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Diagnosis of Obstructive Apnea Disease AHI in Chemical Warfare Veterans based on HRV Signals Analysis using the ANFIS Neural Network

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Abstract: *Sleep apnea is very common in patients with heart failure and is considered a major cause of death. The main causes of this apnea are patients' unawareness, lack of diagnosis, and ignoring the disease without considering any treatment. Currently, sleep apnea is being diagnosed primarily based on night Polysomnography. A complete recording, which is based on the apnea occurrence, is costly, cumbersome, and difficult to conduct. This study aims to provide an algorithm for the diagnosis of sleep apnea from electrocardiogram signals under the treatment of chemical warfare veterans. For this purpose, a study has been conducted with a combination of extracted features from changes in heart rate and signals of the electrocardiogram. Reducing the computational effort and the number of features as well as maintaining the high performance of the classifier are the subjects that are considered in this report. In other words, using ECG signal processing, especially HRV and EDR signal, the apnea is examined and to diagnose, the designed neural network in this study achieved a specificity of 98.94%, sensitivity of 77.21%, and accuracy of 98.38%. This test was conducted in Baqiyatallah Hospital and the mean absolute error in detecting AHI for 96 patients was 2.6. To evaluate the performance, the comprehensive Physionet database with the specificity of 99.73%, sensitivity of 87.43%, and accuracy of 92.95% has been used in the ANFIS model, and for further investigation of the AHI, patients were also studied in the formerly designed neural networks.*

Keywords: *Intelligent model, Prediction, Obstructive sleep apnea, Chemical warfare veterans, Combined learning models, Neural networks, AHI, Obstructive apnea, ANFIS*

INTRODUCTION

Sleep apnea was diagnosed in 1991 for the first time and was defined as a respiratory disease combined with airflow interruption in the respiratory tracts for at least 11 seconds during sleep. This problem is usually combined with a decrease in oxygen saturation in the blood, resulting in sleep disorders and poor respiration in patients (Lyle, 1999). Besides, repeated Apnea during sleep causes a hypothesis called hypoxia that is triggered by the activation of free oxygen radicals and is, in fact, a response to the problem caused by Apnea. Obstructive sleep apnea occurrences are commonly defined based on respiration repetitions of the patient over a period, which is categorized by observing and recording abdominal and chest movements. Obstructive Sleep Apnea (OSA), the most common type of obstructive sleep apnea, is stopping completely airflow in the lungs. In contrast, it is considered a central sleep apnea when there is a complete interruption in both respiratory movements and airflow for at least 10 seconds. Ultimately, the combination of these two symptoms is defined by a central apnea. In a relatively short period, by an obstructive air-conditioning effort, sleep apnea is called mixed sleep apnea (Grigoraş et al., 2008).

Given the importance of occurrence prediction and fast detection of possible obstructive sleep apnea, one can mostly prevent the death of patients.

The consequences of sleep deprivation are the reduction of brain activity and metabolic disorders, resulting in an individual's significant misjudgment. It also increases the risk of chronic illnesses. Other effects of sleep deprivation are memory loss, immune system problems, weight gain, and mood swings. Besides, sleep apnea is very common in patients with heart failure. These studies also show a clear relationship between the percentage and severity of apnea and high blood pressure and cardiovascular disease (Yin et al., 2008). Sleep apnea is known as a risk factor for death in patients with heart failure. Therefore, all patients with high blood pressure, obesity, and heart failure should be studied concerning sleep apnea. (Considering the importance of predicting the occurrence of obstructive sleep apnea, several methods have been considered). The most basic method for diagnosing this disease is to perform a full polysomnography test.

Several physiological monitors are attached to the patient to record breathing, brain activity, and patient activities during sleep. Several electrodes are attached to the patient's head to observe the electrical activity of the brain using an Electroencephalogram. This information allows the physician to observe the patient's deep sleep time. The electrodes recording the visual signals are attached to the skin, close to the outer edges of the eye, to record information of Electron Diagram and to show when the patient experiences deep sleep (Grigoraş *et al.*, 2008). A sensor is placed close to the patient's mouth and nose to measure the airflow. Electrocardiogram electrodes are also placed on the patient's chin to record the activity of the chin muscles because, during deep sleep, the jaw muscles are relaxed. Special strings are tied around the chest and back of the patient to record vertical and horizontal movements of the chest and abdomen, which are related to breathing. A pulse oximeter is also attached to the person's finger. Electrocardiogram electrodes are attached to the chest to measure heart rate. Of course, it should be noted that this diagnostic method is very expensive because it needs the patient to be hospitalized for one night in a sleep lab and the presence of specialists (Foo, 2007).

