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Cervical Cancer Screening and Classification Using Acoustic Shadowing

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ABSTRACT: Cervical cancer is one of the deadliest cancers known and is also a key research area in image processing. The main problem with this cancer is that it cannot be detected as it doesn't throw any symptoms until the final stages. This is attributed to the cancer itself and also to the lack of pathologists available to screen the cancer. Here we have proposed a novel approach to classify the various malignancies in cervical images using acoustic shadowing.For classification we have used SVM classifier that would help us to classify the stages of the cancer and help the pathologist detect the cancer better.The proposed image has been tested with a set of images and has proved to be efficient.

KEYWORDS: Cervical cancer, cervix, acoustic shadowing, trim mean filter, ROI

I. INTRODUCTION

Cervical cancer has become one of the major causes of death among women worldwide. It can be cured when it is detected and treated in its earlier stage. But for most of the cases it throws symptoms only in the advanced stages. The traditional visual procedures are time consuming and error prone. Further it is impossible for a handful pair of eyes to sit and screen each and every woman on the planet. To solve this problem we need some automated process that could accelerate the process and also produce accurate results. The automated system would consist of three phases [1] namely pre-processing phase for noise removal, segmentation phase to identify the cells and to separate nucleus and cytoplasm and feature extraction phase to identify and locate the cancerous cells which is shown in figure 1.

Image segmentation is a very important image analysis task by which you can decompose the image into disjoint regions so that the features within each region have strong statistical correlation, visual similarity and reasonable homogeneity. Image segmentation algorithms may be classified into number of groups depending on their segmentation techniques like feature thresholding, region based techniques, contour based techniques, clustering techniques [2]-[12] etc. All these approaches have their own set of advantages and limitations in terms of performance, computational cost, applicability and suitability. Since the detection of cervical cancer mainly depends on the results of segmentation phase this paper mainly concentrates on segmentation techniques. Each segmentation algorithm works well for certain class of images and not for all images.

Classification of medical images using textural classification have been successfully performed various medical images such as breast cancer, liver cancer, lung disease etc., [13 -17]. Textural features looks directly into the compensation of the image itself, hence it reveals a lot about the image. Here we utilize SVM to classify the features extracted.Support vector machines (SVMs) are a set of related supervised learning methods which analyze data and recognize patterns, used for statistical classification and regression analysis. Since an SVM is a classifier, then given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other. Intuitively, an SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible.

New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. More formally, a support vector machine constructs a hyper plane or set of hyper planes in a high or infinite dimensional space, which can be used for classification, regression or other tasks. Intuitively, a good separation

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is achieved by the hyper plane that has the largest distance to the nearest training data points of any class (so called functional margin), since in general the larger the margin the lower the generalization error of the classifier.

II. CLASSIFICATION OF STAGES OF MALIGNANCIES USING ACOUSTICSHADOWING

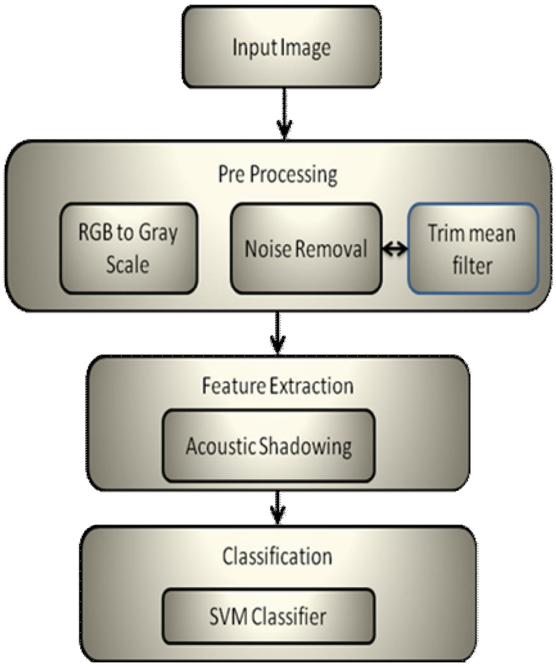

Fig1: Block Diagram.

