A Review: Pap Smear Analysis Based on Image Processing Approach

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Abstract. Nowadays, in the hospital, cervical cancer is in the higher rank (number 2) of the most popular cancer among ladies in the world. This cancer develops in the woman’s cervix which the womb is the entrance. Mostly, doctors in the hospital having trouble to identify the cancer cell because the nucleus of the cell is sometimes slightly hard to observe with eyes. The nucleus of the normal cell is in a smaller size compared to the abnormal nucleus. The abnormal nucleus has a bigger size, which sometimes, the size cannot be identified accurately by seeing with bare eyes to classify the stages of cervical cancer. This is because every doctor has different perspectives to observe the classification of the stages of cancer by observing the nucleus without accurate dimensionality reduction in the accuracy of the classifier. Recently, many researchers proposed a method to detect and classify the Pap smear cell images for cervical cancer diagnosis. This approach may improve the accuracy of the detection and the classification which to show better performance with the balance data and samples precisely. Some of the patients got the result that they are on stage 2, however after re-testing, they actually on stage 4 which the chance to heal is very low. This happens because the doctor can’t find the accurate balance data and sample precisely. In this paper, a comprehensive review of cervical detection based on segmentation nucleus and classification was studied.

Keywords; cervical. Cancer, Image, Review

1. Introduction

Cervical cancer is universal disease cancer which is the most common among women, and at the same time, this is one of the preventable and curable cancers [1,2]. Human Papilloma Virus (HPV) or also known as cervical disease is one of the most popular types of woman cancer globally [3]. The Papanicolaou experiment has become the cornerstone of cervical screening for most of the past 60 + years. The Papanicolaou test, as well recognized as the Pap test or Pap smear, has been implemented by Georgios Papanikolaou in the 1940s. It contains exfoliating cells from the cervix's improvement range to allow microscopic assessment of these cells for the tracking of cancerous or precancerous caries.

The numerous factors that are because of cigarettes, prescription medications, body immune suppression of cells. There are almost no precise early signs of Cancer cervix in the early phases, so PAP's smear regimen testing is accomplished. Screening smear test seems to be time-consuming as well as often results are wrong. Representation has irregular patterning, disproportionate or dead blood
on a cell and also overlapped. Computerized tracking and trend analysis of the smear test has become one of the impressive functions of screening images. Figure 1 shows the cervical cancer stages.

![Cervical cancer stages.](image)

Fig 1. Cervical cancer stages.

Yet, many types of research concentrated on preventative on the Pap smear issues, HPV DNA testing, HPV vaccine, and other suggestions for the preventative of cervical cancer. Prevention of secondary screening remains a hugely important part since screening even now plays a huge role in even with the HPV vaccine because the vaccine doesn't quite compensate for all high-risk HPV [4]. Cervical cancer is communal cancer among woman in universal but in the same period, it is one of the furthermost preventable and treatable cancer. Most cervical cancer starts with pre-cancerous changes and develops very slowly [5]. Doctors in the hospital having trouble to identify the cancer cell because the nucleus of the cell is sometimes slightly hard to observe with bare eyes. The nucleus of the normal cell is in a smaller size compared to the abnormal nucleus. On the other hand, the problem to know the accurate data of the cancer stages also the problem. Some of the patients got the result that they are on stage 2, but after re-testing, they actually on stage 4 which the chance to heal is very low. This happens because the doctor can't find the accurate balance data and sample precisely. Nowadays, the technique of computerized image analysis used to assist artificial diagnosis of cell abnormalities or tumors in cytopathology or histopathology also can provide accurate and the objective evaluation of nuclear morphology [6]. However, even the expert doctor will have different perspectives about the cancer stages based on the images screening.

2. Review of study

2.1 Nucleus Detection

The narrative review from another existing method of screening image of Pap smear test was studied. In 2015, Putri et al. [7] examined cervical cancer disease which used the adaptive thresholding method. In this research, a system was invented to identify signs of human papillomavirus using Matlab 2009a software to address these issues. The data processing of the whole image begins from turning the type of picture, thresholding, eliminating noise using a filtration system, the image prepared for detection of the thresholding process and applied adaptive thresholding used local independent legal threshold value. This system possible to divide the visual image out into two different types, normal and abnormal (precancerous cells). The nucleus tracking precision was expected to improve by using shape-based nucleus identification was studied by Ragothaman et al. [8]. The presentation of the suggested solution, taking into account two cases where cells not seeded in the nucleus are supposed to be a part of the Cells class and non-cells class. The image is supposed to be obtained from either the Gaussian mixture and the parameters were discovered using the E-M
algorithm. This method continues to improve even for cells which occur as clusters and weakly stained slides. Figure 2 shown a resulting image after applying the proposed technique.

