International Journal of Advance Research, Ideas and Innovations in Technology

INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact Factor: 6.078
(Volume 7, Issue 4 - V7I4-1256)
Available online at: https://www.ijariit.com

Performance evaluation of GMM super-pixel model-based technique with various bleeding detection techniques in WCE images

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Abstract— ***Wireless Capsule Endoscopy (WCE) is a non-invasive medical process which permits the assessment of whole gastrointestinal tract that includes small intestine parts ahead of the conventional endoscope scope. This in turn needs the approach of computer-aided scheme to assess the video frames for reducing the time of diagnosis. In this approach, the performance comparison on various existing techniques like color based feature extraction, histogram based approach, Discrete Wavelet Transform (DWT), K-nearest Neighbor (KNN), K-means, and Support Vector Machine (SVM) techniques employed in the detection of bleeding to that of the proposed Gaussian Mixture Model (GMM) super-pixel model has been carried out. The study is carried out in terms of feature extraction models used so far and the classification approaches employed so far. Then the experimental study is carried out in terms of existing techniques and the performance is compared with GMM super-pixel feature extraction model and linear SVM to prove the effectiveness of GMM super-pixel based model for bleeding detection. From the experimental analysis, the GMM super-pixel model is concluded better for automated bleeding detection.***

Keywords: Wireless Capsule Endoscopy, GMM super-pixel, linear SVM, color based feature extraction, histogram based approach, DWT, and KNN algorithm.

I. INTRODUCTION

Bleeding of Gastrointestinal (gI) is the most often experienced anomaly on the gastrointestinal tract [1] and may also show a large number of other intestinal illnesses, such as vascular tumour, ulcers, polyps and crohn's disease [2]. The typical diagnostic procedure involves physical examination of the whole GI tract by an expert clinician in order to diagnose bleeding as one of the most common disease anomalies [3]. Standard endoscopy procedures such as probe and push enteroscopic therapy are uncomfortable and dangerous for patients, because in the event of serious medical problems they will tear intestinal walls. They also have limits on the small intestine to enter and imagine. An electronic interface recording photographs, recordings, and other images of the whole GI tract is used for the wireless endoscopy (WCE) technology [4], that started around 2000 [5]. In the presence of health experts, the tablet, shaped like a regular pill, should be swallowed without distress by the patient. It examines the entire GI tract of the patient without any pressure, rest of the network and air inflations, in contrast to traditional endoscopy procedures [6]. WCE was licensed as a diagnostic instrument to analyze stomach and small intestines mucosa as a means to identify multiple anomalies and diseases by the Food and Drug Administration, (FDA), in 2001. More than 1,6 million patients worldwide have so far been helped by WCE technology [7]. In GI bleeding detection, wireless capsules (WCE) have been used commonly since 2001 due to its non-invasive capabilities of the whole GI tract. The advances in research in the area of medical imaging have recently taken place. [8] One of the most important advancements in this area is wireless capsule endoscopy. WCE is widely used for small intestines inspections where it is impossible to use conventional endoscopic techniques like colonoscopy, push enterosacopy or enteroscopy, where it is also possible for traditional GI exams to be performed except for the colonoscopy. [9]. At WCE, the evaluation process must not be practiced constantly by physicians and practitioners. The data collected by the capsule after passing through the whole gastrointestinal tract must instead be treated. Doctors have to analyze about 8 or 55000 video hours and pick those where anomalies are found. However, this is also a time-consuming procedure that can be cumbersome for physicians and human mistakes during the process. [13] Study in this field is also important to optimize the analysis process and to reduce the time for image evaluation. A variety of methods in WCE images have been proposed in the last two decades for creation of automatic anomaly (e.g. polyps, ulcers, and bleeding)[16]. One of the main practices is to detect bleeding in this field. Sparse coding is an important technique that is mostly used in imaging, computer vision and machine learning. It can produce discriminating descriptors, which can easily differentiate between normal and bleeding images from solid WCE files [16]. Several attempts have been made in WCE images to identify automatic bleeding patterns. A new method for automated blood detection in images of WCE is discussed in this paper. The technique first proposed that GMM [10] be used as a function descriptor to delete features in WCE images. Those function descriptors are then coded such that each WCE image can be provided with one feature vector in a new array. These vectors are used to discern using SVM at the end of the operation. A data collection of 1647 images will validate the process . The paper's findings, provided in the context of a comparative analysis, illustrate the reliability and effectiveness of the proposed process. The remainder of the article is structured as follows. Sections 2 and 3 equate bleeding identification approaches to recent state-of-the-art methods for feature extraction and classification. Section 4 summarized the experimental analysis. Section 5 portrayed the success assessment. Finally, in Section 6, we ended the paper..

