MRI Brain Image Segmentation Using Supervised Classifiers (SVM and RVM)

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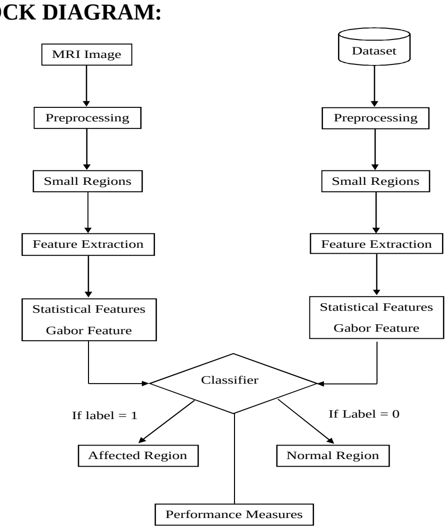
ABSTRACT:
Computer technology covers a wide range of medical area in the area of cancer research, heart diseases and brain diseases. Accurate automatic detection and classification of image is a very challenging task. MR images are widely used method of high quality medical imaging especially in brain images. In this project from MR brain images we segments and classify the tumor using soft computing method called support vector machine (SVM) and relevance vector machine (RVM). The brain tumor in MR images can be identified by finding tumor pixels in the image. The identified tumor pixels were then segmented based on clustering or contour extraction or thresh holding. The features like mean standard deviation and Gabor feature were extracted from the image. After this procedure it undergoes training phase and testing phase. Based on the features extracted the pixels and the image were classified as tumorous and non tumorous. Hence the tumor portion is segmented accurately. Finally the performance of the segmentation method is measured. The parameters such as classification rate, accuracy and time consumptions using SVM and RVM for brain MR images are compared for performance analysis. The accuracy level is 90% and 92% ,specificity is 6.26% and 5.2% and sensitivity is 99.4% and 99.6% for SVM and RVM respectively.

1. **INTRODUCTION**: Image processing is to convert an image into a digital form and to perform some operation on it, in order to set an enhanced image and to extract some information from it. Image processing mainly includes images as 2D signals. In this paper an user friendly tumor segmentation approach by classifier called as support vector machine was proposed. Tumor in brain is not always easier to identify. The brain tumor in MRI can be identified by tumor pixels in image. This is achieved by classifying and then grouping the image pixels by some trained pattern classifier and by preprocessing techniques. The classification can be treated as two classes as tumor and non tumor data. For this SVM classifier was developed. The SVM based classification has been applied for regression and classification. Hyper spectral imaging systems give continuous reflectance spectra for each pixel. The Support Vector Machine (SVM) based classification approach has recently been applied for regression and classification of hyper spectral images. Recently relevance vector machine (RVM) has been proposed. Although RVM offers some advantages compared with SVM, its application to hyper spectral images is very recently been proposed. RVM is suitable for low-complexity applications. The hyper spectral image classification using relevance vector machines with a pre-segmentation step is presented in this paper. The offset parameter are related to scale factor of segmentation was adjusted manually to obtain a good visual result. A higher initial resolution will lead to smaller and more detailed segmented objects [1]. SAFIS algorithms are based on several benchmark problems in nonlinear identification and prediction area. In sequential learning, the data arrive one after, the learning of each data is discarded and the notion of epoch does not exist [2]. In one-pass, recursive, and therefore, has extremely low memory requirements. Genetic and evolutionary algorithms are computational techniques for a "directed" random search for a solution to a loosely formulated optimization problem [3]. Theoretical approach minimizes or maximizes the image information such as index of fuzziness or crispness, its simplicity and high speed. Thresh holding has the highest average performance of 97.67% and lowest standard deviation of 2.19% Image thresh holding is a difficult task in image processing and never find a super algorithm that can be successfully applied to all kinds of images [4].

2.PROPOSED METHOD:
The proposed system has five modules: Pre-processing, segmentation, feature extraction, classification and performance calculation.

BLOCK DIAGRAM:



2.1. PRE PROCESSING:
The preprocessing commonly involves removing low frequency background noise reflections and masking portion of images. The preprocessing work is done by two filters they are Weiner and Histogram equalization. This is shown in fig[3]

Wiener filter is used an linear time-invariant filtering an observed noisy process. The Wiener filter minimizes the mean square error between the estimated random process and the desired process. It is assumed to have knowledge of the spectral properties of the original image and the noise. It seeks the linear time-invariant filter whose output would come as close to the original signal as possible.

