International Journal of Multimedia and Ubiquitous Engineering
Vol.12, No.11 (2017), pp.13-20
http://dx.doi.org/10.14257/ijmue.2017.12.11.02

Optimized Artificial Neural Network based Digital Mammogram Analysis for Breast Cancer Diagnosis

Satish Saini[1] and Ritu Vijay[2]

[1]*department of Electronics and Communication Engineering,*
Chandigarh Engineering College, Landran, Mohali,India
[2]*Department of Electronics*
Bansthali University, Jaipur, Rajasthan, India.
satishsainiece@gmail.com and rituvijay1975@yahoo.co.in

Abstract

This paper works on the detection of the breast cancer at early stage, by utilizing the mammogram images. This work pre-processes the given image by using histogram equalization to enhance the contrast of the image. Then the grey level co-occurrence matrix is used to extract the features from the image. The extracted features are reduced to the significant subset of features by using the sequential backward selection. Then, the image is classified as malignant or benign on the basis of significant subset of features by using the ANN classifier. Moreover, ANN classifier is optimized by selecting the optimized error value as stopping criteria. The result comparison and analysis on DDSM and MIAS datasets using parameters sensitivity, specificity, accuracy signifies effectiveness of the work.

Keywords*: Image Registration, Breast Cancer Diagnosis, Mammogram, Artificial Neural Network*

1. Introduction

The most frequently analyzed growth in ladies is bosom disease barring the malignancy of skin [1] and is the second primary reason of ladies tumor passing [2]. Ultrasound imaging, MRI imaging and advanced Mammography are accessible for imaging of bosom growth [3]. Mammography is most broadly utilized for recognition of bosom disease [4]. It is exceptionally troublesome for the Radiologists to effectively read the mammogram in view of low differentiation [5] prompting distortion of the outcomes. Twofold perusing of mammogram is taken to decrease the extent of missed diseases, in spite of the fact that it is tedious and immoderate. Selection of a CAD framework could decrease the specialists' workload and enhance the recognition rate [6-7].

Image registration strategies are exceptionally useful for breast cancer analysis [8]. Diverse techniques, for example, wavelets [5] and statistical strategies [9] utilized Feature Extraction to identify bosom malignancy. A few Researchers utilized element choice extraction strategies for ANN based bosom tumor analysis [10-15]. Ritthipravat *et al*. clarified the utilization of Artificial Neural Networks for Recurrence Prediction of disease [16]. Kala *et al*. proposed transformative neural system engineering for bosom malignancy determination. [17]. Salim *et al*. utilized Artificial Neural Network and Hidden Markov Model technique (HMM) for diagnosing bosom cancer[18]. Ahmad *et al*. have examined the mammogram understanding by utilizing Probabilistic Neural Network. [19]. Guzman-Cabrera *et al*. examined the computerized mammograms utilizing surface division [20]. Senapati *et al*. proposed K-molecule swarm streamlining (KPSO) which

Received (July 1, 2017), Review Result (October 30, 2017), Accepted (November 20, 2017)

ISSN: 1975-0080 IJMUE

gives more exact result and better classification [21]. This paper proposes a methodology to classify the tumour in a optimized manner discussed in next section. The novelty of the paper lies in the steps combination of the methodology described.

2. Methodology

The process of classification needs the pre-processing and few other steps for the optimized performance. The flow of the work has been shown in Figure 1. It includes the pre-processing of the image using the histogram equalization. The features are extracted from this pre-processed image by using the GLCM matrix. The extracted features may include the insignificant information so the sequential backward selection (SBS) is applied to select the subset of significant features. Then the optimized ANN classification using error as stopping criteria is applied to classify the image based on selected subset of features.

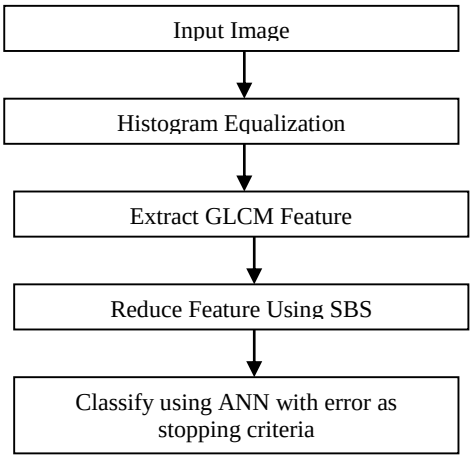

Figure 1. Flow of Proposed Work

This whole process is applied only to the region of interest. The detail of each step involved in the methodology is described below:

2.1. Selection of ROI

At first mammogram images might be trimmed to expel undesired regions as a piece of preprocessing in order to keep zone of interest just for further preparing. This is done to select the ROI.

