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Detection of Obstructive Sleep Apnea from ECG Signal Using SVM Based Grid Search

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***Abstract*—Obstructive Sleep Apnea is one common form of sleep apnea and is now tested by means of a process called Polysomnography which is time-consuming, expensive and also requires a human observer throughout the study of the subject which makes it inconvenient and new detection techniques are now being developed to overcome these difficulties. Heart rate variability has proven to be related to sleep apnea episodes and thus the features from the ECG signal can be used in the detection of sleep apnea. The proposed detection technique uses Support Vector Machines using Grid search algorithm and the classifier is trained using features based on heart rate variability derived from the ECG signal. The developed system is tested using the dataset and the results show that this classification system can recognize the disorder with an accuracy rate of 89%. Further, the use of the grid search algorithm has made this system a reliable and an accurate means for the classification of sleep apnea and can serve as a basis for the future development of its screening.**

***Keywords*—ECG signal, Grid Search, RR intervals, Sleep Apnea, Support Vector Machine**

I. INTRODUCTION

A. Background

GETTING enough sleep is essential for helping a person in maintaining optimal health and well-being. For a normal person to be physically fit and mentally active, sleep is as vital as regular exercise and eating a balanced diet. Sleep helps the body in benefitting it physically and mentally, and so when the body lacks sleep, it affects the normal functioning of the body. There are around 90 sleep-related disorders [1] including the most common disorders such as sleep apnea, insomnia and restless leg syndrome. The most serious amongst them is sleep apnea.

Sleep Apnea occurs at the time of sleep where the person's breathing gets interrupted. There are two types of Sleep Apnea. The first type, obstructive sleep apnea (OSA) occurs when muscles in the backside of the throat relax. When these muscles relax, the airway narrows or closes as the oxygen is inhaled. This lowers the oxygen level in the blood [2]. When the oxygen level is lowered, the brain senses the inability to breathe and briefly arouses the affected person from sleep. This awakening is usually brief that it cannot be remembered. OSA affects 1 to 6% of adults and 2% of children. It affects males as twice as it affects females. It is generally caused by a collapse in the upper respiratory airway. The other one is the central sleep apnea (CSA) which are mostly mixed, that is, it often comes along with OSA.

Polysomnography is the available gold standard method for the detection of sleep apnea. Through the polysomnography method, information about oxygen saturation, heart rate and breathing, electroencephalogram (EEG), electrooculogram (EOG), electrocardiogram (ECG) and electromyogram (EMG), as well as eye and leg movements are recorded [3]. But, it is very expensive and requires an extensive examination of the patient. It necessitates the patient to be available at the sleep centre throughout the night and the sleeping data is collected by a human observer. Most cases of sleep apnea go undiagnosed due to these inconveniences caused by the polysomnography method.

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B. Contribution and paper organization

Polysomnography thus poses a lot of constraints and makes the detection of sleep apnea difficult. In order to make the detection process easier and ubiquitous, this project relies on a method that detects the presence of sleep apnea using ECG signals by extracting features from them. The proposed method combines the most effective RR interval features of the ECG signal with a machine learning algorithm in developing a model that can effectively detect sleep apnea. This proposed work uses Support Vector Machine (SVM) for the classification purpose. The grid search algorithm is combined with the machine learning model in order to improve the performance of the system. A classifier contains many parameters that can be altered. But the value for each parameter for which the classifier shows the highest performance is not explicit. Thus, the grid search algorithm is used to find the value of each parameter for which the classifier performs the best. This work also provides an insight into the effect of Grid search algorithm on the performance of the system and to make the detection process more reliable.

The rest of the paper is organized as follows. Section II explains different methods for the detection of sleep apnea. Section III deals with the overview and details about the methodology of the proposed system. The steps by which the R-peaks and RR intervals (that is used as a basis for detecting sleep apnea) are determined is discussed along with the classification method in this section. In Section IV, the results of the proposed system are presented and the performance is analyzed. Finally, in Section V, the paper is concluded with an insight into the Grid search algorithm in improving the performance of the system. It also highlights some of the possible future work explorations with regard to the proposed method.

