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A Neural Network Approach for Risk Assessment of Asthma Disease

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Abstract

The work in this paper illustrates the deployment of neural network as a machine learning approach for the risk assessment of the asthma disease as indicated by a significant pulmonary function parameter called Tiffeneau-Pinelli index used in the prognosis of obstructive respiratory diseases such as Asthma. The approach is trained and tested on samples taken from SPIROLA dataset. We deploy different neural network types for the prediction of the index and evaluate the performance with respect to their predictive capability, thereby concluding that a few of the neural network types can be relied on for the effective prediction of the disease. The transformed features used in the input features set have proved to yield good prediction results thereby avoiding the need to employ individual raw features for the prediction process.

Keywords: SPIROLA; Neural network; Tiffeneau-Pinelli index; Feature transformation; MAE

Introduction

Asthma, a chronic disease of the lungs characterized by inflammation and narrowing of the bronchial tube, leads to difficulty of passage of air that enters and leaves the lungs [1]. Tests for Asthma basically rely on assessing lung function through tests such as methacholine challenge tests and spirometry tests [2]. Spirometry tests basically tests the amount of air that can be blown out of the lungs and how quickly it can be done. The test is often done to assess the degree of progress of Asthma disease and adopt treatments accordingly [1,3]. The most important parameters that are assessed during the spirometry tests include:

FEV1 - Forced Expiratory Volume in 1 Second. The volume that was expired in the first second.

FVC - Forced Vital Capacity - The total volume the patient expired during the test.

Tiffeneau index - FEV1/FVC *100.

A frequently expressed preferred standpoint of neural systems over ordinary projects lies in their capacity to take care of issues that either don't have an algorithmic arrangement or a solution is too complex to find. Neural networks are well suited to tackle problems that people are good at solving, like prediction and pattern recognition. Neural networks have been applied within the medical domain for clinical diagnosis, image analysis and interpretation, signal analysis and interpretation, and drug development. ANN applications in healthcare can be categorized under four headings: clinical diagnosis, image interpretation, signal interpretation and drug development. ANNs (Artificial Neural Networks) are only one of the numerous models being brought into the field of social insurance by developments like AI and enormous information [4]. Their motivation is to change enormous measures of crude information into valuable choices for treatment and care. Neural Networks are a computational approach which depends on an expansive gathering of neural units freely displaying the way the cerebrum takes care of issues with extensive bunches of natural neurons associated by axons. Each neural unit is associated with numerous others. These frameworks are self-learning and prepared as opposed to expressly customized.

We present a neural network approach for the risk assessment of asthma disease via spirometry readings. The spirometer readings such as Tiffeneau-Pinelli index are a very good indicator of presence of obstructive lung diseases such as asthma. They even signify the severity of the disease. The predicted values for FEV1 and FEVC are used to find the index. If the actual index obtained is lesser than predicted FEV1/FVC, then it can be a strong risk indicator towards the development of asthma disease. The work gives good results for a healthy population that show consistently right values for spirometry readings. However in poorly controlled asthma population, it was not possible to get the index predicted rightly as several other parameters such as continuous decline in FEV1, FEV1/FVC and various other parameters come into consideration. In this paper, an attempt has been made to study the performance of the various neural network types for the prediction of Tiffeneau index, an important index that decides the severity of asthma disease. The inputs used to predict the target are FEV1P and FVCP, which are obtained as discussed in the section on Feature Transformation. The target corresponds to the actual Tiffeneau index, obtained through spirometry tests. This helps one in predicting the index using the approach proposed well before getting the spirometry tests done as the inputs very closely predict the target as observed by experimental results.

In Section 2, we present a survey of the related work in relevance to spirometry readings that decide the severity of the asthma disease, followed by a discussion of the dataset worked on and various neural network techniques with the network specific parameters in Section 3 under Materials and Methods. In Section 4, we present the results obtained on the dataset along with a discussion that compares the performance of the various neural network types. Lastly we provide concluding remarks on the work in the section 5.

Review of Related Work

Pulmonary function tests play a very important role in respiratory medicine [4]. They are utilized to analyze obstructions to airways, evaluate its seriousness and outcomes, outline hazard factors, recognize early lung ailment, and screen for ordinary lung development and lung work decay [5,6]. Pulmonary function shifts with age, height, sex and ethnicity. Along these lines, test comes about should be contrasted with anticipated qualities, and lower and maximum points of confinement of typical values that are suitable for the individual being tried. There are plenty of reference conditions, contributing to reference equations and most productions identify with Caucasians [7,8]. With generally couple of special cases, the suitability of the equations and its appropriateness was not tried and the LLN or ULN (lower and upper limits of normal) were not legitimately inferred. Likewise numerous prediction equations depend on less number of subjects, utilizing information gathered decades back. Changes in spirometry methodology and secular trends (i.e. a pattern in respiratory functioning in progressive birth associates) may influence the applicability to today's recordings [1,9,10]. Also it becomes difficult to overcome the shortcoming by any studies whether recent or past and irrespective of the number involved in the population study.

