Classification of MRI Brain Images using Wavelet based Features

Naheeda PP, Thasneem Fathima

Abstract— Classification of brain images using Magnetic resonance Imaging (MRI) is a difficult task due to the variance and complexity of various disease like Tumor, Intracranial Bleed, Alzheimer's and Stroke. This study presents Artificial Neural Network (ANN) techniques, linear discriminant analysis and Support Vector Machine (SVM) for the classification of the magnetic resonance human brain images. The classification problem was addressed as two class and four class classification cases. The proposed techniques consist of three stages, preprocessing, Discrete Wavelet Transform based feature extraction and classification. Wavelet Transform is used to decompose the Image with Daub-4 wavelet. In the classification stage the Artificial Neural Network, Linear and SVM has been used as classifiers to classify subjects as normal, Tumor, ICB and Alzheimer's MRI brain images. In this study, MRI images collected from Moulana hospital, Perinthalmanna have been used for training and testing the proposed method. The result of the ANN classifier was compared with the results of linear classifier. By using SVM classifier the number of features being used was reduced comparing to linear classifier. An accuracy of 100% with sensitivity and specificity of 100% was achieved in this study using SVM classifier.

Index Terms— Artificial Neural Network, Linear classifier, MRI, SVM classifier, Wavelet Transform

1 Introduction

Magnetic resonance imaging (MRI) is a test that uses a magnetic field and pulses of radio wave energy to make pictures of organs and structures inside the body. In many cases, MRI gives different information about structures in the body than can be seen with an X-ray, ultrasound, or computed tomography (CT) scan. MRI also may show problems that cannot be seen with other imaging methods. For an MRI test, the area of the body being studied is placed inside a special machine that contains a strong magnet. Pictures from an MRI scan are digital images that can be saved and stored on a computer for more study. The images also can be reviewed remotely, such as in a clinic or an operating room. In some cases, contrast material may be used during the MRI scan to show certain structures more clearly. MRI is a noninvasive method for producing three-dimensional (3D) tomographic images of the human body. MRI is most often used for the classification of Normal, tumors, Alzheimer's, Intracranial Bleed and other abnormalities in soft tissues, such as the brain. Clinically, radiologists qualitatively analyze films produced by MRI scanners. Classification of brain images using MRI is a difficult task due to the variance and complexity of disease. The proposed techniques consist of three stages, preprocessing, Discrete Wavelet Transform based feature extraction, and classification

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This work presents Artificial Neural Network techniques, linear discriminant analysis and Support Vector Machine for the classification of the magnetic resonance human brain images. The result of the ANN classifier was compared with the results of linear classifier and showed that the classification accuracy of ANN is 100% when using DWT. SVM classifier can reduce the features and improve the accuracy of prediction. MRI medical imaging techniques is a relatively new technology with its foundations beginning during the year of 1946. Until the 1970s MRI was being used for chemical and physical analysis. Then in 1971 MRI was used to study different diseases. With the advent of computed tomography (using computer techniques to develop images from MRI information) in 1973 by Hounsfield, and echo-planar imaging (a rapid imaging technique) in 1977 by Mansfield. Many scientists over the next 20 years developed MRI into the present technology. Perhaps one of the most exciting developments of these was the advent of superconductors. These superconductors make the strong magnetic fields used in MRIs possible. The first human being MRI examination did not occur until 1977. The most significant advancement in MRIs occurred in 2003. Many methods have been proposed for classification for MRI brain images. This chapter briefly presents some of the methods used in classification for MRI brain images.

