International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 9 (2018) pp. 6709-6716

Fuzzy NSCT based Feature Extraction Method for Automated Classification of Pap Smear images

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Abstract

There are few well established facts: cervical cancer is the most prevalent cancer amongst women worldwide; it is completely curable if diagnosed early and Pap smear test is the gold test for early detection. The main objective of the current work is to perform Fuzzy Non Sub-sampled Contourlet Transform (NSCT) based classification of Pap smear images which in turn will detect the cervical dysplasia. In doing so four pyramidal and directional NSCT filter combinations namely {(*pyr*,*dir*) : (9− 7, *sinc*)(9 − 7, *pkva*)(*pyrexc*, *sinc*)(*pyrexc*, *pkva*)} is used to design feature vectors. Fuzzy entropy based feature selection technique is used for removing irrelevant and redundant features. Finally Least Square Support Vector Machine and Multilayer Perceptron is used for classification where final classes give the degree of malignancy present in an image and categorize the samples as per the established Bethesda framework of classification, to find out the pre-cancerous lesion of cervix. All the experiments are performed on a generated database containing 1611 Pap smear single cell images which requires lots of expertise. The study is also tested on a publicly available online database to check the consistency of the results as well as compared with other techniques. Extensive experiments proved that our proposed technique outperforms the existing methods in transform domain analysis for Pap smear classification.

Keywords: Pap smear; Multi-class classification; NSCT; Fuzzy entropy; LSSVM; MLP

INTRODUCTION

Cervical cancer is the uncontrollable growth of the cells lining the cervix, which is the lower part of the uterus connecting the body of the uterus with the vagina [1]. Cervical cancer is one of the most prevalent cancers among women worldwide. Its incidence and mortality is more in developing (low and middle income) countries as compared to developed ones [2,3]. In India 1,32,000 new cases were diagnosed and 74,000 death cases annually accounting nearly 1/3rd of the global cervical cancer deaths [4]. Lack of awareness and early as well as affordable diagnostic services is the main determining factor for this status. North Eastern region of India (where this study has been carried out) is in a sorrier status as it has the second most prevalent cervical cancer among women in India. According to a hospital based survey done by Dr. B. Borooah Cancer Institute, Guwahati (which is the premier cancer institute for the entire region) the incidence rate is as high as 11.1% in the year 2015-2016 [5]. Pap smear test is an established international standard of diagnostic technique for early screening [1]. It is a painless procedure where doctors collect cervical cells from the cervix, prepare the slides and visualize the image under microscope to give their decision. According to a survey performed by the authors 80% of the medical institutes of India still use the manual conventional Pap smear screening approaches [6]. This method is adopted by non-developed countries primarily because it is cost effective and does not have the technical and linguistic gaps compared to other commercial systems available in the market like Thin Prep Imager (Cytyc Corporation, now Hologic Inc.) and BD (Becton Dickinson) Sure Path Liquid-based Pap Tests. Hence, an automated diagnosis system from conventional samples is the need of the hour.

In medical image processing feature extraction is very crucial. Image features can be categorized into two categories: shape feature and texture/colour features [7, 8, 9]. *Shape feature* analysis is performed when external characteristic of the object is of main interest. These features help in describing the object. For example, it may include area, perimeter, eccentricity, compactness etc., of the object using which changes in the nuclei can be monitored as cancer progresses. In context with this study shape features can quantify the features like nuclear enlargement, irregularity in nuclear membranes, variation in nuclear size, distinguishing inflammatory cells etc. The shape features of Pap smear images were studied through segmentation techniques namely Water immersion [10], Watershed [11], FCM [12], Joint optimization technique [13], Genetic algorithm [14] etc. Researchers have tried to extract the ROI i.e. either the cervical nuclei or the cytoplasm so that variation in their morphometric features can be monitored.

