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WAVELET-BASED BRAIN MRI IMAGE CLASSIFICATION – A SURVEY

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Abstract— *One of the diagnostic and treatment evaluation tools for brain interpretation is magnetic resonance imaging (MRI). MR images can also be used to determine a normal and abnormal brain. This paper presents a survey on few wavelet based brain image classification systems. The reviewed systems initially pre-process the MRI images for picture quality improvement. This is followed by extracting relevant features from those images, as required by Discrete Wavelet Transformation (DWT) and HAAR wavelets. DWT and HAAR wavelets are well known tools for extracting frequency space information from non-stationary signals. The feature space is reduced by using Principal Component Analysis (PCA). In classification, training a classifier involves feeding known data to the classifier along with previously known decision values that forms a finite training set. During testing new decision is made for the input data according to the training set. Support Vector Machine (SVM), feed forward back propagation Artificial Neural Network (FP-ANN), k-nearest neighbour (k-NN) are the classifiers used to classify the brain images into normal or abnormal images. A performance evaluation of the classifiers is done in terms of accuracy %, sensitivity %, and specificity % and the results are graphically represented. Discussion on the comparative results and further recommendation for future research in the area are presented.*

Keywords— MRI, SVM, FP-ANN, k-NN, PCA.

I. INTRODUCTION

Image processing is a method to convert an image into digital form in order to get an enhanced image or to extract some useful information from it by performing some operation on it. Basically image processing includes importing the image, analyzing and manipulating the image which includes data compression, image enhancement and spotting patterns that are not visible to human eyes. Output is the last stage in which result can be an altered image or report that is based on image analysis [1].

Medical image analysis and processing plays wide role in the field of medicine, especially in non-invasive treatment and clinical study. The modalities used to obtain medical image are X-rays, Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Ultrasound Imaging. In medical imaging, MRI is one of the scanning devices which use strong magnets and radio waves that interact with the hydrogen atom in human body. Then, computer can generate the image by using signals received from the atoms. MRI is advantageous in creating better soft tissue contrast than X-rays which leads to production of high quality images, mainly in brain and spinal cord scan.

Brain tumour is one of the major causes of death among the people. It is found that chances of survival can be increased if the tumour is detected correctly at early stages. Tumours have variety of shapes and sizes, it can occur at any location and any intensity. Benign tumour is not cancerous; it doesn’t affect nearby healthy tissue or spread to other parts of the body. Malignant tumour is cancerous and quickly spread to other parts of the body. Glioblastima Multiform (GBM) is the most common and most aggressive malignant primary brain tumour in a human. The objective of this survey is to study the various techniques employed for classifying brain images as normal, abnormal and detect the degree of abnormality. There by identifying the optimized techniques for classifying brain MRI images into normal and abnormal, and classifying an abnormal image into benign or malignant [2]. Recommendations for researchers in the area of brain MRI classification are provided in terms of the key factors that influence the overall efficiency of the system.

II. SURVEY OF LITERATURE

The following Fig 2.1 explains the flow diagram for the image classification. The steps included are image pre-processing, feature extraction, feature selection, and classification. Two types of data set are used, one training set and another is the testing set. From the classifier output, the decision whether the input image is normal or abnormal is taken.

