INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact factor: 4.295
(Volume 4, Issue 3)
Available online at: www.ijariit.com

A hybrid video mining approach for Cancerous polyp detection in endoscopy videos

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ABSTRACT

Video mining on endoscopic videos is a challenging task due to interesting features of unstructured data. This paper presents a new feature descriptor to automatically recognize the images with cancerous polyps in endoscopic videos. This approach uses the features of cancerous polyps, determining polyp as cancerous by one feature descriptor is not possible. To overcome this the work combines two different feature descriptors for much more accurate identification. The two feature descriptors are Complete Local Binary Pattern (CLBP) descriptor and the Global-Local Oriented Edge Magnitude Pattern (Global LOEMP) descriptor. CLBP is used to detect the texture information in the image and the Global LOEMP is used to extract the color features. By combining both feature descriptors a stronger technique can be employed to identify cancerous polyps.

***Keywords**: video mining, endoscopy*

1. INTRODUCTION

An endoscopy is a procedure which uses an endoscope, as shown in figure 1 the device involves a small and flexible tube with a light to see the lining of the gastro intestinal tract. The healthcare technician passes a small tool with the endoscope to remove cancer inducing polyps. Polyps are the most common symptoms in human beings and some are harmless, whereas, some polyps can turn into cancerous polyps. The identification and removing harmful polyps in the beginning stage is necessary to prevent and control cancer.

The disadvantage of this technology is to analyze a large amount of data to detect an abnormality in gastro intestine, which can be more time consuming, the burden for technicians and in this manual procedure a few portions of the video may be left out from analysis due to the human tendency. In order to overcome the disadvantages of a manual process, computer-aided diagnosis is used to provide assistance for clinicians.

Many efforts have been made in the literature for automatic ulcer detection.

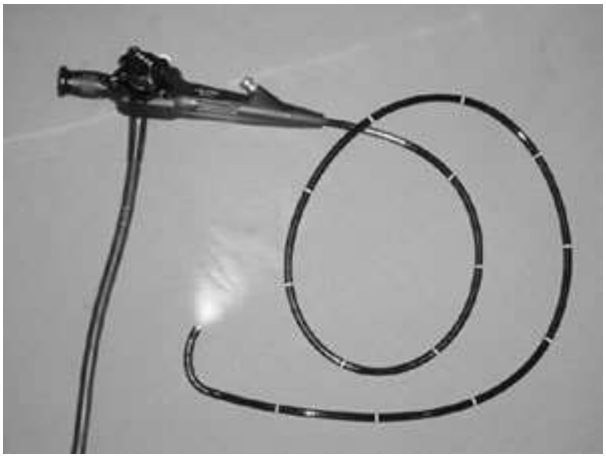

Fig. 1: Endoscope

Baopu et al. [1], [2] have proposed two approaches based on wavelet and curvelet-based local binary pattern, which distinguish ulcer regions from normal regions selected from endoscopy images. Charisis et al [3] have proposed another approach based on the extraction of texture features using several color spaces for wireless capsule endoscopy image analysis. This approach based on color texture features in to discover the distribution of information structure of unhealthy abnormal and normal healthy tissues on RGB, HSV, and CIE lab color spaces. On wireless capsule endoscopy images, a pre-processing step has been being carried out to simplify differential lacunarity analysis using bi-dimensional ensemble empirical mode decomposition intended towards extracting the texture patterns of normal and abnormal ulcerous regions. In [4], a method based on Contourlet transform and Log Gabor filter to differentiate ulcer regions from normal ones were proposed by Koshy et al. Color and texture features were proposed in [5] to detect bleeding and ulcer in wireless capsule endoscopy images. An improved bag of feature for automatic polyp detection and method for bleeding detection in wireless capsule endoscopy images were stated in [6], [7]. The twofold system was proposed to characterize wireless capsule endoscopy images by histograms based on color words, followed by applying SVM and Knn methods to observe the wireless capsule endoscopy image [7]. The pixel-based detection method has been proposed for WCE videos using support vector machine [8]. The two stages approach for automatic ulcer detection has been proposed in [9], and one more method for automated detection of polyp in wireless capsule endoscopy images in [10]. Yuji Iwahori et al. [11] Has proposed Hessian filter and HOG features to distinguish between polyp and non-polyp regions, then used K-means++ for classification phase. In recent work, directional wavelet-based features method was stated in [12]. In [13], [14], systems for small intestine motility characterization and bleeding detection, based on Deep Convolutional Neural Networks were introduced. The capsule endoscopy and deep enteroscopy in irritable bowel disease were investigated in [15]. Study of the effectiveness of capsule endoscopy in the detection of colon polyps was presented in [16]. A novel approach based on discrete wavelet transform and LBPV for colon abnormalities detection was proposed [17].

