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Texture Feature Extraction and Classification of Brain Neoplasm in MR Images using Machine Learning Techniques

Padmavathi K, Maya V Karki

Abstract*: *Identification of pathology in brain such as tumor lesions is a tedious task. MRI is most of the time chosen medical imaging procedure that often pacts with lenient tissues such as brain tissues, tendons and ligaments. This study aims at texture feature extraction and segregation of brain tumor cases into benign and malignant conditions. The stages involved are segmentation, feature extraction and classification. K-means clustering method is preferred for segmentation and selecting the required region of interest. The textural information is captured from region of interest using GLCM, HOG and LBP patterns. ANN, SVM and k-NN classifiers are used to analyze performance accuracy in classifying the tumor data into benign and malignant conditions in brain MR images. ANN with LM training algorithm provides high accuracy with best performance compared to other two classifiers in identifying benign and malignant conditions of tumors by using a combination of GLCM, LBP and HOG feature extraction process successfully. The recommended method is compared with few current approaches in terms of feature extraction and classification.

Keywords*: *Segmentation, Feature extraction, Tumor, MRI, classification.

I. INTRODUCTION

Brain neoplasm is a rapidly increasing disease among the children, adult and aged people. They are abnormal and uncontrolled growth of cells. Primary tumors are the once that initiate in the brain itself while secondary tumors are the once that blowout to brain from some other parts of the body. Benign tumors are primary tumors that are not cancerous and less harmful since they do not spread across the other cells. Malignant tumors are secondary tumors that are cancerous, harmful and also spread across other cells and tissues. Magnetic resonance imaging is a most time preferred and non-invasive medical imaging technique that represents high clarity images. The indications of lesions is precise and very high in MRI that assist the physicians to further diagnose the disease and make decisions for treatment. MRI scan is a more effective method when compared with CT and other imaging modalities. Different types of MRI scans that can be utilized are MR-T1, MR-T2, MR-GAD and MR-PD.

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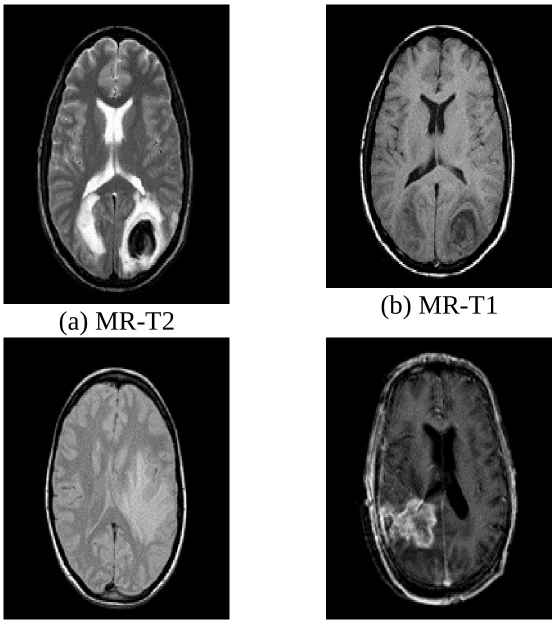
* Correspondence Author
Padmavathi K*, Department. of EC, NMAMIT, Nitte, Karnataka, India Email: padmavathik@nitte.edu.in
Maya V Karki, Department. of EC, Ramaiah Institute of Technology. Bengaluru, Email: mayavkarki@msrit.edu

T1 and T2 indicate the two relaxation times (longitudinal) and (transverse). Short time of echo (TE) and reflection time (TR) are used to generate T1 weighted images.

