ISSN 2348 – 9928

IJAICT Volume -1, Issue-8, December 2014 Doi:01.0401/ijaict.2014.01.30 Published Online 05 (05) 2014

AN EFFICIENT APPROACH TO DETECT BLEEDING REGION IN GI TRACT USING SEGMENTATION AND CLASSIFICATION TECHNIQUES

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Abstract - Wireless Capsule Endoscopy (WCE) is a device to detect abnormalities in colon, oesophagus, small intestinal and stomach to distinguish bleeding in WCE images from non-bleeding is a hard job by human reviewing and very time consuming. WCE is a new technology that enables close examination of the interior portion of the entire small intestine without the surgery. In digital image processing the segmentation and classification is very difficult task. If the segmented result is poor then the detection accuracy is very poor. In this paper, we propose a new method for segmentation and classification of bleeding images in WCE video using the threshold technique and neural networks method to obtain the high detection accuracy of bleeding and non-bleeding images. First, the image is converting into HSI colour domain since it is closer to human perception than the other colour domains. Second we segment each images into bleeding and non-bleeding regions using threshold technique. Finally we classify the segmented images into bleeding and non-bleeding by the neural network method with the help of GLCM feature extraction to obtain the better classification performance.

Keywords: Wireless Capsule Endoscopy, Normalized Cut Segmentation, Threshold Technique, Neural Network, Gray Level Co-Occurrence Matrix.

I. INTRODUCTION

The far old endoscopy techniques such as colonoscopy push enteroscopy and intraoperative enteroscopy are helped doctors to visualize up to stomach from the upper part of terminal ileum and colon from the bottom. There is no method to view most of the small intestine without surgery. The endoscopic capsule is the first autonomous micro device to explore the human inner body of wide clinical application. It is ingested to the patient and films the whole gastrointestinal tract during 6-8 h. The full system consists of the capsule itself, an external receiving antenna and a portable hard drive carried in the patient's belt. The capsule endoscopy is a disposable plastic capsule. The weight is 3.7g and measures (11mm ×26 mm) 11 mm in diameter x 26mm in length. The contents include complimentary metal-oxide-silicon (CMOS) chip camera, a short focal length lens, four white light emitting diode (LED) illumination sources, two silver oxide batteries and an ultrahigh frequency band radio telemetry transmitter. Fig.1 shows the endoscopic capsule with 8 parts (1) Optical dome, (2) lens holder, (3) lens (4) illuminating LEDs, (5) CMOS imager, (6) battery, (7) ASIC RF transmitter, (8) antenna.

The activated capsule after removal from the magnetic holder provides image accrual and transmission at frequency of two frames per second until the battery expires after 7±1h.

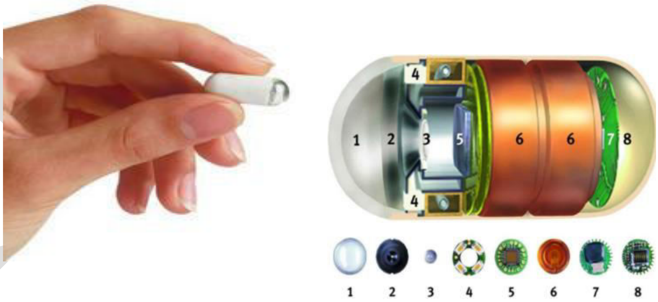


Fig.1: Image of endoscopic capsule

In this paper, we propose a new method that classifies bleeding images in WCE video using the HSI (Hue, Saturation and Intensity) colour domain. While performing the segmentation based on existing N-cut segmentation algorithm, poor detection of bleeding region is resulted. To overcome this problem threshold technique is used for the segmentation.

The outline of this paper is as follows. We will briefly discuss about HSI Colour space conversion (see Section II), Image segmentation strategy (see Section III). Then, we discuss the neural networks of image classification strategy (see Section IV).We will later explain our experimental result (see Section V) followed by conclusion (see Section VI) and Future work (see Section VII).

ISSN 2348 – 9928
IJAICT Volume -1, Issue-8, December 2014 Doi:01.0401/ijaict.2014.01.30 Published Online 05 (05) 2014

II. HSI COLOUR SPACE CONVERSION

Although colour receptors in the human eye (cones) absorb light with the greatest sensitivity inthe blue, green and red part of the spectrum. In the perception process a human can easily recognize basic attributes of colour i.e., hue, saturation and intensity (HSI). The hue is a colour attribute that describes a pure colour and represents the impression related to the dominant wavelength of the colour stimulus.