The research work in this paper proposes a novel computer-aided diagnosis system for the classifying the cancerous polyp images from the normal ones in endoscopy videos. Based on the work done by several researchers CLBP descriptor is used to extract the texture features but the single feature descriptor is not sufficient to identify the harmful cancerous polyps. To overcome this it is very important to extract the color features of the mucosa. Therefore research work proposes to use Global LOEMP with the CLBP extracted features in frames. The above-mentioned approach begins with pre-processing of frames of endoscopic videos with respect to eliminate the illumination and enhance the speed of analysis time. After pre-processing the texture features are derived using CLBP. The next step is to extract the color features using LOEMP in the HSB model. Finally, the feature vectors are combined and given to the classifier. For classification, the Support Vector Machine or Multilayer Perceptron classification techniques can be used.

2. PROPOSED APPROACH

Figure 2 is the proposed architecture. The proposed approach targets to extract the features for identifying the harmful cancerous polyp in endoscopy videos. The retrieved features are supplied to the classifiers like Support Vector Machine or Multilayer Perceptron. The process starts with pre-processing the endoscopy videos by reducing the illumination and masking regions which are not necessary. The second step is to pass pre-processed endoscopy frames for texture feature extraction using CLBP descriptor. Then, color features are derived by applying Global LOEMP to endoscopy image represented in the HSB color space. Next, we combine together the feature vectors derived by CLBP and LOEMP descriptors. Finally, the feature vectors are sent to a classifier to decide whether the frame is normal with a harmless polyp or contains harmful cancerous polyps.

Preprocessing

The Images are filtered using 3-D median filtering in a 3×3×3 neighborhood around each pixel for removal of noise and certain regions are masked trying to speed up analysis time specifically, the work tries to apply an automatic illumination correction scheme [18], for avoiding the effect of illumination based on symmetric distribution of the radial gradient.

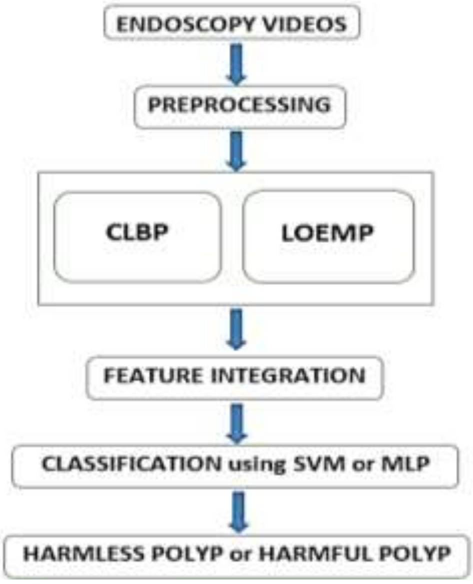

Fig. 2: Proposed architecture

Texture Feature Extraction

Complete Local Binary Pattern (CLBP) is known as a generalized version of LBP [19]. CLBP is capable to represent the discriminant information of the local structure that simple LBP may miss [20], CLBP is very effective for texture analysis.