W. Yu and Y. Xiaowei [2] proposed Application of decision tree for MRI images of premature brain injury classification. To reduce background noise in the training set use optimization classification algorithm. Features extracted from the images include: angular second moment, inverse difference moment, and contrast ratio, entropy based on the gray-level co-occurrence matrix, and the 60-dimensional Gabor wavelet texture feature. Classification the input data set based on the generated decision tree and build a decision tree by using the training sets. B. Mohammad-Jafarzadeh et al [3] proposed a Spectral regression discriminant analysis for brain MRI classification. The primary features were obtained using a three-level-two-dimensional discrete wavelet transform. Dimension of primary feature vector was high-dimensional vector requires huge computational complexity. Spectral regression discriminant analysis was used to reduce the dimension and Support vector machine was used to classify low-dimension feature vector. Mubashir Ahmad et al [5] proposed a classification of Tumors in Human Brain MRI using Wavelet and Support Vector Machine. A Hybrid technique was designed for Feature extraction from MRI data set using Discrete Wavelet Transform Daub-4 Wavelet, Principle Component Analysis was used for feature reduction and Support Vector Machine for classification using two SVM kernel functions; Linear Kernel and Radial Basis Kernel. Classification accuracy of 98.7% with Radial Basis Kernel and by using SVM accuracy was 94.7 %. V. S. Takate and P. S. Vikhe [6] proposed a system for classification of MRI Brain Images using K-NN and k-means algorithm. They combined feature extraction techniques with classification and used segmentation techniques for diagnosis of the brain as normal or abnormal. Segmentation of MRI images was done using K-mean clustering. The k-nearest neighbor classifier was used to classify the MRI image as cancerous or non-cancerous. Properties of Image classification were calculated such as Accuracy, Sensitivity, Specificity, PPV (Positive predictive value), NPV (Negative predictive value), FPR (False predictive rate), Skewness, Kurtosis and Mattews correlation coefficient (MCC). Segmentation of MRI Brain images were done using k-means clustering. K-NN is a non-parametric or one of the simple machine learning method of classification. Classification was done by determining the k closest training vectors according to a suitable distance metric. Ms. Girja Sahu et al [7] proposed a system for Classification of MRI Brain images using gray level co-occurrence matrix (GLCM), Neural Network, Fuzzy Logic & Genetic Algorithm. The database contains both normal brain and abnormal brain images. Original brain images were converted to gray scale image. Features of the MRI brain images were extracted through gray level co-occurrence matrix (GLCM). Various features were extracted from the image such as Autocorrelation, Contrast, Entropy, Correlation etc. Genetic algorithm optimization technique was used to reduce the features which help for the classification purpose. Combined Neuro-Fuzzy classifier was used for the classification. Pravada Deshmukh and P. S. Malge [8] proposed a system for Classification of Brain MRI using Wavelet Decomposition and SVM. Segmentation was used to extract tumor region in brain, which is carried out by fuzzy c-means clustering algorithm. The features were extracted from horizontal vertical sub bands of the wavelet transform. The classifiers categorize the images as normal and abnormal and detect the location of tumor by fuzzy clustering. For the system, 45 images were considered for testing and 90 for training. The overall accuracy of the system was 93.33%. A. Kharrat et al [10] proposed a technique based on MRI brain tumor classification using Support Vector Machines and meta-heuristic method. 2D Wavelet Transform and Spatial Gray Level Dependence Matrix (DWT-SGLDM) was used for feature extraction. For feature selection Simulated Annealing (SA) was applied to reduce features size. The classification performance of 95.65 % was obtained with 7 of the whole available features. SVM classification was used to distinguish brain abnormality.

Majority of the reported classification methods fail to detect all the diseases under their test. The promising tendencies showed by some were marred by the computational complexities involved due to large number of features or classifiers requiring rigorous training. So there exists a need for more effective algorithm for classification of brain images.

2 MATERIALS AND METHODS

The main steps of a typical image processing system consist of three steps: Preprocessing, feature extraction and classification. MRI images of various diseases were obtained from Moulana Hospital, Perinthalmanna. After the preprocessing stage, wavelet-based features were extracted from these MRI images. These extracted feature values were then given to the classifier and the results were analyzed. Accuracy, sensitivity, and specificity of the classifier were found as their performance evaluation metrics. The image classification problem is addressed as two cases: two class classification and four class classification. In two class classification, normal and abnormal MRI images were used whereas in four class classification, normal, tumor, intracranial bleed and Alzheimer's images were used. The method used in this work is depicted in Figure (1) and (2).

