DEVELOPMENT OF A TOOL TO DETECT AND CLASSIFY BRAIN TUMORS FROM MRI IMAGE USING SVM LEARNING MODEL

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Abstract: One of the most challenging tasks in image based medical diagnosis system is to know how severe the disease is even after all the necessary data have been collected. This is especially true when the image contains critical information which highly affects treatment procedures like in case of brain tumors severity identification. Brain tumors are the most life threatening type of tumors. Brain tumors form because of abnormal division of cells inside the brain. Based on their level of severity, they are classified as benign (non-cancerous) and malignant (cancerous) tumors. My aim in this work is to classify MRI based brain tumors on the basis of both intensity and texture features. The employed technique's phases are, preprocessing, image compression using 2D discrete wavelet transform, textural features computations, feature dimensionality reduction, training and testing the model. For classification, Support Vector Machine (SVM) is used. Different kernels are compared and Radial basis function (RBF) outperforms the others.

Keywords: Medical diagnosis, brain tumors, magnetic resonance imaging, DWT, support vector machine, RBF.

I.   Introduction

Brain tumors form because of abnormal and uncontrolled division of cells inside the brain. Depending on their level of severity, brain tumors are divided into two. The first is Benign tumor (non-cancerous) which is less severe and the second one is Malignant tumor (cancerous). Early detection of the tumors helps in saving the life of the victims. In any medical diagnosis-treatment pair, the correct treatment is given only if the diagnosis is correct.

Brain tumors can be diagnosed either invasively or non-invasively. The invasive way of diagnosis includes: pneumo-encephalography and cerebral angiography [1]. However, these methods have been abandoned in favor of non-invasive, high-resolution techniques, MRI and computed tomography (CT) scans. The most commonly used medical imaging modality to detect and diagnose brain tumor is MRI. The diagnostic significance of MRI is highly dependent on the classification accuracy of the disease of interest. It is performed through image segmentation and is carried out manually by medical experts. However, this is very prone to errors and may sometimes be complex due to similarity of tumor tissues with normal tissues, the presence of different cases, many patients with different statuses, and the large variety of tumor tissues appearance. Therefore, automatic medical image classification remains a real challenge which attracted many researchers in this field over the last few years. Different techniques have been proposed to automate MRI brain tumors classification over the past decade.

II.   Literature Surveys

Mohd Fauzi Bin Othman, Noramalina Bt Abdullah, and Nurul Fazrena Bt Kamal, in 2011 proposed an MRI based Brain tumor Classification using SVM [2]. This methodology extracts features from the magnetic resonance imaging based brain tumors using DWT. The input data set consisted of axial, T2 FLAIR weighted, 256 x 256 pixels. The determination of normal and abnormal brain image was done using the symmetry that it exhibits in the axial and coronal images [2]. The classification accuracy with RBF kernel was 65% (39 out of 60 images).

Y. Zhang and L. Wu, in 2012 [3] developed a computer aided diagnosis system which classifies brain tumors into normal and abnormal from MRI based brain images. The proposed method first employed 2D DWT to extract features from images, followed by applying PCA to reduce the dimensions of features [3]. The reduced features were submitted to a kernel SVM for classification. Four different kernel functions (Linear, quadratic, polynomial, and RBF) were compared. Finally, RBF was found to be best.

Dr.A.R. Kavitha, L.Chitra, and R.kanaga, in 2016 proposed Brain Tumor Segmentation using Genetic Algorithm with SVM Classifier [4]. The work segmented and classified the MRI brain tumor image as benign or malignant. The methodologies involved are Preprocessing, Segmentation, Feature Extraction and Classification. The preprocessing phase includes removal of noise in an image using wiener filter. Next, the segmentation of the tumor was carried out using Genetic Algorithm. Finally, they used Support Vector Machine (SVM) classifier in order to classify the type of the brain tumors from the filtered and segmented image.

N.Vani, A.Sowmya, N.Jayamma in 2017 proposed, Brain Tumor Classification using SVM [5]. In their work, they first extracted the region of interest (ROI) and applied 2D DWT to the extracted tumor region. Then, features are extracted using the necessary parameters used in describing the region: Area, Euler number, height & width, eccentricity, and compactness. Finally, SVM is used for classification of the type of the tumor. The classification accuracy was found to be 82% (22 out of 27 images).