In contrast *texture and colour* analysis normally helps in interpreting internal characteristic of the object. It is of four types: (i) Statistical methods, (ii) Structural methods (iii) Model based methods and (iv) Transform domain methods [15]. Some of the statistical methods are first order statistical features obtained through histogram analysis and second order statistical features obtained from the techniques like GLCM, GLRLM etc. In statistical methods feature values are obtained from pixel level intensity variations. Structural methods describe texture as the composition of well-defined texture elements or primitives. Model based features generate empirical model of each pixel in the image based on the

weighted average of the pixel intensities in the neighborhood. Transform domain features, where the digital images are converted from spatial to frequency domain, are divided into two types: (i) Unitary transform (Example: Discrete Cosine Transform, Discrete Fourier Transform etc.), (ii) Space/Spatial Frequency Transform (Example - Discrete Wavelet Transform, Gabor, Non Subsampled Contourlet Transform etc.). Texture and colour analysis is a hierarchical process involving two steps. In the first phase texture primitives are extracted using texture analysis techniques and then some statistical measures are used to represent those primitives which are termed as texture/colour features. In context with this work texture and colour features helps in quantifying hyperchromasia, cytoplasmic changes, removal of RBC etc. Some researchers have tried to study the textural features from the ROI [12, 16]. Also attempt has been made to study features using conventional transforms like DFT [17], MPEG 7 descriptors [19] etc.

MOTIVATION AND CONTRIBUTION

Automated classification of medical images is fully determined by the image features under consideration. These features help in quantitative conversion of subjective morphological features which changes as cancer progress. Shape features can be obtained using segmentation technique. But no segmentation technique is ideal (i.e. 100% efficient). Shape feature statistics are fully influenced by the efficiency of the proposed segmentation technique, which always need qualitative analysis to determine the stopping criteria of the algorithm. But texture and colour feature analysis are not slave of underlying segmentation technique. This motivated us to work on texture and colour features. Pap smear images contain very complex details of the objects (namely nuclei and cytoplasm) with different curves and contours. So the feature vector which can represent these details can lead to an efficient automated system design. Multi-resolutional transforms has the capability of representing images with fewer coefficients which can be observed along multiple scales, directions and resolutions. They are also localised in both time and frequency domain and no prior segmentation technique is needed for analysis. That is why multi-resolutional transforms are explored in application with Pap smear image classification to detect cervical dysplasia in this contribution. There are many multi-resolutional transforms which are used in Content Based Image Retrieval (CBIR) works namely Discrete Wavelet Transform (DWT), Ridgelet, Curvelet, Contourlet, Ripplet, Non Subsamples Contourlet Transform (NSCT) and many more. DWT is localized in both time and frequency domain but unable to resolve 2D singularities along curves and edges [19]. Ridgelet resolves 1D singularity along horizontal and vertical direction but always fails along arbitrarily shaped curves [20]. Curvelets are able to represent 2D singularity but it uses a parabolic scaling law and there is an issue related to scalability of the law [21, 22]. Contourlet offers high degree of directionality and anisotropy but lack of shift invariance property [23]. Ripplet performs good generalization of scaling law used by CVT by adding two extra parameters i.e. support c and degree d but has complex mathematical base which is hard to understand [24]. NSCT is considered superior among all having the property of full shift invariance, multi-scale anisotropy and multidimensional expandability [25]. Due to these properties NSCT is applied in this work as a feature extraction technique. NSCT has been widely used in many CBIR works [7, 28] but to the best of our knowledge it is not used in Pap smear image analysis till date. Being an advanced multi-resolutional technique which is having property like multi-scale anisotropy, multi-directional expandability, full shift invariance and many more; NSCT can be a perfect tool for Pap smear feature vector generation, which motivates us to apply this technique in Pap smear analysis to study the morphological changes of cervical cells as the cancer progresses in different stages.

Further, a fuzzy entropy based feature selection technique is used to deal with unwanted redundant features. This is a possibility based solution to deal with unpredicted real data. The final reduced set is then classified using Least Square Support vector Machine (LSSVM) and Multilayer Perceptron (MLP). Final classes give the degree of dysplasia present in a Pap smear image according to The Bethesda System (TBS) of classification. TBS helps in maintaining uniformity with the current reporting standards.

