Automated Detection of Cervical Cancer

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Abstract— Cervical Cancer is an abnormal growth in the cervix - the lower part of the uterus which joins to the vagina. Human Papilloma Virus (HPV) is identified as the main cause for cervical cancer. Cervical cancer is the second most deadly disease among women next to breast cancer in developing countries. However, it is considered to be the most preventable female cancer if identified at an early stage. The cancerous cells may spread to other parts of the body if not identified at an early stage. Pap Smear test and acetic acid test are usually done for cancer screening. In pap test cells are taken from the vagina and cervix and are examined under a microscope for the presence of an abnormal cell. In acetic acid test, the change in features after and before the application of acetic acid is analyzed to find the existence of abnormal cell. Automated screening is becoming most common than manual screening because the latter is erroneous. This paper surveys the different automated methods available for screening the abnormal cells in pap images.

Keywords: Human Papilloma Virus (HPV), Pap Smear test, vagina, cervix

I. INTRODUCTION

HPV is considered to be the root cause for the fatal disease Cervical Cancer. There are several types of life-threatening virus. HPV goes away by its own as time passes away. HPV sometimes causes low grade (mild) changes in the cervical cells but sometimes it causes high grade (severe) changes in the cervical cells which is more likely to be cancer. Pap smear test is the most recommended method of testing the HPV existence and its severity. Unfortunately, the screening test results have defects like inadequate and incorrect sampling, reduction in sensitivity of the test, poor mean sensitivity, high false negative and false positive, expensive test and follow-ups. These characteristics of laboratory reports gave way for the automated detection and classification system. Section II presents a brief overview of various segmentation methods employed so far. Section III gives a review of various feature extraction and section VI gives a detailed view on classification techniques. Section V elaborates commonly used evaluation metric to quantify the efficiency of the proposed algorithm. Finally, the conclusion is included in section VI.

II. SURVEY ON SEGMENTATION

Segmentation is defined as the process of dividing the image into different categories. More accurately, segmentation is the process of assigning a label to every pixel in the image such that pixels belonging to a particular label have some common characteristics. The pap smear images will be segmented into background, nucleus and cytoplasm. The different existing segmentation algorithms are

- Deep learning and conditional random field
- Region growing segmentation
- Threshold method
- Multi-Pass Fast Watershed
- Gradient Vector Flow (GVF)
- Edge based Laplacian of Gaussian
- Multi-scale watershed segmentation
- Active contour technique

Jun Liu et al.(2018), proposed and automated system for the detection of cervical cancer from acetic acid test [1]. The main aim this paper is to find the difference between before and after the acetic acid test. The region of interest i.e., cervical region have high grayscale intensity, high red color intensity and more centered locations. Threshold method of segmentation is done to segregate the irrelevant parts of the image and the area of interest. Features such as percentage of area of region of interest, texture coarseness, and entropy are identified. These three features are given as the input to the fuzzy reasoning system. The output of the fuzzy reasoning system named as index of CIN gives the severity of the abnormality. The texture features gave high specificity than temporal gray scale change. Combining both texture and temporal gray scale change improved the overall classification performance. Finally the classification results were compared.

Yiming Liu et al.(2018), proposed an automated segmentation of cervical nuclei based on Deep Learning and a Conditional Random Field [2]. Mask regional convolutional neural network (MRCNN) is used to obtain the coarse segmentation and the nuclei boundry. For fine tuning the segmentation Local Fully Connected Conditional Random Field (LFCCRF) method is used. Final Segmentation is achieved by minimizing the energy of LFCCRF.

Afaf Tareef et al.(2018), projected a method for the segmentation of the overlapping cells [3]. This paper uses a three pass fast water shed based method for segmenting the overlapping cells. The first pass locates the nucleus, second pass segments the touching, isolated and partially overlapping cells and the third and final pass uses iterative watershed algorithm applied on the nucleus present in the overlapping cluster which gives the cell shape. The proposed algorithm is validated by parameters like accuracy, detection rate, and time complexity. Jie Song et al. (2018), developed a method for the segmentation of the isolated cells and overlapping cells [4].

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They worked on the problems like segmentation of stained nucleus, various levels of occlusion for nucleus and cytoplasm, low contrast cell segmentation with various shapes. They performed the detection and segmentation by viewing it as a unified regression problem. They use Cascade Sparse Regression Chain Model (CSRCM) in which a regressor is trained to avoid the problem of poor localization accuracy and multiple response in the boundaries.

