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Texture Feature Analysis for Identification of AIS using Multi- Otsu's Thresholding

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***Abstract*—Computing and characterizing Acute Ischemic Stroke (AIS) lesions remains a challenge. This technique precisely diagnoses the stroke lesion, allowing the radiologist to provide prompt and appropriate treatment with the goal of lowering the death rate due to brain stroke. The procedure is divided into three sections: preprocessing, multi-level thresholding, and feature extraction. The noise and skull part are removed in the pre-processing module, and then Multi Otsu's thresholding is applied. To identify the affected area, the image is divided into four regions. The affected region, which contains a stroke lesion, is statistically defined using a first-order histogram. The paper proposes an effective algorithm to support ischemic stroke lesion detection and feature extraction based on MRI images.**

***Index Terms*— Ischemic Stroke, Magnetic Resonance Imaging, Feature Extraction, Multi-Otsu's Thresholding, Image Partitioning.**

I. Introduction

Ischemic stroke is a disorder in which the brain stops functioning as a result of a clot in the blood supply to the brain, causing brain tissue death and necrosis [1]. To use clinical applications effectively, efforts must be made to enhance the diagnosis process. The damage part of the brain must be identified using MRI, so computer-assisted diagnosis is needed [2]. Early and accurate stroke lesion detection is important for developing better therapy and treatment planning [3]. The thresholding technique is essential in medical image analysis for segmentation and pattern recognition. It is the division of an image into different parts. The most straightforward approach is to automatically learn some grayscale values as thresholds and classify the image into more than one region. There are 2 kinds of automatic thresholding methods: global and local. In global methods, a fixed threshold value is used for the whole image, whereas in local methods threshold changes dynamically. Although, all these techniques optimize a criterion function based on information obtained from the histogram [4]. In this paper, we propose a method of identifying ischemic stroke lesion using texture analysis from MRI images using multi-otsu's thresholding. This method helps the radiologists to find the stroke and the location it occurred.

II. The Proposed Method

The following diagram "Fig. 1" explains the processing of proposed method which includes pre-processing, multi-level thresholding, and feature extraction.

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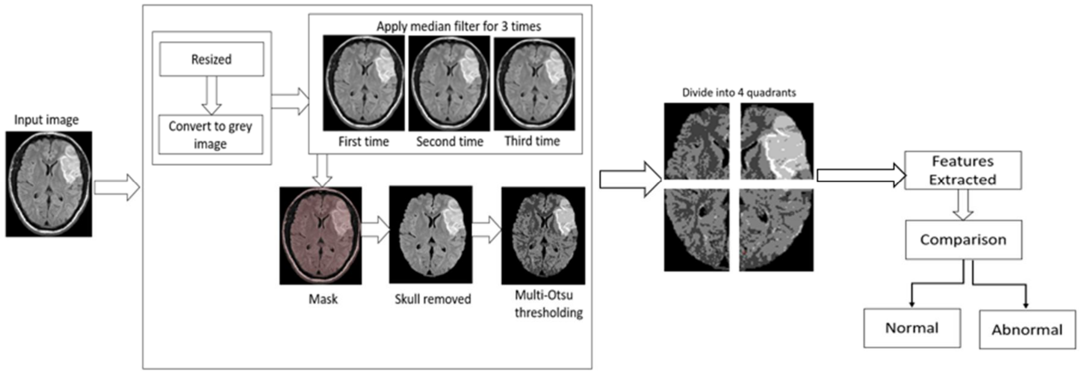


Figure 1. The Flow diagram of proposed method

B. Modules Description

Pre-processing: Image can be resized to (256 X 256) and converted into gray scale. To enhance the image intensity and to remove the noise a median filter [3 X 3] has been applied for three times. To process with brain area the skull part has been removed by masking. The original Otsu's threshold is applied to the image. With the use of threshold, colormask is applied and the skull part is removed

Multi-level Thresholding: The multilevel Otsu algorithm aids in the identification of multiple thresholds in the image histogram and reduces the intra-class variance of the input image. Otsu's thresholding method [5], some very well and widely accepted global thresholding methods, is based on discriminant analysis to determine the maximum separability of classes and is used to automatically perform histogram shape-based image thresholding. The original Otsu's algorithm assumes that the image is divided into two basic classes, foreground (Co) and background (C1), and it generates a normalised histogram using the discrete probability density function, as shown by:

$$p_r(r_q) = \frac{n_q}{n}, \; q = 0, 1, 2, ..., L-1 \quad (1)$$

where n denotes the total number of pixels in the image and nq denotes the number of pixels with an intensity level. The highest intensity level in that image is represented by rq and L. The initial threshold is the midpoint between the image's maximum and minimum intensity values.If k is selected as the initial threshold then C0 is the set of pixels with levels [0,1, . . . , k -1] and C1 is the set of pixels with levels [k, k + 1, . . ., L - I} .Otsu's method picks the threshold value k* that maximizes the intra-class variance , which is well-defined as:

