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Analysis of various Computing Techniques for Diagnosis of Sleep Disorders

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Abstract: - **This paper is based on the analysis of various soft computing techniques for the diagnosis of sleep disorders especially sleep apnea, insomnia, parasomnia and snoring on the basis of following three performance parameters: accuracy, sensitivity and specificity. Many techniques and methods are adopted by researchers to implement and diagnose these sleep disorders. The current traditional technique used to diagnose these sleep disorders is polysomnography which is costly and requires human specialists and done in unique labs. Subsequently, there is a need of a more comfortable and less expensive technique to detect such types of disorders. As of late analysts concentrated on signal processing and pattern recognition as substitute modes to reveal them. The following research is focused on the detection of sleep disorders using ECG signals by applying Tunable Q-Factor wavelet transform (TQWT) and accuracy achieved by this method is 94.2%.**

Index Terms- **Computing Techniques, ECG Signals, Sleep Disorders, TQWT.**

I. INTRODUCTION

Sleep assumes a key part in time of neuroscience. The zone of sleep issues turns out to be critical because of its recognition in universe [1]. In 1987, Klink [2] examined that 41% of every single considered subject had no less than one disorder of upset sleep. Sleep apnea and narcolepsy are two issues raised because of outrageous daytime sleep [3]. These two issues constitute a confounding or some time crucial impact on standard exercises. Practically 20% of all certified heap up wounds in the comprehensive group are connected with driver sluggishness, free of alcohol impacts. Further, sleep misfortune and sleep issues have an enormous fiscal impact. The high evaluated costs to society of leaving the most widely recognized sleep issues untreated are significantly more than the costs that would be achieved by passing on adequate treatment. A few billions of dollars a year are spent on facilitate therapeutic costs related with master visits, mending focus organizations, cures, and over-the-counter meds. Appeared differently in relation to strong individuals, individuals encountering rest misfortune, rest issues, or both are less gainful, have an extended restorative administrations utilization, and an enhanced likelihood of accidents [26]. In India, 93% of the populaces is restless, however just 2% Indian talk about their sleep issues with doctors. The commonness of sleep apnea is high in Western India. Measurements uncover that sleep apnea in Indian guys changed from 4.4% to 19.7% while among females it extended from 2.5% to 7.4%. In setting to sleep apnea predominance in various age gatherings, the elderly has been seen to have high wheezing and high inordinate daytime drowsiness with 27% being constant snorers. Sleep apnea is likewise connected with heart disappointment which is 12-16% more pervasive in apnea patients. It has likewise been watched that around 60-70% of sleep apnea patients are obese [27].

Fundamentally, sleep apnea is a sleep related breathing issue [4]. It is treatable; regardless, around 90% of fatalities go mysterious and accordingly unprocessed. They encounter daytime lethargy and weariness which can raise to traffic mischances, melancholy, and memory misfortune [5]. Likewise, it is viewed as a hazard factor for morbidity and mortality cause of its longterm impact on cardiovascular. This impact is identified with various physiological instruments like fundamental hypertension and expanded thoughtful balance that in a long haul bargains the well-working of the heart [4]. Patients in danger for sleep apnea should be recognized for demonstrative testing and treatment [6].

A sleeping disorder or sleeplessness is a sleep issue in which there is a failure to nod off or to stay unconscious insofar as wanted. The pervasiveness of a sleeping disorder happened every now and again in obstructive sleep apnea patients and methodicallly related with poor sleep quality however had no impact on long haul inconveniences and as indicated by [7], half patients experienced a sleeping disorder with go from direct to extreme.

Parasomnia alludes to physical aggravations amid rest that include the skeletal engine and autonomic sensory systems. Grown-ups with parasomnias regularly report the behavioral, perceptual, enthusiastic, and fanciful unsettling influences that may wrongly propose a mental issue [8].

