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Identification of Brain Tumor using Gabor Wavelets Techniques

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ABSTRACT

In the field of medical science is biomedical application are used for Medical image analysis, it is used for detect abnormalities for human bodies through examine image. Magnetic resonance (MR) images are one of the excellent tools to identify the tumor growth in brain but in this case accurate brain image segmentation is a not easy and time consuming procedure. In this paper we propose a process for automatic brain tumor diagnostic system with Gabor Wavelets techniques. This method includes three phases to detect a brain tumor. In the first phase, input data sets of MR image are required for detection of brain tumor. In Second phase preprocessing, image is in the form of noise and artifact this image images is converted into Gray image. In the third phase, threshold segmentation is done on the sharpened image. This experiments demonstrate that technique is accurately identifies and segments the brain tumor in MR images.

Index Terms: Wavelets

1. Introduction

Brain tumor segmentation in MR images has been recent area of research in the field of automated medical diagnosis as the death rate is higher among humans due to brain tumor [1]. In automated medical diagnostic systems, MRI (magnetic resonance imaging) gives better results than computed tomography (CT) as MRI provides greater contrast between different soft tissues of human body. Hence MRI is much more effective in brain and cancer imaging [2].

Brain image splitting is essential for brain tumor detection. There are too many variations for Manual brain MR images. These images necessitate a lot of time, non- repeatable task, non-Uniform Segmentation and also this result may differ from expert to expert. An automated brain tumor is a detection system, it should acquire less time and provides accurate outcome for brain tumor.

Many issues and challenges of detecting and splitting are automatic brain tumors. This is a difficult task for the segement of brain tumors in a computerized system. The major issue with brain tumor division is that the tumor differs in figure, dimension, position, and image intensity. So this process makes an automatic system for brain tumor detection and segmentation a desirable method.

To detect brain tumors, an automatic diagnosis system should have several stages, including noise removal, brain image segmentation and brain tumor extraction. This paper presents a computer aided system for brain tumor detection. Our systems extracts tumor by using three phases, pre processing. Edge detection and Feature Selection.

2. Gabor Wavelets

This section presents the Gabor wavelet analysis of the ROIs of a tumor image for extracting the texture features. Because Gabor wavelets capture the local structure corresponding to spatial frequency (scales), spatial localization, and orientation selectivity, they are widely applied in many research areas, such as texture analysis and image segmentation [4-6].

A 2D Gabor filter is a product of an elliptical Gaussian in any rotation and a complex exponential representing a sinusoidal plane wave. The sharpness of the filter is controlled through the major axis and minor axis, which is

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perpendicular to the wave. The filter can be defined as

$$\varphi(x,y;f,\theta)=\frac{f^2}{\pi\gamma\eta}e^{-\left(\frac{f^2}{\gamma^2}x'^2+\frac{f^2}{\eta^2}y'^2\right)}e^{j2\pi f x'}$$

$$x'=x\cos\theta+y\sin\theta$$

$$y'=-x\sin\theta+y\cos\theta$$

where f is the central frequency of the sinusoidal plane wave, ϑ is the rotation angle of both the Gaussian major axis and the plane wave, γ is the sharpness along the major axis, and η is the sharpness along the minor axis. The sharpness values along the major axis γ and along the minor axis η are set to 1. Image texture features can be extracted by convolving the image M(x,y) with Gabor filters

$$g(x,y;f,\theta)=M*\varphi(x,y;f,\theta)$$

Gabor filters with different frequencies f_i and orientations θ_j are selected to obtain the texture features of the tumor area.

3. Proposed Work

In this technique we describe working of the Gabor Wavelet, input units utilized by it, static and dynamic functions, capabilities extracted from the tissue pix the use of neural networks, locating defiant systems, accurate tumor detection and type of mind tumor.

Medical imaging is split to two classes of anatomical and physiological. The anatomical imaging includes CT, Ultrasound and MRI. MR imaging technique, because of precise ability in showing difference between gentle tissues, high resolution, desirable comparison and non invasive method for using no ionization rays is very appropriate. Segmentation is the primary and maximum vital step in each work that related to picture processing. in this section after a short clarification approximately the picture facts set and approach that's used to create input photographs, is explained approximately the preprocessing steps. Pictures commonly incorporate one or more type of noise and artifact. At subsequent phase, paper explains about the photo processing strategies that it divides to feature extraction, kernel F-rating characteristic selection and neural community subsections. In every subsection it's been explained approximately info. At end result phase, it will likely be stated some consequences and show one of the output pics has been furnished from this project. The yield and accuracy of method is measured, the usage of sufficiency indexes [4]. Fig 1 shows Automatic brain tumor detection system from Gabor Wavlet

