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# Performance Analysis in Detecting Brain Tumor Tissue Using SVM in MR images

**R. Preetha*, S. Priyadharshini** and G.R. Suresh*****

**ABSTRACT**

Tumor detection is important in medical images for medical practices. Image Segmentation becomes essential and challenging to visualize the tissue of human for analyzing the MR images. In brain MR images, the boundary of tumor tissue is irregular. Region based methods are extensively used for medical image segmentation, to locate the boundary of the tumor. Problems associated with non-linear distribution of real data, User interaction and poor convergence to the boundary region limited their usefulness. Clustering of brain tumor tissues, using Fuzzy C means is robust and effective for tumor localization. SVM is a most powerful tool and an accurate classifier, which can act as an expert assistant to medical practitioners. FCM clustering and classification using SVM is very promising in the field of brain tumor detection.

***Keywords:*** MRI, Brain Tumor, Fuzzy C means, SVM.

## 1. INTRODUCTION

In 2013, an estimated 69,720 new primary brain tumor diagnoses are made in U.S., in which 24,620 are malignant and 45,100 are nonmalignant [1]. This shows the importance to implement new tools and methodologies, for identifying and analyzing the brain tumor. Brain tumor is the mass formed by the aggregation of abnormally growing cells. There are two types of tumor which are benign (non-cancerous) and malignant (cancerous). Benign tumor is a slow growing tumor that lacks the ability to invade the neighboring tissue. Where as, malignant tumor is fast growing and invades the adjacent tissue of the brain [2]. Magnetic resonance Images shows the brain structure, tumor size and its location. MRI possesses good contrast resolution for different tissues [3]. So, it is used in majority of research work. One of the most important techniques to extract useful information for medical images is segmentation [4]. Many of the image processing techniques are based on threshold based, edge based, region based methods and cluster based. Clustering is the most popular technique for medical image segmentation. The task of partitioning a set of entities into number of homogenous clusters is called partitioned clusters. Number of fuzzy clustering methods was developed based on fuzzy set theory [5]. The main difference between hard and soft clustering is that, in the former the data elements belong to one cluster and in the latter the data elements belong to more than one cluster with different degrees of membership. K-Means clustering is a simple unsupervised learning algorithm, which defines K centroids, one for each cluster [6]. It assigns each pixel in the image to the cluster. This algorithm is widely used because of its simplicity, efficiency and self organizing capability. But, it belongs to hard clustering and it is a linearly separating algorithm [7]. The extension of K means algorithm is called as fuzzy K means or fuzzy C means algorithm. Fuzzy C means is widely preferred, as the data element can belong to more than one cluster and associated with each element is a set of membership levels [8-10]. Classifying data is common task in machine learning. In practice, many classification methods

* Assistant Professor, Department of ECE, Rajalakshmi Institute of Technology, Chennai, India, *Email: Preetha.r@ritchennai.edu.in*

** Assistant Professor, Department of ECE, Rajalakshmi Institute of Technology, Chennai, India, *Email: Priyadharshini.s@ritchennai.edu.in*

*** Professor, Department of ECE, Easwari Engineering College, Chennai,, India, *Email: sureshgr@rediffmail.com*

are used namely, Linear discriminant analysis (LDA), and quadratic discriminant analysis (QDA) by [11], Artificial neural network (ANN), and Support vector machines (SVM). The basic Support vector machine 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 [12]. Weighted SVM [13] [14] is an elegant generalization of conventionally used SVM which allows the assignment of different weighted features to classes. This paper is based on analyzing the performance of fuzzy c means algorithm with the extension of weighted feature extraction and SVM classification.

## 2. SUPPORT VECTOR MACHINE

Support vector machine is the discriminative classifier grown up from statistical learning theory [15,16]. The Basic idea of SVM is as follows: 1) Transform the input space to high dimensional feature space by non-linear mapping 2) construct the separating hyperplane with maximum distance from the closest points of the training set. In this paper, without loss of generality, SVM is described. In two class classification, the training dataset is given as $S = (x_1, y_1),\ldots..,(x_l, y_l)$, where $x_i \in R^d$ and the class label $y_i \in \{\pm 1\}$. A hyper-plane acting as a two class decision function in this N-Dimensional space is defined by $f(x) = w \cdot x + b = 0$, $w \in R^N$ and $b \in R$ and the corresponding decision rule is given by

$$f(x) = \text{sgn}(w.x + b) \tag{1}$$

Consider the training data is linearly separable, then the optimal hyper-plane yields maximum margin classification. This can be obtained by solving the quadratic optimization problem.

