OBSTRUCTIVE SLEEP APNEA CLASSIFICATION USING SNORE SOUND DATASET

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Abstract- Obstructive Sleep Apnea (OSA) is a potentially fatal chronic condition that increases the risk of cardiovascular illnesses. One of the most common symptoms of OSA is snoring. This paper aims to present and test a highly efficient Classification method as well as a sensitive whole-night snore sound detector that relies on non-contact knowledge. The goal of this ensemble approach is to combine several classifiers, such as the Quaternions Firefly Algorithm and Particle Swarm Optimization (PSO), to create a new classification method. Progressively enhance the optimization-based classifiers' accuracy.

Index Terms - Obstructive Sleep Apnea (OSA), Particle Swarm Optimization (PSO), Quaternions Firefly Algorithm (QFA).

I. Introduction

Obstructive Sleep Apnea (OSA) is a most serious continual disease. OSA is described as a chronic disease by means of reducing airflow at the time of sleep to finish or incomplete collapse of the upper airway used for more than ten seconds and with additional occurrences for each hour in sleep. Moreover, it is a risk factor for some of diseases such as cardiovascular diseases, stroke, and pressure. Loud snoring, as a usual symptom of OSA, is described in almost eighty per cent of OSA patients. PSG is presently used as the gold standard for sleep analysis. This PSG needs an entire night laboratory stay and persons are linked to many electrodes and sensors, which are emotionally involved on the patient's body. But PSG is more time consumption task, difficult, and costly because of the complexity. The technique known as drug-induced sleep endoscopy (DISE) is used gradually to identify the type and location of obstructions and vibrations. While DISE is a difficult, costly, and uncomfortable procedure for patients, a more straightforward method for both physicians and patients to determine the upper airway vibration systems is acoustic analysis. There aren't many publications discussing how to determine the location, kind, and obstruction of upper airway vibrations causing snoring sounds.

The design of this ensemble approach is to create a new classifier model by combining two classifiers namely Particle Swarm Optimization (PSO) and Quaternions Firefly Algorithm (QFA). Consecutively increase the accuracy of the optimization-based classifiers; each classifier is trained based on the bootstrap algorithm drawn from the snore sounds training set before on the entire snore sounds training set. By using Drug-Induced

Sleep Endoscopy to record the snore sounds of forty male patients and classifying them using classification techniques.

2. Literature Review

Duckitt et al introduces an easy and convenient diagnostic as an alternative solution to PSG. The system introduces the procedure of Hidden Markov models (HMMs) with their general elements.

Karunajeewa et al proposed a novel technique for categorizing breat hing sounds and snores using four distinct features taken from the time and spectral domains .Those four features are zero crossings, energy, standardized autocorrelation coefficient and the LPC analysis, and thus achieve the classification accuracy results of 90.74%.

Azarbarzin et al introduce a new automatic and unsupervised fuzzy C-means (FCM) clustering algorithm based snore sound detector. This FCM clustering algorithm results higher performance via the use of tracheal microphone, and produces higher Signal-to-Noise Ratio (SNR).

Sun et al proposed a new Support Vector Machine (SVM) based classifier by analyzing the acoustic characteristics of the snoring sounds.

3. Proposed Work

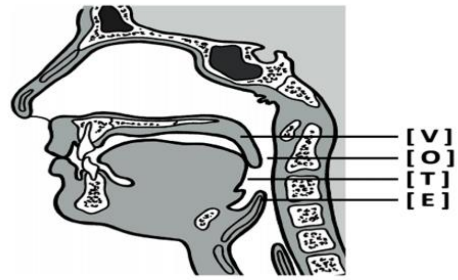

Figure 1: VOTE classification

3.1. Ensemble classifier

Ensemble Classifiers is employed to classify the sleep apnea on processing the snore sounds obtained from the perceptive non-contact knowledge-based whole-night snore sound detector.

