F-FMRI IMAGE MINING AND CLASSIFICATION USING EDGE DETECTION TECHNIQUES OF BRAIN TUMOUR

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Abstract: The accurate and automatic segmentation of brain tumor on F- Magnetic Resonance Imaging (FMRI) image is of great interest for assessing tumour growth and treatment responses, enhancing computer-aided surgery, planning radiation therapy, and constructing tumor growth models. The shape and boundary information of the brain tumor affected area is taken into consideration; hence, the edge detection operator is employed on different FMRI cancer tumour images. The five edge-detection methods of Sobel, Prewitt, Robert, Laplacian and Canny Operators are displayed by running MATLAB code on of FMRI cancer image. These five edge-detectors are the most commonly used techniques which are selected and tested. To smooth the image, a special approach is introduced, namely Parallel Median Method (PMM) and for removing the impulsive noise in images. The process of image smoothing is used to remove noise in the FMRI image. Initially, FMRI brain cancer image is taken, this color image is converted into gray scale image and then this gray scale image is converted into two-tone image that is binary image, for further processing of cancer affected areas in the FMRI brain cancer image**.**

Keywords: **Brain tumors, Classification, Feature extraction, Gray level values, brain tissue pathology, FMRI images, tumor, quantitative grading, Segmentation.**

I. INTRODUCTION

The brain is the center of thoughts, emotions, memory and speech. Brain also controls muscle movements and interpretation of sensory information (sight, sound, touch, taste, pain etc). An abnormal growth of cells within the brain can be cancerous or non-cancerous (benign). It is defined as any intracranial tumor created by abnormal and uncontrolled cell division, normally either in the brain or in the cranial nerves, in the brain envelopes, skull, pituitary and pineal gland, or metastatic tumors. Primary (true) brain tumors are commonly located in the posterior cranial fossa in children - anterior 2/3 of the cerebral hemispheres in adults, although they can affect any part of the brain. The edge detection of an image is implemented using localization properties [6]. It also searches for the edge pixels. The edge image obtained prominently produces rectangular shapes in the image [11]. An edge is a property attached to an individual pixel and is calculated from the image function behaviour in a neighbourhood of the pixel. It has magnitude of the gradient and direction of an edge.

Prevalence of primary brain tumors is estimated at 221.8 per 100,000 people in 2010, compared with 209 per 100,000 in 2004. In 2013, an estimated 69,720 new primary brain tumor diagnoses were made in the U.S., 24,620 malignant and 45,100 nonmalignant [34]. About 43% of brain and CNS tumors occur in men and about 57% occur in women. About 120 types of brain and CNS tumors have been identified to date, and some have multiple subtypes [35]. Each tumor type or subtype is genetically distinct, making the search for treatments or a cure extremely difficult. The most prevalent brain tumor for adults is meningioma, accounting for almost 35% of all brain tumors. Meningioma tumors grow from the tissues, or meninges, covering the brain and spinal cord. Most are non-malignant but they can grow to the point of being life threatening [36, 37].

The rest of the paper is organized as, Section 1.2 deals literature review, Section 2 discusses, brain cancer symptoms, grades and its treatment. Section 3 gives elaborated segmentation process of brain tumour edge detection using famous five edge detection operators. Section 4 analyses experimental result. Section 5, concludes the conclusion and finally, section 6, discusses the future scope of the paper.

1.1 Literature Review

In the last decades, FMRI approaches have evolved into the most powerful and versatile imaging tool for brain tumor diagnosis, prognosis, therapy evaluation, monitoring of disease progression and planning of neurosurgical strategies [27]. The pathological classification of gliomas and its implications for FMRI diagnosis, continuing with the applications of diffusion weighted imaging

(DWI), diffusion tensor imaging (DTI) and tractography to the characterization of these brain tumors. Decision making is performed in two stages to implement an automated brain tumor classification [23] using the principal component analysis and the Probabilistic Neural Network (PNN) [25, 28]. In edge detection algorithm, to reduce the rate of error of while identifying the edges in an image, the edge points must be localized. Therefore, Canny's operator is applied [25] to increase the performance of the proposed edge detection algorithm. Even though it is quite old, it has become one of the standard edge detection methods and it is still used in research [26].