![Original Image](image1.png) ![Image showing segmented regions](image2.png)

**Figure 2.** Segmentation of cell clusters even with poor staining [8]

Then, Neghina et al. [9] introduced a new method of Polar Transformation-based on cell detection and segmentation. The method tends to assume that a certain inside the nucleus is the grain point of every candidate. Constructed all over the seed, the polar depiction is segmented by segmentation k-means towards a cluster of candidate-nucleus, a cluster as well as up to three various clusters representing non-candidate cell objects. Using the silhouette method, the pure number of clusters is evaluated. The number of parameters can also be recognized and assessed easily throughout the segmented polar recognition as fuzzy memberships from which it can define the decision on the matter. The proposed idea performance was taking into account two situations if cells were presumed not dispersed throughout the nucleus in the context from the cell of class and as non-cells (refer Table 1).

To determine the performance of the method, the initiatives were chosen [9]:

- **True Positive =** cells detected as cells
- **True Negative =** non-cells detected as non-cells
- **False Positive =** non-cells detected as cells
- **False Negative =** cells detected as non-cells

- **Correct Detection Rate [%]:**
  
  \[
  CDR = \frac{TP}{TP + FN}
  \]

- **Correct Rejection Rate [%]:**
  
  \[
  CRR = \frac{TN}{TN + FP}
  \]

- **Total Success Rate [%]:**
  
  \[
  TSR = \frac{(CDR + CRR)}{2}
  \]
Table 1. Performances of the proposed method [9].

|                      | Considering cytoplasm seeds as cells | Considering cytoplasm as non-cells |
|----------------------|--------------------------------------|-----------------------------------|
| **TP**               | 6652                                 | 6394                              |
| **TN**               | 8362                                 | 9110                              |
| **FP**               | 2381                                 | 2639                              |
| **FN**               | 2753                                 | 2005                              |
| **CDR (%)**          | 70.73                                | 76.13                             |
| **CRR (%)**          | 77.84                                | 77.54                             |
| **TSR (%)**          | 74.28                                | 76.83                             |

However, interestingly, this is contrary to a study conducted by Plissiti et al. [10]. They suggest a new cell cluster segmentation in Pap smear images based on intensity variability among superpixels. This research found an extremely efficient algorithm to separate the cytoplasm region from the overlapping cells. The stated technique is based upon the fact which cytoplasm pixels develop similar characteristics in isolated cells as well as the region of cytoplasm is homogenous. From the first phase of the proposed idea, the image is examined in perceptually relevant individual provinces that used a superpixel algorithm. Then these regions are merged into regions with the same unique characteristics, ultimately resulting in each and every cytoplasm exact area being clearly identified and the corresponding nuclei being positively identified. This method has been analyzed onto a collection of standard Pap smear images involving two intersected cells each. The resulting performance is shown in figure 3. The overlapping cell successful detected.

![Figure 3. Representative segmentation of the overlapped region [10].](image)

Figure 3 show that the fair representation method segmentation outcomes proving precise overlap region estimation. The overlap region was then identified using an algorithm specifically stating minor changes throughout the cytoplasm intensity within each cell. The method was determined on its cytological images of conventional Pap smears. The aim is to investigate the effectiveness of the method is much more complex images actually contains a large percentage of overlapped cells which would include a post-processing system [10]. Besides, Zhao et al. [11] proposed a new automatic cytoplasm and nuclei segmentation by using effective gap-search MRF for color cervical smear image. This research also applied a Markov Random Field (MRF) super-pixel-based segmentation mechanism to accumulate composition nucleus, cytoplasm, and cell image. As the effort showed that to reach to categorize non-overlapping super-pixel extensions on one image for image segmentation. The moment is the main limitation for both pixel-based and super pixel-based methods. Thus, using either a gap-search MRF, managed to make this structure faster. Representative segmentation of the overlapped region can be seen in Figure 4 below.
Figure 4. Representative segmentation of the overlapped region [11].

