2016 2nd International Conference on Next Generation Computing Technologies (NGCT-2016)
Dehradun, India 14-16 October 2016

Mammogram's Denoising in Spatial and Frequency Domain

Mukesh Kumar[1]., V. M Thakkar[2]., H. S Bhadauria[3]., Indrajeet Kumar[4].
GB Pant Engineering College, Pauri, Uttarakhand, India-246194.
[1]mukeshks.kn30cse@gmail.com, [2]vmthakkar1@rediffmail.com, [3]hsb76iitr@gmail.com, [4]erindrajeet@gmail.com

Abstract— **Breast cancer is one of the most incurable diseases, which leads to the death of women globally every year. For early detection of a tumor in the breast, a basic technique called 'Mammography' is used, which is an x–ray analysis of breast. This work emphasizes on the proper selection of denoising techniques for the mammographic images. To achieve the objective of this work, exhaustive experiments are carried out using spatial domain filtering techniques as well as frequency domain filtering techniques on mammograms of the Mammographic Image Analysis Society (MIAS) data. The effectiveness of the techniques is evaluated in terms of Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Mean Structure Similarity Index (MSSIM), Maximum Difference (MD), Normalized Absolute Error (NAE), and Structural Content (SC). It is observed that Wavelet denoising and Median filter show better results than Adaptive Histogram Equalization (AHE), Butterworth and Frost filters.**

Keywords— Mammograms, Breast cancer; Adaptive histogram equalization; Median filter; Frost filter; Butterworth filter; Wavelet denoising.

I. INTRODUCTION

Cancer is concerned with the unrestrained amplification of large number of cells in an intrinsic area of the human body [1]-[2]**.** Reduplication of such group of cells swiftly may cause to the formation of microcalcifications or contortions which are generally known as tumors [3]-[4]. Breast cancer is nothing but a form of such destructive tumor which occurs due to unconfined augmentation of breast cells [5]. Breast cancer is the main leading cause of death among the women in developed as well as developing countries for years [6]. Breast cancer is the second major cause of cancer-related deaths in the world. In 2008, about 1.38 million women were treated with breast cancer, which increased by more than 20% in 2012 and in 2013, this incidence rate was expected to be 29% among the women as per cancer statistics of USA [7].
Medical studies show that the chances of deaths due to breast cancer can be reduced if diagnosed in the early stages. A study shows that the chances of survival increased exceptionally from 24% to 99% if it is diagnosed in its early stage [8]. Nowadays, there are various techniques for diagnosis but mammography is the best known technique for early stage perception of such anomalies. Mammography is so much efficient that it can observe breast cancer before the malignant tissues cause any symptoms. Mammography is the only technique which is identified as a gold standard by American Cancer Society (ACS) for breast cancer [9]. Gathering of microcalcifications is the only sign at the local stage of breast cancer. That is why the perception of such anomalies is the most important part of analysis. Microcalcifications, very small in size varying from 0.1 mm to 1 mm, are nothing but the small calcium deposits in the breast tissue which are nearly impossible to observe by naked eyes even for the experienced radiologists [10]-[11].
The prime objective of this paper is to compare five different filters and to select the more suitable ones for the mammographic image enhancement on the basis of Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Mean Structure Similarity index (MSSIM), Maximum Difference (MD), Normalized Absolute Error (NAE), and Structural Content (SC) image quality assessment parameters. This paper aims to focus on enhancing the images in order to make them sharper and clearer for the radiologist because the mammographic images contain noise, which has to be attenuated towards the diagnosis and early detection of breast cancer.

II. LITERATURE REVIEW

Different approaches and techniques have been proposed by different authors in the field of breast cancer. Some of the authors in this field with their work are being discussed as follows.
Mohanalin, et al. Proposed a different approach for enhancing the microcalcification which was based on fuzzy algorithms using the Tsallis Entropy. A technique for pectoral muscle removal was used by them which was quite efficient as it can enhance microcalcification's details along with this it can enhance all the types of mammary densities. However, it requires a long time to compute parameters [12]. Gao Qinqing, et al. Proposed a technology which could enhance the gray images. The technology was based on simulated annealing PSO algorithm. The algorithm proposed by them had an upper hand or had advantages over several existing methods, e.g.: HE, LCS, GA. The motion of particles and disturbance can be used to achieve the better results. In addition to this, by adjusting the evaluation function could get desired image. Though, the production of special particles needs the use of HE or LCS [13]. Dr. Anamika Yadav, et al. Proposed a method called Hybrid Method which could efficiently detect the breast cancer tumor. Clinically the proposed method is one of the best methods because after enhancement of original digital mammogram, breast tissues

978-1-5090-3257-0/16/$31.00 ©2016 IEEE

are clearly visible. For evaluating the performance analysis, authors used two methods. The first measure is PSNR (Peak signal-to-noise-ratio) and the second measure is CNR (contrast-to-noise ratio). Experimentally is has been proved that enhancement algorithm produce significant bump in image quality and higher PSNR and CNR values [14].

