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ORIGINAL ARTICLE

A machine learning approach for colorectal polyp detection, density analysis, and Cancer risk prediction using CVS-LBP-MRF model

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ABSTRACT

Colon cancer ranks as the second leading cause of cancer-related mortality globally, with incidence rates contingent upon the cancer's progression through various stages. The disease typically initiates with the formation of small, benign cellular masses known as polyps. The early identification and removal of these polyps are crucial to prevent their progression into malignant tumors. Colonoscopy serves as a standard medical procedure for polyp detection, enabling clinicians to distinguish polyps based on their morphological characteristics. In this study, we propose a novel approach for automatic polyp analysis utilizing a saliency-based visual technique. Our method employs the CVS-LBP-MRF algorithm, which integrates a biologically inspired visual saliency model with Local Binary Patterns (LBP) features and a Markov Random Field (MRF) framework. This combination aids in the effective extraction of LBP features from sequences of colonoscopy video frames, focusing on the identification of polyp areas. The algorithm calculates the saliency and density of polyp regions, leveraging the strengths of the integrated methodologies to enhance detection accuracy. We validate our approach through extensive testing on a diverse set of colonoscopy videos, demonstrating its efficacy in distinguishing polyps from surrounding tissue. The results indicate that our saliency-based model significantly improves the automatic detection and analysis of polyps, thus bolstering the diagnostic capabilities of colonoscopy. By streamlining the identification process, this method has the potential to facilitate earlier interventions, thereby reducing the incidence of colon cancer progression. Future work will aim to refine the algorithm further, incorporate real-time analysis, and enhance its application in clinical settings, ultimately contributing to better outcomes in colon cancer screening and treatment.

KEY WORDS

Saliency; Local binary pattern; Markovian random field; Colonoscopy videos; Polyp detection

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Introduction

Colon or colorectal cancer begins as non- cancerous clumps of cells called polyps; these polyps do not have any earlier symptoms. It can be only detected through the medical screening procedures. These polyps may lead the patient to the risk stages of cancer. Its symptoms depend upon the age group of the patient, size and location of polyp. Some common symptoms include changes in stool consistency, blood in stool, diarrhea, constipation, changes in bowel habits etc. To prevent colon cancer doctors, recommend regular screening tests to detect and remove polyps. Survival rates of colon cancer depend on the stages of cancer. If the diagnosis is earlier 75% illness can be cured by five years of treatments including surgery, radiation, chemotherapy etc. Colonoscopy or coloscopy is the medical imaging technique used for the examination of the large intestine and helps for identifying the situations like rectal bleeding, gastrointestinal problems and bowel habits etc. Wireless endoscopy images help the clinicians to detect polyps. Polyp contains a mass of abnormal tissues, so that the clinicians detect them by their different characteristics. To model this ability of human eyes in visual analysis saliency-based object detection can be used. Object detection is one of the emerging approaches in the field of visual analysis. Saliency methods are applicable in object detection and attained auspicious results in the case of ordinary images. Saliency is the idiosyncrasy of an object or a pixel to stand them out of its background. This method is focused on the salient region to diminish the computational intricacy by evaluating the contingency of the foreground regions. Saliency methods are useful in many areas like target tracking, boundary detection, video or image compression and behavior detection. Emphasizing the most attractive features of a video will help for video summarization, compression and surveillance. Video object extraction methods will detect and extract significant objects from the videos. Saliency methods play a vital role in the detection of salient objects from the background. A video sequence is divided into a set of frames and saliency methods are applied separately into the individual frames. Then saliency map of each individual frame is merged to generate the final saliency map of a video sequence. Moving objects will acquire more attention than that of stationary objects; this capability makes saliency methods more precise in videos so that contrast-based methods can be applied directly. In the proposed method colonoscopy videos are converted to a set of individual frames, these frames are used for further studies. Due to the lack of availability of larger datasets in the medical field, it makes fully automated polyp detection a difficult task. Many existing methods are available for shape-based polyp detection. Main disadvantages of these methods

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are it may wrongly detect mucosal cells as polyp. Saliency based polyp detection in colonoscopy videos is not available yet. The proposed algorithm utilizes the texture feature of polyps, which helps for segmentation and classification easier. CVS-LBP-MRF algorithm integrates the visual saliency model along with texture information and density estimation of MRF method through depth segmentation method.

