A CAD System for Lesion Detection in Cervigram Based on Laws Textural Feature

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***Abstract*— Cervical cancer is the second most common cancer among the women worldwide. A computer aided diagnosis system can help colposcopist to analyze cervical images more accurately. This work aims to detect lesion in cervical images based on Laws textural feature and nearest neighbor classifier and it can be used as a diagnostic tool. The images used for the detection of cervical cancer are taken by using colposcope which magnifies the cells of cervix. The Laws textural features are extracted from the cervical images and input to nearest neighbor classifier. A totally 240 images are used for the evaluation and an overall accuracy of 96% is obtained.**

Keyword- Cervical images, texture, Laws features, nearest neighbour.

I. INTRODUCTION

Cervical cancer is considered a public health problem due to increasing cases that arise every year with a late diagnosis which reflects the high level of female mortality. However, it has high potential for healing and easily diagnosed through examination of screening. An automated detection of cervical cancer using digital colposcopy is implemented in [1]. This method eliminates the specular reflection and makes the colposcopic images called cervigram ready for segmentation algorithms. The cervix region occupies about half of the cervigram image. The other parts of the image contain irrelevant information's such as equipment, frames, text and non-cervix tissues. The cervical borders are focused to identify the irrelevant information. The robust k-means clustering algorithm is used to evaluate the region of interest.

The elastic light single-scattering spectroscopy system has the potential for use in real-time diagnosis of high-grade squamous intraepithelial lesions tissues as an adjunct to Pap smear test and colposcopy is explained in [2]. A novel preprocessing technique identifies the region of interest and makes the cervigram ready for segmentation algorithms for automating early detection of cervical Cancer is introduced in [3]. Geometric boundary on the relevant image area is focused and irrelevant information's are eliminated

A domain-specific diagnostic feature in a probabilistic manner using conditional random fields to detect pre-cancerous and cancerous lesions of the uterine cervix is presented in [4]. Image regions corresponding to different tissue types are indentified for the extraction of domain-specific anatomical features. The unique optical properties of each tissue type and the diagnostic relationships between neighboring regions are incorporated in the proposed conditional random field model. An automated semantic image analysis method for cervical cancerous lesion detection based on semantics map is developed in [5]. The anatomical structure of the cervix is extracted from colposcopic images and identifies and summarizes different tissue types and their locations in an image semantics map.

Colposcopic image registration system able to help physicians for cervical cancer diagnosis is introduced in [6]. The goal is to make registration between the cervical tissues throughout the whole temporal sequence. An analysis of the colposcopic images to help the expert to make a more robust diagnosis of precursor lesions of cervical cancer is reviewed in [7]. This is a complete methodology to evaluate temporal changes of tissue color. A segmentation analysis of major lesions observed in early stages of cervical cancer is described in [8]. The purpose of segmentation is to automatically determine the location for a biopsy.

The colposcopic image classification based on contour parameters used in a comparison study of different artificial neural networks and the k-nearest neighbor method is proposed in [9]. An automatic detection of anatomical landmarks in uterine cervix images is explained in [10]. Multistage scheme for segmenting and labeling regions of anatomical interest within the cervigram is discussed. The colposcopic image segmentation based on integrated color and texture tools is described in [11]. Principal component analysis and multidimensional histogram analysis are used for preprocessing. Semi-automatic cervical cancer segmentation based on active contours without edges automatically extracts the region where the cervical cancer starts to occur in [12].

In this paper, an efficient segmentation of lesion in cervix images based on laws textural features is developed. The laws texture features are discussed in section 2. In section 3, the proposed method for the segmentation of lesion in cervix images is explained. The experimental results are evaluated in section 4 and finally concluded in section 5.

II. LAWS TEXTURE ENERGY MEASURES

Texture is an important feature that can help to segment images into regions of interest and classify those regions. Laws [13] developed a texture energy approach that measures the amount of variation within a fixed-size window. A set of nine 5 x 5 convolution masks is used to compute texture energy, which is then represented by a vector of nine numbers for each pixel of the image being analyzed. The masks are computed from the following vectors.

$$\begin{aligned} L5\ (Level) &: [\ 1 \quad 4 \quad 6 \quad 4 \quad 1\ ] \\ E5\ (Edge) &: [-1 \quad -2 \quad 0 \quad 2 \quad 1\ ] \\ S5\ (Spot) &: [-1 \quad 0 \quad 2 \quad 0 \quad -1] \\ R5\ (Ripple) &: [\ 1 \quad -4 \quad 6 \quad -4 \quad 1\ ] \end{aligned}$$

The names of the vectors describe their purposes. The L5 vector gives a center-weighted local average. The E5 vector detects edges, the S5 vector detects spots, and the R5 vector detects ripples. The 2D convolution masks are obtained by computing outer products of pairs of vectors. For example, the mask E5L5 is computed as the product of E5 and L5 as follows.