II. RELATED WORK

Several systems have been developed in the past two decades for the detection of sleep apnea. Commonly used approaches include statistical features based on pulse oximetry, features of ECG signal, respiratory signals, breathing sounds and combined approaches. Since the ECG signal records the electrical activity of the heart, it contains information about the heart rate variability which is related to breathing. This is closely related to the sleep apnea episodes and thus can serve as a potential tool for the detection of sleep apnea.

Almazaydeh [4] proposed a model for detecting sleep apnea using ECG signals. Features had been extracted from RR intervals based on the signals. SVM model was used for classification in this method. 80% of the dataset was used as training data and the remaining as test data. A total of 10 features were used for the classification. This method proved that it is possible to achieve good results with a lesser number of features. Philip de Chazal [5] used single-lead electrocardiogram to detect the presence of sleep apnea. Features based on the QRS complexes and the amplitude of the ECG signal were used for the classification process. Linear and quadratic discriminants were the classifiers used for the classification process. A R Hassan [6] proposed a method where DT-CWT and Logitboost were used for screening of OSA from single-lead ECG. This method has an advantage of higher sensitivity which ensures a lower number of false detections. Less number of features were used in this method which reduced the computational burden.

Other than ECG signals, Respiratory signals are also used in detecting sleep apnea. The Energy of respiratory signals contains information about the breath and hold of breath. This has been used in the detection of sleep apnea. Respiratory signals can be of two types. One is the raw respiratory signal extracted directly and the other one is the respiratory signal derived from the ECG signals. W C Fang [7], presented a method based on the frequency analysis of ECG derived respiration and heart rate variability. This method proved to be computationally simple and also involved a Lomb Periodogram to perform the computations in a wearable real-time application. ECG signals were used by Andre Pinho [8] for detecting sleep apnea. Feature extraction was performed based on both heart rate variability (HRV) and ECG-derived respiratory signals (EDR). Further, the feature selection and classification processes were interleaved to obtain features that yield the optimum results. The final set of features used in the detection process had been the subset of the list of features that yield maximum results.

There are a lot of methods that used respiratory signals, but Thommandram [9] used a different approach that had the highest performance. Features such as stability of peak height value, peak to peak time, the occurrence of long pause and flat-lining were extracted. K-nearest neighbors (KNN) classifier was further used for classification. In [10], features were extracted from heart rate variability (HRV) and respiratory rate variability (RRV) for the detection of sleep apnea. A complementarity was identified between time-domain HRV and RRV systems which lead to the fusion of the feature sets to improve the performance.

Variational mode decomposition method proposed in [11] used two features; energy and RR interval of the ECG signal were extracted using the variational mode function. These features were fed into a support vector machine classifier and the performance metrics of the system were calculated. Both online and offline detection of sleep apnea using variational mode decomposition were discussed in this work. A ten-fold cross-validation method was used to validate the performance of the classifier. This system claims to perform better compared to the other methods that made use of empirical mode decomposition and wavelet-based feature extraction techniques.

Sleep signals contain the RR index values. This sleep RR index is calculated by counting the number of breathing periods per minute. This value can also be used as a basis for the detection of sleep apnea. A Gaussian mixture model-based system [12] was developed that classifies sleep apnea depending on the sleep signals. This technique relied on the vocal tract length and linear prediction coefficients using the feature selection technique. In [13], thoracic and abdominal signals were used and considered as good parameters for detecting sleep apnea. This system used the mean of the amplitudes of the signals to train the classifier and achieved good performance with very high receiver operating characteristic (ROC).

Also, the classifiers and various feature sets based on the oxygen saturation signal measured from pulse oximetry and ECG signals are used in detecting sleep apnea. Pulse oximetry contains the information about the oxygen level in the blood and it has been used as a tool for the detection of sleep apnea. One such method given in [14] where Bagging with REPTree classifier was used for the classification method and the detection of sleep apnea was performed.