The saturation corresponds to relative colour purity (lack of white in the colour). For example, in the case of a pure colour it is equal to 100%. Intensity is brightness. Maximum intensity is sensed as pure white, while minimum intensity as pure black. As a result of the HSI model is an ideal tool for developing image processing algorithms based on colour descriptions that are natural and intuitive to humans. Therefore, we are going to use HSI colour domain by converting the input raw data format RGB into HSI. For the HSI conversion we use Kender's Formulation as follows:

$$\frac{\quad \mathrm{in}((\quad)))}{\quad} \quad (1)$$

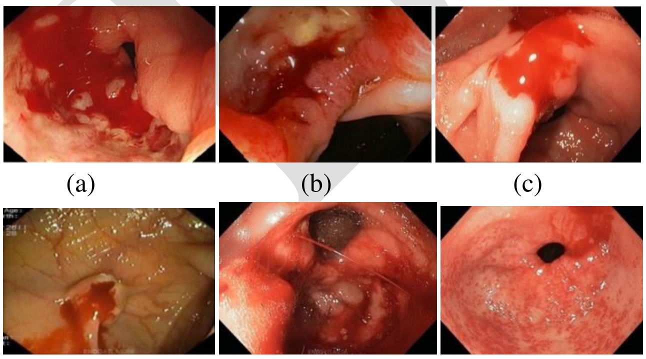
$$\frac{\quad}{\quad} \quad (2)$$

if

$$\left\{ \frac{5[(\quad)]}{[(\quad)]^{-}} \right\} \quad [0 \ \pi]$$

else

$$\left\{ \frac{5[(\quad)]}{[(\quad)]^{-}} \right\} \quad [\pi \ 2\pi] \quad (3)$$

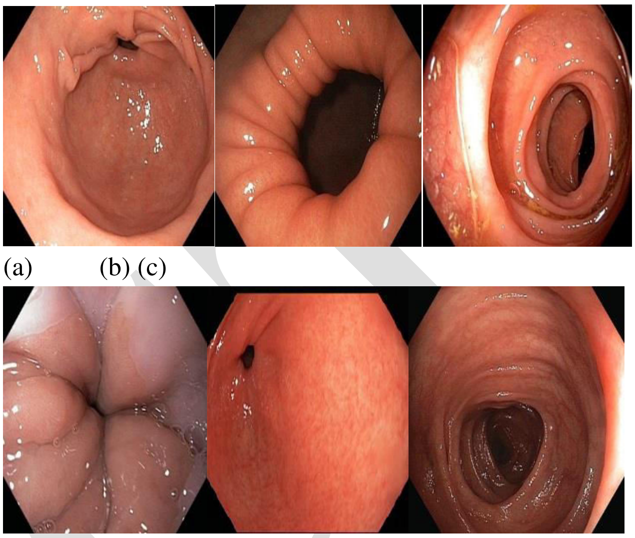


(a) (b) (c)

(d) (e) (f)

Fig.2 : (a)Ulcer with bleeding,(b) Gastric antrum ,(c) Stomach,(d),(e)pyloric ulcer ,(f)-Different organs of bleeding images.

The two class of images from GI tract are given as a inputs. Fig.2 and Fig.3 shows the some examples of bleeding and non-bleeding WCE images.



(a) (b) (c)

(d) (e) (f)

Fig.3(a)Gastric antrum and pylorus,(b)Peristaltic wave in the gastric antrum,(c)Sigmoid colon normal,(d)Cardia,(e)Gastric antrum and pylorus,(f)Colon descende: Different organs of non-bleeding images.

III. IMAGE SEGMENTATION

The existing N-cut segmentation algorithm with combining multiple visual features such as edgemaps, creaseness, and colour features are applied to the bleeding images. Then we obtain the result using N-cut segmentation algorithm is shown in Fig.4.

