NUCLEUS CELL SEGMENTATION ON PAP SMEAR IMAGE USING BRADLEY MODIFICATION ALGORITHM

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Abstract: Early detection of cervical cancer can help patients obtain the best treatment through various means. In general, computer-aided diagnosis has a high impact on the accuracy, reliability, and convenience of cervical cancer. However, several limitations have been faced through the design process in detecting or classifying the cells, such as variation of image features and low-image resolution. Moreover, shape indifference is one of the limitations in terms of image processing scope. The metrics used to measure the size and shape of the cells have not been developed to distinguish the differences between the shape of the objects. This paper focused on the detection and segmentation of the nucleus cell region in Pap smear images based on Bradley local thresholding. The proposed method evolved several steps, such as color adjustment, k-means, and a Bradley modification algorithm. Based on image quality assessment (IQA), the numerical evaluation results indicate that the proposed approach has segmented a full area of the nucleus cell region significantly and efficiently compared to the original Bradley algorithm. We obtained F-measure (98.62%), sensitivity (99.13%), and accuracy (97.96%). It has also been proven that the proposed method can effectively address the issue of low contrast and black noise. Hence, the proposed method differs from the previous research in terms of color disproportion adjustment and the modification of Bradley's algorithm for Pap smear image convenience.

Key words: *cervical cancer, Pap smear test, image quality assessment, nucleus cell recognition, Bradley's method*

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1. Introduction

Cervical cancer is a frequently reported cancer among women and curable cancer. For both incidence (6.6%) and mortality (311,000) in 2018, the World Health Organization (WHO) reported 570,000 cases of cervical cancer (7.5%) [1]. Human papillomavirus (HPV) is one of the most prevalent diseases in women [2–6]. Fig. 1 illustrates the number of new cancer cases anticipated for 2020 by the International Agency for Research on Cancer. Globally, there is a 15.48% increase in patients of all ages [7, 8]. A Pap test, commonly referred to as a Pap smear, is a process used to screen for cervical cancer. It examines the cervix for the existence of precancerous or cancerous cells. Note that the preparation steps of the image database are performed using a speculum gently inserted into the vagina during the procedure. The speculum maintains the vaginal walls open, thus making it easier to access the cervix. A small sample of cells from the cervix will be scraped by the doctor. This sample would be collected in a variety of ways by the doctor, such as using a spatula, a brush, or a cytobrush (a spatula and brush in one). Subsequently, the cervical cells are kept and sent to a lab to evaluate the existence of cancerous cells.

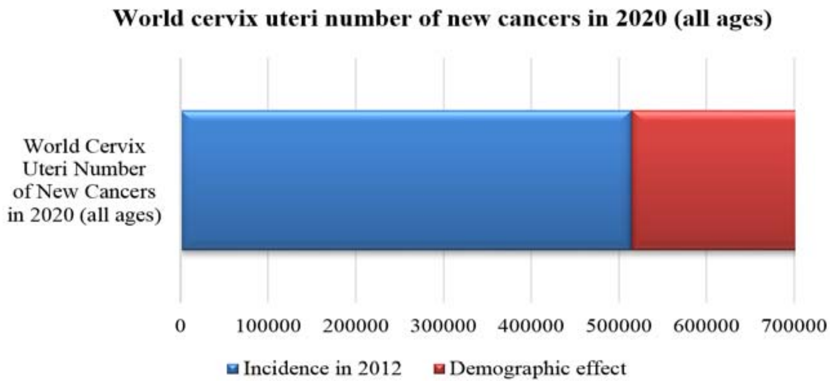


Fig. 1 *World cervix uteri number of new cancers in 2020, includes all ages [6, 7].*

The majority of cervical cancer begins with early abnormalities and gets worse over time [9]. However, there is a shortage of research on the malignant nature of cervical cancer in Malaysia [3]. The researchers believe that part of the screening method and the comprehension of Malaysian females and their distinct culture might contribute to the increase in the incidence and ability to survive cervical cancer [10, 11]. This explains why these investigations have been carried out into the Pap test, HPV DNA testing, and HPV vaccination for preservation. Yet, many studies have focused on addressing the prevention of cervical cancer [12, 13]. Other than that, early detection can occur even with the HPV vaccination, making it even more imperative that we attempt to prevent it [9, 14]. This technique has been popularised many times in healthy living but only reached about the 80% mark to reduce the risk of dying from cervical cancer. Therefore, strengthening Pap testing in Malaysia is a wise practice.