$$\sigma^2{}_B = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \quad (2)$$

$$\omega_0 = \sum_{q=0}^{k-1} p_q(r_q) \quad (3)$$

$$\omega_1 = \sum_{q=k}^{L-1} p_q(r_q) \quad (4)$$

$$\mu_0 = \sum_{q=0}^{k-1} q p_q(r_q) / \omega_0 \quad (5)$$

$$\mu_1 = \sum_{q=k}^{L-1} q p_q(r_q) / \omega_1 \quad (6)$$

$$\mu_T = \sum_{q=0}^{L-1} q p_q(r_q) \quad (7)$$

The Otsu algorithm assumes the image is divided into two basic classes: foreground (C0) and background (C1) . When segmenting an image into m regions (C0, C1,..., Cm-1) k-1 thresholds must be chosen. The best thresholds can be found by maximising the intra-class variance, as shown below [4]:

$$\left\{k_0^*, k_1^*, ..., k_{m-2}^*\right\} = \underset{0<k_0<...<k_{m-2}<L-1}{\arg\max} \left\{\sigma_B^2(k_0, k_1, ..., k_{m-2})\right\} \quad (8)$$

Feature Extraction: Textures are calculated from a single pixel and do not take pixel neighbour relationships into account. The intensity histogram is being extracted from the given input image in this work. The gray-level histogram is computed from each pixel, whereas the intensity level histogram is a simple summary of the image's statistical information. The histogram provides first-order statistical information about the image (or subimage). The processing steps for feature extraction are as follows. The image is divided into four quadrants (regions). The histogram and pixel values for each quadrant were then calculated, as well as statistical features for all four regions. Finally, the abnormal regions were identified using the texture feature value. The grey levels of the image region are represented by the random variable i. The definition of the first-order histogram p(i) is:

$$P(I) = \frac{\text{number of pixels with gray level I}}{\text{total number of pixels in the region}} \tag{9}$$

P (i) = H (i)/NM

Where i=0, 1, 2………G-1

P (i) is the probability of occurrence of the i, G is the gray level of an image (255), N is the number of cells in the horizontal domain, M represents the number of cells in vertical domain [6].

The texture features are calculated as follows:

The average value of all pixels in an image, Mean $$\mu = \sum_{i=1}^{G-1} \mathrm{ip(i)} \tag{10}$$

The measurement of the average contrast, Standard deviation $$\sigma = \sqrt{\sum_{i=0}^{G-1} (1-\mu)^2 (p(i))} \tag{11}$$

The intensity variation around the mean, Variance $$\sigma^2 = \sum_{i=1}^{G-1} (1-\mu)^2 (p(i)) \tag{12}$$

The measurement of the symmetries of the histogram around the mean,

Skewness $$\sigma^{-3} = \sum_{i=1}^{G-1} (1-\mu)^3 (p(i)) \tag{13}$$

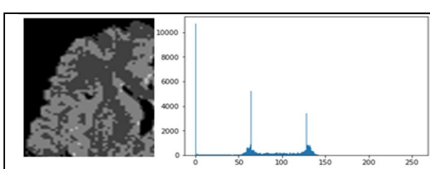
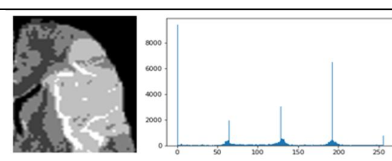
The fatness of the histogram, Kurtosis $$\sigma^{-4} \sum_{i-1}^{G-1} (1-\mu)^4 (p(i)) \tag{14}$$

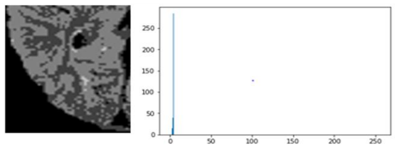
C. Experiment Results

The experiment results obtained from the proposed method is demonstrated below.

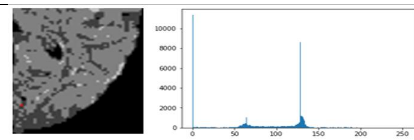
Table II displays the values of first order statistical features for various regions. The stroke region has a high mean, variance, and standard deviation because the brightness part represents the stroke area. Skewness and Kurtosis are both high for the normal part. The standard deviation displays a high value for abnormal parts and a lower value for normal parts.

TABLE I. HISTOGRAM AND TEXTURE FEATURES OF EACH REGION

	
Mean : 0.31700	Mean : **0.50899**
Variance : 0.07094	Variance : **0.15387**
Std. Deviation : 0.26635	Std. Deviation : **0.39226**
Skewness : -0.06852	Skewness : **-0.07906**
Kurtosis : 1.47956	Kurtosis : **1.56077**



Mean	:	0.33690
Variance	:	0.07314
Std. Deviation	:	0.27045
Skewness	:	-0.06490
Kurtosis	:	1.57219



Mean	:	0.40817
Variance	:	0.08748
Std. Deviation	:	0.29577
Skewness	:	-0.27637
Kurtosis	:	1.59310

III. Conclusions

This paper proposes an ischemic stroke detection technique based on feature extraction using a computer-aided diagnostic ability. Statistical features have significantly improved the proposed method's performance and accuracy. By comparing these several features, normal and abnormal portions of the brain have been recognized. This prediction and diagnosis of stroke lesion system aids radiologists in recognizing strokes. Machine learning and deep learning techniques will be used in the future to identify different types of strokes.

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