Global Journal of Pure and Applied Mathematics.
ISSN 0973-1768 Volume 11, Number 2 (2015), pp. 699-714

http://www.ripublication.com

Cervical Cancer Related Knowledge And The Need For Clustering And Classification In Intelligent Screening - A Analysis

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Abstract

Advancement of medical image digitalization leads to image processing and computer-aided diagnosis systems in numerous clinical applications. These technologies could be used to automatically diagnose patient or serve as second opinion to pathologists. This paper briefly reviews cervical screening techniques, available so that this can motivate the researcher to concentrate more on medical related issues which becomes a small contribution to our country which is very essential. The digital data of the screening techniques are used as data for the computer screening system as replaced in the expert analysis. Four stages of the computer system are enhancement, features extraction, feature selection, and classification reviewed in detail.

Key words: Cervical Cancer, intelligent Screening System, Clustering, Statistical Features,

I. INTRODUCTION

Cancer is the public health problem for men and women in this century. According to the survey more than 8% of women will affect breast cancer [1][2] 29% of men will affect prostate cancer [3][4][5][6][7], 31% of women will affect cervical cancer [8] and 70% of women will affect ovarian cancer [9]. Since the causes of cancer still remain un-known, better treatment can be provided to detect from the early stage [10][11][12][13][14]. The most modality for detecting the diagnosing is mammography [10] [15] [16]. To the low specificity mammography many biopsy operations are used [17][18][19]. Currently one of the best alternative method is called ultrasound imaging technique, and it will show cancer detection[20][21][22][23][24]. According to the survey showed that more than one out of every four researches using ultrasound images. It provided accuracy results [25]. Ultrasound techniques are more convenient and safer than mammography [26]. It is also cheaper than mammography. Different countries and continents used for ultrasound [27][28]. ultrasound are more sensitive [29][30] and faster method. Hence it is valuable for people than 35 years of age [31]. Elastography is an automatic method for measuring the elasticity of tissue based on analysis of ultrasound tissue compression [32][33][34]. Recently developed some of the computerized approaches [35] used for ultrasound imaging. This survey focuses different approaches for breast [36], prostate [37], cervix [8], and ovarian [9] cancer detection and classification method for Ultrasound images. Usually this involves four stages. Our work conserdrates on the cervical cancer. TheCervical cancer is a leading cause ofmortality andmorbidity, which comprises approximately 12% of all cancers in women worldwide according toWorld Health Organization (WHO). In fact, the annual global statistics of WHO estimated 470 600 new cases and 233 400 deaths from cervical canceraround the year 2000. As reported in National Cervical Cancer Coalition (NCCC) in 2010, cervical cancer is a cancer of the cervix which is commonly caused by a virus named Human Papillomavirus (HPV) [37]. The virus can damage cells in the cervix, namely, squamous cells and glandular cells that may develop into squamous cell carcinoma (cancer of the squamous cells) and adenocarcinoma (cancer of the glandular cells), respectively. Squamous cell carcinoma can be thought of as similar to skin cancer because it begins on the surface of the ectocervix. Adenocarcinoma begins further inside the uterus, in the mucus-producing gland cells of the endocervix [38]. Cervical cancer develops from normal to precancerous cells (dysplasia) over a period of two to three decades [39]. Even though the dysplasia cells look like cancer cells, they are not malignant cells. These cells are known as cervical intraepithelial neoplasia (CIN) which is usually of low grade, and they only affect the surface of the cervical tissue. The majority will regress back to normal spontaneously. Over time, a small proportion will continue to develop into cancer. Based on WHO system, the level of CIN growth can be divided into grades 1, 2, and 3. It should be noted that at least two-thirds of the CIN 1 lesions, half of the CIN 2 lesions, and one-third of the CIN 3 lesions will regress back to normal [39]. The median ages of patients with these different precursor grades are 25, 29, and 34 years, respectively. Ultimately, a small proportion will develop into infiltrating cancer, usually from the age of 45 years onwards. In 1994, the Bethesda system was introduced to simplify the WHO system. This system divided all cervical epithelial precursor lesions into two groups: the Low-grade Squamous Intraepithelial Lesion (LSIL) and High-grade Squamous Intraepithelial Lesion (HSIL). The LSIL corresponds to CIN1, while the HSIL includes CIN2 and CIN3 [40]. Since a period of two to three decades is needed for cervical cancer to reach an invasive state, the incidence and mortality related to this disease can be significantly reduced through early detection and proper treatment. Realizing this fact, a variety of screening tests have therefore been developed in attempting to be implemented as early cervical precancerous screening tools. But our work effectively identifies the cervical cancer with stastical data of the patients. there are many methods available to identify the classification of cervical cancer. but though there are many algorithms avalible, the main objective of this paper is to identify a better method which gives an efficient method to identify the cancer tissues with statistical data.