MATERIAL AND METHODS

Overview of the work

Figure 1 shows the block diagram of the proposed work. It is completed in 4 phases. First phase is the database generation phase. Second phase is for feature extraction using NSCT. This is followed by feature selection using fuzzy entropy. Finally classification is performed using LSSVM and MLP where the final classes reflect the degree of malignancy present in an image.

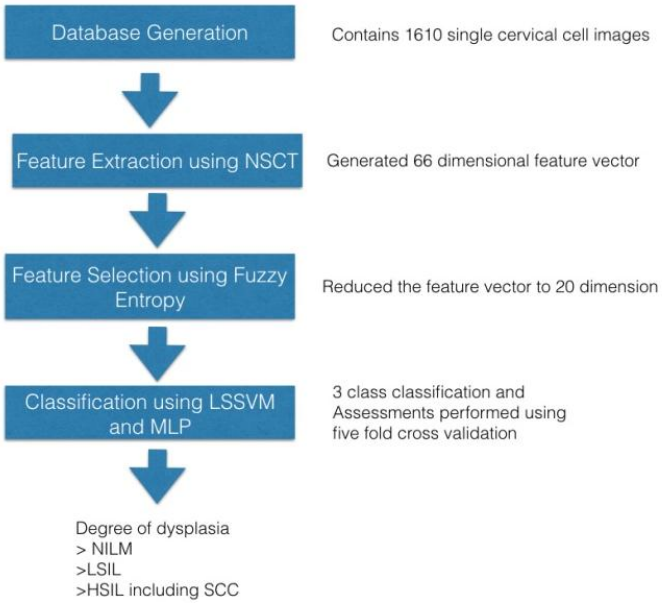

Figure 1. Overview of the proposed work

Database Generation

A single cell image database is generated at Ayursundra Healthcare Pvt Ltd (the most popular diagnostic laboratory in Guwahati) and Dr B. Borooah Cancer Institute, Guwahati, India. Staining and preparation is performed at their respective laboratories. Samples were collected from 132 patients. Then doctors annotated the cervical cells in a smear level image and accordingly a single cell repository of 1611 images was created. Image acquisition is performed using Leica ICC50 HD microscope using 400X resolution with 24 bit colour depth. The single cell repository has three sub-repositories by category type: 1001 Negative for Intraepithelial Malignancy (NILM) cells, 400 Low-grade squamous Intraepithelial Malignancy (LSIL) cells and 210 High-grade squamous Intraepithelial Malignancy (HSIL) cells (including Squamous cell carcinoma (SCC)) as shown in **Figure 2**. This categorization is done by expert pathologists following TBS framework of classification.

Another publicly available database (Herlev database) is used in the experiments which is available in http;//labs.fme.aegean.gr/decision/downloads. This dataset contains 917 single cervical cells. Since we are following TBS framework, we have rearranged the images with the help of doctors. The rearranged database contains 242 NILM, 182 LSIL and 493 HSIL (including SCC) images.

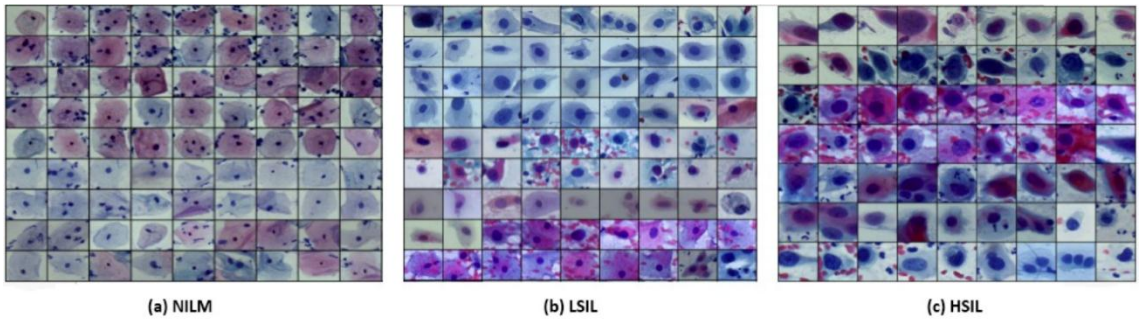

Figure 2. Snapshot of the generated image database which is showing three classes NILM, LSIL and HSIL

This work has been approved by institutional ethical committee bearing registration no- ECR/248/Indt/AS/2015 of Rule 122D, Drugs and Cosmetic Rule, 1945.

