A Novel Approach for Identifying the Stages of Brain Tumor

Y.V.Sri Varsha [1], S.Prayla Shyry [2]

[1] PG Scholar,Department Of CSE, Sathyabama University, Chennai.

[2]Assistant Professor, Faculty Of Computing, Sathyabama University, Chennai.

ABSTRACT-In recent years, brain tumor is one of the major cause for death in people. The most efficient way to reduce the brain tumor is to detect it at the earlier stage itself. Traditional systems use various image processing techniques to identify the brain tumor at the earlier stages. Among the multi modal images each one has their own importance. In the proposed system, neural network is used. The neural network is trained with selected features and then features are extracted and tumor affected regions can be detected. The future enhancement is to detect the stages of brain tumor for each Multimodal image in more efficient and short duration.

KEYWORDS: Brain Tumor, Multimodal, Neural Network.

I.INTRODUCTION

Brain tumor is very hazardous disease to human beings due to which death may occur. Brain Tumor is created by abnormal cell division in brain. Brain tumors are typically categorized into Primary and Secondary. Primary brain tumors are named according to the type of cells or the part of the brain in which they begin. When cancer cells spread to another part of the body they are called secondaries or metastases**.** Secondary brain tumors are malignant.

Brain tumors are mainly divided into two types.

- Benign Brain Tumor (non-cancerous)
- Malignant Brain Tumor (Cancerous)

A benign brain tumor is rapid mass of cells which grows slowly in the brain. Benign tumor usually stays in one place and does not spread.

Malignant tumors are secondary cancers which means they start at some part of the body and spread to brain. .This brain tumor is a fast-growing cancer that spreads to other areas of the brain.

Automated detection of brain tumor becomes difficult due to variations in size, shape, locations and positions. A multi modal framework for automatic tumor detection by fusing different images is applied. The Multi modal images with the generated coefficients have been used for training neural networks and then features are extracted.

Feature Extraction involves simplifying the amount of resources required to describe large set of data accurately. There are different types of features like statistical features, non statistical features, and textural features. In these methods different types of feature extraction can be studied by recognizing the size, shape, location.

The Remainder of this paper is organized as follows. Related articles are reviewed in section 2. Summary of the existing system in section 3. Proposed methods are described in section 4. Results and the discussion are quoted in section 5. Conclusions are presented finally in Section 6.

II. RELATED ARTICLES

Dhanalakshmi et al.(2013) developed a paper for automated segmentation of Brain tumor using K-means clustering and its area calculation. They identified that the anatomy of the brain can be viewed by the CT scan or MRI. Generally the images produced by the CT scan should be examined by the physician to get the outcome of the disease and CT scan produces large amounts of radiation. To overcome this they go for MRI because MRI scan is more comfortable than CT scan for diagnosis. It will not affect the human body as it doesn't use any radiation it is based on the magnetic field and radio waves. There are numerous algorithms developed for brain tumor detection but they may possess some problem in detection and extraction. So, they proposed a simple algorithm for detecting the range and shape of tumor in MR images has been described.

This system uses the combination of two algorithms for segmentation K-means clustering and K-means segmentation. If there is any noise present in the MR image it is removed before the K-means process. The input to the K-means is given as a noise free image and then the tumor is extracted from the MR image.

Meghana et al. (2013) developed a paper for detection of brain tumor by mining Functional MRI images**.** They identified that clustering algorithms were not able to produce 100% accuracy. The accuracy rate of clustering algorithms is 86% which is not up to the level of satisfaction. So, a novel approach based on decision tree algorithms was developed.

When compared with clustering algorithms decision tree algorithms are proven to be better. Because system stores the values in data sets instead of storing in FMRI images. So, they have concluded that supervised algorithms can be better than unsupervised learning algorithms in brain tumor detection.

Gladis et al. (2012) developed a paper for MRI image classification with feature selection and extraction using linear discriminant analysis. They have identified that when dealing with the number of variables there exists a complexity. Analysis with a large number of variables generally requires a large amount of memory and computation power. So, this drawback was overcome by a novel based method which combines intensity, texture, color and shape. This technique has been carried out over a large database. When compared to previous works this technique is more robust and effective.

Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) were applied on the training sets.PCA and LDA methods are used to reduce the number of features used. The feature selection method will be more beneficial which analyses the data according to grouping class variable and gives reduced feature set with high accuracy rate.