II. BLEEDING DETECTION WITH FEATURE EXTRACTION TECHNIQUES USED

This section provides a study on various existing techniques employed so far in terms of feature extraction to detect bleeding.

A. Color based feature extraction

Since clinicians distinguish frames of bleeding from the entire WCE image set primarily depending on colour specifics, it is critical to choose the proper colour space to convert colours with human eye sensors into values that computer programmes may use [12]. The color space that is most effective for exposing the abnormality of bleeding is not clear in advance. The experimental results for the suggested extraction methods in commonly used colour areas such as RGB, HSV, YCbCr, and LAB are then examined and used to make the best choice. They delete sufficient colour functionality in the endoscopic imagery to describe bleeding frames after choosing the reference colour space. Many existing feature extraction approaches concentrates on histograms in an entire colour spectrum and histogram predictive properties. [15]. Certain colours, however, such as blue and violet, do not appear in WCE recordings. Furthermore, the majority of the colours detected in WCE images were concerted in a slight colour space area. In order to resolve these concerns, we proposed a new colour feature to characterize WCE images. We can get the specific colour spectrum for the WCE images by selecting randomly bleeding images 10% and normal images 10% from datasets and measuring appropriate cluster centers separately through applying the pixel signified picture vectors to the K-means clustering technique in the colour space. This technique makes use of the colour information in the WCE frames to minimize the colour feature measurements. Cluster K from bleeding data collection and a dataset WCE are merged to form a graphic word vocabulary. They then use three-dimensional colour data to map respective WCE image point to the adjacent visual terms, compute to each visual message number, and provide a histogram. The WCE images are characterized as colour histograms based on terms using this technique. Any colour is represented as a vector whose intensity is determined by a triple RGB.

$$\mathrm{R}=\int_{400}^{800} N(\lambda)R(\lambda)d(\lambda) \qquad (1)$$

$$\mathrm{G}=\int_{400}^{800} N(\lambda)G(\lambda)d(\lambda) \qquad (2)$$

$$\mathrm{B}=\int_{400}^{800} N(\lambda)b(\lambda)d(\lambda) \qquad (3)$$

Where R signifies Red, G signifies green, B denotes blue and λ is the color wavelength, N represents the nearest visual terms, d represents the diameter.

B. Histogram based feature extraction

The most challenging process in any pattern recognition problem is feature extraction. As a result, the accuracy of the extracted functionality is highly dependent on the performance of a bleeding detector programmed in the same way as all patterns [12]. However, one of the most important obstacles to extracting consistency features is that the zone of bleeding in a bleeding frame can assume an arbitrary shape cover incredibly very to small large areas. The ransomed existence of bleeding zones is troublesome where general image statistics such as a median pixel value are used as features where Region Of Interest (ROI) is not available, which means that derived features frequently result in contamination of tiny bloating zones with wide no bleeding zones. However, if the extracted ROI is available, normalization of the target area can be viewed as a solution to the issue of different area sizes under function extraction. The main problem here, though, is the amount of statistical characteristics needed to enhance the discrimination of bleeding and non-bleeding images. The attributes of the bleeding zone must be individually integrated into the feature vector, regardless how small or massive, in order to solve these issues. Thus, the histogram of standardized ROI planes is suggested as features in their article. Histograms can represent bleeding ranges simply regardless of how big or small in those containers, and still retain the property of bleeding. The histogram for each pixel of ROI resulting from the normalised WCE image plane is determined in the proposed approach and the frequencies in each bin is estimated. This histogram-based image pixel representation can also ensure that any blood pixel functions, even though they are tiny, are included in the vector. As this representation means that any bleeding pixel set is used in the feature vector, a histogram-based feature is better to use as feature rather than a complete number of pixels in the ROI. Since bleeding is determined by human colour, it is thought that the histogram of bleeding and non-bleeding pictures is significantly different, thereby ensuring that consistency characteristics are extracted. In normalized colour planes, 64 bin histograms of the selected ROI have been used to illustrate difference between the pixels of bleeding and non bleeding images. Finally, histogram bin frequencies on the derived ROI are used in distinguishing colours to achieve a vector function.