NSCT

NSCT has the property of flexible multi-scale anisotropy, multidimensional expandability, full shift-invariance and fast implement ability [26]. The proposed work used the Cunha *et al.,* [16] algorithm to decompose the frequency plane into sub-bands. Here Non Sub-sampled Pyramid (NSP) is applied to achieve multi-scale anisotropy and Non Sub-sampled Deterministic Filter Bank (NSDFB) is used to provide multi-directional property. **Figure 3** shows the decomposition of Pap smear image using NSCT. First, a NSP split decomposes the input into a low-pass and a high-pass sub-band. Then a NSDFB decomposes the high-pass sub-band into several directional sub-bands. The scheme is iterated repeatedly on the low-pass sub-bands. To display the coefficients of different sub-bands histograms are used in Figure 3 showing all 11 sub-bands generated in the process.

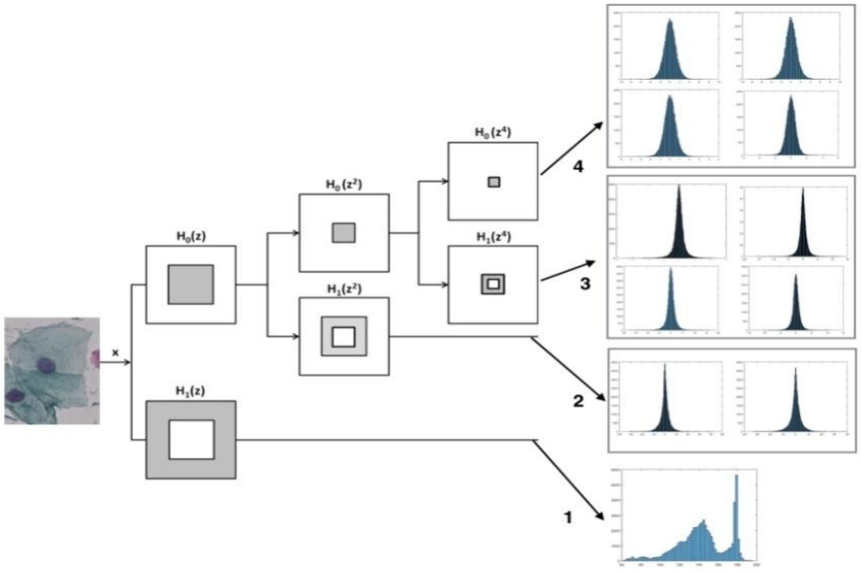

Figure 3 .NSCT based decomposition of Pap smear image

NSCT experimental setup with feature representation method

Following function can be used to explain NSCT transform setup:

$$F = NSCT(I, 'pyr', 'dir', decom-level); \quad (1)$$

Fdenotes the feature vector generated by applying NSCT transform function on an image I using '*pyr*' pyramidal filter and '*dir*' directional filter with decomposition level as '*decom-level*'. The decomposition level considered for this study is [1, 2, 2]. This indicates that there are three pyramidal decompositions and the number of directional decomposition in each pyramid level from coarse to fine resolution is 1, 2, 4 and 4. The output F has cell vectors such that -

$F1 = [F[1]]$indicate low pass sub-band image.

$F2 = [F[2,1], F[2,2]]$ are high pass sub-band.(Obtained from 2nd level decomposition)

$F3 = [F[3,1], F[3,2], F[3,3], F[3,4]]$ are four directional sub-band of the next finer pyramidal level.

$F4 = [F[4,1], F[4,2], F[4,3], F[4,4]]$ are four directional sub-band of the finest pyramidal level.

