

## SVM Classification an Approach on Detecting Abnormality in Brain MRI Images

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### Abstract

Magnetic resonance imaging (MRI) is an imaging technique that has played an important role in neuro science research for studying brain images. Classification is an important part in order to distinguish between normal patients and those who have the possibility of having abnormalities or tumor. The proposed method consists of two stages: feature extraction and classification. In first stage features are extracted from images using GLCM. In the next stage, extracted features are fed as input to SVM classifier. It classifies the images between normal and abnormal along with type of disease depending upon features. For Brain MRI images; features extracted with GLCM gives 98% accuracy with SVM-RBF kernel function. Software used is MATLAB R2011a.

**Keywords:** GLCM, Image retrieval, Feature Extraction, MRI, SVM classifier.

### I. Introduction

Medical Image analysis and processing has great significance in the field of medicine, especially in Noninvasive treatment and clinical study. Medical imaging techniques and analysis tools enable both doctors and radiologists to arrive at a specific diagnosis. Medical Image Processing has emerged as one of the most important tools to identify as well as diagnose various disorders. Imaging helps the Doctors to visualize and analyze the image for understanding of abnormalities in internal structures. The medical images data obtained from Bio-medical Devices which use imaging techniques like Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and mammogram, which indicates the presence or absence of the lesion along with the patient history, is an important factor in the diagnosis. Magnetic Resonance Imaging (MRI) is a scanning device that uses magnetic fields and computers to capture images of the brain on film. It does not use x-rays. It provides pictures from various planes, which permit doctors to create a three-dimensional image of the tumor. MRI detects signals emitted from normal and abnormal tissue, providing clear images of most tumors. It has become a widely-used method of high quality medical imaging, especially in brain imaging where soft tissue contrast

and non-invasiveness are clear advantages. MRI is examined by radiologists based on visual interpretation of the films to identify the presence of abnormal tissue. Brain images have been selected for the image reference for this research because the injuries to the brain tend to affect large areas of the organ. The brain controls and coordinates most movement, behavior and homeostatic body functions such as heartbeat, blood pressure, fluid balance and body temperature. Functions of the brain are responsible for cognition, emotion, memory, motor learning and other sorts of learning. The classifications of brain MRI data as normal and abnormal are important to prune the normal patient and to consider only those who have the possibility of having abnormalities or tumor.

Approaches used for classification falls into two categories. First category is supervised learning technique such as Artificial Neural Network (ANN), Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) which are used for classification purposes. Another category is unsupervised learning for data clustering such as K-means Clustering, Self Organizing Map (SOM). In this paper, SVM is used for classification as it gives better accuracy and performance than other classifiers.

### II. Methodology

The proposed method as described in the flowchart is based on following discussed techniques: Grey-Level Co-occurrence matrix (GLCM) and Support Vector Machine (SVM). This method consists of two stages: Feature. Extraction and Feature Classification. As SVM is binary classifier; it is used to classify the extracted features into further two classes. For medical images; it classifies between normal and abnormal images along with type of abnormality exist. Two classes have been defined i.e. class 0 and class 1. In Brain MRI images; class 0 is defined for normal images and class 1 is defined for abnormal images. Images are classified by specialist and SVM. Database used for Brain MRI images consists of total 110 images; out of which 60 are normal and 50 are abnormal which are of bleed, clot, Acute-infarct, tumor and trauma. All the images are T2-Weighted MRI images with different views but with same resolution. Only few of Brain MRI images are shown here with the applied methodology.

