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A Comparative Study of Two MRI Brain Tumor Classification Techniques

KEYWORDS: Brain tumour, MRI, SVM, Neural network, classification.

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ABSTRACT *MR images are progressively emerging as a significant measure of brain activity and they possess immense potential for the diagnosis and treatment of brain diseases and abnormalities. MRI brain tumour images classification is a difficult task due to the variance and complexity of tumours. This work presents an automated system for efficient classification of MRI brain tumours using support vector machine (SVM). The results obtained from the above method are compared with artificial neural networks (ANNs). The performance analysis shows that qualitative results obtained from the proposed technique is better than ANN.*

Introduction

A brain tumour is a mass of abnormal tissue growing in any part of the brain. For some unknown reason, some brain cells grow in an uncontrolled manner and form these tumours. These tumours can arise from any part of the brain. Brain tumours can have a variety of shapes and sizes; it can appear at any location and in different image intensities. Broadly these tumours can be divided into benign and malignant tumours. Benign tumours grow slowly and never spread to other parts. But as they slowly increase in size they can cause pressure on the normal brain and interfere with mental and functions of the body. Malignant tumours are tumours that grow fast and infiltrate the surrounding brain and sometimes spread to the other parts of the brain or spine. The task of manually classifying brain tumours from MRI is generally time consuming and very difficult to diagnose. So an automated classification method is desirable because it reduces the load on the operator and generates satisfactory results for classifying tumour. The aim of this work is to provide an automated tool which locates the tumour on MRI image.

A large number of techniques have been developed for medical image analysis in the last decade. Image segmentation is the task of dividing an image into homogeneous regions. Brain tumour segmentation methods can be classified into three categories according to the degree of required human interaction as manual segmentation, semiautomatic segmentation, and fully automatic segmentation [1]. In manual segmentation of brain tumours involves manually drawing the boundaries of the tumour and structures of interest, or painting the region of anatomic structures with different labels. In semiautomatic segmentation the human intervention is often needed to initialize the method, to check the accuracy of the result and even to manually correct the segmentation result while in fully automatic methods, the computer segments the tumour MR image without any human interaction. This method generally incorporates human intelligence and prior knowledge in the algorithms. Two types of learning methods have been used in image segmentation, viz, unsupervised and supervised methods. In unsupervised segmentation we use an objective function to segment the image into at least two meaningful regions i.e. ; tumorous and non tumorous while supervised segmentation involves both a training phase that uses labelled data to learn a model that maps from features to labels, and a testing phase that is used to assign labels to unlabeled data based on the measured features[1], [2]. Another mostly used existing method is based on the edge detection [3] . A region prop and skull is used to detect the contour of the tumour and its geometrical dimension [4]. Even K-means clustering algorithm for segmentation of brain MRI images followed by morphological filtering can be applied for detection of tumour location [5]. For decision making probabilistic neural network is used followed by a series of operation like Gaussian filtering method, image segmentation and thresholding, feature extraction through gray level co-occurrence matrix (GLCM) method, and principal component analysis for dimensionality reduction [6]. Sometimes uses information extracted from some training MRI samples related to mean intensities of the various MR tissues to guide the minimization of the data driven objective function and by using this information automatic segmentation of these tissues can be done from the MRI datasets [7]. The paper discusses the results of ANNs and SVM [8] applied on brain tumour MR images.

2 Proposed Methodology

The proposed method is outlined in Fig. 1. First the training data set of MR images is fed as the input to the system. This input data set consists of normal as well as tumorous MR brain image than image is pre-processed to remove noise. After Pre-processing, feature extraction is done for training set of data [9]. After this we train our system using this training data set through SVM and ANN and then test set of MR brain image data having normal brain or abnormal brain is fed as input to the proposed system. Final result will give classification of test set of data.

