

ORIGINAL ARTICLE

Color Contrast Enhancement On Cervical Cell Images

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ABSTRACT

Introduction: Cervical cancer, commonly detected via the Pap Smear test, involves identifying precancerous changes in cervical cell nuclei and cytoplasm. Manual image analysis is time-consuming as well as error-prone due to subtle textural and colour differences. This study compares several colour contrast enhancement methods, evaluates their effectiveness, and develops a Graphical User Interface (GUI) for easier use. **Materials and Methods:** The study investigates the visual and numerical effect of Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Contrast Stretching (CS), as well as Image Adjustment on the Herlev dataset. The evaluation employs metrics, for example, Mean Absolute Error (MAE), Peak Signal-to-Noise Ratio (PSNR), and Mean Squared Error (MSE). Furthermore, visual assessments are conducted to compare the contrast quality between the processed images. Matlab App is utilized to develop a GUI with a Pick button, allowing for individual image analysis. **Results:** The findings indicate that CLAHE consistently achieves the highest average PSNR and the lowest MAE and MSE scores across all cervical cell classes, outperforming other contrast enhancement techniques. Visual assessments further corroborate that images processed with CLAHE exhibit superior contrast, effective noise removal and detail preservation. **Conclusion:** These results collectively demonstrate that CLAHE is the most effective method for colour contrast enhancement of single-cell Pap Smear images.

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INTRODUCTION

In Malaysia, 1913 new cases of cervical cancer were diagnosed, resulting in 1018 female deaths in 2022, based on the latest figures provided by Global Cancer Observatory (1). This makes cervical cancer rank as the third most common cancer that affects women. According to managing director Dr. Murallitharan Munisamy of the National Cancer Society Malaysia (NCSM), the elevated mortality rate is attributed to the late detection of cervical cancer cases, resulting in diminished survival prospects (2). The death rate for cervical cancer in Malaysia was historically two times greater than the death rates observed in the Netherlands, the United Kingdom, and Finland (3). The most common

way to detect cervical cancer is to employ the Pap Smear screening test. Furthermore, the problem with screening tests is that it usually takes time to determine the result, which is around 8 to 10 weeks. Furthermore, the number of experts in this field is low, making it more problematic (4). Using image processing, the image of the cell can be operated, and the result can be obtained in a brief period. Even when the image quality is bad, the image processing method can optimize the quality of the images to detect the precancerous cell and obtain a more accurate result.

Several research studies on techniques for adjusting colour and contrast have been conducted. Image enhancement is crucial to image processing, given that it increases important information while removing unnecessary information from an image (5). During the last several decades, there has been an emphasis on improving image appearance through contrast and luminosity adjustments (6–12). A number of cutting-

edge approaches have been studied recently. Bilal Bataineh, for instance, suggested a unique method for correcting colour images using the benefits with regard to non-linear function concerning grey transformation as well as Histogram Equalization (HE) techniques (13). A cervical cell image segmentation Gaussian Mixture Model (GMM) was examined by Ragothaman et al. (14). The GMM is employed to delineate cellular regions while concurrently assessing the limitations of pre-existing methodologies. The overall approach integrates nucleus-based strategies to enhance the precision and quality of nucleus segmentation. Karishma Rao introduced using the Just Noticeable Distortion (JND) model and multiple layers of Contrast Limited Adaptive Histogram Equalization (CLAHE), a compelling image enhancement method to improve the contrast as well as luminosity with regard to colour retinal fundus images (15). Saroj proposed a new technique for this purpose that combines Multi-scale Switching Morphological Operator (MSMO), Principal Component Analysis (PCA), as well as CLAHE methods in a novel sequence (16). Based on a fuzzy approach, Mousania et al. proposed a new composition of CLAHE as well as brightness-preserving dynamic fuzzy HE methods having appropriate weights regarding the histogram situation (17). Similarly, Trisha et al. (18) suggested an alternative approach for enhancing dark images in low-light conditions, utilizing a Convolutional Neural Network (CNN) with a Dual Attention Unit (DAU) and Selective Kernel Feature Synthesis (SKFS), which integrates with the Retinex theory-based model.