However, in our proposed method, instead of using costly methods and specialists, one can use data mining with deep learning. Most of the methods used in this field are based on classical statistical techniques. In this study, the purpose is to use hybrid models based on artificial neural networks which practically overcomes the weakness of previous models.

Designed systems are tested with laboratory data. Because of the weakness in analyzing and performing the calculations on real (normal) data, the analysis and staging performed by the aforementioned systems are reviewed by the physician again and it takes the physician's time as much as the analysis of the signal diagrams. In this study, we have used the latest standard of sleep classification from the American Academy of Sleep Medicine (AASM) and also the experience of physicians in classifying sleep stages, to design an intelligent system for the diagnosis of obstructive apnea. Considering that in the given problem, there is no exact and definite relationship between the inputs and the output, therefore, the supervised learning AI techniques should be used to solve the problem, so a Case-Based Reasoning (CBR) system is chosen for this problem. Using such a system in the detection process reduces the time spent on data analysis and improves its accuracy. Hence, the sleep pattern of patients is more accurate and less time-consumingly extracted and will help the physician in the process of diagnosing and treating sleep disorders.

Related Works Review

In 2013, Hatami et al. used an algorithm to categorize the electrocardiogram signals of patients in two groups of apnea and normal, using a support vector machine, which achieved a sensitivity of 87.5% and specificity of 80%. In this study, the electrocardiogram signal has been used, but the used electrocardiogram signal has been converted to the heart rate variability signal by the Domain Frequency method.

In a study conducted in 2013, to diagnose apnea using ECG and features extracted from reconstruction phase space and frequency domain, Ja’fari proposed a hybrid feature extraction method based on some features extracted from the Reconstruction Phase Space (RPS) and electrocardiogram (ECG) based on most of the features commonly used to detect apnea. Six nonlinear features extracted from the RPS are combined with 3 frequencies based on the final reconstructed features. These nonlinear features are composed of Detrended Fluctuation Analysis (DFA), Correlation Dimensions (CDs), three Large Lipopunos (LLEs), and Spectral Entropies (SEs). The proposed final feature set represents an accuracy of about 94.8 percent on the Physionet sleep apnea dataset using an SVM-based classifier core. In addition to the electrocardiogram signal, other features have been used in this study. The SVM method has also been used. In this study, only the ECM signal has been used which is converted to the heart rate variability and EDR signal and We have implemented the ANFIS method that has the best accuracy.

In a study conducted by Ghafourian et al., in 2012 on the automatic diagnosis of sleep apnea and its type by using a linear classifier based on the features of the signals of the ECG and the blood volume change measurement sensor, the main purpose of this research was to design and provide a system for the automatic diagnosis of sleep apnea and its type that they achieved an accuracy of 67.2% (Hatami *et al.*, 2013).

In this study, the signals of chemical warfare veterans are also studied, and the study on this group of patients is only possible by using the database of Baqiyatallah Hospital.

In 2005, Abdul Nasir et al. conducted a study for a soft decision algorithm for sub-band decomposition of heart rate variability analysis in patients with obstructive sleep apnea and control groups, a new method for diagnosing obstructive sleep apnea has been investigated. The best classification accuracy achieved with experimental data (MIT-chal and SQU data) is close to 93% using the LF / VLF rate. In this case, the sensitivities of MIT-chal and SQU data are 95% and 100%, respectively, while the specificity for both data groups is 90% and 86%, respectively (Hossen *et al.*, 2005).

The findings of this study, considering the use of heart rate variability, LF, and VLF, are relatively similar to this study. However, we used the Domain Frequency method to obtain the heart rate variability signal and the ANFIS method to implement the neural network.

Although the difference between the sensitivity and specificity of the above studies and the present study is not significant, in this study and by using ANFIS, we achieved an accuracy of 98.38%, specificity of 98.46%, and a sensitivity of 98.8% which is the highest accuracy. Table 1 shows a comparison of previous research.

Table 1: The Comparison of Previous Research Results

Improvement Conclusion	Medical Methods Used	Engineering Techniques Used	Paper	Row
High Accuracy 66/91% Sensitivity 97% Average Accuracy 93%	HRV Analysis PSD RRI AHI PSG ECG	Soft Decision-making Classification Algorithm	Subband Decomposition Soft-decision Algorithm for Heart Rate Variability Analysis in Patients with Obstructive Sleep Apnea and Normal Controls	1
Accuracy %94/80 Average Accuracy %94/16 Sensitivity 42/95%	ECG RPS LLEs Spectral Antropy RPS	Calculate the Mean Deviation and Evaluation Variance SVM Classification	The Diagnosis of Sleep Apnea using the Extracted Features of the Reconstructed Phase and Frequency Domain (Demuth *et al.*, 1992)	2
Accuracy 83% Sensitivity 82%	RQA RQI Multiple Frequencies of Wavelet	ROC Classification Variance	Modeling and Analyzing the Heterogeneous Recurrence of Heart Rate Dynamics to Identify Sleep Apnea (Moody *et al.*, 1985)	3

