

Asthma Diagnosis Using Neuro-Fuzzy Techniques

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Abstract— Asthma is one of the most common causes of respiratory diseases. By taking into consideration the possibility of this disease worsening over time and its negative impact on patients' daily activities, the continuous monitoring and managing of this disease has become a necessity. In this work, a system is proposed for Asthma diagnosis using adaptive neuro-fuzzy techniques. The proposed diagnosis system takes key parameters as input including Forced Expiratory Volume (FEV1), Peak Expiratory Flow Rate (PEF) and Forced Vital Capacity (FVC) and predicts Asthma severity condition. A mobile application that allows for easy interface between the patients and the analysis tool is also developed. The proposed system was trained and tested on patient records obtained from two hospitals. The proposed system was able to correctly classify Asthma severity conditions with an average accuracy of 97%.

Keywords—Asthma, Neuro-Fuzzy, Diagnosis, Mobile Applications

I. INTRODUCTION

Asthma is a lung disease which consists of airways becoming inflamed and narrow leading to obstruction. This in turn results in increased mucus, wheezing, shortness of breath and frequent coughs [1]. Asthma remains a chronic condition that requires lifetime treatment and monitoring. More importantly, as shown in Figure 1, Asthma condition of patients has varying levels of severity which requires accurate diagnosis followed by adequate treatment. Failure to properly correlate the severity level to the most suitable control mechanisms can exasperate the patients' conditions and lead to serious illness [2-4]. Thus, a platform which can assist both patients and physicians in the successful diagnosis of Asthma severity conditions is of great value.

Using fuzzy logic techniques in Asthma diagnosis was studied in the literature. Reported attempts where fuzzy logic techniques have been used to detect severity of illnesses related to respiratory problems and other diseases include the work discussed in [5]. Authors discussed mathematical models for spirometry plots that are built as fuzzy numbers and categorizing coefficients of mathematical models which are introduced as a set of rules. In [6] and [7] medical fuzzy expert systems are used in classification of diseases. In [8] a fuzzy logic controller and genetic algorithms based techniques are used to diagnose certain types of diseases. In [9] a system based on neural networks, and that uses different measurement methods on impulse oscillometry system and spirometry tests to diagnose Asthma or COPD patients is discussed. In [10], a

study signifies the use of neural fuzzy systems along with evolutionally computation to generate unseen data from available data such as reported symptoms, and diagnosis readings by forming fuzzy logic rules and its training needs. Similarly, in [11] a support system for the Asthma diagnosis using a combination of fuzzy, Artificial Neuro Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS) is presented.

The use of mobile applications in support of diagnosis was also discussed in the literature [12-16]. Using built-in sensors in the mobile and connected wearable devices, patient's vital signs are constantly collected and observed with a provision to transmit data to health facilities for further analysis.

In this work, a mobile application is implemented to assist Asthma patients in assessing the severity level of the disease at any point in time using algorithms based on adaptive neuro fuzzy techniques running on the cloud to diagnose a given condition. The application also allows for storage of medical history of a patient, and has a user friendly interface that illustrates the results of the analysis in a clear to understand graphical display.

The remainder of the paper is organized as follows. The next section describes the methodology and the design of the system. Section III presents the experimental results. The paper is concluded in Section IV.

II. METHODOLOGY

The proposed method uses the following key parameters as input:

- Forced Expiratory Volume in 1 Second (FEV1)
- Forced Vital Capacity (FVC)
- Peak Expiratory Flow Rate (PEF)
- Forced Expiratory Flow 25-75% (FEF 25%-75%)

These parameters are typically obtained using Spirometers and Peak Flow Meters [6] which are assumed to be available for the patient. The patient feeds these readings to the mobile application which forwards the data to a remote server running an instance of a trained Fuzzy Inference System (FIS) developed for this work. The FIS takes these measurements as inputs and calculates the severity as an output on a hundred-point scale. The classification of severity on this scale is as shown in Fig. 1.

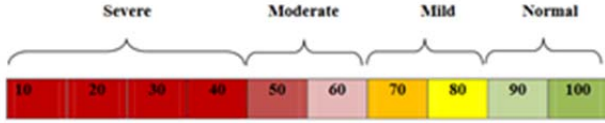


Fig. 1: Output Classification of Severity.

The computed output severity level is displayed on the mobile application and also recorded in a database. The mobile interface allows users to view their medical history and track the PEF, FEV1, FVC and FEF 25%-75% values as well as the calculated severity using illustrative graphs as shown in Fig. 2. As an added feature, the mobile application allows users to monitor their heart rate and oxygen saturation using a Bluetooth Low Energy (BLE) enable oximeter.

