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SVM Kernels comparison for brain tumor diagnosis using MRI

Wedad Abdul Khuder Naser *, Eman Abdulmunem Kadim and Safana Hyder Abbas

Department of computer science, University Al Mustansiriyah, Baghdad, Iraq.

Abstract

Magnetic Resonance Image (MRI) brain images have an essential role in medical analysis and cancer identification .In this paper multi kernel SVM algorithm is used for MRI brain tumor detection. The proposed work is involving the following stages: image acquisition, image preprocessing, feature extraction and tumor classification. An automatic threshold selection region based segmentation method called Otsu is used for thresholding during preprocessing stage. SVM classification algorithm with four different kernels are used to determine the normal and abnormal images. SVM with quadratic kernel results in best classification accuracy of 86.5%.

1. Introduction

Because of the unusual brain growth of cells, humans are severely affected by brain tumors. It can affect the proper function of the brain and can be a serious threat to life. There are two kinds of brain tumors, benign and malignant. Benign tumors are less risky than malignant tumors as malignant ones develop quickly and dangerously while benign tumors grow slowly and harmlessly. Medical imagery method is used to provide an internal human body visual illustration for health purposes and this technique can detect noninvasive possibilities. Based on noninvasive method, different kinds of medical imaging technologies like; MRI, Ultrasound, X-ray, PET, SPECT and CT scan are used [1]. Magnetic resonance imaging (MRI) is used in the majority and offers a greater contrast in the brain with cancer tissue compared with other medical imaging methods. For brain tumor identification, MRI images may therefore be used. In this paper an MRI brain tumor is recognized using SVM algorithm with four different kernels.

This paper is organized as follows: Section 2 provides a review of related works; then a brief explanation of SVM algorithm is described in section3. Section 4 shows the detailed steps of the used methodology. Section 5 presents the experimental result and finally section 6 summarizes the conclusions and finally the list of references.

2. Related works

Many studies on MRI brain image segmentation and tumor detection techniques have been proposed. The following is a short review of some of these studies:

A hybrid segmentation technique is proposed   for detection of MRI image brain tumor. Author combined FCM and seed region growing algorithm as hybrid technique for segmentation. This method outputted average segmentation score S of 90% with noise level of 3% and 9%, respectively [2].

* Corresponding author: Wedad Abdul Khuder
Department of computer science, University Al Mustansiriyah Baghdad, Iraq.

A neural network technique for MR image brain tumor detection and classification has been presented. This method has an accuracy of 83% and segmented white matter, Gray matter, CSF and obtained quality rate separately [3].

Developed a localized fuzzy clustering method to segment MRI images. The author used jaccard similarity index as a metric to obtain accuracy. This localized fuzzy clustering method obtained the segmentation accuracy of 95% [4].

A novel tissue segmentation algorithm by combination of wavelets and neural networks, providing effective segmentation of brain MRI images into a tumor, was proposed. Features based on textures are then extracted using the segmentation and classification tool of the artificial neural network (ANN)[5].

3. SVM (Support Vector Machine)

SVM is an algorithm of supervised learning based on the statistical learning concept. Just let a labeled data set (training set): D={|x,y||x→data sample,y→ class label}, SVM tries to calculate the mapping function f such that f(x) = y for all the samples of the data set. The correlation between data samples and their specific class labels is defined in this mapping function and is used for classifying unknown different data. SVM classification is carried out using the following classification function: SVM classification.

$$D(z) = sing\left(\sum_{i=1}^{N} \propto_i y_i K(z,s_i) + b\right) \qquad (1)$$

The alpha parameters are $\propto_i$, the support vector's class labels are y_i, the support vectors are S_i, the input vector is z, the chosen kernel function is $K(Z,S_i)$, and the bias is b. The below are four types of kernels:

Linear: K(X,Z)=X●Z $\qquad (2)$

Polynomial : $K(X,Z) = ((X●Z) + 1)^d, d > 0 \qquad (3)$

$RBF : K(X,Z) = \exp(-\|X - Z\|^2/(2\sigma^2)) \qquad (4)$

Quaratic: $\{\Phi(x)_1, \Phi(x)_2\} = \{x_1^2, x_2^2\} \qquad (5)$

SVM adopts the idea of converting the domain of input into large dimension space to improve classification function [6].

4. Methodology
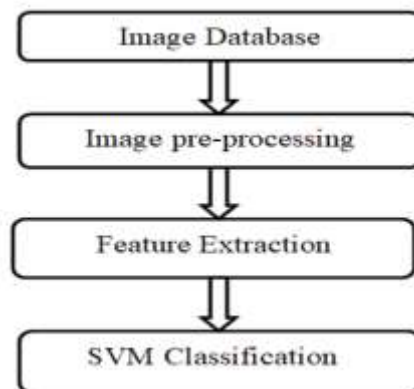
The proposed approach is illustrated in figure (1).

Figure 1 The proposed approach

4.1. Image data base

The dataset consists of MRI brain images downloaded from Harvard Medical School's website (URL: http://med.harvard.edu/AANLIB/) and OASIS dataset (URL: http:// www.oasis-brains.org [7].