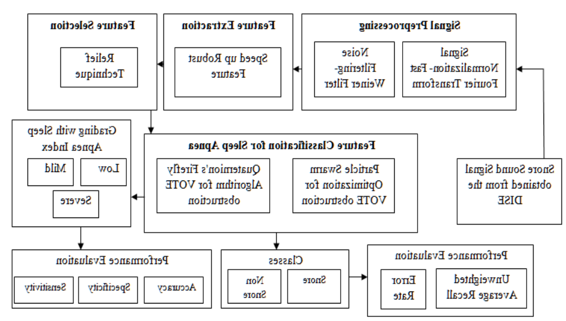

Figure 2: Proposed Architecture of the Ensemble Classification

Ensemble model integrates several classifiers to classify the obstruction in the sound signal. Ensemble Classifier utilizes the Particle Swarm Optimization (PSO)" classifier and Quaternions Firefly Algorithm (QFA) classifier in this work. The overall architecture diagram of the proposed system is illustrated in Figure 2.

3.2. Signal normalization

The audio signals obtained in the sleep laboratory were easily normalized by the rate of frequency ranges 44.1 kHz to the "Pulse Code Modulation (PCM)" and 16KHz to down sample. It is considered which predict the lowest rate of sample for the recorder based on voice which collected during the signal captured using "Drug-Induced Sleep Endoscopy".

3.3. Signal Noise Filtering - Wiener Filtering

The noises present in the audio signals were eliminated using a noise suppression algorithm based on the Wiener-Filter (WF) algorithm. By boosting the gain of the noisy voice input, the Wiener filter minimizes noise. The Wiener filter divides an input speech signal into N frames by removing noise.

Figure.3 represents the noise signal input and filter output of signal

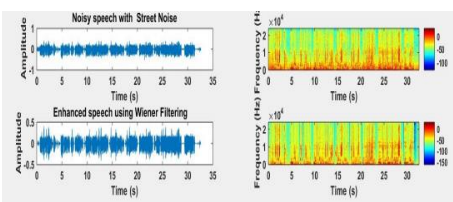

Figure 3: Noise Elimination using Weiner filter

Originally, this noise spectral was predictable from the lower energy frame of the initial 10 seconds of the audio signal and simplified for the length of the adaptive noise reduction procedure. A specific suppression noise spectral algorithm suppressed each frame's frequency portion and confined the range increases from 0 to 255 dB, which prevents the distortion of SNR at a slow rate.

3.4. Feature Extraction using Speeded Up Robust Features

Feature extraction using speeded up Robust Feature extract the sound of OSA and normal snore effectively. It is also termed as multiple feature extraction method to identify the suitable acoustic capabilities on perceiving obstructive occasions, separating among fundamental snoring and OSA and summarizing the seriousness of OSA. Feature is extracted in frequency waveform of the sound signal.

Crest Factor: It is considered as important feature of OSA detection which determines the peak signal in vibration analysis. It identifies the Peak signal in the waveform of the sound signal. It is also termed as peak to rms ratio. It is represented as

$$\text{Crest Factor} = V_{90}/\ V_{rms}$$

where V90 is the 90th centile of greatest fixed value in the epoch based on the digitized sound and Vrms values based on amplitude with Root Mean Square in a single epoch.

F0 Approximate It is considered as basic frequency (F0) of signal which depends on frequency based on logarithmic with shifting spectrum and computing the "Sub harmonic-to-Harmonic Ratio (SHR)".

Formants: It is considered as broad spectral maximum value of the signal. It identifies cestrum using the LPC parameters are computed by using the Yule-Walker autoregressive method which follows the procedure of Levinson- Durbin recursive.

Spectral Frequency Features(SFF**):** It is considered as another important feature which play important in snore detection and sleep apnea classification. The spectral frequency of SnS plays very important information on the condition of the upper airway. Some of the frequency features in terms of center, peak, and mean frequency were developed by analyzing OSA and the difference position of a snore.

$$F_{mean} = \frac{\sum_{f_{i=0}}^{f_c} f_i \, s(f_i)}{\sum_{f_{i=0}}^{f_c} s(f_i)}$$

where f_c=8 kHz is the frequency cut-off of the sound signal spectrum and $S(f_i)$ the frequency based on the spectrum with fixed amplitude of f_i as 16 Hz.

Power Ratio It measures the amount of power consumption on the specified frequency. It ranges relatively below or greater than the specified frequency. Many of the research work in the literature may select the frequency at 800 Hz, and some of the works select it to be 750 Hz. In this research work make power ratio with a range of 800Hz.