Hence, the medical expert may occasionally have trouble identifying the cancer cell because the nucleus of the cell is sometimes possibly a bit difficult to observe with the human eye. Despite the poor visibility of the sample image, medical experts will hardly discover cervical cancer classification with constant precision mainly inconsistent, repetitive, and relentlessly tedious work. To eliminate this issue, the research study and the related parameters that will be utilised for the nucleus structure require further examination.

Apart from that, cancer cells are notoriously difficult to see because the nucleus is buried within the body's center. At the cellular level, organismic, the nucleus is smaller than the aberrant nucleus [15, 16]. These parameters for their computer-aided attestation structure, including cytoplasm levels, shading strength, and wave-based attributes, allow them to benefit from positive acceptance variation within the cervical cells [17]. As an additional point, understanding the accurate stages of the disease is an additional challenge. This happens because the data cannot be found in the right location or because the sample is too small. Nowadays, computer-assisted cell morphology and cytology are used to assist imaging methods to determine if abnormalities or tumours are present to provide accurate morphology evaluations [18]. Even highly qualified physician has differing views on the stage of the disease, depending on the images they saw. The method was used to produce a better outcome, and the data were analysed using the Pap smear technique to demonstrate the performance.

Note that image processing is the process of converting an image into a digital medium and then performing various procedures on it in order to obtain a significantly enhanced image or extract some relevant data [19–21]. It is a compelling equipment interest in which the transition is an image, such as a video image or photograph. The findings are an image or matters pertaining to that image [22,23].

One of the most common approaches for detecting a single tissue portion in a cell is the segmentation method. Manual Pap smear analysis is susceptible to human error and therefore is tedious and time [24–27]. Thus, developing a computer-aided diagnosis tool might improve the Pap smear test's accuracy and reliability [28]. The segmentation technique developed here will be used to integrate decision support systems for cervical cell diagnosis [29]. Many techniques are employed in image processing, such as preprocessing, enhancement, segmentation, feature extraction, or texture analysis and classification, which are used to identify cancer as well as other diseases [30]. Image segmentation divides a digital image into numerous sections, each with the same pixel and intensity [31,32]. For high abnormal region segmentation, preprocessing enhances interior regions of the cervical image [33,34].

On the other hand, the RGB images of the cervical area are transformed into grayscale images for further processing [35]. Low-resolution cervical images require further enhancement to the edges [36]. The segmentation quality is critical for the extraction of cell information and classification outcomes [37]. Classification of individual cells requires morphological, structural, and contextual data extraction as well as optimal classifier selection [38]. For segmentation and feature extraction, traditional computer vision approaches are constrained by the complexity of cervical cells and the pathological complexities involved with cervical cancer development [39,40]. Furthermore, the drawbacks of the Pap smear are also contributed by the excessive noises and blurriness, which may lead to misdiagnosis [41]. To address these limitations, a few image processing techniques, such as contrast enhancement and image segmentation, were applied on Pap smear images [42]. An image enhancement stage involves enhancing and denoising Pap smear images to increase the quality of the image [43]. Thus, the cell segmentation method divided the input images into two parts, which are the nucleus and the cytoplasm [44, 45].

Prior to identifying cervical cells, a novel method for detecting nuclei on Pap smears via image segmentation should correctly detect the cervical cell's nucleus. However, as of now, the poor sensitivity associated with the smear test has become a concern. It includes possible scenarios such as the time required by the medical expert to diagnose the cervical cell, particularly at the initial stage of the epithelial cells involved, and any other classification stages. Furthermore, the temporal fluctuations in illumination are also automatically handled, unlike global thresholding [46]. In certain instances, a foreground component's nucleus will be classed as background. Nevertheless, the result of the test usually takes a few weeks, which is extremely time-consuming, especially at the government hospital.

In this paper, one image segmentation based on the Bradley method was studied and improved. This method was chosen for improvement since it is more robust to image illumination fluctuations. This approach is also relatively easy to be implemented as it requires the integral picture of the input to do real-time adaptive thresholding [47]. Consequently, k-mean colour classification is used to minimise the number of colours required to have appeared in the image's background and foreground. As a result, this study has improved the approach using a Pap smear image database. The main focus of the proposed technique is to support the medical expert in identifying cervical cancer in different classes, which is the implementation of the new nucleus detection approach. This research aims to study the detection and classification method of the Pap smear image to resolve the time-consuming issues and support better system performance to prevent low precision results of the HPV stages. This study was conducted to understand one of the image processing techniques, Bradley's method, by modifying the algorithm to observe the nucleus cell segmentation image for cervical cancer diagnosis. Therefore, the Bradley modification algorithm succeeds in producing better output compared to the original Bradley method.