3.1 Image segmentation using multiple features with N-cut algorithm

N-cut is a graph-theoretic approach for solving the grouping problem in vision. It is a clustering-based segmentation approach in which an image is represented as a weighted, undirected graph whose nodes correspond to individual pixels and graph weights are based on affinity between the pixels. N-cut has the intrinsic ability to combine a set of features to calculate the affinity matrix to be used for images segmentation.

Experiments show that a more simple strategy such as multiplication of affinities from various visual features can make multi feature fusion much simpler, unsupervised and avoids the problems incurred by the optimization process:

ISSN 2348 – 9928
IJAICT Volume -1, Issue-8, December 2014 Doi:01.0401/ijaict.2014.01.30 Published Online 05 (05) 2014

(4)

Wherew_D $_*$,w_{D_C} and w_{D_C} are affinities obtained usingedgemaps, creaseness, and colour features, respectively.

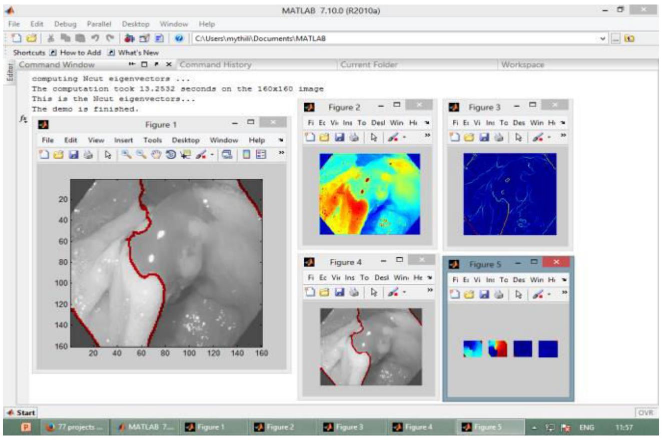


Fig.4 Segmentation result of N-cut algorithm with multiple features

While performing the segmentation based on N-cut segmentation algorithm, poor detection of bleeding region is resulted. To overcome this problem simple segmentation method is used for the segmentation process.

3.1 Image segmentation using Threshold technique

Several threshold methods are used for the segmentation. One of the main and important methodis Otsu's method. It is used to automatically perform clustering-based image thresholdingfrom the reduction of a graylevel image to a binary image. The algorithm assumes that the image to be threshold contains two classes of pixels or bi-modal histogram (e.g. foreground and background) then calculates the optimum threshold separating those two classes so that their combined spread (intra-class variance) is minimal.

It works by first computing a set of histogram data usually from pixel based image data of a greyscale image. Then for each possible threshold value (the histogram bin number) we calculate the variance of all the bins before and the bins after that point to evaluate the spread within each of the classes. As each potential threshold is evaluated, we keep track of the threshold that produced the minimum intra-class variance so far. Mathematically speaking, this can be defined by:

$$_2{}^2 \quad (5)$$

Where is the weighting of the class given by:

$$\sum \quad (6)$$

Where P (i) is the class probability

The total number of pixels in the image divided by the number of pixels in the class.For practical purposes, calculating the intra-class variance can become very time consuming. Alternatively, variance between classes can be calculated. The between class variance is the opposite of the intra-class variance in that we take the threshold that produces the maximum amount of variance rather than the minimum and can be calculated using the following formula

$$^2 \quad (7)$$

IV. IMAGE CLASSIFICATION

The image classification is performed based on the feed forward neural network with GLCM feature extraction.

4.1 GLCM feature extraction

Gray-level co-occurrence matrix (GLCM) is the statistical method of examining the textures that considers the spatial relationship of the pixels. It is widely used to discriminate texture images. Texture is one of the important characteristics used in identifying objects or regions of interest in an image. Texture contains important information about the structural arrangement of surfaces. The textural features based on gray-tone spatial dependencies have a general applicability in image classification. There are four GLCM textural features are used to extract the information from the given image.

Contrast:

$$\sum_i \sum \quad (8)$$

This statistic measures the spatial frequency of an image and is difference moment of GLCM. It is the difference between the highest and the lowest values of a contiguous set of pixels. It measures the amount of local variations present in the image. A low contrast image presents GLCM concentration term around the principal diagonal and features low spatial frequencies.

Correlation:

$$\frac{\sum_i \sum_j}{\quad} \quad (9)$$

Where μ_x, μ_y, σ_x and σ_y are the means and standard deviations of g_x and g_y .The correlation feature is a measure of gray tone linear dependencies in the image.

