IEEE Access
Multidisciplinary Rapid Review Open Access Journal

Received 26 June 2023, accepted 12 July 2023, date of publication 17 July 2023, date of current version 31 July 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3295833

RESEARCH ARTICLE

An Improved Boykov's Graph Cut-Based Segmentation Technique for the Efficient Detection of Cervical Cancer

M. ANOUSOUYA DEVI[1], R. EZHILARASIE[2], K. SURESH JOSEPH[3], KETAN KOTECHA[4,5], AJITH ABRAHAM[6,7], (Senior Member, IEEE), AND SUBRAMANIYASWAMY VAIRAVASUNDARAM[2]

[1]Department of Computational Intelligence, SRM Institute of Science and Technology, Kattankulathur Campus, Chennai 603203, India
[2]School of Computing, SASTRA Deemed University, Thanjavur 613401, India
[3]Department of Computer Science, Pondicherry University, Pondicherry 605014, India
[4]Symbiosis Centre for Applied Artificial Intelligence, Symbiosis International (Deemed University), Pune 412115, India
[5]UCSI University, Kuala Lumpur 56000, Malaysia
[6]School of Computer Science Engineering and Technology, Bennett University, Greater Noida, Uttar Pradesh 201310, India
[7]Center for Artificial Intelligence, Innopolis University, Innopolis, 420500 Republic of Tatarstan, Russia

Corresponding authors: Ketan Kotecha (head@scaai.siu.edu.in) and Subramaniyaswamy Vairavasundaram (vsubramaniyaswamy@gmail.com)

This work was supported by the Analytical Center for the Government of the Russian Federation under Agreement 70-2021-00143 dd. 01.11.2021 and Agreement IGK 000000D730321P5Q0002.

ABSTRACT The accurate and reliable derivation of the pap smear cell, which contains cytoplasm and nucleus regions, depends on the segmentation process employed in the cervical cancer detection mechanism. In this paper, an Improved Boykov's Graph Cut-based Conditional Random Fields and Superpixel imposed Semantic Segmentation Technique (IBGC-CRF-SPSST) is proposed for efficient cervical cancer detection. This proposed IBGC-CRF-SPSST embeds the complete benefits of constraint association among pixels and superpixel edge data for accurate determination of the nuclei and cytoplasmic boundaries so as to ensure efficient differentiation of the healthy and unhealthy cancer cells. Finally, the pixel-level forecasting potential of Conditional Random Fields is included for enhancing the degree of semantic-based segmentation accuracy to a predominant level. The experimental evaluated results of the proposed IBGC-CRF-SPSST aim to produce an accuracy of 99.78%, a mean processing time of 2.18sec, a precision of 96%, a sensitivity of 98.92%, and a specificity of 99.32% value which is determined to be excellent and on par with the existing detection techniques used for investigating cervical cancer.

INDEX TERMS Cervical pap smear cells, conditional random fields, fully convolution networks, simple linear iterative clustering, superpixel.

I. INTRODUCTION

Cancer that occurs in women classified in groups of all ages is the second most common type of cancer, which is considered to be cervical cancer [1]. The worldwide burden of cervical cancer cases and mortality, India alone contributes to about nearly 25.42% and 26.48% [1], respectively. Traditionally, cervical cancer is determined to be prevented by periodic screening in order to identify and treat the precancerous lesions in contrast to most kinds of cancers. Cervical cancer is preventable when the precursor lesions are identified and treated on par with most other kinds of cancer. The large scale of mortality and morbidity imposed by cervical cancer is completely unwarranted since the definite cause of cervical cancer is known, and the disease takes a long duration to develop after the initial infection that happens with high-risk Human Papillomavirus (HPV).

The associate editor coordinating the review of this manuscript and approving it for publication was Chao Tong.

The selection of appropriate cervical cancer detection techniques depends on the resources available, the essentiality of reliable biopsy samples, morbidity, and the cost of the screening method. The process of screening is considered to minimize the mortality and incidence of cervical cancer. However, the development of the Pap smear [1] test by George Papanicalou in the early 1950s improved the mortality of cervical cancer cases in developed countries. The manual screening test is used so that cervical cancer can be identified from the pap smear test, which is used in all clinical trials because the cytology-oriented screening has better results than any other screening method. However, the integration of automated computer-assisted techniques with Pap smear tests is confirmed to be highly suitable for the effective screening of cervical cancer.

In the last decades, uterus cancer has been considered a bog-standard disease in females that affects the genital tract featured by cervical cancer. Cancer which is declared the world's second most dangerous type of cancer is cervical cancer as per records of the World Health Organization (WHO) since it has caused 2 78, 608 deaths each year [2] including 4, 93, 246 women diagnosed with it in each and every year. Cervical cancer deaths happen most frequently among the age of women who lies between 15 and 44 years [3]. The cervix, called the uterine cervix, is located in the lowest portion of the uterus in women and connects the uterus body (endo-cervix) with the birth canal through the exo-cervix [4].

This cervical region is covered by squamous and glandular cells. Generally, cervical cancer occurs in the cervix core layer, [5] which is the intersection region between the uterus and the vagina through the infection of the Human Papilloma Virus (HPV). HPV is mostly transmitted during sexual intercourse from the male to the female. The two common categories of cervical cancer are Squamous cell carcinoma and adenocarcinoma. In the recent past, it has been identified that 80-90% [6] of cervical cancers are mainly due to squamous cell carcinoma, which originates at the junction part of the Exo and endo-cervix.

According to a survey by the Indian cancer society in 2017, women [7] who had more than three full-term pregnancies and younger women at their first full-time pregnancies are considered to have a higher degree [8] of risk of having cervical cancers. In this context, passive smoking, which dramatically damages the DNA present around the cervical cells, is also considered the second factor for getting the risk of cervical cancer, predominately for women. The most symptoms of cervical cancer are pelvic pain, post-menopausal bleeding [9], and abnormal vaginal bleeding. Women may also experience vaginal discharge with blood, bone fractures around the pelvic region, and urine leakage [10] in the advanced stages of cancer detection. The automated detection of cervical cancer techniques is considered to be highly suitable for the potential identification of abnormalities that occurs in the cell regions [11]. The graph cut-segmentation [12] schemes are considered to be an option for the accurate determination of abnormalities in the nuclei and cytoplasm boundaries [13]. However, the existing methods for [14] detection of cervical cancer techniques were determined to be unsuccessful in estimating nuclei and cytoplasm boundaries under the issue of irregular staining and contrast that are more common in Pap smear tests.

In this proposed paper, an Improved Boykov Graph Cut-based Conditional Random Fields and Super Pixel imposed Semantic Segmentation Technique (IBGC-CRF-SPSST) is used for efficient cervical cancer detection. This proposed IBGC-CRF-SPSST embeds the complete benefits of constraint association among pixels and superpixel edge data for accurate determination of the nuclei and cytoplasmic boundaries so as to ensure efficient identification of the healthy and unhealthy cancer pap smear cells. The proposed IBGC-CRF-SPSST also possesses the merit of facilitating superior boundary adherence and remarkable feature extraction potential where cervical cancer can be detected efficiently. The experimental results and investigation of the proposed HLC-BC-GCST approach are facilitated based on the classification accuracy, specificity, processing time per image, and sensitivity for quantifying its predominance over the benchmarked schemes of the literature.