N.Rajalakshmi et al. (2013) developed a paper for Brain MRI using color converted K-means clustering segmentation with multiclass SVM. They identified that Computer aided Diagnosis (CAD) did not produce accurate results compared to MRI and it requires large amounts of computing processing power. So, they proposed the MR images by wrapper approach with Multi Class support vector machine and a hybrid clustering segmentation algorithm for K-means.

These algorithms are used for identification of tumors, this approach is efficient for classification of the human brain normal or abnormal (benign or malignant tumor) with high accuracy rates sensitivity and specificity.

Shaheen et al. (2011) developed a paper for image features and segmentation. They have identified to detect pediatric brain tumor in multimodal MRI which does not provide accurate segmentation of images and efficacy. So to overcome this drawback they have proposed Kullback–Leibler divergence (KLD) measure for feature ranking and selection and the expectation maximization algorithm for tumor segmentation and feature fusion.

Texture feature obtained using a stochastic multifractional Brownian motion (mBm) model is shown effectively to segment brain tumor. So, they have concluded that KLD feature selection technique with mBm is the best feature for both T1 and fluid-attenuated inversion recovery (FLAIR) modalities while intensity is for T2 modality.

Anjali et al. (2013) developed a paper for fast Discrete Curvlet Transformation. The drawback was based on Wavelet transformation. Only spatial correlation of the pixels inside the single 2-D block is considered and the correlation from the pixels of the neighboring blocks is neglected. This drawback was overcome by proposed method named curvlet transform.

Curvlet transform is more useful for the analysis of images having curved shape edges. The proposed method preserves both high spatial resolution and high spectral quality contents with good directionality and can be best suitable for medical applications.

A.Padma et al. (2011) developed a paper for brain tumor in CT images using Optimal Gray level run length texture features. The problem of this paper deals with the study of Computed Tomography images. The limitations of CT scan are due to partial volume effects which affect the edges and produce low brain tissue contrasts and yield different objects within the same range of intensity due to which segmentation becomes a difficult task. So, proposed system is based on new dominant run level feature extraction methodology for the classification and segmentation of tumor in brain CT images using support vector machine (svm) with genetic algorithm feature selection, this gives us better classification and segmentation method when compared with other texture analysis methods. The SVM identifies abnormal tumor region detection and segmentation thereby saving a lot of time and minimizing the complexity involved.

III. SUMMARY OF EXISTING SYSTEM

Segmentation relies on intensity differences between structures in an image. It is the process in which image can be partitioned into several different images to acquire region of interest. It has long been used for dividing the images into regions as well as detecting the boundaries. Image segmentation may use thresholding ,statistical classification, region detection, edge detection, or any of these combinations.

Drawbacks of segmentation are due to low tolerance to intensity rescaling and it is difficult to set threshold. Thresholding techniques are also applied to detect the tumor. The main problem with thresholding is that we cannot determine threshold values because intensities are scattered and wrong selection may label healthy parts as tumors. So, this technique is not reliable. Region growing is also very common for tumor detection this requires a seed point to segment and determine the threshold values. To overcome these drawbacks we are going for proposed system.

IV. PROPOSED SYSTEM

The proposed image fusion method is used to detect the tumor by utilizing multimodal scanning images such as computed tomography (CT), Magnetic Resonance image (MRI), Positron Emission Tomography (PET) and single photon emission computed tomography (SPECT). Image Fusion is applied to combine any of the images like CT, MRI or any of the images in order to get the clear view of the images as each image gives clear view so by combining we get the exact clarity of the images. To these inputs discrete wavelet transformation is applied to get the coefficient values. Wavelet transformation produces a few significant coefficients for the signals with discontinuities. Thus, we obtain better results for Wavelet transformation nonlinear approximation when compared with the Fourier transformation.