Literature Review

Saliency detection methods are classified into different types as follows, biologically inspired algorithms, purely calculation based and hybrid methods. Based on visual attention the methods can be classified as top- down and bottom- up methods. Based on processing areas methods are classified into space domain and frequency domain methods. Gupta et al. [1] explained a comprehensive analysis of the most recent deep learning-based studies on colorectal cancer screening, as polyps can be precursors to cancer and their identification is vital for early treatment. Mei et al. [2] discussed Polyp segmentation is crucial for the early detection and treatment of colorectal cancer (CRC), as it helps clinicians accurately locate and segment poly regions. Tajbakhsh et al. [3] proposed a method that includes shape features and surrounding environmental information to automatically detect polyps in colonoscopy videos. Iwahori et al. [4] utilized edge and color information to create a "likelihood map," and then extracted directional gradient histogram features. Wei et al. and Zhao et al. [5,6] discuss improving the features generated by the encoder part of the network. Yang et al. [7] discusses the significant challenge in this field is the variation between datasets collected from different devices. This means a model trained on data from one hospital's equipment might not perform as well on data from another's. Yao et al. [8] developed an automatic method that combined .several techniques. It started with a knowledge-guided intensity adjustment to normalize the images, followed by fuzzy c-means clustering to group similar pixels, and finally used deformable models to accurately outline the polyp's shape. Lu et al. [9] designed for 3D CT colonography and used a three-stage probabilistic binary classification approach. It integrated both low-level features (like pixel intensity) and mid-level information (like local texture) to segment polyps. Gross et al. [10] focused on edge detection. It used multiscale filtering to enhance primary edges, which are critical for defining the boundaries of a polyp. The algorithm then likely used these enhanced edges to segment the polyp from the surrounding colon wall. Zhao et al. [11] studied how lines of curvature help in polyp detection. In their work they proposed a method for generating and rendering lines on the surface of polyp. To visualize the vector fields streamlines of curvature were used, both implicit and explicit superficial representations show good results. Some areas contain closed streamlines and it is the indication of polyp regions. Local surface geometry is aimed for streamline selection and is utilized for further feature selection. These features are highly correlated with true positive detection of a preprocessing polyp detection method. Konukoglu et al. [12] studied how to use the colon wall evolution algorithm for polyp datasets. The proposed method keeps the other structural features constant and increases the spherical symmetries as much as possible. This process is continued until perfect spherical patches are obtained. CT slices of colon and abdomen are given as input; the first step is to extract the colon wall. In the second step they tried to deform the colon wall in such a way that only spherical symmetry gets affected. The proposed method includes both regularization and enhancement, which improves the efficiency of existing CAD algorithms. Liu et al. [13] discussed saliency detection based on background priors. In this model, a border set is obtained by taking image border super pixels. To obtain true background super pixels, remove super pixels with strong image edges. The above process will reduce the background noises. Then background saliency maps and centered anisotropic Gaussian distribution were calculated. Initial saliency map is computed by merging background saliency maps and anisotropic Gaussian distributions. Hwang et al. [14] studied the elliptical feature of the polyps in colonoscopy videos. It consists of following limitations like fixed size window analysis; accuracy heavily depends upon the training dataset. To eliminate the above limitations, they proposed a new method which concentrates on the shape feature. They generated ellipses on the surface of polyp through continuous region segmentations. To obtain clear object boundaries, the proposed method uses a watershed algorithm. After segmenting the image into several regions, an ellipse fitting method is adopted. In the second stage authors tried to find out the polyp candidate by eliminating the wrongly predicted ellipses. Le and Sugimoto [15] proposed saliency-based object detection using spatiotemporal deep features in video. These deep features are used for utilizing the global and local context over different frames. They introduced a spatiotemporal conditional random field (STCRF) to calculate the saliency from spatiotemporal deep features. Temporal information generated from the STCRF describes the relationships between the nearest regions. STCRF concentrates on the temporal consistent saliency maps, so that the method can provide more accurate detection of salient regions. Fang et al. [16] proposed a method considering the shape and context information of polyps. Here a hybrid context method is used to localize the polyp regions. Colonoscopy images are studied under edge maps, using unique feature extraction methods and classification criteria they eliminate the non- polyp structures from the crude edge maps. Utilized a voting scheme to localize the polyp edges. Yuan et al. [17] investigated a new saliency detection model for videos which is based on feature contrast in the compressed domain. Using discrete cosine transform extracted color, luminance and texture features for unpredicted frames. Motion features are extracted from the video using motion vectors for predicted frames. Unpredicted frames consist of three features and corresponding static saliency map is computed. Finally motion saliency map and static saliency map are combined. Ratheesh et al. [18] proposed a method containing convolutional neural network and an auto- encoder for detection. The proposed convolutional encoder-decoder model is trained using TensorFlow library. Imaug library is used for image augmentation process. Then they trained the model using new colon polyp dataset, estimated the accuracy on selected databases. Results show the algorithm works best and give high accuracy. Yuan et al. [17] developed a novel bottom up and top-down saliency approach. First, they segmented the image into multilevel super pixels, each super pixel contains diverse information. This super pixel is given to a sparse encoder to obtain different features. Sparse encoder is normally used for learn the discriminative features in unsupervised way. Supervised learning methods requires large datasets; it is very difficult produce in medical domain. Bernal et al. [19] Saliency based features will reduce the training steps of machine learning algorithms. After calculating the saliency, the result is given to the new feature learning algorithm, for highlighting the polyp regions.

