A Survey on the different ways of Diagnosing Asthma by Using Artificial Neural Networks Technology

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Abstract:

Breath is the most important and better sample for diagnosing infections and other diseases, the analysis of the breath demonstrate that advantage more than other fluids such as blood. Besides one of the most important technologies used on the tasks of applications of Artificial Neural Networks ANN, is the recognition that uses in many areas such as health, video games, and more.

This seminal paper highlighted distinction between two classification method that used to select and analyze features from breath print, the first one is the Mutual Information (MI) which uses an Information-theoretic approach for feature selection, the Mutual Information approach uses the features as input for classifier: support vector machine (SVM),k-nearest neighbors(K-NN),Bayesian Network (BN), Maximum Likelihood (ML) which all discussed in (Wang. et al.,2014), the second one is the time-frequency analyses methods (Wavelet Transform) and frequency analyses (Fourier) approach that is used for feature selection, in addition it uses these features as input to the classifier: machine learning algorithms Artificial Neural Network (ANN) and k-NN are both used and discussed in (Göğüş. et al.,2015) which used to classify the asthmatic breath sounds.

Keywords: Breath-print, E-Nose, Auscultation, Mutual Information, Discrete Wavelet Transform, Wavelet Packet Transform, Artificial Neural Network

الملخص :

يعتبر التنفس هو العينة الأكثر أهمية والأفضل على الاطلاق في مجال تشخيص العدوى والامراض التنفسية المختلفة الأخرى وقد تبين أن استخدام عينات التنفس الأقرب الى الدقة في النتائج من استخدام السوائل كالدم وغيرها , الى جانب ذلك فإن أهم تقنيات العصر الحديثة المستخدمة في التشخيص والتحديد هي تطبيقات الشبكات العصبية الاصطناعية والتي تعتبر الأكثر شيوعاً في العديد من المجالات المختلفة مثل الصحة وألعاب الفيديو وغيرها .. سلطت هذه الورقة الضوء على المقارنة بين طريقتين مختلفتين من التصنيفات التي تم إستخدامها لتحديد وتحليل المميزات

مريض الربو من خلال من بصمة التنفس, وقد إعتمدت الطريقة الأولى على استخدام طريقة المعلومات المتبادلة (Mutual Information) وهى الطريقة التي تستخدم نهجاً نظريا للمعلومات لاختيار المميزات التي تميز بصمة التنفس من شخص الى آخر ومن ثم استخدامها كمدخل ليتم تصنيفيها وتشخيص وتحديد مريض الربو عن غيره من الامراض التنفسية المختلفة ذات الاعراض المتطابقة وذلك من خلال استخدام مصنفات مختلفة وهى : SVM – K-NN-BN-ML , أما الطريقة الثانية تعتمد على استخدام التحليل الترددى للزمن (التحويل الموجى) لاختيار المميزات التي تميز بصمة الصوت من شخص الى اخر ومن ثم استحدامها إيضا كمدخل للمصنفات المختلفة المتمثلة في : ANN – K-NN- , وذلك لتصنيف وتحديد مرض الربو من خلال تحليل الصوت عن غيره من الامراض التنفسية أيضا.

I. Introduction

Our breath may be as unique as our fingerprints. The Compounds in exhaled air produce a unique and stable molecular autograph or “breath-print” that could be used to monitor disease or to track response to medication. The analysis of exhaled breath much easier to collect than bio-fluids. Therefore, two ways used to analysis mass spectrum and e-nose. However the mass spectrum allows detailed analysis of the composition of breath samples, but they are generally immense, expensive and require the user to have expert knowledge (Wang. et al.,2014). The electronic nose (e-nose) technology is a novel technique, that consist of a gas sensor array and provides a sort of fingerprint of exhaled breath (breath-print, BP) by detecting VOCs through multiple sensors, this technology has been used typify exhaled breath for research purposes(Wang. et al.,2014), also have been tested for diagnosing lung cancer(Spieth, Zhang .,2011), asthma (Sankur. et al.,1994), etc.

