Endometrial Cell Images Segmentation: A Comparative Study

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Abstract

Uterine cancer, also known as endometrial cancer, is a form of cancer that affects the female reproductive system. Nowadays, there are 2 step methods that the physician or health care provider tend to use to diagnose cancer, which is using ultrasound technique and endometrial biopsy. The biopsy procedure is used to extract the cell and sent to the pathologist for histopathological image analysis. The histopathological image analysis is the crucial step in all the procedures because it determines the situation for the patient, whether positive or negative. They are two types of cell images known as high grade squamous intraepithelial lesion (HSIL) and low grade squamous intraepithelial lesion (LSIL). The problem occurs when both LSIL and HSIL are different, needing different medical treatment techniques but showing slighter differences in nucleus size cell histopathological image analysis. Therefore, the pathologist usually requires more time to identify whether it is LSIL or HSIL. Based on the limitation, the paper aims to compare a few popular detection methods, which are the Wolf method, Bernsen method, Otsu method and Feng method. Based on the Image Quality Assessment (IQA), the Wolf method shows good performance compared to the others. In a precise term, this finding could benefit the health care community to reduce the diagnosis time to categorize the cell and lead to early treatment of endometrial cancer.

Keywords: Uterus, Endometrial, Cancer, Detection, Segmentation, Nucleus

1 INTRODUCTION

Endometrial cancer or uterus cancer is the fifth-deadliest cancer, accounting for more deaths than any other cancer of the female reproductive system[1]–[3]. Women above the age of 50 are more likely to get uterine cancer. It is estimated that around 21,750 women will receive a new diagnosis of ovarian cancer this year alone,

and approximately 13,940 of those women will die from it. Like other forms of cancer, this also benefits from earlier detection because treatment could start as soon as possible[4]. Endometrial cancer develops when cells in the endometrium (the inner lining of the uterus) begin to proliferate uncontrollably. Cells in almost any part of the body can develop into cancer and spread to other parts of the body. The uterus is a hollow organ that is approximately the size and shape of a medium-sized pear. When a woman is pregnant, the uterus is where the fetus grows and develops. It is divided into two sections (as shown in Figure 1)[5], [6].

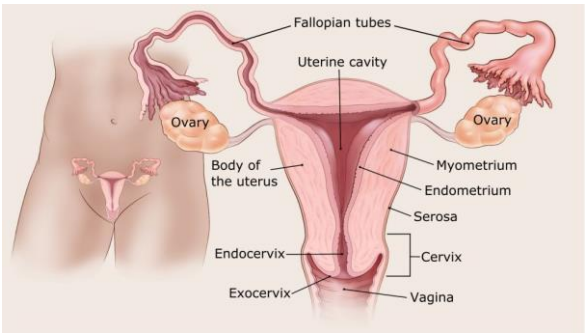

Fig. 1. Structure of Uterus

Due to the complexity of human cells, some pathologists may have a hard time differentiating between Low-Grade Squamous Intraepithelial Lesion (LSIL) and High-Grade Squamous Intraepithelial Lesion (HSIL) cells[7]. The outcome for this problem is that the pathologist may take a longer time to diagnose the cell. This might cause the pathologist to miss diagnosing the condition of the cell. However, by quickly categorizing the type of cell between LSIL and HSIL, quick treatment can soon be started for that particular patient. Thus, like all cancer, the patient can be saved with quick treatment.

Currently, they are 2 step methods that the physician or healthcare provider uses to diagnose cancer, which is by using ultrasound technique and endometrial biopsy. If the patient is suspected of having cancer, ultrasound is first used to measure the length of the endometrial lining. Then, if the lining is greater than four millimetres, the endometrial biopsy will be performed. At this stage, a small tubular instrument is gently placed inside through the endocervical canal into the endometrial cavity. This instrument is used to extract the cell and sent to the pathologist for histopathological image analysis.

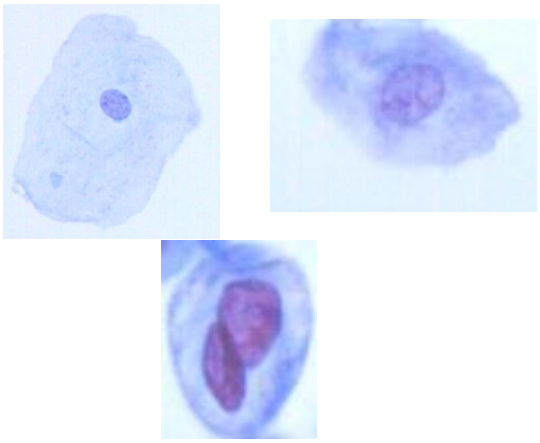

Fig. 2. Sample image of endometrial cell

The histopathological image analysis is the most important step in all the procedures because it determines the situation for the patient, whether positive or negative[8], [9]. They are two types of cell results, known as LSIL and HSIL. The difference for LSIL is a low grade that can be false positive even though the test comes as a low grade but may not tell the abnormality on the cell. For HSIL or the high grade, it always points to something abnormal that can point to cancer. The HSIL are so important even if other tests are out negative. Furthermore, the physician will still have to look further into that case. Another approach employed by the doctor was content-based picture retrieval (CBIR). Using machine vision techniques, this methodology was utilized to locate pictures in large databases. Physicians may only give effective decision-making as a means of detecting illness so that patients can rest and receive treatment at the right moment. When the CBIR model receives a query, it extracts the same set of characteristics and compares them to the indexed features to find comparable pictures in the database. Medical pictures saved on both distributed and centralized servers are also utilized for teaching, information, and diagnosis.