Cervical cancer has become the second leading cause of female-based cancer-associated deaths after breast cancer, which accounts for the total cancer deaths of about 8% [15] in women and needs to be prevented by detecting precancerous cells at its early stage through the employment of precise screening tests. The Pap smear test is [16] considered to be the most successful screening method due to its potential to minimize the morbidity and mortality of cervical cancer. Cervical cancer-infected patients need to be treated at an early stage once the abnormal cells in the cervix are detected. Traditionally, a Pap smear test is based on microscopic observations [17] with the objective of identifying abnormalities in the morphological structure [18] of cells extracted from the cervical region. However, the microscopic observations in the Pap smear test may be inconsistent due to the subjective variation exhibited by various observers or clinicians. This subjective variation in [19] Pap smear tests necessitates the development and introduction of commercial devices and advanced technologies for the purpose of minimizing the false negative rate under the process of screening for cervical cancer. Further, a number of cervical cancer systems and approaches were propounded for detecting abnormalities through the enhancement of specimen preparation and screening in the dimension of visibility and machine-based detection. However, cost-effective automated screening methodologies that completely replace the judging process of visual systems are not available till now. In this context, [20] computer-aided image processing techniques are determined to be suitable for assisting in the artificial diagnosis of tumours or cell abnormalities. This computer-aided image processing technique is confirmed to minimize the impact of manual intervention and enhance the accuracy and efficiency of the screening process [21] From

TABLE 1. Related woks pros, cons, dataset and accuracy.

Author's name	Method	Pros	Cons	Dataset	Accuracy
Thanatip Chankong et. al, 2014 [23]	Fuzzy C Means Clustering Scheme	The cell based features are extracted by ANN for clear analysis	the boundary values and extraction of cells are not clear	LCH, ERUDIT	97.93%
Zhang, L et.al, 2014 [24]	Local and global graph cut approach	The enforcement of automation supported reading approaches that aids in minimizing the error code with increased more productivity	The concave points of nucleus are not clear	21 cervical images	93%
Teeyapan et.al, 2015 [25]	Support Vector Machine (SVM) classifier-based segmentation scheme	The images with high sensitivity rate are segmented	The training of images in svm is time consuming	PWS images	95%
Su Et.al, 2016 [26]	Dual level cascaded classifier-based segmentation approach	The elimination of false positive rate is achieved at a greater extent of 1.44%	There is an ambiguity in the level of the segmentation when overlapped.	Real time LCB images	93.2%
Kashyap et.al, 2016 [27]	k-Nearest Neighbor, SVM and Decision Tree for effective segmentation	A non-ordinal process is defined for non-parametric interferences for efficient segmentation	The constraints used for the segmentation process is not clear	Real time images	81.4%
Al-Kofahi et.al, 2015 [28]	Binary graph cut and alpha extensible graph cut	The seed points are detected automatically and the operation takes place with two mouse clicks	The process is semi-automated and needs manual attention	Vitro and vivo images	94%
Zhang, L et.al, 2015 [29]	A Graph Search-Based Improved Segmentation Technique (GSBIST)	The abnormal nucleic detected with graph search algorithm with optimal path	The cost of the nodes and the regional information of cells are not clear	Herlev with E stain	-
Bora, K et.al, 2017 [30]	Automated Cancer detection scheme for Pap Smear Methodology Improvement (ACPSMI) using Ripple Type I transform	The two level segmentation is effective in identifying the pre-cancerous lessions	The shape features and the determination of shape is not clear	Herlev	-
Zhang, J et.al, 2016 [31]	Graph Segmentation for Automated Cervical Cancer	The spatial relationship values helps to identify the cells where the	The proposed model is not clear with the stated values of the overlapping regions	Real time images from	-

TABLE 1. *(Continued.)* Related woks pros, cons, dataset and accuracy.

	detection (GSANCC)	regions are overlapped		The First Affiliated Hospital of Guangzhou University of Chinese Medicine.	
Anousouya Devi et.al, 2018 [32]	Neutrosophic Graph Cut-based Segmentation Scheme (NGCSS)	The extraction of overlapping boundaries is discussed	The cost of energy function and the defining process of the boundaries are not mentioned	herlev	99.42%
N. Dong et. al, 2020 [33]	Inception V3	The features are extracted and selected for classification makes the process effective with pixel classification	Time consumption is more for each iteration	-	98%
Venkatesan et.al, 2021 [34]	Convolution Neural network with VGG19 model	The CEYENET along with CNN architecture helps to identify cervical cancer cells automatically	The feature identification and selection are not discussed	-	92.3%
Anousouya Devi et.al, 2022 [35]	Hybrid Linear Iterative Clustering and Bayes classification-based Grab Cut Segmentation Technique (HLC-BC-GCST)	The identification of nucleus and cytoplasm regions are effectively segmented	The convergence of pixels during the clustering area makes the process time consuming	Herlev	99.51%

the past decades, computerized methods that include cell nuclei and cytoplasm detection, classification, and segmentation have been increasingly developed in the medical image analysis field.

At this juncture, segmentation and classification are the two important activities in the process of cervical cell screening, whether semi-automatic or more automatic screening methods are employed in the diagnosis process. In specific, the cell segmentation methods used in the semi-automatic or more automatic screening process are classified into pure nuclei segmentation and integrated nuclei and cytoplasm segmentation. A diversified number of techniques that include active contour, thresholding, level sets, and graph cuts are widely used for facilitating the process of predominant cell segmentation. In particular, Graph cut methods of cervical cancer detection techniques are identified to be potent in the accurate detection and delineation of cell nuclei, cell cytoplasm, or cells under varying staining conditions. These Graph cut methods are identified to resolve the issues of overlapping the disturbing objects existing in the direct vicinity of the process for the detection of cervical cancer.

However, these segmentation techniques based on Graph cut need to be computationally efficient since the complete screening [22] process needs to be executed in an acceptable time period. In addition, the cell nuclei and cytoplasm boundaries need to be accurately detected through the incorporation of a potentially strengthened graph cut-based segmentation scheme since they are quite significant in handling the influence of staining and contrast in Pap smear tests.

The contributions of this paper are stated below.

- A novel, Improved Boykov Graph Cut method (IBGC)is proposed to detect the boundaries of the nucleus and cytoplasm cells for cervical cancer detection.

- Semantic segmentation is used to identify the regions of the pixel between the nucleus and cytoplasm area, where a superpixel imposition method is introduced to accurately differentiate both areas.
- A VGG-based FCN model is proposed for feature extraction from the cervical cells in order to classify the area of the nucleus and cytoplasm cells.
- A CRF-based accurate boundary recovery is proposed for the classification of the boundary area and to identify whether it is a normal or cancerous cell.

The other sections of this proposed work are organized as follows: Section II presents significant review results on recent segmentation schemes based on Graph –cut propounded in the survey with the prediction of their outcome. Section III describes the series of steps included in the implementation of the proposed IBGC-CRF-SPSST method. Section IV briefs the outcomes of the experimental analysis organized for quantifying the proposed IBGC-CRF-SPSST approach potentiality over the existing cervical cancer schemes used for detection in the investigation. Section V summarizes the conclusion of the proposed IBGC-CRF-SPSST method and also discusses the future direction.

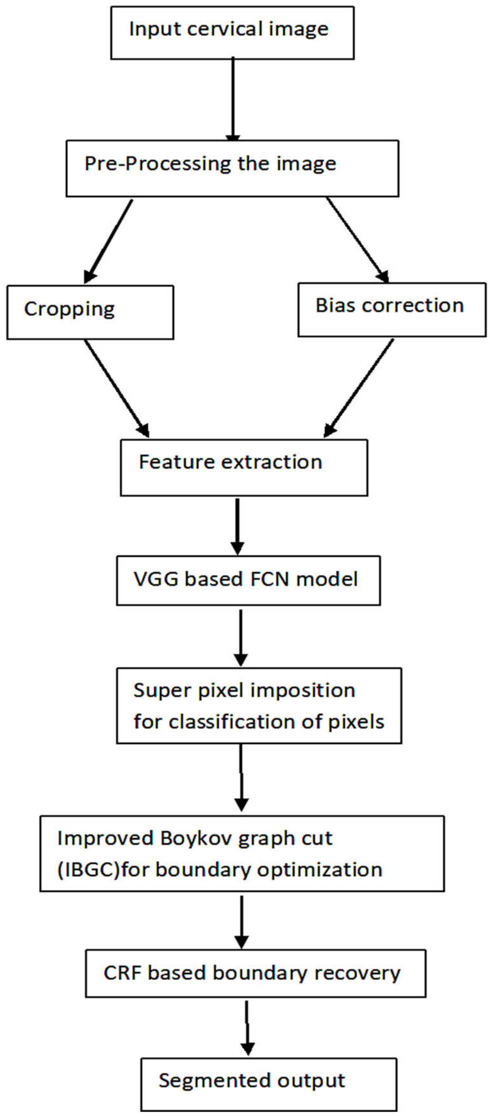

FIGURE 1. Proposed IBGC-CRF-SPSST Schemes implementation.