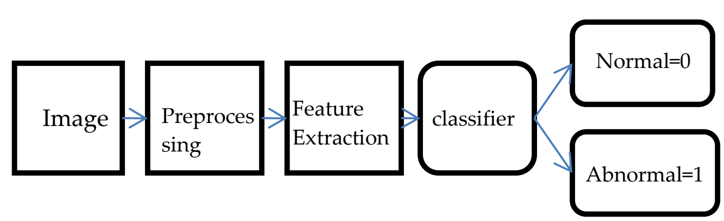


Fig1: Image processing system for normal and abnormal

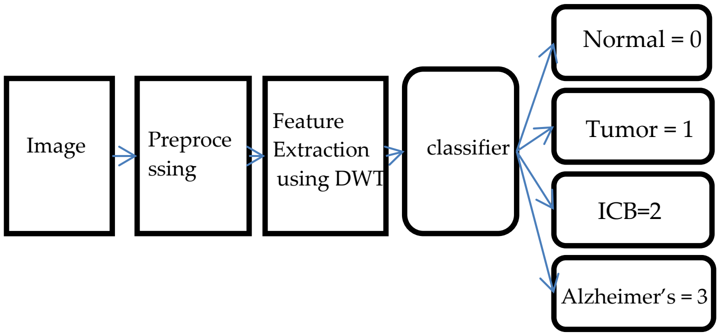
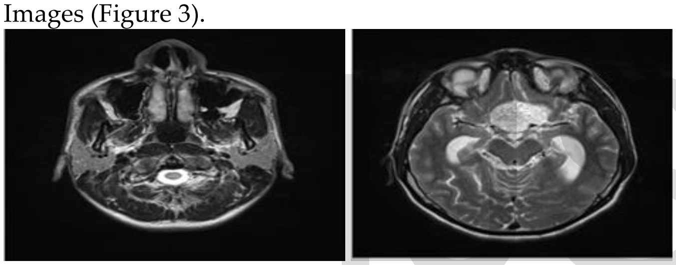


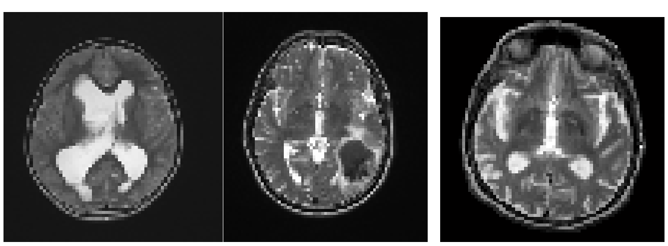
Fig2: Image processing system for 4 classes

2.1 Image Acquisition

The proposed method was applied to analyze the MRI images taken from Moulana Hospital. The data set consists of two sets of data. First set having 40 normal images and 40 abnormal images. The second set consists of 75 brain MR images in which 20 images with normal cases, 20 Tumor Images, 20 Intracranial Bleed Images and 15 Alzheimer's Images (Figure 3).



a: Normal brain **b: Abnormal brain**



c: Tumor d: Intracranial Bleed e: Alzheimer's

Figure: 3 Images of normal, abnormal, tumor, intracranial bleed and Alzheimer's

2.2 Pre-Processing

Median filtering is a nonlinear method used to remove noise from images. It is widely used as it is very effective at removing noise while preserving edges. It is particularly effective at removing 'salt and pepper' type noise. The median filter works by moving through the image pixel by pixel, replacing each value with the median value of neighboring pixels. The pattern of neighbours is called the "window", which slides, pixel by pixel over the entire image to pixels, over the entire image. The median is calculated by first sorting all the pixel values from the window into numerical order, and then replacing the pixel being considered with the middle (median) pixel value. In median filtering, the neighboring pixels are ranked according to brightness (intensity) and the median value becomes the new value for the central pixel. Median filters can do an excellent job of rejecting certain types of noise, in particular, "shot" or impulse noise in which some individual pixels have extreme values. In the median filtering operation, the pixel values in the neighborhood window are ranked according to intensity, and the middle value (the median) becomes the output value for the pixel under evaluation.

