Intelligent System for Detection of Micro-Calcification in Breast Cancer

M. Abdul Rehman, Jamil Ahmed, Ahmed Waqas, Ajmal Sawand
Department of Computer Science, Sukkur IBA University
Sukkur, Pakistan

***Abstract*—Recently; medical image mining has become one of the well-recognized research area(s) of machine learning and artificial intelligence techniques have been vastly used in various computer added diagnostic systems. Specifically; breast cancer classification problem is considered as one of the most significant problems. For instance, complex, diverse and heterogamous malignant features of micro-calcification in DICOM (Digital Communication in Medicine) images of mammography are very difficult to classify because the persistence of noise in mammogram images creates lots of confusions for doctors. In order to reduce the chances of misdiagnosis and to discernment the difference between malignant and benign lesions of micro-calcification this paper proposes a system so called "Intelligent System For Detection of Micro-Calcification in Breast Cancer" by considering all above stated problems. Overall our system comprises over three main stages. In first stage, adaptive threshold algorithm is used to reduce the noise, and canny edge detection algorithm is used to detect the edges of every macro or micro classification. In second stage, deginated as feature selection is done by using auto-crop algorithm, which crops all types of calcifications and lesions by proposed algorithm so called CFEDNN (Calcification Feature Extraction Deep Neural Networks) which is designed to avoid the manual ROIs (Region of Interest). Decision model is constructed by using DNN (Deep Neural Networks) and the best classification accuracy is measured as 95.6%.**

Keywords—Medical image mining; machine learning; feature extraction; classification; Digital Communication in Medicine (DICOM)

I. Introduction

Recently artificial intelligence (AI) techniques have been frequently applied in healthcare industry and computer added diagnostics systems have been witnessed with significant impact to mold the traditional procedures into computerized DSS (decision support systems) for diagnosis and prognosis of various diseases such as colorectal cancer, lung cancer, breast cancer and so on. According to recent statics [1]-[3] breast cancer accounts for 1.7 million yearly deaths in world population and many people are badly suffering from such type of cancers. Breast cancer is one of the common diseases found in female gender but male gender is also facing casualties related to the breast cancer. Traditionally mammography [4]-[6] is one of the non-invasive techniques used to diagnose the breast cancer but there are some limitations associated with X-Ray based technologies. It is really challenging to differentiate between the malignant and non-malignant behaviors from the film base masses, lesions, micro and macro calcifications of human breast tissues due to some cultural, regional and socio-economic problems which are likely to be found to form the dense and tender tissues because race, gender, occupation, geographic conditions, social system and other contributing factors create [7], [8] lots of variations in the composition of human breast tissues. On the other side there are lots of limitations associated with mammogram image accusation process due to improper acquisition processes caused by unavoidable technological noise seen in medical images [9], [10]. This create lots of confusions for radiologist to interpret the particular type of malignant behaviors and sometime ultrasound guided biopsies are recommended for deep analysis of the disease and results may reveal no malignancy. In recent past some of the related works [11], [13], [15] have been seen and these approaches have attempted to resolve the classification problem of mammograms but some of approaches consider the malignant masses accumulatively set of pixels, since detection of micro-calcification in massive masses may enhance the diagnostic accuracy of breast cancer. For example micro-calcifications may exists between the dense or soft margins of breast but due to diffuse shapes, sizes and malfunctioning of mammogram x-ray technology, there are several chances of miss-diagnosis because fibro adenoma cancer persists with complex patterns of massive masses along with set of calcifications. In-order to reduce the chances of misdiagnosis and to identify the difference between malignant and benign lesions of connected micro-calcifications, this paper proposes a system so called "Intelligent System for Detection of Micro-Calcification in Breast Cancer" by considering all above stated problems. Overall proposed system comprises over three main stages. In first stage noise reduction techniques are applied and each macro or micro calcification is detected by using canny edge detection algorithm. In second stage feature selection is done by using proposed algorithm so called CFEDNNs (Calcification Feature Extraction Deep Neural Networks) which is designed to avoid the manual ROIs (Region of Interest). Classification model is built by using the DNNs (Deep Neural Networks) and best epochs were measured as 95.60%.

