CSE3018 : Content Based Image and Video Retrieval

Brain Tumor Classification

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Abstract

The brain is one of the most important organs in the human body which is responsible for controlling memory, thought, touch, vision, breathing and regulating all critical functions of the body. It interprets information coming from outside through our five senses which are sight, smell, taste, touch and hearing. A tumor is an abnormal mass of tissues which gets formed when cells do not die or when a huge number of cells keeps on growing and dividing itself. Brain tumors are also similar but they get formed in the brain. Detecting brain tumors at the initial stages is very important as the brain is a critical organ of the human body.

We have proposed a cbir system which will detect brain tumors from the MRI scans which are for the management of the brain tumor diagnosis.In this project we have implemented a model that segments images using Watershed and PSO algorithms and we have used DWT and PCA algorithms which extract features and are used to finalize the classification of tumors.

Introduction

The human body consists of a number of myriad cells. When cell growth cannot be controlled and the cells which get created accumulate to form a tumor.The aim of this project is to detect tumors accurately and to classify them through several techniques like medical image processing,pattern analysis and computer vision. This model will improve the sensitivity, specificity and diagnostic efficiency of the brain tumor using a software tool called MATLAB.The methods implemented here will involve a pre-processing of MRI scans which are collected from the online cancer imaging archives. The images will be resized and will be applied to the proposed algorithm for segmentation and classification of brain tumors. This will help in reducing health care costs as the need for follow up procedures are decreased.

Motivation

The motivation for this project was to help neurosurgeons,radiologists and other medical personnel in detecting brain tumors in a faster and a non-invasive manner.

Project definition

Our project aims to deal with automated brain tumor and classification.MRI and CT scans are generally used to analyze the anatomy of the brain.The goal of this project is to detect whether the MRI scan taken of the brain has been found and classified as malignant or benign.

Literature Survey

This chapter discusses the papers referenced in preparation for this project

MRI Pre-Processing Techniques

MRI scan is a medical imaging technique used in radiology to form pictures of the anatomy and the physiological processes of the body. The following are the various types of MRI scans :

a. **T1-Weighted :** It allows for easy annotation of the health parts of the brain.
b. **T2-Weighted :** It allows for easy identification of the edema region of the brain
c. **FLAIR :** It allows for a clear separation of the edma region from the Cerebrospinal fluid in the brain.

Gradient based image enhancement is a common method used in the enhancement of MRI images. It is based on the first derivative and local statistical measures. This method involves the removal of film artifacts such as labels or arrow marks and X-ray marks.

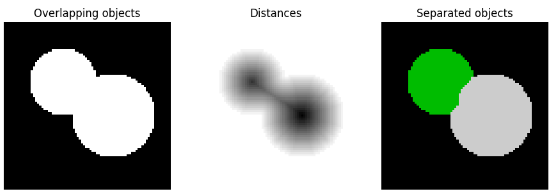
Once the MRI is clear of noise, high frequency components are removed using weighted median filtering techniques. This results in a high resolution MRI image.

Canny Edge Detection - Segmentation Method

Canny edge detector uses a multi-stage algorithm to detect a wide range of edges in images. It was developed by John F Canny in 1986. It uses Gaussian filters to compute the intensity of the gradients to reduce the noise. Potential edges are then thinned down to 1-pixel curves by removing non-maximum pixels of the gradient magnitude. Canny edge detection is widely used to generate unbroken edges for the posterior boundary of the brain.

Watershed Segmentation Method

Watershed algorithm is a classic segmentation technique used for separating different objects in an image.



As we can see in the above image the algorithm computes the distance to the background and the maxima is chosen as a marker to separate the two circles along the watershed line.

Lazy IBK

Lazy Learning is a machine learning technique in which generalization of the training data is left not done until a query is made by the system. The motivation behind the algorithm is that new data is always created and it can be used to train the system better every time a query is initiated than training the system once using a training data set.

Lazy IBK is a K nearest neighbor Lazy classifier that can be used to speed up the task of finding the nearest neighbors. This classification technique can be used on the features extracted from the MRI to classify it as benign or malignant.