This structure represents the entire image as an indirect deterministic graphic structure and it was produced using an automatic tag-map process to specify nuclear, cytoplasmic and background regions. A gap-search algorithm was designed to enhance the model's efficiency. Clearly, demonstrate that this model's implemented discrepancy-search algorithm has become much quicker and more efficient than pixel-based algorithms and superpixels [11].

In 2015, Nosrati M S and Hamarneh proposed a cervical cell segmentation technique using star-shape preceding variability [12]. It stated that accurate and instantaneous cervical cell tracking and delineation are two problematic precursor moves for the instantaneous analysis of Pap smear image as well as the detection of precancerous changes in the cervix. Most segmentation techniques are using shape prior convictions to eliminate noise and cell occlusion [13,14]. However, they suggest to apply the constant segmentation structure with star-shaped images and then perform directional derivatives to segment the cervical cells that overlap in Pap Smear Images. Figure 5 shown that Star-shape prior models of cervical cells are better than elliptical priors.

Figure 5. Elliptical and star-shape prior [12].

In contrast, the study by Wang et al. [15] indicated that implement a learning-based technique of segmenting human cells in Pap smear images with reliable proportion prior convictions to support automatic processing of cell changes is more efficient. High-level proportion data collected incorporated to lead segmentation in which cell limitations might be ineffective or lost as a result of
cell overlap. This method attempts to address the segmentation issue efficiently, including for images with a large percentage of overlapped cells.

2.2 Classification

The experimental data are rather controversial, and there is no general agreement about improving the characteristics of the cervical cancer extraction method as well as the classification of the Neural Pap system. The study indicates that the Pap smear test has several disadvantages, such as less effective slide preparing and human error, hence a computer-aided diagnosis and treatment system is proposed as a solution to this issue. Neural Pap becomes one of the diagnostic processes which is being constructed. However, the performance of Neural Pap is restricted by a few limitations. In 2015, Mariarputham and Stephen proposed a new method in order to segment the nucleus on pap smear image. However, the overlapping of cell images and blurred images causes difficulties in segmentation to over-expose or under-expose light in the microscope. Two major challenges are considered when analyzing all of the above issues. First, the choice of distinctive texture characteristics best suited for classification. Second, further precision is improved by selecting the most effective and scalability classifier [16].

They proposed a system consists: preparing and preprocessing of smear test images, nucleus segmentation and cytoplasm segmentation, texture extraction, and classification. The input images are then inverted throughout this step, and subsequently binarization of the image by the morphological shutdown of five implementing elements. Then, Table 2 shows a detailed overview of Pap smear cells. All pictures will be divided into seven groups by cautiously extracting 24 characteristics, which include Surface squamous, squamous intermediary, columnar, mild dysplasia, moderate dysplasia, dysplasia severe and in-situ carcinoma. The literature above simply shows that neither of the single texture features is ideal for ways to improve classification precision.

| Class | Category | Cell Type             | Cell Count | Subtotal |
|-------|----------|-----------------------|------------|----------|
| 1     | Normal   | Normal squamous       | 74         |          |
| 2     | Normal   | Intermediate squamous | 70         | 242      |
| 3     | Normal   | Columnar              | 98         |          |
| 4     | Abnormal | Mild dysplasia        | 182        |          |
| 5     | Abnormal | Moderate dysplasia    | 146        |          |
| 6     | Abnormal | Severe dysplasia      | 197        | 675      |
| 7     | Abnormal | Carcinoma in situ     | 150        |          |

The researches show its technique doesn't really just to throughout categorization but also in choosing the properties of all specializations which are most appropriate. Those same results indicate that there were no characteristics exists in all classes. It is concluded from the analysis in this classification method that the linear classifier of the SVM kernel performs out than any other classifier [16].