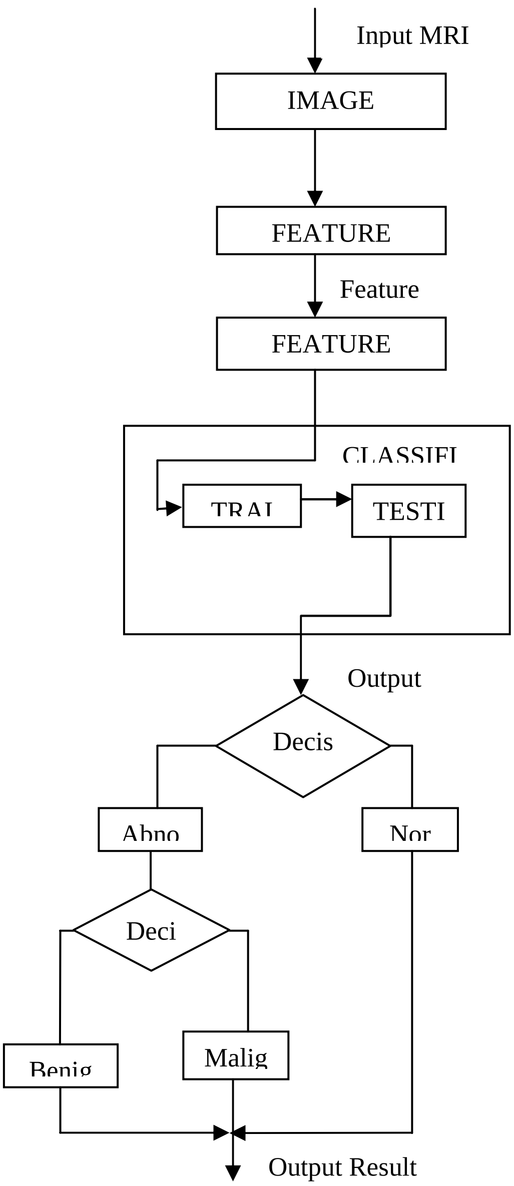

Figure: 2.1 Flow diagram for Brain MRI image classification

2.2 DAUB4, PCA & SVM based system

2.1 DAUB4 & SVM based system

Abdullah, N. Ngah, U.K. Aziz, S.A [3] have taken images from Advanced Medical and Dental Institute which are of type axial T2 FAIR weighted of size 512x512. The images are symmetrical, which is exhibited in the axial and coronal images. Number of images taken for the experiment was 32, in which 10 images were normal images and remaining 22 images were abnormal, affected by brain tumour for pre-processing, image denoiseing and noise filtering technique were used in order to enhance the images using Matlab 2009. Wavelet transformation was applied to the image and wavelet coefficients obtained were manipulated to eliminate noise point. Two wavelet transform were chosen which were Dubehics-4[DAUB4] and Haar. The reason for choosing Haar was since it is simple to compute and easier to understand. But DAUB4 had higher computational overhead and was conceptually more complex. But DAUB4 algorithm was used to support the Haar wavelet algorithm. For more accurate classifiers and constructing more compact models, feature extraction was implemented using17689 wavelet approximate coefficients that have been extracted from the MRI brain images. SVM was used for classifying an image into normal and abnormal images. SVM determines the decision boundaries in the training step and the method can also provide good generalization in high dimension input space. Software tool used in this experiment is lab view which is an advanced signal processing toolkit. It obtained only 65% of accuracy because of noise and misclassification of image.

Abdullah, N. et al. [4] used Principal Component Analysis in their research. The input images were taken from original patients of Advanced Medical and Dentist Institute in Bertam, Pulau Pinang, Malaysia. It consists of axial, T2 FLAIR weighted, 256x256 pixels. Symmetry in an axial MRI brain image strongly indicates abnormalities. 32 images were taken for experiment in which 10 are normal images and 22 are abnormal images. In their research, for feature extraction wavelet transformations is used to remove noise. Wavelet transform is applied to the image and wavelet coefficients obtained are manipulated so noise points were eliminated. Then inverse wavelet transform is used to recover the new image. They decided to extract the DAUB4 wavelet approximation coefficient of the MRI brain images and use them as feature of a given wavelet. The regular signal component can be accurately approximated using a small number of approximation coefficients and some of the detail coefficients. The display of wavelet transform with DAUB4 implementation can also be seen by using the wavelet toolbox. Feature reduction was done by using (PCA) Principal Component Analysis, to transform the existing input feature into a new lower dimension features space. PCA limits the feature vector to the component selected by the PCA which leads to an efficient classification algorithm [5]. SVM is used for classification since it is attractive and more systematic to learning linear or non linear class boundaries [6].

