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An Efficient Approach for Classification of Brain MRI Images

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Abstract— Automatic identification of brain diseases through image processing has become a pivotal phase of diagnosis of brain illness. Classification of brain MRI images can provide a greater strength in diagnosis of brain problems for further stages of treatment Image classification can play a very important role in medical imaging by identifying the cancerous brain slices and non cancerous. Although there are some other important stages in medical imaging analysis but after performing a better classification, the process of analysis would provide an enhance result The proposed work includes an approach to classify the brain MRI images in two categories namely as normal and abnormal. It consists of three stages pre-processing, feature selection and application of supervised classification based on selected features. The pre-processing stage includes an image enhancement using Gaussian filter and contrast stretching. Next step is extracting features using gray level co occurrence matrix of each MRI image and finally followed by a supervised classification using feed forward Neural Network using scale conjugate gradient descent as learning algorithm The performance evolution of this research, work 50 MRI slices of both tumour and non tumour have been used. The experimental data for the research work has been taken from Harvard Medical School database which is available publically for research purposes Since the classification is feature dependent which leads to selection of most effective features, an improper selection of features leads to an extra computation to algorithm. Subsequently there will be need for a feature reduction process to reduce less important features; it also leads to an extra computation. Thus here a method is introduced having no inclusion of any feature reduction process, with an effective selection of features. A better selection of features omits an extra function of feature reduction techniques. The result of classification over the total slices of brain MRI reveals following important aspects about brain; first whether it is normal or there is any abnormalities and criticality of the disease present.
The proposed technique has shown a result of 100% accuracy over classification of Brain MRI images to normal and abnormal.

Keywords— Image Processing, Image Classification, Feature Extraction, Brain MRI, GLCM based feature Extraction,

I. INTRODUCTION

Imaging has strengthen the medical science through the visualizing the structure of human anatomy. Clinical diagnosis and evaluation of various therapy supported using various imaging modalities. Some imaging techniques are CT (computed tomography), PET (positron emission tomography), X-Ray imaging, MRS (Magnetic Resonance Spectroscopy) and MRI (Magnetic Resonance Imaging) etc [1]. All these imaging techniques have their own specifications. X-Ray best suited for study of human skeleton system, except in case of Brain imaging MRI has been opted for its better result in medical analysis of brain. MRI has been proven for examination of brain infirmity. MRI is especially capable for soft tissues of brain whether presence of abnormalities. Medical imaging result is very much affected and attentive during the diagnosis phase of a patient. A human brain can be attacked through various kind of illness which can be cancerous or non cancerous or normal. The important aspect of diagnosis is to provide a differentiated result of these two categories, before the further stage of treatments. Some most important steps are enhancement of generated medical image, identification of area of interest, selection of affected area, and classification of medical images. In the diagnosis of brain infection, radiologist needs information gathered using MRI slices of brain. Although MRI equipment generates all slices of brain but, all of them do not acquire abnormality, as a result the classification stage has become an important phase. Since Manual classification of all the slices is complex and time consuming stage.

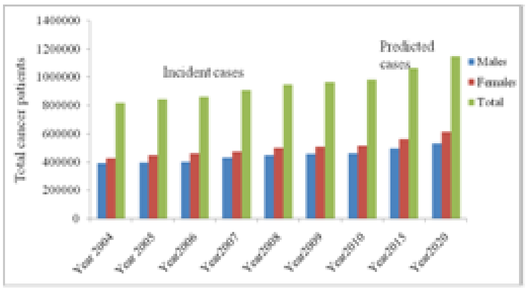


Figure I (a)

Figure I (a) represents data of cancer patients observed from 2004 to 2009 over a period of 5 years in India. Based on trends of increasing the number of cases in last few decades, an approximated number of cancer patients have been predicted for the next period of ten years. This report is generated by Indian Council of Medical Research [3].

