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Classification of Uterine Cervical Cancer Histology Image Using Active Contour Region Based Segmentation

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Abstract: This research work move toward for the studyof cervical region based Pap imagesof cervical cell and analysis of the range of features based on the shape and size of particular cervical cell. Pap smear analysis of cervical region is an effective and simple technique to study any abnormality in cervical cells. But in practice human observationis not always satisfying and this analysis is a time consuming and difficult task to manually observe anenormous number of Pap smear images. In this work, an approach for grading of cervical cancer has been proposed which classifies the classes of cervical cancer according to the severity of cancer. The MATLAB Toolbox for Image Processing is used to segment the Pap images and extracta range of features. By distinct cell nuclei distribution of cervical cell and consideringa range offeaturesthat can be programmed to discriminate normal cervical cell to cancerous cells using support vector machine.In our work, the support vectors machine technique, which are critical for classification, are obtained by learning from the training samples based the extracted features of pap images. In this paper we have shown the comparative results of classification using different kernel functions for all extracted features. In addition, this work gives the accuracy of the classification of cervical cancer to 87.15%.

Keywords: *Cervical cancer, Pap smear test, Cell images, Segmentation, SVM Classification.*

1. INTRODUCTION

The discovery of a Cervical Cancer is one of the most frightening and feared health problem women can face. This is due to the fact that cancer of uterine cervix holds the second place in the category of common cancer that cause problemsto the women in most parts of the world [1]. The aim of this research work is the advancement of the tools used for the discovery of cervical cancer based on the analysis of Pap smear images [2]. In the 1940'ties, Georges Papanicolaou[2] found a method to make an identificationof the pre-cancerous lesions of cervical cells of the uterine. This approachfor detecting cancer is referred to as pap (anicolaou)-smear diagnosisas shown in figure 1. The Pap smear has made it easy to identify pre-cancerous cells in the cervix, so that the effective treatment can be given. The Pap smear screening process needs skilled and trained cyto-technicians, but they are costly and can be hard to find. Several systems are available to analyze Pap smear, but they are more expensive to use than skilled cyto-technicians.

The accurate discoveryof cervical cell nuclei in pap images of cervix isdeciding for investigation because the nucleus of cervical cell is a very influential structure within the cell of cervix and it presents considerabledistortion when the cell is damaged due to disease. However, the imageanalysis of these cervical cellimages is a laboriouspractice, because these cell images holdsa range of characteristics, such as the high amount of various cell overlapping, the be short of homogeneity in image strength and the fluctuations in dye concentration.

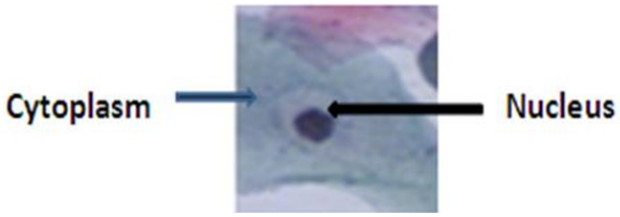

Figure 1: Asample cell from a Pap smear slide

There exist a variety of systems for classifying premalignant cervical cancer, including cytology and histology cervical images as describe in Table 1.

Table 1
Classification Systems of Cervical Cell

Papanicolaou	*NIC*	*OMS*	*Bethesda*
CLASS I	Normal	Normal	Normal
CLASS II	Atypia	Atypia	ASC
CLASS III	NIC I	Mild Dysplasia	LSIL
CLASS III	NIC II	Moderate Dysplasia	HSIL
CLASS III	NIC III	Severe Dysplasia	HSIL
CLASS IV	NIC III	in suit cancer	HSIL
CLASS V	Invasive Carcinoma	Invasive Carcinoma	Invasive Carcinoma

In past, the computer generatedstudy of cervical cell images is a question of concern for a number ofresearchers. In 1999 Byrielprovides a benchmark dataset for classification of Pap smear images [3]. In context of his work cervical cell features are extracted using champ software. Byriel proposed the ANFIS technique for the classification [3].

A variety of methods have been developed[4-9] for this reason, such as pixel based classification schemes [4], morphological based watersheds [5], active contours based methods[9], and methodologies based on fuzzy logic [14]. The techniques used for segmenting particular nuclei in cytological pap images have been studied by a number of researchers [5-14].

