



MRI Brian Image Classification Using SVM

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ABSTRACT

Early detection of abnormality is very important in clinical practice. The shortage of radiologists and the large volume of medical images to be analyzed make such readings labor intensive, cost expensive and often inaccurate. The sensitivity of the human eye in interpreting large number of images decreases with increasing number of cases. There are several types of non-invasive brain imaging techniques; Magnetic Resonance Imaging (MRI) is one of the versatile imaging modality which is used to acquire several different types of images. So there is a need for automated system for the analysis of the MRI images to identify the abnormality. This identification detects even the smallest part of brain that cannot be identified by bare eyes. This will save the radiologists time, increases accuracy and yield of diagnosis. The article discusses about the different phases of processing MRI images to identify abnormality efficiently. The first phase emphasis on the efficient wavelet based feature extraction method. To reduce the time and memory, the wavelet coefficients are reduced by applying PCA and these are used as feature vectors. These feature vectors are subsequently subjected to the binary Support Vector Machine (SVM) classifier for the classification in a precise way. The adopted process in this article is proved to be more efficient than the existing ones.

Key Words: MRI, SVM, PCA, Classification etc.

I. INTRODUCTION

MRI is the medical imaging technology with non-ionizing radiation. The MRI may contain both normal and abnormal slices of brain. Interpreting large number of images decreases the accuracy with increasing number of cases, especially in MRI images because of inhomogeneous magnetic



fields, patient motions, duration of imaging time, thermal noise and existence of any metal things in imaging environment, are some reasons that can create noises and artifact. And also the images obtained by the low magnetic strength (measured in tesla) MRI machine, will be having low contrast. So it is difficult for radiologists to process such type of images.

Hence, there is a need for automated systems for analysis and classification of such medical images. The objective of our proposed method is to classify the brain images to normal/abnormal classes automatically. This will save the radiologist time, increases accuracy and yield of diagnosis. Early detection of abnormalities is very important in clinical practice.

The paper is organized into five sections: Section two gives the literature survey. Section three gives the proposed methodology. The results and discussion are given in section four. Section five deals with conclusion of the work.

II. LITERATURE SURVEY

Literature survey carried out related to technology impact in the study of MRI brain feature extraction and classification, are discussed as below.

Ahmed Kharrat et.al [1] have proposed a approach for automated diagnosis and classification of MRI human brain images as normal and abnormal, using Wavelets Transform (WT) as input to Genetic Algorithm (GA) and Support Vector Machine (SVM). EL-SAYED A. et.al [2] have presented two hybrid techniques for the classification of the MRI human brain images, using discrete wavelet transformation (DWT), PCA and feed forward back-propagation artificial neural network (FP- ANN), k-nearest neighbor (k-NN). H. Selvaraj, et.al [3] has proposed an advanced classification techniques based on Least Squares Support Vector Machines (LS-SVM) , applied to brain image slices classification using features derived from slices.

Katarina Trojancanec et.al [4] has compared several Support Vector Machine (SVM) techniques, neural networks and k_nearest neighbor classifier for classification of MRI images. Madhubanti Maitra et.al [5] has proposed a method that uses an improved version of orthogonal discrete

wavelet transform (ODWT) for feature extraction, called Slantlet Transform. The features, obtained are used to train a SVM based binary classifier that automatically infers whether the images that of a normal brain or that of a pathological one. SHEN Lin-Lin et.al [6], proposed a Gabor wavelets and SVM based framework for object recognition.

From the above survey it is clear that work based on classification of Brain MRI is very less, used very limited features and one or two classifiers. Hence we are proposing a novel feature extraction and classifier method for classification of brain MRI images, is developed and demonstrated its effectiveness using a set of realistic MRI brain images obtained from different hospitals. Experimental evidence shown that this technique gives lower error rates than the other methods used in survey.

III. PROPOSED MODEL

The block Diagram of the proposed methodology is as shown in figure 3.1.

