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Classification of Respiratory Abnormalities using Deep Learning Techniques

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Abstract— **Chronic Obstructive Pulmonary disease (COPD) is the most prevailing and progressive respiratory disorder. Measurement of respiratory mechanics helps in monitoring pulmonary disease. Exacerbations of COPD cause the disease to become more aggressive, physical functions to deteriorate, and results in declined life quality. Prevention of exacerbations by providing optimizing treatment becomes mandatory. The most frequently used clinical test to measure the volume of lung is spirometry. It depends on the maximal effort of the patient for perfect diagnosis of pulmonary disorder. An attempt has been made in this work to detect pulmonary abnormality using flow-volume spirometry. A portable Spirolab II spirometer was used to collect respiratory data from 1030 subjects (N = 1030) using a standard acquisition Procedure. Totally 1030 subjects with16 features were consider for investigation purpose. The categorization of normal and abnormal groups of spirometric data were performed using deep learning techniques. Deep architectures have drawn a lot of interest from a variety of domains due to their representational power. It is one of the most powerful architecture of unsupervised learning, which acquires features through empirical observation from data. The effort of the architecture to model high level abstractions in data allows to perform automated analysis of raw physiological data with minimal human intervention. The proposed work uses Restricted Boltzmann Machines with variable learning rate (DRBM) and Deep Belief Network (DBN) for classification of spirometric data. This approach was demonstrated to have the capability to classify the spirometric patterns in to normal and obstructive classes using DRBM and normal restrictive and obstructive classes using DBN. Further validation is carried out using k-fold cross validation. This show that, with raw spirometric data DRBM and DBNs allow us to achieve an average accuracy of 98% for two class and 85.58 % for three class classification respectively. Thus this analysis appears to provide better clinical significance.**

***Keywords*— Spirometer, pulmonary function test, forced expiratory flow, obstructive disease, restrictive disease, DRBM, DBN**

1. INTRODUCTION

Pulmonary Disorders exhibit the abnormal conditions of the respiratory system and are frequently caused by diminished air flows in the lungs. Pulmonary disease can cause symptoms of increased cough, chest pain, sputum production and dyspnea. Conditions and symptoms of pulmonary disorder may differ from individual to individual. The limitation in expiratory flow is the physiological characteristic of COPD. Chronic respiratory disease causes significant increase in morbidity and mortality rate globally and will be the fourth leading cause of death in 2030 [1]. The economic impact of treating respiratory disease is becoming more and more challenging worldwide. Pulmonary disease is a curable and preventive disease. The prevalence of morbidity and mortality can be reduced by early detection [2, 3].

Pulmonary function analysis is one of the most beneficial and practical methods for assessing the respiratory system. The most popular, non-invasive and simple technique for evaluating pulmonary function is spirometry. The spirometry measures the dynamic changes in lung capacities and volumes during forced inspiration and expiration as a function of time [4]. Different flow and volume parameters at different time intervals generates a flow-volume pattern curve, the spirogram. The tidal, inspiratory, and expiratory phases of breathing are represented by the flow volume loop during forced manoeuvre represents [5, 6]. It measures the volume of air inhaled and exhaled as a function of time. The parameters recorded using spirometry are influenced by various factors such as age, height, weight and ethnicity. These spirometric parameters aid in the interpretation of respiratory diseases and their severity are interpreted based on [4].

A few highlighted parameters are forced expiratory volumes in one second (FEV_1), peak expiratory flow (PEF),forced vital capacity (FVC), ratio of FEV_1 to FVC (FEV_1%), forced expiratory flow at 25–75% of FVC ($FEF_{25–75\%}$) , Inspiratory Vital Capacity (FIVC), Percentage of Forced Inspiratory Volume at first second (FIV_1%),Forced Expiratory Flow at 50% of FVC (FEF_{50}%), Forced Expiratory Flow at 75% of FVC (FEF_{75}%) [7] . Based on these parameters identification of restrictive and obstructive respiratory disease is carried out. FEV_1 and FVC are the most significant parameter which contributes much in the diagnosis of the pulmonary disease. Diagnosis of obstructive disorders can be perfectly made by measuring low FEV_1/FVC ratio. A normal or high FEV_1% together with low spirometric FVC has been characterized as a restrictive abnormality.

Spirometry is an effort based test that involves the cooperation among the patient and the technician. The test results obtained will rely on both technical and individual factors. Spirometric data may also contain mislaid values and patients with abnormal lung function might not be able to replicate the procedure for recording the missing data. The significant parameters obtained from the manoeuvre are used to distinguish between different pulmonary complications [2]. Spirometric investigations are subjected to inter individual variations and also impacts increased probability of misclassification due to the occurrence of high mutuality with in the spirometric parameters .Spirometric test results may not always be optimally recorded, and even when done by appropriately trained people, interpretation may be inaccurate. Physicians as well have different opinions while diagnosing COPD. Furthermore, the results of the investigations may be probably susceptible to false positive rates because the physician must have to analyse a large database during spirometric investigations. Additionally, because of inter-individual variations and the extensive interdependency of the dataset, results may be misinterpreted. It is now crucial to identify the important aspects of spirometric pulmonary function that aid in the disease's diagnosis [8]. This initiates a need for selection of composite hand-crafted engineered features for stratification [9].