To conclude, medical image diagnosis remains a highly challenging task in the field of image processing as well as analysis, primarily due to the presence of noise, shadows, random backgrounds, overlapping objects, including illumination issues. Sensitivity and accurate diagnostic information are crucial in assisting doctors and pathologists in evaluating a patient's condition. Note that the poor sensitivity related to the smear test has become a significant concern. This research applied several contrast enhancement methods on cervical cell images to find the best image enhancement methods. Therefore, this study is relevant in preparing an improved dataset for cervical cancer diagnosis.

MATERIALS AND METHODS

This study was conducted in four main stages: image acquisition, contrast enhancement, GUI development, and performance evaluation as shown in Figure 1. Initially, cervical cell images were obtained from the Herlev Pap Smear Database, which includes both normal

and abnormal classes. These images were then processed using five contrast enhancement techniques; Contrast Stretching (CS), Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Image Adjustment, and Multi-Scale Retinex (MSR) to improve image clarity. Subsequently, a Graphical User Interface (GUI) was developed in MATLAB App Designer

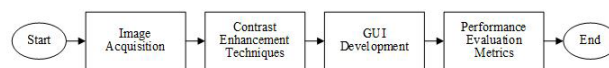


Figure 1: Flow Diagram of Study. The overall process begins with image acquisition from the Herlev Pap Smear Database, followed by the application of five contrast enhancement techniques: Contrast Stretching (CS), Histogram Equalization (HE), Contrast Limited Adaptive Histogram Equalization (CLAHE), Image Adjustment, and Multi-Scale Retinex (MSR). Next, a Graphical User Interface (GUI) was developed using MATLAB App Designer to enable interactive image processing. Finally, the performance of each enhancement technique was evaluated using three quantitative metrics: Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Mean Absolute Error (MAE), providing both visual and numerical assessments of image quality.

to provide an interactive platform for applying these enhancement techniques. Finally, the performance of each method was quantitatively assessed using Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Mean Absolute Error (MAE) to identify the most effective enhancement technique.

Image Acquisition

The image utilized in this research was sourced from the Herlev database, which was established at Herlev University Hospital in Denmark. This database is part of Nature-Inspired Smart Information Systems (NiSIS), an EU Coordination Action under Contract 13569, focusing on Nature-Inspired Data Technology. Note that it is publicly available online at <http://fuzzy.iau.dtu.dk/download/smear2005>. A total of 917 Pap Smear image samples were utilized in this research, with the samples unevenly distributed across seven different classes. There are three classes of normal cells (242 images) and four classes of abnormal cells (675 images). Normal cells consist of superficial squamous (74 images), intermediate squamous (70 images) and columnar (98 images). In comparison, abnormal cells consist of mild dysplasia (193 images), moderate dysplasia (146 images), severe dysplasia (197 images), as well as carcinoma in situ (150 images). The sample images, as shown in Figure 2 below, show the sample images of each class.