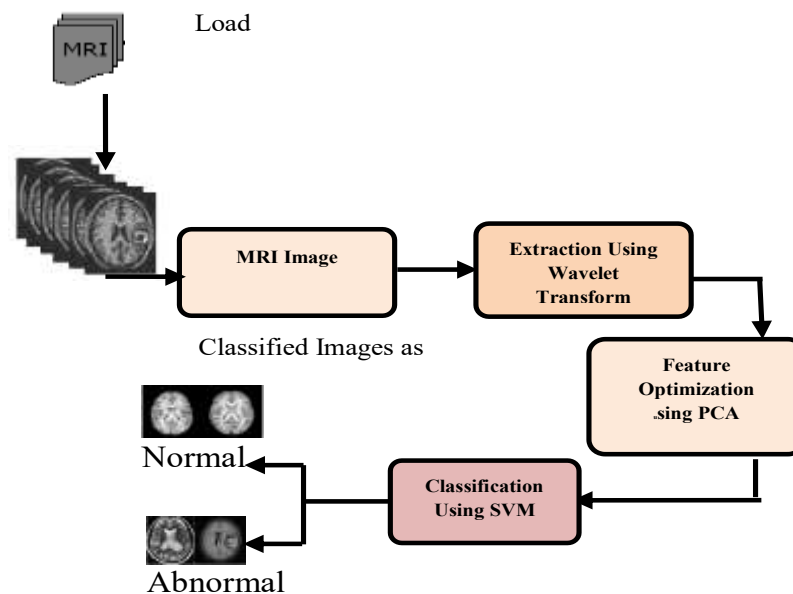


Fig: 3.1. Block Diagram of Proposed Method



The images obtained from MRI are in Digital Imaging and Communications in Medicine (DICOM) format used for distribution and viewing of medical images. The images required for training and testing are collected from [8][9][10], and from the different hospitals.

The proposed system uses wavelet coefficients as features for the classification of brain MRI images. The wavelet is a powerful mathematical tool for feature extraction. Wavelets are localized basis functions, which are scaled and shifted versions of some fixed mother wavelets. The main advantage of wavelets is that they provide localized frequency information about a function of a signal, which is particularly beneficial for classification.

The number of wavelet coefficients obtained from decomposition is very large. These coefficients require more space and processing time. Hence, to reduce these coefficients and to extract the more discriminative values, wavelet coefficients are given as input to the Principal components analysis (PCA) algorithm. Only the most informative features are extracted by the MRI images using PCA and are utilized in the classification process. The main idea behind using PCA in our approach is to reduce the 256*256 dimensional coefficients of 65536 wavelet coefficients to 10 desirable features for each brain MRI image. These reduced features are stored in the database.

SVMs are very popular for discrimination tasks because they can accurately combine many features to find an optimal separating hyper plane [4]. The classifier used in our proposed method is SVM, which is widely used in medical imaging for brain image classification, detection of tumor and malignancy prediction, white matter lesion segmentation etc. The reduced features from PCA are given as input to the SVM classifier, to differentiate as normal/abnormal.

A. FEATURE EXTRACTION

The proposed system uses the wavelet transform coefficients and statistical features extracted from wavelet coefficients as feature vectors.



In 1984, Jean Morlet a French geophysicist introduced the concept of a wavelet. It provides the time-frequency representation. The function $\psi(t)$ is called a mother wavelet which satisfies the following properties[7].

- The function $\psi(t)$ integrates to zero:

$$\int_{-\infty}^{\infty} \psi(t) dt = 0 \dots\dots\dots 3.1$$

- It is square integral or equivalently has finite energy:

$$\int_{-\infty}^{\infty} |\psi(t)|^2 dt < \infty \dots\dots\dots 3.2$$

Wavelet transforms used today comes in distinct classes: the continuous wavelet transform (CWT), the discrete wavelet transform (DWT) and stationary wavelet transform (SWT).