Methodology

Colonoscopy videos are given as the input. The system converts the videos into a set of frames. Frames are given for

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the pre- processing module. After a set of noise removal operations frames are given for super pixel extraction. These are the group of pixels having similar characteristics. After obtaining super pixels of each image, various meaningful features were extracted. After obtaining diverse information from the images, saliency computations were done. SVM classifier is used for the classification of normal and abnormal images. To depict meaningful salient regions, specular reflections should be removed. After the specular reflection removal, images are represented by a multilevel super pixel method. Then corresponding texture, color, shape and gradient information are collected from each super pixel. Proposed methodology consists of the following six modules as shown in figure 1.

- Preprocessing
- Super pixel Extraction
- Feature Extraction
- Saliency Detection and Segmentation
- Classification
- Polyp Detection and Density Estimation.

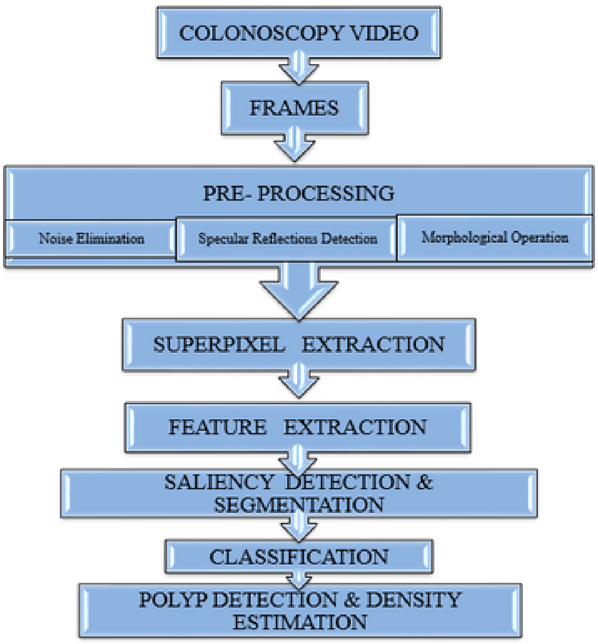

Figure 1. Workflow of proposed method.