In [15], a new parameter based on the eigenvalues of the covariance matrix computed from the QRS complex was used along with the conventional feature set. This is on par with the best results that are available. N Sadr [16] proposed a model where the extracted features were trained using extreme learning machines (ELM) classifier which showed similar results to that of the other classifiers. ELM is a flexible non-linear classifier that is easy to train.

The study in [17] used a set of features from ECG signal, respiratory signal and SpO2 signals for the detection of sleep apnea. This was done in order to test the possibility of detection through three signal variation patterns. A portable sleep monitoring system was also developed based on this for performing self-administered sleep tests for the detection of sleep apnea. This system does not require hospitalization and diagnosis can be performed from anywhere. The data can be sent via Bluetooth to a nearby smartphone which was used for processing and storage of data. Delta index, oxygen desaturation indices of 3% (ODI3) and central tendency measure with radius 0.5 (CTM50) were the obtained features from the SpO2 signal. Voice activity detection (VAD) was used in the case of the respiratory signals. This VAD algorithm measured the energy of the acoustic respiratory signals.

Even though different methods had been tested with different aspects, none of the above methods suggests an optimization procedure for improving the performance of the classifier which is required to make the system highly reliable and robust for the detection of sleep apnea. The proposed work addresses this problem by providing a solution through Grid search to optimize the classification which is crucial in this field.

III. METHODOLOGY

The block diagram of the proposed system is as shown in Fig.1. The flow as depicted in Fig.1 receives an ECG signal as input and processes it. Every heartbeat of an ECG signal comprises of the QRS complex and the position where the maximum amplitude of the ECG signal occurs is called R-peak. All the R-peaks are detected for each heartbeat from the ECG signals. These R-peaks have to be detected with high accuracy for the better performance of the system. After R-peaks identification, RR-intervals for the entire ECG signal are calculated with the location of the detected R-peaks based on which the required features are extracted for classification. After feature extraction, the features are used for training the classifier that is used for classifying sleep apnea thus obtaining a reliable and accurate sleep apnea detection system.

A. Subjects

The dataset of the ECG signals used for this work is available at the Physionet [18]. It is named as Apnea-ECG Database (apnea-ecg) and contains ECG signals of both apneic and non-apneic data. The Apnea-ECG Database(apnea-ecg) was contributed by Phillips University, Germany. The dataset contains 70 records, each containing an ECG signal with a duration varying from 7 to 10 hours and also the annotation file for each ECG signal.

B. R-peak detection

Since the performance of the system largely depends on the accurate detection of R-peaks from the ECG signal, a method named Nonlinear Transformation and First Order Gaussian Differentiator is used [19] in the proposed work to achieve an accurate R-peaks detection.

The procedure for detecting R-peaks from the ECG signals mainly consists of four steps:

First, the filtering of the signal is done to reduce the effect of P/T waves in the ECG signal for R-peaks identification. For the filtering of the ECG signal, a 15th order FIR (Finite Impulse Response) digital filter is used with a passband between 6 and 20 Hz. Next to filtering, first-order forward differentiation is applied to emphasize high-frequency content and large slope of the QRS complex.

The differentiated signal of the filtered ECG signal is implemented as given in (1),

$$d[n] = f[n+1] - f[n] \tag{1}$$

where f[n] is the filtered signal and d[n] is the differentiated signal.

The squaring is done on the differentiated ECG signal and adaptive thresholding is further performed to narrow down the region of interest (RoI). The squaring is implemented as given in (2),

$$e[n] = d^2[n] \tag{2}$$

The squaring gives only a positive valued signal that eliminates the problems caused by the negative QRS complexes.