3.1 INPUT DATA SETS

Nervous tissue is the primary issue of the anxious gadget - the brain, spinal wire, and nerves-which regulates and controls frame features. it's far composed of neurons, which transmit impulses, and the euroglia cells, which help propagation of the nerve impulse as well as offer vitamins to the neuron. Apprehensive tissue is made from nerve cells that are available many varieties, all of which are exceedingly feature by using the axon or lengthy stem like part of the cellular that sends action potential alerts to the following cell. Functions of the frightened machine are sensory input, integration; manage of muscle groups and glands, homeostasis, and mental hobby.

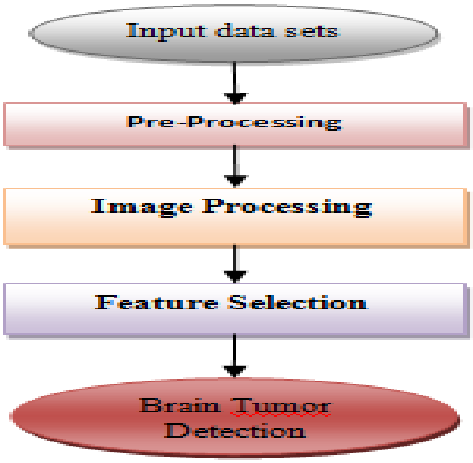


Fig1: Automatic brain tumor detection system from Gabor Wavlet

All residing cells have the ability to react to stimuli. anxious tissue is specialized to react to stimuli and to behavior impulses to numerous organs within the frame which bring about a reaction to the stimulus. Nerve tissue are all made of specialised nerve cells referred to as neurons. Neurons are easily inspired and transmit impulses very swiftly. A nerve is made from many nerve cellular fibers (neurons) bound collectively by connective tissue. A sheath of dense connective tissue, the epineurium surrounds the nerve. This sheath penetrates the nerve to shape the perineurium which surrounds bundles of nerve fibers [7]. Blood vessels of various sizes may be visible within the epineurium. The endoneurium, which includes a skinny layer of loose connective tissue, surrounds the individual nerve fibers [8].

The mobile body is enclosed by using a cellular (plasma) membrane and has a primary nucleus.

The axon is surrounded via the myelin sheath, which bureaucracy a whitish, non-cellular, fatty layer around the axon.

3.2 PREPROCESSING

Pictures normally incorporate one or more form of noise and artifact. In medical snap shots, because of diagnostic and healing applications, this difficulty is important. Mainly in MR images, inhomogeneous magnetic fields, patient motions duration imaging times, thermal noise and exist of any steel matters in imaging environment, are some reasons that could create noises and artifact, even though in most of times, are not very critical because of human studies on pics ,however those are one of the principal causes for computational mistakes in automated or semi automatic picture reading methods and so it's far needed to be eliminated via preprocessing tactics before any studying. here, preprocessing is equal to put off seeds from images and increase contrast among everyday and extraordinary mind tissues. The technique were used here are Histogram equalization, the use of Median filter out, using Un sharp masks, thresholding and the usage of from imply clear out respectively for each image.on this step, twodimensional discrete Fourier remodel is computed for pictures. To lessen the noise a 3 by using three pixel suggest filter out turned into applied. This filtered averaged nine factors for that reason decreasing the noise through 3. because a unmarried skip of this filter did not appear to offer sufficient noise discount, the image turned into exceeded via the filter out a 2nd time [7, 8].

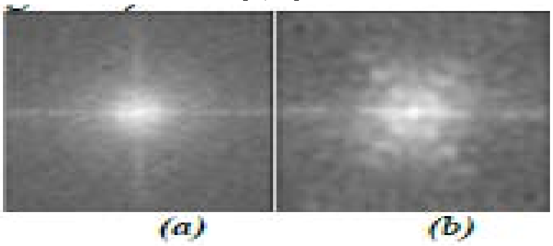


Figure 3.1: Fourier Transform a) abnormal b) normal

3.3 IMAGE PROCESSING

The purpose of feature extraction is to reduce the original statistics set by measuring certain homes, or capabilities that distinguish one input pattern from every other. The extracted features provide the characteristics of the enter kind to the classifier by thinking about the outline of the relevant properties of the picture. The reading techniques had been finished till now used values of pixels intensities, pixels coordinates and a few different statistic capabilities along with imply, variance or median that have much error in determination manner and low accuracy and robustness in class [10]. it has been defined approximately the capabilities which have been used in this paper which can be divide to two lessons of statistic and nonstatistic capabilities. X (i,j) is the price of depth for place of (i,j) at variant of y, x among pixels.