$$\text{Normalized Histogram}=\frac{\text{Number of pixel with intensity n}}{\text{Total number of pixels}} \qquad (4)$$

$$D_{(z,a)=}\left[(Z_R - a_{R^2}) + \left(Z_{G-a_{G^2}}\right) + \left(Z_{B-\,a_{B^2}}\right)\right] \qquad (5)$$

Here D represents the distinguishing colors, z, a represents the pixels.

C. Discrete Wavelet transform

DWT is an important method for separating characteristics from different directions and sizes. The 2D DWT wavelet coefficients from WCE images are obtained in this work. The wavelet locates frequency information that helps to obtain correct grading data. Before being used for calculating DWT, the input signal is transferred through low and high-pass filters. For a signal and a low pass filter, DWT is described [14],

$$J=\sum_{j=i}^{k}\sum_{i=l}^{x}\left\|X_{j-c_J}\right\| \quad (6)$$

Where J represents the discrete wavelet transform, i,j,k represents the frequency information, c represents the transferred input signal Segmentation in RGB vector space results in the development of an approximation of the average color to be segmented as vector a and z as a leading point in the RGB color space, with z being equivalent to an if the difference between them is less than the defined threshold.

$$D_{(z,a)=}\left[(Z_R-a_{R^2})+\left(Z_{G-a_{G^2}}\right)+\left(Z_{B-\,a_{B^2}}\right)\right] = \mathrm{j} \quad (7)$$

D. GMM super pixel algorithm

The GMM super pixel process, is regarded as the type of clustering-dependent segmentation approach that aggregates the pixels in the rectangular windows into the super-pixel depending on the distance measure among the color feature vectors and the spatial vectors at the five-dimensional space. This algorithm in turn illustrates the pixel windows depending on the super-pixel numbers, the user-input L. This in turn limits a clusters number to L and then based on their proximity to the clusters center, the pixels were grouped.

The algorithm of SLIC in turn offers the weight factor for generating the super-pixel equal in size in an approximate manner. Therefore, the super pixels SLIC were not so precise in the image segmentation process along with various regions that were isolated heterogeneously. The GMM super pixels is presented for the enhancement of accuracy in segmentation thereby modelling each super pixel to be the gaussian distribution having unknown parameters. A typical probabilistic at which the samples of data were derived from the finite number mixture of gaussian distribution labeled *l*ϵ *{1,...L},*by unidentified constraints is named a model of Gaussian Mixture. The number of clusters at which the data points are distributed is referred as parameter *L.* It is obligatory to accomplish MLM (Maximum Likelihood Estimates) for determining the fact that the data points were fitted in their respective Gaussians. The prospect that an data point *x* arbitrary fits to a *l* Gaussian, *w*herever N signifies the function of maximum likelihood.

$$\frac{\partial N}{\partial x}\left(\int_0^N pN(x)dz\right)=\partial N(N)(x^{-1})(N))d/dN \quad (8)$$

It is obvious that labels of super pixel were assessed depending on their posterior probability after the unknown parameter's estimation for the cluster *Ɵl* for cluster *l.* The pixels are very precisely grouped inclined over the Gaussian distribution.