Alternatively, an empirical induction based approach is a better solution for such knowledge based problems. Recently, learning features empirically from data by unsupervised machine learning has emerged in the field of engineering. Recent advancements in Restricted Boltzmann Machines (RBMs) have led to various novel developments, particularly in areas like deep learning, generative models, and hybrid architectures.

The principles of RBMs, their architecture, training methods, and common applications are analyzed along with the overview of key theoretical concepts related to RBMs and how these models can be effectively used in machine learning tasks [10]. A hybrid model that combines a stacked Restricted Boltzmann Machine (RBM) with Sobel directional patterns for predicting melanoma in colored skin images is carried out. The hybrid approach is designed to improve prediction accuracy and robustness [11]. A novel approach for image feature extraction using a Fuzzy Restricted Boltzmann Machine (FRBM), an extension of the traditional Restricted Boltzmann Machine (RBM). This method aims to enhance image processing tasks, such as feature learning, dimensionality reduction, and classification [12]. Traditional training methods for RBMs often rely on a fixed learning rate, which can lead to suboptimal performance due to issues like slow convergence or unstable updates. a dynamic learning rate can improve the efficiency and effectiveness of RBM training [13]. An adaptive learning rate strategy (SADSN) semisupervised deep stacking network is suggested as a solution to the sample loss resulting from manual feature extraction and supervised learning of EEG data. The SADSN accelerates the convergence of a contrastive divergence (CD) algorithm by including the concept of an adjustable learning rate [14]. An approach for leveraging Restricted Boltzmann Machines (RBMs) for link prediction in dynamic networks by incorporating both the current network structure and its temporal evolution which offers a more powerful and adaptable method for forecasting future links, improving upon traditional static models in various real-world applications [15]. DBNs has been shown to outperform traditional methods that rely on GMMs and HMMs for speech recognition applications in acoustic modeling by learning hierarchical representations of speech features [16]. Exacerbation frequency in the COPD Gene cohort classification with deep belief networks, a deep learning neywork has achieved an optimal accuracy of 91.99% [17]. Techniques for more effective feature extraction and reconstruction through periodic RBM training are suggested.

Then, in collaboration with the anti-vibration coefficient and the reconstruction error, the Improved Dynamic Learning Rate (IDLR) is devised to achieve an automatic and exclusive training step [18]. Deep Belief Networks (DBNs) to Electroencephalography (EEG) data analysis, plays a crucial role in diagnosing and understanding various neurological conditions [19]. A survey of intrusion detection techniques based on Deep Belief Networks (DBNs) and their application in the field of network security have been elucidated in [20].

2. RELATED WORK

Here a brief literature survey has been provided to bring up the algorithms used in the past years. Veezhinathan et al., proposed that feed forward architecture is useful in classifying abnormal and normal pulmonary disorder. The accuracy, sensitivity, and specificity of NN were found to be 96%, 95%, and 100% [21]. Sujatha C. M *et al*. explored the use of Artificial Neural Networks (ANN) to classify respiratory data and Radial basis function neural network was found to be more sensitive than compared to back propagation neural networks [4, 22]. Prasad *et al*., proposed different machine learning algorithms for classification of asthma data. Particle swarm Optimization (PSO) has found to outperform all the others with sensitivity 100%, specificity 80% and accuracy of 84.16%. [23]. Chatzimichail *et al*., employed ANN technique such as MLP and PNN topologies for children suffering with recurrent wheezing with asthma. A best prediction accuracy of 96.77% was able to achieve in both cases [24]. Mythili *et al.,* has proposed SOM for classifying normal and abnormal spirometric subjects for which the classification accuracy of varying SOM units were observed. The classification accuracy of 95% was recorded [25]. Mythili *et al*., worked out Logistic model tree classifier based on QPSO features and Decision tree-based classifier and reported a classification accuracy of 95% in both the cases [26]. Pramila et al., carried out Neural Computing and Genetic Computing to classify spirometric patterns. Extreme Learning Machine (ELM) was compared with Evolutionary Extreme Learning Machine (EELM) and an accuracy of 91.03% and 100% was reported [27].

Majority of the current works concerned with classification of data based on the use of traditional pattern recognition and classifiers training. Majority of the works are connected to extraction of hand crafted features that is considered to be shallow and the absence of automatic extraction of deep features is a major lacuna.