Preprocessing module

The main aim of the image preprocessing stage is to remove unwanted noises from the images. Polyp images always contain specular reflected regions. These are bright spots on the surface of each polyp image having high intensity and reflectivity. These highly reflected areas make artificial boundaries during the saliency computations. Preprocessing consists of three steps.

a)Noise Elimination
b)Specular Reactions Detection
c)Morphological Operation
d)Image Inpainting

Noise elimination

In the Noise Elimination stage a set of filters like Median filter, mean filter, Gaussian filter was applied, from the output images Gaussian filter is selected for further use. Gaussian filter is a linear filter, used for blurring the image or reducing the noise. It helps for smoothing, enhancing and detecting the edges of the input image.

Specular reflections detection

This step is usually used to detect and remove candidates of specular reflection. These regions have small saturation and large intensity values. To better characterize this specular reflected region, images are converted from RGB color spaces to HSV and YCbCr color space. If the intensity is larger than a threshold t1 and saturation is less than a particular threshold t2 that pixel is considered as a high confidence pixel.

Morphological operation

Operations like Dilation and erosion are done based on some structuring element. Usually, morphological erosion is performed to remove the unwanted pixels from object boundaries. Dilation is done to add missing pixels in the object boundaries. Output of morphological erosion and dilation is given for area opening. Area open operation removes the undesired object from the background.

Image inpainting

To remove the effect of specular pixels a dynamic search based inpainting algorithm is used. Algorithms search for a particular specular pixel and its 8- neighbors are selected. If more than 6 pixels in the neighboring window contains any information, those values are averaged and assigned to the specular pixel. If the 8 neighboring windows don't provide any information the window is moved in clockwise direction to get enough information.

Super pixel extraction

The proposed system uses a superpixel based method for preserving image information. Simple Linear Iterative Clustering (SLIC) algorithm is used for superpixel extraction. Superpixels are the group of pixels having similar information. Here SLIC algorithm is a color-based segmentation method, it processes the pixels based on color similarity and proximity in the image plane. The algorithm converts the image into a 5-Dimensional plane of LAB color space. L represents the lightness from black to white, green to red and blue to yellow are represented by A and B respectively.

SLIC algorithm works as follows

1. Each pixel in the (x,y) position has a corresponding LAB vector which denotes color and intensity information of that particular pixel.
2. Assuming that each pixel in the image is associated with a nearest cluster center.
3. The new center is calculated by averaging the LABxy vector. For each pixel's LABxy value is used for finding new clusters and then the cluster centers are updated.

Feature extraction

Normally color, texture and shape information are collected for storing various contextual structures. In the proposed system, the feature set contains a combination of color histograms, LM Filter features, LBP features and Multi-Orientation Histogram Gradient (HOG) as features.

Texture feature

It is a primary feature used by clinicians to recognize polyps. It includes LBP features and Filter features. In the case of Local Binary pattern (LBP), or a pixel if the center pixel value is greater than 8 neighboring pixel values then it is assigned with a 0 else it is 1.

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Color feature

Normal polyp images are represented in RGB color format. But the various diverse information can be obtained only through various color spaces. So, the input image is converted into other color spaces and then the information is collected. In the proposed system it uses two different color spaces HSV and YCbCr. Color histograms are used to characterize the color features.

Shape feature

Usually, polyp have elliptical or circular shapes, HOG is used to extract shape features from the colonoscopy images.

Saliency detection and segmentation

To focus the actual area of interest of polyp in colonoscopy images saliency computations should be done. Here, saliency computations are done based on the Contrast Based Saliency Map method. Saliency of each superpixel is calculated as the sum of the feature distances to all other superpixels and which is weighted by their corresponding spatial distances. Contrast based saliency at i^{th} superpixel is defined as

$$S_c^1(y,z) = \frac{\sum_{j=1}^{N} d_f(i,j)}{1+d_{location}(i,j)}$$

$D_{location}$ (i,j) represents the spatial euclidean distance between the center of the superpixel i and center of the superpixel j. N denotes the total number of superpixels in the given colonoscopy image. Where $d_f(i,j)$ calculates the euclidean distances between the feature vectors of superpixel i and j. After getting saliency values of each pixel then linear thresholding is done. If the saliency values of a pixel i is greater than the threshold T then it is assigned with 1 else it is 0. Output of thresholding will give a masked output in which polyp regions are shown by white color. Here Segmentation is done by the MRF algorithm. MRF uses intensity as a parameter for the segmentation process. It actually defines the probability of a pixel having a specified feature. Normally MRF performs initial segmentation through K- Means clustering method. MRF works as follows.