"Subband Energy Ratio (SER)"The SER defines the qualified energy distribution in subbands of Spectrum of the signal. It is concluded to successful results in detection of snore and nonsnore. Spectrum of the signal is meant as signal magnitude and phase characteristic function of frequency. It is measure of changes in magnitude of the signal to frequency changes related to obstruction. The Signal magnitude of 1000Hz is considered as SER feature which extracted using following equation.

$$SER(j)_{1000Hz} = \frac{\sum_{1000j-1}^{1000j} s(f_i)}{\sum_{f_{i=0}}^{f_c} s(f_i)}$$

where f_c=1000 Hz is the frequency cut-off of the sound signal spectrum and $S(f_i)$ the frequency based on the spectrum with fixed amplitude of f_i as 200 Hz. In this work, sub band frequency is set to 1000hz to measure spectral changes of particular band. In specific, entire spectrum represents the total airways whereas each band of spectrum represents the airways in the specified region such as velum, oropharynx, tongue base, epiglotti

Mel-Scale Frequency Cepstral Coefficients (MFCCs)" MFCCs is considered as feature of the OSA and it is termed as every effective features for speech identification. However, the MFCCs are able to perform better than the other spectral features on the detection of SnS. It is possible to extract thirteen MFCCs on the range of 0–12. It is computed from SnS transient 27 triangular Mel filter banks in this work.

"Empirical Mode Decomposition (EMD) based Features" Particular EMD feature is performed based on selecting the basic functions which is adaptive to differentiate non-stationary signals. The subband EMD energy ratio to the obstruction is computed using the equation

$$EMD_{ratio}(k) = E_k/E$$

Ek is the energy value of the Intrinsic Mode Functions (IMFs) at the k-th level that are extracted from the SnS by EMD. E is the total SnS energy present in the EMD.

Wavelet Energy Features: Energy features is extracted using "Wavelet Transform (WT) "as it examine the non-stationary signals.

3.5. Feature Selection - ReliefF

Most appropriate features were ranked and selected using a multi-feature selection algorithm termed as ReliefF. It improves the accuracy of the optimization-based classifiers consecutively. ReliefF-based feature selection phase is the classification process to achieve greater snore detection accuracy. The multi-feature selection algorithm based on "ReliefF" is an enhanced version of "Relief " which handles multiple classes and enhances performance with noise.

Rank Ratio = $\sum_{a=1}^{M} w\, a^{+} \,/\, \sum_{a=1}^{M} w\, a^{-}$

Where W_a^+ denotes the positive class weights of the features ranked in descending order and M is the number of features incorporated in the feature subset. The features with positive class weights (W_a^-) are removed and eliminated easily. In this rank ratio is to compute the optimal feature for the obstructive classification. W_a assesses the quality of every feature, ranks the features regarding their performance results, and chooses the best optimal features to create a new subset of the original features. weighted through every class's probability priority. By training the ensemble classifier with optimal feature subsets of varied Rank Ratios, better classification performance can be recognized simultaneously as the size of the essential feature set can be reduced and used for the recognition process

3.6. Ensemble classifiers

In this mechanism, each classifier is trained on the basis of the bootstrap algorithm drawn from the snore sounds training set before on the entire training set of snore sounds. The classifier VOTE, which distinguishes between the four levels of the airway based on the upper level of "the Velum (V)," is found in the oropharyngeal region and comprises "the palatine tonsils (O)," "the tongue base (T)", and "the epiglottis (E)". Here, the Ensemble approach procedure is followed by the VOTE classifiers, which divide the recordings into four main classes: "(V,O, T, and E)".

"Snoring sounds (SnS)" have been omitted from original records with multiple vibration positions or unknown vibration base. The number of patients from 3 to 5 Sns were considered for the demonstration which acts as no character based on obstructive, which manually selected for each integrated recording. Based on the ensemble method, these SnS retrieved from the signal based on voice and graded according to them.