2.2. Image Enhancement by Histogram Equalization

Histogram Equalization or Enhancement may be used for Image Enhancement of Mammogram images. Histogram evening out is utilized to modify the contrast of the picture utilizing the Image histogram by expanding dynamic scope of dim levels.[22-23]. Figure 1 demonstrates the Image improvement by histogram Equalization.

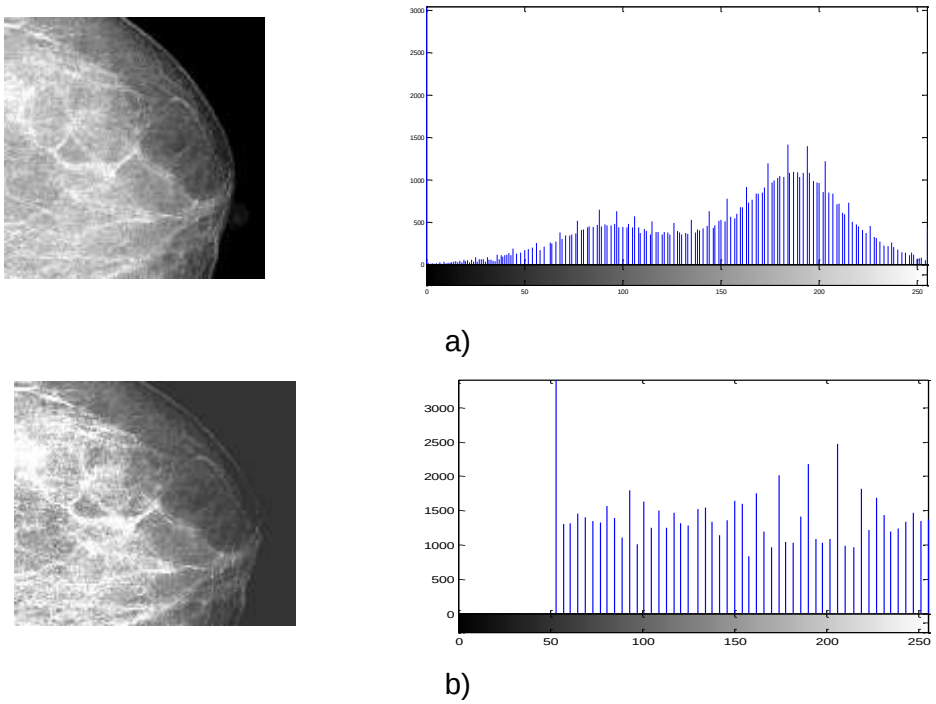

Figure 2. Histogram Equalization a) Original Image and Its Histogram b) Enhanced Image and Its Histogram

2.3. Feature Extraction

Feature extraction is extracting the most important features from the images using image-processing techniques. Initially Intensity Histogram features were used for feature selection which includes mean, energy, skewness, entropy and kurtosis *etc* [22].

2.3.1. GLCM Features

The GLCM (Gray Level Co-occurrence Matrix) is method in which the spatial relationship between pixels of different gray levels is considered [25]. Second-order texture features such as Inertia Autocorrelation, Contrast, Correlation, Dissimilarity Energy and Entropy may be computed using GLCM which gives the complete details of the image. [22, 26].

2.3.2. Feature Reduction

The features have been reduced to significant features by using the following technique:

Suppose $D = \{d_i; 1 \leq i \leq n\}$ where n is the number of features in a dataset. The selected feature subset having f number of features is $S_f = \{x_j; 1 \leq j \leq f, x_j \in D\}$. The value of the objective function $(d_i) 1 \leq i \leq n$; only if the ith feature is selected will be known as $R(d_i)$ of the feature.

The relevance of any feature $R_{k-1}(x_j); j = 1,2,3 \ldots f$ in the set S_f is given by $R_{k-1}(x_j) = OF(S_f) - OF(S_f - x_j)$ while the relevance $R_{k+1}(d_i)$ of the feature d_i from the set $D\text{-}S_f$

$D - S_f = \{d_i; i = 1,2,3, \ldots . n - f, d_i \in D, d_i \neq x_p for\ all\ x_p \in S_f$ is given by $R_{k+!}(d_i) = OF(S_f + d_i) - OF(S_f)$.

