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Detection of Cervical Cancer using the Image Analysis Algorithms

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ABSTRACT

Cervical cancer affects the cervix region which is the lower part of the uterus of women that opens into the vagina which does not leads to any symptom for early stage detection. Pap smear test is the manual screening method of cervical cancer which leads high false positive rates due to human error. The manual screening method is expensive and only few experienced pathologist are available to diagnosis this screening test. The segmentation of Pap smear slides is very challenging due to the irregular boundaries of the nucleus and cytoplasm. in cell structure. The complexity rises when the cells are overlapping with each other where it is difficult to detect the nucleus and cytoplasm boundary. The automatic and semi-automatic computer assisted methods are used for segmenting the nucleus and cytoplasm of cervical cells. In this paper, the various segmentation algorithms and techniques for segmenting Pap smear slides are discussed. The paper also describes the features which are extracted for effective segmentation.

Keywords: cervical cancer; pap smear slide; segmentation techniques

1. INTRODUCTION

Cervical cancer is the third type of cancer which has the highest death rate. For every two minutes at least one woman dies due to this terrific disease. Cervical cancer is caused usually with age group of 35 and above women. The survival rate of this cancer is very low because there are no symptoms for this cancer woman must undergo a manual screening test, namely, Pap smear test once in three years to detect the pre-cancerous cells in the cervix regions and treated at the earliest. The Human Papillion Virus (HPV) is the cause of the cervical cancer which has nearly 170 types out of which the HPV16 and HPV18 are known to cause around 70% of cervical cancer. Cervix is the passageway that connects the uterus and vagina. The cervix is made up of three types of tissues the Pap smear test also called as Papanicolaou is a manual screen method carried out by cytologists. The cervical intraepithelial neoplasia (CIN) is to be detected from the HPV 16 which leads to cancer cells. The main disadvantage of this method is its expensiveness since there are only few experienced cytologist available to perform this test effectively. There are many chances for human errors in this process which causes high false positive rates. There are many computer based systems available to detect cervical cancer where the segmentation of the cervical cells is very challenging. The cervix layer is made of tissues which are categorized under three types: squamous epithelium (SE), columnar epithelium (CE) and Aceto white (AW) region. The AW region is exposed to 5% acetic acid test which turns into white colour detect the symptoms of cervical cancer. The cell structure is very complex with irregular boundaries and difficult to separate the nuclei and cytoplasm region. When the nucleus cells overlaps with each other it is difficult to mark the overlapping boundaries and calculate the nucleus and cytoplasm ratio (NC). The segmentation process involves three steps first the nucleus segmentation second

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the cytoplasm segmentation and the last step is detecting the nucleus and cytoplasm (NC) ratio. The Pap smear slides are taken as the input image, where the digital image processing steps are applied. The first step is the pre-processing by removing the unwanted noise from the input image many filters and morphological operators are used for this process. The next step is feature extraction, by extracting the selected portions from the image. In cervical cancer there are four common features extracted the size of the nucleus, size of the cytoplasm, ratio of nucleus and cytoplasm and background. The image segmentation of cervical cancer cells is still very challenging task because of the complex cell structure with irregular boundaries. The segmentation of nucleus and cytoplasm is very tedious task in the identification of nucleus region and cytoplasm region. The rest of the paper is organised as follows. Section 2gives a detailed description about the image segmentation algorithm, section 3 describes the boundary marking tool used to detect the boundaries of cytoplasm and nucleus, section 4 describes the pattern recognition algorithm used for segmentation, section 5 describes the Gaussian model used in cervical image segmentation, section 6 describes the region growing algorithm in image segmentation, the paper is discussed in section 7 with survey table. Finally the paper is concluded in section 8.