Considered the sample of 40 subjects, 11, 11, 8, and 10 subjects were correspondingly graded into four main grades, including "V"," O"," T", and "E-type snorers". As per individual, the number varying from 1 to 5 events of snoring per class may be extracted. Overall, we have 164 snoring events for implementation work (41 episodes for each SnS sensor group, with a duration varying from 0.728 to 2.495s with an average of 1.498 s).

For additional feature extraction, feature selection and "Ensemble Classifiers", they segmented the episodes into different segments. Each segment's length is '200 ms', and the adjacent segments extend up to 50 percent.

Particle Swarm Optimization (PSO) based classifier

Setting up the particle encoding is the first stage in creating the Nearest Centroids Classifier (NCC) based on PSO. To reduce the classification error, it is imperative to ascertain the centroids of the classes, as outlined in Equation (6). Thus, as demonstrated, the particle encodes the closest snore sounds using the centroids of each class's coordinates as real numbers.

$$Error = \frac{1}{N} \sum_{x_m} \delta(C(x_m), \arg\min d(\mu_c, x_m))$$

where the exact value of $\delta(c, c')$ is equal to 0 when $c = c'$, and elsewhere $\delta(c, c')$ =1. The objective function

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of each multi-dimensional feature (particle) is computed using equation 8. The centroids values are computed using PSO from the multi-dimensional snore sound feature vectors only. The distance measure from the multi-dimensional to each of the centroids encoded in the particle is computed to classify multi-dimensional features.

Then, the multi-dimensional features are classified as four (V,O,T and E) classes with the lesser distance with its centroids. This PSO classifier is repeated over the multi-dimensional features training set to determine the fitness of the particle. At finally PSO, the particle with the lesser error value is used as a character model to recognize unknown samples. The most generally used distance measure for snore sound detection is the Euclidean Distance(ED) which is used in this work:

$$d(\mathrm{x_m}, \mu_c) = \sqrt{(\mathrm{x_m} - \mu_c)^T (\mathrm{x_m} - \mu_c)}$$

A prototype example for class 'c' is described as the arithmetic mean:

$$\mu_c = \frac{1}{|c|} \sum_{x_{m\,\varepsilon\,c}}^{x} x$$

Quaternion's Firefly Algorithm (QFA) classifier

Firefly Algorithm (FA) is one of the most important meta-heuristic algorithms to solve many real-world problems. In FA, each fireflies are insects. This algorithm's major properties are the flashing lights with the purpose of being admired in the summer atmosphere at night. In general, these flashing lights have two major functions, i.e., to attractiveness and to warn off potential predators. The flashing lights 'intensity I decrease with the distance from equation(7) 'r' increases depending on the term $I\alpha\frac{I}{r^2}$ to formulate the FA . In order to increase the searching speed of the FA algorithm introduces a quaternion's representation.

The fitness value is determined based on the distance between the centroids and the data instance x_m. The flashing lights 'intensity I decrease with the distance from equation(7) 'r' increases depending on the term $I\alpha\frac{I}{r^2}$ to formulate the FA . The distance between the centroid and the data instance x_m is directly proportional to the light intensity $I(f)\alpha fit(f)$ where f=error represent a snore sound classification results.

Algorithm: Automatic Snore Sound Detection using ensemble

Signal Preprocessing using Weiner Filter
SF=weinerfilter(Sound signal)
Feature extraction ()
FE= SURF(SF)
FE={ Crest Factor F0 Approximate Formants Spectral Frequency Features(SFF) Power Ratio Subband Energy sRatio (SER) Mel-Scale Frequency Cepstral Coefficients (MFCCs)}
Feature Selection using ReliefF
FS=Relief(FE)
FS= Optimal Feature
Feature Classification using optimal feature
VOTE classification ={ OF}
Class = { velum obstruction , oropharynx obstruction, tongue base obstruction, epiglottis obstruction}
Obstructive Sleep Apnea Detection
Grading of classes { velum obstruction , oropharynx obstruction, tongue base obstruction, epiglottis obstruction}

Grading > 5 API Index
Severe Apnea
Grading >3 and <5 API Index
Mild apne
Grading <3 API Index
Low Apnea
Sound Detection = class of obstruction
Sound Detection = (snore, Wheezing)

3. EXPERMENTAL RESULTS

Dataset Description

Data for analysis is collected from the Drug Induced Sleep Endoscopy data in the kaggle database. Each recordings of single continuous sound signals running for approximately 8 hours were acquired for analysis. These signals were obtained from complete DISE recordings with a sampling rate of 1000 Hz, 16-bit resolution configuration. These recordings were originated from a variety of subjects.