This research work mainly focused on segmentation of cervical cell and classification based on SVM. Segmentation methodprimarily concentrates on detachment of the cervical cells from the surroundings as well as detachment of the nucleus from the cytoplasm within the cell regions. After this, categorizationprimarily focuses on automatic categorization of the cervical cells into separate classes: normal versus abnormal.

2. METHODOLOGY

2.1. Image Dataset

In our framework as shown in figure 2, we have consider data sets, that is collectedfrom Fortis Hospital Mohali of India (Punjab).In this data set there are 50 images of Pap smear Cell including its nucleus, cytoplasm and background, and each of these cells are manually classified into one of the seven classes by doctors.

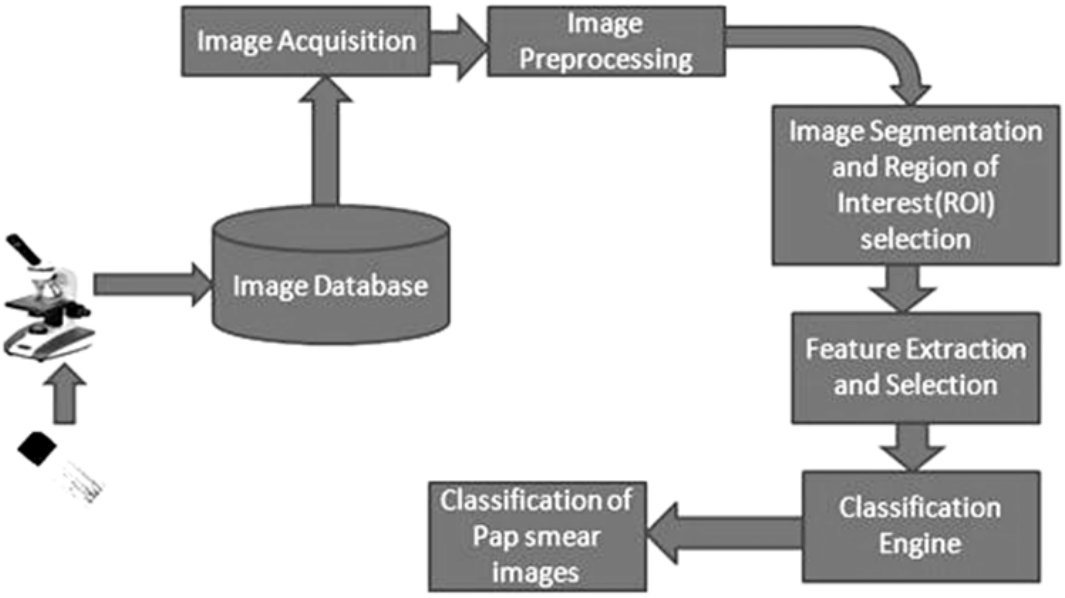

Figure 2: Proposed Framework

2.2. Image Acquisition

Image acquisition is the process of acquiring the Pap smear image from the sample obtains from the uterine cervix using the wooden stick and transferred to the rectangular slide. The sample is stained by applying the Papanicolaoumethod[2].The images used in this work are taken through a Digital camera personalized with an optical microscope. Images are taken using 40X magnification lens and stored in JPEG format. The Pap smear images are acquired through a powerful microscope by the expert cytotechnicians. All images captured with a resolution of 0.201 μm/pixel. For acquiring optimal set of image data following requirements must be consider:

1. Low variance in illumination is atomically adjusted by Camera and Microscope itself.
2. High resolution images must be captures using 40X or 400 X magnification.
3. For better result only single cell must be acquired.

2.3. Image Preprocessing

The purpose of the image preprocessing step is to suppress the undesirable noise found in cervical Pap smear image samples and enhances them for further processing. The image preprocessing enhances the quality of the images.

In our framework the median filter is used to reduce noise and to improve the contrast of the pap images by means of histogram studybased on imadjust function in MATLAB. Further the quality of image is improved using pseudo colour.

2.4. Image Segmentation

Since in pap images the nucleus area is darker than the surrounding cytoplasm .In image segmentation step, we basically aim to develop an accurate segmentation of nucleus regions.For this purpose we first convert the pap image into binary image using structuring function that contain only cell nuclei after that we fill the holes and then removes the filled region to outline the cell nuclei.