Arnau, et al. Exploited local future extracted from a bank of filters for individual microcalcification detection to describe the local mircocalcification. However, the complexity and time of the approach increased while comparing each filtered sample to that of the filtered database microcalcification [15]. Mouna Zouari, et al. Proposed a method which nonlinearly stretching the gray level to focus selectively on microcalcifications which efficiently enhanced the digital mammographic images. After this enhancement algorithms were compared by an evaluation metric. It was experimentally proven that their proposed preprocessing algorithms reached the highest SDME values by achieving 118 of local NSP, 115 of global NSP, 88 of the LRM algorithm, 91 of the negative image and 79 of the original image [16].

III. METHODS AND METHODOLOGY

A. Database description

In this work, the mammographic images are taken from MIAS dataset [17]; which contains 322 mammographic images (both left and right) and is generally used as a standard benchmark database for testing novel application dealing with processing and examination of mammograms for breast cancer detection. In this database, each case is annotated by expert radiologists. The locations of masses in mammograms are indicated by the centers and the radii of the mass regions. This work has been carried on 10 cases (5 benign, 5 malignant), which contains calcification. Therefore, a total of 10 ROIs are extracted for this work as depicted in the ROI extraction section.

B. Experimental work flow diagram

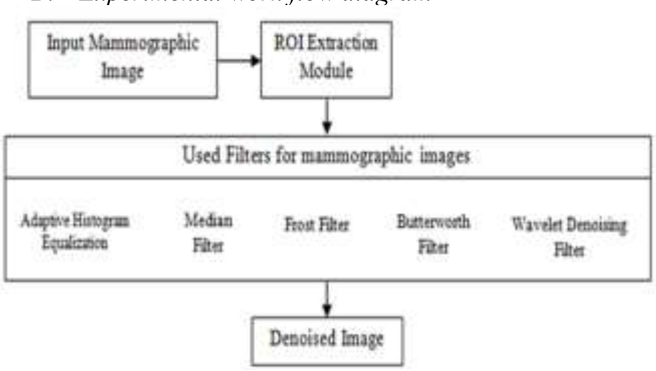


Figure 1- Experimental Work Flow Diagram

The experimental work flow diagram is shown in figure 1, which consists of mainly ROI extraction and filtering section. Each section is depicted below. Initially, the input mammographic images are taken from the MIAS dataset, and then the Region of interest (ROIs) is extracted for each image as described in the ROI extraction section. After selecting the ROI, five different filters namely Adaptive Histogram Equalization, Median Filter, Butterworth Filter, Frost Filter and Wavelet Denoising Filter are applied and the denoised mammographic image/enhanced image is obtained. Finally, MSE, PSNR, MSSIM, MD, NAE and SC image quality assessment parameters are calculated for each case and on the basis of these parameters, filters are selected for spatial domain as well as frequency domain.

C. ROI (Region of Interest) Extraction

The size of original mammograms is quite big, almost amounting to (1024 × 1024 pixels). Instead of processing the whole image, which consists of almost 50% of noise [18], only the infected portion of the image is selected for reducing the noise in order to improve the performance and less processing time. Since the center of abnormality x and y is given in the MIAS database, these information are used to crop out the infected portion from the whole image of size 128 × 128 pixels.

Figure 2 shows the sample of input mammographic image and their respected ROI.

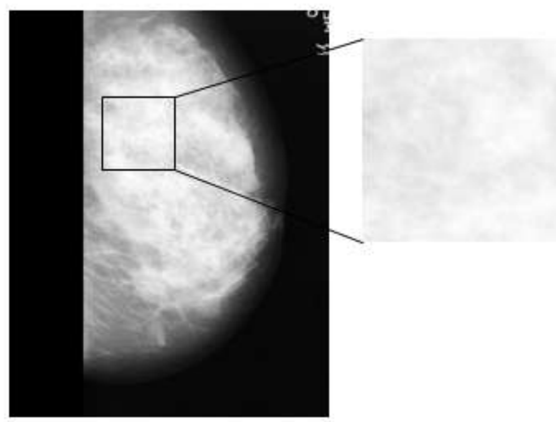


Figure 2: ROI Extraction

D. Enhancement

The image enhancement is the primary concern of the preprocessing phase of digital image processing [19]. In this work, some filters are used in spatial domain and some are in frequency domain depicted one by one below in this section.