The subjects' ages (mean±standard deviation: 43.8±11.1 years), weights (mean±standard deviation: 86.3±22.4 kg), and heights (mean±standard deviation: 175.3±6.1 cm) range from 158 to 184 cm.There were two sets of recordings, with 35 recordings in each set. The first set, which was made public, was utilized to build the model and estimate the parameters. Our method was evaluated and validated using the second set (withheld set). The segments that made up the withheld set totaled 17268; 10718 of these segments were labeled as "normal," and the remaining 6550 as "apnea."
Records with an AHI of at least five were considered to be OSA positive in this study; those without such a value were classified as OSA negative. Thus, there were 24 OSA positive recordings and 11 OSA negative recordings in the withheld set.

After Feature Selection Results

The multi-dimensional feature selection process uses the ReliefF algorithm. The ReliefF algorithm receives as input multiple feature sets, each with its own set of features, and Rank Ratio values ranging from 0.05 to 1.00. According to ReliefF's feature selection, each feature set's mean performance is increased between LR, kNN, SVM, and the suggested ensemble approach. Particularly, for all feature sets, the proposed ensemble approach's average performance considerably increases from 61.5% to 77.55%. For F0 (43% to 82 %), PR (48% to 72 %), and Crest Factor (48% to 76%), improved after the completion of the ReliefF feature selection algorithm discussed in table

Table 1 :UAR ([%]) results obtained with nine features and four classifiers after feature selection

Features	Ensemble (proposed)	LR	k-NN	SVM
Crest Factor	76	58	45	41
F0	82	53	47	42
Formants	75	59	56	54
SFF	78	72	69	61
PR	72	58	52	48
SER	81	72	69	65
MFCCs	83	78	76	73
EMDF	71	65	61	58
WEF	80	72	68	68
ALL	90	79	72	69
Average	77.55	65.222	60.33	58

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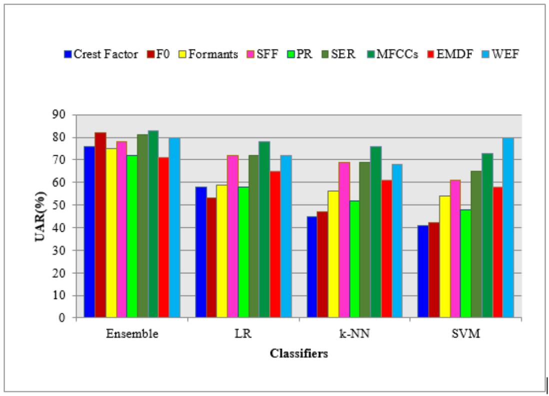

Figure 4.UAR results vs. four classifiers with ReliefF based feature selection

Especially, for all capabilities, the normal presentation of the proposed ensemble approach impressively increments from 61.5% to 77.55% . For F0 (43% to 82 %), PR (48% to 72 %), and Crest Factor (48% to 76%), improved after the fruition of the ReliefF include choice calculation is outlined in fig 4. The normal precision aftereffects of the proposed ensemble approach are 77.55%, 12.33%, 17.22%, and 19.55% lesser than LR, kNN and SVM classifiers separately.

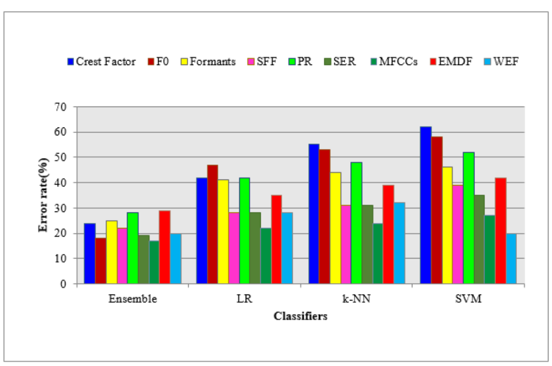

Figure 5. Error rate results vs. four classifiers with ReliefF based feature selection