Further in this work we used active contour region based segmentation that is used to extract the interested nuclei at 20^{th} iterations that is further used to extract various features of nuclei and cytoplasm.

2.5. Feature Extraction and Selection

For the purpose of classification, it is enticing to extract an optimal number of features for classification. The huge amount of features increase the computational overhead, it becomes more complex and time consuming to specify suitable decision boundaries in a large dimensional space. This shows that an optimal subset of features needs to be chosen for the purpose of classification.

During feature extraction; the most desirable characteristics of the ROIs are studied and analyzed. The size of nucleus and cytoplasm plays a vital role in classifying the cervical cell type. Various features are extracted from pap images [3] like Area, Perimeter, Diameter and Elongation of nucleus and cytoplasm are extracted individually.

2.6. Classification

The classification can either determine a cervical cell to be normal or abnormal, or categorize as one of various levels of dysplasia. Various computer generated methods have been proposed to differentiate normal from abnormal dysplasia cells. The classification system proposed in our framework classify the Pap smear images into one of seven classes, namely, superficial squamous, intermediate squamous, columnar, mild dysplasia, moderate dysplasia, severe dysplasia, and carcinoma in situ[3]. The manual classification of the entire dataset has been already done by the expert cytotechnicians. In the proposed framework, we used SVM algorithm to classify the Pap smear images. In our work we use various types of SVM kernels like Linear, Quadratic, Rbf, Polynomial and Mlp. In this we calculated the precision of classifier using set of features.

3. RESULTS AND DISCUSSION

Figure 3(*a*), 3(*b*), 3(*c*), 3(*d*) 3(*e*), illustrate the outcomes after applying the method specifies for improvement of pap images quality. The quality of pap images are enhanced after applying the above mentioned approaches.