II. Methods

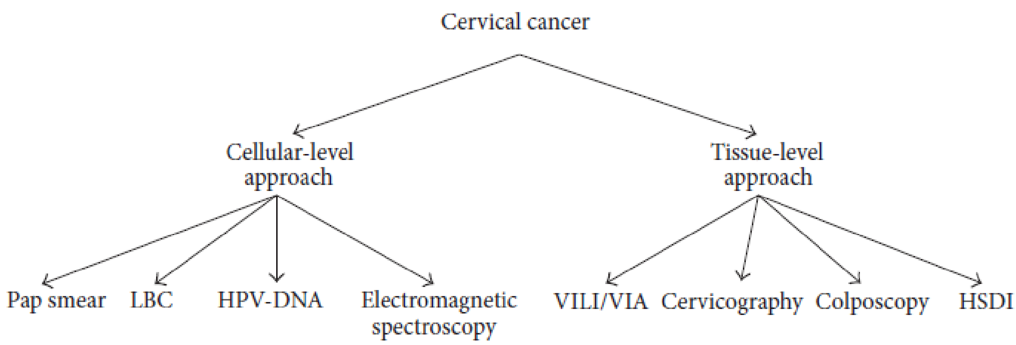

Figure 1: Taxonamy of cervical cancer screening methods

Screening for Cervical Carcinoma

Screening programs for cervical cancer have been implemented in developing countries for decades and have shown to be effective in reducing the overall mortality from this disease. There are two main diagnostic screening approaches for cervical cancer as presented in Figure 1:

(1) diagnostic screening approach based on cellular level (i. e., Pap smear, liquid based cytology (LBC), HPVDNA testing, and electromagnetic spectroscopies);

(2) diagnostic screening approach based on the tissue level (i. e., visual inspection after applying Lugol's iodine (VILI) or acetic acid (VIA), cervicography, colposcopy, and hyperspectral diagnostic imaging (HSDI)).

For diagnostic screening based on cellular-level, the specimen collections are required before it is analyzed for the expert analysis results. In contrast, specimen collection is not required for diagnostic screening based on tissue-level. The expert analysis is required for cervix images visually after applying certain liquid into the cervix surface. Detail of standard procedure, advantages, and disadvantages for Pap smear, LBC, HPV-DNA, VILI/VIA, cervicography, and colposcopy techniques can be found in [41]. On the other hand, current technologies have investigatedthe cervical cell from the specimen under the spectroscopy equipment inducing an electromagnetic light. There are several techniques utilized for cervical cancer detection:

(1) image results: fluorescent in situ hybridization (FISH) [41, 42];

(2) spectra results: Raman spectroscopy [45, 46], fluorescence spectroscopy [47, 48], and Fourier transform infrared (FTIR) spectroscopy [49–50].

