

A Portable System for Screening of Cervical Cancer

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Abstract: Cervical cancer is one of the most common cancers that affect women, with the highest incidence and mortality rates occurring in low- and middle-income countries. Early detection is crucial for successful treatment, but the need for expensive equipment, trained colposcopists, and clinical infrastructure has made it difficult to eradicate this disease. To address such limitations, we propose the development of a portable, low-cost colposcope that is easy to use, which uses image processing techniques to automate lesion detection and provides a quantitative measure to evaluate progression of the disease or to measure treatment efficacy. Through this paper, we present the development of a system that encompasses the above, and preliminary results show that we can achieve a low-cost bioinformatics-based screening for early detection of cervical cancer in a clinical setting.

1 INTRODUCTION

Cervical cancer is a preventable and curable disease. Despite this, it is the fourth most common cancer amongst women worldwide, with an estimated 604,000 new cases and 342,000 deaths reported in 2020 ((WHO), 2022). It has been reported that around 90% of these cases occurred in low- and middle-income countries (Sung et al., 2021), where there is limited access to healthcare, and it is difficult to carry out screening and treatment for this disease.

Approximately 95% of cases of cervical cancer are caused by the human papillomavirus (HPV) (Franco et al., 2001). Prevention of this disease can be made through vaccination against HPV, as well as screening methods to identify cervical dysplasia (abnormal cells on the cervical tissue) prior to the development of cervical cancer. The golden standard for cervical screening is Visual Inspection with Acetic Acid (VIA) during the colposcopic exam, also known as a colposcopy (Sankaranarayanan et al., 2003).

A colposcopy requires a speculum to hold the vaginal walls open and a light source to illuminate the surface of the cervix during the examination. The colposcope is then used to visually examine the cervix and surrounding tissues. The cervix is first rinsed with saline solution and then stained with 3-5% acetic acid. Acetic acid causes abnormal proteins in the epithelium to coagulate and appear white and

opaque when inspected under light. These abnormal cells on the surface of the cervix are termed as cervical intraepithelial neoplasia (CIN) and are usually caused by certain types of HPV. While CIN is not cancer, it may become cancer and spread to adjacent normal tissue. The density of acetowhitening (AW) indicates the grade of the precancerous cells (Li & Poirson, 2006). CIN can be easily treated, and full recovery is possible if it is detected early. Depending on the severity, a diagnosis of CIN1, CIN2, or CIN3 is given, where a mild case is likely to heal on its own, and moderate to severe cases require immediate treatment (Castle et al., 2007). However, even for an expert in the field, it is difficult to diagnose and investigate the presence of such lesions unless a biopsy is performed (Kudva & Prasad, 2018). Other contributing factors to the high mortality rate in low- and middle-income countries include lack of adequate medical facilities, high power requirements for existing colposcopes, social stigma around women's healthcare, and the need for multiple visits to medical clinics, which may be inaccessible, unpleasant, and time-consuming for some women ((WHO), 2022). Therefore, there is a need for a tool with screening capabilities that is easy to use and reliable in communities that lack the necessary resources.

Automated detection of CIN has been made possible by several studies conducted to obtain images of the cervix. Archived digitized cervical

images from screening, taken with a fixed-focus camera, were used to develop a method based on deep learning algorithm for automated visual evaluation of cervical images (Hu et al., 2019). This dataset was obtained during a study of HPV and cervical cancer in Costa Rica (Bratti et al., 2004). Li and coresearchers (Li et al., 2021) collected a large dataset consisting of colposcopic images collected from 8,604 patients, which include pathological information and annotations from expert physicians. Finally, the Atlas of Colposcopy (Basu & Sankaranarayanan, 2017) was developed by the International Agency for Research on Cancer (IARC) with the intention to provide a freely accessible learning tool for researchers and medical personnel.

Challenges to the automated detection of CIN include low quality of the devices used at times, which impair the image resolution; lighting conditions, which can make shadows appear, hindering the ability to find the cervical region of interest (ROI); distortion of the images due to the presence of glare or specular reflections (SR) from the light source; and the appearance of artifacts such as the speculum and surrounding tissue.

Efforts to overcome these challenges include classification of cervical dysplasia using machine learning methods based on image pre-processing and feature extraction (Asiedu et al., 2019; Bai et al., 2019; Fernandes et al., 2018). Other researchers have focused on image pre-processing techniques to detect and remove SR from the cervical epithelium (Das & Choudhury, 2017; Lange, 2005; Meslouhi et al., 2011). While these research teams have achieved promising results in the field, there is still a need for complete systems that can rely on effective techniques for cervical image analysis while in low-resource settings.

