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A New Approach towards Brain MRI Image Segmentation and Classification

V.Keerthi Kiran[1], Y. Lokesh[2], P. Mounika[3], Rohit Kumar K[4], Ch. Mohan Kumar[5].

Assistant Professor, Dept. of ECE, Raghu Institute of Technology,Visakhapatnam,Andhra Pradesh, India[1]

UG Student [ECE], Dept. of ECE, Raghu Institute of Technology,Visakhapatnam,Andhra Pradesh, India[2,3,4,5]

ABSTRACT: A Tumor is a cancer pre-stage that has become a major problem in this period. Scientists have created methods and therapies to reduce it and control the growth of the tumor. Brain tumour is basically an irregular cell development that is not often evident in visual techniques in the brain tissue. There are different imaging methods used to identify the actual location of the brain tumour. Among these, Electron Microscopy plays a significant role in disease diagnostics. In this paper, we have chosen the imaging technique of Magnetic Resonance Imaging (MRI) to detect the tumor attack location. The input MRI brain images are pre-processed with Anisotropic filtering for noise reduction. K-means clustering method is used in the process of segmenting the tumour. In order to distinguish the affected region from the image, morphological operations are conducted to extract the exact position of the tumour. Extraction of features and classification using Support Vector Machine (SVM) was performed as part of the post processing process. By our approach we are able to detect the type of tumours with 80% accuracy.

KEYWORDS: Magnetic Resonance Imaging (MRI), Anisotropic Filtering, Morphological process, k-Means Clustering, Support Vector Machine(SVM).

I. INTRODUCTION

The brain is one of the biggest and most complex human organs. This organ consists of over 100 billion neurons, which are known as synapses with trillions of pairs. Tumour is the unregulated brain tissue development that induces brain anomalies. Every year, about 12.7 million people die of cancer, of which 7.6 million diedue to brain cancer [1]. Benign and malignant are typically two different types of brain tumours. The slow-growth of the tumour indicates benign and it is non-cancerous. Whereas the rapid growth of the tumour indicatesmalignant and it is cancerous. These type of tumor are generally classified as primary brain tumours, which means the tumor has grown in the brain itself. Other tumors which propagate from somewhere else in the body by metastases are considered secondary [2].Benign and malignant are potentially fatal and actually impaired. Due to a small amount of space within the skull, its expansion raises intracranial pressures, induces edema, decreases blood supply and displaces healthier tissue that regulates the functions of essential substances.

The tumour rapidly expands into surrounding tissue and the tumour cells appear very different from typical brain cancer grade III cells. Grade IV brain tumour Images can be used to classify brain tumors using various imaging methods, such as CT (Compute Tomography) [3], PET (Positron Emission Tomography) [4], MRIetc.For better results, MRI is given priority between all of them.Filtering images is a major challenge to reduce noise from these MRI images. Numerous noises can be found in the MRI input brain image.Segmentation of images is the most popular technique which divides an image into different areas.Several segmentation techniques exist, such as Clustering-based segmentation[5], which divides the image pixels into homogeneous clusters and R-CNN(regional convolutional neural network)[6] that gives three outputs for each object in the image which are, its class, bounding box co-ordinates, and object mask.

The cancer tumor study has drawn the attention of many researchers worldwide. Numerous research works are being published yearly that discusses the issues related to brain tumor and the different methods for its early detection. Some of these researches rely on the use of image processing techniques like segmentation in their proposed works. Whereas few other researchers have used artificial intelligence structure to perform classification tasks. In other types of researches, a combination of different detection methods is being implemented to perform the detection. Amsaveniet al.[7] proposed a classification approach that is based on cascaded correlation artificial neural network.MM Ahmedet al.[8] used thethresholding process to segment the brain tumour by anisotropic, morphology operation and SVM for the purpose of segmentation.

Murugesan &Sukanesh, et al. [9] presented their work on how artificial neural networks can be used in electroencephalograms brain tumor detection. Electroencephalogram is mentioned as the most efficient measure of brain activity.Segmentation of MRI brain tumor images using clustering techniques and fuzzy reasoning with