1. Adaptive histogram equalization: It is a technique to enhance the contrast of the image. This method is quite different from ordinary histogram equalization, as it computes several histograms. Each is analogous to a specific part of an image. This technique is very useful for developing local contrast and improving the definitions of edges in every section of the image [20]. The AHE is mathematically expressed by equation 1.

$$H(V) = \left\| \left(\frac{CDF_V - CDF_{\min}}{(M \times N) - CDF_{\min}} \right) \times (L-1) \right\| \tag{1}$$

Where CDF_{min} is the minimum value of cumulative frequency distribution, M × N is size and L is gray level.

2. Median filter: It is a non-linear technique used in removing Salt-and-pepper from digital images. This technique is widely used in image processing as it preserves edges while removing noise. For mammography, 3×3 window provides smart result. The median is good to evaluate extreme values and is better able to take away this outlier without reducing the sharpness of the image**.**

*3. Butterworth filter***:** It provides a maximally flat response, which means that it is proposed so that at zero frequency, the first $2n-1$ derivatives for power function with respect to frequencies are zero [21]. That is why it is also known as a maximally flat magnitude filter. Frequency response is mathematically expressed as

$$\left|\frac{V_{out}}{V_{in}}\right|^2 = \frac{1}{1+\left(f/f_c\right)^{2n}} \tag{2}$$

Where, f = frequency at which calculation is made, $f_c =$ the cut-off frequency, v_{out} = Output image, v_{in} = Input image, n = Number of elements in filter.

4. Frost filter: It is a form of Adaptive speckle filtering used in preserving edges while eliminating the noise spikes. The Frost filter replaces the pixel of interest with a weighted sum of the values within the N × N moving kernel [22]. This filter assumes multiplicative noise and stationary noise statistics and follows the following formula:

$$DN = \sum_{n\times m} kae^{-a|t|} \tag{3}$$

Where $\alpha = \left(\frac{4}{n\bar{\sigma}^2}\right)\left(\frac{\sigma^2}{\bar{I}^2}\right)$

K= Normalization constant, $\bar{I} =$ Local mean, $\sigma =$ Local variance, $\bar{\sigma} =$ Image coefficient of variation value,
$|t| = |X - X_0| + |Y - Y_0|$, N = Moving kernel size

5. Wavelet denoising filter: It is a method by which we can fix up the noisy signals. This method performs parallel analysis; therefore the expected throughput is maximum.

Image Quality Assessment Parameters

The calculated parameters for each case and their respective mathematical expression are listed in Table 1.

Table 1: List of Image Quality Assessment Parameters

$$MSE = \frac{1}{M\times N}\sum (g(x,y) - f(x,y))^2 \tag{4}$$

$$PSNR(dB) = 10\log_{10}\left(\frac{256\times 256}{MSE}\right) \tag{5}$$

$$MSSIM = \frac{1}{M}\sum_{j=1}^{M} SSIM_j \tag{6}$$

$$MD = Max\left(|A_{ij} - B_{ij}|\right), i = 1,2,..,m; j = 1,2,..,n \tag{7}$$

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(|A_{ij} - B_{ij}|\right)}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij}\right)} \tag{8}$$

$$SC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(A_{ij}\right)^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(B_{ij}\right)^2} \tag{9}$$

IV. RESULTS AND DISCUSSION

Exhaustive work has been carried out on the images taken from the MIAS dataset. Initially, ROI of size 128 × 128 pixels are extracted as per the given lesions co-ordinate information in dataset file then these ROIs are fed to the image denoising filters available in spatial domain as well as frequency domain. Finally, MSE, PSNR, MSSIM, MD, NAE and SC image quality assessment parameters are calculated for every filter and results are summarized in tabular form. Sample of this experiment work is expressed in Table 2.

The values of different parameters namely MSE, PSNR (in dB), MSSIM, MD, NAE and SC are compared below for Adaptive histogram equalization filter, Median filter, Butterworth filter, Frost filter, and Wavelet denoising filter.