$$\begin{bmatrix} -1 \\ -2 \\ 0 \\ 2 \\ 1 \end{bmatrix} x \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \end{bmatrix} = \begin{bmatrix} -1 & -4 & -6 & -4 & -1 \\ -2 & -8 & -12 & -8 & -1 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 8 & 12 & 8 & 2 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

The first step in Laws' procedure is to remove effects of illumination by moving a small window around the image, and subtracting the local average from each pixel, to produce a preprocessed image, in which the average intensity of each neighborhood is near to zero. The size of the window depends on the class of imagery. After the preprocessing, each of the sixteen 5x5 masks are applied to the preprocessed image, producing sixteen filtered images. Let $F_k[i, j]$ be the result of filtering with the kth mask at pixel $[i, j]$. Then the texture energy map E_k for filter k is defined by

$$E_k[r, c] = \sum_{j=c-7}^{c+7} \sum_{i=r-7}^{r+7} |F_k[i, j]|$$

Each texture energy map is a full image, representing the application of the kth mask to the input image. Once the sixteen energy maps are produced, certain symmetric pairs are combined to produce the nine final maps, replacing each pair with its average. For example, E5L5 measures horizontal edge content, and L5E5 measures vertical edge content. The average of these two maps measures total edge content. The nine resultant energy maps are L5E5/E5L5, L5S5/S5L5, L5R5/R5L5, E5E5, E5S5/S5E5, E5R5/R5E5, S5S5, S5R5/R5S5 and R5R5. The result of all the processing gives nine energy map images or, conceptually, a single image with a vector of nine textures attributes at each pixel. These attributes are used to segment the lesion in cervix images.

III. PROPOSED METHOD

The proposed method consists of two steps; feature extraction and classification. Figure 1 show the proposed lesion detection system based on laws texture features and nearest neighbour classifier.

In the first stage, the features are extracted from training images based on ground truth images. The extracted features contain sufficient information to allow specific and correct classification of cervical cancer. Initially, the training images are processed as follows to extract the features.

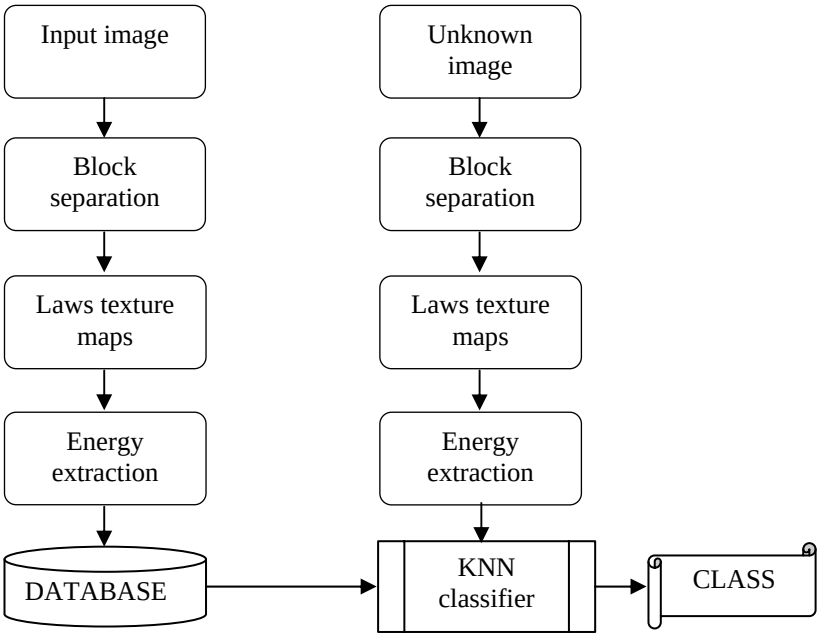

Fig. 1. Automated system for the detection of lesion in cervical images

Initially the abnormal regions are identified from the ground truth images in order to extract the laws features from the abnormal region; the identified regions are split into patches of size 15x15. Then the variation within the patches is calculated by laws texture energy measures. A set of mask is used to compute the energy, and then the mask is represented by set of nine vectors. Finally, nine laws map are developed. The average of these laws map is calculated and considered as a feature. This technique is applied for all the training samples to extract the proposed feature and stored in the database for classification.

In the second stage, each patches extracted from the unknown cervical image is classified into normal or lesion. A simple supervised classifier, nearest neighbor is used. The distance between the extracted features to the feature database is calculated based on euclidean distance metric. A nominal threshold is set to classify the region. If the calculated distance is below the threshold, the region is identified as lesion affected area, else identified as normal area.

