



CAD for Two Class Classification of Lung Cancer using Statistical Features

Aman Deep*, Shruti Jain*, Sahil Bhusri**

*Department of Electronics and Communication Engineering, Jaypee University of Information and Technology, Shimla India.

**Lovely Professional University, Phagwara, Punjab, India.

*Corresponding author's E-mail: aman.barouli@gmail.com

Received: 03-05-2017; Revised: 12-07-2017; Accepted: 28-07-2017.

ABSTRACT

Lung Cancer causes maximum number of death in women and men all over the world. The Lung Cancer is divided into two types: Small Cell Lung Cancer (SCLC) and Non Small Cell Lung Cancer (NSCLC). A large number of techniques are being used for detection and diagnosis of Lung Cancer. The Computer Aided Diagnosis (CAD) is the most common and accurate technique for early detection of abnormal cells which can cause cancer to healthy lung tissues. CAD system works on the basis of analysis of condition of ultrasound images. CAD system follows different steps: Data collection (ultrasound image), Data Preprocessing (ROI Selection), Feature Extraction, Data Partitioning (hold- out method), Feature Classification and Result Calculation. To classify input ultrasound images into benign and malignant, different classifiers were used. The system work is based on the calculation of parameters such as individual accuracy, overall accuracy and sensitivity. These benchmarks are obtained by calculating the matrix of Support Vector Machine (SVM). The results were obtained by using various features using Statistical Methods. The best results achieved were having accuracy of 91.4% by using Gray Level Difference Statistics (GLDS). CAD system will use these results for detection of Lung Cancer cells in initial stage to enhance the capability of survival of patient. In this research work, the results obtained clearly demonstrate a promising accuracy and sensitivity of classes of lung cancer.

Keywords: Lung Cancer, CAD Computer Aided Diagnosis, Feature Extraction, ROI, Gray Level Difference Statistics, Classification.

INTRODUCTION

Lung Cancer originates in (trachea) the main airway (bronchus) or the lung tissue. The most leading and common cause of death across the world is lung carcinoma. It occurs due to the deformity in genetic material of lung cells. The main cause of lung cell deformity is tobacco which is the main reason of 88% deaths of Lung Cancer. Only 12-13% lung cancer occurs in non-smokers. In non-smokers the causes of lung carcinoma growth are due to radioactive gases and some superfine harmful fibers inhaling at workplace¹⁻⁵. Lung Cancer is of two types: SCLC and NSCLC. The SCLC is initial stage of Lung Cancer, when the abnormality starts growing in only one lung. Most of the time, it is undetectable because of its smaller size. NSCLC is basically the developed size of SCLC, when this small size increases and spread into lungs and other body organs then the carcinoma is NSCLC. Lung cancer is measured on the bases of how big it is and how abnormal its cell looks under the microscope. The abnormal cell growth is explained using grades⁶⁻⁷.

Grade 1: In the initial stage of lung cancer, the cells look like normal cells and less likely to spread.

Grade 2: Cells look abnormal and start spreading. This grade is also known as moderate grade.

Grade 3 and 4: The cells are completely deformed and growth is very quick. At this grade the cancer start spreading in other body parts. This grade is known as

poorly differentiated or high grade. The grading is for NSCLC.

METHODOLOGY

The system follows the following steps for the processing of data in order to extract results from its input data. The algorithm is developed to give the basic methodology of classification of Lung Cancer⁸⁻¹³.

Algorithm:

Step 1: *Data Collection:* Create a database of ultrasound images for Lung Cancer.

Step 2: *Data Preprocessing:* Selection of Region of Interest (ROI).

Step 3: Convert the selected ROI to Gray level images.

Step 4: *Feature Extraction:* Extract the texture features from gray level images using statistical methods.

Step 5: *Data Partitioning:* Partitioning the dataset into two sets (Training and Testing) using hold-out partitioning method. Hold-out data Partitioning is to reserve half data for training and other half for testing or to reserve 1/3 for testing and 2/3 for training.

Step 6: *Classification:* Apply SVM to partition database on the bases of classes of cancer.

Step 7: Calculate the Sensitivity and Accuracy of the data.



Database Ultrasound Images

The data is taken from the ¹⁴ for analyzing the lung carcinoma whether the cancer is of SCLC type or NSCLC type. The data is taken of 92 cases and abandon the cases having blood crafts. The database of 92 cases, out of which total 11 cases of SCLC and 81 cases of NSCLC are taken for this work.