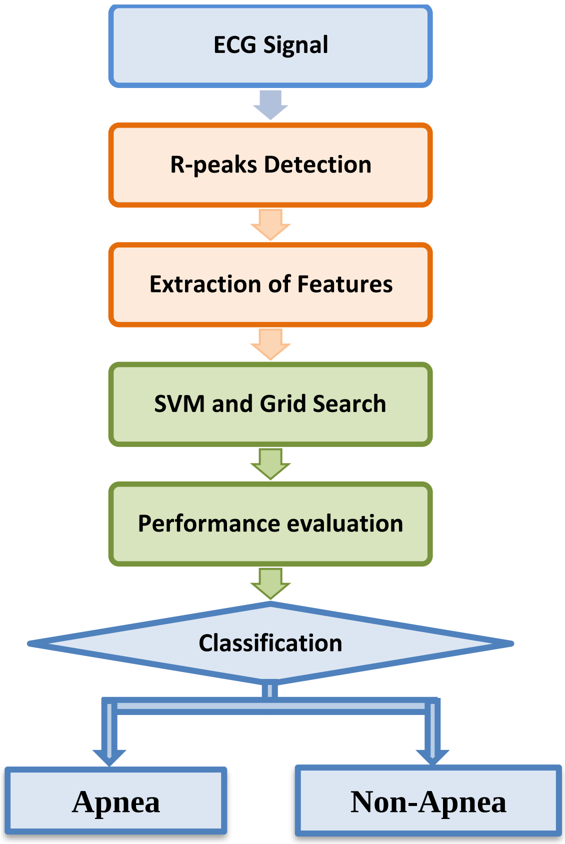

Fig.1. Schematic Diagram of the proposed system

Second, the thresholding is done based on the thresholding parameter η. The energy values less than η are made zero in e[n] signal and the other values are retained. This thresholding value depends on the amplitude of the ECG signal [20]. The threshold has been set as a percentage of the amplitudes maximum value in the signal in order to make the detection of R-peaks adaptive. The threshold value η is calculated as in (3),

$$\eta = (0.6 \pm 0.1) \times \max_{i=1}^{N} (e[i]) \tag{3}$$

where N is the length of the signal and the thresholding is implemented as given in (4),

$$e_{th}[n] = \begin{cases} 0, & e[n] < \eta \\ e[n], & otherwise \end{cases} \tag{4}$$

where $e_{th}[n]$ is the signal for further processing after thresholding. When the thresholding is done, the noise spikes are eliminated which reduces the number of false detections that affect the performance under noisy ECG signal with long pauses.

Third, Shannon energy (SE) computation is then performed on the signal to improve the R-peaks detection accuracy in the ECG signal with wide QRS and small QRS complexes. The thresholded energy signal is first normalized and then the normalized Shannon energy signal is computed which is represented as s[n].

Using an FIR filter, the Shannon energy values are smoothed to reduce the effect of more than one peak around a QRS complex region due to the presence of wide and small QRS complexes. After the smoothing process is performed on the signal s[n], it is observed that the location of the candidate R-peaks in the s[n] signal correspond to approximate R-peaks locations in the ECG signal.

The peak finding is achieved by means of a FOGD that finds the location of candidate R-peaks in the SE envelope after the above processes are done.

The M point Gaussian window is defined as in (5)

$$w[m] = e^{\frac{-1}{2}\frac{(m-\frac{M}{2})^2}{\sigma^2}}, m = 1,2,3,....,M-1 \quad (5)$$

where M is the length of the signal and the FOGD is computed as in (6)

$$w_d[m] = w[m+1] - w[m] \quad (6)$$

which gives the slope at each sample.

Fourth, the convolution output of $w_d[m]$ with the smoothened s[n] signal leads to a zero-crossing function which has both negative and positive zero crossings because of the anti-symmetric nature of the FOGD. The convolution of the Shannon energy signal and the FOGD function is computed as in (7),

$$z[n] = \sum_{k=-\infty}^{\infty} w_d[k]s[n-k] \quad (7)$$

This convolution process attenuates lower frequencies and retains the higher frequencies. The negative zero-crossings of this convolution output are used to find the exact location of the candidate R-peaks. Negative zero-crossings are places where z[n] moves from a positive to a negative value. The positions where the zero-crossings occur are used as a reference to find the actual R-peaks.