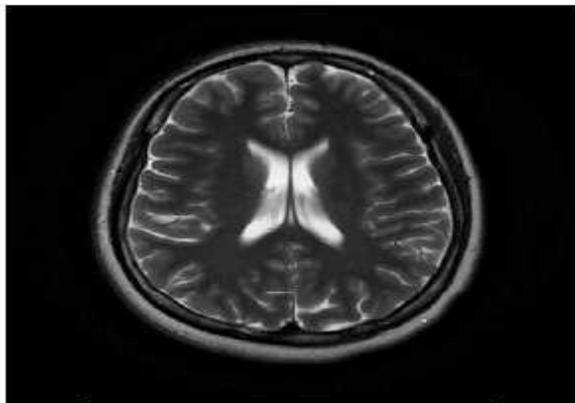
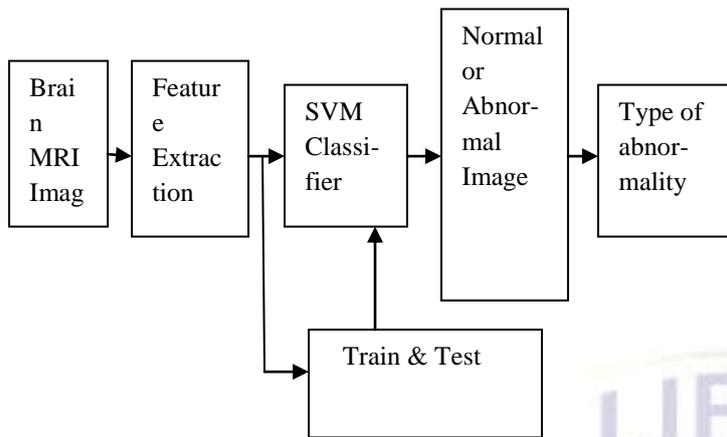


Fig 2.1 Normal Brain MRI Image



Fig 2.2 An Abnormal Brain MRI Image

### III. Feature Extraction

Features are said to be properties that describes the whole image. It can also refer as an important piece of information which is relevant for solving the computational task related to specific application. The purpose of feature extraction is to reduce the original dataset by measuring certain features. The extracted features acts as input to classifier by considering the description of relevant properties of image into feature space. The Gray Level Cooccurrence Matrix (GLCM) method is a way of extracting statistical texture features. A GLCM is a matrix where the number of rows and columns is equal to the number of gray levels,  $G$ , in the image. The matrix element  $P(i, j | \Delta x, \Delta y)$  is the relative

frequency with which two pixels, separated by a pixel distance  $(\Delta x, \Delta y)$ , occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element  $P(i, j | d, \theta)$  contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance  $d$  and at a particular angle  $(\theta)$ . Using a large number of intensity levels  $G$  implies storing a lot of temporary data, i.e. a  $G \times G$  matrix for each combination of  $(\Delta x, \Delta y)$  or  $(d, \theta)$ . Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced.