III.   Implemented Methodology

The aim of this thesis is the classification of a given brain tumor's MR image as benign or malignant. To ensure this task, images need to be preprocessed first to enhance their quality. Next, in order for images to be classified, their corresponding features which separate them from one another should be extracted and arranged in numerical vector form. In fact, these features are not directly extracted from the images themselves; instead, three level 2D DWT is first applied to decompose the images into approximate and detail components. Thereafter, histogram based and texture features are computed from the third level approximation coefficients of the image. Next, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the features by choosing only the most discriminative ones depending on their relative importance. Finally, Support Vector Machine is used to classify the images based on their features. Therefore, the classification method will be based on five main phases, namely pre-processing, features extraction, features dimensionality reduction, SVM training and testing, and classification. Image segmentation is also performed using thresholding and region based morphological operation to visualize the tumor region. The whole process is illustrated by the diagram of Figure 1.
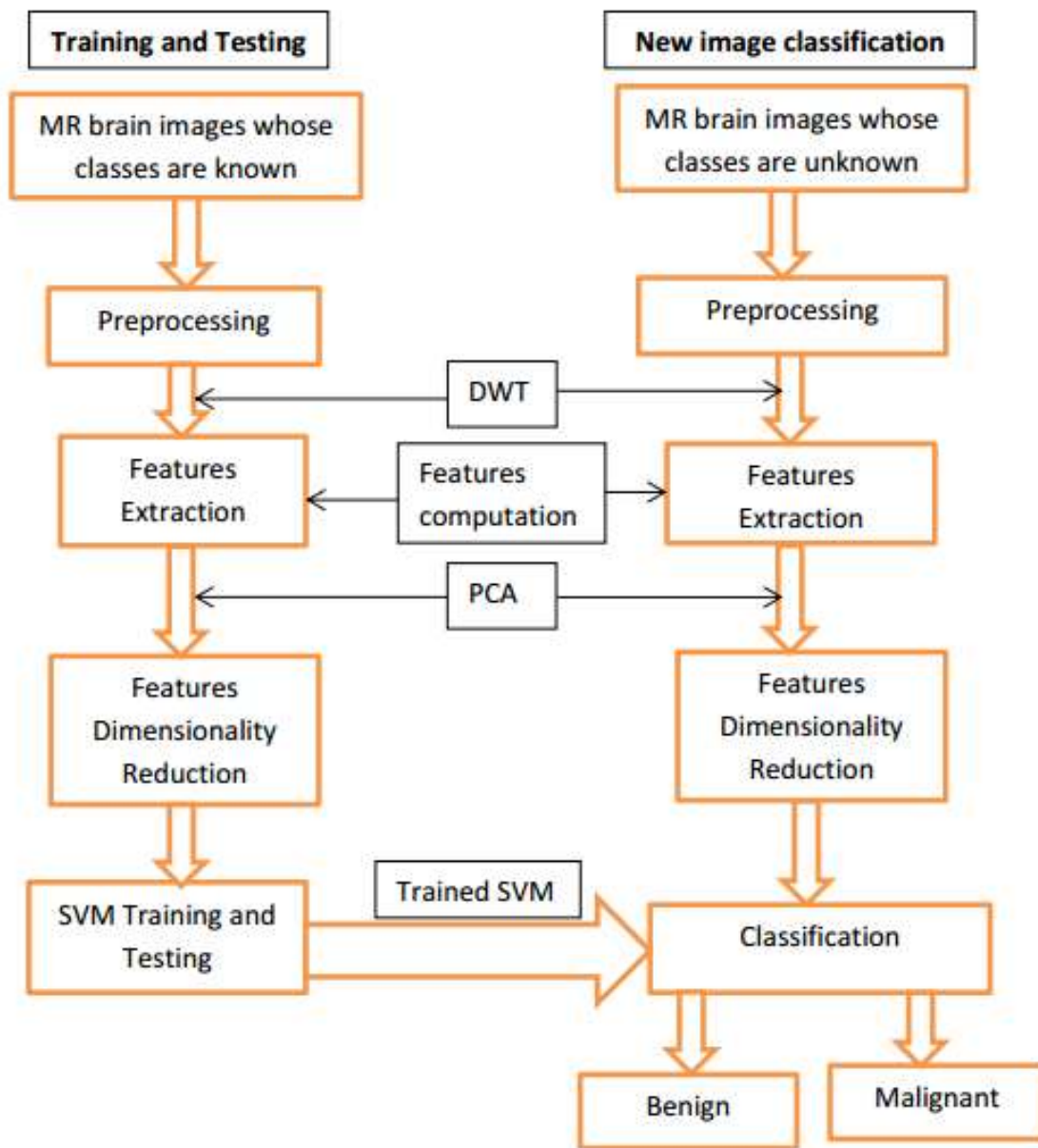
Figure 1: Diagram illustrating the implemented MR Brain Image Classification System

