Performance assessment of Optimized Extreme Learning Machine based on Evolutionary Computing for Spirometric Data Classification

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Abstract: - Spirometry is the frequently performed clinical pulmonary function test to assess the respiratory dynamics. It measures changes in lung volumes and airflows during the forced expiratory maneuver. These investigations are widely used in the diagnosis and management of lung diseases like asthma and chronic obstructive pulmonary disease. However the test requires considerable patient effort and cooperation and is also sometimes prone to misclassification due to interdependency of data. In this work an attempt has been made to differentiate pulmonary obstructive abnormality using neural computing and spirometric data. A fast Extreme Learning Machine (ELM) and evolutionary algorithm based optimized ELM networks are employed for classification and their performance is analyzed. The performance of Extreme Learning Machine (ELM), achieved a generalization accuracy of 91.03% in 0.0019secs. The evolutionary based optimization technique achieved a classification accuracy of 100% yielding a sensitivity and specificity of 100% with a much compact and less complex network. Hence the results indicate that an optimized ELM network is superior in performance but takes longer processing time due to the iterations performed in the optimization of the network weights. Hence it is concluded that the EELM based computerized model is useful in enhancing diagnostic relevance of spirometric investigations and could provide assistance to clinicians in characterizing pulmonary abnormalities.

Key-Words: - Pulmonary Function Test, Spirometer, COPD, FEV_1, Extreme Learning Machine, Evolutionary extreme learning machine, Obstructive lung disease

1 Introduction

Respiratory system is a complex mechanics and one of the most essential elements in maintaining vital functions of the human body. Impairment of respiratory function is a significant factor that may affect quality of life and can lead to increased risks of premature morbidity and mortality [1, 2]. A survey report by the Global Strategy for the Prevention and Control of Non-communicable Diseases (2010) reveals that of the 57 million deaths that occurred globally in 2008, 36 million – almost two thirds – were due to Non Communicable Disease (NCDs), comprising mainly cardiovascular diseases, cancers, diabetes and chronic lung diseases [3]. A regular, healthy functioning lung depends on many mechanical and physiological factors. There are pathologies which disturb the symmetry of this complex mechanics from its natural organisation. Restrictive and obstructive lung diseases are the two broad categories of lung diseases. Failure to inhale completely results in a reduced Total Lung Capacity (TLC) and the defect is restrictive condition. Failure to exhale completely, or when the flow is so slow that the subject cannot exhale long enough to empty the lungs is categorized as obstructive lung disease[4].

Chronic obstructive pulmonary disease (COPD) is a respiratory syndrome associated with a progressive, non-reversible limitation to airflow and abnormal inflammatory responses involving the smaller airways [5,6,7]. Over 80% of cardiovascular and diabetes deaths, and almost 90% of deaths from chronic obstructive pulmonary disease, occur in low- and middle-income countries presenting a huge health and economic burden [3]. The role of co-morbidities in patients with chronic obstructive pulmonary disease has gained more attention in the recent times. The incidence and mortality due to cardiovascular diseases such as cerebral stroke, myocardial infarction, heart failure, and arrhythmias are higher among COPD patients than in the general population[8]. COPD is identified as an independent risk factor for the development of post operative pulmonary complications after thoracic or non-thoracic surgery[9,10].

Spirometry is the recommended Pulmonary Function Test (PFT) for assessment of lung function in patients with suspected chronic obstructive pulmonary disease. It generates the dynamic flow rates dependant on lung volumes during forced breathing maneuver. The interrelationships of flow and volume obtained during various time intervals from spirometer are displayed as graphical loop patterns called spirogram [11]. Four different types of ventilation patterns identified are normal, obstructive, restrictive and a combined restrictive/ obstructive [12, 13, 14]. Forced Vital Capacity (FVC), Forced Expiratory Volume in one second (FEV_1), the ratio of FVC to FEV_1, FEF_{25-75}% are some important measurements acquired using spirometer.

FEV_1 is a vital parameter and most frequently used index for assessing airway obstruction and broncho-constriction[15,16]. FVC is the total volume of air that is exhaled forcibly from full inspiration. The distinction between an obstructive and restrictive ventilatory pattern depends on the absolute FEV_1/FVC ratio. If the absolute FEV_1/FVC ratio is normal or increased, a restrictive impairment may be present. The effect of post bronchodilator in the ratio of forced expiratory volume in 1 second (FEV_1) to forced vital capacity (FVC) less than 0.7 indicates presence of COPD according to the GOLD criteria[17]

Several studies show the usefulness of spirometry to detect subjects at high risk for developing COPD [18,19,20]. Spirometry requires considerable patient effort and cooperation and sometimes can lead to misdiagnosis and inappropriate treatment. International studies have examined the prevalence of COPD misdiagnosis due to lack of Spirometry [21]. A combination of monitoring systems on the use of spirometry in COPD, more education on the importance of spirometry in COPD management, and assistance in interpretation of spirometry results may bring about improvements in the early diagnosis and staging of disease [22, 23]. With the growing impact of computerised modelling in medicine, a good quality control could be achieved by integrating lung function in computerized registers.