The paper is organized in several sections. Firstly introduction is presented, secondly literature review is described, thirdly methodology is explained, fourthly results are shown and finally conclusion & discussion with future dimensions is described.

II. Related Works

Basically this paper proposes an approach, which deals as predictive modeling in the domain of machine learning and proposed system consider the detection of malignant behaviors of breast cancer masses, lesions and macro or micro classifications. Some of the related works have been seen in recent past are cited as below.

A system [11] was proposed to detect the abnormalities of breast cancer using mammograms. AI base Swarm Optimized Wavelet Neural Network algorithms were used and the reported classification accuracy is 92.10%. This paper proposes a system to classify the malignant and benign behaviors by selecting the automated ROIs (Region of Interest) features, which helps to avoid the manual feature selection from breast images.

A system [12] was proposed to classify malignant and benign images of mammograms. The extracted statistical features were classified by using ANN (Artificial Neural Networks) and reported classification accuracy of the system is 94%. Proposed algorithm so called CFEDNN to select the features from several parts of breast neighbored regions such as axilla and breast regions.

A comparison [13] of various machine learning techniques (SVM, AdaBoost) was proposed for classification of breast cancer. Reported best accuracy for AdaBoost measured as 87.42%. Since the proposed system of this paper detects micro calcifications in the environment of complex and diffuse shape of masses at any sight of mammogram images.

A comparison [14] different machine learning techniques was proposed and best accuracy was measured 95.34% for breast cancer detection using cellular tissues RBF. ConvNet layers provide better feature extraction because final layer is fully connected with all previous layers.

A system [15] for diagnosis of breast cancer was proposed by using machine learning techniques. The reported classification accuracy using SVM was measured as 95.23%. Proposed approach of this paper offers contributions from two perspectives. Firstly from the image preprocessing perspective, in which an algorithm is proposed to reduce the noise by considering unnecessary noise and selects the most significant set of regions such as margins of axilla and breast along with the malignant behaviors consideration at pixel levels. Secondly building of ConvNet layers are for mammography lesions and classification of malignant/benign behaviors. The classification accuracy of the system was measured about 95.60%.