Cervical cancer classification which uses neural network systems that play a big role in almost image processing applications [17–19]. Detection of human papillomavirus cells utilizes an ANN (figure 6) for the classification of normal and abnormal cells throughout the cervix region of the uterus. The classification of normal, abnormal and cancerous cells is recognized using a neural network which actually creates accurate readings in comparison with manual inspection methods just like Pap smear and Liquid Cytology LCB testing.
The normal and abnormal classifications of cervical cells were attached to the network which exists to help trace cervical cancer at the beginning stages. A few popular classification techniques discuss to trace cervical cancer based on neural networks and their architectural design [20]. With the same objective, Mahanta et al. [21] suggest a Pap smear image classification using a convolutional neural network. The main emphasis was developing an effective function parameter able to perform different levels of representation of the functions hidden during an age of Pap smear. The main idea is applied a deep convolutional neural network, preceded by function selection to use an unsupervised method with the maximum information compression index as a method of measuring of similarity. The schematic diagram for the suggested tasks can be seen in Figure 7. It usually includes four different stages. Phase I is for the technological revolution of databases, Phase II is about the extraction of features that use deep CNN, Phase III is for selection of features which used the unmonitored method, as well as the final phase, is for classification at which throughput classes represent the developed pathological classification.

Figure 6. The architecture of ANN [20].

Then, the major role is provided in developing an effective parameter meant to represent the image content. The observational evaluation has been shown that the current system is effective and helps to improve suitability performance. This system is to improve efficiency by decreasing variations among observers [21]. Sulaiman et al. [22] found differences suggesting that perform Adaptive Fuzzy-k-Means (AFKM) clustering algorithm in order to minimize these constraints and applied Moving K-Means (MKM) to segmented smear test streams images through to the core, cytoplasm and

Figure 7. Block diagram of the proposed work on [21].
composition areas. In this study, a step forward by offering the characteristic fermentation algorithm to overlap cells with mixing idea for color space together and Semi-Automatic Pseudo Color Feature Extraction (PCFE) algorithm. It’s been shown that the whole planned algorithm produces better achievement than the algorithm used for the Neural Pap.

According to the study by Mbaga et al. [23], the presentation of the pap smear images classification for early detection of cervical cancer using SVM-RFE is being used to pick elements and the RFE algorithm eliminates irrelevant features dependent on inverse sequential selection by iteratively attempting to remove one feature at a moment. The SVM classifier is tempting because of the results of this study from SVM that were taken into consideration to be the best precision. It embraced that 10 cross-validations as a constraint solver evaluation independent study and left one out for classifier experiments. The above findings contradict the study by Kurniawati and Permanasari [24]. They conclude that the SVM has lackluster results because it is actually designed in this class for two classes while multi-class. For each class, disproportionately large data dispersion (imbalance data) led to lower precision of information categorization. Depending on the analysis outcomes, next experimentation can be held out to manage imbalance information increasing its classification presentation using pre-processing data. A new model of classification was proposed by Ramdhani Y and Riana namely as Hierarchical Decision Approach (HDA) [25]. The model of the Hierarchical Decision Approach (HDA) has become the best model of the classification consequence, so a new technique of classification for the Pap smear image was implemented as shown in figure 8. This method is successful to classify the Pap smear images into 7 classes.

![Hierarchical Data Classification](image)

**Figure. 8.** Approach Model-Based on Hierarchical Decision [25].

Interestingly, William et al. [26] reviews image analysis and machine-learning technologies for automatic cervical cancer screening on pap-smear images. This study clearly shows that the applicable techniques still have weaknesses in some cell classes in term of the result is low classification accuracy. Table 3 describes a few classification methods with their own advantages and limitations, respectively.
Table 3. Segmentation Classification Techniques Advantages And Limitations [26].

| Technique                          | Advantages                                                                 | Limitations                                                                 |
|-----------------------------------|-----------------------------------------------------------------------------|----------------------------------------------------------------------------|
| Segmentation                      | Closed boundaries can be detected                                            | Not good for overlapping cells                                             |
| Water immersion                   | Boundaries can easily be detected                                            | Energy minimization consumes time                                           |
| Active contours                   | Detects similarity in shapes                                                | Usually detects only round shapes                                          |
| Hough transform                   | Robust and handles uncertainty in data                                       | Rigid rules and not flexible edge detection subject to user-defined parameters |
| Fuzzy logic                       | Detect edges                                                                |                                                                            |
| Seed based region growing         |                                                                            |                                                                            |
| Genetic algorithms                | Efficiently searches for the best solution                                   | Slow                                                                        |
| K-means clustering                | Automatically detects threshold                                              | Cannot separate overlapping cells                                          |
| Classification                    |                                                                            |                                                                            |
| Artificial neural networks        | Tolerant to noise and can use more than one instance to classify             | Over fitting in case of many attributes, complex, and time consuming       |
| Bayesian network                  | Easy to understand. Based on statistical inference                          | Assumes normal distribution and statistical independence on numeric attributes |
| Support vector machine            | Easy to control and over fitting is unlikely to occur                       | Difficult to obtain optimal parameters for nonlinear data and training is slow |
| Decision tree                     | Easy to understand                                                          | Error in the training set can lead to wrong final decisions                |
| Genetic algorithm                 | Finds a good solution and good for optimization                            | Finds local optima that makes it not the most efficient                    |
| K-nearest neighbor                | Robust, fast, and tolerant to noise                                          | Complex as attributes increase in number and assumes that instances of same attributes are similar |