III. STUDY OF CLASSIFICATION ALGORITHMS USED

This section offers the study on various classification algorithms employed for the detection of bleeding.

A. K-means clustering

K-means clustering can be used to highlight the bleeding mucosa in [13]. The two planes that illuminate the previously mentioned bleeding areas create a saliency map by assigning different weights. A pixel with a value of higher R than a value lower G, B, would look reddish and have a higher sale value. The second regions that are outstanding are known as areas with strong resemblances to the red colour values. As such, we draw from the three stages below the second stage saliency map. Implementing the fine texture, noise, and coding objects, we use a 5 * 5 Gaussian filter on the original image. The R, G and B colour channel saliency maps are then calculated. The two above saliency maps identify bleeding regions in WCE images from a wide variety of viewpoints. One is from the viewpoint of the clinician.

$$S_{Final=\,u_1}\text{*Saliency map (stage 1)} + u_2\text{*Saliency map (stage 2)} \quad (9)$$

Where S represents the overall saliency, U represents the Color chanels.

B. K-nearest neighbor(KNN)

The common K-nearest neighbour (KNN) supervised classificator is used to draw the distinction from bleeding to non-bleeding photographs after the extraction of consistency attributes. In the K-nearest neighbour classifier, a distance function is estimated among test and train data sets. After that, the distances between neighbouring train data sets are used to classify WCE picture frame test data. The KNN classification gives a class membership after classification to a picture frame. The class label assigned to a test item is determined by the votes of the majority of its nearest neighbours. To classify test data, the proposed approach considers the class labels of K nearest image patterns using the Euclidean distance. Following extensive experimentation with different values of, a satisfactory value of is determined to yield the highest output. [13].

C. VGG-16 based Convolution neural network (CNN)

Following the extraction of features, the bleeding region must be distinguished to decide if the diabetic is in the mild, moderate, or extreme stage[13]. For this classification, a VGG-16-based CNN, which is a well-known algorithm, was used. Probabilities are used to score the goal. It is a pre-trained convolution algorithm. Variations between a single dependent variable and one or more independent variables may be analyzed using VGG-16-based CNN. The CNN uses a function to predict probabilities. The distribution is complete. During this method, CNN will first read and resize the image before beginning the classification process by measuring the likelihood of its class, as seen in figure 3. Most of the deep learning neural networks is the convolution neural network. based on the VGG-16 CNN marks a major development in visual detection and classification. They are most often used to deconstruct visual symbols, but they are also used to characterize and classify images. Layers have been generated using a VGG-16-based CNN.

- Convolutional layers
- a Fully connected layer
- Pooling layers
- ReLU layers

VGG-16-based CNN needs the least amount of pre-processing as compared to other image classification algorithms. This CNN could be used for a number of purposes in a variety of fields.

(i) Convolution
The primary feature of this convolution process is to concentrate highlights from the information frame. The convolution layer is always the first step in VGG-16-based CNN. During this process, the features in the input image were defined, and a feature map was created.

(ii) ReLU layer
The redressed straight unit layer comes after the convolution layer. To maximize the network's non-linearity, the enactment function was applied to the feature maps. In this case, negative values are conveniently omitted.

(iii) Pooling:
The pooling mechanism will eventually reduce the size of the input. Overfitting can be reduced by using the pooling step. By reducing the number of necessary parameters, this will easily figure out the required parameters.

(iv) Flattening
The polled feature map should be flattened into a sequential column of numbers, which is a simple measurement.

(v) Fully connected layer
Here is a description of the features that can be combined with the attributes. This has the ability to complete the classification process with a high accuracy percentile. The error would be measured and propagated backwards mainly.

(vi) SoftMax:
SoftMax is often used in neural networks to map a network's non-normalized output to a probability distribution over expected output groups. The SoftMax has been used in a number of testing fields to solve a variety of problems. Those decimal odds have to be 1.0. Consider the SoftMax variants listed below:
• For each conceivable class, the Complete SoftMax is a SoftMax that can calculate a risk.
• SoftMax calculates the probability of all positive names but only for an arbitrary example of negative names.

