Enhanced Boykov's graph cuts based segmentation for Cervical Cancer Detection

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Abstract

Introduction: Cervical cancer is considered as the major curse to women society of the world due to their low survival rate. However, the prognosis of cervical cancer at an early stage through periodic screening was identified to enhance the survival probability of the women patients around the world.
Objective: In this paper, a Boykov-Kolmogorov Graph Cuts and Cloud Model-based Synergy Integrated Segmentation (BKGC-CMSIS) Technique for facilitating predominant cervical cancer detection from the pap smear images used for prognosis.
Methods: This proposed BKGC-CMSIS scheme introduces an effective Boykov-Kolmogorov Graph Cuts-based image partitioning method that estimates the image data through a synergy cloud model for formulating objective functions. The objective function used in this proposed BKGC-CMSIS scheme includes a data item and a smooth term for boundary preservation in order to determine the deviation of each pixel corresponding to the different regions of the cervical pap smear cells.
Results: Also, it identifies the data item through the utilization of X-condition cloud generator for determining and defining the accurate boundaries of cytoplasm and nuclei derived from the pap smear cells. This proposed BKGC-CMSIS scheme uses the merits of membership degree through the incorporation of the smooth term for estimating the degree of similarity existing among the neighboring regions of the cervical pap smear cells.
Conclusion: The experimental results of this proposed BKGC-CMSIS scheme is also potent in enhancing the classification accuracy by 14% superior to the benchmarked cervical cancer detection schemes considered for investigation.

1. Introduction

Nowadays uterus cancer disease is most common in females affecting the genital tract characterized by cervical cancer, with an increasing incidence in the last decades. As per the records of the world health organization (WHO), cervical cancer is declared as the world´s second fatal cancer since it causes 273,505 deaths per year including 493,243 women diagnosed with it every year. Cervical cancer deaths occur most frequently among women aged between 15 and 44 years. The causes which lead to these cancers are the average lifespan increase in the female population above 65 years of age, and the existence of some risk factors such as unopposed estrogen replacement therapy for menopausal women, polycystic ovary disease, obesity, etc. Endometrial cancer is the second most common cancer-causing death next to cervical cancer. However, it is the third most common cause of death among the female genital cancers next to ovarian and cervical cancers. A Computer Aided Diagnosis (CAD) systems [1], [2]can aid the doctors to predict and diagnose the cervical cancer in the early stage.

The cervical cancer is defined as the abnormal cell development in the woman's cervix part. In this context, the automation-oriented reading schemes are determined to be significant in minimizing the errors with improved productivity in the event of screening cervical cancer [3].

The vital role of the automated cervical cancer detection schemes focuses on the effective discrimination or classification between normal and abnormal nuclei cells from the mass of normal cells in the investigation of cervical cytology [4]. The morphological features of cytoplasm and nuclei is responsible for effective classification between normal and normal cervical cells determined in the pap smear test [5]. A number of research works have demonstrated the significant role of cytoplasm and nuclei boundaries in the process of automated cervical cancer detection process [6]. Further, a reliable and automated segmentation or detection of abnormal nuclei and cytoplasm boundaries is determined to be the vital step of accurately estimating the abnormality of the cytoplasm and nucleus in a predominant manner [7]. Furthermore, a diversified number of previous works were contributed through the enforcement of models that include level set, morphological reconstruction and active contour model for effective and accurate nucleus and cytoplasmic boundaries [8]. The segmentation process over the normal cervical nuclei has proved to facilitate maximum accuracy. Thus, the new research focuses on the task of segmenting overlapping nuclei and cytoplasm splitting for superior classification process [9]. However, the process of segmenting abnormal nuclei is determined to be critical due to the diversified changes in size, distribution of non-uniform chromatins and shape irregularity[10].

