International Journal of Applied Engineering Research
ISSN 0973-4562 Volume 10, Number 8 (2015) pp. 19331-19344

http://www.ripublication.com

Rough Set Theory And Support Vector Machine Classifier Based Brain Tumor Detection Of MR Images

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ABSTRACT

Medical Imaging is perceived to designate the set of techniques that noninvasively produce images of the internal aspect of the body. Magnetic resonance Imaging brain tumor segmentation is a complicated task due to the variance and intricacy of tumors. In this paper the MRI Brain image classification of cancer is done based on rough set theory and support vector machine classifier is proposed . The proposed method result will be more accurate and reliable. In this paper, first the features are extracted from the input MRI images using Rough set theory, then the selected features are given as input to Support Vector Machine classifier. Finally, Support vector machine classifier is utilized to perform two functions. The first is to differentiate between normal and abnormal. The second function is to classify the type of abnormality in benign or malignant tumor. Based on the experimental results, the proposed brain tumor classification method is more robust than other traditional methods in terms of the evaluation metrics, sensitivity, specificity and accuracy.

Keywords— Support vector Machine (SVM) ,Magnetic Resonance Images(MRI) , Rough set theory , Radial basics function(RBF), Explicit region. Gaussian Filter

I. INTRODUCTION

Medical imaging is a technique and process used to create images of the human body for clinical purposes such as medical procedures seeking to reveal, diagnose or examine disease. Medical Science incorporates the study of normal anatomy and physiology. In the clinical context, medical imaging is generally equated to radiology or clinical imaging and the medical practitioner responsible for interpreting the images is a radiologist. As a field of scientific investigation, medical imaging constitutes a sub-discipline of biomedical engineering, medical physics or medicine depending on the context. Research and development in the area of instrumentation, image acquisition, modelling and quantification are usually the preserve of biomedical engineering, medical physics and computer science.

A lot of research efforts have been directed in the field of 'Medical Image Analysis' with the aim to assist in diagnosis and clinical studies. Medical image classification is a key task in many medical applications such as surgical planning, abnormality detection, and so on. There are lots of methods for automatic and semi-automatic image classification, though; most of them fail because of unknown noise, poor image contrast, inhomogeneity and weak boundaries that are usual in medical images. Medical images mostly contain complicated structures and their accurate classification is necessary for clinical diagnosis. Brain image classification is very important for detecting tumors. Magnetic resonance imaging (MRI) [1] is an important imaging technique for detecting abnormal changes in different parts of the brain in early stage. MRI images have good contrast in comparison to computerized tomography (CT). The manual interpretation of brain tumor slices based on visual examination by physician may lead to missing diagnosis and time consuming when a large number of MRI brain images are analysed. To avoid human based diagnostic error, computer aided diagnosis system is needed.

Rough sets theory was introduced by Polish Mathematician Pawlak in 1980s [2]. It is regarded as a new mathematical tool to deal with vagueness and uncertainty. It was widely studied in many fields such as machine learning, data mining, and pattern recognition etc. In the authors defined explicit and implicit regions based on the rough sets theory and introduced a new method for inducing decision trees in light of the principle of minimal rough fringe. Based upon the basic concepts of explicit and implicit regions, we define rough hypercuboid in terms of intervals of gene expression levels. Rough hypercuboid classifiers can be induced by dynamically selecting some genes as the dimensions of the implicit hypercuboids, which involve the smallest number of misclassified samples. By dynamically constructing implicit hypercuboids, the approach selects potential functional genes for inducing classifiers. Experimental results for the classifiers are capable of classifying cancers with high accuracy and RCI, while only a small number of genes are involved. The results suggest that the proposed method is a feasible way of classifying different cancer types in applications.

In this paper, automated MRI brain image classification using Rough set Theory and support vector machine is proposed. The proposed scheme consists of four parts: image pre-processing, feature extraction using Rough set Theory then classification based on SVM and finally comparison to exiting techniques. Image pre-processing techniques are applied to improve the quality of image. Texture feature extraction techniques [4] [5] [6] are used for the purpose of feature extraction from MRI brain images. Support vector machine classifier [3] [9]

[10] is utilized to perform two functions via one-versus-all voting scheme. The first is to differentiate between normal and abnormal. The second function is to classify the type of abnormality in benign or malignant tumor. Fig 1 shows the Flow Diagram of the proposed method.