D. Linear SVM

The classification procedure can be performed with the linear SVM [15] At first it creates an N-dimensional hyper plane. The non-linear mapping function α is then used to convert original data into a higher dimension. The knowledge from two groups is strangled by a leading border via a hyper plane. The broader the range, the wider classification is better.
Each pattern x has been altered to the parameter y is given in equation (10)

$$y = \phi(x) \qquad (10)$$

Where, ϕ is the s infinite-dimensional mapping. In an augmented y space, a linear discriminate g (y) is given in equation (11)

$$g(y)=\alpha^t y \qquad (11)$$

Where g represents the augmented space, α represents the non linear mapping function.
A separating hyper plane ensures the condition,

$$Z_k g(yk) \geq 1 \qquad (12)$$

Margin is used as an optimistic area from the hyper plane evaluation. The best possible classification is achieved by optimizing the breadth of the margin between two groups.

$$\frac{Z_{kg}(yk)}{\Delta|a|} \geq b \qquad (13)$$

Where a represents the optimized area. b represents the breadth of the marigin.
The goal in training of the Vector Support Machine is to better generalize the classifier that enhances b in the following equation and to find the hyper-plane with the maximum margin that corresponds to the target.

IV. EXPERIMENTAL STUDY

This section is the depiction of experimental comparative study made on various existing techniques.
We compare the results of classification of the proposed classifier with that of comparable bleeding detection schemes in Tables. These metrics are evaluated with the equations from (14)-(16).

Accuracy= TP+TN/(TP+TN+FP+FN) (14)

Specificity= TN/(TN+FP) (15)

Sensitivity= TP/(TP+FN) (16)

Where, TN- True Negative, TP- True Positive, FN- False Negative, FP- False Positive.

A. Experimental study on various Existing feature extraction techniques and classification algorithms employed

The experimental study on existing techniques studied is shown in this section. The table 1 is the performance analysis of color based feature extraction approach and the K-means classification approach. The outcome is estimated in terms accuracy, sensitivity, specificity and time.

Table 1 Performance of Color based feature extraction and K-means approach

Parameters	**Color based feature extraction [11]**
Accuracy	95.75
Sensitivity	92.00
Specificity	96.50
Time (s)	293.43

Table 2 is the performance estimation of histogram based and KNN based approach. The outcome is shown in terms of accuracy, sensitivity, and specificity for varying histogram bins.

Table 2 Performance of the Histogram based approach and KNN

Parameters	**Histogram bin**			
	16 bin	**32 bin**	**64 bin**	**128 bin**
Accuracy	96.82%	97.37%	**97.86%**	97.20%
Sensitivity	90.97%	94.66%	**95.20%**	94.96%
Specificity	97.89%	98.01%	**98.32%**	97.97%

Table 3 Classification results using DWT and VGG 16 CNN

Parameters	**Values**
Accuracy (%)	91.5
Sensitivity (%)	91.4
Precision (%)	91.36
F1 score (%)	91.38
FNR (%)	8.5
Time (s)	78.278

Table 3 is the performance estimation of DWT and VGG 16 based approach. The outcome is shown in terms of accuracy, sensitivity, F1 score, FNR, Time, and specificity for varying histogram bins.

B. Comparative study on Existing and GMM model:

This section shows the comparative analysis of various existing and GMM model outcomes to prove the effectiveness of GMM model.