II. RELATED WORKS

This section briefs the works that focus on the detection of cervical cancer through an effective segmentation process and is presented with its merits and limitations in Table 1. Initially, the detection of cervical cancer approach using the Fuzzy C Means Clustering Scheme was contributed for segmenting individual pap smear cells into cytoplasm region and nucleus region [23]. Fuzzy C Means Clustering Scheme-based segmentation segmented four categories of cells that are derived from LCH and ERUDIT that are related to the low-grade squamous, normal squamous, carcinoma squamous cell, and high-grade squamous epithelial cells. The classification accuracy of this Fuzzy C Means segmentation method obtained 97.93% and 96.20% under the investigations done with the LCH and ERUDIT datasets. Then, a local and global graph cut approach was proposed for segmenting cervical cells through the enforcement of automation-supported reading approaches that aid in minimizing errors with increased productivity [24]. This local and global graph cut approach increased the rate of sensitivity during the processing of segmenting abnormal cervical cells through the integration of concave points that touches the touching nuclei. The classification accuracy and F-measure of this global and local cut were determined to be 93.21% and 88.46% under the investigations done with the Herlev dataset.

A Support Vector Machine (SVM) classifier-based scheme was proposed for effective segmentation derivation of the cell contours by considering morphology and textual features for classification [25].

Further, a dual-level cascaded classifier-based segmentation approach was proposed for classifying abnormal epithelial cells from normal epithelial cells from the pap smear cells derived from the cervix part [26]. This dual-level cascaded classifier-based segmentation approach aided in classifying morphology and texture features that are unique to each cell category. Then, a Machine Learning Classifier-based detection approach using the merits of k-Nearest Neighbor, SVM, and Decision Tree for effective segmentation and classification process was introduced [27].

Furthermore, an integrated Binary graph cut and alpha extensible graph cut were proposed predominant detection of cervical cancer cells of pap smear cells [28]. This integrated Graph cut utilized binary Graph cut for extracting foreground pixels, in which Gaussian and Laplace filter-based multiple scale filtering process is imposed. A Graph Search-Based Improved Segmentation Technique (GSBIST) of abnormal

pap smear nuclei was proposed for enhancing the degree of coarse features for accurate definition of cytoplasm and nuclei boundaries [29]. This construction of Graph cuts aided in determining the optimal path in a global manner through the enforcement of dynamic programming. An Automated Cancer detection scheme for Pap Smear Methodology Improvement (ACPSMI) using Ripple Type I transform proposed using texture, shape, and colour features using two-level of classification in cervical dysplasia [30]. Furthermore, Graph Segmentation for Automated Cervical Cancer detection (GSANCC) using graph cut locally was introduced for effective segmentation of cancer was considered for detection [31]. In addition, the authors of this paper also have contributed a Neutrosophic Graph Cut-based Segmentation Scheme (NGCSS) that aided in the predominant processing of cervical images for precise detection of cytoplasm and nuclei boundaries [32]. In this section, the most recent works that focus on the detection of cervical cancer through an effective segmentation process are presented with their merits and limitations.

III. PROPOSED WORK

The proposed IBGC-CRF-SPSST facilitates the process of predominant segmentation over the boundaries of the pap smear cells based on three potential steps viz., i) Initial Cropping and Bias Correction-based preprocessing of pap

smear images, ii) VCG-based FCN model for Feature Extraction, iii) Boundary Optimization using Boykov Graph Cuts through superpixel estimation, iv) CRF-based accurate boundary Recovery for effective semantic segmentation as depicted in Figure 1.

A. INITIAL CROPPING AND BIAS CORRECTION-BASED PREPROCESSING OF PAP SMEAR IMAGES

This process of Bias Correction-based preprocessing of cervical images is essential since the boundaries of crop

cervical cells are not well defined due to the noise and intensity inhomogeneity features inherent in them. Hence, the Bias Correction-based preprocessing step is incorporated to prevent the problem of noise and intensity inhomogeneity features for an effective and potential definition of the boundaries of cropped cervical cells. In addition, the false positive rate of the proposed IBGC-CRF-SPSST scheme is highly reduced through this preprocessing approach that focuses on improving the layer boundaries pertaining to the cytoplasm and nucleus boundaries of cervical pap smear cells.

B. VGG-BASED FCN MODEL FOR FEATURE EXTRACTION

The Visual Geometry Group (VGG) is used for image recognition of cervical cells, where a superpixel imposition method is introduced for the classification of pixels. The VGG 16 consists of 16 layers along with the FCN architecture. It classifies the images for the nucleus and cytoplasm regions. In this phase of the proposed IBGC-CRF-SPSST approach, the Fully Convolutional Networks (FCN) are utilized for achieving a predominant feature extraction process for achieving effective semantic segmentation. This FCN model of feature extraction, in contrast to the existing classic Convolutional Neural Network (CNN), is capable of considering arbitrary-size input images for generating related-sized output in order to produce related outputs. In specific, a model using VGG-based FCN is considered in this proposed IBGC-CRF-SPSST approach due to its excellent performance on par with the existing FCN structures. This VGG-based FCN is an enhanced version of the existing VGG-16, which is constructed by replacing the fully connected layers into convolution layers with the first five layers unchanged. This incorporated VGG-based FCN model aids in greatly minimizing the resolution of the resultant feature map after multiple rounds of pooling and convolution. The resolution of feature maps is minimized by 2,4,8, 16 and 32 iterations in the implementation procedure of the proposed IBGC-CRF-SPSST technique.

C. BOUNDARY OPTIMIZATION USING BOYKOV GRAPH CUTS THROUGH SUPERPIXEL ESTIMATION

This phase of the proposed IBGC-CRF-SPSST approach aids in effective superpixel estimation for boundary optimization through the formulation of the best Boykov Graph cut. This Boykov graph cut is a combinatorial graph cut that incurs cost depending on the number of edges derived from the modelled Graph. This Boykov graph cut consists of n-links and t-links, which need to be identified at the segmentation boundary in order to ensure the effectiveness of cervical Pap smear cells' cervical cells segmentation. Thus, the cost of n-links is utilized for efficient segmentation, such that segmentation with the desired balance between the regional and boundary characteristics is facilitated. This Boykov graph cut comprises an arbitrary collection of pixels or voxels with certain neighbouring systems represented through the collection of unordered pairs related to each neighbourhood element. Further, be the considered binary vector that consists of parameters set to in. Thus, the soft constraints that enforce the regional and boundary characteristics of the Boykov Graph cut-based cost function defined through Equation (1)

$$E(P_{(i)}) = k * R(P_{(i)}) + B(P_{(i)}) \tag{1}$$

With the regional and boundary term defined through Equations (2) and (3)

$$R\left(P_{(i)}\right) = \sum\nolimits_{a,b\in \boldsymbol{K}} R(P_{(i)}) \tag{2}$$

$$R\left(P_{(i)}\right) = \sum_{a,b\epsilon K} RP_{(i)} * \xi_{a\neq b} \tag{3}$$

where ξ indicate the relative significance between the regional and boundary characteristics. Furthermore, the boundary term $B(P_{(i)})$ must be represented as the penalty cost based on Equation (4). p(j) is the edge between other vertices and is called edges.