Snoring is a side effect and an indication of rest related upper aviation route deterrent and are very normal, influencing over 9% to half of the grown-up populace. It is alluded to an issue of bed-accomplice or spousal engaging quality. Numerous don't view wheezing alone as a horribleness. Just with others ailment is wheezing viewed as pathologic [6]. It has been accounted for as a hazard factor for the advancement of illnesses, for example, ischaemic mind infraction, fundamental blood vessel hypertension, coronary corridor malady and rest unsettling influences [9].

II. LITERATURE REVIEW

The following Table I represents the analysis of methods and techniques adopted by the researchers by following the physionet.org database for diagnosis of sleep disorders

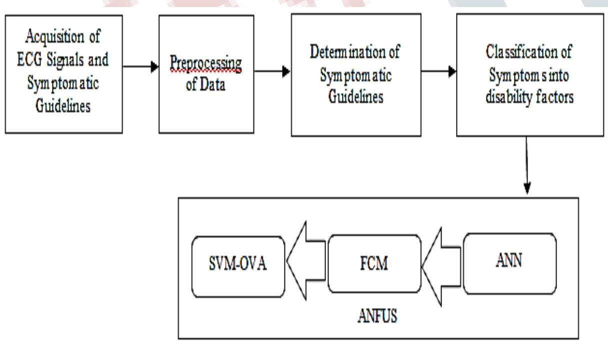
Table I. Analysis of various computing techniques

Author	Technique Used	Accuracy (Ac), Sensitivity (Se), Specificity (Sp)	Application Domain
Varon et al. [4]	Least squares support vector machine (LS-SVM)	Ac- 84.74% Se- 84.71% Sp- 84.69%	Sleep Apnea
Song et al. [10]	Discriminative hidden markov model (DHMM) and SVM	Ac- 97.1% Se- 95.8% Sp- 100%	Sleep Apnea
Khandoker et al. [11]	Probability neural network (PNN) applied on wavelet features	Ac- 70%	Sleep Apnea
Khandoker et al. [11]	K-nearest neighbor (KNN) applied on wavelet features	Ac- 83%	Sleep Apnea
Xie et al. [5]	Classifier combinations (Support vector machine, KNN, decision table, multilayer perceptron, decision tree (C4.5tree, reduced-error pruning tree and functional trees), adaptive boosting with decision stump, bagging with REP tree and bagging with alternating decision tree)	Ac- 77.74% Se- 69.82% Sp- 80.29%	Sleep Apnea
Hassan [12]	Normal inverse Gaussian (NIG) parameters and adaptive boosting	Ac- 87.33% Se- 81.99 % Sp- 90.72%	Sleep Apnea
Nguyen et al. [13]	SVM and neural network and Recurrence Quantification Analysis (RQA) features	Ac- 85.26 % Se- 86.37% Sp- 83.47%	Sleep Apnea
Maier et al. [14]	Recurrence plots	Ac- 76.70% Se- 66.80% Sp- 73.80%	Sleep Apnea
Maier et al. [14]	2D-fast fourier transformation (2D-FFT)	Ac- 84.3% Se- 76.6% Sp- 78.2%	Sleep Apnea
Khandoker et al. [15]	SVM	Ac- 83% Se- 80% Sp- 90%	Sleep Apnea
Babaeizadeh et al. [16]	Quadratic classifier	Ac- 84.70% Se- 76.70% Sp- 89.60%	Sleep Apnea
Hassan et al. [17]	Statistical features and extreme learning machine (ELM)	Ac- 83.77%	Sleep Apnea

Raimon Jane et al. [18]	2-layer feedforward multilayer neural network (FFNN)	Se- 82% Positive predictive value (PPV) - 90.77%	Snoring
R. Jane at al. [19]	FFNN	Se- 76.1% Sp- 82.8% PPV- 75.6%	Snoring
Cavusoglu et al. [9]	Robust linear regression applied for simple snorers	Ac- 97.3%	Snoring
Cavusoglu et al. [9]	Snore episode detection for sleep apnea patients	Ac- 86.8%	Snoring
Cavusoglu et al. [9]	Robust linear regression applied for simple snorers and sleep apnea patients	Ac- 90.2%	Snoring
Raimon Jane et al. [20]	FFNN and AHI value = 5	Se- 87% Sp- 71%	Relation between Snores and AHI values
Raimon Jane et al. [20]	FFNN and AHI value = 15	Se- 80% Sp- 90%	Relation between Snores and AHI values

III. MATERIAL AND METHODS

In this paper, the experimental data of ECG signals related to sleep apnea and snoring is acquired from physionet.org. The beneath Fig.1 speaks to piece outline of the proposed framework.