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Energy:

$$\sum_i \sum \quad {}^2 (10)$$

This statistic is also called uniformity or angular second moment. It measures the textural uniformity that is pixel pair repetitions. It detects disorders in textures. Energy reaches a maximum value equal to one. High energy values occur when the gray level distribution has a constant or periodic form. Energy has a normalized range.

Homogeneity:

$$\sum_i \sum \text{———} \quad {}_{ij}(11)$$

This statistic is also called as Inverse Difference Moment. It measures image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. It is more sensitive to the presence of near diagonal elements in the GLCM. It has maximum value when all elements in the image are same. GLCM contrast and homogeneity are strongly but inversely correlated in terms of equivalent distribution in the pixel pairs population. It means homogeneity decreases if contrast increases while energy is kept constant.

4.2 Feed Forward Neural network for Image classification

This paper will deal mostly with feed-forward ANNs (or multi-layer perceptron's, MLPs). They consist of interconnectedlayers of processing units or neurons. The first layer has weights coming from the input. Each subsequent layer has a weight coming from the previous layer. All layers have biases. The last layer is the network output.

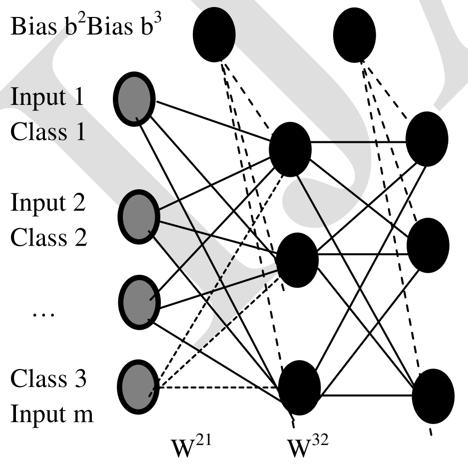


Fig.5 *Structure of feed forward neural network*

In this figure, thenotation of weights and biases follows weights of connections between layer Pand layer Q are indicated by W^{pq}; the bias, input and output vectors of layer Pare indicated by bp, Ip and Op respectively.

Basically, a feed-forward ANN is a (highly) parameterised, adaptable vector function which may be trained to perform classification.

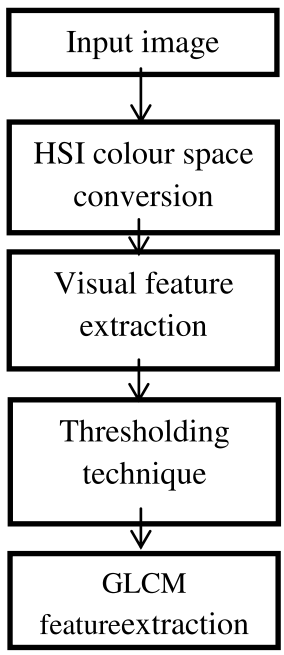
Classification

To perform classification, an ANN should compute the posterior probabilities of given vectors x, $P(w_j|x)$where $w_j$is the label of class j, j = 1, . . . ,m. Classification is then performed by assigning an incoming sample x to that class for which this probability is highest. A feed-forward ANN can be trained in a supervised way to perform classification, when presented with a number of training samples L = {(x, t)}. The back propagation training algorithm tries to minimise the mean squared error by adjusting the weights and bias terms.The MSE function is given below

$$\text{——} \sum \sum (\qquad (12)$$

V. EXPERMENTAL RESULT

The experimental result shows the entire procedure of this paper. First the given input images are converted into HSI space. Then based on the intensity value of the pixels the threshold technique is used for the Segmentation process.