Proposed Work

Step 1 : Segmentation

Canny edge detection is used to extract useful information and to decrease the amount of data that is going to be processed. This algorithm is used widely in various computer vision systems. The process of canny technique can be summarized into five steps which are

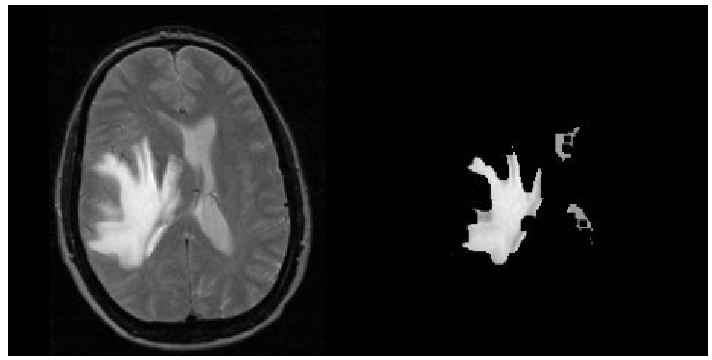
A. Apply the gaussian filter to smoothen or blur the image and remove noise
B. Measure gradients of the image
C. Apply non maximum suppression and remove false responses of the edge detection
D. Determine potential edges using double threshold
E. Suppress the edges which are weak and which are not connected by strong edges to generate a finalized edge structure.

Otsu is the second algorithm which will be used in our project which automatically performs clustering based image thresholding or reduces a grayscale image to a binary level. Two classes are assumed by the algorithm which are classes of pixels. The algorithm calculates the optimum threshold for separating two classes of pixels,as their combined spread is minimal or equivalent,as it will make the inter-class variance maximal. The histogram is computed and the probabilities are calculated of each and every intensity value. Then the initial class probabilities and mean are calculated. The process will go through all the thresholds till it reaches the last threshold where the class probabilities are updated and means are updated and the inner class variance are calculated. The desired thresholds will correspond to the maximum inner class variance.

Any gray scale image can be used where the places where high intensity denote peaks and hills while the places with low intensity will denote the valleys.

As the water level increases depending upon the peaks, water from different valleys with different colors will start to merge. To prevent the merge from happening we build barriers until all the peaks are under water. This approach gives noise and other irregularities.

A marker-based watershed algorithm will be used where all valley points are to be merged and which will not be merged.The respective regions will be labeled as background or non-object or label the region which we are not sure of as zero accordingly.



Step 2 - Feature Extraction

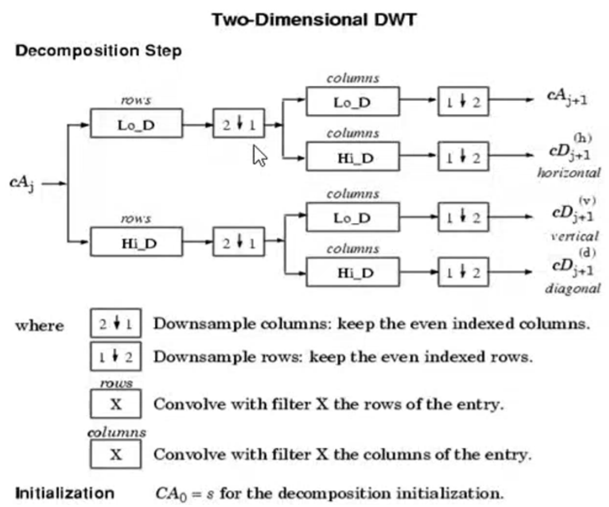
Discrete Wavelet Transform is a significant feature in the transform domain. Discrete wavelet transform handles the images as small signals in both the x and y axis.