Table 2 . Error Rate ([%]) results obtained with nine features and four classifiers after feature selection

Features	Ensemble(proposed)	LR	k-NN	SVM
Crest Factor	24	42	55	59
F0	18	47	53	58
Formants	25	41	44	46
SFF	22	28	31	39
PR	28	42	48	52
SER	19	28	31	35
MFCCs	17	22	24	27
EMDF	29	35	39	42
WEF	20	28	32	20
ALL	10	21	28	31
Average	22.44	34.77	39.66	42.33

The proposed ensemble approach yields lower error results of 10%, which are 11%, 18%, and 21% lower when compared to other LR, kNN, and SVM classifiers with selected feature sets, respectively. The error results of the four different classifiers with ReliefF based feature selection are shown in the figure. It comes to the conclusion that the suggested work outperforms the other classifiers, as shown in the table.

Table 3: Accuracy Analysis with Feature Selection

Feature	ensemble proposed	LR	KNN	SVM
Crest factor	**94**	**86**	**84**	**86**
FO	**93**	**88**	**82**	**84**
SFF	**94**	**89**	**86**	**82**
PR	**92**	**90**	**85**	**80**
SER	**91**	**89**	**84**	**80**
MFCC	**90**	**86**	**82**	**76**
EMDF	**92**	**87**	**80**	**80**

WEF	**96**	**83**	**78**	**80**
ALL	**92**	**88**	**86**	**84**

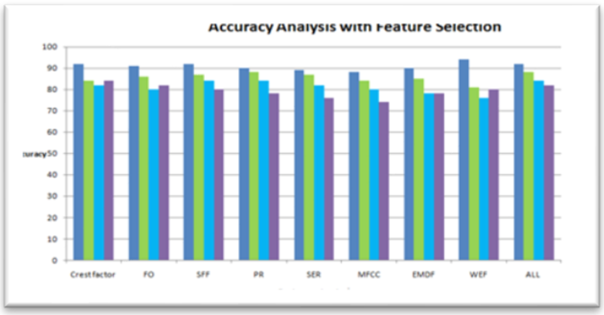

Figure 6 Accuracy Analysis with Feature Selection

Accuracy analysis of the proposed classifier with conventional classifier with feature selection technique is carried out in table and figure. In that accuracy of proposed classifier obtained with value of 94% in sleep apnea classification and snore sound and snore sound detection to 9 feature extracted.

Table 4: Specificity Analysis with feature Selection

Feature	ensemble proposed	LR	KNN	SVM
Crest factor	**94**	**86**	**84**	**86**
FO	**93**	**88**	**82**	**84**
SFF	**94**	**89**	**86**	**82**
PR	**92**	**90**	**85**	**80**
SER	**91**	**89**	**84**	**80**
MFCC	**90**	**86**	**82**	**76**
EMDF	**92**	**87**	**80**	**80**

WEF	**96**	**83**	**78**	**80**
ALL	**92**	**88**	**86**	**84**

Figure 7: Specificity Analysis with Feature Selection

Specificity analysis of the proposed classifier with conventional classifier with feature selection technique is carried out in table and figure 7. In that Specificity of proposed classifier obtained with value of 94% in sleep apnea classification and snore sound and wheezing sound detection to 9 feature extracted.

4. SUMMARY

One of the significant goals of medication at present is to build the early examination and treatment. Here, " Ensemble Classifiers" based snore identification approach with the end goal of introducing a target quantitative measure for whole night snore designs is proposed and experimented in matlab. This Ensemble approach joins the consequences of two classifiers in particular "Particle Swarm Optimization (PSO) classifier " and "Quaternions Firefly Algorithm (QFA) classifier".

The proposed method indicated the better results to snore sounds hints of 40 male patients.

Particularly, for all feature sets, the average performance of the proposed ensemble approach considerably increases from 61.5% to 77.55% . The average accuracy results of the proposed ESIVC approach is 77.55% which is 12.33%, 17.22% and 19.55% lesser when compared to LR, kNN and SVM classifiers respectively.

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