

Automated Lesion Grading and Analysis of Uterine Cervix Images For Cervical Cancer Diagnosis

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Abstract: In order to accurately assess the quality of reconstructed images, it is necessary to employ consistent methods for the extraction of information and the application of metrics. The quantitative analysis of regions in medical images that include a certain tissue can be made possible by partitioning the images into the many types of tissues. The evaluation makes it much simpler to evaluate the capability of an imaging algorithm to reconstruct the properties of a variety of tissue types and find anomalies. To aid in the diagnosis of cervical neoplasia, a magnified visual examination of the uterine cervix using a colposcope, which is a low-power, stereoscopic, binocular field microscope with a bright light source, is performed using a colposcope. Positive screening tests, such as positive cytology and positive visual inspection with acetic acid, are the most typical indicator that a patient should be referred for a colposcopy. This publication outlines a reliable and adaptable method of medical image segmentation that can be used to divide uterine cervix image images into different types of tissue in order to make the process of evaluating uterine cervix images more straightforward. The strategy utilises a combination of statistical methods as well as an adaptive k-means algorithm. When compared to other methods, such as a threshold-based segmentation method, the most significant benefit of utilising the algorithm is that it enables this quantitative analysis to be performed without any prior preparation. In addition to this, it is applicable to circumstances in which there is a lack of data that may be used for supervised learning. In order for the segmentation technique to be successful, it is necessary to be able to differentiate between different types of tissue across a wide range of image qualities. This ability is demonstrated in the second half of the study. Through the process of segmenting pictures into regions of interest according to the different types of tissue, the surface of the cervix is broken up into a number of distinct tissue areas. A colour score-based metric is utilised in order to differentiate between regions that have been retrieved from reconstructed images and ground truth models. The quantitative data provide evidence of the accuracy with which aberrant and normal tissue qualities can be distinguished. 200 standardized colposcopic images are examined as part of our research. The findings of the segmentation are compared and contrasted with the assistance of structural segmentation accuracy, specificity, sensitivity, and positive predictive value. The results of our tests indicate that the approach has an accuracy of 89.35%, a specificity of 84%, a sensitivity of 97.45%, and a precision of 81.25% accordingly. The effectiveness of the method in clinical segmentation has been demonstrated. According to the findings of this study, the use of the K-means algorithm for cervical regional segmentation of colposcopic photos based on HSV colour space has significant clinical value and can assist medical professionals in the detection of cervical cancer.

Keywords- *Specular Reflection (SR), Colposcopy, Segmentation, Automated, K-means, visual inspection with acetic acid (VIA)*

1. Introduction

The human cervix is covered by a very thin layer of tissues that are made up of cells. When a normal cell undergoes the transformation into a cancerous cell, which is characterised by the ability to divide and grow rapidly into a tumour, we call this condition cervical cancer. Treatment options are available for this type of cancer if it is detected at an earlier stage. The diagnosis is often determined by the use of a screening method in addition to a biopsy. Image processing methods might be utilised in order to ascertain whether or not the cancer has metastasized. Cancer of the cervix, often known as cervical cancer, ranks as the fourth most common cause of death in women connected to cancer [1]. One of the main causes of cancer-related fatalities among women in India, cervical cancer continues to be a major public

health concern.

Cervical cancer is more prevalent in rural locations, where access to healthcare and knowledge of preventative measures may be more constrained. The most prevalent malignancies in Indian women is cervical cancer. The Indian Council of Medical Research (ICMR) estimates that there are roughly 60,078 cervical cancer fatalities and 96,922 new cases of the illness each year in India.

Among Indian women, a significant portion of deaths are brought on by cervical cancer. This disease claimed the lives of about 67,477 women in 2020. The analysis of cancerous cells involves both medical image processing and intelligent systems. New approaches are developed, and as a result, they are less expensive and time-consuming. The tissue in the lower portion of the uterus, known as the cervix, is affected by this malignancy. It begins with aberrant cell changes in the cervical tissue and spreads throughout, eventually developing into cancer [2]. Colposcopy is a clinical test that examines the cervix

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visually to look for malignant and pre-cancerous cells [3]. A 3% to 5% solution of acetic acid is rubbed onto the cervix area during the colposcopic examination. Acetowhite epithelium is the term for the tissue that first seems to be anatomically normal but turns white when exposed to acetic acid. To gauge the severity of tissue lesions, medical professionals analyze the colour density of the acetowhite zones. They examine the changes in colour with a colposcope, record some interesting photographs, explain their findings, and, if necessary, offer a biopsy to confirm the diagnosis. During the course of the inspection, there is a possibility that there will be many specular reflections. This can result in a different diagnosis being determined during the colposcopic examination, and it can also significantly reduce the accuracy of the methods utilised for analysing colposcopic pictures, such as image registration and texture analysis. In fact, there is active research being done in a

number of medical imaging domains on the problem of reducing specular reflections.

The colposcopy image is a coloured representation of the RGB model that contains essential clinical characteristics such as the columnar epithelium (CE), the squamous epithelium (SE), and the transition zone (TZ) between the squamous epithelium and the columnar epithelium (CC). Here is where the vast majority of cervical cancers are diagnosed [14]. The initial image obtained from a colposcopy featured an imaging mode that was a little bit difficult. In the initial colposcopic image, which is shown in Figure 1, it is possible to make out both the medical instrument and the cervical region, which is denoted by the area denoted by the black curves. The primary area of study for medical diagnoses is the cervical region. Additionally, it has regions with intense light interference brought on by cervical mucus and Acetowhite Epithelium Original (AW).