2.3 Feature extraction using dwt

Features are extracted for normal, Tumor, Intracranial Bleed, Alzheimer's & abnormal MRI images. Features are Mean, STD, kurtosis, MAD, Variance, RMS value, Entropy and Median. A wavelet transform have properties like Sub-band coding, Multi resolution analysis, Time frequency localization. The wavelet is a powerful mathematical tool for feature extraction and has been used to extract the wavelet coefficient from MR images. 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 origin of a wavelet transform that is restricted or localized is called the mother wavelet. Daub-4 wavelet is a family of orthogonal wavelets defining a discrete wavelet transforms and differentiated by a highest quantity of disappearance moments for some given support. Daub-4 are the best tool for feature extraction, due to this reason we decide to extract the Daub-4 wavelet coefficients of brain MRI and use these coefficients as feature vector for classification. Daub-4 Wavelet improves the low signals which are neglected by other Wavelet transforms because Daub-4 improves the contrast of an image. DWT is used as a first step to extract features from images. Fourier transform (FT) provides representation of an image based only on its frequency content. The FT decomposes a signal into a spectrum of frequencies whereas the wavelet analysis decomposes a signal into a hierarchy of scales ranging from the coarsest scale [5].

The continuous wavelet transforms of the signal $f(t)$ relative to a real valued wavelet $\varphi(t)$ is defined as,

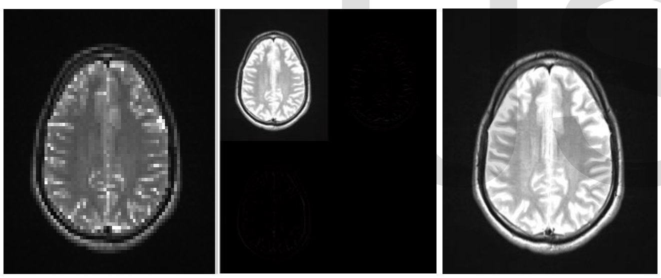
$$W(a,\tau)=\int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\varphi^*\left(\frac{t-\tau}{a}\right)\, dt$$

$W(a,\tau)$ is the wavelet transform, τ acts to translate the function across 'f (t)' and the variable 'a' acts to vary the time scale of the probing function φ . Equation can be discretized by restraining 'a' and 'τ ' to a discrete lattice $(a = 2^j \ \& \ \tau = 2^j k)$ to give the discrete wavelet transform and expressed as,

$$cA_{j,k}(n) = \left[\sum_n f(n) l_j^*(n - 2^j k) \right]$$

$$cD_{j,k}(n) = \left[\sum_n f(n) h_j^*(n - 2^j k) \right]$$

Here, $cA_{j,k}$ and $cD_{j,k}$ refer to the coefficients of the approximation components and detail components respectively. l (n) and h (n) denote for the low pass and high pass filters respectively. j and k represent the wavelet scale and translation factors respectively. The approximation component contains low frequency components of the image while the detailed components contain high frequency components. The original image is processed along the x and y directions by low pass and high pass filters which is the row representation of the image. In this study, a one-level 2D DWT with Daubechies-4 filters is used to extract efficient features from MRI. Sub bands obtained during feature extraction are shown in Fig.4 for a typical image.



