AN OPTIMAL NEURAL NETWORK BASED CLASSIFICATION TECHNIQUE FOR BREAST CANCER DETECTION

Kulsoom Iftikhar[1], Shahzad Anwar[1], Izhar Ul Haq[1], Muhammad Tahir Khan[1] and Sayed Riaz Akbar[1]

ABSTRACT

Breast carcinoma is one of the most significant health diseases in the world. Early identification of breast carcinoma could be beneficial for in time treatment of the disease. This study presents an efficient classification method for benign and malignant breast cancer. The proposed method employs an optimal feature classification employing artificial neural network. The proposed architecture has five input nodes, two hidden layers with eight neurons each and one output node. Five features (cluster thickness, uniformity of {cell size, cell shape}, marginal attachment and radius of circle enclosing the abnormality) are nominated as input features to the ANN to predict the benign or malignant breast carcinoma. The network is trained, tested and validated on data bases that comprises of a set of previously extracted features provided by Wisconsin and Essex Universities. For the established neural networks comparative analysis is performed to study the optimum parameters required for prime mass classification. The execution of suggested methodology is estimated using ROC curve. The accuracy rate of developed method is 93.1% or 0.93 with sensitivity of 0.99 and specificity of 0.83 according to the receiver operating characteristic (ROC).

KEYWORDS: *Benign; malignant; artificial neural network; mass classification; ROC curve*

INTRODUCTION

Cancer describes the pathological condition of the uncontrolled growth of the affected body cells. The well- known cancer includes carcinoma (lung, breast and ovarian), Sarcoma (bones and cartilage), Lymphoma (lymph nodes) and Leukemia (blood cancer)[1]. According to World Health Organization (WHO), the rate of breast carcinoma is more than any other form of cancer in both advanced and developing countries[2]. Breast cancer, although is considered to be the ailment of the established countries of the world, yet almost 50% of mammary carcinoma cases and 58% of fatalities occur in developing countries[2] Hence, early breast cancer detection and treatment is a major public health matter.

Primary diagnosis of mammary cancer has a foremost role in the treatment of the carcinoma. Mammography is commonly used for the diagnosis of early breast carcinoma. Magnetic resonance imaging (MRI) and computer aided diagnosis (CAD) are also used for the early breast cancer detection. The important signs of malignancy are the presence of microcalcification and masses; hence, their detection is very important for the diagnosis of the disease[3]. Some of the small calcifications and low contrast could be mistaken during medical consultation and therefore, the task of radiologists becomes more difficult where fast and accurate interpretations are required. Hence, (CAD) provides a second opinion to the radiologists about the presence of masses or microcalcifications[3-6]. In addition to the MRI and CAD, some databases are also helpful for the detection of microcalcifications. In these mammographic databases i.e. Nijmegen and the Mammographic Image Analysis Society (MIAS), features of interest are already extracted from mammograms that help in the prediction of carcinoma's presence[4].

Various techniques have been established for the diagnosis and presence of masses in the literature. Support Vector Machine (SVM) learning a method in which microcalcification cluster detection was formulated as a supervised learning problem and the detection algorithm was developed by applying SVM. In the image, SVM was used at each location to detect the presence/absence of a micro cluster[7]. Liu et al.[4] proposed an intelligent system comprised of a two-step procedure for breast ultrasound images (BUS) including ROI generation step followed by ROI classification step. Shi et al.[3] proposed a method involving four step CAD scheme based on fuzzy support vector machine, i.e. image preprocessing, image segmentation, feature removal and selection, sorting and diagnosis was proposed. In addition, ANNs have been used to foresee the outcomes using clinical data[8,9]. An artificial neural network based approach incorporating

1 Institute of Mechatronics Engineering, University of Engineering & Technology Peshawar, Pakistan

twenty five features was adopted for the determination of presence of breast tumor. The network was trained using a back propagation (BP) feed forward neural network whose primary results were presented after training of the network[10]. Ultrasonography has been proposed by Kuo et al.[11] to detect the solid breast tumors. The proposed segmentation algorithm was applied to separate the tumor from the normal tissue. Three features extracted from the ROI were variance distinction, autocorrelation distinction and scattering alteration of wavelet coefficients for auxiliary classification by using a multilayered perceptron (MLP) neural network.

