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RESEARCH ARTICLE

MULTI CLASS CERVICAL CANCER CLASSIFICATION IN PAP SMEAR IMAGES USING HYBRID TEXTURE FEATURES AND FUZZY LOGIC BASED SVM

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ABSTRACT

Cervical cancer is the highest rate of incidence after breast cancer, gastric cancer, colorectal cancer, thyroid cancer among all malignant cancers that occurs to females; also it is the most prevalent cancer among female genital cancers. Manual cervical cancer diagnosis methods are costly and sometimes result in inaccurate diagnosis caused by human error but machine assisted classification system can reduce financial costs and increase screening accuracy**.** In this research article, we have developed, multi class cervical cancer classification system based on hybrid texture features and fuzzy logic based support vector machine using Pap smear images. Two major contribution of the proposed system is feature extraction & its classification. In feature extraction, multiple features are extracted using multi texton histogram and Gabor filter based orientation image. This system classifies the Pap smear cells into anyone of four different types of classes using Fuzzy-SVM. The performance of the proposed algorithm is tested and compared to other algorithms on public image database of Herlev University Hospital, Denmark, with 452 Pap smear images. The overall classification accuracy of the proposed MMTH+ Fuzzy HKSVM is 96.8%, but the existing methods MMTH+RBF and MMTH+SVM produce 91.32 % and 94.32% respectively.

INTRODUCTION

Cervical cancer has become one of the major causes of death among women universal. It can be treated when it is discovered and preserved in its earlier stage. But for most of the cases it throws signs only in the progressive stages. The out-dated pictorial procedures are time consuming and error prone[1]. The Pap smear has made cervical cancer one of the most avoidable cancers, but older, poorer, and less educated women are fewer probable to be selected and screening is not presented in many low-resource regions of the world. The Pap smear screening is to diagnose premalignant cell alterations afore they progress to cancer. Smears contain mainly two types of cells: squamous and columnar cells. The columnar epithelium is found in the upper part of cervix, and the squamous epithelium in the lower part. The screening of smears is done by a cytotechnologist and/or cytopathologist[2-3].

Cervical dysplasia is the hypothetically premalignant change and abnormal growth of squamous cells on the surface of the cervix [4]. It is not cancer, and is usually curable. Most cases are eliminated by the host's immune system without intervention. It is mainly classified as three stages such as mild dysplasia, moderate dysplasia and severe dysplasia. In mild dysplasia, not ample of the tissue looks abnormal, and it is measured the least serious cervical pre-cancer but moderate dysplasia contains most of the tissue looks abnormal. Severe dysplasia is the most serious pre-cancer, it contains most of the tissue looks abnormal [5-6].

Dysplastic cells are cells which have undertaken precancerous variations. They usually have bigger and darker nuclei and a have a tendency to cling together in bulky clusters. Squamous dysplasia is separated into three classes: mild, moderate and severe. Mild dysplastic cells have engorged and light nuclei. On behalf of moderate dysplastic cells, the nuclei are larger and darker. The nuclei may have instigated to deteriorate, which is perceived as a granulation of the nuclei[7-8]. In the last stage of precancerous changes, severe dysplasia, the nuclei are vast, dark and often warped. The cytoplasm of severe dysplasia is dark and small when compared to the nuclei. Hence, pre-cancers and cancers are associated with a variety of morphologic and architectural variations, including the textures, sizes, and shapes of cytoplast and nucleus, hyperchromasia and pleomorphism [9-11].

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The process of extracting the original image based on the certain features which undergo a transformation of pixel regions. Feature extraction can be based on two approaches; they are human centered and machine centered approaches. Human centered approach measures with perception based features such as texture, and the perfect mathematical representation is selected for it. In machine centered approach, a unified computing scheme is selected for extracting certain ad-hoc features. There are many techniques for feature extraction, e.g. texture Features [12], Gabor features, feature based on wavelet transform, principal component analysis, minimum noise fraction transforms, discriminate analysis, decision boundary featureextraction, weightedfeature extraction and spectral mixture analysis. The texture elements act as attributes based on the pixel region that digitizes the individual object into binary forms of information through computer imaging based on the silhouette of image info [13-14].