The simulated brain tumour growth dynamics using a three-dimensional cellular automaton was discussed [1]. Dynamics of a model for brain tumors reveals a small window for therapeutic intervention [2]. The growth of Brain Tumor was discussed [3]. The Methods on Tumor Recognition and Planning Target Prediction for the Radio therapy of brain Cancer was identified [4]. A Classification of Tumors in Human Brain FMRI images using Wavelet and Support Vector Machine was implemented [30, 33]. Biological Early Brain Cancer Detection and classification using Artificial Neural Network was discussed [31, 32]. An Efficient Design Method for Optimal Weighted Median Filtering is used to smooth the image [20].

2. BRAIN CANCER

The tumors can be detected through Physical exam, Neurological examination, Angiogram, Spinal tap, FMRI , CT scan or a PET scan (Positron Emission Tomography) which is a nuclear medicine imaging technique that produces a three-dimensional image of functional processes in the body. Once detected, depending on the location of tumor, a biopsy test is conducted to diagnose cancer. The Survival Rate for people aged between 15 years and 44 years is five years that is, survival rate of 55%. For people aged between 45 years and 64 years, the survival rate is five years that is, 16%. For people over aged 65 years it is five years or 5%.

2.1 Symptoms of Brain Cancer

The symptoms of brain cancer are: increased intracranial pressure, confusion, lethargy, sometimes decrease in consciousness and headache in the early morning and made worse by coughing or straining, vomiting. Also, the symptoms may include headaches, nausea, vomiting, coordination problems, seizures, or extreme sleepiness which requires consulting a doctor for diagnosis. Diagnosis is the process of determining the cause such disease.

2.2 Data Acquisition

A brain scan depends on factors including the pulse sequence, cost, time, resolution, slice thickness, inter-slice distance, noise signal, etc. These data allow us to show that treated tumor volumes, observed on FMRI , change little between 2 measurements, while spectroscopic profiles and Cho/Cr or mI/Cr ratios decrease.

2.3 WHO Classification

Brain tumours are classified as intrinsic, extrinsic and spread from adjacent structures. Adults usually present with supratentorial tumours. Commonest primary tumour in adults include gliomas . For those above 65 metastatic tumours are common. Paraneoplastic syndromes are non-metastatic complications of an underlying malignancy. Imaging genomics has emerged as a new field which links the specific imaging traits with gene-expression profiles [22]. The different FMRI characteristics can be correlated with the underlying genomic composition in tumors, in this case Glioblastoma (GBM). The tumour cell types are displayed in Table 1.

Table 1 Tumour cell types

S.No	Cell type	S.No	Cell type
1.	Glial Cells	6.	Glial Tumour
2.	Astrocytes	7.	Astrocytomas
3.	Oligodendrocytes	8.	Oligodendrogliomas
4.	Ependymal cells	9.	Ependymomas
5.	Different types of glia	10.	Mixed gliomas (oligoastrocytomas)

2.4 WHO Tumour Grading System

Tumour Grades are Microscopic apperance of cancer cells consisting of 4 degrees of severity is displayed [22] in Table 2.

2.5 Treatment of Brain Tumor

The treatment of a brain tumour is based on a variety of medical treatment modalities, including chemotherapy and radiotherapy, are used. Supportive care include: Steroids, Anticonvulsant drugs, Nursing management, Assessment, Nursing intervention, Post-operative Nursing care considerations [24].

Table 2. Tumour Grading System

Grade I Tumour	Well-differentiated (Low grade)	Slow-growing cells, Almost normal appearance under a microscope Least malignant, Usually associated with long-term survival
Grade II Tumor	Moderately differentiated (Intermediate grade)	Relatively slow-growing cells, Slightly abnormal appearance under a microscope Can invade adjacent normal tissue, Can recur as a higher grade tumor
Grade III Tumor	Poorly differentiated (High grade)	Actively reproducing abnormal cells, Abnormal appearance under a microscope Infiltrate adjacent normal brain tissue, Tumor tends to recur, often as a higher grade
Grade IV Tumor	Undifferentiated (High grade)	Abnormal cells which reproduce rapidly, Very abnormal appearance under a microscope Form new blood vessels to maintain rapid Growth, Tumors are classified by their location.