Magnetic resonance imaging (MRI) is new and harmless imaging technology as compared to other technology that consent to radiologists to perform analysis at the soft tissue present in human body. MRI imaging tool is slightly different with respect to other medical imaging techniques i.e. in the case X-ray radiations are very harmful due to its nuclear radiation whereas in case of MRI machine implementing technique depend on property of Hydrogen atom. They move in random direction and emit some kind of electrical signal. The MRI machine designed in such a way that it easily detect electrical signal using magnetic field within it. A machine dedicated for image processing uses these signals to generate a detailed image of soft tissues. MRI has greatly made improvement in the diagnosis process and enhances the ability of the doctors to analysis of soft tissues [4]. Medical imaging is basically divided in two classes as anatomical and physiological. The human brain has maximum part having soft tissue. Brain consists of three main part white matter (WM), gray matter (GM) and cerebrospinal fluid (CF). MRI is best suited to classify these three types of tissues. Due to only these three components complexity of brain structure is much higher as compared to other part of body. Therefore the feature extraction becomes a much demanding task for purpose of classification [5]. In the diagnosis of brain disease the most dependent technology is MRI scanning. MRI generates MRI images as slices. The number of slices is depending upon the radiologist. Before proceeding to final decisive output for treatment stage based on the MRI output, the classification of MRI slices plays crucial role for further stages of treatments.

In this research work an enhancement approach for brain MRI image classification has been proposed, to classify the whole slices of brain MRI as normal and abnormal (having property of being cancerous). The proposed technique has been implemented using Feed forward Neural Network. The training algorithm put into operation to train the Neural Network is Scale Conjugate Gradient descent

II. LITERATURE REVIEW

The complete process of an image classification includes:

- Perform basic enhancement of all MRI images.
- Generating GLCM (Gray level co occurrence matrix) of each MRI slices.
- Feature extraction from the image i.e. MRI slices based on the GLCM calculated above.
- Creating input vectors through using features and images.
- Generate target vectors.
- Training of the Neural Network using input vector and target vector and perform classification.

There is no standard theory of image enhancement. After an image is being processed the viewer is final person to judge the image for a particular application. The purpose of enhancement of an image is not only to process the image for being more suitable but also more informative as per the application that uses that image. Various techniques are available as the combination of different filters and methods. Enhancement of images has two broad categories:

- Spatial Domain methods
- Frequency Domain

Spatial Domain:

Techniques depended on spatial domain are conceptually straightforward and simple to recognize and with having low complexity. The property of low complexity favors real time system application based image enhancement. These methods generally lack in providing sufficient robustness and imperceptibility requirements [26].

Frequency Domain:

Where as in case of enhancement techniques based on frequency domain involves a low complexity as compared to spatial domain based technique, easy to analyze and easy to modify through the modification of the frequency of pixel values in image. The major drawback includes its limitations in not being able to enhance all parts of image simultaneously and automating the enhancement procedure is also difficult [26].

There are various techniques of feature extraction from an image. Some important techniques are DWT (Discrete Wavelet Transform), GLCM (Gray level Co occurrence Matrix). These two are most powerful techniques used for purpose of feature extraction from MRI images. After extracting statistical features the role of feature reduction technique comes in, it tries to reduce less centric features form all the features, and ultimately reduce the dimension of the data. Some renowned techniques are PCA (Principal Component Analysis), LDA (Linear Discrimination Analysis), and probabilistic PCA etc.

The process of classification can be categorized in two parts as supervised classification and unsupervised classification. In supervised classification training of the classifier is done through the input data, target data and features extracted from the data. In this research the input data are MRI images. Unsupervised classification comes in the case where there is less information in the area to be classified.

Recent researches made known that the process of classification of brain MR images is possible through supervised techniques such as artificial Neural Network and Support Vector Machine and unsupervised techniques like Self Organizing Map, and Fuzzy C-Means. Other supervised technique is k-Nearest Neighbor is also used for classification of MR images.

1. MRI brain classification using Neural Network

In this paper Ibrahim et al. [9] proposed a Neural Network technique for the purpose of better classification of brain magnetic resonance images. The technique consists of three stages preprocessing, dimensionality reduction and classification. They apply the contrast adjustment in preprocessing stage. The result of the preprocessing has much sharper and contrast enhanced image. The dimensionality reduction is performed using PCA (Principal Component Analysis). PCA is one of most fundamental linear dimensionality reduction technique. In classification back propagation Neural Network has been implemented. The whole research is performed over MRI brain segital images. The experimental result of proposed algorithm has shown a efficiency with an accuracy of 96.33% in the classification.

2. Computer aided medical diagnosis tool to detect normal/abnormal studies in digital MR brain images

In this paper Gutierrez, Beltran [10] represent a medical system for the purpose of medical diagnosis through the process of classification brain images into normal and abnormal, to assist radiologists as pre stage in the process of brain diagnosis. The proposed method implemented using content-based image retrieval system; they design a useful tool for radiologists. The first step generate the feature vectors from MR image for the data to train and test, then as second step features vector of training data are indexed within the module of CBIR (Content Based Image Retreival). The third step initiate the training, as the fourth step the test data set is classified with trained data. At the final stage, the classified result of brain MRI is presented with a set of some similar images of the query as output. The result obtained is very efficient for classification. The result shows that the proposed model is effective as a software tool to aid support to medical diagnosis.