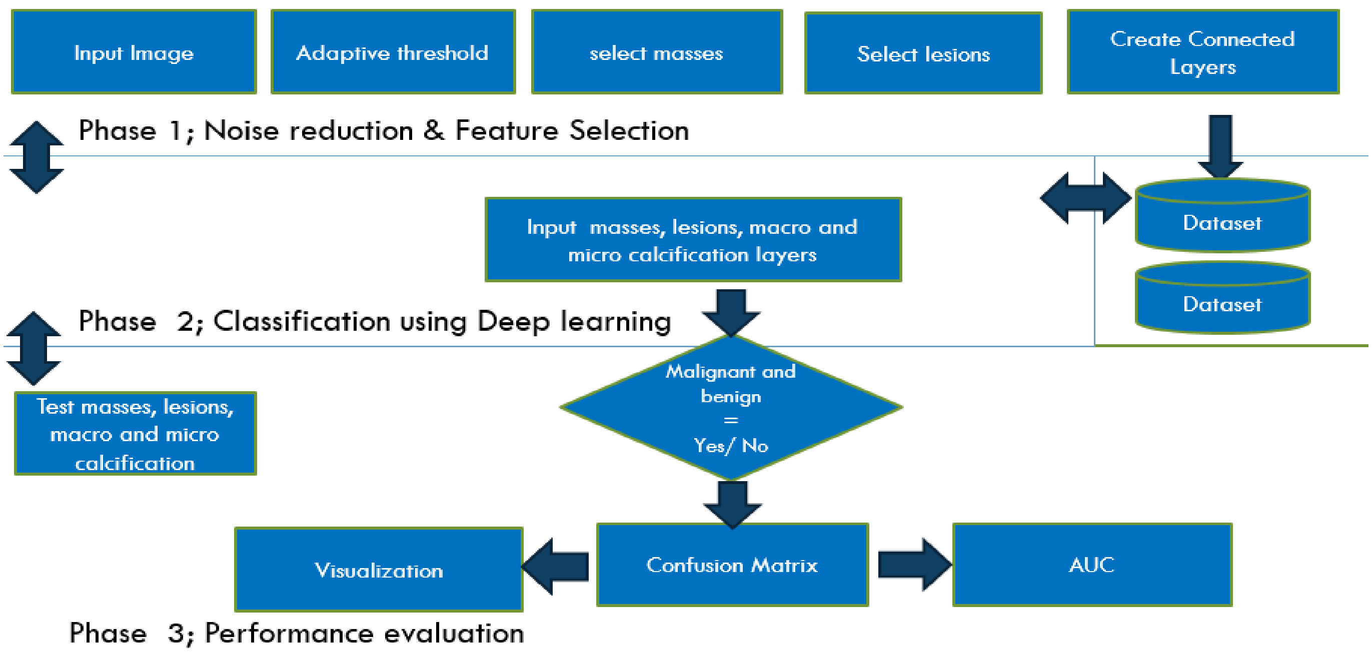

Fig. 1. Intelligent system for detection of micro-calcification in breast cancer workflow.

III. Methodology

Basically proposed approach of this paper falls into the category of predictive modeling and machine learning techniques have been used to construct the decision model based upon the deep learning techniques as per following systematic procedure (Fig. 1). A mammogram consists upon thickly populated set of pixels. This paper presents novel algorithm so called CFEDNN (Calcification Feature Extraction Deep Neural Networks) which deals with the object detection, feature selection and classification. Since the appropriate object detection and feature selection is highly desirable for good results to solve the classification of DICOM (Digital Communication in Medicine) of mammography. The proposed system is divided into three major phases and each phase is assigned interconnected tasks. The first phase deals with the data preparation such as noise reduction and feature selection, whereas second phase is assigned the task to build the classification model where associated quantities selected from the related pixels based upon information in the form of tensor data type. The classification model has to classify the micro and macro classifications to assist the doctors during the diagnostic phase.

Algorithm 1: (CFEDNN)
Calsification_Feature_Extraction_Deep_Neural_Networks
Input: Mammogram image as D
Output: Axilla margins, breast tissues and Class Label Malignant = Yes/No

$D \leftarrow HCV\ Breast_{Tissues} components\ for\ Binarization\ \mathcal{B}$
$Visit = each\ pixel\ as\ q_n\ (x_i, y_i)$
$for\ each\ \sigma^2 w(t)\ \leftarrow q1(t)\sigma_1^2 + q2(t)\sigma_1^2(t)$
$\sigma_1^2\ \ (t) \leftarrow \sum_{i=1}^{i} [i - \mu_1(t)]^2 \frac{iP(i)}{q_1(t)} \wedge\ \mu_1(t) = \sum_{i=t+1}^{i} [i - \mu_1(t)]^2 \frac{P(i)}{q_2(t)}$
$for\ each\ P_i \in q_i(t)\ do$
$K \leftarrow g(x,y)^{q1(t)} \leq 0_n(k) \leq 1$
$if\ g(x,y)^{q1(t)} = 1$
$Count\ \ \leftarrow p_i\ 1 + +||axila\ regions||$
$if\ g(x,y) = 0$
$Count\ \ \leftarrow p_i\ 0 + +||breast\ regions||$
$end\ if$
$Return \leftarrow Breast_{Tissues}$
$create\ ConvNet\ Layers \leftarrow g_h(\tau) = h_b(x) * g(x)$
$for\ each\ g_g(\tau) \in T\ do$
$h_0(x) = \sigma(\theta^T) = + \frac{1}{1\ exp\ (\theta^T)}$
$Where\ a(z) = 1/(1 + \exp(-z)$
$end\ if$

Stage 1: Noise Reduction and Feature Selection:

A. Calcification feature extraction Deep Neural Networks algorithm:

In DICOM (Digital communication in medicine) [16] mammogram images have different contrasts and entropies at each set of pixels in complex, dense and diffuse set of pixels because mostly in all types of breast tissues are found with varying behaviors from many perspectives in terms of shapes, sizes and other properties (such as malignant masses, lesions, macro and micro calcifications). Thus these types of circumstances produce lots of confusions for the radiologists during the interpretation of mammograms. Proposed system comprises upon the main three stages. In first phase of image preprocessing the noise reduction techniques are used, in second phase a decision model is constructed. In third stage performance evaluation and result visualization is shown. Let's consider a dataset D of mammogram images and the digital information is scattered between (x_i, y_i) spatial locations. The first object of our algorithm CFEDNN (Calcification feature extraction + deep neural networks) is to classify the breast cancer using mammogram images. Adaptive threshold algorithm [17] is used to reduce the noise. The technique calculates accumulated values of neighborhood pixels that represent the small set of objects in medical images by considering mean values of concerned regions and the results of segmentation can be transformed into better illumination despite of varying requirements of different thresholds prerequisite for dissimilar regions of image designated as objects such like malignant behaviors. Since Otsu's algorithm tries to find a threshold value (t) which minimizes the weighted within-class variance given by the relation in a medical image.

The second objective of proposed algorithm is to avoid unnecessary information from the mammograms and to select the most significant feature without using manual ROIs (region of interest) [18]. ROI is a method to select the different regions of image to measure the entropies and other operations. This technique is also compatible to manual cropping of various objects from image. The proposed algorithm partition the image into three regions, in first step it selects the regions of axilla, in second step different regions of breast masses are detected and finally irrelevant regions such as noise is determined and omitted (Fig. 2). Proposed system creates the three layers using ConvNet based features [19]-[22] as observation collected from selected regions. Let's consider a dataset D of mammogram consisting upon the MXN pixels scattered over the size of in (x_i, y_i) and the regions of interest persist as $q_n(x_i, y_i)$ (Fig. 2). These regions q_n are also often known as several number of image partitions based upon the clustering set of homogenous neighborhood pixels. In human breast there are two partitions having most significant importance number one any existence of nodular quantity or breast is affected due to involvement of calcifications.

B. ConvNet Architectures

Proposed preprocessing algorithm selects automated regions as defined in Section 3. This paper uses Deep Neural Networks and builds the dataset with three common layers, in first two layers CONV and POOL layer are created as max pool where each pixel value is represented into tensor data type. In third layer which is fully-connected layer of related pixel representation and a doctor defined class label attribute for malignant and benign classes is included RELU activation function into the training datasets of mammograms as layer.

C. Pooling Layer

The successive Conv Layer architecture includes a pooling layer from time to time. The function is responsible increasingly to reduce the spatial size of image pixel interpretation. It not only controls the overfitting of parameters but also regulates computation throughout the computational activities of related layers and incorporates the in-depth inputs received from the pooling layer operations by applying consideration to the set of depth slice observations during the interpretation of image interpreted inputs in Max operations in such way that pooling filters consisting upon the number of max over 4. Since the depth height and width can be reduced up to 75% and builds small regions comprising upon the 2 x 2 at the low levels of depth since these depth features remain with constant quantities.

D. Fully-connected layer

In fully connected layer, the last layer (class label attribute) is final output layer which fully connected set of observations related to particular class along with the consideration of biased and weighted values of all previous activated connections exists between the different layers.

Stage 2: Classification using Deep Learning:

The DNN (Deep Neural Network) uses weighted matrix W and bias vector b and the inputs of set of observation which collects inter connected input quantities consisting upon the image features as neurons. Hidden layers of neurons depend upon the complexity of problem. Weighted and bias values has to construct hyperplane to decrement the behaviors of image data by considering vector $x \in class\ i$ and variable Y is a stochastic variable.

ReLU (Rectified linear units) layer is used as activation function $f(x) = \max(0, x)$ and receptive fields of Convolution layer promotes to increase the properties related to nonlinear decision by considering no effect to the above stated layer. Since some other functions may also be used to enhance into the incremental support for nonlinearity. Hyperbolic tangent $f(x)\tanh(x)$, $f(x) = |\tanh(x)|$ and to boost the training phase of neural network the sigmoid function $f(x) = (1 + e^{-z})^{-1}$ offers very nice services at ReLU layer. Since the $softmax$ loss can be used to classify the k classes by using the sigmoid cross entropy loss by considering the prediction of class label k as independent probability based quantities as [0,1] and to regress the real label as Euclidean loss $[-\infty, \infty]$.

