Classification of Respiratory Abnormalities Using Adaptive Neuro Fuzzy Inference System

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Abstract. Spirometric evaluation of pulmonary function plays a critical role in the diagnosis, differentiation and management of respiratory disorders. In spirometry, there is a requirement that a large database is to be analyzed by the physician for effective investigation. Hence, there is a need for automated evaluation of spirometric parameters to diagnose respiratory abnormalities in order to ease the work of the physician. In this work, a neuro fuzzy based Adaptive Neuro Fuzzy Inference System (ANFIS), Multiple ANFIS and Complex valued ANFIS models are employed in classifying the spirometric data. Four different membership functions which include triangular, trapezoidal, Gaussian and Gbell are employed in these classification models. Results show that all the models are capable of classifying respiratory abnormalities. Also, it is observed that CANFIS model with Gaussian membership function performs better than other models and achieved higher accuracy. This study seems to be clinically relevant as this could be useful for mass screening of respiratory diseases.

Keywords: Flow-volume spirometry, forced expiratory maneuver, Adaptive Neuro Fuzzy Inference System, Multiple Adaptive Neuro Fuzzy Inference System, Complex-valued Adaptive Neuro Fuzzy Inference System.

1 Introduction

Spirometry is a valuable tool for the primary care clinician when making respiratory diagnoses, assessing progress and predicting prognosis. Various international guideline updates for respiratory disorders have stated that spirometry is mandatory in order to confirm the diagnosis of chronic obstructive pulmonary disease and other related diseases [1]. Spirometric pulmonary function test can detect the presence of airflow obstruction, lung volume reduction and is also useful in distinguishing respiratory diseases from cardiac diseases. Thus, Spirometry is established as an essential diagnostic tool and can be performed in most physicians' offices, with the patient sitting comfortably in front of the spirometer [9].

Spirometry is a measure of dynamic changes in lung volumes and capacities as a function of time during forced expiration and inspiration. The spirogram, a flow-volume pattern curve, is characterized by various flow and volume parameters during

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various time intervals. Respiratory diseases and their severity are interpreted based on these patterns and the parameters obtained from them [2,3]. Some of the important parameters obtained from the maneuver are Forced Expiratory Volume of air in one second (FEV_1), Forced Vital Capacity (FVC) and Peak Expiratory Flow (PEF). FEV_1 is the volume of air exhaled in one second, FVC is the total amount of air exhaled and PEF is the maximum flow achieved during the expiration. Automated diagnosis methods that evaluate respiratory flow volume patterns, and classify spirometric data, for appropriate interpretation are very much essential [6-8].

Artificial Neural Networks (ANN) have already been used in the classification of respiratory data [3]. ANN employed for classification problems do not guarantee high accuracy, besides being computationally heavy [4]. The necessity for a large training set to achieve high accuracy is another drawback of ANN. On the other hand, fuzzy logic technique which promises better accuracy depends heavily on expert knowledge, that may not always be available [5]. Even though it requires less convergence time, it depends on trial and error method in selecting the fuzzy membership functions. These problems are overcome by the hybrid neuro fuzzy model which removes the stringent requirements as it includes the benefits of both ANN and the fuzzy logic systems [4]. Successful implementations of ANFIS have been reported for classification, data analysis [10-12] of many biomedical engineering applications such as detection of breast cancer [16], analysis of EEG and ECG signals [17,18].

Multiple ANFIS, which is an extension of the ANFIS network, has been employed for human facial expression recognition [19] and multiple objective decision making problem [20]. Complex valued ANFIS model is based on Sugeno fuzzy system. Each fuzzy rule of this model is realized by a neural network. CANFIS has been widely used for classification problems [21, 22]. In this work, the classification of spirometric data has been demonstrated using ANFIS, MANFIS and CANFIS models and their performance are compared.

2 Methodology

The spirometer recordings are carried out on adult volunteers (N = 250) for the present study. The age, gender and race of the subject are recorded and height, weight are being measured before recording. The portable Spirolab II spirometer with a gold standard volumetric transducer is used for the acquisition of the data.