Consider g_c a central pixel and $g_p, p = 0, 1, ..., P-1$. Here P equally spaced and neighbors circled around, Now calculate the difference d between the central pixel, g_c, and a pixel in its neighborhood g_p.

$$d_p = g_c - g_p.$$

The center pixel represents its local region and the difference between the values of the neighbourhood pixels and local center pixel which is called as Local Difference Sign- Magnitude Transform (LDSMT) will be calculated in CLBP, and the operators, namely CLBP-Center (CLBP_C) indicates the difference between local pixel value and average central pixel value, CLBP-Sign (CLBP_S) indicates the sign (positive or negative) of difference between the center pixel and local pixel. The traditional LBP descriptor extracts only the sign component of d_p and CLBP-Magnitude (CLBP_M) indicates the magnitude of the difference between the center pixel and local pixel. The difference of the intensity values in the central pixel neighborhood is represented in CLBP_C, which is least significant in texture feature extraction. In this regard, CLBP_S and CLBP_M are combined and the resulting features vector is used in combination with the LOEMP's one in the proposed approach. The dp is decomposed into two components.

$$d_p = s_p * m_p \text{ and } \begin{cases} s_p = sign(d_p) \\ m_p = |d_p| \end{cases} \quad (1)$$

Here s_p is the magnitude of d_p, CLBP considers the intensity of the central pixel g_c for more discrimination.

The CLBP_M operator is defined as:

$$CLBP\_M_{P,R} = \sum_{p=0}^{P-1} t(m_p, c)2^p, \; t(x,c) = \begin{cases} 1, x \geq c \\ 0, x < c \end{cases} \quad (2)$$

Where c is mean value of the complete image. CLBP_C operator is defined as:

$$CLBP\_C_{P,R} = t(g_c, c_I) \quad (3)$$

Where t is defined as in CLBP_M and the threshold c_I is the average gray level of the complete image.

Color Feature Extraction

The color Global LOEMP is a descriptor that is able to incorporate color, local and global spatial structure and directions information [21], [22], [23], [24]. The color Global LOEMP has the ability to balance the two concerns of robustness and distinctiveness. The color Global LOEMP feature acquires the following three characteristics.

1) Colour angle patterns that can extract the discriminative features obtained from the spatio-chromatic patterns of different spectral channels within the specific local region. Hence, makes it richer than the LBP as it contains more information.
2) A framework that is able to incorporate color, local and global spatial structure and directions information.
3) Robust to rotation by using global-level rotation compensation method, which shifts the principal orientation of HOG to the first position.

The second component of the transformed endoscopy images in the HSV color space highlights the abnormal ulcerous regions and separates ulcer mucosa parts from the uninformative regions [9]. LOEMP descriptor extract the color features of all the endoscopy images in the color plane.

Feature Integration

It is important to concatenate the extracted features for distinguishing cancerous polyp. The work uses CLBP descriptor to the endoscopy image represented in the RGB color space. Then, jointly combine the CLBP_S and CLBP M. The resultant joint histogram is of the 256-dimensional vector. The same manner, the work applies LOEMP descriptor to the endoscopy image, represented in HSB color space, to compute color features which are represented by a 140-dimensional vector. Finally, CLBP and LOEMP vectors are joined to form a combined 396- dimensional vector to serve as a descriptor of the endoscopy image [25], [26].

3. EXPERIMENTS

A set of experimental data was built based on the image sequences acquired by an endoscope from different patients and downloaded from [27]. The dataset is composed of 2333 endoscopy images extracted from 16 ulcer and 7 normal patients' video clips. The dataset contains 733 normal and 1600 ulcer images that were randomly divided into two sets, 1400 endoscopy images for training, in which 1000 with ulcer and 400 are normal and 933 endoscopy images for testing containing 600 with ulcer and 333 normal images [28].

The proposed method was first applied to the training dataset. A validation set was implicitly created from the training set and used to tune the parameters of the classifiers. P=8 and R=1 were experimentally chosen for the calculation of the CLBP components (i.e., CLBP_C and CLBP_M), the thresholds c and t (equations 1, 2 and 3) are set to be, the mean value and the average gray level of the whole image, respectively. Samples of abnormal and normal WCE frames are depicted in Figure 3 respectively. The resolution of the images is 243 × 424.