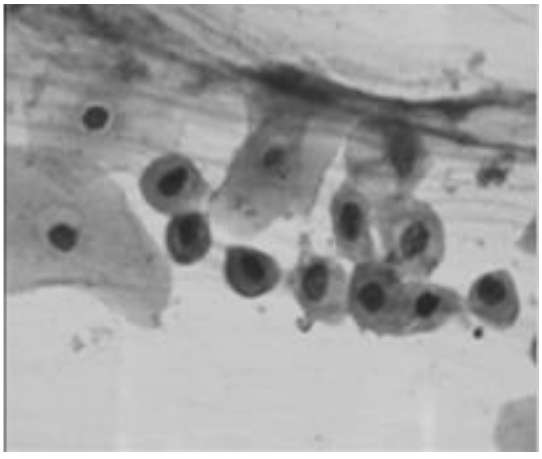

Figure 3: (*a*) Original grayscale image showing Cancerous cells

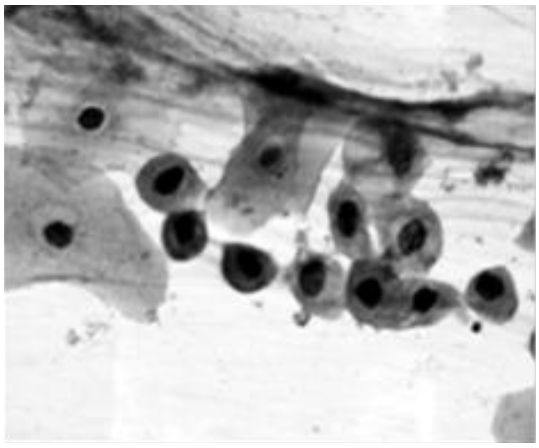

Figure 3: (*b*) Enhancedgrayscale image showing Cancerous cells

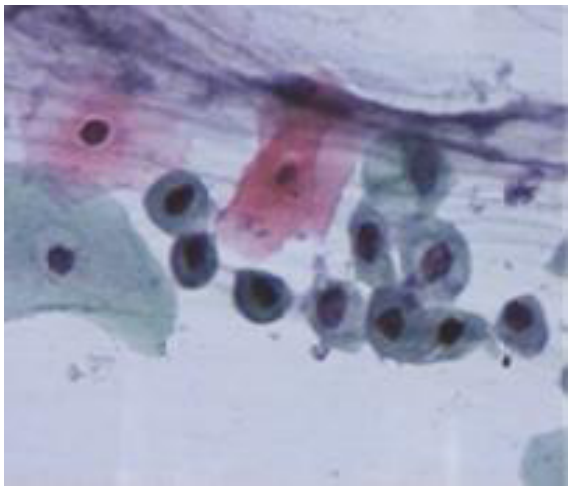

Figure 3: (*c*) Original rgb image showing Cancerous cells

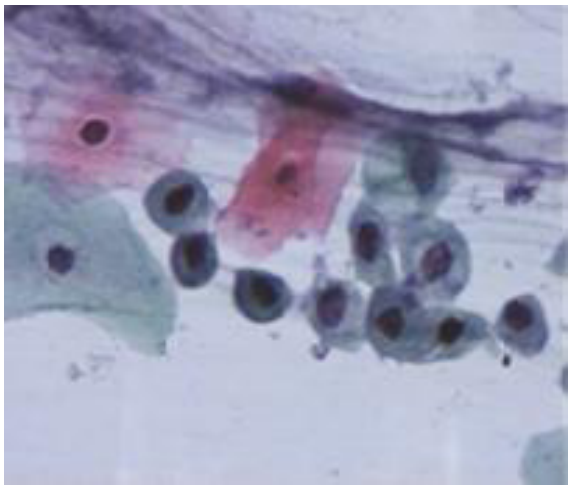

Figure 3: (*d*) Enhancedrgb image showing Cancerous cells

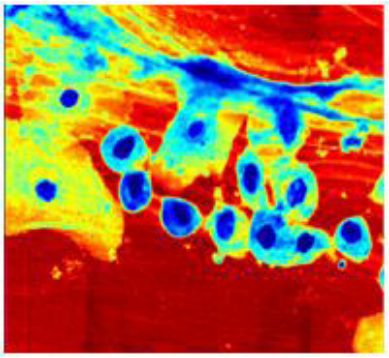

Figure 3: (*e*) Enhanced image using Pseudo colour

The pap images are segmented using above mentioned techniques. The pap images that are segmented for the particular region of interest of cell nuclei are shown below figure 4(*a*), 4(*b*), 4(*c*).