IV. Experimental Results

In this section, the performance of the proposed classification algorithm based on Law's texture feature extraction is described. 200 normal and 40 abnormal cervical images are taken for the evaluation of the proposed system. The cervical images used in this study are obtained from Government Kasturibaigandhi Hospital (KGH), Chennai, India. All the images in the database are used for testing the classifier using Euclidean distance measure. 4 sample images along with the detected lesion are shown in Figure 2.

It is observed from the Figure 2, the performance of the proposed system is significant for the detection of lesion in cervical images. As non-overlapping patches of 15x15 are used to classify the region into normal or lesion, the output of the proposed system have square effects. The performance metrics of the images shown in Figure 2 such as specificity, sensitivity, Dice and classification accuracy are tabulated in Table 1.

TABLE I
Performance matrices obtained by the proposed Laws based texture features

No	Sensitivity	Specificity	Accuracy
1	0.86	0.98	96.778%
2	0.86	0.98	97.01%
3	0.84	0.98	96.94%
4	0.86	0.99	97.13%

From the sensitivity and specificity measures, it is clearly known that an average of 86% of the lesion is detected in a cervical image whereas 2% of the normal regions in the same image are identified as lesion. The overall accuracy obtained by the proposed approach is over 96%.

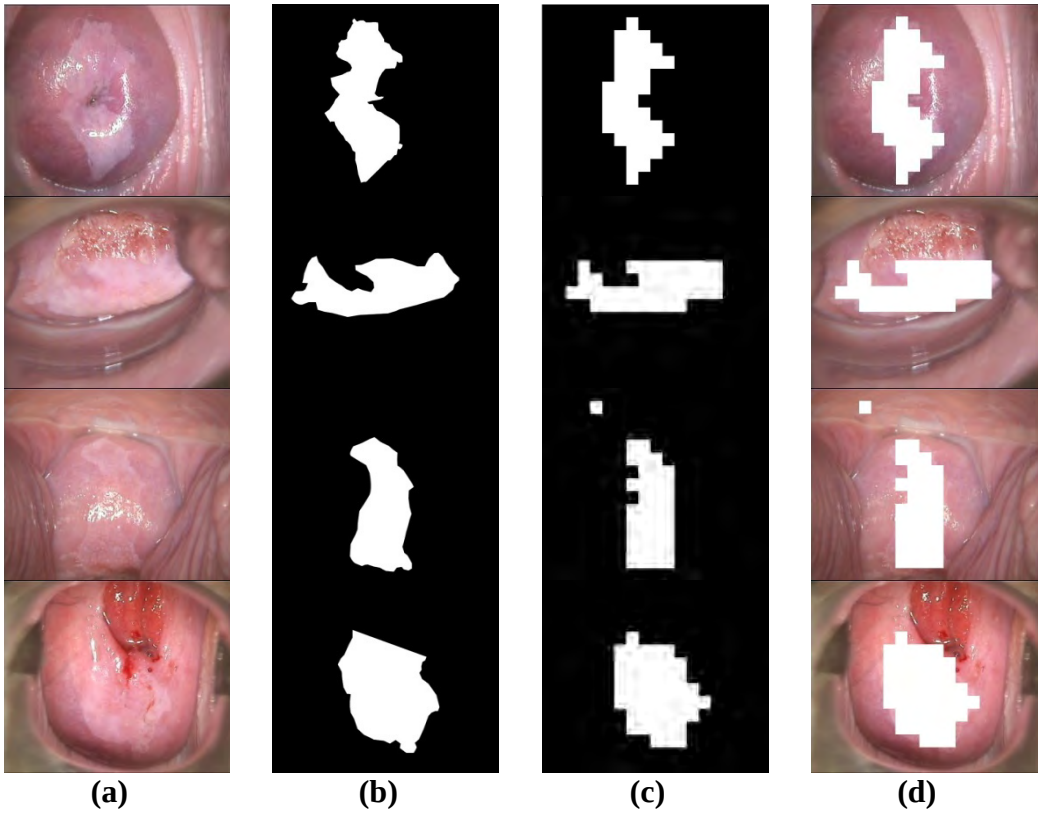

Fig. 2. (a) cervical image (b) ground truth image (c) detected by the proposed system (d) detected region in cervical image

V. Conclusion

In medical field, the classification or segmentation systems are used to examine the medical images in shorter time and more in-depth. In this paper, Law's texture features based detection of lesion in colposcopic cervical images is proposed. For training, the Law's texture features are extracted by fixed window size of 15x15 on lesion region identified by the ground truth images. These features are used as reference for the classification. The euclidean distance measure is used to detect/classify the region into normal or lesion. The evaluation of the proposed algorithm is carried on totally 240 images and good results are achieved. The average classification accuracy of the proposed method is over 96%.

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