Machine learning classification techniques, including supervised and unsupervised clustering or fuzzy clustering are also introduced into cervical cancer classification. Trained classifiers estimate the probability for each image in the testing volume, judging whether the images belong to the target or the background. The threshold of the probability map is calculated to obtain the segmentation result or provide for post-processing. These techniques make it possible for high-dimensional features to be utilized in order to achieve a better discriminatory power for cancer compared with sole dependence on intensity information [15].

Moreover, the methods realistic in the field of pattern analysis can be transplanted into medical image segmentation, such as a distance metric learning algorithm, to make the intra-class samples closer while keeping extra-class samples as far away from each other as possible. Unfortunately, these classifications based segmentation approaches consider the voxels in the image to be liberated of each other, with no spatial connection both in the training and testing phases [16]. The rest of the paper is organized as follows: Our proposed multi class cancer classification system is presented in section 2. The detailed new results and discussions are given in section 3, while the conclusion is summarized in section 4.

MULTI CLASS CERVICAL CANCER CLASSIF ICAT - ION SYSTEM

Current manual screening methods are costly and sometimes result are inexact diagnosis caused by human error. The introduction of machine assisted screening will bring significant benefits to the community, which can reduce financial costs and increase screening accuracy. In this research article, we have developed, multi class cervical cancer classification system based on hybrid texture features and fuzzy logic based support vector machine using pap smear images. Two major contribution of the proposed system is feature extraction and feature classification.

Feature Extraction

The purpose of feature extraction is to reduce the original data set by computing definite properties, or features, that extricate one input pattern from another pattern. The extracted feature is expected to provide the characteristics of the input type to the classifier by considering the description of the related possessions of the image into a feature space. The proposed method, feature extraction method consists of four stages such as

- Computation of Feature Vector F(V1) using GLCM.
- Computation of Feature Vector F(V2) using Gabor Orientation Image.
- Computation of Feature Vector F(V3) using Texton Image.
- Concatenated of three Feature Vectors.

Computation of Feature Vector F(V1) using GLCM

Histogram based features are local in nature. These features do not consider spatial evidence into deliberation. Consequently for this persistence gray-level spatial co-occurrence matrix $h_d(i,j)$ based features are well-defined which are recognized as second order histogram based features. These features are based on the joint probability dispersal of duos of pixels. Distance d and angle θwithin a given neighbourhood are used for calculation of joint likelihood spreading between pixels. Generally d=1,2 and θ=0^o,45 ^{o}, 90 ^{o},135 ^{o} are used for calculation. Texture features can be labelled using this co-occurrence matrix [17-18]. In our proposed method, Feature Vector F(V1) (Five features such as, ASM, entropy, IDM, contrast and Maximumprobability) is extracted from the co-occurrence matrix.

Computation of Feature Vector F(V2) using Gabor Orientation Image

A 2D Gabor function is a Gaussian modulated by a complex sinusoid. It can be specified by the frequency of the sinusoid ω and the standard deviations $\pm_x and \pm_y$ of the Gaussian envelope as follows:

$$\cdot\ (x,y) = \frac{1}{2®\pm_x \pm_y} e^{(-(1/2)(x^2/\pm_x^2 + y^2/\pm_y^2)+2® j\mu x}$$

The response of Gabor filter is the convolution of Gabor window with image I, and is given by

$$G_{mn}(x,y) = \sum_j \sum_t I((x-s,y-t)\cdot {}^{*}_{mn}(s,t)$$

After the Gabor orientation process of the original image, feature Vector F(V2) (Five features such as, ASM, entropy,

IDM, contrast and Maximumprobability) is extracted from the Gabor orientation image.