A. Acquisition of ECG Signals and Symptomatic Guidelines

The experimental data of ECG signals related to sleep apnea and snoring was acquired from physionet.org [22] and symptomatic guidelines of sleep apnea, insomnia, parasomnia and snoring are collected from online database which contained 300 patient's records. The motivation to utilize Physionet and online database is its accessibility in the general population area and its across the board use in the contemporary writing.

A few knowledge regarding symptomatic guidelines was acquired from various physicians as shown below in which 188 Patients were those who suffered from sleep disorders and 178 patients were those who had some where same type of symptoms but not suffered with any such disorder like from physician 1, information of 40 patients were acquired who was actually suffered from sleep disorders while 38 patients were those who was not

suffered from any disorders but their symptoms were of same type as of sleep disorders. Likewise, more knowledge was acquired from other physicians.

- Physician 1: 40 + 38
- Physician 2: 43 + 37
- Physician 3: 58 + 57
- Physician 4: 47 + 46

Then, symptomatic guidelines were categorized into four sleep disorders for sake of their essence in the comparable disorder. The underneath Table II points represent each one of the symptoms taken together to analyse the sleep disorders which impact the particular human body parts by different angles

TABLE II. Symptoms of Sleep Disorders

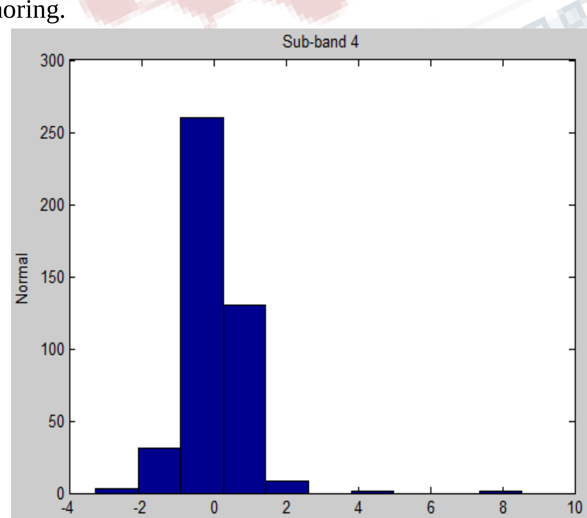
Sleep Disorders	Symptoms
Sleep Apnea	High Blood Pressure (HB), Dry Throat (DT), Bedwetting (BW), Irregular Heart Rhythm (IHR), Breathing (BT), Headache (HD), Unusual Sleep Positions (US), Teeth Grinding/Clenching (TG/TC), Nightmare Choking (NC), Napping/Drowsiness (NP), Sleep Disturbances (SD), Daytime Sleepiness (DS), Night Awakening (NA), Moodiness (MD), Concentration Loss (CS), Forgetfulness (FG), Learning Problem (LP)
Insomnia	Dry Throat, Irregular Heart Rhythm, Eye Movement (EM), Disturbance, Daytime Sleepiness, Night Awakening, Moodiness, Tiredness (TD), Concentration Loss
Parasomnia	Bedwetting, Irregular Heart Rhythm, Unusual Sleep Positions, Teeth Grinding/Clenching, Eye Movement, Nightmare Choking, Sleep Disturbances
Snoring	High Blood Pressure, Dry Throat, Irregular Heart Rhythm, Breathing, Headache, Napping (Drowsiness), Daytime Sleepiness, Night Awakening, Learning Problem