ANFIS model used in this work is based on Sugeno fuzzy model [11]. This multilayer neural network based fuzzy system generates fuzzy rules and parameters of Membership Function (MF) from a given input data set. Each rule in the ANFIS model is formed as:

$$\text{IF } x_1 \text{ is } A_{1,j} \text{ AND } x_2 \text{ is } A_{2,j} \text{ AND ... AND } x_n \text{ is } A_{n,j} \tag{1}$$

$$\text{THEN } y=c_0 + c_1x_1 + c_2x_2 + \ldots + c_n x_n \tag{2}$$

where $A_{i,j}$ is the j^{th} linguistic term of the i^{th} input variable x_i, and n is the number of inputs. y is the output variable and c_i are consequent parameters to be determined in the training process.

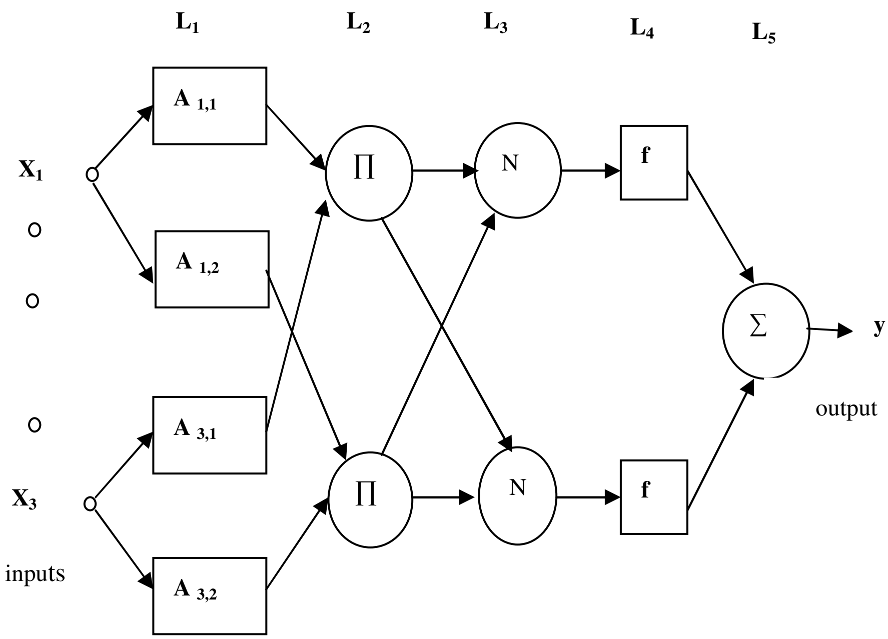


Fig. 1. Architecture of ANFIS

The architecture of the ANFIS model consists of five layers with their associated nodes and is shown in Fig. 1.

Layer 1 represents the membership functions. In this layer, there are n × k nodes, where n is the number of the input variables and k is the number of membership functions. The MF maps each input element to a membership grade value between 0 and 1.

Every node in this layer 2 is a fixed node labelled , whose output is the product of all the incoming signals. Each node output represents the firing strength of a rule and it is given by:

$$w_i = \prod \mu_{Ai}\left(x_j\right), i = 1,2; \; j = 1,2,...,n \tag{3}$$

where w_i represents multiplication of the input values from the previous layer, with respect to firing strength of the i^{th} rule.

Layer 3 is the normalization layer where the rule strength is normalised as:

$$\overline{w}_i = \frac{w_i}{\sum w_i} \tag{4}$$

where w_i is the firing strength of the i^{th} rule.

Layer 4 is an adaptive layer. Every node in this layer is a linear function and the coefficients of the function are adapted through a combination of least squares approximation and back propagation.

$$\overline{w}_i f_i = \overline{w}_i (c_0 + c_1 x_1 + c_2 x_2 ..... + c_n x_n) \tag{5}$$

Layer 5 is the output layer which computes overall output as the summation of all incoming signals. The output is computed as:

$$\sum_i \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{6}$$

where $\overline{w_i f_i}$ is the output of the node i in layer 4. The overall output is linear, even though the premise parameters are nonlinear. The values of input and output nodes of ANFIS represent the training values and the predicted values respectively.