(a) **(b)** **(c)**

Fig.4. (a) Normal brain image, (b, c) obtained sub band in One level 2D DWT

2.4 Ranking of features using T-test

Ranking features give the most significant features in sequential order. T-test is the absolute value of 2-sample test with pooled variance estimate.

$$\text{T-test value} = \frac{\text{Difference between means}}{\text{Variance}/\textit{Sample size}}$$

$$\bar{X}_1 - \bar{X}_2 \Big/ \sqrt{S_1^2/n_1 + S_2^2/n_2}$$

$\bar{X}_i$: Mean of the sample

S_i : Standard deviation of the sample

n_i : Sample size

After ranking the eight features using t-test class separability criterion, the most significant features were selected. These features were submitted to different classifiers. The results were compared with changing the number of features.

2.5 Classification

2.5.1 Artificial Neural Network classifier

ANN is based on a large collection of neural units (artificial neurons). In an ANN, processing element, weight, add function, activation function and exit nods are present respectively to neuron, synapse, dendrite, cell body, and axon in a biological neural network.

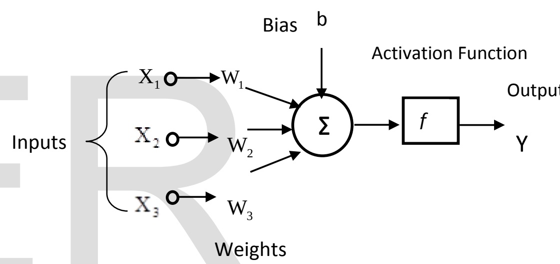


Figure 5 Artificial Neural Network classifier

An artificial neuron is a computational model, inspired by the natural neurons. Natural neurons receive signals through synapses located on the dendrites or membrane of the neuron. When the signals received are strong enough, the neuron is activated and emits a signal though the axon. This signal might be sent to another synapse and might activate other neurons. The higher a weight of an artificial neuron is, the stronger the input which is multiplied by it will be. Depending on the weights, the computation of the neuron will be different. There are weights assigned with each arrow, represent the information flow. These weights are multiplied by the values which go through each arrow, to give more or less strength to the signal which they transmit. The neurons of this network just sum their inputs [1].

$$v = w_1 x_1 + w_2 x_2 + \ldots + w_m x_m = \sum_{i=1}^{m} w_i x_i$$

The output is some function $y = f(v)$ of the weighted sum.

2.5.2 Linear classifier

In, linear classifier classification achieves by making a classification decision based on the value of a linear

combination of the characteristics. Linear classifiers work well for practical problems such as document classification, and more generally for problems with many variables (features), reaching accuracy levels comparable to non-linear classifiers while taking less time to train and use.
A classification algorithm that makes its classification based on a linear predictor function combining a set of weights with the feature vector

$$y = f(w.x) = f(\sum_j w_j x_j)$$

Where 'w' is a real vector of weights and '*f*' is a function that converts the dot product of the two vectors into the desired output. The weight vector 'w' is learned from a set of labeled training samples.

2.5.3 Support Vector Machine classifier

Support vector machines (SVMs) are a set of new supervised learning methods used for binary classification, regression and outlier's detection. SVM is strong because of its simple structure and it requires less number of features. SVM is a structural risk minimization classifier algorithm derived from statistical learning theory. Support Vector Machines is used to solve the pattern classification and regression problems [8]. SVM constructs a hyperplane or set of hyperplanes in a high or infinite-dimensional space, which can be used for classification, regression, or other tasks [5].
Given a training dataset of n points of the form $(x_1, y_1), \ldots\ldots, (x_n, y_n)$
Any hyperplane can be written as the set of points x satisfying

$$w.x - b = 0$$

Where 'w' is the normal vector to the hyperplane. The parameter 'b' determines the offset of the hyperplane from the origin along the normal vector 'w'