The gold standard for identifying endometrial cancer is histological image analysis. This method involves using traditional machine learning techniques used in previous computer-aided diagnostic (CAD) methodologies[10], [11]. But this method frequently failed to produce satisfactory results. Hence, a new technique was introduced to detect the endometrial cancer cell involved in developing a CAD approach based on a convolutional neural network (CNN) and attention mechanisms, called HIENet. A computer-aided diagnostic (CAD) system works intending to be able to identify endometrial cancer early.

By standardizing texture features, choosing multifeatured in a consistent manner, and presenting physicians with comparative distributions of extracted texture features, the CAD system aids reproducibility. In addition, the RGB images were gamma-corrected before being converted to HSV and YCrCb to ensure consistency.

2 METHODOLOGY

The algorithm is developed using MATLAB 2017 from Toshiba laptop (L50A) with processor Intel® Core™ i5-4200M CPU @ 2.50GHz. All the images were provided by an established database using the microscopic capturing technique. All the processed images are in color level, where the size of each image is random. Four methods which are Otsu, Wolf, Bernsen and Feng, are selected to be applied on cell images.

2.1 Otsu Method

The most known method is the classical segmentation invented by Nobuyuki Otsu in 1979[12]. It is also a global segmentation method that separates the pixels into foreground and background by choosing the optimal threshold. The algorithm works by exhaustively searching for the threshold that minimizes the weighted within-class variance. In other words, it maximizes the between-class variance. The weighted within-class variance of two classes are given in Equation 1 as below:

$$\sigma^2 p(t) = p_1(t)\sigma_1^2 + p_2(t)\sigma_2^2 . \quad (1)$$

This method works best when it is applied to images with a clear bi-modal pattern. Due to that, images with uneven illumination and shadow will not yield the best performance for this method.

2.2 Wolf Method

Wolf Method is a modification of the Sauvola Method, which is claimed to normalize the contrast and mean grey value of the image and compute the threshold as in Equation 2[13]:

$$T = (1-k)m + kM + k\frac{s}{R}(m-M), \quad (2)$$

where the value of k is fixed to 0.5, m and s represent mean and standard deviation, while M is the minimum grey value of the image and R is a maximum value of the standard deviations over all local windows. Thus, misleading in the calculation of binarization thresholds may happen when even a tiny, noisy patch influences M and R values, although this method performs better than other previous methods before it.

2.3 Bernsen Method

This method uses the contrast of images[14]. It includes the estimation of an average of the highest and lowest intensity values in the window. The local contrast of the window is calculated as in Equation 3:

$$C(i.j) = I_{max} - I_{min} . \quad (3)$$

The local contrast is compared to the threshold value based on the pixels, which are foreground and background. When the local contrast is less than the threshold value, the pixel is classified as background and vice-versa.

2.4 Feng method

This method calculates the notion of two local windows contained within one another instead of calculating the dynamic range of grey value's standard deviation from the whole image[15]. As a result, the binarization threshold is computed as follows:

$$T = (1-a_1)m + a_2\frac{s}{R_s}(m-M) + a_3 M, \quad (4)$$

where R_s is a dynamic range of grey value's standard deviation, m is a mean value, s is standard deviation, α is coefficient, while M is the minimum value of the grey levels.

3 IMAGE QUALITY ASSESSMENT (IQA)

IQA works to evaluate the magnitude of differences (or amount of similarity) between the original (reference) image and processed image[16]. In this study, a few selected IQAs were reviewed, including specificity, accuracy and precision. The IQA of specificity, accuracy and precision are generally described in terms of true positive (TP), true negative (TN), false negative (FN) and false positive (FP)[17], [18]. The diagnostic test is considered a true positive if a disease is proven present in the patient. Similarly, the test result is a true negative if the disease is proven absent in the patient. On the other hand, the false positive indicates a patient with no disease, but the diagnose test indicates the presence of disease. Similarly, the test result is false negative when the disease is absent for a patient with the disease. Therefore, the test results are opposite to the actual condition if both are false positive and false negative.

3.1 Specificity

As suggested in equation [5], specificity is the proportion of the true negatives correctly identified by a diagnostic test. It suggests how good the test is at identifying the normal (negative) condition.

$$specificity = \frac{TN}{TN+FP}. \quad (5)$$

The probability of diagnostic tests identifying patients with a particular disease without giving false positive results represents the numerical value of specificity. For instance, there is a 99% chance for the patient without a certain disease to be identified as negative when the specificity test is 99% and vice versa.