2.6 Brain Tumour Analysis

In the suspected intracranial tumours, imaging of brain is often required at various stages and has a significant role at each level such as:

i. Detection / confirmation of a structural abnormality
ii. Localization and assessment of extent of the lesion
iii. Characterization : distinction between neoplastic and non-neoplastic lesions, if neoplastic then differentiation among malignant and benign
iv. Staging of the tumour: lymphatic spread or other organ involvement
v. Looking for involvement of any vital brain area which might be of concern for therapy planning
vi. Facilitate surgical planning or other therapeutic interventions
vii. Intraoperative control of resection procedure
viii. Monitoring prognosis and follow up

CT scan is the first step of cancer study, because it is cheap and widely available in almost all clinics. It is a very good screening method in demonstration of supratentorial abnormalities, but FMRI is mandatory to take decision of surgical operations. The radiologist must ensure answers for the following critical questions in tumour analysis, before arriving at proper conclusion [29].

i. Signal contrast with respect to normal brain parenchyma
ii. Tumour structure, margins, extent of perifocal edema
iii. Indirect tumour signs (compression syndrome, midline shift etc.)
iv. Tumour vascularity, main vessels supplying the tumour and its course
v. Degree of contrast enhancement

The information provided by FMRI in evaluating brain lesions is critical for accurate diagnosis, therapeutic intervention and prognosis. Contrast-enhanced MR neuro-imaging using gadolinium (Gd) contrast agents depicts blood-brain barrier disruption, thereby demonstrating the location and extent of the tumour by depicting the increased extracellular-extravascular space (EES) contrast concentration in detecting brain cancer.

II.IMPLEMENTATION

3. BRAIN CANCER SEGMENTATION

After brain detection from other parts (such as skin-neck-bone and ventricle) using thresholding segmentation, the algorithm is used to separate different parts of brain such as tumor. In the region is iteratively grown by comparing all unallocated neighbouring pixels to the region. The difference between a pixel's intensity value and the region's mean is used as a measure of similarity [23].

3.1 Pre-processing:

In medical images, removal of noise plays major role in segmentation and detection disease region for further dosage system. Specially, in FMRI , inhomogeneous magnetic field, patient motion while acquiring the image and external noise may yield undesired results. Therefore, it is necessary to remove them in the pre-processing procedure before any image analyzes can be performed. In this paper, the pre-processing step consists of image enhancement, smoothing and image restoration [5, 14].

3.2 Image Smoothing

Smoothing makes the image more ‘normal’. Each mask may contain noise and this noise is to be cleaned by the Smoothing Technique [7]. The neighbours around the center pixels should be of more or less similar pixel values. The output values are obtained as 50% of the source value plus 30% of immediate neighbours and 20% of their distant neighbours [15]. This influences the old image and helps us to derive new smoothed image. The signal is shown in Figure 1 and the smoothed signal is shown in Figure 2. The Original image is shown in Figure 3, smoothed image is shown in Figure 4, Gray image is shown in Figure 5 and the binary image is shown in Figure 6.