ROI Extraction Module

The deformity in the ultrasound images are exposed with the help of expert radiologist and then marked using MATLAB 14.7 software. In order to mark these areas, the x, y coordinates of the interested regions were calculated¹⁵⁻¹⁷. Further segmented areas of dimensions 32×32 pixels were obtained. The dimensions of the ROI pixels may vary. The ultrasound image of carcinoma is shown in Fig. 1 and its segmented ROI is presented in Fig. 2

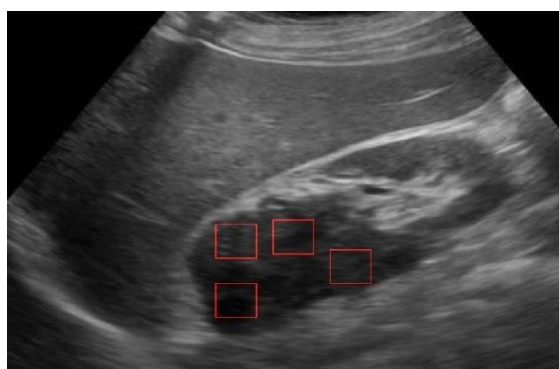


Fig. 1 Ultrasound Image of Lung Cancer



Figure 2: ROI's of ultrasound image

Feature Extraction Module

The infected field which has been destructed by any problem or illness is called lesion. Feature extraction module is divided into Morphological methods, Signal Processing Based Methods, Transform Domain Methods and Statistical Methods¹⁸⁻²². This work is focused on Statistical Methods to extract the Texture features of database.

Statistical Methods

The methods used for extraction of texture features based on pixel's gray level intensities of an ultrasound image, is known as statistical methods^{11-13, 23}. The statistical methods can be classified on the bases of the number of pixels used to calculate the texture features. The statistical features are divided into three types: First Order Statistics (FOS), Second Order Statistics (SOS) and Higher Order Statistics.

1) *FOS Feature*: The FOS is derived from the gray level intensities histograms of the image. The features like

standard deviation, kurtosis, average gray level, smoothness, and entropy were calculated for every ROI.

2) *SOS Feature*: In second order statistics, there are calculations with the Gray Level Co-occurrence Matrix (GLCM). In GLCM the different combinations of pixel gray level occurs in an image which are used for second order statistics calculation. The relationship between groups of 2 pixels is considered in GLCM which are called reference and neighbor pixel. These pixel pair having different gray level occurring in image having separation of different dimensions in different directions. The GLCM includes features of calculating contrast, entropy, sum entropy, difference entropy, correlation, inverse difference moment, sum average, variance, sum variance, difference variance angular moment etc. GLCM runs on the bases of following algorithm :

Step 1: Different extracted ROI images (database) were imported.

Step 2: Conversion of database images to gray level images.

Step 3: Assume initial value of co-occurrence matrix as zero.

Step 4: Assign index to co-occurrence matrix.

Step 5: Calculation of co-occurrence matrix.

Step 6: Calculation of pixels (reference pixel and neighbor pixel) of the row matrix.

Step 7: Normalization (Z Normalization) of data. Normalization in GLCM is to transform the matrix into a close approximation of probability table. The normalization is only an approximation because the gray levels are integer value so they are discrete in nature but probability work on the continuous values.

$$Z \text{ normalization} = \frac{\text{basic value} - \text{mean}}{\text{standard deviation}} \quad (1)$$

Step 8: Calculation of GLCM features. There are different features of GLCM: entropy, sum entropy, correlation, inverse difference moment, variance, contrast etc. Formulae used for calculation of features are:

1. Entropy is calculated by:

$$\text{Entropy} = - \sum_{i,j} P_{i,j} \log(P_{i,j}) \quad (2)$$

2. For calculation of Sum Entropy:

$$\text{Sum Entropy} = - \sum_{i=2}^{2Ng} P_{i,j}(i) \log(P_{x+y}(i)) \quad (3)$$

3. For calculating correlation:

$$\text{Correlation} = \sum_{i,j} P_{i,j} \left[\frac{(i-\mu_i)(j-\mu_j)}{\sigma_i \sigma_j} \right] \quad (4)$$

4. For calculating Inverse Difference Moment:

$$\text{Inverse Difference Moment} = \sum_{i,j} \frac{P_{i,j}}{1+(i-j)^2} \quad (5)$$

5. For calculation of variance:

$$\text{Variance} = \sum_{i,j} P_{i,j} (i - \mu_i)^2 \quad (6)$$

6. For calculation of contrast:

$$\text{Contrast} = \sum_{i,j} P_{i,j} (i - j)^2 \quad (7)$$

where i and j are horizontal and vertical coordinates respectively. μ is expected value and P is Probability Mass Function (the function that gives the probability that a discrete random variable is exactly equal to some value).