$$\min_{w,b} \frac{1}{2}\|w\|^2 \tag{2}$$

Subject to $y_i(w.x_i + b) \geq 1$ for $1 \leq i \leq l$. This is probably optimized by lagrangian primal and dual problems. By introducing lagrangian multiplier $\alpha_i \geq 0$, the lagrangian primal form is given by

$$\min_{w,b} \frac{1}{2}\|w\|^2 - \sum_i \alpha_i \left(y_i \left(w.x_i + b\right) - 1\right) \tag{3}$$

formula (3) can be transformed to lagrangian dual problem as,

$$\max \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j x_i^T x_j \tag{4}$$

Subject to

$$\sum_i \alpha_i y_i = 0 \tag{5}$$

Where as $\alpha_i \geq 0$ for any $i = \{1, \ldots., n\}$. This is tractable convex quadratic programming (QP). The optimal parameters $\alpha i^*$ and $b^*$ can be easily obtained. The decision function is given by

$$f\left(x\right) = \text{sgn}\left(\sum_{i=1}^{l} y_i \alpha_i^* x^T x_i + b^*\right) \tag{6}$$

Solving a linearly constrained convex quadratic programming problem is equivalent to training a SVM. So, the solution of SVM is global optimal and absent from local minima. Actually, the solution is determined only by support vectors, which are the subset of training data. So, it can be determined sparsely.

By introducing non-linear kernel function $k(x, y)$, non-linear classifiers can be formulated. The dual problem becomes

$$\max \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j K\left(x_i, x_j\right) \tag{7}$$

And the decision function is given by

$$f\left(x\right) = \operatorname{sgn}\left(\sum_{i=1}^{l} y_i \alpha_i^* K\left(x, x_i\right) + b^*\right) \tag{8}$$

There are number of kernels available in support vector machine like, linear, Polynomial, Radial basis function (RBF), and Sigmoidal function. In this paper, RBF is chosen as the kernel function. The kernel is given by,

$$\textbf{RBF: } K\left(x, x'\right) = \exp\left(-\gamma \left\| x - x' \right\|^2\right), \text{ for } \gamma > 0 \tag{9}$$

In real world, data is often non-separable. This can be tackled by introducing slack variables $\varepsilon_i$.

$$\min_{w,b,\varepsilon_i} \frac{1}{2}\|w\|^2 + C \sum_{i=1}^{n} \varepsilon_i \tag{10}$$

Such that $yi(w.xi - b) \geq 1 - \varepsilon i$, $1 \leq i \leq l$, Where $C$ is the regularization parameter, it controls the trade-off between maximizing the margin and minimizing the training error. $K = 1$ is usually used in practice and $k = 2$ can also be used. For $k = 1$, lagrangian dual as in formula (7) is used but subject to $0 \leq \alpha_i \leq C$. The decision function is same as formula (8).

## 3. EXPERIMENTAL RESULTS AND DISCUSSION

In this paper, three datasets each in three different types of T1 weighted tumor MR images with 256 × 256 matrix size and 5 mm slice thickness were acquired from the radiologists. The datasets have tumors like Glioblastoma, Lower Grade Glioma and meningioma. The Images are Preprocessed and clustered for tumor segmentation. The generalization ability depends on extracting features from the segmented image. Almost 39 features are extracted namely, mean, variance, standard deviation, median, skew ness, kurtosis, gray level co-occurrence matrix, Autocorrelation, contrast, correlation, cluster prominence, cluster shade, Dissimilarity, energy, entropy, Homogeneity, maximum probability, sum of squares, sum average, sum variance, sum entropy, difference variance, Difference entropy, Information measure correlation, Inverse difference, Inverse difference normalization, Inverse difference moment normalization, statistical moments of order 6.

SVM classifier is implemented and the result is used to detect True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) values. For training phase of SVM classifier, one slice which was the Ground truth (GT) of tumor was randomly chosen in each subject dataset. Accuracy, Sensitivity and Specificity factors are determined. The performance of SVM using Linear, Polynomial, Sigmoidal and RBF kernel was analyzed. Among which the results of Sigmoidal and polynomial kernel were equivalent to RBF. Therefore, the results of linear and RBF is shown below.

**Table 1**
**General Performance Measure on Different Types of Tumor**

| *Type of Tumor* | *Linear* | | *RBF* | |
|---|---|---|---|---|
| | *TP (%)* | *TN (%)* | *TP (%)* | *TN (%)* |
| GBM | 93.85 | 96.28 | 97.4 | 98.5 |
| LGG | 90 | 95.24 | 95 | 97.8 |
| Meningioma | 89.19 | 95.24 | 96 | 96.82 |

In Table 1, general performance measure was done to determine the True Positive (TP) and True Negative (TN) values for both Linear and RBF Kernel. The RBF kernel shows better results than linear kernel.

