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Efficient Brain Tumor Detection Using Wavelet Transform

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ABSTRACT
Brain tumor detection is a challenging task and its very important to analyze the structure of the tumor correctly so a automatic method is used now a days for the detection of the tumor. This method saves time as well as it reduces the error which occurs in the method of manual detection. In this paper the tumor is detected using wavelet transform. MRI is an important tool used in many fields of medicine and is capable of generating a detailed image of any part of the human body. The tumor is segmented from the MRI images, features are extracted and then the area of the tumor is determined. PNN can successfully handle the process of brain tumor classification.
Keywords: Brain tumor, detection, MRI, segment, wavelet.

I. INTRODUCTION

The buildup of extra cells often forms a mass of tissue called a growth or tumor. Brain tumor is one of the major causes of death among people. The symptoms of a brain tumor depend on tumor size, type and location. Symptoms may be caused when a tumor presses on a nerve or harms a part of a brain. Also they may be caused when a tumor blocks the fluid that flows through and around the or when the brain swells because build up of fluid. Headaches, nausea and vomiting, Changes in speech, vision or hearing, problem balancing or walking, changes in mood, personality or ability to concentrate, problems with memory, muscle jerking or itching, numbness or tingling in the arms or legs.

Accurate detection of the type of brain abnormality is highly essential for treatment planning which can minimize the fatal results. Manual detection of brain tumor is a tedious job and takes a lot of time and not accurate, varies from one doctor to another. Accurate results can be obtained only through computer aided automated systems. Besides being accurate, these techniques must coverage quickly in order to apply them for real time applications. Brain tumor can be diagnosed by using magnetic resonance imaging (MRI), ultrasonic, CT images and X-rays. Magnetic Resonance Imaging is an important tool used in many fields of medicine and is capable of generating a detailed image of any part of the human body.

MRI stands for Magnetic Resonance Imaging. A MRI scanner uses powerful magnets to polarise and excite hydrogen nuclei (single proton) in human tissue, which produces a signal that can be detected and it is encoded spatially, resulting in images of the body. The MRI machine emits radio frequency (RF) pulse that specifically binds only to hydrogen. The system sends the pulse to that specific area of the body that needs to be examined. Due to the RF pulse, protons in that area absorb the energy needed to make them spin in a different direction. This is meant by the resonance of MRI. The RF pulse makes the protons spin at the larmour frequency, in a specific direction. This frequency is found based on the particular tissue being imaged and the strength of the main magnetic field.

Classification of the brain tumor is also a important task for treatment planning. There are two types of tumor which are- benign (non-cancerous) and malignant (cancerous) tumors. Conventional methods involve invasive techniques such as biopsy, lumbar puncture and signal tap method, to detect and classify brain tumor into benign and malignant which are very painful and time consuming.

Wavelet analysis is an effective methodology capable of revealing aspects of data which other signal analysis techniques. Analyzing the images at multiple levels, the method is able to extract finer details from them and in turn improves the quality of the image. In addition, wavelet analysis is capable of compressing or de-noising a signal without appreciable degradation. Wavelet analysis is of at most importance in case of delicate information, such as in case of medical imaging.

II.   IMPLIMENTED WORK

2.1 MR image to gray scale image:

MRI images are magnetic resonance images which can be acquired on computer when a patient is scanned by MRI machine. We can acquire MRI images of the part of the body which is under test or desired. Generally when we see MRI images on computer they looks like black and white images. In analog practice, gray scale imaging is sometimes called "black and white," but technically this is a misnomer. In true black and white, also known as halftone, the only possible shades are pure black and pure white. The illusion of gray shading in a halftone image is obtained by rendering the image as a grid of black dots on a white background (or vice versa), with the sizes of the individual dots determining the apparent lightness of the gray in their vicinity. The lightness of the gray is directly proportional to the number representing the brightness levels of the primary colors. Black is represented by R = G = B = 0 or R = G = B = 00000000, and white is represented by R = G = B = 255 or R = G = B = 11111111.

Grayscale is a range of shades of gray without apparent color. The darkest possible shade is black, which is the total absence of transmitted or reflected light. The lightest possible shade is white, the total transmission or reflection of light at all visible wavelengths. So because of the above reasons first we convert our MRI image to be pre-processed in grayscale image.