3) *Other Statistical Features*: Other statistical features like Edge Features, Neighborhood Gray Tone Difference Matrix (NGTDM), Statistical Feature Matrix (SFM), and Gray Level Difference Statistics (GLDS) were calculated in this paper.

a) Edge Features:

The information present in the edges is higher as compared to the other parts of the image. The spatial variation in an image is calculated by the gradient value. If there is an instant change in pixels then gradient will be high else it will be low. It calculates two features: absolute gradient and absolute gradient variance. The algorithm followed for Edge feature is shown below:

Step 1: Collection of dataset.

Step 2: Data preprocessing was done by selection of ROI's

Step 3: Import ROI images.

Step 4: Conversion of ROI to gray level images.

Step 5: Calculation of horizontal and vertical edges using sobel filter. (Sobel Filter is used to calculate the approximation of the gradient of the image intensity function. It creates an image emphasizing edges in image processing and computer vision).

Step 6: Compute probability distribution of gray level images.

Step 7: Compute mask to selected ROI's.

Step 8: Discard elements which counts pixels outside ROI.

Step 9: Normalization of matrix.

Step 10: Calculation of the features (absolute gradient). For calculation of absolute gradient formula is given in eq 8.

$$\nabla_j A^k \equiv \frac{\partial A^k}{\partial x^j} + A^i \Gamma_{ij}^k \quad (8)$$

where Γ_{ij}^k is Christoffel symbol, A is basis vector and k is free index.

b) NGTDM:

In NGTDM, the calculation of busyness, coarseness, complexity, contrast, strength takes place. In this it considers a difference between the gray levels between pixels. The steps of algorithm are :

Step 1: Collection of dataset.

Step 2: Data preprocessing was done by selection of ROI's

Step 3: Import ROI images.

Step 4: Conversion of ROI to gray level images.

Step 5: Calculation of NGTDM vector by comparing pixels to its neighborhood gray tone values of pixels.

Step 6: Calculation of normalization coefficient.

Step 7: Define neighborhood kernels (Kernel is the small matrix which is useful for blurring, sharpening, edge detecting etc).

Step 8: Convolve the kernels of ones to select pixels for which the kernel lies entirely within ROI.

Step 9: Compute NGTDM matrix by convolving these kernels with gray level images.

Step 8: Calculation of the features (busyness, coarseness, complexity, contrast (same as in eq.7)).

Formula for calculating image complexity is:

$$\text{Complexity} = \frac{\text{RMSE}}{\text{CR}} \quad (9)$$

where RMSE = root mean square error between lossy compressed image and original image.

CR = Compression ratio.

c) **SFM**: It calculates contrast, coarseness, periodicity and roughness of pixels at different distance within an image. For statistical feature matrix calculation the algorithm is shown below:

Step 1: Collection of dataset.

Step 2: Data preprocessing was done by selection of ROI's

Step 3: Import ROI images.

Step 4: Conversion of ROI to gray level images.

Step 5: Define coordinates of statistical matrix.

Step 4: Shift images by deleting rows and columns.

Step 6: Define ROI in original and shifted images.

Step 7: Common pixels in both areas are considered.

Step 8: Compute statistical feature matrix.

Step 9: Calculation of the features (contrast (same as in eq.7), periodicity and absolute roughness).

Formulae for feature calculation:

$$\text{Roughness} = \frac{1}{n} \sum_{i=1}^n |y_i| \quad (10)$$

where y_i = the vertically distance from i^{th} data point to the mean line.

n = the order of equally spaced point in the pixels.

d) **GLDS**: The contrast, energy, entropy, homogeneity and mean were calculated by GLDS on the basis of the co-occurrence of the pixel pair that has difference in gray levels separated by particular distance.



Step 1: Collection of dataset.

Step 2: Data preprocessing was done by selection of ROI's

Step 3: Import ROI images.

Step 4: Conversion of ROI to gray level images.

Step 5: Calculate the probability distribution of gray level differences for different dimensions and angles.

- a. Compute mask to select ROI.
- b. Setup gray level difference vector.
- c. Initialize gray level difference count vector.
- d. Calculate gray level difference.