$$B\left(P_{(i)-(a,b)}\right) = \frac{1}{dis(a,b)} * \exp(-\frac{\left|\left|I_{p(i)} - I_{p(j)}\right|\right|^2}{2\sigma^2}) \tag{4}$$

This boundary term $B(P_{(i)})$ embeds the penalty cost that is incurred in representing the boundary features of the segmented image 'I' with its positive value. This penalty cost depicted in Equation (4) highlights the discontinuity existing between two pixels, a and b investigated for the classification process. If the value of the penalty cost $B(P_{(i)})$ seems to diverge away from zero, then the pixels are with similar intensity and highly optimized. In contrast, the intensity of pixels is different and non-optimized when the value of the penalty cost $B(P_{(i)})$ converges toward zero. This estimation of penalty cost in the proposed IBGC-CRF-SPSST approach is achieved through the benefits [33] of Laplacian zero crossing. This method of Laplacian zero-crossing aided in estimating the superpixel that guides the boundary optimization process. A superpixel is considered a collection of pixels that are similar in texture, colour, and location. Thus, the superpixel possesses a distinct value of visual importance with the generalized pixels, even though the superpixel does not possess quantifiable semantic information.

D. CRF-BASED EFFECTIVE SEMANTIC SEGMENTATION FOR ACCURATE BOUNDARY RECOVERY

In this phase of the CRF-based accurate Boundary Recovery process, it is essential for enhancing the segmentation accuracy of weak edge, thin structure, and complex superposition of the boundaries of the nucleus and cytoplasm in order to facilitate an effective cervical cancer detection process. Hence, the model of CRF is utilized in this phase of the proposed IBGC-CRF-SPSST approach for effectively recovering the boundaries of the nucleus and cytoplasm for further Optimization in order to ensure maximum accuracy. The Boykov Graph cuts $G = (V, E)$ with pixel-associated labels are modelled after the derivation of global observations that are generally extracted from the input images considered for the detection process. This derivation of global observations is represented as the input images that consist of pixels. Let 'R' be the vector modelled through the utilization of random variables with 'R_1, R_2, …R_N' representing the label set to each pixel 'i'. In this context, a CRF follows the Gibbs distribution with pair represented through Equation (5)

$$P(R = r/I) = \frac{1}{G(I)} e^{-E(r|I)} \tag{5}$$

where G(I) is the partition function with the Gibbs energy E(r)of the pixel-associated labels $r \in L^N$, further, the CRF model that is fully connected is incorporated using Equation (6).

$$IE\ (r) = \sum\nolimits_i w_i\ (r_i) + \sum\nolimits_{i,j} \delta(r_i, r_j) \tag{6}$$

Which $w_i\ (r_i)\ , \delta\ (r_i, r_j)$ corresponds to the pairwise and unary potentials for representing the cost and pixel probability associated with each pixel 'i' considering the label at a similar point in time. The initial part of the formula with respect to Gibbs energy is considered with the ri because it is the initial start of the vertex and edges from where the consecutive flow of the Graph takes place to the next. The unary potential used in this proposed IBGC-CRF-SPSST approach is considered as the significant boundary optimization feature map in order to enhance the importance of the CRF model. Furthermore, the pairwise potential aid in modelling the association between neighbouring pixels based on colour similarity weighting. This pairwise potential is enforced based on Equation (7)

$$\omega_i\ (r_i, r_j) = \alpha\ (r_i, r_j)\ [w_1\beta_2 + w_1\beta_2] \tag{7}$$

With β_1 and β_2 represented through Equations (8) and (9), respectively

$$\beta_1 = \exp(-\frac{||P_{p(i)} - P_{p(j)}||^2}{2\sigma_\lambda^2}) - \frac{||I_{p(i)} - I_{p(j)}||^2}{2\sigma_\partial^2}) \tag{8}$$

$$\beta_2 = \exp(-\frac{||P_{p(i)} - P_{p(j)}||^2}{2\sigma_\gamma^2}) \tag{9}$$

At this juncture, β_1 depends on the pixel colour intensities and pixel positions, while β_2 highly dependent only on the pixel position ($P_{(p(i))}, P_{(p(j))}$) highlights pixel positions and ($I_{(p(i))}, I_{(p(j))}$) representing colour vectors). This proposed IBGC-CRF-SPSST $\alpha(r_{i,} r_j)$ approach is assigned to 1 under the condition $r_{i \neq} r_j$ or 0 under the condition $r_{i=} r_j$as per the Potts model. In addition, the neighbouring pixels set to each individual label of the image pixels need to be penalized, with each similar pixel motivated for assigning a similar label that deviates in terms of pixel distance set to different labels derived from the input pap smear cells used for cervical cancer detection.

IV. EXPERIMENTAL ANALYSIS AND INVESTIGATIONS REPORTS

The proposed scheme IBGC-CRF-SPSST is implemented using MATLAB 2018 to compare it with the benchmarked NGCSS, GSANCC, ACPSMI, and GSBIST schemes by incorporating the Herlev dataset. This utilized the Herlev dataset comprised of cervical pap smear [34] cells, as shown in Figure 2 of 917 images which were collected and also predominantly stored over a number of years in the University of Herlev Hospital.

The utilized dataset of Herlev consists of seven types of infected pap smear cells which relate to the columnar epithelium, superficial epithelium, columnar epithelium, mild dysplasia, intermediate epithelium, severe dysplasia, and moderate epithelium. In particular, the number of severe dysplasia, carcinoma, mild dysplasia, and moderate dysplasia-infected cervical pap smear cells are 192, 146, 183, and 150, respectively, as shown in Figure 3 and Figure 4.

Further, Figure 5 and Figure 6 portray the predominance of the IBGC-CRF-SPSST proposed scheme compared with the benchmarked NGCSS, GSANCC, ACPSMI, and GSBIST approaches using classification accuracy and specificity by increasing the number of rounds under implementation [35]. The accuracy of the classification by the proposed IBGC-CRF-SPSST method is estimated at 99.78%, which is an

Algorithm 1 IBGC CRF SPSST

*1:**procedure** IBGC CRF SPSST(cervicalSmearImage)*
2: biasCorrectedImage ← performBiasCorrection(cervicalSmearImage)
3: croppedImage ← crop(biasCorrectedImage)
Select the predominant features from VGG16 and FCN 32
4: features ← generateFeatureMap (vgg16, imageToVectorcroppedImage, ′ conv5_3′)
5: minimizedFeatures ← getMinimizedFeatures(fcn32, features)
Boundary Optimization with Boykov Cut
6: H, W ← dim(cervicalSmearImage)
7: nodeNum, edgeNum, edgeStruct ← createGraph(H, W)
8: P_k = calculateUnaryPotentials(minimizedFeatures)
9: r ← calculateRegionVector(initialSegmentation)
10: pairwisePotentials ← calculatePairwisePotentials(croppedImage)
11: optimizedSegmentation ← GraphCut(nodeNum, edgeNum, Pk, r, pairwisePotentials)
CRF based boundary recovery
12: while true do
13: crfLabels ← associatePixelsWithCRF(croppedImage, optimizedSegmentation)
14: r ← calculateRegionV ectorCRF(crfLabels)
15: $r_1, r_2 \leftarrow \sum_{\mathbf{i-1}}^{\mathbf{len(r)}} r\,[i] == \mathbf{0}, \sum_{\mathbf{i-1}}^{\mathbf{len(r)}} r\,[i] == \mathbf{1}$
16: if $r_1 == 0$ & $r_2 == 0$ then continue
17: else if $r_1 = r_2$ then
18: boundaryValues ← extractBoundaryValues(crfLabels)
19: semanticSegmentation ← doSemanticSegmentation (inputImage, boundaryValues)
20: break
21: end if
22: end while
23: end procedure