Research has been reported related to mass classification as benign or malignant breast cancer using different approaches merging ANNs. Babu et al.[10] studied prognosis of breast tumors using back propagation (BP) feed forward neural network ANN with twenty five input features. The primary results were presented after training of the network. Saini et al.[6] partitioned a clinical dataset comprising of data compiled from 42 positive case patients arbitrarily into two datasets.

The datasets were utilized for training and testing of the ANN based classifier. Core features from the mammograms were obtained using their Gray Level Co-occurrence Matrix (GLCM) and provided to two different classifiers. Feed-forward back propagation and Cascade forward back propagation were trained for the detection and discrimination of benign and malignant cells. The final performance of the classifiers was assessed using the Mean Square Error (MSE) and the obtained sensitivity and specificity. The classifiers such as Linear Discriminants (LDA), ANN, Bayesian network and Binary decision tree have been used for mass classification as well[4].

In this study, ANN based methodology is suggested for classifying the tumors. The proposed method consists of four modules i.e. Extracted features used as input, comparative analysis and training of created artificial neural networks to select the best neural network for analysis, classification using ANN and performance evaluation using Receiver Operating Characteristics (ROC) and confusion matrix (ROC/confusion matrix of proposed methodology or evaluation tool). The phases involved in the proposed methodology are shown in Figure 1.

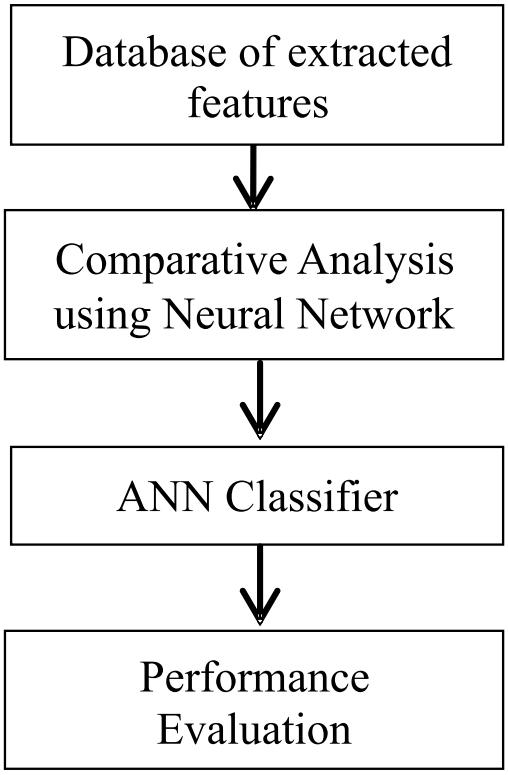


Figure 1. Flow chart of the suggested methodology for the classification of breast carcinoma into benign/ malignant.

MATERIALS AND PROPOSED METHODOLOGY

The proposed methodology incorporates three steps i.e. training, testing and validation and classification as illustrated in the flowchart shown in Figure 2.

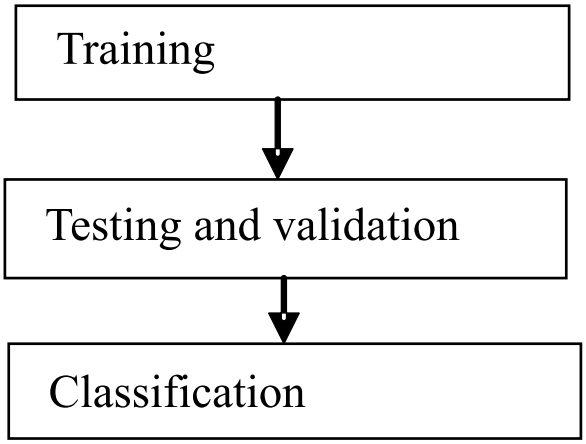


Figure 2. Flowchart representing the steps involved in proposed methodology

The Wisconsin Breast carcinoma database given by the University of Wisconsin hospitals Madison, Wisconsin, USA[12,13,14,15] and Essex Breast carcinoma database given by the University of Essex Colchester, UK[16] were adopted in this study. These experimental purpose databases provide completely anonymous and unidentified fourteen extracted features from mammograms. In our approach, out of fourteen features the optimal features from the two databases were chosen and fourteen features were reduced to five, establishing a new database with only five features for experimentation. The new database incorporates 699 instances (458 benign cases and 241 malignant cases) with six class attributes (i.e. five attributes were used as input features to the ANN and one as output) i.e. whether benign or malignant.