The CWT is a time–frequency analysis method for allowing arbitrarily high localization in time of high frequency signal features. The CWT with respect to a mother wavelet $\psi(t)$ is defined as [7]:

$$X_{wt}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t) \psi \left(\frac{t-\tau}{s} \right) dt \dots\dots\dots 3.3$$

The translation parameter τ relates to the location of the wavelet function as it is shifted through the signal. Thus, it corresponds to the time information in the wavelet transform. The scale parameter s is defined as (1/frequency) and corresponds to frequency information. Scaling either dilate (expands) or compress a signal. Large scales (low frequencies) dilate the signal and provide detailed information hidden in the signal, while small scales (high frequencies) compress the signal and provide global information about the signal.

The DWT is the most useful technique for frequency analysis of signals that are localized in time of space. It decomposes signals into basis functions that are dilations and translations of a single prototype wavelet function as given in the equation 3.4:

$$f(x) = \sum_{m=0}^{\infty} \sum_{n=0}^{\infty} C_n^m \psi_{m,n}(x) \dots \dots \dots 3.4$$

Where $\psi_{m,n}(x) = 2^{-m/2} \psi(2^{-m}x - n)$, are obtained by translates and dilates of the wavelet function $\psi(x)$. The DWT coefficients c_n^m can be calculated by the inner products $(\psi_{m,n}(x), f(x))$ which are the estimation of signal components at $(2^{-m}n, 2^m)$ in the time frequency planes.

The DWT corresponds to multiresolution approximation expressions. This method permits the analysis of the signal in many frequency bands or at many scales. In practice, multiresolution analysis is carried out using 2 channel filter banks composed of a low-pass (G) and a high-pass (H) filter and each filter bank is then sampled at a half rate (1/2 down sampling) of the previous frequency. By repeating this procedure, it is possible to obtain wavelet transform of any order. The down sampling procedure keeps the scaling parameter constant ($n=1/2$) throughout successive wavelet transforms so that it benefits for simple computer implementation. In the case of an image, the filtering is implemented in a separable way by filtering the lines and columns. An example can be illustrated in [4] Figure 3.2..

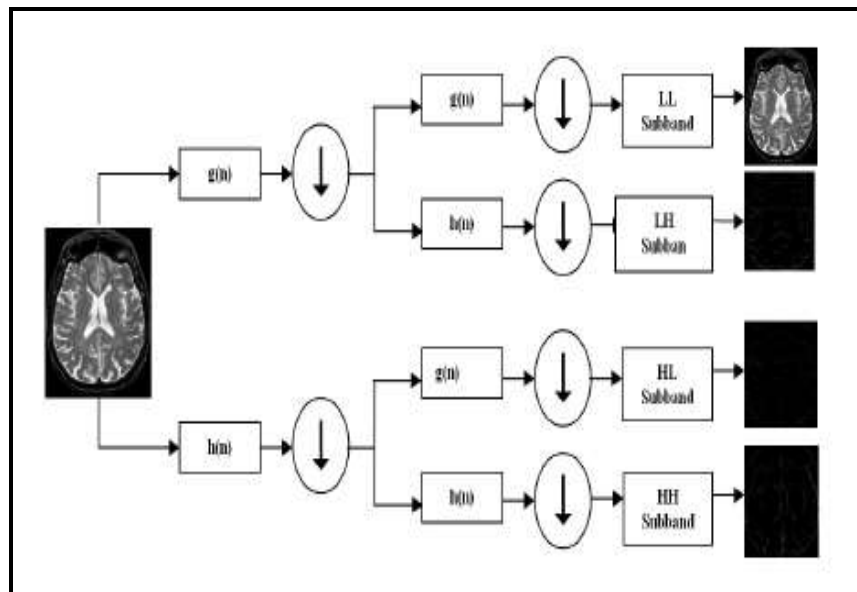


Fig: 3.2. Wavelet transform applied to MRI brain image



According to this procedure, the original image can be transformed into four sub-images, namely:

- LL sub-image: Both horizontal and vertical directions have low-frequencies.
- LH sub-image: the horizontal direction has low-frequencies and the vertical one has high-frequencies.
- HL sub-image: The horizontal direction has high-frequencies and the vertical one has low-frequencies.
- HH sub-image: Both horizontal and vertical directions have high-frequencies.