2.1 Pre-processing

The purpose of this step is basically to improve the image and the image quality to get more surety and ease in detecting the tumour. In pre-processing image is converted to gray scale and then a 3x3 median filter is applied on image using Eqn. (1) in order to remove the noise .

$$\bar{f}(x,y) = median_{(s,t)\in S_{xy}}\{g(s,t)\} \qquad (1)$$

The obtained image is then resized and reshaped in accordance with further operations. Here, a resized matrix of

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200 x 200 has been taken and a size of 1 x 40000 is taken for reshaped matrix.

A random sample of diseased brain MR image is shown in Fig. 1. The white abnormal mass accumulation shows the tumour area. By applying the adaptive median filter with 2 dimensions and a block size of [5, 5], image is enhanced and it is shown in other half part of it. Finally, the noise is reduced and the image visibility is smoothened.

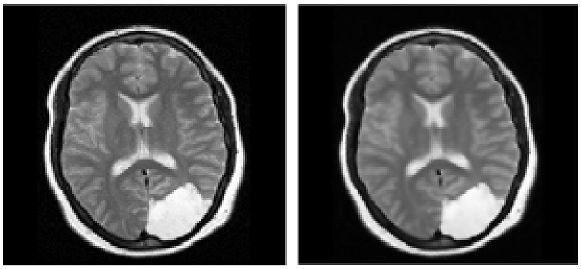

Fig 1: Raw data image and adaptive median

2.2 Support Vector Machine (SVM)
The main objective of machine learning is to achieve good generalization performance, given a finite amount of training data, by striking a balance between the goodness of fit attained on a given training dataset and the ability of the machine to achieve error-free recognition on other datasets. With this concept as the basis, support vector machines have proved to achieve good generalization performance with no prior knowledge of the data. The principle of an SVM is to map the input data onto a higher dimensional feature space nonlinearly related to the input space and determine a separating hyperplane with maximum margin between the two classes in the feature space. Fig. 2 shows SVM separating Class A and Class B [10]. A support vector machine is a maximal margin hyperplane in feature space built by using a kernel function in gene space. This results in a nonlinear boundary in the input space.

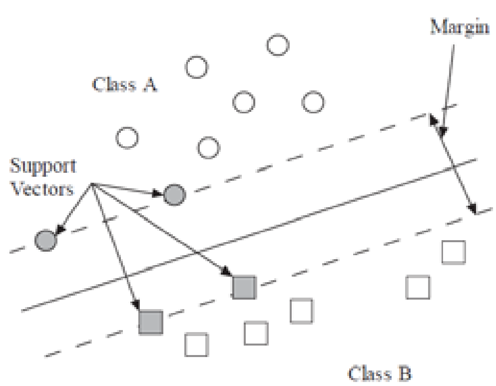

Fig 2 : SVM Separating two classes
The optimal separating hyperplane can be determined without any computations in the higher dimensional feature space by using kernel functions in the input space. Commonly used kernels include [11]:

Linear Kernel : $K(x,y)= x.y$
Radial Basis Function (Gaussian) Kernel : $K(x,y) = e^{-\frac{\|x-y\|^2}{2\sigma^2}}$
Polynomial Kernel : $K(x,y)=(x.y+1)^d$

An SVM in its elementary form can be used for binary classification. The choice of the proper kernel function is an important issue for SVM training because the power of SVM comes from the kernel representation that allows the non-linear mapping of input space to a higher dimensional feature space. The use of appropriate decision function can give better classification. Support vector machines are a particular family of learning machines, as an alternative to neural networks and that have been successfully employed to solve clustering problems. SVM are classifiers with the distinct characteristic that they aim to find the optimal hyperplane such that the expected generalization error is minimized. Instead of directly minimizing the empirical risk calculated from the training data, SVMs perform structural risk minimization to achieve good generalization. The optimization criterion is the width of the margin between the classes and the goal of training a SVM is to find the separating plane with the largest margin.