Computation of Feature Vector F(V3) using Texton Image

Texton is one of the very important concepts for texture analysis; it was developed 20 years ago. It is a set pattern sharing a common property all over the image**.**According to the neuropsychological findings, different types of incentive are processed disjoint, yet concurrently, by dissimilar neural mechanism previously to the stimulus are intentionally perceived as a whole. In the proposed method, feature extraction process is done with the help of modified Multi texton histogram (MMTH). In this method, both Histogram and co-occurrence matrix are used for feature extraction process. The relationship between the values of neighboring pixels is characterized by TCM. Histogram based techniques are simple to compute, but highest indexing performance. The co-occurrence matrix directly uses a feature representation of the image. If the dimension of the image is high, then the performance is decreased. The spatial information is lost when the histogram is used only for feature representation of the image [19-20]. Hence combine both histogram and co-occurrence matrix for feature extraction and depiction. In the MMTH method, four special types of textons are used for detecting the texton in the original image. It is shown in Figure1.

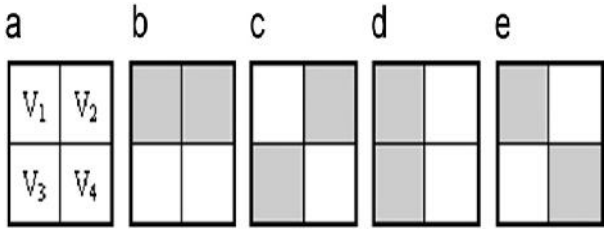

Figure 1 Special texton types of MMTH (a) original 2x2 matrix (b)Texton T1 (c) Texton T2 (d) Texton T3 (e) Texton T4

Consider a 2 × 2 matrix in the image with four pixels P1, P2, P3 and P4. If two pixels have the same, then these pixels form a texton. The possible textons formed with different combination of pixels with same intensity values are denoted by T1, T2, T3 and T4 which are shown in Figure 1. The texton image is formed overriding these four texton patterns with two pixel length as shown in Figure 2.

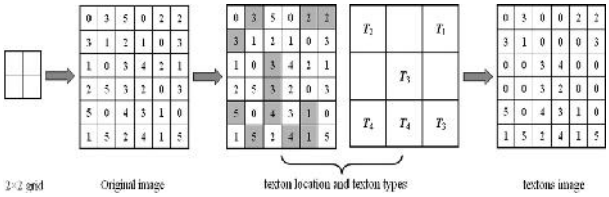

Figure 2 Texton image formation process using MMTH (a) 2x2 matrix (b) Original image intensity value (c) Texton location of the original image (d) Four texton types (e) Final texton image of MMTH

In Figure 2, the 2 × 2 matrices are shown in Figure 2 (a), the experimental image data are shown in Figure 2 (b), the four texton templates that photo over the entire tentative image from left to right and top to bottom with two pixel length to detect four textons is shown in Figure 2(c). The four different type textons are given in Figure 2(d). The four texton component images that are composed to form a last texton image is shown in Figure 2(e). After the formation of final texton image, the feature vector F(V3) (Five features such as, ASM, entropy, IDM, contrast and Maximumprobability) is extracted from the final texton image.

Concatenated of Feature Vectors

Hence, total Feature vector uses $F(V) = F(V_1) + F(V_2) + F(V_3)$ dimensional vector as the concluding image features in cancer classification.

Feature Classification using Fuzzy-SVM

TheSVMhasbeenlargely usedinpatternrecognition solicitationsduetoitscomputationalefficiency andgood generalizationperformance. It is widely used in object detection and recognition, content-based image retrieval, text recognition, biometrics, speech recognition, etc. It creates a hyperplane that separates the data into two classes with the maximum margin. Originally it was a linear classifier based on the best hyperplane algorithm.A support vector machine searches an optimal splitting hyper-plane between members and non-members of a certain class in a high. In SVMs, the training process is very sensitive to those training data points which are away from their own class. In our proposed method Fuzzy logic based SVM (FSVM) is pragmatic for classification.It is an operative supervised classifier and accurate learning technique, which was first proposed by Lin and Wang [21]. In FSVM is to assign each data point a membership value according to its relative importance in the class. Since each data point x_i has an assigned membership value $\ll_i$, the training set s_f and is given by

$$s_f = \{x_i, y_i, \ll_i\}_{i=1}^{n} \tag{5}$$

For positive class $(y_i = +1)$, the set of membership values are denoted as $\ll_i^+$, and are denoted as $\ll_i^-$ for negative class $(y_i = -1)$, they are assigned independently. The main process of fuzzy SVM is to maximize the margin of separation and minimize the classification error.