Asthma is a chronic disease of the airways that transport air to and from the lungs. No full cure is available, but management methods can help a person with asthma lead a full and active life. For this reason, early detection and treatment of asthma disease is one of the most important medical research areas (Güler. et al.,2009). The most common diagnostic method is auscultation (Göğüş. et al.,2015) is inexpensive, efficient, easy to apply and harmless for the patient. Also, there is a lot of benefit of auscultation which gives direct information about the function of the lungs and provides close patient-physician interaction (Göğüş. et al.,2015). But there is the limitation of auscultation also problems which made the results inaccurate and incorrect also the critical diagnosis like asthma requires an experience basis. In the last decades, with the advent of computer technology and data processing methods, researchers

have tried to parameterize pulmonary sounds to make auscultation a more objective and valuable diagnostic tool (Yeğiner, Kahya ,2009)

In this study, there will be a comparison between two difference ways which will be applied to solve limitation, unreliable and inability of mass spectrum technology and auscultation to classify features and how they used different classifiers of neural network, to get accuracy detected of asthmatic. Furthermore, we will present the most efficient result between the two ways of diagnosing.

The first way applied in (Wang. et al.,2014): MI method which is a measure of the amount of information, one random variable contains another (Erdogmus, Pekcakar, 2009). The approaches is used to get a high percentage of accuracy, of classification on feature selection, by maximizing the value of information, then taking a very small subset of e-nose measuring the feature to achieve better classification performance, also to get rid of the disadvantage of using the mass spectrum. The neural network classifiers which are used to classify the features were selected and measured by e-nose: SVM, KNN, ANN, ML, PCA that provided the effectiveness of MI method.

The second way which applied in (Göğüş. et al.,2015): respiratory sound recorded as signals from normal people and people with asthma in different degrees. These signals are divided into exhalation and inhalation then it will be separated into segment, wavelet transforms (DWT), (WPT) are both used to analysis these segment, after that, it will be decomposed into frequency sub-bands the statistical features which extracting from sub-bands are used as inputs into ANN, K-NN classifier at the end both DWT and WPT performance compared based on their accuracies of classification.

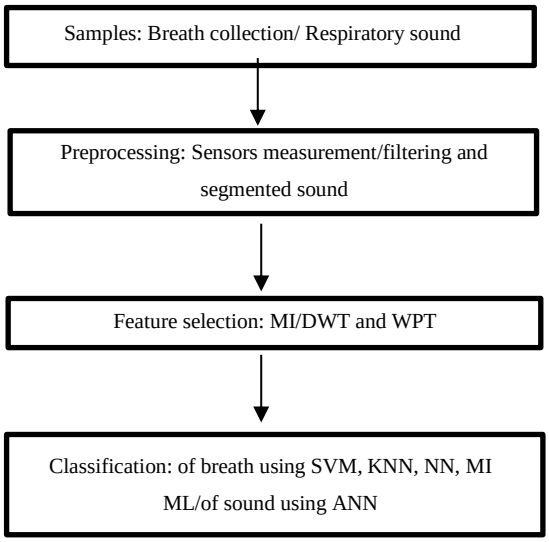

Fig .1. Block Diagram of the process of comparing

II. Materials and Methods:

This section will first describe two different ways, which are used by two papers for collecting samples and instruments, to measure and select features.

Breath collection and nose measurement:

In (Wang. et al.,2014) the experiment of analysis was by collecting breath samples of 10 volunteers (5 males, 5females) from the staff of CSIRO Ecosystem Science at Black Mountain, the age between 18 and 45, healthy non-smokers. The volunteers breathed extreme more than the normal way through a mouthpiece connected to a three-way sliding valve, after that the volunteers performed a single breath with a slow exhalation and opened the slide valve the last portion of breathed trapped in a 3-L which connect to the port of sampling valve. The total of samples 120 collects over 4 visits, all samples stored in a room with cretin temperature to analyzed the next day. The e-nose was the instrument used to analysis, the measure happened every 20s.

The temperature of the sensor surface modulated with 32 sinusoidal started at ~305c which is between 260 and 300c, fig.3(a) showed the response of differing sensors due to temperate over the 20s, fig.3(b) showed the response of sensor based on the actual temperature.