1. Specify the number of clusters say K
2. Randomly select the K data- points and cluster centers.
3. Each data- points is assigned to any of the clusters based on the Euclidean distance's measures.
4. After the assignments of data- points each cluster centers are updated with new values.

MRF performs segmentation in depth- wise so that the input image is being segmented into a set of layers. Based on intensity and texture as parameters MRF finds the probability of each pixel to have a feature, computed probability values are used for K- means clustering. The main assumption is that polyps are highly textured so that the region of polys is more salient. MRF segmentation results in a layer having a polyp region, in which the layer having highest density is taken for further studies.

Classification

SVM (Support Vector Machine) classifier is used for classification procedures. During the feature extraction stage feature vectors are collected from each input image. These features are used for classification tasks. SVM has so many advantages like it needs small no of positive examples compared with the other classifiers. In the proposed method two class classifiers are required, SVM works best in the case of binary classification. Given input, the colonoscopy image is classified into either normal or abnormal. If it is abnormal then it is given to the Density Estimation stage.

Polyp detection and density estimation

Image classified into the abnormal category is taken to the density estimation stage. Input is the layer having the highest density of the polyp region. Highest density is obtained through the total volume of the polyp layer and Gaussian kernel distributions.

Implementation

The proposed system is implemented by the following six stages.

Data set description and implementation details

Describes the dataset and implementation of each stage are explained in this section. For the evaluation of the proposed CVS-LBP-MRF algorithm an open database named CVC Clinic DB is adopted. It contains 1200 colonoscopy images from 6 colonoscopy videos. Another open database KVASIR is also used for evaluation. The dataset contains videos of six patients; each video is converted to 1200 frames for this study. Implementation of the proposed model is discussed below.

Preprocessing

It includes the following steps.

Step 1: The filter is applied using a small matrix called a kernel or convolution matrix. This kernel's values are a 2D Gaussian distribution. Linear Gaussian filter is used for noise reduction as shown in figure 2.

Step 2: Converting from the RGB (Red, Green, Blue) colour space to the HSV (Hue, Saturation, Value) colour space is a multi-step mathematical process. This conversion is often done in computer graphics and image processing because HSV is more intuitive for human colour perception than RGB.

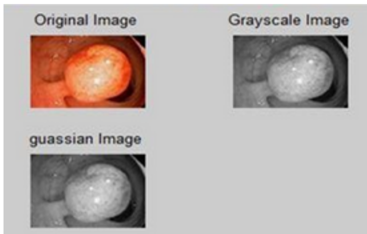

Figure 2. Conversion from RGB to HSV.

Specular reflection detection

Specular reflections are that their colour is determined by the light source, not the object's colour. In a pure white light source, the reflection will appear white. Algorithms can detect secularities by looking for pixels that are very bright and have similar values across all colour channels (e.g., high red, green, and blue values). Images converted from RGB to HSV and YCbCr color spaces as shown in figure 3.

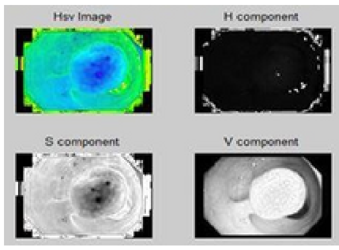

Figure 3. Conversion from RGB to HSV.

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After obtaining HSV images, Specular reflected pixels are shown in figure 4.

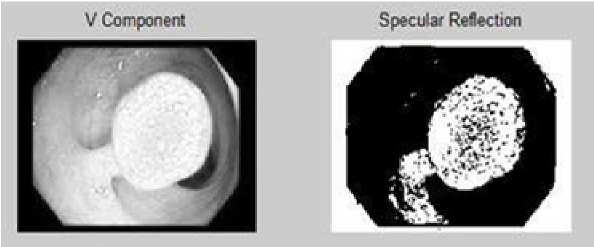

Figure 4. Specular reflection detection.