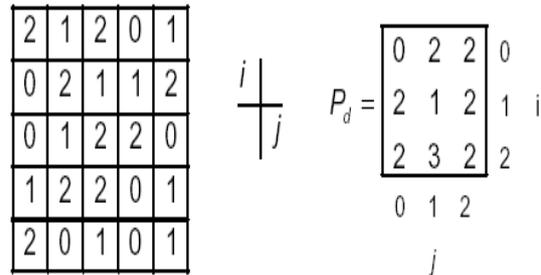
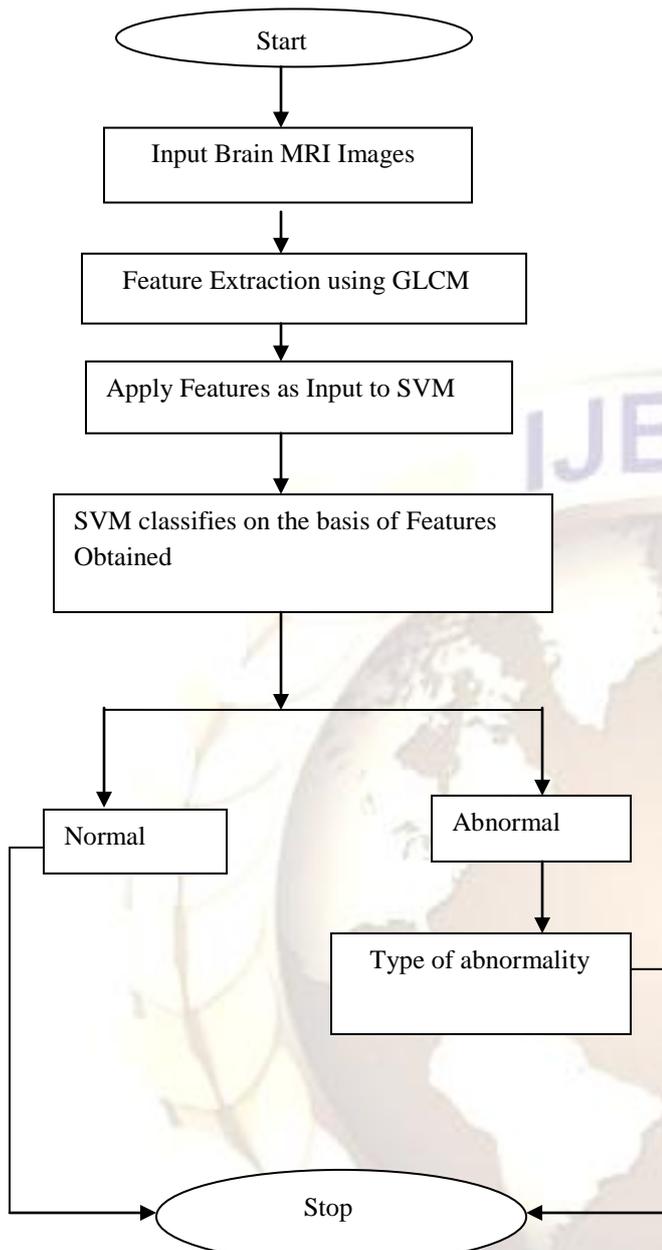


Figure 3.1 GLCM Matrix

In this matrix Count all pairs of pixels in which the first pixel has a value  $i$ , and its matching pair displaced from the first pixel by  $d$  has a value of  $j$ . This count is entered in the  $i$ th row and  $j$ th column of the matrix  $P_d[i,j]$ . Note that  $P_d[i,j]$  is not symmetric, since the number of pairs of pixels having gray levels  $[i,j]$  does not necessarily equal the number of pixel pairs having gray levels  $[j,i]$ . Afterwards various parameters like energy, entropy, mean and contrast has been calculated.



**Fig 3.2 Flowchart to train and test SVM Classifier**

**3.1.Extracted Features:**

Five texture measures are computed in the present work described below.

**Entropy:** A measure of non-uniformity in the image based on the probability of co-occurrence values.

$$\sum_{i,j=0}^{N-1} p(i,j) [-\ln(p(i,j))]$$

**Mean:** It is an average value and measures the general brightness of an image

$$\frac{\sum_{i,j}^{N-1} p(i,j)}{N-1}$$

**Contrast:** It is a measure of intensity contrast between a pixel and its neighbor pixel over a whole image. It is zero for constant images

$$\sum_{i,j=0}^{N-1} |i-j|^2 p(i,j)$$

**Energy:** It returns the sum of squared elements in GLCM. It is 1 for constant image.

$$\sum_{i,j=0}^{N-1} p(i,j)^2$$

**Inverse Difference Moment:** Inverse Difference Moment is the local homogeneity. It is high when local gray level is uniform and inverse GLCM is high.

$$\frac{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_{ij}}{1 + (i-j)^2}$$

**IV. Classification**

Classification analyses the numerical properties of image features and organize the data into different categories. It employs two phases of processing- training phase and testing phase. In training phase, characteristic properties of image features are isolated and a unique description of each classification category is created. In testing phase, these features space partitions are used to classify image features.