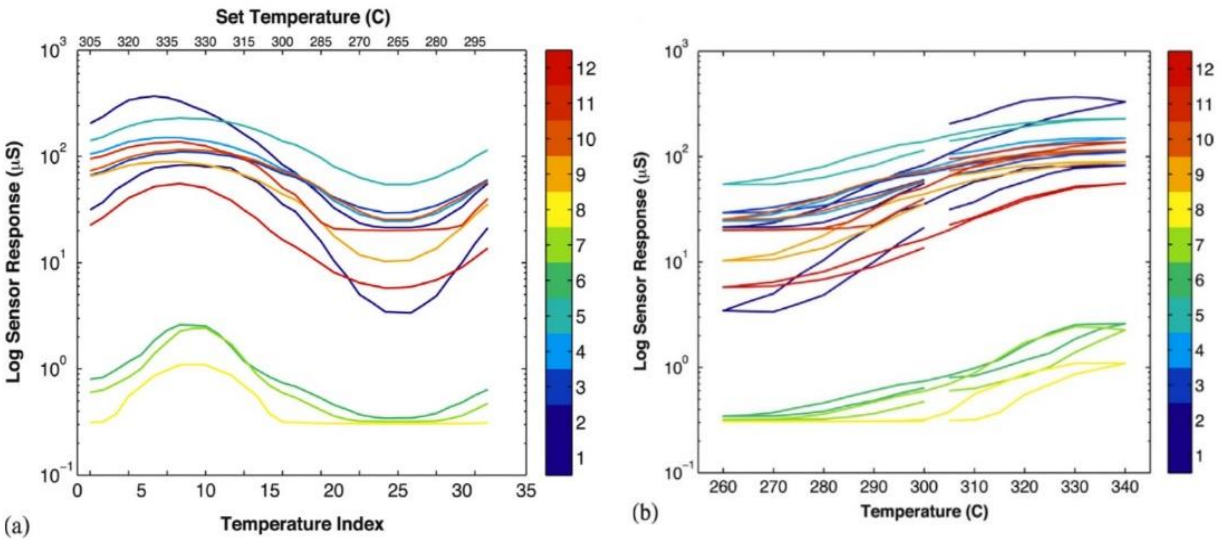

Fig .3. On x-axis (Bottom) index of measurement, on x-axis (Top) index of temperature, y-axis index sensor reading. The colors of curve is index sensor id number showed on the right.

Acquisition of Respiratory Sounds:

In (Göğüş. et al.,2015), the respiratory sound recorded from 11 patients with three levels of asthmatic (high-level asthma, moderate, mild) and normal subject, which all of these recorded

as signals by using Sony ECM T-150 microphone with a cap with frequency (8 kHz). The duration of recorded between 11-12sec with different respiration cycles. To extraction high accuracy of recorded sounds from mixed heart and muscle and another sound they used low-pass and high-pass filtration, the frequencies for low-pass more than 2000Hz for high-pass less than 100Hz, after that these singles are grouped into inhalation and exhalation.

The amount of respiratory sound records is not enough for proper classification due to few patients (Göğüş. et al.,2015), the inhalation and exhalation separated into the segment for respiratory cycle phases contain inhalation phase and exhalation phase. The measurement tools used for processing signal is Wavelet Transform (WT), the WT based on decomposed the signal into blocks localized in (time and frequency). The WT used rather than Fourier Transform because the FT did not provide enough for non-stationary singles (Göğüş. et al.,2015). To solve the limitation of FT the Short-Time Fourier transform (STFT) which used by applying the single window technique, WT and STFT both worked with short windows at high frequencies and long windows at low frequencies (Göğüş. et al.,2015). Discrete two bands based on frequency which are low and high. The fig.4 shown the structure of DWT. The two frequency higher and lower decomposed into two sub-bands by used Wavelet Packet Transform (WPT). WPT tree structure with 3 levels is shown in fig.5. (Orhan. et al.,2011)