After obtaining YCbCR images Specular reflection pixels images are shown in figure 5 and figure 6.

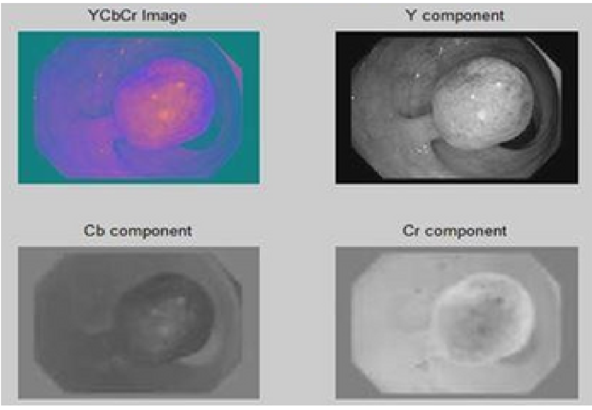

Figure 5. Conversion from RGB to YCbCr.

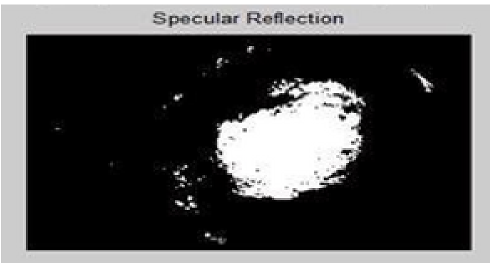

Figure 6. Specular reflection detection.

Morphological operation

These operations are used to modify the shape and size of objects in an image, typically on binary images (black and white). They are essential for tasks like noise reduction, feature extraction, and image segmentation. Operations like image Dilation, erosion and area- open are done as shown in figure 7.

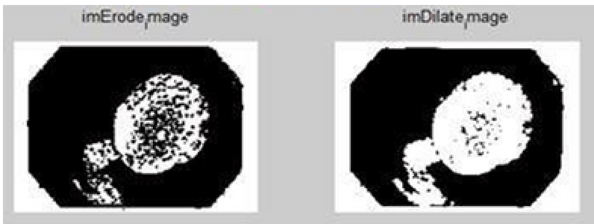

Figure 7. Image after morphological operations.

Image in painting

It's a method of intelligent restoration, not just a simple fill, as it analyses the surrounding area to generate new pixels that blend seamlessly with the original content. This makes the restoration or removal of an object virtually undetectable. Effect of Specular pixels are reduced using image in the painting algorithm as shown in figure 8.

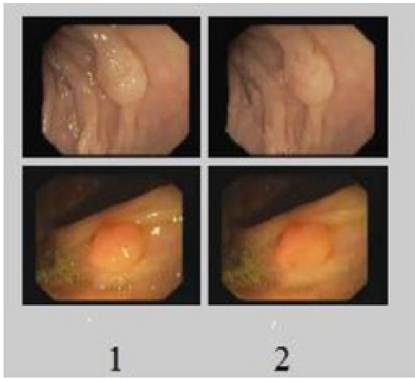

Figure 8. Image Inpainting operations. (1) Before inpainting, (2) After inpainting.

Super pixel extraction

The basic idea is to replace the rigid, grid-like structure of pixels with a more natural, flexible representation. Think of it as a form of image segmentation, but instead of classifying regions, it simplifies the image into a more manageable number of a few hundred or thousand superpixels.

A super pixel is the group of pixels having similar information. SLIC algorithm is utilized to obtain the super pixels as shown in figure 9.

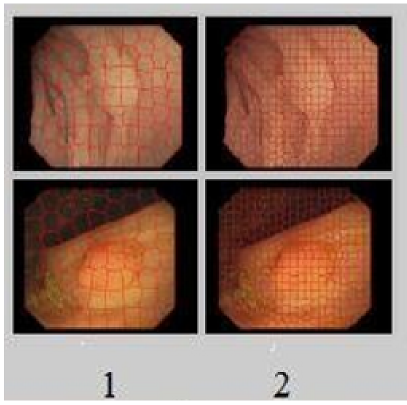

Figure 9. Super pixel extraction. (1) polyp images with 50 super pixels, (2) polyp images with 250 pixels.