optimisation techniques was proposed by Gopal &Karnan, et al. [10]. Modified image segmentation techniques were proposed and implemented on the MR brain images used to detect brain tumor by Dahab et al.[11]. Modified probabilistic neural network technique was implemented in this work. The proposed technique was claimed to decrease the processing time to approximately 79%. Classification result of 100% was also obtained in their work. Discrete cosine transform based brain tumor classification was presented by Sridhar & Krishna et al. [12].Morphology is also used as a post-processing technique to remove the cancer part from the existing image.Without image segmentation process the location of the tumour cannot be identified. The clustering is ideal for the segmentation of biomedical images since the presence of number of clusters of individual human anatomical regions in these images is normal[13].The symmetry bounding box is an indirect segmentation method that examines the structure of the brain system in order to insert an edge box around the tumour that helps for determining the precise location of the tumour.For classification, the SVM method is used many of the works because of its performance. The SVMs are primarily used for classification and nonlinear regression problem, with help of vector machines [14].
Classification is supervised by a group of support vector machines (SVM) and k-Nearest Neighbor(k-NN)[15];The other groups, including the Self-organizing feature map (SOFM)[16] and the fuzzy k-means feature algorithm, are unattended.Although both of these approaches have produced positive results, the classification supervised is more accurate than the unattended classification. Zhang and Wu et al. [17] proposed a technique for classifying MRI images based on SVM classifier. SVM works by mapping data to a high-dimensional feature space so that data points can be categorized SVM works, even when the data are not otherwise linearly separable. A hyperplane is drawn to categorize the different classes. For SVM, the quadratic programming performs the classification.Wavelet transform was used to extract image features, followed by the application of the principle component analysis (PCA) to reduce feature dimensions [18]. The wavelet analytics approach is used to protect the image of the edge when image noise is reduced. DWT is a form of time-frequency analysis that selects the correct frequency band according to the characteristics of the signal[19].The reduced functionality is submitted to a kernel support vector machine (KSVM) [20].

II. PROPOSED METHODOLOGY

The program suggested can be outlined in two phases. The first stage involves filtering technique which removes noise from the brain MRI image by using anisotropic filter (AF) and then threshold-based segmentation which segments the tumor area from the filtered image using a structuring function and then a morphological procedure which indicates the location of the tumor on the original image. The second stage clustering of k-means is used for tumor segmentation and discrete wavelet transformation (DWT) is used for extraction of features and classification input of the SVM.The flowchart below shows the step-by - step phase of our proposed approach as shown in figure 1.Each block of our methodology is discussed in the following sections.

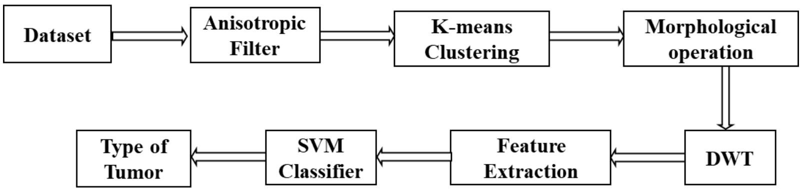
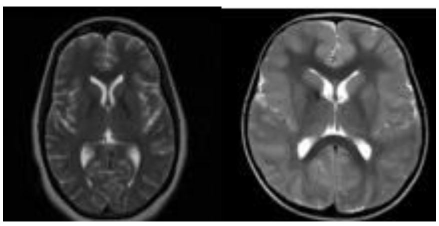


Figure 1. Flowchart of program implementation

2.1 Dataset

A single anomalous MR image is taken as input data to diagnose the tumor. The dataset consists of MR brain images weighted in T2 and the input images are in 256* 256 pixels and 8-bit grayscale. Which were taken from OASIS and ADNI Datasets. This dataset contains MR brain scans of Glioma[21], meningioma [22], Alzheimer's [23], Alzheimer's plus visual agnosia [24], Pick's [25], Sarcoma[26], and Huntington's diseases[27]. The example of normal and abnormal images in the dataset are shown in figure 2.



(a) Ordinary image (b) An anomalous image

Figure 2. Brain MR Images

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2.2 ANISOTROPIC FILTER

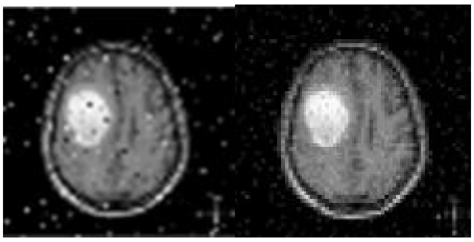
The main purpose of filtering is to eliminate noise from medical images because medical images are cohesive with various noises[28]. There are many ways of filtering MRI images from the noise in the imaging techniques. Most of the image processing algorithms does not give accurate results with noisy environment. In our work, Anisotropic Diffusion Filter is used for denoising purpose as it is widely used to enhance noisy images. But for images with spatially variable noise levels, which are retrieved from sensitivity-encoded data and intensity-corrected pictures, this is not ideal. Linear Diffusion is a traditional way to controlled smooth an image by converting it with a Gaussian kernel[29]. Non-Linear Diffusion reduces noise and improves picture contours, and the diffusion effect is modified locally, thereby being marginal when target boundaries are approached. The general anisotropic diffusion equation is

$$\frac{\partial I}{\partial t} = div(c(x,y,t)\nabla I) \ = \nabla c.\nabla I + c(x,y,t)\ \nabla I$$