Long TE and TR time are used to generate T2 weighted images. These images highlight fat and water within the body and is brighter compared to T1 weighted images. Proton density (PD) MR image structure produces contrast, mainly by minimizing the impact of T1 and T2 alterations with long TR and short TE time. In MR-GAD, gadolinium are the chemical substances used in MR scans. The quality of MR images gets enhanced and improved when gadolinium contrast medium is injected into the body. The goal of this study is to design an accurate classifier system to extricate benign and malignant conditions in brain MRI images. Some of the important categories of MR imaging modalities such as MR- T1, MR-T2, MR-GAD and MR-PD with tumor lesions are depicted in Fig. 1. The structure of the paper is organized as follows. Related work is presented in section 2. A detailed description on suggested method is depicted in section 3.



(a) MR-T2 (b) MR-T1
(c) MR-PD (d) MR-GAD

Fig. 1. Different types of MR medical imaging modalities with tumor lesions [2]

Section 4 describes performance evaluation. Section 5 demonstrates the experimental results and describes the effectiveness of the suggested algorithm with conclusion.

II. RELATED WORK

Vast investigation is being carried out in the area of medical image processing. Disease identification and classification is one of the latest trends these days. Machine learning techniques helps to identify the pathology and show a path for treatment planning. In our work, we have considered MR brain images of different types such as MR-T1, MR-T2, MR-GAD and MR-PD with tumor conditions. The datasets are downloaded from publicly available whole Brain Atlas database http: //www.med.harvard.edu/aanlib/. The images considered for testing purpose has a spatial resolution of 256×256. MRI image shows the clear soft tissue details of brain slices. Several means have been presented for Classification of MR images with normal or abnormal conditions in the literature. It indicates methods to classify diseases such as Alzheimer's, Pick's disease, Parkinson's disease and Huntington's disease [3] and also to classify the tumor conditions as grade I or Grade IV or benign and malignant. Performance and accuracy varies depending on the type of data used, feature extraction methods and classification models framed. In [3], MR brain image classification system is intended to classify the images as normal or abnormal. The feature extraction techniques involved GLCM, LBP and HOG patterns [3]. K-NN classifier was used to classify images that showed 100 % accuracy. An automated method to classify cancerous and non-cancerous MR brain images is described in [4]. The features extracted are based on shape, texture and intensity. SVM classifier was applied with features with diverse cross validations that achieved an accuracy of 97 %. An automated and accurate classification system of MR images with different diseases is proposed in [5]. DWT features were extracted with PCA for dimension reduction. ANN with scaled conjugate gradient training algorithm was used as a classifier that achieved 100 % accuracy. A detailed review was described to classify high and low grade glioma tumor in MR images in [6].

Decision making using multiclass classification of brain tumors from MR images is presented in [7]. Segmentation is performed using gradient vector flow method. The segmented ROIs are then classified using PCA and ANN approach that provided 95 % accuracy. In [8], classifier performance was improved by extracting GLCM and DWT features from the segmented images. Probabilistic neural network classifiers were used to identify normal and abnormal tissues of brain that achieved 100 % accuracy. k-NN based classification of tumor condition is proposed in [9] that uses DWT and PCA for feature extraction and reduction. A hybrid approach of classifying brain tumor images is proposed in [10] that uses DWT and genetic algorithm for feature extraction with SVM as classifier. The hybrid approach optimizes the accuracy and reduces performance MSE. Classification of tumor images as benign or malignant is suggested in [11] that uses GLCM for feature extraction and neural network as classifier with 93.3 % accuracy. In [12] PCA and LDA are used for feature extraction with SVM as classifier that achieved 98 % accuracy. In [13], glioma classification of MR images has been conducted that achieved 89.95% accuracy. In [14-15], PCA and ICA with SGLDM for feature extraction is used that employs SVM as classifier. In [16], GLCM and Haralick texture features are extracted to classify brain tumors as benign or malignant conditions. The objective of the proposed work aims at combining DWT with GLCM, LBP and HOG methods to extract features from MR images and classify images using machine learning techniques to obtain best accuracy.