The location of true R-peaks is finally found by creating a window of a particular size around these candidate R-peaks and then locating the sample number where the amplitude of the ECG signal is maximum. The R-peaks detected through this method is plotted against the ECG signal and has been shown in Fig. 2. From the figure, it can be seen that the detected R-peaks are located at the maxima of each heartbeat which shows that R-peaks are detected accurately.

C. *RR intervals*

RR interval is the time interval between two successive R-peaks in an ECG signal. It is calculated as in (8),

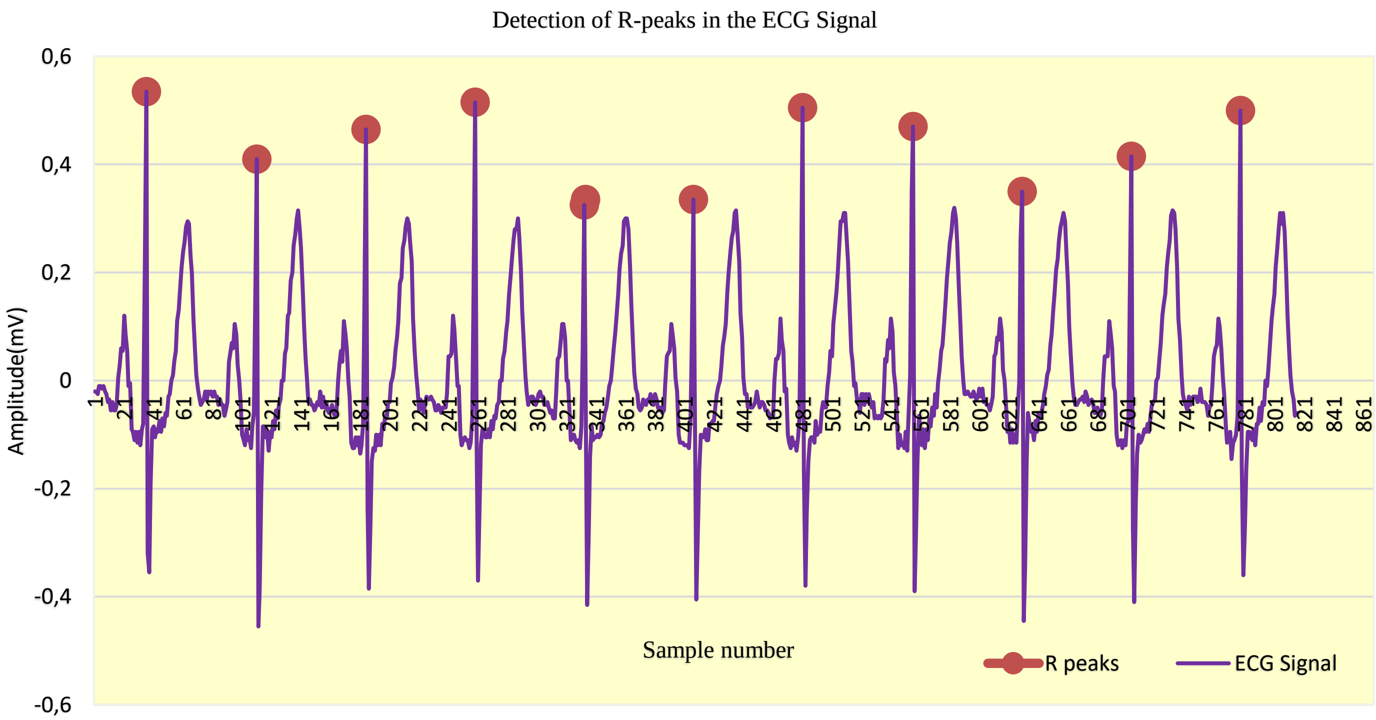

Fig. 2. Detected R-peaks by the proposed method plotted against input ECG signal

$$rr[j] = r(i+1) - r(i), \quad i = 1,2,3,....., N-1 \tag{8}$$

where r(i) represents the detected R-peak's location, rr(i) is the calculated R-R interval and N is the length of the ECG signal.