2. CERVICAL CANCER DETECTION USING THE IMAGE ANALYSIS ALGORITHMS

2.1. Image Segmentation

The segmentation of the cervix tissues is very challenging as the color; texture and format of tissues vary in a larger extent. The cervix region is located within the uterus and consists of three tissues namely Squamous Epithelium (SE)-the texture is smooth and pink, Columnar Epithelium (CE)-the texture is irregular and red, Aceto white (AW)-the texture is transient. The acetic acid test changes the AW into white color. These tissues have irregular boundaries. In order to detect and merge the boundaries, an agglomerative clustering segmentation is proposed by Hiri Gordon et al. [1] to detect the boundaries by segmenting the cervigrams image into a super pixel for non-convex region. The super pixel merges the edge information and region information of the images with a normalized mean cut (NMc) graph. The segmentation process in cervical cancer image is very tedious due to the recursive portioning of segments into sub segments. Pavel Kalinin et al. [2] presented a novel super pixel algorithm, which is in divisive group where the image is represented by a graph. The image segment is recursively partitioned into two sub segments by computing a minimum graph cut. The Berkeley data set is analyzed with the super pixel algorithm. The manual screening and segmentation of cervical cells lacks in poor quality when large number of samples are to be retrieved. To overcome this problem, the segmentation algorithm for cytoplasm and nuclei in cervix is demonstrated by Ling Zhang et al. [3] using global and local graph cuts. The automation assisted reading (ARR) is used to overcome the problems in manual screening but the existing segmentation algorithms are in poor contrast. The Herlev data set is used for the cytoplasm and nucleus segmentation based on the color, shape and texture. The accuracy obtained is 93% for cytoplasm segmentation and 88.4% for abnormal nuclei segmentation. Malm et al. [4] proposed a nuclei segmentation algorithm for Pap smear images by using a dilation with Remannian distance maps which is derived from the local structure image with Tensor field. The segmentation method used a curve closing segmentation that identifies the weak edges in the image and helps to increase the overall performance. The proposed system is used by Samuel W. K Chan et al. [5] for the automatic detection of segmentation and diagnosis process which has outside of the quotation marks. Beihai Chaudhury et al. [6] demonstrate an image segmentation framework using ensemble algorithm in the stereology process of cervical cancer tissues.. The algorithm starts with the initial screening of the input image into pixels, where the image is segmented with larger pixels is the nucleus which is called as the bob level. The mean nuclear volume (MNV) plays an important role in the differentiation of the cancer and normal cell. MNV is calculated for the bob level where the point sampling intercept is calculated to classify the cells. Zhi Lu et al. [7] propose an automated segmentation method for nucleus and cytoplasm in overlapping regions. The scene segmentation is performed by using an unsupervised classification for detecting the nuclei with a maximum stable external region (MSER) algorithm. The edge detector detects the background information and finally an unsupervised classifier is used with the Gaussian mixture model for differentiating the background and cell lumps. Alan C. Bovik et al. [8] propose an automatic segmentation method for cervical epithelial nuclei cells. Gaussian Markov random fields' algorithm is used for the segmentation process with additive Gaussian noise. Kaaviya et al. [9] propose an automatic segmentation algorithm for cervical cell images. The regions are clustered into patches where each patch has a centre value. The lesser patch value is the nucleus region. After the segmentation process, the features are extracted from the nucleus value. The abnormality of the nucleus is detected by its texture analysis. Afaf Tareef et al. [10] propose a fine segmentation method for segmenting the Pap smear images of cervical cancer. A segmentation framework method is provided for segmenting the overlapping cell structures. The shape and contour of the image is analyzed with their land mark features. Masoud S. Nosrati et al. [11] propose a new method for segmenting the overlapping cells with a star shape prior for the Pap smear images. A histogram of oriented gradient (HOG) is used for training the nucleus and cytoplasm ratio by constructing a random forest (RF) decision tree and differentiates the nucleus vs non nucleus regions.