Table 2: Input ROI and their respective denoised image with calculated parameters

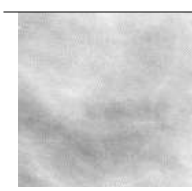
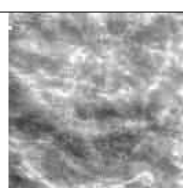
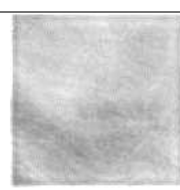
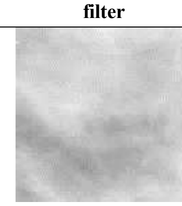
Input image	AHE	Median filter	Butterworth filter	Frost filter	Wavelet denoising filter
					
MSE	1943.3	14.7130	37.5899	2424.4	0.7341
PSNR	15.27	36.4878	32.4141	14.3187	49.5074
MSSIM	0.7236	0.9986	0.9706	0.8643	0.9961
MD	14	4	56	5	3
NAE	0.1961	0.0011	0.0118	0.0443	0.0023
SC	0.7099	0.9996	0.9988	0.9587	1.0001

Table 3- Adaptive histogram equalization filter

Input Image	MSE	PSNR	MSSIM	MD	NAE	SC
mdb209	1129.0	17.63	0.6563	83	0.1907	0.8166
mdb211	451.5939	21.61	0.7325	96	0.1026	1.2179
mdb212	1835.1	15.52	0.7190	63	0.2601	0.6869
mdb213	526.3998	20.95	0.6995	83	0.1212	0.9814
mdb214	670.9958	19.89	0.6858	70	0.1203	0.9320
mdb218	1128.3	17.64	0.7026	80	0.1897	0.7967
mdb222	2238.5	14.66	0.6715	42	0.2650	0.6555
mdb231	1193.7	17.39	0.7364	79	0.1967	0.7671
mdb236	1943.3	15.27	0.7236	14	0.1961	0.7099
mdb238	1080.9	17.82	0.6757	74	0.1726	0.7944
Average	**1219.77**	**17.84**	**0.7002**	**68.4**	**0.1815**	**0.8358**

In Table 3, the Adaptive histogram equalization gives MSE= 1219.77, PSNR (dB) = 17.84, MSSIM= 0.7002, MD=68.4, NAE= 0.1815, and SC= 0.8358.

Table 4- Median filter

Input Image	MSE	PSNR	MSSIM	MD	NAE	SC
mdb209	7.5222	39.4013	0.9902	17	0.0057	0.9986
mdb211	6.0375	40.3562	0.9942	8	0.0044	0.9990
mdb212	7.3412	39.5071	0.9945	9	0.0036	0.9993
mdb213	8.2244	39.0137	0.9939	9	0.0043	0.9988
mdb214	7.5223	39.4013	0.9962	5	0.0028	0.9993
mdb218	6.2861	40.1810	0.9953	8	0.0033	0.9993
mdb222	11.8251	37.4367	0.9950	9	0.0031	0.9991
mdb231	10.9734	37.7614	0.9816	25	0.0055	1.0002
mdb236	14.7130	36.4878	0.9986	4	0.0011	0.9996
mdb238	10.5021	37.9520	0.9945	9	0.0035	0.9991
average	**9.09473**	**38.74985**	**0.9934**	**10.3**	**0.00373**	**0.99923**

In Table 4, the Median filter gives MSE= 9.09473, PSNR (dB) = 38.74985, MSSIM= 0.9934, MD=10.3, NAE= 0.00373, and SC= 0.99923.

Table 5- Butterworth filter

Input Image	MSE	PSNR	MSSIM	MD	NAE	SC
mdb209	121.8901	27.3051	0.9604	72	0.0316	1.0280
mdb211	102.1357	28.0730	0.9736	77	0.0297	1.0297
mdb212	60.6649	30.3354	0.9711	63	0.0221	1.0114
mdb213	132.8464	26.9313	0.9702	81	0.0306	1.0322
mdb214	142.3497	26.6312	0.9745	78	0.0261	1.0269
mdb218	104.1800	27.9870	0.9729	67	0.0253	1.0218
mdb222	119.0566	27.4073	0.9643	79	0.0241	1.0187
mdb231	104.2610	27.9836	0.9675	65	0.0282	1.0243
mdb236	37.5899	32.4141	0.9706	56	0.0118	0.9988
mdb238	140.0264	26.7027	0.9660	73	0.0270	1.0249
average	**106.50007**	**28.17707**	**0.96911**	**71.1**	**0.02565**	**1.02167**

In Table 5, the Butterworth filter gives MSE=106.50007, PSNR (dB) =28.17707, MSSIM=0.96911, MD=71.1, NAE=0.02565, and SC= 1.02167.