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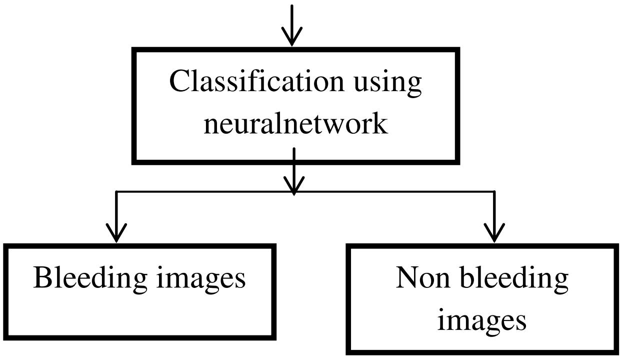
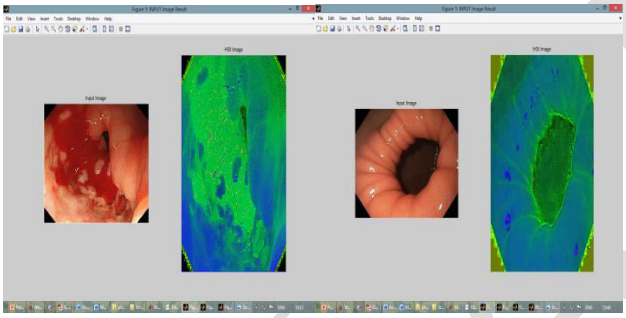


Fig.6 Structure of the entire segmentation and classification process

After the segmentation the classification is performed based on the GLCM textural features. Finally, the Table 1 shows the values of four GLCM textural features for different input images.

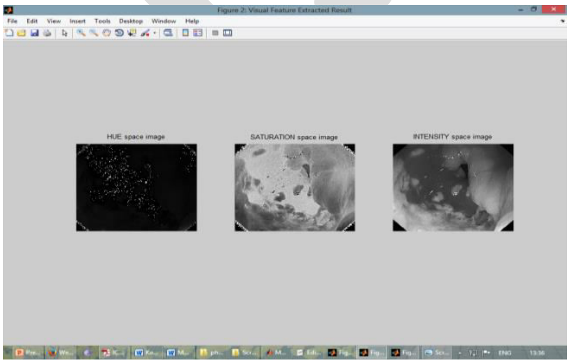
STEP 1: Conversion of given input image into HSI.



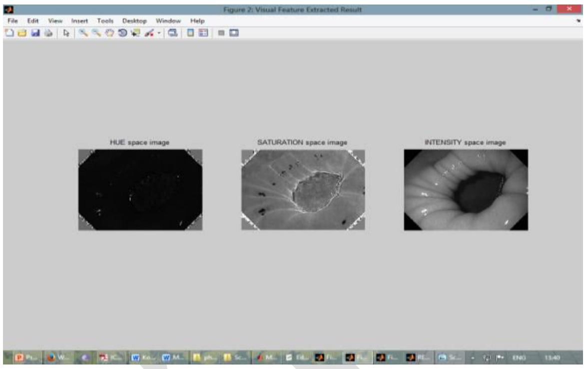
(a) (b)

Fig.7 Result of HSI space conversion (a) Bleeding image (b).Non-bleeding image

STEP 2: Visual feature extraction from HSI image for the segmentation process



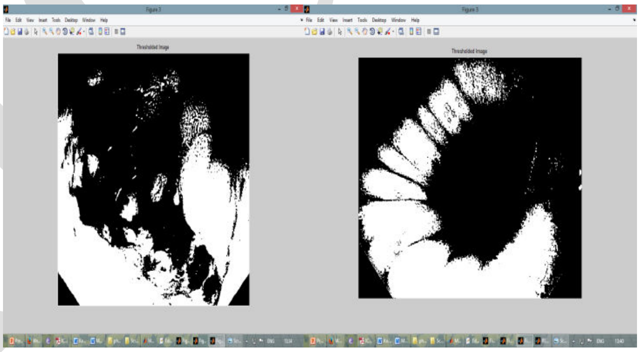
(a)



(b)

Fig.8 Result of visual feature extraction (a) Bleeding image (b).Non-bleeding image

STEP 3: Based on the value of intensity the threshold segmentation algorithm is used.