Where,Δ is Laplacian, ∇ is gradient, $div$is operatorof divergence and $c(x,y,t)$ is the coefficient of diffusion. $C(x,y,t)$ regulates the diffusion rate, and is usually chosen as an image gradient to preserve the pixel edges. The two functions for the diffusion coefficient are

$$c(\|\nabla I\|) = e^{-\left(\frac{\|\nabla I\|}{K}\right)^2};\ c\,(\|\nabla I\|) = \frac{1}{\left(1+\left(\frac{(\|\nabla I\|)}{K}\right)^2\right)}$$

The constant K regulates edge sensitivity and is a function of the noise in the images. The figure 3 shows the images containing salt and pepper noise and how it is filtered out using anisotropic filter.



(a) Salt & pepper noise Image (b) Filtered output

Figure.3. Anisotropic filter input & output

2.3 K-MEANS CLUSTERING SEGMENTATION

Image segmentation is important due to the large number of images generated during the scan. This includes transforming an image into a set of regions of pixels represented by a mask or alabelledimage [30]. By splitting an image into segments, we can process only the relevant segments of the image, rather than the whole image.Segmentation of the image refers to the division of the specified image into several non-overlapping regions. Segmentation defines the image into collections of pixels that are harder to interpret and more important it is extended to identify the borders or artifacts in an image essentially and the subsequent segments comprise the whole image collectively [31]. The algorithms of Segmentation are based on discontinuity and similarity of the strength values of one of two fundamental properties. First type is partitioning an image based on sudden strength shifts, such as edges in an image. The second type is focused on the partitioning of an image into regions related to predefined criteria.

Various segmentation techniques are therefore operational, such as threshold-based segmentation, histogram-based approaches, region-based, edge-based and clustering approaches. A common algorithm for grouping data into k clusters is K-means[32]. K-means clustering classifies or groups objects into K classes based on their attributes and features where Kis a positive integer number. The grouping takes place by minimizing the distances between data and the respective cluster centroid. The distance that will be used here is theL2distance$(d(x,y) \ = \sum i(xi - yi)2)$. The cycle of clustering only ends when all cluster centroids converge.Where there areKclusters$Si, i = 1,2,\ldots,K,$ andci is the centroid or meanpoint of all the points$xj \in Si$.

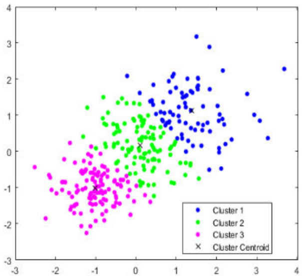


Figure.4 Implementation of clustering

2.4 MORPHOLOGICAL OPERATION

Morphology is a wide range of image processing operations which process images using shapes. Morphological operations add a structuring element to an input image, generating the same size of the output image. The value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbors in a morphological operation [33]. Morphology is useful for the shape of legations and recitals, such as boundaries, skeletons and convexhulls. The structuring of kernel in morphological activity is necessary.Throughout fact, the structuring factor used is usually much smaller than a 3* 3 matrix frequently used in the illustration. Morphological operation is added after segmentation of the image are done.The two commonly used morphology operations are: a) Dilation [34]: which functions by extending the object, covering the holes and eventually adding up all the disjoint objects, and b) Erosion [35]: this activity shrinks the object.

Erosion activity in the binary image erodes the backdrop of foreground pixels. The pixel values greater than the specified threshold are converted to white, while others are converted to black, resulting in specific areas of polluted tumor tissues [36]. Eventually, the eroded area and the initial image are both separated into two equivalent regions and the black pixel component removed from the eroded process is classified as an imagemask.Also, dilation process is basically used to fill the holes(missing pixels) in a continuous object. The dilation procedure, since it adds pixels at the boundary of the object it affects the intensity at that position and can therefore be observed blurring effect. So, it can be said that it is analogous to smoothingspatial low pass filters[37] that are used in linear filtering of theimage.

2.5 DISCRETE WAVELET TRANSFORM(DWT)

DWT is a function of the wavelet with which it samples wavelets at discrete intervals. DWT adds information to the image's simultaneously in space and frequency domain [38]. The combination of analytical filter bank and decimal operations will evaluate the picture in DWT operation. The analytical filter bank comprises of two low-level and high-level filters which correspond to each level of decomposition as shown in the figure below. The low pass filter extracts information about the image while the high pass filter extracts information like margins.