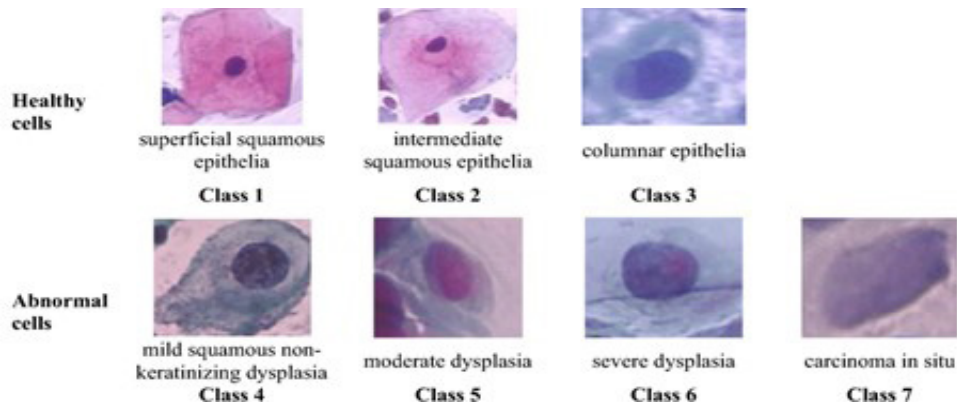


Figure 2: Herlev Dataset Samples. The study used 917 Pap smear images from the Herlev database associated with the NiSIS project. The images are divided into seven classes: three normal (242 images) and four abnormal (675 images). Normal classes include superficial squamous (74), intermediate squamous (70), and columnar (98). Abnormal classes include mild dysplasia (193), moderate dysplasia (146), severe dysplasia (197), and carcinoma in situ (150).

Contrast Enhancement Techniques

a. Contrast Stretching

This technique is carried out by stretching the dynamic range of images, where the dynamic range of the image is between the value of minimum intensity value as well as maximum intensity value of the input image (19). The formula of Contrast Stretching (CS) is:

$$I^{\wedge'}(x,y) = \frac{d}{I_{\max} - I_{\min}} \times (I(x,y) - I_{\min}) + I_{0'} \quad (1)$$

where $I^{\wedge'}(x,y)$ represents the new dynamic range image, d refers to the new dynamic range value, $I(x,y)$ resembles the input image, I_{\min} denotes the minimum intensity value with regard to the input image, I_{\max} attributes the maximum intensity value concerning the input image, and I_0 assigns offset point of the new dynamic range for $I^{\wedge'}(x,y)$.

b. Contrast Limited Adaptive Histogram Equalization (CLAHE)

This technique refers to an advanced technique that is derived from the HE technique. On the other hand, CLAHE resembles a technique that takes care of over-amplification of contrast (20). Instead of operating all over the image, the CLAHE technique is carried out on tiles, which are the small regions of the images. The neighboring tiles are subsequently merged utilizing bilinear interpolation to exclude artificial boundaries.

c. Histogram Equalization

HE represents one of the pixel brightness transformation techniques. Here, it is utilized to improve the images' contrast. It is known well for its simplicity and efficiency. This method was used in this project to optimize the colour contrast of the colour images (21). This operation is carried out by remapping the scene histogram to a histogram with a nearly uniform probability distribution. The image's intensity distribution will be redistributed. HE involves a few calculations. The initial step involves assessing the occurrence frequency of each pixel value.

Once established, the process advances to computing the cumulative frequency, representing the summation of the given frequency and all preceding frequencies. Subsequently, the normalized frequency is derived by dividing the frequency of a specific pixel value by the maximum observed frequency. Finally, the recalibrated pixel value is determined by multiplying the maximum pixel value by the corresponding normalized frequency.

$$I^{\wedge'}(x) = \frac{d}{C_{\max} - C_{\min}} \times (C(x) - I_{\min}) + I_{0'} \quad (2)$$

where $I^{\wedge'}(x)$ represents new intensity level, d refers to new dynamic range value, $C(x)$ resembles normalized cumulative value, C_{\max} attributes maximum value concerning normalized cumulative value, C_{\min} assigns minimum value regarding the normalized cumulative value and I_0 denotes offset point of the new dynamic range for $I^{\wedge'}(x)$.

d. Image Adjustment

This technique is used to adjust the contrast by giving some input. It defines the contrast limits in the input image that are to be mapped to corresponding values in the output image or colormap. Each row in the array represents an RGB color triplet. The value in the range of [0 1], along with the value low RGB triplet, is lesser compared to high RGB triplet.