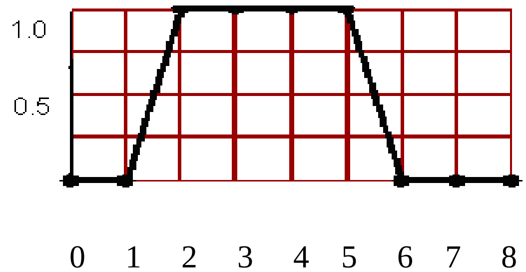

Figure 1. A Signal

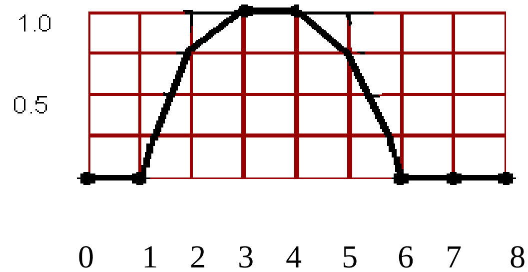

Figure 2. Smoothed Signal

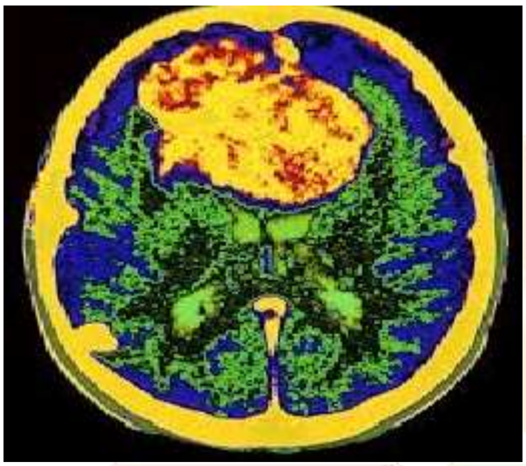

Figure 3. Original Image

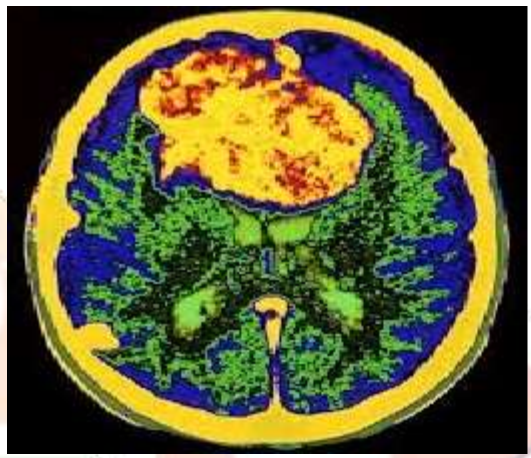

Figure 4. Smooth Image

Figure 5. Gray Image

Figure 6. Binary Image

3.3 Median Filter

The median filter is based upon moving a window over an image and computing the output pixel as the median value of the brightness within the input window [8, 9].

3.3.1 Parallel Median Method (PMM)

A Parallel Median Method (PMM) has been developed to reduce time complexity. The median determines the element, whose gray value will be in the center position of each row in a 3 x 3 mask after sorting. The center position value is obtained from the 8-neighbourhood elements in that row [17]. The center value of sorted row is the median. Similarly, for each row, median value is obtained [13]. The three median values of each row are arranged in order. The center value is the new median by following this smoothing process and then a new image is built [19]. The shifting of 3 x 3 mask row by row and column by column is shown in

Figures 7 and Figure 8. In the case of 8-bit images, the numbers of possible pixel values are constant to find the median value. Hence, bucket sort algorithm is used with a time complexity of O (n^2). The values of mask 3 x 3 are shown in Table 3. The image obtained after applying PMM is shown in Figure 9.

Table 3 Gray values of 3 x 3 masks

Gray values of Row I	120	119	124
Gray values of Row II	123	124	125
Gray values of Row III	124	127	150

Median {120,119,124} = 119, Median {123,124,125} = 124.
Median {124,127,150} = 127, Median {119,124,127} = 124.
Mode = 124, Mean = 126.22 and Median = 124.

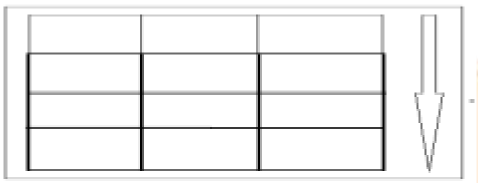

Figure 7. Mask shifting rows

Figure 8. Mask shifting columns

Algorithm 1: Parallel Median Method
Step 1: Choose a small window of size 3x3.
Step 2: The window contains gray values.
Step 3: Choose Row1, Row2 and Row3 elements or Column1, Column2 and Column3 elements.
Step 4: Compute median of each row or each column.
Step 5: Again compute median of 3 elements obtained from Step 4.
Step 6: This median is replaced with center of the element of the 3 x 3 mask.
This is known as smoothing process.
Step 7: Move the mask one row or one column by deleting row1 or column1 and adding row4 or column4.
Step 8: Calculate the median of row4 or column4.
Step 9: Repeat Step 5.
Step 10: Stop the computation when all the rows or columns are smoothed.

This set of rows or columns are computed by removing row1 or column1 and adding row4 or column4 in the case of a 3 x 3 kernel, while retaining row2 or column2 and row3 or column3. Median of this is computed. Updated medians are applied, while filtering the image. Hence, it is needed to calculate only one row or one column. Two rows or two columns are retained. The PMM eliminates noise and smoothes the image nicely and the result is shown in Figure 9. To smooth the image, optimum kernels are used. The larger size kernel involves much computation time. The proposed algorithm for PMM filtering exhibits O (n) complexity.