The least significant feature in S_f can be given as $R_{k-1}(x_j) = \min_{1 \leq i \leq k} R_{k-1}(x_i)$

$\Rightarrow \quad OF(S_f - x_j) = \max_{1 \le i \le k} OF(S_f - x_i).$

Similarly for the feature $d_i \in D - S_f$, the relevancy

$$R_{k+1}(d_j) = \min_{1 \le i \le n-f} R_{k+1}(d_i)$$

$\Rightarrow \quad OF(S_f + d_j) = \min_{1 \le i \le n-f} OF(S_f + d_i).$

The SBS algorithm for any Dataset D having n features can be given as:

1. f=0;
2. Initiate $S_f = D$
3. Remove Least relevant feature from S_f *i.e.*

$x_j = \max_{1 \le i \le f} OF(S_f - x_i).$

4. Update

$S_{f+1} = S_f - x_j;\ f = f + 1$

Repeat step 3 & 4 until stopping criteria achieved

2.3.3. Diagnosis/Classification

After extracting and selecting, the GLCM features are used as inputs to train, test and validate an ANN based Diagnosis System. The ANN is optimized by finding the error for the stopping criteria explained as follow: The error can be found by in a optimized manner by separating hyperplane which is described as $f(v_i) = w * Ø(v_i) + bias$, here bias is the optimal bias, w is weights and ϕ is the mapping to input vectors v applied nonlinear.

The process of optimization is completed by reducing the value of w resulting in maximized distance between the closest point of hyperplane and the hyperplane. It can be given as:

$$\min(Ø(w)) = \frac{1}{2} * \|w\|^2 + c \sum_{i=1}^{P_n} e_i$$

Where c is the constant used for regularization and e is the normalized variation where ei >=0 & $o(w * Ø(v_i) + bias) \geq 1 - e$ and i=1…Pn. Applying Lagrangian method

$$\max L_1(a) = \sum_{i=1}^{P_n} a_i - \frac{1}{2} \sum_{i,j=1}^{P_n} a_i a_j o_i o_j \left(Ø(v_i) * Ø(v_j)\right)$$

Such that

$\sum_{i=1}^{P_n} a_i o_i = 0$ and $c \geq a_i \geq 0$ for i=1…Pn. where a is the Lagrangian multiplier.

On solving the equation the classification can be given as:

$$L_e = \begin{cases} 0 \text{ if } |o_i - f(v_i)| \leq e \\ |o_i - f(v_i) - e, | \text{ if } |o_i - f(v_i)| > e \end{cases}$$

where e is the maximum allowed error. Similarly the output of the ANN is given as $f(v_i) = Ø(w * v_i + bias)$. The minimum error allowed can be determined by the procedure explained above. This error is used as stopping criteria to perform the classification using ANN. The whole process is implemented using the MATLAB and corresponding results are discussed in next section.

3. Result and Discussion

The calculation has been actualized utilizing the MATLAB. The execution examination has been done two standard datasets named as MIAS and DDSM. The MIAS dataset is given by Mammographic Image Analysis Society which is an association of UK exploration assembles The dataset utilizes 322 digitized movies. The DDSM dataset is acronym for Digital Database for Screening Mammography. It is given by collective exertion between Massachusetts General Hospital, Sandia National Laboratories and the University of South Florida Computer Science and Engineering Department. The algorithm has been compared with SVM based classification, ANN based classification. Various parameter analyzed are accuracy, specificity and sensitivity on these dataset are given below:

Table 1. Comparison of Classification Accuracy

Dataset		SVM	ANN	OANN
		Accuracy	Accuracy	Accuracy
MIAS	Benign	0.8405	0.8469	0.8529
	Malignant	0.7500	0.7680	0.7741
DDSM	Benign	0.9817	0.9827	0.9907
	Malignant	0.9167	0.9375	0.9428

Table 2. Comparison of Sensitivity (Se) and Specificity (Sp)

Dataset		SVM		ANN		OANN	
		Se	Sp	Se	Sp	Se	Sp
MIAS	Benign	0.7597	0.9426	0.7607	0.9544	0.7717	0.9624
	Malignant	0.8286	0.6339	0.8857	0.6427	0.8914	0.8367
DDSM	Benign	0.9856	0.9492	0.9904	0.9538	0.9934	0.9618
	Malignant	0.9327	0.8109	0.9512	0.8533	0.9770	0.8700

The graphical analysis of the results shown in Table 1 and 2 is given Figure 3, 4 and 5. The comparison signifies the improvement in the performance using the designed technique.