	Coefficients for Diagnosis of Apnea and Hypopnea			
Not Mentioned	HRV SB MLPNN	Decomposition Tree Decision Making	Estimation and Evaluation of LF and HF Bases in HRV for Patients with Obstructive Sleep Apnea	4
Detection Accuracy At Best 86%	Detecting the Onset of Disturbance Set Threshold Values Diagnosis of Pathologic Events	Classification	Automatic Sleep Disturbance Diagnosis for Obstructive Sleep Apnea Syndrome (Cabrero-Canosa *et al.*, 2004)	5
Accuracy %96/07	Heart Rate (HRV) Fast Breathing based on Fourier Series (EDR) Obstructive Sleep Apnea	Support Vector Machine (LSSVM) Wavelet Transform (DWT)	Providing an Expert System for the Automatic Diagnosis of Obstructive Sleep Apnea with Electrocardiogram Recording (Orth *et al.,* 2005)	6
Accuracy Increased from 65% to 85%	EEGMF DFAVGALS	Classification Algorithms and Genetic Algorithms	Designing a System for Setting Sleep from an EEG Signal using Multi-domain features (Guilleminault *et al.*, 1984)	7

In previous researches, classification using the LDA method, intelligent genetic algorithm, and analysis of variance have been used more than support vector machine, but in this study, ANFIS intelligent neural network will be used. Then, the obtained data will be tested using the ROC chart.

Suggested Methods

In this section, the process of loading, normalizing, and filtering the signal data for more accurate processing are detailed. The steps taken to extract the features include filtering and extraction of statistical parameters, as summarized in Figure 1.

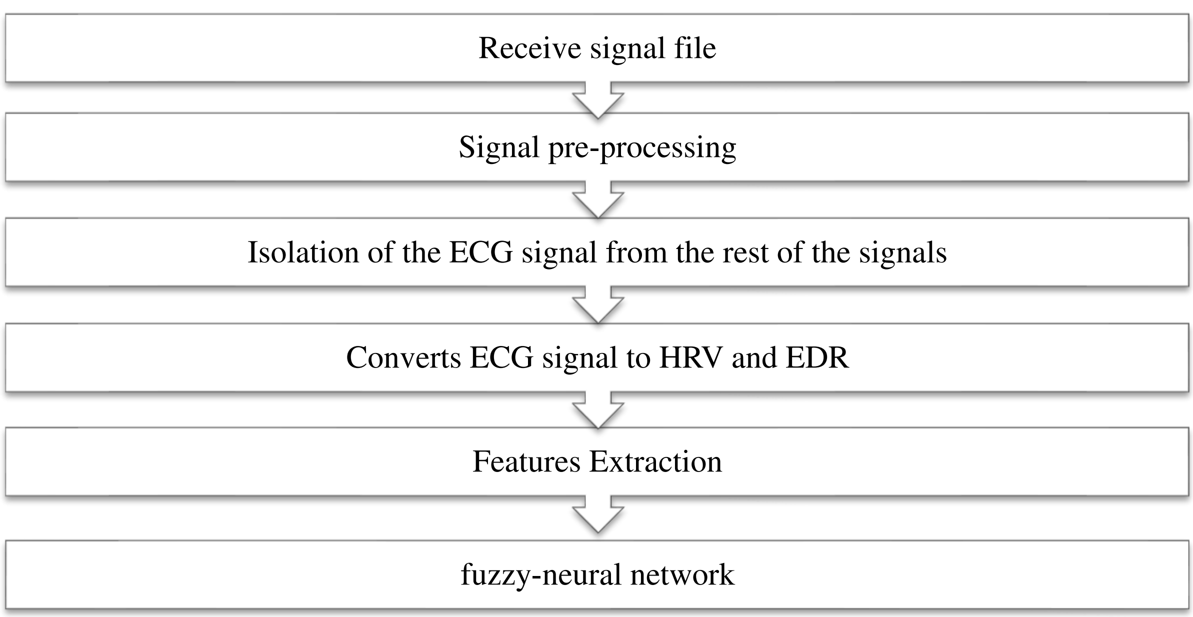

Figure 1: Block Diagram of the Study

Signal

A signal is a description of a variation in regard to another parameter that is expressed in various dimensions such as time, space, etc., or a combination of these. A signal is a function of one or more independent variables that generate information about a physical or biological phenomenon. These signals are electrical, mechanical, or chemical. The electrical signals are the result of the depolarization of the nerve cells or the heart muscles. The sound produced by the heart valves is an example of a mechanical signal while PCO2 of blood is a chemical signal. These biological or vital signals are used for medical diagnosis and biomedical research. Signals can be one dimensional (such as the oscillatory motion of spring over time), multi-dimensional or discrete (such as images produced by a computer) (Smith, 2009).

