Improved Intelligent Classification Technique Based On Support Vector Machines

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Abstract: An abnormal growth of cells are arises a brain tumor, that have proliferated in an uncontrolled manner. When the normal cells undergo death or get repaired by own, they either get injured or grow old. Most of the Research work shows Inaccurate detection of brain tumors, that are People affected to die. This paper proposed a new improved intelligent classification technique based on Support Vector Machines (ICTBSVM) and region growing image segmentation method are applied to recognize normal and abnormal MRI brain image. Here feature extraction from MRI Images will be carried out by gray scale, symmetrical and texture features. After recognize the abnormal repaired cells to identify the type of brain tumors using ICTBSVM. This intelligent system improves accuracy rate and reduces error rate of MRI brain tumor.

Keywords: Brain tumors, Classification, Gray level co occurrence matrix, ICTBSVM

I. INTRODUCTION
A brain tumor is a disease in which cells grow uncontrollably in the brain. Brain tumors have mainly two types. First is Benign tumors are unable of spreading beyond the brain itself. Benign tumors in the brain generally do not essential to be treated and their progress is self-limited. Brain malignancies can be divided into two categories. Primary brain cancer originates in the brain. Secondary or metastatic brain cancer extends to the brain from another site in the body. Cancer arises when cells in the body (in this case brain cells) divide without control. Generally, cells divide in a structured manner. If cells keep separating uncontrollably when new cells are not needed, a mass of tissue forms, called a progress or tumor. Figure 1(a), (b) shows the T2 weighted Magnetic Resonance images are categorized into two distinct classes as normal, abnormal brain tumors.

![Fig. 1: MRI Brain Images](image)

II. RELATED WORKS
R. J. Ramteke, KhachaneMonali Y[5] proposed amethod for automatic classification of medical images in two classes Normal and Abnormal based on image features and automatic abnormality detection. KNN classifier is used for classifying image. K-Nearest Neighbour (K-NN) classification technique is the simplest technique conceptually and computationally that provides good classification accuracy.
SVM is an artificial neural network technique used for supervised learning of classification. Important characteristics of SVM are its ability to solve classification problems by means of convex quadratic programming (QP) and also the sparseness resulting from this QP problem. The learning is based on the principle of structural risk maximization. Instead of minimizing an objective function based on the training samples (such as mean square error), the SVM attempts to minimize the bound on the generalization error (i.e., the error made by the learning machine on the test data not used during training). ShwetaJain[7] classifies the type of tumor using Artificial Neural Network (ANN) in MRI images of different patients with Astrocytoma type of brain tumor. In this study a new and improved method is implemented by combining Discrete Wavelet Transform (DWT) and Discrete Cosine Transform (DCT) for feature reduction and SVM (Support Vector Machine) is used for classification of MRI images. Compared to previous studies a higher accuracy is achieved in extraction.

III. PROPOSED METHOD

The proposed automatic intelligent classification technique architectural diagram (fig. 2) is shown below: Image pre-processing is used to improve the quality of images. Medical images are corrupted by different type of noises like Rician noise etc. It is very important to have good quality of images for accurate observations for the given application. The classification process is divided into two parts i.e. the training and the testing part. Firstly, in the training part known data are given to the classifier for training. Secondly, in the testing part, unknown data are given to the classifier and the classification is performed after training part. The accuracy rate and error rate of the classification depends on the efficiency of the training. The architecture of the proposed is illustrated in Figure 1. The major components are Brain tumor Database, Pre processing, Feature extraction and Classification.

![Proposed Method Diagram](image)

**Fig 2. Outlined of the Proposed Method**

3.1 Preprocessing

The prime objective of pre-processing is to improve the quality of the image data by enhancing the required image features for further processing. The redundancy in the image are eliminated using the pre-processing technique, it eliminates incomplete, noisy and inconsistent data from the image. In order to improve the quality of images taken from the brain MRI images and to make the feature extraction process more reliable and pre-processing is necessary.

3.2 Feature Extraction

Gray-level co-occurrence matrix (GLCM) is a statistical method of finding the textures that consider the spatial relationship of the pixels. The GLCM functions characterize the texture of an image by evaluating how frequently pairs of pixel with specific values occur in a specified spatial relationship present in an image. It is the most widely used and more generally applied method.
because of its high accuracy and less computation time. A gray level cooccurrence matrix (GLCM) contains information about the positions of pixels having similar gray level values [10]. The five features extracted in this paper are explained below.