B. Processing of ECG Signals

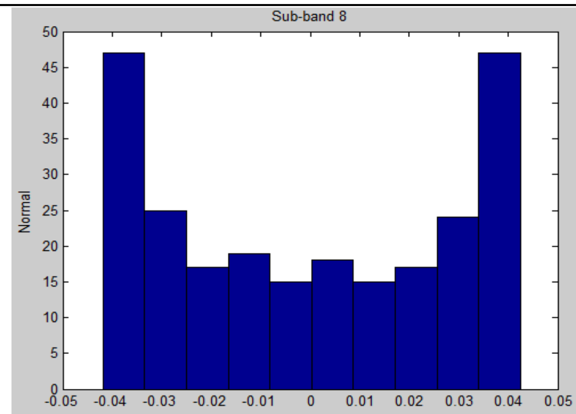
In this study, a total of 345 patient's ECG signals were taken from physionet database [21], out of which 252 patients belong to sleep apnea and 90 patients to snoring. The following Fig.1 represents ECG signals corresponding to normal, sleep apnea and snoring patients. All ECG signals were processed with the help of a signal processing technique i.e. tunable-Q factor wavelet transform (TQWT). Firstly, ECG signals were decomposed in 1 min. basis. Afterwards, ECG signals segments were decomposed into sub-bands using TQWT. Then, modelling of TQWT sub-bands was done using symmetric normal inverse Gaussian (NIG) pdf. To find out the pauses while breathing in sleep apnea and the occurrences of harsh/unpleasant sound caused by the vibration of soft palate in snoring, tunable-Q factor wavelet transform (TQWT) [12] had been applied which is an adaptable and completely discrete wavelet transform. It is a valuable tool to analyse the oscillatory signals

which accomplishes adaptability by changing its input parameters Q-factor Q that controls the quantity of oscillations of the wavelet. Now, the first step was to find out the TQWT parameters Q, R and J [23] which were obtained by verifying Parseval's theorem. This theorem states that the energy of the wavelet coefficients must be equal to the energy of the original signal [23].

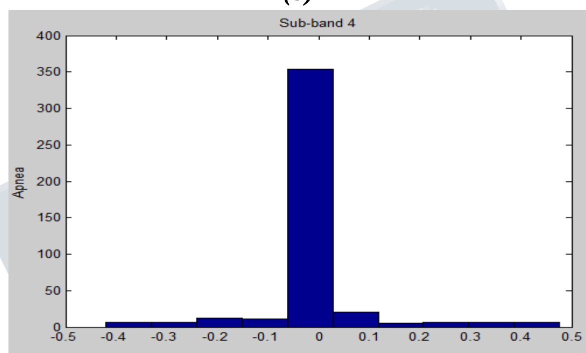
The second step was based on the comparison of sub-bands of the apnea and normal patients as shown in the following Fig. 2. It has been clearly depicted from the following figure that (a) part has less amount of pauses at 0 value than (b) in which a patient is suffering from sleep apnea. Likely, the snore values were computed in case of snoring patients. The histograms of the samples show variations in dispersion and steepness among normal, sleep apnea and snoring.



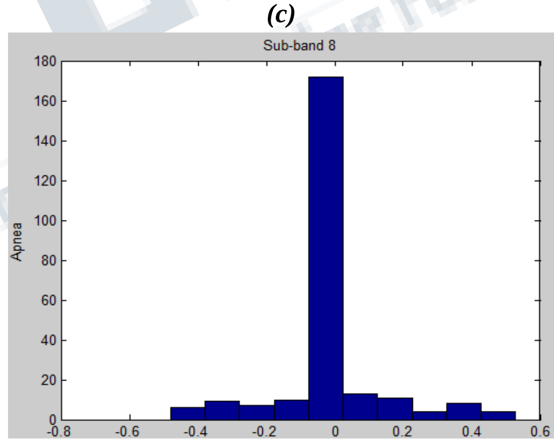
(a)