2.3 PSO & SVM based system

Amita Kumari and Rajesh Mehra [7] proposed a Hybrid PSO & SVM method for detection of Brain Neoplasm. The images were chosen on a real data set consisting of transaxial images of brain MRI. It consisted of 247 images in which 82 were normal, 82 were benign and 82 images were taken as malignant tumour suffering from a low grade glioma meningioma. These normal and pathological images were axial, T2-weighted of 256x256 sizes and acquired at several positions of tranaxial plane. Totally 247 images were used for training purpose and overall 18 images were normal, 20 benign and 20 were malignant. They proposed a hybrid algorithm consisting of 6 stages, namely pre-processing, noise removal, histogram equalization, optimization with PSO, feature extraction, feature selection and then image classification. In pre-processing, histogram equalization technique is used, which increases the contrast of an image. It maximizes the contrast of an image by applying a gray level transform. This tries to flattern the resulting histogram. For feature extraction, discrete wavelet transform (DWT) was used. DWT is a linear transformation that operates on a data vector, whose length is an integer power of two, transforming it into a numerically different vector of the same length. It is a tool that separates data into different frequency components. High pass and low pass filters were used. Particle Swarm Optimization (PSO) is used for feature selection for randomly selected particles and to search for the optimal particle iteratively. PSO is applied for its advantages of proximity, quality, diverse response, stability and adaptability [8]. PSO-SVM is a combination of two machine learning algorithms. This takes the advantages of minimum structural risk of SVM and the quick global optimization ability of PSO. Feeding the known data in SVM along with providing known decision values is called training an SVM, thus forming a finite training set. SVM gets intelligence from training set to classify unknown data. The idea behind SVM is to map the original data points from the input space to a high dimensional or even infinite dimensional feature space such that the classification problem becomes simple in the feature space. The experiment was done in two ways, without PCA and with PCA and obtained accuracy of 65% and 85% respectively. From the result obtained, the author concluded that PCA can be used to reduce the number of feature vectors and could lead to improve the percentage of accuracy.

The performance of the system was measured by three parameters namely accuracy, sensitivity, and specificity. The system obtained 95% accuracy [7].

HAAR Function, PSO & SVM based system

Amita Kumari and Rajesh Mehra [9] proposed a hybrid technique and implemented it on a real data set consisting of transaxial images of brain MRI. It consisted of 246 images: 82 normal, 82 benign and 82 images taken as malignant tumour suffering from a low grade gloima, meningioma. Those normal and pathological images are axial T2-weighted of 256*256 sizes. Feature extraction was done using wavelet based HAAR function. Particle Swarm Optimization (PSO) was used for Feature Selection which is a population based stochastic optimization Technique. The system was initialized with a random solution and searched for optima by updating generations. But PSO had no evolution operation such as crossover and mutation. In PSO, potential solution called particles fly through the problem space by following the current optimum particles. Support Vector Machine (SVM) was used for image classification. In this paper, performance measure was based on three parameters sensitivity, specificity, and accuracy. Accuracy obtained by this system is 97.5%. The proposed technique was accurate, robust, easy to operate and non invasive and inexpensive.

2.5 DWT, PCA, & Neural network based system

N. Hema Rajini, R. Bhavani proposed Classification of MRI Brain Images Using k-Nearest Neighbour and Artificial Neural Network [10]. The input dataset consists of axial T1 and T2-weighted, 256x256 pixel MR brain images. In the data set of 50 images 20 were normal brain images and 30 were abnormal brain images. The abnormal brain images were affected by brain lesion. Normal images are symmetry, axial and