Artificial Intelligence technique are useful statistical modelling technique to examine the underlying functional relationships within a dataset and to perform several tasks like pattern recognition, classification, modelling, and prediction. Neural networks are extensively employed in biomedical research due to their flexibility and high degree of accuracy in fitting to experimental data [24]. It has been reported that ANN techniques based classifier were employed in the classification of spirometric data [25,26,27] achieving fine accuracy and thereby aiding as a support system in disease diagnosis to clinicians. However traditional gradient-descent-based algorithms posses some problems like local minima, improper learning rates, slow convergence, and over-fitting [28].

Extreme Learning Machine (ELM) [28] a fast and efficient learning algorithm proposed for Single Layer Feed Forward (SFLN) presents a good and comparable generalization performance. Here, the weights and biases randomly initialized for hidden nodes contributes to the increased speed of learning model. But there may exist an non optimal solution as the output weights are computed based on these prefixed input weights and biases using Moore-Penrose(MP) generalized inverse. But ELM networks tend to require more number of hidden neurons than conventional gradient-based approaches in which the network is tuned iteratively [29].

Evolutionary strategies [30] are widely used as global searching method for optimization of network parameters. A hybrid approach of modified Differential evolutionary algorithm and ELM called Evolutionary Extreme Learning Machine (EELM) is used to search for the optimal connection weights and hidden biases. The MP generalized inverse is used to analytically calculate the output weights.

The objective of this work is to classify obstructive subjects using artificial neural networks that are coordinated to the intelligence and behaviour of human brain. Spirometric pulmonary data are input to these computerised data modelling systems and the performance of these networks in classifying the normal and abnormal subjects are analyzed.

2 Materials and Methods

2.1 Data Acquisition

In this work, a total of 70 subjects were considered and data was acquired using InspireX Spirometer. The age, height and weight of each subject were recorded prior to the test. The tests are performed in a sitting position. The subjects were advised to inhale to their full lung capacity, then exhale forcibly and completely and the data was recorded. Spirometry with flow volume loops were obtained and each participant completed up to three iterations to measure the FEV_1 and FVC volumes according to the American Thoracic Society (ATS) standards [7].

The input data derived from the flow-volume loop are normalized between 0 and 1. The behaviour and performance of the ELM and the EELM learning algorithms with changes in initial parameters are analyzed.

2.2 Extreme Learning Machine

In machine learning, classification is the problem of identifying which of a set of classes a new observation belongs to, on the basis of a number of observed attributes related to that object. Extreme Learning Machine (ELM) a Single hidden Layer Feed forward Neural network (SLFN) has the advantages of very fast learning speed than the traditional gradient-based learning algorithm and higher accuracy [28,31,32]. It is shown that Single Layer Feed forward (SFLN) network with randomly chosen input weights and hidden bias can approximate any continuous function to any desirable accuracy [33]. The performance of SFLN is evaluated for two activation function – Sigmoid and Gaussian. The choice of activation functions were from the literature Mahesh *et al.* [5], Guillermo M Albaiceta *et al.* [34] in which the authors have established in their work that a Radial Basis Function Neural Networks (RBFNN) model can classify an obstructive abnormality from the normal subjects and sigmoid models showed a goodness of fit of $R^2 > 0.92$

A multi-category classification problem can be stated as [26]. Suppose we have N observation samples $\{X_i, Y_i\}$, where

$$Xi = [X_{i1}, X_{i2}, X_{i3}, \dots \dots \dots X_{in}] \in R^n \quad (1)$$

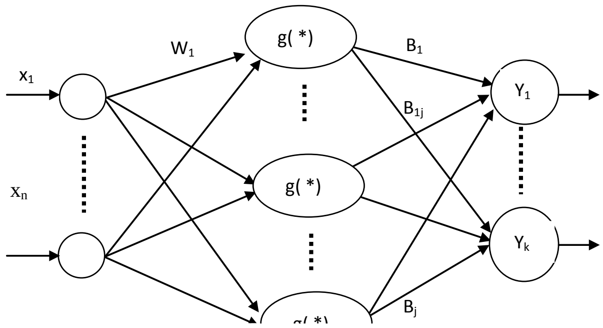

Fig.1 Single layer feed forward network

is an n-dimensional feature of the input sample Xi and

$$Y_i = [Y_{i1}, Y_{i2}, Y_{i3} \dots \dots \dots Y_{ic}] \in R^c \quad (2)$$

is its coded class label. If the sample X_i is assigned to the class label C_k then k^{th} element of Y_i is one i.e. (Y_{ik}=1) and other elements are -1. Here, it is assumed that the samples belong to C distinct classes. The initial input weights and hidden biases of ELM are randomly chosen, and the output weights are analytically determined by using Moore-Penrose (MP) generalized inverse.