Histogram equalization method usually increases the global contrast of many images, usually when the usable data of the image is represented by close contrast values. Through this, the intensities can be better distributed on the histogram. The histogram equalized images contains intensities uniformly distributed over the image. The histogram equalization process increases the quality of the input image in a better way.

2.2. FEATURE EXTRACTION :

The features were extracted by calculating the mean and standard deviation, this helps to identify the tumors portion. The Gabor filter is used to find the texture based information are also needed to identify the tumors portion accurately. Gabor filter is a Gaussian kernel function and filters are directly related to Gabor wavelets. The feature extraction is shown in fig [4]

A 2-D Gabor function g(x, y) and its Fourier transform G(u, v) are defined as

$$g(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right]$$

A self-similar filter dictionary can be obtained by associating an appropriate scale factor α and a rotation parameter θ with the mother wavelet g(x, y) . M and N represent the scales and orientations of the Gabor wavelets.

$$g_{mn}(x,y)=\alpha(x',y'),\ 0\le m\le M-1,\ 0\le n\le N-1$$

$$x'=\alpha^{-m}(x\cos\theta+y\sin\theta),\ y'=\alpha^{-m}(-x\sin\theta+y\cos\theta)$$

2.3. CLASSIFIER:

Classification analyzes the numerical properties of various image features and organizes them into categories. Classification includes two phases of processing they are testing and training. Classification includes wide range of theoretic approaches to the identification of images. Here classification is done by SVM and RVM. This grouping is used to train SVM classifier

2.3.1. SUPPORT VECTOR MACHINE (SVM):

Support vector machines are supervised learning that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms of output. After training the SVM model is created. SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap. Support vector machines are a supervised learning models with associated learning algorithms that analyze data and recognize patterns used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Classification accuracy is computed and optimal hyper plane is constructed. Among the many hyper planes available, there is only one hyper plane that maximizes the distance between itself and the nearest data vectors of each category. This hyper plane which maximizes the margin is called the optimal separating hyper plane.

Expression for hyper plane

$$w.\ x + b = 0$$

x – Set of training vectors

w – vectors perpendicular to the separating hyper plane

b –offset parameter which allows the increase of the margin

. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

The original problem may be stated in a finite dimensional space, it often happens that the sets to discriminate are not linearly separable in that space. For this, it was proposed that the original finite-dimensional space be mapped into a much higher-dimensional space. To keep computational load reasonable, the mappings used by SVM schemes are designed to ensure that dot products may be computed easily in terms of variables in the original space, by defining them in terms of a kernel function K(x,y). The hyper planes in higher-dimensional space are defined as the set of points whose dot product in that space is constant. The vectors defining the hyper planes can be chosen to be linear combinations with parameters α_i of images of feature vectors that occur in the data base. With this choice of a hyper plane, the points x in the feature space that are mapped into the hyper plane are defined by the relation: $\sum_i \alpha_i K(x_i, x) = \mathrm{constant}.$ If K(x,y) becomes small as y grows further away from x, each term in the sum measures the degree of closeness of the test point x to the corresponding data base point. The segmented SVM is shown in fig [5].

2.3.2. RELEVANCE VECTOR MACHINE (RVM):

A **relevance vector machine (RVM)** is a machine learning technique that uses Bayesian inference to obtain parsimonious solutions for regression and probabilistic classification. The RVM has an identical functional form to the support vector machine, but provides probabilistic classification. Compared to support vector machines (SVM), the Bayesian formulation of the RVM avoids the set of free parameters. This is unlike the standard sequential minimal optimization (SMO)-based algorithms employed by SVM, which are guaranteed to find a global optimum.