Deep Neural Networks performs well by using the standard backpropagation algorithm and can be discriminated as nested discrete connected networks. The efficiency could also be find by using spars networks. Stochastic gradient descent can be expressed in weighted backpropagation by this equation $w_{ij}(t+1) = w_{ij}(t) + n\frac{\partial C}{\partial w_{ij}} + \epsilon(t)$ where hidden layers of neural network perform like human brain neurons. Since learning rate is represented by cost function designated as C and $\epsilon(t)$ term is derived as scholastic theorem. The reinforcements refers to the choice of cost functions where supervised or unsupervised learning is applied specially is multiclass problem can be learned with the functions of softmax and cross entropies where $P_j = \frac{\exp(z_j)}{\sum_k \exp x_k}$ is used to denote the representation of the class probability as output by considering the quantities of x_j and z_k. Since the cross entropies could be interpreted as $C = -\sum_j d_j \log(p_j)$. A binary mask can be bounded with deep neural networks based regression to increase the localization precision and to learn the features by using regression because some of the layers are convolutional, pooling and fully connected where each object has to be reflected linear unit for transformation perspectives of nonlinear as well.

Stage 3: Performance Evaluation and result visualization:

Total number of 1273 images (Table 1) of mammogram were used out of these 362 images were belonging to the category of malignant and 911 were belonging to the benign class. The 327 true positive and 35 true negative and 890 benign number of images were classified as false negative and 21 false positive. The comparison with literature is presented in (Table 2) and the measured classification accuracy (Table 3) is about 95.60%.

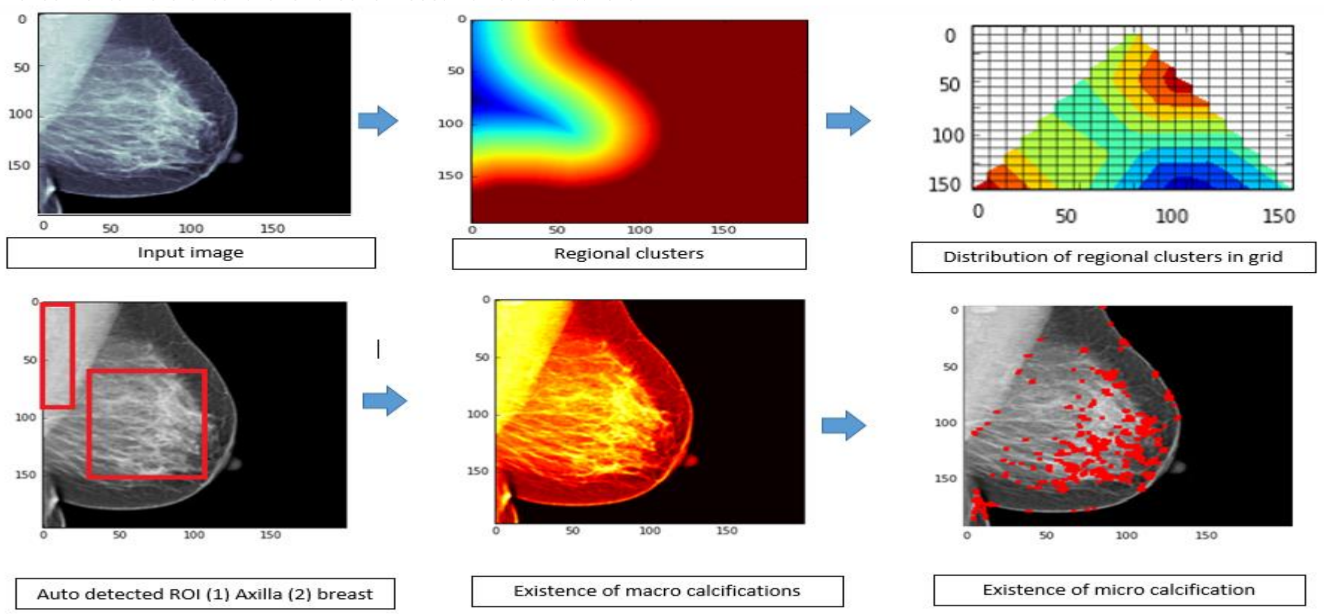

Fig. 2. Preprocess Method, Input image, Regional clusters, Distribution of clusters in grid, Auto detected ROI (1) Axilla (2) Breast, Existence of Macro-Calcification, Existence of Micro - Calcification