Table 6- Frost filter

Input Image	MSE	PSNR	MSSIM	MD	NAE	SC
mdb209	6.4410	40.0752	0.9711	19	0.0121	0.9993
mdb211	6.5405	40.0087	0.9834	8	0.0095	0.9995
mdb212	16.0269	36.1163	0.9822	11	0.0093	0.9990
mdb213	3.8740	42.2832	0.9815	11	0.0092	0.9996
mdb214	11.4489	37.5772	0.9886	9	0.0065	0.9995
mdb218	3.6650	42.5241	0.9838	10	0.0085	0.9994
mdb222	3.5785	42.6278	0.9840	13	0.0069	0.9997
mdb231	7.0093	39.7080	0.9692	24	0.0108	0.9994
mdb236	2424.4	14.3187	0.8643	5	0.0443	0.9587
mdb238	3.7402	42.4358	0.9830	12	0.0075	0.9997
average	**248.67243**	**37.7675**	**0.96911**	**12.2**	**0.01246**	**0.99538**

In Table 6, the Frost filter gives MSE=248.67243, PSNR (dB) =37.7675, MSSIM=0.96911, MD=12.2, NAE=0.01246, and SC= 0.99538

Table 7- Wavelet Denoising filter

Input Image	MSE	PSNR	MSSIM	MD	NAE	SC
mdb209	3.8484	42.3120	0.9821	6	0.0095	0.9997
mdb211	2.0778	44.9888	0.9891	5	0.0077	0.9999
mdb212	3.5034	42.7200	0.9839	6	0.0087	0.9998
mdb213	2.9904	43.4075	0.9851	6	0.0086	0.9998
mdb214	1.9460	45.2733	0.9903	5	0.0058	0.9999
mdb218	2.5187	44.1531	0.9883	5	0.0074	0.9999
mdb222	3.2530	43.0420	0.9843	6	0.0069	0.9999
mdb231	3.5422	42.6721	0.9832	6	0.0093	0.9997
mdb236	0.7341	49.5074	0.9961	3	0.0023	1.0001
mdb238	3.0714	43.2914	0.9851	6	0.0073	1.0000
Average	**2.74854**	**44.13676**	**0.98675**	**5.4**	**0.00735**	**0.99987**

In Table 7, the Wavelet denoising filter gives MSE=2.74854, PSNR (dB)= 44.13676, MSSIM=0.98675, MD=5.4, NAE=0.00735, and SC= 0.99987.

It can be observed from the above tables that wavelet denoising and median filter give better performance compared to the other three filters, namely adaptive histogram equalization, Butterworth filter and Frost filter.

V. CONCLUSION

In this paper, five image denoising techniques in spatial as well as frequency domain namely adaptive histogram equalization, median filter, butterworth filter, frost filter, and wavelet denoising filter have been considered to find their appropriateness to mammogram images. These denoising techniques have been tested on a set of 10 images consisting of 5 benign and 5 malignant cases and the result shows that median filter for spatial domain and wavelet denoising for frequency domain are giving higher PSNR (peak signal to noise ratio) and low MSE (mean square error), MD (maximum difference), NAE (normalized absolute error) and SC (structural content) values. So these techniques will be more suitable in pre-processing stage of mammogram images. The acknowledged pre-processing techniques will be followed by segmentation, feature extraction and classification to produce more accurate results and also improve the detection rate of masses, microcalcification, and breast cancer. These methods can help the radiologists for exact diagnosis of breast cancer in its primary stage.

REFERENCES

[1] W. Schulz, Molecular Biology of Human Cancers. New York, USA: Springer, 2007.

[2] I Kumar, HS Bhadauria, J Virmani, "Wavelet Packet Texture Descriptors Based Four-class BIRADS Breast Tissue Density Classification", Procedia Computer Science, Vol.: 70, pp. 76-84, 2015. Publisher: Elsevier.

[3] M.P. Sampat, M.K. Markey, and A.C. Bovik, Computer-Aided Detection and Diagnosis in Mammography, Handbook of Image and Video Processing. London, U.K.: Elsevier, 2003.