3.3.1.1 STATISTIC FEATURES

Mean: The mean is defined as below:

$$\mathrm{Mean}\ (\mathrm{M}) = \frac{1}{x+y} \sum_{i=z}^{x} \cdot \sum_{j=1}^{y} X(i,j)$$

Standard Deviations: It is square of variance. The variance is defined as below:

Variance (V) =

$$\frac{1}{x+y} \sum_{i=z}^{x} \cdot \sum_{j=1}^{y} X\big((i,j) - m\big)^{2}$$

Entropy: A measure of non uniformity in the image based on the probability of co-occurrence values:

Entropy =

$$\sum_{i=1}^{n} \cdot \sum_{j=1}^{n} \cdot \left(\frac{\cup(i,j)}{R}\right) \log\left(\frac{\cup(i,j)}{R}\right)$$

Where, N is the number of gray levels, equal to 256 for images in the present study. R is equal to the total number of pixel pairs used for the calculation of texture features in the specified angular direction.

Median: The value that multiplicity of upper values and lower values are equal.

Contrast: A measure of difference moment and is defined as below:

Contrast = $$\sum_{i=1}^{n} \cdot \sum_{j=1}^{n} \cdot (i,j)^{2}$$

Energy: A measure of homogeneity that can be defined as:

Energy = $$\sum_{i=1}^{n} \cdot \sum_{j=1}^{n} \cdot \left(\frac{u(i,j)}{R}\right)^{2}$$

Inverse Difference Moment: A measure of local homogeneity that can be defined as below:

I = $$\sum_{i=1}^{n} \cdot \sum_{j=1}^{n} \cdot \frac{\left[\frac{ij\ P(i,j)}{R}\right]}{1 + (i-j)^{2}}$$

Correlation: A measure of linear dependency of brightness and can be defined as below:

Correlation = $\sum_{i=1}^{n} \square . \sum_{j=1}^{n} \square . \frac{\left[\frac{ij\,P(i,j)}{R}\right] - \mu x \mu y}{\sigma x \sigma y}$

$\mu x = \sum_{i=1}^{n} i \sum_{j=1}^{n} \square . \left(\frac{u(i,j)}{R}\right)$, $\mu y = \sum_{i=1}^{n} j \sum_{j=1}^{n} . \left(\frac{u(i,j)}{R}\right)$

$\sigma^2_x = \sum_{i=1}^{n} (i - \mu x).^2 \sum_{j=1}^{n} \square . \left(\frac{u(i,j)}{R}\right)$, $\sigma^2_y = \sum_{i=1}^{n} (j - \mu y).^2 \sum_{j=1}^{n} \square . \left(\frac{u(i,j)}{R}\right)$

3.3.1.2 NON STATISTIC FEATURES

Gabor wavelets transforms like different wavelets transforms have an excellent attribute in photo processing and device imaginative and prescient. these wavelets gather equipment for processing the picture at frequency area and first-rate gain of them is unruffled versions in frequency area. if I(z) be the input image with gray stage depth values, photo Gabor wavelets transforms is computed from convolution of one detail from Gabor wavelets with input images ,which includes below:

$O_{u,v} = I(z) * \Psi_{u,v}(z)$

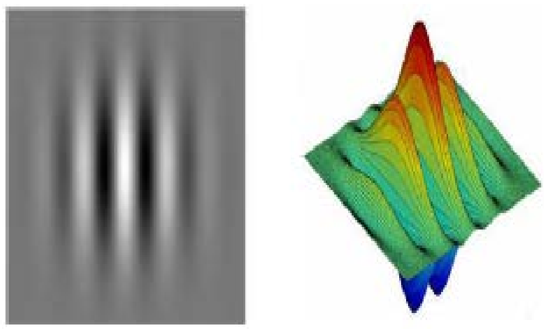
where * is convolution operator, O is transform end result, ψ is the wavelet that has been applied in the transform with the aspect of μ and magnification of υ. Gabor wavelet equations sincerely specific the easy wave with the positive frequency and side which has been trammeled below the Gaussian characteristic. This equation can be defined with exclusive forms rely on form of coordinate systems which includes Cartesian and polar. the same old system of Gabor wavelet is as underneath:

$$\Psi_{u,v}(z) = \frac{\| K(u,v) \|}{\delta^2} \exp\left(\frac{\| K(u,v) \| \, \| z \|^2}{2\delta^2}\right)\left(e^{ik(u,v)z} - e^{\frac{\delta^2}{z}}\right)$$