Table 4 State-of-the-art schemes for the Bleeding detection

Classifier	**Feature selection**	**Bleeding detection method**	**Accuracy**
Proposed [10]	Ratio of Red-Green, Excess Red, Ratio of Red-Blue Chromaticity, Contrast, Entropy, Energy	GMM superpixel+Texture feature+color feature+SVM	99.88
Deeba et al. [15]	Mean (G), Mean (R), Standard Deviation (G) Mean (V), Mean(H), Mean (S), Standard Deviation (S)	Color features+ HSV features+ 3 SVM Classifiers	99.66
Pogorelov et al. [2]	Ratio of Red-Green, Normalized Red, Ratio of Red-Blue, Red channel to green vector amplitude and Chromaticity, blue channels Ratio	Color + Random Tree	93.4
Yuan et al. [12]	histogram features with 80 bin word color	Color histogram+KNN+SVM	98.05
Kundu et al. [13]	64 histogram frequencies from RGB channels	RGB Histogram + KNN	97.86

From the above table, it was evident that the better accuracy will be attained by a smaller feature set by our model. However a similar performance is stated in the effort of Deeba et al. [15], that approaches excerpts features from the spaces of HSV and RGB and in turn employs dual SVM classifiers and wraths their outcomes for classification with 3rd SVM. In Pogorelov et al.[13] work, numerous examines are offered depending on texture features, color features with their groupings established with numerous classifiers. This table in turn comprises the performance statistics attained by this technique having reduced number of features. Likewise, we have taken the finest outcomes from Kundu et al. [2], attained regardless of the bins number. Similarly, Yuan et al.

[13] employs two trained classifiers on an 80 word color feature. This technique seemingly attains improved accuracy of classification with dataset2 which is specified in the table above.

A time of computation is an important system of measurement that depends on the size of feature vector and mathematical operations cost, suggesting the system performance. We presented a computational cost comparison of our technique with that described in the Deeba et al. [15] work in Table 5.

Table 5 Computational Time

Scheme	Classifier	Time of Training	Time of Classification
Proposed	SVM	9.7225e-04 secs /Image	2.6736e-05 secs /Image
Deeba et al. [15] (2018)	C_{rgb}	Not Reported	0.0924 secs /Frame
	C_{hsv}	Not Reported	0.1584 secs /Frame
	C_{fusion}	Not Reported	0.2145 secs /Frame

In [15], the authors have only reported the time of classification intended for the 3 classifications kinds where C_{rgb} andC_{hsv} were SVM classifiers proficient on HSV and RGB features spaces correspondingly. Likewise, C_{fusion} is an SVM classifier that categorizes the frame depending on the C_{rgb} andC_{hsv} outputs. From the projected system, we both continuous and discrete images of WCE were considered. The cost of computation specified in Table 7 is the testing and training average costs. It was evident that these costs were very lower for the proposed scheme.

Table 6 Performance Comparison

Classifier	Accuracy	Specificity	Sensitivity
Proposed	**99.88**	**1**	**99.83**
Deeba et al. [15] (2018)	94.5	95.07	92.32
Kundu et al. [13] (2019)	97.86	95.20	98.32
Pogorelov Et al. [2] (2018)	97.7	95.5	97.6
Yuan et al.[12] (2015)	91.96	98.7	97.15

It is perceived that the projected method displays finest performance metrics on comparing other systems. However, though the same dataset is taken in all the approaches, they differ in the nature of features employed in classification. For a fair comparison, we do a performance analysis with various SVM classifiers constructed with several kernels having a cross validation 10-fold on a test data. This process is accomplished by the App Classifier Learner in Matlab 2017b. The accuracies of classification in Table 6 illustrates that the projected system shows closely best performance corresponding the respite of the classifiers. This outcome is a strong suggestion of the appositeness of the features selected in the proposed system for bleeding detection.

V. CONCLUSION

This paper was an attempt to study the performance assessment of various existing techniques employed in the detection of bleeding image. The performance of the existing system is related with GMM[10] super-pixel based model by showing extensive experimental works, statistical and comparative evaluations. The experimental study along with theoretical study is carried out for existing techniques like color based approach, histogram based scheme, DWT, KNN, VGG 16 and SVM. The comparative analysis shows that the GMM super-pixel based model and linear SVM classifier performs well in the detection of bleeding image on comparing other existing schemes. Thus, the effectiveness of GMM super-pixel model and linear SVM classifier is evident from this performance study.

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