In this paper, BKGC-CMSIS is proposed for ensuring superior cervical cancer detection process from the input pap smear images used for prognosis. This proposed BKGC-CMSIS scheme incorporated Boykov-Kolmogorov Graph Cuts-based image partitioning method for determining the image data based on a synergy cloud model that aids in formulating objective functions. This proposed BKGC-CMSIS scheme identifies the data item through the utilization of X-condition cloud generator for determining and defining the accurate boundaries of cytoplasm and nuclei derived from the pap smear cells. This proposed BKGC-CMSIS scheme uses the merits of membership degree through the incorporation of the smooth term for estimating the degree of similarity existing among the neighboring regions of the cervical pap smear cells. The simulation experiments of the proposed BKGC-CMSIS scheme is conducted using accuracy, sensitivity, specifity and average processing times with the benchmarked cervical cancer detection schemes considered for investigation.

2. Literature Survey

An automated scheme using the method of block image processing was proposed for identifying the suspicious cancer cells from the pap smear image [11]. This block image processing approach partitioned the pap smear image into blocks in spite of segmented cells as they minimize the complexity under computation process. This block image processing approach also used the method of color histogram and potential features using data analysis for the purpose of differentiating cervical pap smear image blocks into cancer and normal cells. This block image processing approach used support vector machine classifier for training 1100 non background blocks and 110 cancer blocks for building the training model. Then, an improved graph search-based abnormal cervical nuclei segmentation process was proposed for accurate determination of nuclei boundaries [12]. This graph search-based abnormal cervical nuclei segmentation process included better extraction of cytoplasm and nuclei characteristics for effective determination of cervical cell boundaries. The classification accuracy of graph search-based abnormal cervical nuclei segmentation process confirmed to an improvement of 14% compared to the block image processing-based segmentation method. A global and local cut graph-based abnormal cervical nuclei segmentation process was proposed for precise estimation of cytoplasm and nucleus boundaries for differentiating normal cells from cancerous cells [13]. This global and local cut graph-based abnormal cervical nuclei segmentation process inherited the merits of semi contours for detecting the boundaries of pap smear cells in an effective manner. The classification accuracy of this global and local cut graph-based abnormal cervical nuclei segmentation process was confirmed to be predominant by 21% compared to the graph search-based segmentation method. This A graph-based segmentation scheme for distinguishing abnormal nuclei from normal pap smear cells was proposed for detecting cervical cancer [14]. This graph-based segmentation scheme initially pre-segments the nuclei for framing the nuclei size and coarse center. This graph-based segmentation scheme used the method of image unfolding for transforming the ellipse-like border of the pap smear cells into its Cartesian coordinate systems for graph construction. This mechanism used the characteristics of nucleus region and border to estimating cost function. This mechanism finally used the method of dynamic programming for determining the global optimal path for facilitating optimal closed contour for detecting cervical cancer.

Further, an intermediate segmentation qualifier-based cervical cell segmentation process was proposed for effective cervical cancer cell detection [15]. This intermediate segmentation qualifier-based cervical cell segmentation process incorporated the benefits of iterative clustering super-pixel and convolutional neural network for training and testing the cervical pap smear nuclei. This method also used the method of gradient vector flow snake model for enhancing the potential of the cervical cell segmentation process. Then, a Gaussian Mixture Model-based cervical cancer cell detection scheme was proposed for estimating the nucleus and cytoplasm features for effective identification of segmented pap smear cell

regions [16]. This Gaussian Mixture Model-based cervical cancer cell detection approach integrated the process of shapes-based extraction for enhancing the accuracy degree under the segmentation of the nucleus. This Gaussian Mixture Model-based cervical cancer cell detection approach also facilitated accurate tracing of active contours and cells that could be combined into clusters for effective semantic segmentation process. This mechanism was also efficient in handling the inconsistent staining process that could be a hurdle in effective cervical cancer detection process.