Similar to the work of Wang *et.al*[9], classification is chosen as the prediction method for the establishment of network model . Linear Discriminant Analysis (LDA) and (ANN) are well established classifiers in mass classification[4]. First the ANN was trained for the selected features, known outputs of a known database to determine the weights. The weights were adjusted accordingly to obtain the known output i.e. either the weights were increased or decreased. After training, the ANN is incorporated for classification of masses.

In the proposed methodology feed forward neural network architecture was employed. A total of 49 ANNs were created and trained using the scaled conjugate gradient (SCG) back propagation algorithm in which weights and bias values were updated accordingly. Once the ANN was trained, the next step was to test the capability of the proposed method and this was achieved via feeding the test data to the network. Once the network performed classification, it was necessary to compare the performance. The comparison process was performed by incorporating the method proposed by Chan et.al[17] which maximized the separation of the two class distributions, subsets of texture features were selected from the multi-dimensional feature space. A backpropagation artificial neural network (ANN for experimentation. ROC Analysis confirms the establishment of the proposed method. The steps of the proposed methodology A and B are discussed as under in detail.

A. Training, Testing and Validation Step

In the experimentation, first step was training the network on a given data set. The data input to the network was randomly selected. Once the data was trained, next step was testing and validation; this was achieved via

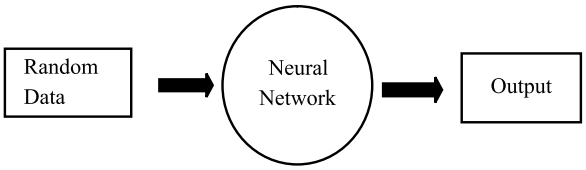


Figure 3. Flowchart representing the training, testing and validation of ANN

testing the remaining data (which were kept silent from the network). The process is illustrated in Figure 3.

The performance was validated with the help of performance graph. Total number of epochs for the progression was 30000 and best validation performance

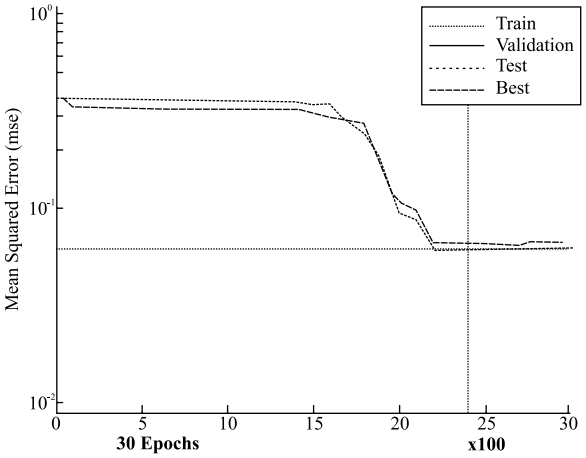


Figure 4. Performance evaluation graph showing best validation performance of 0.062352 at epoch 2440

was achieved at epoch 2440. The performance was evaluated with mean squared error MSE as shown in the following Figure 4.

B. Classification Step

In medical applications, the practice of artificial intelligence (AI) is broadly acknowledged. A huge quantity of therapeutic devices entrenched with AI algorithms featuring artificial neural networks ANN are currently available. Work on such medical devices is being

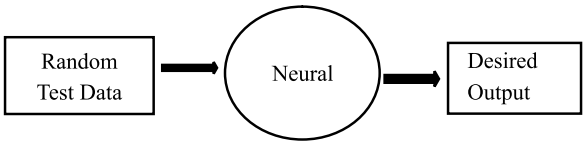
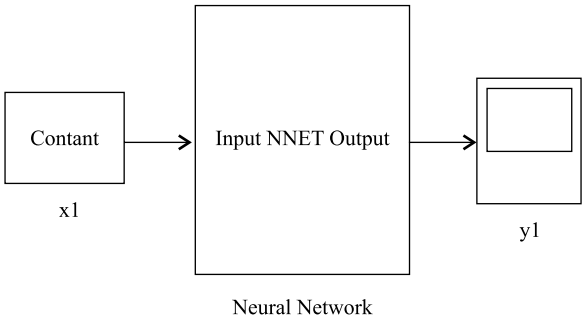