RVM is a recent development in kernel based machine learning approaches and can be used as an alternative to SVM for image classification. The RVM is a possibilistic counterpart to the SVM. The RVM is based on a hierarchical prior, which is defined on the weight parameters in the first level and an independent Gamma hyper prior is used for variance parameters in the second level. Advantages of RVM over the SVM includes reduced sensitivity to the hyper parameter settings. A case then be allocated to the class with which it has the greatest likelihood of membership. Using a Bernoulli distribution the likelihood function for the analysis would be:

$$p(\mathbf{y}|\mathbf{g})=\prod_{i=1}^{n}\sigma\{(y(\mathbf{x}_i))\}^{y_i}\ [1-\sigma\{(y(\mathbf{x}_i))\}]^{1-y_i}$$

As a result only a small number of training cases are required for final classification. The assignment of an individual hyper parameter to each weight is the ultimate reason for the sparse property of RVM. The RVM produced the highest accuracy than the SVM. The segmented RVM is shown in fig [6]

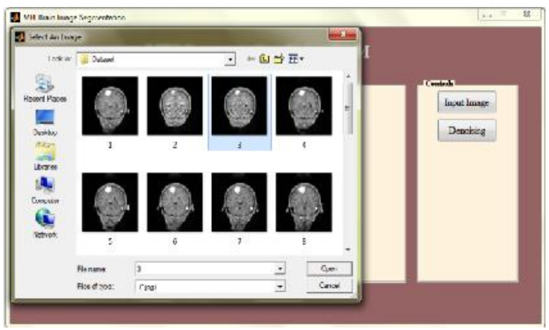
3. PERFORMANCE ANALYSIS :

In performance analysis the accuracy, sensitivity and specificity of the classifier is measured. The performance is calculated for both SVM and RVM. The sensitivity shows how the algorithm gives correct classification, the accuracy represents the capabilities or efficiency of the process. The specificity shows how the classifiers reject wrong classification result. The example performance analysis for SVM and RVM is shown in fig [7] and [8] respectively. The Average of 10 input MR images are shown below with accuracy in fig. [0].

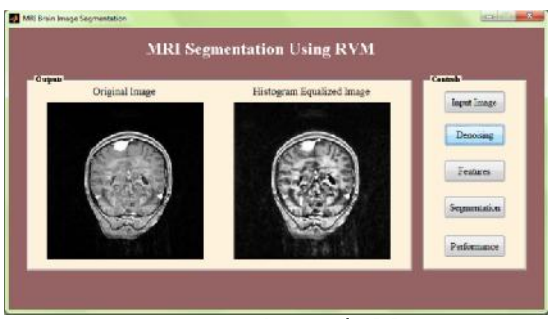
INPUT MR IMAGE	SUPPORT VECTOR MACHINE			RELAVANCE VECTOR MACHINE		
	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity	Accuracy
	99.6	4.21	82.47	99.84	4.24	82.36
	99.8	3.88	79.80	99.8	3.8	79.80
	99.8	5.80	81.11	99.8	3.89	80.77
	99.2	6.41	82.84	99.50	5.23	82.80
	99.69	4.25	84.45	99.69	4.25	84.45
	99.53	7.52	82.95	99.81	6.57	83.01
	99.72	5.22	85.09	99.72	5.22	85.09
	99.24	8.70	85.71	99.63	6.83	85.76
	99.15	8.86	86.71	99.5	7.05	86.83
	99.15	7.77	85.6	99.66	6.89	85.83
AVERAGE	99.4%	6.26%	90.81%	99.69%	5.20%	92.44%

Fig. [0]

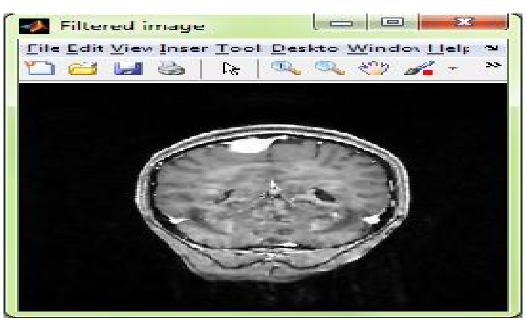
4. RESULTOFDISCUSSION:



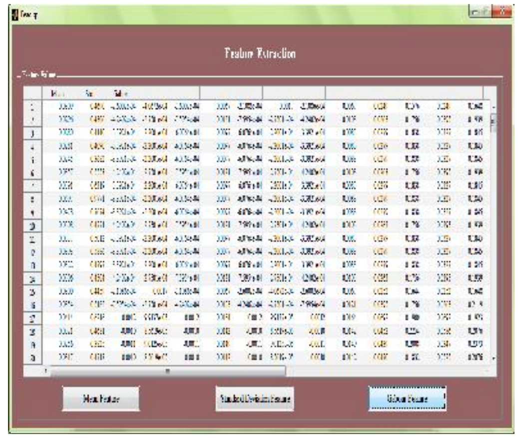
Input image fig [1]