We choose 10 images for benign case and 10 images for malignant case to be applied to svm algorithm . For each case, for training 7 images are used and for testing 3 images are used.

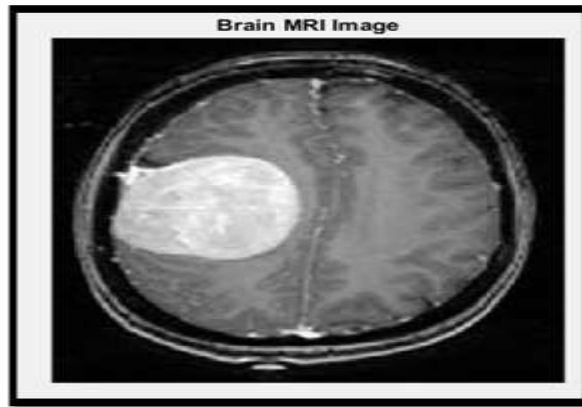An example of MRI images for brain tumors are shown in figure 2. a and b

Figure 2(a) Benign Tumor

Figure 2(b) Malignant Tumor

Figure 2 Examples of brain tumors MRI images

4.2. Image pre processing

MRI images must be preprocessed before extracting the important features. The simplest approach to segment an image is using thresholding. Otsu, an automatic threshold selection region dependent segmentation method, is employed. The Otsu method is a type of global thresholding that it depends on the image's gray value [8,9]. By minimizing the within-class variance of the two groups of pixels separated by the thresholding operator, Otsu's method selects the threshold. Figure (3) illustrates an Otsu thresholded image.
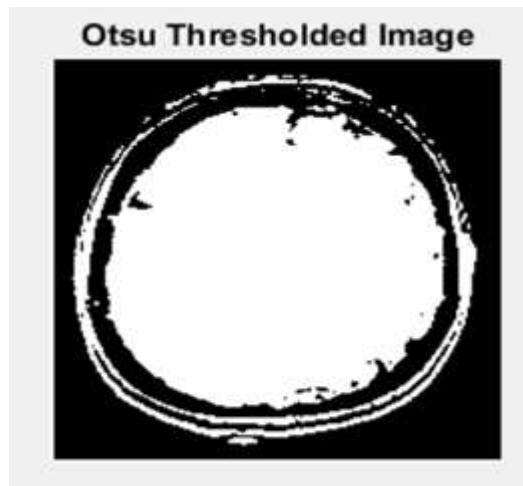
Figure 3 Otsu thresholded Image

The segmented tumor in malignant and benign cases are shown in figures (4) and (5).
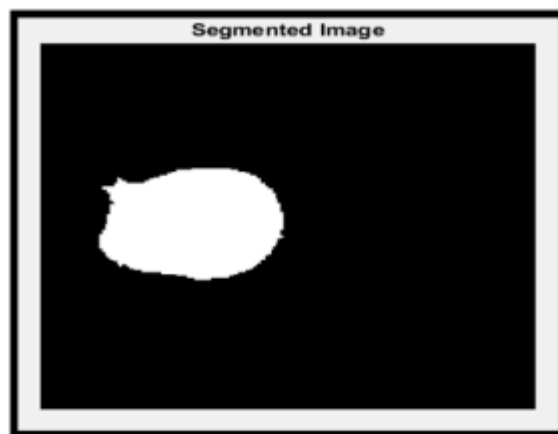

Figure 4 Segmented benign tumor image

Figure 5 Segmented Malignant tumor image

4.3. Extracted features

The malignant and benign MRI images of brain tumor are not visually distinguishable. Hence, different features are extracted of both benign and malignant images to determine the tumor type.

From an MRI image 13 features are extracted:

4.3.1. The co-occurrence probabilities

it gives a second-order method for creating texture features [10]. The probability measures can be estimated from this formula:

$$\mathbf{Co_{ij}} = \frac{\mathbf{P_{ij}}}{\sum_{i,j=0}^{G} \mathbf{p_{ij}}} \tag{6}$$

Where:

- Coij   indicates the probability of co-occurrence between grey level i and j
- pij   indicates the number of gray levels i and j that exist in the given window.
- G is the gray levels quantized number [11].