ECG Signal Record

Ten wires exit the electrocardiogram, with 4 wires attached to the hands and feet and 6 wires to the front of the heart. After smearing the suction cup with the Lubricant gel, the wires are connected to the appropriate place. Small metal electrodes are placed on the wrists, ankles, and chest of the individuals, and electrical signals are transmitted from the electrodes and through the wires to the ECG, and the device displays signals in the form of waves. Electric currents contract and expand the heart muscle. The P wave represents the electrical current in the upper cavity of the heart (atria). The QRS complex represents the electrical current in the lower cavity of the heart (ventricles). The T wave represents a short period of heart rest when recharged between two heartbeats. Electrical waves are recorded in the electrocardiogram as alternative peaks and valleys. Each period of the electrical activity of the heart consists of several intervals. These intervals begin with the P wave and continue to the next P wave. P is a relatively small wave that shows the atrium contraction. After a brief interruption, there is a combination of QRS, in which the ECG line goes down rapidly, goes up, and then again goes down.

This combination is caused by the contraction of the ventricles and ultimately, after a long interruption, the T wave is observed indicating that the ventricles are suddenly filled. (Al-Angari and Sahakian, 2007)

Heart Rate Variability Signal

The heart rate variates under the influence of sympathetic and parasympathetic nervous systems, so that short-term and long-term changes in heart rate reflect the function of the autonomic nervous system (Malik *et al.*, 1989). These changes of the heart signal during two consecutive beats are referred to as Heart Rate Variability (Horn *et al.*, 1965).

EDR Respiration Rate Signal

The respiration rate signal is one of the most important signals in monitoring vital signs and has various clinical applications. Due to the high clinical value, it is also important in mobile care systems. A method for recording respiration signals is to use strain gauges to measure the thoracic volume and respiratory transducers. These methods require special tools and will be able to provide relatively accurate information about vital volumes. These methods also have disadvantages. For example, inductance bands are somewhat exposed to slipping, have motor artifacts, and have a high cost (Moody *et al.*, 1986).

Method for Extracting the EDR Signal from the ECG

The signal first passes through the main filter to eliminate noises. The purpose of this section is to provide the main signal frequency spectrum. Because the data is already pre-processed, only a high-pass filter is used to remove DC resulted from electrodes and other low-frequency noises. After passing the signal from the filter, in order to extract R Peaks, the derivative, the square, and the time average (integral) of the signal are calculated. Derivative and square of the sampled signal are calculated to extract and emphasize the R waves. The derivative filter in this section amplifies and detects the peaks of the signal. In the final stage of the integration, this algorithm uses the estimation of the adaptive amplitude of the peak signal to see if the final determination of the detected signal is an R wave or not. The above operation leads to the production of two vectors, one of them is for the occurrence of R peaks and the other one is the domain. The R peaks were detected and extracted. Now, if we can connect these points with proper interpolation, the EDR signal is obtained. Considering f (x) as a function of x, the usual methods of interpolation depend on the assumption that, in the neighborhood of x, f can be estimated by a polynomial p whose value in x is an approximation of f. The simplest method is the linear interpolation in which the curve f is approximated between two values close to x0 and x1 with the chord. The second-order interpolation approximates the curve of the function f between x0 and x2 = x0 + rh with the second-order curve passing through the points (x0, f0) and (x1, f1) and (x2, f2). Finally, using a second-order interpolation, we will obtain the respiratory signal estimation (Moody *et al.*, 1986).

Method of Extracting the Heart Rate Variability Signal from the ECG Signal

Today, there are several ways to measure the heart rate variability that can be categorized into two linear and non-linear methods. In linear methods, the total changes are calculated by statistical methods. These linear methods can be divided into the time domain and frequency domain (Malik and Camm, 1990).

Time-domain methods are one of the easiest methods for analyzing heart rate variability. To calculate time-domain indices, after recording the ECG and calculating RR intervals, the standard deviations of these distances are calculated, which is referred to as SDNN and is one of the easiest indices of heart rate variability. Other indicators, such as the Average of Deviation Standard Intervals (SDANN LNNs), calculate the longer intervals. In addition, RMSSD or NN indices can also be used (Malik and Camm, 1990).

Frequency domain methods are used to determine the variation of frequencies. One of these methods is the Fourier method. Using the Fourier method, spectral analysis is performed on autonomic changes in the heart. In Fourier analysis, a diagram, which is usually called the Spectrum Power is drawn. In axes, the heart rate changes are shown at each frequency. These methods act like a Prism and separate the frequency signals in the structure of autonomic changes of heart diseases and identify some hidden information of autonomic changes in heart rate. Variables are as follows:

- High-Frequency waves (HF): This frequency range which starts from 0.15 to 0.4 Hz is influenced by the respiratory system and the parasympathetic system and variates very fast.