The steps involved in the ELM algorithm are as follows:

i) For a given training samples (X_i,Y_i), the appropriate activation function G (*) is selected and the number of hidden neurons H.

ii) For a given number of hidden neurons, it is assumed that the input weights W and bias B of hidden neurons are selected randomly. Let W be H × n input weights, B be H ×1 bias of hidden neurons and V be C × H output weights. The output of the ELM network for H hidden neurons is as follows

$$\widehat{Y} = \sum_{j=1}^{H} V_{kj}\, G_j\,(W_i, B, X_i) \quad k = 1,2 \dots C \quad (3)$$

where $G_j(.)$ is the output of j^{th} hidden neuron and G(*) is the activation function. The sigmoid activation function can be described as

$$g(x) = \frac{1}{(1 + e^{-x})} \quad (4)$$

For a radbas hidden node, the activation function is a Gaussian function, with each node having its own center and impact factor. The output of the function is given by a radially symmetric function of the distance between the input and the center. It is given as

$$g(b_i \|x - c_i\|) = \exp\left[-\beta \|x - c_i\|^2\right] \quad (5)$$

where c_i is the node center and b_i its impact factor.

The above equation in matrix form is written as

$$\widehat{Y} = VY_H^{\dagger} \quad (6)$$

Assuming that the predicated output $\widehat{Y}$ is equal to the coded labels Y, the output weights are estimated analytically as

$$V = YY_H^{\dagger} \quad (7)$$

where $Y_H^{\dagger}$ is the Moore-Penrose generalized pseudo-inverse of Y_H [35]

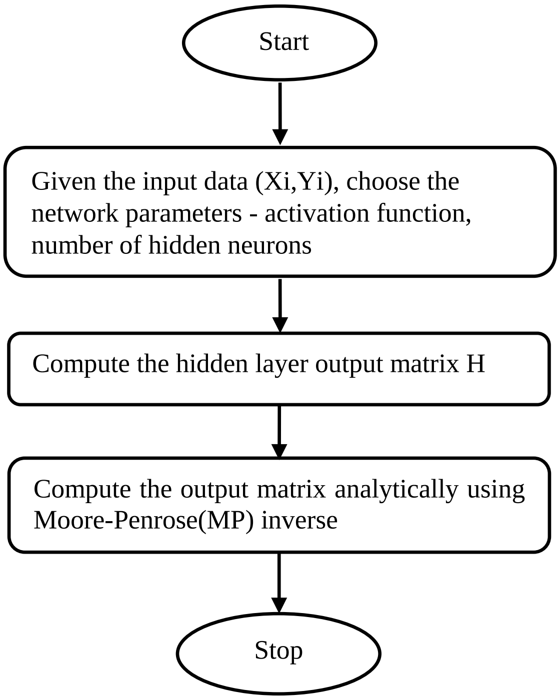

Fig.2 Flowchart of ELM algorithm

Although ELM is fast and presents good generalization performance, as the output weights are computed based on the prefixed input weights and hidden biases, there may exist a set of non-optimal input weights and hidden biases [23]. Hence finding the optimal parameters for the ELM classifier is a complex issue. Neural networks should also evolve the best architecture and therefore, it claims that the performance of a SLFNs can be improved if the input weights and biases of hidden units are optimized.

2.3 Evolutionary Extreme Learning Machine

Genetic algorithms (GA) [36, 37] are amongst the most widely used artificial intelligent techniques for optimization. A GA is a stochastic searching algorithm based on the mechanisms of natural selection and genetics. The two key parameters are the number of generations N_G and the population size N_P. GA is mainly composed of three operations: selection, genetic operation and replacement.

To optimize the ELM network, a hybrid approach called Evolutionary Extreme Learning Machine (EELM) [38] is employed. It utilizes the advantages of both ELM and Differential Evolutionary (DE) algorithm [39]. The input weights and biases are determined by using the DE process and the output weights are analytically determined by using Moore-Penrose (MP) generalized inverse. The algorithm is as follows:

i) Generate the initial generation composed of parameter vectors { $x_{i,G}$ | i=1, 2 ,…, NP } as the population. Each individual in the population is composed of a set of input weights and hidden biases [31]

$$x = [W_{11}, W_{12}, \dots W_{1k}, ., W_{n1}, W_{n2}, \dots, W_{nk}, b_1, b_2, \dots, b_k] \quad (8)$$

ii) At each generation G, we do:

a) Mutation: the mutant vector is generated by

$$v_{j,i,G+1} = x_{r1,G} + F\left(x_{r2,G} - x_{r3,G}\right) \quad (9)$$

where r1, r2, and r3 are different random indices, and F is a constant factor used to control the amplification of the differential variation and takes a value between 0 and 2.

b) Crossover: The trial vector $u_{i,G+1}$ is developed from the elements of the target vector, $x_{i,G}$ and the elements of the donor vector, $v_{j,i,G+1}$

$$u_{j,i,G+1} = \begin{cases} v_{j,i,G+1} & \text{if } rand_{j,i} \leq CR \text{ or } j = I_{rand} \\ x_{j,i,G} & \text{if } rand_{j,i} > CR \text{ or } j \neq I_{rand} \end{cases} \quad (10)$$

where $rand_{j,i}$ is the j-th evaluation of a uniform random number generator, CR is the crossover constant.

