

# SVM Classifier Based Extraction of Brain Tumor from MRI Images using MATLAB

Garima Sharma<sup>1</sup>, Rajesh Kumar<sup>2</sup>, Raj Kumar Thenua<sup>3</sup>

<sup>1,2</sup> Department of ECE, Sachdeva Institute of Technology, Farah, Mathura, U.P (India)

<sup>3</sup> Department of ECE, Anand Engineering College Technical Campus, Agra, U.P (India)

## ABSTRACT

Image segmentation algorithms and techniques find its applications in a wide number of domains. Extraction of brain tumor and overall internal structure of the brain is one of the main applications in the field of medical imaging. Magnetic resonance imaging (MRI) technique is one of the many imaging modalities that are available to scan and capture the internal soft tissue structures of the body. In this work, Support Vector Machine (SVM) technique is used to extract the tumor portion, successfully demarcate the tumor boundary, locate the tumor with a bounding circle and calculate the size of the tumor with processing time. The complete simulation is done using MATLAB software.

**Keywords:** MRI, segmentation, SVM

## I. INTRODUCTION

Nowadays, the introduction of information technology and e-health care system in the medical field helps clinical experts to provide better health care to the patient. Brain tumor is an abnormal mass of tissue in which cells grow and multiply uncontrollably. Brain tumors can be primary or metastatic, and either malignant or benign. A metastatic brain tumor is a cancer that has spread from elsewhere in the body to the brain. According to the World Health Organization and American Brain Tumor Association [1], the most common grading system uses a scale from grade I to grade IV to classify benign and malignant tumor types. On that scale, benign tumors fall under grade I and II glioma and malignant tumors fall under grade III and IV glioma. The grade I and II glioma are also called low-grade tumor type and possess a slow growth, whereas grade III and IV are called high-grade tumor types and possess a rapid growth of tumors. If the low-grade brain tumor is left untreated, it is likely to develop into a high grade brain tumor that is a malignant brain tumor. Patients with grade II gliomas require serial monitoring and observations by magnetic resonance imaging (MRI) or computer tomography (CT) scan every 6 to 12 months.

Magnetic Resonance Imaging (MRI) is an advanced medical imaging technique used to produce high quality images of the parts contained in the human body. MRI imaging [2] is often used when treating brain tumors, ankle, and foot. From these high-resolution images, we can derive detailed anatomical information to examine human brain development and discover abnormalities. Nowadays there are several methodology for classifying MR images, which are fuzzy methods, neural networks, atlas methods, knowledge based techniques, shape methods, variation segmentation [3-6]. MRI consists of T1 weighted, T2 weighted and PD (proton density) weighted images.

## II. PROBLEM DESCRIPTION

The segmentation, detection, and extraction of infected tumor area from magnetic resonance (MR) images is a tedious and time taking task performed by radiologists or clinical experts, and their accuracy depends on their experience only. So, the use of computer aided technology and software becomes very necessary to overcome these limitations.

Wavelet transform is an effective tool for feature extraction from MR brain images, because it allows analysis of images at various levels of resolution due to its multi-resolution analytic property. However, this technique requires large storage and is computationally expensive. In order to reduce the feature vector dimensions and increase the discriminative power, the principal component analysis (PCA) was used [7]. PCA is appealing since it effectively reduces the dimensionality of the data and therefore reduces the computational cost of analyzing new data [8]. Then, the problem of how to classify on the input data arises.

In recent years, researchers have proposed a lot of approaches for this goal, which fall into two categories. One category is supervised classification, including support vector machine (SVM) [9-10] and  $k$ - nearest neighbors ( $k$ -NN). The other category is unsupervised classification, including self-organization feature map (SOFM) and fuzzy  $c$ -means. While all these methods achieved good results, and yet the supervised classifier performs better than unsupervised classifier in terms of classification accuracy (success classification rate).

Among supervised classification methods, the SVMs are state-of- the-art classification methods based on machine learning theory. Compared with other methods such as artificial neural network, decision tree, and Bayesian network, SVMs have significant advantages of high accuracy, elegant mathematical tractability, and direct geometric interpretation. Besides, it does not need a large number of training samples to avoid overfitting.

## III. METHODOLOGY

In this work SVM classifier is used for image segmentation. The SVM classifier algorithm can be implemented in four major steps as shown in Fig1. First step is pre-processing & Image acquisition of given MRI image in MATLAB then second is filtering the image to reduce the noise and third is image resizing and finally fourth step is tumor extraction using SVM classifier.

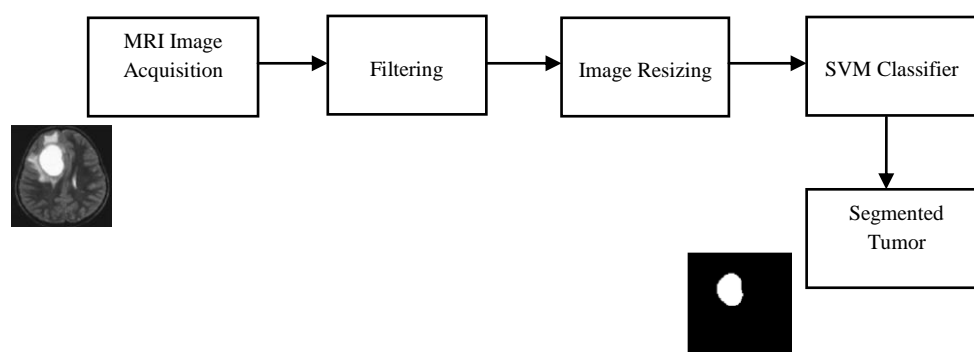


Fig.1 Steps for Tumor Segmentation

### **3.1 MRI Image Acquisition:**

The input MRI images have been collected in DICOM (Digital Imaging & Communications in Medicine) and JPEG (Joint Pictures Expert Group) format. All images are of type T2. Majority of the images collected was in DICOM format. The MATLAB does not support DICOM format therefore we have to convert these images in JPEG format using MicroDicom tool [11]. The images acquired from different MRI machines may vary in size. Therefore input image size has to be normalized to 256×256 pixels and a bit depth of 8.