1. Preprocessing Phase:

This phase consists of the following steps:

Image acquisition: This step is ensured via MRI and represents a primordial step since the remainder of the process will depend on the quality of acquired images. For this, the relevant labeled brain images are downloaded from reliable medical image data collections website (www.cancerimagingarchive.net) provided from different recognized health care and medical research institutions.

Selection of slices of interest: Here, only slices with tumors are selected for further processes as the main aim is to classify the tumor type. The type of imaging modality and imaging orientation selected are FLAIR weighted (motivated by tumor region's clarity) axial images.
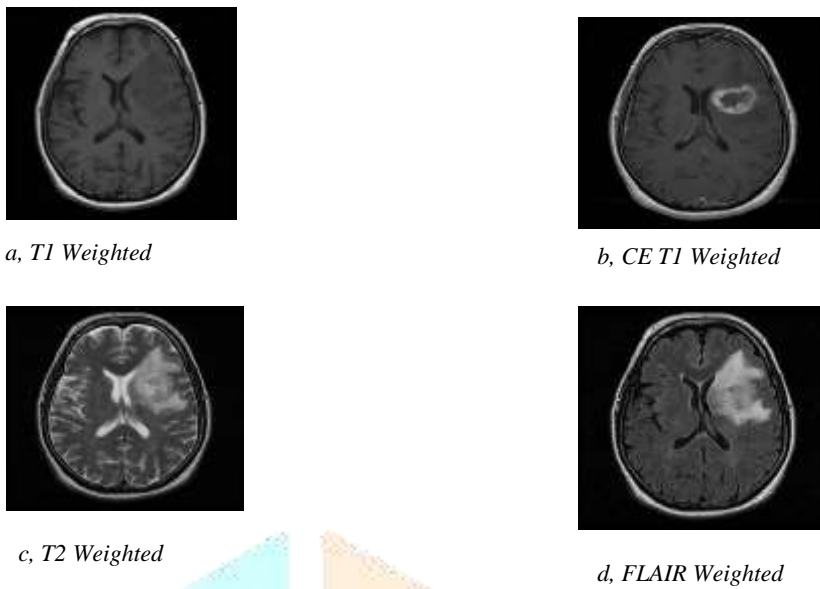
a, T1 Weighted

b, CE T1 Weighted

c, T2 Weighted

d, FLAIR Weighted

Figure-2: MRI Scan Orientations

Skull Stripping: Non-brain tissue (skull), which is also part of the image, is stripped in this phase using erosion based morphological operation by defining a disk shaped structuring element.

a, Original Image

b, Skull Stripped Image

Figure-3: Skull stripping

Noise Reduction: In order to enhance the suitability of the images for succeeding processes, median filter with 3x3 window size is applied to remove unwanted noises.
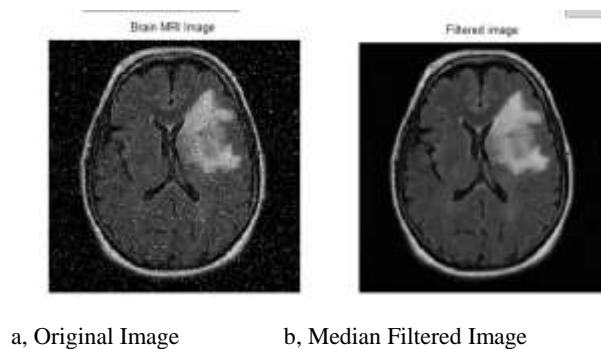

a, Original Image   b, Median Filtered Image

Figure-4: Noise Reduction

2. Features Extraction:

Given preprocessed images, this phase refers to various quantitative measurements decision making regarding the class of the input image (benign or malignant). More precisely, for each image, we should compute a feature vector. To do this, image is first decomposed into its approximation and detail components coefficients using three levels 2-D DWT. In fact, 2D-DWT is preferred because of its capability to allow analysis of images at various levels of resolution [3]. Next, thirteen histogram based and texture features, namely: mean, standard deviation, variance, skewness, kurtosis, IDM, contrast, correlation, energy, homogeneity, entropy, RMS, and smoothness are computed from the third level approximation component's coefficients of the image.

