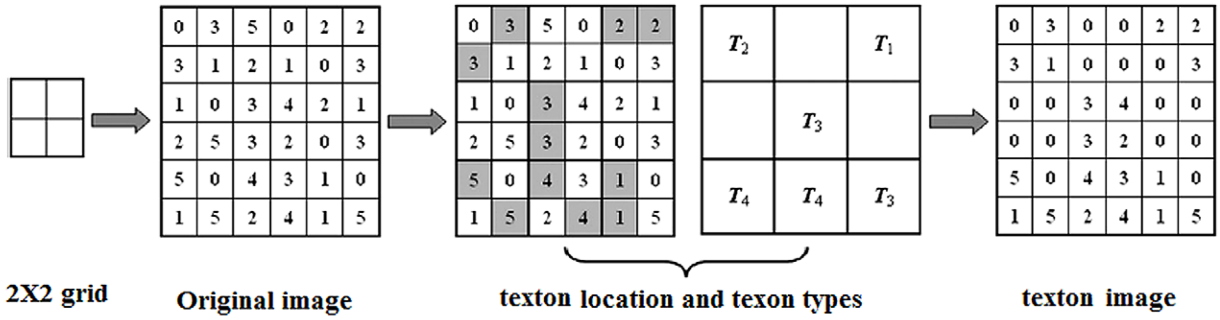

Figure 4. The texton image formation process.

The Lagrange multiplier function of the FSVM is

$$L(w,b,\xi,\beta)=\frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}f_i\xi_i$$
$$-\sum_{i=1}^{n}\alpha_i(y_i(wz_i+b)-1+\xi_i)-\sum_{i=1}^{n}\beta_i, \tag{7}$$

which satisfies the following parameter conditions:

$$w-\sum_{i=1}^{n}\alpha_i y_i z_i=0,$$
$$-\sum_{i=1}^{n}\alpha_i y_i=0,$$
$$f_iC-\alpha_i-\beta_i=0.$$

Then, the optimization problem can be transferred to

$$\text{Max}\ \ W(\alpha)=\sum\alpha_i-\frac{1}{2}\sum\alpha_i\alpha_j y_i y_j H(x_i,x_j), \tag{8}$$

$$\text{subject to}\quad \begin{array}{l}\sum\alpha_i y_i=0,\\ 0\le\alpha_i\le f_iC,\quad i=1,2,\ldots,n,\end{array}$$

where the parameter α_i can be solved by the sequential minimal optimization (SMO) quadratic programming approach.[20] In non-linear data, the input space X can be mapped into higher dimensional feature space ψ. It becomes linearly separable. The mapping function ψ should be in accordance with Mercer's theorem:[21]

$$H(x,x_i)=\psi(x)^t\psi(x_i), \tag{9}$$

where $H(x,x_i)$ is the kernel function.

It can be chosen from the following functions.

Polynomial learning machine kernel function:

$$H(x,x_i)=(x.x_i+1)^d,\quad i=1,2,3,\ldots,n, \tag{10}$$

where d is an integer.

Linear network kernel function:

$$H(x,x_i)=x^T x_i. \tag{11}$$

Radial basis function (RBF) kernel function:

$$H(x,x_i)=\exp(-\gamma\|x-x_i\|^2),$$
$$i=1,2,3\ldots,n,\ \gamma>0. \tag{12}$$

FSVM process: To train the fuzzy SVM classifier, we need some data features to identify the normal brain region and tumor affected brain. The data features will then train the classifier and the classifier will find whether the given MRI image is a tumor or not. The data features that we have chosen to train the FSVM classifier are concatenated from two vectors (detailed in section 2.2.2) such as the block count value of the original image for each intensity (1–255) and the block count value of the texton image for each intensity (1–255). The FSVM classifier then compares the values of the concatenation of the two data features such as the block count value of the original image for each intensity (1–255) and the block count value of the texton image for each intensity (1–255) with the stored values for normal and abnormal MRI images. After comparison, the FSVM classifier will identify whether the given MRI image comes under the normal category or the abnormal category and give the result.