3. Artificial Neural Network design for classification of brain tumor

The main objective of this study is to examine the pros and cons of two algorithms in a variable environment. Here Deepa and Devi [11] develop the system to exploit the capability of Back Propagation Neural Network and Radial Basis Function Neural Network for task of classification of brain magnetic resonance image to either cancerous or non cancerous. The major problem of the classification is optimal selection of features to describe the images. Classification is done on basis of symmetry of the brain image. The results demonstrate that performance of Radial Based Function Network (RBFN) is better when compared with the Back Propagation Network (BPN) with the classification accuracy.

4. Improvement of MRI brain classification using Principal Component Analysis

In this paper, Chun et al. [12] proposed a comparative study of hybrid technique to classify the brain magnetic resonance image. In this paper the comparison is performed in dimensionality reduction stage of the classification process. First the result is computed with dimension reduction using PCA (Principal Component Analysis). In second same is calculated without using PCA. In the final stage the two results are compared and it is found that the PCA incorporated result evident that it helps reduction of feature dimensions to an optimal level. The classification is done using SVM (Support Vector Machine)0. It's concluded that the PCA can be used for the dimension reduction of the feature in much better way.

5. Extension Neural Network approach to classification of brain MRI

Since MRI has capability to generate multiple slices of same section of tissues. As a consequence the analysis of the slice becomes more complicated. In this paper Wang et al. [13] present a solution to this drawback by implementing Extension Neural Network theory. The intent of this term paper is to combine the Artificial Neural Network and the Extension Theory. The concept of adding a double layer Neural Network with extended distance will enhance the training interval for Neural Network and also make the recognition rate high.

6. Classification of brain cancer using Artificial Neural Network

Joshi et al. [14] here presented a computer based system to classify various types of brain tumor using magnetic resonance image. The features are extracted using Gray Level Co- occurrence Matrix. A Neuro Fuzzy Classifier is developed for the classification. The whole technique is sub divided in two phases, first phase of learning and training, based on the features evaluated using GLCM and the second phase of recognition and testing of the affected MRI images. The system designed is tested efficiently for the classification of the brain MRI having any abnormalities. The scope of the system can be advanced to improve using some other medical images.

7. Brain tumor detection using unsupervised learning based Neural Network

In this paper Goswami and Kumar [1] present classification technique for brain MRI based on unsupervised learning based Neural Network. This work divides the brain diagnosis process in following stages. First stage includes the preprocessing of the MRI image using basic enhancement technique Histogram Equalization, edge detection and noise filter. In second stage the features of the MRI images are calculated using Independent Component Analysis. In third stage the diagnosis of the brain accomplished using Self Organizing Map. Finally for the segmentation of the different brain tissues are performed using k-Means Clustering algorithm. The proposed system is more appropriate for classification of MRI images. The accuracy of classification using this hybrid technique is 98%.

8. MRI brain classification using Support Vector Machine

In this paper Nandpuru et al. [15] proposed a classification technique using SVM (Support Vector Machine) with linear and different kernels, to identify the normal and abnormal of brain MRI images. The technique follows the three stages method of image classification. The stage of feature extraction is performed using GLCM and all the texture features are calculated. After sorting of all features the authors has applied the feature reduction through application of PCA (Principal Component Analysis). And finally the classification is done by applying SVM. The result is tested with SVM having different essence, linear, quadratic and polynomial. The final result shown is that quadratic kernel has maximum accuracy rate of classification.

9. Automated classification of MRI based on hybrid Least Square Support Vector Machine and Chaotic PSO

In this paper Sivapriya et al. [16] explore the implementation of (Least Square Support Vector Machine) training LS-SVM with Chaotic PSO (Particle Swarm Optimization) for the purpose of distinguish of brain MRI images. Implementing an efficient method is more objective than a manual process of medical analysis of the brain MRI. The whole projected algorithm includes three major steps feature extraction, feature selection and classification. The final result of classification is compared with two different classifiers SVM-PSO and LSSVM-PSO. The proposed technique i.e. LS-SVM have better performance as compared with above when it trained with Chaotic PSO, in term of parameter sensitivity specificity and accuracy.