The original images are labeled manually by the clinicians to annotate the ground truth. The images containing any abnormal region are labeled as a positive sample; otherwise, they are labeled as negative samples. In order to prevent over-fitting of the classification, we exploit 3-fold cross-validation for all the experiments. In order to exploit the discrimination ability of the proposed approach, we provide the features to SVM (linear kernel) and MLP (number of hidden neurons ranging from 5 to 50) classifiers and compare their performances with the methods presented in [9], [28]. The classification results are assessed in terms of the accuracy, specificity and sensitivity measures, which are defined as follows [24]:

$$Sensitivity = \frac{\text{No.of correct positive predictions}}{\text{No.of positives}} \tag{4}$$

$$Sensitivity = \frac{\text{No.of correct negative predictions}}{\text{No.of negatives}} \tag{5}$$

$$Sensitivity = \frac{\text{No.of correct predictions}}{\text{Total samples}} \tag{6}$$

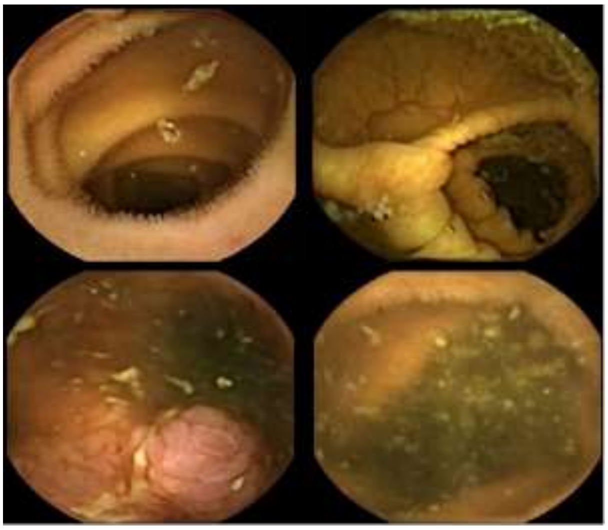

Fig. 3: Two normal images (top) and two images with ulcer (bottom)

Table 1: Comparison of state-of-the-art methods

Methods	Acc	Sens	Spec
Proposed method (SVM)	94.07	96.86	91.14
Proposed method (MLP)	93.93	95.50	92.29
Method [9]	92.65	94.12	91.18
Method [28]	87.27	88.64	85.75

Table 1 presents a comparison of the classification results of the proposed scheme with the state of the art methods. The Table 1, concludes that the proposed algorithm surpasses the approach [9] with enhancement of 1.42% in accuracy and 2.74% insensitively, respectively. The specificity is almost same for both the approaches while using the SVM classifier.

In Table 1, there are improvements of 1.28%, 1.38% and 1.11% in terms of accuracy, sensitively and specificity, respectively compared with [9] by using MLP as the classifier. Comparing with [28], the proposed method gives better results with improvements of 6.8%, 8.22% and 5.39% inaccuracy, sensitivity, and specificity, respectively, by using SVM classifier in the proposed approach.

By using MLP as the classifier and comparing the result of the proposed algorithm with those of the method in [28]. There is an enhancement of 6.66%, 6.86% and 6.54% in terms of accuracy, sensitively and specificity, respectively, as shown in Table 1.

Figure 4 depicts a detected image with ulcer (Figure 4(a)) and a detected normal image (Figure 4(b)).

Fig. 4: Illustration of visual detection results

4. CONCLUSION

In this paper, we have presented a novel and effective two-stage approach for ulcer detection in wireless capsule endoscopy videos. It is based on a combination of texture feature extraction approach, (i.e., CLBP) and a color feature extraction method, (i.e., Global LOEMP) to better characterize the wireless capsule endoscopy images. We experimentally evaluated the proposed approach on a dataset containing normal and abnormal frames from wireless capsule endoscopy videos. The results of the experiments confirm that the proposed scheme is efficient and accurate in the detection of the ulcer with 94.07%. For future work, we envisage experimentation with other bigger datasets and even testing the proposed method for other types of abnormalities.

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