Saliency detection and segmentation

Saliency is detected using the Contrast based saliency method. The MRF algorithm is used for the segmentation process as shown in figure 10.

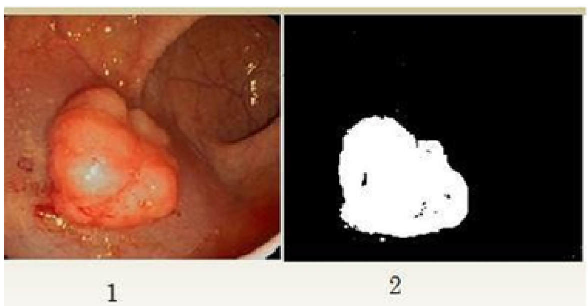

Figure 10. Saliency detection.

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MRF segmentation

The MRF algorithm results in a set of layers, in which the most salient region is more textured and there we get the polyp portions as shown in figure 11,12.

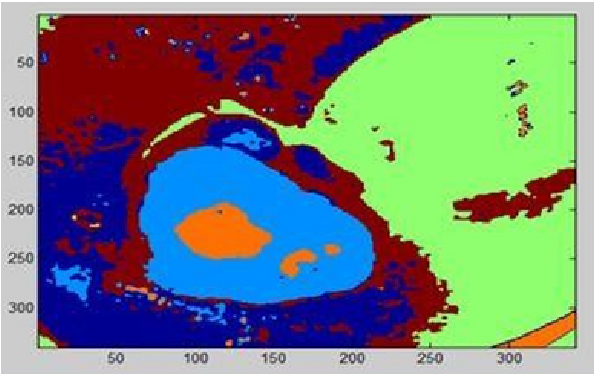

Figure 11. MRF segmentation.

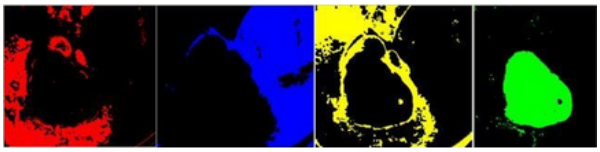

Figure 12. Layers extracted through MRF.

Polyp detection and density estimation

Density estimation using a Gaussian kernel distribution is a non-parametric method. It models a set of data points as a continuous, smooth distribution. In the context of the CVS-LBP-MRF algorithm for polyp detection, this means that for each data point or feature (like the texture of a pixel or a region), a Gaussian (or bell-shaped) curve is placed. The overall density is then estimated by summing up all these individual Gaussian "bumps." The "volume of the polyp detected layer" likely refers to the aggregated probability or density value over a region, which helps the algorithm determine if a given area is part of a polyp. Density is estimated by the help of Gaussian kernel distribution and the volume of polyp detected layer as shown in figure 13 & figure 14.

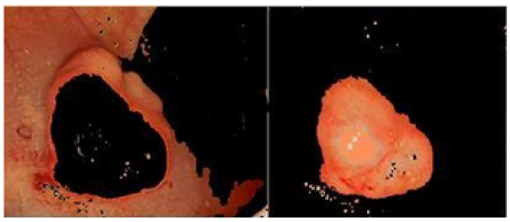

Figure 13. Density estimation.

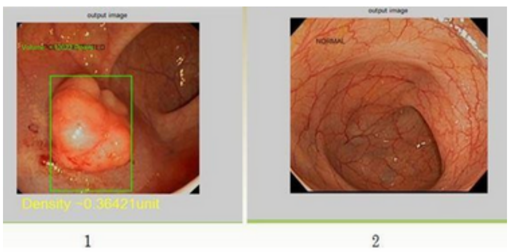

Figure 14. Images after classification and density estimation.

Performance Analysis

To evaluate the performance of a machine learning model like CVS-LBP-MRF, a set of standard performance measures are used to assess its effectiveness. These metrics are crucial because they provide a comprehensive view of how well the model performs beyond a simple "correct or incorrect" answer (Table 1).