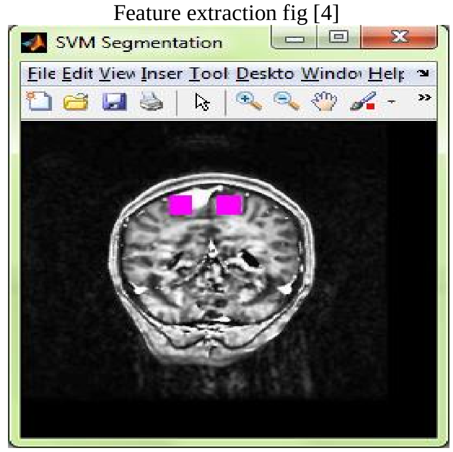
Preprocessed image, fig [2]



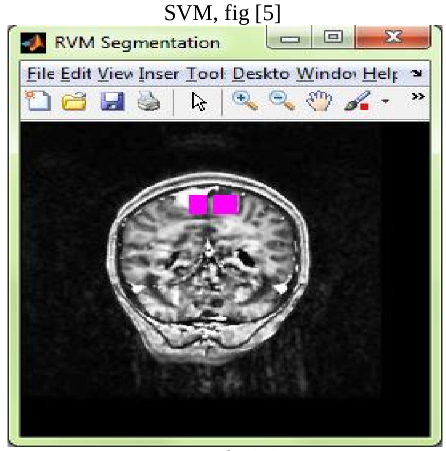
Filtered image fig [3]



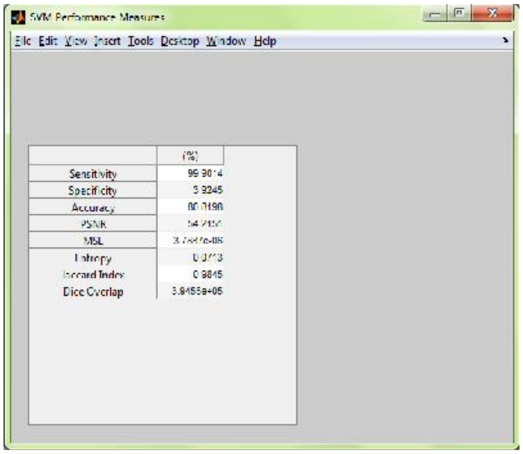
Feature extraction fig [4]



SVM, fig [5]



RVM fig [6]



Fig[7]

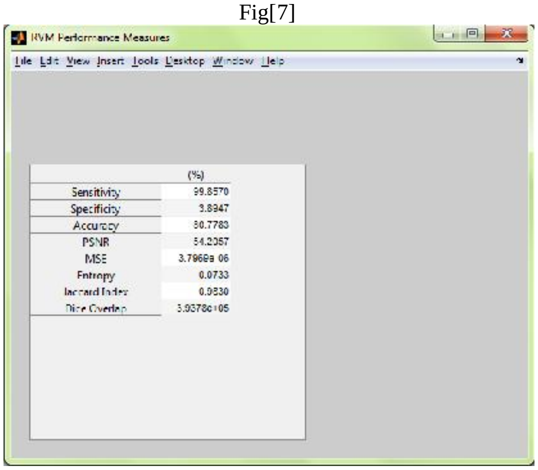


Fig [8]

5. CONCLUSION:

A novel image segmentation method using SVM has been developed and tested with MR images. The proposed technique demonstrated great potential of MRI tumor segmentation. A smaller relevance vector amount with a slightly lower testing (i.e. classification) accuracy is obtained using RVM. The proposed approaches give a better comparison of relevance vector machine and Support vector machine, and it is suitable for low complexity applications. The proposed method is automated process that segments the brain tumor automatically. The supervised classification process is also more reliable and the classifier gives the correct result. The segmentation of the brain tumor is done on different classification techniques. In segmentation the accuracy increases in each employed segmentation methodology. The performance is also calculated by measuring PSNR, MSE, Jaccard index, Entropy, Sensitivity, Specificity and accuracy. The measured values show that the RVM possess higher accuracy than SVM in most of the cases.

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7. REFERENCES:

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