Step 6: Calculate gray level difference at 0, 45, 90 and 135 degree.

Step 7: Normalize gray level difference matrix for all angles.

Step 8: Calculation of the features (contrast (same as in eq.7), homogeneity, energy, entropy (same as in eq. 2), and mean).

1) The homogeneity is calculated by:

$$\text{Homogeneity} = \sum_{i,j} \frac{P_{i,j}}{1+(i-j)^2} \quad (11)$$

2) Energy is computed by following formula :

$$\text{Energy} = \sqrt{\sum P_{i,j}^2} \quad (12)$$

3) Mean is calculated using:

$$\text{Mean} = \frac{1}{m} \sum_{i,j} iP_{i,j} \quad (13)$$

where i, j and P are same as mentioned for eq. 2 to eq.7.

D). Classification Modules

There are two type of characterization of classification; Supervised Classification and Unsupervised Classification²⁷⁻²⁹. When the classes are defined for the training sets in classification, then it is supervised classification and opposite is for unsupervised classification. The classifier used in our work is SVM classifier. The SVM is supervised type of classifier. For implementation of SVM classifier a library is used in MATLAB, called LibSVM³⁰⁻³². SVM classifier proceeds on the principle of decision planes, where the boundaries of decision are defined. It works on both linear and non-linear classification with higher speed and accuracy¹¹⁻¹³. Kernel Based Classifier; the training data of non-linear aligning to higher dimensional feature space from input space has been done using kernel functions. There are different types of kernels. For classification task in this paper we have used the *Gaussian radial basis function*. The appraisal of kernel parameter γ and parameter of regularization C is always a diagnostic step for having desired abstract performance. By doing the expanded search that is carried out in the parameter space for the

values of $C \in \{2-4, 2-3... 215\}$, $\gamma \in \{2-12, 2-11... 24\}$, the admirable values of γ and C are obtained³³⁻³⁵.

RESULTS AND DISCUSSION

In this paper, we have calculated Sensitivity and Accuracy of Lung Cancer by using confusion matrix. This confusion matrix is basically a table that often describes the performance of classifier using set of test data for which the true values are given shown in Table 1. The confusion matrix is obtained by SVM classifier.

The parameters used for computation of matrix are shown in Table 1.

Table 1: Confusion matrix for calculation

	Estimated No	Estimated Yes
Real No	TN = 83	FP = 7
Real Yes	FN = 2	TP = 13

True Positive (TP): The true positives are those cases of matrix, when we predict positive result and result is also positive.

True Negative (TN): A true negative occurs in matrix when our predication is negative and outcome is also negative.

False Positive (FP): These are the cases when we predict positive result but result is opposite of it.

False Negative (FN): The predicted value is negative but the result is positive, this is the false negative parameter for confusion matrix.

The results obtained by calculating the co-occurrence matrix using various features of Statistical Methods and SVM classifier is shown in Table 2.

The formulaes for parameters used in calculation of sensitivity and overall classification accuracy are :

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (14)$$

Sensitivity is also known as individual classification accuracy or true positive rate.

$$\text{Accuracy} = \frac{TP+TN}{\text{Total Number of Cases}} \quad (15)$$

Accuracy is known as Overall Classification Accuracy (OCA).

Table 2 shows the results of various features. EDGE and NGTDM achieve highest accuracy of 100% but has lower individual accuracy in case of benign class so the accuracy achieved with GLDS feature is considered as best accuracy because it acquires overall accuracy of 91.4% along with the individual accuracy (Sensitivity) of benign and malignant as 86.6% and 92.2% respectively.

Table 2: Two-Class Lung Cancer Classification using SVM

Features	Confusion Matrix			ICAM	ICAB	OCA
		M	B			
GLDS	M	83	7	92.2%	86.6%	91.4%
	B	2	13			
GLCM	M	85	5	94.4%	46.6%	87.6%
	B	8	7			
NGTDM	M	90	0	100%	0%	85.7%
	B	15	0			
SFM	M	71	19	78.8%	33.3%	72.3%
	B	10	5			
Edge	M	90	0	100%	0%	85.7%
	B	15	0			

Note: M:Malignant, B:Benign, ICAM: Individual Classification Accuracy of Malignant, ICAB: Individual Classification Accuracy of Benign, OCA: Overall Classification Accuracy

The GLCM achieves an OCA of 87.6% with individual accuracies for benign and malignant class as 46.6 % and 94.4 % respectively. Different researchers have

investigated using different methods, so for better observation of work, a comparison is displayed in Table 3.