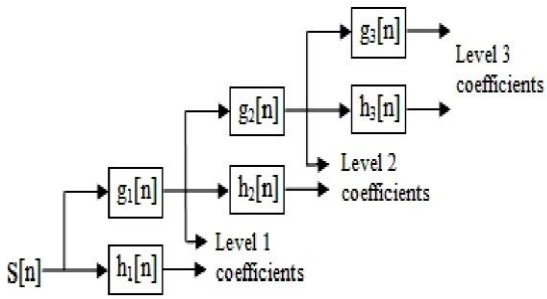

Fig .4. DWT Structure

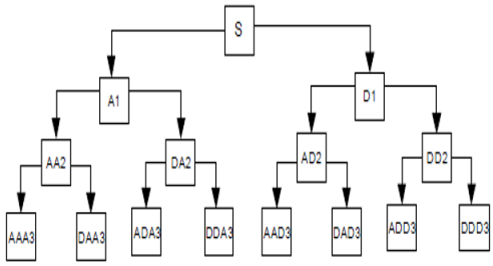

Fig .5. WPT Tree Structure

III. Feature Selection:

This section describes the feature selection ways, which are used by researchers on (Wang. et al.,2014) and (Göğüş. et al.,2015) due to different techniques of diagnosing the asthmatic which one is from sound and the other is from breath. The task of selection feature is so difficult and important because it will be used as inputs to the classifier, two different ways used by the researcher.

1. For that the approach which used on (Wang. et al.,2014) to select features: Maximizing the MI I (Z^{υ}, C) between selected features Z^{υ} = {Zi1,….,Z^{in}} which υ number of features and C for class

   $$I(Z^{\upsilon}, C) = \sum p(Z^{\upsilon}, C) \log 2 \frac{p(c|z^{\upsilon})}{p(c)} \quad (1)$$

2. Take the highest MI to the class.
3. Employed the Kraskov-grassberger technique (Göğüş. et al.,2015) for estimating MI.

The common approaches which used by researcher on (Göğüş. et al.,2015) for selection features:

1. Using DWT to decompose each segment of respiratory sound to 7 levels.
2. Each single of sound divided into D1-D7 "sub-band detail" and A7 approximation which is shown on fig .6.(Göğüş. et al.,2015)

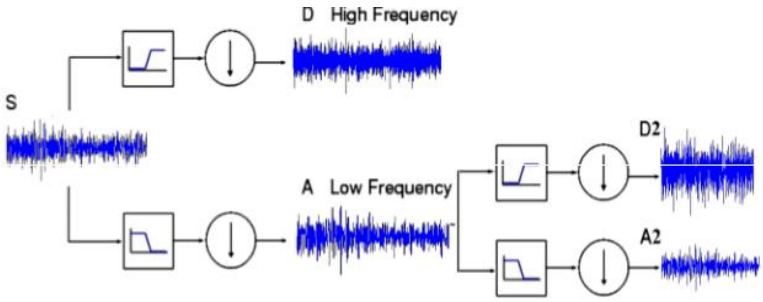

Fig .6. Approximation and sub-band detail sub-bands of an asthmatic

3. Applied WPT to each segment of the sound for decomposition which shown on fig .7. (Göğüş. et al.,2015)

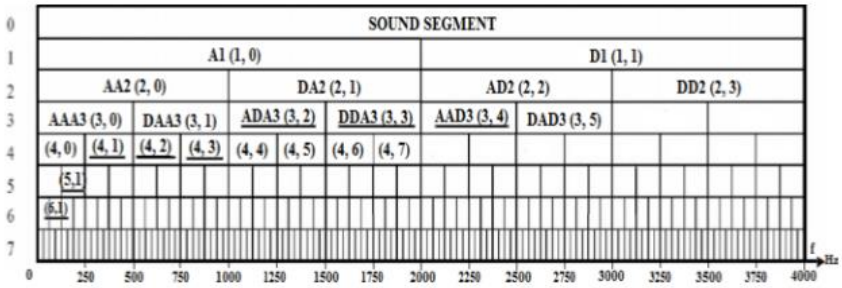

Fig .7. Decomposition of sound segment using WPT

4. Used statistical feature which extracted from D2-D6 detail sub-bands for DWT and same statistical features are extracted from selected sub-bands of tree for WPT (Göğüş. et al.,2015).
5. Applied power spectrum (energy per unit time) fig.8. Shown asthmatic sound segment and power spectrum of D2 detail, also the Power spectrum of coefficients of DDA3 sub-band of WPT tree shown on fig.9.