Furthermore, a k-Means clustering and Otsu thresholding scheme for cervical cell segmentation process was proposed for fully automated detection of cervical cancer cell [17]. This k-Means clustering and Otsu thresholding scheme included initial cell segmentation that created the primitive for automatic selection of sample background and background pixels extracted from the pap smear cells. The classification accuracy of this k-Means clustering and Otsu thresholding scheme was confirmed to be predominant by 13% and 18% compared to the graph search and graph cut-based segmentation method. In addition, a cervical cancer detection scheme using k-Means and simple linear iterative clustering process was contributed to improving the accuracy in segmenting cervical pap smear images [18]. In [19], a two-phase approach for cell segmentation in Pap smear test images was proposed. The first phase consists of segmenting an image by a non-parametric hierarchical segmentation algorithm that uses spectral and shape information. In the second phase, the nucleus regions and cytoplasm areas are obtained by classifying the segments resulting from the first phase based on their spectral and shape features. This

cervical cancer detection scheme inherited a sequence of morphological operations for superior correction of segmented nuclei in order to prevent the false findings. This cervical cancer detection scheme included the analysis of contour concavity and shape prior to detecting and partitioning the nuclei that are overlapped. This cervical cancer detection scheme facilitated the segmentation process by extracting 181 texture features, 6 colorimetric features and 14 morphometric features from the cytoplasm and nucleus of pap smear cells.

3. Methodology

This proposed BKGC-CMSIS Technique ensures a significant segmentation process of the nuclei and cytoplasmic boundaries present in the cervical pap smear cells by incorporating Boykov-Kolmogorov Graph Cuts and Cloud Model-based Synergy Integrated Segmentation as depicted in Figure 1.

The cervical region is determined using the method of weighted voting after the propagated atlas labels are integrated together. The multidimensional graph cuts utilized by the proposed BKGC-CMSIS technique depends on the cost function determined from the classical graph cut [20] that reflects the characteristics of the initial shape of the nuclei and cytoplasm extracted from the pap smear cells. In this context, the process of segmentation [21] using multidimensional graph cuts estimated as the cost function minimization problem is expressed in Equation (1).

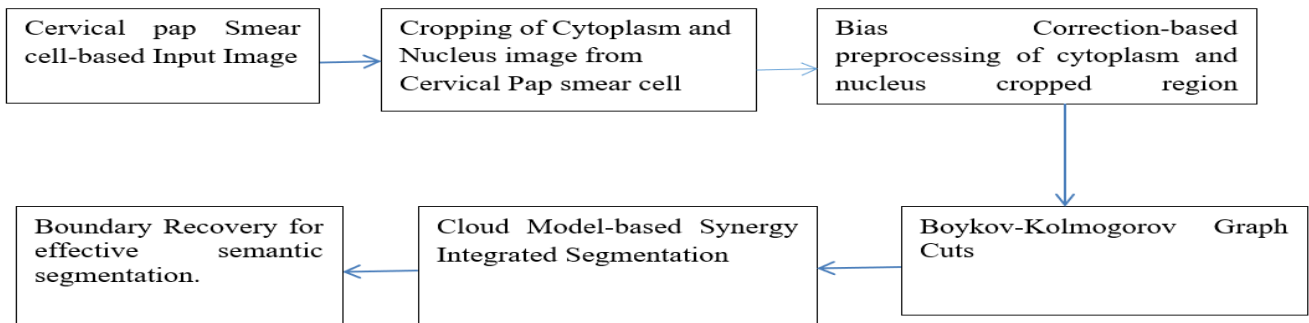$$E(D_{GC}) = \kappa E_{BT}(D_{GC}) + E_{RT}(D_{GC}) \qquad (1)$$

Figure 1. Implementation steps of the proposed BKGC-CMSIS Scheme for achieving effective semantic segmentation in cervical cancer detection.

Where, $E_{BT}(D_{GC})$ and $E_{RT}(D_{GC})$ are the boundary term and regional term with ' κ ' as the balanced coefficient. Further, the cost function presented in Equation (1) that depends on shape constraints derived based on automatic graph construction is expressed in Equation (2)

$$E(D_{GC}) = \sum (\lambda D_T(D_{GC}) + \varpi S_T(D_{GC}) + \phi L_{AT}$$
$$(D_{GC}) + \sum B_{e,f}(D_{GC(e)}, D_{GC(f)}) \qquad (2)$$

'Where, P is the pixel set and NP as the set of neighboring pair elements adjacent to P that are labelled D_{GC} as with

λ, ϖ, ϕ being the weight factors. Furthermore, $DT(D_{GC})$, $ST(D_{GC})$ and LAT (D_{GC}) refers to the data term, shape term and local appearance term with the boundary term denoted by Be, $B_{e,f}(D_{GC(e)}, D_{GC(f)})$.