Though SVM uses the kernel functions and are capable of handling unlabled data, it is still a type of perceptron in which the features are directly obtained from the data but not learnt from the data. The domain experts aid in hand engineering the required features and identification of feature selection algorithms is also taken care of. The process is time-consuming needs human intervention. The whole process has to be repeated due to the abrupt changes in data types and prediction tasks. There is a dire need for automatic extraction of discriminant features from the physiological data with minimal human intervention.

An architecture, which is capable of learning the features from the data as well as dealing with the unlabeled data is required. Also to overcome the limitations of existing methods such as large search time, over-fitting, extensive memory requirements and challenging huge databases [28]. Recently, the deep learning model with deep architecture and good learning algorithms performs the intellectual learning of the features. The need to extract high-level abstract features has paved the way to leverage the deep machine learning framework, which is a multi-layer neural network that exhibits tolerance to characteristics of rotation, scaling, and translation [29].

Recently, the association between respiratory health issues and mental health has garnered a lot of attention and research is in full swing in this area [30]. Respiratory abnormalities especially obstructive and restrictive conditions have been strongly shown to be associated with the likely chances of the onset of mental health problems [30,31]. The prevalence of anxiety and depression have been shown to have a huge association with improper lung function especially in people suffering from COPD [32]. However, the mechanisms of the underlying factors linking lung function and mental health are still under research. Hence, it is critical to predict the respiratory abnormalities accurately that may be swiftly addressed and alleviated such that the onset of mental health problems can be evaded.

The objective of this work has been framed to address an impending problem of identification of the unexplored area of interpreting raw spirometric patterns to assist in the accurate clinical interpretation. This has been explored by focusing on the use of powerful and high-level computationally intelligent techniques namely, Dynamic Restricted Boltzmann Machine (DRBM) and Deep Belief Network (DBN) for the classification of raw spirometric patterns thus eluding the process of feature selection.

3. METHODOLOGY

A. Data Acquisition

A total of (N = 1030) volunteers' spirometric recordings were collected for the current study. The demographic features such as height and weight are measured prior to recording the age, gender and race of the subject. The portable Spirolab II spirometer with a gold standard volumetric transducer is used for recording data. The data acquisition is carried out in a room that had a temperature maintained at 25°C and tests are performed in a sitting position. The subjects were instructed to inhale as much as possible and then exhale forcibly and completely. This process is recorded to obtain the flow volume loops. Each subject is given a chance to complete three consecutive iterations to measure the values of FEV1 and FVC volumes as per the norms of American Thoracic Society (ATS) standards. The data is normalized for further processing.

B. Deep Learning Techniques

Here, two techniques namely, Dynamic Restricted Boltzmann Machine, a form of Restricted Boltzmann Machine and Deep Belief Network have been discussed in detail.

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1) ***Restricted Boltzmann Machine:*** A RBM is a two layered random neural network. The first set of units which represent the observation is defined as visible layer and the second layer which functions as a feature detector is called hidden layer. According to the architecture the two layers in an RBM are fully connected in such a way that each unit in a layer is connect to all the units of the other layer [13]. Conversely, there exists no connection within the same layer, which indicates that the units in the same layer are conditionally restricted to each other. Restricted Boltzmann machine with four visible units and three hidden units is shown below in Fig 1.

The symmetric weights are used for interlinking of units between visible and hidden layer. The objective of RBM is to adjust the parameters to lower the energy on training samples as far as possible which is equivalent to maximize the log-likelihood for the training samples [14].

Energy function is given by

$$E(v,h\,|\,\theta) = -\sum_{i=1}^{I} v_i b_i - \sum_{j=1}^{J} h_j c_j - \sum_{i=1}^{I}\sum_{j=1}^{J} v_i h_j w_{ij}$$

where $\theta = \{\, w_{ij}\,, b_i\,, b_j \,\}$

w_{ij} indicates the strength of edge connections between the ith visible unit v_i and the jth hidden unit h_j . b= b_i and c = c_j are the biases. The joint probability [13] of the status $(v\,,h)$

$$P(v\,,h\,\,|\,\theta\,) = \frac{e^{-E(v,h\,\,|\,\theta)}}{Z(\theta)}$$

where $Z(\theta)$ is a constant for normalization and given by

$$Z(\theta) = \sum_{v,h} e^{-E(v,h\,\,|\,\theta)}$$

The conditional probabilities of binary RBM inferred from the joint probability are expressed as

$$P(h_j = 1|v\,,\theta) = \sigma(c_j + \textstyle\sum_i v_i\, w_{ij})$$

$$P(v_i = 1|h\,,\theta) = \sigma(b_j + \textstyle\sum_j h_j\, w_{ij})$$

The parameters are adjusted to lower the energy on training samples, which is equivalent to maximize the log-likelihood for the training samples [13].