2.3 Artificial Neural Network (ANN)
An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurones) working in unison to solve specific problems [12]. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. ANNs, like people, learn by example. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data, can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. A trained neural network can be thought of as an expert in the category of information it has been given to analyze.

An artificial neuron is a device with many inputs and one output. The neuron has two modes of operation; the training mode and the using mode. In the training mode, the neuron can be trained to fire (or not), for particular input patterns. In the using mode, when a taught input pattern is detected at the input, its associated output becomes the current output.

An ANN is one of the most common classifiers used in MR image processing. We have used multilayer perception neural networks to classify the patterns extracted from the spectra. This method neural network extracted the patterns related to metabolite peaks and the second one extracted several features expressing the whole signal characteristics. We used this class of patterns in various sets to find the best features describing each lesion. In order to train the network and verify its ability to distinguish between different tumour spectral features we divided the available data into two sets. The first set was used for training and the remaining set was used for testing [12].

2.4. Proposed algorithm
In our proposed algorithm there are several steps to be followed as shown in Fig. 3. In both the techniques different steps are followed in a sequence. Fig 3 (a) shows the flow chart for SVM technique while Fig 3 (b) shows the sequence of steps to be followed for classification using ANN.

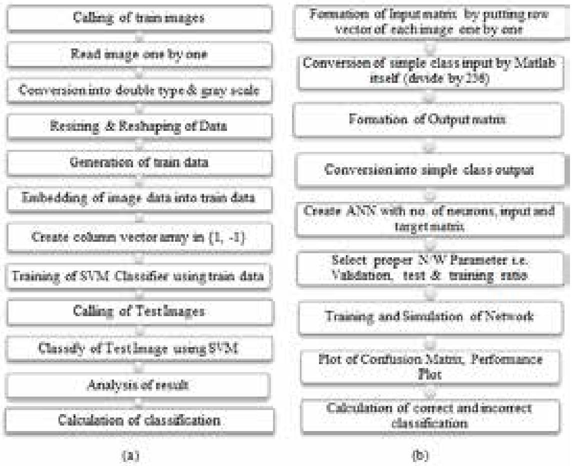

Fig. 3: (a) Algorithm for SVM, (b) Algorithm for ANN

Results

This section describes the results of both techniques in terms of plots and snapshots. All our experiments have been performed on a computer with 2.3 GHz Intel Core I3 processor and 2 GB main memory. The correct and incorrect classification accuracies are 96.77% and 3.22 for SVM as shown in Table 1 whereas the Fig. 5 shows the bar graph of test images shown in Fig. 4. Higher limit peaks (up to 3) indicates the presence of tumour and lower limit peaks (up to 1) indicates the absence of tumour. Next is the case of neural network which is working as a classifier for input test images. The correct and incorrect classification accuracies are 58.33 and 41.67, whereas for ANN. Fig. 7 and 8 shows the confusion matrix and performance plot for this classifier. Confusion plot (Fig. 7) is another measure of how well the neural network has fit the data. Here the confusion matrix is plotted across all samples. The confusion matrix shows the percentages of correct and incorrect classifications. Correct classifications are the green squares on the matrices diagonal. Incorrect classifications form the red squares. If the network has learned to classify properly, the percentages in the red squares should be very small, indicating few misclassifications. Performance is measure of network's performance which improved during training in terms of mean squared error in log scale. The version of the network that did best on the validation set is was after training. The mean squared error of the trained neural network can now be measured with respect to the testing samples. Table 1 shows the correct and incorrect percentages of classification. So, it can be concluded easily by comparing the correct and incorrect classification percentage and other performance aspects of both techniques that SVM is much better technique than neural network.