Low-frequency waves (LF): This frequency range which starts from 0.04 to 0.15 Hz is mostly influenced by Baroreceptors and sympathetic nervous systems.

- Very Low-Frequency waves (VF): This frequency range is from 3 to +/- 4 Hz. Generally, very low frequencies are associated with adjustment mechanisms or changes in circadin and other less well-known variables. Time-domain and frequency-domain methods provide a lot of information about the heart rate changes (Demuth *et al.*, 1992).

Adaptive Network-Based Fuzzy Inference System (ANFIS) Neural Network

The ANFIS structure, introduced in 1993, is the result of the integration of adaptive neural networks and fuzzy logic, which by using the learning process, one can adjust modeling parameters of the systems based on the existing inputs-outputs. The structures that had been introduced before 1993 were less adaptable. After ANFIS, in comparison with 1993, a variety of fuzzy-neural structures were introduced, most notably the Fuzzy-Mesh network, dynamic Gaussian systems, GenSoFNN and SAFIN. Today, artificial neural networks are widely used to solve complex problems. Applications of artificial neural networks are in aerospace, transportation, finance, construction, manufacturing, robotics, speech recognition, electronics, and medicine. In general, the error back-propagation technique is used to train an artificial neural network. In most of these studies, an artificial neural network has been used to estimate the relationships between control variables and response variables. To achieve an accurate estimation of these relationships, there is an urgent need to adjust the artificial neural network parameters (Demuth *et al.*, 1992).

In traditional methods, the parameters of the neural network were adjusted by trial and error, which is usually a time-consuming method. Therefore, finding a method to determine the best combination of control parameters that affect the performance of an artificial neural network seems necessary (Demuth *et al.*, 1992).
Here, after identifying the performance criteria of the artificial neural network and controlling factors influencing them, the design of the experiments is carried out using the Box-Benck method. After recording the tests, analysis of variance is performed on them and the non-influencing factors are eliminated. Then, we find the regression relation between the control factors and the determined performance criteria for the artificial neural network. In the following, the fuzzy programming method is used to find a combination of controlling factors that will provide the best performance for the neural network. As mentioned above, in most of the related studies, the neural network is used to optimize control variables in multi-criteria problems, while the present study uses a multi-criteria optimization approach to set network parameters (Demuth *et al.*, 1992).

The Number of AHI Obstructive Apnea

The number of obstructive apnea attacks per sleep hour is called AHI, which includes four stages: no apnea, mild apnea, moderate apnea, and severe apnea, as indicated in the table below. In this study, for a more accurate examination of patients, this item was extracted using ANFIS networks.

Evaluation Methods

ROC curves were developed in the 1950s, which were first used to detect noisy radio signals. Recently, it has been found that these curves have significant applications in medical decision making. Of course, that does not mean that they can be used for every application.
One of the suitable methods for evaluating the results of a classifier and assessing its ability to identify the intended class is to use the receiver operating curve to verify the sensitivity of the method.
The sensitivity is the relationship between the number of correctly classified cells and incorrectly classified ones. The higher the deviation from the baseline for a particular class in the ROC curve, the more efficient the classifier is in identifying that class. In addition to examining the trend of the chart in the table, the area is also calculated. This area represents the probability of which a selected cell will be randomly categorized correctly. The bigger the area, the more reliable the method is. For this indicator, the cells that are correctly assigned to the target cell are TP, the cells that are not assigned correctly to the class are TN, Cells that are incorrectly assigned to the target class are FP, and cells that are not incorrectly assigned to the target class are FN. In order to plot this curve, the x-axis must represent the characteristic and the y-axis, which contains the sensitivity of relation, must be calculated for each value of the threshold of the intended class.

Database Introduction

Data were collected from patients with sleep disturbances who came to Baqiyatallah Hospital for treatment. The target sample consists of information and data of the sleep-related signals of patients, which is about 900 patients.
Given the limited access to information, data from ninety-six periods of sleep were used. With a 200-Hz sampling rate, this data is related to ninety-six patients with sleep disorders during a complete night sleep for each of the patients.
In addition, for testing and validation, the data from 35 patients from the Apnea database in Physionet has been used. ECG data are obtained from a full night polysomnography record with a sample rate of 100 Hz, a resolution of 16 bits, and a modified V2 electrode. Each record is about eight hours long. Apnea diagnosis has been reported by experienced personnel on the Polysomnographic data and according to the clinical standard. Annotation of signals is done minute by minute. One minute is labeled as apnea if it contains at least one part of the apnea or Hyperpnea. Otherwise, it is labeled as non-apnea.