The rest of the paper is organized as follows: A brief review of researches related to the proposed technique is presented in section 2. The proposed technique is presented in Section 3. The detailed experimental results and discussions are given in Section 4. The conclusions are summed up in Section 5.

2. RELATED WORK

Lots of researches have been performed for the segmentation of normal and abnormal tissues in MRI brain images. Some of the recent related works regarding the segmentation of brain tissues are reviewed in this section.

Soft Computing techniques such as fuzzy logic and neural networks have been used for segmentation of brain tumor. Segmentation of brain tumor using HSOM (Hierarchical Self Organizing Map), an unsupervised clustering technique maps high dimensional inputs to one or two dimensional discrete lattice of neuron units [7]. HSOM method aids physicians in tumor diagnosis and monitoring. Another segmentation technique which is an extension to traditional Fuzzy C-Means (FCM) clustering algorithm which considers two influential factors : feature difference between neighbouring pixels and the relative locations of neighbouring pixels in the image [8].

As well, a template-based framework for multi-object segmentation of deep brain structures (caudate nucleus, putaen and thalaus) in medical brain images has been presented by Jue Wu and Albert C.S. Chung [11]. This framework combines the information of edge features, region statistics, and inter-structure constraints for identifying and locating all target brain structures. The multi-object template has been structured in the form of a hierarchical Markov Dependence Tree (MDT), and manifold objects have been successfully matched to a target image via a top-to-down optimization approach. The final segmentation has been achieved through refinement by a B-spline based non-rigid registration between the exemplar image and target image. The approach necessitates only one example as training data. The technique has been validated using a publicly available T1-weighted MRI database with expert-segmented brain structures and obtained satisfactory results as 0.80 Dice score for the caudate nuclei, 0.81 Dice score for the putaina, and 0.84 Dice score for the thalai on average.

In order to enhance the performance of automated image segmentation, especially in the field of brain tissue segmentation from 3D MRI towards classical image deterioration including the noise and bias field artifacts that arise in the MRI acquisition process, caldairou et al. [12] have proposed to integrate into the FCM segmentation methodology concepts stimulated by the Non-Local (NL) framework. The major algorithmic contributions of this paper were the definition of an NL data term and an NL regularization term to effectively handle the intensity inhomogeneity and noise in the data. Then, the resulting energy formulation was built into an

NL/FCM brain tissue segmentation algorithm. Experiments carried out on both the synthetic and real MRI data, leading to the classification of brain tissues into grey-matter, white matter, and cerebrospinal fluid, have shown a substantial enhancement in performance in the case of higher noise levels, when compared to a range of standard algorithms.

The performances of Seed-Based Region Growing (SBRG), Adaptive Network-Based Fuzzy Inference System (ANFIS), and Fuzzy c-Means (FCM) in brain abnormalities segmentation have been compared by Shafaf Ibrahim et al. [13]. Here, controlled experimental data has been utilized, which designed in such a way that prior information of the size of the abnormalities was known. This was done by cutting several sizes of abnormalities and sticking it onto the normal brain tissues. The normal tissues or the background have been divided into three different categories. The segmentation has been performed with 57 data of each category. Then, the knowledge of the size of the abnormalities by the number of pixels has been compared with the segmentation outcomes of three proposed methods. Finally, it has been found that the segmentation performance of ANFIS was excellent in light abnormalities, while the SBRG has performed well in dark abnormalities segmentation.

3. PROPOSED METHOD

3.1. Pre-processing

Gaussian Filter:

A Gaussian filter [15] is a filter whose impulse response is a Gaussian function. Gaussian filters are created to shun overshoot of step function input while reducing the rise and fall time. Gaussian filter has the minimum possible group delay. In mathematical terms, a Gaussian filter changes the input signal by convolution with a Gaussian function and this change is also called as Weierstrass transform. The input image undergoes smoothing using a Gaussian smoothing filter for elimination of noise. Gaussian filter is a linear spatial filter which is used for reducing the high frequency components of an image as a result it smooth's the edges of the input image. Gaussian Smoothing is performed by convolving the input image with the Gaussian function i.e.

$$G_\sigma(x,y) * I(x,y)$$

$$G_\sigma(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Where I(x, y) is the input image, G_σ (x,y) is Gaussian smoothing filter with standard deviation σ , x and y are the spatial coordinates, and * is the convolution operator.