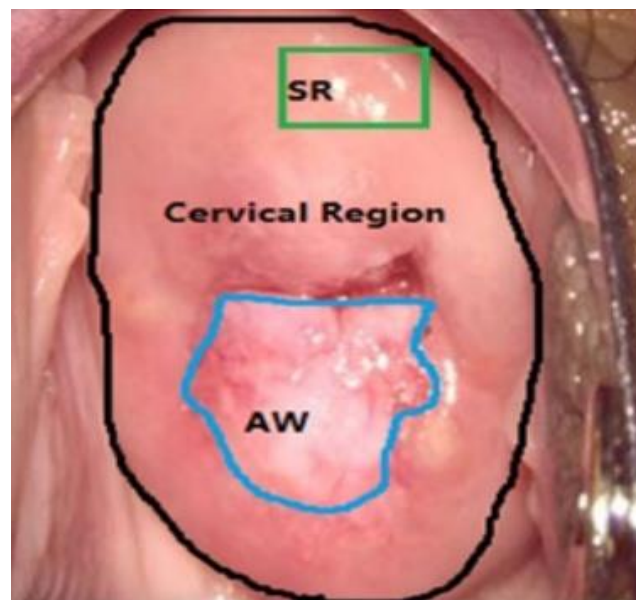


Fig 1. Tissue types of interest marked on a cervigram and Manual segmentation based on SR, cervical region, and AW of the original colposcopic images by human experts.

Specular reflections are identified by Oh et al. [4] by the establishment of two classifications of regions: regions with extremely light, which are referred to as absolutely bright regions, and regions with moderately bright, which are referred to as comparably bright regions. Both regions combined are regarded as a single set of specular reflections. Arnold and others [5] describe a segmentation technique for specular reflection that is based on non linear filtering and colour picture thresholding. This technique can be used to divide an image into its component parts. During thoracoscopy, it is recommended by Saint-Pierre et al. [6] to make use of a non-linear filter in order to increase the contrast between specular and non-specular reflections. They localise the specular bump in the very last image in the image histogram, which enables them to calculate a threshold for extracting specular reflections from the image.

There are a variety of approaches that have been proposed in relation to colposcopic images; however, Lange [7] recommends utilising the green (G) channel of the RGB colour space to locate areas that are saturated. These regions are retrieved with the use of an adaptive threshold by finding the last image in the histogram that corresponds to the green channel and utilising that image as a starting point.

The method that was presented by Zimmerman et al. [8] is founded on the Intensity and Saturation channels that are found in the representation of the HIS colour space. This technique takes advantage of the fact that the intensity channel value is high in specular reflections, whilst the saturation channel value is low. As a result, it is much simpler to differentiate between regions that reflect light

and those that do not. This technique makes use of two Gaussian distributions and four Gaussian distributions, which are respectively utilised to describe specular and non-specular reflections, in order to characterise specular reflections using Gaussian mixture models. Because it typically assumes knowledge of the number of Gaussian distributions, this method is inconvenient because the number of Gaussian distributions is unknown in many cases.

Hervet et al. present a two-stage semi-automatic segmentation method in their paper [9]: the first step segments images by quantifying colour information, and the second step segments images spatially by using a region-growing algorithm. Both steps are semi-automatic. Then, in order to get rid of specular reflections, a histogram transform is applied to manually chosen frames (frames consist highlight and normal tissue). This process is also known as histogram equalisation. On the other hand, this strategy has a fault, which is that the results of colour segmentation are usually influenced by highlights, which makes them less accurate. The Dichromatic Reflection Model is used in the technique that is described in reference [10]. Utilising this method allows one to take full advantage of the chromatic qualities that highlight areas possess. The implementation of this paradigm is supported by colposcopic images having homogenous zones, uniform colours, and a light texture. These characteristics lend support to the paradigm. In addition, the suggested approach does not call for any threshold manipulation to be performed. By acting in this manner, the estimation of the optimal threshold value, which is generally a difficult problem to solve, can be circumvented. Both the method

that was offered to extract specular reflections and the method that was detailed to remove specular reflections using inpainting are provided and discussed in [10].

2. Detection of Specular Reflection

A. RGB and CIE colorspace

The CIE-XYZ color space's ability to separately describe colour and brightness justifies this decision to choose the colorspace along with RGB colorspace. The following transformation is used to derive the chromaticity coordinates x and y from the CIE-XYZ representation.

$$x = X / (X + Y + Z) \dots (1)$$

$$y = Y / (X + Y + Z) \dots (2)$$

B. Extracting specular reflections

We search for pixels whose luminance component is higher than their chromatic luminance in order to retrieve specular reflections. We provide an approach based on three basic phases to accomplish this objective. Enhancing the specular reflections is the first stage. The image is changed from CIE-RGB to CIE-XYZ representation space in the second stage, and then equation (2) is used to calculate the chromatic luminance y from the CIE-XYZ representation. Finally, pixels with chromatic luminance less than their luminance (Y) are selected. The full method [11] as it was implemented was described.

- Reflection enhancement

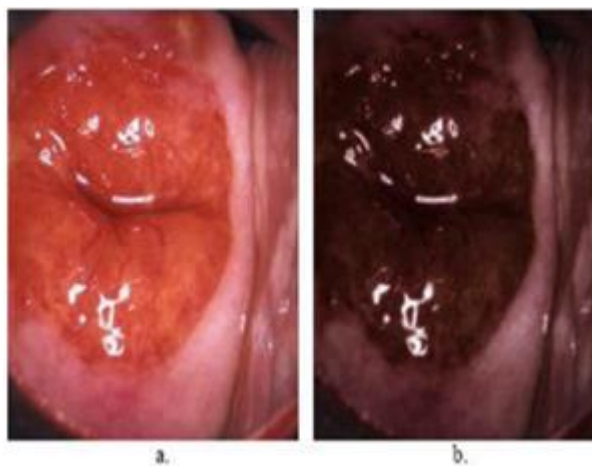


Fig 2. a) Input Coploscopic Image **b)** Enhanced Image

Fig 2. b) Shows an example of the effect of applying this filter and LHS is filtered image.