The general architecture of the system is illustrated using a component architecture in Fig. 3. The ANFIS module is built using MATLAB and designed after careful evaluation and review of related work [17-19]. Since the performance of the ANFIS system is heavily dependent on the type of membership functions used, a set of FIS systems were generated using different membership functions and their accuracies were compared. The membership functions used for this project are Triangle, Trapezium, Bell, Gaussian and Differential Sigmoid membership functions.

To build the ANFIS system, a set of initial Sugeno models were built by changing the membership functions for the input parameters [20]. The membership function used for each of the trials was kept constant (i.e., the entire input variable for any given trial had the same membership function). The parameters for the membership functions were computed using grid partitioning method for clustering with four membership functions for each input [21].

Once the Fuzzy Inference System (FIS) files are generated, each system is next trained. A hybrid technique is used for training the FIS system. The error function used to evaluate the training phase was mean squared error function as shown in Eq. (1).

$$Error = \frac{1}{2n} \sum (\hat{y} - y)^2 \quad (1)$$

Additionally, a back propagation technique is used with gradient descent to optimize the weights of the hidden neural network layers [22]. The activity flow diagram for the ANFIS system is illustrated in Fig. 4.

To prevent the neural network from overfitting (i.e., to ensure that the system generated is not specific to the training data provided), two different training epochs were used for each system. The trained systems are tested. The training and testing errors for each system are recorded and discussed later in the results subsection.



Fig. 2: Mobile Interface Screenshots.

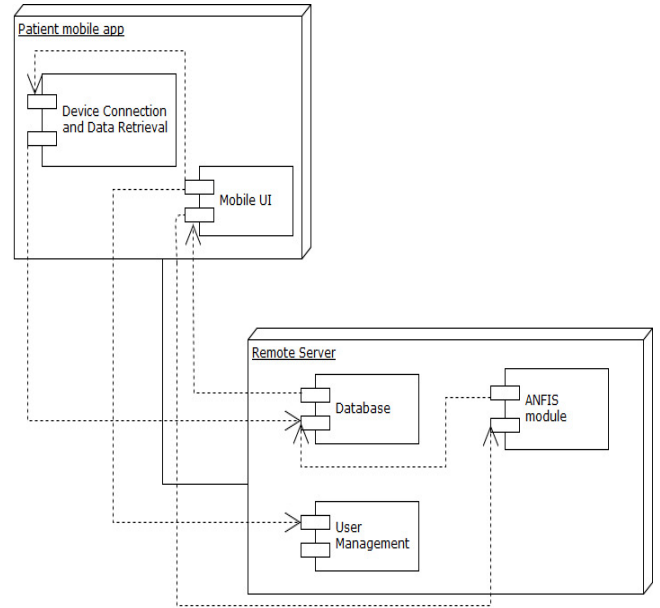


Fig. 3: System Component Architecture.

III. EXPERIMENTAL RESULTS

The performance of the proposed work was tested using two datasets: a dataset of 800 patients records obtained from Integral University in India [18] and a dataset of 300 patient records obtained from a local hospital in Sharjah, UAE. The first dataset of 800 patient cases was used for training while the other local dataset of 300 patients was used for testing.

The training and testing errors for each membership function using 30 and 50 epochs are recorded as shown in Table I. From the recorded values, it was found that the lowest training and testing errors were achieved by the Gaussian membership function (4.614% as the training error and 4.754% as the testing error), and hence it was used to build inference application run by the server.

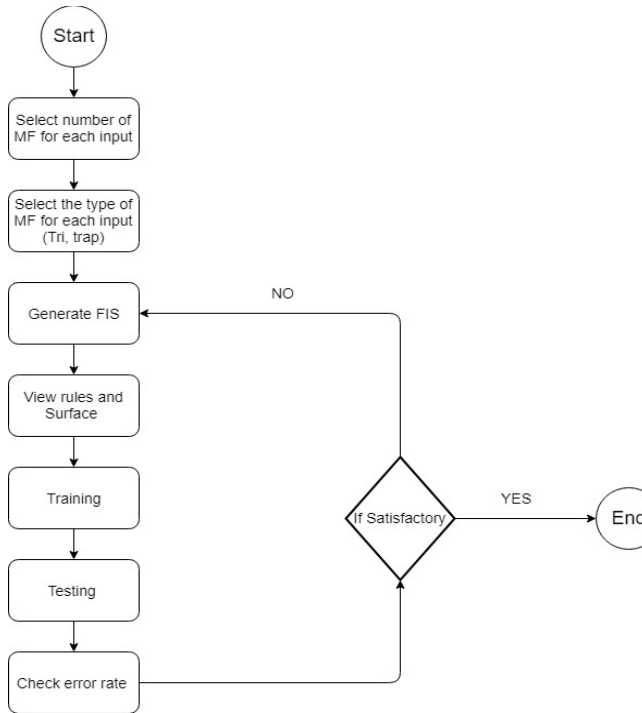


Fig. 4: Activity Flow Diagram for ANFIS.