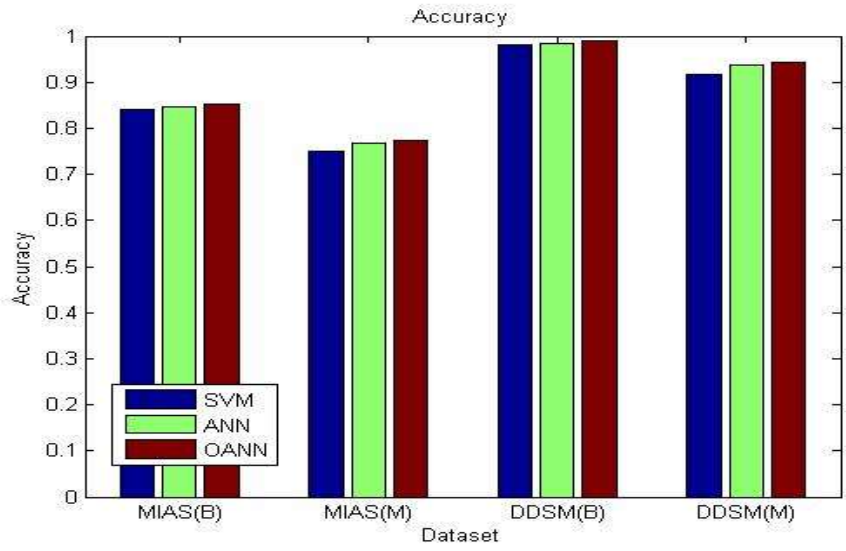

Figure 3. Comparison of Accuracy of SVM, ANN and Optimized ANN Algorithm

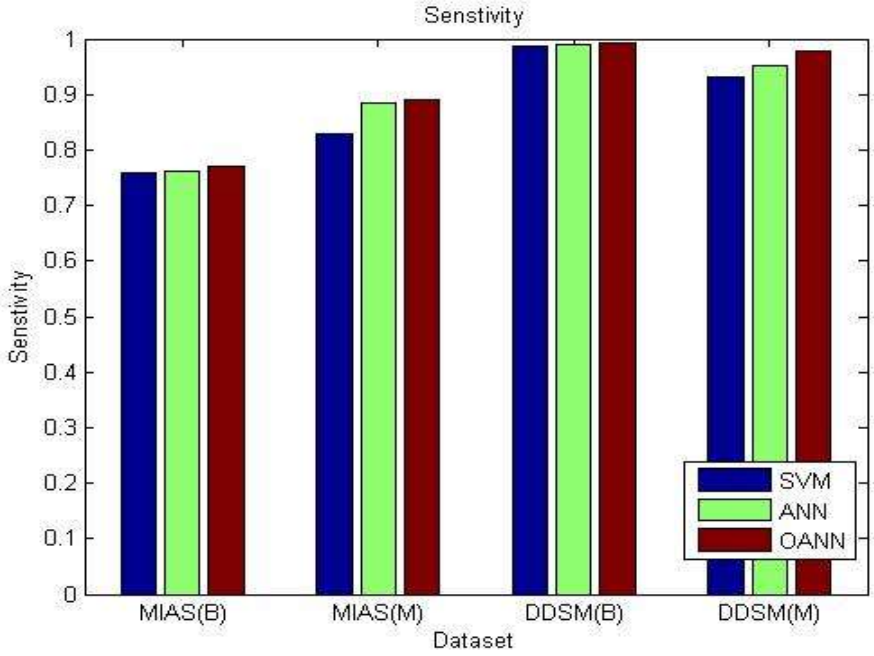

Figure 4. Comparison of Sensitivity of SVM, ANN and Optimized ANN Algorithm

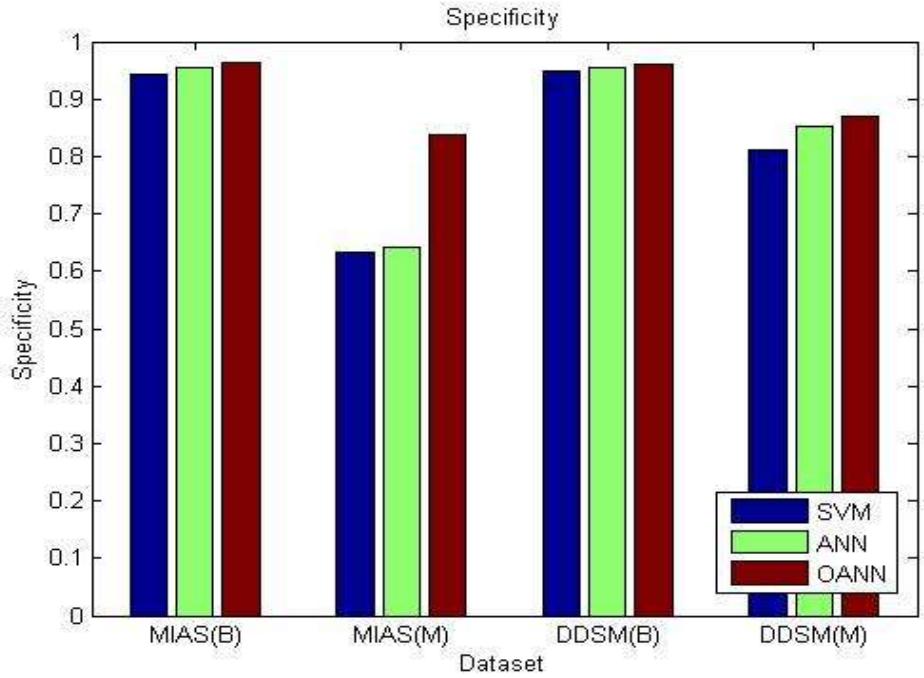

Figure 5. Comparison of Specificity of SVM, ANN and Optimized ANN Algorithm

The graphical as well as the tabular comparison shows that the given methodology separates the positive and negative classes better (analyzed using specificity and sensitivity parameter) as compared to other existing techniques.

4. Conclusion

This paper designs a methodology for the classification of the breast cancer tumour in an optimized manner. The designed methodology performs the pre-processing, feature extraction, feature reduction as well as the classification. The stopping criteria of the classification using ANN are selected as error, selected by using the Lagrangian multiplier along with the hyperplane for classification. The result of the technique are compared with SVM and ANN based classification techniques using accuracy, sensitivity and specificity as the parameters on DDSM and MIAS datasets. The effectiveness of the work is shown by the results. In future the significant feature selection process can be optimized by using meta-heuristic feature selection technique.