4.3.2. Entropy Measure

The unpredictability or complexity of the image data is measured [12]. When the image is not texturally uniform, the entropy is large. As a result, complex textures have a high entropy [11]. The following is a definition of the entropy equation.:

$$\mathbf{Entro} = -\sum_{i,j=0}^{Ng} \mathbf{Co(i,j)Log_2\,Co(i,j)} \tag{7}$$

Where (Ng) is the number of gray levels

4.3.3. Energy Measure

It is also referred to as uniformity or Angular Second Moment (ASM). It measures the uniformity of the textures, i.e. pixel pair replications. It recognizes textural differences [11, 3]. This measure can be defined according to this formula:

$$\mathbf{Energ} = \sum_{i,j=0}^{Ng} \mathbf{Co(i,j)^2} \tag{8}$$

4.3.4. Contrast Measure

This statistic estimates an image spatial frequency. It is the difference between a contiguous set of pixels' highest and lowest values. It measures the amount of local variations present in the image [10]. The equation of contrast is defined as follows:

$$\mathbf{Contr} = \sum_{i,j=0}^{Ng} \mathbf{(i-j)^2 Co(i,j)} \tag{9}$$

4.3.5. Variance Measure

 It's a heterogeneity measure. When the gray levels differ from their mean, the difference increases. The following is the represented formula [11]:

$$\mathbf{Var} = \sum_{i}^{N} \mathbf{|i-\mu|^2\;Co(i,j)} \tag{10}$$

Where the mean of Co(i, j) is μ , concentration as

μ_x and μ_y

$$\mu_x = \sum_i i \sum_j Co(i,j) \qquad\qquad (11)$$
$$\mu_y = \sum_j j \sum_i Co(i,j) \qquad\qquad (12)$$

Where (N) is the numbers of pixels

4.3.6. Auto Correlation Measure

This measure can be represented by this formula [13]:

$$\textbf{Autoc} = \sum_{i,j=1}^{Ng} ij \, Co(i,j) \qquad\qquad (13)$$

4.3.7. IDM (Inverse Difference Moment)

It is the local homogeneity. This measure can be represented by   this formula:

$$\textbf{IDM} = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} CO(i,j)}{1 + (i-j)^2} \qquad\qquad (14)$$

Where (G) is the gray levels quantized number.

4.3.8. Mean

It is the rate value, where the common brightness of the image and can be determine as : [12,14]:

$$\breve{g} = \sum_{g=0}^{N-1} gp(g) \qquad\qquad (15)$$

Where ($\breve{g}$) the mean
 P(g) is histogram probability and known as follows:

$$\textbf{P(g)} = \frac{N(g)}{M} \qquad\qquad (16)$$

 Where:
P(g)= image gray level of g probability .
N(g)= image number of pixels with gray level g .
M= image total number of pixel.

4.3.9. The standard deviation

It is identified as the square-root of the variance, where the disparity, standard deviation equation is known as [14]:

$$\sigma_g = \sqrt{\sum_{g=0}^{N-1} (g-\breve{g})^2 \, P(g)} \qquad\qquad (17)$$

Where (N) is the numbers of pixels

4.3.10. Homogeneity Measure

This statistic is also referred to as IDM. It measures the homogeneity of the image as it proposes greater values for smaller variations in gray tones in elements pair [15,16]. The homogeneity equation is defined bellow :

$$\mathbf{Homg} = \sum_{\mathbf{i,j=0}}^{\mathbf{Ng}} \frac{\mathbf{1}}{\mathbf{1 + (i - j)^2}} \, \mathbf{CO(i,j)} \qquad (\mathbf{18})$$

4.3.11. Kurtosis

Qualitatively, kurtosis is a metric to non -specifically describe the peakendness and/or heavy tail shape in a probability distribution through the standardized fourth moment [17].

$$\mathbf{K} = \frac{\mathbf{(x^4)}}{\mathbf{(x^2)^2}} - \mathbf{3} \qquad (19)$$

The remaining features are MATLAB instructions.

4.4. Support vector machine (svm) classification

An SVM classifier is applied in the proposed work, due to its outstanding, generalization, capability and reputation in the training data set to accomplish high accuracy. Classification of normal and abnormal tumor cases are done using Kernel SVM classifier. An error rate is possible with all classification results and have the probability of either fail to recognize an abnormality, or recognize not existing abnormality. This error rate is defined according to the following terms true and false positive and true and false negative:

True Positive (TP): It is positive for the a clinical abnormality of the classification.

True Negative (TN): It is negative where there are no clinical abnormalities in the classification.

False positive (FP):it is positive for the absence of clinical abnormality in the classification.

False Negative (FN): When the classification leads to clinical abnormality it is negative. Depending on the above parameters three evaluation measures can be concluded:

Sensitivity = TP / (TP + FN) *100 %

Specificity = TN / (TN + FP) *100 %

Accuracy = (TP + TN) / (TP + TN + FP + FN)*100 %

4.5. Experimental results

In this work consider total of 20 images contain both benign and malignant Brain tumor MRI , out of these 20 images 30% of images are used for testing and remaining70% are used for training .Thirteen features are estimated for each image and then fed to the SVM classifier for training and testing. The 13 extracted features from MRI images for 3 persons as an examples are Illustrated in table (I).