On the other hand, there is an alternative technique based on tissue level known as hyperspectral diagnostic imaging (HSDI). The surface of the cervix is scanned with ultraviolet and white light for detecting lesions [51]. The scanning is achieved one line at a time, with the scan time varying from 12 to 24 seconds. By taking a series of scan lines, a hyperspectral data cube is obtained. This hyperspectral data cube contains spatial information (pixels) in two dimensions and spectral information (bands) in the third dimension [52]. This technique produces a 3D cervix image that is easier to interpret. Based on the references, the techniques have several features required for considerations as summarized in Table 1. Each of the technique has advantages and disadvantages. The general cervical cancer classification system is given in fig2. The basic data can be classified as follows and the results can be identified.

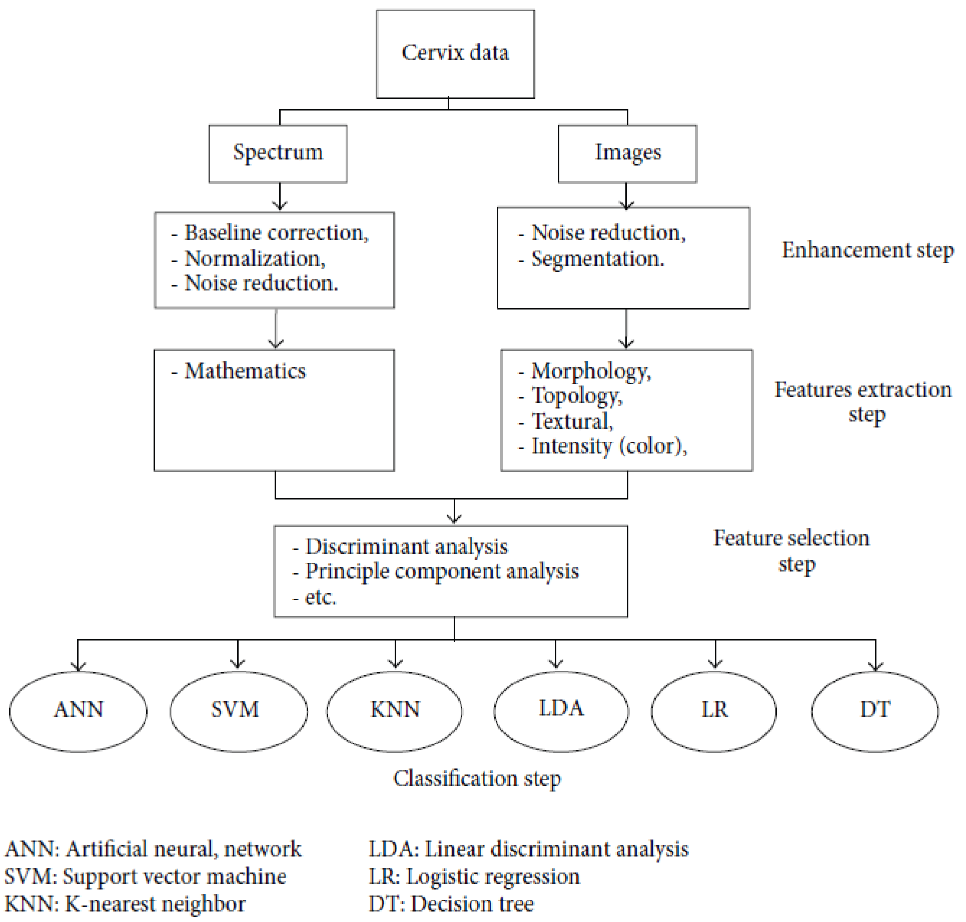

Figure 2:cervical cancer classification system

Nowadays, there are several instrumentswhich have been used to screen for abnormal cervical cells such as semiautomated or interactive system (PAPNET) and automated systems (AutoPap 300, FocalPoint, and ThinPrep Imaging System (TIS)) [53, 54]. These instruments have been approved by United States Food and Drug Administration (USFDA) for screening system. These instruments utilize algorithmic image analysis to extract morphological features. Most of these systems help the expert to perform better diagnosis by improving cervical cell images quality so that the morphological features can be seen easily. In fact, to build the current intelligent cervical screening system, two types of raw data (i. e., digital images and spectra) as presented in Section 3 can be used for the purposes. To construct the intelligent system, data enhancement optional), features extraction, and classification steps are applied to the raw data to obtain good screening results approach of the human expert knowledge in some areas of their expertise. Therefore, here we review some current features extraction techniques and classification of two types of cervical data.