Since there is no distinction between the appearance of pale-colored tissues and specular light reflections, colposcopic images are difficult to analyse. The image is subjected to a nonlinear filter in the manner described below to amplify this difference:

$$\begin{pmatrix} R' \\ G' \\ B' \end{pmatrix} = \frac{\min(R, G, B)}{\max(R, G, B)} \begin{pmatrix} R \\ G \\ B \end{pmatrix} \dots (3)$$

- Computing luminance and chromatic luminance

By first calculating the colour image's luminance, we may get the brightness value. The conversion of CIE-RGB to CIE-XYZ yielded this brightness. Y is defined as follows in CIE-XYZ space:

$$Y = 0.2126 \times R + 0.7152 \times G + 0.0722 \times B \dots (4)$$

Then, we evaluate each pixel's brightness and chrominance. Therefore, using the RGB normalised data, we determine the chromatic luminance as follows:

$$y = 0.2126 \times r + 0.7152 \times g + 0.0722 \times b \dots (5)$$

r, b, and g are the normalized values determined from RGB space.

- **Extracting Mask of specularities**

The final phase involves comparing luminance and chromatic luminance. Pixels that adhere to the inequality Y_y (chromatic luminance is less than luminance) are considered as specular reflection-related points. An example of a mask depicting specular reflection that was created using this automatic detection approach can be seen in Figure 4.

3. Methodology of Proposed Research Work

Figure 4 illustrates the process through which the research is carried out. It demonstrates the numerous procedures that are performed in order to diagnose cervical cancer. The proposed approach takes a colposcopic image as its starting point. The National Cancer Institute in the United States is the source for the accurate data. Colposcopy is a medical technique that involves inspecting the cervix, vagina, and vulva with a specialised device called a colposcope. This operation is performed on female patients. In most cases, this procedure is carried out when the findings of a Pap smear come back abnormal or when there are obvious abnormalities seen on the cervix. During a colposcopy, a healthcare provider will magnify and illuminate the cervix using a device called a colposcope. This will allow for a closer evaluation of any abnormal areas that may be present. In addition to this, a solution may be applied to the cervix in order to highlight any aberrant cells. In the event that any questionable spots are found, a biopsy might be performed so that additional investigation can be conducted. A colposcopy is a technique that is typically carried out in the office of a physician and takes only a short amount of time and is not overly complicated. Patients tolerate it well in general, however a few could report some moderate discomfort or cramping as a side effect. The findings of a colposcopy can assist in deciding whether additional treatment or monitoring is required for any abnormalities that were found during the procedure.

Colposcopic images are photographs or visual representations of the cervix, vagina, and vulva taken during a colposcopy procedure. These images are captured using a colposcope, which is a specialized instrument that

provides magnification and illumination for a closer examination of the tissues. Colposcopic images can show various features and abnormalities, such as abnormal blood vessels, areas of abnormal cell growth, inflammation, or lesions. These images are used by healthcare providers to assess the health of the cervix and to identify any potential abnormalities or signs of disease. The images can be helpful in guiding the healthcare provider's decision-making process.

Normalization in color image processing refers to the process of adjusting the color values of an image to a standard range or scale. This is done to enhance the visual appearance of the image and to ensure consistency in color representation across different images. Normalization typically involves mapping the color values of an image from their original range to a new range, such as scaling the values from 0 to 255. This can be done using various techniques, such as linear scaling or histogram equalization. The purpose of normalization is to improve the contrast and visibility of the image by spreading out the color values across the entire range. It can also help in comparing and analyzing images, as normalized images have consistent color representations. Normalization is commonly used in various applications of color image processing, including image enhancement, image analysis, and computer vision tasks.

In colposcopic images, specular reflection refers to the phenomenon where light is reflected directly off a smooth or shiny surface, such as the surface of a liquid or a highly reflective object. This reflection can cause bright, intense spots or highlights in the image, which can interfere with the visualization and analysis of the underlying tissue [8]. Specular reflection in colposcopic images can occur when the colposcope's light source is directed at an angle towards the tissue surface. The reflected light can create glare or bright spots that obscure the details of the tissue, making it difficult to accurately assess the presence of abnormal cells or lesions. To minimize the impact of specular reflection in colposcopic images, various techniques can be employed. These include adjusting the angle and position of the colposcope to minimize the direct reflection of light, using polarized light to reduce glare, and employing image processing algorithms to enhance the visibility of the underlying tissue by reducing the intensity of specular reflections. By reducing the impact of specular reflection, colposcopic images can provide clearer and more accurate information for the diagnosis and management of cervical abnormalities. In color image processing, a gradient refers to the change in color intensity or color values across an image. It is calculated by taking the derivative of the color values with respect to the spatial coordinates (x and y) of the image. The spatial gradient can be calculated separately for each color channel (e.g., red, green, and blue)

or for a combined grayscale. Gradient represents the overall strength or magnitude of the color change in an image.

In unsupervised machine learning, K-means and Gaussian mixtures both play an important role, as stated by et al. [24]. They provide obvious and natural techniques to clustering, on top of the fact that they are easy to put into practise. In most cases, they are incorporated into the software package of any substantial machine learning programme. When applied to the group of test photos, the K-means algorithm produced results that were comparable to those produced by the multi-modal thresholds algorithm. GMM is used in situations where K-means is unsuccessful. Because K-means is capable of performing well enough on the majority of photos, we only apply GMM in situations in which K-means is unable to determine good boundaries. In order to launch the GMM model for the same amount of mixtures, we make use of all of the cluster centres that were calculated using K-means.