10. Comparison of ANFIS and SVM for the classification of brain MRI pathologies

Lahmiri and boukadoum [17] perform comparison of Adaptive Neuro Fuzzy Interference System (AFNIS) and Support Vector Machine over the detection of anomaly within brain using MRI diagnosis. They perform the three stages, first feature extraction using Two Dimensional Discrete Wavelet Transform. Twenty features are extracted and then PCA (Principal Component Analysis) is applied to reduce the number of features and retain most specific ones. In the experimental result SVM leads over the ANFIS.

Multilayer Feedforward Neural Network explains itself, by exhibiting more than one layer in the network as the type of hidden layer whose processing unit is called as hidden neurons. Their function is to arbitrate between input and output in some useful manner. Adding hidden layers in network enables it to a higher order statistics. In some manner the Neural Network acquires a global prospective despite of some local level computation.

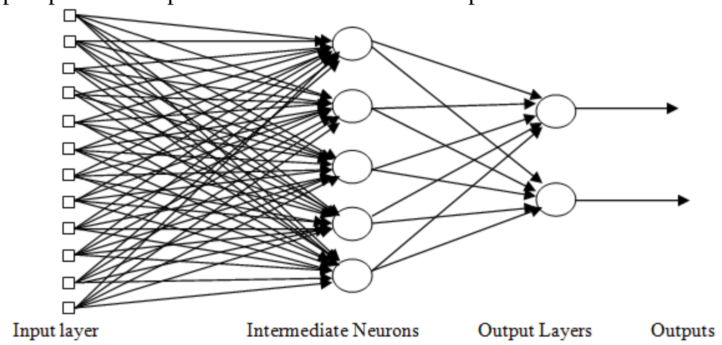


Figure: 2(a). Feedforward Neural Network with multilayer of neurons

Gray level co-occurrence matrix GLCM

GLCM is a statistical technique to compute the features of an image which takes into consideration of the relationship among the gray level i.e. pixel values, the GLCM called the gray-level spatial dependence matrix too. The GLCM detect some texture features of an image by computing from the gray level matrix through analyzing simply the connection between the pixels contain some specific value with each other in a particular fashion occur in the image.[8].

Matrix's dimension is number of gray level present in the image, i.e. the number of row and column of the matrix is equal to the intensity level i.e. gray level of the image. Due to the presence of grayscale image applied in this research work, the square matrix has the dimension of 8.

Gray-level Co-occurrence Matrix (GLCM) can be designed by computing some relationship between the number of the intensity (gray-level) value *x* occurs with the pixel having value y. In general case, the spatial relationship is defined a horizontal connection between two pixels, but one can define other spatial relationships between the two pixels. The value of the matrix element (*x*, *y*) is the total number of pixel with value *I* in specified spatial relationship to another pixel with value J within the same input image.

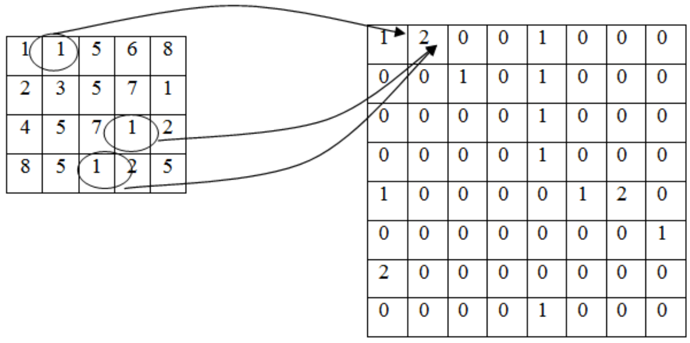


Figure: 2(b) Calculating Gray level matrix from an image [8]

III. PROPOSED METHODOLOGY

In the proposed system the technique applied to tackle the problem of Brain MRI classification consists of following stages:

- Preprocessing of MRI images
- Calculating Gray Level Co occurrence Matrix of MRI
- Calculating statistical features using GLCM
- Creating input vector
- Defining target vector depending on classes
- Defining Multilayer Feedforward Neural Network
- Perform training of Neural Network using Scale Conjugate Gradient Descent algorithm
- Perform classification using the trained Neural Network.

In this research work these two enhancement technique have been combined in one customized function to perform better enhancement to the input image.

The entire enhancement process is composite as follows

$X = imgaussfilt(I, 2);$

$S = I - X;$

$Y = 2 * S + X;$

$Final_{Im} = imadjust(Y);$

Where

X is processed image form function *imgaussfilt()* of input image I .