An endeavor was made to investigate the assignment of forecasting spirometry readings based on statistical spectrum descriptor (SSD) from cough and wheeze signal [11,12]. Support vector regression was utilized to foresee the spirometry readings from the SSDs of the wheeze and cough sound. Examinations were performed in a leave one-sample setup (where a subject is excluded at every point of time) with cough and wheeze recordings from 16 healthy subjects and 12 asthmatic patients. Support vector regression (SVR) was utilized as the regression approach. Deeper analysis showed that nonlinear ϵ-SVR approximated the capacity between the SSDs and FEV1, FEV%, FVC, FVC% and FEV1_FVC (target factors) [13]. SVR is a utilization of SVM to discover the mapping capacity amongst info and yield. Also ϵ-SVR was deployed, which tries to locate the ideal relapse hyperplane so that a large portion of the training subjects exist in a ϵ-edge around this hyperplane. Non-linear regression is done in an effective manner by applying the Kernel work, i.e., to supplant the inner product in the solution by a non-linear kernel work.

Height and age are the most vital illustrative factors in spirometry reference conditions. Guidelines for the estimation of spirometric indices, trying to improve exactness and accuracy, center around hardware, estimation systems and quality control. However they do not address the similarly critical issues of precise height and age estimation. For instance, in the Global Lungs Initiative (GLI) dataset, just 45% of the heights were recorded to 1 mm exactness, 12% of heights were self-revealed, and 45% of ages were recorded in entire years, numerous adjusted by software rounding off. These all can possibly lead to false inclination of the forecast of spirometric indices especially in children [14]. Anticipated FEV1 is figured in light of reference esteems for typical lung work. Reference esteems are gotten from healthy subsamples of overall communities, and age and tallness are viewed as basic condition parts. Since populaces change after some time with respect to both anthropometric attributes and natural exposures, it is prescribed to refresh reference esteems frequently. Amid the most recent 30 years various spirometry reference equations have been published. Nonetheless, none of them depended on spirometry after reversibility testing. It is impossible that the contrast amongst pre-and post-bronchodilator lung work is constant [12].

Material and Methods

Dataset description

The data is taken from the SPIROLA dataset. The dataset basically contains longitudinal data with respect to individual patients recorded over time, however the data is not strictly periodic in nature though closer to being called time series data [15]. The dataset contains the following features: Age, Sex, Race, pulmonary function parameters such as FEV1, FVC are included as the primary attributes along with optional attributes such as second best FEV1, second best FVC. For the sex attribute male value is encoded as 1 in our dataset and female attribute as 2.

Feature transformation

The FEV1P, i.e FEV1 predicted and FVCP i.e, FVC predicted is computed using the formulae published by Association for Respiratory Technology and Physiology for males and female as given below. The figures in the formulae below are based on a regression model from a cohort study where "height" is in meters and "age" is in years. The formula for the predicted FVC and FEV1 is published by the Association for Respiratory Technology and Physiology which is based on a regression model from a cohort of subjects aged 18-60, and includes height, age and genders as the important parameters.

(i)Male:

fev1=4.30*height-0.029*age-2.49

fvc=5.76*height-0.026*age-4.34

(ii)Female:

fev1=3.95*height-0.025*age-2.60

fvc=4.43*height-0.026*age-2.89

Deploying neural network to predict the ratio

For all the neural networks discussed below, the following parameters were deployed for the training process: Number of neurons: 10, training function: TRAINLM, trainlm is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization. Trainlm is often the fastest backpropagation algorithm, and is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. This function uses the Jacobian for calculations, which assumes that performance is a mean or sum of squared errors. Therefore, networks trained with this function must use either the mse or sse performance function. The adaption function used here, learngdm calculates the weight change dW for a given neuron from the neuron's input P and error E, the weight (or bias) W, learning rate LR, and momentum constant (mc), according to gradient descent with momentum, gW, using the formula, dW = mc*dWprev + (1-mc)*lr*gW.