III. MATERIALS AND METHODS

The proposed scheme of classification is implemented on MR dataset that consists of modalities like MR-T1, MR-T2, MR-GAD and MR-PD with tumor lesions. The benign class consists of 87 images and the malignant class consists of 54 images. The datasets were downloaded from publicly available whole brain atlas database from Harvard medical school with website, http://www.med.harvard.edu/aanlib/ whose spatial resolution is 256×256. The planned scheme of classification is shown in Fig. 2. The major steps are segmentation of ROI, Extraction of intensity, texture and shape based features and classifying the tumors as benign or malignant conditions.

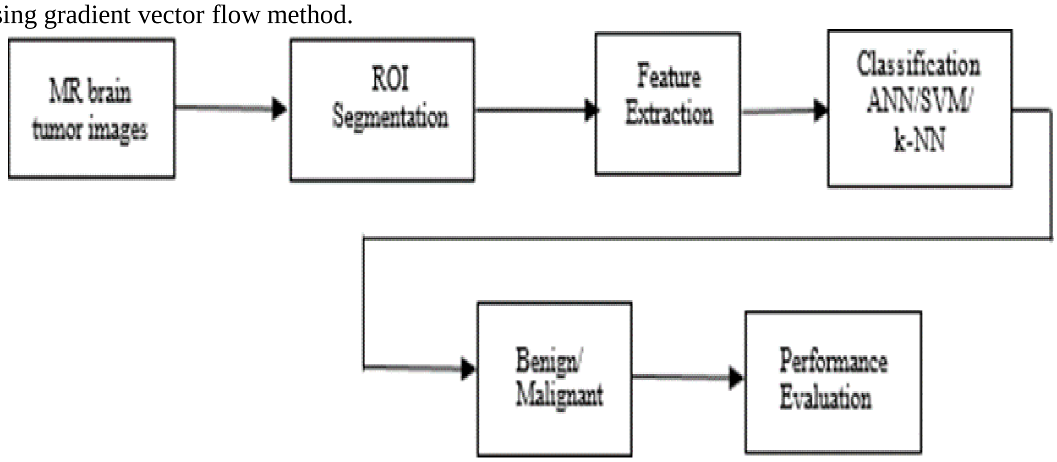


Fig. 2. Proposed classification system [16]

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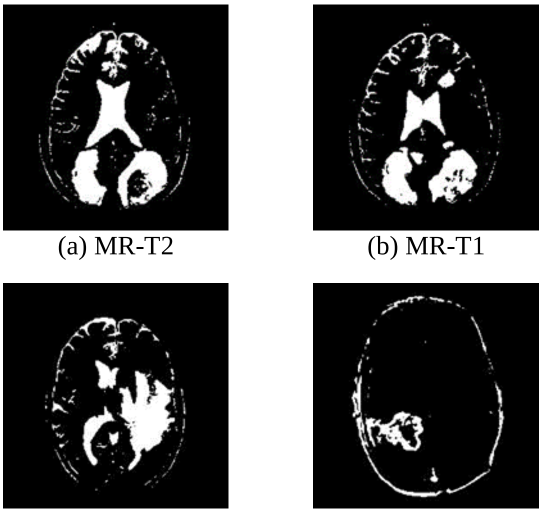
3.1 Segmentation

For each of the images, feature extraction follows once the segmentation operation is applied so as to improve the performance of classifiers. In this work, k-means clustering with Euclidian distance measure is applied to segment tumor area. It is one of the unsupervised learning algorithm that solves clustering problems and targets at minimizing an objective function given by

$$P(V) = \sum_{i=1}^{a}\sum_{j=1}^{a_i}\left(\|x_i - v_j\|\right)^2 \qquad (1)$$

Here, $\|x_i - v_j\|$ is the Euclidian distance between x_i and v_j. a_i is the amount of data points in the cluster and a is the number of cluster centers. Segmented MR images are as shown in Fig. 3.