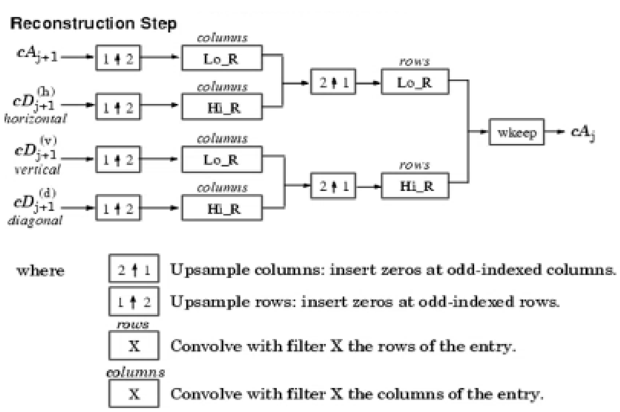
The continuous wavelet function for a function $x(t)$ relative to $\psi(t)$ is given by

$$W_{\psi}(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt$$

where

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-a}{b}\right)$$





Grey level Co-occurrence matrix is also used in the feature extraction process to extract features such as :

a. **Mean** - represents the mean of the pixel values of the input image. Given by the equation

$$Mean = \sum_{i,j=0}^{N-1} i(P_{i,j})$$

b. **Standard Deviation** - It defines the dispersion of pixels in relation to the mean of the pixels of the input image. GIven by the equation

$$Standard\ Deviation = \sqrt{\sigma_i^2}$$

c. **Entropy** - Represents the amount of information available in an image for compression. It given by the equation :

$$Entropy = \sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij}$$

d. **Root Mean Square** - It is the square root of the sum of squares of each pixel subtracted from the mean. It represents the amount of noise in the image. Given by the equation

$$\text{RMS noise} = \sqrt{\frac{\sum_{i=1}^{n}(X_i - \frac{\sum_{i=1}^{n} X_i}{n})^2}{n}}$$

e. **Variance** - Given by the equation

$$Variance = \sum_{i,j=0}^{N-1} P_{i,j}\,(i-\mu_i)^2$$

f. **Smoothness** - It is the measure of uniformity in the image. Given by the equation :

a = sum(double(G(:)));

Smoothness = 1-(1/(1+a));

g. **Kurtosis** - It is the representation of uniformity of the grey level distribution of the input image. Given by the equation :

$$kurtosis = \frac{m_4}{m_2^2} = \frac{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4)}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2)^2}$$

h. **Skewness** - It measures the asymmetry of the image.

i. **Inverse Difference Moment** - It represents the local homogeneity.

$$IDM = \frac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} P_{ij}}{1+(i-j)^2}$$

j. **Contrast** - It is the sum of square variance of the image. It is the amount of color or grayscale differentiation that exists between various image features.

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2$$

k. **Correlation** - Measures the linear dependency of the grey levels of the certain pixel with its neighbouring pixels.

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$$

l. **Energy** - Measures the degree of pixel pair repetitions.

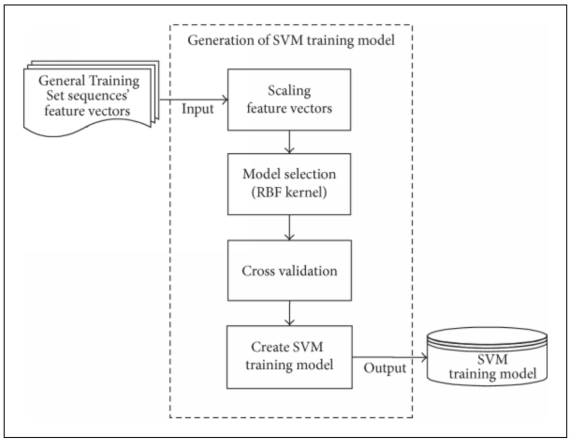
$$Energy = \sum_{i,j=0}^{N-1} (P_{ij})^2$$

m. **Homogeneity** - It measures the closeness of the distribution of elements in the grey level co-occurrence matrix. Given by the equation :

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2}$$

Step 3 - Classification

Support vector machines(SVM) are a type of supervised learning model where associated algorithms are used along with it to analyze data and identify various patterns which are used for classification analysis. The inputs are taken by SVM and they will predict for each input being given which two classes that are malignant and benign forms the output which makes a non-probabilistic binary file classifier. The SVM model is a representation of examples as points in space, mapped from the categories that are separate that divides a clear gap which is wide as possible. SVM’s construct a hyper plane or a set of hyper-planes which are used for classification. Good separation will be achieved by hyper planes which have largest distances to the closest training data points of any class. A SVM takes a set of feature vectors as inputs and produces a training model after processes like scaling, selecting, validating and uses the training model to get the output.