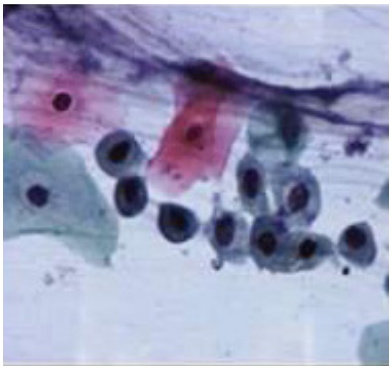

Figure 4: (*a*) Original image

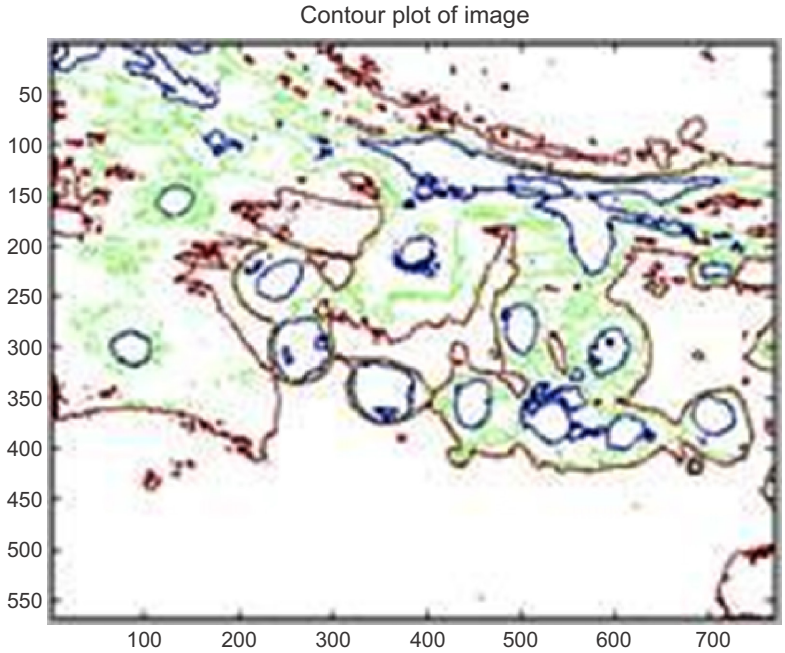

Figure 4: (*b*) Contour plot of image

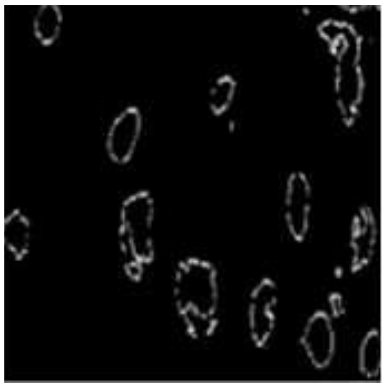

Figure 4: (*c*) Segmented image showing cell nuclei boundary

Further the cell nucleus is segmented using active contour method at iteration of 20 cycles as shown below figure 5(*a*), 5(*b*).

20 Iteration

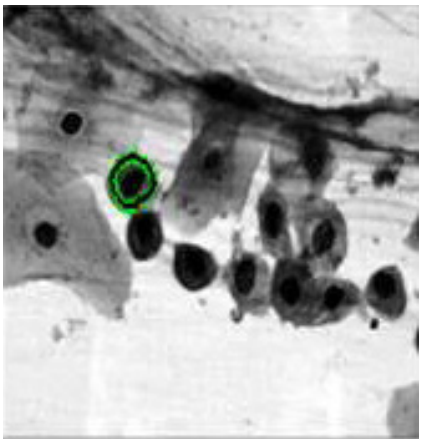

Figure 5: (*a*) Active Contour at 20 iterations

Active contour Region-Based Segmentation

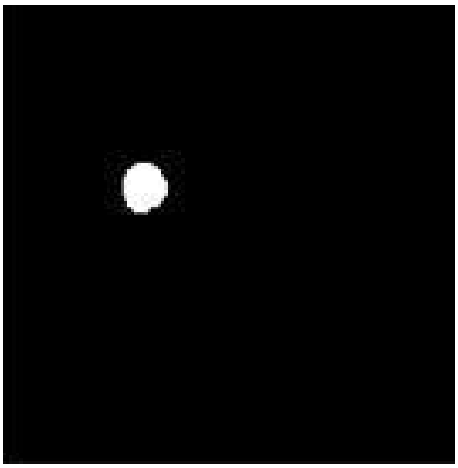

Figure : (*b*) Segmented Nuclei

The features that are extracted from sample pap images for nucleus and cytoplasm are shown in tables belowin Table 2. and Table 3.

Table 2
Extracted Features of Nucleus

Nucleus			
Area	*Perimeter*	*Diameter*	*Elongation*
2426	178	65.30697	0.78476
1475.25	140.5	55.07268	0.607319
1314.5	129	46.64762	0.849265
1192.125	125.25	47.53946	0.7

Table 3
Extracted Features of Cytoplasm

Area	*Perimeter*	*Diameter*	*Elongation*
3384.875	292.25	0.55866583	0.339832574
65191.875	1062.125	339.8411394	0.88738614
48970.875	910.25	362.9325006	0.52465837
2876.375	246.25	77.88452991	1.07566766

The result for every class has been shown in the given in Table 4. andTable 5 .for every features and kernel function and shown in figure 6. These results have been taken using MATLAB.