e. Multi-Scale Retinex

Multi-Scale Retinex (MSR) refers to a colour picture improvement method referring to human perception that consistently provides Dynamic Range Compression (DRC) as well as colour constancy. DRC combined with the MSR effectively attains colour as well as lightness rendition (22). The formula of MSR is shown in Equation (3), where N resembles the number of scales and $R_{(n_i)}(x,y)$ is i th component of the n th scale. The colour image the formula as presented in Equations (4) and (5), where β is the gain constant α refers to the strength of non-linearity.

$$F_{MSRI} = \sum_{n=1}^N W_n R_{ni}(x,y) \tag{3}$$

$$F_{MSRCRI} = C_i(x,y) F_{MSRI}(x,y), \quad i \in \{R,G,B\} \tag{4}$$

$$C_i(x,y) = \beta \{ \log[\alpha I_i(x,y)] - \log[\sum I_i(x,y)] \}. \tag{5}$$

GUI Development

A Graphical User Interface (GUI) was developed using MATLAB App Designer to provide an interactive platform for image pre-processing and to simplify the overall image enhancement process. The GUI automatically generates the processed image based on the selected technique through programmed commands. It was designed using MATLAB’s drag-and-drop environment for creating and coding applications, as illustrated in Figure 3.

The interface includes three main components: axes for displaying images, buttons for selecting input images and applying pre-processing methods, and labels for displaying computed quality metrics such as PSNR, RMSE, and MAE. The development process followed four stages. First, the application layout was created by adding the required components. Second, these components were customized by assigning appropriate names and arranging them for ease of use. Third, callback functions were implemented in the Code View to enable functional interactivity, allowing image selection, enhancement application (HE, CLAHE, CS, imadjust, MSR), and display of processed outputs. Finally, the GUI was tested to ensure accuracy and seamless performance.

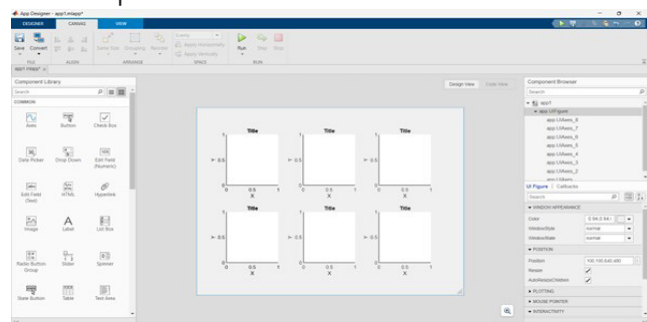


Figure 3: Matlab App Designer Layout. The GUI includes three main components: axes for displaying images and buttons for image selection and applying pre-processing methods. This setup enhances efficiency by allowing users to generate images using programmed commands.

Performance Evaluation Metrics

a. Peak signal-to-noise ratio (PSNR)
 Peak Signal-to-Noise Ratio (PSNR) refers to the ratio between an image's theoretical maximum power as well as the power of corrupting noise affecting its quality. To determine the PSNR of an image, as shown in Equation (6), it is compared to an ideal clean image having the greatest possible power.

$$PSNR = 10 \log_{10} \left(\frac{(L-1)^2}{MSE} \right) \tag{6}$$

where L in the formula above represents the maximum possible intensity levels concerning the image, while on the other hand, the value of the minimum intensity level is 0.

b. Mean Square Error (MSE)

Mean Squared Error (MSE) quantifies the cumulative squared error between a compressed image and its original counterpart. Specifically, for two images (denoted as A and B), the MSE involves calculating the squared difference that exists between corresponding pixels in both images, summing up these squared differences, and subsequently averaging them over the total number of pixels. A lower MSE value indicates higher similarity between the images, while a higher MSE signifies increased dissimilarity. MSE is calculated as shown in Equation (7):

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} (O(i,j) - D(i,j))^2 \tag{7}$$