Gradient operator is then applied to the smoothened image to find edges in the image which have been suppressed by the Gaussian filter i.e.

$$\nabla(G_\sigma(x,y) * I(x,y))$$

Where ∇ is the gradient operator which calculates the directional changes in intensity values.

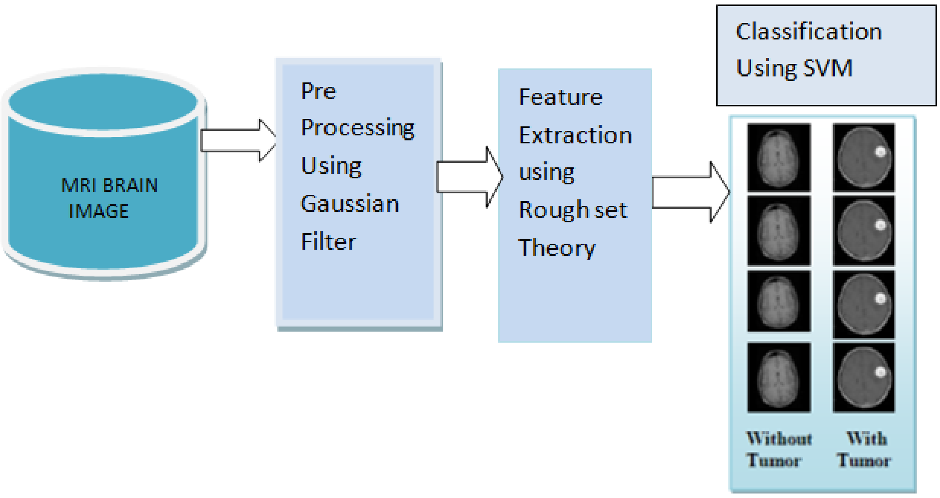

Figure-1 proposed System Flow Diagram

Binary Boundary Map Generation

The boundary map is defined as

$$MB(x, y) = \nabla(-G_{\sigma}(x, y) * I(x, y))$$

Where $G_{\sigma}(x, y)$ is the Gaussian smoothing filter with standard deviation σ , * is the convolution operator, and ∇ is the gradient operator. The normalized boundary map is defined as

$$M_{NB}(x, y) = \frac{M_B(x, y) - \min(M_B(x, y))}{\max(M_B(x, y) - \min(M_B(x, y))}$$

Similar to BVF[3] a threshold $T \in [0,1]$ is applied to generate the binary boundary map

$$\begin{aligned} M_{BB}(x, y) &= 1 \ \mathit{if}\ M_{NM}(x, y) > T \\ &\quad \mathit{else}\ 0 \end{aligned}$$

The choice of suitable threshold value varies depending on the intensity distribution and contrast associated with the set of images being analyzed. For the brain MR images a threshold of 0.1 is used to achieve object continuity and for extracting the low intensity region. The extracted boundary provides an envelope to ensure that final convergence is not out of bound.

3.2. ROUGH SET THEORY

Rough set theory can be regarded as a new mathematical tool for imperfect data analysis. The theory has found applications in many domains, such as decision support, engineering, environment, banking, medicine and others. Rough set theory has an overlap with many other theories dealing with imperfect knowledge, e.g., evidence theory, fuzzy sets, Bayesian inference and others. Nevertheless, the theory can be regarded as an independent, complementary – not competing discipline, in its own rights.

The set of all indiscernible (similar) objects is called an elementary set, and forms a basic *granule (atom)* of knowledge about the universe. Any union of some elementary sets is referred to as a *crisp (precise)* set – otherwise the set is *rough (imprecise, vague)*. Each rough set has boundary-line cases, i.e., objects which cannot be with certainty classified, by employing the available knowledge, as members of the set or its complement. Fig 2 shows the Schematic view of the four regions of the class in RST.

