Detecting Brain Mri Anomalies By Using Svm Classification

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ABSTRACT

This research paper proposes an intelligent classification technique to identify anomalies present in brain MRI. The manual interpretation of anomalies based on visual examination by radiologist/physician may lead to missing diagnosis when a large number of MRIs are analyzed. To avoid the human error, an automated intelligent classification system is proposed which caters the need for classification of image slices after identifying abnormal MRI volume, for anomalies identification. In this research work, advanced classification techniques based on Support Vector Machines (svm) are proposed and applied to brain image classification using features derived. SVM is a artificial neural network technique used for supervised learning of classification. This classifier is compared with other pre store images for detecting the anomalies. From this analysis, The performance of svm classifier was evaluated in terms of classification accuracies and the result confirmed that the proposed method has potential in detecting the anomalies.

***Keywords* – anomalies ,classification, detecting, MRI, SVM**

I. INTRODUCTION

The field of medical imaging gains its importance with increase in the need of automated and efficient diagnosis in a short period of time .Computer and Information Technology are very much useful in medical image processing, medical analysis and classification. Medical images are usually obtained by X-rays and recent years by Magnetic Resonance (MR) imaging. Magnetic Resonance Imaging (MRI) is used as a valuable tool in the clinical and surgical environment because of its characteristics like superior soft tissue differentiation, high spatial resolution and contrast. It does not use harmful ionizing radiation to patients [1, 2].Magnetic Resonance Images are examined by radiologists based on visual interpretation of the films to identify the presence of anomalies . The shortage of radiologists and the large volume of MRI to be analyzed make such readings labor intensive, cost expensive and often inaccurate. The sensitivity of the human eye in interpreting large numbers of images decreases with increasing number of cases, particularly when only a small number of image are affected. Hence there is a need for automated systems for analysis and classification of such medical images .

The MRI may contain both normal image and defective image. The defective or abnormal image are identified and separated from the normal image and then these defective image are further investigated for the detection of anomalies. This is for separating abnormal image from the data collection containing both normal and abnormal image. This results in significant cost and time saving. The motivation behind this paper is to develop a machine classification process for evaluating the classification performance of different classifiers to this problem in terms of statistical performance measure.

II. OVERVIEW OF *SVM* LEARNING FOR CLASSIFICATION

The Support Vector Machine algorithm was first developed in 1963 by Vapnik and Lerner [3] and Vapnik and Chervonenkis [4] as an extension of the Generalized Portrait algorithm. This algorithm is firmly grounded in the framework of statistical learning theory – Vapnik Chervonenkis (VC) theory, which improves the generalization ability of learning machines to unseen data [5] [6]. In the last few years Support Vector Machines have shown excellent performance in many real-world applications including hand written digit recognition [7], object recognition [8], speaker identification [9], face detection in images [10] and text categorization [11]. SVM is a classification algorithm based on kernel methods [12], [13] and [14]. SVM very attractive is that classes which are nonlinearly separable in the original space can be linearly separated in the higher dimensional feature space. Thus SVM is capable of solving complex nonlinear classification problems. 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). As a result, an SVM tends to perform well when applied to data outside the training set. SVM achieves this advantage by focusing on the training examples that are most difficult to classify. These "borderline" training examples are called *support vectors*.
In this paper, we treat image classification as a two class pattern classification problem. We apply all the MRI image to classifier to determine whether the anomalie is present or not. We refer to these two classes throughout as "white" and "non-white" image. The problem is how to construct a classifier [i.e., a decision function $f(x)$] that can correctly classify an input pattern x that is not necessarily from the training set.

i. 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
$f(x) = w^T x + b$ (1)
such that for each training example xi, the function yields ( ) ≥ 0 *i f x* for = +1, *i y*
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 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 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.