**4.1. Support Vector Machine**

The Support Vector Machine (SVM) was first proposed by Vapnik and has since attracted a high degree of interest in the machine learning research community. Several recent studies have reported that the SVM (support vector machines) generally are capable of delivering higher performance in terms of classification accuracy than other data classification algorithms. SVM is a binary classifier based on supervised learning which gives better performance than other classifiers. SVM classifies between two classes by constructing a hyperplane in high-dimensional feature space which can be used for classification. Hyperplane can be represented by equation-

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

w is weight vector and normal to hyperplane. b is bias or threshold

**4.2. Linear SVM Classifier**

Let us begin with the simplest case, in which the training patterns are linearly separable. That is, there exists a linear function of the form  $f(x) = w \cdot T x + b$  (1)

such that for each training example  $x_i$ , the function yields  $f(x_i) \geq 0$  if  $y_i = +1$ ,  $y_i$

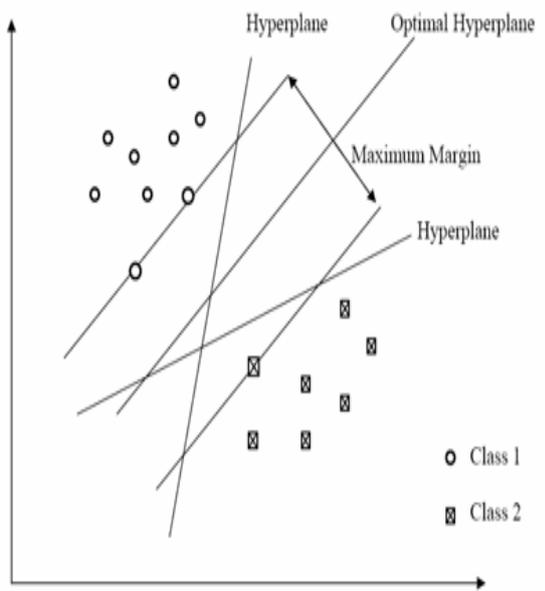
and  $f(x_i) < 0$  for  $y_i = -1$ .

In other words, training examples from the two different classes are separated by the hyperplane

$$f(x) = w^T x + b = 0,$$

where  $w$  is the unit vector and  $b$  is a constant.

For a given training set, while there may exist many hyperplanes that maximize the separating margin between the two classes, the SVM classifier is based on the hyperplane that maximizes the separating margin between the two classes (Figure 5.1). In other words, SVM finds the hyperplane that causes the largest separation between the decision function values for the "borderline" examples from the two classes. In Figure 5.1, SVM classification with a hyperplane that minimizes the separating margin between the two classes are indicated by data points marked by "X" s and "O"s. Support vectors are elements of the training set that lie on the boundary hyperplanes of the two classes.



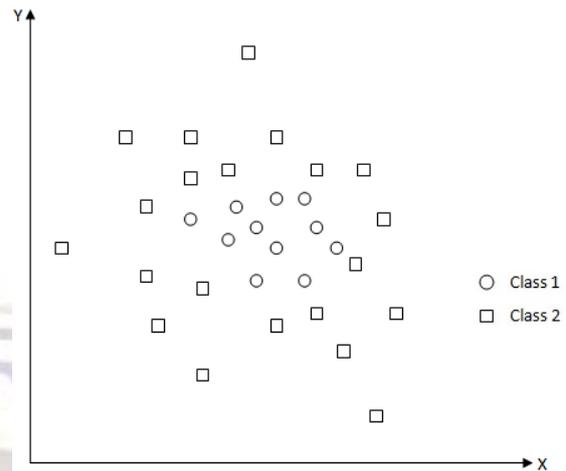
**Fig 4.1 Linear SVM Classification**

### 4.3. Non-Linear SVM

In the above discussed cases of SVM classifier also shown in fig. straight line or hyperplane is used to distinguish between two classes. But datasets or data points are always not separated by drawing a straight line between two classes. For example the data points in the below fig. can't be separable by using above SVMs discussed. So, Kernel functions are used with SVM classifier. Kernel function provides the bridge between from non-linear to linear. Basic idea behind using kernel function is to map the low dimensional data into the high dimensional feature space where data points are linearly separable. There are many types of kernel function but Kernel functions used in this research work are given below:

1. Radial basis function (RBF)
2. Linear

### 3. Quadratic



**Figure 4.2 Non-linear data points**

## V. Classifier Performance

All classification results could have an error rate and on occasion will either fail to identify an abnormality, or identify an abnormality which is not present. It is common to describe this error rate by the terms true and false positive and true and false negative as follows:

*True Positive (TP)*: the classification result is positive in the presence of the clinical abnormality.