2.2. Boundary Marking Tool

The medical image analysis faces a tedious process in automatic image segmentation process. The cervical cancer is detected in the cervix region present inside the uterus. The tissues in the cervix region, identified with irregular boundaries are segmented with the help of the web accessible tools by Xwe et al. [12]. It allows providing a collaboration with the medical experts and engineering tools. The data can be conveniently exchanged between the tools during execution. There are three parts: the boundary marking tool (BMT) which is used to collect the ground truth information from the medical experts and draw irregular boundaries with an early prototype model in image region data. The cervigram segmentation tool (CST) is used for the segmentation of the image. The Multi-Observer Segmentation evaluation system (MOSSES) is used to validate and evaluate the segmentation. Jose Jeronimo et al. [13] proposed a boundary marking tool (BMT) for the squamous columnar junction (SCJ) in the epithelium layer of the cervix which covers more than 90% of the cervical area. The BMT is designed to operate in a stand-alone mode for data collection. The cervical intraepithelial neoplasia (CIN) is used to classify the cervical cancer cells as CIN1, CIN2 and CIN3. A knowledge based image analyzer is used by Samuel W.K Chan et al. [14] to detect the cervical cells where the first step is preprocessing and removal of noise from the image, the second step is to label the regions with respect to feature descriptions. The image is first segmented with respect to low level vision kernel (LLVK) initiated by a segment generator (SG). The list of instructions is given from the SG where the image object model is computerized by the High level vision kernel (HLVK). The segmentation is domain-independent and robust.

2.3. Pattern Recognitions

The Squamous cell Carcinoma (SCC) tissue in the cervix region is segmented for the detection of cervical cancer cells. There are different patterns for tumor invasion with histological phenomena. The new morph metric parameter C is used by Jens Einenkel et al. [15] for classical representation and D is used for compactness representation in quantification. The patterns recognized are classified as closed, finger-like or diffuse patterns. The values of C and D are used for referring the front patterns assigned is more suitable for practical use than D. The patterns recognized can be differentiated between the classified groups. The cervical cells collected from the cervix region in the uterus by the Pap smear test are colposcopy images which are to be tested manually by the cytoplascian. The segmentation of the cervical cells is very challenging in identifying the precancerous cells. The Aceto–white test is one such method which is used to identify the pre cancer cells. The proposed system demonstrates the aceto-white temporal pattern when used with acetic acid changes into white. The K-nn classification algorithm is used over the entire length of Aceto white region. The temporal patterns are used by Gabriel et al. [16] to detect the sensitivity and specificity in the level of aceto white color intensity. The high sensitivity 98% and low specificity of 48% classification K-nn algorithm is used to analyses the changes in the level of sensitivity and specificity of the aceto white region.

Abhishek Das et al. [17] propose an identification method for the cervical intraepithelial Neoplasia (CIN) in cervical cells, which is very challenging for image segmentation. The automatic pattern classification method is used to append the content based on image retrieve from the cervix image database. The cervical epithelium helps to distinguish the normal cells from the abnormal cells using the vascular pattern and intercapillary distance. The proposed method has four models, viz., the removal of specular reflection (SR), segmentation of cervix region of interest (ROI), the segmentation of cervix ROI into Aceto white region, finally classify the abnormal regions into mosaic patterns. Ulf-Dietrich Baumann et al. [18] demonstrate the reconstruction of cervical tissue from the histological sections in a three dimensional manner. The variation patterns from the invasion fronts of the tumor. The rigid registration of the image is taken place at first followed by the color adaptation by using the polynomial nonlinear registration where a staining based tumor probability is calculated for the curvature based nonlinear registration and the total variation is calculated. The tumor is segmented with an automatic pattern reconstruction algorithm where a polar logarithmic Fourier mellin invariant (FMI) descriptor and phase only matched filtering (POMF) are used for reconstructing the 3D cervical tissues. David Escarcegen et al. [19] propose a pattern recognition technique in cervical cancer (CC) with signaling the pathways. The mRNA microarray expression data is used with the robust multi array average (RMA) algorithm to integrate the signaling pathways. The clustering of pathways is used to express the given expression with gene expression pattern with KEGG with signaling pathways. This method gives better performance and accuracy in extracting the signaling pathways.