Table 1. Evaluation measures are shown below.

Number of frames	True Positive (TP)	True Negative (TN)	False Positive (FP)	False Negative (FN)
200	95	95	3	5

Table 2. Performance measures as shown below.

Accuracy	Precision	Recall	F- Measure
96%	97%	95.09%	96.03%

Performance comparison

The CVS-LBP-MRF method's performance is being evaluated on three different datasets to test its generalizability and robustness. Using multiple datasets is a standard practice in research to ensure a model isn't just effective on the specific data it was trained on.

Table 3. Comparison with other standard datasets as shown below.

Measures	TMC Data	CVC Colon DB	KVASIR
Accuracy	96%	97%	96.3%
Precision	97%	98%	97.4%
Recall	95%	96%	96.3%
F- measure	96%	97%	96%

Comparison of saliency method with ground truth

A saliency method produces a saliency map, which is a grayscale image where the intensity of each pixel represents its likelihood of being a "salient" part of the image. The brighter the pixel, the more likely it is to be part of the salient object as shown in figure 15.

The comparison process involves several steps:

1. Thresholding the Saliency Map: The continuous saliency map is converted into a binary mask by applying a threshold. Pixels with a saliency value above the threshold are classified as a salient object, while those below are classified as the background.
2. Pixel-wise Comparison: The resulting binary mask from the saliency method is then compared, pixel by pixel, to the ground truth mask. This comparison allows researchers to calculate the metrics mentioned earlier:
    - True Positives (TP): Pixels correctly identified as part of the polyp.
    - False Positives (FP): Pixels incorrectly identified as part of the polyp (background).
    - False Negatives (FN): Pixels of the polyp that were missed by the model.
3. Calculating Performance Metrics: These values are then used to compute standard metrics like Precision, Recall, F-measure, and Accuracy, as described previously. High

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precision and recall are both desirable for saliency-based object detection, as they indicate that the model is both accurate in its predictions and comprehensive in its detection.

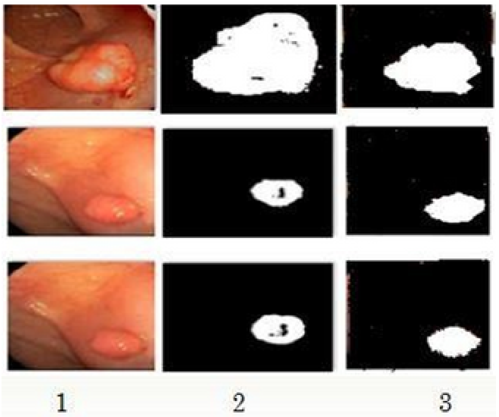

Figure 15. Comparison with ground truth. (1) original image (2) proposed saliency method, (2) ground truth.

Conclusions

Video object extraction methods are used to automatically detect and identify significant objects within colonoscopy videos. These methods are designed to highlight and segment polyps from the surrounding tissue, assisting clinicians in their task. One effective technique for this is saliency-based object detection. Saliency methods identify parts of an image that are visually distinct or prominent, much like the human eye would. By training a model to recognize the features that make a polyp "salient" against the colon's background, this visual ability can be used for automatic polyp analysis. Ultimately, these automated methods aim to improve the accuracy and efficiency of colonoscopies, reducing the risk of missed polyps and helping to prevent colon cancer. Saliency models are inspired by the human brain's ability to quickly and unconsciously identify areas that are different from their surroundings. In a colonoscopy video, a polyp often has different color, texture, shape, or brightness compared to the healthy colon wall, making it a "salient" object. The proposed method introduces a novel saliency based visual ability, which is used for automatic analysis of polyps. The CVS-LBP-MRF algorithm uses a biologically inspired visual saliency model combined with LBP Feature and MRF algorithm for polyp analysis. The proposed algorithm utilizes the texture feature of polyps, which helps for segmentation and classification easier. CVS-LBP-MRF algorithm integrates the visual saliency model along with texture information and density estimation of MRF method through depth segmentation method and this method achieved 96% accuracy.

Disclosure Statement

No potential conflict of interest was reported by the authors.

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