In this paper we describe a portable colposcope and its use in automated detection of CIN. We present details about our ongoing pilot study for data collection and validation of our image analysis algorithms. Furthermore, we use a technique that can help remove specular reflections prior to identifying the presence of lesions and determining their size in relation to the cervical ROI. Images from the Atlas of Colposcopy are used to demonstrate the removal of SR. The steps in detecting and classifying lesions on the surface of the cervix are presented in the next section, and the results are discussed in section 3.

2 EQUIPMENT AND METHODS

2.1 System Overview

In this paper, we propose a low-cost and portable tool for screening and detecting abnormal changes in the cervix. The Cervitude Imaging System (CIS) (Patent Appl. 63/121,432, 2020) consists of a digital microscope used in conjunction with a speculum during the colposcopic exam and a desktop application to analyze the captured images. The digital microscope is capable of 50 to 1000X magnification and provides illumination to the cervix via an embedded LED ring. The microscope is placed at the opening of the speculum, outside the patient's body, using the setup shown in Figure 1. It is then powered on and used to capture digital images of the cervix. The images are then processed using the proprietary CIS algorithm to detect the presence, size, and extent of lesions on the cervix.



Figure 1: CIS Digital Microscope with Speculum.

The CIS desktop application, developed in MATLAB, is built around an image analysis algorithm that can quickly detect and locate lesions on the surface of the cervix as images are collected. Figure 2 shows our framework for image acquisition and analysis. After capturing images of the cervix with our probe, the images are transferred via Bluetooth to a laptop where the desktop application is running. The CIS application pre-processes the image in three stages: removal of specular reflections; segmentation of the cervical region of interest; and segmentation of acetowhite (AW) lesions.

Upon completing the image pre-processing steps, classification to determine different severities of CIN will be performed. In this paper, we cover the steps involved in the removal of SR. Identification of ROI can be found in (Cepeda-Andrade & Commuri, 2022).

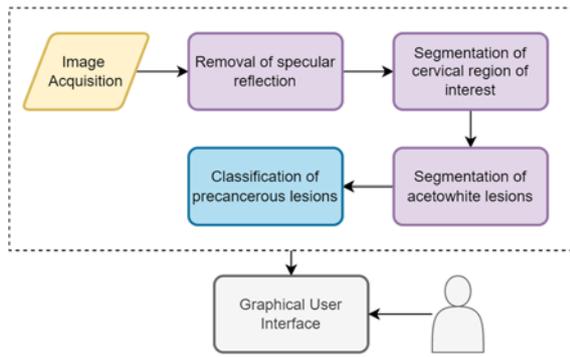


Figure 2: Steps for Lesion Detection and Classification.

2.2 Pilot Study

We obtained approval from the Institutional Review Board (IRB number 1629150-4) from the University of Nevada, Reno to conduct a pilot study to acquire cervical images with CIS. This small-scale study, consisting of 30 participants, is ongoing, and we expect to finalize our image acquisition step in the upcoming weeks.

The study is directed towards adult female participants aged between 21 and 65 years old that have been identified with having abnormal cervical screening, and where follow-up evaluation is recommended. Informed consent is required from all patients participating in this study. The process of consent is as follows: upon checking in for their appointment, a member of the research team hands the patient an information form explaining the details of the research and any preliminary questions the patient might have about the study will be answered by the principal investigator. If the patient is interested in participating in the study, she will go through the consent form with the physician who will be performing her colposcopy.

Following our protocol, standard procedure for colposcopy is followed, that is, the speculum is placed, the cervix visualized, the CIS probe is then placed in a clean protective sleeve and inserted into the speculum and an image is captured using the CIS image capturing system and colposcope. Next, 5% acetic acid (AA) solution is applied to the cervix and the cervix will be evaluated by the standard colposcope. The findings are documented by the standard colposcope and the CIS system. Directed biopsy and ECC (endocervical curettage) is obtained as indicated utilizing the standard colposcope.

To protect the privacy of research participants, once the initial organization of data is completed, the name of the participant will be replaced by her initials and a five-digit identification number. In addition to collecting images of the cervix, we also use the CIS

desktop application to collect demographic information and relevant health information as directed by the participating physicians. A registration form (shown in Figure 3) is filled out for every new patient. There are also options to attach the camera and capture images or video, as well as an option to quickly analyze and save these images. All data except for identifying information is collected through this application and is then encrypted and stored in a secure server.