2.4. Region Growing Algorithms

The cytoplasm and nucleus region is detected by using a cytoplast and nucleus contour (CNC) detector. The clear cut separation for the pixels laid between two objects uses a maximal color difference method by which the paptest nucleus contour can be drawn. The CNC detector adopts a median filter to sweep off the noises. The dysplastic cells should undergo the precancerous changes. The larger nuclei is identified under dark shaded which as the tendency to cling together in larger clusters. The proposed feature extraction Seeded region growing (SRGFE) extracts the size and grey scale images. The threshold value is fixed for the pixels where the user needs to determine the regions which are interested by clicking the mouse on any pixels in the region. The CHAMP software is used by Meng Husuim Tsai et al. [20] to segment and classify cervical smear images. The proposed method is an automated image segmentation system where the K means algorithms with two different adjacent objects have dissimilar color distributions. The CNC detector bi groups the cytoplast and nucleus contour detection. The bi group emphasizes the edge pixels and suppresses the noise. 26 cervical smear images are collected from Taichung Hospital and analyzed.

The cervical cancer detection must be detected at early stages where the precancerous cells needs to be identified. The proposed system uses intelligent diagnosis which automatically extracts the features and detects the precancerous cervical cells. The feature extraction consists of nucleus size, cytoplasm size, nucleus and cytoplasm grey level. The region growing based features extraction (RGBFE) algorithm is used by Ashide Mat-Esa et al. [21]to extract the features from cervical cells. The input image is feed which intelligently diagnostic the parts in the image. A new artificial neural network called hierarchical hybrid multilayered perception (H2MLP) for predicting the cervical precancerous stage cells. The features extracted are compared and intelligently diagnosed. Yue Cui et al. [22] propose the computer aided detection method for cervical smear for assisting medical experts as it is easy for handling the microscope and diagnosis. The tumor marker ki-67 stains the microscopy images of cells in the cervix. The abnormal cells in the nuclei are present in brown color. The segmentation process is very difficult and the calculation of the NC ratio is tedious. A multilevel segmentation is used to check the abnormal cells. The first level segmentation is used to partition the abnormal nuclei regions and the second level partition is based on the clustered nuclei. The region of interest is collected from the segmentation features and based on that the final level of the nuclei is obtained. Abhiskesk Das et al. [23] demonstrate the prevention of screening programs. The specular reflections (SR) appear as bright spots which will be heavily saturated with white light. The first step is to remove the unwanted boundaries in the cervix region. The modified k means algorithm is used to enhance and evaluate the region of interest. The features to be extracted from the image are the ROI, SE, AW and CE region. The AW region is first performed with the acetic acid test and it is then classified. The details are stored in a knowledge data base where a user interface is created to diagnosis the classification created to diagnosis the classification based on ROI.

2.5. Gaussian Models

Yeshwanth Srinivasan et al. [24] propose a fully automated diagnostic system for cervical intraepithelial neoplasia (CIN) to detect the cervical cancer the segmentation is classified into two types the macro tissue segmentation and micro segmentation. The Gaussian mixture model (GMM) along with clustering is used for image segmentation of the cervix region. The input of the image is obtained from the region of interest (ROI). The detection of cervical cancer is made from CIN, AW and SR regions in the cervix. The mosaic tile and punctuations are used for classifying the normal and abnormal tiles for the detection of cervical cancer. N. B. Biju et al. [25] demonstrate a reliable and fast segmentation method using Laplacian of Gaussian (LoG) filter to segment the nuclei structure of the bright microscopic Pap smear images. The image is obtained in RGB format which is then converted into gray scale conversion. Shiri Gordon et al. [26] propose a Gaussian mixture model (GMM) for segmentation of uterine cervix images. The first step is to analyze the texture and shape of the cells. The columnar epithelium (CE) tissues is less clustered than other tissues, Viara Van Raad [27] proposes a Gaussian mixture model (GMM) color based segmentation in aceto cervix region of cervical cancer analysis. The maximum a prior (MAP) optimization algorithm is used to set the pixels of the cervical tissues in a compartmental like mode.