$F3$and $F4$ are obtained from third level decomposition. So total sub-bands generated is $11(1 + 2 + 4 + 4)$. Different (pyr, dir) combinations used for the study is $\{(pyr, dir): (9-7, sinc)(9-7, pkva)(pyrexc, sinc)(pyrexc, pkva)\}$. Prior to NSCT decomposition image I is converted to YCbCr colour model and three colour planes are extracted. YCbCr model divides the image information according to luminance (Y) and chrominance (Cb and Cr) component. Luminance component helps in studying the texture information and chrominance component helps in studying colour information. Also YCbCr colour models always carry maximum information of an image during uneven illumination. In such cases models like RGB always fail as it can only portray the uniform features of an image.

The dimension of generated feature vector is 66. This includes 11 sub-bands across 3 colour planes of YCbCr. During feature representation mean and variance of coefficients along each sub-band is extracted. Feature vector of an image I is represented as follows –

$$F_1^I = \left[f_\mu^{\emptyset^Y}, f_\sigma^{\emptyset^Y}, f_\mu^{\emptyset^{Cb}}, f_\sigma^{\emptyset^{Cb}}, f_\mu^{\emptyset^{Cr}}, f_\sigma^{\emptyset^{Cr}}\right]$$

Where $f_\mu^{\emptyset^{plane}}$ represent mean of transform coefficients along a colour plane and $f_\sigma^{\emptyset^{plane}}$ represents the variance of the transform coefficients along colour plane.

Mean can be calculated as follows –

$$Mean = \frac{1}{M*N}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|\emptyset_a^{pane}(m,n)\right|$$

Variance can be calculated as –

$$Variance = \sqrt{\frac{1}{M*N}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|\emptyset_a^{plane}(m,n) - f_\mu^{\emptyset^{plane}}\right|}$$

Here $\emptyset_a^{plane}(m,n)$ represents the transform coefficient at location (m,n).

Fuzzy Entropy based feature selection

Fuzzy entropy is an extension of Shannon entropy where the latter is a probabilistic method opposed to fuzzy entropy which is a possibility based method. In fuzzy entropy based method fuzzy sets are used in entropy calculations. In this feature selection technique required membership of each sample along different feature dimensions are measured. In this work we have followed the work of Khushaba *et al.,* [27] to estimate the membership function. Unlike feature selection techniques like PCA, ICA etc, our proposed technique does not fully transform the image features, rather it helps in ranking the features based on their contribution to an assigned class. This helps in proper monitoring of the features during feature reduction.

Let us consider a feature vector $F = \{f_1, f_2, \ldots\ldots, f_l\}$, where $l = 1,2,\ldots\ldots,66$. l is the number of total features. Fuzzy membership value that k[th] feature vector will be in i[th] class is $\mu_{ik} = \left(\frac{\|f_i - f_k\|_\sigma}{r+\epsilon}\right)^{\frac{2}{\rho-1}}$, where ρ is the fuzzification parameter and $\epsilon > 0$ is a value to avoid singularity and σ is the standard deviation.

Normalization of the obtained membership values is performed to get standard set of features. In case of total c numbers of classes, c numbers of fuzzy sets along each feature f needs to be considered. Each of these reflect the membership degree in c problem classes. Fuzzy joint probability of a particular feature vector belonging to class c can be given by the formula

$$P(f, c_i) = \frac{\Sigma_{k\epsilon U_i}\mu_{ik}}{T},$$

where $P(f, c_i)$ gives the degree of contribution of a feature to a particular class. U_i indicate the indices of the training feature vector that belong to class I and T indicates the dimension of feature vector. Joint fuzzy entropy of features of each class can be calculated as follows

$$H(f, c_i) = -P_{f,c} log P_{f,c_i}$$

The complete fuzzy entropy can be obtained as –

$$H(f, C) = \sum_{i=1}^{c} H(f, c_i)$$

Marginal entropy $H(f)$ can be found as

$H(f) = -P_{f_{S_i}} log P_{f_{X_i}}$, where X_i indicate the c numbers of fuzzy sets and $P(f_{X_i})$ can be calculated as,

$$P(f_{X_i}) = \frac{\sum_k \mu_{ik}}{T}$$

Marginal class entropy $H(C) = -P_{c_i} log P_{c_i}$. Then mutual information (MI) between particular feature and class label can be calculated using following formula –

$$MI(f;C) = H(f) + H(C) - H(f,C)$$

For this fuzzy entropy based feature selection method features are ranked based on increasing and decreasing value of MI based on the application.