(a) (b)

Fig.9 Result of segmentation process (a) Bleeding image (b).Non-bleeding image

STEP 4: Classification based on the neural network

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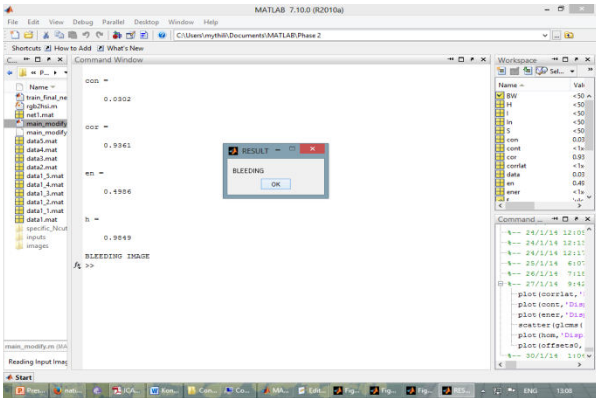
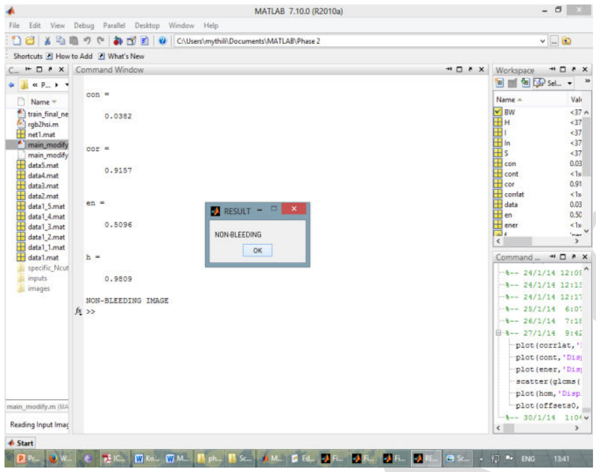


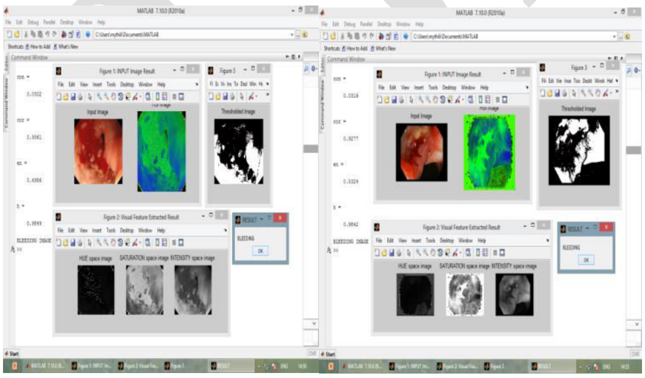
(a)



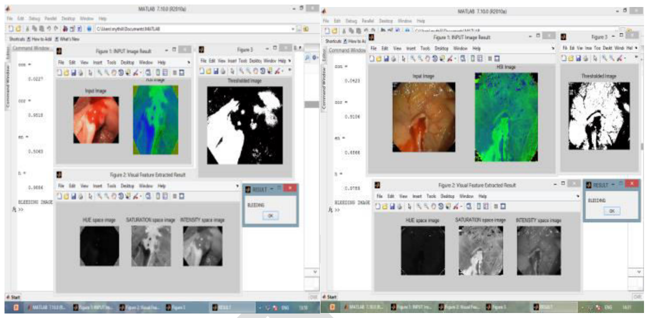
(b)

Fig.10 Result of classification process (a) Bleeding image (b).Non-bleeding image

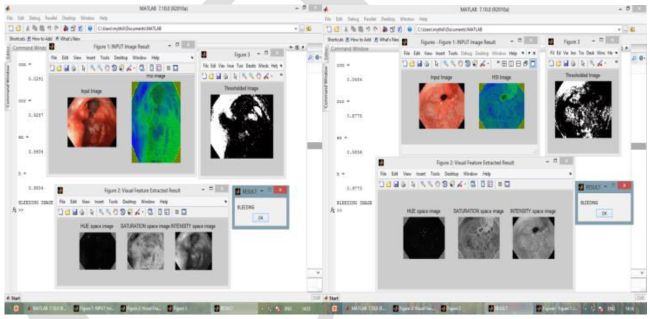
CLASS 1: Different organs of bleeding images are taken from GI tract.