2.3 Removal of Specular Reflections (SR)

As mentioned earlier, abnormal cells present in the epithelium of the cervix become opaque when treated with acetic acid. The reflected light from the opaque epithelium gives it a white color, indicating the presence of a precancerous lesion.

Specular reflections are observed when light from the colposcope is reflected from the cervical epithelium or from the speculum. SR on the cervical images will also appear white, but with high brightness and low saturation values. This could cause a problem in which reflections of light on the tissue could be misconstrued as AW lesions, producing incorrect diagnostic results. Therefore, it is necessary to identify and remove SR areas without affecting the acetowhite regions in the image.

We approach the removal of specular reflections through exemplar-based image inpainting (Criminisi et al., 2004; Le Meur et al., 2013). It is important to maintain the structure and texture of the surrounding epithelial tissue or AW lesion, and this method has been shown to take into account these factors to properly restore images (Shroff & Bombaywala, 2019).

The method to achieve this begins with identifying the target regions, Ω , to be removed and inpainted. Given a patch, Ψ_p , centered on a boundary pixel, \mathbf{p} , in the target region, its priority can be computed as:

$$P(\mathbf{p}) = C(\mathbf{p})D(\mathbf{p}) \quad (1)$$

where $C(\mathbf{p})$ is a confidence term that measures the amount of reliable information surrounding the pixel \mathbf{p} and $D(\mathbf{p})$ is a data term that reflects the presence of contour information. These are defined as:

$$C(\mathbf{p}) = \frac{\sum_{\mathbf{q} \in \Psi_p \cap \Omega} C(\mathbf{q})}{|\Psi_p|} \quad (2)$$

$$D(\mathbf{p}) = \frac{|\nabla I_{\mathbf{p}}^{\perp} \cdot \mathbf{n}_{\mathbf{p}}|}{\alpha} \quad (3)$$

where $|\Psi_{\mathbf{p}}|$ is the area of $\Psi_{\mathbf{p}}$, α is a normalization factor ($\alpha = 255$ for an image of type uint8), $\nabla I_{\mathbf{p}}^{\perp}$ shows the direction of curves of constant light intensity on a surface (isophotes), and $\mathbf{n}_{\mathbf{p}}$ is a unit vector orthogonal to the point \mathbf{p} . The priority term is calculated for every border patch, with different patches for each pixel on the boundary of the target region.

Next, data is extracted from the source region, Φ , which is computed by subtracting the target region from the input image. Image texture is propagated by directly sampling the source region until a patch, centered around a point \mathbf{q} , most similar to $\Psi_{\mathbf{p}}$ is found:

$$\Psi_{\mathbf{q}} = \arg \min d(\Psi_{\mathbf{p}}, \Psi_{\mathbf{q}}) \quad (4)$$

where the distance between the two patches is calculated through the sum of squared differences (SSD). Finally, after finding the exemplar $\Psi_{\mathbf{q}}$, the pixel values are copied into the target patch and the confidence values are updated.

A summary of the described algorithm for removal of specular reflections is given below:

1. Identify target regions, Ω , from the input image, to be removed and inpainted.
2. Create a binary mask where the nonzero values are the pixels that correspond to the target regions.

3. Identify the source region, Φ , which corresponds to the input image minus the target region.
4. For every patch of size Ψ centered on a boundary pixel in the target region, compute the patch priority.
5. Find the patch with the maximum priority. This patch constitutes the target patch to be inpainted.
6. Given the target patch, search for the best-matching patch in the source region by using the sum of square difference (SSD).
7. Copy image data from the best-matching patch to the target patch.
8. Update the input image, binary mask, and patch priority.

Steps 4–8 are then repeated until all target regions have been inpainted. We applied this algorithm to regions identified as specular reflections in our dataset, and the results are shown in section 3.

2.4 Segmentation of the Cervical Region

We presented the steps to achieve segmentation of the cervical region in detail in (Cepeda-Andrade & Commuri, 2022). We follow a five-step approach to the analysis of cervigrams and detection of precancerous lesions on the cervix, summarized as follows:

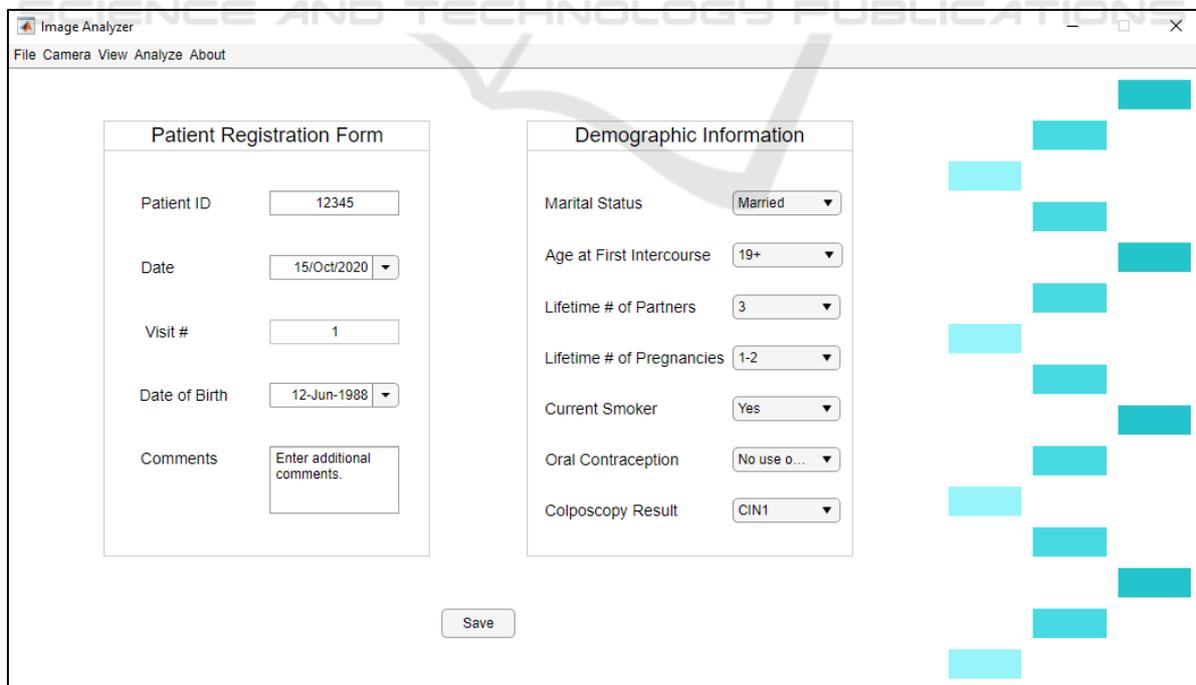


Figure 3: Example of the CIS desktop application.

1. Convert the cervical image from sRGB to LAB color space and combine the information from the L* and a* channels.
2. Use the k-means algorithm (Luo et al., 2003; Tariq & Burney, 2014) to obtain clusters, segment the image, and identify the cervical ROI.
3. Implement morphological filters (Burger & Burge, 2016) to eliminate holes and connect similar regions.
4. Automatically crop the segmented and filtered image to maximize the ROI.
5. Identify AW lesions and calculate their area in proportion to the cervix.

2.5 Annotation Tool

Through the pilot study, we seek to assess the Cervitude Imaging System’s functionality and ease of use at each step of colposcopy exam compared to a standard colposcope while observing the patient’s comfort level throughout the evaluation. The quality of screening information and accuracy of detection will also be evaluated.

For this purpose, we have developed our own image annotation tool. The participating physicians have agreed to help with annotating the images that we collect. They can select between segmenting the cervical ROI, lesions on the cervical epithelium, or specular reflections. Their input is extremely valuable to our ongoing research, as we will pursue quantitative, rather than qualitative, assessments regarding the performance of our segmentation and lesion detection algorithms. Their input also helps us as we increase the size of our dataset through further clinical studies. A large data set is necessary to increase the accuracy of automated detection through machine learning techniques.

Figure shows an example of the information that can be collected from cervigrams. The segmented regions are saved as binary masks and masked images to facilitate further analysis by the research team.

3 RESULTS AND DISCUSSION

3.1 Removal of Specular Reflections

We implemented the algorithm described in section 2.3 on the Atlas of Colposcopy dataset. A sample of results is presented in Figure 4.

