IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 18, Issue 5, Ver. II (Sept - Oct. 2016), PP 08-15
www.iosrjournals.org

Discriminant Analysis and Neural Network Based Breast Cancer Classifier Using Electrical Impedance

Praveen C. Shetiye, Ashok A. Ghatol and Vilas N. Ghate

Abstract: *Breast cancer presents a serious medical and social problem worldwide. Early detection is key to effective breast cancer treatment. Therefore, scientists are consistently looking for new diagnostic techniques that would be more efficient, easy to use and safe for the patient. Electrical impedance tomography (EIT) is an attractive alternative modality for breast imaging. The procedure is comfortable; the clinical system cost is a small fraction of the cost of an X-ray system, making it affordable for widespread screening. Artificial neural networks (ANNs) may be good pattern classifiers for this application. A preliminary study to show the potential of neural networks to distinguish benign from malignant skin lesions using electrical impedance is presented. In this paper Discriminant Analysis and ANN based classifiers are verified for breast cancer detection using electrical impedance imaging in frequency scanning. Neural networks were able to classify measurements in a test set with 99% accuracy and 93.7% accuracy for the Discriminant Analysis. These results indicate electrical impedance may be a promising clinical diagnostic tool for detection of breast cancer.*
Index Terms: *Breast cancer, Electrical impedance, MLP, Discriminant Analysis*

I. Introduction

The term "breast cancer" refers to a malignant tumor that has developed from cells in the breast. Usually breast cancer either begins in the cells of the lobules, which are the milk-producing glands, or the ducts, the passages that drain milk from the lobules to the nipple. Less commonly, breast cancers can pegin in the stromal tissues, which include the fatty and fibrous connective tissues of the breast.[1]

Over time, cancer cells can invade nearby healthy breast tissue and make their way into the underarm lymph nodes, small organs that filter out foreign substances in the body. If cancer cells get into the lymph nodes, they then have a pathway into other parts of the body. The breast cancer's stage refers to how far the cancer cells have spread beyond the original tumor. Breast cancer is always caused by a genetic abnormality. However, only 5-l0% of cancers are due to an abnormality inherited from mother or father. About 90% of breast cancers are due to· genetic abnormalities that happen as a result of the aging process and the "wear and tear" of life in general.[2][3]

The first noticeable symptom of breast cancer is typically a lump that feels different from the rest of the breast tissue. More than 80% of breast cancer cases are discovered when the woman feels a lump. The earliest breast cancers are detected by a mammogram.[4]

Those who have been diagnosed with cancer, a number of treatments may be used, including surgery, radiation therapy, chemotherapy, and targeted therapy. Types of surgery vary from breast-conserving surgery to mastectomy. Breast reconstruction may take place at the time of surgery or at a later date. In those in whom the cancer has spread to other parts of the body, treatments are mostly aimed at improving quality of life and comfort. Outcomes for breast cancer vary depending on the cancer type, extent of disease, and person's age. Survival rates in the developed world are high, with between 80% and 90%. In developing countries survival rates are poorer. Worldwide, breast cancer is the leading type of cancer in women, accounting for 25% of all cases.[5]-[9]. It is more common in developed countries and is more than 100 times more common in women than in men.[10][11].

Early detection of the disease increases the percentage of survival, avoids breast removal and saves the normal life style of the patients. Stage-0 has a survival rate of 93%, and stage-I cancer has a survival rate of 88%. At stage-IIA, it is 81% which is 74% at stage-IIB. When tumor grows to stage-IIIA, survival rate declines to 67% and it is 41% at stage III-B. At the fourth or final stage it is reduced to 15%.[12]

II. Breast Cancer Detection Using Eit

The relatively new technique of Electrical Impedance Tomography (EIT) has attracted much interest as a low-cost, non-invasive imaging tool for the human body. EIT may also be useful in the detection of breast cancer since cancerous tissue has a much higher conductivity and permittivity than the normal tissue. These changes in electrical properties occur very early in the cancerous cycle. Therefore EIT may potentially provide earlier detection of cancer than is currently possible. This technique would also be effective on younger women.

Research on freshly-excised malignant breast tissues and surrounding normal tissues in an in vitro impedance cell has shown significant differences in the frequency spectrum of the admittivity between normal or non-malignant tissues and cancerous tumors. This contrast may provide a basis for breast cancer detection using electrical impedance imaging in frequency scanning. We develop a prototype method for the classification of electrical impedance spectroscopy (EIS) data collected from breast cancer patients using electrical impedance imaging system.[13]-[17].