Table 3: Comparison of our work with existing papers

Author	Classifier	Accuracy	Feature
Land WH, Jr., Mckee D, Zhukov T, Song D and Qian W ⁶	SVM	72%	Morphological Features (seeded watershed transforms)
Pawar DP: and Gulhane Sanjay.M ⁷	SVM	79.2%	Morphological Features
Haranshvir G and Khushali D ¹	FFT	85.1%	Texture Features (Gabor)
Proposed work	SVM	91.4%	Texture Features (GLDS)

CONCLUSION AND FUTURE WORK

The ambition of this paper is to provide high accuracy and enhanced images for diagnosis of Lung Cancer. This classifies lung cancer into two categories and achieves higher accuracy as compare to former results of different authors. In this work GLDS attains the best results. The cases benign misclassified of NGTDM and Edge feature, so in future the authors will focus to enhance the results of the system with NGTDM and Edge feature and also try to achieve higher overall performance of system. For accomplishment of this target, the author will use various filters and various texture feature extraction methods by using different classifiers for betterment of results.

REFERENCES

- Haranshvir G and Khushali D: A Review of Techniques for Lung Cancer Detection. International Journal of Current Engineering and Technology. June 2015, Vol.5, No.3, pp-1597-1602
- Kumar R and Srivastava R: Detection and Classification of Cancer from Microscopic Biopsy Images Using Clinically Significant and Biologically Interpretable Features. Hindawi Publishing Corporation J of Medical Engineering. 2015. Volume 2015. Article ID 457906.
- Laws KI: Rapid Texture Identification in Proceedings of SPIE, Image Processing for Missile Guidance. 1980, pp. 376-380.
- Shraddha, Kulkarni G and Sahebrao BB: Techniques for Lung Cancer Nodule Detection: A Survey. International Research J of Engineering and Technology. 2015. Volume: 02 pp. 2593-2597.
- Ajil MV and Sreeram S: Lung Cancer Detection from CT Image using Image Processing Techniques. International J of Advance Research in Computer Science and Management Studies Research. 2015. Volume 3. pp. 249-254.
- Land WH, Jr., Mckee D, Zhukov T, Song D and Qian W: An End-to-End Process for Cancer Identification from Images of Lung Tissue. IEEE. 2007. pp. 233-239.
- Pawar DP: and Gulhane Sanjay.M. Multistage Approach for Biomedical Image Processing: A Review. International Journal of Advancements in Technology. 2013. Volume- 5. pp. 28-35.
- Bhusri S, Jain S and Virmani J: Classification of Breast Lesions using Laws' Mask Texture features. Computing for Sustainable Global Development (INDIACom).2016. pp. 1700-1704.
- Bhusri S, Jain S and Virmani J: Breast Lesions Classification using the Amalgamation of morphological and texture