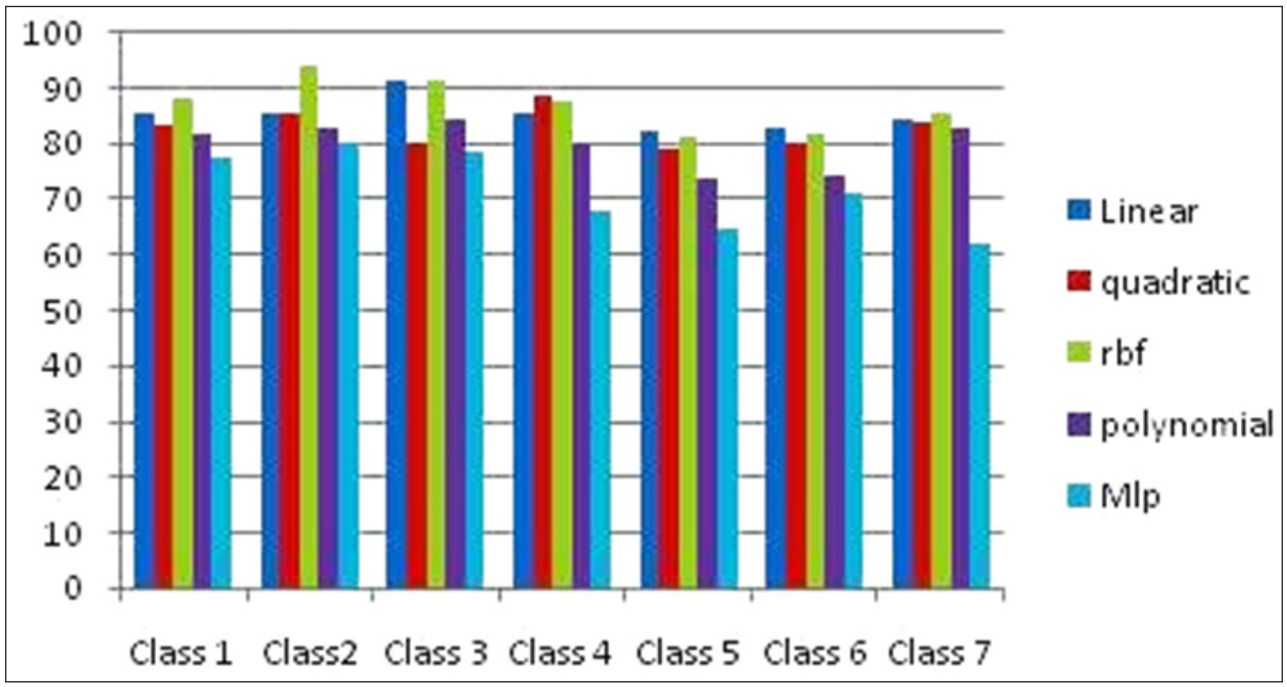

Figure 6: Classification rate of different classes

Table 4
Precision of SVM Classifier for the combination of various features

Features	*Normal_ Superficial*	*Normal_ Intermediate*	*Normal_ Columnar*	*Mild_ Dysplastic*	*Moderate_ Dysplastic*	*Severe_ Dysplastic*	*Carcinoma in situ*
Area	95.06	85.71	91.43	88.57	78.16	82.16	82.86
Perimeter	94.12	72.86	88.57	84.71	83.16	85.71	94.29
Diameter	87.15	84.71	89.18	87.13	80.12	80.00	81.86
Elongation	91.18	85.78	82-86	91.43	84.06	76.16	86.03

Table 5
Precision of various SVM Kernels for different classification of Pap images

Classifiers	*Normal_ Superficial*	*Normal_ Intermediate*	*Normal_ Columnar*	*Mild_ Dysplastic*	*Moderate_ Dysplastic*	*Severe_ dysplastic*	*Carcinoma in situ*
Linear	85.57	85.71	91.43	85.71	82.35	82.86	84.29
Quadratic	83.24	85.71	80.00	88.57	79.41	80.00	83.71
Rbf	88.18	94.29	91.43	87.57	81.05	81.86	85.71
Polynomial	81.78	82.86	84.34	80.00	73.53	74.29	82.86
Mlp	77.56	80.00	78.67	67.90	64.71	71.28	62.12

4. CONCLUSION AND FUTURE SCOPE

The work specifiedin this paper differentiate nucleus and cytoplasm of cervical cell region from Pap smear cervical cytology images using active contour region based segmentation and structuring function. The outputs of workcreatea level of adequate satisfaction. A variety offeatures are extracted from the pap images.

We concluded that SVM has given best classification with 88.18% of maximum performance with rbf kernel for class 1(Normal_Superficial),94.29% of maximum performance with rbf kernel for class 2(Normal_ intermediate), 91.43% with linear kernel for class 3(Normal_columnar), 88.57% with quadratic kernel for class4 (Mild_Dysplastic),82.35% with linear kernel for class 5(Moderate_Dysplastic), 82.86% with linear kernel for class6 (Severe_Dysplastic) and 85.71% with rbf kernel for class7 (Carcinoma in suit) . Also we concluded that with rbf kernel function, best classification results have been obtained.

In future theeffort will be done by attempting to extract more number of features and attempting to computerizecategorization of cytology cervicalimages into any one of the classification groups Bethesda, NIC and OMS using any one of the classification methods.

5. ACKNOWLEDGMENT

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