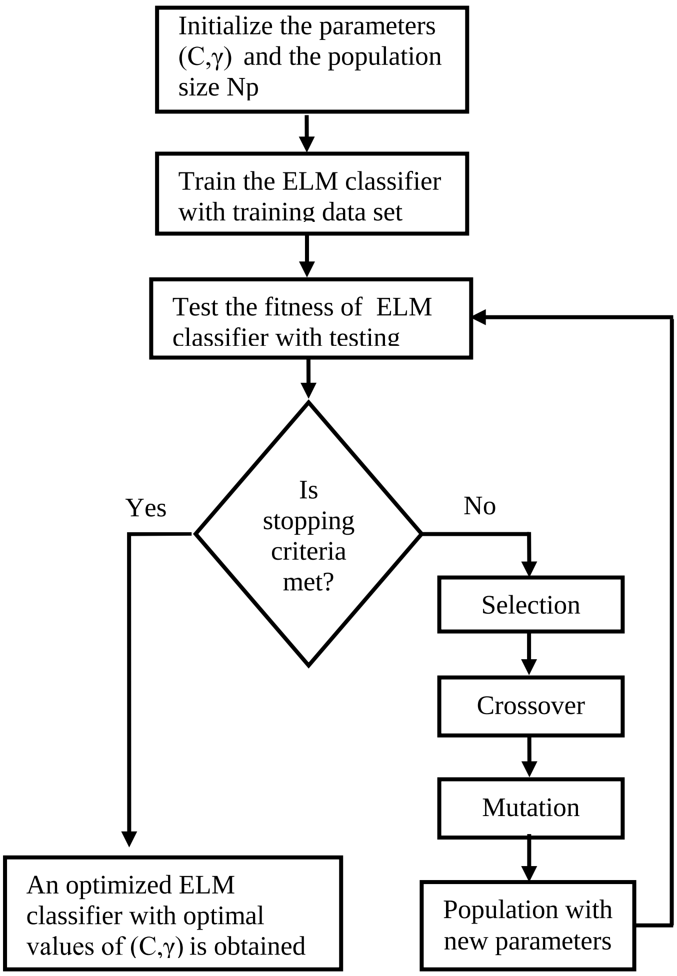

Fig.2 Flowchart of EELM Algorithm

c) Calculate the output weight using (3)

d) Selection: Determination of a new population, $x_{i,G}$ using (9). The norm of the output weight ||A|| is also used as criteria to reinforce the selection

$$x_{i,G+1} = \begin{cases} u_{i,G} & if\ f(x_{i,G}) - f(u_{i,G+1}) > \in f(x_{i,G}) \\ u_{i,G} & if\ f(x_{i,G}) - f(u_{i,G+1}) > \in f(x_{i,G}) \\ & and\ \|A^{u_{i,G}}\| < \|A^{x_{i,G}}\| \\ x_{i,G} & otherwise \end{cases} \quad (11)$$

iii) Iteration of the above process is done once the new population is generated, until the goal is met or a preset maximum number of learning iterations is reached.

The performance of the classifiers are validated with evaluation indices [40] such as accuracy, sensitivity and specificity. The event that classifies a normal data as obstructive one is termed as False Positive (FP) and the event that classifies a obstructive data as normal is termed as False Negative(FN).Events that classify obstructive subjects as obstructive and normal subjects as normal itself are True Positive (TP) and True Negative (TN). Accuracy measures the performance of the classifier in global sense. Sensitivity is the proportion of actual obstructive subjects classified as obstructive and specificity is the proportion of actual normal subjects that are correctly classified as normal. The values of these indices were calculated using the following relation

$$\text{Accuracy} = \frac{TP + TN}{(TP + FP + TN + FN)} \quad (10)$$

$$\text{Sensitivity} = \frac{TP}{(TP + FN)} \quad (11)$$

$$\text{Specificity} = \frac{TN}{(TN + FP)} \quad (12)$$

3 Results and Discussion

Statistical analysis mean and standard deviation of the input parameters are shown in Table1.The analysis values show a significant variation between the normal and abnormal subjects. The statistical analysis of the input demographic parameter is tabulated in table 2. Fig.3 shows the variation in mean for normal and obstructive subjects. It is evident from the figure that the values of significant parameters FEV_1, FVC and FEF $_{25\%-75\%}$ are comparatively lower for diseased obstructive subjects.