Let O represent the matrix representation of the original image, while D denotes the matrix data corresponding to the degraded image. The parameter m signifies the total number of pixel rows within the image, with i serving as the index for a given row. Similarly, n designates the total number of pixel columns in the image, with j acting as the respective column index.

c. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) serves as another crucial metric for assessing image quality. It quantifies the average absolute difference that exists between corresponding pixels in two images, denoted as O and D. MAE considers the absolute differences, making it less sensitive to outliers. A lower MAE indicates greater similarity between the images, while a higher MAE signifies increased dissimilarity. Mathematically, the MAE is calculated as shown in Equation (8):

$$MAE = \frac{1}{n} \sum_{j=1}^n |O(i,j) - D(i,j)|, \tag{8}$$

in which n represents the number of elements in the picture, O is the matrix data regarding the original image, and D is the enhanced image's matrix data.

RESULTS

Visual result of applying five contrast enhancement methods on cervical cell image from seven classes

Table I presents the images that are separated into seven types: normal superficial, normal intermediate, light dysplasia, normal columnar, severe dysplasia, moderate

Table I: Comparison Method for Each Class of Cell

Type of Cells	Original Image	Contrast Stretching	CLAHE	Histogram equalization	Image Adjustment	Multi Scale Retinex
Normal Superficial						
Normal Intermediate						
Normal Columnar						
Light Dysplasia						
Moderate Dysplasia						
Severe Dysplasia						
Carcinoma In Situ						

dysplasia, as well as carcinoma in situ, which undergo five methods of colour contrast enhancement: the HE, image adjustment, CS, CLAHE, and MSR. HE has been globally used as a benchmark in a non-medical and medical field (21,23–25), while the MSR method is not used in the cervical cell except in a paper from (11). Several studies have applied the method in industrial applications (26–28).

Numerical results evaluating the quality of normal cell images based on PSNR, RMSE and MAE

Table II displays the data analysis from twenty normal and abnormal cell database images. In summary, CLAHE shows a high PSNR value as well as low RMSE and MAE value from the result of the suggested method images in contrast to other methods. In other work by (29) and (30), both papers also suggested that CLAHE performs best on histopathology images. Table 2 shows the average result analysis for normal class cervical cells, which consist of normal superficial, intermediate and columnar cells. These classes are characterized

Table II: Average score of PSNR, RMSE, and MAE for Normal Cell.

Methods	Score	Histogram Equalization	CLAHE	Contrast Stretching	Image Adjustment	Multi Scale Retinex
Normal Intermediate	PSNR	12.99	20.92	16.44	16.87	14.49
	RMSE	59.09	23.99	38.75	36.97	48.44
	MAE	39.32	10.66	15.06	12.76	24.62
Normal Columnar	PSNR	12.35	18.49	12.05	13.51	12.83
	RMSE	62.98	30.84	64.38	55.35	59.06
	MAE	53.99	18.63	49.44	44.82	43.53
Normal Superficial	PSNR	13.24	21.65	16.46	16.53	13.84
	RMSE	56.68	21.82	38.79	38.89	52.45
	MAE	34.99	7.96	16.86	19.34	26.66

by a normal ratio of nucleus-cytoplasm size. Another significant characteristic is that the roundness of normal cells is smoother compared to abnormal. The colour of the nucleus in normal images is lighter compared to abnormal cells.

Numerical results evaluating the quality of abnormal cell images based on PSNR, RMSE and MAE

Table III presents the average result analysis for the abnormal class cervical cells, which include dysplastic and cancerous cells. These cells are characterized by an abnormal nucleus-to-cytoplasm size ratio, with the nucleus often appearing disproportionately larger. Additionally, abnormal cells exhibit irregularities in shape, resulting in less smooth and more uneven boundaries when compared to normal cells. The color of the nucleus in abnormal cell images tends to be darker, indicating potential malignancy or pre-malignant changes. The distinct features of abnormal cells, such as irregularity in shape and darker nucleus color, make them critical for diagnostic image analysis.