3.1. The utilization of the Cloud model

The cloud model is mainly used in the proposed scheme in order to improve the accuracy of the segmentation process, when the degree of vagueness in the background and the foreground boundary of the cervical pap smear cells is maximized. The cloud model is defined as the vital model used for representing the transition between the quantitative and qualitative parameters of the derived graph cut for resolving the vagueness existing between the background and the foreground boundary of the cervical pap smear cells. Let $U_S = [x]$ is the universal set represented by precise numbers with 'V' as the quantitative factor associated to U_S. In this context, x is the random realizing parameters associated with C_{MCGC} that is considered as the certainty degree involved in the determination of minimum cost graph cut. If $C_{MCGC}(V)$ (x) highlights the degree of uncertainty associated with $x \in V$ with its value ranging between 0 and 1. Further, this degree of uncertainty $C_{MCGC(V)}(x)$ is defined for every ' x ' belongs to $U_S = [x]$. Then, the value of $C_{MCGC(V)}(x)$ is distributed to $U_S = [x]$, which is defined through the cloud with each and every 'x ' considered as an individual cloud drop. Hence, the value of $C_{MCGC(V)}(x)$ highlights the degree of uncertainty associated with $x \in V$ is represented using Equation (3)

$$C_{MCGC(V)}(x): U_s \to [0,1], \forall x \in Y(Y \in U_S,$$
$$x \to C_{MCGC(T)} \qquad (3)$$

Traditionally, the cloud generator is a specific type of cloud generation algorithm that employs three different digital parameters (P_X, P_n, P_e) that highlights the qualitative concept of the determined minimum graph cut model. At this juncture, the normal cloud distribution of x in U_S is defined through (P_X, P_n, P_e) by satisfying the constraints in Equation (4).

$$x \sim N(P_n, P_x)^2 \qquad (4)$$

In this proposed BKGC-CMSIS Technique, the utilized normal cloud generator mainly uses the benefits of X-conditional cloud generator and background cloud generator.

In general, the generality of the graph cut model is determined as the primitive requirement in the process of image segmentation [20]. However, the objective function model associated with the graph cut model is not potent for its incorporation in the practical contexts. The objective function model associated with the graph cut does not get generalized and conducted.

Moreover, the practical utilization of the image process is limited even when the classical graph cut model is widely enforced for facilitating effective segmentation process.

In addition, Figure 2 demonstrates the systematic steps involved in the proposed mechanism contributed for cervical cancer detection. The Figure 2 (a) depicts the Cervical pap Smear cell-based Input Image considered for the proposed BKGC-CMSIS) Technique. Then, Figure 2 (b) highlights the image determined after the process of Cytoplasm and Nucleus image cropping from Cervical Pap smear cell. Figure 2 (c) portrays the image determined after Bias Correction-based pre-processing of cytoplasm and nucleus cropped region.
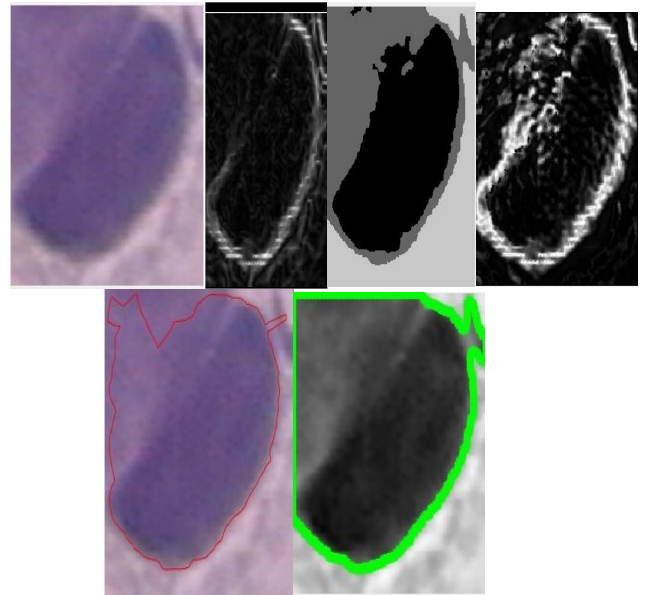