Elman network

An Elman network is a three-layer connect with the expansion of an arrangement of "context units". The center (hidden) layer is associated with these context units attached with a weight of one. At each time step, the input is fed forward and a learning guideline is connected. The fixed back-associations spare a duplicate of the past estimations of the concealed units in the context units. In this manner the system can keep up a kind of state, enabling it to perform such tasks such as sequential forecast that are beyond the capacity of a standard multilayer perceptron

Feed forward back propagation

Despite how it is trained, the signals in a feedforward organize stream one way: from input, through progressive hidden layers, to the output. Given a well-trained feedforward network it is not possible to tell how it was trained (e.g., genetic backpropagation or experimentation). A feedforward backpropagation net is a net that coincidentally was prepared with a backpropagation training algorithm. The backpropagation training algorithm subtracts the output from the objective (wanted answer) to get the error. It at that point backpedals to alter the weights and biases in the input and hidden layers to decrease the error.

Cascade feed forward back propagation

CF models are very similar to feed forward systems, however incorporate a weight association from the contribution to each layer and from each layer to the progressive layers. While two-layer feedforward systems can possibly learn for all intents and purposes any input/output relationship, feed forward systems with more layers may learn complex connections all the more rapidly. The capacity newcf makes cascade forward systems. For instance, a three layer system has associations from layer 1 to layer 2, layer 2 to layer 3, and layer 1 to layer 3. The three layer network likewise has associations from the input to each of the three layers. The extra connections may enhance the speed at which the system learns the desired relationship

Radial basis function network

A radial basis function network (RBF) is an exceptional sort of neural system that uses a radial basis function as its activation function. RBF systems are exceptionally prevalent for estimation of functions, fitting of curves, time series data forecasting, control and classification issues. The radial basis function network is not the same as other neural systems, and has highlighting features that make it distinguishable from the others. Due to their universal approximation, more reduced topology and speedier learning speed, RBF systems have pulled in extensive consideration and they have been broadly connected in numerous science and building fields.

In RBF systems, assurance of the quantity of neurons in the hidden layer is essential since it influences the system multifaceted nature and the generalization capacity of the system. In cases where, the quantity of the neurons in the hidden layer is inadequate, the RBF network can't take in the information sufficiently; then again, if the neuron number is too high, poor speculation or an overlearning circumstance may happen. The location of the focuses in the hidden layer likewise influences the system execution impressively, so assurance of the ideal location of centers is a vital assignment. In the hidden layer, every neuron has an actuation work. The Gaussian function, which has a spread parameter that controls the functioning, is the most favored activation function. The preparation technique of RBF organizes likewise incorporates the streamlining of spread parameters of every neuron. A short time later, the weights between the concealed layer and the yield layer must be chosen properly. Ultimately, the biases which are included with each output are resolved in the RBF network training method.

Feed forward distributed time delay

The Time Delay Neural Network, as other neural systems, works with different interconnected layers made out of clusters. These groups are intended to speak to neurons in a mind and, similar to the cerebrum, each bunch (cluster) require just focus on little areas of the information. A proto-typical TDNN has three layers of clusters, one for input, one for output, and the center layer which handles control of the contribution through channels. Because of their sequential nature, TDNN's are executed as a feed forward neural system rather than an intermittent neural system. Keeping in mind the end goal to accomplish time-shift invariance, a collection of delays are added to the information (sound document, picture, and so forth), with the goal that the information can be represented at various focuses in time. These delays are discretionary and application particular, which for the most part implies the information, is redone for a particular design. A key element for TDNN's are the capacity to express a connection between contributions to time. This connection can be the aftereffect of a feature identifier and is utilized inside the TDNN to perceive patterns between the delayed inputs [16,17]. Distributed delay systems are like feed forward systems, aside from that each input and layer weights has a tap delay line related with it. This enables the network to have a limited dynamic reaction to time series input information. This system is likewise like the time delay neural system (time defer net), which just has delays on the input weight.

NARX

The NARX neural system is determined by a class of discrete time nonlinear frameworks, i.e., the nonlinear autoregressive with exogenous info (NARX) models. When the function f is approximated by a multilayer perceptron, the network is called NARX. At the end of the day, a NARX network comprises of a MLP that takes as info a window of past free (exogenous) inputs and past yields and ascertains the present output. Unlike a traditional neural network, the NARX network has a restricted feedback coming just by the output neuron instead of by the hidden states. As a matter of fact, just the output of the NARX is fed back as input to the feedforward neural system. In any case, it has been shown that it is as much computationally effective as a completely associated intermittent neural system. With a specific end goal to maintain a strategic distance from the experimentation approach for the assurance of parameters, the preparation of NARX has been obtained by GA algorithm in its open shape. The multi-step ahead prediction is done utilizing the NARX in closed loop framework.