III. Classification Of Breast Cancer

Most common class of breast cancer are considered i.e. Car (carcinoma), fad (fibro-adenoma+ mastopathy + glandular), Con (connective), Adi (adipose)..

The classifier has to classify the four classes, namely,

1. Car (carcinoma),
2. fad (fibro-adenoma+ mastopathy + glandular),
3. Con (connective),
4. Adi (adipose).

For this research work, public available dataset is used [28]. Impedance measurements of freshly excised breast tissue were made at the following frequencies: 15.625, 31.25, 62.5, 125, 250, 500, 1000 KHz. These measurements plotted in the (real, -imaginary) plane constitute the impedance spectrum from where the breast tissue features are computed. The dataset can be used for predicting the classification of either the original 6 classes or of 4 classes by merging together the fibro-adenoma, mastopathy and glandular classes whose discrimination is not important (they cannot be accurately discriminated anyway). The following features are taken for the classification of four classes,

I_0 - Impedivity (ohm) at zero frequency
P_A- Phase angle at 500 KHz
HFS - High-frequency slope of phase angle
DA - Impedance distance between spectral ends
A- Area under spectrum
A/DA - Area normalized by DA
MAX IP - Maximum of the spectrum
DR- Distance between I_0 and real part of the maximum frequency point
P - Length of the spectral curve

Total Data is to be classified into four class as, Car (carcinoma), fad (fibro-adenoma+ mastopathy + glandular), Con (connective), Adi (adipose). Typical scatter plot for few samples is as shown in Fig.1

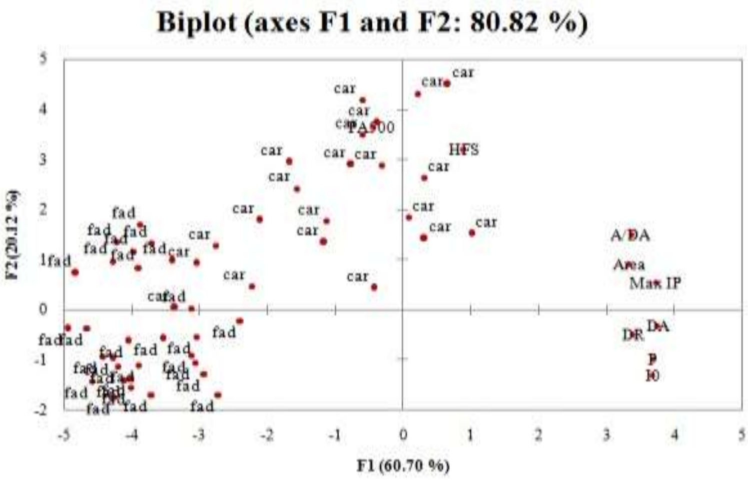

Fig. 1. Typical scatter plot

A. Discriminant Analysis:

Discriminant analysis is a technique for classifying a set of observations into predefined classes. The purpose is to determine the class of an observation based on a set of variables known as predictors or input variables. The model is built based on a set of observations for which the classes are known. This set of observations is sometimes referred to as the training set. Based on the training set, the technique constructs a set of linear functions of the predictors, known as discriminant functions, such that

$$L = b_1 x_1 + b_2 x_2 + \ldots + b_n x_n + c \qquad (1)$$

where the *b's* denote discriminant coefficients, the *x's* denote the input variables or predictors and c is a constant. These discriminant functions are used to predict the class of a new observation with unknown class. For a *k* class problem *k* discriminant functions are constructed. Given a new observation, all the *k* discriminant functions are evaluated and the observation is assigned to class *i* if the i^{th} discriminant function has the highest value. To summarize the discussion so far, the basic idea underlying discriminant function analysis is to determine whether groups differ with regard to the mean of a variable, and then to use that variable to predict group membership

The classification functions can be used to determine to which group each case most likely belongs. There are as many classification functions as there are groups. Each function allows us to compute *classification scores* for each case for each group, by applying the formula:

$$S_i = c_i + w_{i1} * x_1 + \ldots + w_{im} * x_m \qquad (2)$$

where *i* denotes the respective group; *1, 2, ..., m* denote the *m* variables; c_i is a constant for the i^{th} group, w_{ij} is the weight for the j^{th} variable in the computation of the classification score for the i^{th} group; x_j is the observed value for the respective case for the j^{th} variable. S_i is the resultant classification score. We can use the classification functions to directly compute classification scores for some new observations.