(a) MR-T2 (b) MR-T1

(c) MR-PD (d) MR-GAD

Fig. 3. Segmented MR medical images with tumor lesions

3.2 Feature Extraction

One of the important steps in traditional machine learning approach is Feature extraction. Classification accuracy depends mainly on the extracted features. Feature extraction is a process where redundant free data are extracted based on edge information, texture, color, and border information of the given image. DWT is applied to the segmented images as they allow analysis at various levels of decomposition. Haar wavelet is used and the decomposition is carried out till third level to obtain DWT features. Gray level co-occurrence matrix (GLCM) features form the texture features. High level features extracted are Histogram oriented gradient (HOG) [1] and Local binary pattern (LBP) [1].

3.2.1 Grey-Level Co-occurrence Matrix

It is a statistical method that considers the spatial relationship of pixels in the texture. The GLCM is a 2D histogram that illustrates the texture of an image by calculating how repeatedly pairs of pixel with precise values and in a specified spatial relationship occur in an image. The statistical features derived using GLCM are

- Contrast: Calculates the local variance in gray level co-occurrence matrix.

$$\sum_i\sum_j (i-j)^2 A(i,j) \qquad (2)$$

- Correlation: Identifies the joint probability occurrence of the specified pixel pairs.

$$\sum_{i,j}\frac{((i-\mu_i)(j-\mu_j))}{\sigma_i\sigma_j}A(i,j) \qquad (3)$$

- Energy: provides the sum of squared elements in the GLCM. It also finds uniformity.

$$E = \sum_i\sum_j A^2(i,j) \qquad (4)$$

- Homogeneity: Evaluates closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\sum_i\sum_j \frac{A(i,j)}{(1+|i-j|)} \qquad (5)$$

Here $A(i,j)$ is the element (i,j) of normalized symmetrical GLCM. The variables μ_i, μ_j are GLCM mean.

$$\mu_i, \mu_j = \sum_{i,j=0}^{N-1} i\, A(i,j) \qquad (6)$$

σ_i, σ_j are the variance of intensities of all reference pixels in the relationships that contributed to GLCM given by

$$\sigma_i^2, \sigma_j^2 = \sum_{i,j} A(i,j)(i-\mu)^2 \qquad (7)$$

3.2.2. Local Binary Pattern (LBP)

Local Binary Pattern is one of the important texture descriptors [1]. The operator interchanges the value of the pixels in an image with decimal numbers termed as LBP code. All the eight neighbors are compared with the central pixel. If the values of eight neighbors are less than central pixel, it is converted to a bit `0'. If the values are equal to or greater than central pixel, it is converted to bit `1'. Once a matrix of 0's and 1's are generated, from top left corner, all bits are arranged to form a binary number. A decimal value is generated by multiplying this binary number by powers of 2. Texture feature extractor are obtained from the histogram of these 256 labels. The histogram is normalized by L2 normalization method and then all the histograms are concatenated to generate the feature vector of entire window. In this work, for describing the segmented region using LBP operator, eight neighbors are considered. The LBP code is given by

$$LBP_{R,P} = \sum_{P=0}^{P-1} V\left(n_p - n_c\right) 2^P \qquad (8)$$

where, n_p is the neighborhood pixels in each block, n_c is the central value used for thresholding, P is the number of neighborhood pixels, ($P = 8$) is chosen at R. (For 3x3 cell R is 1). Co-ordinates for n_c are (0,0) and for n_p is

$$\left(x + R\cos\left(\frac{2\pi p}{P}\right), y - R\,Sin\left(\frac{2\pi p}{P}\right)\right) \qquad (9)$$

Binary threshold function is

$$V(x) = \begin{cases} 0, for\ x < 0 \\ 1, for\ x \geq 1 \end{cases} \qquad (10)$$

3.2.3. Histogram of Oriented Gradient (HOG)

Histogram of Gradient is a texture feature descriptor that counts the occurrences of gradient orientation in localized portion of an image [1]. The HOG descriptor decomposes an applied image into several squared cells. It computes the histogram of oriented gradients in each cell using a gradient filter. The horizontal and vertical gradients computed are