III.FEATURE EXTRACTION

The characteristics of abnormal and normal cells vary. These varying features are identified and should be used in the classification of cell. The various features usually used are

- multiple texture based feature methods
- color, texture, shape
- cytoplasm and nucleus-cytoplasm ratio
- mean, variance, skewness
- energy, entropy

Mithlesh Arya et al. (2018), developed an automated system for the detection of cervical cancer [5]. Histogram, grey level co-occurrence matrix (GLCM), local binary pattern (LBP), laws textural energy measures, DWT are used for the extraction of texture feature. Color, texture, shape, compactness of cytoplasm, major axis, minor axis, cytoplasm and nucleus-cytoplasm ratio are used as the features to classify the normal and abnormal cells. The training is performed by adaptive resampling of the image patches. Fuzzy C-mean (FCM) and Supported Vector Machine (SVM) are used for classification.

Bastien Rigaud et al. (2019) proposed a three step model for the automated classification of the precancerous cells [6]. In the first step, cervix and bladder meshes were registered in a template. In the second step, Principal Component Analysis (PCA) was performed to extract the dominant mode. Finally posterior PCA model gave specific deformation with the constrain representing the top of the uterus deformation.

Kelwin Fernandes et al. (2018) developed an automated diagnostic system for the detection of cancer using the acetic acid method [7]. They used color, texture, edges, discrete wavelet transform, spatial information as the features for static images and for sequence based recognition the changes in temporal acetowhite response in the pre and post application of acetic acid.

IV. CLASSIFICATION

Classification can be defined as assigning pixels to different classes or categories. Classification can be divided into two types - supervised and unsupervised. Supervised classification method specifies both input and output. This classification algorithm maps the input and output. Unsupervised classification algorithm does not specify the output [13], [14], [15]. The repeatedly used algorithms are as follows

- Supported Vector Machine
- Naïve Bayes,
- Random Forest Tree
- Gabor filters
- Convolutional Neural Network
- Artificial Neural Network

Mercy Nyamewaa Asiedu et al. (2019), used Supported Vector Machine (SVM) for the classification [8]. Two sets of data Visual Inspection with Acetic acid (VIA) and Visual Inspection with Lugol's Iodine (VILI) were used in parallel and series combination and are fed to the SVM classifier. The authors finally concluded that combining both dataset outperforms the physicians.

Sherif fayz et al. (2019), used feature reduction techniques like Principle Component Analysis (PCA) and Recursive Feature Elimination (RFE) [9]. Classification is done using Random Forest (RF) classification technique with Synthetic Minority Oversampling Technique (SMOTE). Random Forest is a supervised method of classification and it converts the weak learner to a slow learner. RF splits the subset in a root node to child node again and again till it reaches the leaf node. RF decides the overall voting based on the majority tree voting.

Qi Zhang et al.(2018) developed an Artificial Intelligent based automated system for the identification of malignant cervical lymph node [10]. For the feature extraction and classification point wise gated Boltzmann machine (PGBM) is used. PGBM have task relevant and task irrelevant hidden units for feature learning and feature extraction. The task relevant features are given as the input to the Supported Vector Machine (SVM). Synthetic Minority Over-Sampling Technique (SMOTE) was used to reduce the unbalance in the data set, since the unbalance data set affect the performance of the classifier.

V. EVALUATION MEASURES & RESULTS

Yiming Liu et al.(2018) [2], proposed the precision, recall, and Zijdenbos similarity index (ZSI) as performance metrics to validate the efficiency of their method.

$$\mathrm{Precision} = \frac{TP}{TP + FP}$$

$$\mathrm{Recall} = \frac{TP}{TP + FN}$$

$$ZSI = \frac{2TP}{2TP + FN + FP}$$

Chen Li et al. (2019), considered precision, recall, specificity, F1-score as quantitative metrics for validating the efficiency of classification of cervical cells using Multilayer Hidden Conditional Random Fields and Weakly Supervised Learning [11].

$$Specificity = \frac{TN}{TN + FP}$$

$$F1-score = \frac{2(\mathrm{Precision})(\mathrm{Recall})}{\mathrm{Precision} + \mathrm{Recall}}$$

Nesrine Bnouni et al. (2019), used accuracy as the evaluation factor for the validating the competence of the shared Dictionary Learning method of classification [12].

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$$Accuracy = \frac{TN + TP}{TN + FN + TP + FP}$$

VI. CONCLUSION

Automated classification of the benign and malignant cervical cells decrease the false negative and false positive cases thereby increasing the efficiency of the overall system. A highly efficient system will help in the reduction of false diagnosis thereby reducing the mortality rate. In this paper a thorough literature survey on different algorithms used for automated detection and different efficiency evaluation metrics employed by different authors is also done.

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