The k-means clustering initializes, K cluster centers randomly or using a predefined method. Assign each pixel to the cluster with the closest mean color value. Once the algorithm converges, each pixel in the image will be assigned to one of the K clusters. This allows for the segmentation of the image into K distinct regions based on color similarity. K-means clustering is a simple and efficient algorithm for color image segmentation. Various extensions and improvements, such as fuzzy K-means and spectral clustering, have been proposed to address these limitations and enhance the accuracy of color image segmentation.

According to the findings and presentation of [25], the robustness of the watermark system is improved by using the k means technique with ROI detection and DFT-based feature extraction. In addition to this, ROI detection produces a feature matrix that is associated with the image. The use of sophisticated signal processing to the image does not affect these characteristics in any way. In addition, K-means clustering is utilised in the process of picture segmentation in order to recognise regions of interest (ROI) and visual patterns for the purpose of locating areas within an image that include significant infrastructures [25].

This paper outlines a reliable and adaptable method of medical image segmentation that can be used to divide uterine cervix image pictures into different types of tissue in order to make the process of evaluating uterine cervix image more straightforward. This strategy utilises a type of unsupervised machine learning in conjunction with statistical methodology. When compared to alternative methods, such as a threshold-based segmentation method, the primary benefit of utilising the algorithm is that it enables this quantitative analysis to be performed without the need for any prior assumptions to be made, such as the

knowledge of the expected dielectric property values that are characteristic of each tissue type. In addition to this, it is applicable to circumstances in which there is a lack of data that may be used for supervised learning.

Cervical cancer grading is a process used to assess the aggressiveness or severity of the cancer cells in a cervical biopsy or surgical specimen. The grading system commonly used for cervical cancer is called the "Bethesda System" or the "Cervical Intraepithelial Neoplasia (CIN) System. "The grading of cervical cancer is based on the appearance of the cells under a microscope and the extent of abnormal cell growth. The grading system categorizes cervical cancer into different stages, ranging from low-grade to high-grade, based on the degree of abnormality and the potential for progression.

Here are the different grades of cervical cancer:

Cervical Intraepithelial Neoplasia (CIN)

CIN 1: This is considered a low-grade lesion. It indicates mild dysplasia or abnormal cell growth, affecting only the lower third of the cervical epithelium.

CIN 2: This is an intermediate-grade lesion. It indicates moderate dysplasia, affecting the lower two-thirds of the cervical epithelium.

CIN 3: This is a high-grade lesion. It indicates severe dysplasia or carcinoma in situ, where the abnormal cells cover the full thickness of the cervical epithelium but have not invaded deeper tissues. Invasive Squamous Cell Carcinoma: This is the most severe grade of cervical cancer. It indicates that the abnormal cells have invaded beyond the cervical epithelium and spread into the surrounding tissues. The grading of cervical cancer helps in determining the appropriate treatment options and prognosis. Low-grade lesions (CIN 1 and CIN 2) may be monitored or treated with procedures like loop electrosurgical excision procedure (LEEP) or cryotherapy. High-grade lesions (CIN 3) and invasive squamous cell carcinoma usually require more aggressive treatments, such as surgery, radiation therapy, and chemotherapy. It's important to note that the grading of cervical cancer is just one aspect of the overall staging and classification of the disease. The staging system takes into account the size of the tumor, lymph node involvement, and the presence of distant metastasis to determine the extent of the cancer and guide treatment decisions.

4. Automated Segmentation of Colposcopic images

The system block diagram is shown in Figure3 which explains the different steps involved in the segmentation and classification of colposcopic image. After detection and removing the Specular Reflection(SR) from the input image to carry out segmentation of cervix tissue, the luminance surface and luminance histogram of the colposcopy picture are first computed. Initially, SR level is

decided by the gradient value analyzed by et al [8] which is greater than 0.15 as shown in Figure 4. Each colposcopic image has a specular reflection area that is brighter than grey scale 220, based on the value of the overlap from the luminance histograms on the several colposcopic images. The threshold for minimising specular reflection is finally decided to be between 220 and 255, per the doctors' (cervical experts') advice.

The threshold value, which has been set, is used to identify the specular reflection component of the original colposcopy picture, as shown in the upper portion of Figure1. The average luminance value of the region around the highlight portion is then selected for luminance replacement. Finally, this portion receives the saturation (S) patch, which is applied using the neighborhood's average saturation.

The segmentation of the cervical region was done using an image that had the SR removed from it. The cervical region is segmented using the V component in the colposcopic image of the HSV colour mode [26]. The colposcopic picture's cervix region takes up the entire center of the image, therefore the V component's similarity allows for segmenting the cervix region within a specific distance of the image's center.

The cervical area segmentation method's flow is shown in crystal clear detail in Figure 4. The luminance component (Y) of the colposcopic image is the primary focus of the preprocessing phase of this method, which is also covered in more detail later in this paper. In this research work, RGB to Y CbCr color conversion is used.