A. Input Image

The input image is an ultrasound image. Normally the image is in gray scale. A sample cervical image is shown Fig.2

Fig 2 Cervical Image

B. Pre-Processing

The Input Image presents a set of weak features which need to be strengthened so that features can be extracted more accurately. Also to reduce the running time it is better that we concentrate only on the regions of interest rather than the whole image. There are numerous methods like edge detection methods and fuzzy clustering proposed for isolating these regions of interest [1]-[11]. Anyone of these methods technique can be used for isolating the regions of interest.

The pre-processing technique first converts the image to Gray scale color model and then filters the noise with the help of trim mean filter. Trim mean filter is the hybrid of mean and median filter. At the end we end up getting an image as shown in fig 3 [18].

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Fig 3 Segmented Image

Now that the ROI is isolated from the rest of the image we can extract the features better.

C. Feature Extraction

Cervical cancer like all other cancers develops through a series of stages. The first stage is the nucleoplasm stage which is the outcome of unwanted mitosis process. The second stage is called the pre-cancerous stage where the unwanted cells clump to form denser regions and in turn form tumors. This is the stage where normally cancers are detected. The last stage is the Cancer stage which is the advanced stage and survival is not guaranteed. To detect cancer in each stage you need different features and hence we in this paper have embodied a set of unique features that will not only say where the cell has symptoms of cancer but also it would tell at what stage the cancer is in.

1) Mean: In the pre-cancerous stage, cells clump together to become denser and in turn form tumors. Using the mean feature extraction we can easily detect when this particular process starts. When you look at a cervical cell it would be light shaded. But if you put two or more cells on top of it, it would look as if it is darker. In order to find these darker elements we use a histogram h(v) to chart the distribution of colors in the image. Then the mean of the color frequency distribution is determined by

$$M1=\frac{1}{M0}\sum_{v} v^{1}h(v)=\sum_{v} vH(v) \qquad (1)$$

2) Standard deviation: Standard deviation is same as mean except for the fact it tends to take into account the total number of pixels or in other words the population and sees how much it deviates from the neighboring cells. This statistical data can tell the difference between a cell and its neighbors and is determined by [19]

$$M2=\frac{1}{M0}\sum_{v} v^{2}h(v)-(M1)^{2} \qquad (2)$$

3) **Skewness:** Each cell process a unique shape. But when cells clump together they lose their shape and become irregularly shaped. This normally happens at the onset of the pre-cancerous stage and is determined by [19]

$$M3=\frac{1}{(M2)^{3}}\left(\sum v^{3}h(v)-3\sum vh(v)\sum v^{2}h(v)+2\sum vh(v)^{3}\right) \qquad (3)$$

4)Kurtosis: When the cancer enters the precancerous stage, tumors start to grow. Tumors are normally denser than normal cells as they are 3 dimensional. To detect these tumors we must first detect the density which is determined by

$$M4=\frac{1}{(M2)^{4}}\begin{pmatrix}\sum_{v} v^{4}h(v)-4\sum_{v} vh(v)\sum_{v} vh(v)\\ +6\sum_{v} vh(v)^{2}\sum_{v} v^{2}h(v)-3\sum_{v} vh(v)^{4}\end{pmatrix}-3 \qquad (4)$$

5) **Acoustic Shadowing:** In an ultrasound image, the absence of echoes produced by the presence of dense material, such as calculi, which impede the transmission of sound waves. It is often used to detect biliary calculi.

Acoustic Shadowing occurs when the sound wave encounters a very echo dense structure; nearly all of the sound is reflected, resulting in an acoustic shadow.

D. Classification

Support vector machines (SVM) are a set of related supervised learning methods which analyze data and recognize patterns, used for statistical classification and regression analysis. SVM is a classifier which constructs a hyper plane or set of hyper planes in a high or infinite dimensional space, which can be used for classification. When given a set of

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training examples, each marked as belonging to one of two categories. SVM training algorithm builds a model that predicts whether a new example falls into one category or the other.

III. CONCLUSION

The proposed algorithm extracts features from the image more accurately. The proposed method can detect the cancer in earlier stages. By detecting cancer in earlier stage, we can save many lives.

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