*True Negative (TN)*: the classification result is negative in the absence of the clinical abnormality.

*False Positive (FP)*: the classification result is positive in the absence of the clinical abnormality.

*False Negative (FN)*: the classification result is negative in the presence of the clinical abnormality.

Table 5.1 is the contingency table which defines various terms used to describe the clinical efficiency of a classification based on the terms above and

$$\text{Sensitivity} = TP / (TP + FN) * 100\%$$

$$\text{Specificity} = TN / (TN + FP) * 100\%$$

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) * 100\% \text{ are used to measure the performance of a classifier.}$$

**Table 5.1: Contingency Table**

Actual Group	Predicted Group	
	Normal	Abnormal
Normal	TN	FP
Abnormal	FN	TP

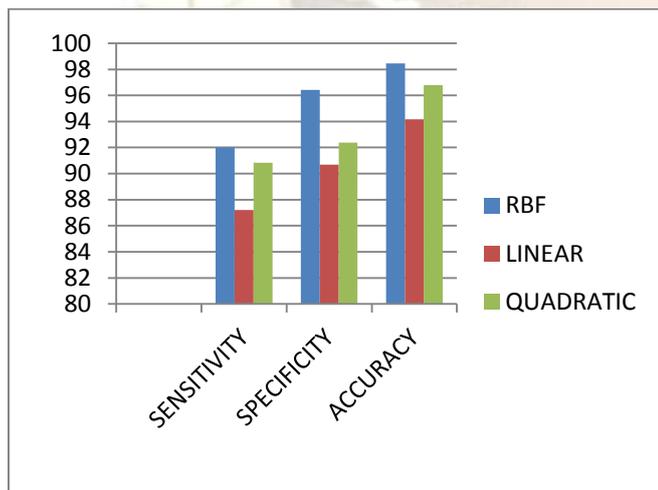
## VI. Result

The input to the feature extraction algorithm is the Brain MRI images. The pattern vectors (features) extracted from the images is given as input to the SVM classifier. Large database are required for

the classifier to perform the classification correctly. In this system a sample of 110 CT brain images are collected. 60 images are taken as normal brain and remaining 50 images are taken as abnormal brain. 60 images are used for training phase and remaining 50 images are used for testing. In Brain MRI images contrast value varies from 0.7000 to 0.7550 for GLCM. Images outside this range are considered as abnormal images. As GLCM gives maximum classification accuracy; images are further categorized into type of existing abnormalities. If mean value lie 14.0000 to 14.5000 then patient is suffering from bleed. For clot; mean value lie 26.1500 to 27.8200 and for tumor mean value lie 24.6500 to 26.1200. Features are classified by SVM with other kernel functions also but not discussed here. Only those kernel functions are discussed in this paper which gives better classification performance

**Table 6.1: SVM Classifier Performance**

Feature extraction technique	Kernel Function	Sensitivity	Specificity	Accuracy	Execution Time(Sec)
GLCM	RBF	92	96.43	98.45	10.3214
	Linear	87.22	90.69	94.16	10.7234
	Quadratic	90.83	92.37	96.78	10.4681



**Table 6.2 Graph of SVM Classifier Performance**

### VII. Conclusion

The proposed approach using SVM as a classifier for classification of brain images provides a good classification efficiency as compared to other classifiers. The sensitivity, specificity and accuracy is also improved. The proposed approach is computationally effective and yields good result. This automated analysis system could be further used for classification of images with different pathological

condition, types and disease status. The future work is to improve the classification accuracy by extracting more features and increasing the training data set.

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