3. Feature Dimensionality Reduction:

Even though DWT reduces the size of the data to represent the original image, still it's not practically simple to work with thirteen features from a single image while we have numerous images to process and classify. Therefore, PCA is used to overcome this difficulty to select only the most important components which can fairly discriminate between the classes.

4. SVM Training and Testing

Once the reduced dimension feature vectors for each image are obtained, the Support Vector Machine can then be trained and tested using the labeled feature vectors. In order to avoid over fitting, the strategy of k-fold cross validation is used to randomly assign the data for training and testing the model. Details about k-fold cross validation can be found from [6].

5. Classification

This phase is performed by one of the robust supervised learning algorithm, support vector machine. Once it is trained, the new image's feature vector can be fed to the model to classify it into either benign or malignant.

Segmentation

In this work, segmentation is very important phase to visualize the actual brain tumor from the image, so that its location can be tracked by the physicians. However, it is not part of the classification algorithm being applied. Therefore, any mistake made in segmentation step will not affect the classification accuracy of the model. As it can be seen from figure-5, segmentation gives a clear view of the region of interest (tumor). For this work, the segmentation is performed by programmatic thresholding and then region's properties (area and density) of the labeled components are used to segment the final tumor region.

IV. Experimental Results

I used 60 total images half of which are benign and the rest are malignant, I applied 100 iterations to assign randomly half of the data points for training and holdout half for testing. Since, this assignment iterates hundred times, there's very high possibility for each to be used as both training and testing data point at least once. This in turn highly increases the accuracy of the model by avoiding over-fitting.

MRI Image data have several characteristics, such as scans orientations, number of slices, inter-slice distance, slices, dimensions, and kind of modalities (T1, T2, FLAIR) [7]. These parameters vary differently from one patient to another depending on tumor

requirements. In this thesis, I used only Flair weighted axial slices during the training and testing phase. Flair MRI images are the best imaging modality to visualize and detect the tumor region as it appears different from other normal tissues [8].

My image database is relative to 60 axial images of 12 patients the first seven of which are suffering from low grade glioma (benign tumor) and the rest five are patients with GBM (malignant tumor). In general, the types and number of images collected can be seen from table 2.

Table 1: Collected images characteristics

Tumor types	No. of tumor slices	Training slices	Testing slices
Benign	30	Random 50% of total images at an iteration i(where i=1:100).	Random 50% of total images at an iteration i(where i=1:100).
Malignant	30		

Results

The implementation of the whole system is performed on Matlab editor and Graphical User Interface (GUI) and it needs consecutively several parameterizations. The technique applies all the steps illustrated in figure 1, and the very accurate and promising results of different kernel functions are obtained and compared as we can see from figure 5.
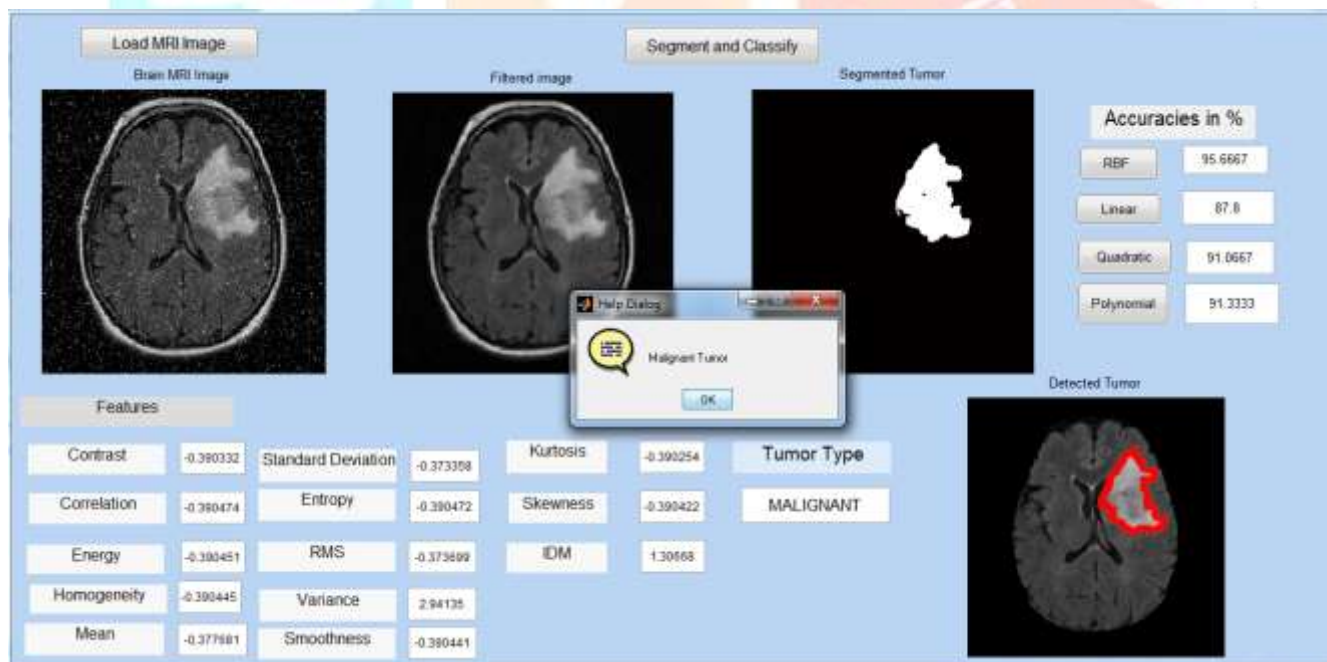