A Soft Computing tool, neural network is used for training the input images. The advantage of using neural network is these are quite simple to implement and will perform faster computation of tasks when compared to other approaches. Neural networks can be used in training the selected features. By feature extraction we can get the image intensity, shape and texture. Feature extraction involves simplifying the amount of resources required to describe large sets of data accurately

BLOCK DIAGRAM

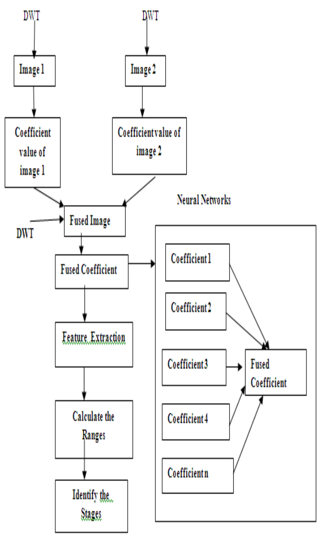

Figure1.1 General Block Diagram

Figure 1.1 shows general block diagram of proposed image fusion method. Firstly, discrete wavelet transformation is applied on the input images. It decomposes input images and gives us the coefficient value for each input image. These coefficient values are been fused to generate the fused image. For this we apply discrete wavelet transformation to get fused coefficient. These coefficients are been trained in neural networks to generate the fused coefficient and then features are extracted by their shape,texture,intensity and then we check the ranges for each of them and finally identify the stages based on the ranges.

V. RESULTS AND DISCUSSIONS

In this section, experimental results on real images and some other existing images are taken. These experiments were conducted on 2.53 Intel(R) Core(TM) i3 Processor with 2 GB of RAM, and running on windows 7 operating system. In this algorithms were implemented in MAT lab Software (MAT LAB7.8.0) and applied both real and existing images to evaluate the performance of the algorithm.After applying the DWT the image is being transformed into 4 levels as shown in the figure 2 and was implemented in Mat lab 7.8. Levels of the Decomposition are Absolute, Horizontal, Vertical, and Diagonal (A, H, D, and V).

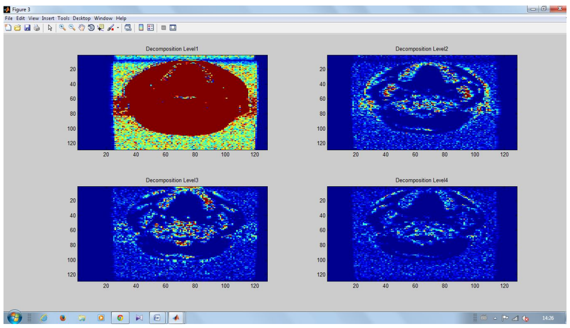

Figure 2: Decomposition Levels

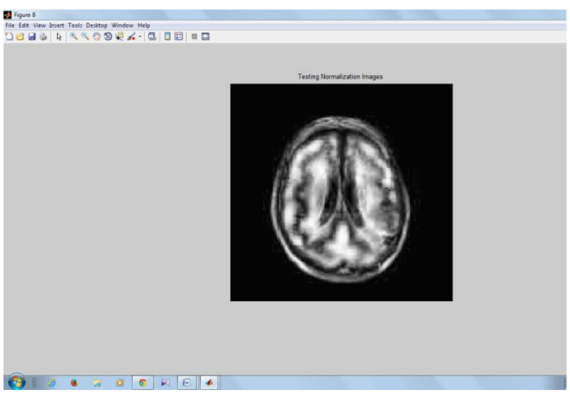

Figure 3: After applying image fusion i.e. combining CT and SPECT.

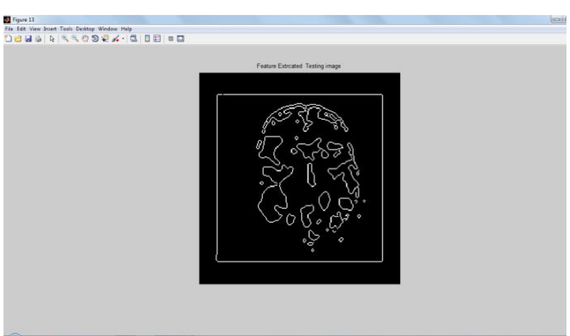

Figure 4: After Applying Feature Extraction by Using MPEG 7 descriptor the image is transformed like this.

VI. CONCLUSION:

The automatic brain tumor segmentation is an important problem in medical imaging. Although much effort has been spent on finding a good solution to this problem, it is far from being solved. This paper presented a fully automatic procedure for tumor segmentation. The proposed method is based on Discrete Wavelet Transform and neural networks. The initialization of the algorithm integrates images and transforms it into new one which leads to an automatic process there by, removing all the noise and reconstructing into a new image. Quality results in the tumor are relatively good due to the combination of fusion technique. In future Image fusion can be carried out using some different optimization like particle swarm optimization and Ant colony etc., techniques and the results can be compared with the present outputs.

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