Table III: Average score of PSNR, RMSE, and MAE for Abnormal Cell.

Methods	Score	Histogram Equalization	CLAHE	Contrast Stretching	Image Adjustment	Multi Scale Retinex
Mild	PSNR	13.92	20.53	16.367	17.08	16.22
Dysplastic	RMSE	52.34	24.61	38.91	35.86	39.60
	MAE	34.81	6.77	16.02	11.84	14.478
Moderate Dysplastic	PSNR	15.13	18.50	15.37	16.08	15.49
	RMSE	45.23	30.64	43.73	40.49	43.20
Severe Dysplastic	MAE	24.00	3.81	20.59	16.30	16.74
	PSNR	15.53	19.87	15.23	16.18	15.93
Carcinoma In Situ	RMSE	43.49	26.17	44.55	39.89	40.99
	MAE	19.66	4.23	23.60	20.24	17.70
Carcinoma In Situ	PSNR	15.06	20.79	13.81	14.33	14.30
	RMSE	45.86	23.59	52.74	49.63	49.83
	MAE	23.45	4.27	29.83	25.57	23.21

Designed GUI for presenting the metrics score of cervical cell images

Figure 4 illustrates a GUI designed for image pre-processing using various methods like HE, CLAHE, CS, imadjust, and MSR. The GUI includes features for selecting input images from a folder and buttons to apply each pre-processing method, displaying the processed images. Additionally, it calculates and displays quality metrics such as PSNR, RMSE, and MAE, ensuring functionality through interactive testing.

DISCUSSION

This section discusses the differences in the thresholding results of Pap Smear cell images, which have been classified based on the five methods examined in this study.

For the CS technique, the cells' nucleus darkened and became the darkest, and the contrast was available. The shape of the cell can be seen in the images. For CLAHE, the image contrast was improved. Some of the details of

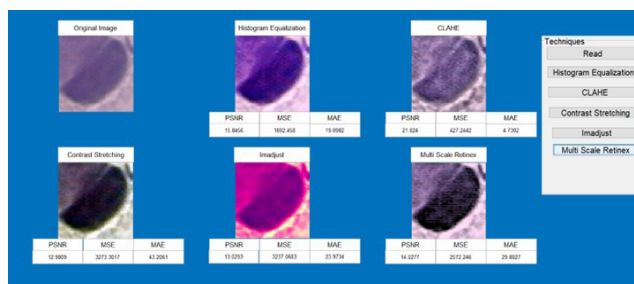


Figure 4: GUI Interface for Cervical Cell Colour Contrast Enhancement. Graphical User Interface (GUI) designed for image pre-processing using various methods like Histogram Equalization, CLAHE, Contrast Stretching, imadjust, and Multi-Scale Retinex. The GUI includes features for selecting input images from a folder and buttons to apply each pre-processing method, displaying the processed images. Additionally, it calculates and displays quality metrics such as PSNR, RMSE, and MAE, ensuring functionality through interactive testing.

the image were enhanced, and the nuclei were darkened. However, excluding the nucleus, some cells' shape has low contrast with the background. Next is HE, with most of the images becoming purple-ish, and some become a bit reddish for light dysplasia images. The nuclei were darkened, and the contrast of the image was clear. Next is the image adjustment technique. This technique will brighten the images, and the nucleus will be seen clearly for some images, such as normal intermediate, normal columnar, and normal superficial. The cell shape of the image is gone, leaving only the nucleus. Lastly is the MSR technique. The image became clearer with this technique, and the nucleus were darkened.