RESULTS AND DISCUSSION

This section describes the experimental results of our proposed segmentation technique using brain MRI images with and without tumors. Our proposed approach can successfully classify the experimental images into tumor and non-tumor if the parameters are set correctly. In our proposed system the classification process is in two stages: the training stage and the testing stage. In the training stage we utilized 30 images (20 tumor images and 10 non-tumor images), and the remaining 50 images were used for testing purposes. The obtained experimental results are shown in Figure 5. It is evaluated through evaluation metrics, namely, sensitivity, specificity and accuracy, using Eq. (13). Sensitivity is a measure that determines the probability of the results that are true positive indicating that a person

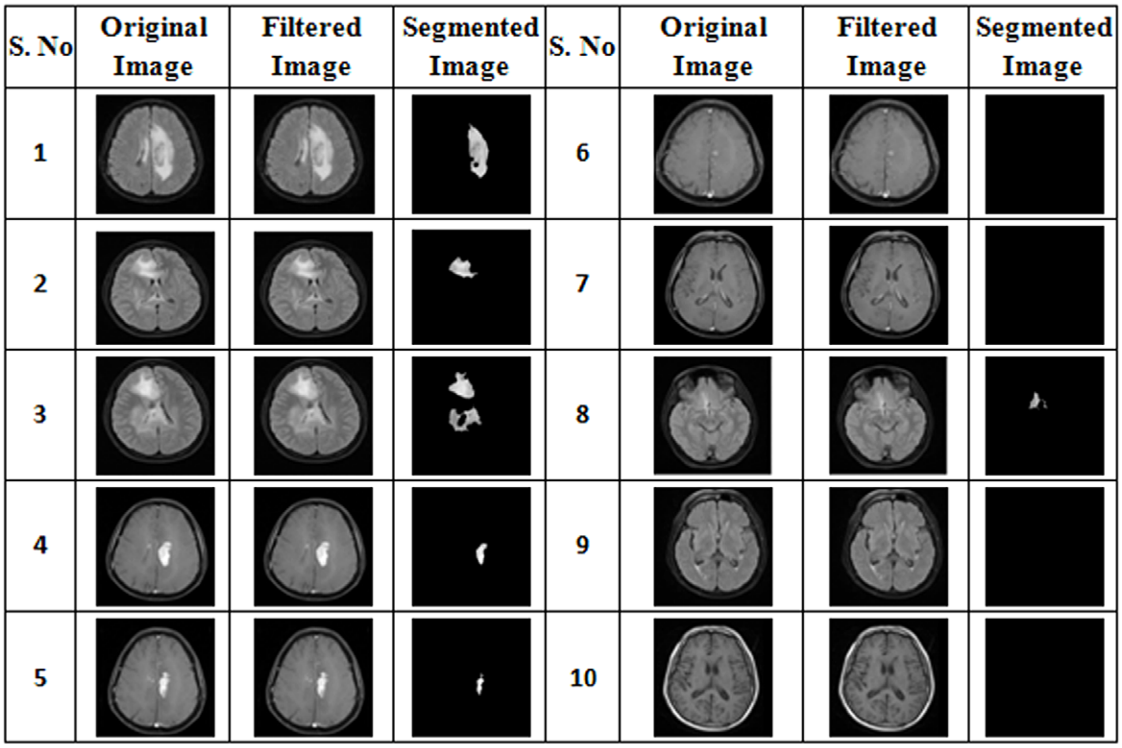

Figure 5. Experimental results: (a) original image, (b) filtered image and (c) segmented image.

has a tumor. Specificity is a measure that determines the probability of the results that are true negative indicating that a person does not have a tumor. Accuracy is the proportion of true results, either true positive or true negative, in a population. It measures the degree of veracity of a diagnostic test on a condition.[22]

$$\text{Sensitivity} = \text{TP}/(\text{TP} + \text{FN}),$$
$$\text{Specificity} = \text{TN}/(\text{TN} + \text{FP}),$$
$$\text{Accuracy} = (\text{TN} + \text{TP})/(\text{TN} + \text{TP} + \text{FN} + \text{FP}), \quad (13)$$

where TP stands for true positive, TN stands for true negative, FN stands for false negative and FP stands for false positive. The obtained experimental results of the existing and proposed methods are given in Table I.