(a) (b)



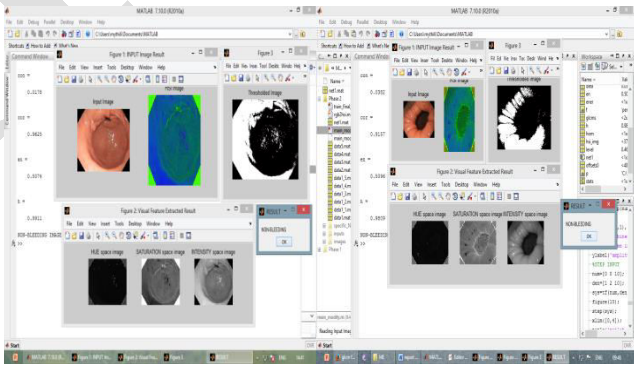
(c) (d)



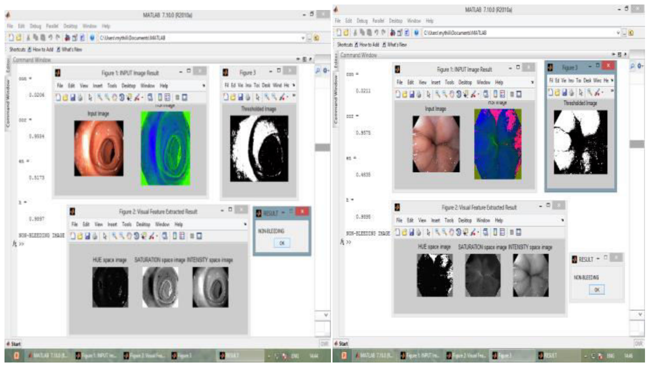
(e) (f)

Fig.11Result of segmenation and classification for bleeding images.

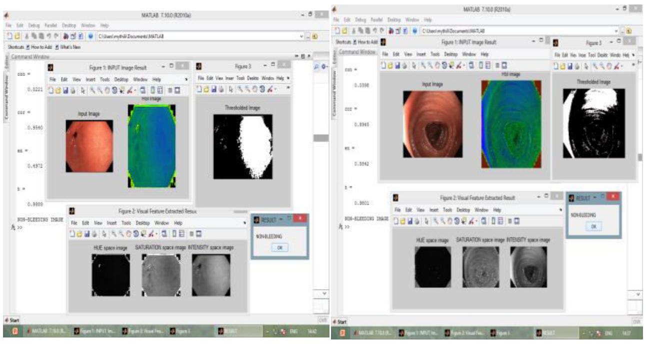
CLASS 2: Different organs of non-bleeding images are taken from GI tract.



(a) (b)



(c) (d)



(e) (f)

Fig.12Result of segmenation and classification for non-bleeding images.

Table 1 GLCM textural feature value for different input images.

Fig.no	Contrast	Correlation	Enegry	Hom
Fig.1(a)	0.0302	0.9361	0.4986	0.9849
Fig.1(b)	0.0316	0.9277	0.5324	0.9842
Fig.1(c)	0.0227	0.9518	0.5063	0.9886
Fig.1(d)	0.0423	0.9106	0.4866	0.9789
Fig.1(e)	0.0291	0.9287	0.5634	0.9854
Fig.1(f)	0.0454	0.8775	0.5856	0.9773
Fig.2(a)	0.0178	0.9625	0.5078	0.9911
Fig.2(b)	0.0382	0.9157	0.5096	0.9809
Fig.2(c)	0.0206	0.9554	0.5173	0.9897
Fig.2(d)	0.0211	0.9575	0.4835	0.9895
Fig.2(e)	0.0221	0.9540	0.4972	0.9889
Fig.2(f)	0.0398	0.8945	0.5842	0.9801

VI. CONCLUSION

Image segmentation and classification is an essential component of CAD systems for diagnosis of bleeding and non-bleeding in GE imaging. It is a challenging problem given the dynamics of imaging conditions and imaging modalities that add to the difficulty of computer-vision-based tasks for assisted decision making. A wide variety of methods are available that can be used for segmentation and classification of GE images. However, we chose threshold technique and neural networkability to avoid over segmentation for high textured images due to a global optimization criterion, and their ability to accommodate various visual features based on the nature/contents of the images. Experiments show that the unique combination of GLCM feature extraction gives the best classification results since it provide complementary features for image analysis. In this paper, we have focused on improving the segmentation and classification performance for GE images without considering the computational time as a key issue.

VII. FUTURE WORK

In the future, we plan to expand the experimental validation of our proposed methodology across various other objectives such as segmentation and classification of polyps, cancer and ulcer with pre-processing of given image. We also plan to quantify the clinical relevance of various regions in a segmented image.

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