To determine the most effective method in this study, the PSNR score must be high, while the RMSE and MAE should be as low as possible. In terms of a normal class, the NI image cell shows that the CLAHE method has the highest value for PSNR at 20.92, and HE has the lowest value for PSNR at 12.99. Observing the same class also shows that HE has the highest value of RMSE at 59.09, while the CLAHE method possesses the lowest value of RMSE at 23.99. Similarly, the HE method possesses the highest value of MAE at 39.32, while the CLAHE method has the lowest value of MAE at 10.66. The trend is constantly shown in NC and NS. CLAHE method has the highest value for PSNR, with 18.49 and 21.65, respectively. Meanwhile, CS has the highest value of RMSE, with 64.38 for NC and HE at 56.68 for NS. Next is HE, which has the highest value of MAE with 39.32, 53.99 and 34.99 for NI, NC and NS. Next, CLAHE achieved the lowest value of MAE for all NC, NI and NS with 10.66, 18.63 and 7.96.

Table III shows the average result analysis for abnormal class cervical cell consisting of severe dysplastic, moderate dysplastic, mild dysplastic, as well as carcinoma in situ. For mild dysplastic cells, CLAHE outperforms all other methods across all metrics. It achieves the highest PSNR of 20.53, the lowest RMSE of 24.61, and the lowest MAE of 6.77. In contrast, HE performs the worst in all three metrics, PSNR with 13.92, RMSE with 52.34 and MAE with 34.81. This suggests

that CLAHE significantly improves image quality while minimizing error for mild dysplastic cells. The trend continues for moderate dysplastic cells. CLAHE again shows the best performance with a PSNR of 18.50, RMSE of 30.64, and MAE of 3.81. HE is once more the worst performer, with PSNR at 15.13, RMSE at 45.23 and MAE at 24.00. The difference in MAE is particularly notable, with CLAHE's error being about 6 times lower than HE. For severe dysplastic cells, CLAHE maintains its superior performance. PSNR with 19.87, RMSE with 26.17 and MAE with 4.23. Interestingly, for this class, CS becomes the worst performer, whereas HE has a PSNR of 15.23, RMSE of 44.55, and MAE of 23.60. This suggests that simple CS becomes less effective as the cell abnormality becomes more severe. In the most severe category, CLAHE continues to excel with a PSNR of 20.79, RMSE of 23.59 and MAE of 4.27. CS remains the worst method, with PSNR of 13.81, RMSE of 52.74 and MAE of 29.83. The performance gap between CLAHE and the worst method is most pronounced in this category, indicating that CLAHE's adaptive approach is particularly beneficial for more complex cell abnormalities.

The superior performance of CLAHE can be attributed to its adaptive approach to contrast enhancement. Unlike global methods such as Histogram Equalization (HE) and Contrast Stretching (CS), which apply uniform adjustments across the entire image, CLAHE operates on small, localized regions (tiles). This allows CLAHE to enhance contrast in low-contrast areas without over-amplifying noise in homogeneous regions. Additionally, the contrast-limiting mechanism incorporated in CLAHE prevents excessive contrast enhancement, which is a common drawback in standard HE. These characteristics make CLAHE particularly effective for Pap smear images, where uneven illumination and subtle textural variations are present. The method enhances important diagnostic features, such as the nucleus, while maintaining overall image integrity. This explains why CLAHE consistently achieved higher PSNR and lower MSE and MAE values compared to other techniques in this study. Similar findings have been reported in previous studies (29, 30), further supporting its suitability for medical image enhancement.

CONCLUSION

A suitable method was studied to enhance the colour contrast image, and the CLAHE method was proposed to achieve the objective. Next, the GUI of the proposed method was developed, achieving the second objective. Lastly, the proposed method was evaluated and compared with existing techniques in the Root Mean Square Error method, PSNR test and MAE test. The outcomes reveal that CLAHE surpasses other contrast enhancement methods, consistently achieving the highest average PSNR and the lowest MAE and MSE scores across all cervical cell classes. Visual evaluations also confirm that CLAHE-processed images have better contrast. These

findings show that, in this situation, CLAHE is the best technique for enhancing colour contrast.

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