2.6. Watershel Algorithms

Pascal Banford et al. [28] demonstrates the segmentation process in the Pap smear slides over the manual screening process. This scheme consists of two stages where the first stage is at low magnification using water immersion segmentation followed by the second stage as a search based dual active contour method at a high magnification. In water immersion algorithm initially the image resolution is increased by using a quadtree smoothing stage, where four pixels are assigned an average value based on one pixel the next level is increased. This image surface is lowered into water where it traps the areas of high ground. A search based dual active contour considers a two circles with a set of N points where the line joining each point on the inner and outer circle is being divided up to M points for segmentation. Amir Alush et al. [29] propose an automated system for the segmentation of the cervical tissues. The water segmentation map is used with the Markav random field (MRF) for segmenting the nucleus. The image is segmented into super pixels which classifies whether the pixels are in the boundary level. The algorithm is divided into two parts; the first part is the supervised boundary extraction process. The second part deals with the segmentation of the arc level. A comparison is conducted with the boost edge learning classifier for the extraction of accurate boundary values. Setugarg et al. [30] proposes an efficient and practical algorithm to detect the cervical cancer cells. To find the edge in the tumor detection is used which is a challenging task in the medical image analysis. The filtering is used to eliminate the noise level in the image without losing the true edges.

3. DISCUSSION

The segmentation of cervical cells is very tedious and challenging because of the complexity in the presence of cell structure. The nucleus, cytoplasm and background are extracted from the input image. Only few

Table 1
The performance analysis on image segmentation algorithms used for the detection of cervical cancer

Author's Name	*Method*	*Features Extracted*	*Advantage*	*Disadvantage*	*Dataset*	*Accuracy*
Shiri Gordon et al [1]	Agglomerative segmentation framework	Similar content	Texture of the tissues are balanced and obtained in convex shape	Threshold is used only for a single pixel value which will vary for each pixel	Cervigram, large set of database collected from national institute of cancer	–
Pavel Kalinin et al [2]	Super pixel algorithm	Pixel Colour intensity	Produces a quality of hierarchical super pixels range	Probability value is high when the boundary value of super pixel is long	500 images of Berkely data set	–
Ling Zhang et al [3]	Automated assisted reading Techniques (ARR)	Nucleus Cytoplasm shapesize texture	Segmentation method is easy for overlapping nuclei cells	Segmentation is difficult for poor staining and contrast images	21 cervical cell images	93%
Malm, P. et al [4]	Anisotropic dilation for curve closing	–	Riemannian dilation performs better than isotropic dilation with close curving for segmentation of pap smear images	More number of parameters without linear dependency	160 images were used, each containing approximately 60 nuclei	–
Samuel W.K. Chan et al. [5]	A novel Knowledge based image segmentation method	–	Large number of suspicious cervical lesions can be detected easily	Knowledge based information is difficult to locate the new centred points	–	–
Chaudhury, B. et al. [6]	Ensemble frame work with stereological procedures	–	Used to accept or reject an image with large data set	Calculation of class seperability measurement is dependent	29 individual biopsy slides	–
Lu, Z., Carneiro 7]	Maximum stable external region (MSER) algorithm	–	Segmentation of overlapping nuclei and cytoplasm is easy	Boundary of cytoplasm is misused on poorly contrasted cell images	Drosophila melanogasterKc167 dataset	0.83
Brette et al. [8]	Gaussian Markov random fields	Nucleus features size color intensity	Helps to detect the falsely detected nuclei at brighter images	Fails to segment the overlapping nucleus	Confocal image video	90%
Kaaviya et al. [9]	Fuzzy C means algorithm	Nucleus cytoplasm	Abnormality is detected from the nucleus and cytoplasm ratio	The patch values used in the segmentation are not clear	–	–
Tareef, et al. [10]	Morphological Technique	Shape contour	Cellular lumps are segmented from the nucleus easily	The morphological techniques and operators are not extracted	–	–
Nosrati, M. [11]	Star shape prior segmentation frame work	–	Voronoi energy level is used with the star shape prior for segmenting the overlapping cells	The cell boundaries of overlapping and dense cells are not detected accurately	ISBI2014 challenge consisting of 135 cervical cytology images	0.88

Table 2
The Performance Analysis Onboundary Marking Tools Used For The Detection Of Cervical Cancer

Author's Name	*Method*	*Features Extracted*	*Advantage*	*Disadvantage*	*Dataset*	*Accu-racy*
Zhuiyum Xwe et al. [12]	MOSES	Nucleus size shape texture	Collaboration between the experts and engineering models with easy exchange of data	Depends only on the ground truth information for validation and evaluation	Cervigram	–
Jose Jeronimo et al. [13]	Boundary marking tool (BMT)	–	Enables archiving and collection of cervical neoplasia images in a database	Subclassification of boundary leads to confusion	100,00 images NIC	–
Samuel W.K. Chan et al[14]	Knowledge base analyzer	Centroid, perimeter, compactness, verticalhorizontal men of gray	Segmentation is robust and domain independent	Rules are not specified clearly	Physical image	–