Figure-5: Experimental Results of MRI brain image classification system using SVM

Tasks of skull masking, image enhancement, segmentation and brain tumor detection are done in the processes. In addition, performances of different kernel functions are compared where RBF outperforms others with the highest classification accuracy of 95.67%. In order to view on 2D space how the hyperplane adjusts itself to correctly classify the data points, I further reduced the dimension of the features to two. Consequently, it is clear that even by taking only the first two components, the accuracy of the

model is very high using 60 data samples half of which are benign (class 1) and the rest 30 are malignant (class 0). Figure 6 shows the output on two dimensional spaces.
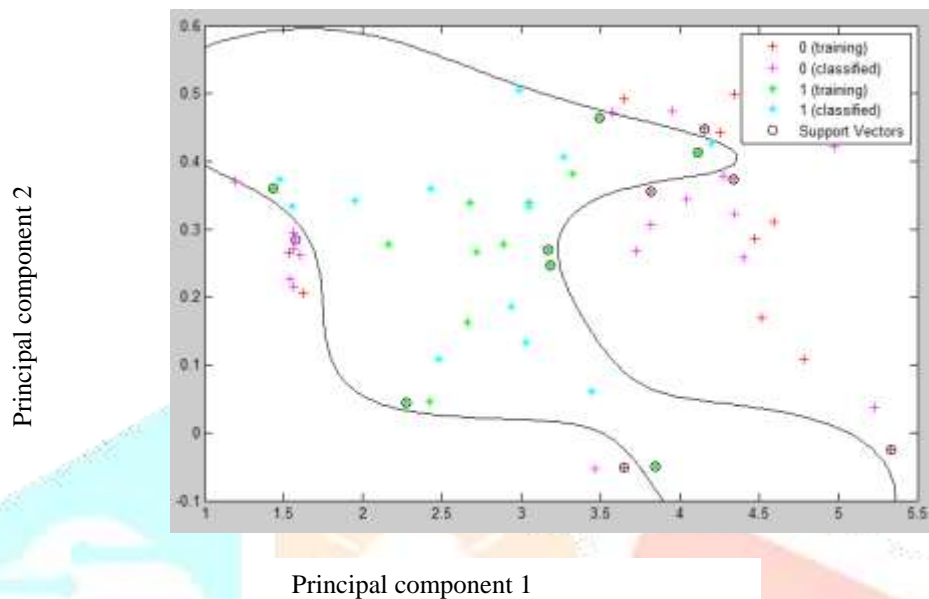

Figure-6: RBF based training and testing result on 2-D Space.

V. Conclusion

The experimentation study shows that the brain tumor classification tool developed on Matlab GUI with the combination of both intensities and texture features gives motivating result. The classification accuracy as it can be seen from the above section is 95.67%, 87.8%, 91.07%, and 91.33% for RBF kernel, linear function, quadratic and polynomial functions respectively. Note that the last two kernels' accuracy (quadratic and polynomial) are very close; that is because a polynomial function of degree two is used.

Acknowledgement

VI. References

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