D. Feature extraction

The proposed method relies on a set of ECG signal features [5] which is an effective combination i.e., a hybrid of features. The selected features for classification by the proposed method are,

i) Mean values of the epochs of the R-R intervals.
ii) Standard deviation of the epochs of the R-R intervals.
iii) NN50 measure that specifies the number of times the first RR-interval exceeds the second R-R intervals by more than 5 samples.
iv) SDSD measure that specifies the standard deviation of the differences between adjacent R-R intervals.
v) RMSSD measure that is the square root of the mean of the sum of the squares of differences between R-R intervals.
vi) Mean absolute deviation values defined as the mean of absolute values obtained by subtracting the mean R-R interval value from all R-R intervals in the ECG signal.

The above features are used for training a classifier for the detection of the sleep apnea. The dataset is split into two sets where 80% of the dataset has been used for training and 20% of the dataset has been used for testing in this work.

E. Classification

For classification of the signal as apnea or non-apnea, all the records are labelled as 0 and 1 for non-apneic and apneic cases respectively for each one-minute intervals. These labels along with their features are classified into two sets – the training set and the testing set. The k-fold cross-validation procedure is performed with k = 10, aimed at improving the performance of the classifier. For comparison with other methods, evaluation metrics such as accuracy, specificity and sensitivity are calculated.

In the classification phase, the Support Vector Machine (SVM) has been used which is a common machine learning algorithm. It is used in binary classification tasks to find the maximum margin hyperplane separating the two classes. The SVM here is implemented with Gaussian Radial Basis Function (RBF) kernel. The kernel is defined as in (9),

$$K(x_i, x_j) = e^{-\gamma \|x_i - x_j\|^2} \tag{9}$$

where γ is the variance (similarity) between two points. A large value of γ means a small variance and a lower value of γ means a large variance. Small variance corresponds to two points being similar when they are together and large variance corresponds to two points being similar when they are distant. The SVM model is then trained with the features extracted from the ECG signal. Once the training is done, test signals are passed onto the model for prediction of sleep apnea.

The SVM model is used along with the Grid Search Algorithm. The values for the parameters such as soft margin, C and the variance γ are estimated with the Grid Search algorithm for attaining the best result using the classifier. Grid Search performs an iterative search over a set of predefined values for each parameter in the classifier and returns the best set of values for each parameter for which the performance of the classifier is the highest.

Thus to extract the features, the R-peak detection method is used as explained earlier to find the R-R intervals. Based on these R-R intervals, different statistical features are calculated. The extracted features passed on to the classifier to obtain the result as apneic and non-apneic. After the training, the proposed method with the classifier is tested with the signals from the test dataset and the performances are verified in terms of the performance metrics.

IV. RESULTS

This section elucidates the experimental results obtained in terms of the performance metrics such as accuracy, specificity and sensitivity. In line with this, the features extracted are used to train and simulate the system. The signals from the test dataset are used to evaluate the performance of the classifier and the data provided to the classifiers are divided manually and ten-fold cross-validation is performed.

The proposed system is divided into two parts – one part for signal processing and feature extraction and another part for feature selection and classification. Initially, the first four features from the list using R-R intervals from ECG signal are extracted and an accuracy of 70.87%, specificity of 97.81% and a sensitivity of 2% have been achieved. It proves that the first four features are not enough to achieve good accuracy.