TABLE. I. CONFUSION MATRIX

	MALIGNANT	NON-MALIGNANT
MALIGNANT	327	35
NON-MALIGNANT	21	890
MEASURED CLASSIFICATION ACCURACY		95.60%

TABLE. II. COMPARISON OF PROPOSED APPROACH WITH LITERATURE

APPROACH	TECHNIQUE	ACCURACY
DHEEBA, J (2014)	SWARM OPTIMIZED WAVELET NEURAL NETWORK	92.10%
LASHKARI (2016)	ANN (ARTIFICIAL NEURAL NETWORKS)	94.00%
RAJESH KUMAR(2014)	SVM, ADABOOST	87.42%
HAMID H (2016)	RBF	95.34%
GRAHAM (2005)	SVM	95.23%
OUR APPROACH	CFENNS (CALCIFICATION FEATURE EXTRACTION CONVOLUTIONAL NEURAL NETWORKS)	95.60%

TABLE. III. OVERALL PERFORMANCE OF PROPOSED METHODOLOGY

	RAW IMAGES	NO OF EXTRACTED NUCLEI	NO OF CLASSIFIED NUCLEI	NO OF MISS-CLASSIFIED NUCLEI	PRECESSION	RECALL
MALIGNANT	10	362	327	35	90.33%	93.96%
NON-MALIGNANT	10	911	890	21	97.69%	96.21%

IV. RESULTS

Overall proposed method for preprocessing is shown in (Fig. 2) and first input image have been shown than its regional clusters have been transformed. These clusters have been further divided into further sub regions in a grid to estimate the ROI (region of interest) where two level regions have been selected, firstly the axilla margins and secondly breast regions. The involvement of axilla margins helps doctors to investigate about the potential presence of lymph nodes, since these nodes may be removed in case of applying surgical procedures such mastectomy or lumpectomy to cure the life of breast cancer patients. High contrast levels have been used by increasing the green color spectrum where massive malignant masses exist and micro-calcification level features have been recorded with the assistance of top edge level behaviors of classifications which would become more useful features to diagnose the fibro adenoma. In Fig. 3, ROC is plotted and measured classification accuracy of the system is approximated about 95.60%.

V. CONCLUSION AND DISCUSSION WITH FUTURE DIMENSIONS

Mammogram X-Rays are very difficult to interpret because complex, diverse and heterogynous malignant behaviors of micro-calcifications are very difficult to visualize without using machine learning techniques. Since presence of massive masses accumulated as huge noise in DICOM (Digital Communication in Medicine) images of mammography and micro calcifications may be hidden between these masses and the persistence of non-palpable lumps and nodular structure in breast is an alarming situation which may assist the radiologist because initial changes of malignant and benign diagnosis may enhance the survival rate of life. This paper proposes a system so called "Intelligent System for Detection of Micro-Calcification in Breast Cancer" to differentiate the malignant and benign calcifications. Proposed system overall comprises over three main stages. In first stage noise reduction techniques are used by using adaptive threshold algorithm and detection of each macro and micro classification is done. In second stage of feature selection auto-crop technique have been used to crop the axilla margins and breast lesions by using proposed algorithm CFEDNN (Calcification Feature Extraction Deep Neural Networks) which is designed to avoid the manual ROIs (Region of Interest). Decision model is constructed by using the DNNs (Deep Neural Networks) and best classification accuracy was measured as 95.6%. As a future work there are some very important dimensions have been observed: How to measure the size of breast malignant masses? How to classify the histopathological images by correlating the mammogram? Another very significant problem is to estimate the growth pattern of malignant and non-malignant masses because it would provide more precise assistance to doctors to assess the survival rate of patients.

ACKNOWLEDGMENTS

We are highly thankful to all officials of Sukkur IBA University and medical partners for providing an opportunity to conduct the research in applied sciences.