LSSVM and MLP –

LSSVM and MLP are two popular classifiers in machine learning. LSSVM has the advantage of fast computational time. LSSVM was initially designed for two class classifications but it can be extended to solve the multi-class problem by solving many two class problems. Here in this approach pair-wise coupling is used for combining two class problems [6, 7]. For M number of total classes pair-wise coupling uses M*(M-1)/2 binary classifier. Then each binary classifier votes for one class. The final class of the LSSVM is that class which wins with the highest votes.

MLP classifier used in this work is a feed forward neural network [27] with one input layer, one hidden layer and one output layer. Dimension of the feature vector determines the nodes of the input layer, and classification problem determine the nodes of output layer. Here in this work number of input nodes is 66 and number of output nodes is 3 (as it is a three class problem). The number of hidden nodes is determined by rule of thumb and set as $\sqrt{(Input - node) \times (Out - nodes)}$. Sigmoid activation function is used in hidden layer and linear activation function is used in output layer. Intially the network is initialized with random weights and biases, which is followed by training of weight using Levenberg-Marquardt algorithm [27]. Finally gradient descent is applied as the learning function with momentum bias.

Evaluation measure

Five evaluation measures are used for assessment of the work namely accuracy, Precision, specificity, Sensitivity, F-score. Formulas are available in Ref [6]. High accuracy indicates the high proportion of true results among all the cases observed. It increases with increase in true positive results. Again higher the value of sensitivity and precision lower will be rate of misclassification. F-Score being the harmonic mean of specificity and precision, so increases with the increase in both values. It will take high values when rate of misclassification and false positive rates are low.

RESULTS AND DISCUSSION

Evaluation of Results before feature selection - **Table 1** lists the statistics of NSCT based classification before feature selection using both generated and Herlev database. It is observed that highest accuracy of 97.02% is achieved using the filter combination (pyrexc, pkva) using generated database. 'pyrexc' NSPF works best in generated database as it has the capability of representing smooth edges. It constitutes of two high-pass filters with two vanishing moments and it uses maximally flat mapping functions. That is why it can successfully represent the variation along smooth contours. 'pkva' NSDFB works satisfactorily as it can capture high frequency components in an image with best Peak Signal-to-Noise Ratio (PSNR) performances. Pap smear images contain very complex objects with high variation curves and contours. That is why strong filters are required to deal with these high frequency components. On the other hand, image quality of Herlev database is different from generated database. That is why a different filter combination (pyrexc, sinc) is working satisfactorily for Herlev database. 'sinc' filters has the ability to remove all frequency components above a threshold frequency which enable it to deal with low resolution images. This combination is giving an accuracy of 91.50% using Herlev database. In both cases MLP classifier is giving better performance than LSSVM in context with accuracy. But MLP classifier consumes more time (120-160 mili-seconds), whereas LSSVM takes much less time (0.2 – 0.5 mili-seconds). This is actually the training time of the classifier. Once trained both MLP and LSSVM classifier performs testing within 0.2 - 0.5 mili-seconds.

