

# Support Vector Machine Based MRI Brain Tumor Detection

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**Abstract:** *The most important method for the detection of brain tumours is magnetic resonance imaging (MRI). A brain tumour is an irregular growth of cells in the brain that affects brain function. If the tumour is detected at an early stage, further tumour growth may be prevented and proper care for the tumour is pursued. The primary organ of the human central nervous system is the brain. For brain tumour classification, we use the Support Vector Machine (SVM) in this suggested work. So here, we made an attempt to locate the tumour in MRI images of the brain. Used methods such as grey scale contract, noise reduction, thresholding, etc. for pre processing using the SVM classifier for classification.*

**Keywords:** Brain tumour, gray scale image, Segmentation, Thresholding, support vector machine, Performance measures etc.

## 1. Introduction

The brain tumour is a mass of tissue in which cells grow abnormally and multiply uncontrollably, unchecked by the processes that govern the growth of normal cells. Metastatic or primary, and either benign or malignant, may be brain tumours. A metastatic brain tumour is a cancer that has spread[1] to the brain from elsewhere in the body.

Magnetic resonance imaging (MRI) is an important medical imaging tool used to obtain high-quality images of various parts of the human body. When treating brain, foot and ankle tumours, MRI imaging is commonly used. The precise anatomical knowledge is obtained from these high-resolution[2][3] photographs to analyse human brain growth and discover anomalies. There are many methodologies for classifying MRI images, which are fuzzy methods, methods of atlas, neural networks, methods of form, techniques of information, segmentation of variation.

One of the most difficult and time-consuming tasks of medical image processing is brain tumour identification and segmentation. Magnetic resonance imaging (MRI) is a medical procedure used primarily by radiologists to image the human body's internal structure without any surgery. MRI offers a wealth of human soft tissue knowledge, which helps to diagnose brain tumours [4]. For the diagnosis of brain tumour by computer-aided clinical method, precise segmentation of the MRI image is critical. Tumor is categorised as malignant and benign after sufficient segmentation of brain MR images, which is a difficult task due to complexity and variability of tumour tissue characteristics such as its form, size, intensity of grey level and position.

The most common [5] [6] signs of a brain tumour are presented below. However, symptoms can be encountered differently by each person. Depending on the tumour size and location, symptoms differ.

- Headache

- Vomiting (usually in the morning)
- nausea
- Personality changes
- Irritability
- Drowsiness
- Depression
- Decreased cardiac and respiratory function and, eventually, coma if not treated.

## Tumor Grades

Brain tumours are classified by grade by physicians. A tumor's grade relates to the way the cells appear under a microscope:

Grade I: It is benign to the tissue. The cells look more like normal cells in the brain and expand slowly.

Grade II: It is malignant to the tissue. The cells in a Grade I tumour appear less like normal cells than cells do.

Grade III: There are cells in the malignant tissue which look very distinct from normal cells. The abnormal cells are growing actively (anaplastic).

Grade IV: Cells that appear most irregular and seem to develop rapidly are in the malignant tissue. Low-grade tumour cells (grades I and II) appear more natural and normally develop more slowly than high-grade tumour cells (grades III and IV).

## 2. Diagnosis

In diagnosing brain tumours, imaging plays a key role. In recent times, early imaging techniques such as pneumoencephalography and cerebral angiography, which are invasive and often risky, have been abandoned in favour of non-invasive, high-resolution techniques especially magnetic resonance imaging (MRI) and computed tomography (CT) scans. In CT or MRI outcomes, neoplasms will also present as differently coloured masses. Using Computed [7] Tomography (CT scan) and Magnetic Resonance Imaging, radiologists test the patient visually (MRI). The brain structures, tumour size and location were indicated by MRI images. From the MRI images,

radiologists provided data such as the position of tumours, a simple way to diagnose the tumour and prepare the surgical method for its removal.

**Support vector machine**

SVM is one of the classification methods used in various fields, such as face recognition, categorization of text, diagnosis of cancer, diagnosis of glaucoma, data analysis of microarray gene expression. SVM utilises binary brain MR image classification as normal or impaired by the tumour. SVM divides the data given into a decision region i.e. a hyperplane) that divides the data into two categories. SVM's primary goal is to optimise the margins between the hyper-two plane's classes. Reduction in dimensionality and precision of the feature set as an input to the SVM both during the training part and during the test part. SVM is based on a binary classifier that offers better outcomes using supervised learning.

A supervised learning algorithm based on statistical learning theory is a support vector machine (SVM). Because of the named data set (training set),  $D = \{[x,y]|x \rightarrow \text{data sample}, y \rightarrow \text{class label}\}$ , the SVM attempts to measure the mapping function  $f$  to  $f(x) = y$  for all data set samples. The relationship between the data samples and their respective class labels is defined by this mapping function and is used to identify new unknown information. The following classification decision function is used to classify SVMs in the sense of (a process called the feed-forward phase)

$$D(z) = \text{sign}(\sum_{i=1}^N \alpha_i y_i K(z, s_i) + b)$$

in which  $\alpha_i$  are the alpha coefficients,  $y_i$  are the class labels of the support vectors  $s_i$ , are the support vectors,  $z$  is the input vector,  $K(z, s_i)$  is the chosen kernel function, and  $b$  is the bias.