Table I: Error Rates using different member functions in the ANFIS system.

Membership Function	Epoch	Training Error	Testing Error
TriangleMF (trimf)	30	5.312	5.308
	50	5.228	5.226
TrapeziumMF (trapmf)	30	7.682	7.66
	50	7.394	7.386
BellMF (gbellmf)	30	5.112	5.101
	50	4.901	4.891
GaussianMF (gaussianmf)	30	4.811	4.802
	50	4.614	4.754
Differential Sigmoidal MF (dsigmf)	30	6.66	6.628
	50	6.114	6.093

Table II: System Validation Errors.

	No. of Test Cases	True Diagnosis	False Diagnosis	% False Diagnosis
Normal	100	100	0	0%
Mild	70	65	5	7.14%
Moderate	70	67	3	4.28%
Severe	60	59	1	1.66%
Average % False Diagnosis				3.27%

Additionally, the number of false diagnosis were recorded for each classification by the generated system for the validation test set as presented in Table II. As depicted in Table II, the returned false diagnosis were as low as 0%, 7.14%, 4.28% and 1.66% respectively. The average percentage of false diagnosis from is 3.27%.

Fig. 5 shows the training error at each epoch. As seen from the figure, the training error decreases with increasing the number of epochs. Fig. 6 depicts a graph of computed output from the trained FIS system and the expected output. Fig. 7 shows the computed output expected output for the test set of data.

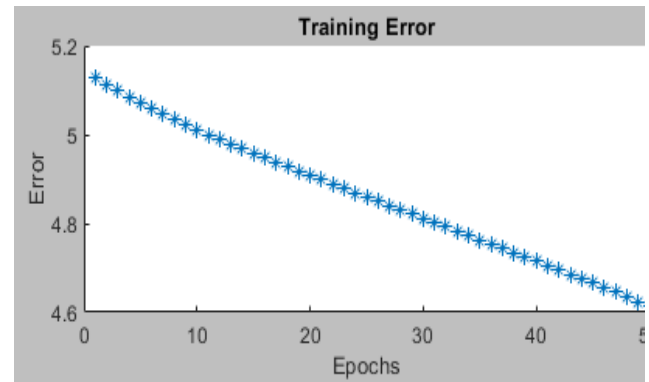


Fig. 5: Training Error for Gaussian MF.

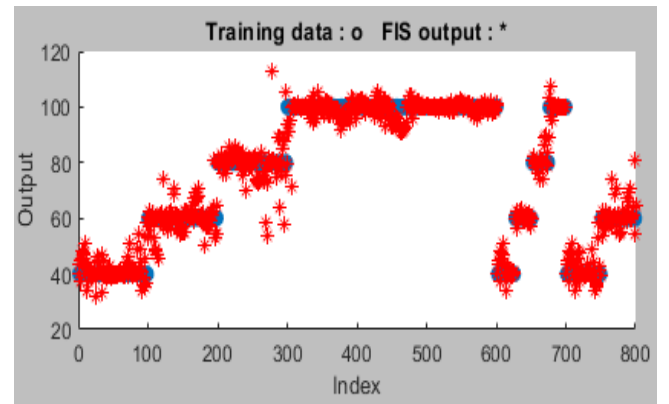


Fig. 6: Expected Output against Calculated Output for Training Data.

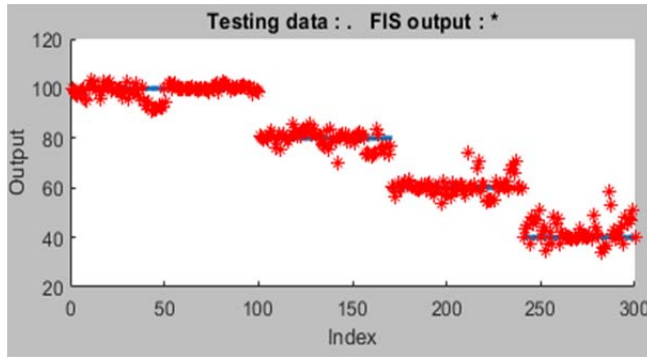


Fig. 7: Expected output against Calculated Output for Test Data.

IV. CONCLUSION

In this work, classifications of Asthma severity condition is estimated using adaptive neuro fuzzy inference system. Two datasets were used to test the performance of the system. The developed system correctly classified Asthma severity in 97% cases out of 300 patients data set used for testing. A mobile application is developed to enable the entry of essential vital values for immediate diagnosis of Asthma severity level which supports the patient use of the inference system.

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