Table 1: Classification results using Generated and Herlev database before feature selection (bold values indicates the best accuracy)

Filters combination	Classifier	Accuracy		Time (in mili-seconds)	
		Generated database	Herlev database	Generated database	Herlev database
(9-7, sinc)	LSSVM	85.51	80.36	0.3015	0.2051
	MLP	92.75	89.33	159.8608	127.2153
(9-7, pkva)	LSSVM	84.06	80.73	0.2482	0.1698
	MLP	92.44	89.01	154.8631	161.4944
(pyrexc, sinc)	LSSVM	86.54	91.00	0.2703	0.1982
	MLP	91.59	**91.50**	156.6721	138.6814
(pyrexc, pkva)	LSSVM	96.07	89.10	0.2713	0.1669
	MLP	**97.02**	90.18	516.7540	122.6904

Evaluation of Results after feature selection - Actual feature set dimension is 66 which may contain many redundant features. Redundancy always leads to lower classification results. That is why fuzzy entropy based feature selection is used for ranking of the features. For this purpose ranking of the features are done first then $k = 10,20,30,40,50,60,66$ dimensions are chosen and seven reduced feature vectors of k dimensions are designed. Then classification accuracy using each dimensional feature vectors is calculated. The results after feature selection for generated and Herlev database after fuzzy entropy based feature selection are displayed in **Figure 4**. It was clearly observed that classification accuracy using generated database has increased to 98.71% using MLP. Again classification accuracy using Herlev database has increased to 95.32% using MLP. This indicates that the use of feature selection technique has improved the results of final classification and reduced the dataset dimension to 40.

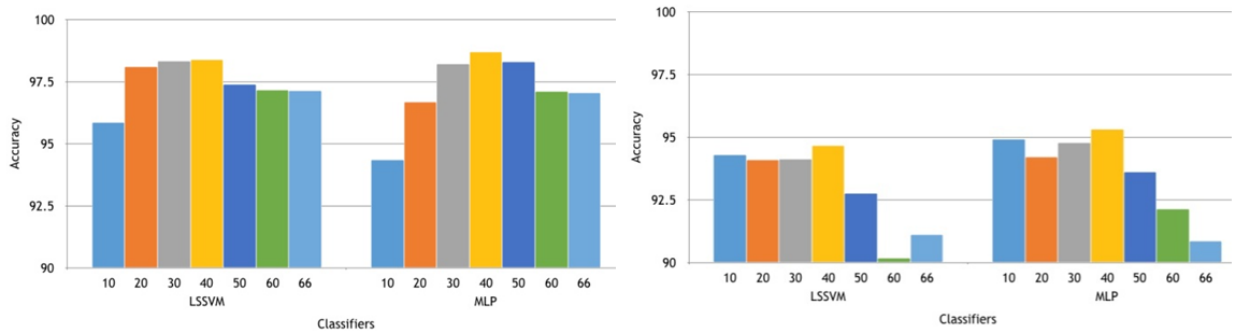

Figure 4: Classification results using generated and Herlev database after using fuzzy entropy based feature selection on NSCT feature vectors. Here X - axis represents different classifier and feature vector combination and Y- axis represents the classification accuracy in percentage form.

Table 2 – Some other assessments measures to check the efficiency of fuzzy NSCT based classification (bold values indicating best performances)

	Classifier	Filters combination	Accuracy	Precision	Specificity	Sensitivity	F-Score
Generated database	LSSVM	(pyrexc, pkva)	98.38	96.51	93.22	89.96	95.71
	MLP	(pyrexc, pkva)	**98.71**	**97.25**	**95.31**	**90.28**	**97.89**
Herlev database	LSSVM	(pyrexc, sinc)	94.66	92.48	90.11	89.65	89.61
	MLP	(pyrexc, sinc)	**95.32**	**94.32**	**90.61**	**92.14**	**90.70**

After feature set dimension is reduced to $k = 40$ another five measures are obtained using LSSVM and MLP classification techniques for both generated and Herlev datasets. These measures are listed in **Table 2.** Statistics can establish the fact that fuzzy NSCT based classification can be satisfactorily used for Pap smear analysis.

Comparison with existing techniques as applied to Pap smear classification - The proposed fuzzy NSCT based classification method is also compared with two existing approaches.

Comparison with Fourier Transform (FT) based method: FT is used by Changkong et al., [12] for classification of Pap smear images. Here in this work we have extracted mean and variance of Pap smear images using one dimensional FT. Then classification is performed using LSSVM and MLP. Comparison statistics are displayed in **Figures 5 and 6**. It shows that FT based classification accuracy is very poor as compared to fuzzy NSCT based classification. It is due to the reason that FT based methods are not generalized in time domain. That is why it is unable to represent different shaped curves and contours of an object along multiple directions.