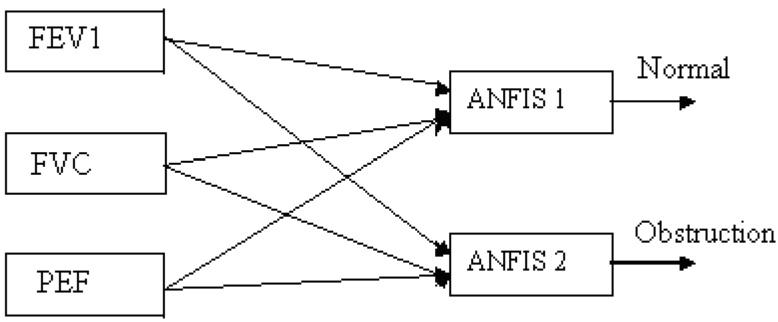


Fig. 2. Architecture of the MANFIS

MANFIS, which is an extension of ANFIS has two ANFIS placed in parallel to differentiate the normal from abnormal values. This architecture serves as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated input-output pairs. The output of each rule is a linear combination of input variables plus a constant term, and the final output is the weighted average of each rule's output. In the forward pass of the learning algorithm, the consequent parameters are identified by the least square estimates. In the backward pass the premise parameters are updated by gradient descent.

In MANFIS, each ANFIS has an independent set of fuzzy rules, which makes it difficult to realize the possible correlations between outputs. The parameters of the membership functions are not shared by the ANFIS models. Also, the number of adjustable parameters drastically increases as number of output increases. In Complex valued ANFIS model the weight normalization and the membership function values are shared to express the correlations. This interaction between the membership functions during training is considered as an added advantage. [22].

In this work, the spirometric parameters FVC, FEV_1 and PEF are given as inputs to the various models. Membership functions which include, Bell-shaped function, Gaussian function, triangular-shaped function and trapezoidal shaped functions are used in the classification process. The functions are defined as:

$$\text{Bell-shaped function } \mu_{Ai} = \frac{1}{1+\left|\frac{x-c}{a}\right|^{2b}} \tag{7}$$

$$\text{Gaussian function } \mu_{Ai} = \exp\left\{-\left[\frac{x-c}{\sigma}\right]^2\right\} \tag{8}$$

where c and σ are centres and widths of the function and are referred to as the antecedent parameters for the membership function

$$\text{Triangular function } \mu_{Ai} = \max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right) \tag{9}$$

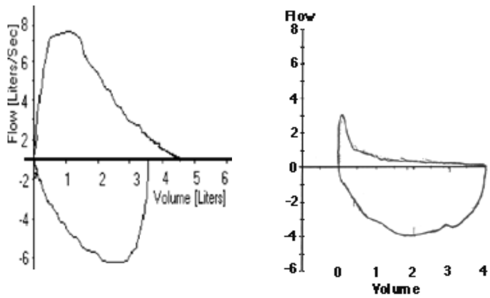
where a, b, c are antecedent parameters, a, c locate the feet of the triangle and b locates the peak.

$$\text{Trapezoid function } \mu_{Ai} = \max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right) \tag{10}$$

where a, c are antecedent parameters locate the feet of the trapezoidal and b, d locates the top. These parameters are adaptive and they determine the value of the i^{th} membership function for each variable to the fuzzy set A_i. As the values of the parameters change, the value of the function also varies accordingly, thereby indicating the degree to which the input variable x satisfies the membership function. The optimal number of membership functions are chosen based on the values of classification accuracy. Receiver Operating Characteristic (ROC) analysis has been used to plot sensitivity with respect to specificity to measure the accuracy of the classifier [14].

3 Results and Discussion

The spirometric pulmonary function test is investigated using flow-volume spirometer. In this study, flow-volume data are recorded for N=250 and the parameters such as FEV_1, FVC and PEF are obtained from them. Fig 3(a) shows a typical response of a spirometer that depicts variation of airflow with lung volume for a normal subject. It is seen that this normal flow-volume curve has rapidly rising flow at the beginning of expiration and then it declines steadily in a linear fashion. The highest flow rate, obtained during the first part of expiration, is effort dependent and is approximately equal to one third of vital capacity.



(a) (b)

Fig. 3. (a) and (b). Typical flow-volume curves of normal and abnormal subjects

Fig 3(b) shows a typical flow-volume curve of subject with obstruction abnormality. There is a rapid peak expiratory flow but the curve descends more quickly than normal and takes on a concave shape. The classifiers are trained with a set of 180 data and their performance is estimated by computing specificity, sensitivity and accuracy for test data of 70 subjects.