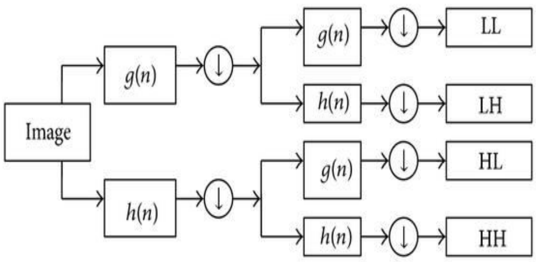
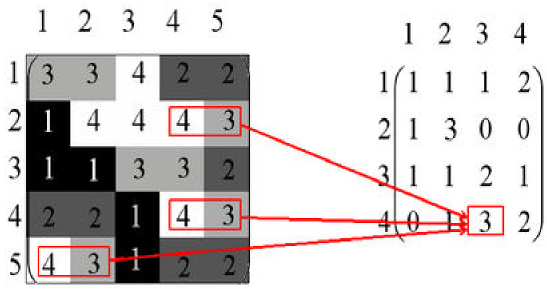


Figure.6 DWT implementation.

Wavelets are also used to denoise signals in two dimensions, such as images. MATLAB software was used to importand filter the image. PCA is a tool which is used to decrease the proportions of a number of interrelated variables whilemaintaining certain variable[39]. That implies that the dimensions of a large set of variables are reduced to a small set that still contains much of the information in the large set.

PCA moves the second variable variance to the first variable by converting and rotating the initial axes and moving the results to new axes.The direction of the projection is determined by means of eigen values and individual vectors. The first few transformed features (called principal components) are therefore rich in information, whereas the last features mostly contain noise with insignificant information. Such transferability allows one to maintain the first few key components, thus substantially reducing the number of variables with limited information loss. Another method called Grey Level Co-occurrence Matrix (GLCM) is designed to obtain statistical texture characteristics so that we can reliably identify and segment images[40]. GLCM method is a means of extracting statistical texture characteristics of second order. This approach has been employed in several applications. GLCM is a matrix in which the number of rows and columns in the image is equal to the number of gray levels. The matrix variable P (i,j|Δx, Δy) is the relative frequency with which two pixels, separated by a distance of pixels (Δx, Δy) occur within a given neighbourhood, one with intensity 'i' and the other with intensity 'j'[41].The matrix variable P (i, j|d, ɵ) contains the second order statistical probability values for changes between the gray rates 'i' and 'j' at a specific displacement distance d and at a specific angle (ɵ). Using a large number of intensity rates G means storing a lot of temporary data, i.e. a matrix of G x G for any combination of (Δx, Δy) or (d, ɵ). The GLCM's are very sensitive to the size of the texture samples on which they are estimated because of their large dimensionality. Consequently, the number of grays is often decreased. GLCM has proven to be a common statistical tool for extracting textural characteristics from images.



(a) Image (b) Co -occurrence matrix

Figure .7 GLCM implementation

2.6FeatureExtraction

DWT is the algorithm used to extract a characteristic from the gray image [42]. Thirteen features were extracted from the images by selecting forward and backward elimination process. One of the key advantages of wavelets is their ability to adjust spatially to functional features like discontinuities and varying frequency behaviors. The features are enlisted belowContrast, Correlation, Energy, Homogeneity, Mean, Standard deviation, Entropy, RMS (Root Mean Square), Variance, Smoothness, Skewness, Kurtosis, IDM (Inverse Difference Moment). Upon extraction of the features, these images are categorized into different categories using the SVM classifier.

2.8 SVMClassifier

In 1963 Vapnik and Lerner [43] created the SVM algorithm for the first time. Support Vector Machines are a group of linked controlled methods of learning for classification and regression. SVM is a binary and supervised learning classifier that provides better performance than others. A peculiar feature of SVM is that it minimizes the error of empirical classification and maximizes the geometric range. This techniqueuses the kernel trick to transform the data and then finds an optimal boundary between the possible outputs on the basis of these transformations.The aim is to construct a hyper plane that classifies all training vectors into two classes.