III. The Steps involved in General Classification :

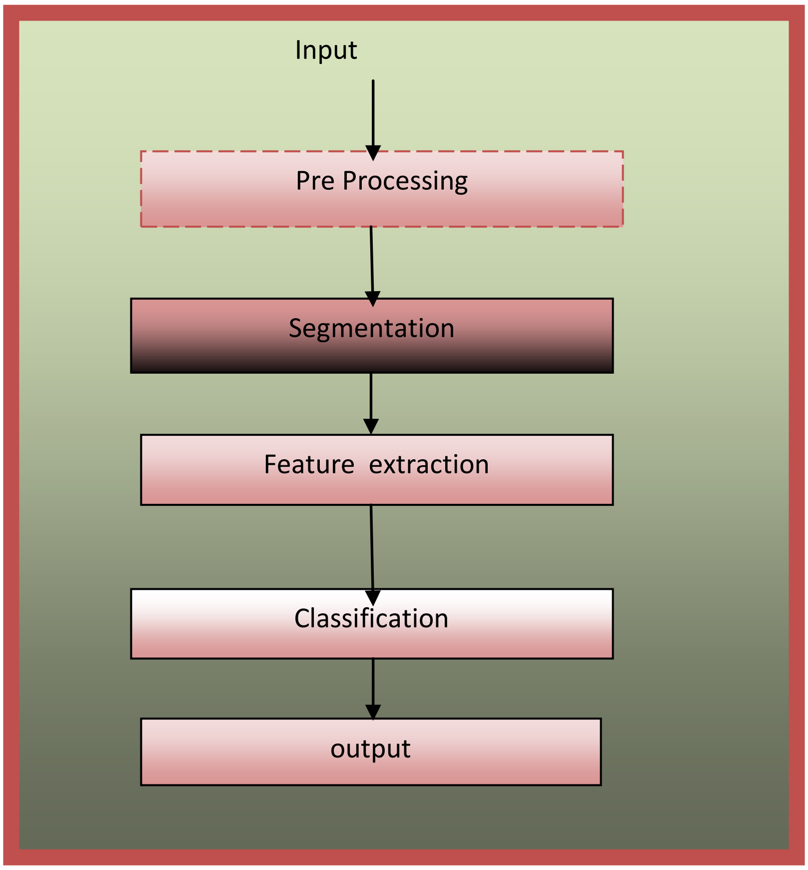

Fig3: The schematic diagram of general classification

i. Input:

The input can be a image are Numerical data depending on the application. The input is pre prosessed and further segmented.

ii. Pre Processing:

The pre-processing of breast, prostate, cervix and ovarian ultrasound images consists of noise reduction and image enhancement. Speckle in the form of noise generated by a number of scatterers with random phase within the resolution cell of ultrasound beam so in case of image a preprocessing is essential with filters. If numerical data is used then outlier detection is essential.

The filters used for preprocessing are:

a) Linear filters Adaptive mean filter (AMF):

To eliminate the blurring effect we used AMF. The Lee, Kuan and frost filters are well known examples of adaptive mean filters.