S is the difference of the original image I and X.

Y is intermediate processed image using images S and X.

$Final_{Im}$ is the final enhanced image for further stage of classification.

Extracting Statistical features using GLCM

The normalization of the GLCM is performed using *normc()* and after normalization this normalized GLCM is being used to calculate statistical features, and these features have employed to create the input vectors for the classifier.

These statistical features are listed below:

The mathematical formulation to compute the variance is

$$Variance = \sum_{i=1}^{G}\sum_{j=1}^{G}(i-\mu)^2 * P(i,j)$$

where

P(i, j) is the element of the Gray level Co occurrence Matrix at an index (i, j).

G is the number of Gray level in the grayscale image.

μ is the mean value of the Gray level Co occurrence Matrix.

The entropy is a scalar quantity which can be calculated from an image. Entropy can be defined as the statistical measure of randomness which is used to identify the feature the input image.

The mathematical formulation to compute the entropy is given by

$$Entropy = \sum_{i=1}^{G}\sum_{j=1}^{G}\log\big(P(i,j)\big) * P(i,j)$$

Homogeneity is defined as measurement of the closeness of the distribution of various values in the Gray level Co occurrence Matrix to its diagonal. The range of the value of homogeneity is always between 0 and 1.

The mathematical formulation of homogeneity is given by

$$Homogeneity = \sum_{i=1}^{G}\sum_{j=1}^{G}P(i,j)/(1+|i-j|)$$

Energy of a grayscale image can be calculated using Gray level co occurrence matrix as the sum of the square of the elements in that Returns the sum of squared elements in the Gray Level Co occurrence Matrix. The range of the value of energy is always between 0 and 1. Energy is 1 for a constant image.

The mathematical formulation is given by

$$Energy = \sum_{i=1}^{G}\sum_{j=1}^{G}P(i,j)^2$$

Contrast is defined as the measure of the intensity between two pixels adjacent to each other in an image; here the measurement is performed over the indices values in Gray level matrix.

The mathematical formulation is given by

$$Contrast = \sum_{i=1}^{G}\sum_{j=1}^{G}|i-j|^2 * P(i,j)$$

The correlation is defined as how the pixels are correlated to each other over the whole. Mathematical definition is given by

$$Correlation = \sum_{i=1}^{G}\sum_{j=1}^{G}[(i-\mu_i)(j-\mu_j) * P(i,j)]/(\sigma_i * \sigma_j)$$

where

$$\mu_i = \sum_{i=1}^{G} iP_i\,(i)$$

$$\mu_j = \textstyle\sum_{j=1}^{G} jP_j\,(j)$$

$$\sigma_i = \textstyle\sum_{i=1}^{G}\left(P_i(i) - \mu_i(i)\right)^2$$

$$\sigma_j = \sum_{j=1}^{G}\left(P_j(j) - \mu_j(j)\right)^2$$

$$P_i(i) = \textstyle\sum_{j=1}^{G} P(i,j)$$

$$P_j(j) = \textstyle\sum_{i=1}^{G} P(i,j)$$

It can be defined as variation in gray level pairs of an image. It is very much similar to contrast with a difference in weight that contrast grows quadratically.

Mathematical definition of dissimilarity is given by

$$Dissimilarity = \sum_{i=1}^{G}\sum_{j=1}^{G}|i-j| * P(i,j)$$

Inverse difference moment is very much influenced from homogeneity. It is also called local homogeneity. Since the weighting factor $(1+(i-j)^2)$ make contribution in local homogeneity, it makes a different as compared to homogeneity.

Mathematical definition of Inverse Difference Moment is given by

$$Inverse\ Difference\ Moment = \sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j)/(1+(i-j)^2)$$

Creating Input Vector

To create input vector all the eight features are used by generating a matrix having dimension 8x50 where 8 represent the number of features and 50 represent the total number of MRI images over which the research has been carried out.

Defining Target Vector

The target vector defines the classes through which the procedure of the classification of the brain MRI has been performed. The target vector is a matrix of having its element 0s and 1s with dimension of *mxn.*

Where

m is the number classes to which the brain MRI images are being classified.

n is the number of images slices of the brain MRI images.

Classification Stage and training of Neural Network

The classification stage is performed using Multi Layer Feed Forward Neural Network using the MATLAB function called *nprtool()*. The training of the Neural Network is being performed using Scale Conjugate Descent Gradient Algorithm.