Thus SVM aims at finding a hyperplane in an N dimensional space that can distinctly classify the data points or training data. The dimension of a hyperplane depends on the number of parameters, suppose we have only two features, say x and y. The hyper plane will be a 1 dimensional line that splits the data points into 2 categories.

Software - Hardware Needed ML/DL Model

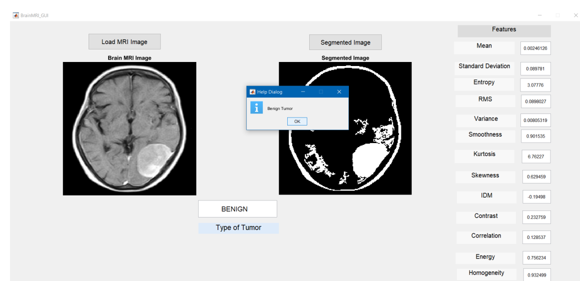
T1 weighted scans of Magnetic Resonance Imaging are used to create the dataset for the machine learning model, the code is based on MATLAB. The additional packages used are Bioinformatics Toolbox, Computer Vision System Toolbox, Image Processing Toolbox, Signal Processing Toolbox, Statistics and Machine Learning Toolbox, Wavelet Toolbox, all from Mathworks.

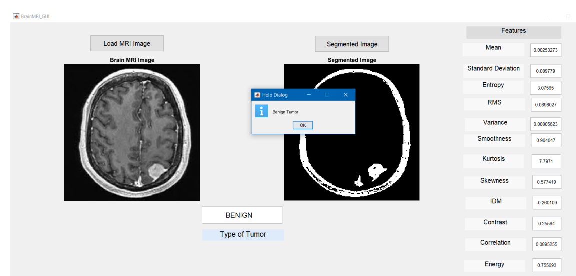
The Machine learning model employed as mentioned earlier is the Support Vector Machine, which is used to classify the tumors with a supervised approach based on the dataset.

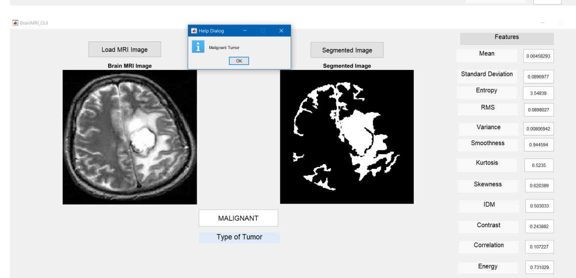
Results obtained

MRI images were collected from Kaggle for testing and training purposes. The folder labeled as 'Benign' and 'Malignant' are benign and malignant tumours with labels which are used for training of the Support Vector Machine.

Images for testing are taken from kaggle as well. A confusion matrix is generated after testing to measure the Accuracy of Classification.







	Bening (predicted)	**Malignant (predicted)**
Bening (actual)	4	2
Malignant (actual)	1	3

Precision = 4 / 6 = 0.67

Recall = 4 / 5 = 0.8

Accuracy = 7 / 10 = 70%

Dataset

Conclusion

We have successfully implemented a CBIR System to extract features of a tumour from an MRI image and use it to classify whether the tumour is benign or malignant with the help of various pre-processing, segmentation and classification techniques.

Reference Papers

1. Hamdi, M. et al., *Study of Detection Brain Tumor with machine learning*, Minia University Faculty of Engineering Computer System Dep.
2. D. Suresha, N. Jagadisha, H. S. Shrisha and K. S. Kaushik, "Detection of Brain Tumor Using Image Processing," 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC), 2020
3. E.Küçükkülahli, P.Erdoğmuş, and K. Polat, "Brain MRI Segmentation based on Different Clustering Algorithms," International Journal of Computer Applications, vol. 155, no. 3, pp. 37–40, 2016.Mohsen, Fahd, et al. "A new image segmentation method based on particle swarm optimization." Int. Arab J. Inf. Technol. 9.5 : 487-493.
4. I. Maiti and M. Chakraborty, "A new method for brain tumor segmentation based on watershed and edge detection algorithms in HSV colour model," 2012 National Conference On Computing And Communication Systems