Rough sets in combination with other soft and computing technologies such as fuzzy sets, evolutionary programming, neural networks or crisp technologies offered, e.g., by statistical or analytical techniques are promising in solving some tasks however they should be further developed to deal with hard real-life problems. For a sample [16], The presented approach is aimed at handling uncertain information during the process of inducing decision trees and generalizes the rough set based approach to decision tree construction by allowing some extent misclassification when classifying objects. In the paper, two concepts, i.e. variable precision explicit region, variable precision implicit region, and the process for inducing decision trees are introduced. The authors discuss the differences between the rough set based approaches and the fundamental entropy based method. The comparison between the presented approach and the rough set based approach and the fundamental entropy based method on some data sets from the UCI Machine Learning Repository is also reported[17].

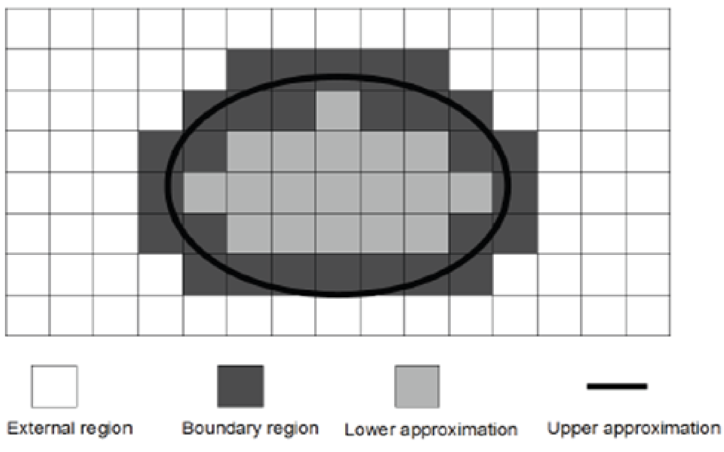

Figure-2 Schematic view of the four regions of the class in RST

Suppose we are given two finite , non-empty sets U and A, where U is the universe of objects, cases, and A---a set of attributes, features. The pair FW =(U,A) is called an information table. With every attribute a €A we associate a set V_a , of its values, called the domain of a . By a(x) we denote a data pattern (a1(x),a2(x),……,an(x)) defined by the object x and attributes from A={a1,a2,-----,an}. A data pattern of FW is any feature value vector V=(v1,v2,----,vn), where v_i €V_{a_i} for i =1; . . . ; n such that v =a(x) for some x € U .

Any subset B of A determines a binary relation I(B) on U, called an indiscernibility relation, defined as follows:

xI(B)y iff a(x) = a(y) for every a € B

where a(x) denotes the value of attribute a for object x.

The family of all equivalence classes of I(B), i.e., the partition determined by B, will be denoted by U / (B), or simply U =B; an equivalence class of I(B), i.e., the block of the partition U=B, containing x will be denoted by B(X).

If **(x,y)** **€** I(B) we will say that x and y are B- indiscernible. Equivalence classes of the relation I(B) are referred to as B-elementary sets. In the rough set approach the elementary sets are the basic building blocks (concepts) of our knowledge about reality. The unions of B-elementary sets are called B-definable sets.

The indiscernibility relation will be further used to define basic concepts of rough set theory. Let us define now the following two operations on sets

$$B_*(x) = \{x \in U : B(x) \subseteq X\}$$

$$B^*(x) = \{x \in U : B(x) \cap X \neq \phi\}$$

Using to every subset X of the universe U two sets $B^*(x)$ and $B^*(x)$ called the B-Lower and the B- upper approximation of X, respectively. The set $BN_B(X) = B^*(X) - B_*(X)$ will be referred to as the B-boundary region of X .

If the boundary region of X is the empty set, ie

$$BN_B(X) = \varnothing$$

then the set X is crisp (exact) with respect to B; in the opposite case, i.e., if $BN_B(x) \neq \varnothing$ the set X is referred to as rough (in- exact) with respect to B.