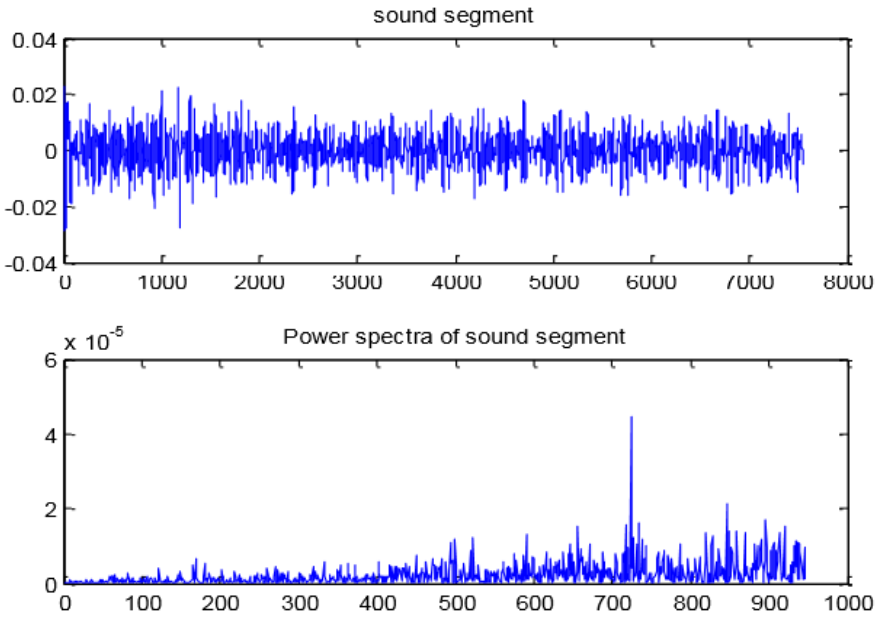

Fig .8. Asthmatic sound segment and power spectrum of D2 detail

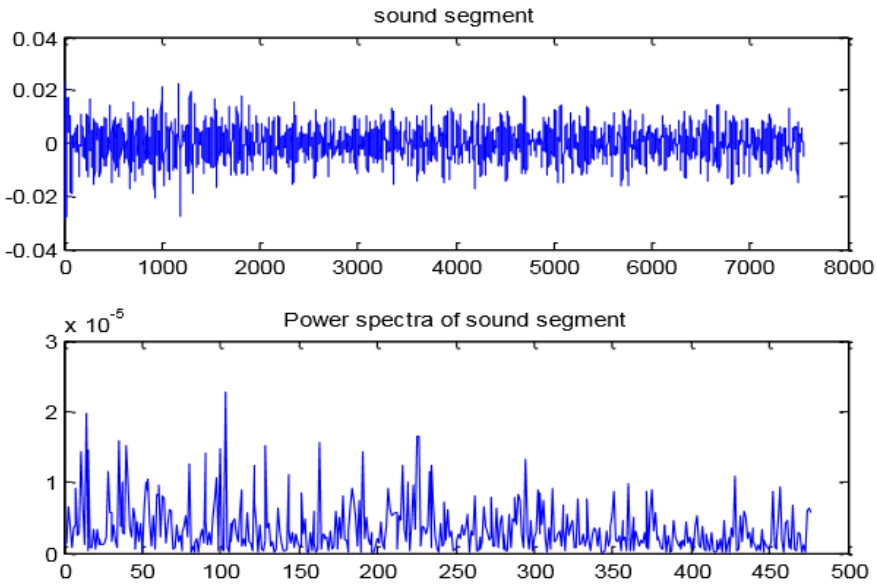

Fig .9. Power spectrum of coefficients of DDA3 sub-band of WPT tree

IV. Classification Using Artificial Neural Network:

This section describes the use ANN for classification, and the different classifier used by researcher's .In addition, the different accuracy of results.