Table 3
The Performance Analysis Onpattern Recognition Used For The Detection Of Cervical Cancer

Author's Name	*Method*	*Features Extracted*	*Advantage*	*Disadvantage*	*Dataset*	*Accu-racy*
Jens Einenkel et al. [15]	Different patterns	Morphological features of Nucleus and cytoplasm	Values of front patterns are easy for classification	More number of patterns	76 patientswith SE	–
Gabriel et al. [16]	K-nn classification algorithm	Cytoplasm nucleus Size shape Texture background	Precancerous cells are detected easily	Overlapping cells are not patterned	Vasconsellos model 10 images	High sensiti-vity 98% and low speci-ficity of 48%
Abhishek Das et al. [17]	Automatic pattern classification method	Nucleus Cytoplasm Morphological features	Four models are used to retrieve the database	Mosaic pattern classification is not clear	1050 samplescervigram	81%
Ulf-Dietrich Baumann et al. [18]	automatic pattern reconstruction algorithm of TNN	13 images	–	Tumor is detected easily	No colour adaptation	–
David Escarce-gen et al. [19]	robust multi array average (RMA)	–	Parthway is clustered as a single way	Clutering pathways is tedious	KEGG pathway database	–

experienced pathologist are available to perform this manually segmentation of pap smear slides. The cell boundaries may be overlapping with each other where many edge and boundary detection techniques are used to enhance the boundaries and edges of the nucleus and cytoplasm. In image segmentation, the dark region in the image is identified as the nucleus and the lighter region is identified as the cytoplasm. The rest of the region is extracted as the background region from the input pap image slides. There are onlyfew experienced pathologist to perform the pap smear test hence this test is time consuming and also cost

Table 4
The Performance Analysis On Region Growing Algorithms Used For The Detection Of Cervical Cancer

Author's Name	*Method*	*Features Extracted*	*Advantage*	*Disadvantage*	*Dataset*	*Accuracy*
Meng Husuim Tsai et al. [20]	Cytoplast and nucleus contour (CNC) detector	Nucleuscytoplasm	Large nucleus is detected easily with dark shades	Does not produce accurate results	26 cervical smear images Taichung Hospital	–
Ashide Mat-Esa et al. [21]	Region growing based features extraction (RGBFE) algorithm	Size of nucleus, cytoplasm, grey level nucleus cytoplasm	Stage of precancerous is identified by segmentation	Applicability of the testing process is not discussed	550 cases of reported Pap smears Kota Bharu Hospital	96.50% accuracy, 100% specificity and 95.33% sensitivity
Yue Cui et al. [22]	Region of interest	Nucleus size shape texture	Nucleus segmentation is easy by using multilevel segmentation	Final level segmentation does not give better performance	10 images with resolution of 1200* 1600 pixels	Abnormal nuclei accuracy 93.55% and nuclei accuracy 95.8%.
Abhiskesk Das et al. [23]	Modified K means Algorithm	Nucleus Size Shape texture	Easy retrieval of the content from image database	Quality of the image is low	1050 samples collected, colposcopic images	0.79 0.77 0.8l Mosaicism Vasculatures punctations

effective to be carried out. The irregular boundaries of the cell structure cannot detect manually with accurate results which leads to false positive rates. The automated image analyzing techniques reduce the human and also give promising results. The segmentation of the cell structure is performed with the extracted features are extracted after the preprocessing is carried out by which the unwanted noise is eliminated from the given input image. The extracted features are analyzed for easy segmentation results. Thus the false positive rates can be reduced by giving accurate results for classification to enhance the segmentation techniques of the cervical cells. The automatic segmentation techniques with computer based are proposed for efficient segmentation of nucleus and cytoplasm. The automated techniques produces better results and also is cost effective than manual screening methods. The image analysis of cervical cells is performed by many segmentation algorithms, boundary marking tools, Gaussian model and pattern matching techniques. Table 1 summarizes the performance analysis on different image segmentation algorithms used for the detection of cervical cancer. The image segmentation algorithms [1] use many frameworks to perform the separation of nucleus, cytoplasm and background regions from the given input image. The segmentation