Figure 5. Flowchart representing the classification step. Random test data is given as input to the NN selected among 49 trained NNs for the classification as benign or malignant breast cancer

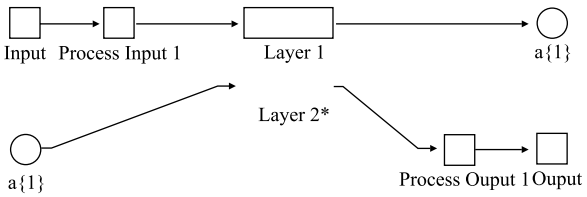
published and accepted wide-reaching[18]. Due to ANN's acclaimed application in clinical decision making and classification, it is used to classify breast tumors. It is depicted by following Figure 5.

ARCHITECTURAL DIAGRAMS

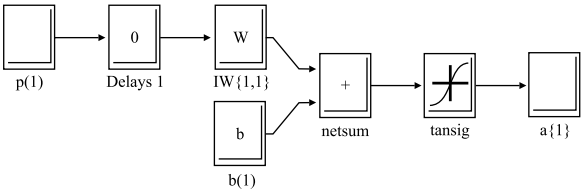
Architectural diagrams of the proposed methodology



(a)

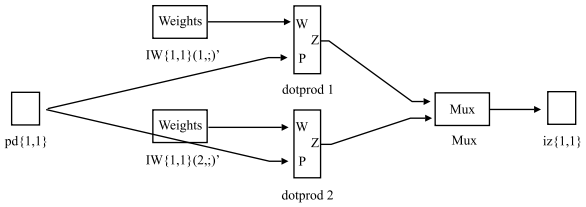


(b)

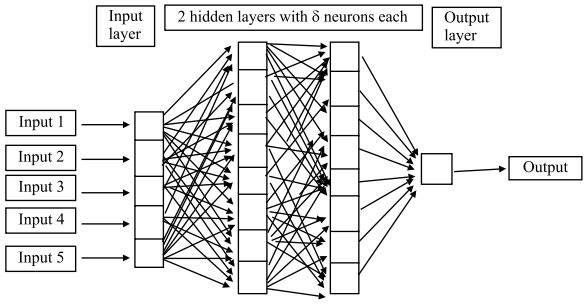


(c)

simulated in MATLAB are presented in following Figure 6. Figure 6 (a) represents the neural network Simulink diagram which is further expanded in Figure 6 (b) (c) (d) to get detailed view of internal structure of the neural network. Figure 6 (e) shows the schematic diagram of NN.



(d)



(e)

Figure 6. (a)-Overall system architectural diagram, (b)-expanded view of neural network, (c)-insight of the architectural diagram, (d)-insight of the weighted diagram of layer 1, (e)-Schematic diagram of the employed ANN showing one Input layer with five input features, two hidden layers with eight neurons each and one output layer i.e. 5-2-1.

***in (b) Layer2 is the replica of layer 1**

RESULTS

The experimentation was performed using MATLAB 8.1.0.604 version on the computing machine with features: Processor-Intel(R) Core(TM) i5-2430M CPU @ 2.40GHz, installed memory (RAM)-4.00GB, system type-64 bit operating system with x64 based processor. Feed forward neural networks were used to perform the experiments. The training of the ANNs was carried out by scaled conjugate gradient (SCG) back propagation algorithm in which weights and bias values are updated accordingly. A total of 49 neurons were trained with SCG algorithm. The data distribution was evaluated using cross validation method in which data is randomly partitioned into testing and training data.