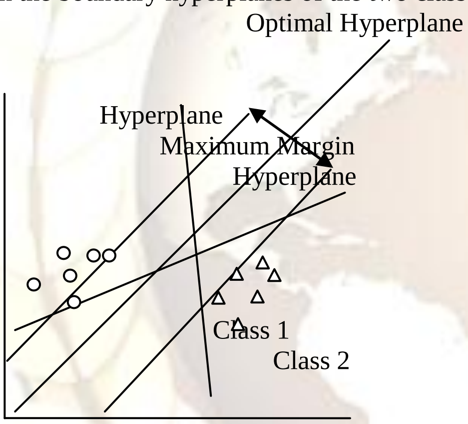

Figure 1. SVM classification

III. PROBLEM IDENTIFICATION

The conventional method in medicine for brain MR images classification and anomalies detection is human inspection. Operator-assisted classification methods are impractical for large amounts of data and are also non-reproducible. MR images also always contain a noise caused by operator performance which can lead to serious inaccuracies classification. The MR images data is by nature, a huge, complex and cognitive process. Accurate diagnosis of MR images data is not an easy task and is always time consuming. In some extreme scenario, diagnosis with wrong result and delay in delivery of a correct diagnosis decision could occur due to the complexity and cognitive process of which it is involved.

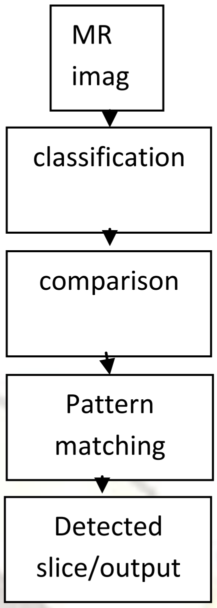

Figure 2. MR Image slices Classification

IV. PROPOSED METHODOLOGY

The proposed methodology of classifying MR image of human brain is shown in Figure 2.The method uses the steps of classification Comparison and pattern matching. Significant difference observed in variety of textural measurements in MR image, is used for this classification. The various measurements based on statistical matrix textural features from the MR images are given as input to the classifiers for training. If the features of new slices are given as input, the trained classifier can able to classify it.
The classifiers such as Support Vector classifiers of neural network classifiers analyzed.

i. MR image data

Magnetic Resonance Imaging (MRI) uses magnetic energy and radio waves to create images ("slices") of the human body. MR imaging measures the magnetic properties of nuclei within the body tissues. The energy absorbed by the nuclei is then released, returning the nuclei to their initial state of equilibrium and this transmission of energy by the nuclei is observed as the MRI signal.MR images are generated by the resonating nuclei for each spatial location. The image gray level in MRI mainly depends on three tissue parameters viz**.,** proton density (PD), spin-lattice (T1) and spin-spin (T2) relaxation time [15]. Generally, for most of the soft tissues in the body, the proton density is very homogenous but may exhibit higher intensity for gray matter. T1 and T2 are sensitive to the local environment; they are used to characterize different tissue types. T1, T2 and PD type images are mostly used by different researchers [16, 17] for different MR applications.

ii. Classifier used for comparison

Support Vector Machine: Support Vector Machine offers an extremely powerful method of obtaining models for classification [18]. They provide a mechanism for choosing the model structure in a manner which gives low generalization risk and empirical risk. The idea behind the support vector machines is to look at the RBF network as a mapping machine, through the kernels, into a high dimensional feature space. The output of an SVM is a linear combination of the training examples projected onto a high-dimensional feature space through the use of kernel functions.

V. IMPLENTATION OF PROPOSED METHODOLOGY

i. MR image data

The image used in this work, were taken from internet. This are 2 dimension image with black and white colour. Any random images of brain were considered in this work.

ii. Training & Testing Data

The MRI image slices were grouped into two classes, namely normal and abnormal depending on the anomalies present in the image. The MRI data set contains 150 image (120 abnormal slices and 20 normal slices) and from which two different sets are grouped to have biased and unbiased
training of classifier and other are used for testing.

iii. Classifier

The MRI were classified using KULeuven's MATLAB SVM matlab toolbox used for classification. Various parameters of the classifiers are selected. In our study, the SVM – classifier, the value of the standard deviation (σ) is used.

iv. Performance measures

Result of classification could have an error rate and on occasion will either fail to identify an abnormality, or identify an abnormality which is not present.

VI. CONCLUSION AND FUTURE WORK

This experiment can detect the first object of class which is fail to identify the other abnormalities present in the image.Focusing on the various features of the object or anomalies. Different parameter should help to find out anomalies. More than one object should be detected.

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