2.2 Image segmentation:

In image segmentation the level to which the subdivision of an image into its constituent regions or objects is carried depends on the problem being solved. In other words, when the object of focus is separated, image segmentation should stop the main goal of segmentation is to divide an image into parts having strong correlation with areas of interest in the image. In medical imaging for analyzing anatomical structures such as bones, muscles blood vessels, tissue types, pathological regions such as cancer, multiple sclerosis lesions and for dividing an entire image into sub regions such as the white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) spaces of the brain automated delineation of different image components are used. In the field of medical image processing segmentation of MR brain image is significant as MRI is particularly suitable for brain studies because of its excellent contrast of soft issues, non invasive characteristic and a high spatial resolution Segmentation is the process of splitting an observed image into its homogeneous or constituent regions. The goal of segmentation is to simplify or change the representation of an image into something that is more meaningful and easier to analyze. It is important in many computer vision and image processing application.

Fuzzy C-means clustering is the overlapping clustering technique. One pixel value depending upon the two or more clusters centers. It is also known as soft clustering method. Most widely used the fuzzy clustering algorithms is the Fuzzy C-means (FCM) algorithm. The FCM algorithm is the partition of the n element X={x1,...,xn} into a collection of the c fuzzy clustering with respect to the below given criteria. It is based on the minimization of the following objective function:

$$J=\sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^{m} |x_i - y_i|^2 \quad (1)$$

Where, m = level of the fuzziness and real number greater than 1.
uij= degree of the membership of xi in the cluster cj
x = data value

Fuzzy C-means is the popular method for medical image segmentation but only consider the image intensity thereby producing unsatisfactory results in noisy images. A bunch of the algorithms are proposed to make the FCM robust against noise and in homogeneity but it's still not perfect. fuzzy c-mean is slower than the K-means in efficiency but gives the accurate prediction of tumor cells which are not predicted by the K-means algorithm.
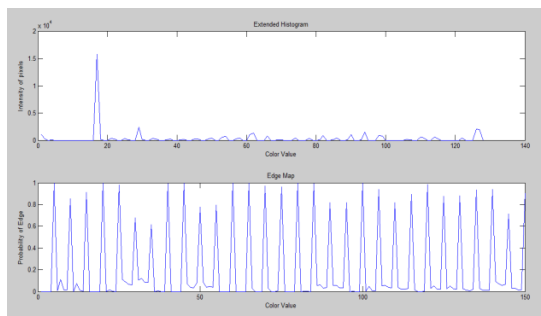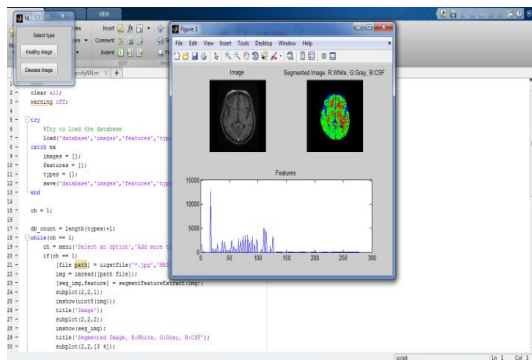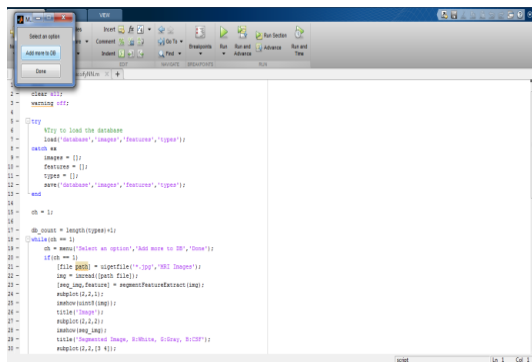