REFERENCES

[1] Torre, L. A., Bray, F., Siegel, et. al. (2015), Global cancer statistics. CA:A Cancer Journal for Clinicians, 65: (2012) pp 87–108.

[2] Parkin, D. Max, et al. "Global cancer statistics." CA: a cancer journal for clinicians 55.2 (2005) pp 74-108.

[3] Jemal, Ahmedin, et al. "Global cancer statistics." CA: a cancer journal for clinicians 61.2 (2011) pp 69-90.

[4] Bleyer, Archie, and H. Gilbert Welch. "Effect of three decades of screening mammography on breast-cancer incidence." New England Journal of Medicine 1998-2005. Vol 367.21 (2012).

[5] Kriege, Mieke, et al. "Efficacy of MRI and mammography for breast-cancer screening in women with a familial or genetic

predisposition." New England Journal of Medicine Vol. 351.5 (2004). pp 427-437.

[6] Fletcher, Suzanne W., and Joann G. Elmore. "Mammographic screening for breast cancer." New England Journal of Medicine Vol. 348.17 (2003). pp 1672-1680.

[7] Harris, Randall E., and Ernst L. Wynder. "Breast cancer and alcohol consumption: a study in weak associations." JaMa Vol. 259.19 (1988). pp 2867-2871.

[8] McGinnis, J. Michael, Pamela Williams-Russo, and James R. Knickman. "The case for more active policy attention to health promotion." Health affairs Vol. 21.2 (2002). pp 78-93.

[9] Ren, Baorui, et al. "Design and performance of the prototype full field breast tom synthesis system with selenium based flat panel detector." Medical Imaging. International Society for Optics and Photonics, 2005.

[10] Lee, Charmaine Pei Ling, et al. "3D Mammography in Diagnostic Environment: A Subjective Review." Journal of Medical Imaging and Health Informatics 6.1 (2016). pp 215-220.

[11] Dheeba, J., N. Albert Singh, and S. Tamil Selvi. "Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach." Journal of biomedical informatics Vol. 49 (2014). pp 45-52.

[12] G. Durgadevi , Himanshu Shekhar , "An Intelligent Classification of Breast Cancer Images" Indian Journal of Science and Technology, Volume 9(28)(2016). pp 20-30.

[13] Lashkari, Amir Ehsan, and Mohammad Firouzmand. "Early Breast Cancer Detection in Thermogram Images using Supervised and Unsupervised Algorithms." The Journal of Engineering Vol. 1.1 (2016).

[14] Rajesh Kumar Tripathy, Sailendra Mahanta and Subhankar Paul, "Artificial intelligence-based classification of breast cancer using cellular images", An international journal to further the chemical sciences, Issue 18 (2014)

[15] Hamid Hassanpour & et. al. "Fully automatic classification of breast cancer microarray images", Journal of Electrical Systems and Information Technology, 2016. pp 2314-7172

[16] Graham, R. N. J., R. W. Perriss, and A. F. Scarsbrook. "DICOM demystified: a review of digital file formats and their use in radiological practice." Clinical radiology 60.11 (2005). pp. 1133-1140.

[17] Hao, Ying-ming, and Feng Zhu. "Fast Algorithm for Two-dimensional Otsu Adaptive Threshold Algorithm [J]." Journal of Image and Graphics Vol. 4 (2005).

[18] Verma, Brijesh, Peter McLeod, and Alan Klevansky. "Classification of benign and malignant patterns in digital mammograms for the diagnosis of breast cancer." Expert systems with applications Vol. 37.4 (2010). pp 3344-3351.

[19] Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems. 2012.

[20] Sermanet, Pierre, Soumith Chintala, and Yann LeCun. "Convolutional neural networks applied to house numbers digit classification." Pattern Recognition (ICPR), 21st International Conference on. IEEE, 2012.

[21] Jia, Yangqing, et al. "Caffe: Convolutional architecture for fast feature embedding." Proceedings of the 22nd ACM international conference on Multimedia. ACM, 2014.

[22] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." arXiv preprint arXiv (2014). pp 1409.155