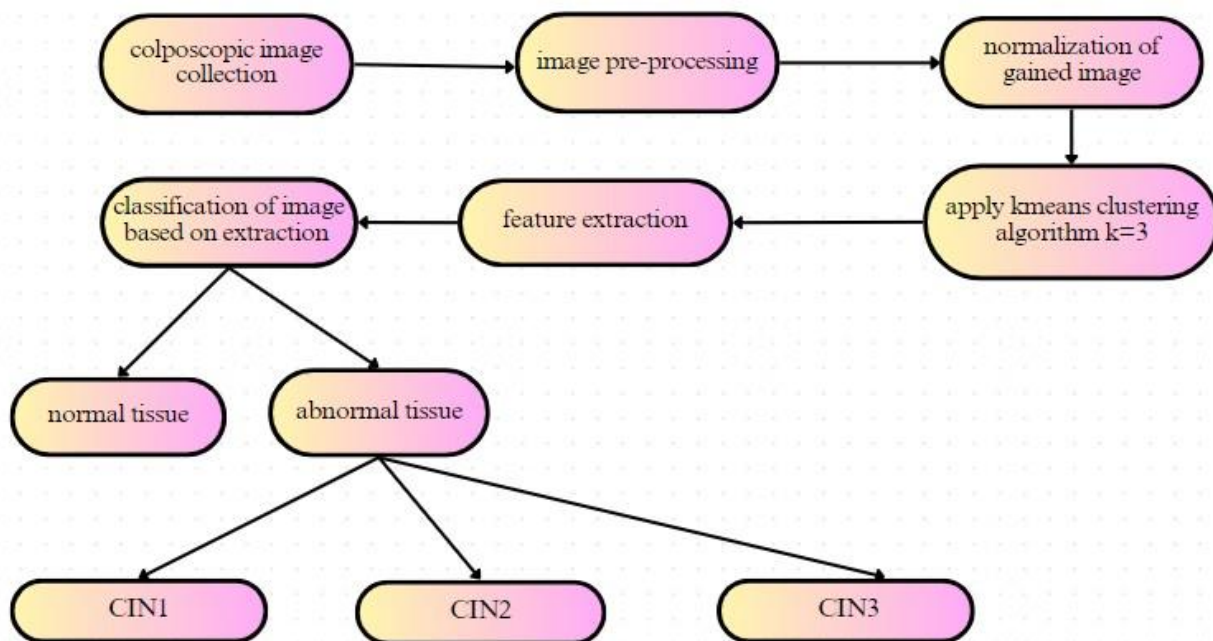


Fig 3. Segmentation of Colposcopic image in to normal and abnormal tissue- region of interest (ROI)

The K-means segmentation algorithm based on various color space conversion is implemented and demonstrated in [26], [27], and [28]. For the segmentation of cervical cancer images, k-means clustering is proposed by Das A et al [28] which uses RGB to LAB color space conversion. The displacement of the segmentation effect of the OSTU cervical segmentation algorithm proposed by Traversi. et al [26] which uses the thresholding method. For the segmentation of cervical cancer images, k-means clustering

proposed by et al [28] uses RGB to HSV color space conversion. After the appropriate conversion the next step is to do the analysis for k=3 as evaluated by et al [29]. The higher the *Acc*, *Spe*, and *Sen*; the better the segmentation effect. The segmentation accuracy of the algorithm presented in [26], [27], and [28] and other performance parameters are compared in Table 2. The specificity of each algorithm is close to 80%, and the sensitivity of our algorithm is 96.45%.