The researcher in (Wang. et al.,2014) the data divided 120 samples into pairs of training sets (119) and test set (1) and the processor repeated 120 times to cover all data also to eliminate the over fit. After that the common classifier is applied to test set to get the effecting of the feature which selected, the classifier which used are listed below:

1.Support Vector Machine (SVM): It works by dividing the data into number of class, the researcher used Libsvm Library (Chang. et al.,2011) to get the classification, they divided the data into nine C value started with 1 and increased by 4 factor (i.e. C= {1, 4, 16, 64, 256, 1024, 4096, 16384, 65536}) to get the best performance over the large number of C values. They used nonlinear and linear types of SVM by applying Gaussian radial kernel function $k(x_i,x_j)=\exp(-\gamma\|x_i,x_j\|^2)$, x_j means the vector of the data , x_i sample of data, γ kernel of width. The result of performance of using two type of SVM is not difference and also did not improve for C>256, therefor they used the performance with C=256 and compared with other classifiers results. (Cortes, Vpnik ,2014)

2.K Neatest Neighbor (KNN): It works by computing the distance metric between input and existing data set where means the data points with smallest distance. They used neighborhood size for k={3,5,7,9,11}, the samples 12 of each class (11 is maximum value of k , 1 leave-one-out cross validation), also there is not any difference on performance for each difference of k value, they used the performance on k=7.(Russell. et al.,1995)

3.Bayesian Networks (BN): It works based on random variable represent from each node X with probability function, the core of how it works depends on the condition of linked edge and their variables(Friedman. et al.,1997). They instead used the BN because of the complexity of using the simplest classifier Naïve Bayes which work by representing the node as parent to all nodes.

4.Neural Network (NN): They used Multilayer Perceptron (MLP)Feed forward with 100 iteration within three optimization algorithms (quasi-Newton, conjugate gradients, scaled conjugate gradients) the number of hidden layer (6 or 12), the best performance that used to compare 12 hidden layer and quasi-Newton optimization. [13]

5.Mutual Information Maximum Likelihoodn(MI ML): It works by maximizing the local MI I ($z^{\upsilon=}$ z^{υ} ,C=c) with selected feature, which is the same with the approach of selecting the class that maximizes the probability p (z^{υ}| c) inadition, it is same with maximum likelihood classifier which was evaluated by Krsskov-Grassberger. [16]

Beside that the researcher in (Göğüş. et al.,2015) used ANN classifier with back propagation algorithm to classify the sounds and divide it into four class depending on degree of asthmatic (serve asthma, mild asthma, moderate asthma, and normal asthma), the input neurons 30 for feature vector (DWT), and 48 neurons for (WPT), 23 neurons for hidden layer, 4 output layer as compare between (DWT and WPT). The structure of ANN is shown on fig.10.

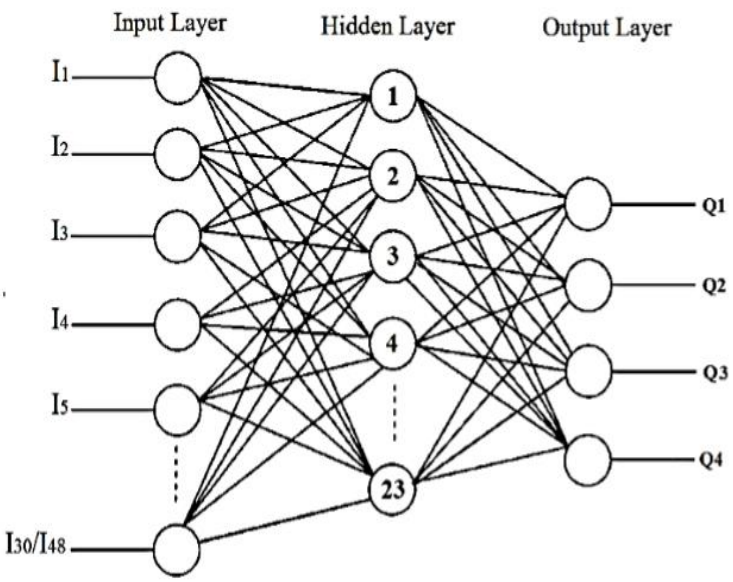

Fig .10. MLP Structure

V. Results and discussion

This section describes the results of two papers based on two different ways which are used to extract features and used it as inputs to classifiers on two papers the accuracy of results was the difference. Also, discussion by made comparing of results. Thereby, in Wang. et al.,2014 the researcher used five number of classifier used the features which selected by MI method and the cross-validation used for classify the results, the accuracy of four out five classifiers (SVM, KNN, MI ML, BN) was 100% with fewer than 10 feature, however, NN classifier was the worst at performance. Fig.11. (Wang. et al.,2014) shown the accuracy of the classifier.