3.4 Image Enhancement

The aim of image enhancement is to improve the perception of the image quality [18]. The image enhancement techniques are used as pre-processing tool as per human perception. Enhancement algorithm is used to reduce image noise and increase the contrast of structures in regions of interest [16]. Image noise can reduce the capacity of region growing filter to grow into large regions or may result in false edges [10]. The enhanced image is shown in Figure 10.

```
% MATLAB code for enhancement brightness
Clc; Close all; Clear all;
A=imread('r1.jpg'); B=double (a)+50;
figure; imshow (a), title ('original image');
figure; imshow (unit 8 (b)), title ('Enhanced image'); end;
```

Figure 9. PMMFilter

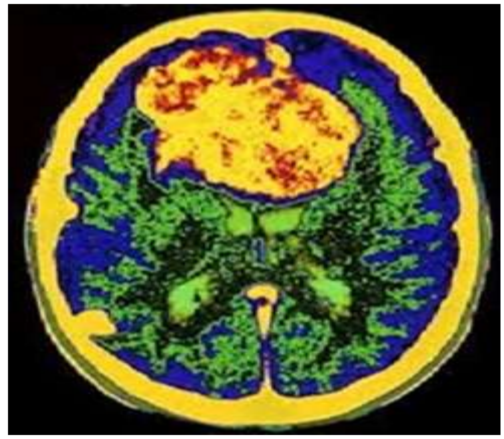

Figure 10. Enhanced Image

3.5 Edge Detection

In this paper, the region of interest (ROI) is proposed to identify different tumor types and infected areas. The area of each related adjacent portion is computed and the irrelevant portions removed resulting in the desired tumor region from FMRI image as shown in Fig. 6. There are many edge finding methods, among which the Sobel, Prewitt, Roberts, Laplacian and Canny edge finding methods are important [12]. The Sobel Method finds edges using the Sobel Approximation Derivative. It returns edges at those points, where the gradient of image 'I' is maximum. The Prewitt method finds edges using the Prewitt approximation derivative. It returns edges at those points, where the gradient of image 'I' is maximum. The Roberts method finds edges using the Roberts approximation derivative. It returns edges at those points, where the gradient of image 'I' is maximum.

The Laplacian of Gaussian (LOG) method finds edges by looking for zero crossings after filtering image 'I' with a LOG filter. The Canny edge detector is a more sophisticated approach of an edge map for an image 'I', which can perform well in finding the edges. The Canny algorithm can be used an optimal edge detector to find the edges by minimizing the error rate. According to Canny, the optimal filter that meets all the criteria and can be efficiently approximated using the first derivative of a Gaussian function. These derivatives are used to calculate gradient magnitude (edge strength) and gradient direction of most rapid change in intensity. There is a trade-off between noise reduction and edge localization. For the smoothing process, the Canny Detector employs a Gaussian Low Pass Filter. Efficient implementation of the Canny Detector combines the smoothing and enhancement step by convolving the image. The Pseudo Matlab code for five edge detection techniques which are applied in this paper are displayed as follows:

% Psuedo Matlab code to detect edges of a FMRI image

```
function edgedetect(x);  f=imread('r2.jpg');f=im2double(f); c=0;
c=input('1: Prewitt\n 2: Roberts\n 3: LoG\n 4: Canny\n 5: Sobel\n 6 Exit\n Enter your choice : ');
while (c~=6)
Switch c;
   case 1: PF=edge(f,'prewitt'); figure, imshow(PF), title('Prewitt Filter');
   case 2: RF=edge(f,'roberts'); figure, imshow(RF), title('Roberts Filter');
   case 3: LF=edge(f,'log'); figure, imshow(LF), title('LOG Filter');
   case 4: CF=edge(f,'canny'); figure, imshow(CF), title('Canny Filter');
   case 5: KF=edge(f,'sobel'); figure, imshow(KF), title('Sobel Filter');
   case 6: display('Program Exited'); otherwise; display('\nWrong Choice\n');
end;     end;
```

III. EXPERIMENT RESULTS

Several algorithms have been developed to extract edges, of FMRI brain cancer images. The simplest the most commonly used edge finding techniques are: Sobel, Prewitt, Roberts, LOG and Canny operators and these operators are selected and tested. Among these five operators, Canny Operator exhibits better performance, but requires more computations because in this operator smoothing of an image involves two stages. The first stage is to execute with a Gaussian Function and the second stage is to compute the Gradient Function. The best set of parameters for a particular image varies and hence the user can select the best method. The quality of an image can be estimated by using Signal to Noise Ratio (SNR). The edges of five operators and its performance are compared as shown in Table 4, and the outputs are shown in Figures 11 to Figure 15 for Sobel, Prewitt, Robert, LOG and Canny operators respectively.