Table 1 Statistical analysis of input spirometric parameters

Parameter	Normal	Abnormal
	Mean± SD	Mean± SD
FVC	3.24± 0.57	2.19± 0.85
FEV_1	2.71 ± 0.51	1.25± 0.58
FEV_1/ FVC	84 0±.08	57 ± 0.2
FEF $_{25\%-75\%}$	1.61 ± 0.87	0.68± 0.92

Table 2 Statistical analysis of input demographic parameters

Parameter	Normal	Abnormal
	Mean± SD	Mean± SD
Age	46.96±13.62	45.42±6.95
Height	156±9.87	167.21±19.09
Weight	58.54±14.26	72.35±10.17

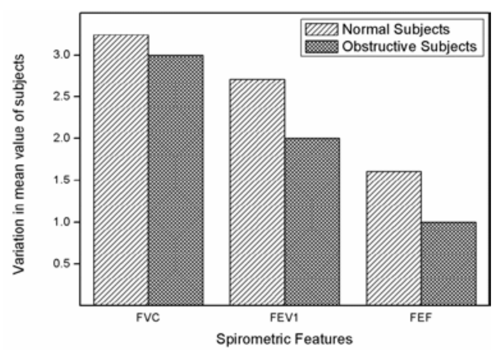

Fig.3 Variation in statistical analysis of mean for normal and obstructive subjects

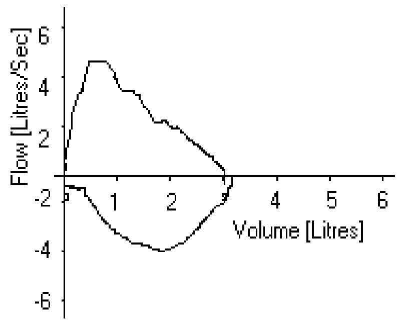

Fig.4 Typical Flow Volume in normal subjects

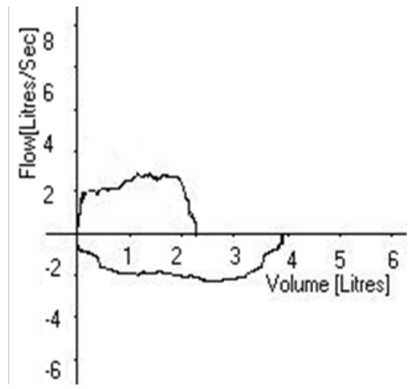

Fig.5 Typical Flow Volume in obstructive subjects

Fig.4 shows the flow volume curve of normal subjects which has a distinct follow through of the inspiratory and expiratory maneuvers. For obstructive subjects the flow volume loop has a concave pattern attributed due to narrow airways as shown in Fig.5

The behaviour of the ELM and EELM classifiers with respect to changes in hidden number of neurons is analyzed. For activation function chosen as radial basis, the variation in mean training accuracy and testing accuracy with varying number of hidden neurons of the ELM and EELM classifiers are plotted Fig.6 and Fig.7. From Fig.6 it is observed that the training efficiency increases with increase in the number of hidden neurons. Similarly mean training and testing accuracy for sigmoid activation function are plotted in Fig.8 and Fig. 9. It is evident from the percentage analysis accuracy graphs, the efficiency of the classifier increases with increase in number of hidden neurons. It is also inferred from Fig.7 and 9, the generalization efficiency of EELM classifier achieved a testing accuracy of 100% with 2 hidden neurons. For the ELM classifier with the identical initial parameters, the mean classification accuracy is 58%. It is also found that the ELM classifier with 10 neurons achieved a mean testing accuracy of 91.03 % . Hence it can be concluded that the generalization efficiency of EELM classifier with a much less complex and compact network is observed to be higher when compared to the ELM classifier.

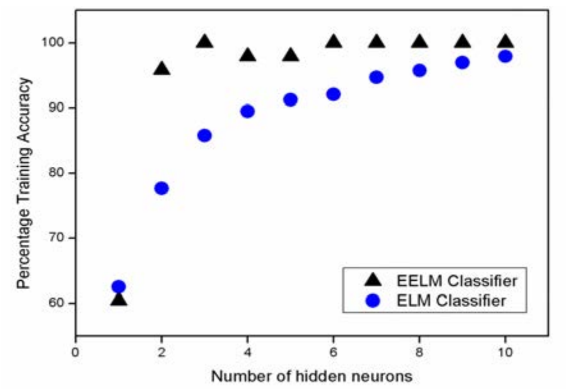

Fig.6 Variation in training accuracy for varying number of neurons with Radbas activation function

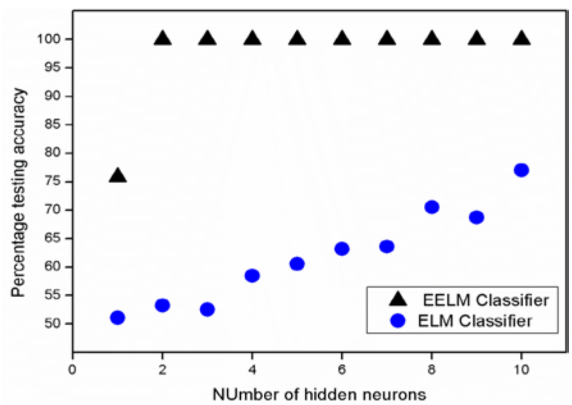

Fig.7 Variation in testing accuracy for varying number of neurons with Radbas activation function