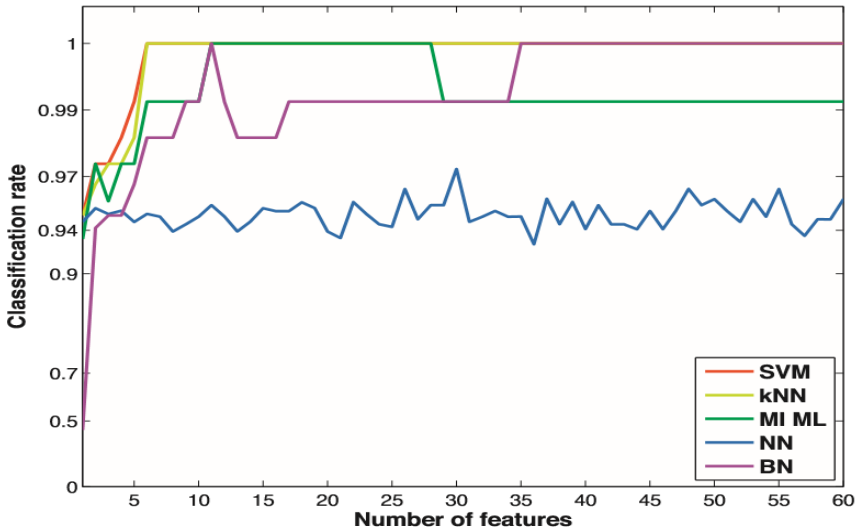

Fig .11. The accuracy of five classifier

On (Göğüş. et al.,2015) the researcher used the ANN classifier for separately feature for inhalation (right basal- left basal) and exhalation (right basal- left basal) which extracted by DWT WPT methods, 10 cross-validation applied and 1000 iteration, the accuracies for normal and three different asthmatic class by used different classifier shown on Table I and Table II below, as showed the DWT more advantageous and the performance slightly higher except exhalation right basal.

As a result, we likely see and encourage the researcher on (Wang. et al.,2014) which proved the best way for diagnosis with high accuracy by using the E-nose assessment tool. Also, they tried with more than one classifier to get the best result, which that lead to reaching to accurate way for diagnoses.

Table I. Classification of accuracy using ANN and DWT

Basals	Classification Accuracies (%)	
	DWT	
	Inhalation	Exhalation
Right Basal	91.67	76.67
Left Basal	90.00	86.67

Table II. Classification of accuracy using ANN and WPT

Basals	Classification Accuracies (%)	
	WPT	
	Inhalation	Exhalation
Right Basal	90.00	80.00
Left Basal	88.33	81.90

VI. Conclusion:

Asthmatic is a chronic disease, also the detection and the treatment is one of the most important medical research areas. Based on the results on (Wang. et al.,2014) and (Göğüş. et al.,2015) in which they used two different ways to diagnose the asthmatic by E-nose measurement and respiratory sound, by comparing the methods and accuracy for each papers, we found the information-theoretic approaches applied in (Wang. et al.,2014) by using 10 volunteers and 120 samples, with different and common classifiers (SVM, KNN, MIML, BN), in addition the feature which was classified by the classifiers was fewer than 10. The ANN also were within 12 hidden layers, therefore as a result of that it showed the high accuracy at (100%) which is better than paper (Göğüş. et al.,2015). However in (Göğüş. et al.,2015) it was applied by using wavelet transform(WPT, DWT) ,11 patients with a different class of asthmatic (normal, serve, moderate and mild), by using NN classifier for separately (inhalation and exhalation) right and left basal , within 23 hidden layers the accuracy was (91.67%). we suggest to use the information-theoretic technique in (Wang. et al.,2014) in which has approved high level of accuracy rather than the physical exam and family history which are normally used in our Libyan hospitals .

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