Subsequently, out of 699 features, five features were selected to establish artificial neural networks and the experimentation was performed using MATLAB 8.1.0.604 for the sorting of mammary carcinoma as

Table 1. The Experimentation Results

Input Features (**)	% Distribution			Best performance at Epoch number (x 100)	Hidden layer neurons	ROC Analysis		Confusion matrix
	Training (%)	Testing (%)	Validation (%)			Sensitivity at zero specificity (Malignant)	Sensitivity at zero specificity (Benign)	Classification Accuracy (%)
5	50	25	25	15	10	0.42	0.20	95.9
5	50	25	25	14	9	0.20	0.32	94.6
5	50	25	25	4	8	0.18	0.43	95.4
5	50	25	25	15	7	0.56	0.22	96.3
5	50	25	25	11	6	0.51	0.32	95.3
5	50	25	25	29	5	0.65	0.29	95.4
5	50	25	25	17	4	0.53	0.27	95.7
5	50	25	25	7	3	0.71	0.13	95.7
5	50	25	25	24	2	0.61	0.45	93.1
5	50	25	25	13	1	0.63	0.56	95.6

** Five features in column 1 are cluster thickness, uniformity of {cell size, cell shape}, marginal attachment and radius of circle enclosing the abnormality

benign or malignant. The selected five features were (cluster thickness, uniformity of {cell size, cell shape}, marginal attachment, and radius of circle enclosing the abnormality). Total of 49 Neurons were recognized for the reason of training and comparison analysis. The network architecture having two hidden layers performs the best output in terms of ROC and confusion matrix and therefore, was selected for data analysis to be classified as benign or malignant breast cancer.

Table 2. Design/ Architecture summary of nominated ANN

Training	50%
Testing	25%
Validation	25%
Number of layers	2
Number of Neurons	8
Total number of epochs	3000
Best performance at epoch	2440
Number of Input features	5
Number of Outputs	1
Number of cases	699
Data distribution	Random
Training Algorithm	Scaled conjugate gradient
Performance	Mean squared error MSE
Type of Neural network	Feed forward

The experimentation was performed having fixed inputs, such as, five and adjusting the hidden layers (from ten to one), for each experiment. The results summarized in Table 1 are the best possible outcomes of the experimentations.

Reviewing experimental results, the architecture selected offering optimum results was based on ROC analysis and confusion matrix was having a configuration of 5-2-1 i.e. with five inputs features, two hidden layers and one output. The preference was based on superlative ROC and confusion matrix. The architecture summary of the designed NN is presented in table 2.

A. Architecture Summary of Designed Neural Network

All the values representing the design of the designated ANN are summarized in the following Table 2.

B. ROC Analysis

Receiver Operating Characteristics (*ROC)* analysis is used as a methodical tool for computing the effect of predictability among individuals' resolution thresholds. ROC curves used for mass classification of the selected

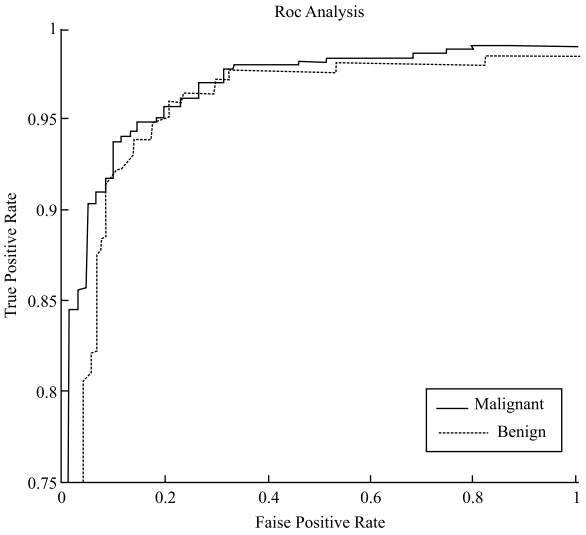


Figure 7. ROC Analysis

NN are shown in Figure 7. The *x-axis* shows the False Positive Rate (FPR) i.e. specificity and the y-axis shows the True Positive Rate (TPR) i.e. sensitivity. Best performance at 2440 epochs with sensitivity of 0.616 for malignant and 0.45 for benign was achieved utilizing the nominated NN by setting an appropriate threshold level of zero specificity. Further calculations were performed to check the validity of results, which are summarized in Table 3 and Table 4. The soundness of the suggested methodology could be observed in the following Figure 7.