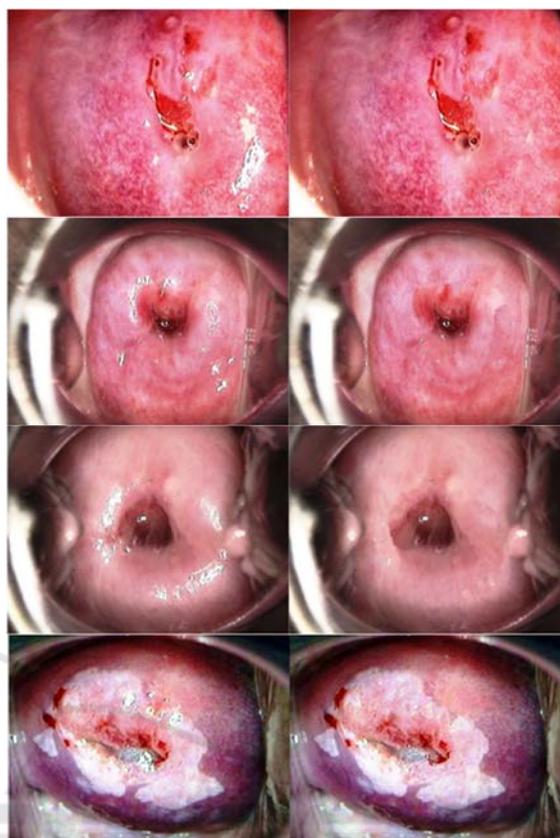


Figure 4: Left: Original image. Right: Results of SR removal.

In the first three rows of the above figure, we show images that do not present signs of precancerous lesions. Without the removal of SR, these images would likely be classified as containing abnormalities, prompting the medical provider conducting the examination to perform a biopsy in the “white” areas for further analysis. The post-processed images present a more accurate state of the epithelial tissue, which reduces the possibility of a misdiagnosis of misclassification by an automated system.

The algorithm also works when SR is present on top of a lesion, as seen on the bottom row of Figure 4. The reflection of light is no longer obstructing the details on the lesion, while the texture and structure matches the surrounding area. This enables the medical provider to more easily understand where the acetowhitening is occurring and decide what the best treatment option is.

A limitation to this algorithm is that it will not work properly if the target regions are relatively large.



Figure 5: Segmentation options through our annotation tool. From left to right: cervical ROI, AW lesions, and SR.

As seen on the third row of Figure 5, the texture remaining after removing the SR does not blend very smoothly with the surrounding tissue. This may affect analysis in situations where it is crucial to examine morphological characteristics such as tissue shape, mosaics, and punctuation vessels, which are also used for determining a diagnosis. Further work is being conducted to improve the observed results.

3.2 Segmentation of the Cervical Region

Figure 6 shows the region of interest (ROI) segmentation results on the Atlas of Colposcopy dataset. The first column shows the original RGB colposcopy image. The second column displays the resulting binary mask outline after our segmentation algorithm. The third column represents the segmented colposcopic image without implementing the SR removal algorithm. We add a fourth column displaying segmentation results after removing SR.

To evaluate the performance of the SR removal algorithm when automatically segmenting the cervical region, we compare the area of the ROI when removing SR and when SR are not removed. Table 1 shows the area of the cervical ROI of the images presented in Figure 6 when performing our segmentation algorithm for each of these cases.

By removing areas with specular reflections, the area of the ROI becomes smaller. A visual assessment also indicates that in most cases, the accuracy of ROI segmentation increased after removing SR. Two clear examples of this are in rows 2 and 4 of Figure. When minimizing sources of error, such as reflection of light on the speculum and cervix, as well as surrounding tissue, it is possible to increase the accuracy of detection of abnormalities that may lead to cervical cancer.

This is a promising step towards automation of AW segmentation and classification of precancerous lesions.



Figure 6: ROI Segmentation Results. Left to right: Original image; binary mask; segmented image; segmented image after SR removal.

Table 1: ROI Segmentation Results.

Row (Figure)	ROI area with SR (%)	ROI area without SR (%)
1	51.89	50.38
2	58.82	49.88
3	64.02	57.37
4	53.32	42.28
5	71.17	64.42
6	50.60	49.28

4 CONCLUSIONS

In this paper, we propose a portable, low-cost, reliable system for automatic detection of precancerous lesions on the cervix. We described our ongoing pilot study, where we seek to assess the functionality and reliability of the Cervitude Imaging System (CIS) and validate our image analysis algorithms. By developing an application where physicians can collect relevant information about their patients, as well as storing images from each visit within the same location, we facilitate the process around screening for cervical cancer.

We used a technique that helps remove specular reflections as the first step in our image pre-processing procedure. Through this algorithm, we can remove specular reflections around and within areas in the cervix that show precancerous lesions. It is an important step, given that it is important to not only detect signs of abnormal cells in the cervix, but also to reduce misdiagnosis and unnecessary biopsies. Removing specular reflections also improves the results of segmentation of the cervical region of interest. Therefore, our image pre-processing method further decreases the chances of incorrect diagnosis and treatment.

Future work includes implementing our methods to images that we collect through our pilot study. Extensive analysis to increase the accuracy of CIS will be performed to our images as we increase the size of our dataset. We believe that our low-cost bioinformatics-based tool addresses the challenges to cervical cancer screening in areas where there is limited access to technology and trained specialists.

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