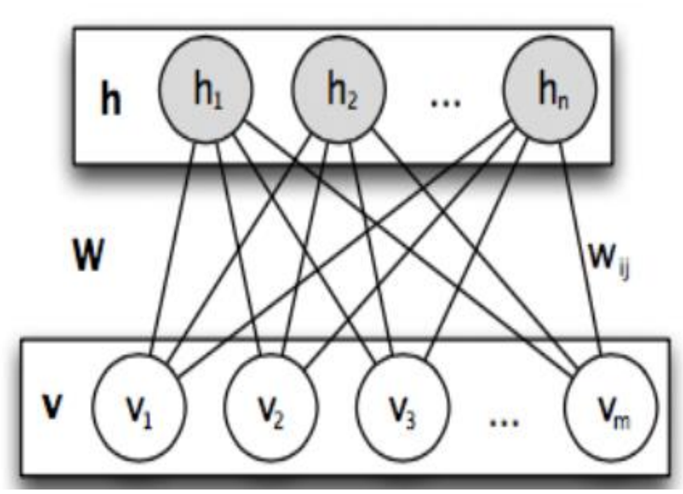

Fig. 1 Restricted Boltzmann machine with four visible units and three hidden units [33]

Dynamic Restricted Boltzmann Machine: *RBM is heavily influenced by the initial values and learning rate. Existing literatures shows that the learning rate was fixed while training RBM. If suitable learning rate is not adopted the results may not be appropriate. This is because if the learning rate is too small, RBM will converge slowly and if the learning rate is too big, it will lead to the large fluctuations of the result. Consequently, a good learning rate plays a significant role while training RBM [13].*

Therefore, dynamically choosing an appropriate learning rate while training RBM can give better results. The optimal learning rate can be found in each iteration. But it is likely to cause the learning rate to fluctuate largely and make the network unstable [18]. The basic idea is to vary the learning rate dynamically until the reconstruction error (RCERR) is declined. Once RCERR is declined, the current learning rate is accepted and there is no change in it [13]. RBM converges slowly for small learning rate and result with a larger fluctuation for high learning rate.

Parameter update equation is given by

$$w = w + \varepsilon\left(P\left(h_{(1)} = 1 \,\middle|\, v\right)v^T - P\left(h_{(2)} = 1 \,\middle|\, v_{(2)}\right)v_{(2)}^T\right)$$

$$b = b + \varepsilon\left(v - v_{(2)}\right)$$

$$c = c + \varepsilon\left(P\left(h_{(1)} = 1 \,\middle|\, v\right) - P\left(h_{(2)} = 1 \,\middle|\, v_{(2)}\right)\right)$$

ε is the learning rate, and v is the training data, $v(2)$ is the generated data of the model $h(1)$, and $h(2)$ is the corresponding status of hidden units. Learning rate is updated dynamically until declined reconstruction error (RCERR) is achieved.

$$RCERR = \sum_{v\epsilon T} \|v - v_{(2)}\|$$

2) ***Deep Belief Network Architecture:*** *The deep learning architecture is explored to aid in effectively reducing the dimensionality of the feature vector for the model. A densely linked series of layers of Deep belief networks (DBNs) are formed by a stack of restricted Boltzmann machines (RBMs). The architecture of Deep Belief Network is shown in Fig 2. The DBN is trained by a greedy layer-wise unsupervised training [17]. After the RBM stacks are trained using a*

generative approach, back propagation algorithm is adopted for fine-tuning of the parameters with the aim of maximizing the probability distributions among the positive instance and the predicted instance

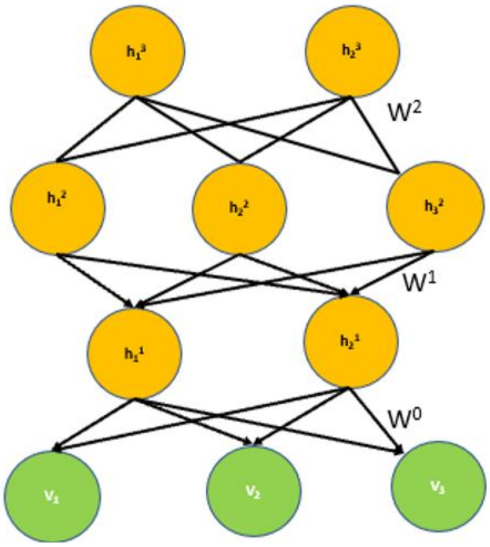

Fig. 2 Deep Belief Network [34]

A three-layer DBN with one layer of visible units and two layers of hidden units are considered to perform feature representation and classification. According to the architecture of deep learning initialization of mathematical model is carried out by considering all the three layers. But most of the critical features are extracted in the first layer and are most sensitive than the features of the next layer which will have high impact on classification applications. The network provides the probability of every input vector by the energy function.