Later, additional features are extracted and the classifier is trained with these features. Now, with a total of six features, an accuracy of 88.88%, specificity of 95.91% and a sensitivity of 20% have been achieved. These results suggest about the evolution of the model. One of the points to be noted is that the specificity of the experimentation is high for this case, suggesting the ability of the proposed method to detect sleep apnea moments. The sensitivity is pretty constant at some point in case of non-apnea detections i.e., the sensitivity is high with more or fewer features. Also, the specificity is lower with more features than with fewer features.

With an increase in specificity, the sensitivity of the classifier reduces, which marks a reduced detection in the number of sleep apneic moments. It is observed here, the specificity of the model is 97.81%, with the sensitivity of 2% or lesser and when the specificity of the model is 95.91%, the sensitivity is around 20%.

Based on the number of features too, the accuracy, sensitivity and the specificity of the classification changes. The classifier parameters also play an important role in the performance of the proposed system which is optimized here with the Grid Search algorithm to yield high-performance metrics.

The training time varies between 1.5 - 2 hours for extracting features and training the SVM model. The time taken for performing grid search depends on the number of values fed for each parameter, and the predicting time for the test signal takes under a minute for classification. It is to be noted that the training speed depends on the platform and the computational resources used in addition to the proposed model. This experiment is performed in a laptop with features – Windows OS, Intel Core i7 – 6700 HQ CPU 2.6 GHz processor and 8 GB of RAM.

The confusion matrix is used for viewing the summary of classification of the testing dataset. Sleep apnea detection is a binary classification problem and thus the number of possible outcomes is four. This matrix displays the number of instances for each outcome. The performance metrics are also derived from this matrix thus serving as an important tool in defining the results of the system. Python software is used for the signal processing and classification procedure.

The evaluation parameters, accuracy, sensitivity and specificity are calculated as in (10), (11), (12),

$$Accuracy = \frac{T_N + T_P}{T_N + T_P + F_N + F_P} \tag{10}$$

$$Sensitivity = \frac{T_P}{T_P + F_N} \tag{11}$$

$$Specificity = \frac{T_N}{T_N + F_P} \tag{12}$$

where T_P, F_P, T_N, F_N are the true positive, false positive, true negative and false negative assessments of the confusion matrix respectively.

When the signal with a length of 1 hour is used, the following performances are obtained.

i) Case 1:

With six number of features, an accuracy of 87.03%, specificity of 93.87% and a sensitivity of 20% are achieved by the classifier. Grid Search has not been implemented in this case and the values of the SVM classifier parameters used are C = 1.4 and γ = 1.6. The results of the confusion matrix are as shown in Table I.

TABLE I
OBTAINED CONFUSION MATRIX FOR CASE 1

Input/ Output	**Regular**	**Apnea**
Regular	93.87%	6.13%
Apnea	80%	20%

ii) Case 2:

With six numbers of features, an accuracy of 88.88%, a specificity of 95.91% and a sensitivity of 20% are achieved by the classifier. Grid Search is implemented in this case and the values of the SVM parameters used are optimized for better performance of the classifier and, in this case, the values used in the classifier are C = 1.6 and γ = 1.8. The results of the confusion matrix are as shown in Table II.

TABLE II
CONFUSION MATRIX FOR CASE 2

Input/ Output	**Regular**	**Apnea**
Regular	95.91%	4.09%
Apnea	80%	20%

iii) Case 3:

With four numbers of features, an accuracy of 71.54%, a specificity of 99.16% and a sensitivity of 2% are achieved by the classifier. Grid Search is implemented in this case and the values used in the classifier are C = 1.2 and γ = 0.8. The results of the confusion matrix are as shown in Table III.

TABLE III
CONFUSION MATRIX FOR CASE 3

Input/ Output	**Regular**	**Apnea**
Regular	99.16%	0.84%
Apnea	98%	2%

iv) Case 4:

With four numbers of features and the entire ECG signal taken into consideration, an accuracy of 70.87%, a specificity of 97.81% and a sensitivity of 2% are achieved by the classifier. Grid Search is not implemented in this case and the values used in the classifier are C = 1.2 and γ = 1.4. The results of the confusion matrix are as shown in Table IV.