3.3 FINAL CLASSIFICATION

After feature extraction process, In-order to detect the presence of the tumour in the input MRI image, we perform the final classification step. Here we use the Support Vector Machine classifier to classify the image into tumorous or not. In 1995, Support Vector Machine (SVM) has been developed, which is an effective supervised classifier and accurate learning. technique. It is derived from the statistical theory invented by Vapnick in 1982

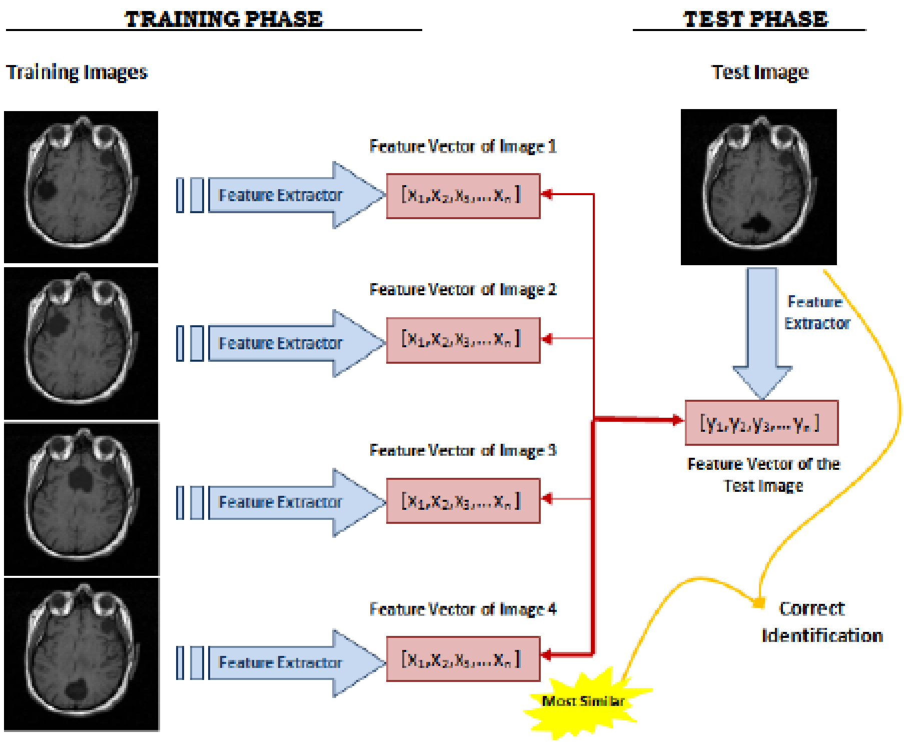

Figure-3 Schematic Diagram of MRI Image Recognizer

It produces successful classification results in several application domains, for e.g. medical diagnosis [Zhang K et al., 2006]. 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 [Zhang J et al., 2004]. A support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high.

SVM has also been applied on different real world problems such as face recognition , text categorization , cancer diagnosis, glaucoma diagnosis, microarray gene expression data analysis. Proposed system used SVM for binary classification of brain MR image as normal or tumor affected. SVM basically tries to divide the given data into decision surface. Decision surface is a hyperplane which divides the data into two classes. Training points are the supporting vector which defines the hyperplane. The kernel function H(x,x1) is defined by

Polynomial kernels is

$$H(x,x^1) = (x^p x^q + 1)^d$$

Where d is an integer.
RBF kernel is

$$H(x,x^q)=\exp(-\gamma\left\|x-x^q\right\|^2)$$

Where γ is positive parameter is slope control

4. Experimental Results

4.1 Input data set:

For our proposed method, we have collected the various tumor and non tumor MRI images from south Indian area severity analysis which is undergone for processing the images. This image dataset contains 100 brain MRI images. In which, a total of 80 T1-weighted gadolinium enhanced MR images were tumorous .These 3D DICOM real images were obtained from the Government Medical College Hospital, Tirunelveli, Tamilnadu, India, using SIEMENS 1.5 Telsa MR unit. In each case ,only T1-weighted post contrast(Gadolinium) images ,Spin-Echo (SE) sequence (TR=480 ms ,TE=8.7 ms) ,Matrix size is 256 *256 and the slice thickness is 1 mm used for analysis.