Low pass filter: It is used to reduce speckle noise and blurring the edges. The stick techniques are used to reduce the noise and improve the edge information. They use the linear projection operation.

b) Non Linear Filters: Order Statistic Filter:

This filter reduces noise. The median filter is one of the order statistic filters. It preserves the edge sharpness and produce less blurring than median filters [40], specifically it is effective but most of the Ultrasound image is affected by impulse noise

c) Wavelength Domain Techniques

The discrete Wavelength transform (DWT) translate the image into sub band consisting of a set of details sub band orientation and resolution scale wavelet coefficient It is a best method for separating noise from an image.

d) Wavelet Shrinkage:

It is based on thresholding It suppresses the coefficient noise and enhances the image features. The drawback of thresholding methods is choice of threshold is usually done manual.

e) Wavelet de-speckling under Bayesian network

It contains Bayesian rules here we apply the Wavelet coefficient statistics. This approach assumes that p is a random variable with PDF. The two sided generalized Nakagami Distribution is used to model the speckle wavelet coefficient or modelled by generalized Gaussian distribution (GGD). The disadvantage of Wavelet de-speckling under Bayesian network is that is relies on prior distribution of the noise free image.

f) Wavelet filtering and diffusion

This method is used to reduce speckle noise [38]. Wiener filtering is applied in the wavelet domain Different speckle images in the image domain and wavelet domain is presented. It compared wavelet coefficient shrinkage and several standard filters [Lee, Kuan, Frost, Geometric, Kalman, Gamma etc]. The disadvantage of wavelet based de-speckling method is the time complexity is increased during transform operations

iii. Segmentation:

In segmentation methods divide the image into number of small segments. The goal of segmentation is to identify the correct areas and to analyse the diagnosis. This method provides neural network segmentation

The different segmentation methods.

a) Active Contour Model

It is an edge based segmentation method. This approach minimizes energy associated with current contour as the sum of the internal and external energies. Level set method is employed to improve the active contour segmentation for ultrasound images

b) Markov Random Field (MRF)

Markov random field model has been used for US image segmentation The algorithms based on Markov random filed and Gibbs Random field was adapted to segment the US images.

c) **Information tracking method**

The ultrasound image u(x) to be scalar function in the subset of R2. M to be the map which transforms u(x) into its corresponding feature image I(x)=M[u(x)], it can be viewed using a vector valued image.

d) **Classical approach**

It is an essential tool for segmentation. It is used to classify the pixel inside and outside of the prostate gland.

Histogram Thresholding Histogram thresholding is one of the widely used techniques for monochrome image segmentation. Histogram thresholding was proposed for segmenting US images.

e) Region based segmentation:

In cervical cancer we use a region based method to segment the left part of the cervical ultrasound image where the internal os is located. A gray level value is selected from the histogram of the image.

Several segmentation techniques have been proposed and applied in cervix images as follows.

(i) Based on shape

(ii) Based on color

(iii) Based on texture
(iv) Based on contour:

iv. Feature extraction

Automated cervical cancer diagnosis relies on using the information obtained from (i) the abnormalities in the cell structures (*cellular-level*) and (ii) the abnormalities in the cell distribution across the tissue (*tissue-level*) Feature extraction and selection are important steps in cancer detection and classification. Textures extracted from the RF series and neural network classifiers used for detection of prostate cancer. In the cervical cancer most of the edge detection algorithms use a linear projection operation. To extract some features such as geometric, statistical, texture and histogram features. In ovarian cancer feature selection algorithms are applied for the two data sets and increase the classification accuracy.

a) Morphologic frames

In prostate cancer a maximum posteriori estimation framework is used to find the contour. i. e, a boundary of the prostate that are closely matches the prior shape model. In ovarian cancer we concentrated four different morphologic characteristics such as wall structure, cyst wall thickness, septation and echogenicity

b) Descriptor features

Descriptor features are easier to understand because they are actually the empirical classification of the radiologists.

c) Spectral Features RF (RF)

The RF time series (RF1-RF6) corresponding to each spatial sample of RF data is a discrete signal of length M, where M is the number of frames acquired in the time series. We deducted the mean of the time series from all samples. The first four RF time series features (RF1, RF2, RF3, RF4) were the average value.