Table 1. Performance estimators for different Membership functions for ANFIS model

MF type	Performance estimator		
	Sensitivity	Specificity	Accuracy
Triangular	78.78	93.3	88.17
Trapezoidal	69.44	90.74	82.22
Gaussian	77.42	89.83	85.56
Gbell	81.25	93.1	88.89

Table 2. Performance estimators for different Membership functions for MANFIS model

MF type	Performance estimator		
	Sensitivity	Specificity	Accuracy
Triangular	92.86	93.55	93.33
Trapezoidal	93.33	98.1	96.67
Gaussian	79.31	88.52	85.56
Gbell	83.33	84.85	84.44

Table 3. Performance estimators for different Membership functions for CANFIS model

MF type	Performance estimator		
	Sensitivity	Specificity	Accuracy
Triangular	93.15	95.4	91.25
Trapezoidal	95	97.2	90.82
Gaussian	92.5	98	97.55
Gbell	85.3	86	82.5

The performance measures of ANFIS, MANFIS and CANFIS classification models with different types of membership functions are presented in Tables. 1, 2 and 3. Table. 1, the values of sensitivity of ANFIS model are found to be high for all the membership functions. This shows that this model is able to identify abnormal subjects well. It also observed that high values of classification accuracy, specificity and sensitivity are obtained for ANFIS model with Gaussian membership function.

From Table.2, it is found that the values of sensitivity for MANFIS model with various membership functions are greater than that of ANFIS model. It is also observed that this model with trapezoidal membership function achieved higher values of accuracy, sensitivity and specificity than MANFIS model utilizing other membership functions.

It is found that CANFIS model with Gaussian membership function performs better in classification as shown in Table.3. It is also further observed that CANFIS model with Gaussian membership function obtained higher values of classification accuracy, sensitivity and specificity than MANFIS and ANFIS model.

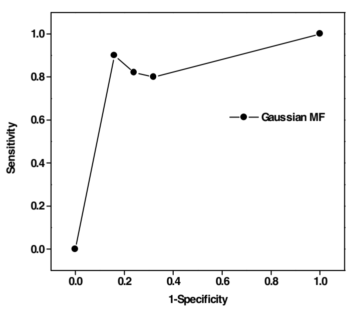


Fig. 4. ROC analyses for Gaussian membership function of CANFIS

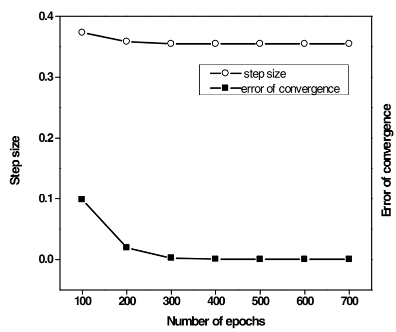


Fig. 5. Adaptation of parameter steps and error of convergence of CANFIS

The ROC curves for CANFIS model with varied number of membership functions (three, five and seven) is shown in Fig 4. Results demonstrate that CANFIS model with three number of Gaussian membership functions achieved better classification accuracy.

The steps of parameter adaptation and the network error convergence curve of CANFIS are shown in Figure 5. The step size had an initial value of 0.1 and converged to 0.0002 after the 200 epochs. Similarly, the network error decreases with increase in number of epochs and converged to constant value at higher epochs.

4 Conclusion

Spirometry is the most frequently performed pulmonary function test and is an essential tool for the diagnosis of respiratory diseases. The clinical utility of spirometer depends on the accuracy, performance of the subject and on the measured and predicted values [5]. It is also reported that a large database is to be analyzed by the physician to investigate the pulmonary function abnormalities. Hence there is a need to provide automated diagnostic support to the physician using hybrid intelligent systems.

In this work, ANFIS, MANFIS and CANFIS models with various membership functions are employed for classification of spirometric data. It has already been shown that automated analysis of spirometric pulmonary function data is carried over using neural networks [15]. ANFIS model achieves higher classification accuracy when compared to the previously employed neural network model. This could be due to the reason that ANFIS combines both the learning capabilities of neural networks and reasoning abilities of fuzzy inference system. Also, it is found that CANFIS obtains higher classification accuracy of 97.5% compared to ANFIS and MANFIS model. The network convergence error was low with three number of membership functions. Results demonstrate that the proposed model can be used to enhance the diagnostic relevance of pulmonary function test. This method can be used for automated mass screening and further enhanced in severity classification of respiratory abnormalities.

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