### **3.2 Filtering:**

Filtering is done using anisotropic diffusion. In image processing and computer vision, anisotropic diffusion is a technique aiming at reducing image noise without removing significant parts of the image content, typically edges, lines or other details that are important for the interpretation of the image.

### **3.3 Image Resizing:**

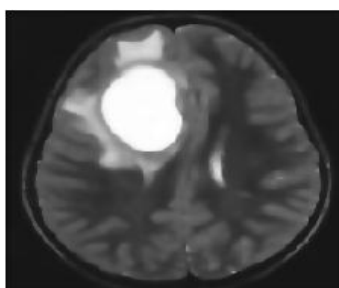
When image acquired in MATLAB, its initial size is 256×256 with unit8 class. To enhance the speed of operation or processing image is resized by 50%, now new dimensions become 128×128 with class as double.

### **3.4 SVM Classifier:**

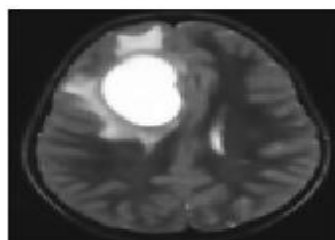
Support vector machine is a machine learning method that is widely used for data analyzing and pattern recognizing. In this algorithm, we plot each data item as a point in n-dimensional space (where n is number of features we have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well [12].

## **VI. SIMULATION RESULTS**

In the simulation the input signal is an image of brain MRI having 256×256 pixels with bit depth of 8 and in JPEG format as shown in Fig2. First of all input image is filtered using anisotropic diffusion technique which smooth the image without changing the edges as shown in Fig3. To increase the image processing speed the size of filtered image is reduced by 50% by using resize command in MATLAB.

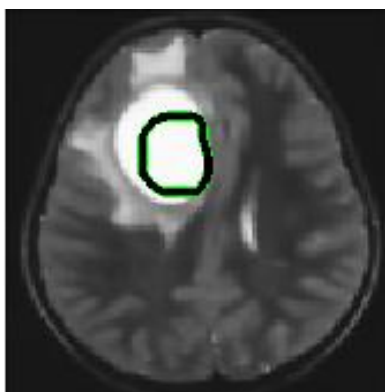


**Fig2. Input Image**

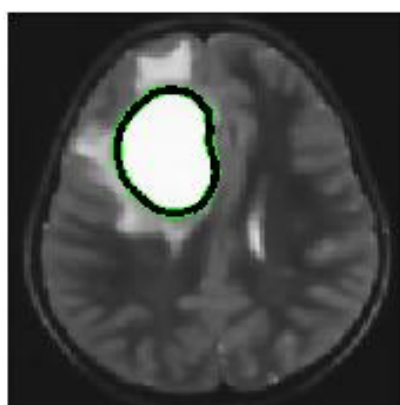


**Fig3. Filtered Image**

The SVM classifier algorithm is applied over the resized filtered image. The initial output of the algorithm is shown in Fig4, which is further refined by the algorithm in successive iterations as shown in Fig5. And finally the tumor portion is segmented as shown in Fig6.



**Fig4. SVM Classifier initial result**



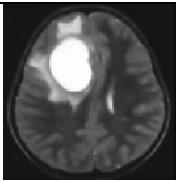
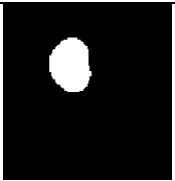
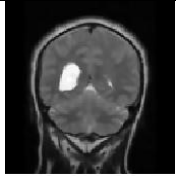

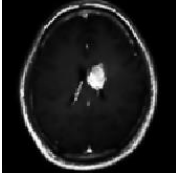
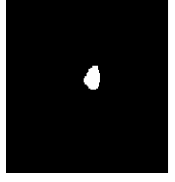
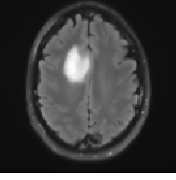
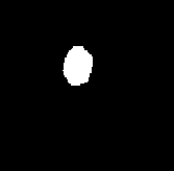
**Fig5. SVM Classifier final result**



**Fig6. Segmented tumor image**

Now the segmented tumor size can be calculated based on white pixels. Table-1 shows the simulation results for four different tumor affected MRI's.

**Table-1: Simulation Results data**

S.No	MRI Image with tumor	Segmented Tumor	Tumor size in pixels	Tumor size in mm	Processing time
1.			949	34.32 mm	45.22s
2.			242	17.32 mm	45.66s
3.			161	14 mm	46.19s
4.			466	24 mm	44.50s

From Table-1 it is observed that the processing time is between 44 s to 46 s and this time may vary based on the system specifications and MATLAB version. Current simulation is done on Intel Core 2 Duo, 2.0 GHz processor with 3GB RAM and MATLAB R2013a version.

## V. CONCLUSION

The technique proposed in this paper was successful in extracting the tumor portion; it has provided an accurate demarcation of the boundary of the tumor, along with correct visual location of the tumor with the help of a bounding circle. This work has also provided a diagnosis decision for tumor presence along with the exact size of the tumor. This decision can assist as a supportive aid which can be used at the doctor's discretion in finally declaring a decision.

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