The discrete wavelet transform provides the information useful for texture analysis in the image. Its fast implementation is usually performed by using multiresolution analysis. The wavelet coefficients are sampled based on the Nyquist criteria. The representation is accordingly non-redundant and the total number of sample in the representation is equal to the total number of the image pixels. The major inconvenience of this representation is that it does not conserve an essential property in image processing, which is the invariance by translation. Thus pyramidal multiresolution analysis is not desirable for estimation/detection problems. In order to preserve the invariance by translation, the down sampling operation must be suppressed and the decomposition obtained is then redundant and is called a SWT [11].

In the proposed method, a Daubechies wavelet family is used for extracting wavelet coefficients using SWT with single level decomposition.

B. FEATURE REDUCTION

The proposed system uses a PCA for generating reduced feature vector as it is very simple and easy to use[2]. We extracted 65536 wavelet coefficients. These are given as input to PCA for dimensionality reduction. We selected only first 10 features from the PCA. These are given as input to the SVM classifier.

C. CLASSIFICATION

Classification is the systematic way of grouping of images according to the structural or evolutionary relationships among them. According to survey, many researchers have used



different classifier techniques for MRI data, such as Bayes classifier, k-Nearest Neighbors (kNN) classifier[2], Artificial Neural Networks (ANN)[2][3], Support Vector Machines (SVMs)[1][4][5][6] and Expectation Maximization (EM) etc.

In the proposed method, SVM classifier is used for Brain MRI image classification, because of its good generalization and high precision capabilities. It is very specific and sensitive process because of the specific nature of the images and overlapping tissue intensity distributions. Images are normally classified based on their features. The aim of the proposed work is to classify the brain MRI images as normal and abnormal classes automatically, based on wavelet features. To increase the performance of classification, some of the statistical features are added. This classification work saves the radiologist time, increases accuracy and yield of diagnosis.

SVM is a function estimation technique based on Statistical Learning Theory, introduced by V. Vapnik since the early 1990s. The standard SVM is a supervised binary classifier based on statistical and optimizing theories, which has found widespread use in pattern recognition problems. The SVM is particularly attractive to biological analysis due to its ability to handle noise, large dataset and large input spaces and mapping of non-linear input data into a high dimensional feature space with minimum error on training set. During this binary classification process, it constructs a hyperplane in the feature space that separates optimally two different classes of feature vectors. These feature vectors are mapped into a feature space by using the kernel function. The hyperplane found by SVM is one that maximizes the separating margins between both binary classes.

In the proposed method, wavelet features of 30 normal and 30 abnormal realistic MRI brain images are given as input to the SVM machine learning system for training purpose.

IV. RESULTS AND DISCUSSIONS

In our experiments, we used a dataset consisting of 52 abnormal and 61 normal realistic T1-weighted MRI DICOM brain images. In the proposed method, wavelet coefficients with only one level of decomposition of MRI images with Daubechies as mother wavelet are computed. These coefficients are used for feature extraction. For reducing the complexity of the



system, PCA was used for feature reduction. The dimension of the feature vector was reduced from 65536 to 10 with the PCA algorithm. Limiting the feature vectors to the component selected by the PCA leads to an increase in accuracy rates and decreases the time complexity. In this experiment, MRI dataset that have normal and abnormal brain images are classified by the proposed classifier.

Following observations shows the classification rates for performing normal/abnormal MRI brain image classification

Experimental Results

In this section, the training and testing performance results are discussed. Based on the statistics of several images in training as well as testing phase, we evaluated the overall system performance. The following graph shows the overall statistics of our experimental results for training as well as testing. From the observation of graph we can conclude that, maximum training performance by considering individual wavelet feature especially 3rd, 4th, 10th and all wavelet features is achieved upto 87.00%. And maximum testing performance of normal and abnormal images by considering 3rd wavelet feature is 83.33% and 80.95% respectively.