[4] Kumar, I., Virmani, J., Bhadauria, H.S., 'A Review of Breast Density Classification Methods', In Proceedings of 2nd IEEE International Conference on Computing for sustainable Global Development, (IndiaCom-2015), 11-13 March, 2015, New Delhi, pp. 1960-1967.

[5] M. F. Akay, "Support vector machines combined with feature selection for breast cancer diagnosis," Expert System with Application., vol. 36, no. 2, pt. 2, pp. 3240–3247, Mar. 2009, 10.1016/j.eswa.2008.01.009, 0957-4174.

[6] Jemal A, et al: Global cancer statistics. CA: Cancer J Clin 61(2):69– 90, 2011.

[7] Siegel R, Naishadham D, Jemal A: Cancer statistics, 2013. CA: Cancer Journal Clinic 63(1):11–30, 2013.
[8] N. Howlader, A. M. Noone, M. Krapcho, J. Garshell, N. Neyman, S. F. Altekruse, C. L. Kosary, M. Yu, J. Ruhl, Z. Tatalovich, H. Cho, A. Mariotto, D. R. Lewis, H. S. Chen, E. J. Feuer, and K. A. Cronin, SEER Cancer Statistics Review, 1975-2010. National Cancer Institute, 2013, based on Nov. 2012 SEER data submission.
[9] American Cancer Society, Breast Cancer Facts & Figures 2013-2014. Atlanta: American Cancer Society, 2013.
[10] L. Tabar, S. Duffy, L. Burhenne, New Swedish breast cancer detection results for women aged 40–49, Cancer 72 (suppl.) (1993) 1437.
[11] J. Bronzino (Ed.), Biomedical Engineering Handbook, CRC Press, Boca Raton, FL, 1995.
[12] J. Mohanalin, P. K. Kalra and N. Kumar,Tsallis Entropy Based Contrast Enhancement of Microcalcifications. IEEE International Conference on Signal Acquisition and Processing (ICSAP), pp. 37, April 2009.
[13] Gao Qinqing, Zeng Guangping ‘’ Image Enhancement Technique Based On Improved PSO Algorithm’’ 2011 6th IEEE Conference on Industrial Electronics and Applications.
[14] Dr.(Mrs.) Anamika Yadav, Mr.Bikesh Singh, Mrs.Shailaja Singh “Comparative Analysis of Different Enhancement Method on Digital Mammograms” International Conference on Computer & Communication Technology (ICCCT)-2011.
[15] O. Arnau, T. Albert, L. Xavier, and T. Meritxell, T. Lidia, S. Melcior, F. Jordi and Z. Reyer ,Automatic microcalcification and cluster detection for digital and digitised mammograms. Elsevier, vol.28, pp. 6875, April 2012.
[16] Mouna Zouari, Alima Dammak Masmoudi, Dorra Sellami Masmoudi “A non linear stretching image enhancement technique for microcalcification detection” 1st International Conference on Advanced Technologies for Signal and Image Processing - ATSIP'2014 March 17-19, 2014, Sousse, Tunisia.
[17] Mammographic Image Analysis Society, http://www.wiau.man.ac.uk/services/MIAS/MIASweb.html.
[18] K Menaka, S Karpagavalli ‘’Mammogram classification using Extreme Learning Machine and Genetic Programming’’ 2014 International Conference on Computer Communication and Informatics (ICCCI-2014), Jan. 03-05, 2014, Coimbatore, INDIA.
[19] R. C. Gonzales R. E. Woods, Digital Image Processing. New York: Addison-Wesley, 1987.
[20] R. H. Sherrier, G. A. Johnson, “Regionally adaptive histogram equalization of the chest,” IEEE Trans.Med.Image, Mi-6(1987), pp.1-7.
[21] Stephen Butterworth, “On the Theory of Filter Amplifiers”, Wireless Engineer, pp. 536–541, 1930.
[22] V.S. Frost, J.A. Stiles, K.S. Shanmugam, J.C. Holtzman, “A model for radar image & its application to Adaptive digital filtering for multiplicative noise”, IEEE Transaction on pattern analysis and machine intelligence, Vol. PMAI-4, pp. 175-16-1982.
[23] Indrajeet Kumar, Jyoti Rawat, HS Bhadauria, “A conventional study of edge detection technique in digital image processing”, International Journal of Computer Science and Mobile Computing, vol. 3(4): pp.328-334, 2014.