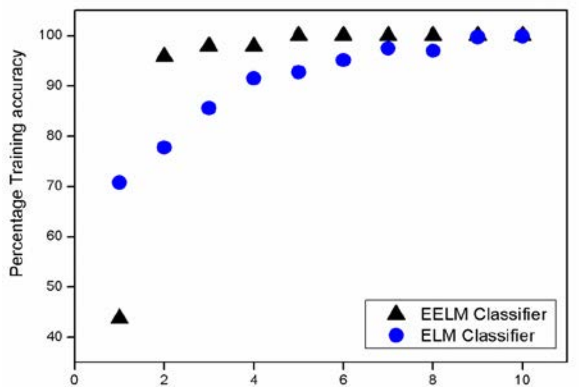

Fig.8 Variation in training accuracy for varying number of neurons with Sigmoid activation function

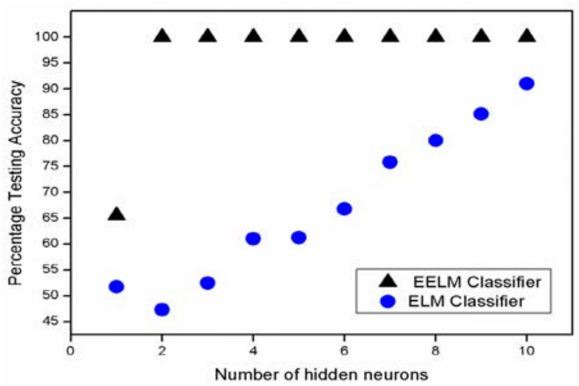

Fig.9 Variation in testing accuracy for varying number of neurons with sigmoid activation function

The performance of classifier evaluated in terms of sensitivity , selectivity on validation data set for two different activation functions namely radial basis and sigmoid is tabulated in Table 2 and 3. It is inferred from the table 2 for the sigmoid activation function, out of 15 normal subjects, the ELM classifier identified 11 of them correctly yielding a specificity of 73.3% and the sensitivity of 35.71% while for the EELM classifier it is 100%. Similarly the ELM network with radial basis activation function (table 3) achieved a sensitivity of 35% and specificity of

80%. The EELM classifier attained 100% . Hence it is concluded that optimizing the input weights, EELM network has higher sensitivity and specificity with a compact network.

A comparison of mean training time of the classifiers for the input spirometric features is tabulated in table 4. The observation reveals that the EELM algorithm takes a longer processing time than the ELM due to the iterations performed to obtain an optimized network.

Table 2. Performance indices for Sigmoid activation function

Parameter	ELM based classification	EELM based classification	Clinical observation
True positive	5	15	15
True negative	11	14	14
False Positive	4	-	-
False negative	9	-	-

Table 3. Performance indices for Radial basis Activation Function

Parameter	ELM based classification	EELM based classification	Clinical observation
True positive	5	15	15
True negative	12	14	14
False Positive	3	-	-
False negative	9	-	-

Table 4. Comparison of Mean training time of the classifiers for Radial basis and Sigmoid activation function

Hidden Neurons	Radial basis activation function(secs)		Sigmoid activation function(secs)	
	EELM	**ELM**	**EELM**	**ELM**
1	1.123	0.0012	1.232	0.0012
2	1.107	0.0012	1.123	0.0006
3	1.234	0.0031	1.170	0.0006
4	1.294	0.0013	1.342	0.0006
5	1.216	0.0018	1.498	0.0006
6	1.435	0.0018	1.435	0.0006
7	1.372	0.0012	1.51	0.0031
8	1.450	0.0018	1.576	0.0031
9	1.606	0.0018	1.747	0.0019
10	1.638	0.0025	1.950	0.0019

4 Conclusion

Spirometry remains the central and fundamental pulmonary function test in the diagnosis and prognosis of respiratory disorders. The investigation depends on ability of investigated subject to complete the test and on the skills and approaches of the investigator. Symptom based clinical diagnosis may sometimes contributes to misdiagnosis and mistreatment. Hence integration of computerized intelligence would result in a better quality controlled diagnosis. In this work an attempt had been made to classify the pulmonary obstructive disease between the normal and abnormal subjects using a fast ELM network and an evolutionary based optimized ELM network. The results show that the EELM network achieved a high accuracy in the classification when compared to ELM network. The performance of ELM, a fast learning classifier achieved a generalization of 97.93% accuracy in 0.0025 seconds. The result shows a higher accuracy value when compared with the previously reported works [25, 26, 27]. On the other hand, the genetic algorithm based global search optimization network called Evolutionary Extreme Learning Machine is observed to achieve a generalization of 100% with a much reduced network size. This classifier can also be extended to incomplete data prediction and automatic classification thereby supporting the clinicians in accurate diagnosis and treatment of pulmonary disorders.