2. Materials and Methods

The primary goal of this study is to propose a new modification method for the detection and classification of Pap smear images. The research design was implemented by troubleshooting and pre-testing Bradley's algorithm to identify a better image segmentation for Pap smear test diagnosis. Correspondingly, the result is compared with the original Bradley to identify a better performance. Lastly, the data on the system performance is then collected and used to observe the data analysis from the proposed method. Finally, the resulting images from the proposed performance were analysed qualitatively and quantitatively.

2.1 Database

This study used databases from the University of Herlev, Denmark, for the analysis. The Herlev dataset, also known as the Herlev University Hospital Pap Smear Database, is a collection of cervical cell images commonly used for research purposes in the field of cytology and medical image analysis. These images are primarily used for developing and testing algorithms for the automatic detection and classification of cervical abnormalities, particularly in Pap smear tests. Pap smear, also known as Pap test, is a screening procedure used to detect cervical cancer or precancerous conditions in the cervix. During a Pap smear, cells are collected from the cervix and then examined under a microscope for any abnormalities. In the context of the Herlev database, the cervical images typically consist of microscopic views of cervical cell samples obtained through Pap smear tests. These images may vary in terms of magnification, resolution, staining techniques, and the presence of abnormalities such as inflammation, infection, dysplasia, or cancerous cells. A total of 150 images from the different category was used, which is Normal Cell Image (50), Intermediate Cell Image (50), and Abnormal Cell Image (50). The database images are in the form of colour images, and it was selected as it is commonly used worldwide by researchers for cervical cancer detection and classification [48, 49]. Note that the image database was collected with the aid of a digital camera and a microscope. If no agreement could be reached, the test specimen was discarded.

Consequently, the dataset includes a definitive diagnosis that is as necessarily equivalent as possible, provided the hospital's practical and financial constraints. The precise details of the Pap smear that are being discovered include the image databases collected using a camera device and a microscope. Furthermore, each cell was manually categorised into seven classes by qualified cyto-technicians and doctors. Researchers use these images to develop and evaluate algorithms that can automatically analyze and interpret Pap smear images to assist healthcare professionals in identifying abnormal cells accurately and efficiently. This can potentially improve the accuracy and reliability of cervical cancer screening programs, leading to early detection and better patient outcomes.

2.2 Bradley's Algorithm

In many computer vision and visual elements applications, segmentation is necessary [50, 51]. The purpose of binarizing an image is to categorize pixel values into different numbers of pixels as "black" for the background and "white" for the foreground [52]. Derek Bradley indicated that an integral produces an image that can be used in the real-time adaptive thresholding technique [53,54]. The approach is an advancement of the previous Wellner approach. In addition, the solution to illuminate picture advancements is more reliable. This technique can be carried out quickly and easily.

The Bradley technique is perfect for processing real-time frame rates and live video streams, making it a great tool for engaging applications such as virtual reality [46,55]. Adaptive thresholding is a type of image segmentation that considers spatial variations in illumination. Moreover, researchers develop an algorithm for real-time adaptive thresholding based on the input's integral image [56]. This method is an extension of the following structure. The solution, on the other hand, becomes more resistant to changes in image illumination. Furthermore, the method is straightforward and simple to integrate. This has become the fast concept for this mathematical formula since each number of pixels is proposed to be black when T is less than the normal pixel light in the assigned size window. If it is greater than that, it is adjusted to white. The advantage of this concept is that the binary image is as useful as the Sauvola method. However, the evaluation is twice as fast as the Sauvola technique. Sauvola evaluates both local mean and local variance because it assesses only the local average in Bradley's technique. In addition, the variance can be established with the variance algorithm as the equation below;

$$Var(X) = E(X^2) - [E(X)]^2. \tag{1}$$

The variance calculation reuses the local mean evaluation product $(E(X))^2$ and measures only $E(X^2)$. As a result, approximating the local average requires a decent amount of time. Note that the Bradley segmentation method is twice as fast as the Sauvola approach [55].