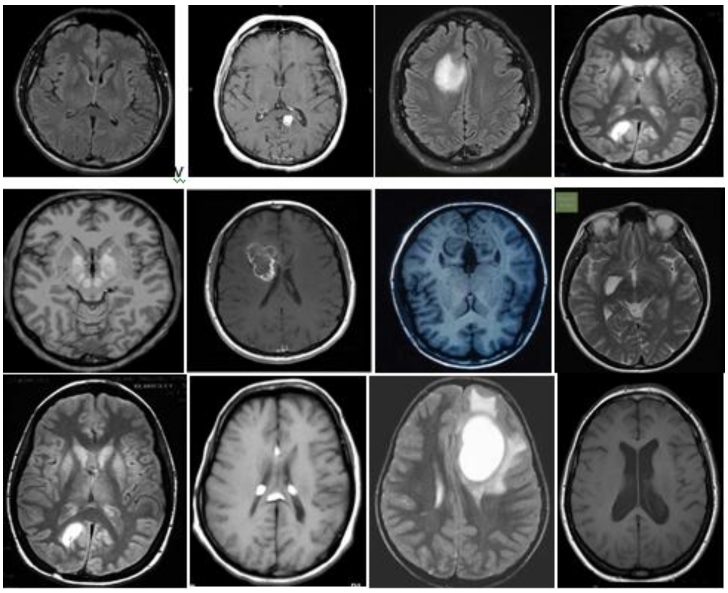

Figure.4. Samples experimental real MRI image dataset

4.2 Performance evaluation of proposed system

Classifier performance evaluation of this work is conducted with widely used statistical measures, sensitivity, specificity, accuracy and error rate [16]. Sensitivity is a measure which determines the probability of the results that are true positive such that a person has the tumor. Specificity is a measure which determines the probability of the results that are true negative such that a person does not have the tumor. Accuracy is a measure which determines the probability that how many results are accurately classified.

$$Sensitivity = TP/(TP + FN)$$

$$Specificity = TN/(TN + FP)$$

$$Accuracy = (TN + TP)/(TN + TP + FN + FP)$$

Where, TP stands for True Positive, TN stands for True Negative, FN stands for False Negative and FP stands for False Positive.. Figure 4 shows some of the sample MR images with and without tumors. The obtained experimental results from the proposed technique are given in **Fig.5.**

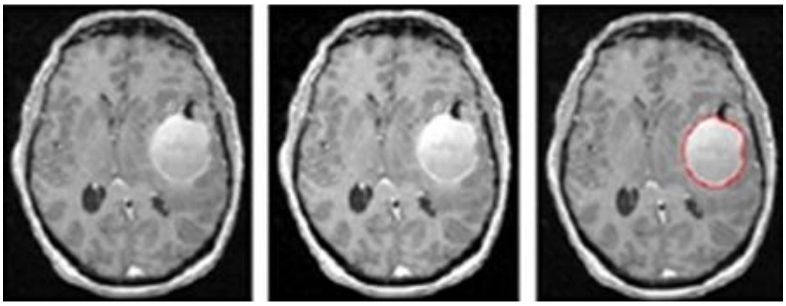

Fig:5 (a) Original Image (b) Filtered Image (c) Segmented Image

4.3 Comparative analysis:

We have compared our proposed tumor detection technique RST+SVM (Rough set theory +Support Vector machine) to other neural network techniques. The neural networks, we have utilized for comparative analysis are an Artificial Neural Network (ANN) and Radial Basics Function (RBF). The performance analysis has been made by plotting the graphs of evaluation metrics such as sensitivity, specificity and the accuracy. By analyzing the plotted graph, the performance of the proposed technique has significantly improved the tumor detection compared with Artificial Neural Network (ANN). The evaluation graphs of the sensitivity, specificity and the accuracy graph are shown in figure 6. The accuracy level proved that the proposed algorithm graph is good at detecting the tumors in the brain MRI images.

Table 1. Experimental results of existing and proposed method

Evaluation metrics		**RST+ SVM**	**RST+ RBF**	**RST+ ANN**
Input MRI image data set	**TP**	**38**	**37**	**35**
	TN	**9**	**8**	**8**
	FP	**1**	**2**	**2**
	FN	**2**	**3**	**5**
	Sensitivity	**95**	**92.5**	**87.5**
	Specificity	**90**	**80**	**80**
	Accuracy	**94**	**90**	**86**
	Total error(%)	**6**	**10**	**14**

The evaluation graphs of the sensitivity, specificity and the accuracy graph are shown in **Fig.6**. Based on the experimental results our proposed method produces better results compared to other neural network based classifiers. The brain tumor classification error bar is also given in **Fig 7**.