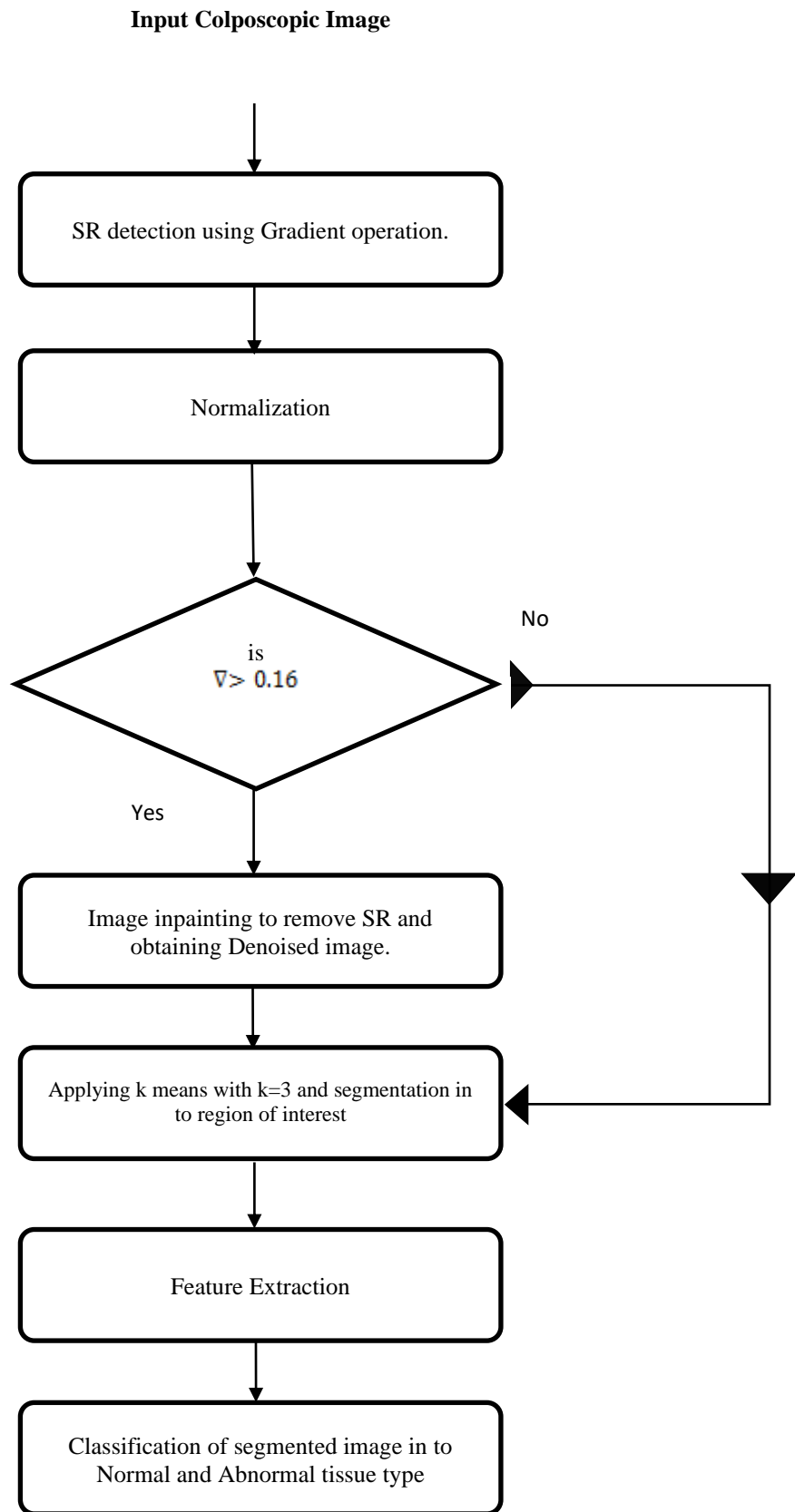


Fig 4. Flowchart of automated cervix cancer lesion grading in uterine cervix images

Specular Reflection Detection and Removal: -

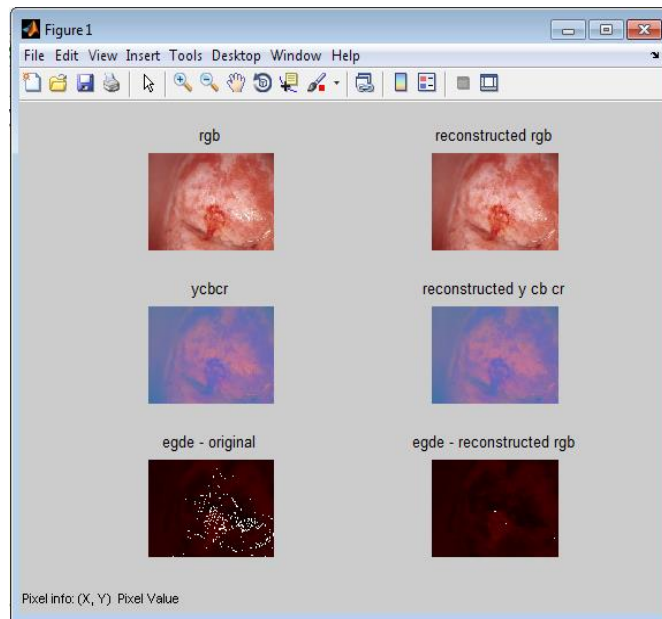


Fig 5. Gradient before and after (white spots)

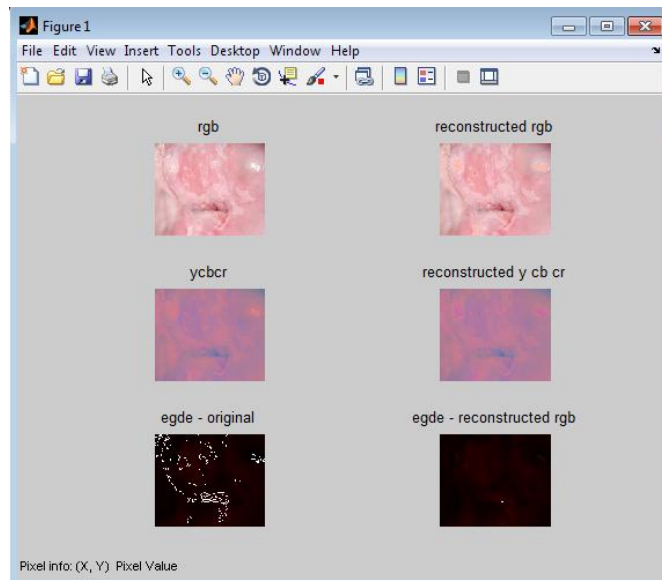
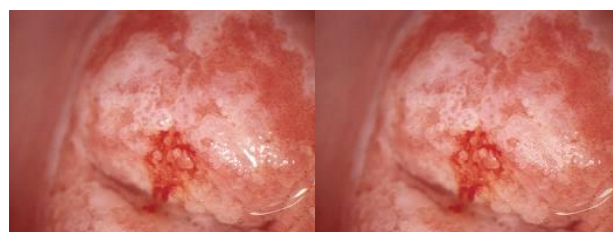


Fig 6. Gradient before and after (white spots)

Comparison of the Resultant Images: -



(a)

(b)

Fig 7. (a) Colposcopic image with reflection

(b) Denoised colposcopic image



(a)

(b)

Fig 8. (a) Colposcopic image with reflection

(b) Denoised colposcopic image

Finding Region of Interest: -

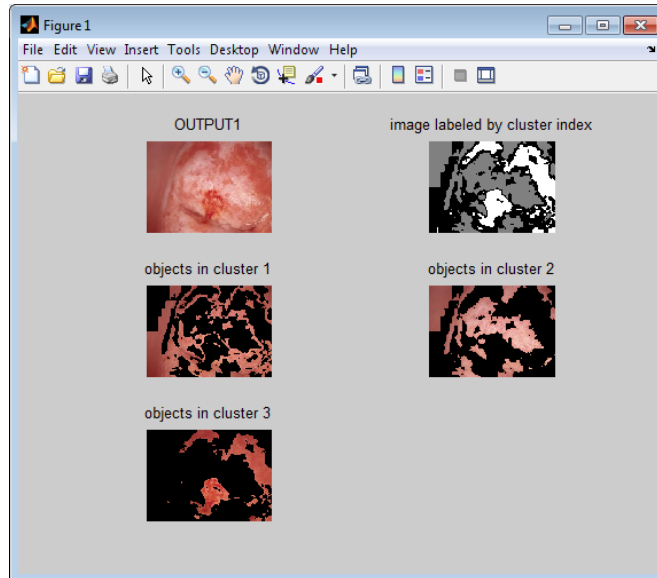


Fig 9. Segmentation of colposcopic image into region of interest (3 clusters)