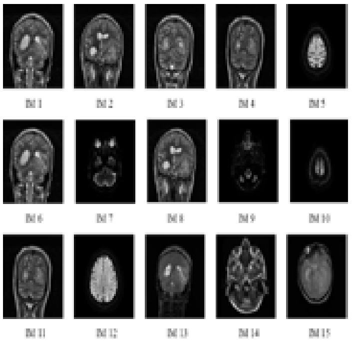

Fig. 4: Test Images

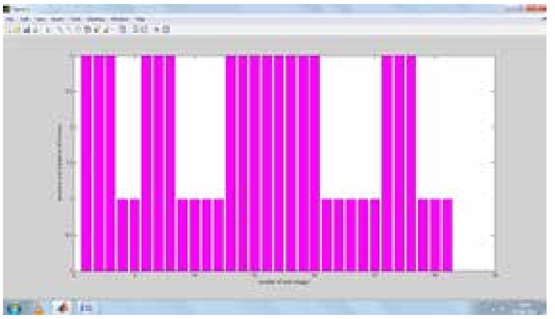

Fig 5: Presence and absence of tumour in MRI using SVM

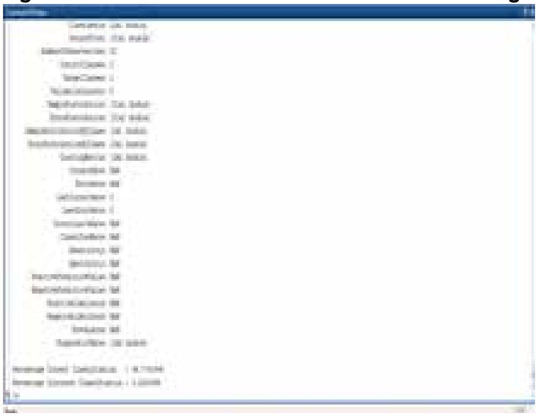

Fig 6: Command window for the results of SVM indicating correct and incorrect classification percentage

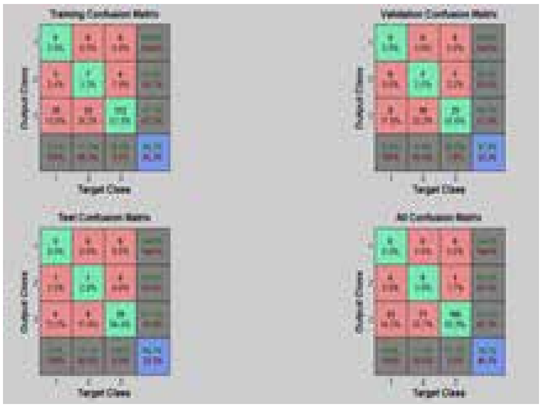

Fig 7: Confusion matrix for ANN

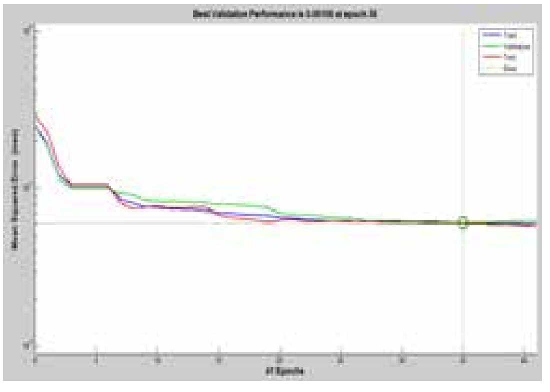

Fig 8: Performance plot for ANN

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Table 1: Comparison between SVM and NN

Methods	Correct classification percentage	Incorrect classification Percentage
SVM	96.77%	3.22%
ANN	58.33%	41.67%

Conclusions

MR images are progressively emerging as a significant measure of brain activity and they possess immense potential for the diagnosis and treatment of brain diseases and abnormalities. MRI brain tumour images classification is a difficult task due to the variance and complexity of tumours. This research paper presents an automated system for efficient classification of brain tumours in MRI images using SVM and ANNs. The correct classification percentage is 96.77 and incorrect classification is 3.22 in case of SVM while 58.33 and 41.67 for ANN. The performance analysis shows that qualitative results obtained from the proposed technique is better than ANN.

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