$G_i(i,j)$ and $G_j(i,j)$. Corresponding magnitude and angle of these gradients are computed as

$$|G(i,j)| = \sqrt{G_i^2(i,j) + G_j^2(i,j)} \qquad (11)$$

$$\theta(i,j) = \arctan\left(\frac{G_j(i,j)}{G_i(i,j)}\right) \qquad (12)$$

In this work, an image is divided into cells of 8×8 pixels. The orientation of histogram bins are set as 9 that are evenly spaced from 0^0 through 180^0. A single block is formed using a four connected cell and L2 norm technique is used to normalize the histogram of cells. The HOG feature vector of an image is formed by combining all the histograms together.

3.3 Classification

Three different classification models are used for the study on selected features. This helps to choose an appropriate classification strategy.

3.3.1. Artificial Neural Network

It is a supervised learning algorithm. It separates samples with different classes by finding common features between samples of known classes. The class labels help to indicate whether the system is performing correctly or not. Multilayer perceptron (MLP) uses feedforward neural network with backpropagation algorithm to classify tumor as benign or malignant. It has an input layer, several hidden layers and an output layer. Generally, one hidden layer with 10 neurons can produce excellent results. The power of the network can be increased with the growth in the number of neurons in the hidden layer. But more computations may result in over tting. Some of the commonly used training algorithms are Levenberg-Marquardt optimization (LM), Scaled conjugate gradient backpropagation algorithm (SCG), Gradient descent backpropagation algorithm (GD) and Conjugate gradient backpropagation with Polak-Ribiere updates (CGP). LM is the fastest training algorithm compared to others. To avoid over training and also to improve the efficiency of the network, K fold cross validation is used during network training.

3.3.2. Support Vector Machines

It is one of the well-known binary classifier in statistical learning domain. Some of its variants are linear, polynomial and cubic kernels. The classification task is performed by constructing hyper-planes that separates cases of different class labels. An optimal hyper-plane is constructed where this method uses an iterative training algorithm that minimizes an error function given by

$$\frac{1}{2} w^T w + B \sum_{i=1}^{N} \xi_i \qquad (13)$$

subject to constraint,

$$y_i(w^T \phi(x_1) + b) \geq 1 - \xi_{i,} \;\; \xi_i \geq 0, i = 1,2, \ldots . N \qquad (14)$$

Here, B is a capacity constant chosen carefully to avoid over fitting, w is the vector of coefficients, b is a constant and ξ_i represents the parameter that can handle the nonseparable data. N training cases are labelled by $i, y \in \pm 1$ indicates class labels with x_i as independent variables. Data from input to feature space is transformed by kernel φ. In this experiment polynomial kernel is used that is given by

$$K(X_i, X_j) = (\gamma . X_i . X_j + C)^d \qquad (15)$$

The variable γ is an adjustable parameter of the kernel function.

3.3.3. k-Nearest Neighbors

It is one of the simplest classification algorithm that belongs to supervised learning domain. It is based on feature similarity as how close an unknown data point resembles the training set. It also decides as how to classify a given data point. In the training set, it finds a group of k samples that are nearest to the test samples based on the distance function. The class of test samples are determined by calculating the average of the response variables from these k samples. The value of k plays a major role in the performance of this algorithm. If k is small, it means that the classifier is highly subtle to noise. If k is too outsized, it indicates that the neighborhood may comprise points from other classes.