Implementation Method

1. The raw values of the signals are extracted in the form of the EDF file and the results of the doctor's analysis are extracted in the form of Text.
2. For the study, the ECG signal is extracted from the EDF file.
3. The electrocardiogram signal is converted by the Frequency Domain method to the heart rate variability signal. In this method, we considered waves ranging from 0.15 to 0.4 Hz as High-Frequency waves and waves ranging from 0.04 to 0.15 as low-frequency waves. After we removed the noise, we saved the resulting signal in a Text file as a neural network input.
4. Derivative and square of the ECG signal to extract and emphasize the R wave are calculated.
5. By connecting these points with proper interpolation, the EDR respiratory signal is obtained.
6. Then, by extracting the characteristics of the EDR and HRV signals for each minute, the input of the neural network is obtained.

The extracted parameters and characteristics of EDR and HRV signals are shown in Tables 2 and 3.

Table 2: Parameters and Features Extracted for the EDR Signal (Khandoker, *et al.*, 2008)

EDR(q)	**EDR(q)=**$\{\boldsymbol{edr}\}_{\boldsymbol{i=1}}^{\boldsymbol{m}}$
Mean	$\mu_{edr} = \frac{\sum edr_i}{m}$
Standard Deviation	$\sigma_{edr} = \sqrt{\frac{\sum(edr_i - \mu_{edr})^2}{m}}$

Table 3: Parameters and Features Extracted for the HRV Signal (Khandoker *et al.*, 2008)

RR(m)	$RR(m) = (rr_i)_{i=1}^{m}$
Mean	$\mu = \frac{\sum rr_i}{m}$
Standard Deviation	$\sigma = \sqrt{\frac{\sum(rr_i - \mu_{rr})^2}{m}}$
Sum Of Beats with Interbeat Difference over 50 ms	$NN50v2 = \sum_{i=1}^{m} unit[\lvert rr_i - rr_{i+1}\rvert - 50ms]$
The ratio of NN50v 1 to Segment Length	$NN50v2 = \sum_{i=1}^{m-1} unit[\lvert rr_{i+1} - rr_i\rvert - 50ms]$
The ratio of NN50v 1 to Segment Length	$pNN50v1 = \frac{NN50v1}{m}$
The ratio of NN50v 2 to Segment Length	$pNN50v2 = \frac{NN50v2}{m}$
Mean of Interbeat Differential	$\mu_{rd} = \frac{\sum rd_i}{m}, where\ rd_i = rr_{i+1} - rr_i$
Standard Deviation of Interbeat Differential	$\sigma = \sqrt{\frac{\sum(rd_i - \mu_{rd})^2}{m}}$
Root Mean Square of Interbeat Differential	$RMSSD = \sqrt{\frac{\sum rd_1^2}{m}}$

7. By putting together all the extracted features and marking them as apnea and non-apnea, we created the neural network's ultimate goal.

8. The extracted features are considered as inputs of each of the items used in the decision-making system based on ANFIS and the results of the doctor's analysis are considered as the output of the same item and will be included in the database.
9. After recording the normalized values, the features in text files were provided to the ANFIS neural networks with the structure of 11 neural network inputs and the features of the heart rate variability signal and the EDR signal of a single neural network separately for all patients. To accurately investigate the results, neural network training was repeated 10 times. Table 4 shows the extracted results of ANFIS neural network training.

Table 4: Results Extracted after 10 Times ANFIS Neural Network Training

ANFIS				No.
AUC	Accuracy	Sensitivity	Specificity	
99.58%	98.23%	93.80%	98.62%	1
99.75%	98.16%	97.97%	98.21%	2
99.67%	98.18%	95.57%	98.35%	3
99.62%	98.31%	97.11%	98.63%	4
99.62%	98.19%	92.01%	98.50%	5
99.54%	97.90%	96.47%	98.29%	6
99.80%	98.21%	98.42%	98.15%	7
99.75%	98.38%	98.08%	98.46%	8
99.29%	97.67%	94.69%	98.51%	9
99.55%	98.19%	96.72%	98.61%	10
99.62%	%98.14	%98.08	%98.43	mean

10. Then we examined patients to more accurately investigate AHI.[as shown in Table5]

Table 5: The Severity of AHI Obstructive Sleep Apnea

The Severity of AHI Obstructive Sleep Apnea	
1-4	The Absence of Obstructive Apnea
5-14	Mild
15-29	Moderate
> 30	Severe

Characteristic Curve of System Performance

The results extracted from Baqiyatallah Hospital database related to ROC and AHI index are shown in Tables 6 and 7, respectively.