d) Fractal Features (FF)

To extract FF Features the computed the mean length of the time series scales. The computed the FF of all the RF time series within an ROI and averaged them to acquire one feature per ROI

f) LF Features (Lizzi, Feleppa)(LF)

Lizzi, Feleppa and their colleagues have shown that the intercept extrapolated to zero structural (LF1), average slope(LF2) and mid point value(LF3) of a line fitted to the mid band portion of the structure. **RF Time series features (TS)** LF features and RF time series features are both computed based on spectral analysis of echo signals. they are fundamentally different. The LF features are computed based on spectral analysis, all originating from the same spatial location in the tissue. LF features are also called spectral features.

g) Geometric features:

In Geometric features due to the relative fixed position and high contrast between the internal cervical os and adjacent tissues, the location of the in **g)**ternal cervical os is desirable. Hence the geometric features of the cervix such as corner, edges are applicable in stepwise fashion

Statistical features:

In SF he statistical features are analyzed using the package for the social sciences. Features are represented as mean, standard error mean or percentage. In ovarian cancer all continuous data expressed as mean and standard deviation. Statistical features in ovarian cancer screening used four terms such as true positive, false positive, true negative, false negative. [55]

v. Classification

After the extraction of feature and selection process we have to classify the images into lesion /non lesion or benign/ malignant or normal/ abnormal classes. Lesion detection is necessary before the classification.

a). **Linear Classifiers:**

Frequently used linear classifiers for breast cancer detection and classification are linear discriminant analysis and logistic regression (LOGREG) [55]. The main idea of LDA is to find the linear combination of the features which best separate two or more classes of the data.

b) **Artificial Neural Networks:**

Artificial neural networks are the collection of mathematical models that imitate the properties of biological nervous system and the functions of adaptive biological learning [10]. In the field of breast cancer detection and classification, three types of artificial neural networks are frequently used: Back-Propagation neural network, self-organizing map (SOM) and hierarchical ANN

c) **Bayesian Neural Network:**

The idea behind BNN is to cast the task of training a network as a problem of inference, which is solved using Bayes’ theorem. A Bayesian neural network is more optimal and robust than conventional neural networks, especially when the training data set is small.

d) **SVM Classifier**

SVM training problem[104] allow for misclassification of noisy. SVM was applied to classify the malignant and benign lesions. This method is 70% faster than ANN method. fuzzy support vector machine(FSVM) based on a regression model. The drawback of SVM is generated training errors.

vi. Output

Out put is obtained after classification may be of image or numerical value depends on the input.

IV. Comparison of Clustering algorithms

Fuzzy C-Means (FCM) algorithm

In hard clustering, data is divided into distinct clusters, where each data elements belongs to exactly one cluster. In fuzzy clustering, data elements can belong to more than one cluster, and associated with each element is a set of membership levels. These indicate the strength of the association between that data elements and a particular cluster. Fuzzy clustering is process of assigning these membership levels, and then using them to assign data elements to one or more clusters. Fuzzy identification is an effective tool for the approximation of uncertain nonlinear systems on the basis of measured data. One of the most widely used fuzzy clustering algorithms is the Fuzzy C-Means (FCM) Algorithm.

Limitation of FCM

The main drawback of FCM is from the restriction that the sum of membership values of a data point x_i in all the clusters must be 1, and this tends to high membership values for the outlier points. So the algorithm has difficulty in handiling outlier points. Secoundly, the membership of adata point in a cluster depents directly on its membership values in other clusters centers and this sometimes happens to produce unrealistic results. In fuzzy c-means method a point will have partial membership in all the clusters. The third limitation of the algorithm is that due to the influence (partial membership) of all the data members, the cluster centers tend to move towards the members, the data points. The fourth constrain of the algorithm is its inability to calculate the membership value if the 3.