Original image   Skull stripped image

White matter   Gray matter

CSF matter   Segmented image
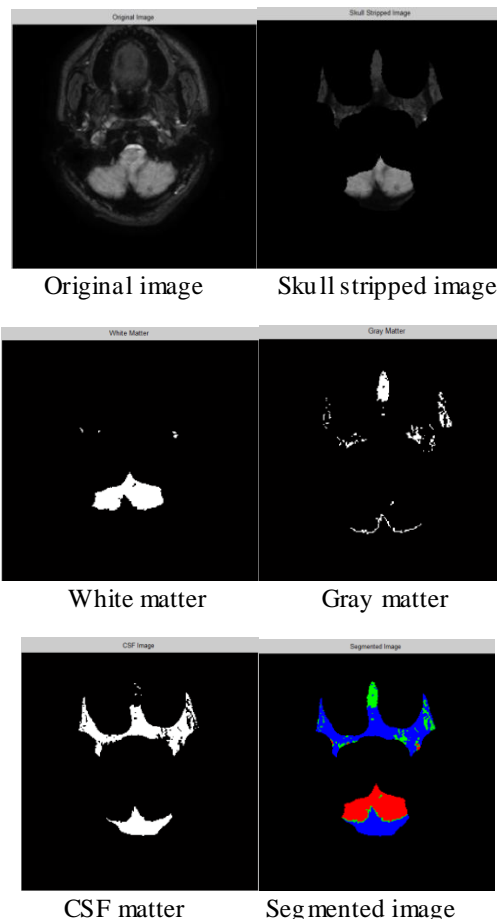
Fig: Extended Histogram and Edge map

2.3 Create database:

A database is an organized collection of data and here it's a collection of images. The database is created using a number of images that are selected and divided into two groups that are healthy and disease image.


2.4 Feature extraction:

Texture analysis makes differentiation of normal and abnormal tissue easy. It even provides contrast between malignant and normal tissue, which may be below the threshold of human perception. Texture analysis using computer aided diagnosis can be used to replace biopsy techniques and plays an important role in early diagnosis and tracking of diseases.

The wavelet is a powerful mathematical tool for feature extraction, and has been used to extract the wavelet coefficients from MR images. Discrete Wavelet Transform is an implementation of the WT using the dyadic scales and positions.

Two dimensional DWT results in four sub bands LL (low-low), LH (low-high), HL (high-low), HH (high-high) at each scale. Sub band LL, is the approximation component of the image, which is used for next two dimensional DWT. Whereas, LH, HL, HH are the detailed components of the image along the horizontal, vertical and diagonal axis, respectively, as shown in the figure:
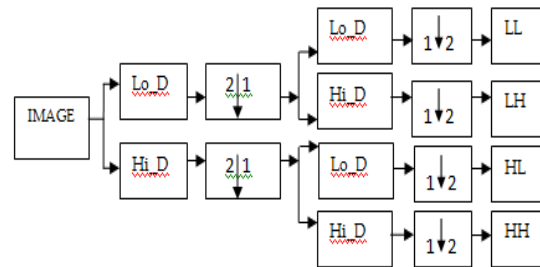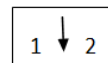

Lo_D: low pass filter
Hi_D: high pass filter
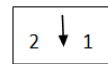
 - Down sampling columns: keeps the even indexed columns.

 - Down sampling rows: keeps the even indexed rows.

2.4 Classification:

Classification is done using probabilistic neural network. Probabilistic Neural Network (PNN) is a Radial Basis Neural Network, which provides a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian classifiers.