Table 1 MRI extracted features for three persons.

Feature number	Features	Image 1	Image 2	Image 3
1	mean	0.0031107	0.0235179	0.00300147
2	standard deviation	0.0897608	0.0897839	0.0897645
3	Entropy	3.17346	3.26983	3.55498
4	RMS	0.0898027	0.0898027	0.0898027
5	variance	0.00804787	0.00805116	0.00801879
6	smoothness	0.920457	0.897422	0.9178
7	kurtosis	7.32819	7.95668	6.36606
8	skewness	0.469022	0.886238	0.649885
9	IDM	-0.0576898	0.492585	0.472915
10	Contrast	0.208843	0.271691	0.241379
11	correlation	0.199005	0.0930892	0.106492
12	energy	0.7621	0.76857	0.744025
13	Homogeneity	0.93515	0.933815	0.927651

Table 2 Performance measures of the KSVM method to benign tumor

Image	Sensitivity %	Specificity%	RBF accuracy	Quadratic accuracy	Polynomial accuracy	Linear accuracy
1	87.8094	90.4219	80	80	80	70
2	68.2927	71.8321	70	80	80	80
3	82.9227	85.6742	70	90	90	80
4	92.6829	95.3516	80	90	80	80
5	90.2439	93.6894	80	80	70	80
6	87.8049	90.3321	80	90	70	80
7	82.9268	85.2563	70	90	90	70
8	75.6098	78.6417	70	90	90	70
9	85.3656	88.7321	70	90	80	80
10	90.2439	93.3688	80	90	70	70
Average			75	87	80	76

Table 3 Performance measures of the KSVM method to malignant tumor.

Image	Sensitivity %	Specificity%	RBF accuracy	Quadratic accuracy	Polynomial accuracy	Linear accuracy
1	93.6829	95.2524	80	90	70	80
2	85.3659	88.9241	90	80	80	80
3	97.5612	99.5241	70	90	80	80
4	95.1225	98.7856	80	90	70	70
5	97.5632	99.6241	80	80	80	70
6	92.6829	95.3521	70	90	80	80
7	95.1224	98.2213	70	80	90	70
8	80.4878	83.7321	70	80	80	80
9	93.6132	96.8215	70	80	70	70
10	88.5672	91.3341	90	100	80	70
Total			77	86	78	75

According to the above tables the quadratic kernel has the higher accuracy value for both benign (87%) and malignant (86%) tumor MRI images.

Figure 6 shows the SVM accuracy using four different kernels applied to benign and malignant tumor MRI,
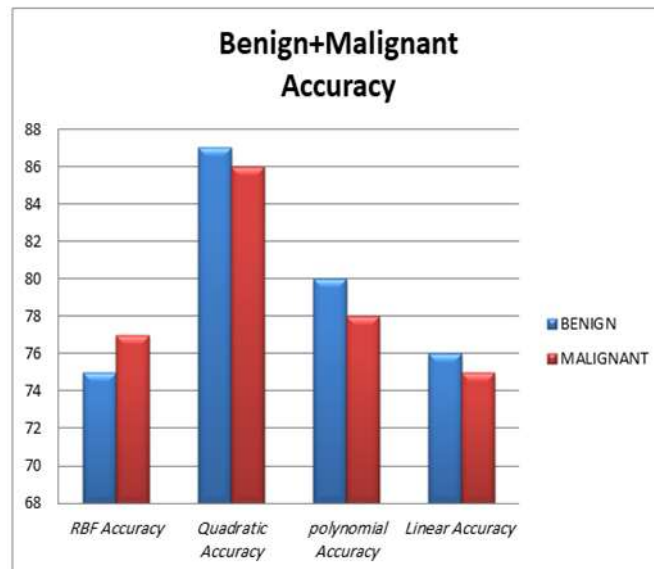

Figure 6 SVM accuracy using four kernels applied to two tumor types

5. Conclusion

Identifications brain tumor through MRI images is a hard mission due to the brain complexity. Ten images are selected for benign tumor and ten images for malignant tumor. These images are preprocessed and segmented to allocate the tumor region. Thirteen features were estimated for each image and fed to SVM classifier. For the classification of MRI brain tumor image, a comparison study on the performance of different SVM's kernels is presented. The experiments evaluations shown that the average precision of the SVM classifiers based on a quadratic kernel for 20 images is 86.5%.

which is higher than other kernels. In future we are trying to increase the dataset of more patients of different age groups.

Compliance with ethical standards

Disclosure of conflict of interest

All authors declare that they have no conflict of interest.

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