2.3 Proposed Workflow

This process flow presents a system for nucleus segmentation and identification by modifying Bradley's algorithm. Additionally, this paper used k-mean coloured classification and image filtering to remove noise from the cell image's composition nucleus [2]. As a result of this approach, it was determined that to identify the cell nucleus, the colour contrast and colour classification should be adjusted for improved image segmentation [48, 57]. The proposed algorithm must consider the primary limitation of both pixel-based and super-pixel-based methods [58, 59].

The proposed Pap smear detection process is depicted in Fig. 2. The first step in the flow diagram represents the acquisition of a true-colour (RGB) image database for computation in MATLAB 2017 from Toshiba laptop (L50A) with processor Intel®Core™i5-4200M CPU @ 2.50 GHz. The cervical dataset experimented is from Herlev University Hospital, Denmark. The images has established database and is used by many researchers around the world for detection or classification purpose

In order to remove noise from the composition nucleus of the cell image, this study used k-mean colored classification and image filtering. For better image segmentation, the colour contrast and color classification were adjusted to better identify the cell nucleus, according to the research. To differentiate the color of the cell nucleus, colour contrast adjustment with k-mean colour classification functions is used. The resulting image is converted to grayscale. Consequently, k-mean colour classification is used to minimize the number of colors required to have appeared in the image's background and foreground. Color contrast adjustment with k-mean colour classification functions is employed to separate the colour of the cell nucleus. The resultant image is converted to a grayscale image [60].

Before performing the image threshold, the true-colour image must be converted to grayscale, as grayscale images are completely sufficient for many functions. Therefore, there is no longer a need to use more complex and time-consuming visual features. Following that, a proposed version of Bradley's adaptive thresholding method was used to diagnose the cell's nucleus. Subsequently, the resultant binary image is denoised using morphological operations. Lastly, the image quality assesment (IQA) is applied to compare the results of the thresholding image with the benchmark image. The gap-search algorithm was created to maximize the performance of the approach.

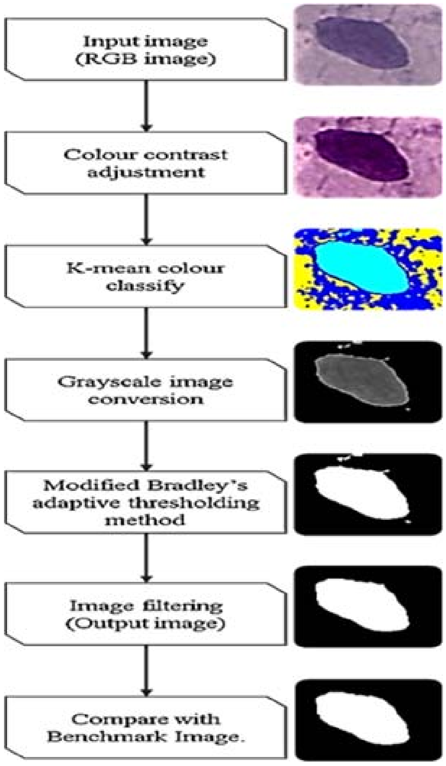


Fig. 2 *The flowchart of the Pap smear detection process.*

2.4 Proposed Bradley's Algorithm

Proposed Bradley's algorithm was developed to provide a new detection technique for cell nuclei. The first modification of this algorithm is the P formula. It is the local mean in Bradley's algorithm, which is divided by 2 (average). The proposed algorithm is depicted below.

$$\begin{aligned} Mean &= averagefilter(image, window, padding), \\ &= (\min(\max(image)) + mean)/2. \end{aligned} \tag{2}$$

The initial stage in the above-described detection technique is to binarize the image as input by segmenting the intensity map. It is performed by selecting a universal threshold level, T, and afterwards creating all pixels in the pixel intensity larger than T to 1 and all pixels less than T to 0. This is referred to as global thresholding. Image segmentation, on the other hand, can be difficult in several image processing applications, particularly in changeable or harsh illumination situations. The P formula is divided by 2 because this is the ideal average pixel value for this Pap smear image database. Determining an average or standard data value might help to comprehend the data's underlying tendencies. Other than that, analyzing a data set's central trend is made easier by averaging past random fluctuations. It is the most accurate approach to determining a value's core tendency because it delivers a more precise response and considers every value in the list. The mean of a few pixels in a specified region is referred to as the local mean. Based on the performed modification, another additional formula has been proposed, which is the variance in the standard deviation algorithm. The algorithm added is given below:

$$MeanSquare = averagefilter(image. \wedge 2, window, padding). \wedge 2, \tag{3}$$

$$Variance = meanSquare - P. \wedge 2. \wedge 1000. \tag{4}$$

Image standard deviation indicates that the image is a variable. The poor variance or standard deviation indicates that the pixel intensities are near the mean, whereas a high variance indicates that the pixel intensities are far from the mean. Besides, the images with high standard deviation values contrast are massive.