3.2 Accuracy

Based on equation (6), accuracy is the proportion of true results, either true positive or true negative, in a population. Thus, it measures the degree of veracity of a diagnostic test on a condition.

$$accuracy = \frac{TN}{TN+TP+FN+FP} \quad (6)$$

The value of accuracy numerically represents the proportion of true positive results (both true positive and true negative) in the selected population. Regardless of positive or negative, the test result is said to be accurate if the accuracy rate is 99%. In other conditions, the accuracy does not suggest to equally high as well, even though both sensitivity and specificity are high.

3.3 Precision

From equation (7), we can immediately see that precision talks about how precise/accurate the model is. In other words, out of those predicted positive, how many of them are actually positive. Thus, precision is a good measure to determine when the cost of false positive is high.

$$precision = \frac{TP}{TP+FP} \quad (7)$$

4 RESULT AND DISCUSSION

Detection is a well-known image segmentation method due to its wide application in digital image processing. For example, it is an effective technique for distinguishing objects from their surroundings. On the other hand, segmentation is a technique for binarizing images based on pixel intensities and is used as a preprocessing step in many applications. For instance, it could be used in medical image processing to detect an abnormal nucleus size for cancer diagnosis. In this study, Otsu, Bernsen, Feng, and Wolf segmentation techniques were studied and implemented on endometrial cancer images. Figure 3 shows the resulting performance comparison of four different segmentation methods.

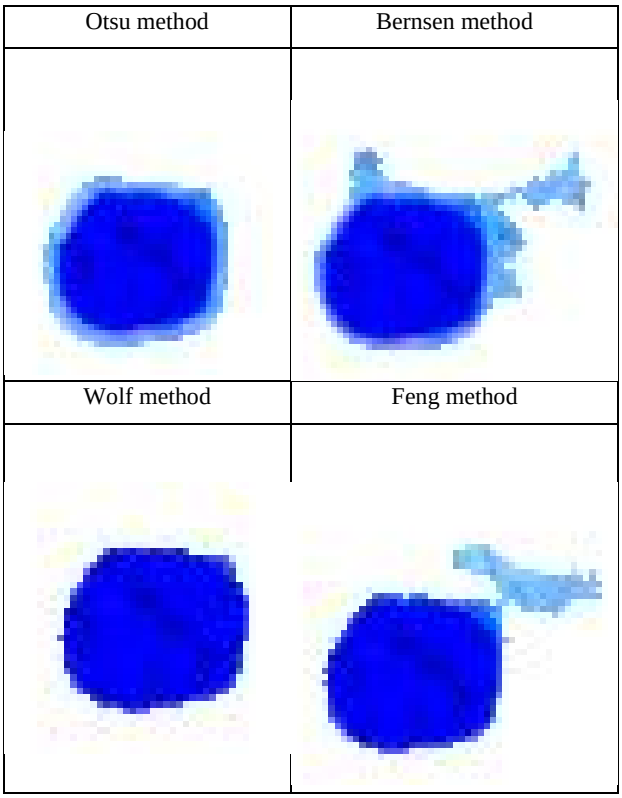

Fig. 3. Comparison images after applying the few selected methods

Based on Figure 3, result images for Otsu and Wolf segmentation have almost identical and obvious forms of nucleus region compared to the Bernsen and Feng method. Moreover, the Feng method also slightly detect unwanted or noise regions. To prove its effectiveness, the resulting images were evaluated using Image Quality Assessments (IQA), assessing the segmented images. In this experiment, IQA is a process to calculate the values of sensitivity (%), accuracy (%), and precision. Thus, the IQA can be used to monitor the image quality of the segmented image. The segmentation results after applying IQA are presented in Table 1.

Table 1. Comparison evaluation each segmentation techniques.

Methods	Specificity (%)	Accuracy (%)	Precision
Otsu	98.90	98.99	0.90
Bernsen	98.52	98.70	0.87
Wolf	99.73	99.76	0.97
Feng	99.40	99.45	0.94

Based on the Specificity, the Wolf method yields the highest value (99.73%), followed by the Feng method (99.40%). In contrast, the lowest value came from the Otsu method (98.90%). In terms of accuracy and precision, again, the Wolf method achieved 99.76% and 0.97, respectively.

5 CONCLUSION

Current development in terms of image processing mostly utilized the CAD approach. Also, the use of CAD systems such as deep learning could increase the accuracy of the result. In this study, the main purpose is to detect the segmented cell nucleus. The segmentation method will be applied to the image so that the nuclear cell image can be more clearly visible for easy recognition and diagnosis. The findings of this study suggest that the Wolf method is an effective approach that can be applied to detect the nucleus region. Future research should therefore concentrate on the proposed automatic classification in order to separate between LSIL and HSIL stages.

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