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Detecting Anomalies present in Brain MRI

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Abstract: **- A brain tumor is a mass of unnecessary cells growing in the brain. Brain tissue classification from magnetic resonance images (MRI) is of great importance for research and clinical studies of the normal and diseased human brain. In just a few decades, the use of magnetic resonance imaging (MRI) scanners has grown enormously. An MRI scan is the best way to see inside the human body without cutting it open. It uses strong magnetic fields and non-ionizing radiation in the radio frequency range. Brain tumor effects may not be the same for each. Brain tumors can have a variety of shapes and sizes person.**

In This Paper, We have take two dimension MRI jpeg image, then Normalized cut segmentation is performed on it after that we get three different images. First one is colour image for separating different parts of images. If any anomalies are present in the brain then it should be seen also. Second one is image noise must be removed from the image. And last part is edges are detected from image after that we are taking the color image and converting those images into matrix format. Then we get some vector value on the basis of that vector value classification must be performed by using the approach of ANN.

***Key Words*— Magnetic Resonance Images (MRI), Brain Tumor Detection, brain MRI classification, Artificial Neural Network (ANN), Normalized cut segmentation**

I. INTRODUCTION

Brain tumor is one of the major causes of death among people. It is evidence that the chances of survival can be increased if the tumor is detected correctly at its early stage. Detection of these tumors from brain is very difficult at the regions where a tumor is overlapped with dense brain tissues. Visually detection of these abnormal tissues may result in misdiagnosis of volume and location of unwanted tissues due to human errors caused by visual fatigue. Nowadays, automatic brain tumor detection in MRI images is very important in many diagnostic and therapeutic applications. In the early research of medical tumor detection, the algorithms have directly used the classic methods of image processing based on gray intensities of images. In recent years, those techniques have been combined with artificial neural networks (ANNs), genetic algorithm (GA), fuzzy logic, and Markov model to improve the performance [1].

Magnetic resonance imaging (MRI), nuclear magnetic resonance imaging (NMRI), or magnetic resonance tomography (MRT) is a medical imaging technique used in radiology to visualize detailed internal structures. MRI makes use of the property of nuclear magnetic resonance (NMR) to image nuclei of atoms inside the body.

An MRI machine uses a powerful magnetic field to align the magnetization of some atomic nuclei in the body, and radio frequency fields to systematically alter the alignment of this magnetization. This causes the nuclei to produce a rotating magnetic field detectable by the scanner—and this information is recorded to construct an image of the scanned area of the body. Magnetic field gradients cause nuclei at different locations to rotate at different speeds.

According to the channels used, the techniques can be classified into single channel and multi-channels MS lesion segmentation techniques.

II. ARTIFICIAL NEURAL NETWORK

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform intelligent tasks similar to those performed by the human brain. Neural networks resemble the human brain in two ways: they acquire knowledge through learning and the knowledge is stored within inter-neuron connection strengths known as synaptic weights. The true power and advantage of neural networks lies in their ability to represent both linear and nonlinear relationships and in their ability to learn these relationships directly from the data being modeled. Traditional linear models are simply inadequate when it comes to modeling data that contains nonlinear characteristics.

Artificial neural networks (ANNs) are parallel networks of processing elements or nodes that simulate biological learning. Each node in an ANN is capable of performing elementary computations. Learning is achieved through the adaptation of weights assigned to the connections between nodes. ANNs can also be used in an unsupervised fashion as a clustering method as well as for deformable models. Because of the many interconnections used in a neural network, spatial information can be easily incorporated into its classification procedures [3].

III. SUPPORT VECTOR MACHINES

Support Vector Machine (SVM) is a supervised learning algorithm, which has at its core a method for creating a predictor function from a set of training data where the

function itself can be a binary, a multi-category, or even a general regression predictor. To accomplish this mathematical feat, SVMs find a hypersurface which attempts to split the positive and negative examples with the largest possible margin on all sides of the hyperplane. It uses a kernel function to transform data from input space into a high dimensional feature space in which it searches for a separating hyperplane. The most common types of kernel functions used are: polynomial for polynomial classifiers, Gaussian for radial-basis function (RBF) classifiers, and tangent hyperbolic for two-layer perceptron classifiers.

The main idea of the SVM is to find a decision boundary between classes in the original feature space by mapping the feature vectors to a high dimensional space, where the features are more likely to be linearly separable.

Support vector machines (SVM) are a group of supervised learning methods that can be applied to classification or regression. Support vector machines represent an extension to nonlinear models of the generalized portrait algorithm developed by Vladimir Vapnik. The SVM algorithm is based on the statistical learning theory. Support Vector Machines (SVMs) apply a simple linear method to the data but in a high-dimensional feature space non-linearly related to the input space.

IV. NORMALIZED CUT ALGORITHM

Our project work includes the embedding of a normalized cuts algorithm and testing its application for image segmentation. Normalized cut tries to define a reasonable objective function for a good segmentation, and then to approximate the solution to this. To keep things simple, we'll just consider the problem of dividing the image into two regions. We consider the image as a graph, in which each pixel is a vertex, and the edge between two vertices represents the extent to which they seem to belong together. Edges have high weight when the pixels are nearby and similar.

A. NCUT Segmentation Algorithm

1. Set up problem as G = (V,E) and define affinity matrix A and degree matrix D.
2. Solve (D – A)x = λDx for the eigenvectors with the smallest eigenvalues.
3. Let x_2 = eigenvector with the 2^{nd} smallest eigenvalue λ_2.
4. Threshold x_2 to obtain the binary-valued vector x'_2 such that ncut $(x'_2) \geq$ ncut(xt2) for all possible thresholds t.
5. 5. For each of the two new regions, if ncut < threshold T, then recurse on the region

V. PROBLEM IDENTIFICATION

In existing paper, detecting single anomalies like tumor, nail or etc. Here in this case no pre defined dataset will be used, we are using image matrix value as a dataset in which there is no use any random brain MRI image as a dataset.

Classification of segmentation methods is done based on the approaches adopted and the domain of application [7]. But problem is that when one class support vector machine is used for classification then accuracy rate should be 60%-87% and time taken is also not exactly defined.

Tumor segmentation from magnetic resonance imaging by learning via one-class support vector machine

VI. SOLUTION APPROACH

Detecting single anomalies like tumor, Multiple Sclerosis Lesions, blood clot or etc. Here in this research i m trying to detect if an image contain any different type anomalies if it is available on the image on the basis of their color intensity

In this project we have take two dimension MRI jpeg image, then Normalized cut segmentation is performed on it after that we get three different images.

- Firstly, color image for separating different parts of images. If any anomalies are present in the brain then it should be seen also.
- Image noise must be removed from the image.
- Edges are detected from image after that we are taking the color image and converting those images into matrix format.

Then we get some vector value on the basis of that vector value classification must be performed by using the approach of ANN.

VII. CONCLUSION

The main purpose of this paper is to design and evaluate an automatic computer aided diagnosis algorithm that increases the accuracy of brain tumor detection. To improve tumor detection accuracy, here we take black and white MRI image and we get a segmentized image with three different output i.e. color image ,grey scale image and black and white image that can detect border of an object. After that we are converting the color image into matrix format.

We used a normalized cut algorithm and used it for the intensity and color segmentation. Even though the approximate eighenvalue method and the algorithm construction optimize implementation; computational complexity remains unsolved for the full-scale image. The performance and stability of the partitioning highly depends on the choice of parameters.

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