Brain Tumor detection and classification using Adaptive boosting

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Abstract - *MRI (Magnetic Resonance Imaging) is a medical test to generate 2/3-dimensional images of body organs. This technique produces clear and high quality images in various medical image format, one of which is '.dcm' which is being used in the proposed system. For medical analysis and interpretation, automated and accurate classification of brain MRI images is extremely important. Over the last decade numerous methods have already been proposed. In this paper, we proposed a novel method to classify the MRI image as normal or abnormal. The proposed system uses these images for brain tumor detection by applying image processing operations such as converting RGB image to Gray Scale image, Gray Scale image to Binary image. K-means clustering algorithm is being used for tumor segmentation . An important step in image analysis is the segmentation. These segmented image is then passed further for feature extraction. The feature extraction operation is performed on the obtained images using Discrete Wavelet Transform(DWT). After the features are extracted, the Principle Component Analysis (PCA) operation is performed to reduce the dimensions of the features. The classification of MRI images is done by using Decision tree with adaptive boosting technique. The Decision Tree is trained using the extracted and reduced features. Once trained, this tree is then used to classify the brain MRI image into normal or abnormal(Benign, Malignant). To increase the accuracy of the system, adaptive boosting is used which provides 100% accuracy. Also we have compared the system with other systems and the comparative study is provided below.*

***Key Words*: MRI, Decision Tree, Classification, Image Processing, Adaptive Boosting**

1.Introduction

Imaging has strengthen the medical science through the visualizing the structure of human anatomy. Some imaging techniques are CT (computed tomography), PET (positron emission tomography), X-Ray imaging, MRS (Magnetic Resonance Spectroscopy) and MRI (Magnetic Resonance Imaging) etc[6]. Brain MRI is taken using a scanner which has strong magnets built-in which produces magnetic field and radio waves that scan patient's brain to produce high quality images[7]. These images contain attributes like echo time, repetition time, inversion time, slice information, flip angle etc. which help doctor find whether that patient is suffering from any brain related diseases or not. Magnetic resonance imaging (MRI) is considered now as an important tool for surgeons. It delivers high quality images of the inside of the human body. A brain tumor is any intracranial mass created by abnormal and uncontrolled cell division. Tumors can destroy brain cells or damage them indirectly by causing inflammation, compressing other parts of the brain, inducing cerebral edema or by exerting internal pressure as they grow.[10] These tumors can be classified into 2 types :

1) Benign and 2) Malignant.

Automated and accurate classification of MRI brain images is extremely important for medical analysis and interpretation. Over the last few years many methods have already been proposed. In this paper, we proposed a novel method to classify a given brain MRI image as normal or abnormal and predict the type of tumor. The proposed method first employed discrete wavelet transform (DWT) to extract features from images, followed by applying principle component analysis (PCA) to reduce the dimensions of features.[9] The reduced features were submitted to Boosted Decision Tree.

In this paper, a system is proposed for detecting brain tumor.It also classifies the tumor(if present) into benign and malignant. This system can be used to assist the neurologist and radiologists. The flow of our system is as follows:

1) Upload test .dcm Image
2) Preprocessing
3) Segmentation (K-means)
4) Feature Extraction (DWT)
5) Feature Reduction (PCA)
6) Classification(Decision tree)
7) Tumor absent or present(Benign/Malignant)

2.System Description

2.1 Pre-processing

When an image is given as input in the proposed system :

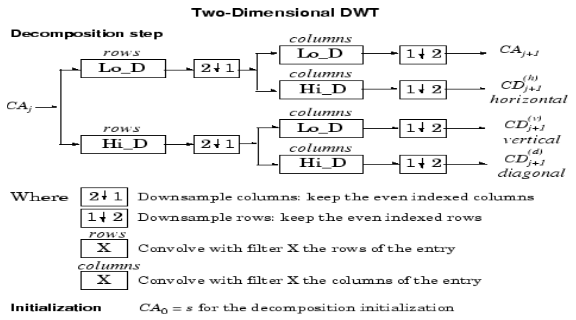
- Resize the image into compatible dimensions.
- Convert the given image into Gray Scale by eliminating the hue and saturation information while retaining the luminance.
- Calculate a global threshold which is used to convert the grayscale image into Binary image. This threshold is a normalized intensity value that lies in the range 0-1.
- Using this threshold, the image can be converted into binary image.The output image has values of 1 (white) for all pixels with luminance greater than threshold value and 0 (black) for rest pixels.

2.2 Segmentation

An important step in image analysis is the segmentation. Segmentation methods are divided into eight categories namely; thresholding approaches, region growing approaches, classifiers, clustering approaches, Markov random field models, artificial neural networks, deformable models, and atlas-guided approaches.[11] In this system, we have used K-means clustering algorithm for tumor segmentation. This approach first calculates the Euclidean distance between centroid of k clusters and pixels and assigns the pixels to respective cluster based on this value.