Comparison with DWT based method: Sukumar et al., [29] has performed experiments using DWT for Pap smear feature extraction. That is why the proposed work is also compared with DWT based classification; also DWT forms the basis of all multi-resolutional transforms, so any comparison based study without DWT cannot be considered as a complete study. DWT is generalized in both time and frequency domain but unable to represent two dimensional singularities. It has limited ability to capture directional information, hence works poorer as compared to NSCT based method which is full shift invariant, have multi-directional property and represent curves and contours more efficiently. We have extracted the mean and variance using 16 filters of DWT (Haar, Coiflet, Daubechies and Bi-orthogonal). Finally bior6.8 is giving good results as compared to other filters. That is why bio6.8 is used in final comparison of results. **Figures 5** and **6** depict the comparison statistics graphically.

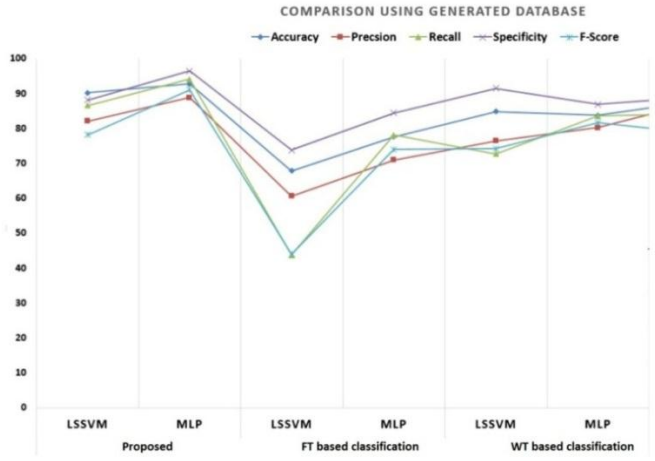

Figure 5. Comparison of the proposed approach with existing approaches using generated database

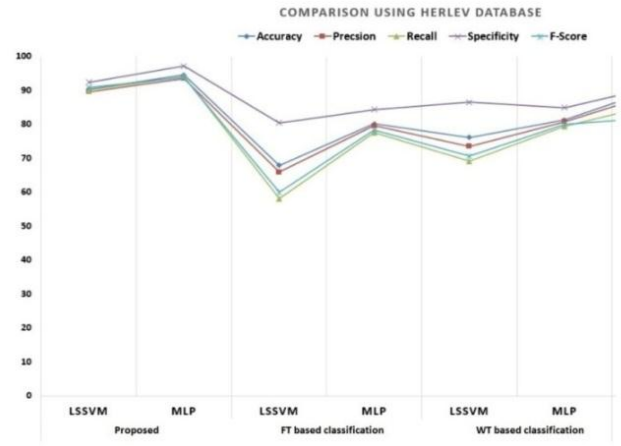

Figure 6 – Comparison of the proposed approach with existing approaches using Herlev database

CONCLUSION

In the present study four pyramidal and directional filter combinations of NSCT are used for feature extraction, which is followed by Fuzzy entropy based feature selection technique for removing irrelevant and redundant features. Finally LSSVM and MLP is used for classification where final classes give the degree of malignancy present in the Pap smear image and categorize the samples as per the established Bethesda framework of classification, to find out the pre-cancerous lesion of cervix. The present study has been able to establish that NSCT based classification of Pap smear images is one of the most effective methods to detect the cervical dysplasia till date, of all researches in this direction. It also outperforms the other conventional transforms like FT and DWT as compared in this paper.

ACKNOWLEDGEMENT

Kangkana Bora would like to thank Inspire Fellowship Scheme of Department of Science and Technology, Government of India for proving research fellowship. We also like to thank the Director of Institute of Advanced Study in Science and Technology, India for providing us the platform to work. This paper has the consent of all co-authors and has no conflict of interest with anyone.

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