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coronal images. Abnormal images consists of brain lesion images which are asymmetry and axial. The paper demonstrated that symmetry in axial MR images was an important feature to be considered in deciding whether the MRI image is normal or abnormal. The proposed method consisted of two stages that are (a) Feature Extraction and (b) Classification. For feature extraction, Discrete Wavelet Transformation (DWT) was used. Feature extracted from MRI have been reduced by PCA to more essential features. PCA is tool for transforming the existing input features into a new lower dimension k-NN. The first classifier was based on feed forward back propagation artificial neural network. The basic building block of a (artificial) neural network (ANN) is the neuron. A neuron is a processing unit which have some (usually more than one) inputs and only one output. Generally the ANN is build by putting the neurons in layers and connecting the outputs of neurons from one layer to the inputs of the neurons from the next layer. Variations are possible: the output of one neuron may go to the input of any neuron, including itself; if the outputs on neuron from one layer are going to the inputs of neurons from previous layers then the network is called recurrent, this providing feedback; lateral feedback is done when the output of one neuron goes to the other neurons on the same layer [11]. The NN had three layers (several trails for different hidden layers with different number of neurons). The first layer consisted of 7 input elements in accordance with the 7 feature vectors selected from the wavelet coefficients by the PCA. The number of neurons in the hidden layer was four. The single neuron in the output layer was used to represent normal and abnormal human brain. The second classifier was k-NN, based on a distance function and a voting function in k nearest neighbours, the metric employed is the Euclidean distance. The features hence derived are used to train a neural network based binary classifier, which can automatically infer whether the image is that of a normal brain or a pathological brain, suffering from brain lesion. Combination of efficient feature extraction tool and robust classifier leads to more robust and accurate automated MR normal/abnormal pathological brain image classification. Three parameters were used to evaluate performance of the proposed method namely sensitivity, specificity and accuracy. The accuracy of DWT-FP-ANN and DWT-k-NN were 90% and 99% respectively.

FPGA based system

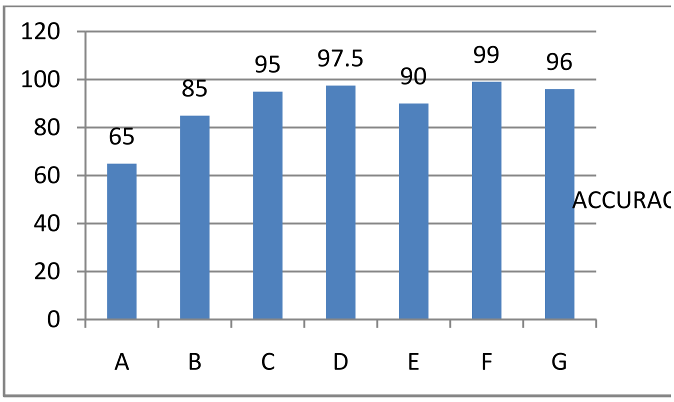
Dr Mohd Fauzi Bin Othman, et al [12] proposed FPGA technique implementation for MRI brain image classification. They used an input dataset consisting of axial, T2 FLAIR weighted, 256x256 pixels. The input dataset consisted of MRI images 32 patients (22 abnormal and 10 normal). The abnormal brain images set consist of images of brain tumour. Asymmetry beyond a certain degree is a sure indication of the diseased brain and this has been exploited in their work for an initial classification at a gross level. The system used Field Programmable Gate Array (FPGA) that is a programmable logic device. FPGA offers more narrow logic resources and a higher ratio of flip-flops to logic resources. It can be implemented as many multipliers as that are necessary in order to calculate one pixel. Each of the images produced 17689 wavelet approximation coefficients. The matrix of coefficient is 133x133 double. They implemented FPGA as hardware re-configurable, so that technology would help to manage image processing in a number of medical applications. For classification Support Vector Machine is used by the author. Accuracy obtained by this system is 65%.