All execution performed within the environment provided by MATLAB application.

IV. RESULT AND ANALYSIS

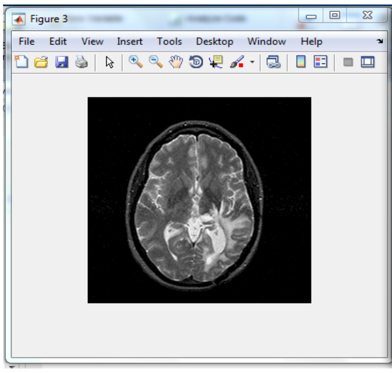


Figure IV (a)

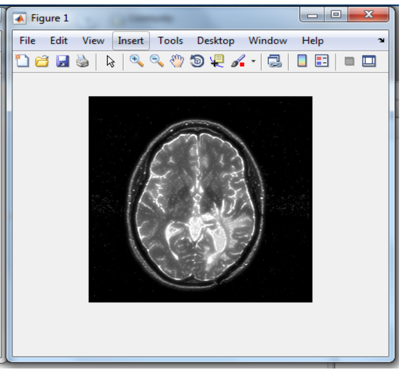


Figure IV (b)

The Figure IV (a) is the original MRI image taken from the source Harvard Medical School and the Figure IV (b) represents the preprocessed image of the brain MRI as a result of the preprocessing stage. The customized function applied here is *funcEnhance()*, which employ two predefined function *imgaussfilt()*, and *imadjust()*.

The classification of brain MRI is being performed through supervised technique, Feedforward Neural Network. The whole experiment is operated over fifty MRI slices of brain MRI. The MRI database is obtained from the Harvard Medical School open source, where it made publically available only for the research scholars.

The result of the classification is elaborated through the confusion matrix with the parameters sensitivity, specificity and accuracy. In the field of Machine Learning a confusion matrix is a special kind of error matrix which can always be used in problem of pattern classification. In case of the classification based on supervised techniques it is called confusion matrix. The row and column of the confusion matrix are known as the number of objects in actual class and number of objects in predicted class respectively after the classification

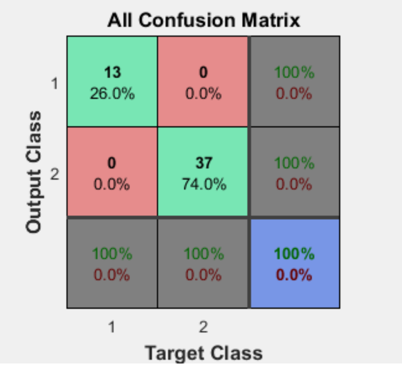


Figure IV(c) The confusion matrix for the classification

Figure IV (c) represents the overall results of the 50 brain MRI slices using the confusion matrix. The row element represents the number of objects in actual class and the column element represents the predicted number of the objects of the same class.

Here

Class 1 represents normal brain MRI slices

Class 2 represents abnormal brain MRI slices i.e. having any kind of abnormalities.

TP = 37,

TN= 13,

FP = 0,

FN= 0,

Where

TP – True positive i.e. correctly classified positive cases

In the confusion matrix TP represents element [2, 2] of the confusion matrix.

TN – True negative i.e. correctly classified negative cases

In the confusion matrix TN represents element [1, 1] of the confusion matrix.

FP – False positive i.e. incorrectly classified negative cases

In the confusion matrix FP represents element [1, 2] of the confusion matrix.

FN – False negative i.e. incorrectly classified positive cases

In the confusion matrix FN represents element [2, 1] of the confusion matrix.

$Sensitivity = TP/(TP + FN)$

The parameter sensitivity is statistical measurement of performance in case of binary classification. The sensitivity measures the positive cases that are correctly classified in the binary classification e.g. number of affected MRI slices which correctly identified in classification as true positive. From the result obtained:

Sensitivity = $\frac{37}{37+0} * 100$ = 100%

The sensitivity value 100% signifies that the all the affected brain MRI slices are correctly classified within defined class as the positive cases without missing any single slice.

$Specificity = TN/(TN + FP)$

The parameter sensitivity is also statistical measurement of the performance in case of binary classification. The sensitivity measures the negative cases that are incorrectly classified in the binary classification e.g. number of healthy MRI slices which correctly identified in classification as true negative. Specificity calculated from the result obtained:

Specificity = $\frac{13}{13+0} * 100$ = 100%

The Specificity value 100% signifies that the all the healthy cases of brain MRI slices are correctly classified within defined class as the negative cases i.e. having no any positive case of found in the slices.