References

[1] "American Cancer Society", Cancer News. American Cancer Society, **(1947)**.
[2] V. Sherring, "Mediating Breast Cancer in India", InNCA 94th Annual Convention, San Diego, CA, **(2009)**.
[3] F.S. Azar, "Imaging techniques for detecting breast cancer: survey and perspectives"/
[4] K.H. Ng and M. Muttarak, "Advances in mammography have improved early detection of breast cancer", Journal-Hong Kong College of Radiologists, **(2003)**, pp. 126-31.
[5] T.C. Wang and N.B. Karayiannis, "Detection of microcalcifications in digital mammograms using wavelets", IEEE transactions on medical imaging, vol. 17, no. 4, **(1998)**, pp. 498-509.
[6] M.J. Morton, D.H. Whaley, K.R. Brandt and K.K. Amrami, "Screening Mammograms: Interpretation with Computer-aided Detection", Prospective Evaluation 1. Radiology, vol. 239, no. 2, **(2006)**, pp. 375-83.
[7] R.F. Brem, J. Baum, M. Lechner, S. Kaplan, S. Souders, L.G. Naul and J. Hoffmeister, "Improvement in sensitivity of screening mammography with computer-aided detection: a multi-institutional trial", American Journal of Roentgenology, 181, vol. 3, **(2003)**, pp. 687-93.
[8] M. Deshmukh and U. Bhosle, "A survey of image registration", International Journal of Image Processing, vol. 5, no. 3, **(2011)**, pp. 245-69.
[9] J. Bozek, M. Mustra, K. Delac and M. Grgic, "A survey of image processing algorithms in digital mammography", InRecent advances in multimedia signal processing and communications, Springer Berlin Heidelberg, **(2009)**, pp. 631-657.
[10] F. Keivanfard, M. Teshnehlab, M.A. Shoorehdeli, K. Nie and M.Y. Su, "Feature selection and classification of breast cancer on dynamic Magnetic Resonance Imaging by using artificial neural networks", InBiomedical Engineering (ICBME), 2010 17th Iranian Conference of 2010, IEEE, pp. 1-4.
[11] M.L. Giger and Z. Huo, "Artificial neural networks in breast cancer diagnosis: merging of computer-extracted features from breast images", InEvolutionary Computation, 1999. CEC 99. Proceedings of the 1999 Congress on 1999, IEEE, vol. 3.
[12] L. Liu and M. Deng, "An evolutionary artificial neural network approach for breast cancer diagnosis", InKnowledge Discovery and Data Mining. WKDD'10. Third International Conference on 2010, IEEE, **(2010)**, pp. 593-596.
[13] L.E. George and E.Z. Mohammed, "Cancer tissues recognition system using box counting method and artificial neural network", InSoft Computing and Pattern Recognition (SoCPaR), 2011 International Conference of 2011, IEEE, **(2011)**, pp. 5-9.
[14] J.Y. Lo and C.E. Floyd, "Application of artificial neural networks for diagnosis of breast cancer", InEvolutionary Computation, 1999. CEC 99. Proceedings of the 1999 Congress on, IEEE, vol. 3, **(1999)**.
[15] Y.H. Chang, B. Zheng, X.H. Wang and W.F. Good, "Computer-aided diagnosis of breast cancer using artificial neural networks: Comparison of backpropagation and genetic algorithms", InNeural Networks. IJCNN'99. International Joint Conference on 1999, IEEE, vol. 5, **(1999)**, pp. 3674-3679.
[16] P. Ritthipravat, "Artificial neural networks in cancer recurrence prediction", In Computer Engineering and Technology. ICCET'09, International Conference on 2009 Jan 22. IEEE, vol. 2, **(2009)**, pp. 103-107.
[17] R. Kala, R.R. Janghel, R. Tiwari and A. Shukla, "Diagnosis of breast cancer by modular evolutionary neural networks", International Journal of Biomedical Engineering and Technology, vol. 7, no. 2, **(2011)**, pp. 194-211.
[18] M.I. Sali, A.H. Ahmad, I. Ariffin, B. Rosidi and E. Supriyanto, "Development of breast cancer diagnosis tool using hybrid magnetoacoustic method and artificial neural network".
[19] A.T. Azar and S.A. El-Said, "Probabilistic neural network for breast cancer classification", Neural Computing and Applications, vol. 23, no. 6, **(2013)**, pp. 1737-51.
[20] R. Guzmán-Cabrera, J.R. Guzmán-Sepúlveda, M. Torres-Cisneros, D.A. May-Arrioja, J. Ruiz-Pinales, O.G. Ibarra-Manzano, G. Aviña-Cervantes and A.G. Parada, "Digital image processing technique for breast cancer detection", International Journal of Thermophysics, vol. 34, no. 8-9, **(2013)**, pp. 1519-31.

[21] M.R. Senapati, G. Panda and P.K. Dash, "Hybrid approach using KPSO and RLS for RBFNN design for breast cancer detection", Neural Computing and Applications, vol. 24, no. 3-4, **(2014)**, pp. 745-53.
[22] RC. Gonzalez and R.E. Woods, "Digital image processing", Nueva Jersey, **(2008)**.
[23] S. Mohan and M. Ravishankar, "Optimized histogram based contrast limited enhancement for mammogram images", ACEEE Int J Inf Technol. vol. 3, no. 1, **(2013)**, pp.66-71.
[24] P. Bethapudi and E.S. Reddy, "Detection of Malignancy in Digital Mammograms from Segmented Breast Region Using Morphological Techniques", IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE), vol. 5, no. 4, **(2013)**, pp. 9-12.
[25] V. Raman, P. Sumari, H.H. Then and S.A. Al-Omari, "Review on Mammogram Mass Detection by MachineLearning Techniques", International Journal of Computer and Electrical Engineering, vol. 3, no. 6, **(2011)**, pp. 873.
[26] A.M. Khuzi, R. Besar, W.W. Zaki and N.N. Ahmad, "Identification of masses in digital mammogram using gray level co-occurrence matrices", Biomedical imaging and intervention journal, vol. 5, no. 3, **(2009)**.