Figure 2. The output images after the enforcement of sequential steps during the implementation of the proposed BKGC-CMSIS scheme

Figure 2 (d) exemplars the image determined after the application of Boykov- Kolmogorov Graph Cuts. Figure 2 (e) glorified the image identified after the process of Cloud Model-based Synergy Integrated Segmentation. Finally, Figure 2(f) portrayed the image after the enforcement of the Boundary Recovery for effective semantic segmentation in the proposed BKGC-CMSIS scheme

4. Results and Discussion

The experimental investigation of the proposed BKGC-CMSIS scheme is conducted using 2013 with the real time dataset named Herlev. This Herlev dataset consists of 917 cervical pap smear images. Among the 917 cervical images, 150 images, 192 images. 146 images and remaining 182 images are associated to the cervical cancer

categories of carcinoma, severe dysplasia, moderate dysplasia and mild dysplasia respectively. Figures 3 and 4 exemplars the classification accuracy and sensitivity of the proposed BKGC-CMSIS scheme and the compared Global and Local Graph Cut-based Cervical Cancer Detection (GLGC-CCD), Graph Search-based Cervical Cancer Detection (GSB-CCD) and

Grapg Cut Segmentation-based Cervical Cancer Detection (GCBS-CCD) schemes considered for investigation. The classification accuracy confirmed during the implementation of the proposed BKGC-CMSIS scheme is 99.58%, which is nearly 3.62%, 2.96% and 2.31% superior to the compared GLGC-CCD, GSB-CCD and GCBS-CCD schemes. Similarly, the sensitivity of the proposed BKGC-CMSIS scheme is 98.62%, which is nearly 4.78%, 3.46% and 3.21% superior to the compared GLGC-CCD, GSB-CCD and GCBS-CCD schemes. This improvement in the classification accuracy and sensitivity of the proposed BKGC-CMSIS scheme over the benchmarked GLGC-CCD, GSB-CCD and GCBS-CCD schemes is mainly due to the integration of enhanced Boykov segmentation and cloud strategy model that contributed towards effective segmentation process.
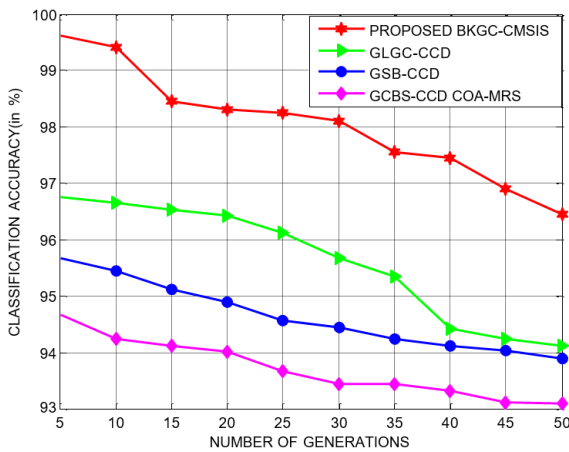

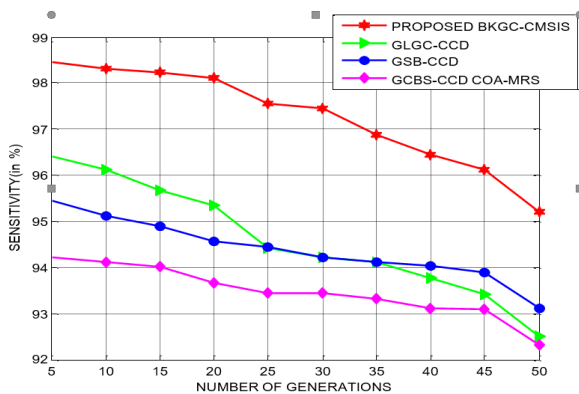**Figure 3.** Classification accuracy of the proposed BKGC-CMSIS scheme