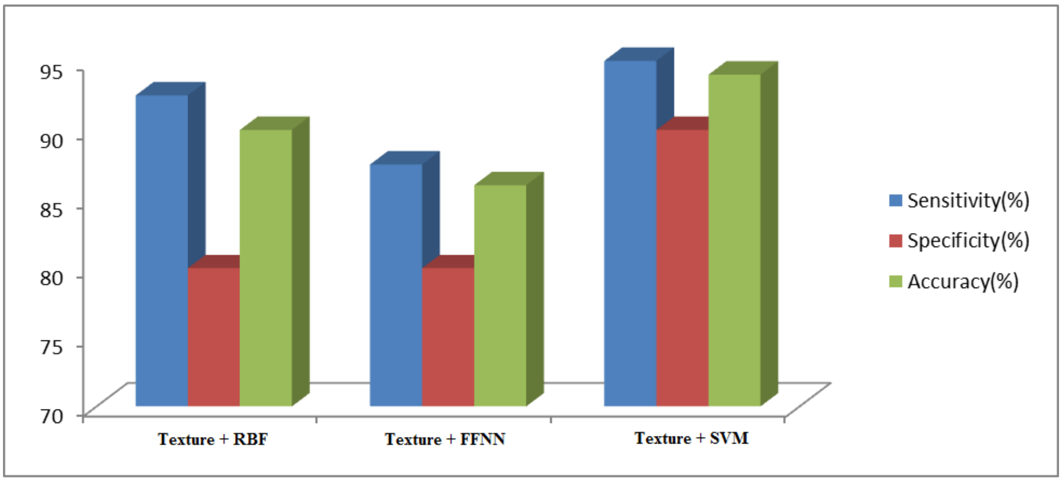

Figure 6 Comparison result analyses of Texture features with SVM, RBF and ANN

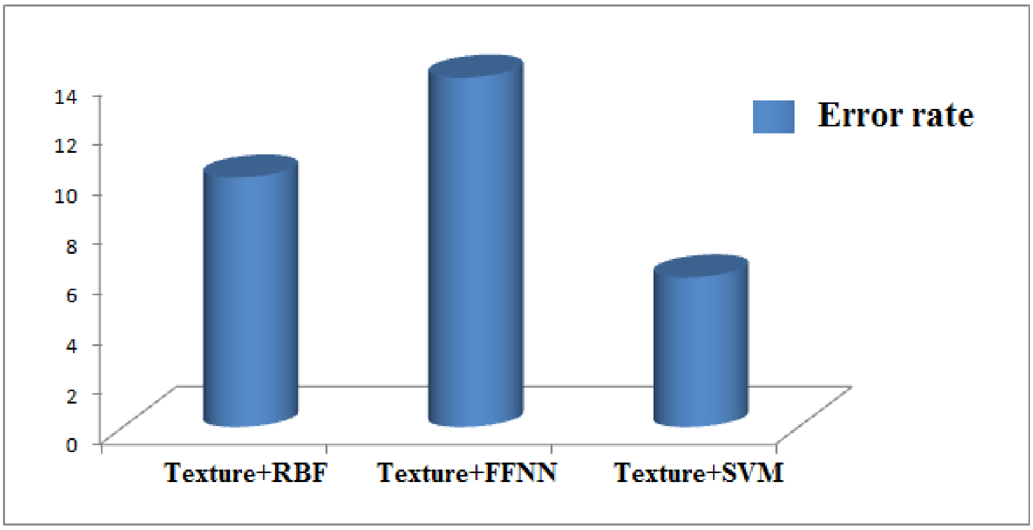

Figure 7 Comparison error bar of the proposed Texture features with various classifiers

5. CONCLUSION

This paper presents an automated system for classification of MRI brain images with different pathological condition.. Many cancer forms can only be diagnosed after a sample of suspicious tissue has been removed and tested. Pathologists view pathologic tissues, typically with microscopes, to determine the degree of normalcy versus disease. This process is time consuming and fatiguing. The system described in this paper classifies the abnormality into benign or malignant in an automated fashion. This paper use conceptually simple classification method using Support Vector Machine. Texture features are calculated using Rough set theory. The proposed system effectively classifies the abnormality of brain tumor.

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