**Table 2**
**Performance analysis using Linear and RBF Kernel**

| *Type of Tumor* | *Sensitivity %* | | *Specificity %* | | *Accuracy %* | |
|---|---|---|---|---|---|---|
| | *Linear* | *RBF* | *Linear* | *RBF* | *Linear* | *RBF* |
| GBM | 98.2 | 99.4 | 94.11 | 96.2 | 92.07 | 98.9 |
| LGG | 94.98 | 99.2 | 90.49 | 95.24 | 92.62 | 97.5 |
| Meningioma | 94.93 | 98.81 | 89.81 | 95.04 | 92.2 | 95.91 |

In Table 2 the classification accuracy is higher, in the case of Glioblastoma than in Lower grade Glioma and meningioma. RBF kernel shows better results than Linear kernel. The impact of increase in number of training data's using SVM is shown in table III. The increase in number of training data increases the detection results of tumor. The Efficiency of SVM classifier depends on the number of training data's. In Table 3, the accuracy increases with the increase in number of training data. Based on this fact, the further work was performed using 121 training datasets and improved results were obtained. The increase in performance measure is also determined using a comparative chart shown in Figure 1. It, clearly highlights that, the inferred measures have exponential increase with the number of training data's. The above specified algorithms are implemented in MATLAB on a PC with 3GHZ and 1.93GB RAM.

**Table 3**
**Detection results of tumor using SVM**

| *No. of Training data* | *TP* | *TN* | *Sn* | *Sp* | *Acc* |
|---|---|---|---|---|---|
| 10 | 12.66 | 14.11 | 12.85 | 13.91 | 13.39 |
| 20 | 15.14 | 21.65 | 16.19 | 20.33 | 18.39 |
| 30 | 23.22 | 36.34 | 26.73 | 32.13 | 29.78 |
| 40 | 38.43 | 52.45 | 44.69 | 46 | 45.45 |
| 50 | 59.15 | 69.33 | 65.85 | 62.93 | 64.24 |
| 60 | 73.31 | 79.13 | 77.84 | 74.78 | 76.22 |
| 70 | 91.16 | 89.90 | 90.03 | 91.05 | 90.53 |

Finally, three different types of tumor namely, Lower grade glioma, Glioblastoma and Meningioma are used to analyze the performance of SVM using RBF kernel with 121 training datasets and the results are

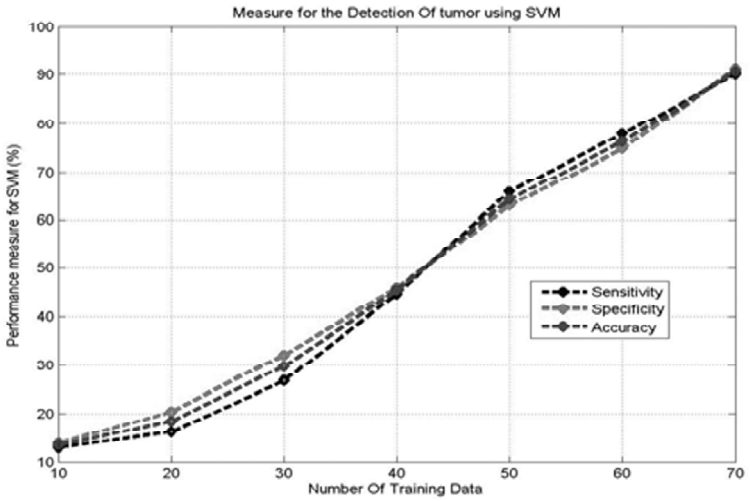


**Figure 1: Performance Of SVM**

**Table 4**
**Performance Analysis on different types of tumor**

| *Type of Tumor* | *Glioma* | | *Meningioma (%)* |
|---|---|---|---|
| | *Lower Grade Glioma (%)* | *Glioblastoma (%)* | |
| TP(%) | 91.56 | 93.85 | 90.12 |
| TN(%) | 95.85 | 98.28 | 95.4 |
| Sensitivity % | 92.67 | 97.5 | 98.96 |
| Specificity % | 94.453 | 96.5 | 98.2 |
| Accuracy % | 95.24 | 99 | 93 |

listed in Table 4.Generally, in medical image analyzes, Accuracy plays a vital role in decision making. The results shown in Table IV reveals that, the classification accuracy of glioblastoma is higher than lower grade Glioma and Meningioma.

## 4. CONCLUSION AND FUTURE WORK

Medical images generally contain noise and uncertainty. So, segmentation performance to the level of clinical acceptance is challenging. FCM performs better in clustering the brain tumor tissue. SVM is a powerful tool and an accurate classifier. SVM shows good performance results in detecting the tumor tissue. In this paper, two different kernels and three different types of tumor are used to analyze the performance of SVM. From the results it can be concluded that SVM shows superior performance in detecting glioblastoma than Lower grade glioma and Meningioma. In future, the application of this method will be extended to investigate three dimensional reconstruction of tumor for different stages.

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