Discriminant analysis is used to determine which continuous variables discriminate between two or more naturally occurring groups. The simplest way of doing this is to consider estimation of the $P(i)$s as the ultimate solution, but be satisfied with the following more modest goal :

- A function $g_i(.)$ will be elaborated for each class.
- Given a new observation $\boldsymbol{x}$, all the $g_i(\boldsymbol{x})$ are calculated.
- The observation is assigned to the class whose $g_i(\boldsymbol{x})$ has the largest value of all.

To perform the discriminant analysis XLSTAT-2009 software is used. Various models listed below are available to perform the discriminant analysis. Each model from the list is verified and the performance is observed. For analysis 70 % data is used for training, 15 % data for cross validation and 15 % data is used for testing.

Following Models are employed,

- Forward Model
- Backward Model
- Stepwise Forward Model
- Stepwise Backward Model

Fig.2 and Table I shows the variations of classification accuracy with models used for DA. From Fig.2 it is observed that different models produce the different classification accuracy on training dataset, CV dataset and testing dataset. But consistency in the results is not seen with any model used. Stepwise Backward and Backward model classify the faults with accuracy of 100% on testing dataset and 88.88 % on training dataset, but classification accuracy is poor on CV dataset.

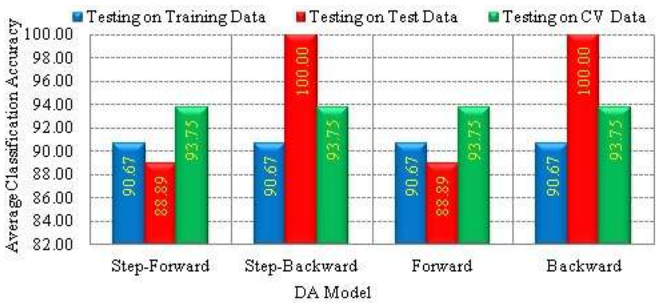

Fig. 2. Variations of classification accuracy with models used for DA

Table I : Model Wise Classification Accuracy Of Da (Individual Fault And Average)

Model	Testing Dataset			
	Training	Testing		CV
Stepwise-Forward	Class	% Correct	% Correct	% Correct
	adi	93.75%	100.00%	100.00%
	car	73.33%	100.00%	100.00%
	con	88.89%	75.00%	75.00%
	fad	97.14%	87.50%	100.00%
	Average	90.67%	88.89%	93.75%
Stepwise-Backwar	adi	93.75%	100.00%	100.00%
	car	73.33%	100.00%	100.00%
	con	88.89%	100.00%	75.00%

	fad	97.14%	100.00%	100.00%
	Average	90.67%	100.00%	93.75%
Farward	adi	93.75%	100.00%	100.00%
	car	73.33%	100.00%	100.00%
	con	88.89%	75.00%	75.00%
	fad	97.14%	87.50%	100.00%
	Average	90.67%	88.89%	93.75%
Backward	adi	93.75%	100.00%	100.00%
	car	73.33%	100.00%	100.00%
	con	88.89%	100.00%	75.00%
	fad	97.14%	100.00%	100.00%
	Average	90.67%	100.00%	93.75%

In discriminant Analysis Factor score (the coordinates of the motor condition in the new space), the probability to belong to each condition, and the squared Mahalanobis distance to the centroid of the group is calculated. Each motor condition is classified into the group for which the probability of belonging is the greatest. Table II shows the eigenvalues and corresponding percentage of variance.

Table II: Eigenvalus And Corresponding Percentage Of Variance For Da

Factors	First Factor	Second Factor	Third Factor
Eigenvalue	15.147	1.858	1.212
Discrimination percentage	83.147	10.202	6.651
Cumulative Percentage	83.147	93.349	100.000

It is observed that within three factors 100% variance is represented. For good classification results number of factors should be *k-1* where *k* denotes the number of classes. In this case we observed that three factors (for 100 % variance) for four classes, means good classification but average classification accuracy is not satisfactory for real world.