Table 5
The Performance Analysis On Gaussian Models Used For The Detection Of Cervical Cancer

Author's Name	*Method*	*Features Extracted*	*Advantage*	*Disadvantage*	*Dataset*	*Accu-racy*
Yeshw-anth Sri-nivasan et al. [24]	Gaussian mixture model (GMM)	Texture shape size features	Mosaic tile is used for the classi-fication of normal and abnormal	Selection of regions is difficult	40 samples	–
N. B. Biju et al. [25]	Gaussian (LoG) filter	Nucleus Cytoplasm regions	Convolution operator makes it easy for feature extraction	Performance of the system is low	14,704 cellsdigitized images of pap smears	–
Shiri Gordon et al. [26]	Gaussian mixture model (GMM)	Texture shape structure	Abnormality is detected by calculation of the polarity	Spectral reflections in tissues is converging	Cervigram	–
Viara Van Raad et al. [27]	Gaussian mixture model	– —-	Pixels of the tissue image are in compatible mode	Boundaries of the cell structure are not detected clearly	–	86%

Table 6
The Performance Analysis On Watershed Algorithm Gaussian Models Used For The Detection Of Cervical Cancer

Author's Name	*Method*	*Features Extracted*	*Advantage*	*Disadvantage*	*Dataset*	*Accu-racy*
Pascal Banford et al. [28]	Water immersion algorithm	Nucleus Non-nucleus regions	Dual contour search extracts the values of contours easily	Low magnificent rate of image	20,130 nucleus image	99.64%
Amir Alush et al. [29]	Markav random field (MRF)	Nucleus Cytoplasm background	Interactive segment-ation of nucleus and cytoplasm by using AW regions	Multiple boundaries creates confusion in separation	211 cervigram images	–
Setugarg et al. [30]	Watershed morphology	Nucleus cytoplasm Morphological features	Histogram pro-cessing enhances the frames and tiles	Tumors are not divided completely	MRI scans MATrixLA Boratory	–

algorithms efficiently separate the irregular boundaries of nucleus and cytoplasm by using super pixel algorithm [2] which uses the intensity of the pixels from the input image. The system suffers a drawback when the pixel value is very long. The automated resisted systems [3] are also used in the segmentation with ensemble framework. The boundaries of the nucleus and cytoplasm are marked by using a boundary marking tool discussed. In table 2, the performance analysis on different image segmentation algorithms used for the detection of cervical cancer is shown. The boundaries are detected easily by using morphological features [12] and color changes [13] but difficult to separate the overlapping regions with nucleus cytoplasm ratio. Table 3 discusses the performance analysis on different algorithms used for the detection of cervical cancer based on the pattern techniques used for the image analysis where different automatic patterns [17] are used for the segmentation of nucleus and cytoplasm where the individual cells are not considered completely with the extracted features. Table 4 discusses the performance analysis on region growing algorithms used for selecting the boundaries of cell structure with nucleus and cytoplasm [21][22]. Table 5 presents the performance analysis on the cervical detection techniques using Gaussian mixture models [24][26] used for selecting the boundaries of cell structure where the nucleus and cytoplasm regions are identified easily and analyzed but this method is still not effective because the boundaries are not clearly identified[27]. Table 6 discusses the water immersion techniques used for cervical image [28][29]. The pixels values are classified with the water level easily which is difficult for calculating [30] the pixel levels in the input image.

4. CONCLUSION

The cervical cancer diagnosis's uses many computerized techniques for easy and accurate diagnosis. In this paper, various image analyzing techniques are discussed for segmentation and detection of cervical cancer. The Pap smear test is the manual screening method which is used for diagnosing cervical cancer which suffers from high false positive rates and cost effective. In order to make this efficient and effective, various computerized methods are discussed to enhance better results.

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