The optimal hyperplane problem of FSVM can be defined as the following problem [22]..

$$\min_{w,s} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} f_i £_i \tag{6}$$

Subject to $y_i(w.x_i + b) \geq 1 - £_i$

$£_i \geq 0 \qquad ,i = 1,.....n$

Where $f_i (0 \leq f_i \leq 1)$ is the fuzzy membership function, $f_i £_i$ is a error of different weights and C is a constant

The inputs to FSVM algorithm are the feature subset selected via MMTH. It follows the structural risk minimization

principle from the statistical learning theory. kernel of this theory is to mechanism the practical risk and classification capacity in order to condense the margin between the classes and reduce the true costs. A Fuzzy support vector machine searches an optimal separating hyper-plane between members and non-members of a given class in a high dimension feature space.

The Lagrange multiplier function of FSVM is

$$L(w,b,\P,\ )=\frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}f_i\P_i-\sum_{i=1}^{n}\sim_i(y_i(wz_i+b)-1+\P_i)-\sum_{i=1}^{n} {}_i \quad (7)$$

Which satisfies the following parameter condition

$$w-\sum_{i=1}^{n}\sim_i y_i z_i=0$$

$$-\sum_{i=1}^{n}\sim_i y_i=0$$

$$f_i C-\sim_i- \ {}_i=0$$

Then the optimization problem can be transferred to

$$Max\ \ W(\sim)=\sum\sim_i-\frac{1}{2}\sum\sim_i\sim_j y_i y_j H(x_i,x_j) \quad (8)$$

Subject to:
$$\sum\sim_i y_i=0$$
$$0\le\sim_i\le f_i C\ \ , i=1,2,...,n$$

Where the parameter $\sim_i$ can be solved by the sequential minimal optimization (SMO) quadratic programming approach.In Nonlinear data, the input space X can be mapped into higher dimensional feature space $\cdot$. It's become linearly separable. The mapping function $\cdot$ should be in accordance with Mercer's theorem [23].

$$H(x,x_i)=\cdot\ (x)^t\cdot\ (x_i) \quad (9)$$

Where $H(x,x_i)$ *is Kernel function*

It can be chosen from the following functions

Polynomial learning machine kernel function

$$H(x,x_i)=(x.x_i+1)^d, i=1,2,3....,n$$

Where d is an integer

Linear network kernel function

$$H(x,x_i)=x^T x_i$$

Radial-basis function (RBF) kernel function

$$H(x,x_i)=\exp(-\¥\left\|x-x_i\right\|^2), i=1,2,3....,n,\¥>0$$

DATA SET AND EXPERIMENTAL RESULTS

Data set and parameter description

The experimental Pap smear images are acquired through a powerful micro scope by the skilled cyto-technicians. All images were captured with a resolution of 0.201 μm/pixel from the open bench mark database of cervical cancer, Herlev University Hospital, Denmark [24-25]. The images were prepared and analyzed by the staff at the hospital using a commercial software package CHAMP^2 for segmenting the images. The cells were selected, not to collect a natural distribution, but to make a good collection of the important classes such as Mild dysplasia, Moderate dysplasia, Severe dysplasia and Carcinoma in situ. The sample Pap smear experimental images of various classes is shown in Figure 3. The data set contains 452 images with the following abnormal class distribution:

- Mild dysplasia, 113 images.
- Moderate dysplasia, 105 images.
- Severe dysplasia, 110 images.
- Carcinoma in situ, 114 images.

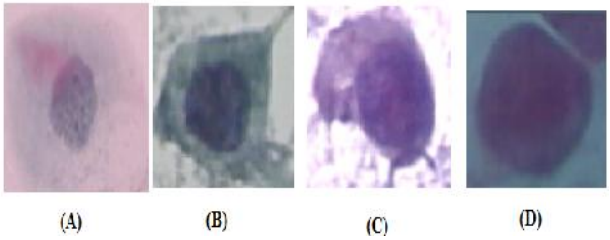

Figure 3 Some of the cells found in cervix: A-C) mild, moderate and severe dysplasia,(D) Carcinoma in situ.