References:

[1] A. G. Polak, D. Wysoczański, J. Mroczka, A multi-method approach to measurement of respiratory system mechanics, *Metrology and Measurement System*, Vol. XIII, No. 1, 2006, pp. 3-17.

[2] Y. Shibata, T. Watanabe, D. Osaka, S. Abe, S. Inoue, Y. Tokairin, A. Igarashi, K. Yamauchi, T. Kimura, H.Kishi, Y. Aida, K. Nunomiya, T. Nemoto, M. Sato, T. Konta, S. Kawata, T. Kato, T. Kayama, I. Kubota, Impairment of Pulmonary Function is an Independent Risk Factor for Atrial Fibrillation: The Takahata Study, *International Journal of Medical Sciences*,Vol.8, No.7, 2011, pp.514-522.

[3] Global Status report on Noncommunicable Disease, Available: *http://www.who.int/nmh/publications/ncd_report_full_en.pdf*

[4] D. Stanescu, Obstructive ventilatory defect with normal forced expiratory volume in one second/vital capacity ratio, *European Respiratory Journal*, Vol. 27, 2006, pp. 1069–1075.

[5] Mahesh Veezhinathan, Swaminathan Ramakrishnan, Detection of Obstructive Respiratory Abnormality Using Flow–Volume Spirometry and Radial Basis Function Neural Networks, *Journal Of Medical Systems*,Vol. 31, 2007, pp. 461–465.

[6] Luigi G. Franciosia et al., Markers of disease severity in chronic obstructive pulmonary disease, Pharmacology and Therapeutics, Vol. 19, No.3, 2006, pp.189–199.

[7] American Thoracic Society/European Respiratory Society: Definition, Diagnosis and Staging of COPD. Available: *http://www.thoracic.org/COPD/1/definitions.asp*

[8] Arne Didrik Høiseth, Torbjørn Omland, Bo Daniel Karlsson, Pål HBrekke, Vidar Søyseth, Standardized evaluation of lung congestion during COPD exacerbation better identifies patients at risk of dying, *International Journal of Chronic Obstructive Pulmonary Disease*,Vol.8, 2013,pp.621-629.

[9] P. Agostini, H. Cieslik, S. Rathinam, E. Bishay, M. S. Kalkat, P. B. Rajesh, R. S. Steyn, S. Singh, B. Naidu, Postoperative pulmonary complications following thoracic surgery: are there any modifiable risk factors?,*Thorax*, Vol. 65, 2010, pp.815-818.

[10] S.R. Bapoje, J.F. Whitaker, T. Schulz, E.S Chu, R.K. Albert, Preoperative Evaluation of the Patient with Pulmonary Disease, *Chest*, Vol. 132, 2007, pp.1637-1645.

[11] R.Thomas, Gildea, Kevin McCarthy, Pulmonary Function Testing, Available at: *http://www.clevelandclinicmeded.com/medicalpubs/diseasemanagement/pulmonary/pulmonary-function-testing.*

[12] R.Pierce, Spirometer: An essential clinical measurement, *Australian Family Physician*,Vol. 34, 2005, pp. 535 – 539.

[13] M. Oud, E.J.W. Maarsingh, Spirometer and forced oscillatory assisted optimal frequency band determination for the computerized analysis of tracheal lung sounds in asthma. *Physiological Measurement*, Vol. 25, 2004, pp. 595 – 606.

[14] B.G. Cooper, F. Madsen, European respiratory buyers guide,Vol. 3, 2000, pp. 40 – 43.

[15] R. Pellegrino, G. Viegi, V. Brusasco, R. Crapo, F. Burgos, R. Casaburi, Interpretative strategies for lung function tests, *European Respiratory Journal*, Vol.26, 2005, pp.948–68.

[16] M.R. Miller, J. Hankinson J, V. Brusasco, F. Burgos, R. Casaburi, A. Coates et al., Standardisation of spirometry, *European Respiratory Journal*, Vol.26, 2005, pp. 319–38.

[17] Global strategy for the diagnosis, management, and prevention of chronic obstructive pulmonary disease. Available at: *http://www.goldcopd.org/uploads/users/files/GOLDReport_April112011.pdf*

[18] Jan Vandevoorde, Sylvia Verbanck, Lieve Gijssels, Daniel Schuerman, Dirk Devroey, Joan De Backer, Jan Kartounian, Walter Vincken, Early detection of COPD: A case finding study in general practice, *Respiratory Medicine*, Volume 101, Issue 3 ,2007, pp. 525-530.

[19] R. L. Mulder et al.,Pulmonary function impairment measured by pulmonary function tests in long-term survivors of childhood cancer, *Thorax*, Vol. 66, 2011, pp. 1065-1071.

[20] Vinaya S Karkhanis, J.M. Joshi, Spirometry in Chronic Obstructive Lung Disease(COPD), *Supplement to JAPI*, Vol. 60, No.23, February 2012.