Probabilistic Neural Network has three layers, as shown in fig., the Input layer, Radial Basis Layer and the Competitive Layer. Radial Basis Layer evaluates vector distances between input vector and row weight vectors in weight matrix. These distances are scaled by Radial Basis Function nonlinearly. Then the Competitive Layer finds the shortest distance among them, and thus finds the training pattern closest to the input pattern based on their distance.
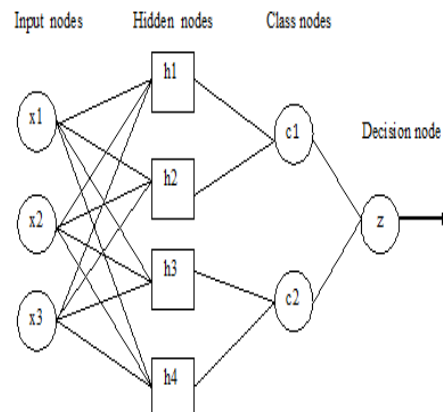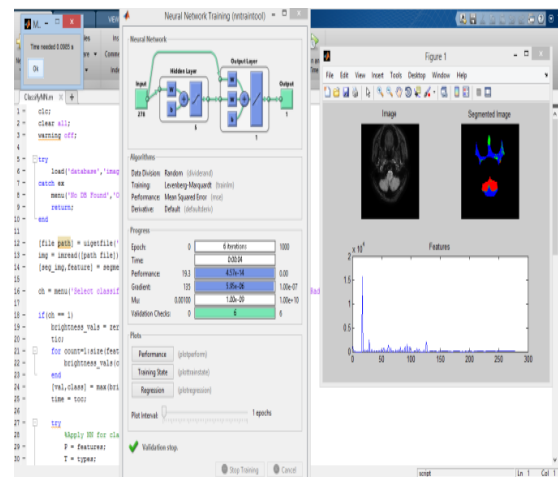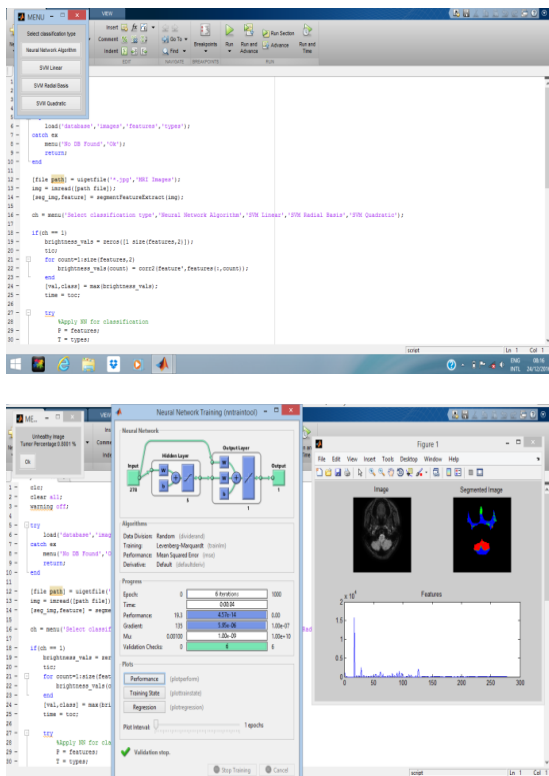
Fig: Architecture of a probabilistic neural network

A PNN is predominantly a classifier since it can map any input pattern to a number of classifications. The main advantages that discriminate PNN are, its fast training process, an inherently parallel structure, guaranteed to converge to an optimal classifier as the size of the representative training set increases and training samples can be added or removed without extensive retraining.

Table: Comparison of four different methods based on time required for the image processing:

| Images	Neural network Algorithm	SVM Linear (Time in sec)	SVM Radial Basis (Time in sec)	SVM Quadratic (Time in sec)	Tumor %
1.	0.0573s	1.4350s	1.6368s	0.4680s	0.8001%
2.	0.0035s	0.1483s	0.5657s	0.5095s	2.032%
3.	0.0050s	0.1528s	0.5787s	0.5339s	1.1444%
4.	0.1178s	0.1528s	1.5465s	0.5393s	1.6780%
5.	0.0867s	1.1615s	1.0087s	0.4699s	0.8713%
6.	0.0374s	0.1424s	0.4937s	0.4622s	1.5935%
7.	0.0039s	0.1545s	0.5315s	0.4689s	1.3418%
8.	0.0040s	0.1439s	0.5119s	0.5073s	1.8031%
9.	0.0036s	0.1456s	0.4946s	0.4599s	1.5274%
10.	0.0040s	0.1444s	0.4965s	0.4665s	2.0335%
11.	0.0035s	0.1438s	0.5232s	0.4738s	1.5340%
12.	0.0035s	0.1487s	0.5099s	0.4625s	2.4760%
13.	0.0035s	0.1476s	0.6110s	0.5326s	1.5869%
14.	0.0047s	0.1471s	0.5136s	0.4611s	2.2949%
15.	0.0037s	0.1562s	0.5153s	0.4796s	1.5406%
16.	0.0036s	0.1416s	0.5275s	0.4639s	2.1851%
17.	0.0035s	0.1445s	0.5248s	0.4561s	0.2218%
18.	0.0044s	0.1423s	0.4995s	0.4730s	1.7431%
19.	0.0038s	0.1672s	0.4922s	0.4752s	1.5630%
20.	0.0037s	0.1438s	0.5139s	0.4666s	1.6469%
21.	0.0036s	0.1448s	0.5164s	0.4746s	0.6470%
22.	0.0035s	0.1425s	0.4978s	0.4629s	1.6713%
23.	0.0048s	0.1442s	0.5077s	0.4729s	1.3667%
24.	0.0035s	0.1587s	0.5056s	0.4892s	1.6795%
25.	0.0036s	0.1444s	0.5189s	0.4584s	0.1221%