Table III: Confusion Matrix For Sample Case

from \ to	adi	car	con	fad	Total	% correct
adi	2	0	0	0	2	100.00%
car	0	4	0	0	4	100.00%
con	0	0	3	1	4	75.00%
fad	0	1	0	7	8	87.50%
Total	2	5	3	8	18	88.89%

B. Design of MLP Network for Classification

ANNs are commonly known as biologically inspired, highly sophisticated analytical techniques, capable of modeling extremely complex nonlinear functions. Formally defined, ANNs are analytic techniques modeled after the processes of learning in the cognitive system and the neurological functions of the brain and capable of predicting new observations (on specific variables) from other observations (on the same or other variables) after executing a process of so-called learning from existing data. We used a popular ANN architecture called the multilayer perceptron (MLP) with backpropagation (a supervised learning algorithm). The MLP is known to be a robust function approximator for prediction classification problems. It is arguably the most commonly used and well-studied ANN architecture. Our experimental runs also proved the notion that for this type of classification problem the MLP performs better than other ANN architectures such as radial basis function, recurrent neural network and self-organizing map. In fact, the right size and the structure, the MLP is capable of learning arbitrarily complex nonlinear functions to arbitrary accuracy levels. The MLP is essentially a collection of nonlinear neurons (also known as perceptrons or processing elements) organized and connected to each other (using what are commonly called weights) in a feed forward multilayer structure. General algorithm used is as follows,

Initialization of Weights:
Step 1: Initialize the weights to small random values
Step 2: While stopping condition is false, do step3-10
Step 3: For each training pair do steps 4-9
Feed forward:
Step4: Each input unit receives the input signal x_i and transmits this signals to all units in the hidden layer rangeofi between 0 to n.
Step 5: Each hidden unit ($\boldsymbol{z_j}$,$j=1,\ldots,p$) sums its weighted input signals

$$z_{-inj} = v_{oj} + \sum_{i=1}^{n} x_i\, v_{ij} \qquad (3)$$

Where $v_{0j}$is bias to hidden unit.
Applying the activation function $Z_j = f(z_{-inj})$ here the activation function is $tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ and sends this signal to all units in output units.
Step6: Each output unit (y_k, $k=1,...,m$) sums its weighted input signals ,

$$y_{-ink} = w_{ok} + \sum_{j=1}^{p} z_j \, w_{jk} \quad (4)$$

Where $w_{0k}$is bias to output unit.
And applies its activation function to calculate the output signals $Y_k = f(y_{-ink})$here the activation function is

$$tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (5)$$

Back Propagation Error:
Step 7: Each output unit (y_k ,$k=1,...,m$) receives a target pattern corresponding to an input pattern error information term is calculated as $\delta_k = (t_k - y_k) f(y_{-ink})$
Step 8: Each hidden unit (z_j,j=1,…,p) sums its delta inputs from units in the layer above

$$\delta_{-inj} = \sum_{k=1}^{m} \delta_k \, w_j \quad (6)$$

The error information term is calculated as

$$\delta_j = \delta_{-inj} \, f(z_{-inj}) \quad (7)$$

Updation of weight and Biases:
Step 9: Each output unit (y_k, $k=1,...,m$) updates its bias and weights *(j=0,…,p)*

$$w_{jk}(t+1) = w_{jk}(t) + \alpha \delta_k z_j + \mu[w_{jk}(t) - w_{jk}(t-1)] \quad (8)$$

Where α is learning rate and μ is momentum factor
And each hidden unit *(z_j,j=1,…,p)* updates its bias and weights *(i=0,…,n)*

$$v_{jk}(t+1) = v(t) + \alpha \delta_j x_i + \mu[v_{ij}(t) - v_{ij}(t-1)] \quad (9)$$

Step 10: Test the stopping condition

One problem appears after the feature extraction. There are too many input features that would require a significant computational efforts to calculate, and may result in low accuracy of the monitoring and fault diagnosis. The potential improvements which can be achieved by first mapping the data into a space of lower dimensionality. Reduction in dimensionality of the input space and hence the network can be achieved by Principal Component Analysis (PCA). PCA is performed by Pearson rule. Fig.3 is related to a mathematical object, the eigenvalues, which reflect the quality of the projection to a lower number of dimensions.