2.3 Feature Extraction

Since 2D images are taken as input, the proposed system uses the Discrete Wavelet Transform (DWT) for feature extraction. It performs single level 2D wavelet decomposition with respect to a particular wavelet. The wavelet used is daubechies wavelet 4 for wavelet decomposition. The input is taken as a 2D matrix of pixels for DWT. After applying DWT on this matrix we get an approximation coefficients matrix CA and detailed coefficient matrices CD,CV,CH as shown in the figure below.



Again DWT is applied on the approximation coefficient matrix for 2 times. The final output is a compressed image from which noise is removed. Here the feature extraction part ends and the final approximation coefficient matrix is the output of this step.

2.4 Feature Reduction

For feature reduction the proposed system uses principal component analysis(PCA).Given a set of data, PCA finds the linear lower-dimensional representation of the data such that the variance of the reconstructed data is preserved. The output of feature extraction step is taken as input for feature reduction step. The output of PCA is a matrix of principal component coefficients also called as loadings. Each column of this matrix contains coefficients for one principal component and the columns are in descending order of component variance. PCA centers the data and uses the singular value decomposition (SVD) algorithm.

Objectives of principal component analysis

1) To discover or to reduce the dimensionality of the data set.
2) To identify new meaningful underlying variables.

This leads to more efficient and accurate classifier. The feature extraction process was carried out through two steps: firstly the wavelet coefficients were extracted by the DWT and then the essential coefficients have been selected by the PCA.[1]

2.5 Classification

After feature reduction we get following parameter:

1) Contrast
2) Correlation
3) Energy
4) Homogeneity
5) Mean
6) Standard Deviation
7) Entropy

8) RMS
9) Variance
10) Smoothness
11) Kurtosis
12) Skewness
13) IDN

These parameters are applicable for all image types like T1-weighted, T2-weighted images. Now the training dataset is created using these parameters. The algorithm used for classification is Decision Tree with Adaptive Boosting. Here large number of weak learners are combined to form a strong classifier. The weak learners are decision trees or decision stumps. Decision stumps are decisions trees with one node. The classes are predicted based on a single feature by calculating the threshold value of that feature. Initially uniform weights are assigned to all the observations in the training dataset. The weak learner may misclassify some observations. The weights of such observations are increased and the next learner will focus on the misclassified observations. Adaptive Boosting works as follows:

- Uniform weights are assigned to all the observations. weight(i)=1/N. where i is the observation number and N is count of observations.
- Create a weak learner i.e. decision stump and train it on the training dataset. C(j)=train(X,Y,weight) where X are the observations, Y are the classes and weight is the vector of weights assigned to the observations.
- Predict the class using the weak learner C(j). Yp=predict(C(j),X)
- Calculate the error rate of misclassified observations for the weak learner. error = sum(weight(i)*terror(i))/sum(weight). where terror is 0 if correctly classified and 1 if misclassified observations.
- Now calculate the coefficient for the learner. alpha(j) = ln((1-error)/error) where ln is natural logarithm.
- Now update the weights of the misclassified observations and then normalize all the weights. weight(i) = weight(i) * exp(alpha(j)*terror(i)) weight(i) = weight(i)/sum(weight)
- These are the steps for a single weak learner. Repeat the above steps for all the weak learners.

Now these weak learners are combined to form a strong classifier. The final classifier will be the weighted sum of the coefficient of the each weak learner. The more the weight the better is the classifier. When the misclassification error rate becomes zero the accuracy becomes 100%.

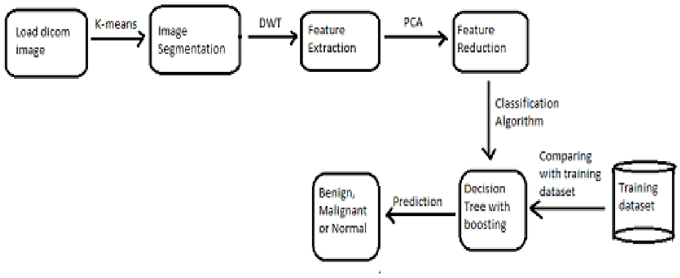
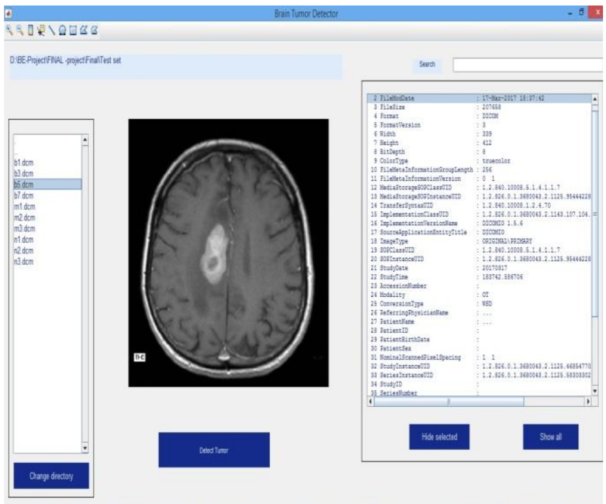