The energy function is given by the equation,

$$E(v,h;\theta) = -(V + H + W)$$

where $V = \sum_{i=1}^{I} v_i b_i$, $H = \sum_{j=1}^{J} h_j b_j$, $W = \sum_{i=1}^{I}\sum_{j=1}^{J} v_i h_j w_{ij}$

The joint distribution of the visible and hidden units is given by the equation

$$P(v,h;\theta) = \frac{1}{Z}\exp\left(-E(v,h;\theta)\right)$$

where Normalization factor,

$$Z = \sum_{i=1}^{I}\sum_{j=1}^{J} e^{-E(v,h;\theta)}$$

The conditional probabilities of the visible and the hidden layers are calculated as

$$P(h_j = 1|v;\theta) = \sigma(W_v + b_i)$$

$$P(v_i = 1|h;\theta) = \sigma(W_h + b_j)$$

$$W_v = \sum_{i=1}^{I} v_i w_{ij}\,, W_h = \sum_{j=1}^{J} h_j w_{ij}\,, \sigma(x) = 1/(1+\exp(x))$$

By taking the gradient of log likelihood $\log P(v,h;\theta)$*, the weight update rule [17] is given by*

$$\Delta w_{ij} = E(D) - E(M)$$

where ***D*** *and* ***M*** *represent the expectation of training set and the model distribution respectively. The Expectation E denotes the learning rate of the network and the proper value of W is obtained during the learning process.*

4. Results and Discussion

It is observed from Fig 3 that the normal flow volume curve has dissimilar inspiratory and expiratory manoeuvres. In abnormal conditions, alteration of lung volume is observed that is in case of restrictive pattern the flow volume loop depicts a normal shape with reduction in overall volume.it is characterised by reduced FVC and possibly a relatively high PEF whereas in obstructive pattern a reduction in lung volume with prolonged exhalation exhibiting concavity in the loop is observed. it is characterised by reduced FEV1 and reduced FEV1/FVC. The mean values of the spirometer parameters extracted for normal subjects are noticeably greater than those of the abnormal cases.

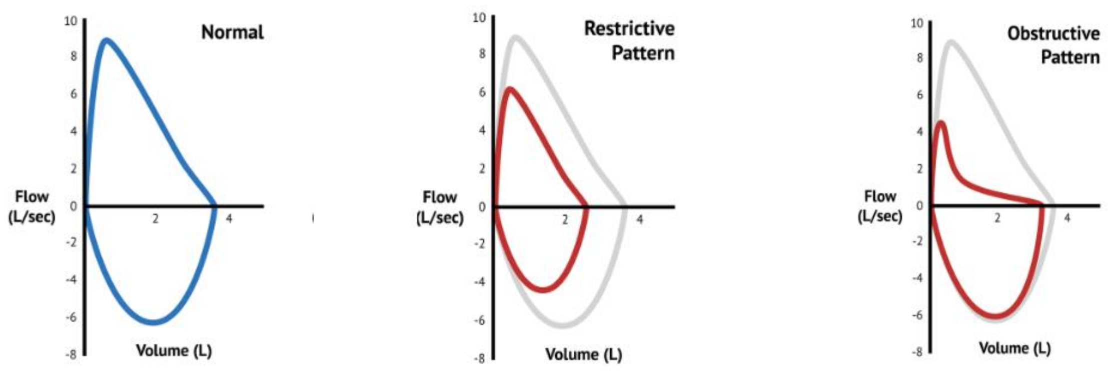

Fig. 3 Flow Volume loop of normal and the respiratory abnormalities [35]

The spirometric data are categorized into different respiratory conditions using deep learning techniques like DRBM (RBM with dynamic learning rate) and Deep Belief Networks.

The results pertaining to the DRBM and DBN networks have been elucidated in the following sections.

*1) **Dynamic Restricted Boltzmann Machine:** Learning rate of DRBM is dynamically updated until reconstruction error is declined for characterizing raw spirometric data. A learning rate that is too high will impede convergence, whereas a learning rate that is too low will result in overfitting or too sluggish convergence. For this investigation, the learning rate is therefore fixed at 0.005. This optimal learning rate results in reduction of energy which in turn allows fine tuning of weights and extracts the critical features from the data. This critical features are highlighted with different colours based on the distribution of weights and is shown in Fig. 4. The signature patterns of normal and abnormal patterns are shown in Fig 5 and 6. Both the figures shows that error rate reduces as the number of output nodes are increased. It is evident that the patterns are distinct in normal and abnormal cases. It also indicates that abnormal data has high variation compared to normal data. From Fig, 5 it is evident that the signature pattern of normal data shows a variation of error rate from .007 to .001.The error rate fluctuates for output nodes varying from 80 and 160 after which it records a minimal error of approximately around .0005. Similarly from Fig.6 it is understood signature pattern of abnormal data shows a variation of error rate from .009 to .04 for same number of output nodes shown in normal case. Here too the error rate fluctuates for output nodes varying from 80 and 160 as identical to normal case after which it records a minimal error of approximately around .005. Variation of average error rates for varied epochs is shown in Fig 7. The percentage of average error rate decreases rapidly as the number of epochs are varied. It reduces drastically at initial epochs and shows variation in reduction for epochs less than 15 and starts settling slowly beyond 15 epochs. After 30 epoch saturation is observed which shows that much variation in average error rate is not visible. The dataset consisting of normal and obstructive classes are feed as input to DRBM and it achieves higher classification accuracy of 98%.*