IV. Performance Measures

Performance of image classification models used are compared based on sensitivity, specificity and accuracy with respect to both training and test samples. Accuracy is the overall classification accuracy in terms of true positives and true negatives of various methods. It can also be measured with respect to training and test data separately.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} = \frac{TP+TN}{P+N} \qquad (16)$$

Sensitivity also known as recall rate is the true positive ratio appropriately classified by diagnosis test. It depicts as how best the correct tumor type is classified by the classifier.

$$SN = \frac{TP}{TP+FN} = \frac{TP}{P} \qquad (17)$$

Specificity is the true negative rate of diagnosis test and shows how best the negative predictions are made by the classifier.

$$SP = \frac{TN}{TN+FP} = \frac{TN}{N} \qquad (18)$$

V. Experimental Results and Discussions

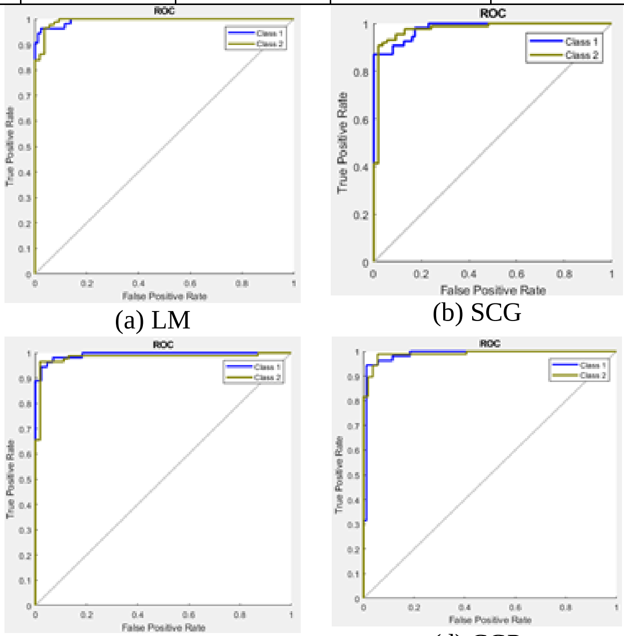
For the performance evaluation of the proposed method, tumor classification has been performed using Harvard datasets. Different modalities of MR such as MR-T1, MR-T2, MR-GAD and MR-PD with benign and malignant lesions are considered. After segmentation, the extracted feature vectors were directly used to train ANN, SVM and k-NN classifiers. Here, 70% of the data was applied for training and rest of the 15% each was considered for testing and validation. Here K=10 fold cross validation was used with various network training algorithms to evaluate the performance. Various ANN training algorithms were used by varying the number of neurons in the hidden layer. With 5 neurons in the hidden layer, LM algorithm shows good training and test accuracy for ANN model as shown in Table I.

Four ANN algorithms were compared with respect to number of neurons in the hidden layer, training time, iterations (epochs) and best performance (training and

Table I: Classification accuracy, sensitivity and specificity for training and test data using various ANN training algorithms (best values are highlighted in bold)

Training algorithms	Hidden layer size	Training accuracy %	Sensitivity %	Specificity %	Test accuracy %	Sensitivity %	Specificity %
LM	**5**	**100**	**100**	**100**	**95**	**92**	**100**
SCG	5	98	97	100	86	85	88
GD	5	100	100	100	91	86	100
CGP	5	99	100	97	91	92	89

testing) in terms of MSE. It was seen that LM training algorithm converges at 8 iterations with 5 hidden layers and 92.501 seconds. SCG algorithm converges at 37 iterations with 5 hidden layers and 27.549 seconds. GD algorithm converges at 997 iterations in time 35.005 seconds. CGP algorithm converges at 24 iterations in time 27.639 seconds. It can be observed from the table that LM algorithm is the best one. When training time (sec) is compared with MSE, with 5 neurons in the hidden layer, although training time is 92.501 seconds, for 8 iterations, performance (MSE) of LM training algorithm is less than performance (MSE) of other training algorithms for training and testing data. Hence it is clear that performance of ANN model using (Levenberg-Marquardt) LM training algorithm is the best with least error using feedforward network model and tan-sigmoid activation function at the hidden layer with linear transfer function at the output layer. Receiver operating characteristics (ROC) for 4 different ANN training algorithms are shown in Fig. 4 The area between baseline ROC and the perfect curve is more in case of LM algorithm compared to that of other algorithms. This indicates that performance level of ANN classifier with LM training algorithm is the best compared to others.