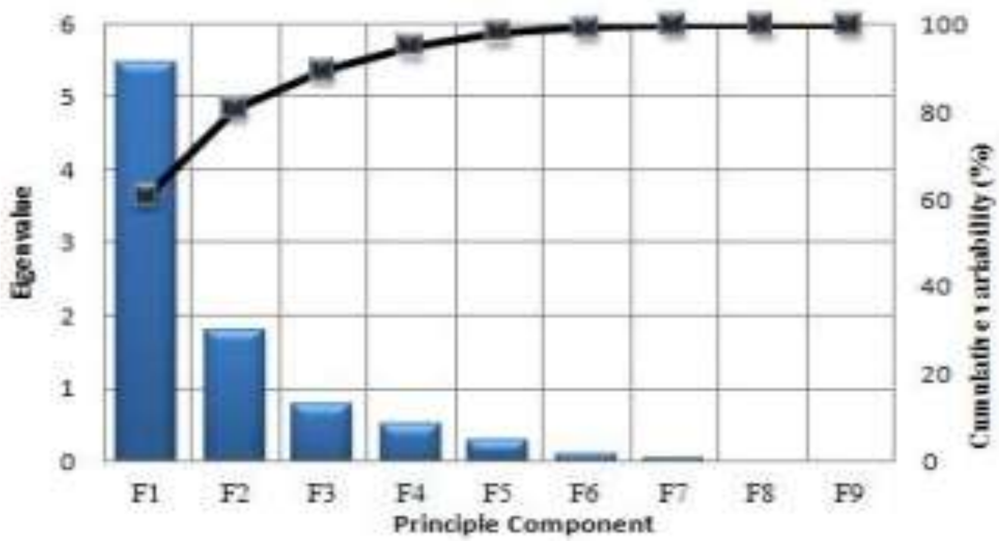

Fig.3.Mathematical object, the eigenvalues of principal Components

Various transfer functions and algorithms are verified for training and testing the network.Average minimum Mean Square Error (MSE) and classification accuracy on training and Cross validation (CV) data is compared; it is found that that Momentum learning algorithm with Tanh transfer function gives minimum MSE and better classification accuracy. Number of processing elements in hidden layers which are mainly responsible for complexity of network, must be selected carefully by observing the minimum MSE. Fig.4 shows the variation of MSE and number of processing elements in hidden layer. From the performance 10 processing elements are selected. Nine principal components are used as inputs and four class of outputs hence nine and four processing elements are used in input and output layer respectively.

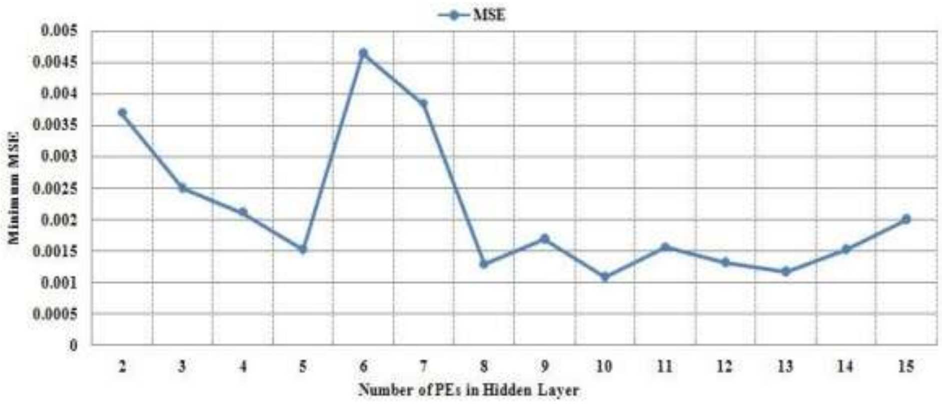

Fig.4. Variation of average minimum MSE with number of processing elements in the hidden layer

The parameters of the hidden layer and output layer i.e. stepsize and momentum are selected by comparing average minimum MSE. In Hidden layer optimum value of Step size is 0.8 and momentum is 1.0 and for output layer Step size is 0.3 and momentum is 0.5. Performance is shown in Fig. 5 and Fig.6.