Experimental Results

This section describes the experimental results of the proposed classification method using Pap smear images with different types of cervical cancer. In the proposed method, the experimental image data set is divided into two sets such as training set and testing set. The classifiers are trained with the training images and the classification accuracy is premeditated only with the testing images. In the testing phase, the testing dataset is given to the proposed technique to find the cancers type in smear images and the obtained results are evaluated through evaluation metrics namely, sensitivity, specificity and accuracy [26], it is given by

$$Sensitivit\ y=TP/(TP\ +FN)$$
$$Specificity\ =TN/(TN+FP)$$
$$Accuracy=(TN+TP)/(TN+TP+FN+FP)$$

Where TP corresponds to True Positive, TN corresponds to True Negative, FP relates to False Positive and FN corresponds to False Negative. These parameters for a specific category, say, Mild dysplasia are as follows: TP is True Positive (an image of 'Mild dysplasia' type is categorized suitably to the same type), TN = True Negative (an image of 'Non-Mild dysplasia' type is categorized correctly as 'Non- Mild

dysplasia' type), FP =False Positive (an image of 'Non- Mild dysplasia' type is categorized wrongly as 'Mild dysplasia' type) and FN is False Negative (an image of 'Mild dysplasia' type is categorized wrongly as 'Non- Mild dysplasia' type).'Non- Mild dysplasia' actually corresponds to any of the three categories other than 'Mild dysplasia'. Thus, 'TP & TN' corresponds to the correctly classier images and 'FP& FN' corresponds to the misclassified images.Experimental Image training data and testing data was shown in Table 1.

Table 1 Experimental image dataset for classification

Cancer type	Training data	Testing data	Total no of images
Mild dysplasia	40	73	113
Moderate dysplasia	40	65	105
Severe dysplasia	40	70	110
carcinoma in situ	40	74	114

The same feature sets are determined for all the categories by replacing 'Mild dysplasia' in the above definitions with other cancer categories. Thus, different parameter values are obtained for each class and also for the different classifiers. These parameters are estimated from the confusion matrix which provides the details about the false and successful classification of images from all categories for each classifiers. The confusion matrix of the proposed method is illustrated in Table 2.

Table 2 Confusion matrix of proposed method (MMTH+FSVM)

Class predicted	Ground Truth C (Assigned by Radiologist)			
	Mild dysplasia	Moderate dysplasia	Severe dysplasia	Carcinoma in situ
Mild dysplasia	68	1	2	2
Moderate dysplasia	1	61	2	1
Severe dysplasia	2	2	65	1
Carcinoma in situ	1	1	2	70
Individual Class accuracy	98.58	99.29	97.87	97.97
Overall classification accuracy				**96.80**

In the Table 2, the row-wise elements correspond to the four groups and the column-wise elements correspond to the objective class associated with that abnormal group. Hence, the number of images correctly classified (TP) under each group is dogged by the diagonal elements of the matrix. The row-wise summation of elements for each group other than the diagonal elements corresponds to the 'FN' of that group. The column-wise summation of elements for each group other than the diagonal element corresponds to the 'FP' of that group. Similarly, 'TN' of the specific group is determined by summing the elements of the matrix other than the elements in the corresponding row and column of the specific group.

For example, among the 73 Mild dysplasia testing images, 68 images have been successfully classified (TP) and the remaining 5 images (first row-wise summation) have been misclassified to any of the non- Mild dysplasia categories (FN). Similarly 4 images (first column-wise summation) from the other three categories (non- Mild dysplasia) have been misclassified as Mild dysplasia category (FP). In the Table 3, the classification accuracy of MMTH with RBF in class 1(Mild dysplasia) type cancer is 95.03%, class 2(Moderate dysplasia)is 96.09%, class 3(Severe dysplasia) is 95.037% and class 4(carcinoma in situ) is 96.09%. The miss classification rate of class 1(Mild dysplasia) and class 3(Severe dysplasia) type cancer is high compared to the other two classes. The individual class and overall class accuracy estimation process are given in Eqn(10) and (11).