- features. *International J of Pharma and Bio Sciences (IJPBS)*. Apr-Jun 2016. pp. 617-624.
10. Rana S, Jain S and Virmani J: Classification of Kidney Lesions using Gabor Wavelet Texture Features. *Computing for Sustainable Global Development (INDIACom)*. 2016. pp. 2528-2532.
 11. Rana S, Jain S and Virmani J: SVM-Based Characterization of Focal Kidney Lesions from B-Mode Ultrasound Images. *Research J of Pharmaceutical, Biological and Chemical Sciences (RJPBCS)*. July- Aug 2016. Volume-7(4). Page No. 837.
 12. Bhusri S, Jain S and Virmani J: Classification of breast lesions using the difference of statistical features. *Research J of Pharmaceutical, Biological and Chemical Sciences (RJPBCS)*. July- Aug 2016. Page No. 1366.
 13. Rana S, Jain S and Virmani J: Classification of Focal Kidney lesions using Wavelet-Based Texture Descriptors. *International J of Pharma and Bio Sciences*. July-Sep 2016. pp. 646-652.
 14. Ultrasound Cases.info
 15. A.Gajdhane V and Deshpande LM: Detection of Lung Cancer Stages on CT scan Images by Using Various Image Processing Techniques. *IOSR J of Computer Engineering (IOSR-JCE)*. 2014. Volume 16. Issue 5. Ver. III. PP 28-35.
 16. Rachidi M, Marchadier A, Gadois C, Lespessailles E, Chappard C and Benhamou C.L: Laws' masks descriptors applied to bone texture analysis: an innovative and discriminant tool in osteoporosis. *Skeletal Radiology*. 2008. vol. 37. pp. 541-548
 17. Virmani J, Kumar V, Kalra N and Khandelwal N: Prediction of cirrhosis from liver ultrasound B-mode images based on Laws' mask analysis. *IEEE International Conference on Image Information Processing, ICIIP-2011*. Himachal Pradesh, India, 2011. pp. 1-5.
 18. Seng H., Chai H.Y. and Swee T.T: Research on Laws' mask texture analysis system reliability *Research J of Applied Sciences. Engineering and Technology*. 2014. vol. 7. pp. 4002-4007.
 19. Kaur S: Comparative Study Review on Lung Cancer Detection Using Neural Network and Clustering Algorithm. *International Jof Advanced Research in Electronics and Communication Engineering (IJARECE)*. 2015. Volume 4. pp. 169-174.
 20. Ada and Kaur R: Feature Extraction and Principal Component Analysis for Lung Cancer Detection in CT scan Images. *International J of Advanced Research in Computer Science and Software Engineering*. March 2013. Volume 3. pp. 187-190.
 21. Jain S: Regression analysis on different mitogenic pathways. *Network Biology*. June 2016. pp. 40-46.
 22. Jain S: Mathematical Analysis using Frequency and Cumulative Distribution functions for Mitogenic Pathway. *Research J of Pharmaceutical, Biological and Chemical Sciences (RJPBCS)*. May - Jun 2016. Volume- 7(3). pp. 262-272.
 23. Virmani J, Kumar V, Kalra N and Khandelwal N: SVM based characterization of liver cirrhosis by singular value decomposition of GLCM matrix. *International J of Artificial Intelligence and Soft Computing*. 2013. vol. 3. pp. 276-296.
 24. Jain S, Naik PK and Bhooshan SV: Nonlinear Modeling of cell survival/ death using artificial neural network. *International Conference on Computational Intelligence and Communication Networks (CICN2011)*, Gwalior, India. Oct 2011. pp 565-568.
 25. Jain S. and Chauhan DS: Mathematical Analysis of Receptors For Survival Proteins. *International J of Pharma and Bio Sciences (IJPBS)*. 2015. Vol-6. pp. 164-176.
 26. Jain S and Chauhan DS: Linear and Non Linear Modeling of Protein Kinase B/ AKT. *International Conference on Information and Communication Technology for Sustainable Development (ICT4SD - 2015)*, Ahmedabad, India, pp 81-88.
 27. Jain S: Communication of signals and responses leading to cell survival / cell death using Engineered Regulatory Networks. PhD Thesis, Jaypee University of Information Technology, Solan, Himachal Pradesh, India, 2012.
 28. Jain S and Naik PK: System Modeling of cell survival and cell death: A deterministic model using Fuzzy System. *International J of Pharma and BioSciences*. 2012. pp. 358-373.
 29. Pathan A, Saptalkar BK: Detection and Classification of Lung Cancer Using Artificial Neural Network. *International Journal on Advanced Computer Engineering and Communication Technology*. 2016.Vol-1. pp. 62-67.
 30. Jain S and Chauhan DS: Implementation of fuzzy system using different voltages of OTA for JNK pathway leading to cell survival/ death. *Network Biology*. 2015. pp. 62-70.
 31. Jain S: Design and Simulation of Fuzzy System Using Two Stage CMOS Operational Amplifier. *J of Active and Passive Electronic Devices*. 2014. pp. 329-338.
 32. Jain S: Mathematical Analysis and Probability Density Function of FKHR pathway for Cell Survival /Death. *Control System and Power Electronics*. 2015 pp 84-93.
 33. Amandeep, Jain S and Bhusri S: CAD System for Non Small Cell Lung Carcinoma using Laws' Mask Analysis. *International Conference on Computing for Sustainable Global Development, BVICAM*. 2017. pp. 6285-6288.
 34. Sharma S, Jain S, Bhusri S: Classification of Breast Lesions using Gabor Wavelet Filter for Three Classes. *International Conference on Computing for Sustainable Global Development, BVICAM*. 2017. pp 6282-6284.
 35. Dhiman A, Singh A, Dubey S and Jain S: Design of Lead II ECG Waveform and Classification Performance for Morphological features using Different Classifiers on Lead II, *Research J of Pharmaceutical, Biological and Chemical Sciences*. July-Aug 2016. pp. 1226- 1231.

Source of Support: Nil, Conflict of Interest: None.