Figure 1 : system Architecture

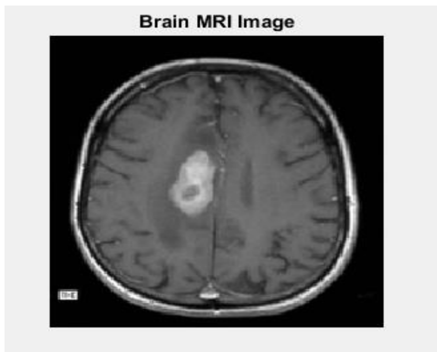
3. Result Set

1. Create training dataset for Normal and abnormal classes.
2. Take Testing ".dcm" image as input.

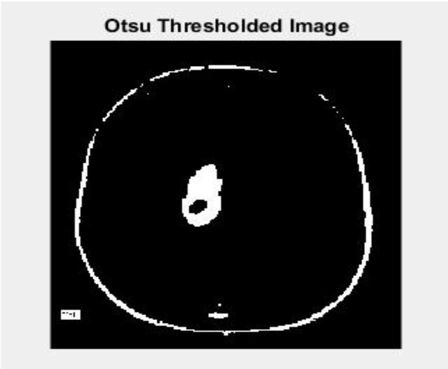


3. Preprocessing stage:

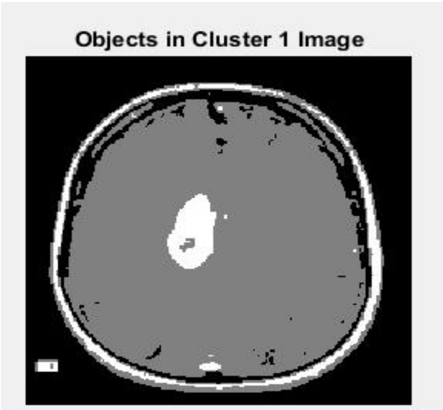
a. Convert Image into Gray Scale.

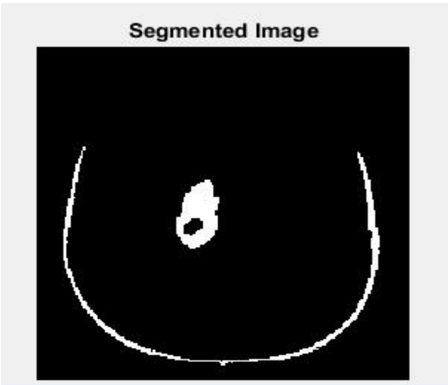


b. Convert Gray scale image into Binary image.

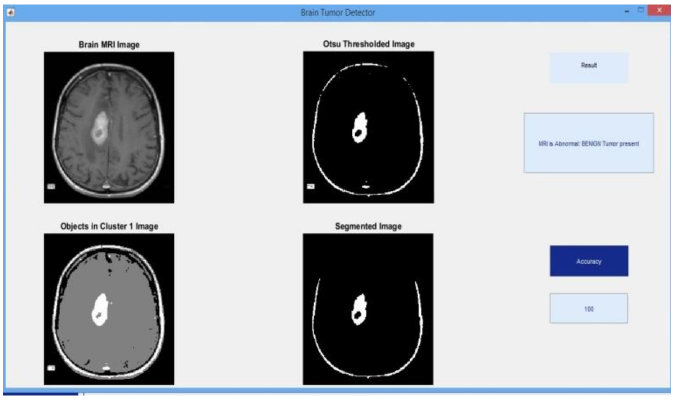


4. Apply Segmentation.





5. Feature Extraction using Discrete Wavelet Transform(DWT).
6. Feature Reduction using Principal Component Analysis(PCA).
7. Classification using Decision Tree with Adaptive Boosting.



4. Comparative Study

Algorithms	Accuracy %
Boosted Decision Tree	100
Naive Bayes	88.2
Probabilistic Neural Network	88.2
SVM with Quadratic kernel	96

5.Conclusion

This system can be helpful for neurologist or radiologist to help analyze the MRI image. Thus we have proposed a system which uses decision tree with adaptive boosting algorithm to classify the given MRI image into Abnormal or Normal classes. This is done using various parameters like Contrast, Co-relation, Mean, Std. Deviation, Entropy, etc. which are obtained by preprocessing techniques like K-means, DWT,PCA algorithms. These parameters are then used to create Decision Trees which allow classification. Also, weak parameters are combined together using boosting which forms a strong learner for classification.This increases the accuracy of the system without needing extra resources. When classification is done the given images gets classified into Normal or Abnormal(i.e. Malignant or Benign). In Future, Various other functionalities like predicting the stage of the tumor, possible medications suggestion can also be added.

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