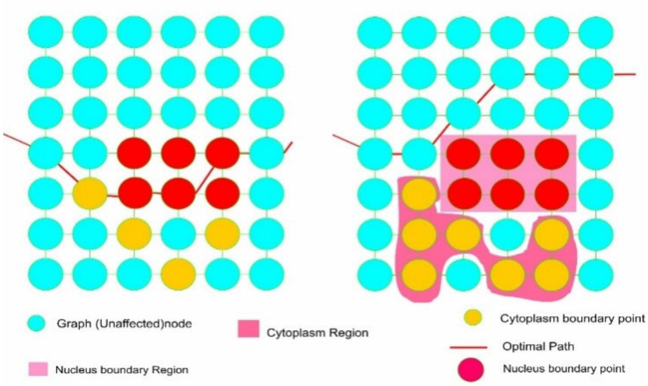

FIGURE 2. Graphical Representation of cell structure.

improvement of 1.73%, 2.11%, 2.85%, and 3.02% compared to the baseline NGCSS, GSANCC, ACPSMI and GSBIST approaches used for comparison. The specificity

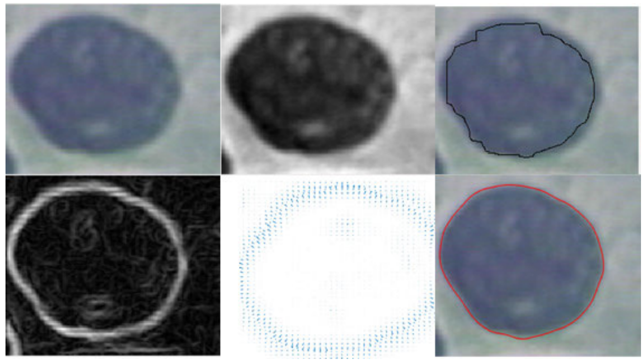

FIGURE 3. (From left to right represents the Herlev dataset consisting of mild carcinoma cells where the initial preprocessing is applied detection of the nucleus and cytoplasm with semantic segmentation where the first row describes the initial input image, preprocessed image and bias-corrected image. The second row represents the boundary detection of cytoplasm and nucleus region using *IBGC_CRF_SPSST*.)

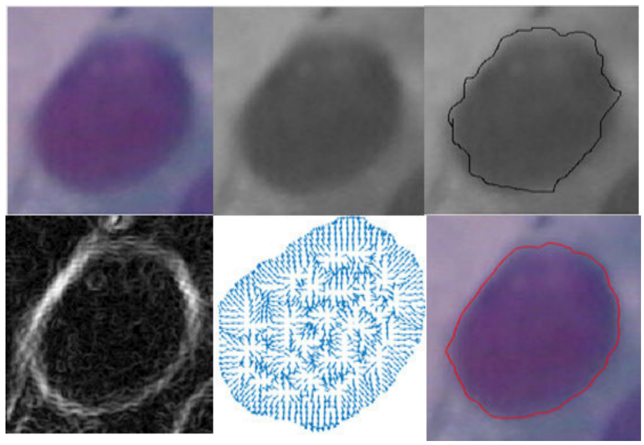

FIGURE 4. (From left to right represents the Herlev dataset consisting of severe carcinoma cells where the initial preprocessing is applied detection of the nucleus and cytoplasm with semantic segmentation where the first row describes the initial input image, preprocessed image and bias-corrected image. The second row represents the boundary detection of cytoplasm and nucleus region using *IBGC_CRF_SPSST*).

of the IBGC-CRF-SPSST proposed scheme is estimated at 99.32%, which is an improvement of 2.12%, 2.34%, 2.93%, and 3.52% compared to the baseline NGCSS, GSANCC, ACPSMI and GSBIST approaches used for investigation.

Furthermore, Figures 7 and 8 exemplars the predominance of the IBGC-CRF-SPSST proposed scheme compared with the benchmarked NGCSS, GSANCC, ACPSMI, and GSBIST approaches using sensitivity and mean processing time by increasing the number of rounds under implementation. The sensitivity of the proposed IBGC-CRF-SPSST scheme is estimated at 99.78%, which is an improvement of 1.92%, 2.23%, 2.93%, and 3.51% compared to the baseline. The time taken to process a single image of the proposed IBGC-CRF-SPSST is estimated to be 2.18 seconds. This can be minimized by 0.14 seconds, 0.43 seconds, 0.60 seconds, and 0.67 seconds excellent to the baseline.

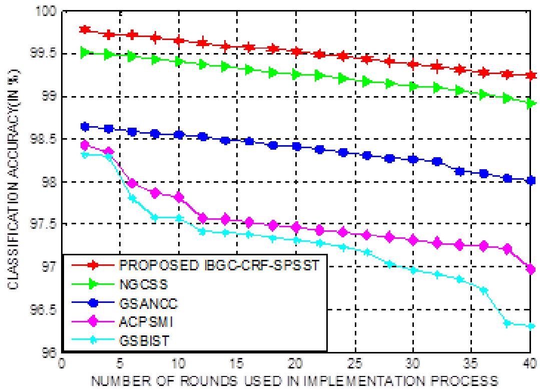

FIGURE 5. Classification accuracy-proposed IBGC-CRF-SPSST scheme.

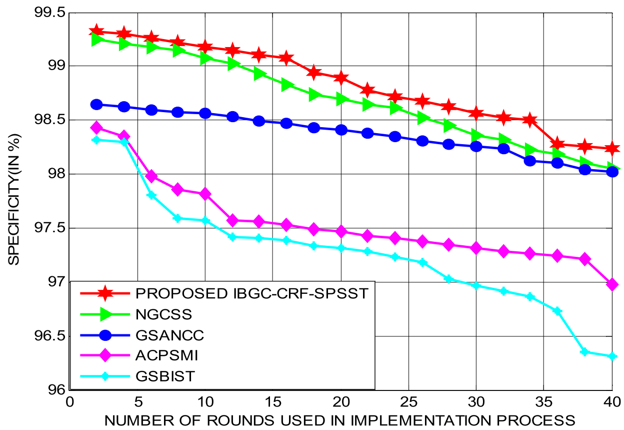

FIGURE 6. Specificity-proposed IB GC-CRF-SPSST scheme-varying.

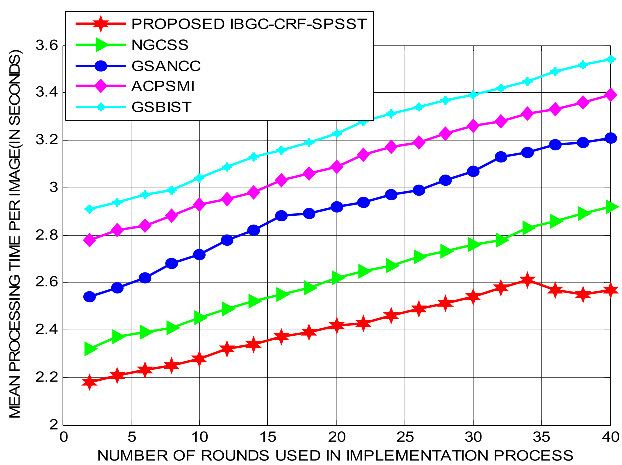

FIGURE 7. Sensitivity-proposed IBGC-CRF-SPSST scheme-varying rounds.