Table 3 Performance measure of MMTH with RBF

Class predicted	TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	Accuracy (%)
Mild dysplasia	65	203	6	8	89.04	97.12	95.03
Moderate dysplasia	60	211	6	5	92.30	97.23	96.09
Severe dysplasia	62	206	6	8	88.57	97.16	95.03
carcinoma in situ	70	201	7	4	94.59	96.63	96.09
Overall classification accuracy							91.13

Individual class accuracy for ith class = $TP(i) / class(i)$ -(10)

Where, $TP(i)$ is correctly classified instances of the class (i)

Overall classification accuracy =

$$\left(\sum_i TP(i) / \sum_i class(i) \right) * 100 \text{ ----------(11)}$$

In the Table 4, the classification accuracy of modified MMTH with SVM in class 1 type is 97.16%, class 2 is 97.51%, class 3 is 96.45%, class 4 is 97.51% and the overall classification accuracy is 94.32. The miss classification rate of class 1 and class 3 types is high compared to the other two classes.

Table 4 Performance measure of Modified MTH with SVM

Class predicted	TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	Accuracy (%)
Mild dysplasia	68	206	3	5	93.15	98.56	97.16
Moderate dysplasia	61	214	3	4	93.84	98.61	97.51
Severe dysplasia	65	207	5	5	92.85	97.64	96.45
carcinoma in situ	72	203	5	2	97.29	97.59	97.51
Overall classification accuracy							94.32

In the Table 5, the classification accuracy of MMTH with Fuzzy-SVM in class 1 type cancer is 98.58%, class 2 is 99.29%, class 3 is 97.87% and class 4 is 97.97%.

For comparative analysis, the proposed cervical cancer classification system is compared to other neural network based methods such as RBF and SVM.

Table 5 Performance measure of MMTH with Fuzzy-SVM

Class predicted	TP	TN	FP	FN	Sensitivity (%)	Specificity (%)	Accuracy (%)
Mild dysplasia	70	208	1	3	95.89	99.52	98.58
Moderate dysplasia	63	217	0	2	96.92	100	99.29
Severe dysplasia	67	209	3	3	95.71	98.58	97.87
carcinoma in situ	73	203	5	1	98.64	97.59	97.97
Overall classification accuracy							**96.80**

The overall classification accuracy of the proposed method is 96.80%, MMTH with SVM is94.32% and MMTHwith RBFis 91.13%. The obtained results depict that the proposed multi class cancer classification method yields improved results compared to the other classifiers. The overall classification

results of sensitivity, specificity and accuracy of existing and proposed method are shown in Figure 4.

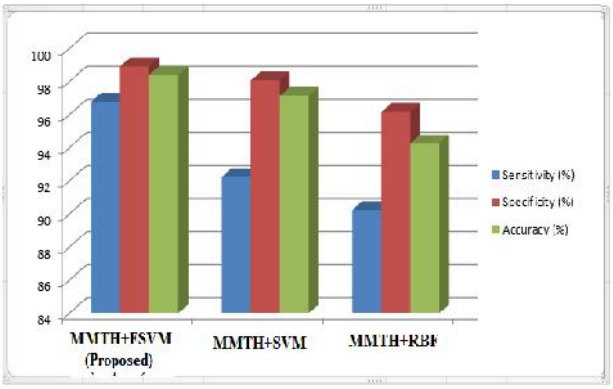

Figure 4 The Overall, Experimental results of Existing and Proposed methods

CONCLUSION

In this paper, a novel cervical cancer classification system is developed,which includes feature extraction, and multiclass classification of four classes of cervical cancer types such as Mild dysplasia, Moderate dysplasia, severe dysplasia and Carcinoma in situ. These cancer classes may have similar characteristics in their intensity and texture pattern; however, these cancer classes contrast in their position, size, and shape. The planned method is developed by multi model-texture features and fuzzy logic based support vector machine. The overall classification accuracy of the proposed MMTH+ Fuzzy SVM is 96.8%, but the existing methods MMTH+RBF and MMTH+SVM produce 91.13 %and 94.32% respectively. The developed methods for feature extraction, and classification of cervical cancer can be amalgamated to develop a CAD system. This system would be beneficial to radiologists for precise localization, diagnosis, and interpretation of cervical cancer on Pap smear images.

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