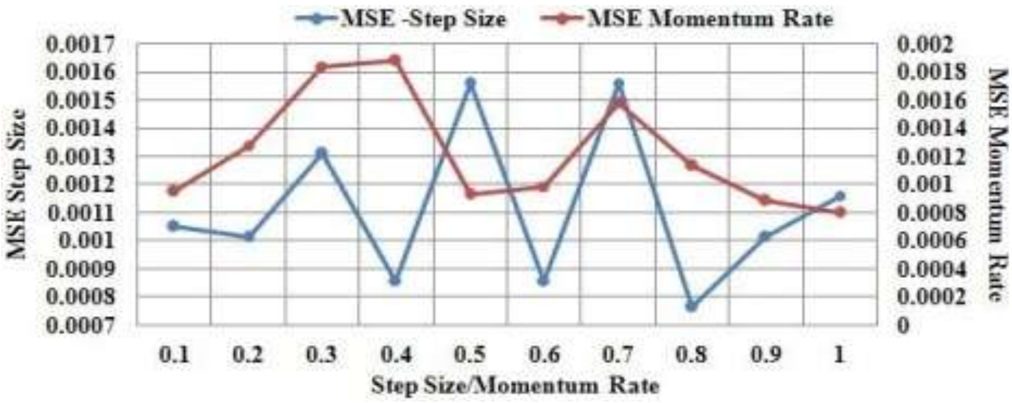

Fig.5. Variation of average MSE on with various parameters in hidden layer

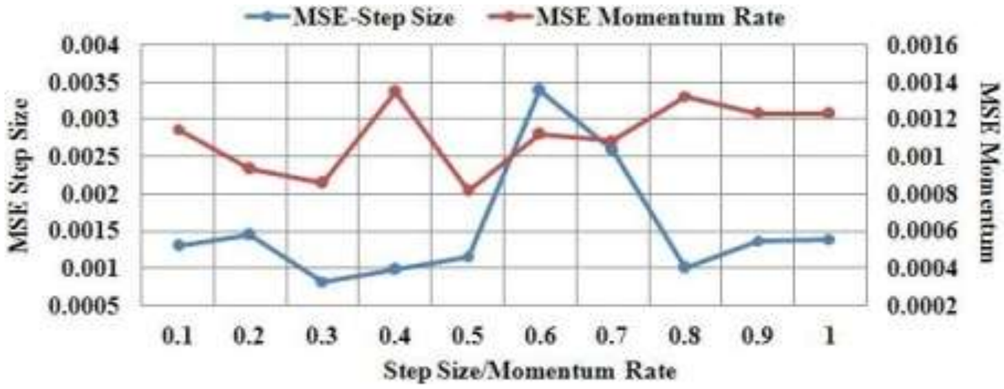

Fig.6. Variation of average MSE on with various parameters in output layer

Different datasets are formed using variable split ratios and leave-N-out cross validation technique. Proposed NN is trained on various datasets and later validated carefully so as to ensure that its performance does not depend on specific data partitioning scheme. The performance of the NN should be consistently optimal over all the datasets with respect to MSE and classification accuracy. Finally designed MLP is trained five times with different random weight initialization and tested on Testing dataset, CV dataset and Training dataset. Leave-N-Out training is a technique that allows one to evaluate how well the model generalizes. It also is very useful for small data sets, since it allows one to use the entire data set for training and testing. The algorithm trains the network multiple times, each time omitting a different subset of the data and using that subset for testing. The outputs from each tested subset are combined into one testing report and the model is trained one additional time using all of the data. The set of weights saved from the final training run can then be used for additional testing. Fig.7 and Fig.8 shows the results of Leave-N-Out method.

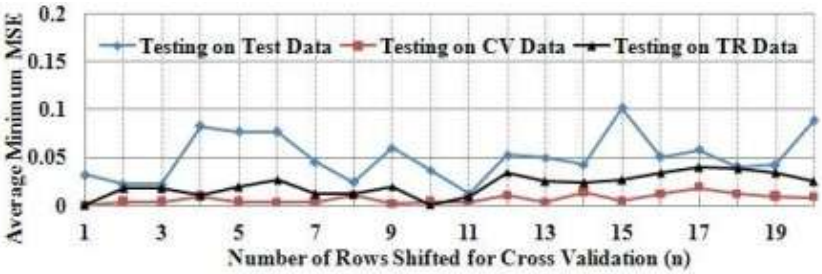

Fig.7. Variation of average MSE with Test on Testing, CV and Training dataset with CV rows shifted (n)

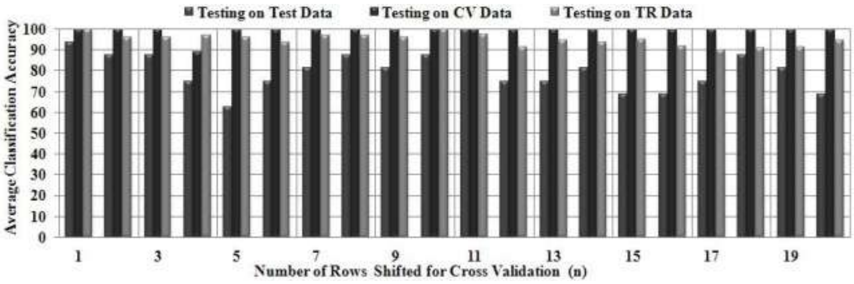

Fig.8. Variation of average classification accuracy with Test on Testing, CV and Training dataset with CV rows shifted (n)