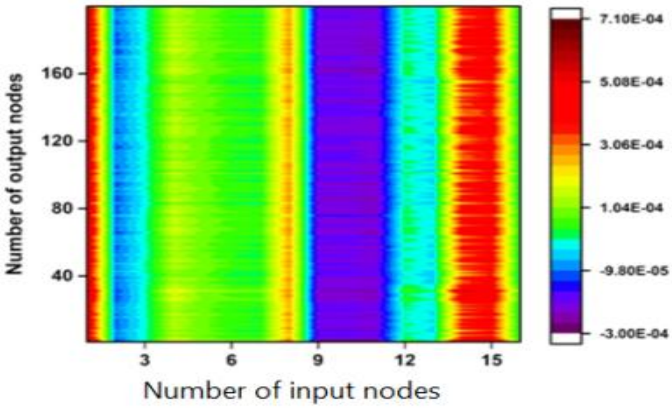

Fig. 4 Distribution of weights of Critical features of DRBM

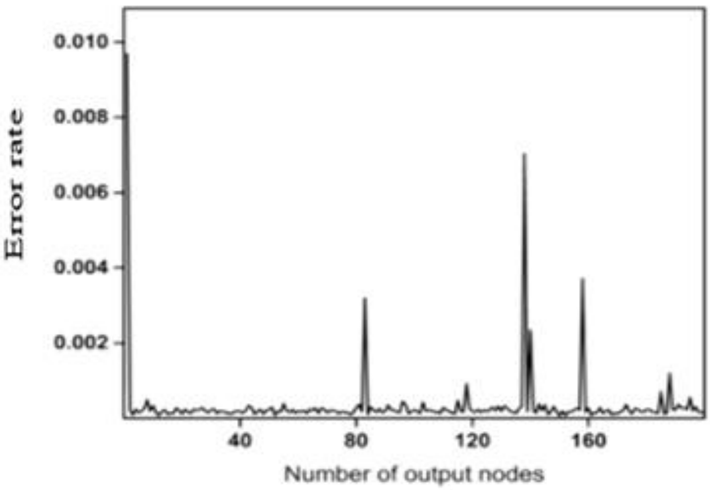

Fig. 5 Signature pattern of normal spirometric data obtained using Dynamic RBM

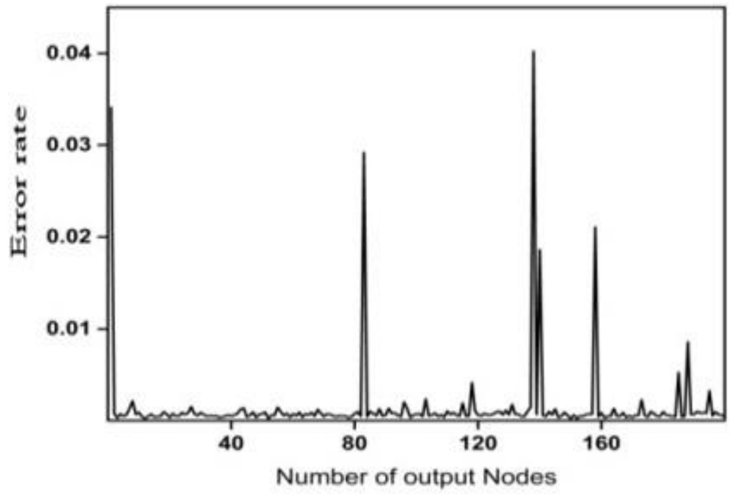

Fig. 6 Signature pattern of abnormal spirometric data obtained using Dynamic RBM

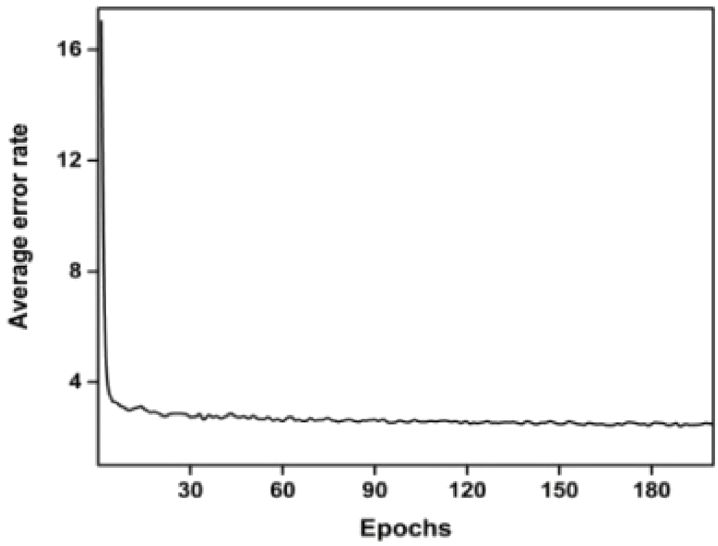

Fig. 7 Variation of average error rates for varied epochs of DRBM

2) ***Deep belief network:*** *A three-layer DBN consisting of two 50-50 hidden layers and one visible layer is considered for this study. The inputs are processed batch-wise with 20 nodes in the visible layer. The DBN weights of second layer and the third layer are set as 50×50 and 50×3. The parameters of DBN such as epochs, batch size and number of iterations are determined in trial-and-error manner. All the variables including W, b and c are initialized randomly and later fine-tuned using back-propagation till all parameters are converged. The performance of the proposed approach is evaluated using k-fold cross validation. Training iterations are varied ranging from 1 to 1000 with a learning rate of 0.001. The accuracy of the classifier is improved until a particular value of iteration and saturates beyond that limit. The number of hidden units in the first and second layer DBN also contributes to improve classifier accuracy. The performance of DBN is enhanced with 50-50 hidden units compared to 50-100 and 100-100 hidden units. A 10-fold cross validation with 930 samples for training and 110 samples for testing are performed.*

Parameters assigned for attaining convergence are: number of features=16; number of subjects=1030;input layer (visible layer) 20 nodes; hidden layers (2-layers) 50-50 nodes; output layer = 3 nodes(C1,C2,C3); iterations=1000; epoch=20; batch size =20; number of batches=46; learning rate=0.001;10 fold cross validation. The number of training samples has considerable impact on the performance of the DBN, which indicates more the training samples, better the selection of critical features and higher the accuracy.

Representation of the visualization of weights of DBN networks is shown in Fig 8. In DBN Critical features of raw spirometric data are obtained from the weights distribution which forms the basis of classification. The dimensionality reduction is achieved when original features are abstracted into critical features. In the first layer, similar distribution for most of the column weights are observed with only few columns showing dissimilar distribution indicating a red color. The features obtained from the previous layer has different color distribution compared to other rows in the second layer. This difference in distribution of color between the layers shows that a few critical features are extracted from the raw data. These critical features serves as input for the classifier.