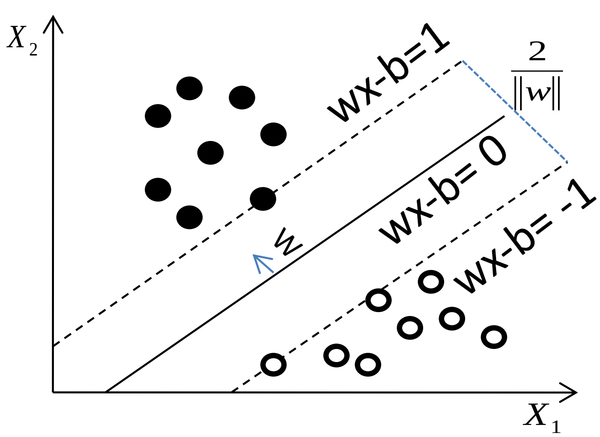


Fig.6. Linear SVM.
If the training data are linearly separable, select two parallel hyper planes that separate the two classes of data, so that the distance between them is as large as possible. The region bounded by these two hyper planes is called the "margin", and the maximum- margin hyperplane is the hyperplane that lies halfway between them.
These hyper planes can be described by the equations,

$$w.x - b = 1$$
$$w.x - b = -1$$

The distance between these two hyperplanes is $\frac{2}{\|w\|}$; to maximize distance is thus to minimize || w ||.

3 RESULTS AND DISCUSSION

Performance evaluation was done by using the metrics accuracy, sensitivity and specificity. The performance metrics Accuracy, Sensitivity and Specificity were calculated as shown below,

$$Sensitivity = \frac{TP}{TP + FN} * 100$$

$$Specificity = \frac{TN}{TN + FP} * 100$$

$$Accuracy = \frac{Sensitivity + Specificity}{2}$$

Where,
TP (True Positives) - Correctly classified positive cases
TN (True Negative) - Correctly classified negative cases
FP (False Positives) -Incorrectly classified negative cases
FN (False Negative) - Incorrectly classified positive cases.

1. For ANN 2-class classification: 20 images for normal and 20 images for abnormal were used. Considering eight significant features extracted from normal and abnormal images with enhancement such as mean, STD, kurtosis, MAD, variance, RMS, entropy, and median from the Ranking features and T-Test of table 1. In order to improve the results further, images were decomposed using wavelet. DWT was done using Daub-4 and images at LL level. Results of ANN classifier using eight significant features without DWT and with DWT is given in table 2.

Table 1: Feature ranking of Normal vs. Abnormal

Rank of the feature	Feature characteristics	T-test value
Rank 1	Mean	5.5839
Rank 2	Standard Deviation	5.3650
Rank 3	Kurtosis	3.7888
Rank 4	Mean Absolute Deviation (MAD)	3.6176
Rank 5	Variance	2.7687
Rank 6	RMS Value	1.8630
Rank 7	Entropy	1.7411
Rank 8	Median	0.9761

Table 2: Performance Evaluation using ANN Classifier

	Number of features	Sensitivity (%)	Specificity (%)	Accuracy (%)
ANN CLASSIFIR	8	87.5%	100%	93.75%
ANN CLASSIFIER with DWT	8	100%	100%	100%

2. For ANN 4-class classification: 20 normal cases, 20 Tumor Images, 20 Intracranial Bleed Images and 15 Alzheimer's Images were used. Results using ANN classifier using eight significant features for various diseases with enhancement and DWT is given in table 3.

Table 3: Confusion matrix using ANN with DWT of various diseases

		Predicted Result			
		Normal	Tumor	Intracranial Bleed	Alzheimer's
Actual Result	Normal	8	0	0	0
	Tumor	0	7	1	0
	Intracranial Bleed	0	0	8	0
	Alzheimer's	0	0	0	6

3. For Linear 2-class classification: 20 images for normal and 20 images for abnormal were used. Results of Linear classifier using eight significant features with enhancement is given in table 4.