V. CONCLUSION AND FUTURE WORK

In this work, we proposed medical decision system for classifying MRI brain images as normal/abnormal. The proposed approach utilizes a combination of different techniques and is composed of several steps including wavelet feature extraction, feature reduction for PCA and SVM classifier for classification of brain MRI images. The accuracy obtained from the system is 83.33% and 80.95% for the classification of normal and abnormal MRI brain images respectively.

In this work, we discussed mainly the application of the proposed approach to brain MRI images. Future work includes the analysis of different body part images. Different scan images can also be taken and their analysis can be performed. We can get more specific

information, such as the information about the tumor type, and growth of the tumor into the classification model.

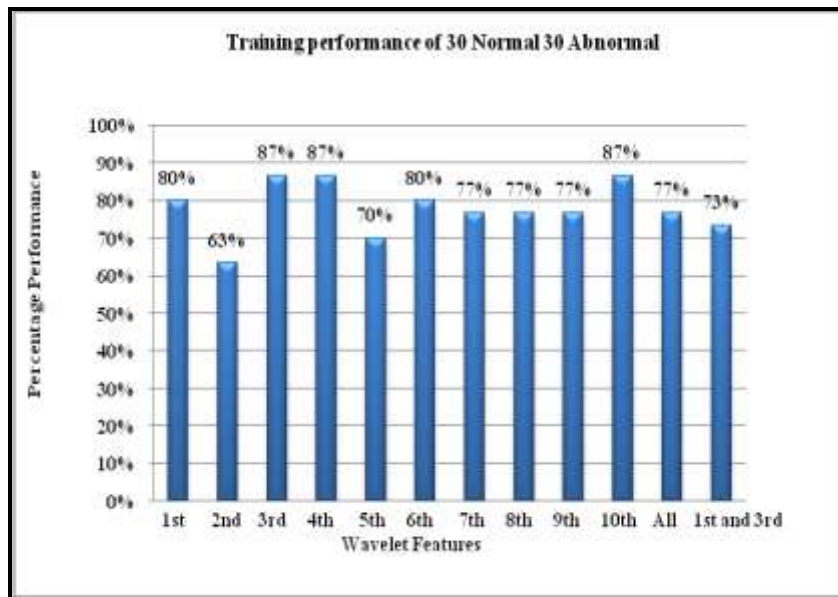


Fig:4.1 Performance graph of Training set

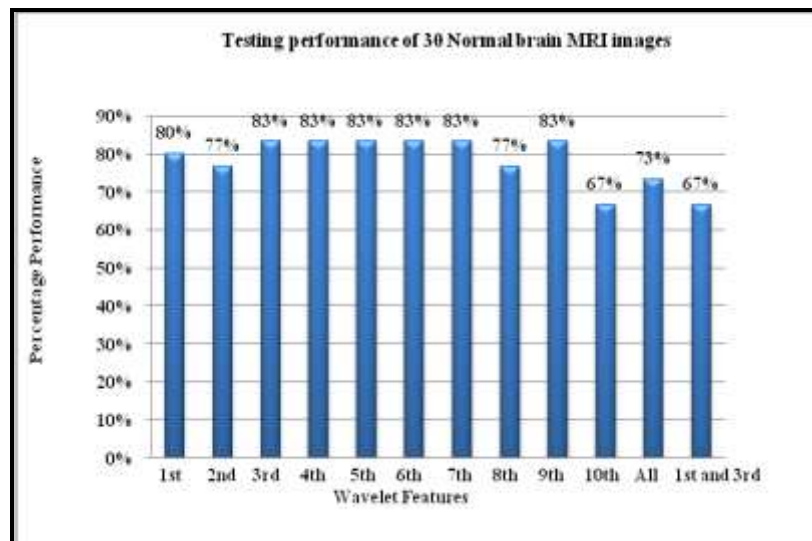


Fig:4.2 Performance graph of Testing normal MRI brain image



Fig: 4.3 Performance graph of Testing abnormal MRI brain image

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