In addition, most current algorithms operate on either single or multiple cervical smear images. This precision can be enhanced by using multi-level classifier hybrid segmentation and classification procedures to fluctuate different parameters such as the features to be extracted, improving noise removal [26,27].

In 2018, a new approach to predict whether the structured method-Principal Component Analysis (PCA) models may advance the effectiveness compared to the Naïve Bayes Image recognition on pap smear dataset images were investigated by Dewi et al. [28]. Depending on the diagnosis, there are 2 (two) different kinds of pre-cancer cells, namely, dysplasia and in situ carcinoma. The dysplasia cell can become separated into three types: mild, moderate, and severe dysplasia. Then, each cell
supposed to contain in the cervical part may indeed be divided into groups into 7 cell groups. This categorization according to each cell of each class displayed in table 4.

Table 4. Single Cell Characteristics Of Pap Smear [28].

| No | Class Name                  | Characteristics                                                                 |
|----|-----------------------------|---------------------------------------------------------------------------------|
| 1  | Normal Superficial          | The cells are oval                                                               |
|    |                             | The nucleus is very small                                                        |
|    |                             | The comparison between the nucleus area and the cytoplasm area is very small     |
| 2  | Normal Intermediate         | The cells are round                                                               |
|    |                             | The nucleus is large                                                             |
|    |                             | The comparison between the nucleus and cytoplasm area is small                   |
| 3  | Normal Columnar             | The cells are shaped like columns                                                |
|    |                             | The nucleus is large                                                             |
|    |                             | The comparison between the nucleus and cytoplasm area is medium                  |
| 4  | Mild (Light) Dysplasia      | The nucleus is large and light-colored                                           |
|    |                             | The comparison between the area of the nucleus and cytoplasm is medium           |
| 5  | Moderate Dysplasia          | The nucleus is large and dark                                                     |
|    |                             | The cytoplasm is dark                                                            |
|    |                             | The comparison between the area of the nucleus and cytoplasm is great            |
| 6  | Severe Dysplasia            | The nucleus is large, dark, and irregular in shape                               |
|    |                             | The cytoplasm is dark                                                            |
|    |                             | The comparison between the area of the nucleus and cytoplasm is large            |
| 7  | Carcinoma In Situ          | The nucleus is large, dark and irregular in shape                                |
|    |                             | The comparison between the area of the nucleus and cytoplasm is great            |

This technique included in the analysis involves multiple phases of pre-processing, information rule, assessment, and performance reporting. Overall, it demonstrates that both Naïve Bayes algorithm models with the Weighted-PCA system substantial not as same as in two single-cell groups of Pap smear. The studies of cursory research data sets with smear test image categorization characteristics.

3. Conclusion

Pap smear screening actually started in Malaysia throughout the 1960s which has been available free in women's health services since 1995. Many healthy living campaigns as well as advertising have introduced this procedure but has not reached further than 70-80 percent populous exposure to minimize mortality rates from cervical cancer. The pap smear screening technique should perhaps be strengthened in Malaysia as a move towards the preventative of cervical cancer. In this paper, a cervical cancer diagnosis based on nucleus detection and classification was studied. The objective is to explore the method or technique for each method. Besides, the advantages and drawback each method also was explained clearly. One of the more significant findings is a very challenging task to detect the overlapping cell. This study could perhaps encourage researchers throughout the field in seeing the researched risk associated with some of the methods and to provide a solid base for design and implementing new algorithms or implementing new ones.
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