Table 6: Results Extracted from the Baqiyatallah Hospital Database related to the ROC

	AUC	C.I	
ANFIS	99.75%	99.58%	99.93%

Table 7: AHI Index (Calculated for many Patients)

Absolute Error ANFIS	The Rate of Diagnosis of AHI by the ANFIS	The Rate of Diagnosis of AHI by the Physician	No.
1.5	21.7	20.2	1
0.4	10.7	10.3	2
3.7	32.2	35.9	3
3.0	21.5	24.5	4

2.2	24.3	26.5	5
1.3	9.3	8	6
4.8	12.9	8.1	7
1.2	13.5	14.7	8
2.3	23.5	25.8	9
2.4	16.5	18.9	10
1.3	6.4	7.7	11
3.3	33.5	36.8	12
1.1	6.9	8	13
0.3	7.1	6.8	14
16.0	18.4	34.4	15
3.3	32.5	35.8	16
3.2	12.9	16.1	17
4.9	45.3	50.2	18
1.8	31.0	32.8	19
0.7	17.5	18.2	20

Comparing this Research with Related Works

For a more detailed study, we conducted all of the tests with the Physionet Database, which evaluations can be seen in the Table8 and figures 2 and 3.

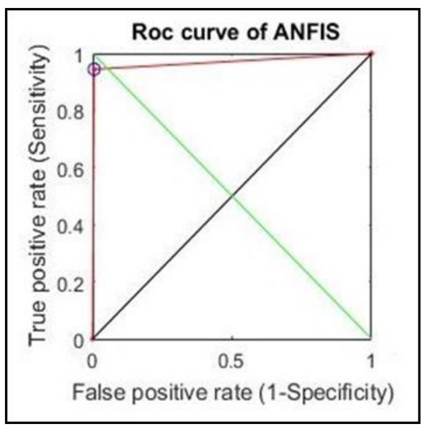

Figure 2: View of the ANFIS Neural Network ROC Curve. ANFIS for Baqiyatallah Hospital Database

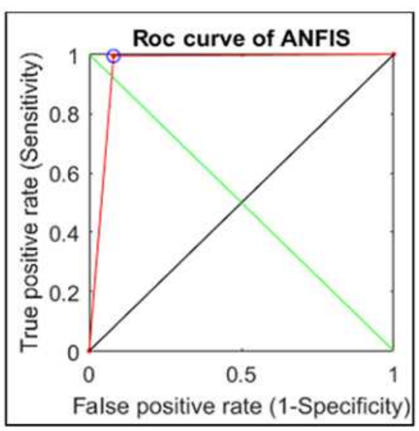

Figure 3. View of the ANFIS Neural Network ROC Curve for Physionet Database

Table 8: Comparison of the Results of the Baqiyatallah Hospital Database with the Physionet Database in the ANFIS Neural Network

ANFIS Neural Network Results						
Neural Network	Accuracy	Sensitivity	Specificity	AUC	C.I	
Baqiyatallah Hospital	98,38%	98,08%	98,46%	99.75%	99.58%	99.93%
Physionet	%92.65	%77.21	%99.73	95.29%	94%	96.58%

Discussion

In this study, using data mining models from the knowledge extraction process, an intelligent neural network-based system was provided to decide whether or not obstructive sleep apnea was existing in the heart rate variability signal and EDR signal. Reduced dimensions of the intended space and also the optimality of the features used, led to decreased similarity measurement calculations and increased accuracy of the values from similarity measurement.

In order to increase the system efficiency, the calculated features for each obstructive apnea including: time domain features, frequency analysis features and ANFIS features method were mined. Based on the findings of the present study, using data mining techniques can increase system efficiency and decision accuracy. Data mining suggested the superiority of the features from the frequency domain. By removing insignificant data, the average system sensitivity increased to 98.08%. The overall accuracy of the system also increased to 98.38%. One of the heart rate variability signals is the optimal choice. Regarding the frequency signal decomposition into different frequency bands, it should be stated that the frequency band threshold should be selected based on the nature of the problem. In the present study, the band threshold values for frequency analysis were selected according to the standard set by the American Academy of Sleep Medicine.

The goal of the proposed neural network is to decide whether or not obstructive sleep apnea exists in the heart rate variability signal in which the EDR signal and its decision-making core are based on the ANFIS model. Reducing the dimensions of the desired space as well as optimizing the used features will reduce the similarity measurement calculations and increase the accuracy of the values of the similarity measurement. In order to increase the system efficiency, data mining was used for the calculated features for each obstructive apnea including features from the time domain and the features from the frequency decomposition. The dominant features were chosen and the decision was made accordingly. Based on the findings of the present study, the use of data mining techniques can lead to improved system optimality and decision-making accuracy. Data mining results show the superiority of the features derived from the frequency domain. By eliminating less important data, the average sensitivity of the system increased to 98.08%, the overall accuracy of the system increased to 98.38**%** percent, and the mean absolute error in diagnosis of AHI was 2.6 for 96 patients. The use of data mining and the removal of less important features as well as the application of the obtained coefficients in superior features resulted in an overall improvement in the system. Considering constant features used to decide in the neural network of the diagnosis of obstructive sleep apnea, 10 layers were selected in the ANFIS neural network.