TABLE IV
CONFUSION MATRIX FOR CASE 4

Input/ Output	**Regular**	**Apnea**
Regular	97.81%	2.19%
Apnea	98%	2%

From the above results, it is observed that the maximum performance is attained with 6 features and when the optimization is performed using the Grid Search. Without Grid search, the performance of the classifier is relatively low. This clearly shows that the grid search has been crucial in determining the parameters for the classifier for its improved performance of the proposed system.

Also, when the selected number of features are four, the accuracy and sensitivity are observed to be less so this system cannot be considered reliable for the detection of sleep apnea. This proves that the number of features used in the classification too plays an important role in increasing the performance of the system.

TABLE V
PERFORMANCE COMPARISON OF SLEEP APNEA DETECTION APPROACHES

Name	Method	Accuracy	Sensitivity	Specificity
Almazaydeh [4]	Feature extraction of ECG signal	96.5	92.9	100
P de Chazal [5]	Frequency domain features extracted from ECG signal using linear discriminant	90.5	-	-
Andre Pinho [8]	Feature subset from the list of features available is used for classification	82.12	88.41	72.29
Smruthi & Suchetha [11]	Energy values obtained from R-peaks and the RR interval's standard deviations are used	97.5	95.45	-
P de Chazal, Nadi Sadr [16]	Features of both time domain and frequency domain are used	79	69	85
Almazaydeh, Khaled Elleithy [17]	Features from ECG, SPO2, Resp signals are used	97.1	-	-
Proposed method	**Time-domain features extracted from the ECG signal**	**88.88**	**20**	**95.91**

When the selected number of features is increased, the specificity of the classifier decreases. Also, we can see the inverse relationship exists between specificity and sensitivity; that is when the specificity increases, the sensitivity decreases and vice versa. It is also observed that ECG signals of one-hour duration perform better than that of the entire duration signal. Hence, depending on the duration of the signal, the performance of the classifier varies.

The results of the proposed system are comparable with other studies that use the same dataset (Physionet ECG-Apnea Database). A summary of all the other works using the same dataset is tabulated as in Table V for performance comparison. It can be observed that the accuracy and specificity are better than some of the published results and comparable to others. In addition to that, none of the above works contains an optimization process for the improvement of the performance of the system. In this proposed work, the use of the Grid Search has aided in improving performance. This can be used as an effective tool for improvement in systems for the screening of obstructive sleep apnea and building a reliable system for detection using ECG signals features.

V. Conclusion

In this work, the detection of sleep apnea is performed using ECG signals. The ultimate goal of this work is the use of Grid Search algorithm for the detection of sleep apnea with the use of a minimum number of features and maximizing the performance of the classification. The different studies demonstrate that the number of features meets different requirements in the performance and the classifiers induce different behaviours.

The model trained in this work supports clinical decision-making based on a single signal, that is the ECG for the detection of the sleep apnea. SVM classifier with RBF kernel is used for building a classifier model. Sleep apnea detection techniques generally use only machine learning algorithms for classification. But the use of Grid search algorithm makes it more effective by optimizing the parameters that could higher the performance of the model. Several values are assigned to each parameter and the Grid search builds a model for each parameter combination. Amongst it, the model with the highest performance is returned. Machine learning and Grid Search algorithm can thus be seen as a powerful combination in improving the performance of the model. Thus without much stress and long hour skilled person's monitoring, OSA can be diagnosed in a more comfortable manner by the proposed method.

In order to make the system more effective, features based on ECG derived respiratory (EDR) signals can also be extracted. The energy of the respiratory signal can be used as a means to detect sleep apnea, since the energy changes during breath and breath-hold. Optimization technique can also be performed for proper selection of feature set that can improve the performance of the model to a major extent.

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