(i) **Mean:** The mean is defined as below

\[
\text{Mean}(m) = \frac{1}{x+1} \sum_{i=1}^{x} \sum_{j=1}^{y} x(i, j) \quad (1)
\]

(ii) **Variance:** It is square of Variance. The Variance is defined as below

\[
\text{Variance}(v) = \frac{1}{x+1} \sum_{i=1}^{x} \sum_{j=1}^{y} (x(i, j) - m)^2 \quad (2)
\]

(iii) **Entropy:** Entropy is a measure of the uncertainty in a random variable.

\[
\text{Entropy} = \sum_{i=1}^{N} \sum_{j=1}^{N} \left( \frac{u(i, j)}{R} \right) \log \left( \frac{u(i, j)}{R} \right) \quad (3)
\]

(iv) **Contrast:** Contrast is defined as the separation between the darkest and brightest area.

\[
\text{Contrast} = \sum_{i=1}^{N} \sum_{j=1}^{N} (i - j)^2 \left( \frac{p(i, j)}{R} \right) \quad (4)
\]

(v) **Energy:** It provides the sum of squared elements in the GLCM. The uniformity or the angular second moment are also identified.

\[
\text{Energy} = \sum_{i=1}^{N} \sum_{j=1}^{N} \left( \frac{u(i, j)}{R} \right)^2 \quad (5)
\]

3.2.1 **The Discrete Cosine Transform (DCT)**

The discrete cosine transform (DCT) helps separate the image into parts (or spectral sub-bands) of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform: it transforms a signal or image from the spatial domain to the frequency domain.

**DCT Encoding**

The general equation for an 1D \((N\) data items) DCT is defined by the following equation:

\[
F(u) = \left( \frac{2}{N} \right)^{\frac{1}{2}} \sum_{i=0}^{N-1} A(i) \cos \left[ \frac{\pi u}{2N} (2i + 1) \right] f(i) \quad (6)
\]

and the corresponding *inverse* 1D DCT transform is simple \(F^{-1}(u)\), i.e.: where

\[
A(i) = \begin{cases} 
\frac{1}{\sqrt{2}} & \text{for } i = 0 \\
1 & \text{otherwise}
\end{cases} \quad (7)
\]

The general equation for a 2D \((N \times M)\) DCT is defined by the following equation:

\[
F(u, v) = \left( \frac{2}{N} \right)^{\frac{1}{2}} \left( \frac{2}{M} \right)^{\frac{1}{2}} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} A(i) . A(j) \cos \left[ \frac{\pi u}{2N} (2i + 1) \right] \cos \left[ \frac{\pi v}{2M} (2j + 1) \right] f(i, j) \quad (8)
\]
and the corresponding inverse 2D DCT transform is simple $F^{-1}(u,v)$, i.e.: where

$$A(\varepsilon) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for } \varepsilon = 0 \\ 1 & \text{otherwise} \end{cases} \quad (9)$$

IV. EXPERIMENTAL RESULTS

4.1 MRI image data set
For the classification and segmentation of normal and abnormal brain images, data set is collected from different sources. One of the sources is the Harvard Medical School Website. [http://www.med.harvard.edu/aanlib/home.html] The types of brain images include Axial, T2-weighted, 256-256 pixels MR brain images. Figure 5 shows one of the databases considered for classification. The images are classified as normal and abnormal.

Figure 3 MRI of the human brain. (a) - (c) Normal. (d) - (f) Meaningiomas (g) - (i) Astrocytomas

4.2 Performance Evaluation
The comparison was done with testing techniques according to the following performance measures

<table>
<thead>
<tr>
<th>Table 1: Testing Techniques for Performance Analysis</th>
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<tr>
<td>OurHybrid Techniques</td>
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<tr>
<td>----------------------</td>
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<tr>
<td>Normal</td>
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<tr>
<td>Tumor</td>
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To compute $F$-measure, 

$$F - measure = \frac{2PR}{P + R} \quad (10)$$

where, $P$ and $R$ are precision and recall. The $F$-Measure computes the average information retrieval precision and recall metrics. Precision is calculated using following equation,

$$Precision = \frac{TP}{(TP + FP)} \quad (11)$$

where, $TP$ and $FP$ are True Positive and False Positive. Recall are calculated using the equation

$$Recall = \frac{TP}{(TP + FN)} \quad (12)$$

where, $TP$ and $FP$ is True Positive and False Positive. TP is the total number of correctly detected Brain tumors. FP is total number of in-correctly detected Brain tumors. False Negative (FN) represents the total number false detections. using the equation
where, TN and FP are True Negative and False Positive. Specificity calculated using the equation
\[
\text{Specificity} = \frac{TN}{TN + FP}
\] (13)

4.3 Experimental Results for tumor detection
The methodology of Region Growing was applied of MR brain tumor images of the head to obtained segmented regions of tumor. The performance was evaluated. All the output parameters in the pattern layer is tested and trained based on SVM values. An element is trained to return a high output value when an input vector matches the training vector.

\[\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + FN + TN)} \] (14)

V. CONCLUSION AND FUTURE WORK
Brain tumors are caused by abnormal and uncontrolled growing of the cells inside the brain. Treatment of a brain tumor depends on its size and location. Although benign tumors do not tend
to spread, they can cause damage by pressing on areas of the brain if they are not treated early. To avoid manual errors, an automated intelligent classification technique is proposed which caters the need for classification of image. In this paper classification techniques based on Support Vector Machines (SVM) are proposed and applied to brain image classification. Here also proposed brain tumor image segmentation based on Histogram thresholding. This automated intelligent system results in the improvement of accuracy rate and reduces the error rate of MRI brain tumor.

REFERENCES