In this equation, k, express the length and side of wave and is computed from the equation which is as below:

$$K_{u,v} = K_{ve}\ , \quad K_v = \frac{K_{ma}}{f^{v}}\ , \quad \Psi_v = \mu \frac{\pi}{8}$$

In this equation, μ has been multiplied by π/8 and have made the phase of k, so have integer values between 0 and 7. Upper values create waves with repetitive sides. Y can have values between 0 and 4 and so, we have 40 wavelets with different sides and sizes. Here has been showed one of the Gabor wavelet elements and δ = 2π, k ma =π, f = 2, μ = 2, υ =3 has been showed at (Figure



(a) (b)

Figure 3.2: Gabor wavelet a) 2D b) 3D

As showed within the (Fig. 2) Gabor wavelet is the wave with descent amplitude. right here, has been defined the manner of extraction function from picture. The Fourier remodel of picture windows that want to decide approximately them is accelerated at Gabor wavelet Fourier transforms and after that, computed inverse Fourier transforms merged and make the functions of desired matrix

3.4 FEATURE SELECTION

First, the F-rating method is defined and after that, it's miles explained about the kernel F-rating approach. Readers can check with [5] for more information. F-rating technique is a fundamental and easy technique that measures the distinguishing between two classes with actual values. In F-rating approach, F-rating values of each function in dataset are computed consistent with following equation (Eq. (12)) and then with a purpose to pick out the functions from complete dataset, threshold price is acquired via calculating the common cost of F-scores of all features. Given training vectors x okay, okay = 1,. . .,m, if the variety of high-quality and negative times are n+ and n-, respectively, then the F-score of the i-th characteristic is defined as follows:

$$F(i) = \frac{(\bar{x}_i^{(+)} - \bar{x}_i)^2 + (\bar{x}_i^{(-)} - \bar{x}_i)^2}{\frac{1}{n_+ - 1}\sum_{k=1}^{n_+}(\bar{x}_{k,i}^{(+)} - \bar{x}_i)^2 + \frac{1}{n_- - 1}\sum_{k=1}^{n_-}(\bar{x}_{k,i}^{(-)} - \bar{x}_i)^2}$$

In this way, the size of datasets have converted to excessive dimensional feature area. After remodeling from input area to kernel area, the F-score values of datasets with high dimensional feature area were calculated using Fscore method. after which the suggest fee of calculated F-ratings has been computed and also this price is selected as threshold cost

4. Performance Analysis

To assess the discrimination efficiency of volumetric features over 3D features a comparative evaluation was performed utilizing Gabor Wavlets techniques

4.1 Detection of Brain Tumor

That is the primary screen of the assignment while we execute the it. on this screen three buttons will seem.

- train button will procedure all the photos earlier than we pick out picture for Tumor Detection.
- choose photograph button will allow us to browse the already stored photo. it will additionally display the photo on right hand facet graph.
- locate button will system the selected picture and will display the message whether or not the image has Tumor or no longer.
- beneath display screen pictures will show us factors explained above.

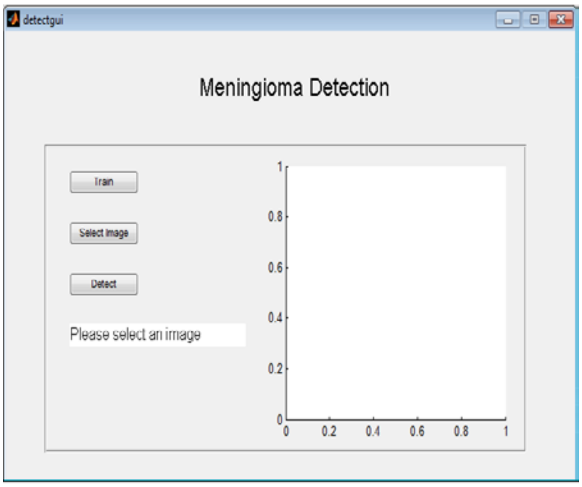


Figure 4.1: Detection Screen

4.2 Brain Tumor Classification

This is the second display, appears while photograph consists of Tumor. This display screen will inform us the kind of brain Tumor image is having.