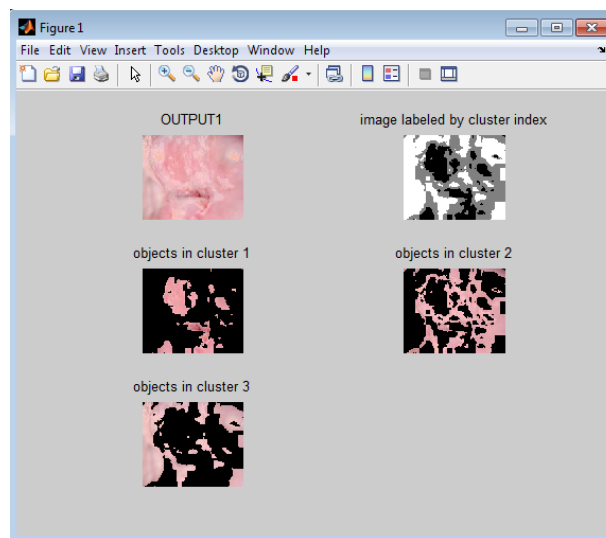


Fig 10. Segmentation of colposcopic image into region of interest (3 clusters)

The purpose of segmentation of the cervical region is to divide the pixels of the colposcopy image into two ROI points and background points as shown in Figure 3. In order to judge the segmentation result, a reasonable evaluation index must be introduced. Comparing cervical region segmentation results with expert annotation results,

the final pixels are divided in to the following four categories:

- (1) true positive (*TP*), which means the correct segmentation of the cervical region.

(2) false positives (*FP*), indicate the point of excision of the cervical defect.

(3) true negative (*TN*), indicates the correct background point.

(4) false negative (*FN*), the wrong background point.

The qualitative and quantitative results of the segmentation accuracy of each test image are presented in Table 1. The findings that were discovered and presented amongst others etc.

On the basis of the aforementioned four pixel categorization categories, it is possible to derive an estimate of the model's accuracy (*Acc*), specificity (*Spe*),

sensitivity (*Sen*), and positive predictive value (*PPV*). In addition to this, we make use of them as a key signal for assessing the effectiveness of the segmentation approach. *ACC* indicates that the pixel with the correct pixel size occupies all of the pixels, *Spe* indicates the ratio of the correct cervix region to the overall ROI region, and *Sen* refers to the ratio of the correct background point to the total background point. The *PPV* suggests that there is a chance that the segmentation point does not contain the background point in its scope. The results of the computation are represented using equations.(6, 7, 8, 9).

$$Acc = \frac{TP + TN}{TP + FN} \times 100 \% \quad \dots (6)$$

$$Sen = \frac{TP}{TP + FN} \times 100 \% \quad \dots (7)$$

$$Spe = \frac{TN}{TN + FP} \times 100 \% \quad \dots (8)$$

$$Precision = \frac{TP}{TP + FP} \times 100 \% \quad \dots (9)$$

Table 1. Accuracy of the cervix region extraction compared with the manual segmentation results.

Performance index standard	Maximum (%)	Minimum (%)	Median (%)	Mean (%)
Acc	87.38	87.15	87.22	89.35
Spe	98.07	53.43	90.20	84.00
Sen	99.10	82.14	97.35	97.45
Precision	99.10	80.10	81.75	81.25

Table 2. Results of four comparison algorithms

Contrast algorithm	Acc (%)	Spe (%)	Sen (%)	Precision (%)
K-means et al [27]	87.25	81.99	96.70	80.21
K-means LAB et al [28]	83.45	80.19	90.03	82.45
OTSU et al [26]	82.42	77.83	89.02	78.89
Our Method	89.35	84.00	97.45	81.25

The selection of a texture region is the very first thing that must be done in order to locate the acetowhite zones. After that, acetowhite zones are extracted with the help of colour and texture data combined together. The detection and classification of multi-level acetowhite zones according to colour ratings is what ultimately determines the severity of the disease. The figure illustrates the particulars. The

sensitivity and specificity of the acetowhite epithelium are what exhibit the hit or miss rate, as stated by the professional annotation of the acetowhite epithelium. The acetowhite epithelium is the only diagnostic feature that can be seen in a VIA and is an important feature that can be seen in colposcopy.

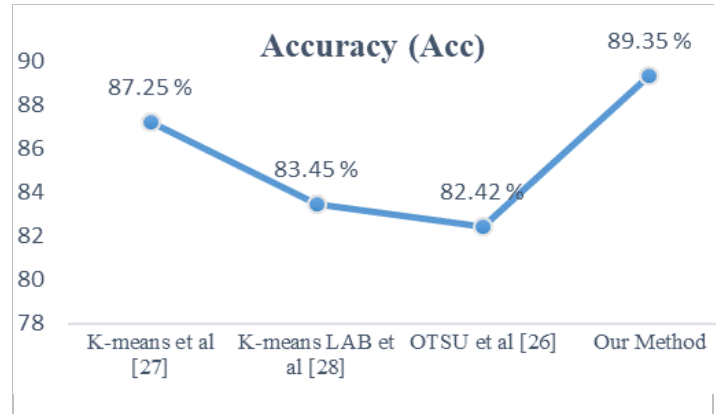


Figure 11a. Comparison of Accuracy (Acc)

Figure 11a. The accuracy of comparing various quality measures using both current and suggested techniques is shown in Figure 11a as a result.