[21] Thomas A Barnes, Len Fromer, Spirometry use: detection of chronic obstructive pulmonary disease in the primary care setting, *Clinical interventions in Aging*, Vol.6, 2011,pp. 47-52.

[22] Christian Ghattas, Allen Dai, David J Gemmel, Magdi HAwad, Over diagnosis of chronic obstructive pulmonary disease in an underserved patient population, *International Journal of Chronic Obstructive Pulmonary Disease*, Vol.8, 2013, pp. 545-549.

[23] Wai Cho Yu, Sau Nga Fu, Emily Lai-bun Tai, Yiu Cheong Yeung, Kwok Chu Kwong, Yui , Chang , Cheuk Ming Tam, Yuk Kwan Yiu, Spirometry is underused in the diagnosis and monitoring of patients with chronic obstructive pulmonary disease (COPD), *International Journal of COPD*, Vol.8, 2013, pp. 389-395.

[24] J. Sanchez-Monedero et al., On the suitability of Extreme Learning Machine for gene classification using feature selection, *10th Internatinal conference on Intelligent System Design and Applications*, 2010, pp 507-512.

[25] Mythili Asaithambi 1, Sujatha C Manoharan 2 and Srinivasan Subramanian, Clustering based analysis of spirometric data using principal component analysis and self organizing map, *Swarm,Evolutionary and Memtic computing*, Vol. 8298, 2013,pp 523-533.

[26] Sujatha, C.M., Mahesh, V., Swaminathan, R.: Comparison of two ANN methods for classification of spirometer data. *Measurement Science Review*, Vol. 8, no.3,2008, pp. 53-57.

[27] Mahesh, V., Ramakrishnan S., Assessment and classification of normal and restrictive respiratory conditions throughpulmonary function test and neural network, *Journal of Medical Engineering and Technology*, Vol.31,No.4, 2007, pp.300-304.

[28] Guang-Bin Huang, Qin-Yu Zhu, Chee-Kheong Siew, Extreme learning machine: Theory and applications, *Neurocomputing*, Vol. 70, 2006, pp. 489–501.

[29] Qing-Hua Ling, Fei Han, Improving the Conditioning of Extreme Learning Machine by Using Particle Swarm Optimization, *International Journal of Digital Content Technology and its application*, Vol.6,No.12, 2012,pp.

[30] Luciano D. S. Pacifico and Teresa B. Ludermir, Improved Evolutionary Extreme Learning Machines Based on Particle Swarm Optimization and Clustering Approaches, *International Journal Of Natural Computing Research*, Vol.3, Issue.3, 2012

[31] Dianhui Wang, Guang – Bin Huang , Protein sequence classification using extremem learning machine, *Proceedings of IEEE International Joint Conference on Neural networks*, Vol.3, 2005, pp. 1406-1411.

[32] S. Suresh, S. Saraswathi, N. Sundararajan, Performance enhancement of extreme learning machine for multicategory sparse data classification problems, Journal of *Engineering Applications of Artificial Intelligence*, Vol.23, No.7, 2010, pp 1149-1157

[33] S. Suresh, R. Venkatesh Babu, H. J. Kim, No-reference image quality assessment using modified extremem learning machine classifier, *Applied Soft computing*, Vol.9,2009, pp.541-552.

[34] Guillermo M Albaiceta, Esteban Garcia and Franciso taboada, Comparative study of four sigmoid model of pressure- volume curve in acute lung injury, *Biomedical Engineering Online*,Vol.6, No.7 2007.

[35] R. Penrose, A generalized inverse for matrices, *Mathematical Proceedings of the Cambridge Philosophicaly Society*, Vol.51, Issue.3, 1995, pp.406-413.

[36] Ravi Kumar Jatoth, Saladi S V K K Anoop,Ch Midhun Prabhu, "Biologically Inspired Evolutionary Computing tools for the Extraction of Fetal ElectroCardioGram, *WSEAS Transactions on Signal Processing*, Vol. 5, Issue. 3, 2009.

[37] Prayoth Kumsawat, Kitti Attakitmongcol, Arthit Srikaew, An Optimal Robust Digital Image Watermarking Based on Genetic Algorithms in Multiwavelet Domain, *WSEAS Transactions On Signal Processing*, Vol.5, No. 1, 2009.

[38] Q.Y. Zhu, A.K. Qin, P.N. Suganthan , G.B. Huang, Evolutionary Extreme Learning Machine, *Pattern Recognition*, Vol. 38,2005, pp. 1759-1763.

[39] R.Storn, K.Price, Differential Evolution – A simple and Efficient Heuristic for Global Optimization over Continuous Spaces, *Journal of Global Optimization*, Vol.11, 1997, pp. 341-359.

[40] V. Mahesh, S. Ramakrishnan, Assessment and classification of normal and restrictive respiratory conditions through pulmonary function test and neural network, *Journal of Medical Engineering and Technology*, Vol.31, No.4,2007, pp.300-304.