Table 3. Confusion matrix showing the accurate and misclassified data

Confusion Matrix

450 64.4%	**40 5.7%**	**91.8% 8.2%**
8 1.1%	201 28.8%	96.2% 3.8%
98.3% 1.7%	83.4% 16.6%	93.1% 6.9%

Target Class

Table 4. Values obtained from the confusion matrix

Sensitivity	**TP/((TP+FN))**	**0.99**
Specificity	TN/((FP+TN))	0.83
Positive prediction value	TP/((TP+FP))	0.91
Negative prediction value	TN/((TN+FN))	0.96
Positive likelihood ratio	Sensitivity/ (1-Specificity)	5.76
Negative likelihood ratio	(1-Sensitivity)/ Specificity	0.0240
True positive rate	TPR	4.5
False positive rate	FPR	0.40

Table 3 is the confusion matrix in which the squares (1, 1 and 2, 2) shows correct responses, the (1, 2 and 2, 1) shows incorrect responses and the last square shows overall accuracy i.e. 93.1%. The accurately classified data showed a percentage of 93.1% with 6.9% of misclassified data using MATLAB software for performance evaluation.

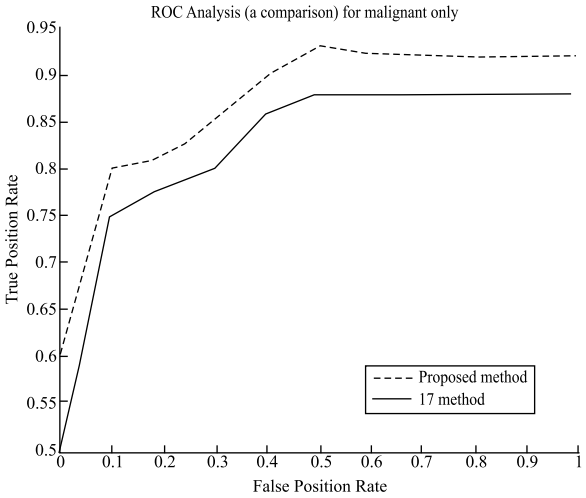


Figure 8. ROC Analysis: A comparison with Chan et.al[17]

Table 5. Comparing results of proposed and Chan et.al[17] methods

	Proposed Method	**[17] Method**
Accuracy	93.1%	88%
Sensitivity	99%	100%
Specificity	83%	39%

Further calculations were performed to achieve the overall sensitivity, specificity, positive predictive value, negative prediction value, positive likelihood ratio and negative likelihood ratio by considering the above outlined confusion matrix in Table 3.

Thus, the nominated NN gives sensitivity of 0.99 and specificity of 0.83 in the proposed methodology.

C. ROC Analysis (A Comparison) for Malignant only

Comparison of proposed method was executed with a method described by Chan et.al[17]. Clearly seen in Figure 8, area under the curve of proposed method is more than Chan et.al[17]. The plots obtained for both methods indicate better performance by suggested methodology, thus, making the proposed method more efficient and accurate as compared to the method proposed by Chan et.al[17].

Accuracy of 93.1%, sensitivity of 99% and specificity of 83% were observed in the proposed methodology, whereas, method proposed by Chan et.al17 had an accuracy of 88%, sensitivity of 100% and specificity of 39% as illustrated in Table 5.

CONCLUSION

Breast carcinoma is one of the main causes of death in women. Through early detection and screening tests, the prognosis and timely treatment of the disease is possible. In this paper, an approach to classify benign and malignant breast cancer was developed and demonstrated employing ANN. A total of 49 neurons were employed and only one with optimum results was selected for mass classification. The nominated NN with five input features, two hidden layers with eight neurons each showed an accuracy of 93.1%, sensitivity of 99%, specificity of 83% with best performance validation at epoch 2440. The performance was evaluated using ROC curve and confusion matrix. The accuracy of training samples was promising as demonstrated by the results. To establish the competence level of the proposed methodology, comparison with a reference method was also performed.

In future it would be fascinating to see, how the proposed method performs in noisy clinical images. It would be interesting to observe the effect upon the accuracy of performance by increasing the number of cases/database.