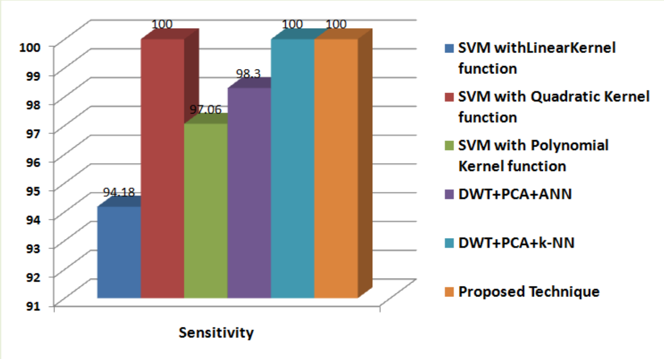
$Accuracy = (TP + TN)/(TP + TN + FP + FN)$

Accuracy is one of the statistical parameters for analyzing the performance of the binary classification. It measures the number of objects which are correctly classified in the defined classes.

Accuracy = $\frac{13+37}{13+37+0+0} * 100$ = 100%

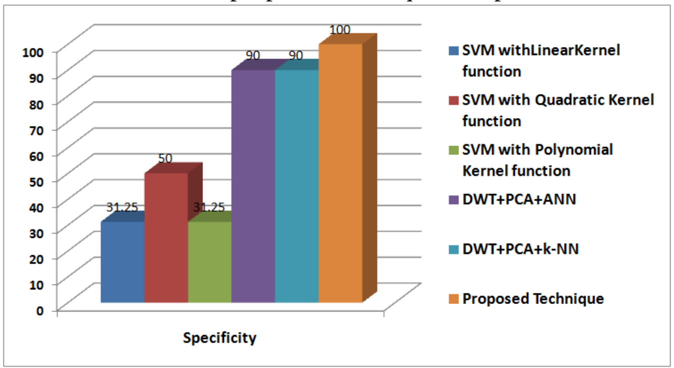
The Accuracy value 100% signifies that the all the healthy cases of brain MRI slices are correctly classified within defined class as the negative cases i.e. having no any positive case of found in the slices and all the positive cases are correctly classified as the affected brain MRI slices i.e. having any kind positive case are categorized correctly within their class.

The performance of the classifier and classification results of various classifiers is being evaluated.



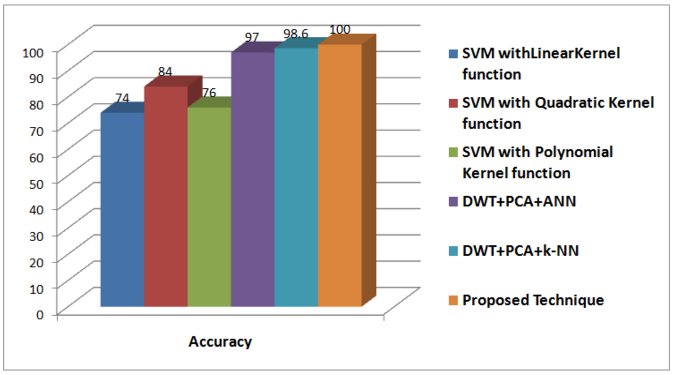
Graph IV (a) Performance comparison of various classifiers in term of sensitivity

Graph IV (a) presents the comparative analysis of various classifiers applied over the classification of brain MRI images. The complete analysis of this graph explained the performance in term of the parameter sensitivity. The comparative analysis is done basically with three classifier having different aspects involved in the process. These three are SVM, Artificial Neural Network and k-Nearest Neighbor. In all the 6 cases sensitivity in the case SVM is with its three different Kernel functions i.e. SVM with Linear Kernel, SVM with Quadratic Kernel and SVM with Polynomial Kernel shows that the SVM with Non-linear Kernel function is better as comparison with SVM with Linear Kernel. The ANN (Artificial Neural Network) classifier with PCA (Principal Component Analysis) as feature reduction and DWT (Discrete Wavelet Transform) as feature extraction is performed efficiently on sensitivity based. The k-NN (k-Nearest neighbor) also performed same level as ANN. The proposed technique also performed at the same level.