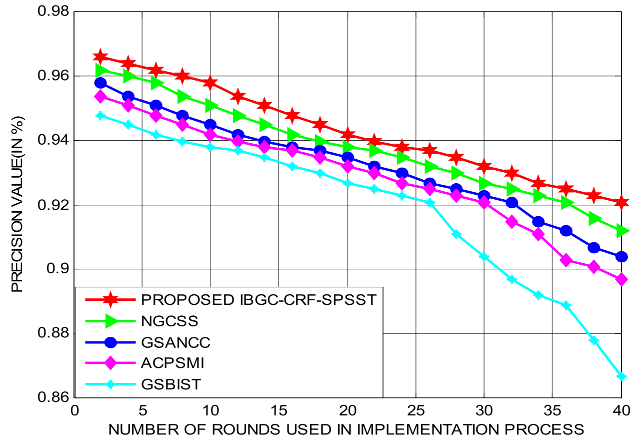

FIGURE 8. Mean processing time -proposed IBGC-CRF-SPSST scheme-varying rounds.

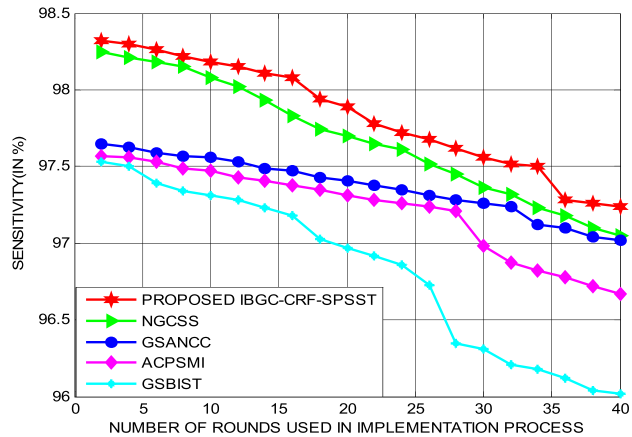

FIGURE 9. Precision value-proposed IBGC-CRF-SPSST scheme.

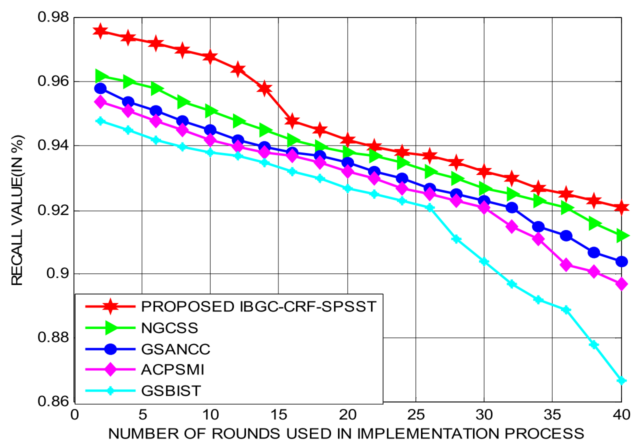

FIGURE 10. Recall value-proposed IBGC-CRF-SPSST scheme.

In addition, Figures 9 and 10 unveils the potential of the proposed IBGC-CRF-SPSST scheme compared with the benchmarked NGCSS, GSANCC, ACPSMI, and GSBIST approaches. The precision of the proposed IBGC-CRF-SPSST scheme is estimated at 0.963, which is an improvement of 2.13%, 2.83%, 3.12%, and 3.57% compared to the baseline. The recall value of the IBGC-CRF-SPSST proposed scheme is estimated at 0.974, which is an improvement of 2.35%, 2.87%, 3.26%, and 3.97% compared to the baseline techniques.

TABLE 2. Accuracy and specificity of the proposed IBGC-CRF-SPSST.

First Author and Year	Classification accuracy (in %)	Specificity (in %)
IBGC-CRF-SPSST proposed	**99.78**	**99.32**
Chankong, 2014 [23]	98.11	96.12
Zhang, 2015 [24]	98.31	96.71
Teeyapan, 2015 [25]	97.56	97.31
Su, 2016 [26]	98.07	97.46
Kashyap, 2016 [27]	98.12	98.11
Zhang,2015 [28]	98.32	98.36
Bora, 2017 [29]	98.12	99.04
Zhang, 2017 [30]	99.21	99.16
Anousouya Devi, 2018 [31]	99.51	99.25
Venkatesan ,2021[32]	73.3%	71.15
Lavanya ,2021[33]	94.7	92.34
Jia ,2022[34]	90.80	89.23

TABLE 3. Sensitivity and the proposed IBGC-CRF-SPSSTmean processing time.

First Author and Year	Sensitivity (in %)	The mean time for processing (in a sec)
Proposed IBGC-CRF-SPSST	**98.92**	**2.18**
Chankong, 2014 [23]	96.13	3.14
Zhang, 2015 [24]	96.54	3.11
Teeyapan, 2015 [25]	96.93	3.04
Su, 2016 [26]	97.11	3.01
Kashyap, 2016 [27]	97.32	2.98
Zhang,2015 [28]	98.11	2.85
Bora, 2017 [29]	98.23	2.78
Zhang, 2017 [30]	98.34	2.73
Anousouya Devi, 2018 [31]	98.52	2.32
Venkatesan ,2021[32]	97.93	2.67
Lavanya ,2021[33]	96.24	2.85
Jia ,2022[34]	96.78	2.78

'The forthcoming Tables 2, 3, and 4 portray the predominance of the proposed IBGC-CRF-SPSST over the reviewed detection schemes of cervical cancer presented under related work using the evaluation metrics of classification accuracy, specificity, sensitivity, mean processing time, recall value, and precision. The results of the proposed IBGC-CRF-SPSST quantified in Table 2 is determined to enhance the accuracy and specificity by a significant margin of 3.32% and 4.82%, superior to the reviewed approaches presented in this related work section.

Similarly, the results of the proposed IBGC-CRF-SPSST quantified in Table 3 prove the enhancement rate of sensitivity and mean processing time by 3.12% and 0.14 seconds, remarkable benchmarked detection approaches of cervical cancer considered for analysis. In addition, results of the

TABLE 4. Precision and recall value of the proposed IBGC-CRF-SPSST.

First Author and Year	Precision	Recall Value
Proposed IBGC-CRF-SPSST	**0.96 ± 0.13**	**0.97 ± 0.06**
Chankong, 2014 [23]	0.94 ± 0.11	0.94 ± 0.04
Zhang, 2015 [24]	0.95 ± 0.18	0.94 ± 0.12
Teeyapan, 2015 [25]	0.95 ± 0.04	0.95 ± 0.12
Su, 2016 [26]	0.95 ± 0.12	0.95 ± 0.13
Kashyap, 2016 [27]	0.95 ± 0.18	0.95 ± 0.06
Zhang,2015 [28]	0.95 ± 0.13	0.96 ± 0.05
Bora, 2017 [29]	0.95 ± 0.09	0.96 ± 0.18
Zhang, 2017 [30]	0.96 ± 0.13	0.96 ± 0.21
Anousouya Devi, 2018 [31]	0.96 ± 0.07	0.97 ± 0.01
Venkatesan ,2021[32]	0.94 ± 0.11	0.97 ± 0.81
Lavanya ,2021[33]	0.96 ± 0.27	0.95 ± 0.18
Jia ,2022[34]	0.94 ± 0.35	0.963 ± 0.26

proposed IBGC-CRF-SPSST quantified in Table 4 inferred an improvement rate of precision and recall by an excellent margin of 4.21% and 3.94% over the benchmarked cervical cancer detection approaches considered for analysis.