IV. Results And Discussion

In this paper, the authors evaluated the performance of discriminant Analysis and the developed ANN based classifiers for detection of four classes of breast tissue based on electrical impedance and examined the results. With step backward model of DA the classification accuracy is found 93.75%. MLP is optimally designed and after completion of the training, the learned network is tested to detect different classes. For MLP NN various learning rules and transfer functions are investigated for different number of hidden layers and processing elements in hidden layer. It is observed that Momentum learning rule and Tanh transfer function gives the optimal results in hidden and output layer. From the analysis, it is seen that optimally designed MLP based classifier works as an elegant classifier, in the sense that, average MSE on testing and cross validation samples is consistently observed as reasonably low such as 0.0508 and 0.0069, respectively. In addition, average classification accuracy on testing as well as cross validation instances is obtained as 99.44% and 94.97%, respectively indicating a reasonable classification. This might suggest that some of the features selected randomly contain too much fault unrelated information and there is a high degree of overlap between the values of these features of these four classes. These features would confuse the classifier and therefore, might cause significant performance degradation. These confirm our idea that the proposed feature selection method based on the PCA can select the most superior features from the original feature set, and therefore, is a powerful feature selection method. Network results are shown Table IV. (Where NMSE: Normalized MSE, MAE: Mean Absolute Error)

Table IV: Performance of The Network

Performance	Testing on Test Data				Testing on CV Data			
	Max. Observed	Min. Observed	Average	SD	Max. Observed	Min. Observed	Average	SD
MSE	0.10161575	0.01159127	0.050803659	0.023732	0.01861840	0.000437223	0.0069624	0.0046302
Percent Correctness	100	88.8888888	99.44444444	2.421610	100	89.6875	94.976562	2.8043610
NMSE	0.097536	0.003018	0.041534	0.02704	0.24143	0.003327	0.119552	0.068581
MAE	0.082525	0.009099	0.047522	0.016548	0.106395	0.013149	0.064557	0.026091
Correlation Coefficient	0.999359	0.952749	0.981614	0.013521	0.999048	0.876447	0.938906	0.035849

References

[1] Jemal, A., Murray, T., Ward, E., Tiwari, R.C., Ghafoor, A., Feuer, E.J., Thun, M.J.: Cancer Statistics, 2005. CA: A Cancer Journal for Clinicians 55 (2005) 10–30

[2] M. Cheney, D. Isaacson, and J. C. Newell, “Electrical impedance tomography,” SIAM Review, 41(1): 85–101, 1999.

[3] S Kimura, T Morimoto, T Uyama, Y Monden, Y Kinouchi and T Iritani, “Application of electrical impedance analysis for diagnosis of a pulmonary mass”, Chest Journal, 105: 16791682, 1995

[4] Y. Kinouchi, T. Iritani, T. Morimoto et al, “Fast in vivo measurement of local tissue impedance using needle electrode”, Medical and Biological Engineering and Computing, 35: 486-492, 1997