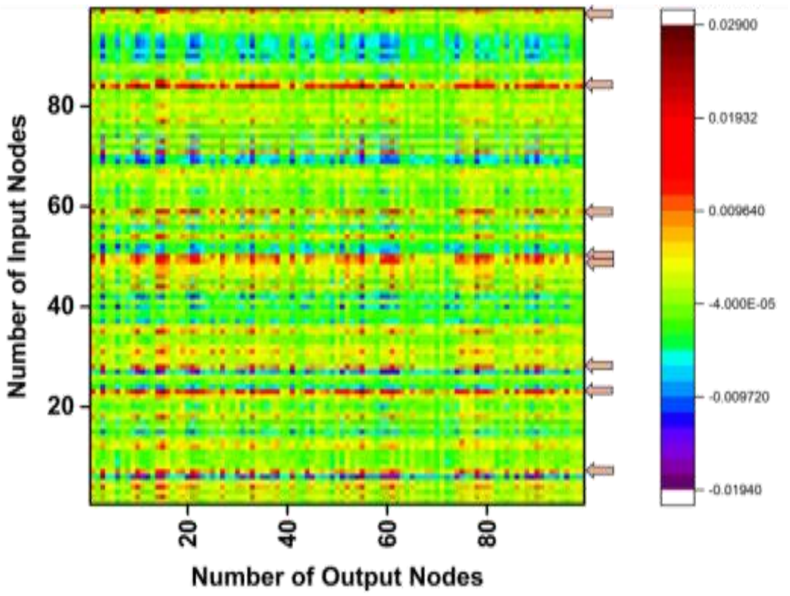

Fig. 8 Visualization of weights of DBN networks

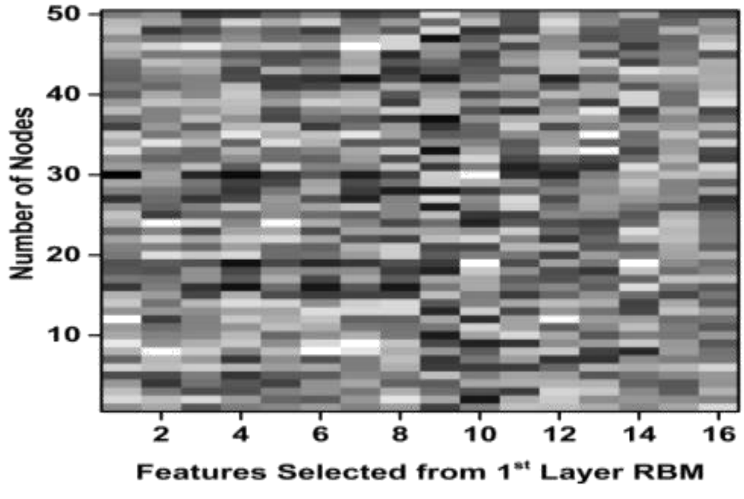

Fig. 9 Features selected from first layer of RBM

Features are fine-tuned using back-propagation till all parameters are converged and are shown in Fig 9 and 10. It is also observed that the proposed algorithm could able to achieve better discrimination amongst normal, restrictive and obstructive spirometric patterns. This three-layer DBN consisting of two 50-50 hidden layers and one visible layer has achieved an average accuracy, sensitivity, and specificity of 85.45%, 82.44% and 89.32% respectively. The Receiver Operating Characteristics (ROC) curve for DBN model is shown in Fig 11.

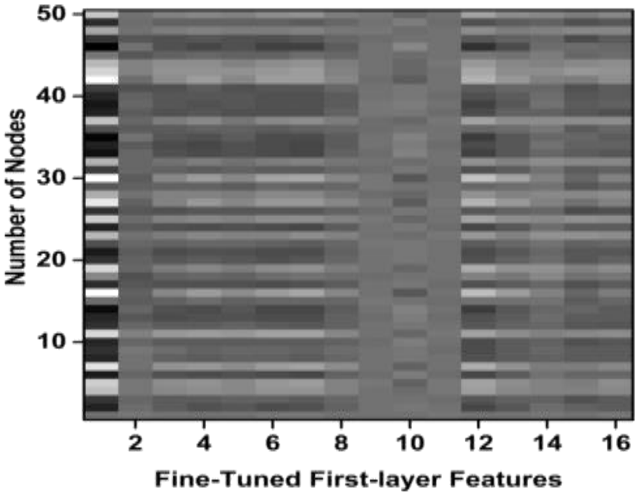

Fig.10 Fine-tuned first layer features

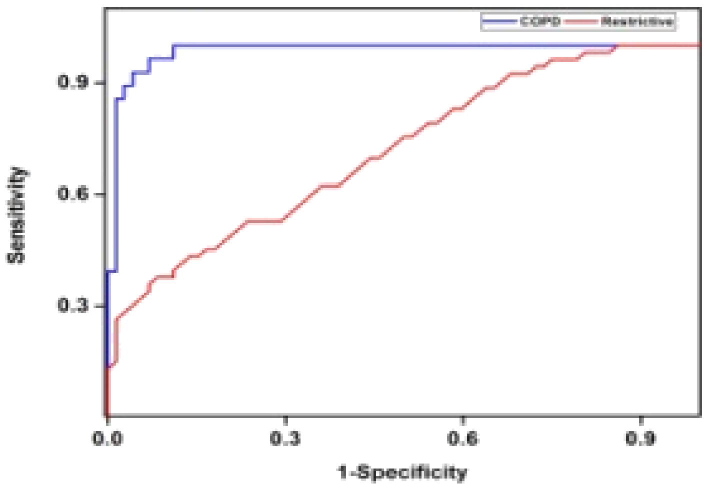

Fig 11. Representation of Area under curve

Results demonstrate that DBN model have high Area under the Curve (AUC) of 0.9842 for obstructive and 0.63 for restrictive class that leads to the inference that this model can achieve better discrimination among normal, restrictive and obstructive spirometric patterns.

5. CONCLUSION

Raw spirometric data are applied directly to Dynamic RBM and Deep belief network for characterization of pulmonary disease and the results show that the network can discriminate the disease well among normal and abnormal classes. This technique is useful in handling raw data of large database and in diagnostically significant in pulmonary function tests. In this work, deep learning is exploited for depicting critical features from raw spirometric data for the classification of data into normal, restrictive and obstructive classes. The performance of the network is validated using 10-fold cross validation for a better assessment of the severity of the disease. The accuracy of the classifiers namely, DRBM and DBN are found to be 98% and 85.45%, respectively. The results demonstrates that as the demarcation between normal and obstructive classes are more distinct, DRBM could able to achieve higher accuracy whereas in DBN since all the three classes normal, restrictive and obstructive were considered for classification and the dataset consist of features that are marginally closer to each other classes, it shows comparatively less accuracy compared to DRBM. Thus the performance of the DBN can be further improved to a higher value if huge database is considered. This limitation will be addressed as the future scope of work. It is observed that as these methods handle raw data directly, feature selection process can be completely evaded thus minimizing time and aid in clinical interpretation of spirometric data with minimal human intervention.

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