V. CONCLUSION

In general, Pap smear tests are inevitable for the potential screening of precancerous and advanced cancerous cervical cells to identify their abnormalities. Computer-assisted Pap smear cell segmentation techniques are identified to be suitable for the precise derivation of cytoplasm and nuclei boundaries in order to confirm abnormalities in cervical cells extracted from women's cervix. However, most of the Pap smear test integrated and computer-automated segmentation schemes are not able to facilitate predominant performance in regular extraction of cytoplasm and nuclei boundaries due to the issue of a hazy and inconsistent staining process. The proposed IBGC-CRF-SPSST was presented for facilitating efficient cervical cancer detection performed by the semantic web where the cervical pap smear cells detections are performed by the predominant definition of cytoplasm and nuclei boundaries. The experimental results of the proposed IBGC-CRF-SPSST are estimated to be improved by 15% in mean accuracy, 18% in mean processing time, 13% in mean precision, 16% in mean sensitivity, and 19% in average specificity value compared to the cervical cancer detection methods for investigation. Future enhancements of the proposed research can be carried out to enhance and address the detection of cervical cancer with sustained classification accuracy, even when the cervical cells contain a double nucleus. The registration process of high and low magnification images can be included in the proposed cervical cancer detection methods for improving the features of the cell that pertain to texture patterns of the nucleus region. The input Pap smear cell images, may be partitioned into blocks, and each individual block may be processed in a parallel way to maintain significant processing time. The Graph cut segmentation process of the proposed research can be enhanced using deep learning-based semantic segmentation techniques for reliable cytoplasm and nuclei boundary estimation in detection.

REFERENCES

[1] *HPV Information Centre Secretariat, Institute Català d'Oncologia, Avda. Gran Via de l'Hospitalet, 199-203 08908*, L'Hospitalet del Llobregat, Barcelona Spain, 2019.

[2] *A Cancer Journal for Clinicians*, Amer. Cancer Soc. J., CA, USA, 2019.

[3] *National Cancer Institute on Cervical Cancer Screening Process*. Accessed: Apr. 27, 2023. [Online]. Available: https://www.cancer.gov/types/cervical/patient/cervical-screening-pdq

[4] K. Li, Z. Lu, W. Liu, and J. Yin, "Cytoplasm and nucleus segmentation in cervical smear images using radiating GVF snake," *Pattern Recognit.*, vol. 45, no. 4, pp. 1255–1264, Apr. 2012.

[5] J.-W. Zhang, S.-S. Zhang, G.-H. Yang, D.-C. Huang, L. Zhu, and D.-F. Gao, "Adaptive segmentation of cervical smear image based on GVF snake model," in *Proc. Int. Conf. Mach. Learn. Cybern.*, vol. 2, Jul. 2013, pp. 890–895.

[6] R. R. Kumar, V. A. Kumar, P. N. S. Kumar, S. Sudhamony, and R. Ravindrakumar, "Detection and removal of artifacts in cervical cytology images using support vector machine," in *Proc. IEEE Int. Symp. IT Med. Educ.*, Dec. 2011, pp. 717–721, doi: 10.1109/ITiME.2011.6130760.

[7] Z. Xue, L. R. Long, S. Antani, and G. R. Thoma, "Automatic extraction of mosaic patterns in uterine cervix images," in *Proc. IEEE 23rd Int. Symp. Comput.-Based Med. Syst. (CBMS)*, Oct. 2010, pp. 273–278, doi: 10.1109/CBMS.2010.6042655.

[8] Y. Wang, D. Crookes, O. S. Eldin, S. Wang, P. Hamilton, and J. Diamond, "Assisted diagnosis of cervical intraepithelial neoplasia (CIN)," *IEEE J. Sel. Topics Signal Process.*, vol. 3, no. 1, pp. 112–121, Feb. 2009, doi: 10.1109/JSTSP.2008.2011157.

[9] Y.-F. Chen, P.-C. Huang, K.-C. Lin, H.-H. Lin, L.-E. Wang, C.-C. Cheng, T.-P. Chen, Y.-K. Chan, and J. Y. Chiang, "Semi-automatic segmentation and classification of pap smear cells," *IEEE J. Biomed. Health Informat.*, vol. 18, no. 1, pp. 94–108, Jan. 2014, doi: 10.1109/JBHI.2013.2250984.

[10] H. Sahli and C. Mihai, "A hybrid approach for pap-smear cell nucleus," in *Proc. Mexican Conf. Pattern Recognit.*, 20211, pp. 174–183.

[11] C. Arteta, V. Lempitsky, J. A. Noble, and A. Zisserman, "Learning to detect cells using non-overlapping extremal regions," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.*, 2012, pp. 348–356.

[12] M. Orozco-Monteagudo, A., Taboada-Crispi, and H. Sahli, "Pap-smear cell nucleus extraction by using morphological watershed," in *V Latin American Congress on Biomedical Engineering CLAIB*. 2011, pp. 17–24.

[13] G. Naghdy, M. Ros, and C. Todd, "Morphological characteristics of cervical cells for cervical cancer diagnosis," in *Proc. 2nd Int. Congr. Comput. Appl. Comput. Sci.*, 2012, vol. 2, no. 1, pp. 235–243.

[14] S. Kaaviya, V. Saranyadevi, and M. Nirmala, "PAP smear image analysis for cervical cancer detection," in *Proc. IEEE Int. Conf. Eng. Technol. (ICETECH)*, Mar. 2015, pp. 1–4.

[15] M. A. Devi, S. Ravi, J. Vaishnavi, and S. Punitha, "Bio-inspired model classification of squamous cell carcinoma in cervical cancer using SVM," in *Proc. Int. Symp. Intell. Syst. Technol. Appl.*, 2016, vol. 3, no. 1, pp. 585–596.

[16] F. Cao, S. Chen, and L. Zeng, "New abnormal cervical cell detection method of multi-spectral pap smears," *Wuhan Univ. J. Natural Sci.*, vol. 12, no. 3, pp. 476–480, May 2007.

[17] R. U. Deepak, "Computer assisted pap smear analyser for cervical cancer screening using quantitative microscopy," *J. Cytology Histol.*, vol. 3, pp. 56–65, Jan. 2015.

[18] M. Sokouti and B. Sokouti, "Artificial intelligent systems application in cervical cancer pathological cell image classification systems—A review," *Biomed. Eng., Appl., Basis Commun.*, vol. 28, no. 2, Apr. 2016, Art. no. 1630001.

[19] S. R. Taghanaki and R. Javidan, "A fast block-based approach for segmentation and classification of textural images using contourlet transform and SVM," *Int. J. Signal Imag. Syst. Eng.*, vol. 7, no. 4, p. 211, 2014.

[20] A. Amole and B. S. Osalusi, "Textural analysis of pap smears images for k-NN and SVM based cervical cancer classification system," *Adv. Sci., Technol. Eng. Syst. J.*, vol. 3, no. 4, pp. 218–223, Aug. 2018.

[21] L. Zhang, L. Lu, I. Nogues, R. M. Summers, S. Liu, and J. Yao, "DeepPap: Deep convolutional networks for cervical cell classification," *IEEE J. Biomed. Health Informat.*, vol. 21, no. 6, pp. 1633–1643, Nov. 2017.

[22] O. U. N. Jith, K. K. Harinarayanan, S. Gautam, A. Bhavsar, and A. K. Sao, "DeepCerv: Deep neural network for segmentation free robust cervical cell classification," *Comput. Pathol. Ophthalmic Med. Image Anal.*, vol. 3, no. 3, pp. 86–94, 2018.

[23] T. Chankong, N. Theera-Umpon, and S. Auephanwiriyakul, "Automatic cervical cell segmentation and classification in pap smears," *Comput. Methods Programs Biomed.*, vol. 113, no. 2, pp. 539–556, Feb. 2014.

[24] L. Zhang, H. Kong, C. T. Chin, S. Liu, Z. Chen, T. Wang, and S. Chen, "Segmentation of cytoplasm and nuclei of abnormal cells in cervical cytology using global and local graph cuts," *Computerized Med. Imag. Graph.*, vol. 38, no. 5, pp. 369–380, Jul. 2014.

[25] K. Teeyapan, N. Theera-Umpon, and S. Auephanwiriyakul, "Application of support vector based methods for cervical cancer cell classification," in *Proc. IEEE Int. Conf. Control Syst., Comput. Eng. (ICCSCE)*, Nov. 2015, pp. 514–519.