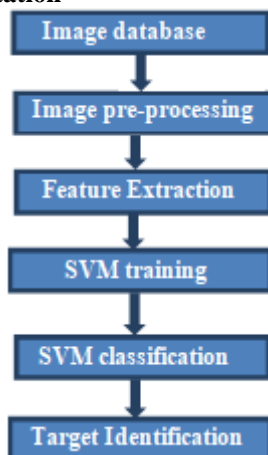
**Linear :**  $K(x, z) = x \bullet z$ ,

**Polynomial :**  $K(x, z) = ((x \bullet z) + 1)^d, d > 0$ ,

**RBF :**  $K(x, z) = \exp(-||x-z||^2 / (2\sigma^2))$ .

Support Vector Machines – Explores the idea of transforming the input domain into high dimensional space to optimize over best of the best classification function which otherwise is capable to realize.

**SVM implementation**



Dataset Used for Analysis Data was collected from various verified sources and then segregated into two types:

- Cancerous (Malignant)
- Non-cancerous (Benign)

**Parameters**

**1) Contrast**

Contrast also called the sum of Square Variance. It defers the calculation of the intensity contrast linking pixel and its neighbour over the whole image.

$$\text{Contrast} = \sum_{i,j=0}^{N-1} P_{ij} (i - j)^2$$

**2) Mean**

Mean defined as the mean of the pixel values of the input image.

$$\text{Mean} = \sum_{i,j=0}^{N-1} i(P_{i,j})$$

**3) Standard Deviation**

It is defined as the dispersion of the pixel in consideration from the mean of the pixels of the input image.

$$\text{Standard Deviation} = \sqrt{\sigma_i^2}$$

**4) Entropy**

It shows the amount of information of the image that is needed for the image compression. Entropy measures the loss of information or message in a transmitted signal and also measures the image information.

$$\text{Entropy} = \sum_{i,j=0}^{N-1} -\ln(P_{ij}) P_{ij}$$

**5) Variance**

It is the expectation of the squared deviation of a pixel from its mean.

$$\text{Variance} = \sum_{i,j=0}^{N-1} P_{i,j} (i - \mu_i)^2$$

**3. Result and Discussion**

MRI scan of brain is taken as input for training and testing. Images are gray-scale and segmented. Discrete wavelet transform is used extract features from segmented image. GLCM features are calculated such as mean, entropy, variance and contrast. SVM classifier is applied to classify image is Benign and Malignant. Accuracy of the model is calculated on the basis of quadratic, linear and polygonal accuracy.

my

Load Image

Segmented Image

Quadratic accuracy: 80

Linear accuracy: 90

Polygonal accuracy: 80

Mean: 0.0031107

Standard Deviation: 0.0897608

Entropy: 3.17346

Variance: 0.00804787

Contrast: 0.208843

Help Dialog: Benign Tumor

my

Load Image

Segmented Image

Quadratic accuracy: 90

Linear accuracy: 90

Polygonal accuracy: 80

Mean: 0.00630907

Standard Deviation: 0.0895928

Entropy: 3.20515

Variance: 0.00801767

Contrast: 0.305895

Help Dialog: Malignant Tumor

my

Load Image

Segmented Image

Quadratic accuracy: 80

Linear accuracy: 80

Polygonal accuracy: 80

Mean: 0.00348476

Standard Deviation: 0.0897471

Entropy: 3.52392

Variance: 0.00798925

Contrast: 0.251669

Help Dialog: Malignant Tumor

Feature	Value
Mean	0.0019318
Standard Deviation	0.0897939
Entropy	2.66316
Variance	0.00805185
Contrast	0.233315

Feature	Value
Mean	0.00282896
Standard Deviation	0.0897701
Entropy	3.62834
Variance	0.00803589
Contrast	0.215517

#### 4. Conclusion and Future Work

The brain tumour grows due to the unusual growth of cells in the brain. Two forms of benign and malignant tumours are commonly known as brain tumours. Fast-growing cancerous tissues are malignant tumours. Benign cancer is a slow-growing, stagnant cancer. Many tumours are life-threatening, and one of them is a brain tumour. In the brain, primary brain cancer originates. In the secondary form of brain cancer, other areas of the body result from the tumour expansion into the brain. More precise brain cancer imaging plays a pivotal role in tumour diagnosis. This includes techniques of high resolution such as MRI, CT, PET etc. MRI is a significant means of researching the visceral structures of the body. MRI is commonly used because, compared to other medical imaging methods such as X-Ray or Computed Tomography, it offers higher quality images of the brain and cancer tissues (CT). In this proposed work we are using Support Vector Machine algorithm that works on structural risk minimization to classify the images. The SVM algorithm is applied to medical images for the tumor

extraction and provides better accuracy. In future work use neural network techniques for mri brain tumor detection.

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