Graph IV (b) Performance comparison of various classifiers in term of specificity

Graph IV (b) presents the same comparative analysis of various classifiers applied over the classification of brain MRI images. Here the graph explained the performance in term of the parameter specificity. The comparative analysis is done basically with three classifier having different aspects involved in the process. In the analyzing the performance based on specificity the performance of the SVM classifier is lower as compared to the other two ANN and k-NN classifiers. The ANN (Artificial Neural Network) classifier with PCA (Principal Component Analysis) as feature reduction and DWT (Discrete Wavelet Transform) as feature extraction is performed efficiently on specificity based. The k-NN (k-Nearest neighbor) also performed same level as ANN. The proposed technique has a performance level is higher than all the three different classifiers.



Graph IV (c) Performance comparison of various classifiers in term of accuracy

Graph IV (c) presents the same comparative analysis of the same three classifiers applied over the classification of brain MRI images. The analysis of this graph explained the performance in term of the parameter accuracy. In the case of accuracy of the classifier in classification the SVM applied with Linear kernel and Polynomial Kernel shows similar level of performance in correct classification where as the SVM with quadratic Kernel function performed better than the other two SVM configurations. The ANN (Artificial Neural Network) classifier with PCA (Principal Component Analysis) as feature reduction and DWT (Discrete Wavelet Transform) as feature extraction is performed efficiently on accuracy based i.e. the result of classification is much better than the three SVM configurations. The k-NN (k-Nearest neighbor) also performs up to some extent of similar level as ANN. The proposed technique performed higher than all the three different classification techniques in context with the classification accuracy.

From the performance level of the proposed technique i.e. application of ANN as a classifier for the binary classification can perform better in absence of the feature reduction technique applied to reduce the features.

Table: IV (a) Table of comparison of various classifiers

Sr. No	**Name of the Classifier to classify the brain MRI**	**Sensitivity**	**Specificity**	**Accuracy**
1	SVM with Linear Kernel function	94.18%	31.25%	74%
2	SVM with Quadratic Kernel function	100%	50%	84%
3	SVM with Polynomial Kernel function	97.06%	31.25%	76%
4	DWT+PCA+ANN	98.3%	90%	97%
5	DWT+PCA+k-NN	100%	90%	98.6%
6	Proposed Technique	100%	100%	100%

Table IV (a) indicates the comparative performance of the various classifiers mainly ANN (Artificial Neural Network), k-NN (k-Nearest Neighbor) and SVM with different Kernel functions.

The performance of SVM is very much influenced from the Kernel functions. SVM has much flexibility by introducing the Kernels since the Kernel implicitly contains non linear transformation. With selection of an appropriate kernel function the performance of SVM can be enhanced. But the non parameterization property of the SVM has lack of transparency in the results. The result of SVM much dependent on the degree of the kernel functions as it can be observed from the table. In case of multidimensionality data the SVM lacks behind ANN in binary classification same with the K-NN. ANN without the use of dimension reduction technique can perform better than the technique ANN having dimension reduction technique. SVM and k-NN are also show a dependency nature on these reduction techniques like PCA and DWT. But with application of ANN an optimal selection of features can greatly improve the results in absence of these dimension reduction techniques. Since ANN shows less dependency on these dimension reduction techniques as compared to other two classifiers.

V. CONCLUSION AND FUTURE SCOPE

In this research work the categorization of brain MRI images is performed. As found during the research survey related to the classification of brain MRI, almost all the previous techniques follow the process of feature reduction i.e. dimensionality reduction technique has been applied. But while working in this research effort the stage of the feature reduction has been omitted. It has been analyzed that the selection of optimal features diminishes the probability of implementation of the feature reduction techniques. In this whole procedure training of the Neural Network has been originated as the most crucial and dependent issue for the performance parameter.

Amplifies the input parameter for the Neural Network affects the estimation of the performance of the classification. The selection of the learning algorithm is very much dependent on the size of the data that has gone under classification. Scale Conjugate Gradient algorithm is performed and providing optimal result in case of the moderate size of the data as compared to other algorithm in same case.

Thus optimal classification of the brain MRI provides strength to the radiologist and physician and leads them to confident decision about the patient diagnosis. The radiologist can predict the patient’s situation better.

Although the classification of the brain MRI has performed optimal in detecting the abnormality however the algorithm of the classification of the brain MRI should be optimized for the all the brain disease. This optimization can be achieved through the perfect selection of the learning algorithm for the Neural Network Classifier. The result of the classification predicts the number of the slices having abnormalities. This result can further be utilized for detection of the brain tumor in human being whether it is critical and calculate the stage of the tumor i.e. the size and the critical level of the patients.

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