REFERENCES

1. *Bano, S., Arif, S., Ahmad, A. and Zafar, P., 2013. "Awareness About Cancer In Pakistan". Munnum (National Academy of Young Scientists, School of Biological Sciences (SBS), University of Punjab Lahore.*

2. *"GLOBOCAN 2008". [Online] Cancer incidence and mortality worldwide Globocan, International Agency for Research on Cancer (IARC), WHO. Available: http://www.iarc.fr/en/media-centre/iarc-news/2010/globocan2008.php*

3. *Shi, X., Cheng, H., Hu, L., Ju, W. and Tian, J. 2010. "Detection and classification of masses in breast ultrasound images". Digital Signal Processing. 20 (3): 824-836.*

4. *Liu, B., Cheng, H., Huang, J., Tian, J., Tang, X. and Liu, J., 2010. "Fully automatic and segmentation-robust classification of breast tumors based on local texture analysis of ultrasound images". Pattern Recognition. 43(1): 280-298.*

5. *Sathya, D. J. and Geetha, K., 2011. "Development of CAD System Based on Enhanced Clustering Based Segmentation Algorithm for Detection of Masses in Breast DCE-MRI". J. Comput. Sci.. 8(5): 378–387.*

6. *Saini, S. and Vijay, R., 2015. "Mammogram Analysis Using Feed-Forward Back Propagation and Cascade-Forward Back Propagation Artificial Neural Network". Fifth International Conference on Communication Systems and Network Technologies, Gwailor.1177 - 1180.*

7. *Huang, Y.-L., 2009. "Computer-aided Diagnosis Using Neural Networks and Support Vector Machines for Breast Ultrasonography". J. Med. Ultrasound. 17(1): 17–24.*

8. *Chiu, J.-S., Wang, Y.-F., Su, Y.-C., Wei, L.-H., Liao, J.-G., and Li, Y.-C., 2009. "Artificial neural network to predict skeletal metastasis in patients with prostate cancer". J. Med. Syst.. 33: 91–100.*

9. *Wang, T.-N., Cheng, C.-H. and Chiu, H.-W. 2013. "Predicting post-treatment survivability of patients with breast cancer using Artificial Neural Network methods". Conf. Proc. IEEE Eng. Med. Biol. Soc.. 1290–3.*

10. *Babu, G., Bhukya, S. and Kumar, R., 2013. "Feed forward network with back propagation algorithm for detection of breast cancer". 28th International Conference on Computer Science &*

Education,Colombo. 181-185.

11. *Kuo, S.-J., Hsiao, Y.-H., Huang, Y.-L. and Chen,D.-R., 2008. "Classification of benign and malignant breast tumors using neural networks and three-dimensional power Doppler ultrasound". Ultrasound Obstet. Gynecol. 32: 97–102.*

12. *Mangasarian, O. L. and Wolberg, W. H., 1990. "Cancer diagnosis via linear programming," in SIAM News. 23: 1 & 18.*

13. *Wolberg, W. H. and Mangasarian, O. L., 1990. "Multisurface method of pattern separation for medical diagnosis applied to breast cytology". Proceedings of the National Academy of Sciences. 87: 9193–9196.*

14. *Wolberg, W. H., Mangasarian, O. L., Coleman, T. F. and Li,Y., 1990. "Pattern recognition via linear programming: Theory and application to medical diagnosis, in: Large-scale numerical optimization". SIAM Publications. 22–30.*

15. *Bennett, K. P. and Mangasarian, O. L., 1992. "Robust linear programming discrimination of two linearly inseparable sets". Optimization Methods and Software. 1: 23–34.*

16. *"Mini Mias Database". [Online]. University of Essex Colchester, Available: http://peipa.essex.ac.uk/info/mias.html.*

17. *Chan, H. P., Sahiner, B., Petrick, N., Helvie, M. A, Lam, K. L., Adler, D. D. and Goodsitt, M. M. 1997. "Computerized classification of malignant and benign microcalcifications on mammograms: texture analysis using an artificial neural network.". Phys. Med. Biol.. 42: 549–567.*

18. *Amato, F., López, A., Peña-Méndez, E. M., Vaňhara, P., Hampl, A. and Havel, J., 2013. "Artificial neural networks in medical diagnosis," J. Appl. Biomed.. 11: 47–58.*