Layer recurrent

Layer recurrent neural systems are like feed forward systems, aside from that each layer has a repetitive association with a tap delay related with it. This enables the system to have an unending dynamic reaction to time series input information. This system is like the time delay and distributed delay neural systems, which have limited input responses.

Generalized regression

GRNN, as proposed by Donald F. Specht, falls into the class of probabilistic neural systems. This neural network system like other probabilistic neural systems needs just a small amount of the training samples as compared to that required by back propagation neural system. The information accessible from estimations of a working framework is by and large never enough for a back propagation neural system.

In this way the utilization of a probabilistic neural system is particularly beneficial because of its capacity to join to the underlying function of the information with just couple of training samples accessible. The extra information expected to get the fit satisfyingly is moderately little what's more, should be possible without extra contribution by the user. This makes GRNN an extremely helpful tool to perform forecasts and make comparisons of systems.

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Results and Discussion

The neural network is first trained on the samples drawn from the SPIROLA dataset. The sample drawn from the dataset contains the longitudinal data with respect to individual subjects recorded over years. Both male and female subjects as well as healthy and asthmatic subjects are drawn to ascertain the correctness of the approach involved. The transformed input dataset with respect to the two attributes FEV1P and FVCP is used to train the different neural networks for the prediction process to predict the target parameter which is obtained by computing the ratio of FEV1 and FVC, ie. FEV1/FVCP, (FEV1 and FVC, as obtained from the tests carried out on the patients). The trained model is now used to predict the target index at any point of time using age, gender and height as input data using the already trained model to predict the index.

Out of the total 7233 samples available in the SIPROLA dataset, first 5000 samples were drawn to train the neural network model and the rest of the 2233 samples were deployed as the test set. However while testing the model, we have tested for individual subjects by trying to predict the vector corresponding to the individual subjects at variable age and constant height parameters.

Network Type	Training Function	Adaption learning function	Number of layers	Properties of layer1		MAE
				Number of neurons	Transfer function	
Feed-forward backprop	TRAINLM	LEARNGDM	2	10	TANSIG	0.0488
Elman backprop	TRAINLM	LEARNGDM	2	10	TANSIG	0.0487
Cascade forward backprop	TRAINLM	LEARNGDM	2	10	TANSIG	0.0488
Linear layer(design)	TRAINLM	LEARNGDM	2	10	TANSIG	0.0489
Generalized regression	TRAINLM	LEARNGDM	2	10	TANSIG	0.0502
(Spread constant =1.0)						
Layer recurrent	TRAINLM	LEARNGDM	2	10	TANSIG	0.0489
Radial basis exact fit	TRAINLM	LEARNGDM	2	10	TANSIG	0.0477
(Spread constant=1.0)						
Probabilistic	TRAINLM	LEARNGDM	2	10	TANSIG	0.2105
Feed forward distributed time delay	TRAINLM	LEARNGDM	2	10	TANSIG	0.0489
NARX	TRAINLM	LEARNGDM	2	10	TANSIG	0.0488

Table 1: Different Neural Network types deployed for training.

Both the input data and target data are transposed to obtain matrices of order 2*5000 and 1*5000 respectively. The prediction process now employs various neural network types with deployed learning functions, adaption functions and network specific parameters as shon in the Table 1.

The performance of the network is assessed using MAE (Mean Absolute Error). The important plots namely Performance plot and Training state plots are however shown for the neural networks that has resulted in a considerably good performance over the others.

It can be observed from, Table 1 that the Radial basis with exact fit outperforms the other neural network types using the methodology adopted in the paper. Thus the various plots including the performance plot and plot for training state are depicted for the same network in Figures 1 and 2. In Figure 1, it can be observed that the optimal performance of Mean Square Error (MSE) 0.0041 is obtained at epoch 4, along with the curves for training, validation and testing converging at the same point indicating that the neural network perform equally well in both training and validation [18-20].