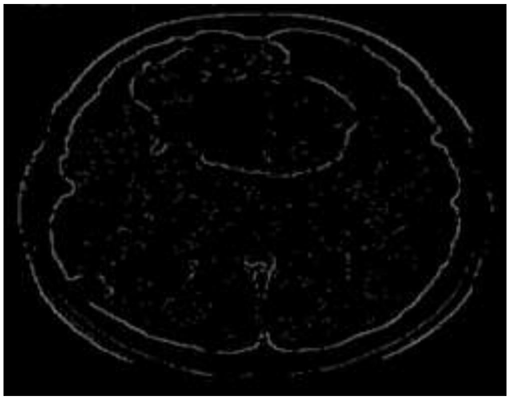

Figure 11. Sobel Edge

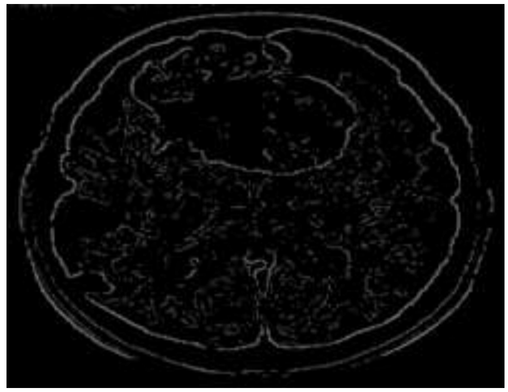

Figure 12. Prewitt Edge

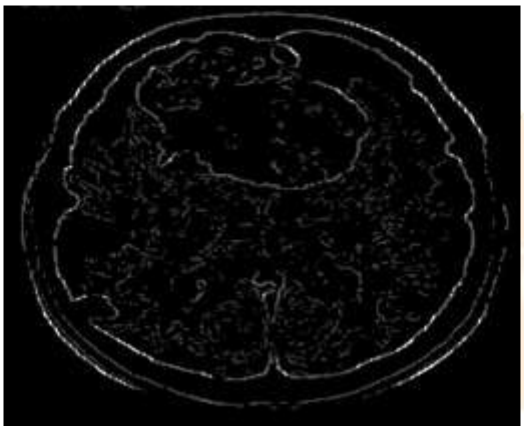

Figure 13. Robert Edge

Figure 14. LOG Edge

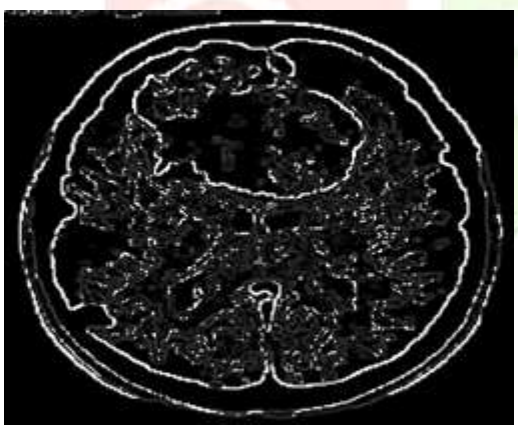

Figure 15. Canny Edge

Figure 16. Segmented image

Table 4 Comparison of edge detectors

S.No	Edge detection operator	Noise	SNR
1	Sobel operator	0.9727	0.9690
2	Prewitt operator	0.9710	0.8590
3	Roberts operator	0.9699	0.7832
4	LOG operator	0.9650	0.5741
5	Canny operator	1.0000	0.5152

IV. CONCLUSION& FUTURE SCOPE

The edge detector is employed to implement localization properties. The five edges: Sobel, Prewitt, Robert, Laplacian and Canny are displayed by running code in MATLAB taking FMRI brain cancer images. Among the five operators, namely, Sobel, Prewitt, Roberts, LOG and Canny, the canny edge detector gives accurate result in recognizing brain cancer by recognizing the edges. The edges are used to define the boundary between two objects or parts of the same object. As the window size for the median filter is selected to an optimum level, better image quality is assured. The PMM can reduce computation time with exchange of $2\times(n-1)$ data elements and $(n-1)$ elements which are sorted in order. But, the ordinary median computation method requires (n^2-1) data exchanges and (n^2-1) elements to be sorted in order. The PMM requires $2\times(n-1)$ data exchanges and $(n-1)$ elements are to be sorted. To detect the brain cancer area accurately, three-dimensional images can be viewed in different angles. The many number of slicing with equal interval of dimension of the image, the area and volume computation of irregular brain tumour affected portion and thickness with color identification of brain tumor will certainly help the physicians to arrive at proper conclusion.

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