The specificity, accuracy, sensitivity, and F-measure of the segmented proposed image were compared to the benchmark image to evaluate performance [61]. This analysis is being performed to evaluate the quality of the segmentation results. Moreover, in the script, the confusion matrix was utilised to allocate the specificity, accuracy, sensitivity, and F-measure using true positive (TP), true negative (TN), false positive (FP), and false negative (FN) [62–64]. The following terminology is employed:

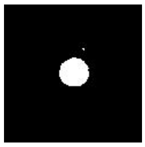
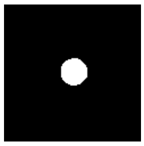
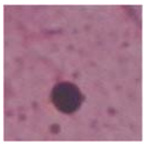
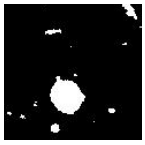
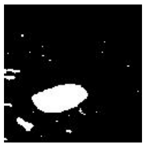
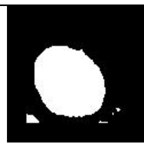
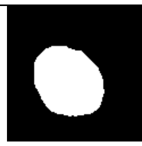
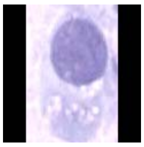
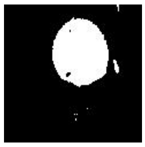
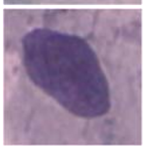
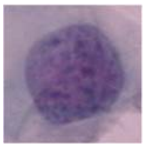
True positive (TP):	Pixels correctly segmented as foreground
True negative (TN:	Pixels falsely segmented as foreground
False positive (FP):	Pixels correctly segmented as background
False negative (FN):	Pixels falsely segmented as background

3. Results and Discussion

The cell nucleus image can be seen based on the results of the comparison method shown in Tab. I. This modification method entails modifying, filtering, and extracting. The proposed method was based on Bradley's algorithm, and 140 image data of each cell classification were analyzed, where the three types of cells were compared with the benchmark image using the new method proposed. This research investigates the significant change between the methods designed with the benchmark image in determining whether the segmented image is likely to be with the benchmark image. The results indicate that the proposed technique is nearly identical to the benchmark image. However, some noise may not be eliminated.

3.1 Comparison of Pap Smear Image

Tab. I presents the comparison result images of the original Bradley's method with the proposed Bradley's method. The table contains three types of cell images,

Class of cell	Original image	Bradley's method	Proposed method
			
Normal cell image			
			
			
Intermediate cell image			
			
			
Abnormal cell image			
			

Tab. I *The comparison results from images of the original Bradley's method with the proposed Bradley's method.*

namely normal cell (non-cancerous), intermediate cell (precancerous), and abnormal cell (cancerous) images. Based on this table, the result of the proposed image clearly presented better nucleus detection compared to the original method.

The results of the proposed method are then analyzed to obtain the result performance based on the IQA. Note that these segmented images were analyzed by comparing the correct pixel as the foreground and background of the image with the benchmark image. This image segmentation performance can be observed in the next section under IQA.

3.2 Image Quality Assessment (IQA)

Fig. 3 demonstrates a horizontal bar chart of the result performance based on the IQA of the proposed Bradley algorithm. These segmented images are then compared with the benchmark image to analyse the F-measure, sensitivity, specificity, and accuracy. The y-axis indicates the IQA performance for the segmentation method, including the accuracy, specificity, sensitivity, and F-measure. In contrast, the x-axis indicates the percentage value for the F-measure, sensitivity, specificity, and accuracy of IQA.