Graph:
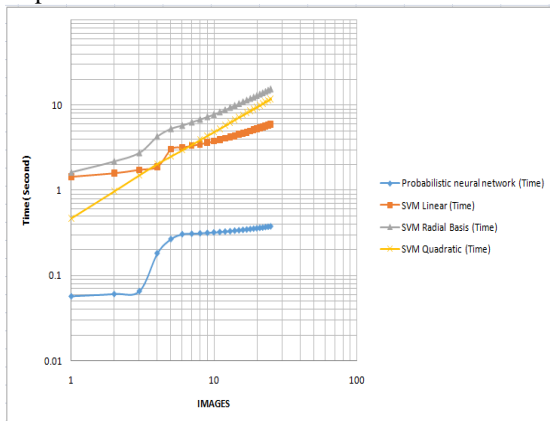
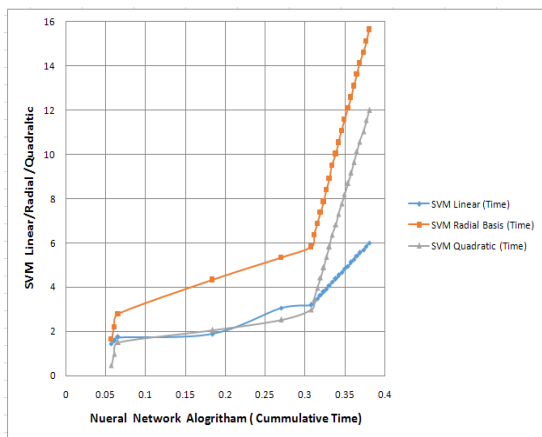**Fig:** Time taken by four methods

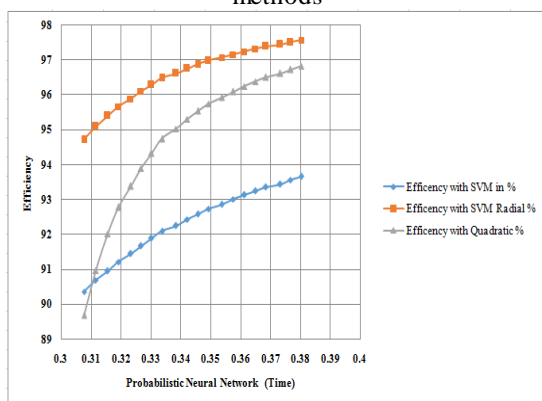**Fig:** Cummulative time comparison of the four methods

Fig: Comparison of efficiency of PNN with the other three methods

III.   FUTURE SCOPE

The goal is to detect, to segment, and to identify most types of pathological tissue that occur within pediatric brain tumors. Future research in the segmentation of medical images will lead towards improving the accuracy, exactness, and computational speed of segmentation approaches, as well as minimizing the amount of time taken for the process.

IV.   CONCLUSION

In this project fuzzy c-mean clustering algorithm is used for segmentation methods, classification of brain tumor and its feature extraction is done using probabilistic neural network algorithm. Many algorithms have been proposed in the literature for each processing stage. So this method used gives the better result. The results are given and the graph showing the comparison in terms of time given by various methods that is neural network, SVM linear, SVM radial basis, SVM quadratic is given.

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