Analysis of the results shows that our proposed approach has better performance. The outcomes of the experimentation prove 94% accuracy of the enhanced texton co-occurrence matrix based method in detection of tumors from the brain MRI images. The proposed method is also evaluated using the similarity index (SI), overlap fraction (OF) and extra fraction (EF) using (14). SI is a measure for the correctly segmented region relative to the total segmented region in both the manual segmentation and the proposed method. The OF and the EF specify the areas that have been correctly and falsely classified as tumor area, respectively, relative to the tumor area in manual segmentation. In a well segmented image, SI and OF should be close to 1 and EF should be close to 0. In practice, a value for SI of more than 0.7 represents a very good segmentation.[23–26]

Table I. Detection accuracy of the proposed approach in testing the data set.

Evaluation metrics		TCM + RBF	TCM + FFNN	TCM + FSVM
Input MRI image data set	TP	37	35	38
	TN	8	8	9
	FP	2	2	1
	FN	3	5	2
	Sensitivity	0.925	0.875	0.95
	Specificity	0.73	0.62	0.9
	Accuracy	0.9	0.86	0.94
	Total error (%)	12.5	17.5	7.5

$$\begin{aligned} \text{SI} &= 2\text{TP}/(2\text{TP} + \text{FP} + \text{FN}),\\ \text{OF} &= \text{TP}/(\text{TP} + \text{FN}),\\ \text{EF} &= \text{FP}/(\text{TP} + \text{FN}). \end{aligned} \quad (14)$$

The experimental results for the proposed and existing methods in terms of SI, OF and EF are given in Table II.

The evaluation graphs of the sensitivity, specificity and accuracy are shown in Figure 6. Moreover, the proposed system error rate is less than those of other classifiers; it is shown in Figure 7.

We have compared our proposed fuzzy logic based SVM with the other neural network classifiers feed forward neural network (FFNN) and radial basis function (RBF). The fuzzy logic based SVM model yields better overall results than other classifiers in terms of the above evaluation metrics.

Table II. Means of criteria, including similarity index (SI), overlap fraction (OF) and extra fraction (EF), of different methods.

	SI	OF	EF
TCM + RBF	93.67	0.925	0.04
TCM + FFNN	90.9	0.875	0.05
TCM + FSVM	96.20	0.95	0.025

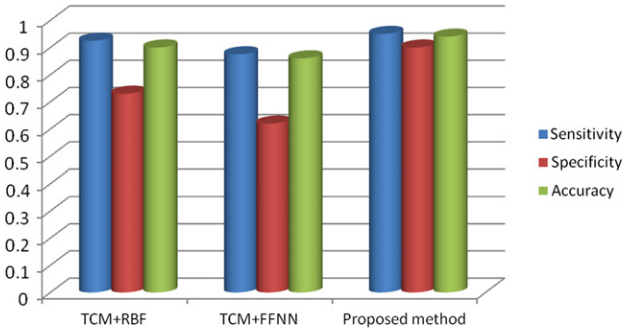

Figure 6. Comparative bar charts of proposed and existing methods.

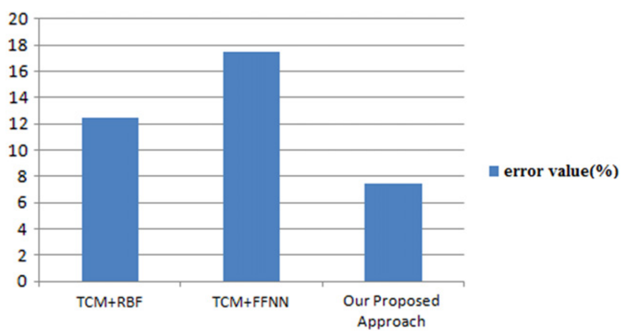

Figure 7. Comparative error bars of the existing and proposed methods.

CONCLUSION

In this article, a novel brain magnetic resonance image classification approach using an enhanced texton co-occurrence matrix and a fuzzy support vector machine has been developed. Two major contributions of this article are feature extraction and classification. In feature extraction, we have taken advantage of both a co-occurrence matrix and a histogram to extract the texture feature from every segment for better classification of the image. In classification, a fuzzy SVM classifier is used to improve the classification process. We have applied this method only to T1-weighted post-contrast brain MRI images. For comparative analysis, the proposed enhanced TCM is compared with other neural network based classifiers. The obtained results show that the proposed brain tumor detection approach produces better results than existing classifiers in terms of sensitivity, specificity and accuracy.

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