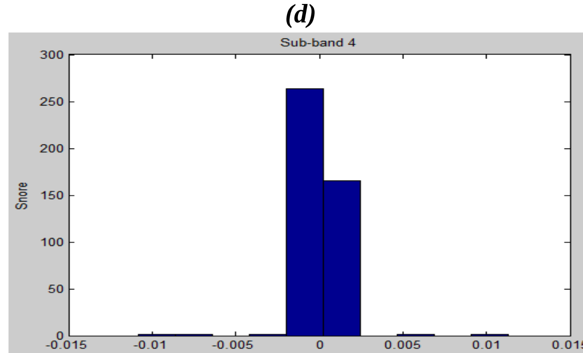
(b)



(c)



(d)



(e)

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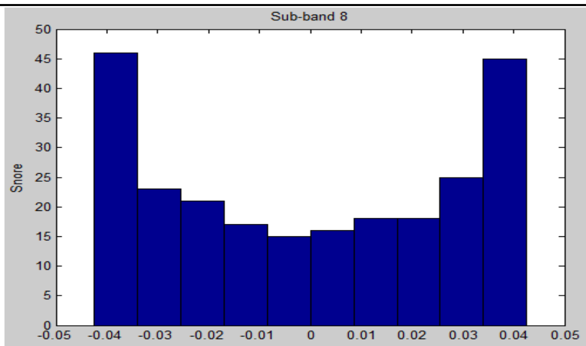

(f)

Fig. 2 Histograms of sub-bands (a, b) 4 and 8 for normal patients, (c, d) 4 and 8 for sleep apnea and (e, f) 4 and 8 for snoring patients

C. Processing of Symptomatic Guidelines

For the examination, an aggregate of 366 patient records were gathered from various physicians and 300 from online database. The detail of the collected symptoms for all sleep disorder is described in 2.3.2.1 heading. Every symptom was sorted into four disability areas in light of its effect on the different human body parts like physical structure, psychological, cognitive and motor functions [24,25] of an individual as shown in Table 1. The whole notation is meant as '0' and '1'. Here "0" speaks to that specific side effects are not connected with the endorsed sickness and "1" implies the vicinity of that manifestation in underlined disorder [24,25]. A sum of 43 symptoms was considered to be as input variables for the whole examination. To lead the analyses, half of the dataset has been arbitrarily picked as training data and whatever remains of the data as testing set, along these lines, it has been guaranteed that the whole dataset can be utilized either to train or for testing, however never in the meantime which additionally diminishes the chance of overfitting.

D. Categorization of disability factors

The below Table III represents the classification of the mentioned sleep disorders based on the following factors: physical, psychological, cognitive and motor function. Now, due the uncertainty problem in ANN, there was a need to normalize the data so that it would be distributed among the entire range. Now, these 19 input variables were converted into 4 input variables.

Table III: Disability Factors associated with Sleep Disorders

Sleep Disorders	Motor Function Disability (MF)				Psychological. Disability (PSY)					Cognitive Disability (CO)			Physical Disability (PY)						
	TG/TC	EM	NC	NP	SD	DS	TD	NA	MD	CS	FG	LP	HB	DT	BW	IHR	BT	HD	US
Sleep Apnea	1	0	1	1	1	1	0	1	1.	1	1	1	1	1	1	1	1	1	1
Insomnia	0	1	0	0	1	1	1	1	1	1	0	0	0	1	0	1	0	0	0
Parasomnia	1	1	1	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	1
Snoring	0	0	0	1	0	1	0	1	0	0	0	1	1	1	0	1	1	1	0

To diminish the multifaceted nature or to lessen the dimension of 19 symptoms, an equation was prepared based on an index value (INV) doled out to all side effects on the reason of their importance in the specific disorder and the binary values (SMT) assembled from the manifestations of various patients. The aggregate sum of the multiplication of SMTi * INVi will create different values as indicated by various sleep disorders. The beneath said formula was passed to ANN to find out the particular values of all disability factors by using the training data set.