The accuracy (*Acc*) of K-means et al [27] is 87.25 %, K-means LAB et al [28] is 83.45 %, OTSU et al [26] is 82.42 % & **Our Method Accuracy is 89.35 %.**

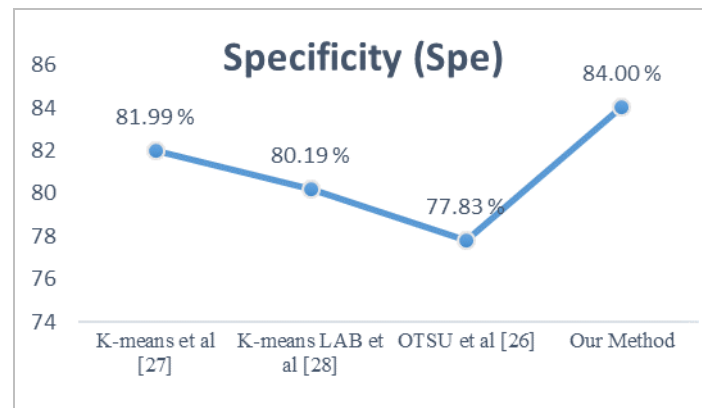


Fig 11b. Comparison of Specificity (Spe)

Figure 11b. The specificity of comparing various quality measures using both current and suggested techniques is shown in Figure 11b as a result.

The specificity (*Spe*) of K-means et al [27] is 81.99 %, K-means LAB et al [28] is 80.19 %, OTSU et al [26] is 77.83 % & **Our Method specificity is 84.00 %.**

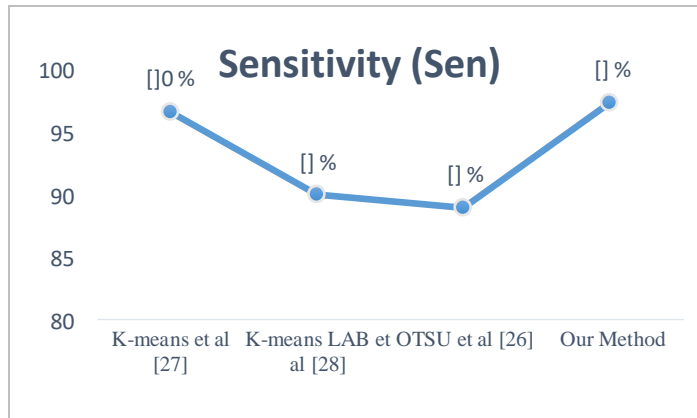


Fig 11c. Comparison of Sensitivity (Sen)

Figure 11c. The specificity of comparing various quality measures using both current and suggested techniques is shown in Figure 11c as a result.

The sensitivity (*Sen*) of K-means et al [27] is 96.70 %, K-means LAB et al [28] is 90.03 %, OTSU et al [26] is 89.02 % & **Our Method sensitivity is 97.45 %**.

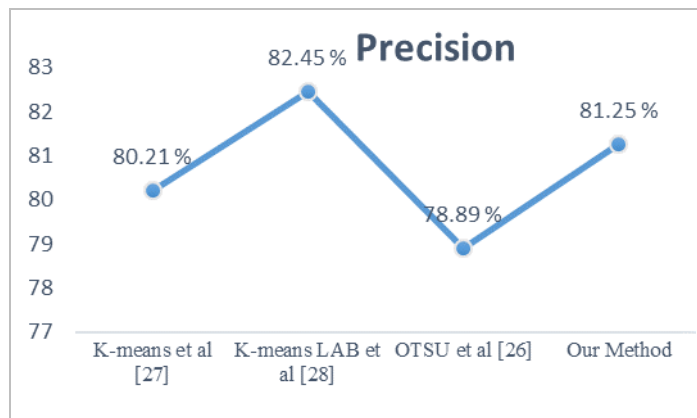


Fig 11d. Comparison of Precision

Figure 11d. The specificity of comparing various quality measures using both current and suggested techniques is shown in Figure 11d as a result.

The Precision of K-means et al [27] is 80.21 %, K-means LAB et al [28] is 82.45 %, OTSU et al [26] is 78.89 % & **Our Method precision is 81.25 %**.

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Also thankful to the National cancer institute USA for providing colposcopic image data of patients. All the ethical guidelines have been followed.

5. Conclusion

In this work, the specular reflections typically exhibit great brightness and little color saturation. The specular reflection area is filled with an image texture and color that match the patch in order to get rid of these specular reflections. The RGB color mode of the image is changed to the Y CB CR color space. Following that, the highlight

area is identified using the brightness threshold, and the pixel brightness value is modified. After that, the colposcopy image's luminance histogram and luminance surfaces calculated for better analysis and understanding. Each colposcopic image's specular reflection area has a threshold gradient greater than 0.16 and has a brightness greater than 220 GRAY scale. The surface of the cervix is divided into several tissue areas through the segmentation of images into regions of interest according to different tissue types. Regions recovered from reconstructed images and ground truth models are distinguished using a color score-based measure. The quantitative findings demonstrate the precision with which abnormal and normal tissue properties are detected. It is also shown how the segmentation is incorporated into the framework to produce a framework that efficiently provides the quantitative assessment of regions that contain cervical cancer-affected tissue.

The effectiveness of the system can be evaluated by quantitative performance analysis. An overall sensitivity, specificity, and accuracy of 97.45%, 84.00%, and 89.35%

respectively, have been reported for the 200 human data samples.

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