2.7 PCA, LDA & SVM based system

V.P. Gladis Pushpa Rathi, and Dr.S.Palani [13] proposed a technique using Linear Discriminant Analysis (LDA). The author focussed on feature extraction and feature selection techniques by which accuracy could be improved. Experiments were conducted on MR images collected from 20 different patients with gliomas. Each patient had 3 sequences of MR images T1, T2 and FLAIR. Each volume contains 24 slices in axial plain with 5 mm slice thickness. Size of the matrix used was 192*256*192. Each set of features are individually normalized to the range of 0 to 255. The author used normalization to make feature extraction much simpler. In this proposed method, they extracted features such as shape, intensity, and texture. In forward feature selection, features were assumed to come from normal distribution with unknown, but equal variances. If the correlation among features is ignored, redundant features can be inevitably selected. So the method is applied to select the more discriminative feature. In backward selection, among the entire set of variables, each step removes the one that decreases the error the most, until any further removal increases the error significantly. Principal Component Analysis is used in this proposed method. Principal components are the projection of the original feature onto the eigen vectors and correspond to the largest eigenvalues of the covariance matrix of the original feature. PCA can be used to approximate the original data with lower dimensional feature vectors. For image classification, Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) were used. LDA methods were used in statistic, pattern recognition, and machine learning to find a linear combination of features. The accuracy obtained by using LDA is 98.8%, and the accuracy achieved by using LDA & SVM is 96%.

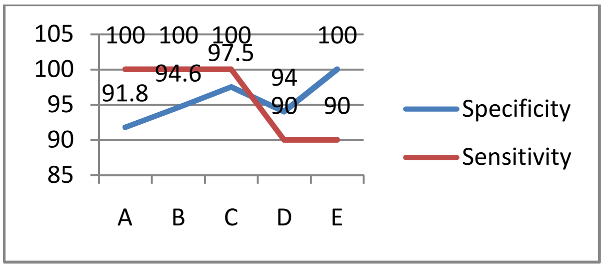
III. RESULTS AND RECOMMENDATIONS FOR FUTURE WORK

Fig 3.1 depicts the graph that shows the comparison between the performances of the studied systems in terms of accuracy. The performance comparison of 2 systems [9, 10] in terms sensitivity % and specificity % is depicted in the graph shown in Fig 3.2. In this work, the merits and demerits of various automated techniques for brain tumour identification is analyzed in detail. The performance of the various proposed systems are compared by using three parameters such as accuracy, sensitivity and specificity. Many novel hybrid approaches may be developed from the ideas conveyed in this report.



A)DAUB4, SVM; B)DAUB4, PCA, SVM; C)Histogram equ, DWT, PSO, SVM; D)HAAR function, PSO, SVM; E)DWT, PCA, FP-ANN; F)DWT, PCA, k-NN;
G) PCA, LDA, SVM

Figure: 3.1 Comparison of various classification techniques based on Accuracy in %



A)SGLDM,GA,SVM B) WT,SGLDM,GA,SVM C)SVM,PSO D)DWT,FP-ANN E)DWT,k-NN

Figure: 3.2 Comparison of classification techniques based on Specificity and Sensitivity in %.

A review of the factors influencing the total efficiency shows that there are some major aspects which appear to control the future trends of MRI tumour classification. Research should be directed towards the identification of the combination of the following design and parameters in future development in MRI classification systems:

Image acquisition	Proper positioning and orientation with appropriate exposure
Image pre processing	Noise removal, background removal, image enhancement.
Segmentation	Image transformation, edge detection, object localization
Feature extraction & selection	Identification of features, excluding irrelevant features, strong feature, reducing feature vector dimensions
Classification	Feature analysis, assigning weightage for features, choice of classifier, and classification techniques analysis of classifier.

IV. CONCLUSION

Brain tumour is one of the major causes of death among the people. It is found that chances of survival can be increased if the tumour is detected correctly at early stage. MRI is efficient in diagnosing the location and size of the tumour but it is very difficult to classify the tumour type. In this survey DWT and HAAR wavelet based diagnosis methods were reviewed. Their performance were compared and analysed for all

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the classifiers. Of all the classifiers, SVM performed the best, giving a maximum of 97.5% accuracy and 97.5% specificity. The report of the study shall be fruitful to researchers in the area of brain MRI image classification. The causes and effects given and the contributing factors highlighted may be deployed in developing efficient brain MRI classifiers. Future work focus on exploiting efficient methods in achieving better results for brain MRI classification of brain tumours.

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