Disease DISi = $\sum$ (SMTi * INVi)

Here, SMTi = Binary values of symptoms,

INVi = Index number of symptoms

Now, due the uncertainty problem in ANN, there was a need to normalize the data so that it would be distributed among the entire range. Now, these 19 input variables were converted into 4 input variables MF, PSY, CO and PY as depicted in following Table IV. To check the normalization of data, Table 3 was formulated in which mean and standard deviation (St. DEV) was computed. Each of the sample training input data was subtracted with the corresponding mean value mentioned in Table V and then divided the output with their respective standard deviation value. Now, if the value was negative then it indicates that the cell does not belong to the corresponding distributed column as shown in Table VI.

Table IV: Sample Input Data

MF	PSY	CO	PY
0.933333	0.580645	0.857143	0.929134
0.533333	0.806452	0.714286	0.850394
0.133333	1.032258	0.571429	0.771654
0.533333	0.258065	0	0.322835
0.133333	0.290323	0.142857	0.519685
0.066667	0.258065	0.285714	0.291339

Table V: Mean and Standard Deviation

	MEAN	St. DEV	MIN	MAX
MF	0.374222	0.315692	0	0.93333
PSY	0.553978	0.280596	0	1
CO	0.299048	0.314003	0	1
PY	0.478215	0.325773	0.06	1

Table VI: Normalization of Data

MF	PSY	CO	PY
1.745776	0.103837	1.798648	1.364901
0.480722	0.917487	1.341365	1.125277
0.78433	1.731136	0.884081	0.885652
0.480722	1.05852	-0.94505	0.48021
0.78433	-0.94228	0.48777	0.118854
-0.99517	1.05852	-0.03049	-0.57606

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After normalization, various computing methods were applied to detect the sleep disorders [24, 25, 28]. In proposed system, artificial neural network (ANN) [28]and fuzzy C-means (FCM) [24] are integrated with support vector machine-one versus all (SVM-OVA) [25]. At layer-1, ANN is used to discover the relationship between collected patient records and disability factors of sleep disorders and the outcome is passed to FCM at layer-2 to define the boundaries of all overlapped disability factors. The result provided by FCM is utilized by SVM-OVA present at layer-3 to classify the sleep disorders.

Table VII: Comparison of different implemented techniques

Performance Parameters (%)	ANN	FIS	AN FIS	SVM-OVA	ANFUS
Ac	80	89.2	90	90.4	94.2
Se	80	89	90.2	90.2	93.4
Sp	79.5	90	89	91	95

Table VIII: Comparison of different techniques on basis of performance parameters

Author	Technique Applied	Ac (%)	Se (%)	Sp (%)
Khandoker et al. [15]	SVM	83	80	90
Xie et al. [5]	Classifier combinations	77.74	69.82	80.29
Babaeizadeh et al. [16]	Quadratic classifier	84.70	76.70	89.60
Varon et al. [4]	LS-SVM	84.74	84.71	84.69
Nguyen et al. [13]	SVM, NN and RQA features	85.26	86.37	83.47
Maier et al. [14]	Recurrence Plots	76.70	66.80	73.80
Hassan et al. [17]	Statistical features, ELM	83.77	-	-
Maier et al. [14]	2D-FFT	84.3	76.6	78.2
Hassan[12]	NIG parameters and adaptive boosting	87.33	81.99	90.72
Proposed Method	ANFUS	94.2	93.4	95

It is found from the above Table VII that the performance of ANFUS method is better than the other standalone and integrated techniques. Hence, it can be a best approach for the early detection of sleep disorders and It has all the features that are used to give better results in other decision making of various systems.

IV. CONCLUSION

This study basically deals with the early detection of sleep disorders primarily focused on sleep apnea, insomnia, parasomnia and snoring. For this, an intelligent computing method ANFUS is proposed based on ANN-FCM-SVM-OVA and compared the performance of ANFUS with other implemented techniques like ANN, FIS, ANFIS and SVM-OVA on the basis of performance parameters like accuracy, sensitivity and specificity. It has been proved from the below Table VIII that the performance of the proposed system ANFUS is better than the other implemented computing techniques. Subsequently, it can be useful for beginners that may develop their examination in other medical areas.

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