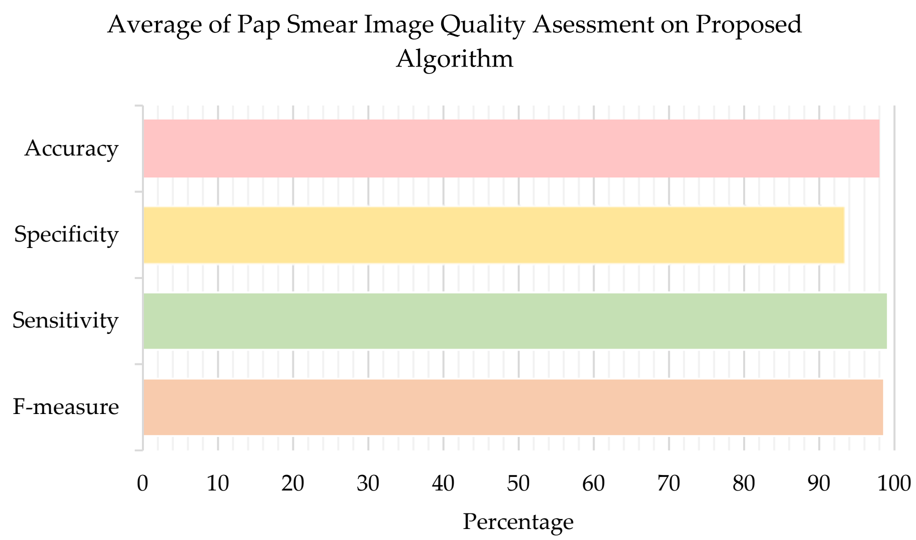


Fig. 3 *The image quality assessment (IQA) analysis for Pap smear cell images.*

Tab. II portrays the minimum and maximum values of the result analysis for the proposed Bradley algorithm. Based on the Tab. II, the F-measure, sensitivity, and accuracy are at a higher percentage, which is more than 77.70% minimum. However, the specificity shows the lowest minimum value of 7.07%.

To compare, the minimum value of the sensitivity, specificity, and accuracy of Tab. II presents that the proposed method performance has a greater value than the original method performance. This indicates that the proposed method is better because the minimum value is higher. However, the minimum value for the F-measure for the original Bradley's method is slightly higher than the original

		F1-measure	Sensitivity	Specificity	Accuracy
Proposed	Minimum	78.78%	85.13 %	70.8 %	77.70%
Method	Maximum	100 %	100 %	100 %	100 %
Performance	Average	98.62%	99.13%	93.36%	97.96%
Original	Minimum	79.01 %	73.04%	84%	70.47%
Bradley Method	Maximum	99.30%	100 %	100 %	98.66 %
Performance	Average	95.70%	93.31%	95.21%	93.68%

Tab. II *Performance algorithm result analysis.*

Bradley's algorithm. Based on this analysis, the maximum value of the proposed Bradley's presented a 100% result of accuracy, sensitivity, and F-measure result compared to the original method performance. In conclusion, the proposed method showed a better percentage of IQA.

In summary, the results demonstrate that the output image based on the newly developed approach produces the best results. Moreover, the algorithm used to analyse the results in the code to assess the results percentage to collect the sensitivity, accuracy, specificity, and the F-measure of the images dataset. Based on data analysis, the proposed method managed to achieve the highest percentage of specificity, sensitivity, accuracy, and F-measure with 100%, implying that the proposed method has mostly attained higher pixels correct segmented as background (black) of the image and most of the images background noise completely removed.

4. Conclusions

Bradley's method and the proposed Bradley's method have been evaluated based on all of the experiments conducted. The proposed method produced the best cervical cancer threshold result, with the darkest black shape of the nucleus appearing clearly and perfectly. As a result, the Bradley method has been chosen to be proposed and used as a new method proposed. Besides this, the alteration method revealed the perfect dark shape of the nucleus, leading to an improved output image with noise removed. As an outcome, the proposed method is superior, with the analysis of the performance of IQA determining the better percentage for the minimum and maximum value. Furthermore, the entire image sensitivity results showed a high percentage, achieving 85.13% of the minimum percentage result. This result defines precise pixels of the image's foreground/object (white). On the other hand, by implementing an innovative approach from the adaptive thresholding Bradley's algorithm, the nuclei detection of the proposed method is successfully implemented. Overall, the study presents a novel approach for nucleus cell segmentation in Pap smear images, with potential real-world applications in computer-aided diagnosis of cervical cancer. The proposed method aims to address some of the limitations and challenges associated with manual analysis and traditional image processing techniques, potentially leading to more reliable and efficient cervical cancer screening and diagnosis. Other than that, this analysis may help researchers across the field understand the concepts affiliated with the techniques, gain knowledge in design, and develop new algorithms for future studies.

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