Regression trees

Linear regression can be used when the features measured have a linear correlation with the dependent variable. The regression can be formulated as(1)where *i*=1,..., *n* and is the vector of the parameters to be estimated. The errors, *i*=1,..., *n* are. i. d. with a mean equal to zero and an unknown variance. The function *f* can be linear or nonlinear. Since the relations of several features to aerobic fitness are nonlinear, good results cannot be obtained by using a plain linear regression model. Nonlinear regression does not guarantee an optimal solution, however, and it is very complicated. The functional expression has to be written, good initial values have to be found for the parameters, and the derivatives of the model may have to be specified with respect to the parameters. Regression trees are binary decision trees. The tree is constructed by splitting the entire data into subsets by using all the independent variables. The goal is to produce terminal nodes that are as homogeneous as possible with respect to the target variable. Regression trees can be notable accurate in the case of nonlinear problems, but the traditional regression will probably work better for linear data.. For every node *t*, is the within node sum of squares. In other words, it is the total squared deviations of the in *t* from their average. The regression tree is formed by iteratively splitting the nodes, so that the decrease in *R(T)* is maximized, where *R(T)* sums up all the sums of squares within all the nodes. After the tree has been constructed, it can be visualized by showing how the data space is divided. Every division contains a rule, which allows the relations between variables to be examined. In other words, every division is based on a decision to divide the sub data into two groups by certain continuous or categorical variable. It is therefore easy to see which variables are the most important in view of the homogeneity of the data space. The size of the tree can be restricted with various limitations. The problem of bias and variance is present along with the size. If the tree is too small, the model cannot fit the data properly, and if the tree is too large, generalization of the model is inadequate. Stopping rules are used to control the size of the tree being built. The maximum depth of the tree and the minimum number of subjects per parent or child node can be defined. The C&RT method in Answer Tree 1. 0 (SPSS) is a method in which generates binary decision trees. It provides a versatile illustration of the results. But modelling within the terminal nodes is laborious. CUBIST by Ross Quinlan is much easier to use, but there are no publications available on the method, and the procedure used is therefore unknown. distance of data points is zero. This helped us further work on random forest method and regression tree to cluster the data and classify the patients based on the features.

The table 1 summarises the features used for classification.

Table1:Computerized Cancer Detection and Classification

Feature extraction of Cervical cancer methods and features used	Geometric features(GF)	Primitive features: corners, edges
	Texture features(TF)	Parameter control function: computer vision, range, average distance, stick size
	Statistical features(SF)	Mean, Standard mean error or percentage
	Histogram features(HF)	Bonferroni approach: pair-wise comparison, Correlation co-efficient Contrast, tumor range, tumor volume, vascularization index(VI), flow index(FI), Vascularization flow index(VFI)

V. Conclusion and future scope:

In General there are many types of cervical data available for the screeing and other tests. In this paper Six types of cervical precancerous data (i. e., cytology, FISH, electromagnetic spectra, cervicography, colposcopy, and HSDI) generally can be used for the intelligent screenin of cervical cancer. Computer screening system for cervical cancer based on cellular level data, namely, cytology, FISH and electromagnetic spectroscopy, achieved better results as compared to tissue level data such as cervicography and colposcopy. Classification tools (i. e., ANN, SVM, logistic regression, KNN, LDA, and decision tree) generally can achieve good performances to classify the cervical precancerous data. The screening systems based on neural network technique are frequently applied due to the better results and potential of the technique to build a real time system. The long training time of the neural network can be reduced by using the features selection stage in the computer screening system. The dimensionality reduction popularly done by using discriminant analysis and principal component analysis can be developed using new techniques that can be proposed as future work in this research field. The developed techniques will reduce the training time and improve the classification result of the neural network. This study motivates me to further proceed with the easy way of identifying the genes whether they are affected with cancer with numerical value since a biopsy results of numerical data is available from jipmer i would like to proceed further in classification through better learning..

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