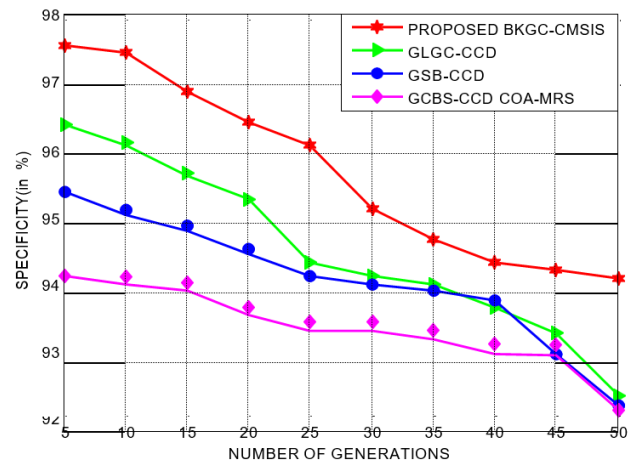**Figure 4.** Sensitivity of the proposed BKGC-CMSIS scheme

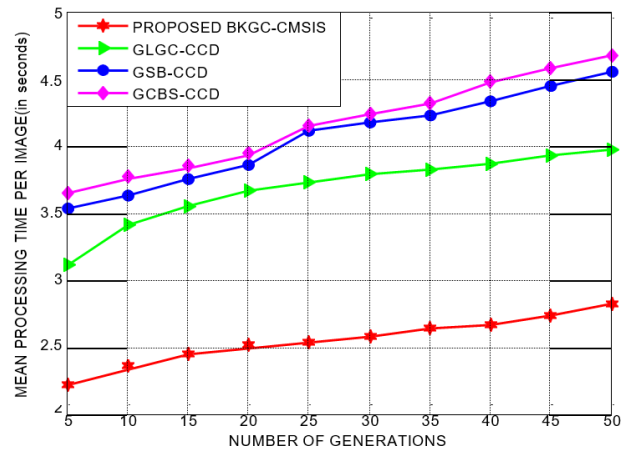**Figure 5.** Specificity of the proposed BKGC-CMSIS scheme

Figure 6. Average Processing time per image for the proposed BKGC-CMSIS scheme

Further, Figure 5 and 6 highlights the specificity and average processing time per image of the proposed BKGC-CMSIS and the compared GLGC-CCD, GSB-CCD and GCBS-CCD schemes. The specificity of the proposed BKGC-CMSIS scheme determined to be 97.82%, which is an average increase of 7.42% to GLGC-CCD, 6.31% to GSB-CCD and 5.81% to GCBS-CCD approaches. In addition, the average Processing time per image for the proposed BKGC-CMSIS scheme is confirmed to be 2.12 seconds, which is nearly 16.21%, 12.18% and 11.52%, reduced on par with the compared GLGC-CCD, GSB-CCD and GCBS-CCD schemes.

5. Conclusions

The proposed BKGC-CMSIS is presented as a reliable attempt for segmenting the nucleus and cytoplasm boundaries for classifying normal cervical cells from abnormal cervical cells. The objective function used in this proposed BKGC-CMSIS scheme includes a data item and

a smooth term for boundary preservation in order to determine the deviation of each pixel corresponding to the different regions of the cervical pap smear cells. This proposed BKGC- CMSIS scheme inherited Boykov-Kolmogorov Graph Cuts-based image partitioning method for determining the image data through a synergy cloud model that aided in formulating objective functions. This proposed BKGC-CMSIS scheme identified data item through the incorporation of X-condition cloud generator for determining and defining the accurate boundaries of cytoplasm and nuclei derived from the pap smear cells. The simulation results of the proposed BKGC-CMSIS scheme is determined to be superior in mean precision, mean accuracy, processing time, sensitivity and specificity to a maximum degree of 13%, 11%, 16%, 15% and 12% superior to the compared cervical cancer cell segmentation schemes considered for investigation. As the part of the future plan, it is decided to formulate a semantic cervical cell segmentation for further improvement of cervical pap smear cancer cell detection process.

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