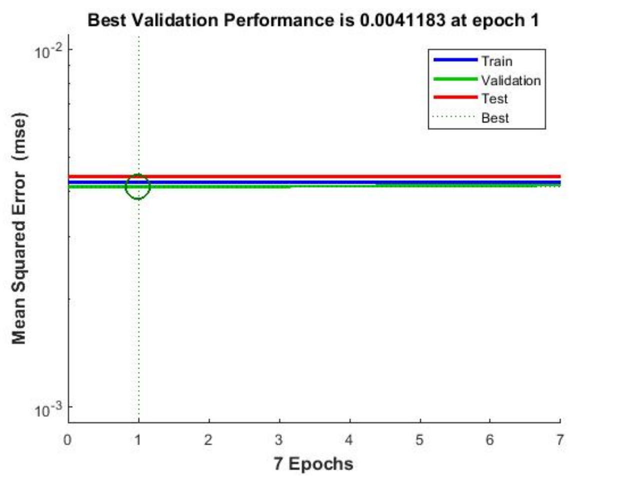

Figure 1: Performance plot.

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The MSE gives the difference between observed and predicted values and lower the value, better would be the prediction network deployed. Further, as can be seen in Figure 2, Gradient 0.0004 indicates the variance occurring in the error rate, Mu (1.00e-06) is the threshold value for each iteration which is updated for each iteration and the Validation Check indicates whether the currently completed iteration has minimized error compared to the previous iterations and confirms again that best performance with minimum error is obtained at epoch 7. However, the other neural networks including Elman network, Feed forward backprop, Cascade forward backdrop and NARX may also be deployed as the MAE values obtained for them also closely follow the ideal radial basis network mentioned above.

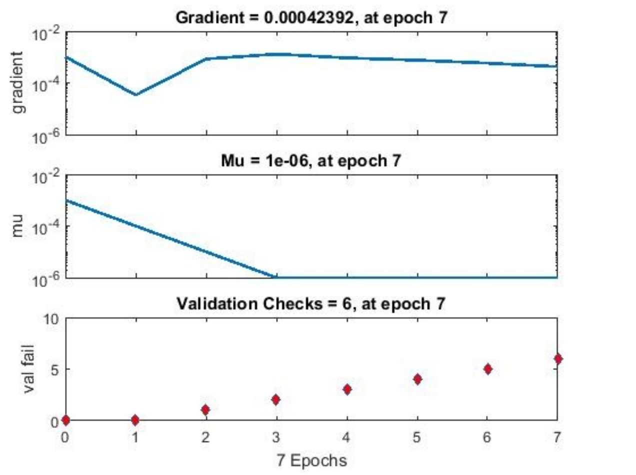

Figure 2: Training State for Training and validation Set.

Tables 2 and 3 present the actual and predicted vectors for Tiffeneau-Pinelli index for female and male subjects respectively. In both the cases, it can be observed that the MAE is quite low as desired and thus can be used to infer the rightness of the approach deployed for the prediction of the vector.

	Subject 1		Subject 2	
	Actual	Predicted	Actual	Predicted
Tiffeneau-Pinelli Index	0.8809	0.8506	0.8515	0.8307
	0.8447	0.8415	0.827	0.8329
	0.8466	0.8354	0.8167	0.8318
	0.8459	0.8205	0.814	0.8276
	0.829	0.7893	0.8207	0.8237
	0.8201	0.7842	0.8194	0.8476
	0.848	0.7812	0.8022	0.8454
	0.858	0.7808	0.741	0.8297
	0.8406	0.7829		
	0.8333	0.7931		
MAE	0.0384		0.0273	

Table 2: Comparison of Actual and Predicted Index Vector using Radial Basis Neural network for Female samples.

	Subject 3 (M)		Subject 4 (M)	
	Actual	Predicted	Actual	Predicted
Tiffeneau-Pinelli Index	0.7903	0.7764	0.8875	0.866
	0.7995	0.7767	0.89	0.8677
	0.8018	0.7764	0.8954	0.8385
	0.7921	0.7754	0.8624	0.8596
	0.7523	0.7734	0.8801	0.8656
	0.7716	0.7704		
	0.8085	0.7667		
	0.7738	0.7623		
	0.7918	0.7576		
	0.7536	0.753		
	0.7906	0.749		
	0.7664	0.7458		
	0.6817	0.7432		
MAE	0.0408		0.0236	

Table 3: Comparison of Actual and Predicted Index Vector using Radial Basis Neural network for Male samples.

Conclusion

The results obtained by deploying the neural network using the approach proposed prove that one can rely on the predictive process adopted in the paper for the early prediction of index, an important spirometric reading based on which inference regarding the severity of the asthma disease can be done. Radial basis neural network has shown to outperform the other neural networks when deployed with the same design parameters. Early prediction of the asthma disease can minimize the number of visits to emergency rooms and high cost hospitalizations. The work in this paper can be viewed as an important intervention to ensure controlled asthma by assessing the risk, which can lead to serious complications.

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