(a) LM (b) SCG

(c) GD (d) CGP

Fig. 4. ROC plots for 4 different training algorithms with 5 neurons in the hidden layer

Table II: Comparison of ANN training algorithms with 5 neurons in the hidden layer and best performance for training and testing (MSE) data (best values are highlighted in bold)

Training algorithms	Hidden layer size	Training time (sec)	No. of iterations epochs	Training best performance (MSE)	Test best performance (MSE)
LM	**5**	**92.501**	**8**	**0.0028**	**0.0527**
SCG	5	27.549	37	0.0309	0.1005
GD	5	35.005	997	0.0079	0.0773
CGP	5	27.639	24	0.0131	0.0615

Table III summarizes the comparison of accuracy, sensitivity and specificity for training and test data for three different classification models. It can be observed that accuracy, sensitivity and specificity for training and test data are high with ANN model using LM algorithm compared to others.

Table III: Classification accuracy, sensitivity and specificity for training and test data using various classification models

Classifier types	Training Accuracy %	Sensitivity %	Specificity %	Test accuracy %	Sensitivity %	Specificity %
ANN	**100**	**100**	**100**	**95**	**94**	**100**
SVM	100	100	100	89	92	80
k-NN	92	93	90	81	92	60

Table IV: Comparison of overall accuracy, sensitivity and specificity for classification of brain tumor data using various classification models

Classifier types	Overall accuracy %	Sensitivity %	Specificity %
ANN	**98**	**97**	**100**
SVM	95	96	90
k-NN	87	94	75

Table V: Classification accuracy comparison for MR datasets

Approach	Overall accuracy %
DWT+SVM (Sanjeev Kumar et.al)	91
GLCM+SVM with linear+RBF+cubic kernel (Javeria Amin et.al)	97
GVF+PCA-ANN (Vinod Kumar et.al)	92
DWT+ GLCM + HOG + LBP +ANN with LM training algorithm (Proposed)	**98**

VI. CONCLUSION

Classification of brain tumor lesions as benign and malignant classes was performed using SVM, k-NN and ANN model to achieve best accuracy and performance. Modalities such as MR-T1, MR-T2, MR-GAD and MR-PD were used from publicly available database of “The whole brain atlas”, Harvard medical school. Implementation is carried out using MATLAB R2019a software with 4 GB RAM and Intel ⓍR Core TM i7 processor. The visual texture features were extracted such as low level and high level features including LBP and HOG features for classifying the images. Various classifiers such as ANN, SVM, k-NN were used in the study for comparison of accuracy and performance. Four different training algorithms were used to train the features in ANN model. LM algorithm provided the best result of 95% test accuracy with least error using 5 neurons in the hidden layers. It can be observed from the results shown in Table V that classification accuracy is high with ANN using LM training algorithm and hybrid feature extraction process compared to that of some of the classical existing methods.

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AUTHORS PROFILE

Padmavathi K. perused her B.E degree from Mangalore University in 2000 and M.Tech degree from VTU, Belagavi in 2007. She is currently working as an Associate Professor in the department of E&C at NMAMIT, Nitte. She has an experience of 19 years in the field of teaching. Her area of interest includes, Signal & Image Processing, Medical Image Processing, Pattern Recognition and Machine Learning.

Dr. Maya V. Karki persued her B.E Degree from Karnataka University, in 1986, M. Tech degree from Bangalore University in 1991 and Ph. D from VTU, Belagai in 2013. She is currently working as a Professor in the department of E&C at Ramaiah Institute of Technology, Bengaluru. Her areas of interest include, Image & Signal Processing, Video Analytics, machine Learning, Neural Networks and Multimedia Communication. She has many conference papers and journal papers to her credit.