[5] Xueli Zhao, Y. Kinouchi, E. Yasuno, "A new method for noninvasive measurement of multilayer tissue conductivity and structure using divided electrode", IEEE Transaction on Biomedical Engineering, 51(2): 362-370, 2004
[6] H. Kato, E. Yasuno, Y. Kinouchi, "Electrical impedance tomography for local bological tissue", Proceeding of 8th International Conference on Control Robotics, Automation and Vision, 942946, 2004
[7] Malich A, Fritsch T, Anderson R, Boehm T, Freesmeyer MG, Fleck M, Kaiser WA: Electrical impedance scanning for classifying suspicious lesions: first results. *EurRadiol* 2000, 10:1555-1561.
[8] T. Tang, S. U. Zhang, R. J. Sadleir, "A portable 8-electrode EIT measurement system", IFMBE Proceeding, 3980-3983, 2007
[9] W. Yan, S. Hong, Z. Shu, R. Chaoshi, "Influences of compound electrode parameter on measurement sensitivity and reconstruction quality in electrical impedance tomography", Proceedings of International Federation for Medical and Biological Engineering, 6, 2007
[10] A.V. Korjenevsky, "Electrical impedance tomography: research, medical applications and commercialization", Troitsk Conference on Medical, Physics and Innovations in Medicine", 2006
[11] B. Blad, P. Wendel, M. Jonsson, and K. Lindstrom, "An electrical impedance index to distinguish normal and cancerous tissues," *J. Med. Eng. Technol.*, vol. 2, no. 23, pp. 57–62, 1999.
[12] Jossinet J, Schmitt M: A review of parameters for thebioelectrical characterization of breast tissue.*Ann NY AcadSci* 1999, 873:30-41
[13] Piperno G, Frei EH, Moshitzky M: Breast cancer screening by impedance measurements. *Frontiers Med BiolEng* 1990, 2:111-117
[14] S. Ollmar, I. Nicander, J. Ollmar, and L. Emtestam, Information in full and reduced data sets of electrical impedance spectra from various skin conditions using a holographic neural network, Med. Biol. Eng. Comput., vol. 35, pp. 415419, 1997.
[15] Martin G, Martin R, Brieva MJ, Santamaria L: Electrical impedance scanning in breast cancer imaging: correlation with mammographic and histologic diagnosis.*EurRadiol* 2002, 12:1471-1478.
[16] Laurence Fauseet, "Fundamentals of Neural Network, 2nd Edition" Prentice Hall. 1998.
[17] Frank, A. & Asuncion, A. (2010). UCI Machine Learning Repository [http://archive.ics.uci.edu/ml]. Irvine, CA: University of California, School of Information and Computer Science

Dr.V.N.Ghate received the B.E. degree in electrical Engineering from Sant Gadge Baba Amravati University, Amravati, India, in 1990, the M.E. degree in Control Systems from Shivaji University, Kolhapur, India, in 1993, and the Ph.D. degree from Sant Gadge Baba Amravati University in 2010. From 1994 to 2001, he was with the Department of Electrical Engineering, Government Polytechnic, Technical Education Government of Maharashtra. Since 2002, he has been with Department of Electrical Engineering, Government College of Engineering, Technical Education Government of Maharashtra. His areas of interest include neural network, and Electrical Machines and Drives Dr. Ghate is Fellow of Institution of Electronics and Telecommunication Engineers (India), Institution of Engineers (India) and member of Instrument Society of India, IEEE and the Indian Society for Technical Education (India).

P.C. Shetiye received the B.E. degree in Computer Science and Engineering from Sant Gadge Baba Amravati University, Amravati, India, in 1990, M.B.A. degree from Nagpur University, Nagpur, India, 1997, M.E. degree in Computer Science and Engineering from Sant Gadge Baba Amravati University, Amravati, India, in 2001, pursing Ph.D. degree from Sant Gadge Baba Amravati University. From 1993 to 1995, he was with department of Computer Science and Engineering, Government College of Engineering, Amravati, from 1996 to 2001, he was with the Department of Computer Science and Engineering, Government Polytechnic, Amravati, later on worked with MSBTE, Technical Education Government of Maharashtra. Since 2002, he has been with Department of Computer Science and Engineering [MCA], Government College of Engineering, Karad, Technical Education Government of Maharashtra. His areas of interest include AI, neural network, and System software.

Dr. A.A. Ghatol born on 29th August, 1948 is presently Vice-Chancellor of Dr. Babasaheb Ambedkar Technological University, Lonere-Raigad. Before joining as Vice-Chancellor, he was Principal/Director at College of Engineering, Pune during 2001-2005 and Principal at Government College of Engineering, Amaravati during 1994-2001. He holds a B.E. (Electrical), Nagpur University, M.Tech. (Electrical) and Ph.D Electrical from IIT, Mumbai in the field of High Power Semiconductor Devices. Over the last 33 years, he has been actively involved in the field of Technical Education as Academician, Researcher, Teacher, Planner and Administrator and handled various aspects of Technical Education including Management, Engineering, Technology etc. Best Teacher Award, of Govt. of Maharashtra was bestowed upon him during the academic year 1998 – 99. He has also received Quality Environment Award in the year 2002. He has to his credit 12 Ph.D. Students, 3 books and number of research scholars working under him for Ph.D. degree. Under his able and effective leadership, the University reached to a newer height and gained a feather in the cap by receiving the UGC recognition under section 12(B). Taking into consideration his active involvement in technical education, AICTE also entrusted a responsibility to Act as Chairman of Western Regional Council for three states for advising and assisting the council on issues and strategies on quality and quantity in the technical education. He is also the Executive Member of Indian Society of Technical Education.