[26] J. Su, X. Xu, Y. He, and J. Song, "Automatic detection of cervical cancer cells by a two-level cascade classification system," *Anal. Cellular Pathol.*, vol. 2016, pp. 1–11, 2016.

[27] D. Kashyap, A. Somani, J. Shekhar, A. Bhan, M. K. Dutta, R. Burget, and K. Riha, "Cervical cancer detection and classification using independent level sets and multi SVMs," in *Proc. 39th Int. Conf. Telecommun. Signal Process. (TSP)*, Jun. 2016, pp. 523–528.

[28] L. Zhang, S. Liu, T. Wang, S. Chen, and M. Sonka, "Improved segmentation of abnormal cervical nuclei using a graph-search-based approach," *Med. Imag., Digit. Pathol.*, vol. 13, no. 1, pp. 45–62, 2015.

[29] K. Bora, M. Chowdhury, L. B. Mahanta, M. K. Kundu, and A. K. Das, "Automated classification of pap smear images to detect cervical dysplasia," *Comput. Methods Programs Biomed.*, vol. 138, pp. 31–47, Jan. 2017.

[30] J. Zhang, Z. Hu, G. Han, and X. He, "Segmentation of overlapping cells in cervical smears based on spatial relationship and overlapping translucency light transmission model," *Pattern Recognit.*, vol. 60, pp. 286–295, Dec. 2016.

[31] M. A. Devi, J. I. Sheeba, and K. S. Joseph, "Neutrosophic Graph cut-based segmentation scheme for efficient cervical cancer detection," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 1, no. 1, pp. 56–67, 2018.

[32] V. Chandran, M. G. Sumithra, A. Karthick, T. George, M. Deivakani, B. Elakkiya, U. Subramaniam, and S. Manoharan, "Diagnosis of cervical cancer based on ensemble deep learning network using colposcopy images," *BioMed Res. Int.*, vol. 2021, pp. 1–15, May 2021.

[33] N. L. Devi and P. Thirumurugan, "Cervical cancer classification from pap smear images using modified fuzzy C means, PCA, and KNN," *IETE J. Res.*, vol. 68, no. 3, pp. 1591–1598, May 2022.

[34] D. Jia, Z. He, C. Zhang, W. Yin, N. Wu, and Z. Li, "Detection of cervical cancer cells in complex situation based on improved YOLOv3 network," *Multimedia Tools Appl.*, vol. 81, no. 6, pp. 8939–8961, Mar. 2022.

[35] A. D. Magaraja, E. Rajapackiyam, V. Kanagaraj, S. J. Kanagaraj, K. Kotecha, S. Vairavasundaram, M. Mehta, and V. Palade, "A hybrid linear iterative clustering and Bayes classification-based GrabCut segmentation scheme for dynamic detection of cervical cancer," *Appl. Sci.*, vol. 12, no. 20, p. 10522, Oct. 2022.

M. ANOUSOUYA DEVI received the Ph.D. degree in computer science and engineering from Pondicherry University. She is currently an Assistant Professor with the Department of Computational Intelligence, SRM University, Katangalathur Campus. Her research interests include medical image processing, machine learning, and computer vision.

R. EZHILARASIE received the B.E. degree from Bharathidasan University, the M.Tech. degree from SASTRA Deemed University, and the Ph.D. degree in IoT and edge computing, in 2020. She is currently an Assistant Professor with the School of Computing, SASTRA Deemed University. Her research interests include the IoT, edge computing, embedded systems, and compiler engineering.

K. SURESH JOSEPH received the master's degree in computer science and engineering and the Ph.D. degree in information and communication engineering from Anna University, Chennai. He is currently an Associate Professor with the Department of Computer Science, School of Engineering Technology.

KETAN KOTECHA is currently an Administrator and a Teacher with the Symbiosis Centre for Applied Artificial Intelligence, Symbiosis International (Deemed University), Pune, India. His research interests include artificial intelligence, computer algorithms, machine learning, and deep learning. He has expertise and experience in cutting-edge research and projects in AI and deep learning for the last 25 years. He has published more than 200 articles widely in several excellent peer-reviewed journals on various topics ranging from cutting-edge AI, education policies, teaching-learning practices, and AI for all. He was a recipient of the two SPARC projects worth INR 166 lakhs from the MHRD Government of India in AI in collaboration with Arizona State University, USA, and The University of Queensland, Australia. He was also a recipient of numerous prestigious awards, such as the Erasmus + Faculty Mobility Grant to Poland, the DUO-India Professors Fellowship for research in responsible AI in collaboration with Brunel University, U.K., the LEAP Grant with Cambridge University, U.K., the UKIERI Grant with Aston University, U.K., and a Grant from the Royal Academy of Engineering, U.K., under Newton Bhabha Fund. He has published three patents and delivered keynote speeches at various national and international forums, including with the Machine Intelligence Laboratory, USA, IIT Bombay, under the World Bank Project, the International Indian Science Festival organized by the Department of Science and Technology, the Government of India, and many more. He is an Associate Editor of the IEEE ACCESS journal.

AJITH ABRAHAM (Senior Member, IEEE) received the B.Tech. degree in electrical and electronic engineering from the University of Calicut, in 1990, the Master of Science degree from Nanyang Technological University, Singapore, in 1998, and Ph.D. degree in computer science from Monash University, Melbourne, Australia, in 2001. He is currently the Pro-Vice Chancellor of Bennett University, New Delhi responsible for the University's Research and International Academic Affairs. Prior to this, he was the Dean of the Faculty of Computing and Mathematical Sciences, FLAME University, Pune, and the founding Director of the Machine Intelligence Research Laboratories (MIR Laboratories), USA, a Not-for-Profit Scientific Network for Innovation and Research Excellence connecting industry and academia. He also held two international university professorial appointments, including a Professor in artificial intelligence with Innopolis University, Russia, and the Yayasan Tun Ismail Mohamed Ali Professorial Chair of Artificial Intelligence with UCSI, Malaysia. He works in a multi-disciplinary environment, and he has authored/coauthored more than 1,400 research publications out of which there are more than 100 books covering various aspects of computer science. One of his books was translated to Japanese and a few other articles were translated to Russian and Chinese. He has more than 53,000 academic citations (H-index of more than 108 as per Google scholar). He has given more than 150 plenary lectures and conference tutorials (in more than 20 countries). He was the Chair of IEEE Systems Man and Cybernetics Society Technical Committee on Soft Computing (which has over more than 200 members) (2008–2021). He served as a Distinguished Lecturer of IEEE Computer Society representing Europe (2011–2013). He was the Editor-in-Chief of *Engineering Applications of Artificial Intelligence* (EAAI) (2016–2021) and serves/served on the editorial board of over 15 international journals indexed by Thomson ISI.

SUBRAMANIYASWAMY VAIRAVASUNDARAM received the Ph.D. degree from Anna University, in 2013. He continued the extension work with the Department of Science and Technology support as a Young Scientist Award Holder. He is currently a Professor with the School of Computing, SASTRA Deemed University, Thanjavur, India. With the experience of more than 18 years as an academician and a researcher, he has contributed more than 200 papers and chapters for many high-quality technology journals and books that are being edited by internationally acclaimed professors and professionals. He has received government funded and consultancy projects from DST-SERB, ICSSR—IMPRESS, MHRD, TVS MOTORS, MHI, and SERB—MATRICS. He is on the reviewer board of several international journals and he has been a program committee member for several international/national conferences and workshops. He also serves as a guest editor for various special issues of reputed international journals. He is serving as a research supervisor and successfully guided five research scholars, and he is also a visiting expert to various universities in India and Abroad. His research interests include recommender systems, the Internet of Things, artificial intelligence, machine learning, and big data analytics.