- gray button will convert given picture in RGB format to grey scale format as shown in display shot under.
- technique button will follow the Gabor wavelet on the chosen picture. The end result is displayed within the third graph.
- All different buttons are defined below at the side of the motion they're acting at the photo.

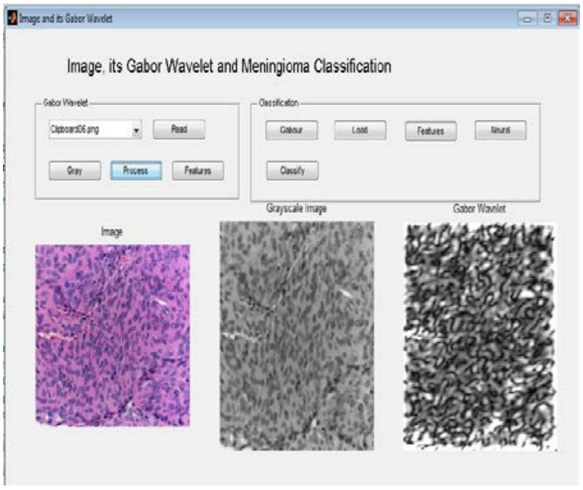
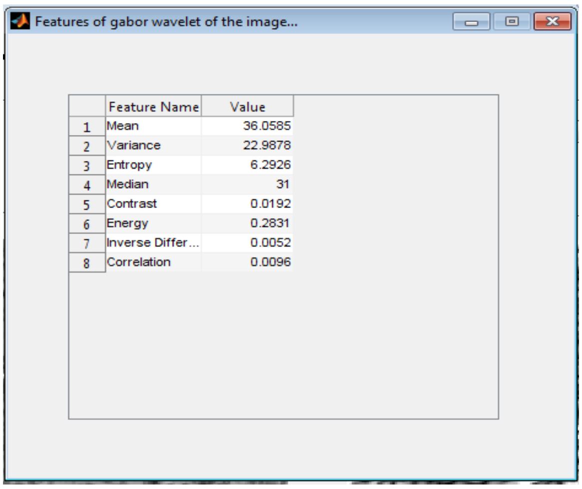


Figure 4.5: Classification

4.3 FEATURE SELECTION

→ Feature button will find Mean, Variance, Entropy etc for the image, as shown in screen shot below.



	Feature Name	Value
1	Mean	36.0585
2	Variance	22.9878
3	Entropy	6.2926
4	Median	31
5	Contrast	0.0192
6	Energy	0.2831
7	Inverse Differ...	0.0052
8	Correlation	0.0096

Figure 4.6: Feature Selection

4.4 TYPES OF BRAIN TUMOR

- Neural button will display the graph as shown below. Our database is divided into 4 groups.
- In the 1st group, Gabor wavelet has detected Meningeothelal tumor in all images.
- In the 2^{nd} group, only two images show Librolastic tumor.
- In the 3^{rd} group, wavelet successfully detected Transitional tumor in 14 images.
- In the 4^{th} group, wavelet detected Psammamator tumor in all the 20 images.

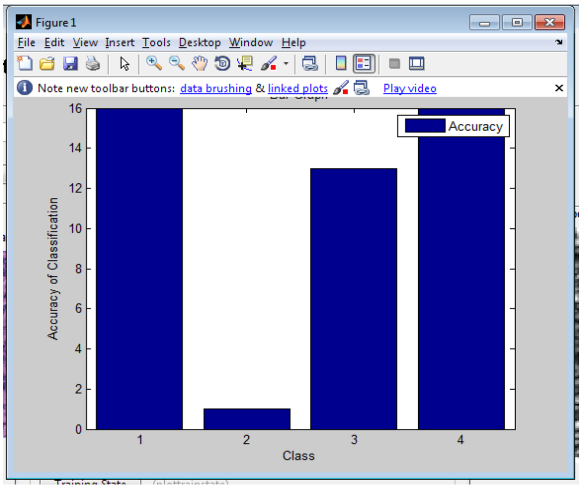


Figure 4.8: Types of Tumor

5. Conclusion

In this paper, we have proposed a new concept for segmentation of tumors from MR images. Gabor wavelets are practical applied to the estimate images and imprison the tumor characteristics at all stages of decomposition. Computation of texture features is then carried out and their peaks are detected. These images are then segmented by using morphological operation to give the final segmented output. The propose method will accurately produces a segmentation of tumor from surrounding brain tissue.

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