Table 4: Performance Evaluation using Linear classifier

	Number of features	Sensitivity (%)	Specificity (%)	Accuracy (%)
LINEAR CLASSIFIER	8	100%	100%	100%

4. For Linear 4-class classification: 20 normal cases, 20 Tumor Images, 20 Intracranial Bleed Images and 15 Alzheimer's Images were used. Results using Linear classifier using eight significant features for various diseases with enhancement and DWT is given in table 5.

Table 5: Performance Evaluation using Linear classifier of various diseases with Enhancement and DWT

		Predicted Result			
		Normal	Tumor	Intracranial Bleed	Alzheimer's
Actual Result	Normal	8	0	0	0
	Tumor	0	8	0	0
	Intracranial Bleed	0	0	8	0
	Alzheimer's	0	0	0	6

Performance of 8significant features for various diseases with enhancement and DWT give 100% accuracy. Next attempt is to reduce the number of features. This is discussed in next section. Comparison between ANN and linear classifier is given in Table6.

Table 6: Comparison between ANN and linear classifiers

		ANN Classifier	Linear Classifier
2 class classification	Accuracy	93.75%	100%
	Time taken	4 Sec	3.35 Sec
Various diseases classification	Accuracy	89.5825%	96.875%
	Time taken	8 Sec	5Sec
Various diseases Classification using DWT	Accuracy	96.875%	100%
	Time taken	8 Sec	5Sec

5. For SVM 2-class classification: 40 images for normal and 40 images for abnormal were used. Confusion matrix for SVM classifier using four statistical features such as mean, STD, kurtosis and MAD is given in Fig 7 and corresponding results using SVM and multiclass SVM is given in table 7.

	Predicted Result		
Actual Result	TN=16	FP=0	16
	FN=0	TP=16	16
	16	16	

Fig 7: confusion matrix for SVM

SVM for multi class classification

1. One against all method

   i. It constructs k SVM models; k is the number of classes.

ii. The m^{th} SVM is trained with all of the examples in the m^{th} class with positive labels, and all other examples with negative labels.

iii. Minimizing $\frac{1}{2}(w^m)^T w^m$ means that maximize $2/\|w^m\|$ the margin between two groups of data.

iv. A penalty term $C\sum_{t=1}^{l}\xi_i^m$ can reduce the number of training errors.

v. Objective function: $\min \frac{1}{2}(w^m)^T w^m + C\sum_{t=1}^{l}\xi_t^m$

2. Load data (different cases).

3. Train the classifier with 60% of data.

4. Take remaining 40% data for testing the classifier.

5. The normal samples were identified with a 0, Tumor with a 1, Intracranial Bleed with 2 and Alzheimer's with 3.

6. Classify the test samples for different cases.

Table 7: Performance evaluation using SVM

	Number of features	Sensitivity (%)	Specificity (%)	Accuracy (%)
2 Class Classification-SVM with four statistical features	4	100%	100%	100%
Multi Class Classification-SVM with DWT	4	100%	100%	100%

4 CONCLUSION AND FUTURE SCOPE

Classification of brain MRI is a main problem for doctors and practitioners to get valuable results. Previously proposed systems have certain problems that require crucial investigation. This research work developed classification methods for normal and abnormal MRI brain images of 2 classes and 4 classes classification. Image pre-processing was used to improve the quality of images. Wavelet Transform was used to decompose the image with Daub-4 wavelet. Neural network gave more accuracy when using wavelet decomposition. Linear classifier gave result with better accuracy, more consistency, more reliability and slow processing time when compared to Artificial Neural Network classifier. The new method is a combination of pre-processing, Discrete Wavelet Transform and Support Vector Machine. SVM is supervising technique of classification. Number of features is being reduced using SVM classification compared to previous systems. An accuracy of 100% with sensitivity and specificity of 100% was achieved by using four wavelet based features and SVM in this study. Future research directions may include the development of a more simple classification method using lesser number of features and increase the number of images in the dataset. Also develop a hardware module incorporating the proposed method of classification MRI brain images.

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