Conclusion:

Comparing the results of the designed neural network with the diagnosis of a specialist, the average absolute error in the AHI diagnosis for 96 patients and in the ANFIS model for 96 patients was 5.9 and 2.6, respectively. The present results are very promising to help early diagnosis of obstructive sleep apnea in chemical warfare victims in a more convenient way via examining and connecting fewer sensors and protecting them from heart disease and mortality.

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References

1. Al-Angari, H. M., & Sahakian, A. V. (2007). Use of sample entropy approach to study heart rate variability in obstructive sleep apnea syndrome. *IEEE Transactions on Biomedical Engineering*, *54*(10), 1900-1904.
2. Cabrero-Canosa, M., Hernandez-Pereira, E., & Moret-Bonillo, V. (2004). Intelligent diagnosis of sleep apnea syndrome. *IEEE Engineering in medicine and biology Magazine*, *23*(2), 72-81.
3. Demuth, H., Beale, M., & Hagan, M. (1992). Neural network toolbox. *For Use with MATLAB. The MathWorks Inc*, *2000*.
4. Foo, J. Y. A. (2007). Pulse transit time in paediatric respiratory sleep studies. *Medical engineering & physics*, *29*(1), 17-25.
5. Grigoraş, C., Grigoraş, V., & Boişteanu, D. (2008). Cross Signal Identification for PSG Applications. *International Journal of Biomedical and Biological Engineering*, *2*(8), 280-284.
6. Guilleminault, C., Winkle, R., Connolly, S., Melvin, K., & Tilkian, A. (1984). Cyclical variation of the heart rate in sleep apnoea syndrome: mechanisms, and usefulness of 24 h electrocardiography as a screening technique. *The Lancet*, *323*(8369), 126-131.
7. Hatami, S., Rahati Quchani, Q., & Rezaeitalab, F. (2013). "Support vector machine training in the diagnosis of obstructive sleep apnea," presented at the First National Conference on New Approaches in Computer Engineering and Information Retrieval in Iran
8. Horn, E., Lee, S., & Gynecology. (1965). Electronic evaluations of the fetal heart rate patterns preceding fetal death: further observation, 87, 824-826,
9. Hossen, A., Al Ghunaimi, B., & Hassan, M. O. (2005). Subband decomposition soft-decision algorithm for heart rate variability analysis in patients with obstructive sleep apnea and normal controls. *Signal Processing*, *85*(1), 95-106.
10. Khandoker, A. H., Palaniswami, M., & Karmakar, C. K. (2008). Support vector machines for automated recognition of obstructive sleep apnea syndrome from ECG recordings. *IEEE transactions on information technology in biomedicine*, *13*(1), 37-48.
11. Lyle, D. V. (1999). Obstructive sleep apnea. American family Physician Book.
12. Malik, M., & Camm, A. J. (1990). Heart rate variability. *Clinical cardiology*, *13*(8), 570-576.
13. Malik, M., Farrell, T., Cripps, T., & Camm, A. J. (1989). Heart rate variability in relation to prognosis after myocardial infarction: selection of optimal processing techniques. *European heart journal*, *10*(12), 1060-1074.
14. Moody, G. B., Mark, R. G., Bump, M. A., Weinstein, J. S., Berman, A. D., Mietus, J. E., & Goldberger, A. L. (1986). Clinical validation of the ECG-derived respiration (EDR) technique. *Computers in cardiology*, *13*(1), 507-510.
15. Moody, G. B., Mark, R. G., Zoccola, A., & Mantero, S. (1985). Derivation of respiratory signals from multi-lead ECGs. *Computers in cardiology*, *12*(1985), 113-116.
16. Orth, M., Duchna, H. W., Leidag, M., Widdig, W., Rasche, K., Bauer, T. T., ... & Kotterba, S. (2005). Driving simulator and neuropsychological testing in OSAS before and under CPAP therapy. *European Respiratory Journal*, *26*(5), 898-903.
17. Smith, S. W. (2009). The Scientist and Engineer's Guide to Digital Signal Processing, San Diago, California Technical Publishing, 1999.
18. Yin, M., Nakayama, M., Miyazaki, S., & Ishikawa, K. (2008). How much influence does inspiration have on pulse transit time in sleep apnea?. *Otolaryngology—Head and Neck Surgery*, *138*(5), 619-625.