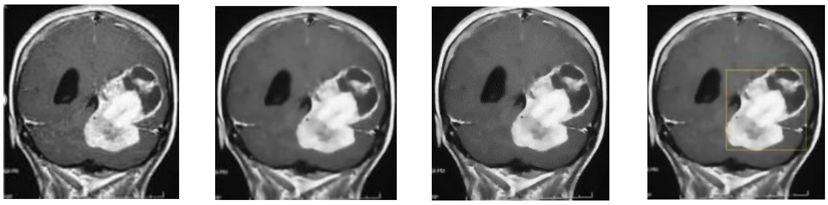
SVMs work by nonlinear projection of training data in the input space to a higher (infinite) dimensional feature space using a kernel function [44]. This results in a linearly separable data set that a linear classifier can separate.This process allows the classification of remote sensing data sets, which are normally nonlinear in the input space. In certain cases, grouping into high-dimensional feature spaces results in over-adjustment of the input space. The Gaussian kernel SVM classifier [45] is essentially a weighted, linear combination of the kernel function with a data point and its supported vector. The Gaussian kernel transforms the dot product into the Gaussian function of the distance between points in the data space in the infinite dimensional space. If two points in the data space are adjacent then the angle in the kernel space between the vectors representing them will be small. If the points are distant then the corresponding vectors are nearly perpendicular.

III. RESULTS

Through MRI brain images, we sought to correctly identify the tumor. Segmentation using k-means clustering and morphological operations was performed with the objective of noise reduction using anisotropic filter to extract the exact position of the tumor and detect the type of tumor (benign or malignant) using the Gaussian kernel SVM function. We achieved classification accuracy of 50% without filtering. For the same images after applying filtering techniques we got an accuracy of 80%. Here are the various approach methods of brain tumor classification and their accuracy shown in the below table1.

Approach methods	Classification accuracy (%)
Anisotropic filter+ Median filter+ DWT + PCA + GLCM + SVM	65
Anisotropic Filter + Median Filter + GLCM + SVM	70
Anisotropic filter + Clustering + DWT + PCA + GLCM + SVM	80

Table.1 Showing different approach methods of classification and their accuracy.



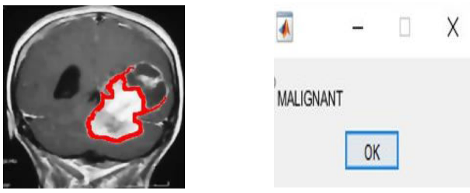
(a) Input image (b)Anisotropic filtering (c) Cluster object (d) Bounding Box

Figure 9: Rsults in different stages of process

The above images shows the input image we have taken from the dataset. As the input image has a noise in it we have filtered it using anisotropic filtering.As we can see a bounding box is appeared in the figure 9(d) after clustering has been applied.

(a) Segmented Tumor (b) Eroded Image (c) Tumor outline (d) Tumor alone

The above image shows how the backdrop of foreground pixels is eroded away by erosion activity in the binary image.The above images d, e, f, and g are the outputs of morphological operation. The eroded area and the initial image are both separated into two equivalent regions and the black pixel component removed from the eroded process is classified as an imagemask.



(c) Detected tumor (d) Tumor type

Finally the tumor is detected and the type of tumor is displayed as shown in the above image(h).

IV. CONCLUSION

Output of the MRI brain images can contain different noises. The MRI input images should be noise-free for proper segmentation and morphological operation accuracy. For this purpose, we used the anisotropic filter to increase its efficiency. K-means Clustering is implemented for image segmentation. SVM classifieris used for classifying the pixels into two types and detect the type of tumor. Since our program has been developed for any MRI brain input image, the tumor is separated from the segmented area using morphological operations. Finally, the device can detect the tumor and classifythe type of tumor.

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BIOGRAPHY

V.Keerthi Kiran, is an Assistant Professor at Raghu Institute of Technology, from Department of Electronics and Communication, Visakhapatnam, India and Ph.D. Scholar from GIET University, Gunupur, India. He has received his B. Tech in 2013 from VITAM College of Engineering, Visakhapatnam, India and M. Tech in 2015 from VR Siddhartha College of Engineering, Vijayawada, India. His research Embedded systems, IoT and Image Processing.

Y. Lokeshis pursuing B.TECH in Electronics and Communication Engineering from Raghu Institute of Technology, Visakhapatnam, AP and India.

P. Mounika is pursuing B.TECH in Electronics and Communication Engineering from Raghu Institute of Technology, Visakhapatnam, AP and India.

Rohit Kumar. K is pursuing B.TECH in Electronics and Communication Engineering from Raghu Institute of Technology, Visakhapatnam, AP and India.

Ch. Mohan Kumaris pursuing B.TECH in Electronics and Communication Engineering from Raghu Institute of Technology, Visakhapatnam, AP and India.