Adaptive Histogram Equalization for Detecting Cancer in Digital Mammogram

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Abstract: ***Breast cancer is a malignant tumor (a collection of cancer cells) arising from the cells of the breast. Breast cancer is the most common cancer among American women. One in every eight women in the United States develops breast cancer. According to the American Cancer society, over 200,000 new cases of invasive breast cancer are diagnosed each year. Nearly 40,000 women are expected to die of breast cancer in 2012. After 50 years of age, yearly mammograms are recommended (American College of Obstetrics and Gyanecology). Patients with a family history or specific risk factors might have a different screening schedule including starting screening mammograms at an earlier age. In this paper, an algorithm for extracting masses in mammographic image is done. Here, we use adaptive Histogram equalization, to provide enhancement to the image. Then, we go for feature extraction using gradient vector flow field. Training of the samples is done using PNN and the tumor is detected. The results are indicated to be effective and efficient.***

Keywords: Adaptive histogram Equalization, Gradient Vector Flow field, Feature Extraction PNN Training and Classification**.**

1. Introduction

In Digital Mammograms, we find the brighter regions as the density regions. Boyd et al proposed a method, which concluded that density description itself paves way for classification of specific regions. Suckling et al proposed an automatic method for segmenting the image first and then use gray level equalization [1]. In this paper, we use Adaptive Histogram Equalization Technique. Various enhancement schemes are used for enhancing an image which includes gray scale manipulation, filtering and Histogram Equalization (HE). Histogram equalization is one of the well known image enhancement technique [2]. The Gradient vector flow field is important model and is being widely applied in segmentation of images. GVF is insensitive to initialization and hence we use that for segmentation process.

2. Algorithm for detecting the masses

The algorithm used in this paper is as follows:

Step 1: Obtain the images and store it in a local disk, retrieve all the images and make it available for extraction.
Step 2: Enhance the mammogram using Histogram Equalization. This produces increased contrast on the images and makes it clear for feature extraction.
Step 3: Generate the boundary regions using a threshold and extract the features.
Step 4: Segmentation is done and wavelet based co-occurrence is used for extracting the required ROI.
Step 5: Finally, the region with suspicious mass is obtained by training the samples.

3. Scenarios taken into consideration

We use the Adaptive Histogram equalization technique to increase the contrast of the mammographic images [3]. We now go for the edge detection process. The edges are clearly obtained and segmentation is done using wavelet based co-occurrence method and the features [4] are obtained as follows:

(1) Energy: Provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.
(2) Contrast: Measures the local variations in the gray-level co-occurrence matrix.
(3) Correlation: Measures the joint probability occurrence of the specified pixel pairs.

The Correlation feature is calculated as:

$$\text{sum}\,(\text{sum}((x-\mu x)(y-\mu y)p(x,y)/\sigma_x\sigma_y))$$

We, then select the mammographic images and classify them as either, suspicious malignant tumors [5] and the ones with benign tumors. Training of the samples is done and the mammographic image clearly reveals the results.

Figure 1: Original image

Figure 2: Enhanced image

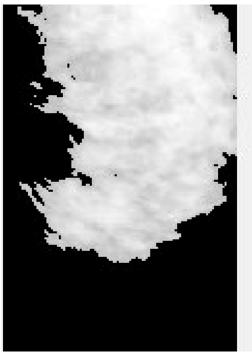

Figure 3: Segmented Image

4. Conclusions and Future Work

Here mammographic images have been used and their feature is extracted, after their enhancement process. The operation gives an efficient result in detecting the tumor [6]. In this work some consideration has been done which can be improved later on.

There is a vast future scope of this work. Some of them are pointed out here. They are to use of some good quality mammographic images to create some better feature extractions, which will reduce the fraudulent features mostly [7].

and to use a different approach for detecting the edges that can be used to extract the edges of ear image more accurately.

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